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Human impact on wildfires varies between regions and with vegetation productivity

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Human impact on wildfires varies between regions and with vegetation productivity

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Abstract. We assess the influence of humans on burned area simulated with a dynamic global vegetation model. The human impact in the model is based on population density and cropland fraction, which were identified as important drivers of burned area in analyses of global datasets and are commonly used in global models. After an evaluation of the sensitivity to these two variables we extend the model by including an additional effect of the cropland fraction on the fire duration. The general pattern of human influence is similar in both model versions: The strongest human impact is found in regions with intermediate productivity, where fire occurrence is not limited by fuel load or climatic conditions. Human effect in the model increases burned area in the tropics, while temperate regions burned area is decreased. While the population density is similar in average for the tropical and temperate region the cropland fraction is higher in temperate regions and leads to a strong suppression of fire. The model show a low human impact in the boreal region where both population density and cropland fraction is very low, but also the climatic conditions often limit fire as well as the vegetation productivity. Previous studies attributed a decrease in fire activity found in global charcoal datasets to human activity. This is confirmed by our simulations which only show a decrease in burned area when the human influence on fire is accounted for and not with only natural effects on fires. We assess how the vegetation-fire feedback influences the results by comparing simulations with dynamic vegetation biogeography to simulations with prescribed vegetation. The vegetation-fire feedback increases the human impact on burned area by 10 % for present day. These results emphasize that projections of burned area need to account for the interactions between fire, climate, vegetation and humans.

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1. Introduction

Fire appeared on Earth around 400 million years before present (Scott 2000) and shaped the evolution of ecosystems and plant traits (Pausas & Schwilk 2012). Humans started to use fire approximately 1-1.4 million years ago, which was an important step in the evolution of human technology (Berna et al. 2012, Gowlett et al. 1981). Habitual use in Europe followed 300-400 thousand years before present (Roebroeks & Villa 2011).

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3 *Human impact on wildfires varies between regions and with vegetation productivity* 2
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5 This tight connection and long evolution of fire, vegetation and humans hampers the
6 separation between natural and anthropogenic fire regimes. Here we use a global
7 modeling approach to separate human influences on burned area from the natural fire
8 occurrence.
9

10 Humans influence different aspects of fire regimes including number of fires, fire
11 size (Hantson, Pueyo & Chuvieco 2015), burned area, intensity, emissions or the
12 seasonality (Magi et al. 2012). Humans directly influence the area burned by igniting
13 and suppressing fires, but also indirectly by modifying the vegetation structure and
14 composition and by fragmenting the landscape (Bowman et al. 2011). These direct
15 and indirect effects can either promote or suppress fire. Conversion of forest to
16 grasslands, can lead to a higher flammability of the landscape increasing fire occurrence
17 (Cochrane 2003). In contrast a reduction or limitation of fire spread due to human
18 acting is expected due to harvesting or built infrastructure.
19

20 Satellite data provide detailed information on fire regimes and reveal a strong human
21 influence across the globe (Archibald et al. 2013). The spatial patterns suggest a decrease
22 in burned area with increasing population density (Bistinas et al. 2014, Knorr et al. 2014)
23 or cropland fraction (Bistinas et al. 2014, Andela & van der Werf 2014). The human
24 influence was also detected in a trend analysis, showing a strong decrease in burned area
25 over the last two decades (Andela et al. 2017).
26

27 In charcoal records, variations which oppose the trend expected due to climatic
28 conditions are interpreted as human driven (Marlon et al. 2008). The increase in charcoal
29 records from 1750-1870 is attributed to human influence, linked to population growth
30 and land-use changes, and a subsequent decrease, due to intensification of land use.
31 The trends in the charcoal record are confirmed by CO ice core records for the Southern
32 Hemisphere (Wang et al. 2010).
33

34 The human influence on fire regimes is also observed locally: Analysis of single charcoal
35 records in New Zealand show a strong change in fire regime with an increase in fire
36 occurrence after the arrival of humans (McWethy et al. 2010). In the tropics land use
37 change is known to influence the fire regime and has potential to modify large parts
38 of this important biome (Cochrane 1999). The higher flammability of deforested areas
39 leads to higher fire occurrence and can further damage the surrounding forested areas
40 and amplify the influence of fires set by humans on the vegetation and fire regime
41 (Cochrane 1999).
42

43 In this study we assess the influence of humans on fire occurrence in terms of burned
44 area in a global fire enabled dynamic vegetation model JSBACH-SPITFIRE. We first
45 evaluate the model along the human dimensions included in the model, which are
46 population density and the cropland fraction, and extend the model with a stronger
47 influence of the cropland fraction. We then investigate where burned area is strongly
48 influenced by humans. We further assess whether the feedback between vegetation
49 and fire amplifies the human impact. We discuss limitations and uncertainties of our
50 approach and compare our results to available literature.
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Human impact on wildfires varies between regions and with vegetation productivity 3

2. Model description and simulation setup

2.1. JSBACH-SPITFIRE

JSBACH (Raddatz et al. 2007, Brovkin et al. 2009) is the land surface model of the MPI Earth system model (MPI-ESM) (Giorgetta et al. 2013). We use the JSBACH version with the soil carbon model YASSO (Goll et al. 2015). The process-based fire model SPITFIRE (Thonicke et al. 2010) has been evaluated for present day burned area and carbon emissions (Lasslop et al. 2014) and is described in detail and in comparison to other global fire models in Rabin et al. (2017). JSBACH simulates the terrestrial carbon and water cycle in a process based way. It provides fuel amounts, vegetation composition and soil moisture for the fire model. The fire model reduces the carbon pools according to the simulated combustion of biomass and computes a tree mortality due to fire. Fire can start if ignitions (lightning or human) occur and a sufficient amount of fuel leads to sufficiently high fire line intensity. Based on the fuel size and moisture the combustion completeness and a rate of fire spread is computed. The combination of the rate of spread with the fire duration (see below) yields the burned area. Tree mortality is a function of the fire line intensity and the residence time of the fire. SPITFIRE accounts for the human influence based on population density and the cropland fraction. Population density (P_D [inhabitants km⁻²]) is used to compute the human ignitions ($n_{h,ig}$).

$$n_{h,ig} = P_D 0.4 e^{-0.5\sqrt{P_D}} a(N_d) / 100 \quad (1)$$

The factor 0.4 was adjusted to tune the model to reproduce the global burned area of the GFED3 dataset (Giglio et al. 2010). The regionally varying factor ($a(N_d)$) was introduced to reflect regional and cultural differences in the human use of fire as a tool. As the burned area fraction varies globally by several orders of magnitude, the factor (which varies between 0.11 and 0.33) has rather low influence. This was found in a study using ORCHIDEE-SPITFIRE (Yue et al. 2014). For JSBACH-SPITFIRE simulations without vegetation dynamics the spatial variability of ignitions has low influence on the spatial patterns of burned fraction (Lasslop et al. 2014). The JSBACH-SPITFIRE model reduces the fire duration (D_F in minutes) with increasing population density to improve the relationship between population density and fire size (Hantson, Lasslop, Kloster & Chuvieco 2015). The maximum fire duration was increased from 4 hours in the original model version (Thonicke et al. 2010) to 12 hours (Hantson, Lasslop, Kloster & Chuvieco 2015), assuming that most fires cease during night. While fires in reality often continue during night, in the model due to the low variation of ignitions, a new fire will start the next day unless the conditions for a fire changes (changes in moisture conditions or fuel load) and therefore reduce the influence of the 12 hours threshold on longer term fire occurrence. D_F is computed in three different ways: (1) as a function of the fire danger index (FDI):

$$D_F = \frac{723}{1 + (240 \cdot e^{-11.06 \cdot FDI})} \quad (2)$$

Human impact on wildfires varies between regions and with vegetation productivity 4

(2) using P_D and the FDI:

$$D_F = \begin{cases} \frac{723}{1+(240 \cdot e^{-11.06 \cdot FDI})} & \text{if } P_D \leq 0.01 \\ \frac{241 \cdot (4 - \log_{10}(P_D)) \cdot 0.5}{1+(240 \cdot e^{-11.06 \cdot FDI})} & \text{if } 0.01 < P_D < 100 \\ \frac{241}{1+(240 \cdot e^{-11.06 \cdot FDI})} & \text{if } P_D \geq 100. \end{cases} \quad (3)$$

and (3) additionally reducing D_F with increasing cropland fraction (f_{crop}) by multiplying eq. 3 with $(1-f_{crop})$. The first approach is used when no human influence is included, the second includes human influences and the third is an extension to improve the model's sensitivity to the cropland fraction (see Appendix).

Land use is included in JSBACH following the protocol of Hurtt et al. (2011) and described in detail in Reick et al. (2013). In SPITFIRE fires are excluded from cropland area and pastures are treated the same as natural grasslands. Moreover, land use influences fire by changing the carbon stocks of the available fuels (Wilkenskjeld et al. 2014).

In this study we use JSBACH in the offline mode, forced with meteorological forcing which was extracted from simulations with the MPI-ESM version 1.1 for the historical period 1850-2005. The spatial resolution is $1.875^\circ \times 1.875^\circ$ and the temporal resolution is 30 min. The fire routine is called once a day. For the spinup the first 28 years of forcing (1850-1877) were recycled and CO_2 concentration fixed at the value of 1850 (284.725 ppm). The historical simulation from 1850 to 2005 uses transient climate, CO_2 concentration and land use. The population dataset is based on (Klein Goldewijk 2001). The decadal temporal resolution is interpolated to annual values and updated in the beginning of the year.

2.2. Simulations

To assess the impact of humans on the fire regime we compare burned area from simulations with (simulation name includes tag "human") and without human influence (tagged "natural"). We include two different ways of accounting for the human impact on the fire duration. The first decreases the fire duration with population density the second additionally reduces fire duration with increases in the cropland fraction (tag "Crops"). As the representation of human ignitions in the model already includes a suppression of ignitions for high population density the simulations cannot factor out fire suppression by humans, only the combined effect of human enhancement and suppression of fires can be separated. A decrease in burned area when including human effects however indicate that human suppression dominates, while an increase in burned area would indicate that the additional ignitions are more important. We assess the importance of the feedback between fire and vegetation on the influence of humans on the fire regime, by comparing simulations with (DynVeg) and without (FixVeg) dynamic vegetation. In that case a consistent initial vegetation cover was necessary and land use needed to be included (NaturalLU simulations). Therefore only the

Human impact on wildfires varies between regions and with vegetation productivity 5

Table 1. List of simulations with settings for the computation of ignitions, fire duration, land use and vegetation dynamics.

Simulation	Human ignitions	Reduced fire duration due to		Land use	Vegetation dynamics
		Population density	Crops		
HumanDynVeg	yes	yes	no	yes	yes
HumanDynVegCrops	yes	yes	yes	yes	yes
NaturalDynVeg	no	no	no	no	yes
NaturalLUDynVeg	no	no	no	yes	yes
HumanFixVeg	yes	yes	no	yes	no
NaturalLUFixVeg	no	no	no	yes	no

amplification of vegetation dynamics on the direct human influence on ignitions and fire suppression could be assessed. The effect of the fire-vegetation feedback on the human impact was quantified by comparing the difference between the HumanDynVeg and NaturalLUDynVeg to the difference between the HumanFixVeg and NaturalLUFixVeg simulations. Overall six simulations with different settings in the computation of ignitions, fire duration, land use and vegetation dynamics were performed (Table 1). We performed a spinup simulation of 1000 years for the simulations with dynamic natural vegetation. The spinup period with the fixed vegetation cover was only 300 years, as only the rather fast litter carbon pools need to be in equilibrium to stabilize the fire regime.

Data analysis and plotting was done using R 3.3.3 (R Core Team 2016). In the regional analysis we define the boreal region as all grid cells with latitudes $>60^\circ$, the temperate region with latitudes between -30° and -60° or 30° and 60° , and the tropical with latitudes between -30° and 30° .

3. Results

3.1. Human impact on the burned area

3.1.1. Global impact and spatial patterns We assess the influence of humans on burned area by comparing the simulation HumanDynVeg (includes human set fires, fire suppression as a function of population density and land use) or simulation HumanDynVegCrops (additionally including suppression as a function of the cropland fraction) with the simulation NaturalDynVeg (only lightning ignitions and no human influence). Globally we can find regions with increased and lower burned area due to human influence for present day (Figure 1). The spatial patterns of the effect of humans is similar for both simulations including the human effects, HumanDynVeg and HumanDynVegCrops. We find a strong suppression of burned area in regions with high population density and high cropland fraction (Eastern part of the USA and Europe, India). Overall we find suppression of fire mostly in the temperate regions. Tropical regions (except India) mainly show strong increases in burned area due to the human

Human impact on wildfires varies between regions and with vegetation productivity 16

Difference in burned fraction of gridcell

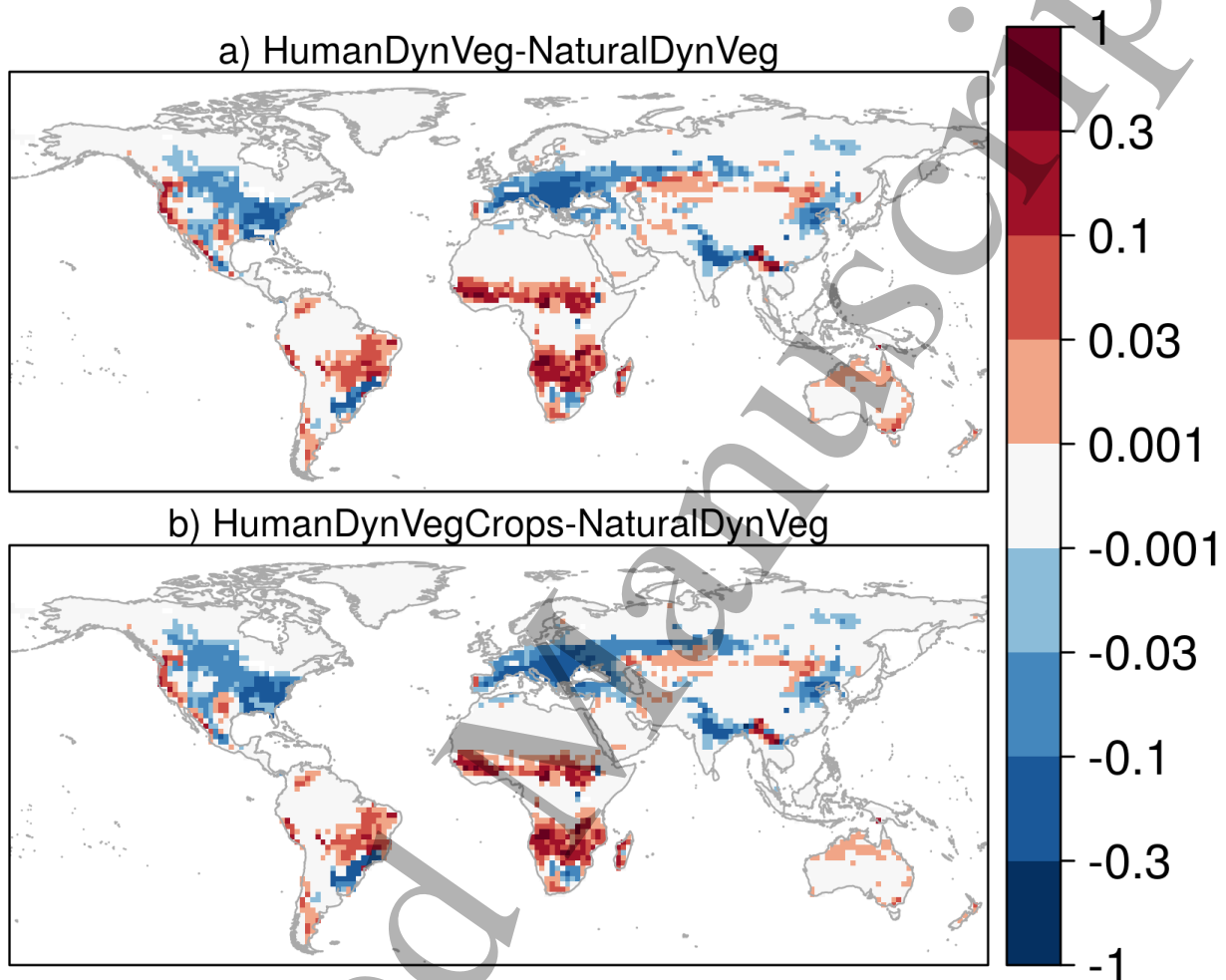


Figure 1. Global distribution of differences in burned fraction with and without human influence. Based on a comparison of the HumanDynVeg and NaturalDynVeg simulation a) and on a comparison between HumanDynVegCrops and NaturalDynVeg b) for present day (average over the years 1996-2005).

impact (Figure 1,2 a), indicating that there the influence of higher ignitions is strong and fire is limited by ignitions. The correlation between the differences in burned area and the human ignitions of the simulation HumanDynVeg and NaturalDynVeg is low ($R^2 = 0.1$), but highly significant (p -value <0.001). The low correlation between human ignitions and change in burned area due to human effects indicates that the effect of increases in ignitions are strongly modulated by other factors, such as climate and vegetation.

From pre-industrial to present day (over the period from 1870 to 2005) burned area decreases by 19.6 % (HumanDynVeg) and 23.6 % (HumanDynVegCrops) if human influences are accounted for (Table 2). In contrast the simulation considering only

Human impact on wildfires varies between regions and with vegetation productivity 7

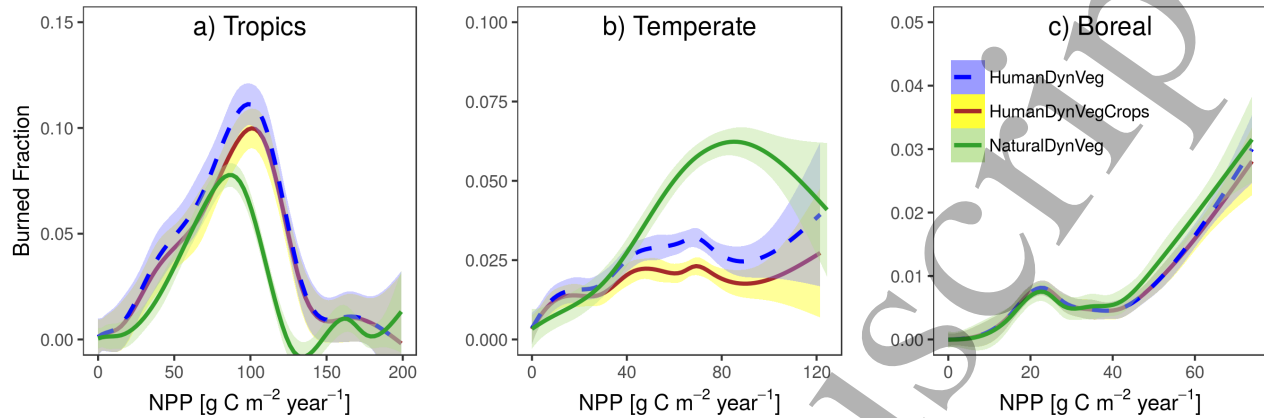


Figure 2. Burned fraction along a gradient of NPP for tropical (a), temperate (b) and boreal regions (c) for present day (average over the years 1996-2005). Lines were fitted using generalized additive models, shaded areas indicate the 95% confidence interval of the mean. Please note the different scales for both axis of the subplots.

Table 2. Global burned area [Mha] for preindustrial (average over 1860-79) and present day (average over 1996-2005) for all simulations.

Simulation	Burned area preindustrial	Burned area present day
HumanDynVeg	449.21	361.16
HumanDynVegCrops	413.20	315.61
NaturalDynVeg	289.76	305.42
NaturalLUDynVeg	228.26	222.84
HumanFixVeg	449.86	366.36
NaturalLUFixVeg	279.46	242.65

natural effects shows a 5.4 % increase in burned area.

3.1.2. Human impact on burned area along gradients of plant productivity The human impact on burned area along gradients of plant productivity is similar for the simulations HumanDynVeg and HumanDynVegCrops. The additional suppression in simulation HumanDynVegCrops leads to a lower burned area. The effect of humans is generally low at low NPP ($< 40\text{gCm}^{-2}\text{year}^{-1}$) (Figure 2). Burned area in regions with low productivity is limited by the fuel buildup (Krawchuk & Moritz 2011, Bistinas et al. 2014). In the tropical region both simulations with human influence show an increase in burned area for intermediate NPP compared to the simulation without human influence, for low and high NPP the difference is small (Figure 2 a). Moreover, the human impact shifts the maximum of burned area towards higher productivity in the tropical regions. While for low productivity burned area is limited by the available fuel, for high NPP climatic conditions are increasingly limiting.

In temperate regions the influence of humans reduces the burned area at intermediate

Human impact on wildfires varies between regions and with vegetation productivity

to high NPP values ($40\text{-}110\text{gCm}^{-2}\text{year}^{-1}$) (Figure 2 b). Population density is in average similar for tropical and temperate regions, cropland fraction is however 50% higher in temperate regions leading to a reduction in burned area in contrast to the higher burned area in the tropics. Another potential explanation is the difference between modeled human and lightning ignitions: Human ignitions are assumed constant within the year, while the lightning ignitions include a seasonality. In temperate regions the lightning strikes are most frequent in summer, the season with high fire risk. In the tropics the number of lightning strikes is highest in the rain season, where fire occurrence is limited by meteorological conditions. This may lead to an ignition limitation in the tropics during the dry season.

For the boreal region no significant differences (95% confidence intervals of the fitted lines overlap) are simulated (Figure 2 c). In the boreal regions NPP is rather low (below $74\text{gCm}^{-2}\text{year}^{-1}$), burned area there is, however, not only limited due to the low productivity but also by shorter periods with high fire risk. Low population density in the boreal region (factor 100 lower compared to temperate and tropical regions) and smaller cropland fraction (in average 0.003 compared to 0.1 in the tropics and 0.15 in temperate regions) additionally explain the small difference between the simulations with and without human impact.

3.2. Amplification of human impacts through vegetation dynamics

Fire leads to a reduction in woody vegetation and an increase in highly flammable herbaceous vegetation, forming a positive feedback. Due to this positive feedback alternative stable states under the same climatic conditions occur in JSBACH-SPITFIRE (Lasslop et al. 2016). This means that increases in burned area can lead to a crossing of a tipping point driving the system in a stable low tree cover state with higher burned area. The effect of humans on fire is therefore expected to be higher in simulations with dynamic vegetation cover. The effect is quantified by comparing the difference between the HumanDynVeg and NaturalLUDynVeg simulation to the difference between the HumanFix and the NaturalLUFix simulation. Both increases and decreases due to the human impact are stronger if vegetation cover is dynamic (Figure 3). When vegetation cover is fixed the human impact increases the burned area for preindustrial from 287.16 (NaturalLUFix) to 454.83 (HumanFix) Mha (58 %), while including the feedback between fire and vegetation the human impact increases the burned area from 235.46 (NaturalLUDynVeg) to 456.61 (HumanDynVeg) Mha (93 %). If the vegetation-fire feedback is excluded the differences in global burned area caused by the human impact are reduced by 24 % in the pre-industrial period and 10 % for present day (Table 2, (HumanFix-NaturalLUFix) divided by (HumanDynVeg-NaturalLUDynVeg)). The lower effect for present day might be due to the larger areas controlled by human land use.

Human impact on wildfires varies between regions and with vegetation productivity 9

Difference in burned area (Human - Natural) [fraction of gridcell]

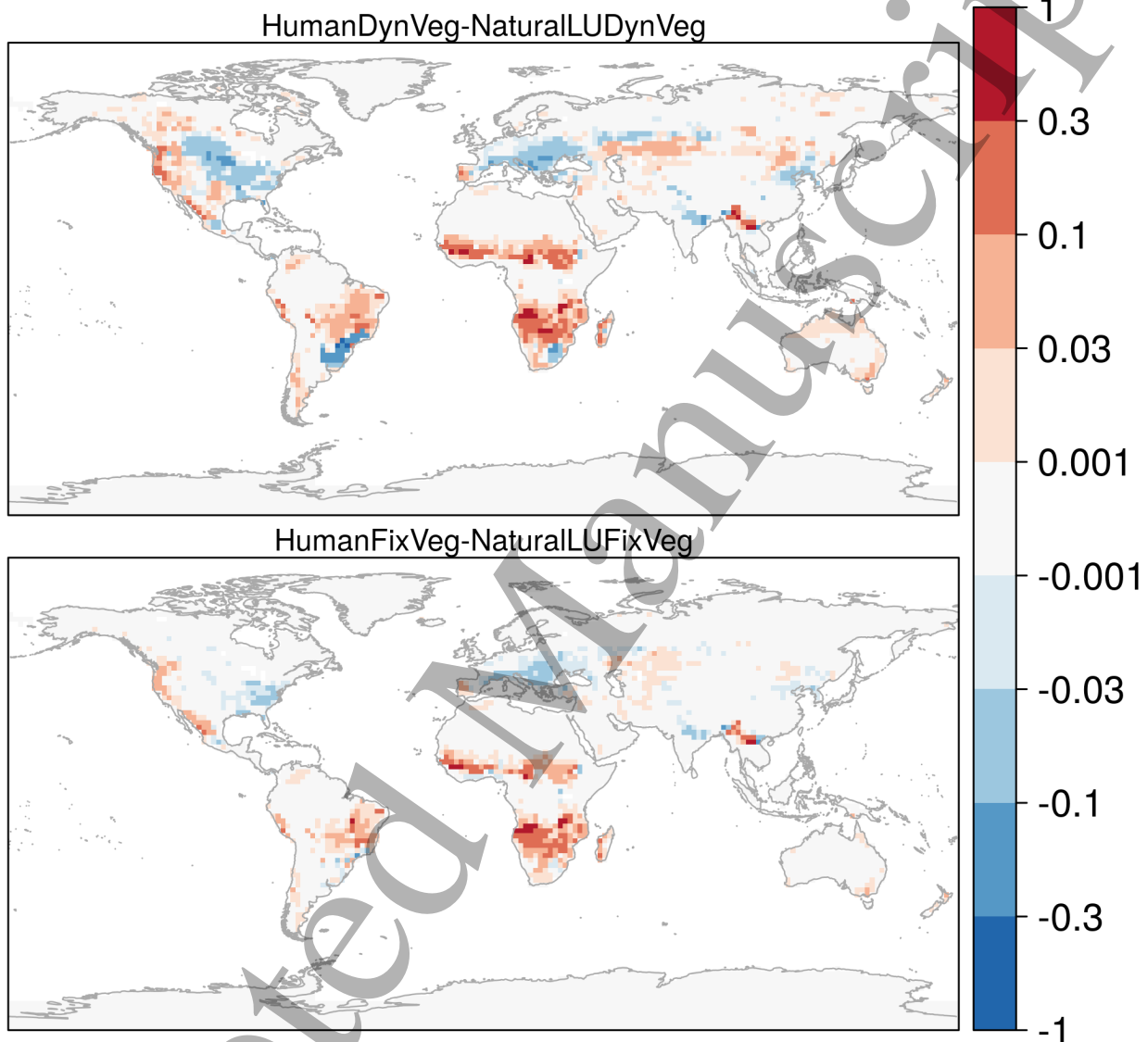


Figure 3. Human impact for present day with dynamic vegetation (HumanDynVeg-NaturalLUDynVeg) and fixed vegetation (HumanFix-NaturalLUFix).

4. Discussion

4.1. Uncertainties in modeling the human impact on fire

Over the last century technological advances in fire fighting and increased resources spent on fire management have certainly impacted the human capacity to suppress fires. Humans change the local vegetation in many ways that may influence the fire regime, for instance the introduction of new species with higher flammability can increase the area burned or land management leading to a fuel reduction through harvest or

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3 *Human impact on wildfires varies between regions and with vegetation productivity* 10
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5 grazing can lead to a reduction of burned area (Bowman et al. 2011). These effects,
6 especially their variation over time, are not represented in the model. The limited
7 generalizable understanding and lack of global information limit the possibilities to
8 reflect this knowledge in global models. The representation of humans in global models
9 is largely based on data analyses of spatial datasets, which show that human parameters
10 (e.g. population density and land use) do explain part of the variation observed for
11 burned area and how they influence burned area.

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14 Modeling human ignitions and suppression as a function of population density is common
15 in global fire models (Hantson et al. 2016). It is often assumed that for low population
16 density ignitions increase and that for high population densities fires are increasingly
17 suppressed. Some models include the suppression for high population density in the
18 function of the ignitions, others include this influence only or additionally on the rate
19 of spread or fire duration and some models include the human suppression in a scaling
20 function that reduces burned area directly (Hantson et al. 2016, Rabin et al. 2017).
21 The suppression of fire for high population density is however now common in global
22 fire models (Hantson et al. 2016, Rabin et al. 2017). This spread in the representation
23 of human impact in models reflects the versatile results of data analysis. On global
24 scale, based on multivariate analysis of global spatial datasets an increase in burned
25 area with increases in population density even for very low population densities was
26 not (Bistinas et al. 2013) or only with high uncertainty (Knorr et al. 2014, Lasslop
27 et al. 2015) detected. In a study for Africa an increase for low population density was
28 found for the number of fires but not for the burned area (Archibald et al. 2009). When
29 applying statistical models to smaller regions in the United States response functions
30 with a distinct maximum, similar to the modeling approach used here were detected for
31 many regions, but the exact shape strongly varied (Parisien et al. 2016).

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34 In the evaluation of the modeled burned fraction along increasing population density
35 we found an underestimation of burned fraction for high and low population densities
36 (Figure A1). These regions with high underestimation however only contribute 2.5% to
37 the global burned area. Occurrence of ignitions in the model is based on the lightning
38 and population datasets, as humans might also set fires in uninhabited places or lightning
39 strikes might not be tracked. A small background ignition rate might help to overcome
40 this model error. Due to the small contribution of these areas to the total burned area
41 we expect that this can only have a small influence on the modeled spatial patterns of
42 human impact. We do not find an indication that our approach of increasing ignitions for
43 low population densities and then decrease after a certain threshold should be replaced
44 by a function that represents only suppression of humans as indicated by some global
45 data analysis (Bistinas et al. 2013, Knorr et al. 2014).

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48 The second human dimension in global fire models is the fraction of croplands. Global
49 data analysis confirms that the effect of croplands is to reduce burned area (Bistinas
50 et al. 2014, Andela & van der Werf 2014). Croplands are often simply excluded from
51 burning in fire models (Rabin et al. 2017). LPJ-LMfire is an exception and includes
52 a passive fire suppression assuming that the cropland fraction is a good proxy for
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3 *Human impact on wildfires varies between regions and with vegetation productivity* 11

4 landscape fragmentation (Pfeiffer et al. 2013).

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6 Overall our model based study therefore shows a plausible picture of limited influence
7 of humans on burned area in regions with low vegetation productivity or meteorological
8 conditions limiting burned area. The strong suppression of humans due to dense
9 population and croplands in temperate regions is well supported by literature and
10 expected for other global fire models due to a similar representation of the human
11 impact. The effects of humans in sparsely populated areas are most uncertain based on
12 available literature and comparing global model structures (e.g. whether they allow for
13 anthropogenic enhancement of burned area). We find enhancement of burned area due
14 to the human influence mostly in the tropics where due to the lower cropland fraction (in
15 average cropland fraction is 50% higher in the temperate regions). A lower suppression
16 for the tropical regions compared to the temperate regions can therefore be expected
17 also for models not allowing for an enhancement of burned area due to human ignitions.
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24 *4.2. Comparison with previous studies on the human effect on fire*

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26 Besides the satellite data analyses discussed in the previous section paleo-data contain
27 information on the variability of fire. These datasets are especially valuable as they cover
28 long time periods. On the other hand the uncertainty of the datasets is larger and it is
29 less clear which aspect of the fire regime is captured (Brücher et al. 2014). Variability in
30 the charcoal record could be the result of variations in the area burned or variations in
31 the biomass consumed, for instance due to changes in vegetation composition. Charcoal
32 (Marlon et al. 2008) and ice core (Wang et al. 2010) data indicate a strong decrease in
33 biomass burning between the pre-industrial era and present day. This decrease has been
34 attributed to human action, as the decrease in fire occurrence is associated with a strong
35 increase in population density, while the climate records cannot explain a decrease in
36 fire occurrence. Our results confirm these previous findings, showing a strong decrease
37 in burned area only, when human effects are included.
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41 Previous studies have posed hypothesis about the effect of humans on fire regimes based
42 on charcoal data analysis and theoretical considerations (McWethy et al. 2013, McWethy
43 et al. 2010). They suggest that in temperate regions the influence of humans amplifies
44 fire in regions with high net primary productivity (NPP), while for intermediate NPP
45 suppression is expected (McWethy et al. 2013). Our model results show the suppression
46 for intermediate NPP, which disappears for higher NPP, but do not show an increase
47 of burned area due to human influence for high NPP. Paleo records indicate that the
48 arrival of humans is often followed by a strong increase in fire occurrence (McWethy
49 et al. 2010). Although the model approach does not distinguish between initial and
50 later phases of human settlement, the cropland fraction might be an indicator for this
51 development. In temperate regions for present day humans have already passed this
52 initial phase and the region is now mainly characterized by fire suppression.
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56 In tropical regions a study investigating the effect of different burning patterns in tropical
57 savannas did not find effects on the total area burned (Van Wilgen et al. 2004). However,
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3 *Human impact on wildfires varies between regions and with vegetation productivity* 12

4 increases are expected, especially if the disturbance of primary forests lead to a higher
5 flammability of the landscape (Cochrane 1999). Based on the uncertainties in how to
6 model the effect of humans for low population densities and the variety of results from
7 data analysis (see above), we consider the very strong enhancement in the tropics as
8 most uncertain.
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12 13 **5. Conclusions**

14
15 We assess the impact of humans on the global wildfire distribution based on a global
16 vegetation model and compare the results to previous studies. The model accounts for
17 the human influence based on population density and land use, which are commonly
18 used human parameters in global fire models. The model reproduces the sensitivity of
19 burned area to both variables in comparison to satellite datasets. This study shows
20 that including the human dimension in global fire modelling is crucial and confirms the
21 human driven decrease since preindustrial times observed in the global charcoal dataset.
22 We find that the human impact is low for the boreal region, strongly suppresses fire in
23 the temperate regions and enhances fire in the tropical regions. The difference between
24 temperate and tropical regions is likely due to the higher land use in the temperate
25 regions, while the low impact in boreal regions can be explained by a much lower
26 population density and cropland fraction. We find the strongest human influence in
27 regions with intermediate productivity, where burned area is neither strongly limited
28 by fuel availability nor by climatic conditions. We show that the interaction between
29 fire and vegetation dynamics amplifies the human impact. This feedback will be
30 important not only when investigating the human impact on fire, but also in other
31 studies investigating changes in fire regimes or changes in vegetation in fire affected
32 areas. Projections of fire occurrence need to understand and account for the interactions
33 between fire, climate, vegetation and humans.
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43 **6. Acknowledgements**

44
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48 like to thank the DKRZ for the excellent computing facilities.
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52 **Appendix A. Evaluation of the response of burned area to the human** 53 **dimensions**

54
55 To evaluate the impact of humans on the simulated fire occurrence we compare the
56 simulated burned area to burned area derived from satellite data for present day along
57 a gradient of the human dimensions of the model, these are population density and
58 cropland fraction (Figure A1). We use the burned area datasets of the GFED database
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Human impact on wildfires varies between regions and with vegetation productivity 13

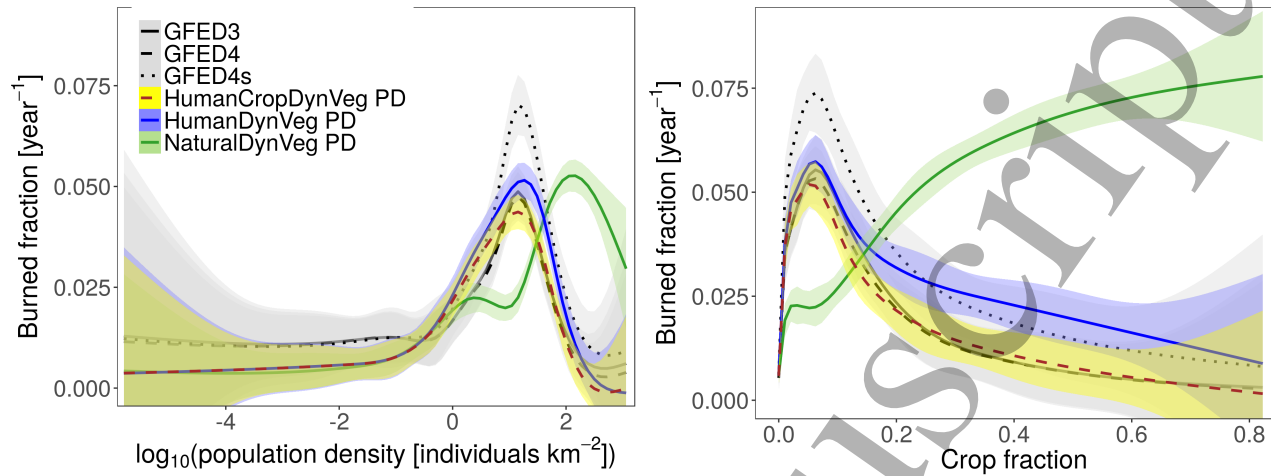


Figure A1. Average annual burned area along a gradient of the logarithmic population density (left) and cropland fraction (right) for present day (average over 1996-2005 for the model simulations and 1997-2006 for the GFED burned area datasets (version 3, 4 and 4s), population density is representative for the year 2000, cropland fraction is the model mean over 1996-2005). Lines were fitted using generalized additive models, shaded areas indicate the 95% confidence interval of the mean.

version 3 (Giglio et al. 2010), 4 (Giglio et al. 2013) and 4s (Randerson et al. 2012). The simulations including the human impact show a similar variation of burned area for different population densities compared to the GFED burned area datasets. The GFED4s dataset shows higher maximum values for the burned fraction than GFED3 and GFED4. GFED4s includes small fires that are usually not captured. These small fires are mostly burned croplands. Cropland burning is not included in JSBACH-SPITFIRE, the comparability of the model is therefore higher with GFED3 and GFED4. The model reproduces the maximum value of the GFED3 and 4 dataset well, but underestimates fire occurrence for low and high population density. The simulation without human effects on the fire regime shows a maximum for higher population densities compared to the observations, the simulation underestimates burned area for low population densities and overestimates burned area for high population densities.

The evaluation along the cropland fraction shows an overestimation of burned fraction for high cropland fraction if the model does simply exclude croplands from burning. Including croplands in the computation of the fire duration (simulation HumanDynVegCrops) improves the mismatch for high cropland fraction. The simulation without human effects mainly increases the burned area with increasing cropland fraction and is not able to reproduce the observed pattern with a maximum for a cropland fraction of around 0.05.

The comparison between the simulations including and excluding human effects confirms that, both human effects, humans as an additional ignition source and the suppression of humans on fire spread are important to reproduce the variation of burned area along gradients of human influence. Natural fire regimes would be shifted towards regions with

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3 *Human impact on wildfires varies between regions and with vegetation productivity* 14

4 stronger human influence. The spatial correlation with the GFED4 dataset increases
5 from 0.05 for the NaturalDynVeg simulation to 0.38 for both simulations including the
6 human impact.
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9 Another benchmark for the human influence on burned area was recently provided by
10 Andela et al. (2017). Satellite data show a negative trend in global burned area over
11 the last 18 years, which was attributed to the human influence (Andela et al. 2017). As
12 our simulations only cover the period until the year 2005, we recomputed the trend over
13 the years 1997-2006 for GFED version 3 and 4. To account for the uncertainty due to
14 the high interannual variability, we computed the trend 10 times, each time excluding
15 one year. We find negative trends for GFED version 3 (-2.6 to -1.2% per year), mixed
16 trends for GFED version 4 (-0.5 to 0.6% per year), negative trends for the HumanDynVeg
17 simulation (-0.6 to -0.02%) and mixed trends for the HumanDynVegCrops simulation
18 (-0.5 to 0.1% per year). This metric is therefore not sufficiently robust over this short
19 time period to clearly indicate whether the human influence is sufficiently strong in the
20 model.
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27 Appendix B. References

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