Spatial and temporal variability in the ratio of trace gases emitted from biomass burning

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Abstract

Fires are a major source of trace gases and aerosols to the atmosphere. The amount of biomass burned is becoming better known, most importantly due to improved burned area datasets and a better representation of fuel consumption. The spatial and temporal variability in the partitioning of biomass burned into emitted trace gases and aerosols, however, has received relatively little attention. To convert estimates of biomass burned to trace gas and aerosol emissions, most studies have used emission ratios (or emission factors [EFs]) based on the arithmetic mean of field measurement outcomes, stratified by biome. However, EFs vary substantially in time and space, even within a single biome. In addition, it is unknown whether the available field measurement locations provide a representative sample for the various biomes. Here we used the available body of EF literature in combination with satellite-derived information on vegetation characteristics and climatic conditions to better understand the spatio-temporal variability in EFs. While focusing on CO, CH_4, and CO_2, our findings are also applicable to other trace gases and aerosols. We explored relations between EFs and different measurements of environmental variables that may correlate with part of the variability in EFs (tree cover density, vegetation greenness, temperature, precipitation, and the length of the dry season). Although reasonable correlations were found for specific case studies, correlations based on the full suite of available measurements were lower (r-max=0.62). This may be partly due to uncertainties in the remotely sensed data, differences in measurement techniques for EF, assumptions on the ratio between flaming and smoldering combustion, and incomplete information on the location and timing of EF measurement. We

derived new mean EFs, using the relative importance of each measurement location. These weighted averages were relatively similar to the arithmnetic mean. When using relations between the environmental variables and EFs to extrapolate to regional scales, we found substantial differences, with for example a ~19% lower CO EF for savannas and grasslands in Australia compared to southern hemisphere South America. We argue that from a global modeling perspective, future measurement campaigns could be more beneficial if measurements are made over the full fire season, and if relations between ambient conditions and EFs receive more attention.

1 Introduction

Although biomass burning is one of the most ancient forms of anthropogenic atmospheric pollution, its importance for atmospheric chemistry has only been recognized since the late seventies (Radke et al., 1978; Crutzen et al., 1979). Interest in this topic grew when studies suggested that for several trace gases and aerosol species, biomass burning emissions could rival fossil fuel emissions (Seiler and Crutzen, 1980; Crutzen and Andreae, 1990), and that these vegetation fires could affect large parts of the world due to long-range transport processes (Andreae, 1983; Fishman et al., 1990; Gloudemans et al., 2006). During the last two decades biomass burning has received considerable interest, leading for example to the realization that vegetation fires impact 8 out of 14 identified radiative forcing terms (Bowman et al., 2009), contribute to interannual variability (IAV) in growth rates of many trace gases (Langenfelds et al., 2002), and influence human health and plant productivity downwind of fires through enhanced ozone and aerosol concentrations (e.g. Sitch et al., 2007).

To assess the atmospheric impact of biomass burning quantitatively, accurate data on the emission of trace gases and aerosols is required. Crucial parameters include burned area, fuel consumption, and the emission factor (EF), usually defined as the amount of gas or particle mass emitted per kg of dry fuel burned, expressed in units of g/kg dry matter (DM) (Andreae and Merlet, 2001).

Pioneering experiments to characterize fire emissions were conducted in South America (Crutzen et al., 1979), Africa (Delmas, 1982), and Australia (Ayers and Gillett, 1988). In the beginning of the 1990s, the experiments of these individual groups were followed by a number of large international biomass burning experiments in various ecosystems throughout the world. These included the Southern Africa Fire-Atmosphere Research Initiative (SAFARI

92 and SAFARI 2000) in southern Africa (Lindesay et al., 1996; Swap et al., 2002), Dynamique et Chimie Atmosphérique en Forêt Equatoriale-Fire of Savannas (DECAFE-FOS) in West Africa (Lacaux et al., 1995), Transport and Atmospheric Chemistry Near the Equator-Atlantic (Trace-A) over Brazil, southern Africa, and the South Atlantic (Fishman et al., 1996), Fire Research Campaign Asia-North (FireSCAN) in central Siberia (FIRESCAN Science Team, 1996), and Smoke, Clouds, and Radiation-Brazil (SCAR-B) in Brazil (Kaufman et al., 1998).

These coordinated studies and numerous independent smaller investigations have resulted in a large body of information on emission characteristics. Several summaries of experimental EF data were given (e.g. Andreae, 1993; Delmas et al., 1995; Akagi et al., 2010). The most extensive and frequently used summary is given by Andreae and Merlet (2001), in which all the available data on fire emission characteristics for a large number of chemical species was synthesized into a consistent set of units. The measurements were stratified by biome type or fire use; tropical forest fires (in general fires used in the deforestation process), savanna and grassland fires, extratropical forest fires, biofuel burning, charcoal making, charcoal burning, and the burning of agricultural residues. The database is updated annually (Andreae, personal communication, 2009) and we will refer to this as A&M2001-2009 in the remainder of this paper.

Including fire processes in dynamic global vegetation models (DGVM) and biogeochemical models led to a better understanding of the spatio-temporal variability in fuel loads and fire processes. For example, annual global burned area estimates (Giglio et al., 2006; Giglio et al., 2010) and global emissions estimates according to the Global Fire Emissions Database (GFED; van der Werf et al., 2006; van der Werf et al., 2010) are decoupled on an annual timescale because most burned area occurs in savanna-type ecosystems with relatively low fuel loads, while the smaller areas that burn in forested ecosystems results in higher emissions per unit area burned due to fuel loads that are at least one order of magnitude larger.

New burned area products (L3JRC [Tansey et al., 2007], MODIS [Roy et al., 2008; Giglio et al., 2010], GLOBCARBON [Plummer et al., 2006]) allow for a better characterization of the timing and locations of fire, although the quality of these burned area products varies and they may have difficulties in capturing small fires (Chang et al., 2009; Roy and Boschetti, 2009; Giglio et al., 2010). When accounting for errors in transport and chemistry as well as uncertainties in satellite retrievals of trace gases and aerosols, combining bottom-up (such as

95 GFED) and top-down methods potentially allows for an assessment of the magnitude of
96 emissions as well as their spatio-temporal variability (Arellano et al., 2004; Edwards et al.,
97 2004; Gloudemans et al., 2006). This requires a thorough understanding of the relations
98 between biomass combusted and emission of the trace gases or aerosols that are used as top-
99 down constrains, most often CO.

100 Although our knowledge on the spatial and temporal variability of fire substantially increased
101 in the last decade due to new satellite information, the total amount of biomass combusted,
102 and especially the partitioning of combusted carbon (C) into different combustion products, is
103 improving but still uncertain. To date, most large-scale studies have used the average EFs
104 provided by A&M2001-2009. EFs, however, show large variability, mainly due to differences
105 in fuel type and composition, burning conditions, and location (Andreae and Merlet, 2001;
106 Korontzi et al., 2003). Even though EFs may vary in time and space, this variability is usually
107 not taken into account in large-scale emissions assessments except for variations due to
108 vegetation type (in general all savanna fires, all tropical forest fires, all extratropical forest
109 fires, and all agricultural waste burning fires have their own, averaged, EFs). In addition to
110 the lack of representation in spatio-temporal variability, the often-used average EFs may have
111 limitations because it is not known whether they are based on a representative sample of a
112 specific vegetation type.

113 In the literature only a few papers on regional emissions estimates considered seasonal and/or
114 spatial variability of EFs into account. Hoffa et al. (1999) related fire emissions in Zambian
115 grasslands and woodlands with PGREEN, defined as the proportion of green grass biomass to
116 total (green+dead) grass biomass. Ito & Penner (2005) applied three different EF scenarios
117 that accounted for both seasonal and spatial variability. Both studies confirmed that a spatial
118 and temporal varying EF can have a significant impact on regional emissions estimates.

119 Here we evaluated existing information on EFs, based on an extensive database of field
120 measurements (A&M2001-2009), and systematically explored several environmental
121 variables that may be related to the spatial and temporal variability in EFs. Data on fraction
122 tree cover, precipitation, temperature, Normalized Difference Vegetation index (NDVI, a
123 measure of vegetation greenness or productivity), and length of the dry season were used to
124 develop relations with the EFs for different vegetations types. We focused on CO, methane
125 (CH_4), and CO_2. However, since the Modified Combustion Efficiency (MCE, defined as the
126 amount of C released as CO_2 divided by the amount of C released as CO_2 plus CO (Yokelson

et al., 1996)) has been used as an effective predictor for the emission of smoke gas composition from biomass fires (e.g., Ward et al., 1996; Sinha et al., 2003; Yokelson et al., 2003) and for certain aerosol species and characteristics (e.g., Christian et al., 2003; McMeeking et al., 2009; Janhäll et al., 2010), our findings on CO and CO_2 EFs can be used to better understand emissions of other trace gases and aerosols as well. We restricted our analysis to in-situ measurements due to the focus on spatio-temporal variability as a result of variability in vegetation and climatic conditions; laboratory measurements of EFs were not taken into account. We present new weighted EFs for specific vegetation types, and indicate how future EF experiments could be more beneficial from a global modeling perspective.

2 Fire processes

To facilitate the description of the main factors that influence the EF of different trace gases (section 2.2), we start with a brief summary of the combustion process (section 2.1). For more detailed information the reader is referred to Chandler et al. (1983), Lobert and Warnatz (1993), and Yokelson et al. (1996; 1997).

2.1 The combustion process

The combustion of the individual fuel elements proceeds through a sequence of stages (ignition, flaming, smoldering, and extinction), each with different chemical and physical processes that result in different emissions.

The initial ignition is the phase before a self-sustaining fire can start, and it depends on both fuel (size, density, water content) and environmental (temperature, relative humidity, wind) factors whether the fuel is ignited or not. Once the fuel is sufficiently dry, combustion can proceed from the ignition phase to the flaming phase. It starts with thermal degradation, in which water and volatile contents of the fuel are released, and is followed by the thermal cracking of the fuel molecules (pyrolytic step); high-molecular compounds are decomposed to char (less volatile solids with high C content), tar (molecules of intermediate molecular weight), and volatile compounds. When diluted with air, a flammable mixture may form. Many different compounds are produced during this phase, particularly CO_2 and H_2O.

After most volatiles have been released and the rate of the pyrolysis slows down, less flammable compounds are produced; the flaming combustion ceases, and the smoldering

157 phase begins. Smoldering combustion is a lower-temperature process compared to flaming
158 combustion emitting large amounts of incompletely oxidized compounds (e.g. CO), and can
159 proceed for days, even under relatively high moisture conditions. The slower rate of pyrolysis
160 results in lower heat production and therefore in a lower decomposition rate, until the process
161 terminates (extinction phase). The most common causes of extinction are a physical gap in the
162 fuels that prevents sufficient heat transfer to additional fuels, rainfall, or fire spread into wet
163 fuels.

164 The combustion processes described above are somewhat simplified, and in most fires all of
165 these processes occur simultaneously in different parts of the fuel bed. For real-time open
166 vegetation fires, different factors that influence the combustion process and which may
167 change over time (e.g. meteorological conditions, differences in aboveground biomass
168 density, topography) also need to be considered. The amount of substances emitted from a
169 given fire and their relative proportions are determined to a large extent by the ratio of
170 flaming to smoldering combustion, which is related to the combustion efficiency (CE),
171 defined as the fraction of the fuel C burned converted to CO_2.

172

173 ## 2.2 Factors influencing the EF

174 The exact physical relations between environmental variables and EFs are not well
175 understood, although recent laboratory studies have aimed to quantify how, for example,
176 moisture content impacts EFs (e.g. Chen et al., 2010). Qualitatively, important parameters that
177 partly govern the flaming / smoldering ratio and thus EFs include vegetation characteristics,
178 climate, weather, topography, and fire practices.

179 A variable that may affect both the behavior and the emissions of a fire is the water content of
180 the vegetation. The water content partly determines whether a plant or tree can ignite and
181 what the combustion efficiency will be. Water in plants or trees has the capability to either
182 stop a fire completely or to slow down the burning process (to a low smoldering stage).
183 However, also wet fuels can ignite if a sustained ignition source is applied. For instance,
184 crown fires spread at high rates with large flames burning fresh foliage with high moisture
185 content.

186 Other fuel characteristics related to vegetation are the size, density, and the spacing of the
187 fuels. Some studies (Bertschi et al., 2003; McMeeking et al., 2009) suggest that combustion

completeness, defined as the fraction of biomass exposed to a fire that was actually consumed (or volatized) in a fire, is impacted more by fuel spacing than fuel moisture. It is likely fuel spacing is equally important in driving variability in EFs. Because fuel has to be heated to ignition temperature, small low-density fuel particles are more easily ignited than larger high-density particles. Once burning, the rate of heat production for smaller particles is higher than for larger particles, and therefore smaller particles are also capable of sustaining flaming combustion and supporting the burning of larger particles. In general, grass fuels in savannas have a large surface to volume ratio, are more easily pyrolized, and therefore burn largely in the flaming phase, while stems and coarse litter that burn in forest fires are not as well oxidized and burn more in the smoldering phase. However, with an efficient heat transfer between fuel elements even large logs in deforestation fires can be consumed mostly by flaming combustion (Christian et al., 2007; McMeeking et al., 2009).

Climate also plays an important role in the existence and settlement of vegetation, and thus determines the availability of fire fuel (Lobert and Warnatz, 1993). Fire frequency and the fire season are also partly determined by climatic factors. Weather has a more short-term impact on fire. Temperature, precipitation, and wind speed are factors that partly determine the occurrence of fires as well as their behavior, especially the CE. Temperature may affect the fire probability and ignition due to its effect on fuel moisture. Precipitation is capable of inhibiting, completely stopping, or preventing a fire. Wind can have an effect on the spread rate of a fire, as fires usually propagate in two different directions; with the wind (heading fires) and into the wind (backing fires). The local topography can also change the burning behavior of a fire; heat rises and an upslope fire therefore achieves better heat transfer from the burning fuels to the unburned fuels. If all other conditions are equal, this leads to fires that spread faster.

In the tropics and subtropics, fire is mainly a human-driven process. We expect that regional variations in fire practices influences EFs, especially in agricultural fires and fires used in the deforestation process. Slash and burn fires, for example, are different from the burning of fuels that have been mechanically piled together into windrows and may burn more intense. This practice requires heavy machinery and is therefore limited to regions with more capital, for example the southern part of the Amazon where forests are cleared for soy production, amongst others (Morton et al., 2006).

In summary, both the combustion process and its inter-relationship with the environment are very complicated. At present, literature focusing on how environmental variables impact EFs from real fires is limited and data from laboratory studies is often conflicting and inconclusive. Nevertheless, empirical relationships between satellite observables and EF may exist and are further explored here.

3 Literature database of EF measurements

3.1 Introduction

We used the EF database for different vegetation types that was compiled by A&M2001-2009. The database consists of EFs measured during individual experiments, as well as during large international measurement campaigns. The database includes both field data (sampled on the ground or from aircraft) and laboratory measurements. We excluded laboratory measurements in our analyses because the focus of our work is on EF variability and the role of local (climatic) conditions, which are better represented by EF measurements in the field. In addition, laboratory measurements may not be fully representative of burning conditions in the field; it is for example impractical to burn a diverse suite of large diameter tropical logs in the lab (Yokelson et al., 2008). In the work of A&M2001-2009, laboratory measurements were also excluded for calculating biome-averaged EFs for CO, CH_4, and CO_2.

Most of the EFs in the database of A&M2001-2009 are measured using the C mass balance (CMB) method (Ward et al., 1979; Radke et al., 1990). The underlying premise of this method is that all C combusted in a fire is emitted into measurable portions in five forms: CO_2, CO, CH_4, non-methane hydrocarbons (NMHC), and particulate C in smoke particles. The EF of a species is then calculated from the ratio of the mass concentration of those species to the total carbon concentration emitted in the plume. To convert the EF to g/kg DM of fuel burned, the data need to be multiplied with the carbon content of the fuel. A&M2001-2009 adopted a C content of 45% when this information was not given in literature cited. However, a detailed study of Susott et al. (1996) suggests a global average C fraction for biomass closer to 50%, with a considerable range, which would indicate an additional ~10% uncertainty in addition to other uncertainties.

When the emission data were given as molar emission ratios, A&M2001-2009 used the molecular weights of the trace and reference species to calculate the EF. Molar emission

ratios can be obtained by dividing excess trace species concentrations measured in a fire plume by the excess concentration of a simultaneously measured reference gas (most often CO_2). If the EF of the reference species was not provided, the mean EF for the specific type of fire was used.

With the A&M2001-2009 database as a starting point, we compiled all EFs and searched the literature for accompanying ancillary data such as measurement location and timing. We then expanded the database to include location-specific parameters related to vegetation type and climate of each measurement. We focused on the EFs of CO_2, CO, and CH_4 because these gases were measured during most campaigns, and the EF of CO_2 and CO can be used to calculate the modified combustion efficiency (MCE), which can be used to predict EFs of other species (e.g., Ward et al., 1996; Sinha et al., 2003; Yokelson et al., 2003).

3.2 Available EF data

Figure 1 provides an overview of the locations where ground- and aircraft EF measurements were conducted for CO and CO_2, with a background of mean annual fire C emissions. Fire emissions were taken from the Global Fire Emission Database (GFED) version 3.1 (Giglio et al., 2010; van der Werf et al., 2010). GFED consists of 0.5°×0.5° gridded monthly parameters; burned area, fuel loads, combustion completeness, and fire C losses. Fire emissions were estimated based on burned area (Giglio et al., 2010) in combination with the Carnegie-Ames-Stanford Approach (CASA) biogeochemical model to calculate fuel consumption. See van der Werf et al. (2010) for more information.

Most locations with both CO and CO_2 EF measurements are in North America, the arc of deforestation in the Brazilian Amazon, southern Africa (South Africa and Zambia), and northern Australia (Figure 1). While these areas are all major biomass burning regions, several other important regions lack measurements. These include Central Africa (e.g. Congo, Angola, but also regions further north such as Chad and southern Sudan), Siberia, Indochina, and Indonesia, although laboratory studies for Indonesian fuel samples exist (Christian et al., 2003). Most of these missing regions likely has relatively high rates of emissions of reduced gases compared to sampled regions; more woodland burning in Central Africa compared to southern Africa where most savanna measurements were made, more groundfires in boreal Asia compared to boreal North America where most extratropical EFs were measured, and moister conditions and more peat burning in Indonesia compared to South America where

most deforestation fire EFs were made. On the other hand, most measurements in Australia were made in the relatively moist part in the North while fires burning in the more arid interior have not been sampled.

To highlight the large variability in EFs, we plotted CH_4 EFs against the molar MCE (based on CO and CO_2 EFs) in Figure 2 for three different biomes. The biome-averaged EF values of A&M2001-2009 are also shown. In general, EFs in savannas & grasslands show high MCEs and a relatively low EF for CH_4, mainly because burning mostly takes place in the flaming phase. Tropical forest measurements on the other hand, show lower MCEs and higher values for the EF of CH_4, because these fires burn predominantly in the smoldering phase. This is also the case for the extratropical forest measurements, although here the values are more variable. The correlation coefficient (r) between MCE and CH_4 for all these in-situ measurements was -0.71 ($EF_{(CH_4)}$ =-85.889 × MCE + 85.278), and correlation coefficients for the different vegetation types were -0.80 ($EF_{(CH_4)}$ =-61.447 × MCE + 61.142), -0.81 ($EF_{(CH_4)}$ =-104.551 × MCE + 104.590), and -0.52 ($EF_{(CH_4)}$ =-59.992 × MCE + 60.967) for savanna and grasslands, tropical forest, and extratropical forest, respectively. Two extratropical forest measurements (Cofer et al., 1998: MCE=0.78, EF CH_4 = 4.5; Hobbs et al., 1996: MCE=0.81, EF CH_4=16.2) were excluded from this graph for clarity, but they were taken into account to calculate the correlation coefficient.

Although lowering the number of EF studies in general decreases the correlation coefficient, several individual studies focusing on a selected number of measurements found higher correlation coefficients than the ones reported above. Yokelson et al. (2003) found a correlation coefficient of -0.93 ($EF_{(CH_4)}$ = -48.522 × MCE + 47.801) for 8 African savanna fires. Korontzi et al. (2003) also found higher correlations and a slightly different slope for the regression of southern African savanna measurements - grasslands had a correlation of 0.94 ($EF_{(CH_4)}$ = -43.63 × MCE + 42.951) and for woodlands a correlation of 0.98 ($EF_{(CH_4)}$ = -58.214 × MCE + 56.710) was found. Both vegetation types combined gave an overall correlation of 0.94, and a trendline of $EF_{(CH_4)}$ = -47.948 × MCE + 47.068.

For the tropical forest biome, Yokelson et al. (2008) found a correlation coefficient of 0.72 for 9 fire-averaged MCEs and CH_4 EFs. The slope of this regression was significantly more gentle ($EF_{(CH_4)}$ = -47.105 × MCE + 48.555) than the slope for this biome using all measurements in the A&M2001-2009 database. In older work, comparisons between the CE (which correlates well with the MCE) and CH_4 EFs was presented. Ward et al. (1992) showed

a correlation of 0.96 and a slope of $EF_{(CH_4)} = -82.1 \times CE + 78.6$ for a regression of 18 deforestation fires in Brazil. We are not aware of any recent comparisons between MCE and EF CH_4 for fires in the extratropical forest biome, but in older work of e.g. Ward & Hardy (1991) and Hao and Ward (1993), an overall higher correlation ($r>0.8$) is found for extratropical forest measurements. The slope of the regression lines of these individual studies was more gentle than the slope we found for the whole dataset. Lab experiments (Christian et al., 2003; McMeeking et al., 2009; Burling et al., 2010) also show overall higher correlations between MCE and EF CH_4 than our results for all data for the different vegetation biomes combined.

Overall, higher correlation coefficients and flatter slopes for the EF CH_4 and MCE relationship were found for individual studies focusing on a relatively small number of EF measurements, compared to the whole EF database of A&M2001-2009. Possible explainations for these differences between the whole dataset compared to individual studies are discussed in section 4. Individual studies (e.g. Hao and Ward, 1993) have shown that the linear relationships between the MCE and EF of CH_4 are quite different for individual biomes, for reasons not fully understood. This is also apparent from Figure 2; the slope and intercept of the savanna and extropical forest biome compare very well, but the regression line of CH_4 EFs and their MCE derived for tropical forest biome shows a steeper slope and larger intercept. Most variation and therefore lower overall correlation coefficient was caused by the extratropical forest measurements.

The large variability (even within biomes) apparent from Figure 2 may be partly explained by the different environmental variables that we described in section 2.2. One is related to the timing of the measurement, and thus to weather conditions during the fire (e.g., Korontzi et al., 2003). Fires in savannas and tropical forest areas usually burn during the late dry season, when fuel moisture is in general at minimum. Prescribed burning in tropical savannas on the other hand is often exercised in the early part of the dry season, and is commonly advocated when fire is used as a land management tool. Early season burns are less intense and result in a smaller amount of vegetation consumed per unit area and –probably more important- lead to less damage to the soil compared to late season fires. Pastoralists burn extensively in the early dry season to stimulate regrowth of palatable grasses for their cattle; fire is used for rapid nutrient release prior to the new growing season by farmers, and early burning is used in

national parks as a preventive measure against late dry season fires which tend to have higher intensities and are in general more destructive (Frost, 1996; Williams et al., 1998).

We explored the seasonal variation of the fire emissions for all EF data where a detailed description of the location and date of measurements was provided. To investigate whether the available measurements captured the fire seasonality we compared the number of EF measurements conducted in a specific biome with the seasonal variation in C emissions according to GFED3.1 (Figure 3). Only the 0.5°×0.5° grid cells enclosing the locations where EF measurements were conducted for CO, CH_4, and CO_2 were used, and the seasonal cycle in each grid cell was normalized to its peak fire month (PFM). Figure 3a shows the seasonality of the number of EF measurements and the GFED3.1 fire emissions for all the EF measurement locations in the savanna and grassland biome for the PFM, and the months before and after the PFM. Results for the tropical forest biome are shown in Figure 3b.

For EF measurement locations in the savanna biome, 46% of the total annual amount of C was emitted by fires in the PFM, and 78% when also including the month before and after the PFM. For the tropical forest biome, this was 66% and 84%, respectively. The percentage of EF measurements conducted in the PFM was 23% for both the savanna and tropical forest biome, and respectively 71% and 88% when also including the month before and after the PFM. In other words, the current body of measurements have undersampled the peak fire month with especially the tropical forest fire measurements sampling earlier than desirable. Extratropical forest measurements were excluded from this analysis, because the fire season is much more variable from year to year compared to the tropics (Giglio et al., 2006).

3.3 Remotely sensed environmental data

One of our main objectives was to model the variability in CO, CH_4, and CO_2 EFs. For this, we compared all the EFs in the database with global monthly datasets of potentially relevant parameters (as described in section 2.2); fraction tree cover, precipitation, temperature, NDVI, and the length of the dry season. These parameters were chosen since globally consistent information is available for a longer period of time, although the spatial and temporal resolution is relative coarse (typically 0.5°×0.5° and monthly data) and may not fully capture key regional variability. Specific local and regional factors that may have a large influence on the EF variability, like e.g. wind, were excluded due to a lack of reliable data.

We used the fraction tree cover (FTC) product regridded to 0.5°×0.5° resolution for the year 2002 to represent the vegetation density and the ratio between herbaceous and woody fuels in the EF measurement locations. In the GFED modeling framework, FTC is the key control on the fraction coarse fuels that burn predominantly in the smoldering phase (e.g., stems, coarse woody debris) as opposed to fine fuels burning mostly in the flaming phase (leaves, grass, fine litter) in a grid cell. The FTC product was derived from the Vegetation Continuous Fields (VCF) collection which contains proportional estimates for vegetative cover types: woody vegetation, herbaceous vegetation, and bare ground (Hansen et al., 2003). The product was derived from seven bands of the MODerate-resolution Imaging Spectroradiometer (MODIS) sensor onboard NASA's Terra satellite. The continuous classification scheme of the VCF product better captures areas of heterogeneous land cover than traditional discrete classification schemes.

The 1°×1° daily (1DD) Global Precipitation Climatology Project (GPCP) precipitation product (Huffman et al., 2001) was used to estimate the correlation of precipitation with EFs. This dataset is based on passive microwave measurements from the Special Sensor Microwave Imager (SSM/I), and infrared retrievals from the Geostationary Operational Environmental Satellite (GOES) and the Television InfraRed Observation Satellite (TIROS) Operational Vertical Sounder (TOVS). The monthly rainfall totals are corrected over some continental areas to match sparse ground-based observations, and at finer time scales the product relies exclusively on satellite-based precipitation estimates. We averaged the daily values to calculate a montly average (mm/month) for the years 1997-2008, the period of availability. For EF measurements conducted before the year 1997, we used the monthly 2.5°×2.5° GPCPv2.1 precipitation product (Adler et al., 2003), which is available from 1979 till present. Monthly averaged precipitation data for the years 1997-2008 were also used to define the mean annual precipitation (MAP). All data was regridded to 0.5°×0.5° resolution using linear interpolation. Since we explored large-scale relations between EFs and the monthly and mean annual precipitation only, we may miss variability related to synoptic scale precipitation.

Temperature data were derived from a climatology and an anomaly source. The climatological data were downloaded from the Climate Research Unit (CRU) website (http://www.cru.uea.ac.uk/). We used the CRU CL 1.0 Mean Monthly Climatology product, with a resolution of 0.5°×0.5° (New et al., 1999). This dataset gives the mean monthly surface

climate over global land areas, excluding Antarctica, and was interpolated from station data to 0.5°×0.5° for several variables. We then used the NASA GISS Surface Temperature Analysis (GISTEMP) as a source of temperature anomalies (Hansen et al., 1999). GISTEMP provides a measure of the global surface temperature anomaly with monthly resolution for the period since 1880, when a reasonable global distribution of meteorological stations was established. Input data for the analysis, collected by many national meteorological services around the world, is the unadjusted data of the Global Historical Climatology Network (Peterson and Vose, 1997). Documentation of the GISTEMP analysis is provided by Hansen et al. (1999), with several modifications described by Hansen et al. (2001). We used the 1961-1990 anomalies with a 1200 km smoothing radius, which were downloaded from the NASA website (http://data.giss.nasa.gov/gistemp/maps/). The CRU climatology and GISTEMP anomalies were combined to estimate the monthly temperatures for the years 1967-2009. Monthly averaged temperature data for the years 1997-2008 were used to define the mean annual temperature (MAT).

The Normalized Difference Vegetation Index (NDVI) represents the amount of live green vegetation and its productivity, and may be a useful indication of vegetation characteristics (fuel abundance and also live fuel moisture conditions). Monthly Global Inventory Modelling and Mapping Studies (GIMMS) NDVI data with a 8×8 km resolution (Tucker et al., 2005) were downloaded from the International Satellite Land Surface Climatology Project website (http://islscp2.sesda.com/). Different satellite series of NOAA's Advanced Very High Resolution Radiometer (AVHRR) were used for this NDVI record. The dataset consists of bi-monthly NDVI data for the years 1981 to 2006, which we averaged to monthly values. For EF measurements that were conducted before 1981 or after 2006, we used the monthly mean of the years 1981-2006.

The length of the dry season for the EF measurement locations was defined by counting the number of consecutive months in the 6-month period before the measurement was conducted with precipitation rates below 100 mm/month (GPCP 1°×1° for the 1997-2008 period, and GPCPv2.1 2.5°×2.5° for 1979-1997). This parameter partly overlaps with the precipitation rates, but the added value lies in containing a memory of precipitation; it may be an indicator of the precipitation conditions before the month of the actual measurement. It may be especially valuable for estimating the moisture content of fuels with low surface to volume ratios such as stems, which often take more than one month to come in equilibrium with

ambient moisture conditions (Bradshaw et al., 1984).

3.4 Correlations between remotely sensed environmental data and EFs

In Table 1 the correlation coefficients between the environmental data and the EFs of CO, CH_4, CO_2, and MCE (based on the EFs of CO and CO_2) are given. Here, we lumped all the EF data of A&M2001-2009 for the three different biomes together. We performed simple linear regressions, with the EF as the dependant variable, and the different parameters that may control the EFs variability represent the independent variables. Besides the correlation coefficients (r), F-values were calculated to test if the regression between the EF and the different driver data was significant (if the F-value exceeds the critical value of F_{crit}, it indicates a significant fit). We also performed a multivariate regression to construct a regression equation that combined the different parameters that accounted for most of the EF variability, in order to see if different variables combined perform better than the variables seperately, and to be able to construct EFs for grid cells where no measurents were performed.

For CO EF we found the highest correlation with FTC (r=0.49) and NDVI (r=0.41). The corresponding F-values (66.2 & 7.0) exceeded the critical F value (Fcrit=6.7) for a significance level of 0.01. When combining the different parameters in one regression equation, the correlation coefficient improved to 0.57. For the CH_4 EF, FTC (r=0.58) and monthly precipitation (r=0.53) were the most dominant parameters, and both correlations were significant at a level of 0.01. Using the additional information of each parameter increased the correlation (r=0.62). For CO_2, FTC and monthly precipitation yielded the highest descriptive power (r=-0.26 and r=-0.37), similar to CH_4. Despite the relatively low correlation coefficients, both fits were significant with F-values of 10.1 and 27.1. The multivariate regression equation gave a slightly higher correlation (r=0.43). In general, the highest correlations were found for FTC, which is not surprising since and this parameter covers the range from open grasslands, through savanna and woodlands, through tropical forest. Also, within biomes, FTC could explain part of the EF variability.

For MCE we found the highest correlation with monthly precipitation (r=-0.52) and FTC (r=-0.47), and both corresponding F-values (62.2 & 46.9) exceeded the critical F value for a

significance level of 0.01. All environmental parameters combined, the correlation coefficient improved to 0.58. For MCE we performed a similar analysis using the dataset of Akagi et al. (2010), which is based on EF data measured in fresh plumes only, which have not undergone significant photochemical processing. Overall, the correlations with the different environmental parameters did not improve compared to the EF dataset of A&M2001-2009; a maximum correlation coefficient of 0.55 was found using all environmental data combined. This is not an indication that one dataset is preferred above the other one; for CO and CO_2 it does not matter whether fresh or aged smoke is sampled. The differences could be the result of a larger number of samples in the A&M2001-2009 dataset. When translating our findings on MCE to other trace gases or aerosols, it may be preferable to use the Akagi et al. (2010) dataset because it consistently only takes those measurements focusing on fresh smoke into account, better representing initial emissions.

In general, repeating the calculations but focusing on each individual biome yielded lower correlations than with all measurements lumped together. However, some of the relations found when using the full suite of data were still valid. For example, also within the savanna and grassland biome we found a negative correlation between FTC and MCE (or positive correlation between FTC and the CO emission factor) with an almost identical slope and offset as when using all measurements. Correlations between the EFs and the environmental data for the extratropical forest were very poor. Possible explanations for these poor correlations are discussed in section 4. Higher correlations between EFs and the driving variables were found when focusing on specific locations, although it must be noted that the sample size of these correlations is relatively small. Figure 4a, 4b, and 4c show correlations for respectively Brazilian deforestation fires and savanna fires in Australia (FTC vs. MCE), Brazilian deforestation fires (FTC vs. CH_4 EF), and boreal fires in Alaska (precipitation vs. CH_4 EF). A similar pattern occurred when focusing on vegetation types: correlations between MCE and CH_4 EF were relatively low when using all data lumped together (Figure 2), and higher correlations were found in different individual studies, using a smaller sample size. Also, the extratropical forest data showed overall lower correlations than data for the savanna and tropical forest biome.

3.5 Weighted EF averages

Most large-scale biomass burning emission estimates are based on some combination of biomass or C combusted and EFs. These EFs are usually based on the arithmetic mean of a large number of measurements, most often using the work of A&M2001-2009. It is not known, however, whether the measurements are representative of the whole biome. Regionally, there is substantial variation in the density of measurements. For example, nearly all tropical forest measurements are made in the Brazilian Amazon and Yucatan province of Mexico (Figure 1), while information from other deforestation hot spots such as Bolivia and Indonesia is lacking. Different regional deforestation practices could in principle lead to variations in EFs, something that cannot be taken into account at the moment due to a lack of measurements. The same holds for the boreal region; according to the estimates of van der Werf et al. (2010), total C emissions from boreal Asia were almost 2.5 times as high as those from boreal North America in the last decade. Nevertheless nearly all the extratropical forest EF measurements were made in North America, and only one was conducted in boreal Asia (Figure 1).

While there are regional discrepancies in measurement locations, the measurements do capture most of the climate window in which most fires occur (Figure 5). To construct new weighted average EFs, we weighted each measurement with its quantitave importance in the fire-climate window. The size of the climatic window bins we used were 1° Celcius for mean annual temperature (MAT), 100 mm / year for mean annual precipitation (MAP), and 2% for fraction tree cover (FTC). Table 2 gives an overview of these new calculated mean values per biome. The weighted values are at most 18% different from the arithmetic mean, but mostly lower (Table 2). Some differences, however, can be noticed: EFs of CO were 8% below and 13% above the mean of A&M2001-2009 for tropical forest and extratropical forest measurements, respectively. EFs of CH_4 were lower for each biome (16% on average). CO_2 EFs were somewhat lower for savannas (1.5%) and more variable for the tropical and extratropical biome.

On average, the weighted MCE for the different climate-windows was 7% and 11% higher than the A&M2001-2009 average for the tropical forest and extratropical biome, respectively. Weighted MCEs for the savanna biome were comparable with the biome-averaged values of A&M2001-2009. Overall, our new calculated weighted averages for CO, CH_4, CO_2 EFs and MCE do not deviate much from the arithmetic mean of A&M2001-2009, and are well within the range of uncertainty, especially when also taking the substantial uncertainties in the GFED

fuel consumption estimates into account. This indicates that the measurement locations were representative with regard to emissions strengths. However, it does not provide information of the representativeness of the measurement locations for the whole biome, which will be addressed next.

3.6 From a discrete towards a continuous classification scheme for EFs

Following the work of Hoffa et al. (2003) and Ito and Penner (2005), we developed a non-vegetative classification scheme for EFs, driven by various environmental parameters. We performed a multivariate regression to construct an equation that combined the different environmental parameters (Table 1) for the CO, CH_4, CO_2 EFs, and the MCE, which is a useful parameter since it can be related to many carboneous gases and certain aerosols (e.g., Ward et al., 1996; Sinha et al., 2003; Yokelson et al., 2003). In Table 2 these new calculated mean values, weighted by the amount of biomass combusted in the 1997-2008 period, are given per biome. EFs of CO and CH_4 were ~13% and ~22% higher than the biome-averaged values of A&M2001-2009 for the savanna biome, and significantly lower for the tropical forest and extratropical forest biome. CO_2 EFs were the same for the savanna and tropical forest biome, and ~5% higher for the extratropical forest. The biome-averaged MCE deviates 0.32%, 2.2%, and 1.2% from the biome-averaged values of A&M2001-2009 for savanna, tropical forest, and extratropical forest respectively.

Using the multivariate regression equation for MCE, which is mostly driven by monthly precipitation and FTC (Table 1), we constructed monthly MCE fields with a spatial resolution of 0.5°×0.5° for the years 1997-2008. In Figure 6a the newly calculated MCE, weighted by the amount of biomass combusted in the 1997-2008 period, is shown on a global scale. In general, tropical forest and boreal areas show lower MCE values compared to savanna regions. Spatial differences within savanna areas are obvious as well; woodland areas (for example, in Angola) have a relatively low MCE compared to areas where grasslands or open savannas are the dominant vegetation type, for example in South Africa or in the Australian interior.

In Figure 6b the difference between our new “continuous“ MCE and the biome-dependent MCE of A&M2001-2009 is shown. The latter was constructed using the MOD12Q1 land

565 cover map for 2001 (Friedl et al., 2002) to distribute the biome-specific MCEs over the globe.
566 Areas where we predict a lower MCE, and thus emit relatively more reduced gases (CO,
567 CH_4), are shown in blue. We expect that these grid cell specific MCEs are more reliable in the
568 tropics than in boreal regions because more measurement locations were in the tropics. This
569 may also be why FTC and monthly precipitation were the two most important parameters. In
570 addition, the regression cannot deal with agricultural waste burning and peat burning regions,
571 and these regions will receive biome-specific EFs. Regarding the savanna and grassland
572 biome: we found the highest MCE in Australia (0.9466), followed by southern hemisphere
573 Africa (0.9432), northern hemisphere South America (0.9403), and southern hemisphere
574 South America (0.9386). Although differences in MCE are relatively small, they have a
575 substantial influence on the amount of CO and other reduced trace gases released. For
576 example, the small difference in MCE between Australia and southern hemisphere South
577 America (~0.9%) may imply a relatively large difference in the amount of CO emitted
578 (~16%) if the total amount of C emitted as CO and CO_2 is kept constant in both regions. An
579 important next step is to implement these spatial and temporal EF and MCE scenarios into
580 GFED, and quantify regional differences in trace gasses emitted.

581

582 ## 4 Discussion

583 We evaluated a large body of available literature describing EF measurements conducted in
584 different biomes throughout the world, and explored the relations between the EFs and global
585 low-resolution datasets of parameters that may influence EF variability. We chose to compare
586 EFs with seven important control parameters for which global datasets were available and
587 extended back to at least the early 1990s. These could account for up to about 32.5% (r=0.57),
588 38.4% (r=0.62), 18.5% (r=0.43), and 33.6% (r=0.58) of the variability for respectively CO,
589 CH_4, CO_2, and MCE. Several factors may account for the remaining variability and are
590 discussed in section 4.1 - 4.4. We discuss the new weighted biome-averaged EFs in section
591 4.5, followed by recommendations for new EF campaigns (section 4.6) and our future steps
592 (section 4.7).

593

4.1 Uncertainty in environmental parameters

Monthly averages of coarse-resolution (regridded to 0.5°×0.5) data were used to assess fire emissions, fraction tree cover, precipitation, temperature, NDVI, and the lenght of the dry season for the different EF measurement locations. The use of spatially and temporal higher resolution data is preferred over lower resolution data, but detailed information on the location and date of the measurements was often lacking. Even if detailed information was given, a large number of EF measurements were conducted in the 1980s and early 1990s, for which period global datasets are often lacking at sufficient high resolution. Also in more recent periods data availability would limit more detailed analyses: while FTC is available at 500-meter resolution, it is only available for the year 2002. And since fires likely impact FTC a multi-year product is required for consistency, so that –for example- each EF measurement can be linked to the FTC before the fire. Here we have not included uncertainties in these environmental parameters because they have not undergone an official error assessment, with the exception of the precipitation data.

4.2 Additional drivers of emission factor variability

Although other environmental data (e.g. precipitation duration, fuel spacing, wind, and topography) may play an important role in fire characteristics and thus in the partitioning of trace gases emitted (e.g. Lobert et al., 1991), we could not take these factors into account because reliable information is not available from global datasets (see Section 4.1). Only few papers describing the measurements include detailed information on climatic and environmental conditions. Fuel composition may be another crucial factor for EF partitioning that was not taken into account here, and which may account for part of the variability not captured by the 7 parameters we could include because consistent information was available for all measurement locations.

In the future, a combination of 1) more EF field measurements, 2) better use of simultaneous satellite retrievals of trace gases (e.g., CO and NO_2), and 3) the availability of higher spatial and temporal resolution satellite datasets may further improve our understanding of how certain environmental parameters influence the EF variability for specific fires.

4.3 Different measurement approaches and techniques

Various analytical techniques have been used in recent field experiments, like non-dispersive infrared analysis (NDIR), Fourier transform infrared spectrospocy (FTIR), and gas chromatography. Detailed descriptions of these different techniques can be found in the literature (Ward and Radke, 1993; Yokelson et al., 1999; Christian et al., 2004). For real-time concentration measurements, the analytical instruments must be close to the fire. A distinction can be made between ground-based (tower, mast) and airborne (airplane, helicopter) measurements. Airborne measurements sample an integrated mixture of the emissions from both combustion types (smoldering and flaming). For ground-based measurements, which have a smaller footprint, the separation between smoldering and flaming combustion is more clear, but even here both processes occur simultaneously in a given patch at most times. Ground-based sampling probably oversamples the emissions which tend to be emitted during less vigorous phases of a fire and therefore remain closer to the ground, while airborne sampling may be biased towards emissions from the flaming phase that rise to higher altitudes (Andreae et al., 1996; Yokelson et al., 2008). Airborne measurements of chapparral vegetation in California (Laursen et al., 1992) were for example compared to ground-based measurements of the same vegetation type (Ward and Hardy, 1989), with overall lower EFs for CO (18%) and CH_4 (60%), and higher CO_2 (5%) due to the bias towards the flaming phase. Yokelson et al. (2008) performed a similar analysis for tropical forest fires, and also found lower EFs of CO and CH_4 for airborne measurements.

Although differences between measurement techniques are more important for sticky or reactive gases, the use of different techniques may have caused variations in CO, CH_4, and CO_2 EFs measured in specific experiments. For example, SAFARI campaign measurements were conducted in South Africa and Zambia, and different research groups were involved to estimate EFs. Airborne Fourier transform infrared spectroscopy (AFTIR) was used by Yokelson et al. (2003) to measure EFs, while Sinha et al. (2003) used gas chromatography. Both measuring techniques gave different EFs of CO, CH_4 and CO_2, even though the location and timing of the burning event was identical. Another example comes from extratropical forest biome; the use of different analytical techniques led to a difference of 23% for CO, 8% for CH_4, and 2% for CO_2 EFs for the same fires in North America (Hegg et al., 1990; Laursen et al., 1992).

4.4 Flaming/smoldering assumptions

The ratio between flaming and smoldering combustion of a fire is crucial for estimating the overall EF for different trace gases. In savanna fires, for example, flaming combustion dominates, and the EF for reduced species is relatively low compared to forest fires where the smoldering phase is often more important. The proportion of flaming and smoldering combustion can vary considerably also within fires in the same biome as a function of internal parameters (for example moisture content). It may seem desirable to provide separate EFs for flaming and smoldering combustion, but this is not always possible given the data available. In the field, EFs are generally determined by averaging several instantaneous measurements from the fire. Most emissions are assumed to be a mixture of flaming and smoldering combustion, and it is essential that averaging of both phases is done correctly when the EF for an entire fire is sought. Generally the individual measurements are weighted according to the amount of fuel combusted in the time interval represented by the measurement (Ward and Hardy, 1991). This approach requires information that is only available in experimental fires in the laboratory or to a limited extent in the field, so often assumptions had to be made on the flaming to smoldering ratio leading to another source of uncertainty and potential to yield different EFs for similar smoke plumes.

Estimates of the relative importance of the flaming and smoldering phases vary in literature; for grass and shrub fires flaming combustion dominates and likely accounts for 80% to 90% of fuel consumption (Shea et al., 1996; Ward et al., 1996). For tropical forest and boreal fires smoldering combustion is more important. Bertschi et al. (2003), for example, assumed that the smoldering and flaming phases combusted equal amounts of biomass in boreal areas, and residual smoldering measurements were combined with airborne measurements of Goode et al. (2000) to calculate an overall EF. For African miombo fires a flaming-smoldering ratio of 90-10 was taken, and airborne FTIR measurements from a study of Yokelson et al. (2003) were used to represent the flaming part. A change in these flaming-smoldering ratio's will impact the overall EF substantially, so the assumptions made by different authors are therefore important to consider (Yokelson et al., 1996).

A&M2001-2009 made the assumption that when smoldering and flaming emissions were given separately in ground-based studies, the emissions were combined to represent the complete fire. For this purpose A&M2001-2009 either used data on the fractions of fuel combusted in the smoldering and flaming stages provided in a given study, or, when this

information was not available, typical values from other studies on the same type of fire were used.

4.5 Weighted means

The biome-averaged EF values of A&M2001-2009 are widely used in the modeling community. These mean values may not be representative for the whole biome (e.g. nearly all extratropical forest measurements were made in North America, and only one measurement was made in Siberia). We performed two levels of weighting. First, by placing the measurements in their climatic window (based on mean annual precipitation, mean annual temperature, and fraction tree cover) we were able to weigh the different measurements with regard to their quantitative importance, using the GFED3.1 C emissions estimates in the corresponding C climatic window. The weighted EFs are within 6.7%, 7.9%, and 13.2% of the arithmetic mean of A&M2001-2009 for CO, 17.4%, 15.2%, and 6.7% for CH_4, and 2.1%, 7.2%, and 11.4% for the MCE for the savanna, tropical forest, and extratropical forest biome, respectively. The weighted EFs of CO_2 are within 3% of the arithmetic mean for all three biomes. According to the linear regression results for the different EF drivers, the climatic window with the most predictive power for CO, CH_4 and CO_2 EFs together is based on fraction tree cover and mean annual precipitation (Table 2, FTC-MAP). Based on the weighting by FTC and MAP, the EFs are systematically lower than the arithmetic mean of A&M2001, with a 8.7%, 3.7%, and 2.1% decrease for CH_4, and 1.2%, 1.5%, and 0.4% for CO_2, for the savanna, tropical forest, and extratropical forest biome, respectively. For CO the weighted EFs were lower than the arithmetic mean of A&M2001-2009 for savanna and tropical forest (1.7% and 7.9%), but higher for extratropical forest (3.8%).

We adjusted the different vegetation types that were defined by A&M2001-2009, and based on these biomes (savanna and grasslands, tropical forest, extratropical forest), we calculated new weighted EF averages. Specifically, several measurements were conducted in vegetation types (for example chaparral in California and pinetree forest in Mexico) that cannot be clearly classified as savanna and grassland, tropical forest, or extratropical forest. While the savanna and tropical forest biome EF measurements were clustered in Figure 5, the extratropical forest measurements show more variation (Figure 5b). For a more specific EF average, it could be helpful to expand the amount of vegetation types, for example by adding a 'temperate forest' and/or 'chaparral' biome as in the Akagi et al. (2010) database.

Second, another level of weighting was performend by moving from a discrete classification based on a limited number of biome types, to stratifying EFs by vegetation density (FTC, NDVI) and climatic conditions (precipitation, temperature, length of dry season). Therefore, we developed a non-vegetative classification scheme for EFs (Figure 6), driven by the different environmental parameters presented in Table 1. The global average MCE, weighted by the amount of biomass combusted in the 1997-2008 period, for the whole savanna biome compared well with the biome-averaged MCEs of A&M2001-2009 and the weighted average MCEs for the different climate windows (Table 2). However, CO and CH_4 EFs were ~13% and ~22% higher than the biome-averaged values of A&M2001-2009 for the savanna biome, possibly linked to the underrepresetation of woodland fires in EF measurements. In addition, regional differences in MCE for the savanna biome were found, with the highest MCE for savanna & grasslands in Australia. Although our temporal and spatial variable MCE captures the grassland to closed savanna range in the savanna biome reasonably well, future adjustments in our scheme are needed –for example for extratropical forests- because it may be biased towards tropical regions where the majority of measurements were made.

4.6 Recommendations for future EF campaigns

Ongoing studies aim to better quantify EFs. They often fill a niche, for example by measuring fuels for which information is lacking, like tropical peat fires. In addition, emphasis has switched towards understanding chemical processes within the fire plume. We have shown, however, that current available information on EFs is insufficient to improve our understanding of the factors driving variability in EFs to levels of uncertainty found in other fire emissions parameters. By taking into account the following recommendations this situation may be improved:

Spatial representation: several areas are undersampled but are key emissions areas, most importantly Central Africa, boreal Asia, and Indonesia. Each of these regions likely has relatively high rates of emissions of reduced gases; more woodland burning in Central Africa compared to southern Africa where most savanna measurements were made, more groundfires in boreal Asia compared to boreal North America where most extratropical EFs were measured, and moister conditions and more peat burning in Indonesia compared to South America where most deforestation fire EFs were made.

Seasonality: to better understand the temporal variation of EFs in specific vegetation biomes, there is a need of measurements made over the full fire season, following Korontzi et al. (2003). In addition, the currently available measurements have placed too much weight to the months before (tropical forest) or the months before and after (grassland and savannas) the peak fire month and a stronger focus towards the peak fire month would yield a better sample of the fire seasonality.

Fuel and ambient conditions: measuring and describing fuel composition, its moisture content, and ambient conditions such as windspeed and temperature may allow for a better understanding of the factors driving EFs, especially when multiple locations are visited with the same measurement protocol. This requires a more multi-disciplinary approach and calls for combining campaigns aiming to quantify biomass loads, combustion completeness, EFs, and satellite validation of e.g. hotspot detection efficiency and the accuracy of burned area.

4.7 Future steps

We found that stratifying EFs by vegetation density (fraction tree cover) and climatic conditions may better represent the large variability in EFs compared to a discrete classification based on a limited number of biome types. Based on these findings we aim to implement different EF scenario's into the GFED modeling framework. In combination with inverse modeling and space-based observations of trace gases, we will then investigate whether these new estimates corresponds better with atmospheric constraints.

5 Conclusion

The partitioning of combusted biomass into trace gases and aerosols shows large variation in time and space. We assessed what fraction of this variability can be explained by coarse resolution, globally available datasets including fraction tree cover, precipitation, and temperature. When combined, these datasets could account for up to about 40% ($r=0.62$) of the variability in emission factors. Uncertainties in driver data, the range of fuel C content, differences in measuring techniques, assumptions on weighting ratios of flaming and smoldering contributions, and insufficient information on the measurements may account for part of the remaining variability. In addition, we neglected driver data such as fuel spacing, topography, and windspeed, which also may explain part of the variability.

782 We have calculated new average EFs for three biomes, by 1) weighting the EF locations by
783 the amount of biomass combusted, and 2) building new maps of MCE using the relations
784 between environmental variables and EFs, and weigh each grid cell by the amount of biomass
785 combusted. Using the climatic window with the highest predictive power, weighted EFs for
786 the individual EF measurement locations were lower than the arithmetic mean of A&M2001-
787 2009, with a 8.7%, 3.7%, and 2.1% decrease for CH_4, and 1.2%, 1.5%, and 0.4% for CO_2, for
788 the savanna, tropical forest, and extratropical forest biome, respectively. For CO the weighted
789 EFs were lower than the arithmetic mean of A&M2001-2009 for savanna and tropical forest
790 (1.7% and 7.9%), and higher for extratropical forest (3.8%). Taking all levels of uncertainty
791 into account, none of these differences may be significant.

792 However, the second level of weighting using a non-vegetative classification EF scheme
793 driven by different environmental parameters indicated that the MCE for savanna and
794 grasslands may be lower than the MCE based on the arithmetic mean of all EF measurements.
795 This would indicate higher emissions of CO and other reduced gases for the same amount of
796 biomass burned for all global grasslands and savannas combined due to an
797 underrepresentation of EF measurements in woodland burning regions. In addition, regional
798 differences in MCE for the savanna biome were found, with the highest MCE (and thus
799 lowest CO EF) for savanna & grasslands in Australia.

800 Currently, most of the literature describing emission factor measurements lack a detailed
801 description of the measurement site and ambient conditions during the experiment. This
802 information is crucial to better understand the differences between the various measurements,
803 and be able to understand the representativeness of large-scale satellite data and ambient
804 conditions as done in this study. In addition, to better facilitate our understanding and ability
805 to model MCE or EFs, more EF measurements should be performed in the peak fire months
806 and in unsampled geographic areas. The development of a more uniform sampling protocol
807 for the sampling and measurements of EFs in different vegetation types is another crucial step
808 to better compare different measurements. For example, the database of Akagi et al. (2010),
809 that compiles EFs based on a more uniform and accurate sampling protocol consistently only
810 takes those measurements focusing on fresh smoke into account, better representing initial
811 emissions.

812 A future step will be to implement our findings into the Global Fire Emission Database
813 (GFED), and in combination with inverse modeling and space-based observations of trace

814 gases, to investigate how a better representation of the spatial and temporal variability in EFs
815 may improve our understanding of biomass burning emissions.

816

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Tables:

Table 1. Correlation coefficients (r) and F-values (F) for CO, CH_4, and CO_2 EF measurements and different driver data. The MCE, based on the CO and CO_2 EF, are also shown. The correlation coefficient for the multivariate regression equation is also shown (r combined). *n* corresponds to the number of samples used, and F-values shown in italic indicate relations that did not exceed the critical F-value for a signifcance level of 0.01.

Driver data	CO (n=216)		CH_4 (n=205)		CO_2 (n=169)		MCE (n=169)	
	r	F	r	F	r	F	r	F
Fraction tree Cover	**0.49**	**66.2**	**0.58**	**104.3**	**-0.26**	**10.1**	**-0.47**	**46.9**
Monthly Precipitation	**0.40**	***1.9***	**0.53**	**13.8**	**-0.37**	**27.1**	**-0.52**	**62.2**
Mean Annual Precipitation	**0.29**	**3.2**	**0.33**	**4.4**	**-0.13**	***0.4***	**-0.15**	**4.1**
Monthly Temperature	**-0.13**	***0.1***	**0.03**	***0.1***	**-0.13**	***2.7***	**0.01**	***0.2***
Mean Annual Temperature	**-0.23**	***1.1***	**-0.24**	***2.2***	**0.16**	***0.9***	**0.29**	**15.9**
Monthly NDVI	**0.41**	**7.0**	**0.39**	***0.5***	**-0.22**	***0.2***	**-0.46**	**46.1**
Length dry season <100mm	**0.17**	**22.1**	**-0.06**	***0.6***	**0.03**	***5.9***	**-0.05**	***0.4***
r combined	**0.57**		**0.62**		**0.43**		**0.58**	

Table 2. EFs of CO, CH_4, CO_2 (in g/kg DM), and MCE for savanna (S), tropical forest (T), and extratropical forest (E), weighted by carbon emissions and stratified by mean annual precipitation (MAP), mean annual temperature (MAT), fraction tree cover (FTC) bins, and a multivariate regression equation that combined different environmental parameters (Table 1). Biome-averaged arithmetic means of A&M2001-2009 are also shown, with standard deviations in parenthesis. The results for the climatic window with the highest predictive power are shown in italic.

	CO (g/kg DM)			CH_4 (g/kg DM)			CO_2 (g/kg DM)			MCE		
	S	T	E	S	T	E	S	T	E	S	T	
Mean Annual Precipitation – Mean Annual Temperature	**56**	**94**	**107**	**1.9**	**5.6**	**4.0**	**1624**	**1636**	**1588**	**0.948**	**0.919**	**0.9**
Fraction Tree Cover – Mean Annual Temperature	**61**	**97**	**120**	**2.1**	**5.8**	**4.7**	**1622**	**1615**	**1529**	**0.944**	**0.915**	**0.8**
Fraction Tree Cover – Mean Annual Precipitation	***59***	***93***	***112***	***2.1***	***5.7***	***4.7***	***1627***	***1578***	***1565***	***0.949***	***0.917***	***0.8***
Environmental parameters combined	**68**	**82**	**95**	**2.8**	**4.6**	**4.2**	**1647**	**1627**	**1648**	**0.943**	**0.930**	**0.9**
A&M2001-2009	**60 (19)**	**101 (16)**	**106 (36)**	**2.3 (0.8)**	**6.6 (1.8)**	**4.8 (1.8)**	**1646 (99)**	**1626 (39)**	**1572 (106)**	**0.946**	**0.911**	**0.9**

Figures

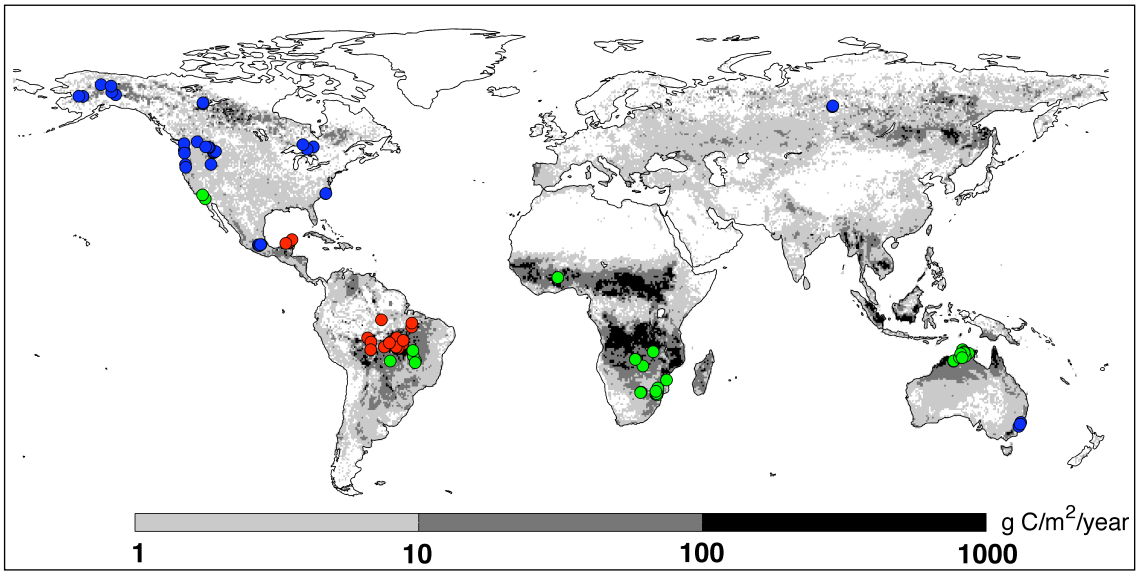


Figure 1: Locations where simultaneous CO and CO_2 EFs were measured. Locations were stratified by biome following A&M2001; savanna & grassland (purple), tropical forest (red), and extra-tropical forest (yellow). Background map shows annual GFED3.1 fire emissions in g C/m^2/year, averaged over 1997-2008, and plotted on a log scale.

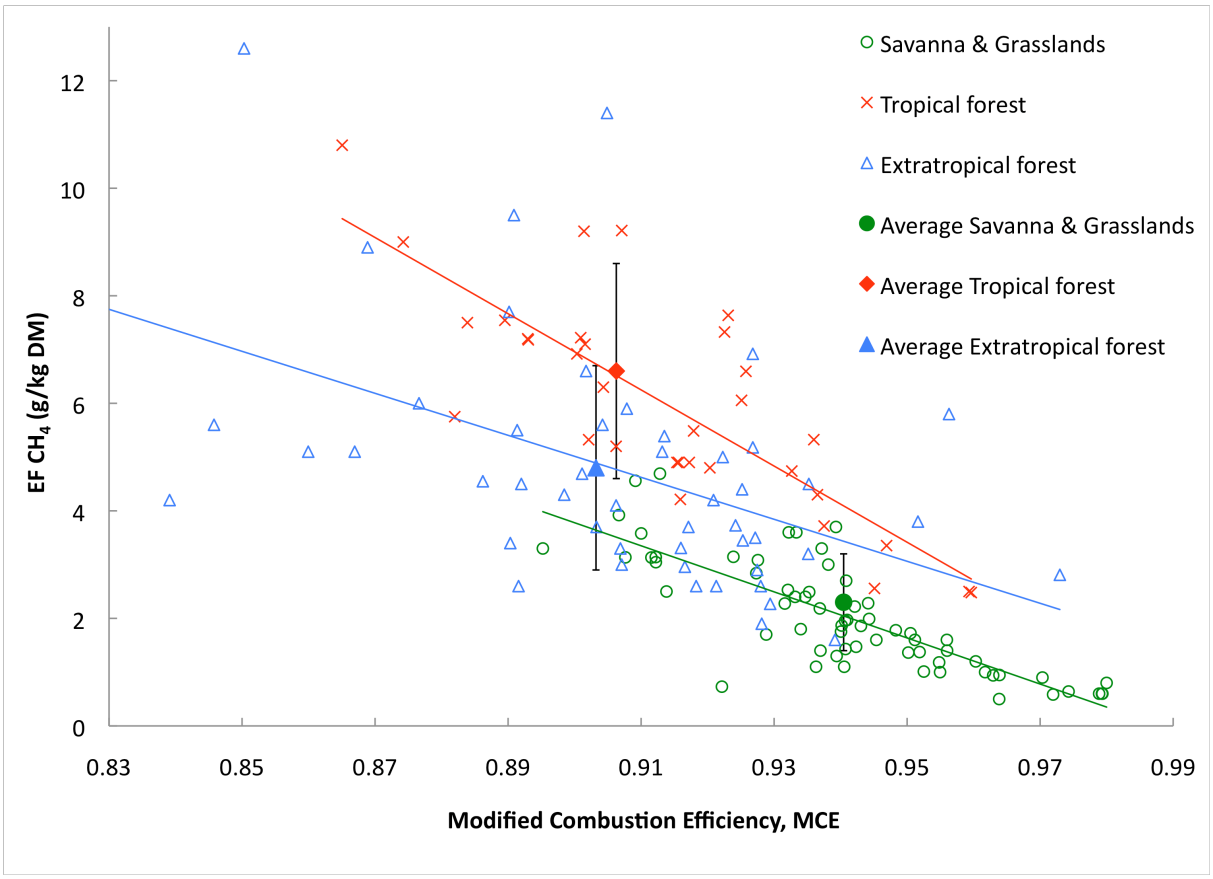
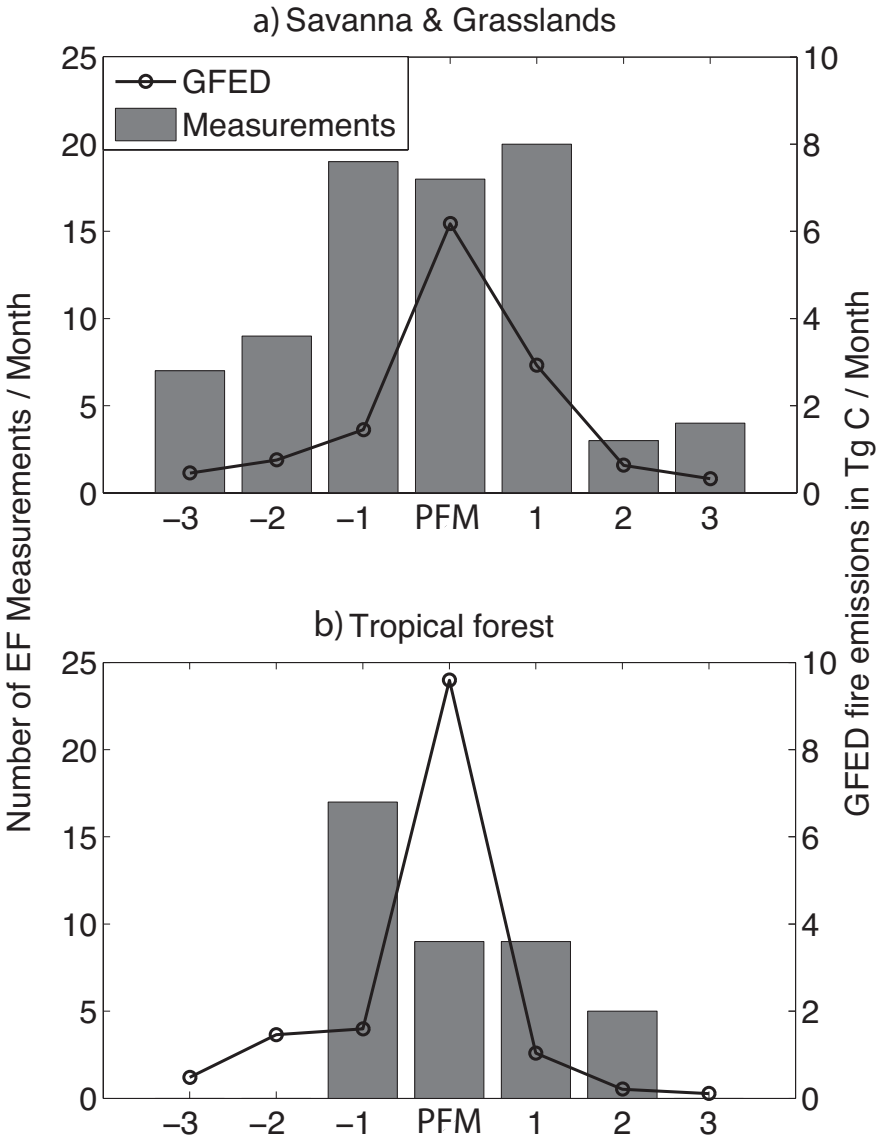


Figure 2: Methane (CH_4) EFs and the molar-based modified combustion efficiency (MCE) for all available measurements, the biome-averaged values presented in A&M2001-2009, and regression lines. The errorbar indicates the standard deviation as reported in A&M2001-2009. Regression coefficients for the different biomes can be found in the text (Section 3.2, lines 292-299).



1164

1165 **Figure 3:** Number of EF measurements (bar) and GFED3.1 fire emissions (line) in Tg C for
1166 the peak fire month (PFM), and the months before and after the PFM, for all EF measurement
1167 locations in the a) savanna and grassland and b) tropical forest biome.

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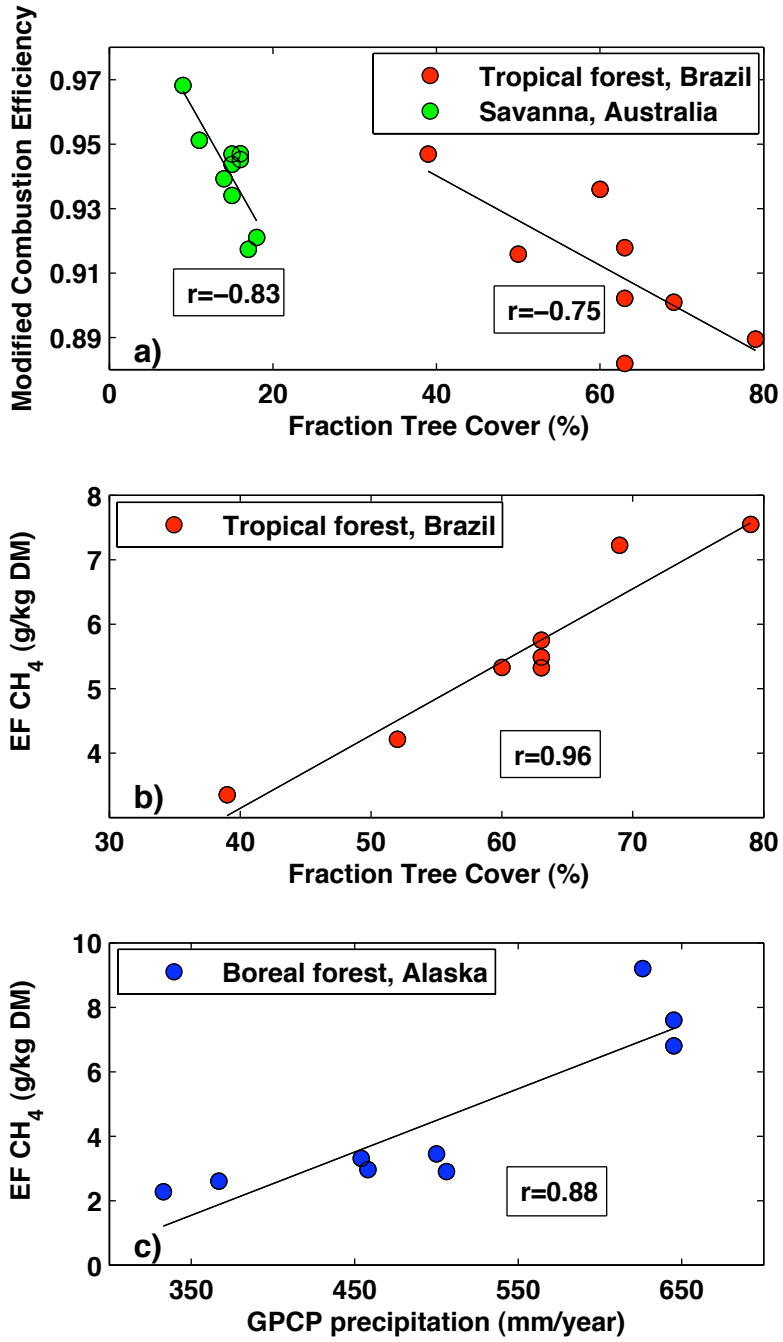
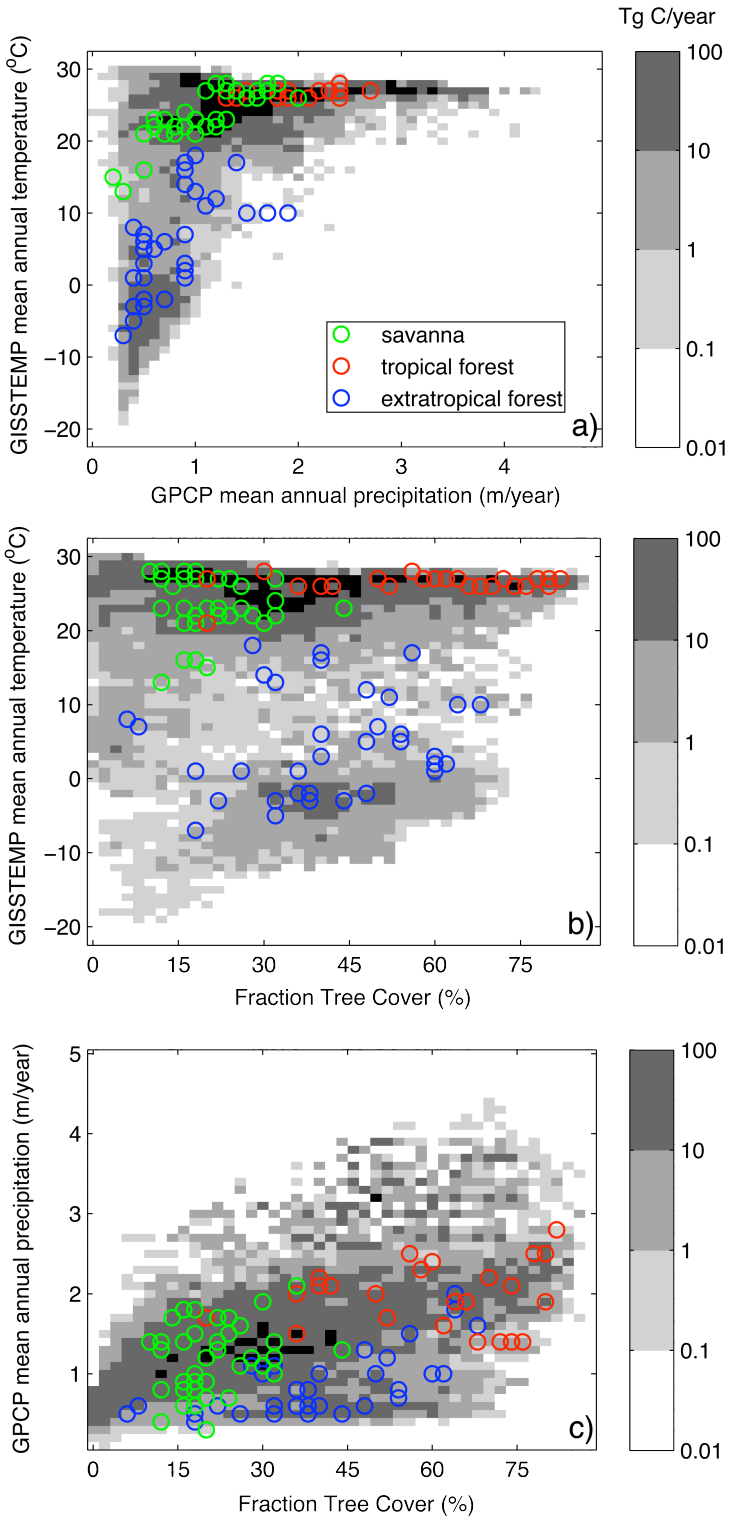


1169

1170 **Figure 4:** Relations between driver data and EFs or MCE for selected regions. a) fraction tree
1171 cover and modified combustion efficiency (MCE) for savanna measurements in Australia
1172 (Hurst et al., 1994; Shirai et al., 2003) and tropical deforestation measurements in Brazil
1173 (Yokelson et al., 2007), b) fraction tree cover and CH_4 EF for tropical deforestation
1174 measurements in Brazil (Yokelson et al., 2007), and c) precipitation and CH_4 EF for extra-
1175 tropical forest measurements in Alaska (Laursen et al., 1992; Goode et al., 2000; Wofsy et al.,
1176 1992; Nance et al., 1993).



1177

1178 **Figure 5:** GFED3.1 fire emissions in Tg C/year (mean for 1997-2008) in a temperature –
1179 precipitation (a), temperature – fraction tree cover (b), and precipitation – fraction tree cover
1180 (c) window overlain by EF measurements in savanna and grasslands (green), tropical forest

(red), and extratropical forest (blue circles). Temperature and precipiation were averaged over 1997 – 2008.

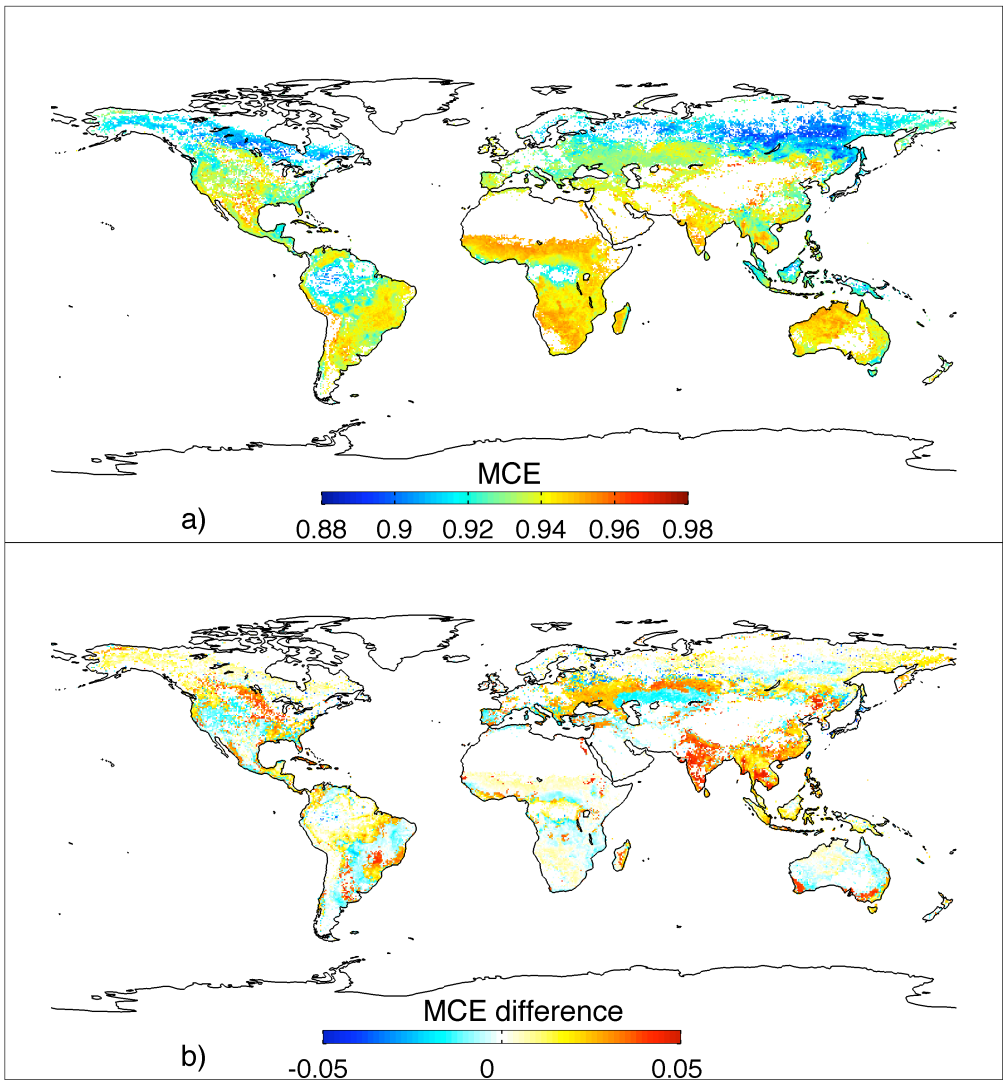


Figure 6. a) MCE based on a multivariate regression equation that combined different environmental parameters (see Section 3.5), with a spatial resoltution of 0.5°×0.5° and weighted by the amount of biomass combusted according to GFED3.1 for the years 1997-2008. b) Difference between a) and the biome average MCE according to data of A&M2001-2009. Here, emissions from peat fires have been neglected.