Hotspots of gross emissions from the land use sector: patterns, uncertainties and leading emission sources for the period 2000-2005 in the tropics.

Short title: AFOLU greenhouse gas emissions hotspots

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Abstract

According to the latest report of the Intergovernmental Panel on Climate Change (IPCC), emissions must be cut by 41-72% below 2010 levels by 2050 for a likely chance of containing the global mean temperature increase to 2 °C. The AFOLU sector (Agriculture, Forestry and Other Land Use) roughly contributes with a quarter (~ 10 -12 $PgCO_2e.yr^{-1}$) of the net anthropogenic GHG emissions mainly from deforestation, fire, wood harvesting, and agricultural emissions including croplands, paddy rice and livestock. In spite of the importance of this sector, it is unclear where are the regions with hotspots of AFOLU emissions, and how uncertain these emissions are. Here we present a novel spatially comparable dataset containing annual mean estimates of gross AFOLU emissions (CO_2, CH_4, N_2O), associated uncertainties, and leading emission sources, in a spatially disaggregated manner (0.5°), for the tropics, for the period 2000-2005. Our data highlight: i) the existence of AFOLU emissions hotspots on all continents, with particular importance of evergreen rainforest deforestation in Central and South America, fire in dry forests in Africa, and both peatland emissions and agriculture in Asia; ii) a predominant contribution of forests and CO_2 to the total AFOLU emissions (69%) and to their uncertainties (98%), iii) higher gross fluxes from forests coincide with higher uncertainties, making agricultural hotspots appealing for effective mitigation action, and iv) a lower contribution of non-CO_2 agricultural emissions to the total gross emissions (ca. 25%) with livestock (15.5%) and rice (7%) leading the emissions. Gross AFOLU tropical emissions 8.0 (5.5-12.2) were in the range of other databases 8.4 and 8.0 $PgCO_2e.yr^{-1}$ (FAOSTAT and EDGAR respectively), but we offer a spatially detailed benchmark for monitoring progress on

reducing emissions from the land sector in the tropics. The location of the AFOLU hotspots of emissions and data on their associated uncertainties, will assist national policy makers, investors and other decision-makers who seek to understand the mitigation potential of the AFOLU sector.

1. INTRODUCTION

Currently unabated CO_2e emissions need effective mitigation action (UNEP, 2015). Emissions modelling suggests that to maintain the global mean temperature increase on track with the 2°C target and to remain close to the 450 ppm of CO_2e by 2100, global greenhouse gas (GHG) emissions must be cut in a range of 41-72% below the 2010 levels by 2050, and global emissions levels must be reduced to zero (a balance between sources and sinks) by 2070 and below zero through removal processes after that (IPCC, 2014; Anderson, 2015; UNEP 2015). To reach these ambitious goals, it is imperative to identify regions where the mitigation of key emission sectors may be most promising in terms of reducing fluxes, reducing emission trends, and/or maximizing returns on mitigation investments. From all the sectors contributing to the total anthropogenic GHG emissions, the Agriculture, Forestry and Other Land Use (AFOLU) sector participates with roughly one quarter (10-12 $PgCO_2e.yr^{-1}$) of the total emissions (49 $PgCO_2e.yr^{-1}$) (IPCC, 2014). Optimistic estimates suggest that the AFOLU sector -here used as synonym of land use sector- could contribute 20 to 60% of the total cumulative abatement to 2030 through land-related mitigation including bioenergy (Smith et al., 2014). However, it is unclear where are the regions with the largest AFOLU emissions (hotspots of emissions), and how large their associated uncertainties are.

Modelling efforts by the carbon community have long offered useful data but their focus is rather global and CO_2-oriented, which omits other land use gases such as CH_4 and N_2O (Schulze et al., 2009; Houghton et al., 2012; LeQuéré et al., 2012; Canadell et al., 2014; Tian et al., 2016). Currently, the most used AFOLU data belong to two global multi-gas (CO_2, CH_4, N_2O) CO_2e databases: FAOSTAT and EDGAR) (Smith et al., 2014; Tubiello et al., 2015). While they offer very valuable data, they suffer from several shortcomings: they do not provide uncertainties or uncertainties are not provided at the spatial scale at which emissions are offered; they suffer from untransparent documentation (e.g. EDGAR) or data are offered at inappropriate spatial scales to effectively navigate mitigation implementation (e.g. country level in FAOSTAT). Thus, unlike aggregated estimates, spatially explicit data favour targeted mitigation action and implementation by identifying where are the areas within a country that hold the largest emissions, and what are the key emission sources to address in these areas (e.g. deforestation, degradation, livestock, cropland soils, paddy rice). Spatially explicit assessments of AFOLU emissions and their associated uncertainties would assist national policy makers, investors and other decision-makers who seek to understand the mitigation potential of the AFOLU sector, and which areas to prioritize This potential is here defined as the maximum mitigation reduction that could be achieved without technical or economic considerations. Better understanding of the AFOLU mitigation potentials will also be important under the Paris Agreement (PA) since the fulfilment of the 2°C target is dependent on the mitigation ambition presented by countries in their Nationally Determined Contributions (NDCs). To safeguard this ambition a stock-take process has been defined, by which countries are required to update their NDCs every five years, starting from 2020, and to enhance their mitigation commitments from previous submissions (Bodle et al., 2016). It is therefore imperative to improve our understanding of where and how much could countries enhance their AFOLU ambition from what they have currently reported.

Mitigation action can be directed to reducing emissions by the sources, or to increasing the absorptions by the sinks, or to both. While gross and net emissions are equally important, they offer different information (Richter and Houghton, 2011; Houghton et al., 2012). Net land use emissions represent the sum of emissions by sources and removals by sinks. Land use sinks refer to any process that stores GHGs (e.g. forest growth, forest regrowth after disturbances, organic matter stored in soils, etc) (see Richter and Houghton, 2011, for further details). Countries report their emissions and their reduction targets based on net AFOLU balances (IPCC, 2006; Iversen et al., 2014; Smith et al.,2014). Assessments of gross emissions offer separate data on emissions by sources (gross emissions) and removals by sinks (gross removals), and are useful for designing mitigation implementation because they offer direct information on the sources and sinks that may be acted upon through policies and measures to enhance and promote mitigation. However, lack of ground data makes the assessment of gross sinks much more difficult than the assessment of gross sources (Lewis et al., 2009; Houghton et al., 2012; Grace et al., 2014; Brienen et al., 2015) with a particular gap on disturbed standing forests (Poorter et al., 2016).

For these reasons, we present here an assessment of AFOLU gross emissions only, for the tropics and subtropics. We exclude sinks (e.g. regrowth of cleared forests or burned areas, and soil carbon storage). We offer spatially explicit (0.5°) multi-gas (CO_2, CH_4, N_2O) CO_2e gross emission data that help identifying the hotspots of land use emissions in the tropics and subtropics, and associated uncertainties for 2000-2005. Our method uses a consistent approach to overcome problems of different definitions, methods, and input data present in other approaches (e.g. nationally reported data), allowing data comparability. It is a top-down approach based on published spatially explicit GHG datasets for the key sources of emissions in the AFOLU sector as identified in the Fifth Assessment Report of the IPCC (AR5) (Smith et al. 2014): deforestation, fire, wood harvesting, crop soil emissions, paddy rice emission, enteric fermentation and manure management. We address three questions at the landscape, tropical, and continental scales: 1. Where are the hotspots of tropical AFOLU emissions and how uncertain are they? 2. What are the main GHGs emissions behind these hotspots?, 3. What are the emission sources behind these hotspots? 4. How do our gross AFOLU emissions relate to other AFOLU datasets such as FAOSTAT or EDGAR?

2. MATERIAL AND METHODS

Our study area covers the tropics and the subtropics, including the more temperate regions of South America (33° N to 54° S, 161° E to 117° W). It expands over a diversity of ecosystems that range from dry woodlands and dry forests such as the African Miombo and South American Chaco, to rainforests and moist forests such as evergreen broadleaved rainforests or montane cloud forests. The years considered by our datasets varied, yet we selected the period 2000-2005 as the common temporal range for all the datasets. The exception was the rice emissions dataset, that took 2010 as its baseline (See Table S2 in supplementary).This time period represents a useful historical baseline against which countries can contrast the evolution of their AFOLU gross emission performances. We consider the pixel size (0.5°) appropriate for landscape research, and useful to visualize emissions hotspots. More detailed information about each data source and a descriptive summary is available in the SOM (Table S2).

2.1 Datasets

Deforestation (Harris et al., 2012): Deforestation refers to gross emissions, associated to the area of forest cover loss (above ground and below ground biomass) that is removed due to human or natural disturbances, at 18.5 km of spatial resolution and aggregated in a 5-year period (2000-2005). Deforestation areas are based on MODIS data at 18.5 km resolution, while carbon loss derives from Saatchi et al., (2012) carbon map, at 1 km resolution. The disparate spatial resolution of these two maps is solved by a randomization procedure (Harris et al. 2012). Information of uncertainties is expressed as 5^{th} and 95^{th} percentiles, estimated through Monte Carlo simulations and showed non-Gaussian distributions. Harris et al data defines the spatial and temporal extent of our tropical AFOLU analysis.

Fire (Van der Werf et al., 2010): Fire emissions (CO_2, CH_4, N_2O) were obtained from the Global Fire Emission Database (GFED) (www1) at 0.5° resolution, based on the CASA model which includes four carbon pools (above and below ground biomass, litter and coarse woody debris). Only carbon from organic soils was included. Original data were of global coverage for the period 1997-2013. We extracted a subset for the tropics and 2000-2005. Annual uncertainties for different regions are expressed in Van der Werf et al. (2010) as the 5th, 25th, 50th, 75th, and 95th percentiles of 2000 Monte Carlo runs. 1σ uncertainties (expressed as percentage of the 50th percentile) were also given, and considered Gaussian distributions. To move to pixel (0.5°) uncertainties, we assigned the regional 1σ to all the pixels within each region, for each gas. Total fire emissions (CO_2e) per pixel were the sum of the annual means. The uncertainties of the different gases (CH_4, N_2O and CO_2) were assumed independent and estimated by square rooting the sum of their variances. Fire emissions are partitioned into six classes (savannah, agriculture, woodlands, forests, peatlands and deforestation), which helped us remove CO_2 emissions from savannahs and agriculture since the burning of these non-woody land uses is assumed carbon neutral (e.g. biomass burned gets recovered by biomass growth in the next growing season) (IPCC, 2006). CH_4 and N_2O emissions were, however, retained. We also removed deforestation fires, to avoid double counting with deforestation emissions from Harris *et al.* (2012). Some overlapping of deforestation and soil peat burning might however occur where peat fires and deforestation fires show similar fire recurrences and might be wrongly labelled (Van der Werf *et al.,* 2010). Some peat fires might, therefore, respond to deforestation fires and cause some double counting with Harris deforestation emissions. This would only affect Indonesia since it is the only country that counts on spatially explicit peatland maps (Van der Werf et al. 2010), and would therefore represent a small bias.

Wood harvesting (Poulter et al., 2015): Wood harvesting is a 1° global gridded data set, generated in the frame of the GEOCARBON project. It uses National Forest Inventory data and the FAO Forest Resources Assessment (FRA). Aboveground biomass data were downscaled using a forest mask from the Global Land Cover (GLC) 2000, and assuming that wood harvest was distributed evenly. The original data were produced at the resolution of the GLC2000 (approx. 1X1 km) and finally aggregated to the 1° scale. Wood Harvesting data consisted of five layers: 1. Round wood Forest Area in hectares for each cell, 2. Fuelwood forest area in hectares for each cell, 3. Round wood (industrial) harvest volume in m^3, 4. Fuelwood harvest volume in m^3, 5. Total harvest volume (round wood + fuelwood) in m^3. We chose fuel and industrial round wood harvest (m^3) as our harvest data. Wood harvest is a gross flux since no regrowth is considered. We assumed instantaneous emissions assigned to the place of removal, without considering lags in decay, nor the fate of the harvested product (i.e., slash, paper, furniture, construction), nor the possible substitution effects (e.g. energy production using wood biomass instead of fossil fuels). We therefore acknowledge that the instantaneous flux from wood harvest would be lower if these effects had been considered. Emissions were transformed from m^3 to $MgCO_2.yr^{-1}$ using an emission factor of 0.25 ($Mg\ C/m^3$) (Grace et al., 2014), and a C to CO_2 factor shown in Table 1. The resolution of this layer was larger than our grid so wood estimates were equally distributed among our 0.5° grid cells. Because wood harvesting relied on official data reported by countries to FAO, the authors assumed that harvesting emissions only derive from forests remaining forests (legal logging), and assigned these emissions to forested areas only. Figure S3 in SOM shows different spatial locations for deforestation and wood harvesting emissions. However, this assumption might be wrong and some unprecise amount of double counting may occur. Uncertainties were not estimated in the original harvest emission data. Therefore, and based on the authors' expert opinion, we chose a 20 percent uncertainty value, per pixel.

Cropland soils (USEPA 2013): Cropland emissions (N_2O and soil dSOC) (changes in soil organic carbon) were produced by Ogle et al., for the Environmental Protection Agency MAC-Report (USEPA, 2013), at 0.5° resolution, for time periods 2000-2030 with five-year increments, based on the DAYCENT ecosystem model (Ogle et al., 2007). For our AFOLU analysis we used the annual mean emission data for the period 2000-2005. The original units (g N_2O-N.m-^{2}.y^{-1} and gC.m^{-2}.5y^{-1}) were transformed to CO_2e.y^{-1}.grid cell^{-1} (Table 1). The original dataset included direct and indirect emissions from mineral-based cropland soil processes: synthetic and organic fertilization, residue N, mineralization and fixation). To be consistent with other data sets we did not include indirect emissions (e.g. NO_3^- leaching, N runoff in overland water flow). Emissions estimated by the DAYCENT include soil and litter pools and modelled six major crop types only (maize, wheat, barley, sorghum, soybean and millet) excluding other important tropical crops (sugar, coffee, cacao, cotton, tobacco, etc). As a result, the cropland area simulated by DAYCENT was about 61% of the global non-rice cropland areas reported by FAOSTAT, which resulted in lower cropland emissions when compared to other databases (e.g. FAOSTAT and EDGAR). Moreover, due to the known poor performance of the DAYCENT model over organic soils, cropland emissions over drained histosols were not part of the estimated emissions. Uncertainties were offered per pixel (0.5°) as standard deviations per dSOC and N_2O separately. Final CO_2e uncertainties per pixel were propagated as independent data using the squared root of the summed variances. To complement the emission gap from the organic cultivated soils, we used a Tier 1 approach that relied on the location of the tropical areas of histosols (ISRIC's global soil database), the location of cropland areas per crop types (Monfreda et al., 2008) and a Tier 1 annual emission factor for cultivated organic soils (20 MgC.ha^{-1} yr^{-1}) derived from the IPCC (IPCC 2006) (Supplementary).

Paddy Rice (USEPA 2013): We used data by Li et al., from the USEPA's MAC Report (2013). Emissions were estimated by the Denitrification-Decomposition (DNDC) model, which simulates production, crop yields, greenhouse gas fluxes (CH_4, N_2O) and organic soil carbon (dSOC) of global paddy rice, at 0.5° resolution under "business-as-usual" (BAU) condition and various mitigation strategies as explained in Li et al., (2001, 2006). This model includes soil, litter, above and below ground biomass as main carbon pools. Model outputs were reported for 2010 as the baseline, and used 22 years of replications to account for climate variability. The original units ($KgC.ha^{-1}.yr^{-1}$ for dSOC and CH_4 and $KgN.\ ha^{-1}.yr^{-1}$ for N_2O) were re-projected to equal-area values, and transformed to CO_2e (Table 1). Emissions were estimated using the MSF (Most Sensitive Factor) method which relies on an envelope approach and estimates maximum and minimum emissions based on extreme soil properties. No mean values were offered. The distribution of the data were known to be right skewed, and through the authors' expert judgement a log-normal approach was considered to be the best –although not perfect- fit, from where to estimate the mean (50th percentile), max and min (10th and 90th percentile) for each cell.

Livestock (Herrero et al., 2013): Livestock emission data includes enteric fermentation (CH_4) and manure management (N_2O, CH_4) for the year 2000, for twenty-eight regions, eight livestock production systems, four animal species (cattle, small ruminants, pigs, and poultry), and three livestock products (milk, meat, and eggs), at 0.1°cell resolution. The CO_2e of enteric fermentation and manure management were then summed to obtain a total emission value of livestock per grid cell. Since no spatially explicit uncertainty data were provided, and based on the authors' expert judgement, we applied a 20% value for livestock emissions per cell and per gas. Per cell livestock GHG uncertainties were estimated by square rooting the sum of their variances.

Other AFOLU databases

FAOSTAT database: covers agriculture, forestry and other land uses and their associated emissions of CO_2, CH_4 and N_2O, following IPCC 2006 Guidelines at Tier 1 (Tubiello et al., 2014). Emissions are estimated for nearly 200 countries, for the reference period 1961–2012 (agriculture) and 1990–2012 (FOLU), based on activity data submitted to and collated by FAO (www1).

FAOSTAT includes estimates of emissions from biomass fires, peatland drainage and fires, based on geo-spatial information, as well as on forest carbon stock changes (both emissions and absorptions) based on national-level FAO Forest Resources Assessment data (FRA, 2010). FOLU carbon balances in FAOSTAT are emissions from afforestation, reforestation, degradation, regrowth, and harvest activities. The FAOSTAT emission estimates are based on annual FAO emissions updates for AFOLU (Tubiello et al., 2014).

EDGAR database: The Emissions Database for Global Atmospheric Research (EDGAR) provides global GHG emissions from multiple gases (CO_2, CH_4, N_2O) at 0.1° and country levels. It covers all IPCC sectors (energy, industry, waste management, and AFOLU), mainly applying IPCC 2006 guidelines for emission estimations (EDGAR, 2012). We selected EDGAR's 4.2 Fast Track 2010 (FT 2010) data (www2). Emissions cover the period 2000-2010 in an annual basis, at the country level and are offered as Gg of gas. No uncertainties are provided. Transformation to CO_2e used AR4 100year-Global Warming Potential values to be consistent with other datasets. Metadata can be found at EDGAR (2012), although further transparency and more complete documentation are required for this database.

2.2 Methods

Hotspots dataset

Our AFOLU assessment is based on several assumptions: we focus on human-induced gross emissions only, excluding sinks. We exclude emissions and sinks from unmanaged land (e.g. CH_4 or N_2O emissions from unmanaged natural wetlands). We focused on direct gross emissions excluding indirect emissions whenever possible (e.g. indirect emissions from nitrate leaching and surface runoff from croplands). Delayed fluxes (legacies) are important (e.g. underestimations of up to 62% of the total emissions when recent legacy fluxes are excluded) (Houghton et al., 2012) but are frequently omitted in GHG analyses that derive from remote sensing, such as our deforestation emissions from Harris et al., (2012). Wood harvesting emissions also excluded legacy fluxes. Therefore, no forest regrowth of cleared, burned, or disturbed forests are included in our AFOLU 2000-2005 assessment. Other important components of the overall terrestrial and carbon balance such as changes in litter, coarse woody debris and soil carbon, are also not part of the emissions from deforestation and wood harvesting, since these pools were not considered in the original datasets (see Table S2, SOM). For the other land uses, fire, agricultural soils, and paddy rice, their emission models (e.g. CASA, DAYCENT and DCDN) included temporal spin-ups to guarantee the stability of the emissions for their temporal scales under analysis. Certain legacies have, therefore, been considered (please see references for further understanding of these models).In the case of fires, since 90 percent of tropical fires are the result of human activity (Roman-Cuesta et al., 2003; Van der Werf et al., 2010), we assumed all emissions to be human-induced, independently of whether they are climate-driven. This might have resulted in some overestimation of fire emissions in drier ecosystems where lightening may start the fires (e.g. African woodlands). However, since we have excluded deforestation fires (to avoid double counting with deforestation), and we have also excluded savanna and agricultural fires (under the assumption of carbon neutrality), we are quite certain that our gross fire emissions for 2000-2005 are rather conservative. As requested by the IPCC (Federici et al., 2016), we have included all biomass burning emissions without considerations of climate extremes, even though we acknowledge the role of increased frequencies and intensities of droughts, and their interaction with fire in human-disturbed landscapes in the tropics (Brando et al., 2014). We assumed instantaneous emissions of all carbon that is lost from the land after human action (Tier 1, IPCC 2006) (e.g. fire, deforestation and wood harvesting), with no transboundary considerations (e.g. the emissions are assigned wherever the disturbance takes place, particularly important for the Harvested Wood Products). Life-cycle substitution effects are neither considered for harvested wood (Peters et al., 2012).

Figure 1 describes the steps followed to produce our spatially explicit layers of gross AFOLU emissions and uncertainties. We first assessed all possible emissions, land uses and human activities under the framework of the IPCC 2006 AFOLU guidelines. We then selected the key AFOLU emissions sources as identified in the IPCC Fifth Assessment Report (AR5) (Smith et al., 2014). There were seven key emission sources, three within the forest sector: deforestation, fire, and wood harvesting (these last two were considered as forest degradation), and four within agriculture: cropland soils, paddy rice, enteric fermentation and manure management (aggregated as livestock). We chose 100-year global warming potentials as provided in the Fourth Assessment Report (AR4) (IPCC, 2007) (Table 1) because all emission datasets were prior to the launching of AR5. We have preserved their choice to be consistent with their published estimates and with emissions that could not be reproduced. To promote the spatial assessment we produced an empty grid with cells of 0.5°x0.5° in a World Geographical reference System (WGS-84, lat-lon). To correct for the unaccounted Earth distortions that come with a geographical system we used equal area re-projected values whenever we needed area-weighted estimates of the emissions. This grid was then populated with the seven emission sources, unit transformed and quality controlled and assessed (see Supplementary). We used Monte Carlo simulations to aggregate the gross AFOLU emissions and their uncertainties and produced four final estimates, per cell: mean annual AFOLU emissions (50^{th} percentiles) ($CO_2e.y^{-1}$), associated variance, and 5^{th} and 95^{th} confidence intervals. Data were then aggregated to continental, and tropical scales. When aggregating uncertainties at the pixel level we assumed emission sources to be mutually uncorrelated. However, when the aggregation of the uncertainties included a change of spatial support (e.g. pixel to continental, or pixel to tropical) we assumed data complete dependence, which offered a conservative (worst-case) scenario approach for the final aggregated uncertainties (see supplementary for further information). To understand which emission sources (e.g. deforestation, degradation, livestock, paddy rice, etc) contributed the most to the final uncertainties at the continental scale, we used the variance data produced per pixel and aggregated them using the dependence assumption expressed above. The attribution of the uncertainty was then estimated as percentages of the final aggregated variance, for each emission source.

Database comparison

We contrast our hotspots of gross AFOLU emissions against the FAOSTAT and EDGAR databases. We run the comparisons at the country level, and produce the estimates selecting the same countries, years, emission sources, assumptions (e.g. carbon neutrality of grasslands and agricultural waste), and rules (e.g. only direct emissions) to guarantee comparability.

3. RESULTS AND DISCUSSION

3.1 AFOLU hotspots of emissions and uncertainties

Tropical AFOLU hotspots were located on all continents but spatially concentrated in a few areas only, with 25% of the tropical area responsible for 70% of the tropical AFOLU emissions (Figure 2a). Gross fluxes reached values of up to 90 $MgCO_2e\ ha^{-1}\ yr^{-1}$in the hotspots, with Brazil, India, Indonesia, Democratic Republic of Congo, Angola, Central African Republic, Mozambique, Zambia, Malaysia, Sudan and Bangladesh, as the major contributors of tropical AFOLU emissions. Hotspots were mainly led by forest emissions, both by deforestation and degradation, with large hotspots over humid rainforests in the arch of deforestation in Brazil, and over the Miombo-Mopane dry forests of Africa. Deforestation and peatland fires were important in Indonesia, combined with agricultural hotspots from livestock and paddy rice. Agricultural emissions contributed less to the hotspots, with Asia, particularly India and Bangladesh, as main emitting regions with different relative contributions from livestock, paddy rice and cropland emissions (Figure 3). Southern Brazil, northern Argentina and southeastern Paraguay also showed agricultural hotspots, mainly related to livestock. Main GHGs followed these patterns, with CO_2 dominating the emissions from forest activities, turning this gas into the main target for mitigation action. CH_4 dominated rice and livestock emissions, while N_2O explained high cropland emissions (Figure 4).

Emissions uncertainties were the highest for the hotspot regions, reaching values of up to 30% of the mean AFOLU emissions (Figure 2b), which is lower than the reported uncertainties for global AFOLU values (e.g. 50 percent) (Smith et al., 2014). The coincidence of high AFOLU emissions and high uncertainties is not surprising since the emissions from the hotspots were led by forests, and forests host the largest emission uncertainties, in particular humid tropical forests undergoing deforestation, such as Brazil and Indonesia, and forests with high fire emissions such as dry Miombo ecosystems in Africa or peatlands in Asia. Deforestation has long been identified as a main source of emissions uncertainties in the tropics due to the combined effect of uncertain areas and uncertain carbon densities (Houghton 2010, Baccini et al., 2012, Houghton et al., 2012). High uncertainties in fire emissions relate to biomass, burned soil depths, and combustion completeness, which are the most uncertain components of Van der Werf et al.(2010)'s fire emission model. Consequently, equatorial Asia and the African continent were the regions with the largest fire uncertainties of the globe (Van der Werf et al., 2010) (Fig S5 in Supplementary).

Areas with high gross emissions that also host high uncertainties (e.g. forests) complicate the effectiveness of the mitigation action. Thus, while these areas have higher mitigation potentials (e.g. high emissions that could potentially be reduced) their uncertainties affect the reliability of their emissions estimates and, therefore, the effectiveness to implement actions to stabilize atmospheric GHGs (Grassi et al., 2008). For this reason, from a climate mitigation perspective and without economic nor technical considerations, optimal mitigation scenarios would rather focus on areas with large gross fluxes and low(er) uncertainties. These areas would include agricultural hotspots (croplands, paddy rice and livestock) without much contribution from forest emissions such as parts of India, Southeastern Brazil, Northern Argentina, and Central and Southern Africa (southern DRC, Zambia, Angola) (Figure 5). Carter et al. (2015) identified that agricultural intensification and the use of available non-forest land offer opportunities for agricultural mitigation of up to 1 $PgCO_2e$. This value coincides with sectorial analyses of mitigation targets for 2030 that would keep agricultural emissions in line with the 2 degree target (Wollenberg et al. 2016). However, food security and economic development in countries with agro-businesses make supply-based agricultural mitigation challenging (Smith et al., 2008; 2013). Moreover, as discussed in Wollenberg et al. (2016) more transformative technical and policy options will be needed to help agriculture achieve this 1 $PgCO_2e$ target. Mitigation in the agricultural sector is further complicate by being technically more complex and more expensive than forest mitigation (USEPA, 2013, Smith et al., 2014). For these reasons, and in spite of their higher uncertainties, forests still remain high in the mitigation agenda, as recently seen in the Paris Agreement, associated COP decisions, and the New York Declaration on Forests.

3.2 Tropical AFOLU emissions

AFOLU data from the AR5 (e.g. Figure 11.2 in Smith et al., 2014) show how the tropics have contributed with ≥70% of the global AFOLU emissions in the last decades, making this region the right place to search for hotspots of land use emissions. Our aggregated gross AFOLU emissions estimates of 8.0 (5.5-12.2) $PgCO_2e.yr^{-1}$ were in the range of other gross estimates for the same region and time period: 8.4, and 8.0 $PgCO_2e.yr^{-1}$ for FAOSTAT and EDGAR respectively (Table 2). In spite of this good agreement, databases disagreed on the relative contribution of the leading emissions sources (Figure 6). Forests emissions showed the largest divergences, particularly forest degradation (fire and wood harvesting emissions). This outcome was expected since forest emissions were responsible for ≥70% of the tropical gross AFOLU emissions in all the databases (Table 2). Gross degradation emissions –rather than deforestation- led the forest emissions in our AFOLU gross emissions (39% *vs* 36% of the tropical emissions, respectively) (Table 2), with a degradation to deforestation emission ratio of 108%, reinforcing the great importance of reducing degradation for effective mitigation. Ratios above 100% for gross degradation *vs* deforestation had already been reported by Houghton et al. (2012) and Federici et al. (2015). Lower ratios have been observed in smaller areas (e.g. 40% Amazon, 47% Peruvian Amazon) (Asner et al., 2010; Berenguer et al., 2014) or when the ratio focuses on net fluxes of degradation (e.g. 25-35% of the net LULCC flux, if wood harvesting and shifting cultivation were not considered, and an extra 11% over the net LUCC flux when excluding peatland fire emissions in Southeast Asia alone) (Houghton et al., 2012).

In our hotspots analyses, fire led forest degradation in the tropics with almost a quarter (24.6%) of the gross AFOLU emissions. Since we had excluded deforestation fires, most of our fire emissions relate to woodlands and forest degradation. Their exclusion or incomplete inclusion would therefore result in large emission omissions in gross AFOLU assessments, and their management are key for reducing tropical emissions. Fire degradation emissions are recurrently omitted in global AFOLU assessments under the assumption of carbon neutrality of the affected burned areas (e.g. whatever carbon is emitted through fire will be fixed again by regrowth and recovery). (Houghton et al., 2012; Le Quéré et al., 2012; Canadell et al., 2014; Smith et al. 2014). This assumption does not consider current evidence of non-steady states after fire due to climatic pressures, humanized landscapes (fragmented, multi-disturbed), and increased frequencies of fires (Cochrane et al., 1999; Roman-Cuesta et al., 2014; Alencar et al., 2011, 2015; Brando et al., 2014; Oliveras et al., 2014; Pütz et al., 2014). Halted successional pathways and vegetation shifts represent a large, yet unknown proportion of the burned forest ecosystems in the tropics that require further research. Recent estimates suggest that post-fire carbon recoveries in the Amazon are leading to degradation emissions in the order of 46±29.9 $MgC.ha^{-1}$ (Balch et al., under review). In spite of our uncomplete knowledge of forest post-disturbance recovery pathways (e.g. poorly understood processes, omitted emissions, missing pools, unconsidered GHGs), the importance of the forest sector for mitigation action is evidenced by the large amount of countries explicitly mentioning it in their INDCs (60%) (Grassi et al., 2015). Moreover, countries count on financial support to minimize their forest emissions and enhance their sinks, at national scale, through the REDD+ mechanism, which has now become part of the Paris Agreement (Climate Focus, 2015).

In the agricultural sector, our emissions reached estimates of 1.9 (1.5-2.5) $PgCO_2e.yr^{-1}$, in the range of the other databases (2.5, 2.1 $PgCO_2e.yr^{-1}$ for FAOSTAT and EDGAR respectively). These values, represent a relatively small part of the AFOLU emissions in the tropics (25-30%) but an attribution of the forest emissions to their drivers would highlight back the importance of agriculture as the main engine behind tropical forest loss and emissions. Thus, for the period 1980-2000, 83% of the agricultural expansion in the tropics was at the expense of forests (Gibbs et al., 2010), calling for integrated mitigation programmes that simultaneously include forestry and agriculture (Carter et al., 2015). Our agricultural estimates represented only ca. half of the agricultural emissions reported globally for 2000-2009 (5-6 $PgCO_2e.yr^{-1}$) (Smith et al., 2014; Tubiello et al., 2015).This highlights the major role of agriculture in non-tropical countries and emergent economies like China, although agricultural emissions are rising faster in developing countries than in developed ones (Smith et al., 2014). The agricultural sector is the largest contributor to global anthropogenic non-CO_2 GHGs, accounting for 56 % of emissions in 2005 (USEPA, 2013). Enteric fermentation and agricultural soils are globally the main sources of agricultural emissions (Smith et al., 2014), and show a strong rising trend since the 70's (1% per decade) due to increases in animal heads and the use of synthetic fertilizers (Tubiello et al., 2015). Areas with growing emission trends are attractive for land-based mitigation action and countries are engaging in agricultural mitigation in their INDCs through climate smart initiatives (Richards et al., 2015). However, more transformative technical and policy options and higher level of financial support will be needed for further achievements in this sector (Wollenberg et al., in press). The most prominent agricultural mitigation practices include improved cropland and grazing land management, restoration of degraded lands, and cultivated organic soils. Lower, but still significant mitigation potential is provided by water and rice management, livestock management and manure management, set-aside, land use change and agroforestry (Smith et al., 2008).

In terms of gases, CO_2 led the AFOLU emissions in the tropics with ca.70% of the tropical emissions 5.5 (3.3-9.5) $PgCO_2e.yr^{-1}$ (Table 2, Figure 4). The remaining non-CO_2 contribution (30%) was mainly led by CH_4 1.5 (1.1-1.9) $PgCO_2e.yr^{-1}$, due to livestock and rice. Non-CO_2 emissions from biomass burning (N_2O and CH_4), represented 15-34% of the CO_2 emissions in the tropics (Table 2). These values reinforce the need to run multi-gas assessments (CO_2, CH_4, N_2O) for the AFOLU sector in order to gain a more coherent understanding on how the land affects the atmospheric composition and forces the climate. Thus, while temperature rise by around the end of this century will relate to the total emissions of long-lived greenhouse gases between 2000 and 2100 (e.g. CO_2) (Anderson 2012) recent research concludes that cumulative warming capacity of concurrent biogenic CH_4 and N_2O emissions is about a factor of 2 larger than the cooling effect resulting from the global land CO_2 uptake in the 2000s (Tian et al., 2016). This results in a net positive cumulative impact of the three GHGs on the planetary energy budget, which calls for shorter-term mitigation initiatives (Tian et al., 2016).

At the aggregated tropical scale, uncertainties were higher (up to 50% of the mean emissions) than at the landscape scale (0.5º) (30%), in line with other reports (Smith et al., 2014; Tubiello et al., 2015). The spatial scale of the emission assessments influences, therefore, the final uncertainties due to assumptions about the spatial correlation of the errors. Several authors have suggested the importance of working at more detailed spatial scales (e.g.30m) to reduce the uncertainties, particularly of forest emissions, by having more accurate data on forest area changes and carbon densities (Houghton, 2005; Grassi et al., 2008; Asner et al., 2010; Baccini et al., 2012; Houghton et al., 2012).

To better understand the uncertainty role of the different emission sources at the tropical aggregated scale, we ran a partitioning of the tropical uncertainty. We found a disproportional contribution of deforestation to the tropical uncertainty budget (92.5%) (Table 2), which agreed with the results from other researchers (Morton et al., 2011) but left the remaining emission sources with a surprisingly modest contribution to the final uncertainty (7.5%). As it was the case for the hotspots, untangling the relative contribution of the emission sources to the tropical uncertainty budget brings in trade-offs between prioritizing mitigation action on sources that are large emitters but are highly uncertain (e.g. deforestation is responsible for 36% of the emissions but carries almost all the tropical emission uncertainty (92.5%) (Table 2) or choosing emitters that contribute less to the total emissions but are more certain (e.g livestock contributed less to the tropical emissions (15%) but had a very small part on the uncertainty budget (1.4%) (Table 2) (Figure 5).

3.3 Continental AFOLU emissions

Continents contributed similarly to the tropical AFOLU gross emissions: 2.7 (1.8-4.5), 2.8 (1.9-4.0), 2.5 (1.7-3.8) $PgCO_2e.yr^{-1}$, for Central and South (CS) America, Africa, and Asia, respectively (Table 2). Area-weighted emissions would, however, turn Asia into the largest continental source with a mean of 3.2 $MgCO_2e.ha^{-1}.\ yr^{-1}$ followed by Africa and CS America with 1.3 and 1.35 $MgCO_2e.ha^{-1}.\ yr^{-1}$, each. The leading sources for the continental emissions disagreed among databases but our hotspot research suggested that African emissions were dominated by fire over dry forests (52.6% of the African emissions, Table 2) which corroborates its description as "the fire continent" (Figure 7) (Mbow, 2014). Any effective mitigation action will therefore need to consider fire management, particularly in Miombo dry forests and Sudano-Sahelian woodlands, which are the most affected forests and the largest contributors to emissions hotspots. Contrastingly, Central and South America were mainly led by deforestation (60% of the continental emissions) and forest degradation (20%), mostly affecting humid forests. And while deforestation in Brazilian rainforests has since reduced, it has increased in dry forest in the region (e.g. the Chaco region in Argentina, Paraguay, and Bolivia) (Hansen et al., 2013), and forest degradation has also increased (Brando et al., 2014; Federici et al., 2015). The Asian emissions were the most diverse and were similarly led by different sources: i) paddy rice (Asia is the world's largest rice-producing region and is responsible for over 80% of the total CH4 emissions) (USEPA 2013); ii) livestock activities (Tubiello et al., 2014); iii) deforestation (Hansen et al., 2013), and iv) fire over peatlands, particularly in Indonesia (Van der Werf et al., 2010; Gaveau et al., 2014) (Table 2). Moreover, the Asian continent has the peculiarity of emitting almost half of the tropical non-CO_2 emissions (47%, Table 2), as observed by other authors (USEPA, 2013) and still has positively growing emission trends (Tubiello et al., 2014). Effective mitigation action on non-CO_2 emissions is therefore key for Asian and global mitigation.

The partitioning of the tropical AFOLU uncertainty at continental level showed that CS America contributed with half of the variance (48%, Table 2), which was expected since the emissions of this continent are led by the most uncertain source (deforestation). Africa and Asia contributed similarly to the rest of the uncertainty (27.3% and 24.7% respectively). Based on the uncertainty of the emissions, mitigation investments in CS America, would be, therefore, less effective than investing in Africa and Asia, particularly out of the forests.

4. CONCLUSIONS

Our dataset offers novel landscape scale information on the spatial distribution of hotspots of AFOLU gross emissions and their uncertainties, disaggregated by gases and by leading emission sources. This AFOLU analysis can be useful as a benchmark against which countries can assess their progress on reducing their AFOLU gross emissions, in a comparable and comprehensive manner across the tropics. Moreover, assessments of gross emissions offer useful insights on potential drivers behind the emission sources, which can then lead to policies and measures to reduce these emissions, through appropriate mitigation actions. Aggregated gross emissions at the country level are offered in the Supplementary Material. Our data highlight: i) the existence of AFOLU emissions hotspots on all continents, with particular importance of evergreen rainforest deforestation in Central and South America, fire in dry forests in Africa, and both peatland emissions and agriculture in Asia; ii) a predominant contribution of forests and CO_2 to the total AFOLU emissions (69%) and to their uncertainties (98%), iii) higher gross fluxes from forests coincide with higher uncertainties, making agricultural hotspots appealing for effective mitigation action, however iv) agricultural non-CO_2 emissions are much lower (ca. 25% of the total gross emissions in the tropics for 2000-2005) than forests, with livestock (15.5%) and rice (7%) leading the emissions. Gross AFOLU tropical emissions 8.0 (5.5-12.2) were in the range of other databases 8.4 and 8.0 $PgCO_2e.yr^{-1}$ (FAOSTAT and EDGAR respectively).

It is worth remarking that under gross emissions, sustainable wood harvesting and fires not leading to long-term declines in carbon storage would still be considered as hotspots of emissions since the subsequent recovery of carbon stocks is not considered. Moreover, gross emission are not to be confused with the overall net land-to-atmosphere flux due to human land use, because legacy effects and changes in litter and soil organic matter are not included. Independently of whether we are working with gross or net emissions, the time scale under analysis (e.g. 5 years in our study) and the selected methodological assumptions, will strongly influence the final AFOLU estimates (e.g. exclusion of indirect emissions, exclusion of non-managed land, exclusion of legacy emissions, consideration of instantaneous emissions, exclusion of transboundary effects) and mitigation options (e.g. exclusion of substitution effects).

Assessments of net AFOLU emissions would be closer to what countries are requested to report under the UNFCCC but, how different would it be from our gross hotspots results? We argue that, under our short-term temporal analysis (5 years), the spatial location of our gross AFOLU hotspots would not differ much, although the absolute emission estimates could be lower. Thus, for agricultural driven hotspots (crops, livestock, rice), assessments of gross and net emissions would result in the same hotspots of AFOLU emissions because only soil organic storage acts as a sink to compensate against agricultural non-CO_2 emissions, and soil carbon storage rates are small and short-lived (Smith et al., 2008). For areas with extended forests, gross and net AFOLU hotspots can differ. This would not be the case for areas affected by large scale deforestation and/or intense degradation, because the 5-year time frame of our study would not allow for significant carbon recovery after disturbance. Most of the differences between gross and net emissions would then concentrate in two forested areas: i) those undergoing large scale, high density removals (e.g. afforestation/ reforestation processes) such as in China –not included in this research-, Viet Nam and India, and in ii) forested areas affected by smaller scale disturbances and less intense carbon processes that do not lead to deforestation, where forest emissions could be compensated by removals from the standing forests. Main differences between gross and net land use hotspots assessments in the tropics would then concentrate on areas with extended forests undergoing small-scale mid-level disturbances: Amazonian areas out of the arch of deforestation, wood harvesting in the Congo Basin, and lower impact disturbances in Mesoamerica, including Mexico.

This study also contributes to the debate on tropical mitigation potentials of agriculture and forestry. Thus, even if global estimates of agriculture and forestry emissions have roughly similar mitigation potentials (Smith et al., 2014; Tubiello et al., 2015), economic feasibilities differ. Forests have two to three-fold greater economic mitigation potentials than agriculture (e.g. 0.2-13 *vs* 0.3-4.6 $PgCO_2e.yr^{-1}$ respectively) at prices up to 100 $USD/MgCO_2e$ (Bajzelj et al., 2014; Havlik et al., 2014; Smith et al., 2014). This means that for the same price, more emission reductions can be achieved in the forest sector. These unequal results relate to forests sector being much more carbon dense, to lower costs per area unit to monitor and implement actions against deforestation and degradation, but also to concerns about food security and adaptation needs (Smith et al., 2013; Havlik et al., 2014, Wollenberg et al, 2016). Thus, notwithstanding the importance of agricultural mitigation, forests are more cost effective alternatives and, although uncertain, their multiple ecosystem services will keep them high as desirable mitigation targets in the political arena.

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6. CONTRIBUTIONS

RMRC, MR, MH1, KBB, TR, JS, LV designed the study. RMRC, MH2, CM, CL, SO, BP provided data and ran quality control, quality assessments and uncertainties expert judgements on the data sets. SdB guided on statistics and developed all the scripts for the Monte Carlo aggregation of the data. JS assisted with GIS analyses and scripts. RMRC, MR, MH1, KBB, TR, SdB, LV, CM, JS, MH2, CL, SO, BP, discussed the results and contributed to writing.

7. ACKNOWLEDGEMENTS

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Figure legends

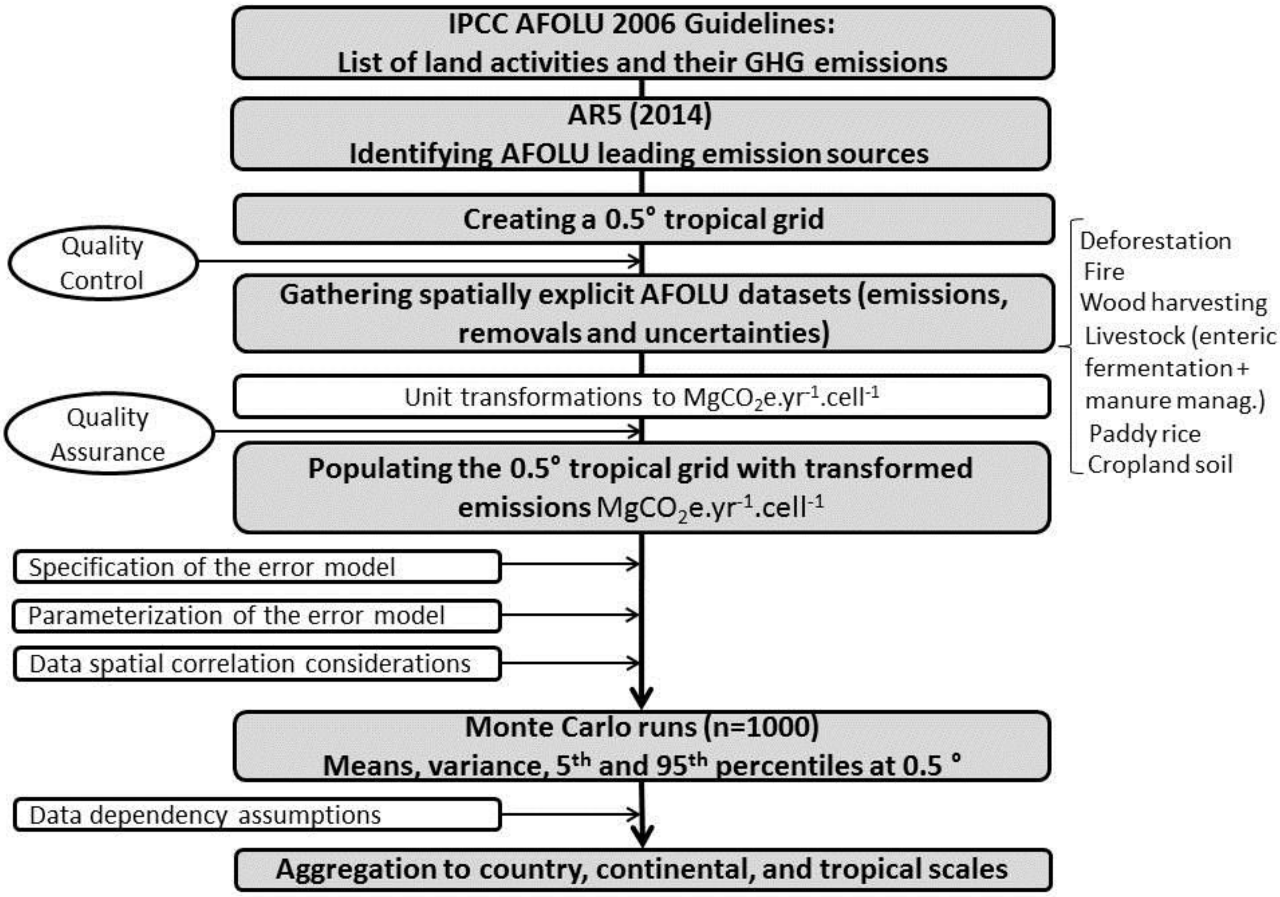

Figure 1: Methodological framework used to estimate the aggregated AFOLU emissions (annual means) and associated uncertainties (variance, 5^{th}, 95^{th} percentiles) at 0.5° resolution, for 2000-2005.

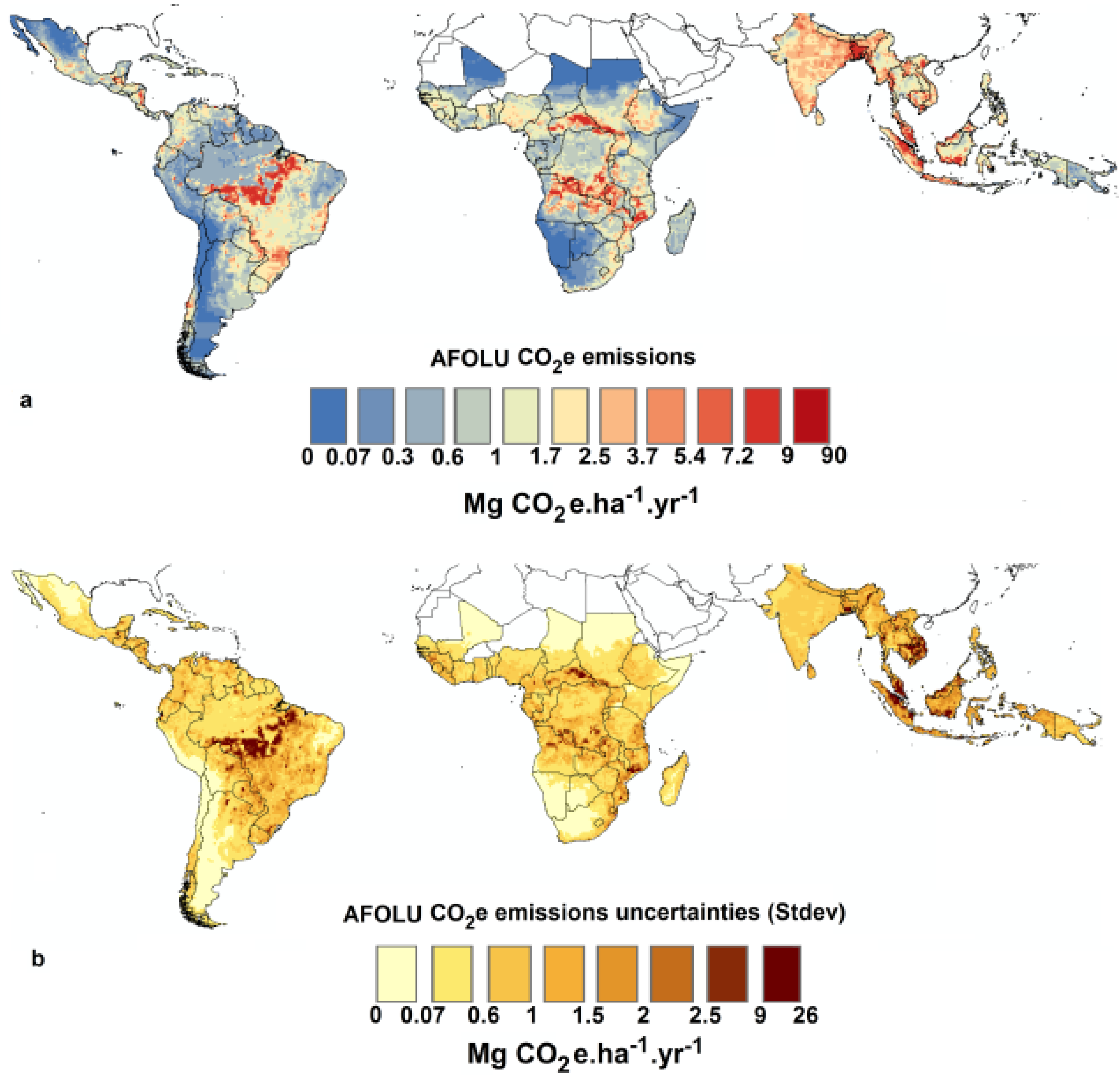

Figure 2: (a) Hotspots of annual AFOLU emissions (red cells) and (b) associated uncertainties (1σ) in $MgCO_2e.ha^{-1}.yr^{-1}$ for the tropical region, for the period 2000-2005, at 0.5°resolution. Emissions are the result of 1000 Monte Carlo simulations for the leading AFOLU emission sources (deforestation, degradation (fire, wood harvesting), soils (crops, paddy rice), livestock (enteric fermentation and manure management)

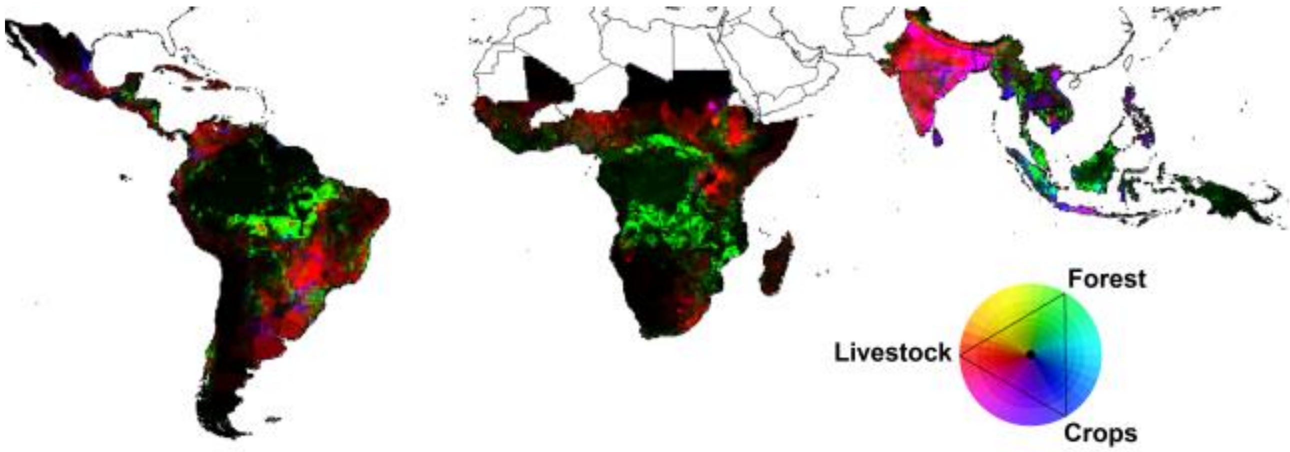

Figure 3: Contribution of the leading emission sources in percent of total emissions (grouped into forests, crops and livestock) to the per pixel (0.5°), for 2000-2005. Forest emissions include fire, deforestation and wood harvesting. Crops emissions includes paddy rice, cropland soil and croplands over drained histosols. Livestock includes enteric fermentation and manure management emissions. This figure is an RGB image where final colours represent the strength of the emissions for the three sources (e,g, fuchsia colours in Asia represent equal emissions from livestock (red) and crops (blue). Dark represent areas of low emissions.

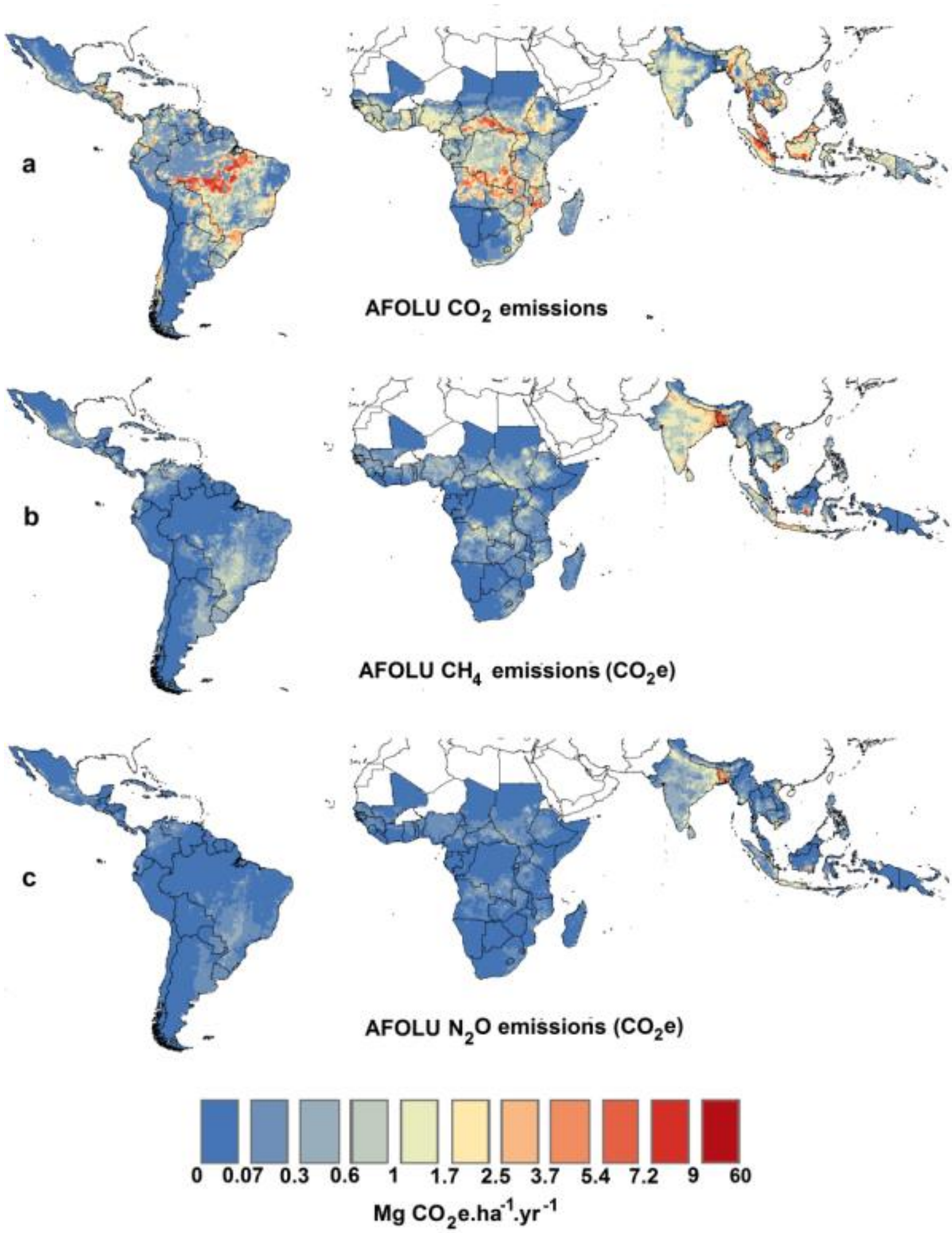

Figure 4: Mean annual AFOLU emissions ($MgCO_2e.ha^{-1}.yr^{-1}$), for the period 2000-2005, disaggregated by greenhouse gases: a) CO_2 emissions, which are a proxy of forest emissions, (b) CH_4, and (c) N_2O emissions, which are proxies of agricultural emissions. Emissions are the result of 1000 Monte simulations for the considered leading AFOLU emission sources.

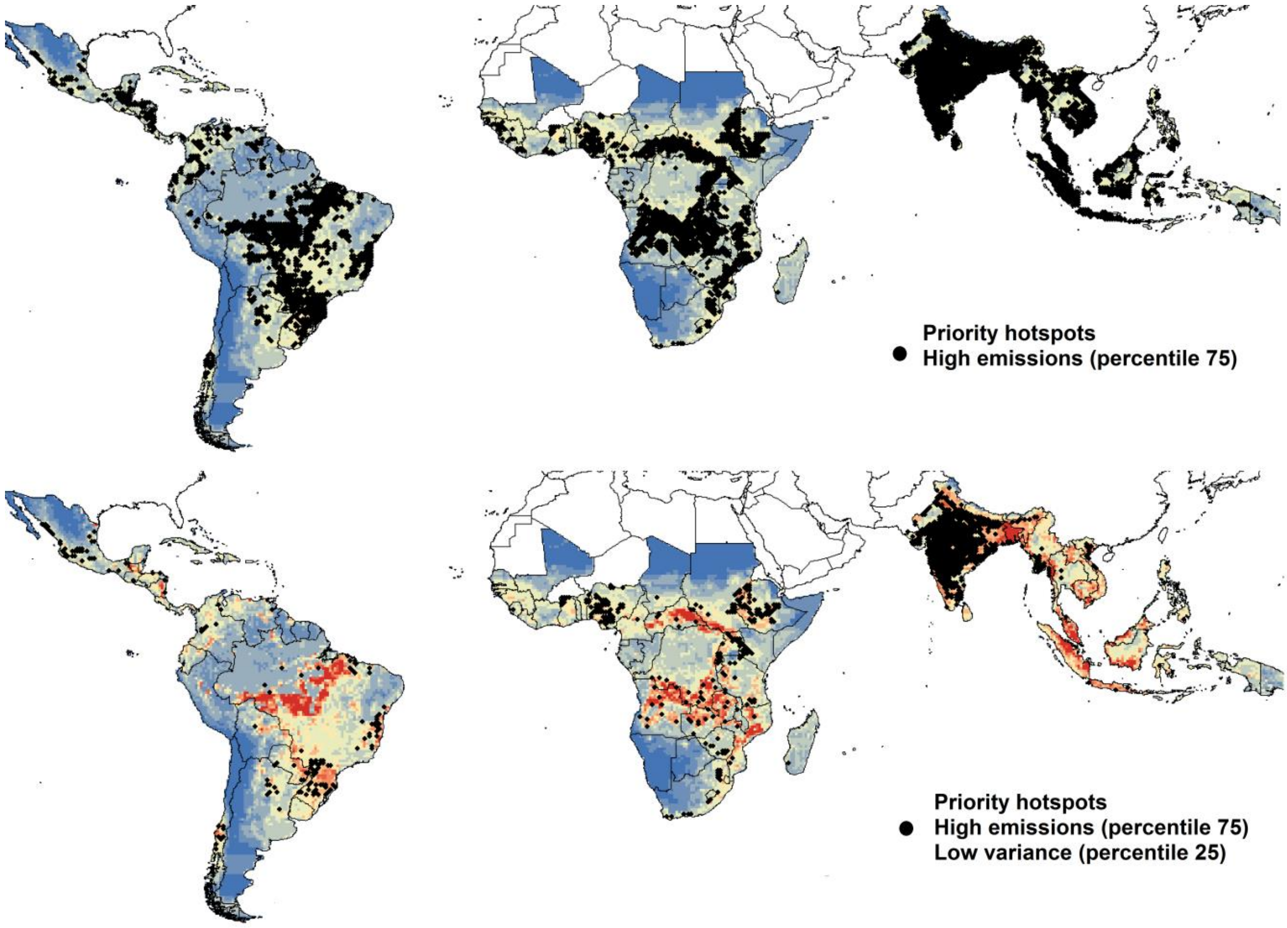

Figure 5: Identification of priority regions for mitigation in the AFOLU sector in the tropics, for 2000-2005 considering mitigation potentials only (higher emissions, percentile 75), and degree of certainty of these potentials (low uncertainties, percentile 25 of the variance). Economic feasibility would lead to different priority regions.

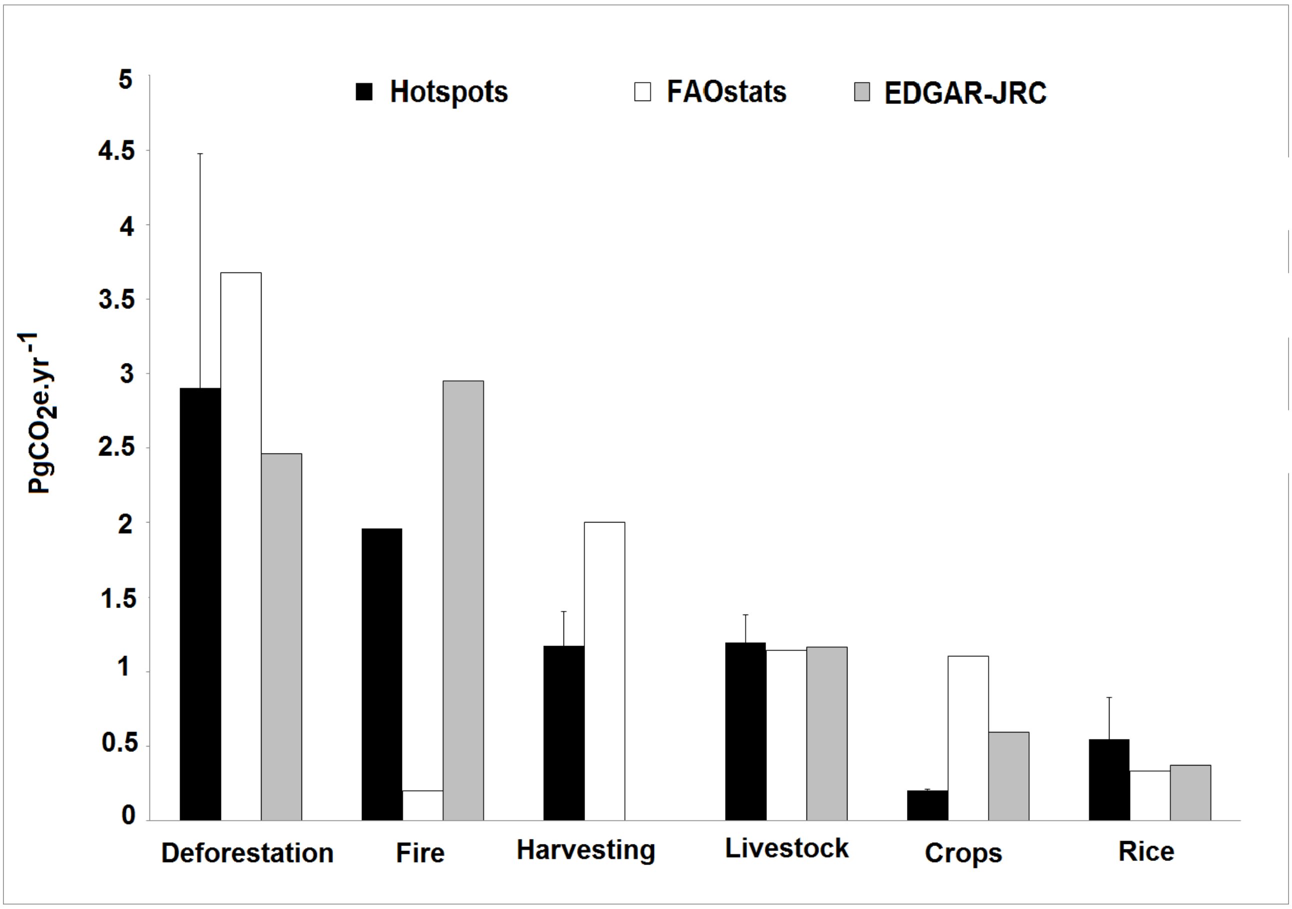

Figure 6: Distribution of mean annual emissions per sources of emissions for the three data bases, in the tropics, for 2000-2005. Bars indicate uncertainty estimates for the hotspot data base, and standard deviations for FAOstats and EDGAR-JRC estimated from country data variability since no uncertainty data exist for these two data bases.

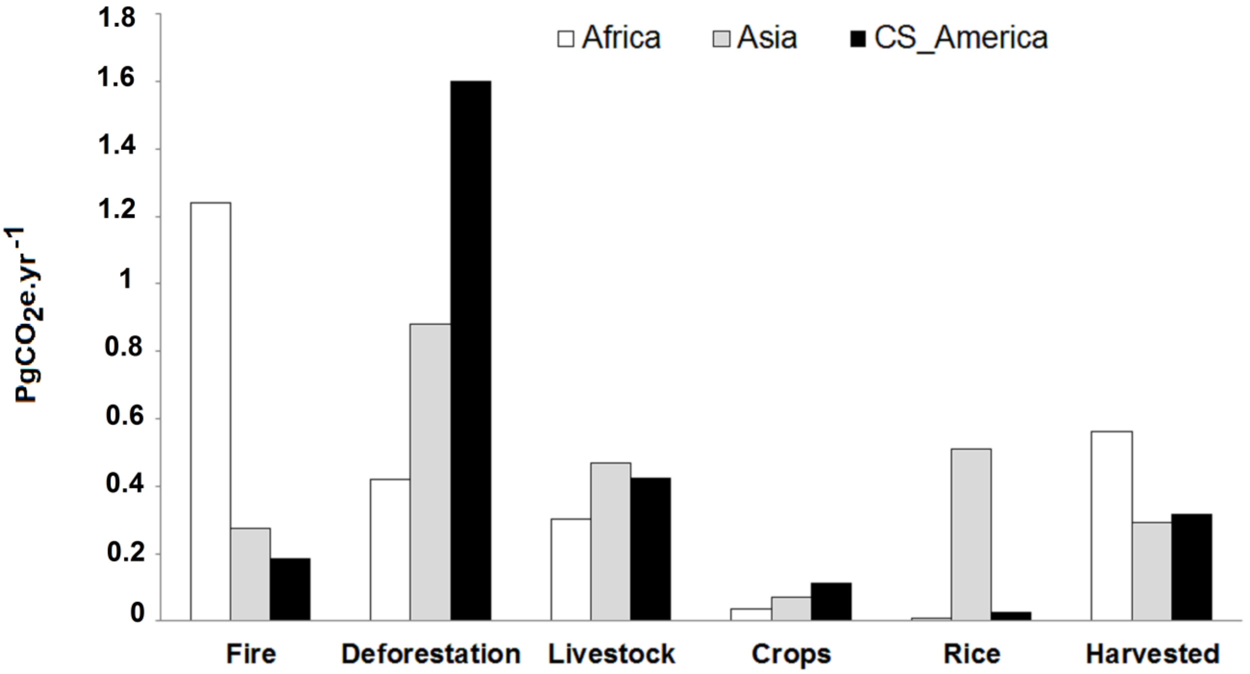

Figure 7: Continental contribution of the leading emission sources in our hotspot dataset, in the tropics, for the period 2000-2005.

Tables

From units	To units	Molecular weights conversion	Global Warming Pontentials 100-yr
kgC (dSOC)	kg CO_2eq.	kgC * 44 / 12	1
kgC (CH_4)	kg CO_2eq.	kgC * 16 / 12	21
kgN (N_2O)	kg CO_2eq.	kgN * 44 / 28	310

Table 1: Data conversions to CO_2e for different chemical elements (C, N). dSOC is the change in Soil Organic Carbon. Molecular weights and global warming potentials use values from the Fourth Assessment Report (IPCC 2007)

Gross AFOLU emissions ($PgCO_2e.yr^{-1}$)						
		CO_2e	**CO_2**	**CH_4**	**N_2O**	
Tropical		8.0 (5.5-12.2)	5.5 (3.3-9.5)	1.5 (1.1-1.9)	1 (0.8-1.2)	
Central & South America		2.7 (1.8-4.5)	2.1 (1.3-3.8)	0.35 (0.25-0.45)	0.25 (0.2-0.3)	
Africa		2.8 (1.9-4.0)	2.1 (1.4-3.2)	0.39 (0.27-0.5)	0.3 (0.22-0.39)	
Asia		2.5 (1.7-3.8)	1.3 (0.7-2.4)	0.74 (0.56-0.95)	0.41 (0.35-0.47)	
Contribution of leading emission sources to the tropical AFOLU gross emissions (%)						
	Deforestation	**Fire**	**Rice**	**Wood Harvesting**	**Livestock**	**Crops**
Tropical	36.3	24.6	6.9	14.6	15	2.5
Central & South America	59.6	8.2	1.1	11.9	15.9	3.4
Africa	15.2	52.6	0.3	20.3	11	0.7
Asia	34.8	11.3	20.2	11.5	18.5	3.7
Contribution of leading emission sources to total uncertainty (%)						
	Deforestation	**Fire**	**Rice**	**Harvesting**	**Livestock**	**Crops**
Tropical	92.5	4.5	0.2	1.4	1.4	0.0
Central & South America	98.4	0.3	0.0	0.5	0.8	0.0
Africa	69.8	25.5	0.0	3.7	1.1	0.0
Asia	91.4	2.4	2.1	1.1	2.9	0.0
Contribution of different gases to the tropical AFOLU gross emissions (%)						
		CO_2e	**CO_2**	**CH_4**	**N_2O**	
Tropical			69	19	12	
Central & South America		34	78	13	9	
Africa		35	75	14	11	
Asia		31	53	30	17	
Contribution of different gases to total uncertainty (%)						
Tropical			98.3	1.3	0.4	
Central & South America		48	99.4	0.5	0.1	
Africa		27.3	98.2	1.1	0.7	
Asia		24.7	95.5	3.9	0.6	

Table 2: i) Contribution of the different greenhouse gases (CO_2, CH_4, N_2O) to continental and tropical AFOLU annual mean gross emissions for the period 2000-2005 (in parenthesis are the 5^{th} and the 95^{th} percentiles of the aggregated AFOLU emissions). ii) Contribution of the different leading emission sources to the tropical and continental AFOLU gross emissions (expressed as % of emissions). And iii) partitioning of the AFOLU emissions uncertainties among the leading emission sources and the considered GHG gases (expressed as % of variance) AFOLU emissions are the result of 1000 Monte Carlo runs for the leading emission sources.