SUPPLEMENTARY MATERIAL

Hotspots of tropical land use emissions: patterns, uncertainties, and leading emission sources for the period 2000-2005

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Acronyms

AFOLU: Agriculture, Forestry and Other Land Use

AR5: Fifth Assessment Report

CO_2: Carbon dioxide

CO_2e: Carbon dioxide equivalent

CH_4: Methane

EDGAR: Emission Database for Global Atmospheric Research.

EPA: Environmental Protection Agency

FAO: United Nations Food and Agriculture Organization.

GHG: Greenhouse Gas

GWP: Global Warming Potential.

IPCC: Intergovernmental Panel on Climate Change

JRC: Joint Research Center.

MAC: Marginal Abatement Costs.

MODIS: Moderate Resolution Imaging Spectrometer

N_2O: Nitrous oxide

UNFCCC: United Nations Framework Convention on Climate Change

1. Expanded description of methods

Our study identified, compiled, and aggregated AFOLU emissions (CO_2, N_2O, CH_4) from several selected emission sources from the AFOLU sector, following the steps described in Figure 1. This Supplementary material will describe each step with the aim of providing clarity about the procedure followed to estimate the AFOLU emissions and uncertainties.

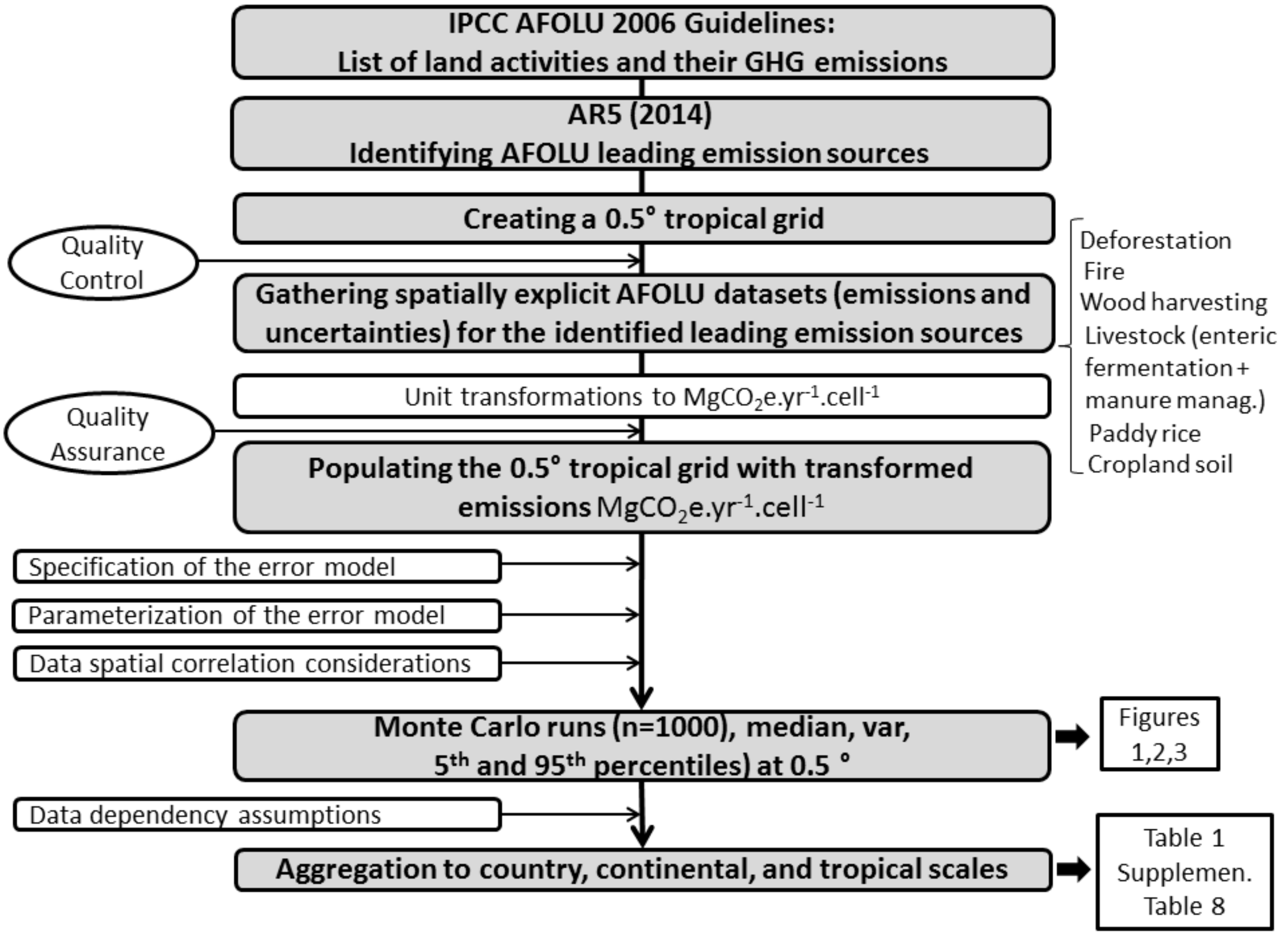

Figure 1: Steps followed to populate the tropical 0.5° grid with AFOLU emissions and uncertainties and scaling up processes.

1.1 List of land activities and their GHG emissions

This study uses the conceptual framework of the IPCC AFOLU (Agriculture Forestry and Other Land Use) Guidelines for National Greenhouse Gas Inventories (IPCC 2006) to identify all possible GHG emitting land uses within the AFOLU sector (forests, croplands, wetlands and grasslands + livestock + soil management), carbon pools (aboveground biomass, below ground biomass, coarse woody debris, litter and soils), and gases (CO_2, CH_4, N_2O). AFOLU emissions considered under this framework were human-induced GHG emissions for the AFOLU sector, understood as emissions under managed land. Further explanations for the concept of managed land can be found in the IPCC 2006 Guidelines (IPCC 2006) Under this definition, fires in tropical ecosystems were included since 90 percent of tropical fires are the result of human activity (Roman-Cuesta et al. 2003; Van der Werf et al. 2010). Naturally occurring fluxes such as wetland CH_4 emissions or N_2O forest soil emissions were not considered. Table 1 includes only those human activities on land uses and land use changes that we suspected to contribute the most to the AFOLU GHG emissions. We excluded relatively small emissions from secondary transitions (e.g. Other land converted to grasslands), and forest sinks (e.g. Other land to Forests: afforestation, regrowth, and Forests remaining Forests: growth). The justification to exclude these forest sinks from the AFOLU GHG budget relied on later publications that confirm that tropical regrowth and afforestation are small (e.g -0.4 $PgCO_2e.yr^{-1}$) (Achard et al. 2014) and -0.06 $PgCO2e.yr^{-1}$ (Baccini et al. 2012), respectively, the fact that forest growth is unlikely to be additional to its baseline (and therefore excluded from mitigation targets), and the lack of spatially explicit, reliable, data on forest removals and associated uncertainties.

1.2 Identifying AFOLU leading emission sources from the Fifth Assessment Report

Roughly, the AFOLU sector contributed with 20-24 percent of the global GHG emissions in 2010, with a value of 10-12 Gt $CO_2e.yr^{-1}$ (Smith et al. 2014, Tubiello et al. 2015). Many activities add to this budget, as exposed in Figure 11.2 of the Fifth Assessment Report (Figure 2) (Smith et al. 2014), which disaggregates the AFOLU emissions for the last four decades. In our study, however, we selected only those activities whose emissions in 2000-2010 added up to 90% of the total AFOLU values, as described in Smith et al. (2014). Four sources of emission were in the agricultural domain, which contributes to ca. 12% to the global GHG (5-6 Gt $CO_2e.yr^{-1}$): 1. Enteric fermentation + agricultural soils (70% of agricultural emissions), 2. Paddy rice emissions (9-11%), 3. Biomass burning (6-12%), 4. Manure management (7-8%). While two other major sources came from the forest domain, which jointly represent the other half of the AFOLU emissions (5-6 Gt $CO_2eq.yr^{-1}$): Deforestation and Degradation (e.g wood harvesting).

We then compiled the most recent spatially explicit data sets that covered these key sources of emissions Table 2 offers a description of the compiled data sets, which will be useful for the Monte Carlo section.

IPCC categories	Activity	Management categories	CO2	CH4	CO	N2O	AGB	Soil
Forest remaining Forest	Degradation-Harvesting		X				X	
	Degradation-Fuelwood		X				X	
	Biomass burning (degradation fires)		X	X	X	X	X	X
Forest to Cropland	Deforestation-Harvesting	Including shifting cultivation	X				X	X
	Biomass burning		X	X	X	X	X	X
Forest to Grassland	Deforestation-Harvesting		X				X	X
	Biomass burning		X	X	X	X	X	X
Cropland remaining cropland	Long-term cultivated	Management regime: Full tillage, reduced tillage, no-till	X			*		X
	Perennial woody crops (agroforestry)		X			*	X	X
	Fallow <20 yr	Input of organic amendment: Low input, medium input, high input with/wo manure						X
	Rice cultivation[1]	Irrigated, Rain fed, upland Input of organic amendment		X		*		X
	Biomass burning (crop residue management)			X	X	X	X	X
Grasslands remaining Grasslands	Grasslands under different management and disturbance regimes.	Management practices: Nominally managed (not degraded); moderately degraded; severely degraded; Improved grasslands. Input of organic amendment: Medium input, high input (only for improved grasslands)	X				X	X
	Biomass burning (savanna burning)			X	X	X	X	X
Wetlands remaining wetlands	Peatlands under peat extraction (managed peatlands under any phase of peat production, Tier 1)	On-site, off-site (horticultural use) CO2 emissions due to AGB biomass clearing and soil respiration due to drainage. Includes deforestation (?). On site N2O for nutrient rich peats only CH4 emissions only > Tier 1 (drained peats)	X			X	X	X
	Peat biomass burning		X	X	X	X		X
Wetlands to Cropland	Peatlands converted to agriculture		X			X		X
	Peat biomass burning		X	X	X	X		X
Livestock	Enteric Fermentation	Rumiants, non-rumiants,monogastric		X				
	Manure management	Management regime (liquid, solid)		X		X		
Managed soils (CL, FL, GL)	N2O Managed soils emissions	Human induced net N additions: Organic and synthetic fertilisers; manure deposition; crop residues; sewage sludge. Mineralization of soil N: drainage; management of organic soils; Cultivation/land use change of mineral soils (FL, GL to CL)				X		X
	CO2 emissions from amendments (lime, urea)		X					X

Table 1: Human derived GHG emissions (CO_2, CH_4, N_2O and main contributing carbon pools: Above ground biomass (AGB)and soils, in managed land for the AFOLU sector (Agriculture, Forestry and Other land uses) following the IPCC AFOLU 2006 guidelines. It includes only major contributing classes excluding sink transitions (e.g. Other land to Forestry) or minor transitions (e.g. Other land converted to grasslands.* N_2O emissions from soils are included under managed soils.

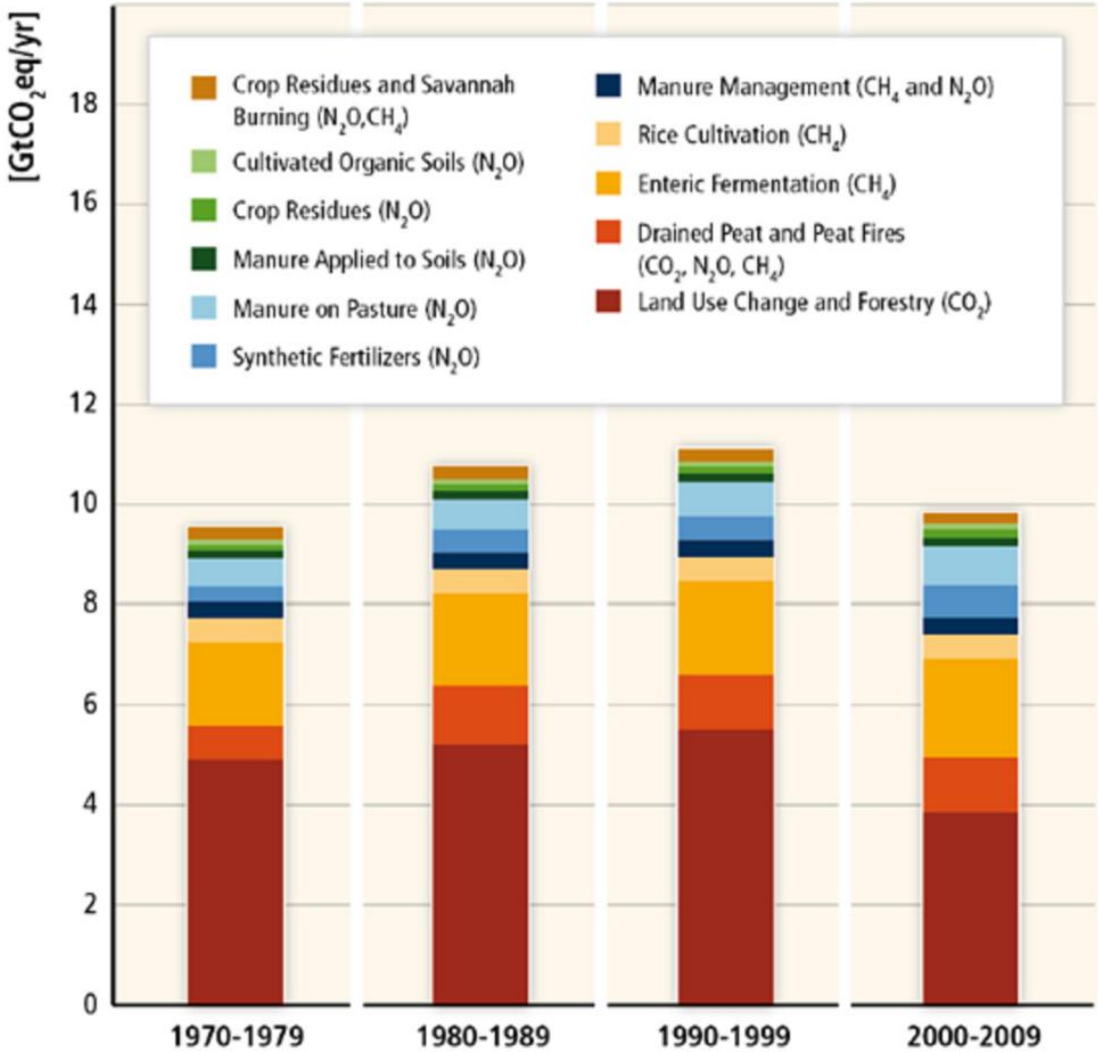

Figure 2. AFOLU emissions for the last four decades. Sub-sectorial agricultural emissions are based on FAOSTAT (2013). Emissions from crop residues, manure applied to soils, manure left on pasture, cultivated organic soils, and synthetic fertilizers are typically aggregated to the category 'agricultural soils' for IPCC reporting. For the Forestry and Other Land Use (FOLU) sub-sector data are from the Houghton bookkeeping model results (Houghton et al., 2012). Emissions from drained peat and peat fires are, for the 1970s and the 1980s, from JRC/PBL (2012), derived from Hooijer et al. (2010) and van der Werf et al. (2006) and for the 1990s and the 2000s, from FAOSTAT, 2013. **Source:** Figure 11.2 Fifth Assessment Report (Smith et al. 2014).

		Data set	Reference	GHG	Spatial resolut.	Available temporal resolution	Method description	Emission units	Data vector type	Uncertainties	Uncertainty data	Data distribution
FOREST	Deforestation	**Deforestation**	Harris et al. (2012)	CO_2	18.5km	2000-2005	Forest cover loss (18.5km) x forest carbon stocks (1km) with randomized, Monte Carlo style sampling technique	MgC.18.5km^{-2}. 5years^{-1}	Area	Pixel level, based on Monte Carlo runs	5th-95th percentiles	Log-normal
	Forest degradation	**Biomass burning**	Van der Werf et al. (2010)	CO_2 CH_4 N_2O	0.5°	1997-2013	Emission model: CASA	ggas.m^{-2}.month^{-1}	Point	Regional level, based on Monte Carlo runs	Stdev	Gaussian
		Wood harvesting	Poulter et al. (2015)	CO_2	1°	2005	National Forest Inventory data and FAO (FRA) for wood harvest **x** Global Land Cover 2000 as forest mask	m^3	Area	No spatially explicit uncertainty on original data: 20 percent of mean value assigned, based on author's expert judgement	Stdev	Gaussian
AGRICULTURE	Crops	**Crop soil emissions**	Ogle et al. (2013)	N_2O dSOC	0.5°	2000-2005 2005-2010	Emission model: DAYCENT-Century	gN2O-N.m^{-2}.yr^{-1} gC.m^{-2}/5yr^{-1}	Point	Pixel level, based on Monte Carlo runs	Stdev	Gaussian
		Rice soil emissions	Li et al. (2013)	N_2O CH_4 dSOC	0.5°	2010	Emission model: DNDC	KgC.ha^{-1}.yr^{-1} for CO_2 & CH_4 KgN.ha^{-1}.yr^{-1} for N_2O	Point	Pixel level, based on MSF method (Most sensitive Factor)	Max/Min	Log-normal
	Livestock	**Enteric fermentation + manure manag.**	Herrero et al. (2013)	CH_4 N_2O	0.1°	2000	Livestock systems + herd modelling+ feeds+ emission model: RUMIANT+ Tier 2 approach for monograstric emissions	kg CO_2e.km^{-2}.yr^{-1}	Area	No spatially explicit uncertainty on original data: 20 percent of mean value assigned based on author's expert judgement	Stdev	Gaussian

Table 2: Summary of data sets and uncertainties used in this hotspot analysis of terrestrial gross emissions. When multiple years were available, we estimated annual means for the period 2000-2005.

1.3 Compiling spatially explicit data sets of emissions and associated uncertainties, for AFOLU leading emission sources

Table 2 summarises the selected emission data sets and associated uncertainties (authors, data units, data resolution, data distribution functions, types of uncertainty, etc). Figure 3 offers a visual representation of the spatial distribution of the data sets as annual means for the period 2000-2005, for our study area, at 0.5° resolution.

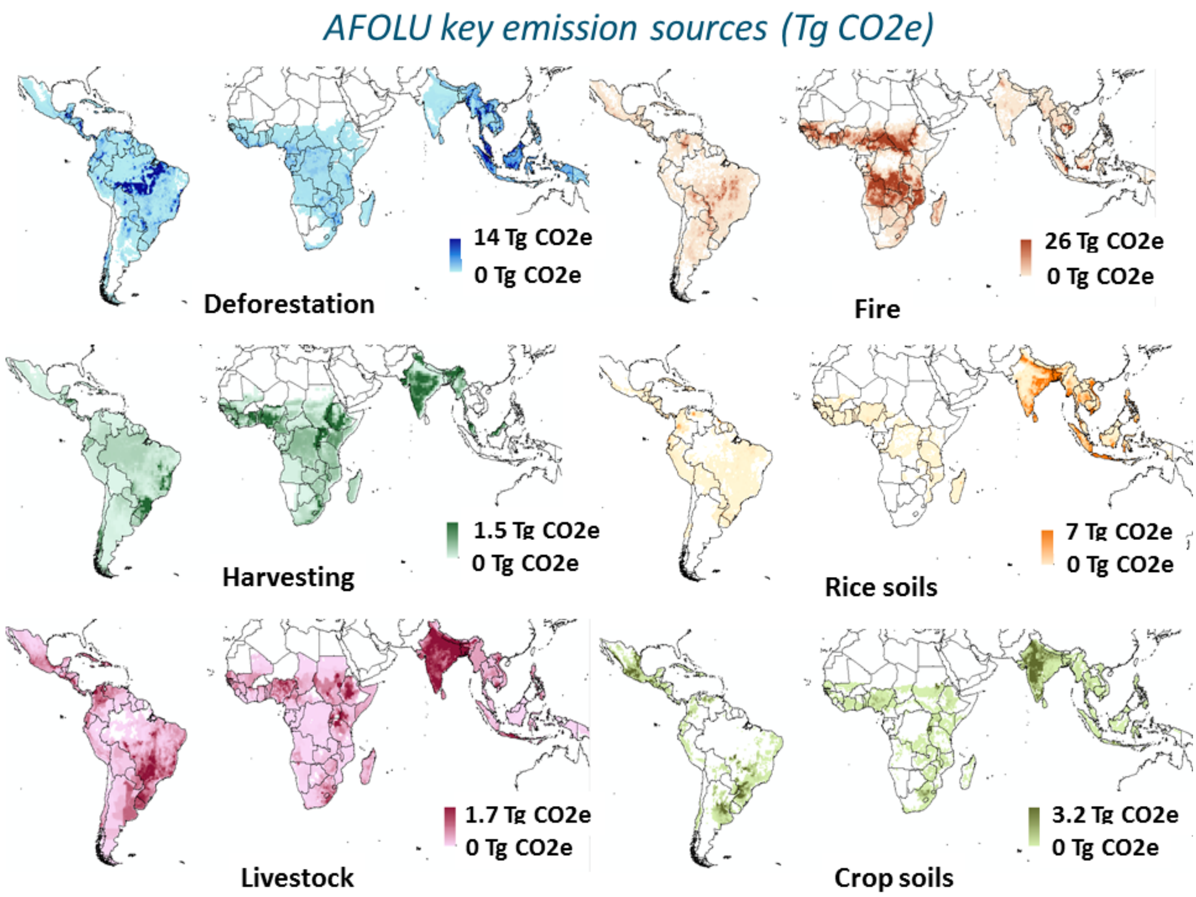

Figure 3: Spatial distribution of the emissions.

1.3.1. Data sets and uncertainties

1.3.1.1 Forest data sets + uncertainties

Deforestation emissions (Harris et al. 2012)

Deforestation emissions correspond to instantaneous carbon losses (aboveground and belowground) in an area where forest cover is completely removed, for the period 2000-2005, at 18.5km resolution, for the tropics. Emissions are assigned to the place of removal, with no transboundary effects. Harris et al. (2012)

did not measure forest recovery (afforestation, reforestation) so their deforestation emissions are gross estimates. Original units $MgC.ha^{-1}.5yr^{-1}$) were transformed to annual CO_2e.grid cell, by applying equal area reprojected values for the 0.5 grid cells, a transformation factor of 44/12 from C to CO_2, and a ratioing by 5 to obtain annual emissions assuming complete data dependence among years. The study area used political rather than biome boundaries so as to provide consistent country-specific deforestation emissions that could be used as reference emission levels. Their data base is freely available and consists of three digital data sets, one for each continent, in raster format, at 18.5 km. Each data set includes three rasters, one for the median emission estimates of deforestation ($MgC.ha^{-1}.5yr^{-1}$), and the other two for the lower and upper deforestation emission bounds (5th and 95th percentiles). The authors produced their deforestation emissions estimates using two variables: 1. gross forest cover loss areas from 2000 to 2005 (ha) and 2. the spatial distribution of forest carbon density maps (above and below ground C) at 1km resolution ($MgC.\ ha^{-1}$) (Saatchi et al. 2012). The areas of forest loss were produced through a nested approach that combined Moderate Resolution Imaging Spectroradiometer MODIS and Landsat satellites, with a final resolution of 18.5 by 18.5-km (called blocks by the authors). To resolve the disparate spatial resolution of the forest loss area and the carbon density data sets, the authors ran a Monte Carlo style procedure in which forested 1-km pixels within a given 18.5-km block were selected randomly (n = 1000 realizations) until the forest loss quota for the block was met. The total carbon values of selected 1-km pixels (MgC) were then summed across the block to derive an emissions estimate. The average of the 1000 estimates associated with forest loss is assigned as the best estimate of emissions per 18.5-km block.

Uncertainties of deforestation emissions

The authors describe the treatment of their deforestation emissions uncertainties in their Supplementary Material. We summarize it here, but for further information consult Harris et al. (2012): Deforestation uncertainty were a combination of the forest area uncertainty and the forest carbon densities uncertainties, which were merged using a randomized, Monte Carlo style sampling technique. In each scenario of the simulation, forested pixels (1-km) within each 18.5-km block were selected randomly until the total cleared area estimated within the block was reached. Carbon stock information for the cleared pixels was then used to calculate an emissions estimate associated with forest loss for that scenario. Iterating through scenarios for each block resulted in a distribution of emissions associated with the estimated level of forest loss. This approach allowed the combination of uncertainty from different sources without making assumptions about the distribution of the underlying data. Uncertainties considered:

1. Estimates of forest loss;
2. Estimates of aboveground biomass;
3. Estimates of belowground biomass;

Uncertainty in forest loss

The authors estimated the uncertainty in the forest loss product by modelling the relationship between two estimates of forest loss at the 18.5-km block scale, one derived from coarse resolution Moderate Resolution Imaging Spectroradiometer (MODIS) imagery and the other from higher resolution Landsat imagery. Earth biomes were divided into forest cover loss strata based on MODIS observations, and included high, medium and low forest cover loss strata per biome. The authors then selected a stratified random sample of 18.5-km blocks from each biome and stratum, and Landsat imagery was analysed to quantify forest cover loss per sample block. They applied stratum-specific regression estimators incorporating MODIS-indicated forest cover loss as the auxiliary variables to generate forest cover loss estimates over the global population of 18.5-km blocks. To conduct the uncertainty analysis, a bootstrapping approach was used (i.e. resampling with replacement) which assumed that the observed data represented only one possible realization out of many, and reconstructed a large number of alternate realizations based on random resampling of residuals.

Uncertainty in aboveground biomass

The aboveground biomass at 1-km spatial resolution provided the best available estimate of biomass (in $MgC.ha^{-1}$) and associated uncertainties across the tropics. The authors derived uncertainties from a bootstrapping exercise conducted as part of the Maximum Entropy (MaxEnt) model estimator through an error propagation approach and from an independent model validation analysis. See Saatchi et al. (2011) for full details of the MaxEnt approach. Saatchi et al. (2011) calculated a minimum and maximum possible biomass value that included a potential bias in the initial data used to train the model. The values represented the 0.5 percentile (minimum) and the 99.5 percentile (maximum) of an assumed Gaussian distribution of errors at the pixel scale. This range of potential error accounted for uncertainty from several sources, including the estimates of vegetation height from the Geoscience Laser Altimeter System (GLAS), onboard the Ice, Cloud, and land Elevation Satellite (ICESat), lidar data, allometric equations used to convert height to aboveground biomass, and prediction errors associated with the MaxEnt model estimator. The potential bias in the model estimate of forest biomass can be related to the ground estimates of biomass used in calibrating the GLAS lidar data or the inventory plots used directly in the MaxEnt model. This bias cannot be quantified systematically due to lack of detailed information on inventory data and the paucity of ground measurements of forest biomass to evaluate the estimates. However, by using the estimate of the potential bias and introducing it in computing emissions, Saatchi et al. (2011) ran the best estimates possible.

Uncertainty in belowground biomass

Belowground biomass was estimated from aboveground biomass using a regression equation developed from field data collected in forests across multiple biomes. Uncertainties in this relationship between above and belowground biomass were estimated from the original model fit; the model fitted a power function to above and belowground biomass data using least squares regression. A bootstrapping approach was then implemented for forest loss uncertainty to create a distribution of regression coefficients.

Merging forest emissions uncertainties

Harris et al. (2012) used a series of distributions representing uncertainty from each of the above three main uncertainty sources to construct 1,000 scenarios of forest emissions. From these 1,000 scenarios, they estimated 90% prediction limits at the block, country, regional, and pan-continental scales by first aggregating each individual map to the targeted scale (e.g., country, continent) and then selecting the 0.05 and 0.95 percentiles (i.e., 50th and 950th out of 1,000 sorted simulations). The identification of the 0.05 and 0.95 percentile values was computed individually for the forest loss area, carbon stock, and emissions, such that the low emission value was not simply a combination of the low bound for forest loss and the low bound for carbon stocks.

Forest degradation: Wood harvesting (Poulter et al. (2015), data accessible upon request)

Wood harvesting is a 1-degree global gridded data set that was generated using National Forest Inventory data and the FAO Forest Resources Assessment (FRA) (Figure 4). The total harvested volume for both round wood and fuelwood was 3,076 million m^3 for the reference year of 2005, which is equivalent to a global carbon estimate of 0.89 PgC. The data set was downscaled using a forest mask from the Global Land Cover (GLC) 2000 data set and assuming wood harvest was distributed evenly. The original data was produced at the resolution of the GLC2000 (approx. 1X1km) and the 1 degree data set was produced by aggregating the 1x1 km cells within a 1° grid. The resulting GEOCARBON Wood Harvest data set consists of the following five variables:

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 m3
4. Fuelwood harvest volume in m3
5. Total Harvest volume (round wood + fuelwood) in m^3

We chose fuel and industrial round wood harvest (m^3) as our harvest data. We assumed instantaneous emissions assigned to the place of removal. 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 factor of 44/12 from C to CO_2. Because the resolution of this layer was larger than our grid, the original value of wood volume at 1° was equally distributed among the 0.5° grid cells. Wood harvesting also includes forest managed areas and, therefore, not all wood removals are degradation.

Consistency checks for the wood harvest data were carried out for each administrative value to ensure that the gridded wood harvest data set was consistent with the volume reported for that administrative unit. Wood harvest statistics were acquired from a range of NFIs around the world. For the remaining countries, either the wood harvest statistics were reported at national level (i.e. same as FAO-FRA) or the data were out of date (e.g., before 2000). In all cases, the cumulative, aggregated harvested volume for all species groups was used. The cumulative volume for the US and Canada included both round wood and fuelwood volume. For the remaining countries, the volume of fuelwood was obtained from the FAO FRA database since the fuelwood volume was not explicitly reported by the NFI.

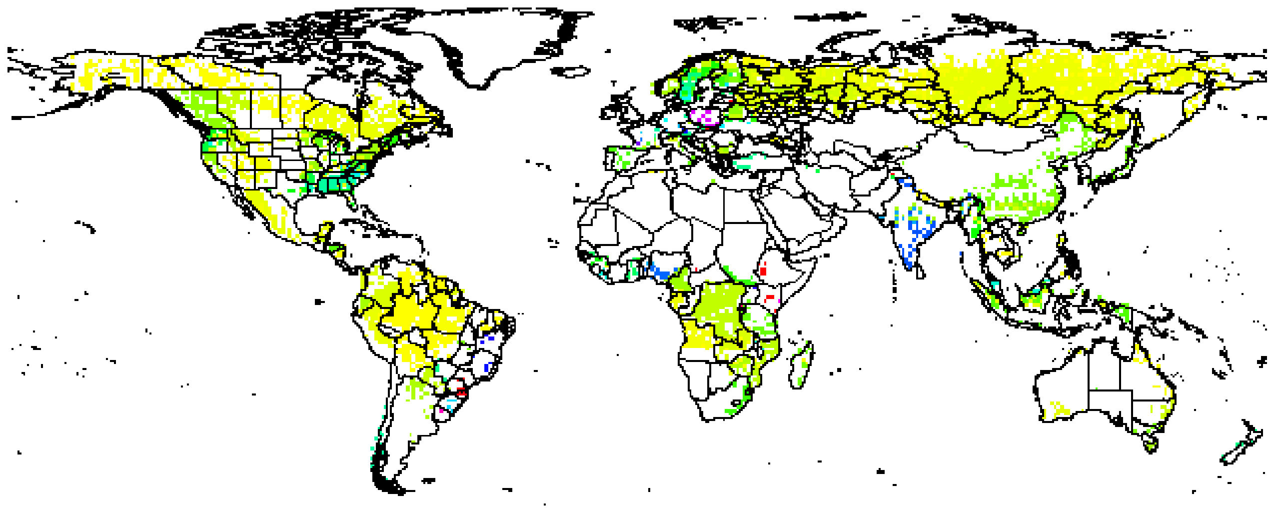

Figure 4: Global wood harvest (industrial roundwood + fuelwood) estmated from Forest Inventories and FAO-Forest Assessment Resource (FRA)

Two land cover masks were generated from the 1-km GLC2000 (GLC2000-JRC, 2003): 1. A forest map derived from used solely for the downscaling of the industrial round wood statistics, and 2. a more inclusive "forest mask" for fuelwood which also included shrub cover and sparsely forested land cover classes, particularly relevant in Africa and parts of Asia.

Wood harvesting uncertainties

Uncertainties were not estimated in the original harvest emission data set. We therefore, applied a first estimate of emission uncertainties considering a 20 percent value of the per-pixel harvest emissions, based on the author's expert opinion.

Forest degradation: Biomass burning emissions (Van der Werf et al. 2010)

We used version 3 of the Global Fire Emission Database (GFED) for our fire GHG emissions (CO_2, CH_4, N_2O) (Van der Werf et al. 2010). Data were downloaded from http://www.globalfiredata.org/data.html Data units were ggas/m^{-2}.month^{-1} at 0.5° resolution. We selected the period 2000-2005, which was originally offered as monthly data, and subsequently transformed into annual emissions for each of the three considered GHGs. We used equal area reprojected values and the factors exposed in Table 3 to transform the original units into CO_2e per grid cell. The original fire data set was partitioned into six fire categories: savannah, woodlands, agriculture, deforestation, forests, peats. We removed deforestation fires to avoid double counting with deforestation emissions, and only considered net fire emissions as those involving woody material. Savannahs and agricultural fires were removed. Monthly data emissions for the selected partitions were transformed to annual values. Total fire net emissions (CO_2e) per pixel were the sum of the annual means for CH_4, N_2O and CO_2.

From units	To units	Conversion
kgC (dSOC)	kg CO_2eq.	kgC * 44.0 / 12.0
kgC (CH_4)	kg CO_2eq.	kgC * 16.0 / 12.0 * 21.0
kgN (N_2O)	kg CO_2eq.	kgN * 44.0 / 28.0 * 310.0

Table 3: Data conversions to CO2e from different gas elements. dSOC is the change in Soil Organic Carbon. Conversion factors use values from the Fourth Assessment Report

Emissions were estimated using a revised version of the Carnegie-Ames-Stanford-Approach (CASA) biogeochemical model and improved satellite-derived estimates of area burned, fire activity, and plant productivity to calculate fire emissions for the 1997–2013 period on a 0.5° spatial resolution with a monthly time step. For November 2000 onwards, estimates were based on burned area, active fire detections, and plant productivity from the MODerate resolution Imaging Spectroradiometer (MODIS) sensor. They used maps of burned area derived from the Tropical Rainfall Measuring Mission (TRMM) Visible and Infrared Scanner (VIRS) and Along-Track Scanning Radiometer (ATSR) active fire data prior to MODIS (1997–2000) and estimates of plant productivity derived from Advanced Very High Resolution Radiometer (AVHRR) observations during the same period.

CASA calculates carbon "pools" for each grid cell and time step based on carbon input from net primary productivity (NPP) and carbon emissions through heterotrophic respiration (Rh), fires, herbivory, and fuelwood collection. CASA version used here had a 0.5°×0.5° grid and a monthly time step. For each grid cell and month, fire carbon emissions were then based on burned area, tree mortality, and the fraction of each carbon pool combusted (combustion completeness, CC). Each carbon pool was assigned a unique minimum and maximum CC value with the fine fuels (leaves, fine litter) having relatively high values while coarse fuels (stems, coarse woody debris) having lower values. The actual combustion completeness was then scaled linearly based on soil moisture conditions with CC closer to the minimum value under relatively moist conditions, and vice versa (van der Werf et al., 2006).

Forest degradation: Biomass burning emission uncertainties

Annual uncertainties for different regions were expressed as the 5th, 25th, 50th, 75th,and 95th percentiles of 2000 runs in a Monte Carlo set up. Figure S6 in Van der Werf et al. (2010) (see Figure 5 below) offers numbers that give an indication of 1σ uncertainties (expressed as percentage of the 50th percentile) assuming a Gaussian distribution. Since the GFED v.3 global data on biomass burning emissions did not include per pixel uncertainties, we assigned these regional uncertainties to all the pixels within each region, under the assumption of complete data dependence . We estimated the regional annual mean uncertainties for the period 2000-2005, by multiplying our mean annual aggregated GHG emissions (CO_2e: CO2, CH4, N2O) per pixel, with the regional mean annual variability percent which represented 1σ uncertainty (as displayed in Figure 5).

CASA model uncertainties

The CASA model estimated emissions and uncertainties of biomass burning. Uncertainties related to a diversity of variables: burned area, fuel loads, combustion completeness, and emission factors. Van der Werf et al. (2010) undertook a formal uncertainty assessment for the burned area (Giglio et al. 2010) but a similar approach for estimating uncertainties in fuel loads, combustion completeness, and emission factors was not possible due to the lack of ground truth data. To get an initial estimate of the spatial variability in uncertainties in carbon emissions the authors propagated the uncertainties from the burned area estimates through their model in a set of Monte Carlo simulations (n=2000). They also assigned subjective best-guess estimates of other model parameter uncertainties in these simulations (Table 3) following approaches described by French et al. (2004) and Jain et al. (2007). The authors attributed best-guess uncertainties to several parameters used to calculate biomass burning emissions (Table 4). They considered normally-distributed uncertainties for the light use efficiency (scaling directly to biomass density), burned area, combustion completeness, and burning depth into organic soil.

CASA model uncertainties		
Burned area	Stdev	(Giglio et al. 2010)
Deforested area	Reported burned area stdev x2	Expert judgement
Woody biomass	22% Based on Amazon biomass comparison with Saatchi et al. 2007	Expert judgement
Herbaceous biomass	Double the uncertainty of woody biomass due to unaccounted impacting factors not well represented in low spatial resolution (e.g. time since last fire, grazing, etc)	Expert judgement
Tree mortality	25%	Expert judgement
Depth soil burning	50% of range	Expert judgement
Combustion completeness	50% of range	Expert judgement

Table 4: disaggregated uncertainties of the CASA model for biomass burning emissions. Source: Van der Werf et al. (2010)

Fire emissions uncertainties results

Results of the Monte Carlo simulation indicated that globally, uncertainties were around 20% (1σ) for annual carbon estimates during the MODIS era (2001–2009) and somewhat higher during the years before, when burned area was derived from ATSR and VIRS hotspots. Regionally, uncertainties were highest in boreal regions and Equatorial Asia where organic soil burning occurs. One factor that had a major impact on the spatial distribution of the uncertainties was whether mapped burned area was available, or whether burned area estimates were derived from fire hot spot – burned area relations. For the latter, uncertainties were much higher. This was not only the case in the pre-MODIS era, but also for about 10% of the total burned area in the MODIS era for which no burned area maps were available (Giglio et al., 2010). Because uncertainties were often higher than the absolute burned area and because negative burned area estimates were truncated at 0, the mode of the Monte Carlo runs was higher than the estimates reported throughout the authors' paper. The uncertainty analysis focused on carbon emissions, for trace gas emissions the added uncertainty of emissions factors should be taken into account (Andreae and Merlet, 2001).

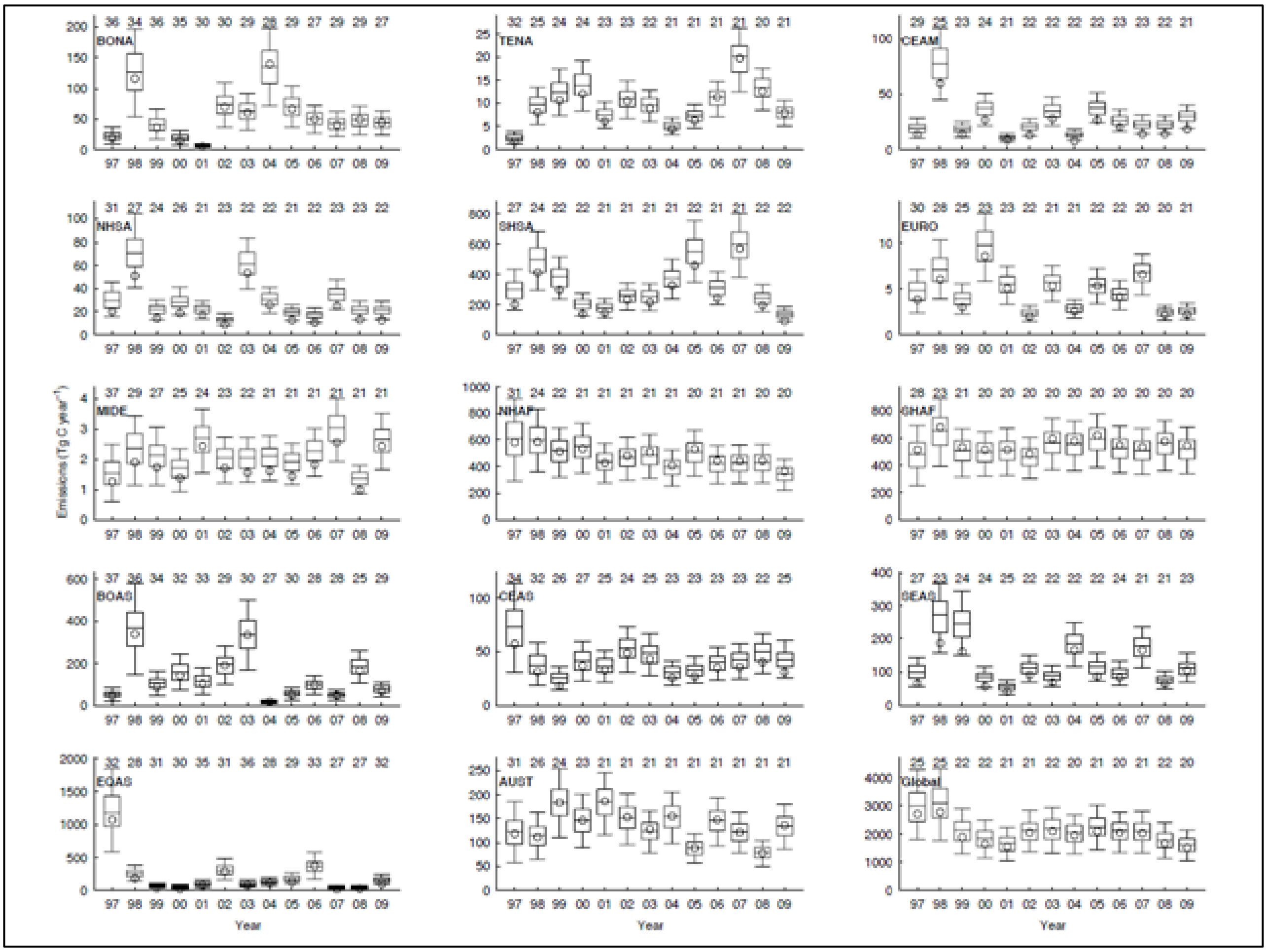

Figure 5. Annual uncertainties for different regions expressed as the 5th, 25th, 50th, 75th,and 95th percentiles of 2000 runs in a Monte Carlo set-up. Circles denote the estimates reported throughout the paper, which do not necessarily align with the 50th percentiles due to truncation of several parameters in the Monte Carlo simulations. Numbers on top give an indication of 1σ uncertainties (expressed as percentage of the 50th percentile) assuming a Gaussian distribution. **Source**: Fig S6, Supplementary Material Van der Werf et al. (2010).

1.3.1.2 Agriculture data sets + uncertainties

<u>Livestock (Herrero et al. 2013)</u>

Livestock emission data sets included enteric fermentation (CH_4) and manure management (N_2O, CH_4) for year 2000, for 28 regions, 8 livestock production systems, 4 animal species (cattle, small ruminants, pigs, and poultry), and 3 livestock products (milk, meat, and eggs), at 0.1°cell resolution. Herrero et al. (2013) presented a unique, biologically consistent, spatially disaggregated global livestock data set containing information on biomass use, production, feed efficiency, excretion, and greenhouse gas emissions. Their data base contained over 50 new global high-resolution maps with information for understanding the multiple roles (biophysical, economic, social) that livestock can play in different parts of the world. We used only the maps on enteric fermentation (CH_4) and manure management (N_2O, CH_4) for the aggregated animal species, at 0.1° spatial resolution. The original units (kg CO_2e.km^{-2}.yr^{-1}) were transformed to CO_2e.grid cell^{-1} by applying equal area reprojected values. The CO_2e of enteric fermentation and manure management were then summed to obtain a total emission value of livestock per grid cell. Livestock was entered in the Monte Carlo simulations as one variable only.

Emissions were estimated using a livestock systems classification based on Seré and Steinfeld (1996), widely used for studying different aspects of livestock. Systems were broken down based on agroecological differentiations (arid-semiarid, humid-subhumid, and temperate/tropical highland areas).Numbers of animals for each of these systems and regions were estimated using the data of Wint and Robinson (2008) for the year 2000, as well as herd dynamics models (Lesnoff 2008) parameterized for each region and production system. Biomass consumption by different species in each region and system relied on estimates of the availability of four main types of feeds (grass, crop residues, grains, occasional feeds) and the development of feasible diets for each species in each region and production system. For ruminants, information on the quantity and quality of the different feeds was then used to parameterize an IPCC Tier 3 digestion and metabolism model (RUMINANT), as described in Herrero et al. (2008) and Thornton and Herrero (2010). The model estimates production of milk and meat, manure production, N excretion, and methane emissions. For monogastrics, information on feed quality was used to estimate feed intake, productivity, and feed use efficiency, using standard nutrient requirements guidelines (NRC 1988). For the estimation of nitrous oxide emissions, the IPCC Tier 2 approach was used with specific manure management practices for each species, system, and region. More information of this process is given in Havlík et al. (2014).

Livestock uncertainties

No spatially explicit uncertainty data were provided in the authors' original data base. Therefore, and based on the author's expert judgement, we considered the uncertainties to be 20 percent of the total emissions values (CO_2e), per pixel. When individual uncertainties were needed for CH_4 and N_2O separately, we also applied 20 percent to the disaggregated emissions.

<u>Cropland soil emissions (Ogle et al. (2013), data available from authors upon request)</u>

Cropland emissions (N_2O and soil dSOC) (changes in soil organic carbon) were produced by Ogle et al. (2013) for the Environmental Protection Agency MAC-Report (2013), at 0.5° resolution, for time periods 2000-2030 with five-year increments, based on the DAYCENT ecosystem model. 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 $cell^{-1}$ using equal area values and the factors displayed in Table 3. The database included direct and indirect emissions from mineral-based cropland soil processes: synthetic and organic fertilization, residue N, mineralization and asymbiotic 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). The authors combined DAYCENT derived NO_x emissions with the IPCC default factors for indirect N_2O emissions (De Klein et al., 2006).

DAYCENT is a process-based model (Del Grosso et al., 2001) that simulates biogeochemical C and N fluxes between the atmosphere, vegetation, and soil by representing the influence of environmental conditions on these fluxes including soil characteristics and weather patterns, crop and forage qualities, and management practices. DAYCENT utilizes the soil C modelling framework developed in the Century model (Parton et al. 1987, 1988; Metherell et al. 1993), with refinement to simulate C dynamics at a daily time-step. Key processes simulated by DAYCENT include crop production, organic matter formation and decomposition, soil water and temperature regimes by layer, in addition to nitrification and denitrification processes.

Emissions estimated by the DAYCENT modelled six selected major crop types (maize, wheat, barley, sorghum, soybean and millet). Estimates are based on emissions per unit (m^2) of physical area in each in each 0.5° x 0.5° grid cell, and so were multiplied by an estimate of cropland area in each grid cell to compute total GHG emissions. The authors approximated crop-specific areas using harvested area data. First, crop-specific harvested areas for each 0.5° x 0.5° grid cell were estimated from Monfreda et al. (2008). Next, harvested areas for analogous crops were added to areas of the major crop types (i.e., oats with wheat, rye with barley, green corn with maize, and lentil, green bean, string bean, broad bean, cow pea, chickpea and dry bean with soybeans) to increase the coverage of cropland area. The sums of harvested areas fractions computed in this manner were less than total cropland areas (Ramankutty et al. 2008) for all but 1.6% of grid cells. In the last step, total harvested area was scaled to match at the country scale data on harvested areas reported in FAOSTAT. By including analogous crops and matching FAOSTAT harvested areas, the cropland area simulated by DAYCENT was about 61% of the global non-rice cropland areas reported by FAOSTAT.

The crop soil emissions provided by Ogle et al. (2013) were lower than those reported in other data sets (e.g. FAO) not only because the above mentioned conservative total crop areas but also because they excluded certain emissions due to data and resources limitations: drainage of organic soils, grassland soils, other crops not considered above (e.g. sugarcane, tobacco, vegetables, cotton, tea, etc), restoration of degraded land, burning of residues or biofuel.

Cropland emissions over organic soils

To complement the emissions of crops from organic soils, which were excluded in Ogle et al. (2013) database, we used a Tier 1 approach where we estimated the CO_2 emissions from drained organic soils. We i) first located the global areas with histosols, ii) we then overlapped them with Monfreda et al. (2008) maps on crop areas, and ii) then applied a Tier 1 annual emission factor for cultivated organic soils of 20 $MgC.ha^{-1} yr^{-1}$ derived from the IPCC (IPCC 2006). To locate the global areas with histosols we used ISRIC's global soil database (Soil grids 1 km) from ftp://ftp.soilgrids.org/data/recent/, and selected a map of histosol probability of occurrence (TAXGWRB_Histosols) with a probability threshold of ≥ 6% (based on the assigned map values of known histosol areas, max probability of occurrence in the original map was 52%), we then overlayed it with a soil carbon content map (OCSTHA) (Mg.ha-1), which we downloaded from the same site. We established a carbon threshold minimum value of 200 Mg C ha^{-1} by visually contrasting the location of our carbon thresholded + histosol probability areas with known maps of tropical peatland distribution (e.g. GLWD). We then downloaded 5 min resolution global harvest fraction maps which represented the fraction of area harvested, in each grid cell, in year 2000, for each of the six major crops considered by Ogle et al. (2013). We downloaded the "Harvested Area and Yields of 175 Crops (M3-Crops Data)" data set from http://www.geog.mcgill.ca/~nramankutty/Datasets/Datasets.html. The areas of each selected crop were transferred to our 0.5° grid by means of zonal statistics, added, and unit transformed to estimate hectares per grid cell of crops over histosol, which were then multiplied by the IPCC Emission Factor (20 $MgC.ha^{-1}.yr^{-1}$) and transformed to $CO_2e.ha^{-1}.yr^{-1}$ (multiplying it by 44/12). Tropical CO_2e emissions from this source resulted in 28 $TgCO_2e.yr^{-1}$. This value is lower than what would be obtained through global peatland drainage emissions (CO_2) at country-level in FAOSTAT (500 $TgCO_2e.yr^{-1}$), and lower than the peatland drainage emissions reported in Asia (630 $TgCO_2e.yr^{-1}$) by Hooijer et al. (2010). Our low values can probably be attributed to the fact that the Ogle's six crop covers (maize, wheat, sorghum, soya beans, millet and barley) are not that frequent in the tropics, and unlikely to be grown on histosols.

Cropland soil emissions uncertainties

The uncertainties of the soil cropland emissions were provided on a per pixel basis (0.5°) as standard deviations. When providing uncertainties for the aggregated CO_2e emissions (dSOC and N_2O), we assumed complete data independence and aggregated the variances. The authors used empirically based methods to provide an alternative to the error propagation techniques. They developed a linear mixed effect model to quantify both bias and variance in modeled soil C stocks, which were estimated using the Century ecosystem simulation model. The statistical analysis was based on measurements from 47 agricultural experiments, They then conducted Monte Carlo analysis by drawing values from the joint probability distribution for the parameters in the linear mixed effect model. They selected 1000 sets of parameters for the stat model, which produced 1000 of the so-called adjusted estimates. They took the mean and the standard deviation from this distribution as the final result of uncertainty (e.g. adjusted stdev).

Limits of the uncertainty analysis in CENTURY data

The uncertainty estimator provided by the authors reflects imperfect knowledge about parameterization, formulation of the model, model evaluation data (i.e., measurements) and initial values. Uncertainties in the model input and scaling of simulation results were not addressed because information about environmental conditions, land use and management activity were known for the sites. The uncertainty estimator was predicated on how well it represented the combination of environmental conditions and land management practices, which was dependent on the robustness of the data set, and data thresholds. First, none of the experiments had measurements below 1200 gm^{-2} or above 9000 gm^{-2}. Therefore the estimator should not be applied to soils with higher or lower C stock values. While a variety of land management practices were represented in the data set, there were only three studies evaluating the effect of grassland management. Consequently, the estimator is not robust for estimating uncertainties in modeled soil C stocks for grazing systems. In the author's data, the experimental data used to develop the uncertainty estimator were mostly independent of the parameterization data, and therefore, the empirically derived estimator was considered robust for determining uncertainties at sites where measurements were not available.

Paddy rice emissions (Li et al. (2013), data available from authors upon request)

We used data from Li et al.'s study for EPA's MAC Report (2013). Emission data 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 Li et al. (2006, 2010). 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 transformed to grid cell values by multiplying by equal area reprojected values, and applying the factors exposed in Table 3.

The original rice emission data set contained the above mentioned GHG emissions expressed as two flux values produced by using the maximum and minimum data on soil properties. Data is based on the MSF (Most Sensitive Factor) method which uses an envelope approach. No mean value was offered. Based on discussions with the author, the distribution of the data was known to be right skewed, and through the authors' expert judgement a log-normal distribution was considered to be the best –though not perfect- fit. This not perfect fit inflated a bit the final AFOLU emission, Monte Carlo derived values.

DNDC model

DNDC is a soil biogeochemical model that simulates the processes determining the interactions among ecological drivers, soil environmental factors, and relevant biochemical or geochemical reactions, which collectively determine the rates of trace gas production and consumption in agricultural ecosystems (Li 2001). Details of management (e.g., crop rotation, tillage, fertilization, manure amendment, irrigation, weeding, and grazing) have been parameterized and linked to the various biogeochemical processes (e.g., crop growth, litter production, soil water infiltration, decomposition, nitrification, denitrification, fermentation) embedded in DNDC (e.g., Li et al., 2006; Giltrap et al., 2010; Dai et al., 2012)(See the end of the Supplementary further information about the model parameterization, management scenarios, and parameterization details). The DNDC predicts daily CH_4, N_2O and soil carbon fluxes from rice paddies through the growing and fallow seasons as fields remain flooded or move between flooded and drained conditions during the season.

Uncertainties of rice emissions

Rice emission uncertainties were expressed as two flux values produced by using the maximum and minimum data on soil properties. Emission and uncertainty data were offered at a 0.5° level. Given the complexities of the global rice sector, the estimated GHG emissions need to consider several limitations (EPA MAC-Report, 2013):

- Availability and quality of data that represent the heterogeneous rice production systems of the world. Management practices, were not always available for all countries or regions and approximations were made based on limited literature or expert judgment.

- Biophysical modelling uncertainties: in particular with respect to soil organic carbon simulations. The DNDC modelling of the business-as-usual baseline conditions and mitigation scenarios was performed using a set of inputs and assumptions developed based on various sources. Soil organic carbon, has a significant impact on the net GHG emissions from the sector, and is particularly challenging to simulate given the lack of monitoring data at the global scale.

1.5 Creating a 0.5 degree grid for the study area

Grid

We created a WGS-84, lat-lon, 0.5° degree polygon vector using the centroid as the origin of coordinates for each grid cell. The areal extent of the grid spanned the tropics and subtropics (31 to -54° N, 130 to -120° E). A list of the countries included in this study can be found in Table 8. The grid contained 17,191 cells (Africa =7,214 cells, Asia= 2,868, and CS America= 7,111). This tropical grid was later used to define the zones for zonal statistics. Each grid cell was identified with an I equal area value obtained from a projection system that took into account the Earth's geometrical distortions (e.g. Albers equal area conic projection). This way, whenever the emissions had to be weighted by area, we used the equal area values, to guarantee consistent area among grid cells. Once the emissions data sets were gathered, we populated the grid with the selected emissions through zonal statistics. We ran quality assessment tests that contrasted the emissions of each data set (e.g. deforestation, livestock, rice, fire, etc) at the country level, against published data, to guarantee that the stored emissions data in each grid cell had been properly processed and unit transformed (see the Quality Assessment Section, for further details). Data stored in this grid, at cell level, were then used as the basis for the Monte Carlo analyses and to produce the final AFOLU rasters. Emission data stored in the grid were annual means for the period 2000-2005. Annual means were the best way to offer the final AFOLU emission data since the temporal range of the different data sets varied. All datasets included the year 2000, except rice whose emissions took the year 2010 as the baseline (see Table 2). Three data sets were for the year 2000 (enteric fermentation, manure management, and wood harvest), three offered multiple years (e.g. fire, crops, deforestation) and we estimated their annual means for the period 2000-2005. Therefore, .we offer an annual snap-shot of AFOLU emissions and uncertainties that are a useful benchmark against which countries can follow up their AFOLU emission trends.

1.6 Uncertainty estimation of AFOLU emissions

The AFOLU sector is well known for its large uncertainties (up to 50 percent) (Smith et al. 2014). These values are the highest of all the emission sectors reported under the IPCC (Tubiello et al. 2014), therefore, for our AFOLU emission analysis to be meaningful, we needed a robust uncertainty analysis. We made two initial decisions:

- ***Working at the pixel level:*** We chose to work at the pixel level because one of the major contributions of our research was its highly disaggregated (0.5°), spatially explicit, data on emissions and uncertainties.
- ***Aggregating uncertainties through Monte Carlo simulations:*** Instead of a simple propagation of errors method, we chose Monte Carlo simulations to aggregate the uncertainties because: i) some data sets were not Gaussian, ii) there possible was correlations among data, and iii) we desired a distribution of the AFOLU aggregated data from where to extract the 5^{th} and 95^{th} percentiles.

We ran our uncertainty estimations as a sequential four-step process: 1. Definition of the error model, 2. Parameterization of the error model, 3. Processing of the data, and 4. Considerations of data spatial correlation.

1. Definition of the error model: At the pixel level, our model assumed *independent* contributions from multiple emission sources due to the lack of reference data on emissions and uncertainties correlations. We aggregated the emissions in each pixel following Equation 1:

(Eq 1) Emission(x) = E1(x) + V1(x) + ... + En(x) + Vn(x), where E1..n are the input emission data sets and V1..n are the uncertainties expressed in variance.

Table 2 describes the different data sets, including their data distributions. Five data sets were Gaussian and two were log-normal (e.g. deforestation and rice). Uncertainties of the original emission data sets were expressed as standard deviations, or as percentiles (e.g. 5^{th} 95^{th}). For those variables where there was no pixel uncertainty (livestock and wood harvesting) we relied on the authors' expert judgements.

2. Parameterization of the error model: To run Monte Carlo simulations at the pixel level, a parameterized model for each emission source was required. Models were based on the distribution functions of each emission data source. Gaussians probability functions used their means and standard deviations. Log-normals used location and scale parameters. However, log-normal models did not match the data perfectly well, which resulted in slightly higher values (2.5%) for the aggregated AFOLU emissions per pixel obtained through Monte Carlo, than obtained through the original data sets.

The Monte Carlo error model followed Equation (3):

Equation(3) AFOLU uncertainties (pixel level) = Gaussian(livestock) + Gaussian(fire) + Gaussian(wood harvest) + Gaussian(crops) + Lognormal(rice) + Lognormal(deforestation)

3. Processing of the data: We ran 1000 Monte Carlo simulations per pixel using the parameterized models in Equation(3), and obtained the mean, variance and 5^{th} and 95^{th} percentiles of the final AFOLU data distribution. We chose two measures of uncertainties at pixel level (variance and 5th-95th percentiles) because they offer different information (total uncertainty *vs* thresholds of uncertainty).

- Aggregated AFOLU variance: We aggregated the variance in each pixel following Equation 2,

Equation (2)
$$\sigma_{X+Y} = \sqrt{\sigma_X^2 + \sigma_Y^2 + 2\rho\sigma_X\sigma_Y},$$

Where σ is the standard deviation, and σ^2 is the variance. Assuming ρ =0 (complete independence) at the pixel level, the variance of the aggregated emissions (AFOLU emissions) is the sum of the variances of the individual emission sources (e.g. crops, deforestation, rice, livestock, etc). All the uncertainties were transformed to variances at the pixel level. In the case of the percentiles, the associated variances were computed from the reported means and percentiles using an optimizer with a sum of squares cost criterion. In the case of the standard deviations, they were simply squared.

- The 5^{th} and 95^{th} percentiles per pixel were obtained from the AFOLU distribution function produced by 1000 Monte Carlo simulations in each pixel.

4. Considerations of spatial correlation in the uncertainty data: scaling up: We ran our Monte Carlo analysis at the pixel level, but we also needed to produce statistics of emissions and uncertainties at other scales. This implied propagating the uncertainties to other levels of spatial aggregation (e.g. continent, tropics). Spatial correlation and cross-correlation are important to correctly aggregate uncertainties when there is a change of scale (e.g. from pixel to country or continental levels). Two extreme situations can occur: complete data dependence or complete data independence. Dependence assumes the variation of individual pixels´ uncertainties to completely depend on neighbouring effects, and independence assumes the opposite. In reality, data behaves between these extremes. However, and due to lack of available information on the data spatial correlation, we assumed complete dependence of the uncertainties when scaling up. This is a conservative approach since data dependence always results in larger uncertainty values due to an additive correlation term ($\rho > 0$), that turns 0 in uncorrelated variables ($\rho = 0$) (Eq. 2).

The aggregation of the pixel AFOLU uncertainties to these larger areas was estimated differently for the two different measures of uncertainty that we use in this research: variance and 5th and 95th percentiles:

1. For the variance: variances at aggregated scales were computed as the squared sum of standard deviations at pixel level. Note that this equals the sum of the cross product of the vector standard deviations at pixel level and its transpose, which implies complete spatial correlation of pixels within aggregation units.

   An easy example of this approach can be explained with 2 random variables (x, y) using Equation 2. If ρ=1 (complete correlation)

   Eq (2) $$\sigma_{X+Y} = \sqrt{\sigma_X^2 + \sigma_Y^2 + 2\rho\sigma_X\sigma_Y},$$

   σ (x+y)= $\sqrt{(\sigma_x^2 + \sigma_y^2 + 2\,\sigma_x\sigma_y)} = \sqrt{(\sigma_x + \sigma_y)^2}$ -----> σ (x+y) = ($\sigma_x + \sigma_y$)

   where σ are standard deviations and σ^2 variances. Under complete data dependence, the aggregation of the uncertainties can be obtained through the addition of the standard deviations, which are the squared to obtained the aggregate variance (from σ to σ^2)

2. For the 5th and 95th percentiles: the scaling up of the percentiles was computed as the sum of the corresponding percentiles at the pixel level. This can be considered a worst-case scenario since the approach produces wider ranges than when *partial* spatial correlations of pixels are modelled (e.g. we are adding the most extreme uncertainties for each pixel, the lower values (5th percentile) or the higher values (95th percentiles).

2. Net vs gross AFOLU assessments

Net assessments consider both emissions by sources and absorption by sinks. For AFOLU emission reporting, both emissions and removals should be considered. For accounting purposes (=inclusion into mitigation commitment targets, however, not all removals will be additional to the baseline. Our net AFOLU balance included sequestration processes from soils under crops, and from paddy rice , both through organic matter fixation (dSOC) . Moreover, our net AFOLU balance excluded short term life-cycle emissions that are compensated by annual growth cycles, such as biomass burning emissions coming from non-woody vegetation (e.g. agriculture and savannah burnings). This assumption is, however, generous, since post-fire climatic conditions and multiple soil degradation sources (e.g. overgrazing) might not allow for a regrowth that compensates for the emitted GHG through biomass burning. Moreover, the equilibrium assumption might apply to CO_2 but it does not to CH_4 nor N_2O gases, and the inclusion of CH_4 and N_2O from non-woody vegetation fire emissions can turn continents like Africa from a quasi-neutral net C-AFOLU budget, into a net continental source of emission (Mbow 2014, Valentini et al. 2014).

Afforestation, forest regrowth and sequestration from forest remaining forests are important processes to consider in net land use AFOLU balances. However, we excluded the forest sink contribution in our net-AFOLU assessments for several reasons: i) lack of spatially explicit GHG absorption emission data and associated uncertainties. It would be possible to derive forest absorption data through Tier 1 approaches that used the existing spatially explicit data on increased canopy cover (Hansen et al. 2013) but the accuracy of the absorption product would be quite lower than the emission data sets, many of which use Tier 3 approaches, ii) the most important sequestration activity would be afforestation but pantropical countries contribute little to large scale afforestation projects (China would be an important exception but it is not included in our study area) Viet nam and India would be the only two countries in the tropics were some level of afforestation is occurring (Smith et al. 2014), iii) forest regrowth is important in net land use emission assessments but its contribution has been reported to be quite small in the tropics (e.g. -0.4 $PgCO_2e.yr^{-1}$) (Achard et al. 2014), moreover iv) the sequestration role of forests remaining forests (e.g. growth) is unlikely to be additional from their baselines, which is fundamental for mitigation efforts. The exception would be large –national scale- forest restoration initiatives over forest land, or effective large scale forest management programmes, which do not seem to be occurring in our pantropical study area with the exception of, perhaps, Viet Nam.

To evaluate that the exclusion of the forest sink would not invalidate our emission budgets, we downloaded FAO data on forest land use emissions and absorptions for 2000-2005 for our pantropical region. Net emissions from forests remaining forests (degradation + sink effects due to growth, regrowth, improved forest management, or/and forest restoration projects) added up to -0.3 $PgCO_2e.yr^{-1}$, while net deforestation emissions added up to 3.2 $PgCO_2e.yr^{-1}$. The net sequestration effect of forests remaining forests was, therefore, one order of magnitude smaller than the deforestation emissions in 2000-2005. While this small contribution could respond to many possible combinations of degradation (e.g. high/low degradation emissions) and sequestration (e.g. high/low sequestration from forests), we at least verified that the net contribution of the sink for the tropic was small, and that some continents, such as Asia do not have net sinks. Table 5 shows the sink contribution (forest remaining forests), the net deforestation (forest land use change) and the net forest emission balance, at aggregated tropical and continental scales.

	Forest remaining forest (net emissions: degradation + sinks)	**Forest land use change (net deforestation)**	**Net forest emission balance**
	Pg $CO_2e.yr^{-1}$		
Tropical	-0.3	3.2	2.9
Africa	-0.05	0.7	0.65
Asia	0.12	0.6	0.7
Central South America	-0.4	1.9	1.5

Table 5: Forest statistics per continent on net deforestation, net emissions from forest remaining forests (sinks and removals), and the net forest balance. Data was extracted at country level from FAOstats

Gross and Net AFOLU estimates under the AR5

Based on the AR5 (Smith et al. 2014), gross FOLU emissions in the tropics were approximately 8.2 PgCO2.yr-1 (2000-2007), which are reported as Baccini's estimates using Houghton's book-keeping model (Figure S7 supplementary, Fig 11.8 AR5). This value contrasts with the approximately 6 PgCO2e.yr-1 (2000-2005), gross emissions estimated in three data bases (Hotspots, AFOLU and EDGAR-JRC). While time periods are not identical, the differences rather relate to the included sources and methods chosen to estimate them. Thus, our lower emissions estimates include multiple gases (not only CO2, but also CH4 and N2O) and forest fire emissions (2 PgCO2e.yr-1), which are fully omitted in the 8.2 PgCO2.yr-1 estimate. However, we did not include soil SOM emissions (0.55 PgCO2.yr-1) nor shifting cultivation (2.35 PgCO2.yr-1).This last we assumed to be part of the deforestation estimates. It is unclear how Baccini's gross estimates separates between shifting cultivation and deforestation. Moreover, Baccini's wood-harvesting estimates were also higher than the estimates in our considered data bases (2.49 PgCO2.yr-1 vs a maximum of 2 PgCO2.yr-1 for FAOSTAT). It is also unclear why the AR5 report selectively uses some gross emission estimates from Baccini et al. (2012)'s study but not all. Thus, Baccini et al. (2012) report a gross FOLU budget of 12.32 PgCO2.yr-1 that derives from larger deforestation values (4.18 PgCO2.yr-1) than the ones selected for the AR5 (2.97 PgCO2.yr-1), includes fire emissions (2.86 PgCO2.yr-1) –not included in the AR5-, wood decay (3.04 PgCO2.yr-1), soil SOM emissions (0.55 PgCO2.yr-1) and shifting cultivation (2.35

PgCO2.yr-1). This estimates maze urgently call for more transparent and more detailed information on methods and assumptions for future AFOLU estimates under the IPCC Assessments Reports.

The same call for higher transparency applies to the AFOLU net estimate under the AR5 (5 PgCO2.yr-1) (Fig S8 supplementary, Fig. 11.2 AR5). This value is reported to be the aggregation of: i) the Land Use Change and Forestry net emissions from Houghton et al. (2012), and the ii) emissions of drained and burned peatlands from FAOSTAT (2013), as explained in the figure caption. However, we believe there are problems with these reported data bases. Thus, Houghton et al. (2012) report a value of 4.03 PgCO2.yr-1 (1.1 PgC.yr-1) (2000-20009) for land use chage and forestry, but Figure 11.2 shows a value closer to 3.67 PgCO2.yr-1 which matches better the estimate reported by Baccini et al. (2012) (2000-2007). On the other hand, emissions from burning peatlands are supposed to derive from FAOSTAT for 2000-2009 but we could not reproduce this number using FAOSTAT, and the value of 1.1 PgCO2e.yr-1 that appears in Fig 11.2 AR5 (Fig S8 supplementary) is closer to peatland fire and decay estimates reported by Houghton et al. (2012) for the period 1997-2010, which includes the very severe El Niño fires 1997 in Indonesia (and does not correspond to the 2000-2009 period). These numbers mismatches urgently call for more dialogue among the AFOLU community and higher transparency on data and methods.

Table 11.1 | Net global CO_2 flux from AFOLU.

	1750–2011 Cumulative $GtCO_2$	1980–1989 $GtCO_2$/yr	1990–1999 $GtCO_2$/yr	2000–2009 $GtCO_2$/yr
IPCC WGI Carbon Budget, Table 6.1[a]:				
Net AFOLU CO_2 flux[b]	660 ± 293	5.13 ± 2.93	5.87 ± 2.93	4.03 ± 2.93
Residual terrestrial sink[c]	−550 ± 330	−5.50 ± 4.03	−9.90 ± 4.40	−9.53 ± 4.40
Fossil fuel combustions and cement production[d]	1338 ± 110	20.17 ± 1.47	23.47 ± 1.83	28.60 ± 2.20
Meta-analyses of net AFOLU CO_2 flux:				
WGI, Table 6.2[e]		4.77 ± 2.57	4.40 ± 2.20	2.93 ± 2.20
Houghton et al., 2012[f]		4.18 ± 1.83	4.14 ± 1.83	4.03 ± 1.83

Notes: Positive fluxes represent net emissions and negative fluxes represent net sinks.

(a) Selected components of the carbon budget in IPCC WGI AR5, Chapter 6, Table 6.1.

(b) From the bookkeeping model accounting method of Houghton (2003) updated in Houghton et al., (2012), uncertainty based on expert judgement; 90 % confidence uncertainty interval.

(c) Calculated as residual of other terms in the carbon budget.

(d) Fossil fuel flux shown for comparison (Boden et al., 2011).

(e) Average of estimates from 12 process models, only 5 were updated to 2009 and included in the 2000–2009 mean. Uncertainty based on standard deviation across models, 90 % confidence uncertainty interval (WGI Chapter 6).

(f) Average of 13 estimates including process models, bookkeeping model and satellite/model approaches, only four were updated to 2009 and included in the 2000–2009 mean. Uncertainty based on expert judgment.

Figure 6: Table 11.1 reported under the AR5-WGIII (Smith et al. 2014)
http://www.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_chapter11.pdf

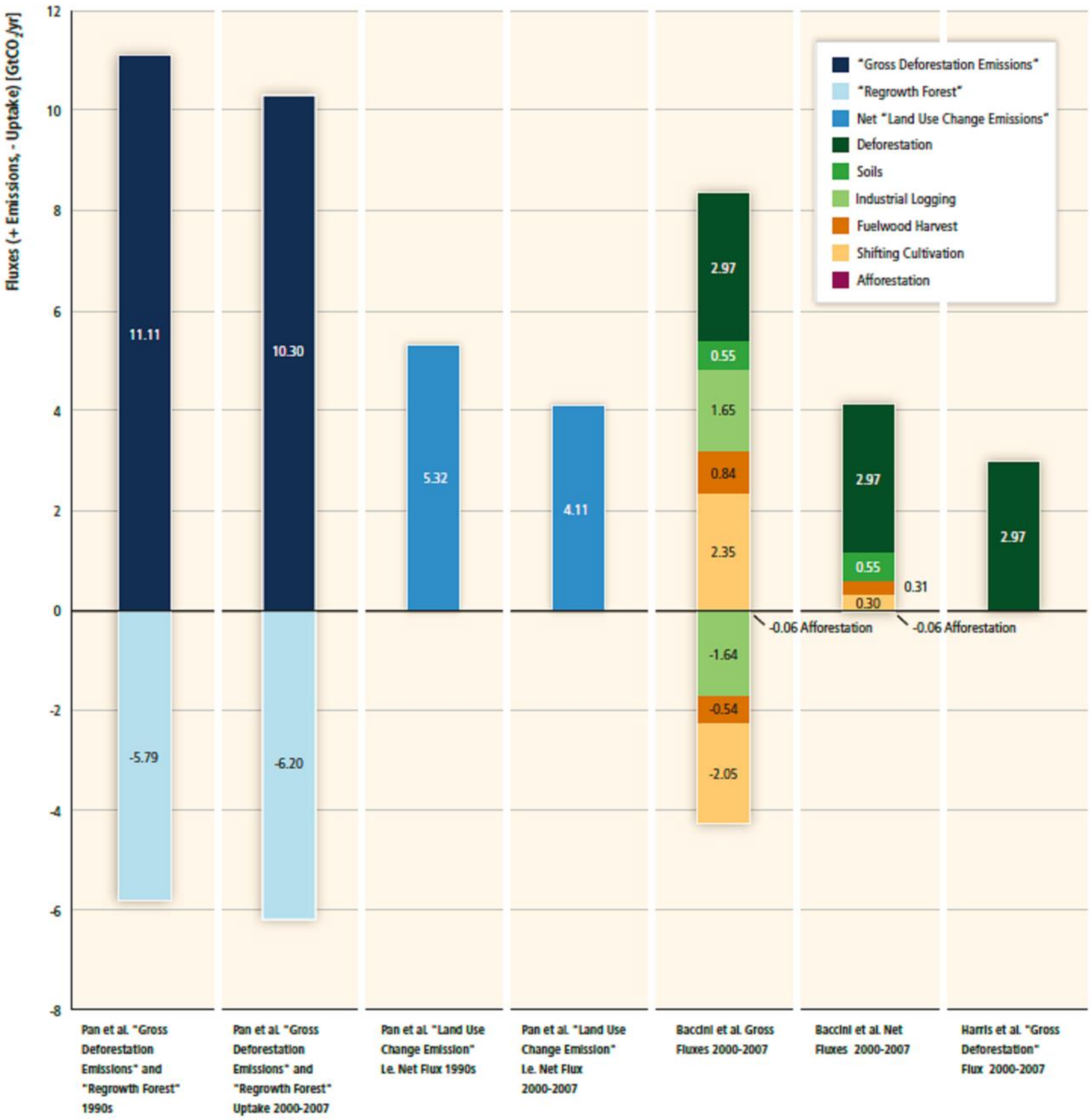

Figure 7: Gross and net contributions of emissions from sources and removal from sinks for the FOLU sector, for different studies. Source: Figure 11.8 from AR5, WGIII (Smith et al. 2014) http://www.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_chapter11.pdf

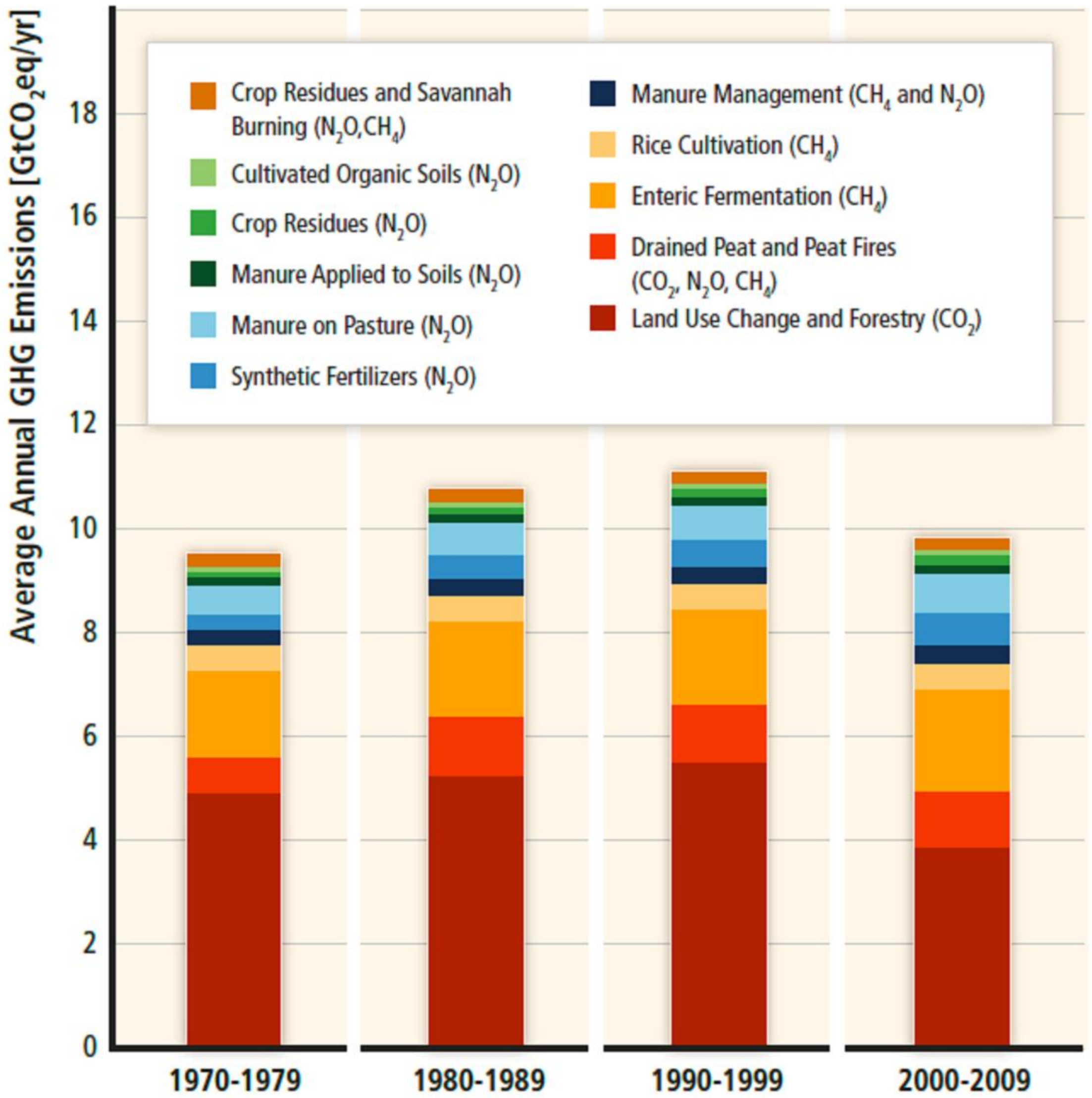

Figure 8: Net AFOLU estimates for different time periods. Source: Figure 11.2 from AR5-WGIII (Smith et al. 2014) http://www.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_chapter11.pdf

3. FAO and EDGAR-JRC databases and comparative AFOLU emissions

To assess the results of our aggregated AFOLU emissions, we contrasted our scaled up country level emission values with other databases that also offer AFOLU country emission data (for a list of countries used see Table 9). No uncertainty data exists in these other databases, so comparisons were restricted to emissions.

Emission data from FAOstats were downloaded from http://faostat3.fao.org/home/E and for EDGAR-JRC v4.2 FT2010 from http://edgar.jrc.ec.europa.eu/overview.php?v=42FT2010 We chose AFOLU N_2O, CH_4 and CO_2 emissions from 2000 to 2005 and then estimated their annual means. The FAO data set had a complete an organized metadata that allowed the understanding of the different variables. Emissions were offered per land use (forests, croplands, wetlands, grasslands) and agriculture. EDGAR-JRC did not count on any metadata and the understanding of the offered data was confusing. Emissions were organized per GHG (CO_2, N_2O and CH_4) and then by a code similar to the IPCC GHG reporting categories. Table 6 isplays the V4.2 FT2010 coding.

Code	Description as in the FT2010 Excel files	Code	Description as in the FT2010 Excel files
4D	direct agricultural soil emissions (fertilizers, manure, crop residues)	5A	Forest fires
4D4	Other direct soil emissions	5C	Grassland fires
4E	Savannah burning	5D	Wetland/peat fires and decay
4F	field burning of agricultural residues	5F2	Forest fires decay

Table 6: Codes offered for each GHG for each year, in the V4.2 FT2010 Excel datasheets.

To make the comparison with our data possible, we chose those variables that match our AFOLU emissions. Therefore, we excluded non-woody vegetation fires, we excluded forest sinks, and we also exclude those emissions that were not included in our analyses (e.g. energy in agricultural emissions). Table 8 shows a brief overview of the included variables as named in each database, and the way to group these variables into forests, crops and livestock, which are then visualized in Figure 6.

For a description of the differences among AFOLU databases, please refer to Tubiello et al. (2015). We estimated the AFOLU emissions for the study area covered by of our research, as annual means for 2000-2005, for the selected data sets in each database (FAO and EDGAR-JRC) (Table 7). Final AFOLU values were 7.9, 6.6, and 5.7 $PgCO_2e.yr^{-1}$ for this study, FAOstats and EDGAR-JRC respectively.

	This study	FAOstats	EDGAR-JRC
Forests	Deforestation (CO_2)	Net forest conversion (CO_2)	No direct deforestation emission exists.
	Biomass burning (CO_2, CH_4, N_2O)	Biomass burning of humid forests and other forests (CH_4, N_2O) Biomass burning of organic soils (CH_4, N_2O, dSOC)	Forest fires and wetland/peat fires + decay of drained soils (CO_2, CH_4, N_2O)
	Harvesting (CO_2)	No direct harvesting emission data available	No direct harvesting emission data available
	Crop soil emissions (N_2O,	Synthetic fertilizers (N_2O)	Direct agricultural soil emissions

	dSOC)	Manure applied to soils (N_2O) Crop residues (N_2O)	(fertilizers, manure, crop residues) (N2O) Other direct soil emissions (CO_2)
	Crop emissions over organic soils (CO_2)	CO_2 emissions of croplands over drained histosols (CO_2) (Cropland-land use)	Not available
	Rice (CH_4, dSOC)	Rice cultivation (CH_4)	Rice (CH_4)
Livestock	Livestock Enteric fermentation (CH_4) Manure management (N_2O, CH_4)	Enteric fermentation (CH_4) Manure management (CH_4, N_2O) Manure applied to pastures (N_2O)	Enteric fermentation (CH_4) Manure Management (CH_4,N_2O)

Table 7: Brief overview of the emissions included in each database.

Figure 6 shows the comparison of AFOLU emissions among these three databases, and the emissions partitioning into three main categories: Forests, Crops and Livestock. Forest emissions were the most uncertain among the three data bases.

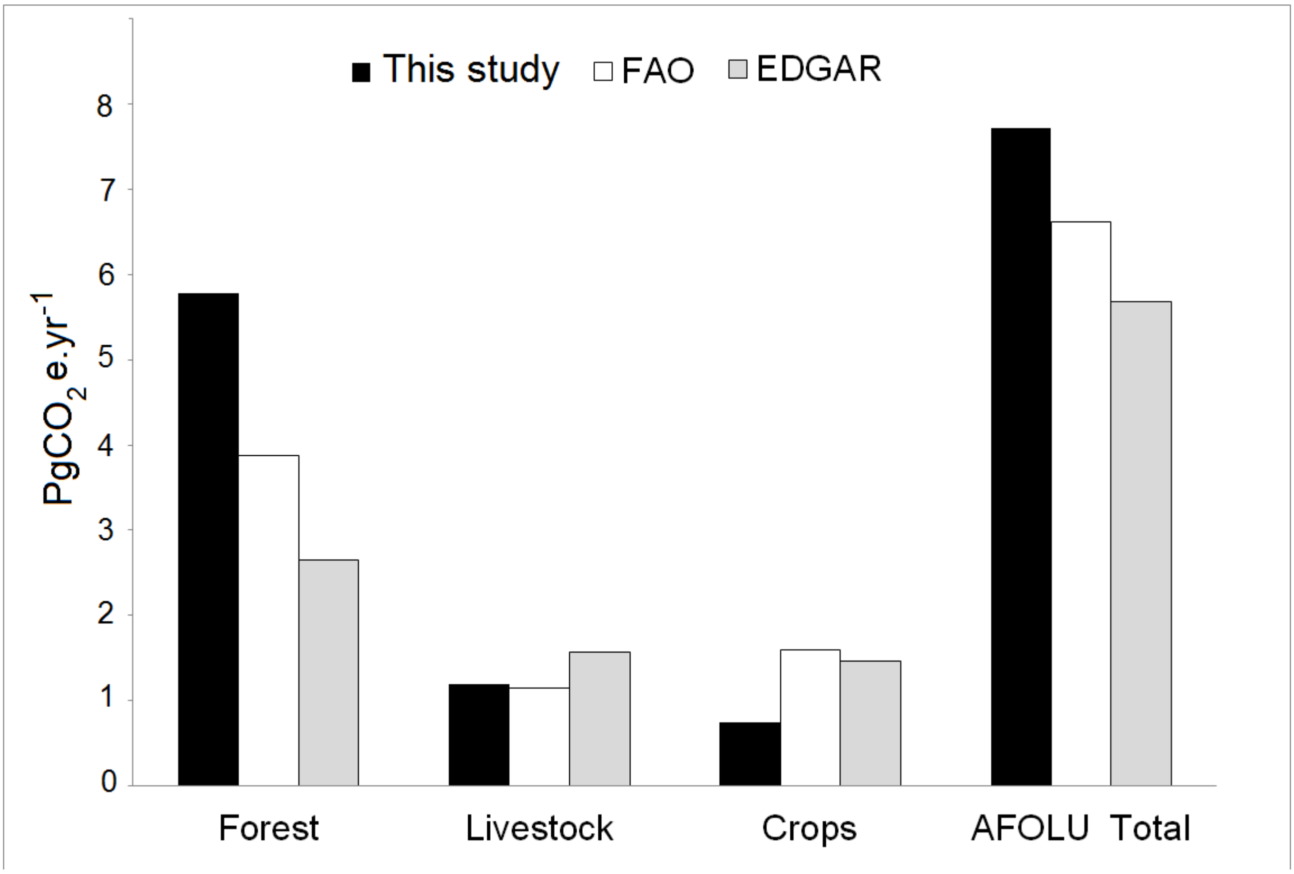

Figure 6: Comparison of AFOLU emissions and three main emission categories (forests, crops and livestock) for three databases: this study, FAOstats, and EDGAR-JRC.

4. Quality Assessment Tests

Deforestation based on Harris et al. (2012) data

	TgC	$TgCO_2$ Harris	$TgCO_2$ this study
Brazil	340	1246.7	**1240.7**
Argentina	10	36.7	**37.3**
Indonesia	105	385.0	**350.5**
DRC	23	84.3	**82.5**

Fire regional Van der Werf et al. (2010)

	Mean $TgC.yr^{-1}$	Mean $TgCO_2.yr^{-1}$	$TgCO_2$ this study
EQAS	113.2	**414.9**	**240.9**
SHSA	251.8	**923.4**	**418.5**
SHAF	551.3	**2021.6**	**1911.2**
NHSA	23.5	**86.2**	**52.6**

Regional biomass burning emissions in our study area were smaller than Van der Werf et al. (2010) values because we had eliminated deforestation fires and non-woody fires, and not all the countries in each region were included in our study area. For fire, the Quality Assesment was more an evaluation of orders of magnitude.

Crop soil emissions (direct N2O) (Ogle data versus EPA's MAC Report 2013)

	$TgCO_2e$ MAC Report	$TgCO_2e$ this study
Argentina	14	**15**
Brazil	35	**36**
India	60	**55**
US	82	**83**
China	109	**119**

Rice emissions (Li data versus EPA's MAC Report 2013)

	$TgCO_2e$ MAC REPORT			$TgCO_2e$ in this study		
	CH_4	N_2O	dSOC (CO_2)	CH_4	N_2O	dSOC (CO_2)
India	91.2	76.7	-50	**133**	**68**	**-36**
Indonesia	81.7	25.5	2.2	**82**	**13**	**-6**
China	72.9	34.6	-69.4	**40.8**	**32**	**-37**
Vietnam	47	25.7	-4.8	**35.6**	**22**	**-4**
Bangladesh	54.4	63	-16	**68**	**77**	**-12**
World	484	260	-179	**526**	**246**	**-126**

Livestock emissions (Mario data versus MAC Report 2013)

	$TgCO_2e$	$TgCO_2e$ this study
India	300	**333**
China	242	**250**
Brazil	235	**218**
US	174	**170**
Bangladesh	80	**78**

5. AFOLU country statistics

	AFOLU country emissions and uncertainties TgCO$_2$e.yr^{-1}				Percent contribution to country AFOLU emissions %						Percent contribution to country AFOLU emissions uncertainties %					
Country	**AFOLU emiss.**	**5th percent**	**95th percent**	**Variance**	**Deforestation**	**Fire**	**Harvest**	**Livestock**	**Crop**	**Rice**	**Deforestation**	**Fire**	**Harvest**	**Livestock**	**Crop**	**Rice**
Angola	282.9	189.5	391.4	4.5E+15	8.3	87.8	2.2	1.5	0.2	0.0	29.3	70.6	0.0	0.0	0.0	0.0
Argentina	153.2	102.4	235.3	2.6E+15	25.5	13.9	11.6	37.2	11.0	0.8	93.1	0.9	0.5	5.5	0.0	0.0
Bangladesh	184.4	154.8	219.5	4.0E+14	1.6	0.1	1.5	23.3	0.2	73.3	0.7	0.0	0.1	25.1	0.0	74.1
Belize	3.1	2.0	4.5	6.2E+11	87.4	2.2	7.0	1.4	1.3	0.7	99.7	0.0	0.3	0.0	0.0	0.0
Benin	13.7	10.1	18.2	8.0E+12	10.2	8.7	57.0	18.9	4.7	0.5	59.9	0.9	35.3	3.9	0.0	0.0
Bhutan	4.4	2.5	8.5	6.3E+12	41.3	2.7	38.5	15.1	2.0	0.4	97.8	0.0	1.9	0.3	0.0	0.0
Bolivia	92.3	49.8	172.2	2.5E+15	49.1	34.8	2.2	11.3	1.9	0.6	98.4	1.5	0.0	0.1	0.0	0.0
Botswana	11.5	7.1	19.0	2.1E+13	51.6	2.6	19.1	26.5	0.2	0.0	97.4	0.0	0.9	1.7	0.0	0.0
Brazil	1870.3	1187.2	2918.3	3.7E+17	68.1	4.9	12.5	12.0	2.1	0.4	98.8	0.1	0.6	0.5	0.0	0.0
Brunei	0.8	0.5	1.2	7.5E+10	33.2	0.2	62.7	3.2	0.0	0.7	89.5	0.0	10.5	0.0	0.0	0.0
Burundi	5.9	4.2	8.1	1.9E+12	11.1	1.1	65.5	10.0	12.0	0.3	59.2	0.0	39.8	0.9	0.1	0.0
Cambodia	66.0	37.0	118.1	1.1E+15	49.9	34.0	0.0	8.7	0.2	7.2	98.2	1.7	0.0	0.1	0.0	0.0
Cameroon	57.2	34.9	96.2	4.9E+14	42.1	16.5	24.8	15.5	1.0	0.1	96.7	0.8	1.8	0.7	0.0	0.0
Central African Republic	231.7	153.8	317.7	2.8E+15	7.2	88.4	2.2	2.0	0.2	0.0	17.8	82.2	0.0	0.0	0.0	0.0
Chad	32.8	23.6	45.3	6.2E+13	12.8	32.1	24.7	30.0	0.2	0.0	74.3	10.9	6.0	8.8	0.0	0.0
Chile	48.1	34.8	67.5	1.5E+14	40.5	5.6	41.2	11.0	1.7	0.0	88.6	0.2	10.4	0.7	0.0	0.0
Colombia	111.7	66.8	191.5	2.2E+15	51.2	1.4	11.6	28.3	3.0	4.6	98.2	0.0	0.3	1.5	0.0	0.0
Congo	20.3	9.3	42.2	1.7E+14	64.5	4.9	30.1	0.6	0.0	0.0	99.2	0.0	0.8	0.0	0.0	0.0
Congo, DRC	438.8	287.8	642.8	1.5E+16	18.8	60.2	20.3	0.5	0.2	0.0	68.0	28.8	3.2	0.0	0.0	0.0
Costa Rica	6.7	4.1	10.7	4.8E+12	69.0	2.3	1.2	20.3	0.1	7.2	98.1	0.0	0.0	1.4	0.0	0.5
Cote d'Ivory	26.0	16.1	42.6	9.8E+13	41.2	3.6	41.5	10.1	3.1	0.6	94.7	0.0	5.0	0.3	0.0	0.0
Cuba	9.6	6.8	13.8	6.0E+12	20.9	12.9	6.1	47.7	1.8	10.6	78.1	1.4	0.2	15.3	0.0	5.0

Country	AFOLU country emissions and uncertainties TgCO$_2$e.yr^{-1}				Percent contribution to country AFOLU emissions %						Percent contribution to country AFOLU emissions uncertainties %					
	AFOLU emiss.	5th percent	95th percent	Variance	Deforestation	Fire	Harvest	Livestock	Crop	Rice	Deforestation	Fire	Harvest	Livestock	Crop	Rice
Dominican Republic	4.0	2.2	6.6	2.2E+12	41.8	1.9	0.0	51.1	1.0	4.2	92.8	0.0	0.0	6.7	0.0	0.5
Ecuador	32.4	20.1	52.6	1.5E+14	52.6	1.3	17.1	20.6	2.1	6.4	97.8	0.0	0.8	1.1	0.0	0.3
El Salvador	2.5	1.6	4.3	1.2E+12	21.7	3.4	3.5	60.9	6.9	3.7	94.8	0.0	0.0	5.1	0.0	0.0
Equatorial Guinea	1.9	0.6	4.5	2.1E+12	89.0	0.0	10.6	0.3	0.0	0.0	99.9	0.0	0.1	0.0	0.0	0.0
Ethiopia	151.4	108.5	202.6	1.0E+15	8.8	10.1	55.0	25.2	0.9	0.0	54.0	1.3	36.9	7.7	0.0	0.0
French Guiana	1.9	0.8	4.3	2.0E+12	62.5	0.3	32.3	0.3	0.0	4.6	99.2	0.0	0.8	0.0	0.0	0.0
Gabon	15.8	5.5	36.9	1.5E+14	87.5	2.0	9.9	0.5	0.1	0.0	99.9	0.0	0.1	0.0	0.0	0.0
Ghana	32.2	21.9	45.9	6.6E+13	23.3	3.7	60.3	10.6	1.6	0.4	71.0	0.1	28.0	0.9	0.0	0.0
Guatemala	25.4	17.3	37.6	4.5E+13	73.9	4.0	5.1	12.9	3.6	0.4	98.9	0.1	0.1	0.9	0.0	0.0
Guinea	28.8	17.3	51.3	1.9E+14	25.1	13.7	40.0	20.1	0.5	0.6	97.3	0.2	1.9	0.5	0.0	0.0
Guinea-Bissau	3.4	2.4	5.1	1.4E+12	14.3	31.2	16.8	24.5	0.9	12.3	94.6	2.9	0.8	1.6	0.0	0.1
Guyana	8.6	3.9	17.6	2.7E+13	63.7	0.3	10.6	1.6	0.2	23.7	95.6	0.0	0.1	0.0	0.0	4.2
Haiti	3.5	2.5	4.6	5.0E+11	10.5	0.6	28.2	58.4	2.1	0.1	52.0	0.0	9.0	38.9	0.0	0.1
Honduras	16.7	10.7	27.8	4.2E+13	34.6	6.9	39.7	12.8	5.8	0.3	96.3	0.1	3.2	0.3	0.0	0.0
India	897.5	706.8	1117.7	1.8E+16	7.7	0.6	27.9	38.6	6.0	19.3	35.6	0.0	20.9	40.0	0.1	3.4
Indonesia	664.4	359.8	1099.4	5.9E+16	50.6	32.9	0.0	2.6	1.0	12.9	84.6	13.6	0.0	0.0	0.0	1.7
Jamaica	1.2	0.7	2.3	3.2E+11	60.1	0.6	0.0	39.3	0.0	0.0	97.1	0.0	0.0	2.9	0.0	0.0
Kenya	49.9	34.8	71.0	1.8E+14	15.0	0.9	50.5	33.1	0.4	0.0	75.4	0.0	17.2	7.4	0.0	0.0
Laos	62.1	34.1	108.9	7.1E+14	89.3	3.5	0.0	5.2	0.2	1.7	99.9	0.0	0.0	0.1	0.0	0.0
Lesotho	3.3	2.5	4.2	3.4E+11	8.7	7.5	47.6	33.2	3.0	0.0	49.7	0.8	33.3	16.1	0.0	0.0
Liberia	11.8	6.1	22.2	3.3E+13	61.4	0.1	37.3	0.8	0.0	0.4	97.4	0.0	2.6	0.0	0.0	0.0
Madagascar	37.0	23.5	60.9	1.9E+14	32.8	11.3	25.2	27.5	0.6	2.7	95.4	0.4	1.9	2.2	0.0	0.2

	AFOLU country emissions and uncertainties				Percent contribution to country AFOLU emissions						Percent contribution to country AFOLU emissions uncertainties					
	$TgCO_2e.yr^{-1}$				%						%					
Country	**AFOLU emiss.**	**5th percent**	**95th percent**	**Variance**	**Defores tation**	**Fire**	**Harvest**	**Lives tock**	**Crop**	**Rice**	**Defores tation**	**Fire**	**Harvest**	**Lives tock**	**Crop**	**Rice**
Malawi	10.9	7.2	17.4	1.6E+13	18.2	34.0	31.9	11.3	4.0	0.7	93.6	3.2	2.8	0.4	0.0	0.0
Malaysia	162.2	91.1	270.1	3.4E+15	84.5	1.4	10.9	0.8	0.1	2.3	99.6	0.0	0.4	0.0	0.0	0.0
Mali	30.6	22.2	41.6	4.9E+13	11.3	14.6	29.9	38.3	1.2	4.7	69.5	2.7	10.5	17.1	0.0	0.1
Mexico	133.4	99.9	183.6	9.1E+14	23.1	13.8	3.8	25.3	33.1	0.8	90.2	2.1	0.1	5.7	1.9	0.0
Mozambique	222.5	142.7	337.3	4.9E+15	15.9	75.4	7.4	0.8	0.5	0.0	75.8	24.0	0.2	0.0	0.0	0.0
Myanmar	180.4	126.3	261.0	2.0E+15	57.7	4.9	13.8	9.5	0.9	13.1	97.1	0.2	1.3	0.6	0.0	0.8
Namibia	5.2	2.8	9.7	8.3E+12	34.3	2.7	9.6	52.9	0.4	0.0	94.9	0.0	0.2	4.9	0.0	0.0
Nepal	29.7	19.6	44.6	8.3E+13	25.2	1.2	4.7	59.4	3.5	6.1	84.4	0.0	0.1	15.4	0.0	0.1
Nicaragua	33.7	23.0	49.4	8.7E+13	75.7	2.3	0.8	14.1	4.2	2.9	98.9	0.0	0.0	0.9	0.0	0.1
Nigeria	129.7	96.2	170.1	6.3E+14	11.0	8.3	46.1	29.1	4.1	1.5	57.8	1.0	29.3	11.7	0.0	0.0
Panama	7.9	4.9	12.6	7.3E+12	60.2	1.2	8.9	18.8	1.1	9.7	96.4	0.0	0.3	1.2	0.0	2.1
Papua New Guinea	26.8	9.2	60.9	3.7E+14	95.3	3.0	0.0	1.7	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0
Paraguay	76.0	47.9	123.2	7.9E+14	46.2	25.9	6.9	15.4	5.2	0.4	97.1	2.1	0.1	0.7	0.0	0.0
Peru	49.0	28.7	86.1	4.8E+14	56.4	1.8	16.4	18.9	3.5	3.1	98.8	0.0	0.5	0.7	0.0	0.0
Philippines	38.8	25.5	61.7	1.6E+14	39.9	0.5	0.0	18.0	15.8	25.9	93.7	0.0	0.0	1.3	0.8	4.1
Rwanda	6.8	5.1	8.7	1.4E+12	9.9	2.0	52.5	16.0	19.4	0.2	43.3	0.1	51.7	4.8	0.1	0.0
Senegal	16.0	11.9	21.3	1.2E+13	11.6	14.5	30.7	39.8	0.8	2.5	70.2	2.5	10.2	17.1	0.0	0.0
Sierra Leone	8.7	4.6	16.6	2.0E+13	69.9	5.0	9.9	6.5	0.2	8.4	99.8	0.0	0.1	0.0	0.0	0.0
Somalia	18.5	12.4	27.8	3.5E+13	17.1	0.0	25.8	53.9	3.1	0.0	80.3	0.0	3.7	16.0	0.0	0.0
South Africa	88.1	62.3	127.4	6.0E+14	19.3	9.6	37.4	30.7	3.1	0.0	85.8	0.5	8.2	5.5	0.0	0.0
Sri Lanka	11.8	8.3	19.1	2.5E+13	23.1	0.7	0.0	20.8	0.2	55.2	97.8	0.0	0.0	0.8	0.0	1.4
Sudan	179.6	128.5	238.0	1.3E+15	7.0	35.5	24.7	26.5	6.3	0.0	43.8	28.5	12.8	14.7	0.2	0.0
Suriname	3.8	1.6	8.2	6.4E+12	74.0	0.6	14.0	0.2	0.0	11.1	99.7	0.0	0.2	0.0	0.0	0.1
Swaziland	2.0	1.3	3.4	9.2E+11	18.7	6.1	40.1	33.4	1.7	0.0	96.7	0.0	1.9	1.3	0.0	0.0
Tanzania	130.8	85.9	202.0	1.9E+15	20.7	41.9	19.1	16.7	1.2	0.4	90.9	6.7	1.4	1.1	0.0	0.0

Country	AFOLU country emissions and uncertainties TgCO$_2$e.yr^{-1}				Percent contribution to country AFOLU emissions %						Percent contribution to country AFOLU emissions uncertainties %					
	AFOLU emiss.	**5th percent**	**95th percent**	**Variance**	**Deforestation**	**Fire**	**Harvest**	**Livestock**	**Crop**	**Rice**	**Deforestation**	**Fire**	**Harvest**	**Livestock**	**Crop**	**Rice**
Thailand	101.6	63.9	166.9	1.5E+15	65.3	2.2	1.4	9.7	1.6	19.7	99.4	0.0	0.0	0.2	0.0	0.4
The Bahamas	0.0	0.0	0.1	5.9E+08	41.6	52.0	3.1	3.3	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0
The Gambia	1.0	0.8	1.3	3.6E+10	6.9	45.3	13.7	31.1	1.6	1.2	58.3	27.4	2.3	11.9	0.0	0.0
Togo	4.2	2.9	6.2	1.6E+12	21.6	6.4	44.0	25.1	2.8	0.2	89.0	0.2	8.1	2.6	0.0	0.0
Uganda	49.6	34.7	70.2	1.8E+14	10.8	12.2	54.8	17.2	5.0	0.1	75.6	1.1	21.1	2.1	0.0	0.0
Uruguay	26.6	17.6	42.2	1.0E+14	12.6	0.3	20.4	62.6	1.2	2.8	91.9	0.0	0.8	7.3	0.0	0.0
Venezuela	74.7	40.8	140.3	1.6E+15	54.1	7.7	4.1	27.5	2.3	4.3	99.2	0.1	0.0	0.7	0.0	0.0
Vietnam	112.2	72.3	183.3	1.8E+15	28.9	6.1	0.1	10.7	1.2	53.0	94.3	0.1	0.0	0.4	0.0	5.2
Zambia	205.1	141.2	277.8	1.9E+15	12.1	80.0	6.1	1.4	0.4	0.0	30.3	69.3	0.4	0.0	0.0	0.0
Zimbabwe	43.8	30.2	65.9	1.6E+14	47.6	10.2	23.4	16.2	2.5	0.0	96.2	0.4	2.3	1.1	0.0	0.0

Table 8: Country statistics with AFOLU emissions, thresholds of uncertainty (5th, 95th percentiles),total uncertainty (variance),contribution of leading emissions sources to the country AFOLU emissions (%), and contribution of the leading emission sources to the country's AFOLU emission uncertainties (%).

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7. Other

Rice emissions (Li et al. (2013))

Fertilizer

Fertilizer N rates were determined to be inaccurate due to low modeled total yields for several countries in initial simulations. The authors recalibrated fertilizer N applications by simulating pure rice systems (i.e. systems with no other crops in the rotation; about 72% of the global total by area) at seven different N rates based on the distribution of available FAO Fertistat national rates for rice (table 9). For each country, based on a comparison of yield generated from each N rate and yield figures from FAO 2009 data, Li et al. (2013) selected the higher of the N rate based on calibration (i.e. the rate of the yield that most closely matched FAO yield) or the N rate given by Fertistat. They then replaced existing rates in the Globe database with the new rates.

Category	N application rate (kgN/ha)
Minimum	4.8
10^{th} percentile	35.1
25^{th} percentile	50.3
Mean	86.4
75^{th} percentile	119.8
90^{th} percentile	144.5
Maximum	250

Table 9: N application rates used in yield calibration of the DNDC model for rice production

1.1 Simulations

Twenty four scenarios were run using DNDC 9.5 (table 10). The scenarios addressed management techniques (Table 11) in various combinations hypothesized to reduce greenhouse gas (GHG) emissions from rice systems: flood regime (continuous flooding / CF, mid-season drainage / MD, dry seeding / DS, alternate wetting and drying / AWD, and switching to non-wetland systems / dryland rice), residue management (partial removal or 50% or total incorporation), conventional tillage or no till, and various fertilizer alternatives (conventional / urea, ammonium sulphate in place of urea, urea with nitrification inhibitor, slow release urea, 10% reduced fertilizer, and 30% reduced fertilizer.

Abbreviation	Scenario	Flooding	Residue	Alt. mgt.	Fertilization
cf	Continuous Flooding	CF	50%	-	conventional
cf_r100	Continuous Flooding, 100% Residue Incorporation	CF	100%	-	conventional
cf_amsu	Continuous Flooding, Ammonium Sulphate Fertilizer	CF	50%	-	ammonium sulfate
cf_ninhib	Continuous Flooding, Nitrification Inhibitor Fertilizer	CF	50%	-	nitrification inhibitor
cf_slowrel	Continuous Flooding, Slow Release Fertilizer	CF	50%	-	slow release
cf_notill	Continuous Flooding, No Till	CF	50%	no till	conventional
cf_f70	Continuous Flooding, 30% Reduced Fertilizer	CF	50%	-	30% reduced
cf_f90	Continuous Flooding, 10% Reduced Fertilizer	CF	50%	-	10% reduced
md	Mid-season Drainage	MD	50%	-	conventional
md_r100	Mid-season Drainage w/100% Residue Incorporation	MD	100%	-	conventional
md_amsu	Mid-season Drainage, Ammonium Sulphate Fertilizer	MD	50%	-	ammonium sulfate
md_ninhib	Mid-season Drainage, Nitrification Inhibitor Fertilizer	MD	50%	-	nitrification inhibitor
md_slowrel	Mid-season Drainage, Slow Release Fertilizer	MD	50%	-	slow release
md_notill	Mid-season Drainage, No Till	MD	50%	no till	conventional
md_f70	Mid-season Drainage, 30% Reduced Fertilizer	MD	50%	-	30% reduced
md_f90	Mid-season Drainage, 10% Reduced Fertilizer	MD	50%	-	10% reduced
md_ds	Mid-season Drainage, Dry Seeding	MD w/DS	50%	-	conventional
awd	Alternate Wetting & Drying	AWD	50%	-	conventional

	(AWD)				
awd_ninhib	AWD w/Nitrification Inhibitor	AWD	50%	-	nitrification inhibitor
awd_slowrel	AWD w/Slow Release	AWD	50%	-	slow release
ds	Dry Seeding	DS	50%	-	conventional
ds_f80	Dry Seeding, 20% Reduced Fertilizer	DS	50%	-	20% reduced
dry	Dryland Rice	dryland rice	50%	-	conventional
dry_f80	Dryland Rice, 20% Reduced Fertilizer	dryland rice	50%	-	20% reduced

Table 10: Rice management scenarios

Management technique	**description**
rice flooding	
CF	rice paddy is flooded on planting date and drained 10 days prior to harvest date - applies to both irrigated and rainfed rice
MD	rice paddy is drained twice during growing season for 8 days - final drainage is 10 days prior to harvest date - applies only to irrigated rice
AWD	rice paddy is initially flooded to 10 cm – water level is reduced through evapo-transpiration to -5cm and reflooded based on available water from precipitation - applies only to irrigated rice
dryland rice	all irrigated and rainfed rice are swapped for dryland rice - no flooding occurs
rice seeding	
DS	rice paddy is flooded 40 days after planting date and drained 10 days prior to harvest date - applies to both irrigated and rainfed rice
residue incorporation	
50%	50% of above-ground crop residue is removed - remaining residue is incorporated at next tillage
100%	all residue remains in place and is incorporated at next tillage
tillage	
conventional	prior to first crop in rotation tillage to 20cm depth; subsequent tillages (following each crop in rotation) to 10cm depth
no-till	tillage only mulches residue

fertilizer	
conventional	fertilizer N applied as urea on plant date using a crop-specific rate
ammonium sulfate	fertilizer N applied as ammonium sulfate on plant date using a crop-specific rate
nitrification inhibitor	nitrification inhibitor is used with urea; reduced conversion of NH4 to NO3 is simulated with 60% efficiency over 120 days
slow-release	slow-release urea applied on planting date – N is released over 90 days at a linear rate
10% reduced	Crop-specified baseline fertilizer N rate is reduced by 10% (applied as urea)
30% reduced	Crop-specified baseline fertilizer N rate is reduced by 30% (applied as urea)

Table 11: rice management techniques

1.2 Post-processing / Summary Statistics

DNDC creates two output files for each scenario: one with mean GHG flux value for full irrigation and one with mean GHG flux with zero irrigation. Based on the percent irrigated value for each grid cell, model result files were combined to derive values based on mean irrigation.

Most of the major rice producing countries have some mix of flood regimes (table 12). To determine baseline management against which to compare all other scenarios (Table 13), simulation results were combined based on flood regime fraction. For instance, baseline emissions for Bangladesh were determined by averaging the results of the CF and MD scenarios (CF * 0.2 + MD * 0.8).

Region	**CF**	**MD**	**DS**
Bangladesh	20%	80%	0%
Cambodia	43%	57%	0%
China	20%	80%	0%
India	30%	70%	0%
Indonesia	43%	57%	0%
Japan	20%	80%	0%
Laos	43%	57%	0%
Myanmar	43%	57%	0%
Thailand	43%	57%	0%
US: California	100%	0%	0%

US: Other	0%	0%	100%
All Other Countries	100%	0%	0%

Table 12: Flood regime by country

Abbreviation	scenario	residue	alt. mgt.	fertilization	weighted average
base	Baseline	50%	-	conventional	cf / md / ds
base_r100	100% Residue Incorporation	100%	-	conventional	cf_r100 / md_r100 / ds_r100
base_amsu	Ammonium Sulfate Fertilizer	50%	-	ammonium sulfate	cf_amsu / md_amsu / ds_amsu
base_ninhib	Nitrification Inhibitor Fertilizer	50%	-	nitrification inhibitor	cf_ninhib / md_ninhib / ds_ninhib
base_slowrel	Slow Release Fertilizer	50%	-	slow release	cf_slowrel / md_slowrel / ds_slowrel
base_notill	No Till	50%	no till	conventional	cf_notill / md_notill / ds_notill
base_f70	30% Reduced Fertilizer	50%	-	30% reduced	cf_f70 / md_f70 / ds_f70
base_f90	10% Reduced Fertilizer	50%	-	10% reduced	cf_f90 / md_f90 / ds_f90
base_ds	Dry-Seeding	50%	-	conventional	ds / md_ds

Table 13: baseline flooding scenarios

For EPA's MAC-Report (2013) results were reported at the country level in either annual per hectare rates or annual national totals. GHG emissions (N_2O and CH_4) and dSOC were reported in their native units or in CO_2 equivalents (global warming potential / GWP).