DATA & METHODS REPORT

This document references data and methods used as part of the report **The State of Jurisdictional Sustainability** published by Earth Innovation Institute and the Center for International Forestry Research, in 2018. Find more at the report website https://earthinnovation.org/state-of-jurisdictional-sustainability and http://gcfimpact.org.

---

1. Annual forest cover area and annual deforestation area

The concepts of forest and deforestation used in the report are based on the physical definition adopted by each country in its forest reference emission level (FREL) and on the functional implementation adopted by each national forest monitoring system. Alternatively, in jurisdictions where official data on yearly deforestation area was not available (7/39) regional or global maps drive the adopted forest definition (see sources and methods below). Figure 1 indicates the concepts used for the analysis of subnational forest cover, deforestation and related indicators.

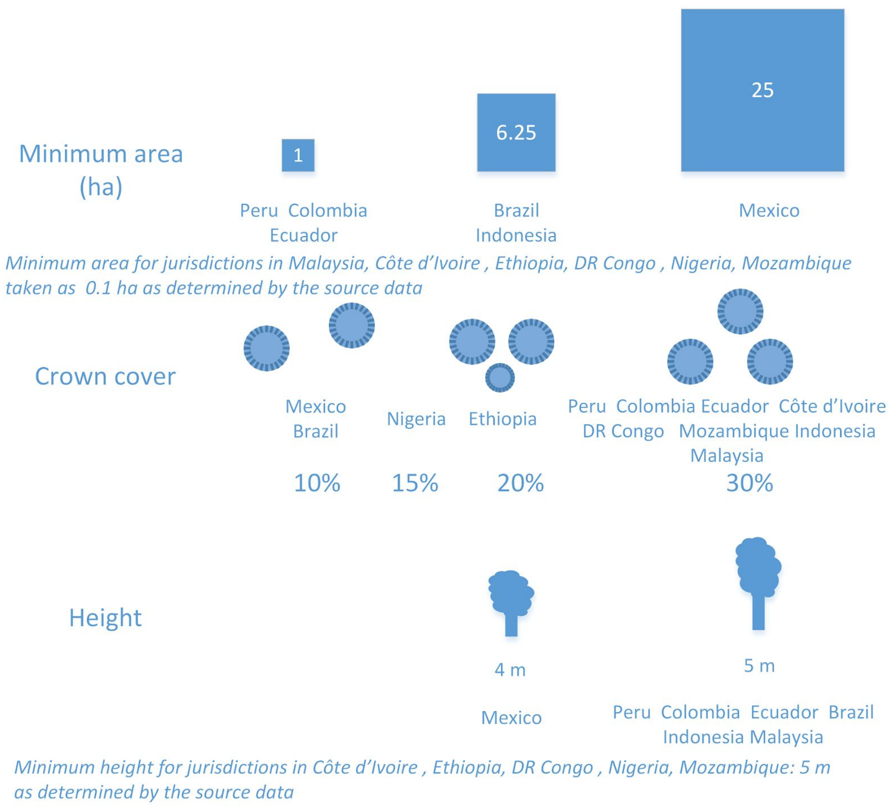


Figure 1: *Functional forest parameter definition used for the reporting of forest and deforestation in the study*

Technical team

Supported by

Sources: forest area and yearly deforestation reported directly at the subnational level by official national forest monitoring systems as follows:

- Brazil: Program for Monitoring Deforestation of the Amazon (PRODES) – National Institute of Space Research (INPE) of the Brazilian Ministry for Science and Technology
- Colombia: Institute of Hydrology, Meteorology and Environmental Studies (IDEAM), Colombia.
- Ecuador: SUIA - Unique System of Environmental Information. Ministry of Environment, Ecuador.
- Mexico: National Institute of Statistics, Geography and Informatics (INEGI) and National Forestry Commission (CONAFOR), Mexico.
- Peru: National Program for the Conservation of Forests for the Mitigation of Climate Change, BOSQUES, Ministry of Environment, Peru.
- Indonesia: Ministry of Environment and Forestry of Indonesia.

In jurisdictions where official data on yearly deforestation area was not available (7/39) the authors estimated the spatially explicit deforestation using the following data:

- Malaysia: integration of forest and deforestation map of Borneo produced by CIFOR (Gaveau, et al, 2014,2016) and Hansen/UMD/Google/USGS/NASA.
- Ethiopia: Hansen/UMD/Google/USGS/NASA.
- DR Congo: integration of forest map from Observatoire satellital des forêts d'Afrique centrale (OSFAC) and Hansen/UMD/Google/USGS/NASA.
- Nigeria: Hansen/UMD/Google/USGS/NASA.
- Mozambique: Hansen/UMD/Google/USGS/NASA.
- Côte d'Ivoire: forest and deforestation map of SEP-REDD+ et FAO, 2017. Données de base pour la REDD+ en Côte d'Ivoire. Cartographie de la dynamique forestière de 1986 à 2015. Abidjan, Rome and Hansen/UMD/Google/USGS/NASA data and Hansen/UMD/Google/USGS/NASA data

Methods

Deforestation and forest areas were taken directly from subnational reports of national forest monitoring systems for jurisdictions in Brazil, Colombia, Ecuador, Mexico, Peru and Indonesia. In Mexican jurisdictions, deforestation is measured over periods that span 4 or 5 years. These figures were annualized by uniformly distributing the observed deforestation among the number of years covered by the report. The same approach was applied for provinces in Indonesia, where annual measurements became available after 2012.

Forest areas in jurisdictions of Malaysia, DR Congo and Côte d'Ivoire were derived from the national or regional maps as indicated in the sources above. For those jurisdictions, the authors calculated the extent of spatially explicit annual deforestation during the period 2001-2017 considering the forest loss reported yearly by Hansen/UMD/Google/USGS/NASA data in areas mapped as forest.

In jurisdictions of Ethiopia, Nigeria and Mozambique the authors calculated the extent of spatially explicit annual deforestation during the period 2001-2017 considering the forest loss reported by

Hansen/UMD/Google/USGS/NASA data in areas mapped by the Hansen data filtered with a tree cover crown threshold above the canopy cover definition of each country (see Figure 1).

---

2. Deforestation rate

The deforestation rate indicates the percentage of remaining forest that is lost each year

Sources: calculated by the authors using forest cover and annual deforestation area using the data sources indicated above.

Methods: Based on the official or estimated yearly deforestation area we defined deforestation rates (q) as the percentage of remaining forest lost each year. This is computed as follows:

$$q = \left(\frac{F_{y2} - F_{y1}}{F_{y1}}\right)$$

Where F_{y2} and F_{y1} is the forest area at time t_1 and t_2

---

3. Remaining forest cover (percentage)

The remaining forest cover indicates the share of current forest cover in the jurisdiction with respect to the original forest cover. Since the extent of original forest cover of a jurisdiction is not observable (the first optical satellite images were obtained in 1970’s), we work with the earliest observed forest area, or alternatively, we modeled an estimate of original forest cover based on landcover data and topographic conditions. The following timeline illustrates the temporality of the original forest cover used in the report for the sample jurisdictions.

***Figure 2:** Reference year of subnational original forest estimation*

Sources and methods: the current forest cover was taken from the forest cover area as indicated above (section 1). The original forest cover was calculated by the authors based on the following data

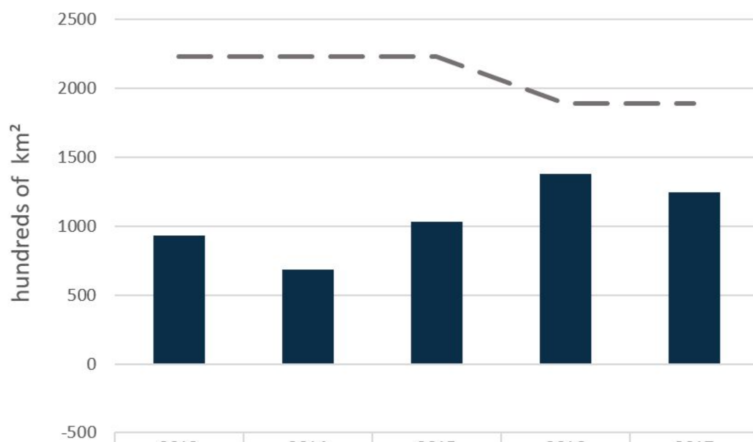
- Brazil: analysis of spatially explicit data of the Program for Monitoring Deforestation of the Amazon (PRODES) – National Institute of Space Research (INPE) of the Brazilian Ministry for Science and Technology
- Colombia: analysis of spatially explicit data for 1990 produced by the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM), Colombia combined with an ecosystem map and elevation layer.
- Ecuador: spatially explicit data of the SUIA - Unique System of Environmental Information. Ministry of Environment, Ecuador.
- Peru: spatially explicit data of the National Program for the Conservation of Forests for the Mitigation of Climate Change, BOSQUES, Ministry of Environment, Peru.
- Mexico: spatially explicit data provided by the map of primary vegetation (1:1'000,000) of the National Institute of Statistics, Geography and Informatics (INEGI), Mexico.
- Indonesia: spatial analysis using Ministry of Environment and Forestry of Indonesia landcover data 1990 and digital elevation model to remove elevations greater than 2500 meters.
- Malaysia: forest map of Borneo produced by CIFOR using satellite images with reference data of 1973 (Gaveau, et al, 2014,2016)
- Ethiopia: based on the jurisdictional estimate of 1973 published in "Monitoring of forest resources in Ethiopia. Ministry of Agriculture of Ethiopia, German Agency for Technical Cooperation (GTZ), 1998".
- DR Congo: based on the forest map from Observatoire satellital des forêts d'Afrique centrale (OSFAC) with reference data of 1990.
- Nigeria: based on the jurisdictional estimate of 1976 published in "The assessment of vegetation and land use changes in Nigeria between 1976/78 and 1993/95, Federal Department of Forestry and Environmental Management Project (EMP), 1998".
- Mozambique: Hansen/UMD/Google/USGS/NASA of 2000.
- Côte d'Ivoire: 1990 forest and deforestation map of SEP-REDD+ et FAO, 2017. Données de base pour la REDD+ en Côte d'Ivoire. Cartographie de la dynamique forestière de 1986 à 2015. Abidjan, Rome and Hansen/UMD/Google/USGS/NASA data

---

4. Change in deforestation relative to FREL

This performance indicator reports the percentage of decrease or increase in deforestation with respect to the projected jurisdictional forest reference level.

Methods: we compute the average variation in deforestation with respect to the subnational FREL of the 5 most recent years. Positive performance is indicated by observed deforestation below the FREL while negative performance as deforestation above the FREL. The figure below presents the example of Rôndonia, which on average has reduced its deforestation with respect to its FREL by 48% over the last 5 years.



	2013	2014	2015	2016	2017
Deforestation	932	684	1030	1376	1243
FREL	2231	2231	2231	1888	1888
Variation	-58	-69	-54	-27	-34

Figure 3: *Example of Rôndonia change in deforestation relative to FREL for the 5 most recent years*

Defining criteria used for the construction of subnational FRELs based on national submissions to the UNFCC are presented in Table 1. Note that due to the recent implementation of African and Peruvian FRELs, average performance was measured for less than five years for jurisdictions in those countries.

Table 1. *Forest reference level criteria used for jurisdictional FRELs in the study*

Country	Reference period from	Reference period to	REDD+ activities included	Pools included
Brazil	1996 1996 1996	2005 2010 2015	Reducing emissions from deforestation	Above-ground biomass Below-ground biomass Litter
Colombia	2000	2012	Reducing emissions from deforestation	"Above-ground biomass Below-ground biomass"
Ecuador	2000	2008	Reducing emissions from deforestation	Above-ground biomass Below-ground biomass Dead wood Litter
Malaysia	1997	2010	Sustainable management of forests	Above-ground biomass Below-ground biomass
Mexico	2000	2010	Reducing emissions from deforestation	Above-ground biomass Below-ground biomass
Ethiopia	2000	2013	Reducing emissions from deforestation Enhancement of forest carbon stocks	Above-ground biomass Below-ground biomass Dead Wood
Indonesia	1990	2012	Reducing emissions from deforestation Reducing emissions from forest degradation	Above-ground biomass Soil Organic Carbon
Peru	2001	2014	Reducing emissions from	Above-ground biomass

			deforestation	Below-ground biomass
Côte d'Ivoire	2000	2015	Reducing emissions from deforestation Enhancement of carbon stocks	Above-ground biomass Below-ground biomass Dead Wood Litter
Mozambique	2003	2013	Reducing emissions from deforestation	Above-ground biomass Below-ground biomass
Nigeria	2004	2014	Reducing emissions from deforestation	Above-ground biomass
DR Congo	2000	2014	Reducing emissions from deforestation	Above-ground biomass Below-ground biomass

5. Change in average annual deforestation rate (5 year trend)

This indicator reports the average yearly variation of deforestation rates considering the 5 most recent observations.

Methods: we calculate a linear trend using the 5 most recent figures of deforestation rates (rates calculated as documented above). The trend is reported in positive or negative percentage points for increasing and decreasing yearly deforestation trends, respectively. The figure below presents the example of Rôndonia, which on average has increased its yearly deforestation rate by 0.1 percent points each year over the period 2013 - 2017.

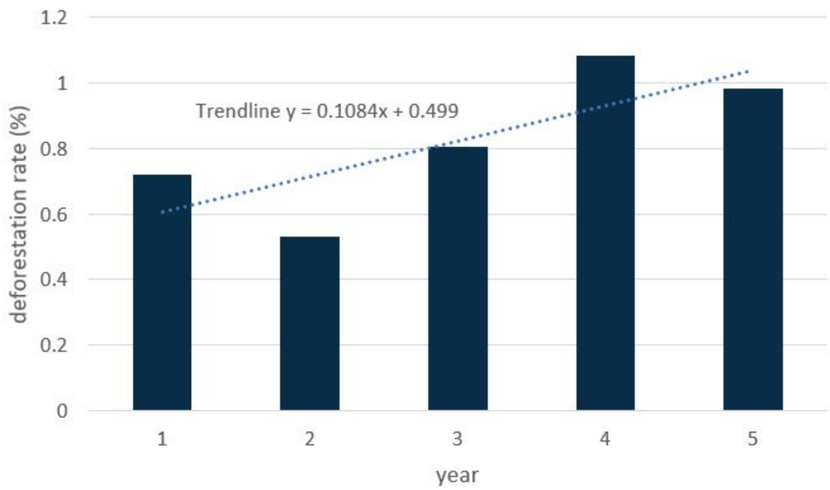


Figure 4: *Example of Rôndonia 5 years trend of change in annual deforestation rate*

6. Potential emissions reductions under a LED-R and LED-R + forest carbon enhancement scenarios

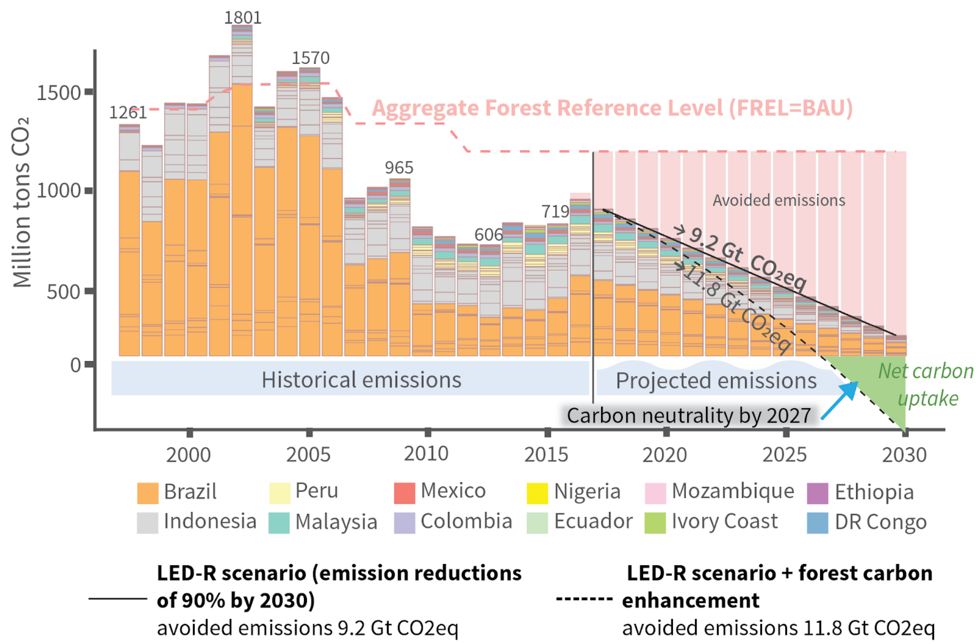


***Figure 5:** Modelling of carbon dioxide emissions modelling under 3 development scenarios (figure 10 of report)*

Observed emissions (1990-2017) derived from annual deforestation as defined in Section 1 and carbon emissions factors as defined by national FRELs submitted to the UNFCCC. Included carbon pools are aboveground and belowground biomass, peat degradation, soil and litter as defined in each FREL (see table 1).

BAU scenario projected by aggregating the emissions from deforestation trends over the period defined by each jurisdictional FREL (see table 1). Bar subdivisions represent jurisdictional contributions within a country.

LED-R scenario projected with a 90% linear reduction of emissions by 2030 relative to the aggregated FREL baseline.

Avoided emissions (2017-2030): calculated as the difference in emissions under the aggregated FREL line and the modeled scenarios (LED-R and LED-R plus carbon enhancement).

Carbon enhancement scenario considers 90% reduction in deforestation (LED-r scenario) plus induced regeneration of degraded and cleared forest areas. Regenerating forest targets are based on subnational/national reforestation pledges and zero net deforestation. The regeneration estimated goal is distributed uniformly between 2017 and 2030. Regeneration goals included:

- Brazil: regeneration of 2.9 million has in Mato Grosso (2030) and 2.73 million hectares distributed among 8 Amazon states considering a national goal of 12 m has by 2030, Atlantic forest commitments (15 m has by 2050) and historical share of deforestation.
- Mexico: explicit subnational pledges 2.35 million hectares.
- For jurisdictions in countries where a national pledge was defined, we estimated a subnational allocation of reforestation by proportionally allocating values based on historical subnational deforestation. This resulted in: Cross River (Nigeria) 320,000 has, Caquetá (Colombia) 52,000 has, Pastaza (Ecuador) 7,000 has and Oromia (Ethiopia) 20,000 has.
- For the rest of jurisdictions, a reforestation goal of 10% of the deforested area after 2010 was assumed. This translates into: 7 Indonesian provinces 590,000 has, Sabah 110,000 has, Zambezia 35,000, 7 Peruvian jurisdictions 137,000 has, Maï - Ndombe 45,000 has,

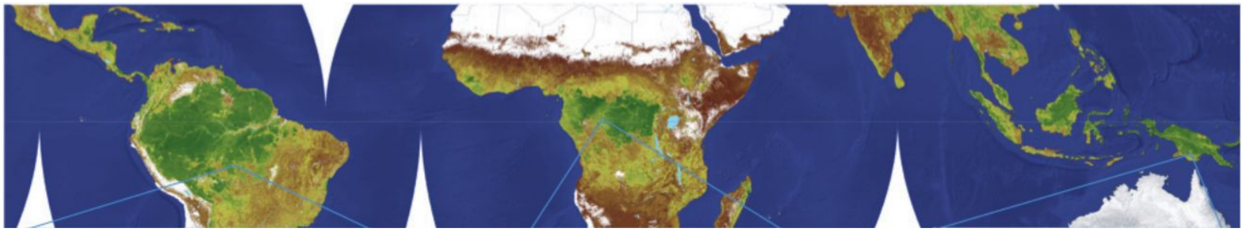
The forest regenerating area reaches 9.4 Mhas in 2030. In the 14 simulated years (2017-2030) regenerated forests reach 1/5 of the projected mature carbon stocks. Carbon increases linearly from year 1 to year 14 and the total carbon stock increases as a function of the weighted distribution of the forest age and forested area over each year.

Above and below ground biomass carbon storage factors used for each jurisdiction based on FREL and carbon explicit maps.

---

7. Carbon stored in jurisdictions and in the tropics.

We estimated the amount of carbon stored in the forest of the 39 jurisdictions and compared it with a pan tropical estimate including reserves in above and below ground biomass (see Baccini, A., et al. (2012)). The total forest carbon estimated in the 39 jurisdictions was 64.19 PgC while the total forest carbon in the tropics was 190.76 PgC. See figure and tables below for a breakdown of pantropical carbon by continent and jurisdiction.



IGBP Classes	Tropical America Mean MgC/HA	Tropical America Total AGC Mt	Tropical Africa Mean MgC/HA	Tropical Africa Total AGC Mt	Tropical Asia Mean MgC/HA	Tropical Asia Total AGC Mt
Water	0	0	0	0	0	0
Evergreen Needleleaf Forest	108	53	65	3	95	16
Evergreen Broadleaf Forest	130	88037	125	30856	120	34380
Deciduous Needleleaf Forest	57	5	38	2	36	4
Deciduoud Broadleaf Forest	69	2448	63	1490	80	674
Mixed Forest	79	626	43	17	87	363
Total Forest		**91169**		**32368**		**35436**

Figure 6. *Average carbon density and total carbon stored in aboveground live woody vegetation derived from the continuous carbon map produced by Baccini, A., et al. (2012)*

Table 2. *Average carbon density, source, methods and total carbon in forest estimated for 39 jurisdictions of the study*

Country	Jurisdiction	ABG C mean T ha-1	Source	Method	forest ha 2014	total C Million tons
Peru	Ucayali	138.30	BOSQUES, Peru	Spatially explicit computation	9,451,995	1496
Peru	Piura	107.53	BOSQUES, Peru	Spatially explicit computation	42,329	5
Peru	Loreto	126.95	BOSQUES, Peru	Spatially explicit computation	35,162,046	5167
Peru	Huánuco	117.10	BOSQUES, Peru	Spatially explicit computation	1,622,877	222
Peru	San Martín	115.25	BOSQUES, Peru	Spatially explicit computation	3,421,106	463
Peru	Madre de Dios	138.12	BOSQUES, Peru	Spatially explicit computation	7,987,761	1263
Peru	Amazonas	109.90	BOSQUES, Peru	Spatially explicit computation	2,861,554	372
Brazil	Mato Grosso	78.37	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	32,146,974	3156
Brazil	Maranhão	60.07	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	4,172,580	330
Brazil	Tocantins	58.34	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	1,014,674	79
Brazil	Amapá	127.2	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	11,041,649	1624
Brazil	Pará	100.54	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	88,167,600	10567
Brazil	Roraima	117.29	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	15,129,474	2075
Brazil	Amazonas	131.24	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	142,724,683	21582
Brazil	Acre	128.29	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	14,461,164	2143
Brazil	Rondônia	102.8	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Spatially explicit computation	12,799,051	1569
Indonesia	Papua West	95.53	Derived from Ministry of Forestry data	Spatially explicit computation	8,888,034	1080

Indonesia	Papua	90.06	Derived from Ministry of Forestry data	Spatially explicit computation	24,995,129	2803
Indonesia	North Kalimantan	95.8	Derived from Ministry of Forestry data	Spatially explicit computation	5,716,670	662
Indonesia	East Kalimantan	98.73	Derived from Ministry of Forestry data	Spatially explicit computation	6,776,371	806
Indonesia	Central Kalimantan	92.04	Derived from Ministry of Forestry data	Spatially explicit computation	7,665,668	847
Indonesia	West Kalimantan	92.11	Derived from Ministry of Forestry data	Spatially explicit computation	5,723,587	641
Indonesia	Aceh	87.71	Derived from Ministry of Forestry data	Spatially explicit computation	3,102,412	330
Ecuador	Pastaza	139.75	SUIA - Sistema Único de Información Ambiental	Spatially explicit computation	2,793,070	432
Colombia	Caqueta	129.3	IDEAM, Colombia	Stratified average carbon stock	6,619,865	955
Mexico	Jalisco	20.71	Cartus et al, WHR, 2015. Post-processing by EII	Spatially explicit computation	4,376,783	113
Mexico	Oaxaca	24.65	Cartus et al, WHR, 2015. Post-processing by EII	Spatially explicit computation	6,737,712	200
Mexico	Quintana Roo	33.85	Cartus et al, WHR, 2015. Post-processing by EII	Spatially explicit computation	3,481,227	135
Mexico	Tabasco	20.94	Cartus et al, WHR, 2015. Post-processing by EII	Spatially explicit computation	307,068	8
Mexico	Yucatán	24.8	Cartus et al, WHR, 2015. Post-processing by EII	Spatially explicit computation	2,630,672	78
Mexico	Campeche	35.37	Cartus et al, WHR, 2015. Post-processing by EII	Spatially explicit computation	4,014,411	162
Mexico	Chiapas	26.02	Cartus et al, WHR, 2015. Post-processing by EII	Spatially explicit computation	3,249,401	101
Nigeria	Cross River	184	Forest Reference Level submission to the UNFCCC	Average forest carbon stock value	866,877	241
Mozambique	Zambézia	32.4	Forest Reference Level submission to the UNFCCC	Average forest carbon stock value	2,980,000	132
DRC	Maï Ndombe	117	Forest Reference Level submission to the UNFCCC	Average forest carbon stock value	9,082,625	1503
Ethiopia	Oromia	66.3	Forest Reference Level submission to the UNFCCC	Average forest carbon stock value	2,234,000	18
Côte d'Ivoire	Bélier	126.5	Forest Reference Level submission to the UNFCCC	Average forest carbon stock value	719,066	138
Côte d'Ivoire	Bélier	126.5	Forest Reference Level submission to the UNFCCC	Average forest carbon stock value	44,484	9
Malaysia	Sabah	115	Global Forest Watch Carbon map 30m, Baccini 2015. Post-processing by EII	Average forest carbon stock value	3,892,608	526

Baccini, A., et al. (2012). "Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps." Nature Climate Change 2(3): 182-185.

8. Soy, palm and cattle production in sample jurisdictions and the tropics.

Soybean and oil palm production (2015): production of soy and palm oil of 31 jurisdictions derived from official data of the Ministry of Agriculture of Brazil, Ecuador, Indonesia, Mexico, Malaysia, and Peru. Total production of tropical areas derived from FAOSTAT database.

Cattle herd size (2015): Cattle herd size of 30 jurisdictions derived from official data of the Ministry of Agriculture of Brazil, Ecuador, Indonesia, Mexico and Peru. Figures of cattle in the tropics data derived from Knoema database.

Technical team

Earth Innovation Institute
CIFOR
GCF task force

Supported by

Federal Ministry for the Environment, Nature Conservation and Nuclear Safety
based on a decision of the German Bundestag
Norad
CGIAR Research Program on Forests, Trees and Agroforestry