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Land use patterns and related carbon losses following deforestation in South America

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Abstract

Land use change in South America, mainly deforestation, is a large source of anthropogenic CO_2 emissions. Identifying and addressing the causes or drivers of anthropogenic forest change is considered crucial for global climate change mitigation. Few countries however, monitor deforestation drivers in a systematic manner. National-level quantitative spatially explicit information on drivers is often lacking. This study quantifies proximate drivers of deforestation and related carbon losses in South America based on remote sensing time series in a systematic, spatially explicit manner. Deforestation areas were derived from the 2010 global remote sensing survey of the Food and Agricultural Organisation Forest Resource Assessment. To assess proximate drivers, land use following deforestation was assigned by visual interpretation of high-resolution satellite imagery. To estimate gross carbon losses from deforestation, default Tier 1 biomass levels per country and ecozone were used. Pasture was the dominant driver of forest area (71.2%) and related carbon loss (71.6%) in South America, followed by commercial cropland (14% and 12.1% respectively). Hotspots of deforestation due to pasture occurred in Northern Argentina, Western Paraguay, and along the arc of deforestation in Brazil where they gradually moved into higher biomass forests causing additional carbon losses. Deforestation driven by commercial cropland increased in time, with hotspots occurring in Brazil (Mato Grosso State), Northern Argentina, Eastern Paraguay and Central Bolivia. Infrastructure, such as urban expansion and roads, contributed little as proximate drivers of forest area loss (1.7%). Our findings contribute to the understanding of drivers of deforestation and related carbon losses in South America, and are comparable at the national, regional and continental level. In addition, they support the development of national REDD+ interventions and forest monitoring systems, and provide valuable input for statistical analysis and modelling of underlying drivers of deforestation.

1. Introduction

Land use change, mainly deforestation, is the second largest source of anthropogenic CO_2 emissions, and causes a net reduction of carbon storage in terrestrial ecosystems as well as other environmental impacts such as biodiversity loss (IPCC 2013). The vast majority of land use change occurs in tropical regions, with Central and South America having the highest net emissions from land use change from the 1980s to 2000s (IPCC 2013). Reducing emissions from deforestation and forest degradation, and enhancing carbon stocks (REDD+) in (sub−) tropical countries is thus a necessary component of global climate change mitigation. Within the REDD+ framework, participating countries are given incentives to develop national strategies and implementation plans that reduce emissions and enhance sinks from forests and to invest in low carbon development pathways. Identifying and addressing the causes or drivers of anthropogenic forest change is considered crucial within the REDD+ framework (UNFCCC 2014), and should be incorporated in national forest monitoring systems.

Few countries, however, monitor deforestation drivers in a systematic manner and national-level quantitative spatially explicit information on drivers is often lacking (De Sy *et al* 2012, Hosonuma *et al* 2012). The distinction between proximate and underlying drivers is important for assessment purposes. Proximate or direct drivers of deforestation are human activities that directly affect the loss of forests (Geist and Lambin 2001), and can be assessed by linking forest area change to specific human activities and follow-up land use (De Sy *et al* 2012). Remote sensing can provide essential information on the intensity, type and pattern of deforestation, and on the follow-up land use in order to attribute deforestation to specific human activities (Gibbs *et al* 2010, De Sy *et al* 2012, GOFC-GOLD 2014). Statistical analysis and modelling of this information, in turn, can be useful for the assessment of underlying drivers (Kissinger *et al* 2012) which are complex interactions of social, political, economic, technological and cultural forces (Geist and Lambin 2001).

Forest loss and related carbon losses in South America have been extensively studied from the continental to the (sub)national scale (DeFries *et al* 2002, Baccini *et al* 2012, Eva *et al* 2012, Harris *et al* 2012, Hansen *et al* 2013, Achard *et al* 2014, Beuchle *et al* 2015, Velasco Gomez *et al* 2015) but the link to specific proximate drivers is not made. Clark *et al* (2012) and Graesser *et al* (2015) studied land use change across the South American continent in a systematic manner with MODIS imagery which gives some insight into drivers of deforestation. MODIS imagery, however, cannot accurately detect small-scale agricultural clearings (<25 ha) and infrastructure expansion due to its low spatial resolution (GOFC-GOLD 2014). Other research that links forest loss or forest carbon emissions to drivers used aggregated continental scale (Geist and Lambin 2002, Hosonuma *et al* 2012, Houghton 2012) or local scale data (Morton *et al* 2006, Barona *et al* 2010, Clark *et al* 2010, Müller *et al* 2012, 2014, Gibbs *et al* 2015). Several studies link overall deforestation rates directly to underlying drivers (DeFries *et al* 2010, Malingreau *et al* 2012). Linking driver-specific deforestation rates (e.g. agricultural expansion) to relevant underlying drivers (e.g. agricultural commodity prices) can provide more insight into complex deforestation pathways.

Although it is clear that agricultural expansion is the main driver of deforestation in South America (Geist and Lambin 2002, Gibbs *et al* 2010, Hosonuma *et al* 2012, Houghton 2012), less is known about the magnitude and the spatial and temporal distribution of different types of agricultural and non-agricultural drivers contributing to forest loss and related carbon emissions. Gaining insight in spatiotemporal dynamics is essential since drivers of forest loss vary from region to region and change over time (Rudel *et al* 2009, Boucher *et al* 2011).

Accordingly, our research aims to quantify proximate drivers of deforestation, their spatiotemporal dynamics and related carbon losses in South America at continental and national scales using a comprehensive, systematic remote sensing analysis. This new dataset will provide insight into complex deforestation pathways and be a valuable source of information for international climate change mitigation and REDD+ monitoring strategies.

2. Data and methods

The 2010 global Remote Sensing Survey of the United Nations Food and Agricultural Organisation (FAO) Forest Resource Assessment was used as input to determine deforestation areas (section 2.1). To assess proximate drivers, land use following deforestation was assigned by visual interpretation of high-resolution satellite imagery (section 2.2). To estimate gross carbon losses from deforestation, default Tier 1 biomass levels per country and eco-zone were used (section 2.3).

2.1. Forest area loss

In a coordinated effort, the European Joint Research Centre (JRC) and the FAO produced estimates of forest land use change from 1990 to 2005 for the Remote Sensing Survey of the Global Forest Resources Assessment 2010 of FAO (FAO FRA-2010 RSS) (FAO & JRC 2012). These estimates were based on a systematic sampling design with sample units of 10 × 10 km centred on each degree latitude–longitude confluence point (Eva *et al* 2012, FAO & JRC 2012, Achard *et al* 2014).

Unfortunately the FAO FRA-2010 RSS currently only covers a limited time period from 1990 to 2005. As mentioned in the introduction, other deforestation datasets are available (e.g. Hansen *et al* 2013) that provide wall-to-wall data extending to 2010 or even later. The FAO FRA-2010 RSS, however, employs a land use classification that is better suited for assessing drivers than a land cover classification. In addition, the FAO FRA-2010 RSS is a global study with consistent methods and time series that could be extended to include more recent periods. Despite the time period limitation, and in view of the paucity of quantitative data on deforestation drivers and related carbon losses, this study provides an unique and relevant overview of the drivers of deforestation in South America, as well as showing that this is achievable with a sample-based time series approach.

We briefly describe the methodology of the FAO FRA-2010 RSS dataset (FAO & JRC 2012), because

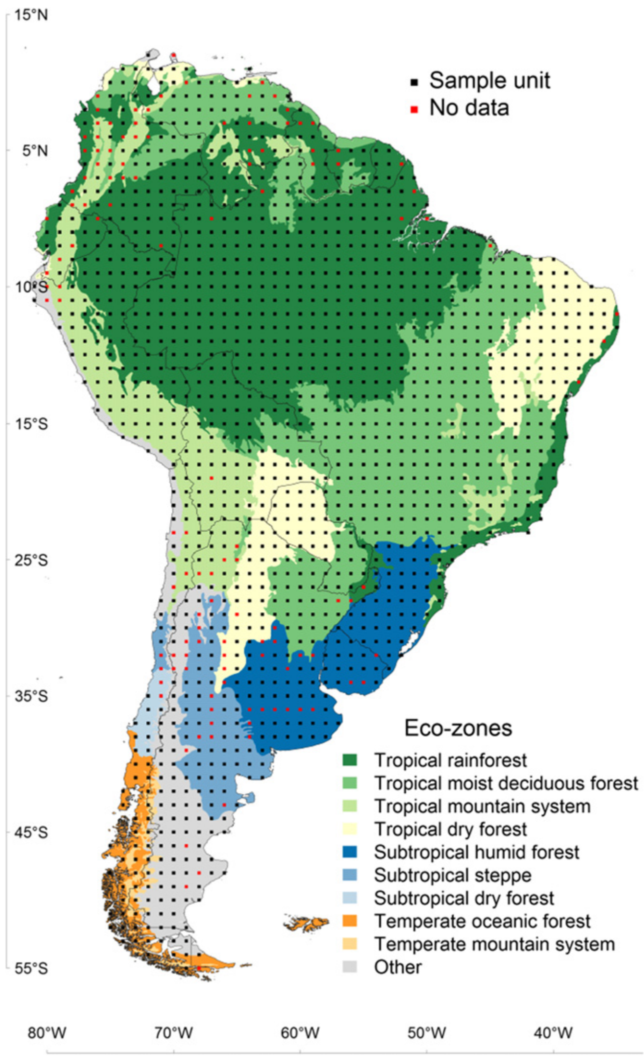

Figure 1. Location of sample units (FAO & JRC 2012), and FAO ecological zones (FAO 2001) in South America.

it served as input data for our study. Medium resolution satellite imagery (mainly Landsat) was acquired for each sample unit, as close as possible to reference years 1990, 2000 and 2005. After preprocessing, the satellite imagery was used in an automated multi-date image segmentation to subdivide the sample unit (10 000 ha) into delineated areas (polygons) with similar spectral and structural attributes. The target minimum mapping unit was 5 ha. On the segmented imagery, a supervised automated land cover classification was carried out, which later was converted to a land use classification with the help of expert human interpretation. The main land use classes were *Forest*, *Other wooded land*, and *Other land*, which are based on FAO forest definitions (FAO 2010). Areas lacking data due to clouds, poor satellite coverage or low quality imagery in any of the reference years were considered an unbiased loss of information and were not analysed. This sample grid provided 1542 sample units in South America, of which 1392 sample units had data for all years and were consequently processed (figure 1).

2.2. Follow-up land use

Land use following a deforestation event was assigned a more detailed land use class, i.e. follow-up land use class, as a proxy for the proximate cause of change. Assessing land use is more challenging than assessing land cover, as factors other than spectral reflectance are important. So, expert human interpretation and relatively fine-scale satellite imagery are required to interpret the proximate causes of deforestation. To assign follow-up land use in this study, we used parameters such as land cover, the presence of certain features within or near changed areas (e.g. crop rows, watering holes, fences) and to a limited extent the spatial context and location of change (e.g. distance to settlements, concessions).

Table 1 gives an overview of the follow-up land use classes and their descriptions, that we used as proxies for the proximate deforestation driver. These land use classes are based on the proximate deforestation drivers as described in Hosonuma *et al* (2012) i.e. agricultural expansion, mining, infrastructural and urban expansion. The class ‘other land use’ was added for deforested areas where no clear human activity could

Table 1. Follow-up land use classes and their description.

	Follow-up land use	Description
Agriculture	Mixed agriculture	Mix of agricultural land uses
	Commercial crop	Land under cultivation for crops, characterised by medium (2–20 ha) to large (>20 ha) field sizes
	Smallholder crop	Land under cultivation for crops, characterised by very small (<0.5 ha) to small field sizes (0.5–2 ha)
	Tree crops	Miscellaneous tree crops (e.g. coffee, palm trees), orchards and groves
	Pasture	Land used predominantly for grazing; in either managed/cultivated (pastures) or natural (grazing land) setting; includes grazed woodlands
Infrastructure	Urban and Settlements	Urban, settlements and other residential areas
	Roads and built-up	Roads, built-up areas and other transport, industrial and commercial infrastructures
	Mining	Land used for extractive subsurface and surface mining activities (e.g. underground and strip mines, quarries and gravel pits), including all associated surface infrastructure
Other land use	Other land use (general)	All land that is not classified as forest, agriculture, infrastructure, mining and water
	Bare land	Barren land (exposed soil, sand, or rocks)
	Other wooded land	Land not classified as forest, spanning more than 0.5 ha; with trees higher than 5 m and canopy cover of 5%–10%, or trees able to reach these thresholds *in situ*, or with a combined cover of shrubs, bushes and trees above 10%. It does not include land that is predominantly under agricultural or urban land use (FAO 2010)
	Grass and herbaceous	Land covered with (natural) herbaceous vegetation or grasses
	Wetlands	Areas of natural vegetation growing in shallow water or seasonally flooded environments. This category includes Marshes, swamps, and bogs
Water		Natural (river, lake etc) or man-made waterbodies (e.g. reservoirs)
Unknown land use		All land that cannot be classified (e.g. due to low resolution imagery)

be distinguished. The 'other land use' subclasses are chosen in such a way that our classification could be translated to IPCC land categories (e.g. wetlands, grasslands) (IPCC 2013) and FAO land use definitions (e.g. other wooded land) (FAO 2010). The water class was added to account for forest loss due to inundation by lakes, meandering rivers and dam reservoirs.

We have used several key criteria to classify land uses. Cropland can be detected by plough lines, rectilinear shapes, and nearby roads and infrastructure (Clark *et al* 2010). We used field size as a proxy for agricultural development and mechanisation (Kuemmerle *et al* 2013, Fritz *et al* 2015). We classified cropland with very small to small fields (<2 ha) as smallholder cropland, and cropland with medium to large fields (>2 ha) as commercial cropland (>2 ha). Tree crops can be recognised by perennial vegetation and the regular spacing of the tree plants (Clark *et al* 2010). Pasture can be distinguished by trails and watering holes, and is usually more heterogeneous in colour and texture than cropland (Clark *et al* 2010).

In order to achieve a detailed follow-up land use classification, we performed the following steps:

(1). We selected those polygons of each sample unit within the FAO FRA-2010 RSS dataset that were deforested, either in the interval between 1990 and 2000 or 2000 and 2005 according to the FAO FRA-2010 RSS classification, i.e. changed from *Forest* to *Other wooded land* or to *Other land*.

(2). Each of these deforested polygons was assigned a single follow-up land use class (table 1) by means of visual interpretation by an expert. If more than one land use was present, the most dominant one in terms of area or human activity (e.g. a road with shrubs on the side is assigned road) was chosen. For the visual interpretation a variety of satellite imagery was used such as Landsat, Google Earth imagery (Google Earth 2015) and ESRI world imagery basemaps. For the Brazilian Amazon, Terraclass 2008 data (Coutinho *et al* 2013) was used to help with the interpretation. We used satellite imagery acquired as close as possible to the deforestation period (e.g. 2000 or 2005).

(3). In addition to follow-up land use, the source and year of the satellite imagery used for the interpretation (e.g. Google Earth 2009) and the confidence (low—medium—high) in the interpretation was documented.

(4). For the areas with low confidence, e.g. due to low resolution imagery, land use and remote sensing experts with local knowledge were consulted. These experts were provided with the follow-up land use classification and descriptions in order to classify the areas based on their local knowledge, and additional sources available to them such as high resolution satellite imagery and land use maps.

(5). Finally, all areas were double checked, and if necessary corrected for errors and consistency.

This means each forest loss area has been looked at least twice by one or more experts.

In the end, 77.8% of follow-up land use classification was assigned with high confidence, 17.6% with medium confidence and only 4.6% with low confidence. In general, small-scale land uses, such as smallholder cropland, were classified with less confidence due to their smaller scale and because these land uses occur more in locations with higher cloud cover and with lower availability of high resolution imagery (Andean countries, Amazon rainforest). In addition, the class 'other land use' also had a higher portion of low confidence classification since it is not always possible to assess whether these areas are used for agriculture. For all land uses, the confidence level was also influenced by the date of the available imagery.

2.3. Carbon losses

Gross carbon loss per sample unit was calculated using spatially explicit forest biomass information. A recent study by Langner *et al* (2014) combined a global forest mask derived from the Globcover-2009 map (Bontemps *et al* 2011), FAO ecological zones (eco-zones; FAO 2001) and the pan-tropical above ground biomass (AGB) datasets of Saatchi (Saatchi *et al* 2011) and Baccini (Baccini *et al* 2012) to derive mean AGB levels in forests (for intact, non-intact and overall forest) per eco-zone and country as an alternative to IPCC Tier 1 values.

We used the country eco-zone AGB forest values derived from the combined Saatchi and Baccini AGB maps (table 3 in supplementary information of Langner *et al* 2014). We used AGB values for the overall forest category since we did not have information on whether the deforested area had intact or non-intact forest. For those AGB forest values where the number of samples per eco-zone was too small, we used the combined AGB values of that eco-zone at the continental (South America) or tropical scale. If these AGB values were also not present we used IPCC Tier 1 AGB values for America (IPCC 2006). For Argentina and Chile, which were not included in Langner *et al* (2014), we used the same procedure. Table 2 provides an overview of the AGB values per country eco-zone used in our study.

We derived total biomass from AGB by applying the equation (1) used by Saatchi *et al* (2011):

$$\text{Total Biomass} = \text{AGB} + 0.489^{*}\text{AGB}^{0.89}. \tag{1}$$

Total carbon was considered to be 50% of total biomass as in Achard *et al* (2014). We considered only the maximum potential loss of carbon stock from deforestation, assuming a carbon stock of zero in potential follow-up land uses, that could be emitted to the atmosphere over a long time period. We did not account for soil carbon loss.

2.4. Aggregation to regional scale

Deforestation and related carbon losses per driver were scaled up from the sample to the continental and national scales using a statistical extrapolation similar to FRA-2010 RSS (FAO & JRC 2012). Cloudy areas were considered an unbiased loss of data, with the assumption that cloudy areas had the same proportion of land uses as cloud-free areas within a single sample unit. This was accomplished by considering the ratio of forest area or carbon loss per driver proportional to the 'visible land' area of the sample unit. The 'visible land' area was the full sample unit area (100 km^2) minus cloudy and 'permanent water' areas (i.e. sea or inland water in all considered years).

Estimates of forest area and carbon losses per driver for each sample unit for the two periods (1990–2000 and 2000–2005) were annualised based on the acquisition dates of the imagery for that sample unit, with the assumption that the change rates were constant during the two time intervals. The average time length across all sample units was 11.9 years for the 1990–2000 epoch and 4.9 years for the 2000–2005 epoch.

Each sample unit was assigned a weight (w_i) (2), equal to the cosine of its latitude (coslat_i), because the actual area represented by a sample unit decreased with latitude due to the curvature of Earth:

$$w_i = \frac{\text{coslat}_i}{\sum_i \text{coslat}_i}. \tag{2}$$

The proportions of forest area changes and carbon losses per driver were extrapolated to a given region (the full continent or one specific country) using the Horvitz–Thompson direct estimator (Särndal *et al* 1992) (3)

$$\bar{x}_c = \frac{1}{M} \times \sum_{i=0}^{n} \left(w_i \times x_{ic} \right), \tag{3}$$

where

$$M = \sum_{i=0}^{n} w_i \tag{4}$$

and where x_{ic} is the proportion of forest cover change or carbon loss in the ith sample unit and w_i is the weight of the ith sample unit. The total area of change or total loss of carbon for this region ($\text{Driver}_{\text{region}}$) is then obtained from:

$$\text{Driver}_{\text{region}} = A \times \bar{x}_c, \tag{5}$$

where A is the total area of the region (excluding permanent water).

We used the usual variance estimation of the mean for this systematic sampling as follows:

$$s^2 = \frac{1}{M} \times \sum_{i=0}^{n} w_i \times \left(\bar{x}_c - x_{ic} \right)^2. \tag{6}$$

The standard error (SE) is then calculated as:

$$\text{SE} = A \times \frac{s}{\sqrt{n}}. \tag{7}$$

Table 2. AGB mean forest values (t ha^{-1}) per eco-zone and country based on combined Saatchi and Baccini datasets (unless otherwise indicated); Source: Langner *et al* (2014), table 3 in their supplementary information.

Eco-zone	Argentina	Bolivia	Brazil	Chile	Colombia	Ecuador	French Guiana	Guyana	Paraguay	Peru	Suriname	Uruguay	Venezuela
Tropical rainforest	—	211	239	—	237	237	280	269	79	276	273	—	250
Tropical moist deciduous forest	123[a]	180	98	—	88	123[a]	—	222	80	—	252	—	154
Tropical dry forest	79[a]	95	68	—	105	116	—	—	68	79[a]	—	—	106
Tropical mountain system	195[a]	199	126	—	162	187	—	280	—	208	—	—	240
Subtropical humid forest	110[a]	—	110	—	—	—	—	—	—	—	—	110[a]	—
Subtropical dry forest	—	—	—	57[b]	—	—	—	—	—	—	—	—	—
Subtropical steppe	80[c]	—	—	—	—	—	—	—	—	—	—	—	—
Temperate mountain system	130[c]	—	—	—	—	—	—	—	—	—	—	—	—
Temperate oceanic forest	—	—	—	180[c]	—	—	—	—	—	—	—	—	—

[a] Continental (America) value (Langner *et al* 2014, table 2a in their supplementary information).

[b] Global value (Langner *et al* 2014, table 1 in their supplementary information).

[c] IPCC continental (America) value.

— Eco-zone and country combinations that do not exist or are without forest loss.

Table 3. Estimates of deforested area (10^3 ha (SE) and per cent of total) and related carbon loss (Tg C (SE) and per cent of total) per follow-up land use from 1990 to 2005.

	Area		Carbon loss	
Follow-up land use	10^3 ha (SE)	%	Tg C (SE)	%
Mixed agriculture	470 (233)	0.8	57 (32)	0.9
Smallholder crop	1 168 (272)	2.0	173 (42)	2.7
Commercial crop	8 100 (1463)	14.0	782 (162)	12.1
Tree crops	243 (75)	0.4	20 (6)	0.3
Pasture	41 118 (3244)	71.2	4 624 (431)	71.6
Agriculture total	**51 099 (3618)**	**88.5**	**5 657 (472)**	**87.6**
Infrastructure	985 (346)	1.7	124 (52)	1.9
Other land use	3 770 (517)	6.5	433 (65)	6.7
Water	1 748 (543)	3.0	228 (79)	3.5
Unknown land use	131 (108)	0.2	18 (15)	0.3
Other total	**6 634 (897)**	**11.5**	**802 (123)**	**12.4**
Total	57 733 (3837)	100	6 460 (501)	100

The SE represents only the sampling error. Countries or states with a SE of more than 35% for forest area and carbon losses estimates were not reported at the national scale (i.e. French Guyana, Guyana, Ecuador and Chile).

3. Results

3.1. Deforestation and carbon losses per driver from 1990 to 2005

We estimated that total deforested area and related gross carbon losses in South America from 1990 to 2005 reached 57.7 million ha and 6 460 Tg C, respectively (table 3). Agriculture was the dominant follow-up land use (88.5%), in particular pasture (71.2%) and to a lesser extent commercial cropland (14.0%). In the non-agricultural category, other land use was the largest driver (6.5%). This class can be further subdivided in other wooded land (4.4%), wetlands (1.4%), grass and herbaceous (0.6%) and bare land (0.1%). The contribution of smallholder cropland (2.0%), infrastructure (1.7%) and water (3.0%) was small. Within the infrastructure class, urban and settlements accounted for 0.9%, roads and built-up areas for 0.6% and mining for 0.2% of deforestation. The water driver can be divided into natural (1.3%) and man-made water bodies (1.8%). Unknown land use only represented a small fraction (0.2%) of total deforestation.

The spatially explicit nature of our dataset shows the distribution of follow-up land use across the continent (figure 2(a)). The Brazilian arc of deforestation was dominated by pasture expansion, except for a commercial crop agriculture cluster in Mato Grosso State. Considerable deforestation, mainly due to the expansion of pasture, occurred in the Brazilian Pantanal and Cerrado ecoregions. Toward the Atlantic coast, in the Mata Atlântica ecoregion, the follow-up land use became more diverse with a mix of pasture, commercial cropland and tree crops. Pasture expansion was also an important driver of deforestation in the Western Paraguayan and Argentinean Chaco. Commercial crop expansion was prevalent in Eastern Paraguay, Central Bolivia (around La Paz) and Northern Argentina; while smallholder crop expansion occurred mostly in the Andean region (Peru, Ecuador, Colombia, Venezuela and Bolivia).

Forest biomass levels in East Brazil, Paraguay and Argentina were much lower than in the Brazilian Amazon (figure 2(b)). This influenced the relative contribution of follow-up land uses for forest carbon losses as compared to deforested area (table 3). For example, commercial crop agriculture proportionally contributed more to deforested area (14.0%) than to forest carbon losses (12.1%) indicating that this follow-up land use, as well as tree crops, occurred more in lower forest biomass eco-zones as compared to pasture, mixed and smallholder crop agriculture, water and infrastructure.

Deforestation drivers at the national level varied in their contribution to deforestation (figure 3, for more detail see table A1 in the appendix). Pasture expansion caused at least 35% or more of forest loss in all countries except in Peru (19.9%) where smallholder cropland (41.9%) was a more dominant driver. In Argentina deforestation caused by commercial cropland (43.4%) was almost as dominant as pasture driven deforestation (44.6%). Commercial crop expansion could also be found in Paraguay (25.5%) and Bolivia (27.2%), while in Colombia smallholder crop and mixed agriculture (23.6% together) was more important for deforestation. In Bolivia one fifth (20.0%) of deforestation was followed up by other land use, mostly wetlands (13.4%) and other wooded land (6.0%). For other land use in Peru (16.2%) most was other wooded land (8.9%) and wetlands (7.3%). In Colombia (12.7%) and Venezuela (13.7%) other land use, mainly other wooded land also played a considerable role in deforestation. In Peru infrastructure was a relatively large driver (5.6%) compared to the other countries, due to mining activities (2.0%) and substantial urban, roads and built-up development

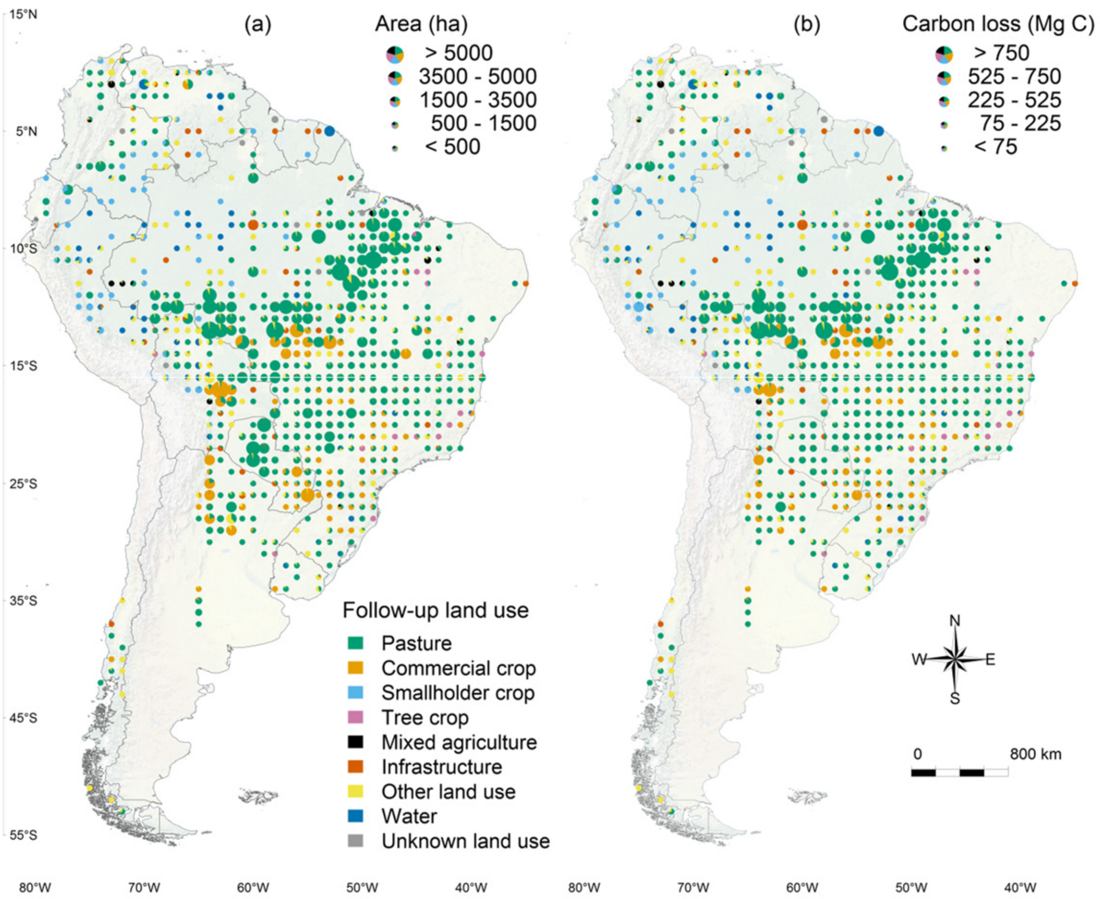

Figure 2. (a) Forest area loss (ha) and (b) related forest carbon losses (Mg C) per follow-up land use from 1990 to 2005, in South America.

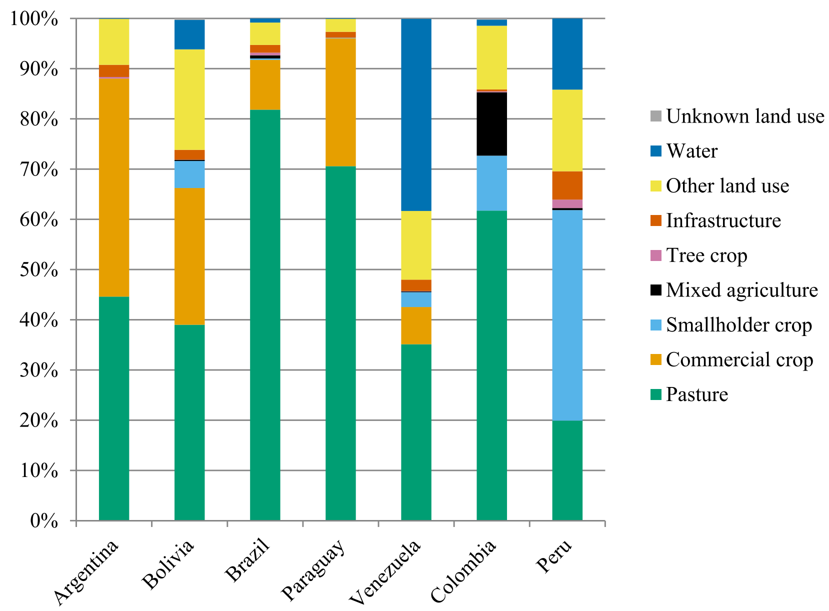

Figure 3. Area proportion of deforestation driver from 1990 to 2005 (%) at the national scale.

(3.7%). Water as a follow-up land use contributed considerably to deforestation in Venezuela (38.2%) due to two large dam projects. In Peru (14.2%) and Bolivia (5.9%) deforestation followed up by water was the result of natural processes such as meandering rivers.

Brazil emitted the most carbon from 1990 to 2005 (4372 Tg C), followed by Bolivia (488 Tg C), Argentina

Table 4. Estimates of deforested area (10^3 ha yr^{-1} (SE)) and related carbon loss (Tg C yr^{-1} (SE)) per follow-up land use for 1990–2000 and 2000–2005, and the change in carbon loss (Tg C yr^{-1}) in the second period additional to the change in forest area loss.

	1990–2000		2000–2005		
Follow-up land use	Area	Carbon loss	Area	Carbon loss	Additional change in carbon loss
Mixed agriculture	36 (21)	5 (3)	25 (12)	2 (1)	−0.78
Smallholder crop	85 (22)	13 (3)	58 (13)	9 (2)	0.02
Commercial crop	409 (84)	37 (7)	802 (180)	82 (21)	8.79
Tree crops	13 (3)	1 (0)	22 (11)	2 (1)	−0.46
Pasture	2 642 (224)	295 (30)	3 062 (307)	351 (39)	9.17
Agriculture total	**3186 (244)**	**351 (31)**	**3969 (359)**	**445 (45)**	**16.73**
Infrastructure	64 (25)	8 (4)	62 (17)	7 (2)	−0.31
Other land use	232 (38)	27 (5)	324 (60)	36 (6)	−2.07
Water	128 (47)	18 (7)	93 (42)	11 (4)	−2.33
Unknown land use	9 (7)	1 (1)	9 (7)	1 (1)	−0.04
Other total	**433 (73)**	**54 (10)**	**489 (77)**	**55 (8)**	**−4.75**
Total	3 619 (261)	405 (34)	4 458 (382)	500 (48)	11.98

(297 Tg C) and Colombia (289 Tg C). Paraguay (179 Tg C), Venezuela (174 Tg C) and Peru (170 Tg C) had less forest carbon losses in the same period (table A2 in appendix).

3.2. Trends in annual deforestation and carbon losses per driver from 1990 to 2000 and 2000 to 2005

Annual deforestation increased from 3.62 to 4.46 million ha yr^{-1} between the periods 1990–2000 and 2000–2005, while the related carbon losses increased from 0.41 to 0.50 Pg C yr^{-1} (table 4). The increase in carbon losses was partly driven by an increase of forest area loss due to commercial cropland, pasture and other land use. Water, mixed and smallholder crop agriculture, on the other hand, decreased as drivers of deforestation. Not all the increase in carbon losses can be attributed to an increase in forest area loss alone. Pasture (+9.17 Tg C yr^{-1}) and commercial crop expansion (+8.79 Tg C yr^{-1}) caused additional carbon losses by occurring more in higher forest biomass eco-zones in the 2nd period, only minimally countered by other drivers occurring more in lower forest biomass eco-zones (table 4).

Clearly, the spatial distribution of hotspots of deforestation and their change in time has an influence on forest carbon losses. Moving hotspots of the two main deforestation drivers, crop agriculture (commercial and smallholder) (figure 4(a)) and pasture (figure 4(b)), illustrate this effect. Pasture expansion in Brazil occurred more and deeper in the Amazon (especially Rondônia and Pará States) in the 2nd period, and less in lower forest biomass ecoregions of the Cerrado and Mata Atlântica. In Paraguay, pasture expansion into forests moved away from urbanized areas in the first period to mainly the Alto Chaco region in the second period. Hot spots of crop expansion occurred in Mato Grosso State and the lowlands around Santa Cruz in Bolivia mainly in the 2nd period, while in Southern Paraguay crop expansion moved from Alto Paraná Department to central Paraguay. In Peru we see both crop and pasture related deforestation occurring deeper in the Amazon in the second period. In Northern Argentina, pasture and crop expansion occurred mainly near important highways.

4. Discussion

In this study we quantified proximate drivers of deforestation and related carbon losses in South America between 1990 and 2005. Previous estimates of deforestation ranged from 3.74 to 4.09 million ha yr^{-1} for the 1990s, and 3.28 to 4.87 million ha yr^{-1} for (part of) the 2000s (DeFries *et al* 2002, Hansen *et al* 2008, 2010, Eva *et al* 2012, Harris *et al* 2012, Achard *et al* 2014, FAO 2015). Previous estimates for carbon losses from deforestation ranged from 306 to 698 Pg C y^{-1} for the 1990s, and 322 to 845 Pg C yr^{-1} for (part of) the 2000s (DeFries *et al* 2002, Baccini *et al* 2012, Eva *et al* 2012, Harris *et al* 2012, Houghton 2012, Achard *et al* 2014, Tyukavina *et al* 2015). Our estimates of deforestation and related carbon emissions are of similar magnitude, but comparisons between studies are difficult due to differences in methodology, forest definition, considered time frame and region (Keenan *et al* 2015). The latter is also the case for previous studies (Hosonuma *et al* 2012, Houghton 2012) on proximate drivers of deforestation.

Agricultural expansion, in particular pasture, was the most dominant driver of deforestation in South America. Gross carbon losses from forest conversion to pasture were 4 624 Tg C from 1990 to 2005. In the same time frame, carbon losses amounted to 782 Tg C for commercial crop agriculture and 173 Tg C for smallholder crop agriculture. Before the 1990s deforestation was mostly attributed to shifting cultivators and smallholder colonists (Rudel *et al* 2009). More recent decades saw the rise of large-scale agribusinesses, increasingly producing for international markets, as the main agents of deforestation (Rudel 2007,

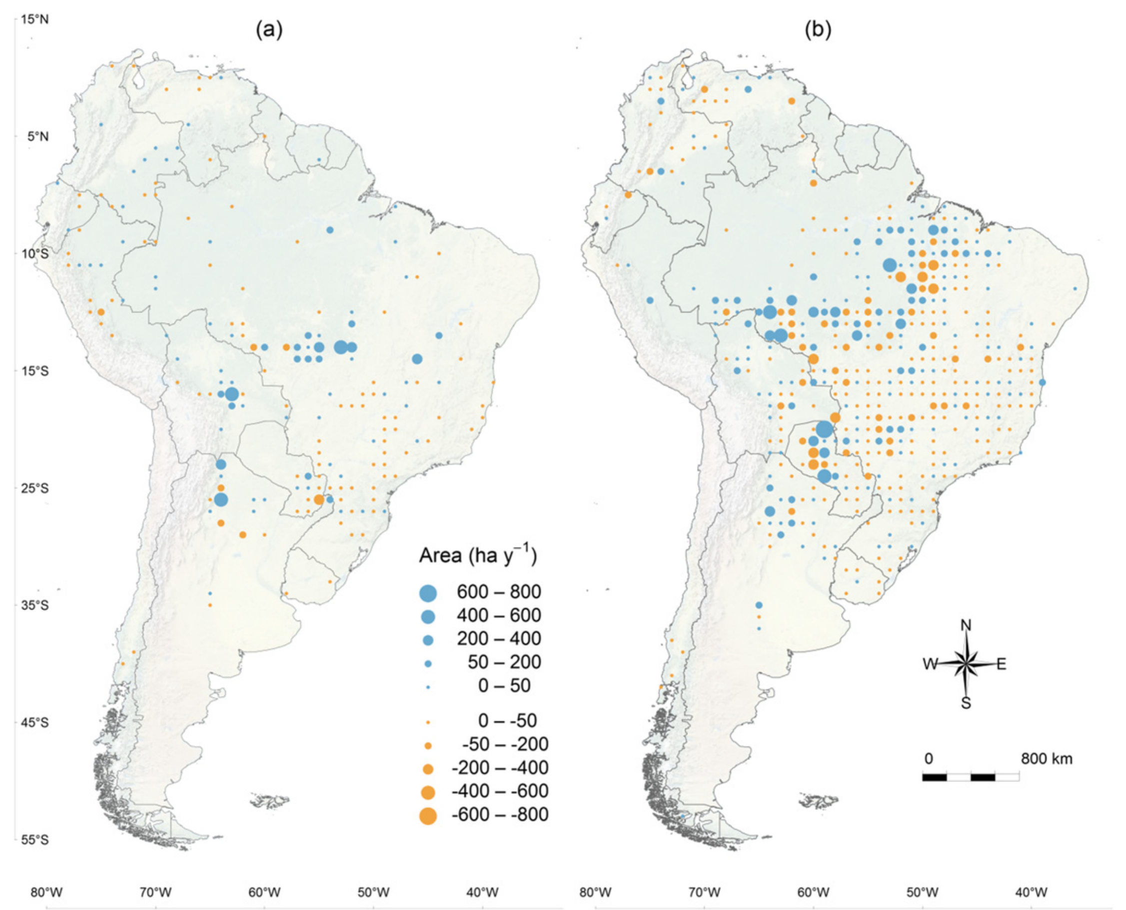

Figure 4. Changes in annual rate of deforestation (ha yr^{-1}) followed up by crop agriculture (a) and pasture (b) between the periods 1990–2000 and 2000–2005, in South America.

Rudel *et al* 2009, Pacheco and Poccard-Chapuis 2012). Our data confirmed this, especially in Brazil, Argentina, Paraguay and Bolivia where large ranches and commercial crop agriculture were the main drivers. In the Andean countries (Peru, Colombia and Venezuela) smallholder and mixed agriculture were still important drivers of deforestation.

Our study shows that the annual rate of deforestation driven by commercial crops doubled in the early 2000s compared to the 1990s. Although much of the increase in deforestation in the early 2000s could be attributed to commercial crop expansion, this driver contributed to only 14% of overall deforestation in South America. Our study identified hotspots of forest conversion for crop agriculture in Mato Grosso State (Brazil), Bolivia, Argentina and Paraguay. Several studies showed that the expansion of commercial crops (e.g. soybean) increased substantially in these regions (Morton *et al* 2006, Macedo *et al* 2012, Müller *et al* 2012, Graesser *et al* 2015). A large part of this expansion, however, was conversion of pasture and not forests (Graesser *et al* 2015). Even so, crop expansion still places direct pressure on forests (Morton *et al* 2006) and can be an indirect driver of land use change by pushing pasture lands forward into the forest frontier (Nepstad *et al* 2006, Barona *et al* 2010, Arima *et al* 2011). These dynamics changed after 2005 when deforestation slowed down in the Amazon, particularly in Mato Grosso State, coinciding with a fall in crop commodity prices and the implementation of policy measures such as improved monitoring and enforcement, and other control actions (Macedo *et al* 2012, Malingreau *et al* 2012, Gibbs *et al* 2015).

Hotspots of pasture- and crop-driven deforestation moved into higher forest biomass eco-zones in the early 2000s which caused additional carbon losses. Efforts to reduce carbon emissions might be in vain when countries only concentrate on reducing the deforested area without taking into account variations in forest biomass. However, beyond carbon emissions, the environmental impact (e.g. biodiversity loss) of high deforestation rates in low-carbon biomes such as the Cerrado in Brazil and the Chaco in Paraguay is considerable. This emphasises the importance of spatial and temporal information, not only on drivers of deforestation but also on biodiversity and other safeguards, in designing effective REDD+ interventions. In this study we used mean forest biomass values per eco-zone to estimate carbon losses as a simple and conservative approach (Langner *et al* 2014). In reality, however, there are gradations of forest biomass within eco-zones (Saatchi *et al* 2011, Baccini *et al* 2012) which might influence the spatial and temporal dynamics of carbon losses from different drivers.

Infrastructure, including urban expansion and roads, contributed little (1.7%) to deforestation as a direct driver. As an indirect driver, however, urbanisation can contribute significantly to deforestation because it changes consumption patterns and increases the demand for agricultural products (DeFries *et al* 2010). Better road infrastructure in the Amazon opened up the forest frontier and expanded the market for cattle (Rudel 2007). In Peru, infrastructure was a relatively important driver, mostly due to (illegal) mining activities (2.0% of deforestation) which in addition to forest carbon losses also causes other environmental impacts (Swenson *et al* 2011, Asner *et al* 2013). The example of Venezuela shows that large infrastructure projects, such as dams, can make a substantial contribution (37.8% of deforestation) to national forest carbon emissions.

Deforestation drivers and their relative importance on the national level emphasise the need to understand drivers to design effective REDD+ policies. Countries have a variety of policy- and incentive-based interventions at their disposal (Angelsen and Brockhaus 2009, Kissinger *et al* 2012) to affect local to national drivers, which ideally should be adapted to the characteristics of these drivers. For example, countries mostly affected by deforestation due to commercial agriculture might opt for different interventions than countries mostly affected by deforestation due to smallholder agriculture. Most drivers of deforestation originate outside the forest sector which indicates that REDD+ interventions should include non-forest sectors such as the agricultural, urban and mining sectors instead of only focusing on forest interventions such as sustainable forest management. Salvini *et al* (2014) found that most countries focus more on forest degradation than on deforestation interventions, and that countries with higher quality data on drivers include more non-forest sector interventions (e.g. agricultural intensification) in their REDD+ readiness documents. Clearly, REDD+ countries are struggling with designing effective REDD+ policy interventions partly due to limited understanding of their deforestation drivers.

Unfortunately, our data only covers the timeframe between 1990 and 2005. This limits the applicability for designing up-to-date REDD+ strategies since, as discussed above, the drivers and processes of deforestation in South America have undergone changes after 2005. An important aspect to consider for further research is the influence of the temporal resolution on the follow-up land use. High resolution imagery is usually only available for few points in time within the 1990–2005 timeframe. The immediate follow-up land uses might be missed if a land use transition (e.g. pasture to crop) has occurred between the deforestation event and the closest available high-resolution imagery. In contrast, some land uses only become apparent after some time has passed (e.g. cleared land for urban development). Most REDD+ countries, however, have low capacities for forest monitoring (Romijn *et al* 2012) and often do not have spatial quantitative data on drivers of deforestation at their disposal (Hosonuma *et al* 2012). This study provides insight into specific drivers of deforestation that can help REDD+ countries with targeted capacity-building and the stepwise improvement of their national forest monitoring systems to provide more up-to-date and detailed information on drivers of deforestation. In turn this allows for the (re)design of more effective national REDD+ strategies (Salvini *et al* 2014).

5. Conclusion

In this paper we quantified proximate drivers of deforestation and related carbon losses in South America based on remote sensing time series in a systematic, spatially explicit manner. This contributes to the understanding of drivers of deforestation and related carbon losses at the national and continental level and allows for comparisons across national and regional boundaries. In addition, this spatially explicit quantitative information on deforestation can provide valuable input for statistical analysis and modelling of underlying drivers of deforestation. Our findings can also support the development of national REDD+ interventions and forest monitoring systems.

Our results show the importance of temporal and spatial patterns of deforestation drivers. The future priorities for getting more insight into drivers of deforestation in a REDD+ context lie in expanding the geographical area to all REDD+ focus areas (Central America, Sub-Saharan Africa, South East Asia), in using more recent remote sensing time series, and in using more detailed forest biomass maps to capture spatial forest biomass gradations.

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Appendix A

Table A1. Estimates of deforested area (mean, 10^3 ha) and standard error (SE, 10^3 ha) per follow-up land use and country from 1990 to 2005.

	Argentina		Bolivia		Brazil		Colombia		Paraguay		Peru		Venezuela	
Follow-up land use	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Mixed agriculture	0	0	10	10	229	121	269	263	0	0	4	4	3	3
Smallholder crop agriculture	0	0	223	136	103	37	233	93	4	4	423	184	50	37
Commercial crop agriculture	1929	701	1128	611	3632	867	0	0	967	522	0	0	125	109
Tree crops	14	13	1	1	193	68	4	4	0	0	17	15	1	1
Pasture	1982	523	1616	472	29 949	2716	1315	562	2680	813	201	141	593	215
Infrastructure	108	40	81	32	563	320	8	4	45	18	57	28	38	18
≻ Urban and Settlements	3	3	29	25	392	316	1	1	0	0	12	6	25	14
≻ Roads and Built-up	105	40	52	21	95	21	7	4	45	18	25	17	5	3
≻ Mining	0	0	0	0	76	41	0	0	0	0	20	20	9	9
Other land use	406	214	829	364	1629	185	270	148	97	30	164	66	231	90
≻ Bare land	4	4	6	4	17	15	7	4	0	0	0	0	28	28
≻ Other wooded land	163	57	247	68	1495	180	232	135	92	29	90	58	161	62
≻ Grass & herbaceous	235	197	19	13	34	19	14	12	2	2	0	0	41	34
≻ Wetlands	4	3	557	346	83	31	17	11	3	3	74	30	1	1
Water bodies	4	3	243	102	300	89	26	14	4	3	143	50	646	402
≻ Natural	4	3	243	102	253	88	26	14	4	3	143	50	8	5
≻ Man-made	0	0	0	0	47	12	0	0	0	0	0	0	638	402
Unknown land use	0	0	12	10	2	2	5	3	0	0	0	0	1	1
Total	4441	989	4142	943	36 599	3008	2129	650	3798	921	1010	264	1689	586

Table A2. Estimates of forest carbon losses (mean, Mg C) and standard error (SE, Mg C) per follow-up land use and country from 1990 to 2005.

	Argentina		Bolivia		Brazil		Colombia		Paraguay		Peru		Venezuela	
Follow-up land use	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Mixed agriculture	0	0	1235	1232	22 521	12 357	40 119	39 454	0	0	738	737	325	324
Smallholder crop agriculture	0	0	27 155	16 068	13 557	4823	34 802	13 926	225	223	70 760	31 848	7714	5867
Commercial crop agriculture	127 523	47 503	135 073	79 944	416 421	117 043	0	0	50 349	27 204	0	0	11 949	10 768
Tree crops	962	930	78	77	15 531	4813	234	234	0	0	2195	2025	139	138
Pasture	129 699	37 173	174 770	51 130	3605 826	384 314	180 656	84 179	121 185	36 091	33 394	24 346	59 368	21 417
Infrastructure	7121	2983	7847	3599	79 345	48 346	1019	513	2108	820	9876	4830	4063	1754
➢ Urban and Settlements	230	218	3864	3354	56 699	47 904	116	114	0	0	2102	954	2691	1421
➢ Roads and Built-up	6890	2956	3983	1426	11 315	2764	903	503	2108	820	4324	2903	451	287
➢ Mining	0	0	0	0	11 332	6197	0	0	0	0	3450	3449	921	913
Other land use	31 893	16 896	108 734	48 763	184 727	23 604	29 922	15 634	4666	1400	28 139	11 462	26 242	9973
➢ Bare land	325	340	634	477	2481	2272	834	580	0	0	0	0	2746	2729
➢ Other wooded land	12 649	4379	31 603	9138	173 326	23 307	26 730	14 292	4407	1364	15 446	10 058	17 192	6609
➢ Grass and herbaceous	18 587	15 634	2025	1481	2032	986	1336	1239	98	82	0	0	6160	5098
➢ Wetlands	331	235	74 472	46 463	6889	2352	1022	627	161	132	12 693	5290	143	143
Water bodies	289	201	31 967	13 641	34 173	10 731	2292	1130	162	131	24 666	8647	63 690	39 629
➢ Natural	289	201	31967	13 641	28 914	10 656	2292	1130	162	131	24 666	8647	769	496
➢ Man-made	0	0	0	0	5259	1434	0	0	0	0	0	0	62 922	39 647
Unknown land use	0	0	1536	1218	298	263	448	280	0	0	0	0	156	154
Total	297 486	68 154	488 395	117 738	4372 400	426 070	289 492	96 679	178 695	42 935	169 769	45 669	173 647	58 141

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