Food and Agriculture
Organization of the
United Nations

How much do large-scale and small-scale farming contribute to global deforestation?

Results from a remote sensing pilot approach

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Rome, 2023

Required citation:
Branthomme, A., Merle, C., Kindgard, A., Lourenço, A., Ng, W.-T., D'Annunzio, R. & Shapiro, A. 2023. *How much do large-scale and small-scale farming contribute to global deforestation? Results from a remote sensing pilot approach*. Rome, FAO. https://doi.org/10.4060/cc5723en

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ISBN 978-92-5-137842-7
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Acknowledgements

The study is the result of a joint effort of various units in the Food and Agriculture Organization of the United Nations (FAO) Forestry Division. In particular the report was prepared in the framework of the Global Forest Resources Assessment (FRA) and under the initiative "Turning the tide on deforestation". FAO Plant Production and Protection Division, Animal Production Division and Statistics Division also provided recommendations in the definition and implementation of the methodology.

The study was coordinated by Caroline Merle. Anne Branthomme, Caroline Merle, Adolfo Kindgard, Ana Lourenço, Wai-Tim Ng, Rémi D'Annunzio and Aurélie Shapiro contributed to the methodology development, the photo-interpretation, the analysis and the drafting of the report. Valeria Contessa and Pedro Vivar participated in the photo-interpretation and the review of satellite imagery. Makiko Taguchi, Haekoo Kim, Anne Mottet, Neli Georgieva Mihaylova and Flavio Bolliger provided their reviews and insights at different stages of the study. The study was carried out under the guidance of Tiina Vähänen, Serena Fortuna and Anssi Pekkarinen.

Copy editing of the report was managed by Malcolm Dickson, while the layout and design were carried out by Roberto Cenciarelli, cover design by Lucia De Canio and Chiara Patriarca supported the publication process.

The study was implemented with financial support from the European Union and the Government of Norway.

FAO is also grateful for the support of all countries, organizations and experts that contributed to the implementation of Global Forest Resources Assessment (FRA) 2020 Remote Sensing Survey which was used as a basis for the study.

Abbreviations and acronyms

CEO: Collect Earth Online

DRC: Democratic Republic of the Congo

EO: Earth Observation

FAO: Food and Agriculture Organization of the United Nations

FRA: Global Forest Resources Assessment

ha: hectares

JRC: Joint Research Centre of the European Commission

m: metre(s)

Mha: million hectare(s)

NICFI: Norway's International Climate and Forest Initiative

OWL: other wooded land

RSS: Remote Sensing Survey

VHR: very high resolution

Executive summary

Despite some progress in curbing deforestation, conversion of forests to other land use remains a major threat to these critical resources and a serious shortcoming in achieving climate and biodiversity global goals. According to various analyses on forest cover and land use change, expansion of agricultural land and deforestation are closely linked and therefore solutions to sustainable agriculture and forestry need to be determined together.

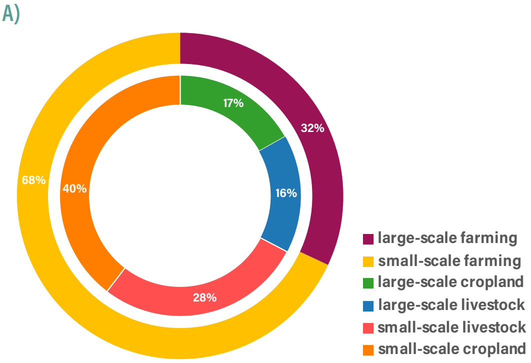
The Global Forest Resources Assessment (FRA) 2020 Remote Sensing Survey (FRA 2020 RSS) of the Food and Agriculture Organization of the United Nations (FAO), through a remote sensing and sampling-based approach, has confirmed this nexus. Indeed, the survey showed that the impact of agricultural expansion on forests over the period 2000–2018 has been greater than previously thought, driving almost 90 percent of deforestation.

The study presented in this document expands on the work conducted during the FRA 2020 RSS by refining the original analysis to obtain additional information on deforestation drivers linked to agriculture. Notably, considering the importance it would have in designing appropriate strategies for halting deforestation, **the study assesses the share of agriculture-driven deforestation linked to small-scale and large-scale farming, both for cropping and livestock systems**.

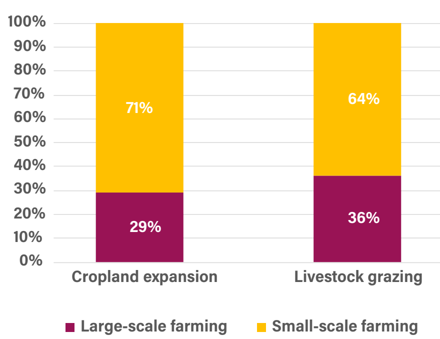
Worldwide, in the period 2000–2018, most of the forest conversion to cropland and grassland occurred in the context of small-scale farming, which accounted for 68 percent of agriculture-driven deforestation – 40 percent for cropland and 28 percent for livestock grazing (Figure A). Deforestation due to **cropland expansion** was for 71 percent linked to small-scale farming and 29 percent to large-scale farming (Figure B). With regards to deforestation due to **livestock grazing**, 64 percent was associated to small-scale farming and 36 percent to large-scale farming.

Figure A and B.
Share of agriculture-driven deforestation associated to large-scale and small-scale livestock and cropland in the world over the period, 2000–2018

A)



B)



a) as percentage of the total area deforested for agriculture (left) and b) as percentage of the area deforested for cropland expansion and for livestock grazing (right).

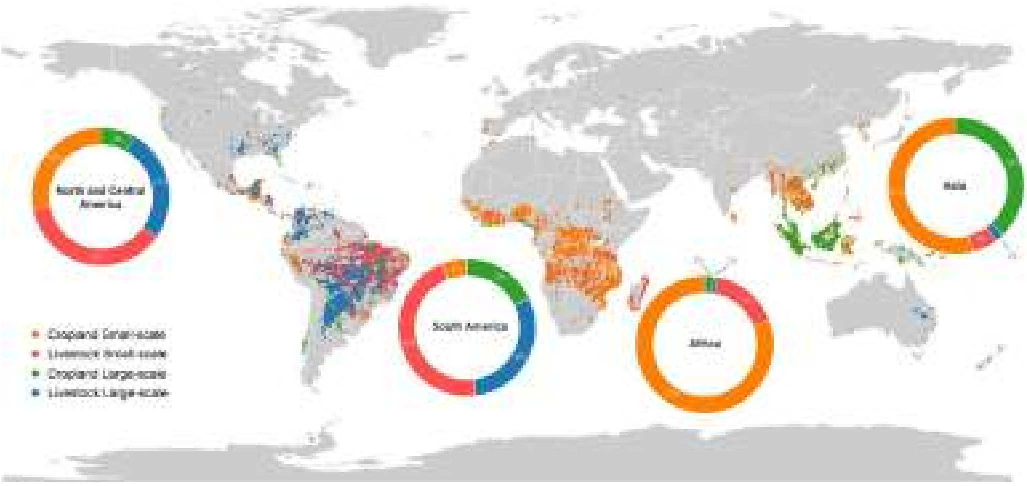
However, **results varied between regions**. Small-scale farming was linked to most agriculture-driven deforestation in all regions but at different degrees, representing a share of 97 percent of agriculture-driven deforestation in Africa (80 percent for cropland, 16 percent for livestock), 65 percent in North and Central America (37 percent for livestock, 28 percent for cropland), 59 percent in Asia (54 percent for cropland, 6 percent for livestock) and 52 percent in South America (46 percent for livestock and 6 percent for cropland) (Figure C). Highest shares of forest losses due to large-scale farming were found in South America where 30 percent of agriculture-driven deforestation was associated to large-scale livestock production, as well as in Asia, with 38 percent linked to large-scale crop production, mainly for oil palm plantations.

The study methodology was based on visually re-assessing FRA 2020 RSS samples where forest losses have been detected since 2000 to identify, more specifically, agricultural drivers behind the losses. The analysis was focused on about 35 500 samples where forest was identified by the FRA 2020 RSS as being converted to cropland or to grassland. The results are presented at the global level and for the regions of Africa, Asia, North and Central America, and South America, where the number of samples was large enough to provide statistically valid results.

The study **proposes spatial characteristics** of activities related with forest conversion to agriculture **that help to identify a context of large-scale or small-scale farming**. The characteristics relate to field and landscape level observations and need to be analyzed together to understand the farming scale. These include: i) landscape context and fragmentation; ii) speed of clearing; iii) field size; iv) field boundaries; v) field shape; vi) field patterns; and vii) presence of infrastructure.

Using a combination of diverse characteristics is necessary for robust differentiation between deforestation linked to large-scale and small-scale farming using Earth Observation imagery. **The set of characteristics is relevant for all the regions, though at different levels according to the new land use (cropland or grassland) and to the region.** It can be adjusted to reflect the specificities of farming systems depending on regional patterns. However, decisions were easier to make when assessing forest conversion to cropland compared to forest conversion to grassland.

Figure C.
Share and distribution of large-scale and small-scale livestock and cropland as agricultural deforestation drivers by region, over the period, 2000–2018



Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties. Final boundary between the Republic of Sudan and the Republic of South Sudan has not yet been determined.

Note: The figure illustrates geographical distribution of deforested RSS samples classified according to the type of agricultural deforestation driver. The samples have been greatly enlarged, therefore the figures provide only a general indication of the main deforestation processes and patterns occurring in different areas rather than the precise location and extent of deforestation.

Source: United Nations Geospatial. 2020. Map geodata [shapefiles]. New York, USA, United Nations, modified by the authors.

International discourse has tended to focus mainly on "commercial" or "industrial" agriculture ("agribusiness") as the main cause of deforestation. This study shows a more nuanced situation, where small-scale farming also plays a significant role in deforestation dynamics. This result does not contradict available literature, statistics and practical knowledge that show the important contribution of small-scale farming to the production of many commodities in regions where deforestation is observed. It suggests a need to strengthen efforts to address the weaknesses of current production systems when designing strategies against deforestation and to consider the strong concomitant needs including food security, decent income and secure tenure rights. On the other hand, the study illustrates that deforestation driven by large-scale interventions is still ongoing and has significant impacts in some regions. Therefore, the study findings can support more tailored policymaking.

1 Introduction

Forests provide invaluable benefits to human health and livelihoods, as well as regulating climate and hosting considerable amounts of biodiversity. However, despite some progress over the last decade, deforestation and forest degradation continue to take place at an alarming pace. Since 1990, an estimated 420 million hectares (Mha) of forest has been lost through deforestation. From 2015 to 2020, the rate of deforestation was estimated at 10 Mha per year, down from 16 Mha per year in the 1990s (FAO, 2020).

Various studies on forest cover monitoring and land use analysis have established a prominent link between agricultural land expansion and deforestation. Hosonuma *et al*. (2012) assessed that 73 percent of deforestation was caused by agriculture – 40 percent from commercial agriculture and 33 percent for subsistence agriculture. Curtis *et al*. (2018) found that 27 percent of global forest cover loss could be attributed to deforestation through permanent land use change for commodity production, and another 24 percent to shifting agriculture. They also underlined that despite corporate commitments, the rate of commodity-driven deforestation had not declined between 2001 and 2015. A recent report on "Illicit harvest, complicit goods" (Dummett and Blundell, 2021) confirmed that commercial-scale agricultural expansion is by far the single largest driver of deforestation worldwide. It also estimated that almost half of all tropical deforestation between 2000 and 2012 was driven by the illegal conversion of forest to commercial agriculture and half of the production from this agro-conversion was destined for export markets. The World Wide Fund for Nature recently analysed the dynamics of land use changes in 24 "deforestation fronts". While acknowledging that causes of deforestation change over time and place, they found that "commercial agriculture and tree plantations are the biggest drivers of deforestation", sometimes coupled with land speculation (Pacheco *et al*., 2021).

The Food and Agriculture Organization of the United Nations (FAO) has complemented and updated these studies through the Global Forest Resources Assessment 2020 Remote Sensing Survey (FRA 2020 RSS), which uses a remote sensing and sampling-based approach (FAO, 2022). This was launched in 2018 to build national capacities to use remote sensing for forest monitoring and to produce novel information on forest resource dynamics and drivers of deforestation at global, regional and ecological zone levels. The survey was based on visual interpretation of satellite images conducted by national experts with knowledge of local landscapes.

The FRA 2020 RSS results confirmed an overall slowdown in global deforestation in 2010–2018 compared to 2000–2010. However, the survey also showed that the impact of agricultural expansion on forests was greater than previously thought, driving almost 90 percent of global deforestation.

The objective of the study presented in this document is to deepen the analysis conducted during the FRA 2020 RSS to produce additional information on deforestation drivers linked to agriculture. Notably, considering the importance it would have in the design of appropriate strategies for halting deforestation (for example, REDD+ strategies or action plans), the study sought to assess the share of deforestation linked to small-scale and large-scale farming. Indeed, the tight interlinkages between agricultural production and deforestation deserve a more detailed understanding to inform decisions on measures that are able to ensure forest protection without threatening food security and rural livelihoods.

To address this issue, samples from the FRA 2020 RSS where forest losses have been detected since 2000 were visually re-assessed to identify agricultural deforestation drivers in a more detailed manner. The analysis was focused on about 35 500 samples where forest was identified by the FRA 2020 RSS as being converted to cropland or to grassland. Results are presented at the global level as well as for those regions where there were enough samples to provide statistically valid results, namely Africa, Asia, North and Central America, and South America, bearing in mind that the vast majority of deforestation was identified in tropical biomes. Indeed, according to the FRA 2020 RSS, tropical and subtropical areas represent 95 percent of global deforestation. The results obtained here were compared to findings described by Hosonuma *et al*. (2012) and Curtis *et al*. (2018), among others.

Finally, the study aimed at identifying methods and tools that can help explore and understand deforestation drivers using Earth Observation by considering additional variables to the original FRA 2020 RSS questionnaire and by defining geospatial characteristics of activities related to forest conversion that could help distinguish finer categories of deforestation drivers.

2 The FRA 2020 RSS methodology and key results on deforestation

2.1 Overview of the FRA 2020 RSS process and methodology

Monitoring the forest resources of the world through periodic assessments, conducted in cooperation with member countries, has been a core activity for the FAO, since its foundation. The collection, analysis and dissemination of information through the FRA, presenting a comprehensive view of the world's forests and the ways they are changing, has become a regular highlight for the international forestry sector.

Since 1990, FAO FRA Remote Sensing Surveys have complemented country-based FRA reporting processes to generate independent, robust and consistent estimates of forest area as well as changes over time. The fifth FAO FRA RSS (FRA 2020 RSS) began in 2018, conducted in close collaboration with countries, the Joint Research Centre of the European Commission (JRC) and other partners.

FRA 2020 RSS emphasized analysis of changes in forest and tree cover area as well as providing an insight into land use dynamics and key drivers at global, regional and ecological zone scales for the periods 2000–2010 and 2010–2018.

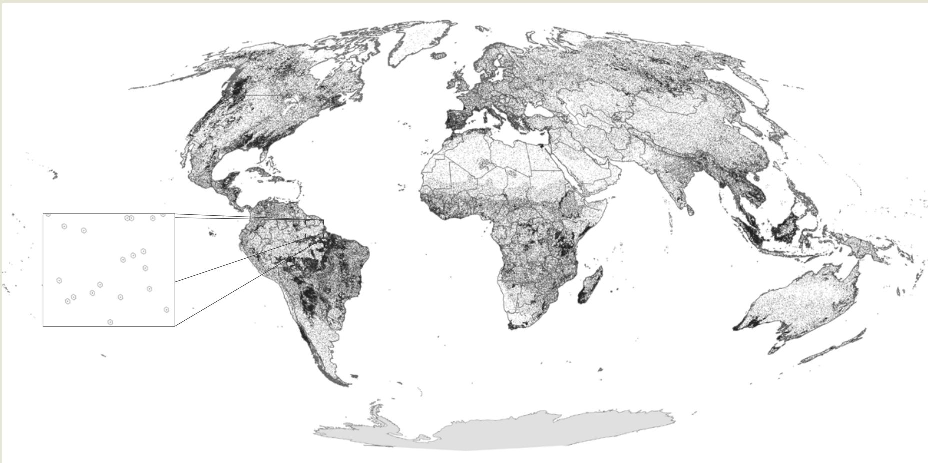
The survey, which took three years to complete, involved visual interpretation of satellite images from more than 400 000 sample sites worldwide by a network of over 800 national experts from 126 countries (see Box 1 for more detailed information on the methodology).

Box 1. Overview of FRA 2020 RSS methodology

The sampling frame for FRA 2020 RSS (FAO, 2022) was based on a tessellation of the Earth's surface into 40 ha hexagons. An additional assessment was carried out for a one ha square centroid in each hexagon to collect more detailed information on land use and tree cover, land-use change and related drivers. To reduce the uncertainty of forest area change estimates, a stratified random sampling approach was adopted based on global ecological zones and tree cover change. In total, around 400 000 samples were selected worldwide (Figure 3).

The assessment was carried out using visual interpretation of medium and high-resolution satellite imagery provided in Open Foris Collect Earth Online (CEO) – custom-built, free, open-source and user-friendly software that enables the visualization and interpretation of satellite imagery in a cloud-based environment (Saah *et al.*, 2019). The analysis was conducted using Landsat and Sentinel-2 images as primary data sources. Best available Landsat 5 or Landsat 7 data were used for years 2000 and 2010, and best available Landsat 8 and Sentinel-2 for 2018. Very high resolution (VHR) images from Bing Maps, DigitalGlobe and MapBox were also available as additional data to support the analysis. The photo-interpreters analysed the samples using an interactive CEO survey form (Figure I and Figure II). One section of the form focused on the categorical classification of the hexagon's centroid into defined variables for each land-use class and subclass for 2018, as well as land-use change classes for the given time intervals (2000–2010 and 2010–2018). Another section of the survey form focused on the quantitative estimation of the proportion of the area of the hexagon falling into each primary land-use class (forest, other wooded land, other land and water) in 2018. Forest gains and losses were recorded for 2000–2010 and 2010–2018.

Figure I.
FRA 2020 RSS global distribution of 400 000 samples using a stratified sampling design and single hexagon plot with 1 ha square centroid



Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties. Final boundary between the Republic of Sudan and the Republic of South Sudan has not yet been determined.

Sources: FAO, 2022. FRA 2020 Remote Sensing Survey. FAO Forestry Paper No. 186. Rome. United Nations Geospatial, 2020. Map geodata [shapefiles]. New York, USA, United Nations.

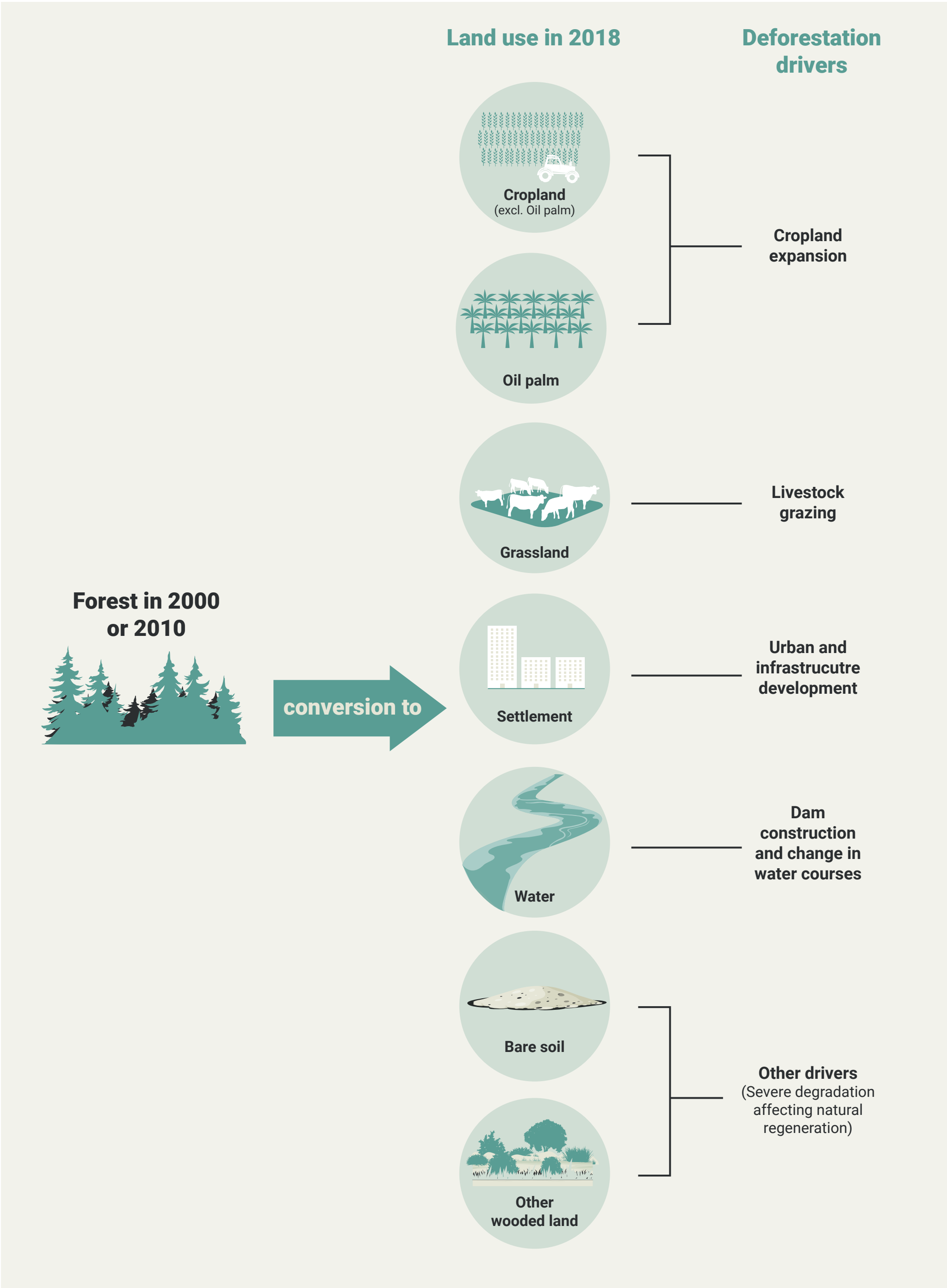
Notes: The darker areas show a higher density of samples (mainly in forest loss hotspots) than the lighter areas.

Figure II.
Illustrated example of variables collected during the FRA 2020 RSS for sample centroids and hexagons

Source: FAO, 2022. FRA 2020 Remote Sensing Survey. FAO Forestry Paper No. 186. Rome.

When assessing deforestation drivers, only the information collected on the one ha centroid was used. Each sample where forest was converted into another land use in 2000–2010 or 2010–2018 was assigned a deforestation driver class considering the land use class in 2018 (Figure 1). FAO defines deforestation as "the conversion of forest to other land use independently whether human-induced or not" (FAO, 2018a).

Figure 1.
Main forest land use conversion types and deforestation drivers identified in FRA 2020 RSS



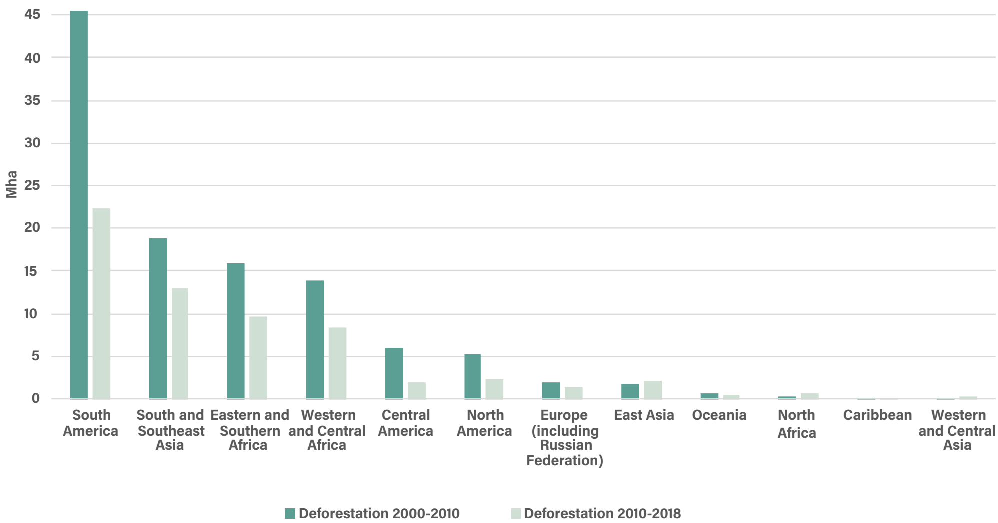
2.2 Key FRA 2020 RSS findings on deforestation

FRA 2020 RSS provided estimates on forest and other land use changes at global, regional (UN regions; Asia, Africa, Europe, North America, Oceania and South America – Annex 1), subregional and ecological zone level for the periods 2000–2010 and 2010–2018. In addition, the survey characterized the direct drivers of deforestation and identified the most threatened forest ecological zones.

The survey confirmed a slowdown in the global deforestation trend. It showed that annual deforestation declined by almost 30 percent during the period 2010–2018, compared to the period 2000–2010, from 11 Mha/year to 7.8 Mha/year.

However, the findings confirmed that there is no room for complacency, as high deforestation rates were still observed in South America, followed by Africa and Asia (Figure 2), while the vast majority of deforestation took place in tropical biomes.

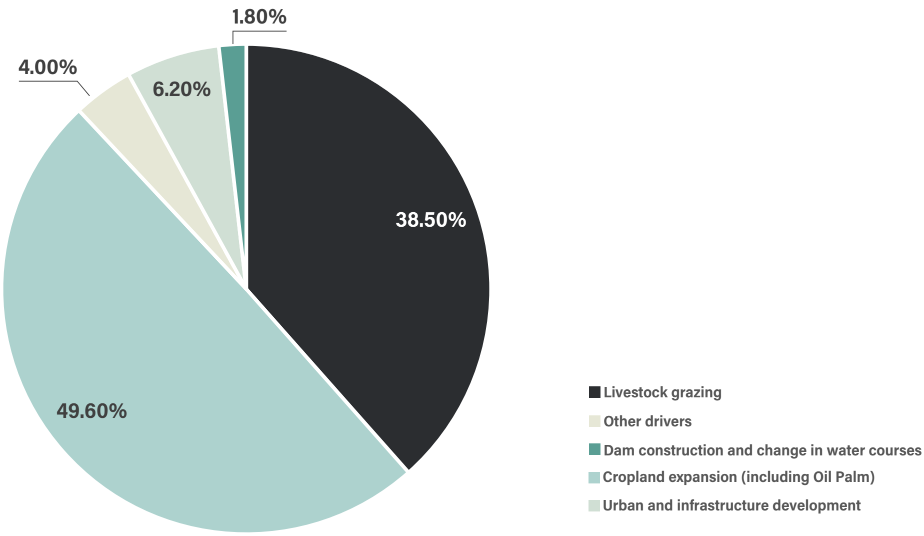
Figure 2.
Subregional deforestation trends 2000–2010 and 2010–2018 (Mha)



Source: FAO, 2022. FRA 2020 Remote Sensing Survey. Forestry Paper No. 186. Rome.

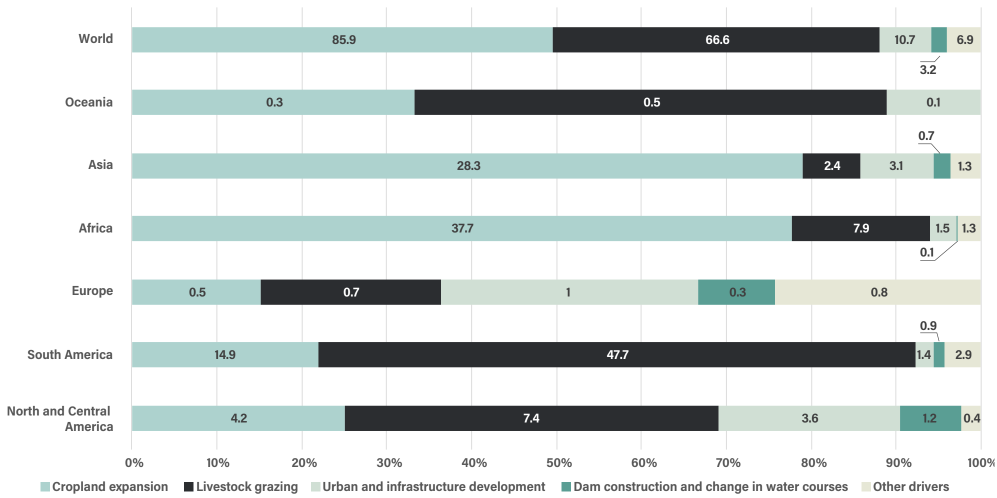
Overall, agricultural expansion was responsible for almost 90 percent of deforestation worldwide in 2000–2018. Cropland expansion (including oil palm cultivation) was the main driver, causing almost 50 percent of global deforestation, followed by livestock grazing, which accounted for 38.5 percent (Figure 3). During the period 2000–2018, the expansion of oil palm cultivation alone caused seven percent of all deforestation globally. The importance of cropland expansion or livestock grazing varied between continents (Figure 4). While cropland expansion was the predominant driver in Asia (79 percent of deforestation) and Africa (78 percent), in the Americas and Oceania, livestock expansion was the main driver.

Figure 3.
Global causes of deforestation in 2000-2018



Source: Adapted from FAO, 2022. FRA 2020 Remote Sensing Survey. FAO Forestry Paper No. 186. Rome

Figure 4.
Regional differences in deforestation drivers in 2000–2018, in percent (below the chart) and Mha (on the bars)



Source: Adapted from FAO, 2022. FRA 2020 Remote Sensing Survey. FAO Forestry Paper No. 186. Rome.

3 Pilot methodology for assessing the share of large-scale and small-scale farming as deforestation drivers

3.1 Defining farming categories for the study

The initial objective of the present study was to deepen the analysis conducted during the FRA 2020 RSS and update and complement the findings of studies published by Hosonuma *et al.* (2012) and Curtis *et al.* (2018). These authors (and others) have used specific terms to distinguish different categories of agricultural drivers of deforestation.

Hosonuma *et al.* (2012) adopted, along with other deforestation drivers, two categories of direct drivers linked to agriculture:

- "Agriculture (commercial): forest clearing for cropland, pasture and tree plantations, for both international and domestic markets, usually large to medium scale."
- "Agriculture (subsistence): forest clearing for subsistence agriculture, includes both permanent subsistence and shifting cultivation, usually by (local) smallholders."

Curtis *et al.* (2018) instead defined drivers of tree cover loss, including "deforestation through permanent land use change for commodity production (notably agriculture)"and "shifting agriculture or forestry".

Starting from previous studies, the initial approach was to study the share of deforestation driven by "commercial" or "subsistence" agriculture. However, it appeared that this terminology was not the most appropriate, as crop production and livestock breeding are, in essence, business activities, and therefore all farmers undertake some sort of commercial activity.

Furthermore, the option to separate categories such as industrial or corporate farming from family farming was also discarded considering that the definition of family farming includes criteria that cannot be observed through a remote sensing-based approach, and additional socio-economic information would be required to ensure correct classification according to these categories.

For this study, we use the categories of "small-scale farming" and "large-scale farming" which were both adapted to the applied remote sensing-based methodology and are relevant in terms of informing decision-making on halting deforestation. The categories were defined as follows:

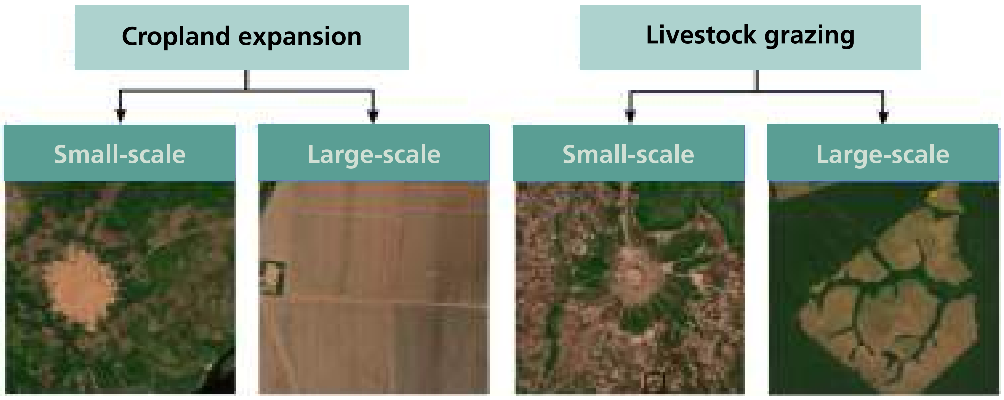
Small-scale farming – agricultural activities that apply non-industrial methods and low technology production processes, over limited areas, and for which the labour force is the main production investment.

Large-scale farming – agricultural activities that apply industrial and medium-to-high technology production processes, extend over large areas and are likely to involve significant capital investment on machinery or infrastructure.

Unlike some other authors (for example, Lowder, Sánchez and Bertini, 2021), we did not set farm size thresholds to separate small-scale from large-scale farming, mainly because we did not have access to systematic information on farm boundaries and ownership. In addition, setting such a threshold is not straightforward as deforestation in a specific area can be driven simultaneously by several farms. Neither did we use the definition proposed by FAO for identifying "small-scale food producers" (FAO, 2018b) as it is not suited to remote sensing-based methodologies.

We divided the two main types of agricultural deforestation drivers (cropland expansion and livestock grazing) into four subclasses (each with large-scale and small-scale components) and accounted for their global occurrence (Figure 5).

Figure 5.
The driver categories "Cropland expansion" and "Livestock grazing" with their subclasses small- and large-scale farming, including examples



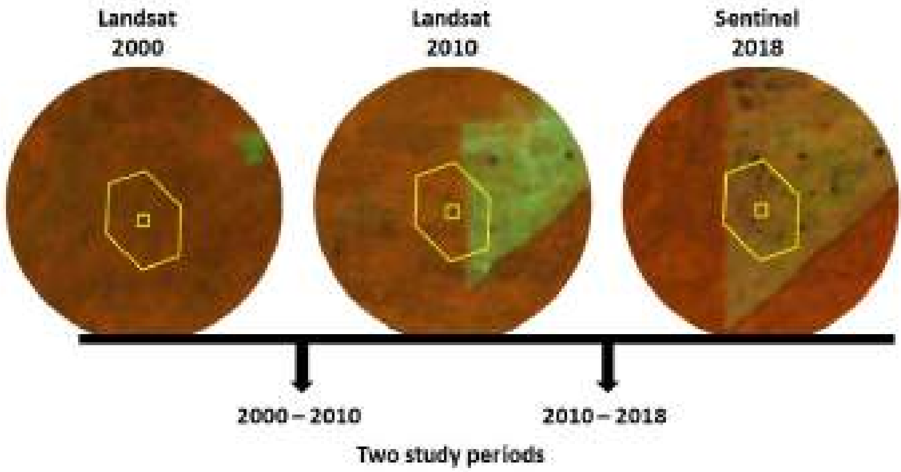
Source: Collect Earth Online, MapBox Imagery.

3.2 Samples and remote sensing data

The analysis was conducted on all FRA 2020 RSS samples where deforestation due to agriculture (that is, cropland expansion or livestock grazing) had been observed in 2000–2010 or 2010–2018. In total, 35 522 samples (15 109 samples with forest conversion to cropland and 20 413 samples to livestock), mostly from the tropics and subtropics (only 111 samples accounting for 0.3 percent of the samples were from temperate and boreal climatic domains), showed conversion from forest to agriculture use in one of the study periods (see Annex 2). The samples where deforestation was due to conversion to oil palm plantation were not re-interpreted during this pilot study, as the geospatial criteria applied in the original RSS study to classify oil palm land use considered only large-scale oil palm plantations (meaning that small-scale oil palm farming was classified as "other cropland") and were aligned to the criteria used in this pilot study for "large-scale farming". Therefore all samples classified as oil palm in FRA 2020 RSS could be considered as "large-scale farming" for the present study.

For each sample, the time series of satellite images collected at years 2000, 2010 and 2018 in the FRA 2020 RSS (Figure 6) were analyzed to determine the subclass of deforestation driver (small-scale or large-scale farming). Additional satellite images from high-resolution sensors (MapBox, Bingmaps and Planet Norway's International Climate and Forest Initiative (NICFI) time series from 2016 to 2018) were also used to support the analysis and provide complementary, more detailed information. Planet, Landsat and Sentinel datasets were provided in both true colour and false colour composites.

Figure 6.
Time series of satellite images (Landsat and Sentinel) used for the study



3.3 Defining observable spatial characteristics to assess agriculture-driven deforestation

3.3.1 Criteria for small-scale and large-scale farming

Satellite remote sensing is an invaluable source of information for global and regional studies as well as supplying a comprehensive and consistent representation of the Earth's surface. However, there are a number of limitations linked to use of these data for assessing agricultural practices or features of farming systems. This represents a challenge when describing land use changes across the world in the absence of globally available, auxiliary data layers such as cadastral data which could offer additional information to support interpretation of the images. Despite these limitations, spatial characteristics derived from satellite images can serve as indicators or proxies for assessing agricultural practices and differentiating between large-scale or small-scale farming.

In order to carry out an objective and comprehensive analysis for assessing agriculture-driven deforestation, we defined common characteristics (or criteria) that allow separation of small-scale and large-scale farming in the context of deforestation in Africa, Asia, Central and North

America and South America which were the regions where sufficient numbers of samples were available.

The criteria applied for separation of large-scale and small-scale activities included: i) landscape context and fragmentation; ii) speed of clearing iii) field size (FAO, 2017); iv) field boundaries; v) field shape; vi) field pattern; and vii) presence of infrastructure. All those criteria need to be analyzed collectively to achieve an understanding of the farming scale.

Other potential criteria, such as crop type, were not considered as, apart from particular crops such as oil palm, they cannot be determined easily without further *in situ* data and field knowledge.

3.3.2 Landscape context and fragmentation

Understanding the general context in which deforestation takes place is an important step towards interpreting specific characteristics at field level. This means that interpreters should use their knowledge about local processes as well as reliable auxiliary sources of information to discern the dominant patterns of land use around each sample they need to validate. They should also observe the landscape around the selected point of interpretation, for example, assessing if small-scale agriculture is dominant or if the presence of roads and infrastructure in the surrounding landscape infer larger scale agriculture that is well connected to markets or larger population centres, increasing the potential to produce for resale. This "landscape level observation" is key for ensuring accurate interpretation of more local characteristics, at field level (Ickowitz *et al*., 2015).

Landscape fragmentation (fragmented landscape vs. concentrated activities and mosaics (Figure 7) can also provide information on the nature of the agricultural activities. For example, shifting cultivation such as slash-and-burn agriculture is characterized by a mosaic of crops and forest at different successional vegetation stages (mature, young forest, regrowth). The presence of burning can also provide information on the type of agricultural practices. On the other hand, the presence of a highly artificial landscape can indicate a context of large-scale farming (Figure 8).

Figure 7.
Example of fragmented landscape showing small-scale agricultural activities in Angola

Source: Collect Earth Online, MapBox Imagery.

Figure 8.
Example of agro-industrial landscape showing large-scale agriculture activities in Zambia

Source: Collect Earth Online, MapBox Imagery.

For livestock grazing, soil erosion and compaction were also considered as good indicators to identify grazing intensity. This was assessed through the observation of bare soil, traces of trampling or absence of grass regrowth in the pasture area (Figure 9).

Figure 9.
Example of soil erosion and compaction due to livestock grazing in Brazil

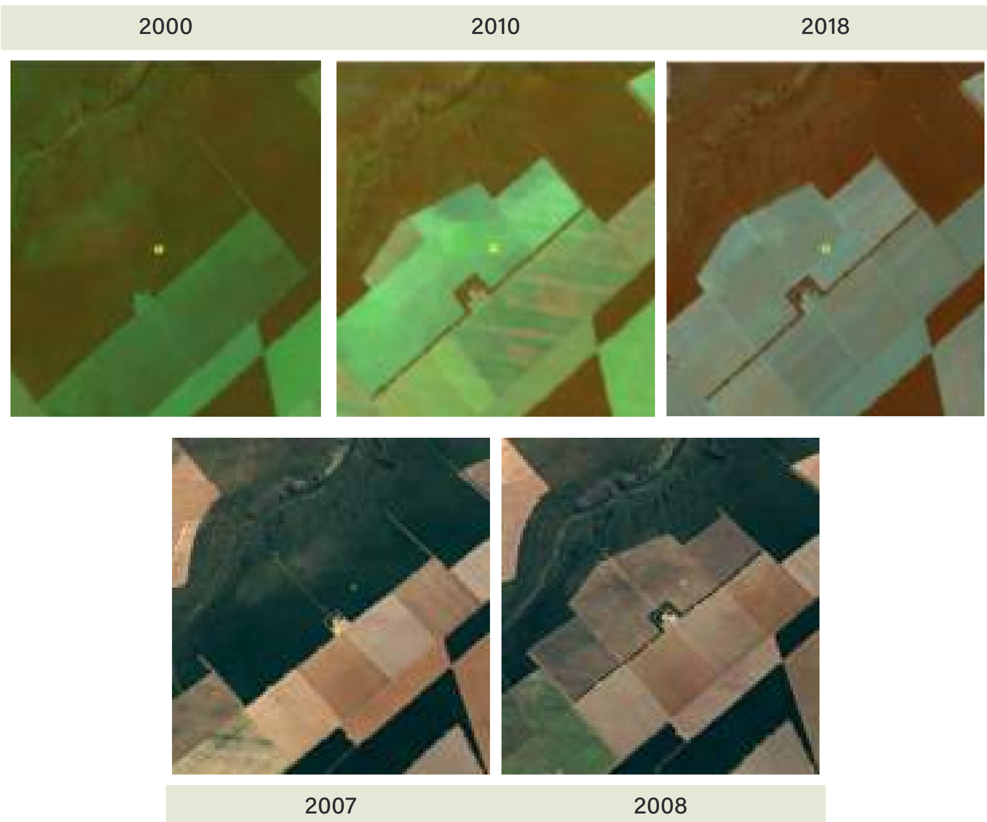
Source: Collect Earth Online, MapBox Imagery.

3.3.3 Speed of forest clearing

The rate of deforestation in a given area depends on the capacity of the land owner or land user to change the land use. Time and potential use of machinery to proceed to the removal of forest and replacement by crops or grassland represent an investment, both in terms of capital and direct labour force. Therefore, the speed of the forest conversion to a single farming unit (area cleared in a limited time, such as in one year, to establish or expand the farm) is a good indicator of the scale of the related investment.

This indicator is based on multi-temporal analysis of the imagery available both from the Landsat and Sentinel CEO Dashboard for 2000, 2010 and 2018, as well as Google Earth for intermediary dates. It was considered that large and continuous deforestation in a short time period were often associated with large-scale farming due to related large investment (Figure 10). However, large deforested areas in a short period with a high level of fragmentation (many contiguous small plots cleared) often indicate small-scale agricultural activities involving many small-scale stakeholders (Figure 11).

Figure 10.
Example of large deforested area happening in a short period (one year), associated with large-scale agriculture in Brazil



Note: On top CEO dashboard Landsat composite imagery right 2000, center 2010 and left 2018; below Landsat image from Google Earth 31/12/2007 and 31/12/2008. The squares represent one-hectare sample plots.

Source: Collect Earth Online, Google Earth.

Figure 11.
Example of a large deforested area happening over an 18-year period (images from 2004, 2010 and 2019), associated with small-scale agriculture in Madagascar

Note: The squares represent one-hectare sample plots.
Source: Google Earth.

3.3.4 Field size

The average area of a single field can be an indicator of the scale of agricultural activity. However, it should be noted that the size depends on the crop or livestock system. For example, to be considered as large-scale farming, the field size will be smaller for market gardening than for cereals. Examples of different field sizes are presented in Figure 12.

The field size is correlated to the investment scale, as larger parcels and the subsequent large deforestation actions require considerable capital and labour investment. In the case of livestock grazing, the size of a field is also closely related to the number of animals, the ratio being specific to each livestock system and ecological zone.

Figure 12.
Examples of different field sizes: a large parcel in Bolivia (Plurinational State of) (left) and small parcels with different crop and growing stages in Cambodia (right)

Note: The squares represent one-hectare sample plots.
Source: Collect Earth Online, MapBox Imagery.

3.3.5 Field boundaries

The type of parcel boundary (clearly defined or not) is often a good indicator of the level of management and scale of the farm. Field parcels can be separated by fences, wooded hedgerows, paths, roads and ditches while in other cases no clear edge of the parcel is visible. This can be a good indicator of small-scale or large-scale farming and indicates the use of machinery to support the activity. Different boundary types are given as examples in Figure 13.

Figure 13.
Examples of different types of field boundaries: rows of small trees and paths separating agricultural parcels in Brazil (left) and indistinct boundaries of agricultural parcels bordered by forest in Brazil (right)

Note: The squares represent one-hectare sample plots.
Source: Collect Earth Online, MapBox Imagery.

3.3.6 Field shape

Many different field shapes can be encountered, including irregular or regular shapes, such as circular fields, grids and patchwork fields. These generally provide a good indicator of the agricultural practices, farming system and scale. Regular field shapes such as circles, rectangles or squares are usually adopted when machinery is used for planting, water supply, treatments or harvesting activities. In particular, they can give an indication on irrigation practices, for example the circular pattern linked to centre pivot irrigation systems (Carlson, 1989). Examples of different field shapes are illustrated in Figure 14.

Figure 14.
Different field shapes: circular agricultural parcels in Chile (upper left) and regular gridded agricultural parcels in Paraguay (upper right); irregular (patchy) agricultural parcels in Zimbabwe (bottom right) and in Angola (bottom left)

Note: The squares represent one-hectare sample plots.
Source: Collect Earth Online, MapBox Imagery

3.3.7 Field patterns

Field patterns (spatial arrangement within the field such as rows, heterogeneity and complexity) offer another efficient indicator of farming practices, such as cropping practices (for example, single cropping vs. multiple cropping agroforestry or tree cropping), crop types, as well as farming management practices including harvest and post-harvest techniques (for example, burning or mechanical harvesting), irrigation (for example, rainfed, flood, drip or spray irrigation) and soil preparation practices such as soil tillage (Bégué *et al*., 2018; Mahlayeye, Darvishzadeh and Nelson, 2022). Examples of different field patterns are given in Figure 15.

Figure 15.
Examples of field patterns: terraces in DRC (upper left) and China (upper right); palm oil plantation in Indonesia (bottom left) and mechanized planting in Bolivia (Plurinational State of) (bottom right)

Note: The squares represent one-hectare sample plots.
Source: Collect Earth Online, MapBox Imagery.

3.3.8 Presence of infrastructure

The presence of infrastructure can help determine if deforestation observed in a sample is due to large-scale or small-scale farming. The most common types of associated infrastructure are listed below.

a) ***Dwellings***. The presence of a single dwelling, multiple dwellings or their absence can serve as an indicator of the agricultural practices. Figure 16 presents, on the left, an example of large-scale farming activity in Brazil with many interconnected medium-sized parcels of grassland for raising cattle. The property includes a single cluster of buildings and forested areas to comply with national legislation. The second example, on the right, also in Brazil, shows a small access road and small dwellings. In this case, we can assume each farmer has access and works on an identical parcel, distributed equally among the bigger deforested area.

Figure 16.
Examples of agricultural parcels within their context (on landscape-level): connected parcels in Brazil most probably belonging to the same holding (left) and identical small parcels with several dwellings in Brazil (right)

Note: The squares represent the one-hectare sample plots.
Source: Collect Earth Online, MapBox Imagery.

b) **Farming infrastructure.** The presence or absence and type of infrastructure associated with farming such as agricultural buildings (for example, barns, warehouse, silos, stables and holding pens), greenhouses and irrigation facilities (for example, a hydropower station or water well) are other indicators of the scale of agricultural activities (an example is shown in Figure 17).

Figure 17.
Examples of infrastructure: large cattle pens, barns and silos in Latin America

Note: The square represents a one-hectare sample plot.
Source: Collect Earth Online, MapBox Imagery.

c) **Road network.** The type and intensity of the road network within and close to the studies area can also provide information on the farming scale (Figure 18).

Figure 18.
Road infrastructure in a livestock farm context in Paraguay

Note: The square represents a one-hectare sample plot.
Source: Google Earth Pro, Maxar Imagery.

d) **Water ponds.** Ponds holding water are often essential for grassland activities. Their size and number can indicate the level of investment (Figure 19).

Figure 19.
Presence of water-holding ponds in large-scale grassland in Colombia

Note: The square represents a one-hectare sample plot.
Source: Collect Earth Online, MapBox Imagery.

4 Results

4.1 Regional relevance of spatial characteristics distinguishing large-scale and small-scale farming

4.1.1 Background

The set of characteristics used for determining if deforestation was caused by large-scale or small-scale farming and their relevance in separating large-scale from large-scale agriculture, varied according to the new land use (cropland or grassland) and to the region. The main characteristics and criteria used to associate deforestation to small-scale or large-scale farming, per continent, are provided in Table 1, Table 2, Table 3 and Table 4 and explained below.

Note that, due to rounding, the numbers and percentages given in the text, tables and figures in this report may not add up to the total numbers indicated or to 100 percent.

4.1.2 Conversion of forests to cropland

All characteristics and criteria proposed in the methodology were useful in all regions to distinguish deforestation due to large-scale farming from deforestation involving small-scale crop farming.

The set of criteria proposed to identify large-scale vs small-scale crop farming was particularly relevant for cases observed in both **South America** and **North and Central America** (Table 1). In those regions, under large-scale crop farming, fields were mainly very large, had regular shapes, with clearly defined boundaries and were homogeneous (monocrop) and served with roads, while farm buildings were often visible. The speed of forest clearing was very fast for large-scale farming. In the case of small-scale crop farming, fields were mostly small or medium size and heterogeneous, while homesteads could be seen and the landscape was often more fragmented.

In **Africa**, observations on field patterns, infrastructure, as well as landscape context and fragmentation were more informative on the scale of crop farming than field size, boundaries and shape. Large-scale cropland tended to have fields with clearly defined boundaries, homogeneous patterns (monocropping) and buildings, while in small-scale cropping, fields often had vague boundaries and heterogeneity (multicropping) with the presence of paths and homesteads.

In **Asia**, almost all criteria were found to be relevant, except for field shape that was not always informative as regular plots were associated with both small- and large-scale cropland. In the case of oil palm plantations, the crop pattern was very specific and easily recognizable.

In all regions landscapes presenting mosaics of small fields of crops, fallow areas and forests at different stages were strong indicators of small-scale farming through shifting cultivation.

Table 1.
Relevance of spatial criteria to identify large-scale vs small-scale farming driving conversion of forest to cropland in South America, North and Central America, Africa and Asia using satellite imagery

Spatial criteria	South America	North and Central America	Africa	Asia
Landscape context and fragmentation	++	+++	++	++
Speed of forest clearing	+++	+++	+	++
Field size	+++	++	+	++
Field boundaries	+++	+++	++	++
Field shape	++	++	+	+
Field pattern	+++	+++	++	+++
Infrastructure	+++	+++	++	+++

Criteria relevancy: +++ high; ++ medium; + low; and 0 not significant/not observed

For the specific case of conversion of forest to oil palm plantations, spatial criteria characterizing large-scale farming, for all regions, included clearly defined field boundaries and homogeneous patterns (monocrop system with regular planting), as well as the presence of infrastructure such as roads and buildings (Table 2). This classification was performed during the initial work of the FRA 2020 RSS.

Table 2.
Relevance of spatial criteria to identify large-scale farming driving conversion of forest to oil palm in South America, North and Central America, Africa and Asia, using satellite imagery

Spatial criteria	South America	North and Central America	Africa	Asia
Landscape context and fragmentation	+++	+++	++	++
Speed of forest clearing	+++	+++	++	++
Field size	+++	+++	+++	+++
Field boundaries	++	++	++	++
Field shape	+	+	+	+
Field pattern	+++	+++	+++	+++
Infrastructure	+++	+++	++	+++

Criteria relevancy: +++ high; ++ medium; + low; and 0 not significant/not observed.

4.1.3 Conversion of forests to grassland

The differentiation between deforestation caused by large-scale and small-scale farming using Earth Observation imagery poses bigger challenges when forest conversion is to grassland, compared to forest conversion to cropland. The grassland area needed per animal unit depends on climatic conditions, soil type, vegetation, the kind of animal being raised and livestock management practices. At the same time, the types of land cover classified under the grassland category range from natural grassland with low yields or productivity to artificial or fertilized pasture. The level of intensification is usually connected to the productivity of the farm.

Both small-scale and large-scale livestock grazing activities can share similar spatial characteristics that are visible in satellite imagery. The main determinants are the parcel size and specific aspects of the context, as well as the speed of deforestation.

To differentiate large-scale livestock grazing from small scale livestock grazing, field characteristics (including size, shape and pattern) were strongly relevant in **South America** as well as in **North and Central America** regions. Large-scale livestock grazing often showed very large pastures, that were regularly shaped (often rectangular or square), with some remaining trees (Table 3). In those regions, livestock production systems even over 10 ha were often classified as small-scale because other criteria showed low levels of investment and technical sophistication. This was less the case in **Africa** and **Asia,** where livestock systems, especially for cattle ranching, sometimes extended over indistinct boundaries, making the concept of field or parcel less relevant for the analysis. In all regions, the presence of infrastructure, notably those directly related to livestock systems, including pens and stables, dwellings, and watering systems, was a very good indicator of large-scale farming, as well as the observation of soil erosion and compaction. The speed of clearing was also seen as a very relevant indicator in all regions, notably in South America as well as North and Central America regions where large-scale livestock rearing leads to rapid forest clearing while the rate of deforestation was relatively much slower in areas with small-scale livestock activities.

Table 3.
Relevance of spatial criteria to identify large-scale and small-scale farming driving conversion of forest to grassland in South America, North and Central America, Africa and Asia using satellite imagery

Spatial criteria	South America	North and Central America	Africa	Asia
Landscape context and fragmentation	++	++	+++	++
Speed of forest clearing	+++	+++	++	++
Field size	+++	++	++	++
Field boundaries	+++	++	+	+
Field shape	+++	+++	++	+
Field pattern	+++	+++	+	+
Infrastructure	+++	+++	++	++

Criteria relevancy: +++ high; ++ medium; + low; and 0 not significant or not observed.

4.2 Share of small-scale and large-scale farming as direct drivers of deforestation in 2000–2018

4.2.1 Analysis of deforestation linked to agriculture

The study results indicated that, worldwide, most of forest conversion to cropland and grassland in the period 2000–2018 occurred in the context of small-scale farming. The proportion of agriculture-driven deforestation associated to small-scale farming was 68 percent, equivalent to 103 Mha (Figure 20, Figure 21 and Table 4).

While small-scale farming was linked to most of the agriculture-driven deforestation in all regions, its share varied widely between regions, accounting for 97 percent of recent deforestation due to agriculture expansion in Africa (44 Mha), 65 percent in North and Central America (8 Mha), 59 percent in Asia (18 Mha) and 52 percent in South America (33 Mha) (Figure 24).

Figure 20.
Share (percent) of deforestation associated to small-scale and large-scale farming over the period 2000–2018, by region and globally

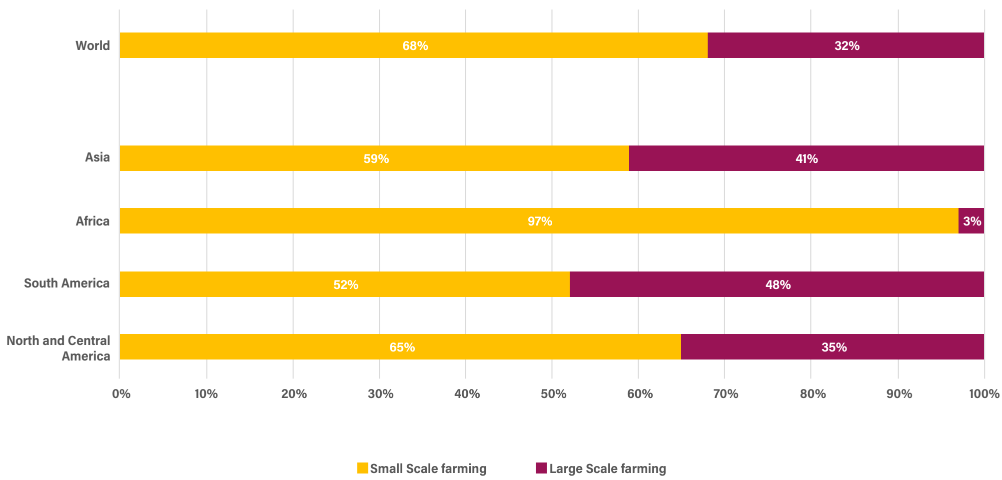


Figure 21.

Forest area converted to small-scale and large-scale farming over the period 2000–2018, by region and globally (Mha)

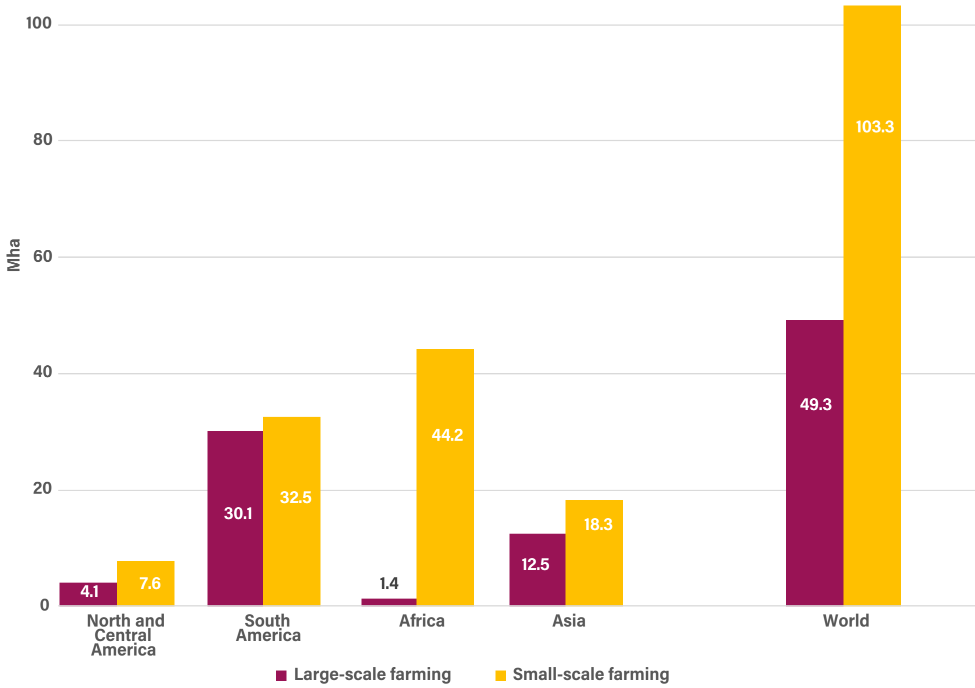


Table 4.

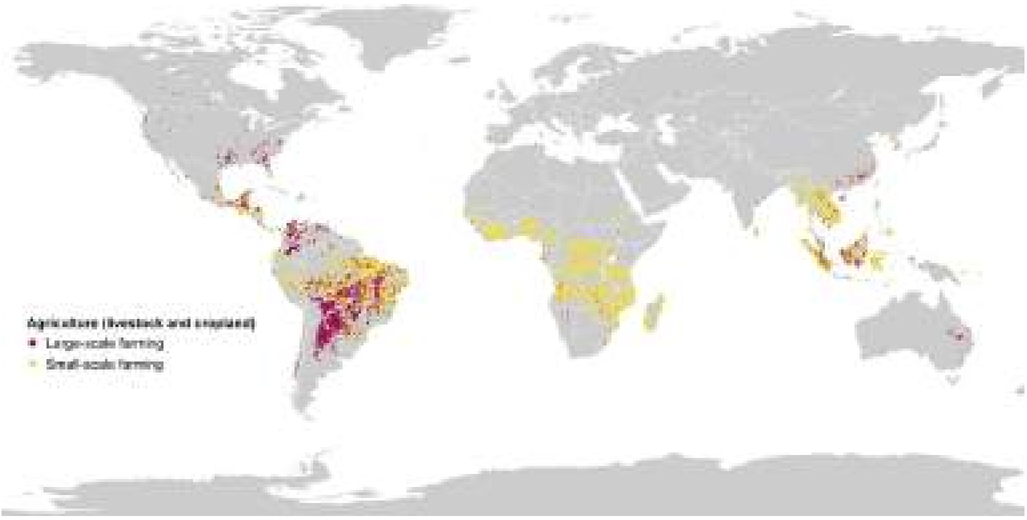
Forest areas (Mha and percent of total forest area converted to agriculture) converted to small-scale and large-scale farming over the period 2000–2018, by region and globally

Region	Forest area converted to large-scale farming		Forest area converted to small-scale farming		Total forest area converted to agriculture
	Mha	Percent	Mha	Percent	Mha
North and Central America	4.1	35%	7.6	65%	11.6
South America	30.1	48%	32.5	52%	62.6
Africa	1.4	3%	44.2	97%	45.6
Asia	12.5	41%	18.3	59%	30.8
World	49.3	32%	103.3	68%	152.6

Note: Europe and Oceania were not included in the table as the sample numbers were too small to derive statistically robust estimates.

Figure 22 shows where most of the deforestation linked to large-scale and small-scale farming was observed in the study. In Africa, small-scale farming was associated with most of the conversion of forest to agriculture. Deforestation due to large-scale farming was observed only in a few areas such as in the southern coast of Western Africa. In South America and in Asia, there were clear areas where large-scale farming was linked to deforestation such as in the Gran Chaco, and several parts of Southeast Asia, related to the main areas of palm oil production.

Figure 22.
Distribution of Remote Sensing Survey samples deforested to large-scale and small-scale farming between 2000 and 2018



Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties. Final boundary between the Republic of Sudan and the Republic of South Sudan has not yet been determined.

Note: The figure illustrates geographical distribution of deforested RSS samples classified according to the type of agricultural deforestation driver. The samples have been greatly enlarged, therefore the figures provide only a general indication of the main deforestation processes and patterns occurring in different areas rather than the precise location and extent of deforestation.

Source: United Nations Geospatial 2020. Map geodata [shapefiles]. New York, USA, United Nations, modified by the author.

4.2.2 Analysis of deforestation linked to cropland expansion

Globally, 71 percent of deforestation driven by cropland expansion in 2000–2018 was linked to small-scale farming, corresponding to 61 Mha while large-scale farming represented 29 percent (equivalent to 25 Mha), with large-scale oil palm plantations responsible for 13 percent (11 Mha) of this (Figure 23, Figure 24 and Table 5).

South America was the only region where large-scale cropping contributed to most of the deforestation for cropland expansion (76 percent, corresponding to 11 Mha). In the other regions, the conversion of forest to cropland was mainly linked to small-scale farming, accounting for 97 percent of deforestation for cropland expansion in Africa (37 Mha), 78 percent in North and Central America (3 Mha), and 58 percent in Asia (17 Mha). In Asia, large-scale oil palm plantations were notably responsible for 36 percent (more than 10 Mha) of the forest area deforested for cropland.

Figure 23.
Share (percent) of deforestation driven by cropland expansion linked to small-scale and large-scale farming over the period 2000–2018, by region and globally

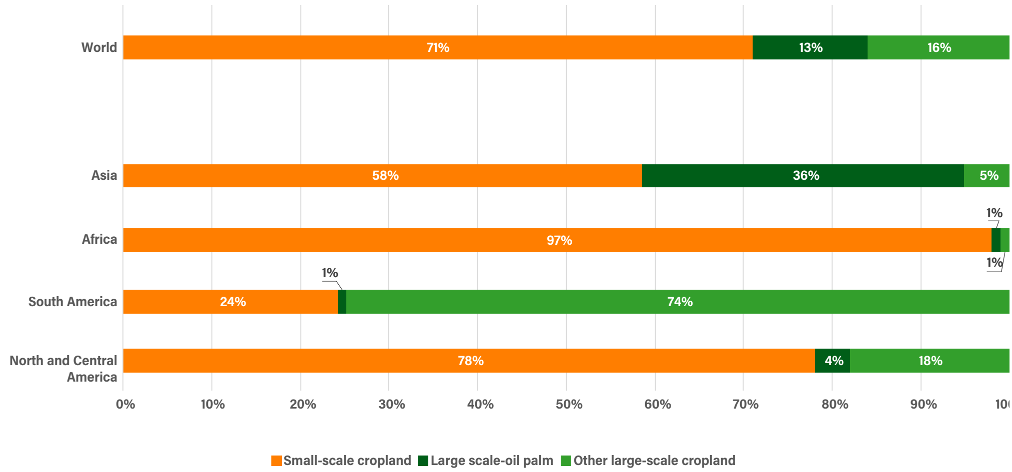


Figure 24.
Forest area (Mha) converted to small-scale and large-scale cropland (oil palm and other crops) over the period 2000–2018, by region and globally

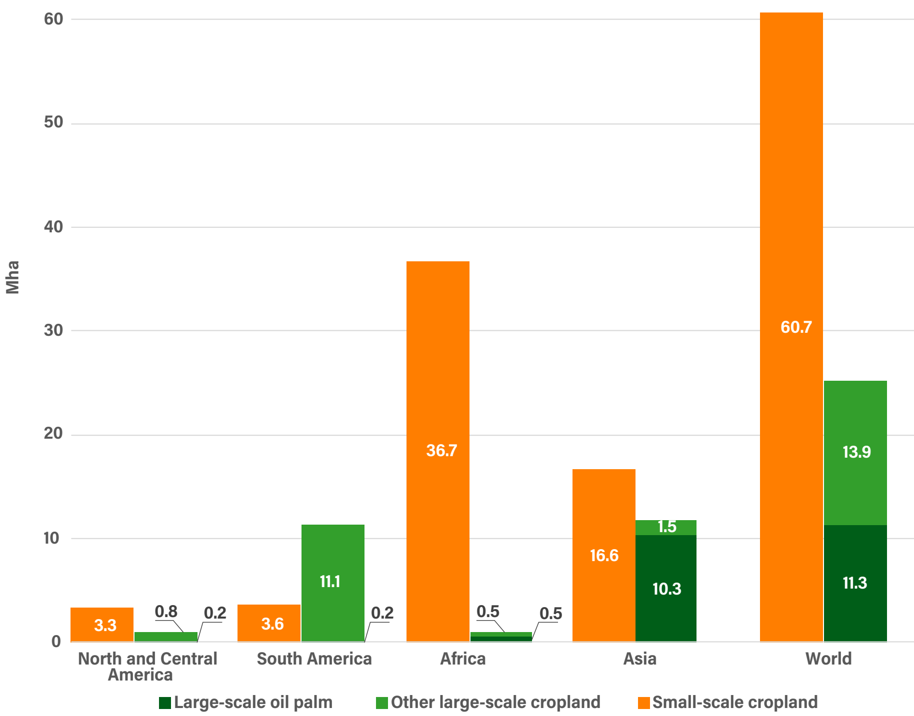


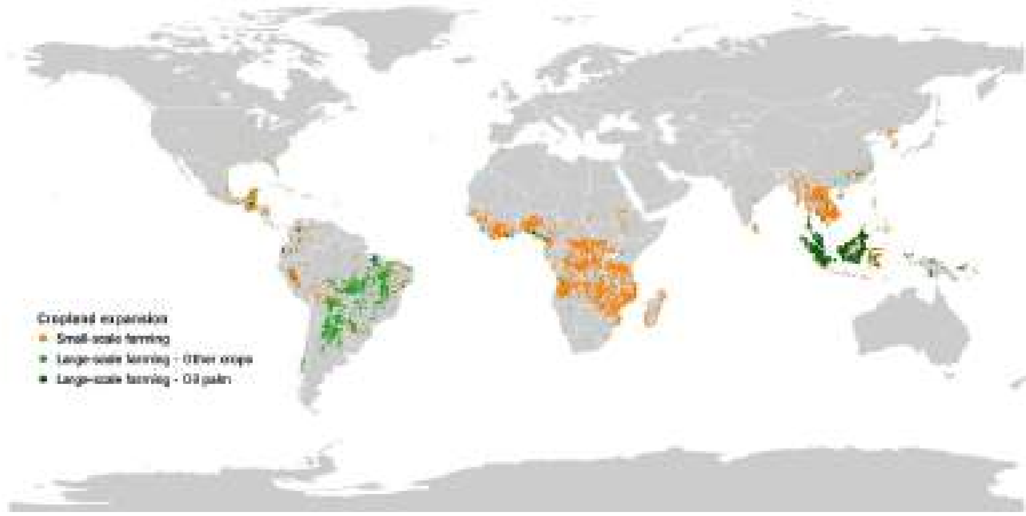
Table 5.
Forest areas (Mha and percent of total forest area converted to croplands) converted to small-scale and large-scale crop farming over the period 2000–2018, by region and globally

Region	Forest area converted to large-scale cropland						Forest area converted to small-scale cropland		Total forest area converted to cropland
	Large scale-oil palm		Other large-scale cropland		Total large - scale cropland				
	Mha	Percent	Mha	Percent	Mha	Percent	Mha	Percent	Mha
North and Central America	0.2	4%	0.8	18%	0.9	22%	3.3	78%	4.2
South America	0.2	1%	11.1	74%	11.3	76%	3.6	24%	14.9
Africa	0.5	1%	0.5	1%	1.0	3%	36.7	97%	37.7
Asia	10.3	36%	1.5	5%	11.8	42%	16.6	58%	28.3
World	11.3	13%	13.9	16%	25.3	29%	60.7	71%	85.9

Note: Europe and Oceania are not included in the table as the sample numbers were too small to be statistically significant.

Figure 25 shows the spatial distribution pattern of deforestation caused by cropland expansion linked to large-scale or small-scale farming. Throughout Africa and Central America, forest conversion to croplands was mainly led by small-scale farming, while large-scale cropping was observed in most of South America. In Southeast Asia deforestation linked to both small-scale and large-scale cropping was evident with a few extended deforestation hotspots linked to large-scale oil palm plantations.

Figure 25.
Distribution of Remote Sensing Survey samples deforested to large-scale and small-scale crop farming between 2000 and 2018



Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties. Final boundary between the Republic of Sudan and the Republic of South Sudan has not yet been determined.

Note: The figure illustrates geographical distribution of deforested RSS samples classified according to the type of agricultural deforestation driver. The samples have been greatly enlarged, therefore the figures provide only a general indication of the main deforestation processes and patterns occurring in different areas rather than the precise location and extent of deforestation.

Source: United Nations Geospatial 2020. Map geodata [shapefiles]. New York, USA, United Nations, modified by the author.

4.2.3 Analysis of deforestation linked to livestock grazing

The study found that 64 percent (43 Mha) of deforestation due to livestock grazing was related to small-scale farming in 2000–2018, while large-scale livestock grazing accounted for 36 percent (24 Mha) of forest conversion to grassland for livestock production (Figure 26, Figure 27 and Table 6).

The conversion of forest to grassland due to small-scale livestock grazing was prevalent in all regions. The American continent had the strongest linkage between large-scale livestock grazing and deforestation, accounting for 42 percent (3 Mha) and 40 percent (19 Mha) of total deforestation due to livestock grazing in North and Central America, and South America regions, respectively. In contrast, the share of deforestation due to livestock grazing by large-scale farming was only five percent in Africa (0.4 Mha) and 30 percent in Asia (0.7 Mha). However, these results need to be taken with caution as the distinction between small-scale and large-scale farming for livestock production was challenging in some regions, particularly in Africa.

Figure 26.
Relative share (percent) of deforestation driven by small-scale and large-scale livestock grazing over the period 2000–2028, by region and globally

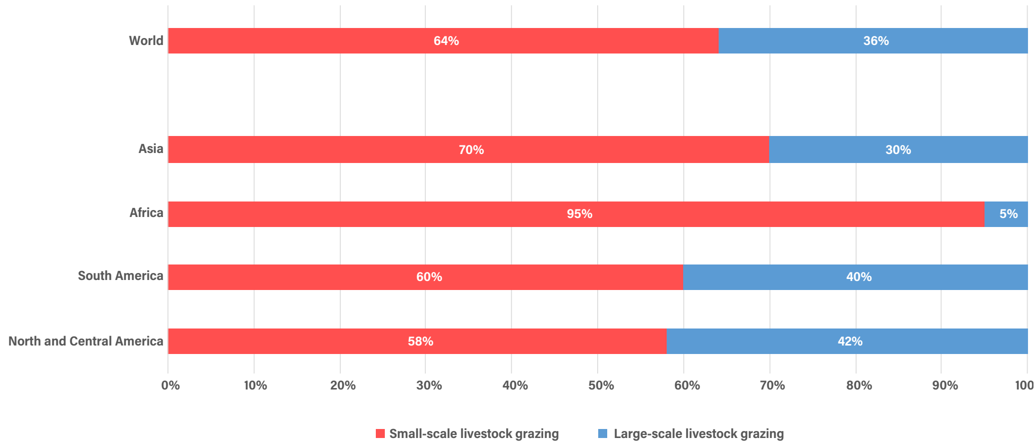


Figure 27.
Forest area (Mha) converted to grassland for small-scale and large-scale livestock production over the period 2000–2018, by region and globally

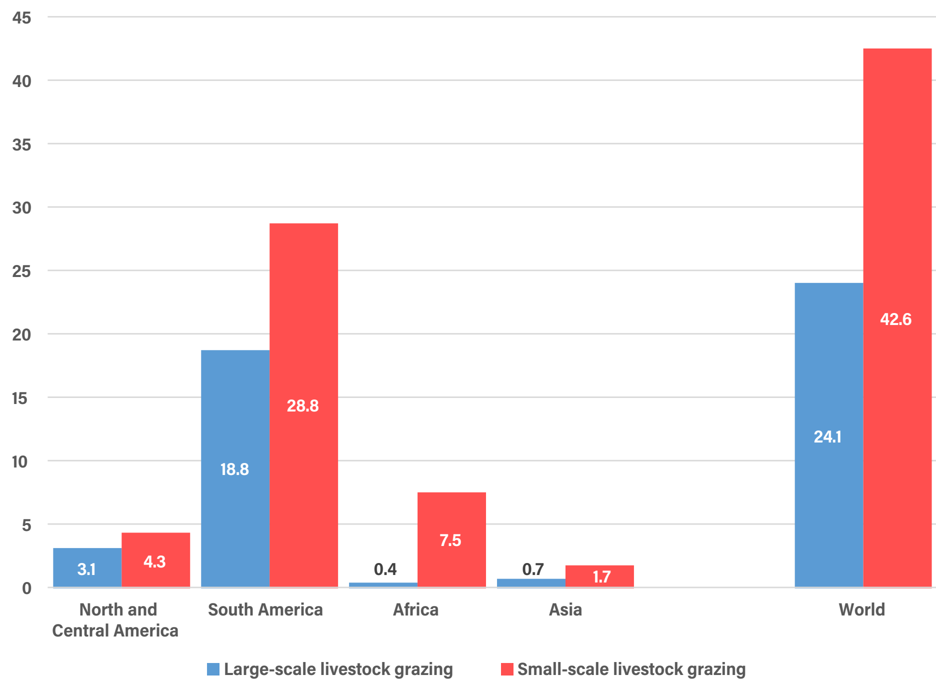


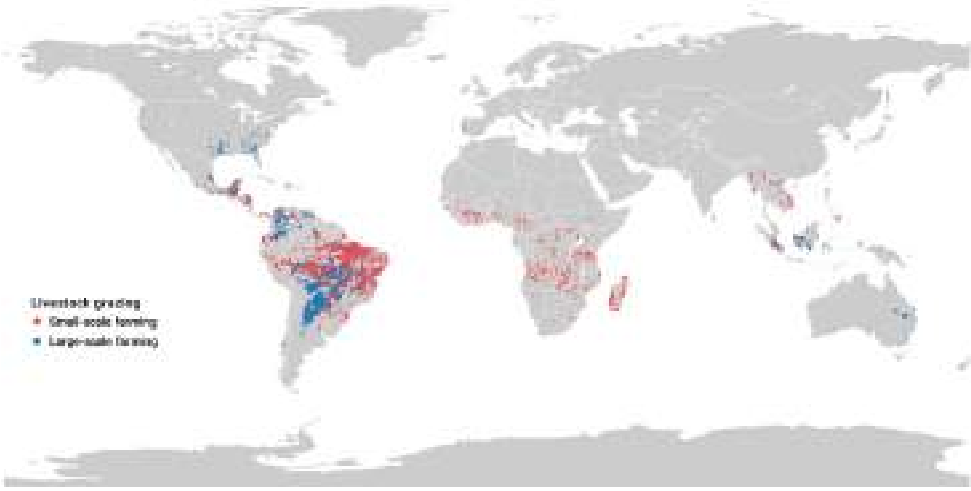
Table 6.
Forest areas (Mha and percent of the total forest area converted to grassland for livestock production) converted to small-scale and large-scale livestock grazing over the period 2000–2018, by region and globally

Region	Forest area converted to large-scale livestock grazing systems		Forest area converted to small-scale livestock grazing systems		Total forest area converted to livestock grazing systems
	Mha	Percent	Mha	Percent	Mha
North and Central America	3.1	42%	4.3	58%	7.4
South America	18.8	40%	28.8	60%	47.7
Africa	0.4	5%	7.5	95%	7.9
Asia	0.7	30%	1.7	70%	2.4
World	24.1	36%	42.6	64%	66.6

Note: Europe and Oceania are not included in the table as the sample numbers were too small to be statistically significant.

The processes are spatially illustrated in the Figure 28 which shows where forest losses were attributed to large-scale livestock grazing, such as in the area of the Gran Chaco, Bolivia (Plurinational State of) and Brazilian Cerrado in South America and in Colombia compared to where they are mainly linked to small-scale farming, such as in Africa.

Figure 28.
Distribution of Remote Sensing Survey samples deforested to large-scale and small-scale livestock grazing between 2000 and 2018



Dotted line represents approximately the Line of Control in Jammu and Kashmir agreed upon by India and Pakistan. The final status of Jammu and Kashmir has not yet been agreed upon by the parties. Final boundary between the Republic of Sudan and the Republic of South Sudan has not yet been determined.

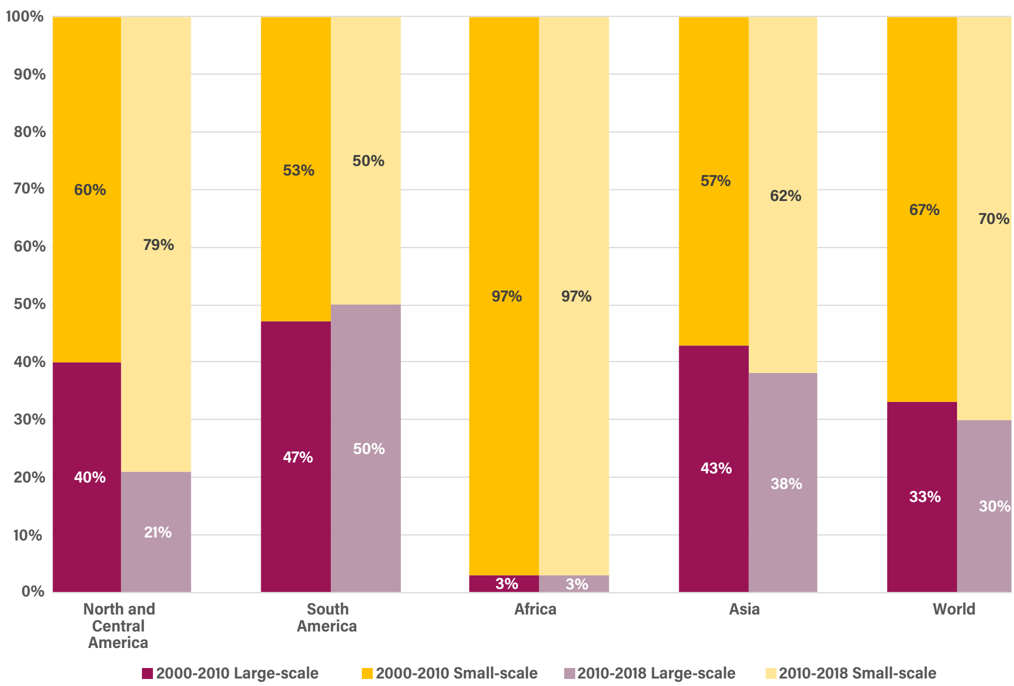
Note: The figure illustrates geographical distribution of deforested RSS samples classified according to the type of agricultural deforestation driver. The samples have been greatly enlarged, therefore the figures provide only a general indication of the main deforestation processes and patterns occurring in different areas rather than the precise location and extent of deforestation.

Source: United Nations Geospatial 2020, Map geodata [shapefiles]. New York, USA, United Nations, modified by the author.

4.2.4 Trend analysis

There were no significant differences at both global and regional levels when comparing the proportion of deforestation caused by large-scale and small-scale farming in the two study periods of 2000–2010 and 2010–2018 (Figure 29) with the exception of North and Central America, where the proportion of small-scale farming as a deforestation driver increased from 60 percent in 2000–2010 to 79 percent in 2010–2018.

Figure 29.
Shares (percent) of agriculture-driven deforestation associated to large-scale and small-scale farming over the periods 2000–2010 and 2010–2018, by region and globally



Note: Europe and Oceania are not included in the chart as the sample numbers were too small to be statistically significant.

5 Discussion, conclusions and recommendations

5.1 Discussion

The objectives of the study were to produce new information on agricultural drivers of deforestation through deepened FRA 2020 RSS analysis. This was achieved through development of a methodology for classifying agricultural activities into small-scale or large-scale categories using satellite imagery. Spatial characteristics observed on high-to-medium resolution satellite imagery (below ten metres resolution) offers useful information which, analyzed jointly with auxiliary information or local knowledge, allowed the categorization of remote sensing samples with a relatively high level of confidence. Small-scale and large-scale farming can be strongly associated to field size, patterns, boundaries as well as the presence of infrastructure, landscape fragmentation and the speed of forest clearing.

To provide further information on the farming type, other data related to the characteristics of land holdings would be needed to complement the satellite image analysis. For example, the size of the farm under single ownership would be useful to further link the deforested land to a holding which would create a more holistic and refined picture of agricultural activities. Unfortunately, these data (that is, cadastral or georeferenced census data) do not exist on a global or even continental level. Consequently, the methodology presented relied strongly on the analytic capacity of the photo-interpreters as well as on their field knowledge and on the application of auxiliary information.

The methodology presented here was based on clear criteria which were easy to implement. However, division of some specific activities into the chosen categories remained problematic. Differentiation between small-scale and large-scale livestock grazing systems was difficult in some regions, particularly in Africa, where this categorization might not be efficient or even meaningful. Different categories or subclasses and criteria would be required to analyze further livestock practices leading to deforestation in those regions. There was also high variability in the spatial characteristics of agricultural activities within regions, which calls for further fine-tuning criteria at the subregional level when interpreting the samples.

It was challenging to compare the results of the present study to other deforestation driver studies, such as Hosonuma *et al.* (2012) or Curtis *et al.* (2018), because of the use of different methodologies, categories, study periods and regional breakdowns. While data used in Hosonuma *et al.* were derived from national sources, the actual analysis was based on continental-level proxies. In addition, the comparison of what the authors defined as "commercial agriculture" with the definition used in this study for "large-scale farming", was not straightforward as many areas classified by Hosonuma *et al.* as commercial agriculture could also include small-scale farming according to the methodology in the current study. Similarly, the terms "subsistence agriculture" and "small-scale agriculture" were not directly comparable.

Curtis *et al.* (2018) classified drivers of global forest loss, from 2001 to 2015, by various factors, including commodity production, forestry, shifting agriculture, wildfire and urbanization, using high-resolution satellite imagery. They concluded that 27 percent of global forest loss was due to permanent land use change for the production of commodities such as beef, soy, palm, oil palm and mining, while 24 percent was linked to shifting to agriculture. There were differences in forest definition and scope meaning that their results cannot be compared directly with the current study. The Curtis *et al.* study covered all types of tree cover loss while the current study focused on deforestation as defined by FAO, including tree cover and land use. However, there were some similar conclusions, notably the dominance of small-scale and shifting cultivation in Africa and Central America, as well as the highest share of forest loss through commodity driven or large-scale farming in South America and in Asia in oil palm production areas. The main differences observed between the current and Curtis *et al*. results, particularly in Asia and South America might be explained by the fact that small-scale farming in the current study could be commodity-oriented, for example, livestock farms spanning over relatively large areas but with insignificant capital investment and low levels of technical sophistication.

Finally, the results of Austin *et al.* (2017) can be noted for their analysis of the size of forest clearings across regions for the period 2000–2012, working with four categories: small clearings (less than 10 ha for one year of observation), medium clearings (10 ha—100 ha), large clearings (100 ha–1000 ha) and very large clearings (more than 1000 ha). They found that globally, the proportion of forest loss comprised of small clearings fluctuated between 53 percent to 65 percent of the total loss due to clearings over the period. While the methodology and outcomes were different from the current study, this global ratio indicated that forest loss was mainly due to small-scale activities, which is in agreement with the current findings. Furthermore, the specific regional patterns they revealed were similar to the observations in the current study for Africa, with a strong dominance of forest loss due to small-scale activities (for example, 90 percent to 93 percent in Western and Central Africa), and Asia, with 67 percent of small forest clearings, while small-scale clearings represented 42 percent of forest loss in South America.

5.2 Conclusions

5.2.1 Methodology relevance and replicability

The methodology used in this study proved to be efficient, easy to implement and produced robust information about the share of deforestation linked to large-scale and small-scale farming. The set of spatial characteristics used to distinguish the proposed four classes (small-scale cropland expansion, large-scale cropland expansion, small-scale livestock grazing and large-scale livestock grazing) worked for all the regions as they were flexible enough to be further adjusted to reflect the regional specificities of farming systems.

The results also demonstrated the value of combining field size with other parameters to distinguish small-scale from large-scale farming, field size not being sufficient for classification on its own.

The margins of errors were relatively small at the global level accounting for around three percent at a 95 percent confidence level for each of the large-scale and small-scale farming classes, and four percent to five percent when there were divided into livestock and cropland subclasses (Annex 3, Table 9). At the regional level the statistical precision was also very acceptable.

The visual interpretation approach adopted in this study, while being relatively time consuming, is easily replicable with different high-resolution imagery. The subjectivity of interpretation in the results was analysed by reinterpreting approximately 55 percent of the samples by different photo-interpreters. The comparison showed a high level (90 percent) of agreement.

5.2.2 Relevance of results

The distinction between large-scale and small-scale farming provides important information for policymaking and design of practical interventions. Policy tools may differ significantly according to the level of private investment and production systems associated with deforestation. This study informs the reader about the type of farming contributing to conversion of forest to agricultural land in different regions. It also demonstrated how indirect spatial indicators that relate to scale of investment, technology level and access to infrastructure, allow attribution of land use changes to small-scale or large-scale agricultural activities.

International discourse has tended to focus mainly on “commercial” or “industrial” agriculture (or “agribusiness”) as the main cause of deforestation. In contrast, this study shows that small-scale farmers also play a significant role in the conversion of forests to agricultural land. While at first glance this result may partly diverge from previous publications on deforestation drivers, it has much to do with the definition chosen for the two categories of small-scale and large-scale farming. These were not based on an absolute threshold for the size of forest clearings or production units, but on a set of criteria that aims to reflect the type of farming according to investment capacity, level of technology and local patterns of land use. This approach explains that production units of relatively large size have been classified as small-scale when all criteria were met, notably for livestock systems in South America, explaining the major difference between this study and previous publications for this region.

Furthermore, our results echo available literature, statistics and practical knowledge showing the important contribution of small-scale farming to food production (Galli *et al.*, 2020; Lowder, Sánchez and Bertini, 2021; IFAD and UNEP, 2013), notably in Asia and Sub-Saharan Africa (IFAD and UNEP, 2013). As regards to commodities known to be associated to deforestation, 70 percent of cocoa (Voora, Bermúdez and Larrea, 2019), 73 percent of coffee (Enveritas, 2018 cited by Panhuysen and Pierrot, 2020) and 25 percent to 30 percent of palm oil (Descals *et al.*, 2021; Solidaridad, 2022) are produced by small-scale farms. Responses to reduce deforestation when small-scale farming is involved must take into consideration the weaknesses of the current production systems, as well as strong concomitant needs including food security, decent income and secure tenure rights.

On the other hand, this study illustrates how deforestation driven by large-scale interventions is still ongoing and has significant impacts in some regions and sub-regions.

These results may be considered in the context of efforts to transform food systems towards more sustainability, including the promotion of practices that will fulfil the objectives of economic development and food security while preserving forests.

5.3 Recommendations for future work

There is a need to continue, consolidate and deepen the study of direct deforestation drivers and future remote sensing surveys, while complementary analysis of the existing deforestation datasets could be expanded and further refined.

Additional questions could be included in FRA Remote Sensing Survey questionnaires to collect information on sets of characteristics including crop type and crop system, livestock system type, field parcel size (while we found that the size of the parcels depends largely on the region and the context is important, an indication of the area while the survey is being completed can help future analysis), the presence and type of infrastructure (such as, pivot irrigation, warehouses and silos), the speed of clearing and visible signs of population expansion.

The inclusion of, or links to, available global datasets in CEO could improve the speed and accuracy of analysis. In particular, data on population and agglomerations (such as cities and villages) as well as the distance to settlements and the road network are important indicators when deforestation is linked to accessibility, population expansion or to commercial activities, for example, where there is no presence of a settlement but an intensive expansion due to company investment. Indicators such as distance to road or settlements could be generated automatically using available global datasets on infrastructures and networks.

In the context of future surveys such as FRA RSS, the two-step approach, as applied in this study, is recommended with first an analysis of the land use and land use change, then deforestation driver analysis on those samples where deforestation has been observed. This would also allow further quality control of the first interpretation.

Finally, and most importantly, knowledge of local agricultural practices should be further integrated in the photo-interpretation process. The analysis of deforestation drivers should be carried out with support from regional agricultural specialists. For this, the FRA RSS network of photo-interpreters could be enlarged to include local agricultural experts.

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Annex 1. Regional breakdown

Figure A1.1.
Regional breakdown used in FRA 2020 Remote Sensing Survey and this study

Source: United Nations Geospatial. 2020. Map geodata [shapefiles]. New York, USA, United Nations, modified by the author.

Annex 2. Number of FRA 2020 RSS samples with deforestation linked to agriculture over the period 2000–2018, by region and climatic domain

Table A2.1.
Number of FRA 2020 RSS samples where losses to cropland and grassland have been observed in the period, 2000–2010 or 2010–2018, by region

Region	Forest converted to cropland	Forest converted for livestock grazing	Total forest converted to agriculture
North and Central America	375	861	1 236
South America	5 647	18 175	23 822
Europe	22	17	39
Africa	5 203	916	6 119
Asia	3 839	369	4 208
Oceania	23	75	98
World	15 109	20 413	35 522

Table A2.2.
Number and proportion (percent) of remote sensing samples showing conversion of forest to agriculture in the periods 2000–2010 or 2010–2018 by climatic domain

Climatic Domain	Number of RSS samples	Proportion (percent)
Boreal	7	0.0
Temperate	104	0.3
Subtropical	351	1.0
Tropical	35 060	98.7
World	35 522	100.0

Note: a few samples where forest was converted into natural grassland (with no sign of agricultural activities) or misclassified as deforestation (no land use change) were disregarded for the analysis and are not included in the above tables.

Annex 3. Regional and global results with confidence intervals

Table A3.1.
Regional and global statistical estimates on areas (Mha) of forest conversion to large-scale and small-scale farming with relative margin of errors

Region	Conversion to large-scale cropland (incl. oil palm)		Conversion to large-scale oil palm plantations		Conversion to small-scale cropland		Conversion to large-scale livestock		Conversion to small-scale livestock		Conversion to large-scale agriculture		Conversion to small-scale agriculture	
	Mha	**±**	**Mha**	**±**	**Mha**	**±**	**Mha**	**±**	**Mha**	**±**	**Mha**	**±**	**Mha**	**±**
North and Central America	0.9	25%	0.2	34%	3.3	16%	3.1	12%	4.3	13%	4.1	11%	7.6	10%
South America	11.3	6%	0.2	35%	3.6	14%	18.8	5%	28.8	5%	30.1	4%	32.5	4%
Europe	0.2	NR	0	NR	0.3	NR	0.5	35%	0.3	22%	0.6	38%	0.5	NR
Africa	1.0	36%	0.5	NR	36.7	5%	0.4	NR	7.5	13%	1.4	34%	44.2	5%
Asia	11.8	5%	10.3	5%	16.6	7%	0.7	35%	1.7	23%	12.5	5%	18.3	7%
Oceania	0.1	NR	0.1	NR	0.2	NR	0.5	NR	0.0	NR	0.6	NR	0.3	NR
World	**25.3**	**4%**	**11.3**	**5%**	**60.7**	**4%**	**24.1**	**5%**	**42.6**	**4%**	**49.3**	**3%**	**103.3**	**3%**

± = relative margin of errors at 95 percent confidence level

NR = Not representative, when above 50 **percent**.

ISBN 978-92-5-137842-7

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CC5723EN/1/05.23