Orbae

BY ADASTRA

# Methodology for Jurisdictional Direct Land Use Change

VERSION 2.2

JANUARY 2026

ADASTRA
SUSTAINABILITY

## FOREWORD

Orbae makes land conversion visible in your supply chain. It's the first technology to automatically calculate the impacts of land conversion from agriculture for all crops, anywhere in the world.

We built Orbae because we must urgently stop converting land and begin restoring it. Agriculture drives at least 75% of land conversion worldwide, contributing around 11% of global greenhouse gas emissions and fueling biodiversity loss.

But meaningful action starts with good data. Until now, getting that data meant tracing complex supply chains to pinpoint the origins of agricultural commodities. Orbae challenges this idea. Rather than calculating the environmental impacts of agriculture for individual locations, we simply leverage technology to calculate everything, everywhere.

We've tapped into the best available science to map greenhouse gas emissions from land conversion for every field on Earth, cell by cell. Most of the satellite-based data layers we use as input data come from the public domain — and it's because of the work and dedication of those who've come before us that we are able to generate new insights. Making Orbae available as open data is our way of paying it forward.

Orbae was made possible in part by Innosuisse, the Swiss Innovation Agency, which awarded us a grant of 1.28 million Swiss francs in 2023 to accelerate its development.

Thank you to our clients, supporters and everyone using Orbae's open data to drive real-world change — because the best data is the data that gets put to work.

*Per aspera ad astra*,

Jürgen Reinhard, PhD | Xavier Bengoa | Simon Gmünder

Co-founders, AdAstra Sustainability

ADASTRA SUSTAINABILITY

## About AdAstra Sustainability

AdAstra is shifting the paradigm of agricultural supply chains with data solutions that change our understanding of how agriculture impacts the environment.

Founded in 2022 by three experts in quantitative sustainability, geospatial data science and food and agriculture systems, we support stakeholders along agricultural value chains in taking decisive action for operating within planetary boundaries.

In 2024, AdAstra was named a winner of MassChallenge Switzerland, an industry-led accelerator for startups taking on the world's biggest challenges. In 2025, the team received the special jury prize from the Commodities Innovation Awards for their work on Orbae.

More at adastra.eco.

## Disclaimer

AdAstra Sustainability cannot be held responsible or liable for any harm or damage resulting from business decisions based on this methodology, or on data extracted from Orbae.

## Terms and conditions



## Suggested citation

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## Contact

Have questions? Get in touch.

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## CHANGE LOG

*Change log from version 2.1 (July 2025) to version 2.2 (January 2026)*

| Chapter / section | Description of changes |
|---|---|
| **Commodities in scope** | The list of commodities available in Orbae was updated. |
| **Geographies in scope** | The list of geographies available in Orbae was updated. |
| **Crop masks for palm** | The crop mask for palm was updated with a composite.<br><br>The global palm plantation layer by Descals et al. (2024) maps oil palm extent and estimated planting years since 1990. However, it cannot distinguish new plantations from replanting cycles, where mature palms are clear-cut and replaced with seedlings. This leads to systematic GHG emissions overestimation, as Orbae treats all detected plantations as new establishments.<br><br>Under Greenhouse Gas Protocol rules, recent land conversion carries heavier weight than historic conversion, amplifying this error. The result is overcounted forest-related emissions and distorted separation of emissions from peat occupation versus transformation.<br><br>To address this, we integrated the Danylo et al. (2017) dataset, which uses Sentinel-1 and Landsat time series to map oil palm plantations, and estimate stand age in Indonesia, Malaysia and Thailand. By identifying areas already cultivated before 2017, we filter out replanting events misclassified as new plantations in the Descals layer. This effectively reduces replanting bias in the major producing regions (MY, ID, TH).<br><br>The geographic limitation to Southeast Asia means replanting errors in other producing countries remain uncorrected. Nevertheless, the Danylo-based correction substantially improves regional accuracy and offers a pragmatic solution for aligning emissions estimates with actual plantation dynamics. |
| **Forecasting for palm** | In the first implementation of the forecasting approach (Orbae v2.0), we underestimated LUC emissions for forecasted crop-country combinations (CCCs) driven by forest conversion due to a forecasting error. Correcting this error slightly increases the LUC emissions of forecasted palm oil, essentially offsetting the reduction previously attributed to false positive corrections. |

| | |
|---|---|
| Peat map for Canada | The Canadian soil classification from Geng et al. 2025 replaces the default peat map used previously (Xu et al. 2018) to locate peatlands. Soil classes interpreted as peatland in Canada are fibrisol, mesisol, humisol and folisol, following direct recommendations from Canadian peat scientists. |
| Forecasting land conversion | Refinements to the exponential smoothing technique, which is applied in Orbae to forecast land conversion from the expansion of a specific crop for situations where crop masks are not representative of the most recent year. A safeguard is implemented to ensure that results stay within realistic bounds. |
| Breakdown of emissions data for each principal GHG ($CO_2$, $CH_4$ and $N_2O$) | GHG emissions from land use change (expressed as $CO_2e$) are disaggregated into $CO_2$, $CH_4$ and $N_2O$ using global average emission factors from WRI, with $CO_2$ accounting for roughly >98.5% of total emissions across regions, and the remainder coming from $CH_4$ and $N_2O$, mainly due to fires and soil processes following land use change. |

*Change log from version 2.0 (December 2024) to version 2.1 (July 2025)*

| Chapter / section | Description of changes |
|---|---|
| Geographies in scope | The list of geographies available in Orbae was updated. |
| Conversion from forest / Tropical Moist Forest | Orbae provides new datasets for cocoa (Côte d'Ivoire and Ghana) following the World Cocoa Foundation's *GHG Accounting Manual for Cocoa* (WCF 2025). Two different methods are available in Orbae. The default one, which AdAstra recommends, leverages TMF as a forest layer (Option B in the WCF manual). |
| Conversion from natural grassland | For cocoa, the Global Pasture Watch dataset *Annual grassland class and extent maps at 30-m spatial resolution* (Parente et al., 2024) is used to estimate grassland conversion, following the World Cocoa Foundation's *GHG Accounting Manual for Cocoa* (WCF 2025). |

| | |
|---|---|
| **Carbon stock losses / biomass loss** | Orbae provides new datasets for cocoa (Côte d'Ivoire and Ghana) following the World Cocoa Foundation's *GHG Accounting Manual for Cocoa* (WCF 2025). Two different methods are available in Orbae. The second one, available on request, and which AdAstra does not recommend, leverages the Global Forest Watch *Forest Greenhouse Gas Emissions* layer (Gibbs et al., 2024). This is used both to assess forest conversion and to estimate related GHG emissions (Option A in the WCF manual). This comes with specific limitations outlined in this methodology as well as in the dataset documentation. |

*Change log from version 1.0 (February 2024) to version 2.0 (December 2024)*

| Chapter / section | Description of changes |
|---|---|
| **Commodities in scope** | The list of commodities available in Orbae was updated. |
| **Geographies in scope** | The list of geographies available in Orbae was updated. |
| **Conversion from pastureland** | Conversion from pastureland is now deployed globally, wherever data is available to distinguish natural grassland from pastureland. |
| **Conversion over peat soils** | Conversion over peat soils is now deployed globally. |

| | |
|---|---|
| **Conversion from forest** | The latest Global Forest Watch (GFW) Tree Cover Loss (TCL) dataset is now used instead of the Tropical Moist Forest (TMF) dataset to derive forest loss from the expansion of palm plantations.<br><br>The palm plantation establishment date integrated into the updated global palm plantations map enables the calculation of annual expansion in palm plantation areas. This allows us to use GFW TCL datasets more effectively by consistently excluding TCL on already established palm plantations, ensuring that TCL is only attributed to expanding plantations.<br><br>Additionally, a global comparison between the TMF dataset and TCL reveals that the TMF "undisturbed forest" category does not capture all forest-related land conversion. In countries like Thailand and Brazil, a significant but unidentified portion of forest-related land conversion is embedded within the "other land" category. This inconsistency makes it challenging to rely on the TMF dataset for tracking palm expansion.<br><br>Finally, a >10% canopy cover threshold is now applied globally for all GFW tree cover losses in alignment with the Accountability Framework initiative and SBTi FLAG Guidance. |
| **Carbon stock losses / biomass loss** | The belowground biomass quantification method was updated to a spatially explicit data layer at 1 km resolution.<br><br>Carbon stocks in converted grassland were updated to reflect different grassland typologies in different geographies. |
| **Carbon stock losses / peat oxidation** | The peat oxidation model was updated, distinguishing peat transformation from peat occupation emissions and using different emission factors based on the climate regime.<br><br>For palm, the new model is further extended to differentiate between young and mature plantations. |
| **Forecasting land conversion** | *New chapter:* A new model was added to Orbae to forecast land conversion from the expansion of a specific crop for situations where crop masks are not representative of the most recent year. The model applies an exponential smoothing technique. |
| **Non-LUC GHG emissions** | *New chapter:* Orbae includes non-land use change (LUC) greenhouse gas (GHG) emissions from land management, transport and processing to provide further context on the relative materiality of LUC emissions. |

## ABBREVIATIONS

| | |
|---|---|
| AFi | Accountability Framework initiative |
| AGB | Aboveground biomass |
| BCB | Belowground biomass |
| C | Carbon |
| $CH_4$ | Methane |
| $CO_2$ | Carbon dioxide |
| CoC | Chain of custody |
| dLUC | Direct land use change |
| DOM | Dead organic matter |
| FAO | Food and Agriculture Organization of the United Nations |
| FLAG | Forest, land and agriculture |
| GFW | Global Forest Watch |
| GHG | Greenhouse gas |
| GHGP | Greenhouse Gas Protocol |
| GHGP LSRS | Greenhouse Gas Protocol Land Sector and Removals Standard v1 |
| GPS | Global Positioning System |
| ha | Hectare |
| iLUC | Indirect land use change |
| IPCC | Intergovernmental Panel on Climate Change |
| jdLUC | Jurisdictional direct land use change |
| kg $CO_2$e | Kilogram of carbon dioxide equivalent |
| LCA | Life cycle assessment |
| LCI | Life cycle inventory |
| LUC | Land use change |
| $N_2O$ | Nitrous oxide |
| RSPO | Roundtable on Sustainable Palm Oil |
| RTRS | Round Table on Responsible Soy |
| SBTi | Science-Based Targets initiative |
| sLUC | Statistical land use change |
| SOC | Soil organic carbon |
| TCL | Tree cover loss |
| TMF | Tropical moist forest |

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# About Orbae

Orbae reveals the environmental impacts of land conversion in agricultural supply chains at any level of traceability.

Working from the ground up, it calculates metrics at the level of individual cells much smaller than an average plot, then combines the cells to reflect any area of interest — a farm, a country or anywhere in between. Companies can prioritize their hotspots, take action at scale and track their progress toward zero land conversion.

Orbae is freely accessible to anyone. Access the Orbae web app and learn more about our philosophy on open data at orbae.eco.

# Methodology overview

Orbae envelopes the earth in layers of geospatial data in 30-meter resolution or higher to build a picture of land conversion over the last 20 years.

It uses a combination of geodata[1] to assess land conversion patterns caused by specific commodities and calculate their respective GHG emissions:

- Commodity mapping (farm polygons or crop masks)
- Forest cover and forest loss
- Natural grassland cover
- Pastureland cover
- Cropland cover
- Carbon stock losses (biomass stocks, mineral soil maps, peatland maps)

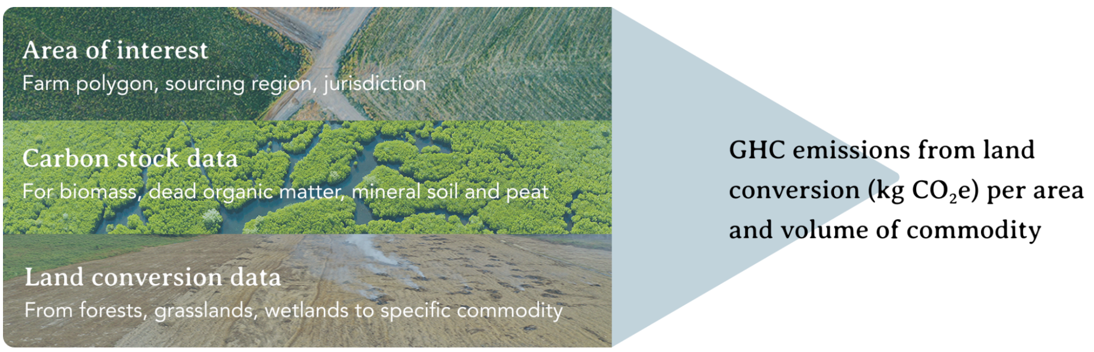


*Figure 1: Orbae's combination of geodata*

[1] "Geodata" refers to digital data to which a specific spatial location can be allocated on the Earth's surface.

There are four main steps:

1. **Delineate the assessment area** using farm polygons and crop masks.
2. **Identify land conversion** over the past 20 years based on IPCC land classifications and the land conversion definition from the Greenhouse Gas Protocol Land Sector and Removals Standard (2026).
3. **Model carbon fluxes**, taking into account carbon stock losses from biomass loss, loss of soil organic carbon and peat oxidation.
4. **Calculate emission factors**, factoring in farm yields and production volumes.

These steps are further detailed in the subsequent sections.

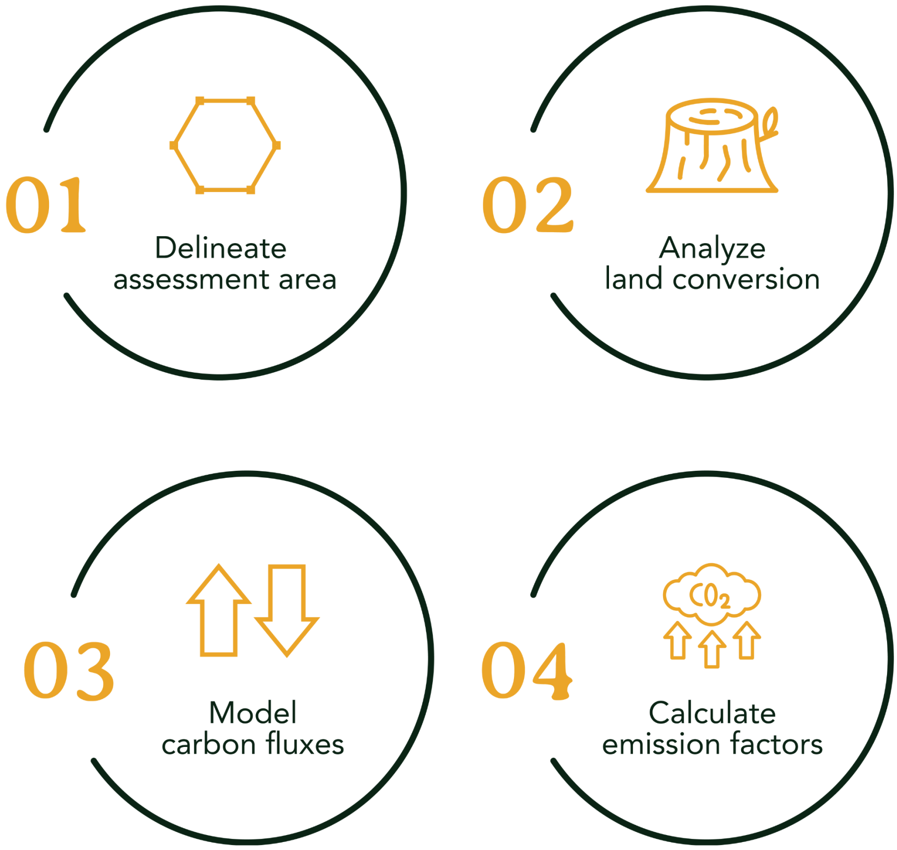


*Figure 2: Orbae calculation steps*

# Commodities in scope

Orbae can assess any agricultural commodity globally. It currently focuses on commodities produced in countries with a high risk of deforestation, which are concentrated in the tropical belt. However, land conversion also occurs in temperate and boreal regions and must not be overlooked. New insights are revealed with each new dataset Orbae calculates.

As commodities are typically traded on global markets in the form of products for the food, feed, cosmetics, biochemical and bioenergy sectors, Orbae provides land conversion insights for both the commodity (e.g., palm) and its products (e.g., palm oil).

At the time of writing, Orbae includes more than 60 datasets, each of which represents a commodity in a country, and is continuously expanding.

*Table 1: Commodities and products included in Orbae*

| Commodity | Products |
|---|---|
| Barley | Barley (grain), malted barley, barley starch, barley feed |
| Beef cattle | Beef cattle (live weight), beef meat, beef hides, beef (category 3) byproducts |
| Cocoa | Cocoa beans, cocoa butter, cocoa liquor, cocoa powder |
| Coffee | Green coffee beans, roasted and ground coffee, spray-dried soluble coffee |
| Corn (maize) | Corn (grain), corn silage, corn oil, corn meal, high-fructose corn syrup, ethanol from corn |
| Cotton | Seed cotton, cotton lint, cottonseed, cottonseed oil, cottonseed meal |
| Oats | Oat grain, oat silage, oat hulls, oat flakes |
| Palm | Fresh palm fruit bunch, crude palm oil, crude palm kernel oil, palm kernel meal, refined palm oil |
| Peanut (groundnut) | Peanut in shell, shelled peanut, peanut oil, peanut meal |
| Rapeseed (canola) | Rapeseed, rapeseed oil, rapeseed meal |
| Soy | Soybean, soybean oil, soybean meal, soybean lecithin, biodiesel from soy |
| Sugarcane | Sugarcane, cane sugar, ethanol from sugarcane |
| Sunflower | Sunflower seed, crude sunflower oil, sunflower meal, refined sunflower oil |
| Wheat | Wheat (grain), wheat starch, wheat feed, wheat gluten, malted wheat |

# Geographies in scope

The following countries are currently included in Orbae. For each, Orbae provides data at country level and on two subnational levels (e.g., state and municipality).

*Table 2: Geographies included in Orbae*

| Region | Countries |
|---|---|
| Africa | Côte d'Ivoire, Ghana, South Africa, Egypt*, Ethiopia*, Uganda* |
| Americas | Argentina, Bolivia, Brazil, Canada, Colombia, Guatemala, Honduras, Mexico, Paraguay, United States, Uruguay, El Salvador*, Nicaragua*, Peru* |
| Asia | China, Indonesia, Malaysia, Thailand, India*, Philippines*, Sri Lanka*, Turkey*, Vietnam* |
| Europe | Austria, Croatia, Czechia, France, Germany, Hungary, Italy, Poland, Romania, Slovakia, Spain, Belgium*, Denmark*, Finland*, Ireland*, Lithuania*, Netherlands*, Sweden*, Ukraine*, United Kingdom*, Russia* |
| Oceania | Australia, Papua New Guinea, Solomon Islands |

*Upcoming

# Unit of analysis

## Resolution

Orbae is based on geodata derived from earth observation in a spatial resolution of 30 meters or higher, when available. End to end, its data processing workflow is built on H3, an open-source geospatial indexing system that structures the Earth's surface into a hierarchical grid of hexagonal cells.

H3 harmonizes all of Orbae's geodata into a common reference system. It also enables seamless multi-scale analysis, from farms to entire countries, by efficiently embedding geographical coordinates into an index key. This dramatically simplifies costly spatial operations such as overlay and zonal statistics, optimizing performance for large-scale geospatial processing.

We operate H3 at a resolution of about 44 $m^2$ per cell. This resolution is higher than any plot size, including most smallholder farming systems. As such, and independently from any further spatial aggregation, it qualifies as direct land use change.

This means that:

- There is no allocation of land conversion to a given commodity based on its place of production or on its expansion rate. Instead, direct spatial attribution of all land conversion events is applied, cell per cell.

- Indirect land use change, or the influence that increasing demand for certain commodities can have on global agriculture (e.g., forcing other crops to move to natural areas), is not accounted for.

## Time

Orbae assesses land conversion on an annual basis. As such, certain land management situations require special attention[2]:

- **Year-to-year rotations of annual crops and/or managed pasture:** When a given land serves different uses in the course of the 20 years preceding the assessment year, land conversion is fully attributed to the commodity being produced in the assessment year.

- **Multicropping of annual crops:** When two or more crops are grown on the same land during one calendar year (e.g., consecutive summer and winter crops), land conversion is equally attributed to both crops (100% each), providing they are both detected during the assessment year.

- **Intercropping:** When two or more crops are grown simultaneously on the same land, current crop masks only provide a classification for the primary crop, to which land conversion is therefore fully attributed. In such cases, secondary crops are not attributed any land conversion.

- **Perennial crops:** For perennial tree crops (e.g., oil palm, cocoa) and perennial grasses (e.g., sugarcane) with a multi-annual growth cycle, land conversion is attributed to the commodity being produced in the assessment year, using a four-year productivity factor (yield) independent of the crop's establishment year.

[2] The Greenhouse Gas Protocol is not yet prescriptive with respect to accounting rules in such situations. In the absence of scientific standards justifying a different treatment, Orbae systematically applies a conservative modeling approach. AdAstra is conducting further research on the topic.

# Commodity mapping

## Farm polygons

Many companies work with their suppliers to gather spatial information about their farms. Farm boundaries can be delineated with GPS coordinates collected on site, resulting in a polygon.

Ideally, each polygon represents the actual shape and area of the land cultivated on the farm for a given crop. Often, however, farm polygons include areas for other land uses, such as fallow land, buffer zones, hedges, gardens or buildings. Consequently, farm polygons tend to be oversized in comparison to the actual land area used to cultivate a specific crop.

Plantations of perennial crops such as oil palm and sugarcane can be delineated similarly.

Whenever available, farm polygons can be used as initial inputs to the Orbae data processing workflow to derive LMU-level direct land use change (dLUC) patterns and metrics.

Field boundaries can also be delineated over large areas with remote sensing, using drones, aerial photography or satellite observation. Orbae can process such data products in the same way as farm polygons.

## Crop masks

To identify areas of commodity production, Orbae leverages crop classification maps called crop masks. Crop masks are raster-format geospatial data products built from earth observation data, most often, from the Landsat and Sentinel-2 satellites.

The crop masks Orbae uses come primarily from published scientific literature in a minimum resolution of 30 meters. Higher resolution (e.g., 10 meters) is used when available. When quality crop masks are not available on the public domain, Orbae supplements with data from private providers.

To create these high-precision maps that show where a particular crop is grown, remote sensing experts first correct and combine the satellite images to highlight vegetation. Then, using computer algorithms, they classify crop fields based on their unique spectral signatures, refining the results and validating them against real-world data.

Different crop masks are used for different commodities and countries, but the same crop mask is always used throughout a given country. When several crop masks are available, various criteria are considered to select the one for use in Orbae, including spatial granularity, spatial comprehensiveness and time representativeness. Whenever possible, Orbae uses crop masks from government institutions.

In the ideal case, crop masks are available for assessment year Y, as well as for 20 years before the assessment year, i.e., Y-20. Orbae can then detect changes in the spatial repartition of a certain commodity and combine this with the land conversion history (see next sections) for the highest accuracy assessment.

In most cases, however, crop mask availability varies, leading to two common scenarios:

- **Case 1: The crop mask is only published for recent years and not for Y-20.**

  In this case, land conversion is assessed based on the assessment year, excluding changes in that crop's spatial distribution between Y-20 and Y. This means that some of the crop expansion patterns are not captured.

- **Case 2: The crop mask is not published on an annual basis and the last available year is older than the assessment year Y.**

  In this case, land conversion is assessed based on the latest crop mask year, excluding more recent years. As such, observed land conversion in more recent years is not attributed to the commodity.[3]

## Composite crop mask for palm

In the case of palm, a crop mask is available for the assessment year Y, as well as for the 20 years before. However, Orbae uses a composite crop mask to refine the estimated planting year and better distinguish new plantations from replanting cycles.

The global palm plantation layer by Descals et al. (2024) maps oil palm extent and estimated planting years since 1990. The annual expansion of palm plantations is therefore an inherent part of the crop mask. But the mask cannot differentiate between new plantations and replanting cycles, where mature palms are clear-cut and replaced with seedlings. This leads to systematic overestimation of LUC emissions, as the accounting framework treats all detected plantations as new establishments.

Under Greenhouse Gas Protocol rules, recent land conversion carries heavier weight than historic conversion, amplifying this error. The result is overcounted forest-related emissions and distorted separation of emissions from peat occupation versus transformation.

To address this, Orbae integrates the Danylo et al. (2017) dataset, which uses Sentinel-1 and Landsat time series to map oil palm plantations and estimate stand age in Indonesia, Malaysia and Thailand. By identifying areas already cultivated before 2017, replanting events misclassified as new plantations in the Descals layer are filtered out. This effectively reduces replanting bias in the major producing regions.

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[3] This approach is subject to further research and refinement to account for probable crop expansion in the recent years not covered by the crop mask.

The geographic limitation to Southeast Asia means that replanting errors in other producing countries remain uncorrected. Nevertheless, the Danylo-based correction substantially improves regional accuracy and offers a pragmatic solution for aligning emissions estimates with actual plantation dynamics.

# Spatial aggregation procedure

## LMU-level direct land use change approach

When farm polygons are available, Orbae calculates direct land use change (dLUC) emissions at the land management (LMU), or farm, level.[4] Orbae can process hundreds of thousands of farm polygons at once to derive dLUC metrics for individual farms, groups of farms or large-scale sourcing regions.

The aggregation procedure depends upon the information available from the stakeholder providing the farm polygons. Three scenarios can occur:

1. **Aggregation based on sourcing volumes**

   If the sourcing volume from individual farms is known, it is used as a weighting factor when aggregating to groups of farms or sourcing regions. Known as a "sourcing-volume weighted average" ($sv_{wavg}$), it provides the highest accuracy.

   It is calculated by multiplying the land use change greenhouse gas emissions (LUC GHG) of all farms *i* with the relative volume sourced from each farm and summing up the relative LUC GHG contribution across all *n* farms:

*Equation 1*

$$luc\ sv_{wavg} = \sum_{i=1}^{n} \left( \frac{sv_i}{\sum_{i=1}^{n} sv_i} * LUC_{GHG_i} \right)$$ with i denoting a specific farm and n representing the number of all farms.

2. **Aggregation based on monitored production volumes**

   If the yield from each farm is known, the farm-specific production volume is used as a weighting factor when aggregating to groups of farms or sourcing regions. This is a "production-volume weighted average" and provides the second-best accuracy.

[4] See "Land conversion definitions".

It is calculated by multiplying the LUC GHG of all farms *i* with the relative production volume produced by each farm and summing up the relative LUC GHG contribution across all *n* farms:

*Equation 2*

$$luc\ pv_{wavg} = \sum_{i=1}^{n} \left(\frac{pv_i}{\sum_{i=1}^{n} pv_i} * LUC_{GHG_i}\right)$$ with i denoting a specific farm and n representing the number of all farms.

3. **Aggregation based on estimated production volumes**

   In the absence of farm-specific sourcing volumes or yield data, the average yield in the region is used to estimate each farm's production volume. This is then used as a weighting factor when aggregating to groups of farms or sourcing regions. This is a "production-volume weighted average" and provides the lowest accuracy.

   It is calculated with the equation described in equation 1. The only difference is that the production volume is calculated with the average yield, not the farm-specific yield.

In rare situations, such as in small-holder farming systems, a farm polygon can have an area smaller than the pixel resolution of the unit of analysis (generally 30 x 30 meters, or 900 $m^2$). When a dLUC event is detected for such a polygon, the dLUC area is capped to the farm area (or cultivated area, if known).

## Sourcing region direct land use change approach

When traceability is limited to the supplier location (e.g., soybean crusher, palm oil mill, slaughterhouse), it is common practice to consider a buffer zone (radius) around the supplier location to delineate the catchment area.

The size of the sourcing radius determines the catchment area or sourcing region (or supply shed). Default sourcing radiuses and ranges for individual commodities and countries are derived from the scientific literature. Orbae applies this approach to calculate sourcing region dLUC.[5]

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[5] See "Land conversion definitions".

*Table 3: Default sourcing region radius around supplier locations*

| Commodity | Country | Sourcing region radius |
|---|---|---|
| Beef slaughterhouse | Brazil | 360 km |
| Palm oil mill | Indonesia, Malaysia | 50 km |
| Soybean crusher | Brazil<br>Argentina<br>United States | 250 km<br>400 km<br>50 km |
| Sugarcane mill | Brazil | 30 km |
| Other crops (corn, rapeseed, wheat) | - | *Research ongoing* |

Orbae can process hundreds of thousands of supplier locations at once to derive sourcing region dLUC metrics for individual supplier locations (e.g., mills) and calculate company-specific averages for each country. The aggregation procedure depends on the information available from the stakeholder providing the supplier locations. Two scenarios can occur:

1. **Aggregation based on sourcing volumes**

   If the sourcing volume from each supplier location is known, this is used as a weighting factor when aggregating to country level. This approach provides the highest accuracy (see equation 1).

2. **Aggregation based on estimated production volumes**

   The average yield achieved in the region or country is used to estimate each sourcing region's production volume. This is then used as a weighting factor when aggregating to country level. This approach provides a lower accuracy (see equation 2).

## Jurisdictional direct land use change approach

Orbae performs jurisdictional direct land use change (jdLUC) assessment using crop masks in 30-meter resolution or higher.[6] National and subnational administrative boundaries serve as polygons delineating different production areas. Orbae implements divisions at country

[6] See "Land conversion definitions".

level, subnational level 1 (e.g., states, provinces, regions) and subnational level 2 (e.g., municipalities, counties, districts).

Orbae calculates dLUC metrics in 30-meter resolution for individual cells, then aggregates the cells to jurisdictional level based on estimated production volumes (i.e., the average yield achieved in the subnational level 2 jurisdiction is used to estimate its production volume). The production volume is used as a weighting factor when aggregating to the subnational level 1 and country levels. The most granular yield data available are used to estimate production volumes.[7]

[7] See "Farm yield and production volume".

# Land classification

Land classification is based on the standards of the Intergovernmental Panel on Climate Change (IPCC), which recognizes six land categories that are a combination of land cover and land use classes: forest land, grassland, cropland, wetlands, settlements and other land.

*Table 4: Land classifications considered in Orbae (GHGP LSRS, 2026, based on IPCC)*

| Land class | Definition |
|---|---|
| Forest | Land area with woody vegetation, often further specified by ecosystem type (e.g., tropical rainforest, boreal coniferous forest).<br><br>Managed lands in this category include plantations and natural forests managed for various reasons, including forest fire management and timber extraction. Natural forests are primary forests and secondary forests following natural regrowth due to land abandonment or afforestation/reforestation. |
| Grassland[8] | Grasslands can span a wide range of climate conditions globally and are generally defined by perennial grasses and vegetation structures below the forest land threshold. These systems are most commonly used for grazing and withstand regular perturbation from both grazing and fire.<br><br>Managed land areas in this category include rangeland, pastureland and silvopastoral systems. Natural grasslands may include native grasslands, savannahs, bushlands and shrublands, as long as animal stocking rates and fire regimes are not intensively managed. |
| Wetland[9] | Land in this category is saturated by water for all or part of the year, and does not otherwise fall into forest land, cropland, grassland or settlements categories. |
| Cropland | Cropland includes arable and tillage land, rice fields, and agroforestry systems where vegetation structure consistently falls below established forest land thresholds. Annual croplands, including cereals, vegetables and root crops, as well as perennial croplands, such as orchards, vineyards, and plantations, are included. |

[8] Whenever data permits, grassland is split between subclasses "natural grassland" and "pastureland".

[9] Wetland areas are currently approximated with lands classified as peatland.

Agroforestry, subsistence agriculture, and shifting cultivation also fall within the cropland category. Mixed systems that are rotated between cropland and pastureland are also typically included as cropland, as the land's use for forage crops or grazing is temporary.

Note that the data used to assess land use change may deviate from the definitions above (e.g., for annual crops Orbae uses tree cover loss as a proxy for deforestation as described in the subsequent sections).

# Definitions

## Land conversion

Orbae applies the definition of land conversion — also referred to as conversion or land use change (LUC)[10] — from the Greenhouse Gas Protocol Land Sector and Removals Standard (GHGP LSRS, 2026), where it is described as a transition from one land use category to another. Land conversion includes deforestation as well as any other type of natural ecosystem conversion.

The GHGP LSRS and Science-Based Targets initiative (SBTi) FLAG Guidance have aligned their definitions and terminology related to land conversion with those of the Accountability Framework initiative (AFi).

[10] Land use change (LUC) is the term used in greenhouse gas accounting under the GHGP LSRS and in life cycle assessment. It is synonymous to land conversion.

*Definition of conversion from AFi Terms and Definitions*

**Conversion**

Loss of a natural ecosystem as a result of its replacement with agriculture or another land use, or due to a profound and sustained change in a natural ecosystem's species composition, structure, or function.

- Deforestation is one form of conversion (conversion of natural forests).
- Conversion includes severe and sustained degradation or the introduction of management practices that result in a profound and sustained change in the ecosystem's species composition, structure, or function.
- Change to natural ecosystems that meets this definition is considered to be conversion regardless of whether or not it is legal.

*Source: Accountability Framework initiative (February 2024)*

AFi (2022) states: "Land use change also…includes the transition between natural and modified ecosystems in subcategories of land use, such as from natural forest to planted forest or from a natural grassland to an improved pasture."

In addition, AFi (2022) notes: "Transitions between different agricultural systems, changes in management with agricultural systems, and transitions that increase rather than decrease carbon storage (for example, reforestation) are not considered land use change events" and shall be reported as land management emissions or removals under the GHGP LSRS.

For both annual and perennial crops, Orbae considers the conversion from forest land or grassland to cropland to beland use change, in accordance with the GHGP LSRS. Orbae does not yet consider wetland conversion explicitly but does include emissions from peat oxidation.

The GHGP LSRS recognizes different calculation approaches to quantifying land use change impacts: land management unit-level direct land use change (LMU-level dLUC), jurisdictional direct land use change (jdLUC) and statistical land use change (sLUC). Orbae operates within the boundaries of LMU-level and jurisdictional dLUC. The following section offers further detail on how Orbae applies key terms.

## LMU-level direct land use change assessment

Assessment of land use change directly on the area of land that a company owns or controls, or on specific lands in the company's value chain that can be identified with farm- or plot-specific geographical boundaries (e.g., in the form of a GPS polygon).

*Definitions from the Greenhouse Gas Protocol Land Sector and Removals Guidance*

**Land management unit (LMU)**

A predefined, spatially explicit area of a given land use, managed according to a clear set of objectives and according to single land management plan to produce a given raw material or set of raw materials. An LMU may represent spatially explicit areas such as a farm, field or plot.

**Harvested area**

A spatially explicit area of productive agricultural land that was harvested at a given time to produce the relevant raw material.

*Source: [GHGP LSRS (2026)]*

## Sourcing region direct land use change assessment

An assessment of land use change on a predefined, spatially explicit land area that supplies harvested materials to the first collection point or processing facility in a value chain.

A souring region may be identified with a specific geographical location in the form of GPS coordinates (latitude-longitude) that are combined with a sourcing radius around that location and a crop mask on a resolution that is higher than a typical plot size.

Sourcing regions are also sometimes referred to as supply sheds or supply bases.

## Jurisdictional direct land use change assessment

An assessment of land use change within a country or subnational jurisdiction, calculated using a crop mask on a resolution higher than a typical plot size. Orbae uses crop masks in 30- or 10-meter resolution.

## Statistical land use change assessment

An assessment of land use change within a country or subnational jurisdiction, estimated using either land use statistics (generally on a national level) or spatial attribution using a crop mask on a resolution that is lower than a typical plot size (typically several kilometers).

Orbae uses statistical land use change assessment only for consistency checks.

# Conversion from forest

## Global Forest Watch Tree Cover Loss

Orbae applies the Global Forest Watch (GFW) Tree Cover Loss (TCL) dataset on a spatial resolution of 30 meters to identify land conversion from forest (Hansen et al., 2013).

GFW, a program of the World Resources Institute, provides annually updated global-scale forest loss data derived using Landsat time-series imagery going back to 2001. The GFW TCL data after 2011 was produced using an updated methodology, so comparisons between the original 2001–2010 data and the 2011 update should be performed with caution.

This dataset indicates pixels of tree cover loss globally, where "tree cover" is defined as all vegetation greater than 5 meters in height and may represent natural forests or plantations across a range of canopy densities. Tree cover loss is defined as "stand replacement disturbance", or the complete removal of tree cover canopy at the Landsat pixel scale. Tree cover loss may be the result of human activity, including forestry practices such as timber harvesting or deforestation, or natural causes such as disease, fire or storm damage.

TCL is a solid, consistent and widely used data product that performs well in assessing deforestation caused by arable crops. Orbae uses the GFW TCL product with >10% canopy cover threshold in alignment with AFi and SBTi FLAG. In Orbae, TCL events are overlaid with farm polygons or expanding crop pixels to derive the commodity-driven forest conversion cell per cell.

## Tropical Moist Forest

For certain tropical tree crops, such as cocoa, Orbae uses the Tropical Moist Forest (TMF) dataset from the European Commission Joint Research Centre (Vancutsem et al., 2021). Whereas GFW TCL tends to underdetect cocoa-associated deforestation because of spectral and structural similarities between cocoa plantations and natural forests, TMF shows to have a lower classification uncertainty.

Forest area in the TMF dataset is not defined by any percentage of tree cover as it covers tropical moist forests, which include all closed forests in the humid tropics with two main forest types: the tropical rainforest and the tropical moist deciduous forest.

The mapping approach consists of observing the evolution of spectral signatures over time and identifying potential disruption observations (i.e., detection of an absence of tree foliage cover within a Landsat pixel for a single-date observation) for each single-date image of the time series. The temporal sequence of those disruption observations at pixel scale was analyzed to first determine the initial extent of the TMF domain (period 1982–1989) and then to identify the change trajectories from this initial forest extent (from 1990 to present day).

The TMF dataset was developed using 41 years of Landsat time series at 30-meter resolution. It depicts the extent of tropical moist forest and related disturbances (deforestation and degradation), and post-deforestation recovery (or forest regrowth) through two complementary thematic layers: a transition map and an annual change collection over the period 1990–2024. Each disturbance (deforestation or degradation) is characterized by its timing and intensity.

The four classes are defined as follows:

- **Undisturbed forest:** Closed evergreen or semi-evergreen forest without any disturbance (degradation or deforestation) observed over the full observation period defined by the Landsat data availability.
- **Degraded forest:** Closed evergreen or semi-evergreen forest (covered by existing or regrowing trees) that has been temporarily disturbed during a period of maximum 2.5 years. Includes different types of degradation such as selective logging, fires, and unusual weather events (e.g., hurricanes, drought, blowdown).
- **Deforested forest:** Permanent conversion of forest into non-forested land. Disruptions were observed over more than 2.5 years and no vegetative regrowth was detected over the last 3 years.
- **Forest regrowth:** A two-phase transition from moist forest to (i) deforested land and then (ii) vegetative regrowth. A minimum 3-year duration of permanent moist forest cover presence is needed to classify a pixel as forest regrowth.

A forest is only categorized as “undisturbed” at the beginning of Orbae’s accounting period, if there was no disturbance between 1982 and 2002. Deforestation, under the TMF classification, refers to a change in land cover (from forest to non-forested land), whereas degradation refers to a temporary disturbance in a forest that remains forested.

Orbae treats all disturbance events in undisturbed forest as land conversion, while any disturbance event in degraded forest is considered to be land management in existing tree crop plantations. This approach prevents the detection of many false-positive disturbance events (e.g., plantation renewal) and allows Orbae to handle land conversion consistently. Such handling of TMF degradation follows option B of section 5.3, *dLUC step-by-step*, in the World Cocoa Foundation’s *GHG Accounting Manual for Cocoa* (WCF 2025).

In the future, Orbae may consider the duration and intensity of the disturbance event to refine the distinction between land conversion and land management.

Land conversion events are overlaid with farm polygons or crop masks to derive the commodity-driven forest conversion, cell by cell.

# Conversion from pastureland

In geographies where high-resolution pastureland data is available, Orbae assesses conversion from pastureland to cropland. This has been consistently tested and deployed in Brazil, Argentina, Paraguay and Bolivia (MapBiomas 2023), as well as for Europe (Parente et al., 2021) and the United States (Homer 2020). It will continue to be extended to other relevant countries.

Land conversion events are overlaid with farm polygons or crop masks to derive the commodity-driven pastureland conversion, cell by cell.

# Conversion from natural grassland

Orbae deploys a deductive approach to estimate conversion of non-forest native ecosystems (which, by convention, are referred to as "natural grasslands"). It is based on crop expansion that has not occurred at the expense of other natural ecosystems, or over preexisting cropland or pastureland.

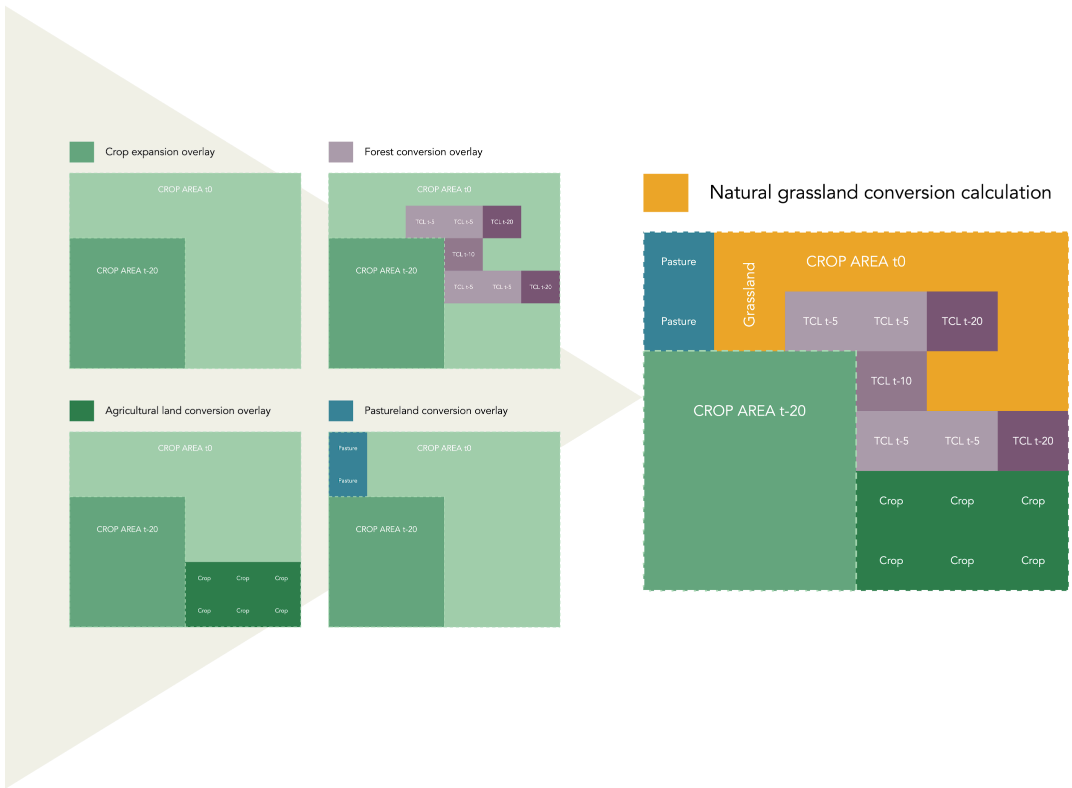



*Figure 3: Deductive approach to derive natural grassland conversion*

The crop expansion over grassland is calculated by subtracting from the total crop expansion, and for the 20-year assessment period, all cells correlating with:

- Forest loss[11]
- Pre-existing cropland[12]
- Pastureland[13]

The approach potentially overestimates grassland conversion because crop expansion at the expense of urban areas and perennial woody crops (tree plantations) may end up being included in the "residual" grassland. Also, since the GLAD data layer does not come in an annual resolution, the deductive approach cannot estimate annual expansion but only expansion for the entire assessment period.

For cocoa, the Global Pasture Watch dataset *Annual grassland class and extent maps at 30-m spatial resolution* (Parente et al., 2024) is used to estimate grassland conversion. Following the World Cocoa Foundation's *GHG Accounting Manual for Cocoa* (WCF 2025), any pixel classified as "natural/semi-natural grassland" and changed to "cultivated grassland" or "other land" from one year to the next is considered a grassland conversion.

For palm, natural grassland conversion is currently not calculated using the deductive approach.

[11] See "Conversion from forest".

[12] Based on the Global Land Analysis and Discovery (GLAD) laboratory global cropland expansion dataset (Potapov et al., 2021).

[13] See "Conversion from pastureland".

# Land conversion over peat soils

Orbae uses a peer-reviewed peatland geodata layer from Xu et al. (2018) that draws on high-quality, freely available data. Compiled from a wide range of sources, the layer maps peatland distribution at global, regional and national levels.

It estimates global peatland area is 4.23 million $km^2$, or approximately 2.8% of the global land area, with 38.4% in Asia, 31.6% in North America, 12.5% in Europe, 11.5% in South America and 4.4% in Africa.

For Canada, the Geng et al. (2025) soil classification system is used, which allows for a more up to date and accurate view of crop-related peat emissions in the country. Soil classes interpreted as peatland in Orbae are fibrisol, mesisol, humisol and folisol.

Land conversion over peat soils is assessed after overlaying crop masks with the peatland layer, which informs on the cultivated area of a certain crop on peatland.

# Assessment period

In accordance with the Greenhouse Gas Protocol Land Sector and Removals Standard (2026), Orbae uses an assessment period of 20 years.

# Forecasting land conversion

## Introduction

There are inherent limitations regarding the temporal representativeness of certain crop masks available on the public domain. For example, the most recent crop mask for palm (Descals et al., 2024) provides palm data up to the year 2021, and the crop mask for cocoa (Kalischek et al., 2023) also refers to the year 2021. Yet, corporate reporting cycles and supply chain interventions require more recent years to be assessed.

To fill that gap until such crop masks are annually updated, a forecasting model for the extrapolation of historic time series was developed and integrated in Orbae. Grounded in the historical patterns of data such as annual forest area loss or annual crop expansion per municipality, the model uses an exponential smoothing approach.

## Exponential smoothing

Exponential smoothing is a weighted moving average technique that is frequently used in the production and inventory environment, where only the next period’s value is required to be forecast.[14]

Virah-Sawmy et al. (2015) applied exponential smoothing to the forecasting of forest cover changes and found that exponential smoothing outperforms the linear trend and historical average models. The technique involves using historic and current data observations along with a smoothing coefficient to quickly forecast the next period's value.

Orbae uses an iterative exponential smoothing approach to forecast annual forest conversion metrics and cropland expansion at the third administrative unit level (ADM3), such as of municipalities and counties. For each year to be forecast, Orbae uses the exponential smoothing model from the Statsmodels library, which is a full implementation of the Holt-Winters exponential smoothing approach (Hyndman and Athanasopoulos 2021).

This model is initialized with the historical data at the level of administrative units and fitted to generate the forecast for the next year. The forecasted value for the next year is appended to the historical data, and the model is re-fitted with the updated data. This iterative process ensures that each year's forecast is based on the most recent data, incorporating the forecasted values from previous years.

For palm, the forecast is built on a rich data foundation, as not only historic data on forest area losses are available, but also the annual expansion of palm plantations in general, and on peatland specifically (Descals et al., 2024).

Orbae distinguishes between forecasted and related attributes. Forecasted attributes are calculated based on exponential smoothing. Related attributes are updated based on forecasted attributes to maintain consistency among attributes (e.g., the total crop expansion over the time period is updated with the forecasted crop expansion over the forecasted years).

Relevant related attributes are

- The cropland area in the forecasted year and the corresponding production volume
- The total crop expansion over the new period
- Peatland occupation
- Peatland transformation area

For cocoa, less temporally specific data on cropland expansion is available. The model therefore focuses on total and cocoa-driven forest area losses (see table 5).

[14] More information: Holt-Winters Forecasting for Dummies (or Developers) - Part I

*Table 5: Attributes considered in the forecasting model for palm and cocoa*

| Attribute<br>in hectares per ADM3 | Palm | Cocoa |
|---|---|---|
| Forest area loss (crop related) | x | x |
| Forest area loss (total) | x | x |
| Crop expansion on peatland | x | |
| Crop expansion (total) | x | |

# Carbon stock losses

## Biomass loss

Three carbon pools are derived from biomass:

- Aboveground biomass (AGB)
- Belowground biomass (BGB)
- Dead organic matter (DOM)

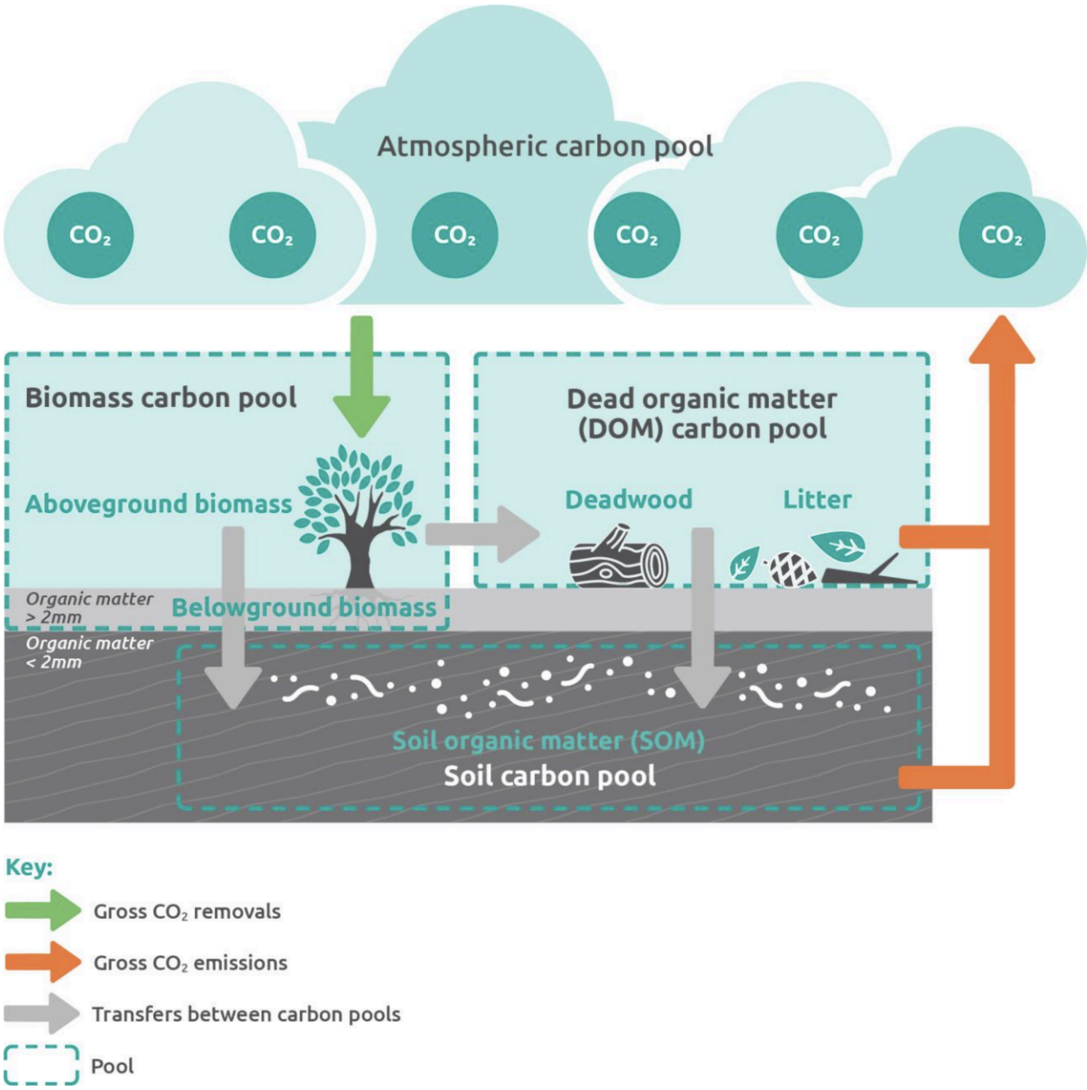



*Figure 4: Land-based carbon pools and fluxes (GHGP LSR, 2022, figure 4.2)*

Orbae leverages the global map of aboveground live woody biomass (AGB) density from GFW (Harris et al., 2021) in 30-meter resolution for the year 2000. For each pixel of forest loss in the period of interest, the corresponding AGB loss is computed in megagrams[15] of biomass per hectare. This allows globally consistent consideration of AGB. However, the value of individual pixels is known to have large uncertainty and is expected to differ from biomass estimates in field-measured plots.

Belowground live woody biomass (BGB) loss is computed by combining forest loss pixels with the BGB layer from Huang et al. (2021). The study combined 10,307 field measurements of forest root biomass worldwide with global observations of forest structure, climatic conditions, topography, land management and soil characteristics to derive a spatially explicit, global belowground biomass dataset, including fine and coarse roots, in approximately 1-kilometer resolution.

Biomass in the form of dead organic matter (DOM), which includes dead wood lying on the ground, as well as litter and leaves, is calculated with a default global factor of 5.2 metric tons of dry biomass per hectare of tree cover loss (IPCC, 2019).

The annual biomass loss from forest conversion in year *y* ($BL_y$) is calculated with equation 3 (IPCC 2006a, volume 2, equation 2.11).

*Equation 3*

$$BL_y = AGB_y + BGB_y + DOM$$

The biomass loss is calculated for every Orbae cell and year where a forest conversion event is detected. It is then converted into corresponding carbon dioxide ($CO_2$) emissions by

1. Multiplying with the carbon fraction (*cf*) in dry mass (default factor of 0.47 as per IPCC 2006b, volume 4, chapter 4, table 4.3), and
2. Multiplying with the mol ratio between carbon (C) and $CO_2$ of 44/12.

The $CO_2$ emissions from biomass loss are calculated for every Orbae cell and year with equation 4 (IPCC 2006a, volume 2, equation 2.13), where *CLy* is the loss of biomass in the form of $CO_2$ in year *y*.

[15] 1 megagram = 1,000 kilograms

*Equation 4*

$$CL_y = BL_y * cf * 44/12$$

Similarly, $CO_2$ emissions linked to biomass loss from grassland and pastureland conversion are calculated for every Orbae cell and year using biome-specific biomass values (Zimbres et al., 2021; IPCC, 2019):

*Table 6: Carbon stocks in converted grassland*

| Land class | Natural grassland | Pastureland |
|---|---|---|
| Argentina, Bolivia, Colombia, Guatemala, Honduras, Mexico, Paraguay, Thailand, Uruguay | 24.75 tC/ha | 7.6 tC/ha |
| Brazil | 32.33 tC/ha (mix of grassland and savanna) | 7.6 tC/ha |
| Canada, Europe, United States | 24.75 tC/ha | 5.1 tC/ha |
| Australia, China, South Africa | 24.75 tC/ha | 5.1 tC/ha |
| Côte d'Ivoire, Ghana | 44 tCO2e/ha[16] | n.a. |
| Indonesia, Malaysia, Papua New Guinea, Solomon Islands | Not yet included | Not yet included |

[16] Following the World Cocoa Foundation's *GHG Accounting Manual for Cocoa* (WCF 2025), based on IPCC 2019, table 6.2.

### Alternative approach specific to cocoa

In addition to the default approach based on the Tropical Moist Forest dataset (see Tropical Moist Forest), Orbae provides a second method for assessing LUC GHG emissions from cocoa, following option A of section 5.3, *dLUC step-by-step*, in the World Cocoa Foundation's *GHG Accounting Manual for Cocoa* (WCF, 2025).

In this approach, the Global Forest Watch *Forest Greenhouse Gas Emissions* layer (Gibbs et al., 2024) is used to both assess forest conversion and estimate related GHG emissions. This comes with the following limitations:

- **Classification uncertainty:** The spectral and structural similarities between cocoa plantations and natural forests reduce the algorithmic accuracy of land cover classification by Global Forest Watch. This leads to an underdetection of cocoa-associated deforestation by a factor of approximately 2–3 for Côte d'Ivoire and Ghana.
- **Emissions overestimation:** Emission estimates per hectare are systematically biased upward due to generalized assumptions regarding aboveground biomass densities and soil carbon losses, which may not be representative of actual cocoa land use transitions.

Cocoa datasets calculated with the Global Forest Watch *Forest Greenhouse Gas Emissions* layer are available upon request.

## Mineral soil organic carbon

The carbon fraction of the soil organic matter is referred to as soil organic carbon (SOC). Orbae uses SoilGrids (Poggio et al., 2021) to estimate the SOC stock up to a depth of 30 cm and calculate SOC loss from land conversion.

SoilGrids maps are a global soil data product generated at ISRIC – World Soil Information through international collaboration. It is a collection of soil property maps covering the entire world at 250 m resolution, produced using machine learning. SoilGrids uses global models that are calibrated with all available input observations, such as sampling locations and globally available environmental covariables. This results in globally consistent predictions (e.g., avoiding abrupt changes in predicted values at country boundaries).

Orbae calculates SOC losses by combining the SOC stock from SoilGrids with the IPCC default stock change approach (IPCC 2019, volume 5, table 5.5). For each cell of forest loss, pastureland loss and natural grassland loss, the initial SOC stock is multiplied with the corresponding land use change factor from the IPCC, considering the mix of climate domains in each country.

Orbae does not consider the influence of the input and the management factors, meaning that it works with default factors of 1, which imply no change.

## Peat oxidation

Orbae calculates peat emissions on cell level, both from cropland expansion into peatland and from cropland cultivation on peatland in the reference year. GHG emissions from peat transformation (the result of land conversion) and peat occupation (the result of continuous exploitation of drained peatland) are computed separately.

## Peat transformation

Peat transformation emissions are the result of crop expansion into peatlands during the 20 years prior to the assessment year. Corresponding peat emissions (*PE*) are calculated by multiplying the crop expansion onto peatland area (in hectares) over the last 20 years (*cep*), with the corresponding peat emission factor (*ef*) (see table 7). Since peat emissions are annually recurring, they are multiplied with the mean time of peat emissions recurrence (*mt*). It is assumed that peat emissions are recurring over the last 10 years, i.e., *mt* = 10.

Except for palm, where more detailed temporal data on crop expansion into peatland is available, these peat emissions are annualized with an equal depreciation scheme, as the exact timing of the land transformation is not known. That is, the emissions are divided by the amortization period (*at*) of 20 years. See equation 5.

*Equation 5*

$$PE_{transformational} = \frac{cep*ef*mt}{at}$$

*Table 7: Emission factors of important greenhouse gases associated with peat drainage across major climate regimes*

| Climate regime | Carbon dioxide kg $CO_2$-C ha-1 yr-1 | Methane kg CH4 ha-1 yr-1 | Nitrous oxide kg $N_2O$-N ha-1 yr-1 | All GHGs t $CO_2$e ha-1 yr-1 |
|---|---|---|---|---|
| Cropland, drained boreal and temperate | 7,900 | 0 | 13 | 40.1 |
| Cropland and fallow, drained tropical | 14,000 | 7 | 5 | 55.8 |

*Source: IPCC 2013, "Wetlands" supplement*

The timing of palm plantation establishment can be derived from the crop mask (Descals et al., 2024). This allows for more nuanced modeling of peat transformation emissions that considers when peat emissions started recurring.

Peat emissions are expected to decline with the maturity of the palm plantations (Cooper et al., 2020).[17a] Therefore, different emission factors are used for young palm plantations (≤7 years after palm has expanded into peatland) and mature palm plantations (>7 years after palm establishment). (See table 8.) These factors are based on direct measurements of GHGs emitted during the conversion of peat swamp forests into oil palm plantations, accounting for methane ($CH_4$) and nitrous oxide ($N_2O$), as well as carbon dioxide ($CO_2$) (Cooper et al., 2020).[16b]

For each year, the cumulated plantation area is calculated for young and mature palm plantations respectively, considering year-to-year palm expansion into peatland, then assigning the corresponding emission factor.

*Table 8: Emission factor of palm plantation cultivated on peatland for different maturity stages (based on Cooper et al., 2020)*

| Unit | Young palm plantation ≤7 years after first establishment | Mature palm plantation >7 years after first establishment |
|---|---|---|
| Emission factor t $CO_2$e ha-1 yr-1 | 210.7 | 49.5 |

[17a, 16b] Greenhouse gas emissions resulting from conversion of peat swamp forest to oil palm plantation, Cooper et al., 2020

## Peat occupation

Emissions from peat oxidation continue with drainage and can last for centuries, depending on the thickness of the peat layer.

Peat occupation emissions are considered for cropland and plantations established on converted peatland over 20 years prior to the assessment year. They are detected as the fraction of total peatlands occupied today by cropland that have not been subject to land conversion over the last 20 years.

Peat occupation emissions are calculated based on the difference between the total peatland occupied by the crop in the reference year (*tp_ref_year*) and the crop expansion onto peatland area over the last 20 years (*cep*). These peat emissions are computed by multiplying peat occupation area with the annual emission factor of 49.5 metric tons $CO_2$e per ha and year for palm and 40.1 for other crops. See equation 6.

*Equation 6*

$$PE_{occupational} = (tp_{refyear} - cep) * ef$$

Peat transformation emissions are only considered in the LUC GHG impact factor, while peat occupation emissions are reported separately under emissions from land management.

## Breakdown of emissions data for each principal GHG ($CO_2$, $CH_4$ and $N_2O$)

LUC emissions, expressed as $CO_2$ equivalents, are disaggregated into the three major greenhouse gases — $CO_2$, $CH_4$, and $N_2O$ — using the average global contribution of each gas, based on emission factors provided by WRI. Non-$CO_2$ emissions result from tree cover loss through fires and peat fires, as well as from nitrogen mineralization following the loss of soil organic carbon under certain conditions. The relative contribution of each gas ($CO_2$, $CH_4$, and $N_2O$) to the total LUC emission factor ($CO_2$e) is shown in table 9.

*Table 9: Breakdown of emissions data for each principal GHG across global regions*

| Region | Carbon dioxide $CO_2$ (%) | Methane $CH_4$ (%) | Nitrous oxide $N_2O$ (%) | All GHGs (%) |
|---|---|---|---|---|
| North & Central America | 98.93 | 0.52 | 0.55 | 100 |
| South America | 98.81 | 0.87 | 0.32 | 100 |
| Europe | 98.49 | 0.32 | 1.17 | 100 |
| Africa | 99.67 | 0.08 | 0.25 | 100 |
| Asia | 99.65 | 0.07 | 0.28 | 100 |
| Oceania | 99.39 | 0.30 | 0.32 | 100 |

*Source: Fitts et al., 2025*

For example, the relative contribution of each principal GHG for 1 kg $CO_2e$ of LUC emissions from soybean production in Brazil is calculated as follows:

- 0.9893 for $CO_2$
- 0.0052 for $CH_4$
- 0.0055 for $N_2O$

These global factors provide an initial consistent, top-down disaggregation of LUC emissions into the principal greenhouse gases. More advanced region- and gas-specific emission factors for principal GHGs are planned for integration in a subsequent version of Orbae using a bottom-up approach.

# Carbon stock in the crop

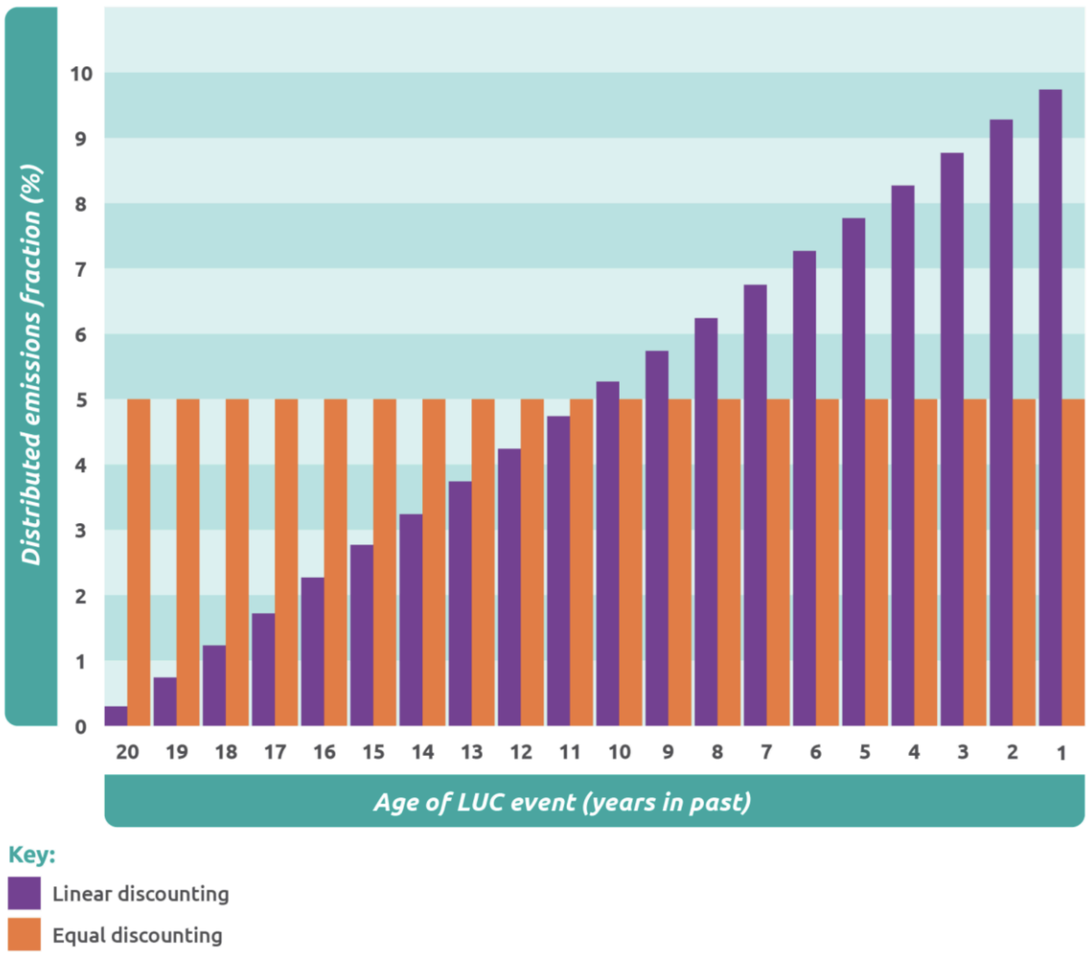
Annual and perennial crops hold a certain carbon stock in their biomass. This is particularly true for perennial tree crops. In order to clearly separate carbon emissions from land conversion from the carbon uptake of crops, Orbae does not account for such carbon stocks. Not accounting for the crop carbon stock reduces the risk of double counting if a company claims removals, e.g., from agroforestry systems.

According to the Greenhouse Gas Protocol Land Sector and Removals Standard (2026), the carbon stock of the current land use may be added to calculate a net LUC value if it does not lead to a net removal (i.e., the carbon stock of the previous land use is lower than the current land use).

# GHG emissions depreciation

Emission factors from forest conversion for the reference year are calculated by weighting annual emissions with a linear discounting approach. As such, more recent emissions are assigned a higher burden.

Due to a lack of sufficient historic data, emission factors for grassland and pastureland conversion for the reference year are calculated by weighting annual emissions with an equal discounting approach.




*Note: The sum of all years is equal to 100 percent.*

*Figure 5: Linear and equal discounting approaches over 20 years (GHGP LSR, 2022, figure 7.2)*

# Certification schemes

Companies that source commodity volumes certified under many common certification schemes (e.g, RTRS, RSPO, Bonsucro, Rainforest Alliance) may use information contained in the certification assurance process to demonstrate an absence of LUC emissions over a given time period for those volumes.

By default, Orbae values do not consider any type of certification to demonstrate the absence of land conversion. When determining for which volumes and time periods this may be applicable, companies should consider the following:

- Time period

  Certification schemes that have no-deforestation/conversion criteria include a cutoff date, after which deforestation or conversion renders a given area or production unit non-compliant with certification requirements.

  Companies are required to use a 20-year or greater assessment period to account for LUC emissions, so where the cut-off date for the certification program is less than 20 years from the reporting year, companies must calculate the LUC emissions for certified volumes that occurred in the time between the beginning of the assessment period and the certification cutoff date.

- Chain of custody model

  A chain of custody model (CoC) is the approach taken to demonstrate the link, physical or administrative, between the verified unit of production and the claim about the final product.

  To assure an absence of LUC emissions since the certification system's cutoff date, the model must physically link all or a certain percentage of commodity volumes to certified farms, plantations or forests. This includes:

  a. Segregated or identity preserved CoC models

  b. Percentage-based mass balance models, with a known minimum percentage of product that is deforestation and/or conversion-free

  c. Models that mix percentage-based mass balance models (batch-level, site-level or group-level in same country and sourcing region) with other volumes known to be free of LUC emissions since the cutoff (e.g, FSC controlled wood)

     Book and claim, credit-based and other mass-balance CoC models do not provide assurance that all or a known portion of commodity volumes are sourced from certified farms and therefore cannot be used as evidence of a lack of LUC emissions.

- **Ecosystems and their definitions included in certification criteria**

  Each certification scheme includes a definition of the types of ecosystems included in their no-deforestation or no-conversion criterion and how those ecosystems are identified.

  i. To be credible, certification schemes should use definitions aligned with the Accountability Framework.

  ii. Some certification schemes may cover only deforestation — not conversion of other ecosystems. When this is the case, certification may be used for assurance related to LUC emissions from forest conversion, but LUC emissions associated with conversion of non-forest ecosystems must be calculated for the full assessment period.

- **Traceability**

  Aligned with removal requirements of the GHGP LSRS, an adjustment of the LUC emission factor is only conducted if traceability to the land management unit or sourcing region is available.

# Farm yield and production volume

Data for crop or livestock yields at the farm are gathered on the most granular level available. Yield is both a critical parameter in calculating GHG emission factors and a highly variable parameter across farms, geographies and years.

In order of priority, the following approach is applied when selecting yield data for Orbae:

1. Consistently sampled and verified data on farm level
2. Official national data sources with subnational level granularity, such as government statistics
3. Data reported by Food and Agriculture Organization of the United Nations (FAO) through the FAOSTAT portal

In the last two situations above, a four-year average (five-year average for cocoa) is calculated to smoothen years that might be outliers due to extreme events (e.g., natural disasters, pest invasion, conflicts).

The production volume in a given year is measured in metric tons. It is calculated as the production area in hectares multiplied by the crop yield in metric tons of product per hectare.

In some geographies, data for the detected production area may be incomplete, so production volume may be underestimated.

# LUC emission factor

Commodity-specific LUC emission factors are calculated by dividing depreciated LUC emissions with the corresponding commodity production volume in the assessment year.

LUC emission factors are measured in kilograms of carbon dioxide equivalent per kilogram of product (kg $CO_2e$ / kg of product).

# Commodity processing

Commodities at the farm gate are often processed into different products before being traded. By the time a raw crop reaches its tradeable form, it may have passed through several processing steps, such as drying, shelling, washing, sorting, milling, bleaching, refining, extracting and/or malting.

At each of these steps, a certain amount of input material is needed to produce a certain quantity of output product, resulting in a particular processing yield. Several co-products often result from the same processing step; for instance, milled oilseeds produce both oil and oilseed meal (also called cake). Similarly, livestock slaughter results in several co-products, such as fresh meat, hides and other by-products.

*Table 9: Examples of unprocessed commodities and their products*

| Unprocessed commodity | Products |
|---|---|
| Soybean | Soybean oil, soybean meal, soybean lecithin, biodiesel from soy |
| Corn grain | Corn meal, corn oil, ethanol from corn |
| Palm fruit bunch | Crude palm oil, refined palm oil, crude palm kernel oil, palm kernel meal |
| Beef cattle (live weight) | Beef meat, beef hides, beef by-products |

To translate LUC emissions per kilogram of product at the farm to their equivalent per kilogram of processed product, Orbae applies conversion factors. Conversion factors are calculated as the multiplication of the different processing yields (in kilogram input product per kilogram output product) and, when relevant, allocation factors.

Processing yield data are retrieved from the scientific literature or from reference life cycle inventory (LCI) databases. In line with common LCA standards, such as the EU Product Environmental Footprint (PEF) and LCI databases that include agricultural processing (e.g, GFLI, ecoinvent, Agri-footprint, World Food LCA Database, European Platform on LCA), economic allocation is applied using default factors that represent the average market value of each product.

The conversion factors, processing yields and other data sources used for the commodities in Orbae are specified in the documentation of each dataset.

# Criteria and rating

Orbae's land conversion data is based on the best available peer-reviewed scientific research. Each input dataset must meet strict minimum criteria to be considered for use in Orbae.

Since no globally consistent and comprehensive data source is available for all parameters in Orbae's data workflow, certain extrapolations or simplifications are made where needed, particularly with respect to crop masks, which come from a diverse set of data sources.

A qualitative data quality assessment is applied to each Orbae dataset to indicate the accuracy of the LUC emission factors calculated for individual commodities and countries. It relies on three criteria commonly used in life cycle inventory data quality assessment methods:

- Spatial representativeness
- Temporal representativeness
- Comprehensiveness

*Table 10: Spatial representativeness data quality criteria and rating*

| Spatial representativeness | Rating | Score |
|---|---|---|
| Specific high-resolution (30 m or higher) crop mask with less than 15% deviation from the country's FAO cultivation area | Excellent | 4 |
| Specific high-resolution (30 m or higher) crop mask between 15% and 30% deviation from the country's FAO cultivation area | Very good | 3 |
| Specific high-resolution (30 m or higher) crop mask with more than 30% deviation from the country's FAO cultivation area | Good | 2 |
| Generic high-resolution (30 m or higher) crop mask (e.g., annual crops) | Fair | 1 |

*Table 11: Temporal representativeness data quality criteria and rating*

| Temporal representativeness | Rating | Score |
|---|---|---|
| Crop mask for assessment year Y and for Y-20 | Excellent | 4 |
| Crop mask for assessment year Y and historic cropping patterns approximated with GLAD cropland layer | Very good | 3 |
| Crop mask extrapolated for assessment year Y | Good | 2 |
| Crop mask extrapolated for assessment year Y and no historic (Y-20) crop mask | Fair | 1 |

*Table 12: Comprehensiveness data quality criteria and rating*

| Comprehensiveness | Rating | Score |
|---|---|---|
| Forest, peatland, natural grassland and pastureland conversion considered | Excellent | 4 |
| Forest, peatland and undefined grassland conversion considered | Very good | 3 |
| Forest and peatland conversion considered | Good | 2 |
| Only forest conversion considered | Fair | 1 |

# Visual representation

Each Orbae dataset — characterized by a unique combination of commodity, country and assessment year — is qualified and rated with respect to the above criteria.

The overall quality rating is based on the average of the spatial representativeness, temporal representativeness and comprehensiveness scores, and represented by dots.

*Table 13: Visual representation of Orbae's dataset overall quality rating*

| Representation | Rating | Average score |
|---|---|---|
| ●●● | Excellent | 3.51 to 4.00 |
| ●●○ | Very good | 2.51 to 3.50 |
| ●○○ | Good | 1.51 to 2.50 |
| ○○○ | Fair | 1.00 to 1.50 |

# Definitions

To contextualize and illustrate the materiality of LUC emissions, data for other emissions in the product life cycle (i.e., non-LUC emissions) are provided in Orbae Pro.[18] These include land management emissions from farm operations[19] and downstream, off-farm emissions from transport and transformation into processed products.

Retrieved from the scientific literature or from reference life cycle inventory databases, non-LUC emissions are best estimates of GHG emissions from typical farming practices (land management) on a country or subnational level, or typical technology and supply chain patterns (processing and transport).

Following the requirements of the Science Based Targets initiative FLAG Guidance, non-LUC emissions are split into two categories:

- **Land management emissions:** Includes all on-farm emissions (e.g., nitrous oxide emissions from fertilizer application, methane emissions from enteric fermentation) and upstream emissions (e.g., emissions related to the production of fertilizer, pesticides, electricity and fuel).
- **Transport and processing emissions (non-FLAG):** Includes all emissions from the transport and processing of a commodity into (semi-) finished products.

[18] Orbae Pro is the paid version of Orbae, designed to serve particular corporate use cases.

[19] Emissions from the production of inputs materials and capital goods (e.g., fertilizers, machinery) and energy carriers (e.g., electricity, fuel) are included in land management emissions.

# Data sources

The data sources for non-LUC GHG emissions exposed in Orbae Pro are outlined in the tables below.

## Land management emissions

*Table 14: Data sources used for land management emissions*

| Commodity | Geography | Data source |
|---|---|---|
| Barley | Australia | Ecoinvent 3.10 (Wernet et al., 2016) |
| Beef cattle | Brazil | Embrapa (Folegatti Matsuura et al., 2018) |
| Cocoa | Côte d'Ivoire, Ghana | Ecoinvent 3.10 (Wernet et al., 2016) |
| Coffee | Brazil | Embrapa (Folegatti Matsuura et al., 2018) |
| Corn | Brazil | Embrapa (Folegatti Matsuura et al., 2018) |
| | Argentina, Austria, China, Germany, Hungary, Italy, Poland, Romania, Spain, Thailand, United States | Ecoinvent 3.10 (Wernet et al., 2016) |
| | France | Agribalyse 3.0 (Asselin-Balençon et al., 2022) |
| Cotton | Australia, United States | Ecoinvent 3.10 (Wernet et al., 2016) |
| Oats | France, Germany, Poland, UK | Ecoinvent 3.10 (Wernet et al., 2016) |
| Palm | Indonesia, Malaysia, Papua New Guinea, Solomon Islands | Schmidt and De Rosa (2020) |
| | Thailand | Saswattecha et al. (2015) |
| | Brazil, Colombia, Guatemala, Honduras | Ecoinvent 3.10 (Wernet et al., 2016) |
| Peanut | United States | Ecoinvent 3.10 (Wernet et al., 2016) |

| | | |
|---|---|---|
| Potato | Canada, United Kingdom | Ecoinvent 3.10 (Wernet et al., 2016) |
| Rapeseed | Australia, Canada, Czechia, Germany, Hungary, Poland, Romania, United States | Ecoinvent 3.10 (Wernet et al., 2016) |
| | France | Agribalyse 3.0 (Asselin-Balençon et al., 2022) |
| Soy | Austria, Canada, China, Croatia, Czechia, Germany, Hungary, Poland, Romania, Slovakia | Ecoinvent 3.10 (Wernet et al., 2016) |
| | France | Agribalyse 3.0 (Asselin-Balençon et al., 2022) |
| | Bolivia, Brazil Paraguay, Uruguay | Embrapa (Folegatti Matsuura et al., 2018) |
| Sugarcane | Argentina, Brazil | Embrapa (Ramos et al., 2024) |
| | China, Mexico, South Africa, United States | Ecoinvent 3.10 (Wernet et al., 2016) |
| Sunflower | Spain, France, Hungary, Russia | Ecoinvent 3.10 (Wernet et al., 2016) |
| Wheat | Australia | Ecoinvent 3.10 (Wernet et al., 2016) |

## Transport and processing emissions

*Table 15: Data sources used for transport and processing emissions*

| Commodity | Geography | Products | Data source |
|---|---|---|---|
| Barley | Australia | Malted barley | CarbonCloud (2024b) |
| | | Barley starch, barley feed | Vercalsteren et al. (2022), Vasanthan and Hoover (2009) |

| | | | |
|---|---|---|---|
| Beef cattle | Brazil | Beef meat, beef hides, beef by-products | Calculated, based on European Commission (2017) |
| Cocoa | Côte d'Ivoire, Ghana | Cocoa butter, cocoa liquor, cocoa powder | Ogunsina et al. (2017), Ntiamoah and Afrane (2008) in Bengoa et al. (2020) |
| Coffee | Brazil | Roasted and ground coffee, spray-dried soluble coffee | Humbert et al. (2009) |
| Corn | Argentina, Austria, Brazil, China, France, Germany, Hungary, Italy, Poland, Romania, Spain, Thailand, United States | Corn oil, corn meal, ethanol from corn | Ecoinvent 3.10 (Wernet et al., 2016) |
| | | High fructose corn syrup | Taylor et al. (2023) |
| Cotton | Australia, United States | Cotton lint, cottonseed, cottonseed oil, cottonseed meal | Ecoinvent 3.10 (Wernet et al., 2016) |
| Oats | France, Germany, Poland, UK | Oat forage, oat flakes, oat hulls | Rodrigues et al. (2023) |
| Palm | Indonesia, Malaysia | Crude palm oil, refined palm oil | Schmidt and De Rosa (2020) |
| | | Crude palm kernel oil, palm kernel meal | Hong (2022) |
| | Brazil, Colombia, Guatemala, Honduras | Crude palm oil, refined palm oil, crude palm kernel oil, palm kernel meal | Moreno García et al. (2018), Schmidt and De Rosa (2020), Hong (2022) |
| | Papua New Guinea, Solomon Islands, Thailand | Crude palm oil, refined palm oil, crude palm kernel oil, palm kernel meal | Saswattecha et al. (2015), Schmidt and De Rosa (2020), Hong (2022) |

| | | | |
|---|---|---|---|
| Peanut | United States | Shelled peanut, peanut oil, peanut meal | McCarty et al. (2014) |
| Potato | | Potato starch | Ecoinvent 3.10 (Wernet et al., 2016) |
| | | Dry pulp | Vercalsteren et al. (2022), Bazan et al. (2020) |
| Rapeseed | Australia, Canada, Czechia, France, Germany, Hungary, Poland, Romania, United States | Rapeseed meal, rapeseed oil | Ecoinvent 3.10 (Wernet et al., 2016) |
| Soy | Argentina, Bolivia, Brazil, Paraguay, Uruguay | Soybean oil, soybean meal | Ramos et al. (2023) |
| | | Soybean lecithin | CarbonCloud (2024a) |
| | | Biodiesel from soy | Cerri et al. (2017) |
| | Austria, Canada, China, Croatia, Czechia, France, Germany, Hungary, Poland, Romania, Slovakia, United States | Soybean oil, soybean meal, biodiesel from soy | Ecoinvent 3.10 (Wernet et al., 2016) |
| | | Soybean lecithin | CarbonCloud (2024a) |
| Sugarcane | Argentina, Brazil, China, Mexico, South Africa, United States | Cane sugar, ethanol from sugarcane | Ecoinvent 3.10 (Wernet et al., 2016) |
| Sunflower | Spain, Russia, France, Hungary | Crude sunflower oil, sunflower meal, refined sunflower oil | Nilsson et al. (2010) |
| Wheat | Australia | Wheat starch, wheat feed, wheat gluten | Vercalsteren et al. (2022) |
| | | Malted wheat | CarbonCloud (2024b) |

# Impact assessment

Global warming potential (GWP) factors from IPCC's sixth assessment report (Masson-Delmotte et al., 2021) are used to express all greenhouse gases in the common unit of $CO_2e$.

GWP factors are calculated over a 100-year timeframe, considering climate carbon cycle feedback, excluding long-term effects and excluding effects of short-lived climate forcers.

## REFERENCES


AFi (2020) Terms and Definitions - Defines key terms that are used in the Accountability Framework Core Principles and Operational Guidance. Accountability Framework initiative. Available from https://accountability-framework.org.

AFi (2022) Deforestation- and conversion free supply chains and land use change emissions: A guide to aligning corporate targets, accounting, and disclosure. Accountability Framework initiative. Available from https://accountability-framework.org.

Asselin-Balençon A., Broekema R., Teulon H., Gastaldi G., Houssier J., Moutia A., Rousseau, V., Wermeille A., Colomb V., Cornelus M., Ceccaldi M., Doucet M., Vasselon H., (2022). AGRIBALYSE 3 : la base de données française d'ICV sur l'Agriculture et l'Alimentation. Methodology for the food products. Initial publication Agribalyse 3.0 - 2020, update 3.1 - 2022 Ed. ADEME 2022.

Bazan, G., Koelemeijer, R., & van Dam, D. (2020). DECARBONISATION OPTIONS FOR THE DUTCH STARCH INDUSTRY. Available at: https://www.pbl.nl/uploads/default/downloads/pbl-2020-decarbonisation-options-for-the-dutch-starch-industry_3656.pdf

Bengoa X., Chappuis C., Guignard C., Liernur A., Kounina A., Papadimitriou C., Rossi V. & Bayart J-B. (2020) World Food LCA Database Documentation. Version 3.5.1, January 2020. Quantis, Lausanne, Switzerland.

CarbonCloud (2024)a Carbon footprint of Soybean lecithin. https://apps.carboncloud.com/climatehub/product-reports/id/149612882563. Accessed 21-07-2024.

CarbonCloud (2024)b Carbon footprint of Malted Barley. https://apps.carboncloud.com/climatehub/product-reports/id/109995365680. Accessed 15-10-2024

Cerri, C. E. P., You, X., Cherubin, M. R., Moreira, C. S., Raucci, G. S., Castigioni, B. D. A., … & Cerri, C. C. (2017). Assessing the greenhouse gas emissions of Brazilian soybean biodiesel production. PLoS One, 12(5), e0176948.

Cooper, H., Evers, S., Aplin, P. et al. (2020) Greenhouse gas emissions resulting from conversion of peat swamp forest to oil palm plantation. Nat Commun 11, 407 (2020). https://doi.org/10.1038/s41467-020-14298-w.

Danylo, O., Pirker, J., Lemoine, G. *et al.* A map of the extent and year of detection of oil palm plantations in Indonesia, Malaysia and Thailand. *Sci Data* 8, 96 (2021). https://doi.org/10.1038/s41597-021-00867-1

European Commission (2017), PEFCR Guidance document, Guidance for the development of Product Environmental Footprint Category Rules (PEFCRs), version 6.3, December 15 2017.

Folegatti Matsuura Marília I. S., Juliana Ferreira Picoli (2018) Life Cycle Inventories of Agriculture, Forestry and Animal Husbandry - Brazil. Embrapa. https://www.infoteca.cnptia.embrapa.br/infoteca/bitstream/doc/1113475/1/LCI-Agriculture-2018.pdf.

Gibbs, D. A., Rose, M., Grassi, G., Melo, J., Rossi, S., Heinrich, V., & Harris, N. L. (2024) Revised and updated geospatial monitoring of twenty-first century forest carbon fluxes, Earth Syst. Sci. Data Discuss. [preprint], https://doi.org/10.5194/essd-2024-397 (in review).

GHGP LSRS (2026) Land Sector and Removals Standard. Version 1.0: Agriculture and CO2 removal technologies. January 2026. Washington, D.C.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 342 (15 November): 850-53. Data available online from https://glad.earthengine.app/view/global-forest-change.

Harris, N.L., D.A. Gibbs, A. Baccini, R.A. Birdsey, S. de Bruin, M. Farina, L. Fatoyinbo, M.C. Hansen, M. Herold, R.A. Houghton, P.V. Potapov, D. Requena Suarez, R.M. Roman-Cuesta, S.S. Saatchi, C.M. Slay, S.A. Turubanova, A. Tyukavina. (2021). Global maps of twenty-first century forest carbon fluxes. Nature Climate Change. https://doi.org/10.1038/s41558-020-00976-6.

Homer, C., Dewitz, J., Jin, S., Xian, G., Costello, C., Danielson, P., …  & Riitters, K. (2020). Conterminous United States land cover change patterns 2001–2016 from the 2016 national land cover database. ISPRS Journal of Photogrammetry and Remote Sensing, 162, 184-199.

Hong, W. O. (2022). Review on the Carbon Footprint of the Palm Oil Industry: Insights into Recent Developments.

Humbert S., Loerincik Y., Rossi V., Margni M., Jolliet O. (2009). Life cycle assessment of spray dried soluble coffee and comparison with alternatives (drip filter and capsule espresso), Journal of Cleaner Production, Vol 17 (15), 1351-1358.

Hyndman, R.J., & Athanasopoulos, G. (2021) Forecasting: principles and practice, 3rd edition, OTexts: Melbourne, Australia. OTexts.com/fpp3. Accessed on 02.08.2024.

IPCC (2006a) IPCC Guidelines for National Greenhouse Gas Inventories. Volume 2: Energy. Kanagawa.

IPCC (2006b) IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, forestry and other land use (AFOLU). Kanagawa.

IPCC (2019) Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, forestry and other land use (AFOLU). Kanagawa.

MapBiomas (2023) Collection 7.1 of the Annual Land Use Land Cover Maps of Brazil, MapBiomas Project. https://mapbiomas.org/.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., … & Zhou, B. (2021). Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change, 2(1), 2391.

McCarty J., Sandefur H.N., Matlock M., Thoma G.J. (2014) Life Cycle Assessment of Greenhouse Gas Emissions Associated with Production and Consumption of Peanut Butter in the U.S. Transactions of the ASABE (American Society of Agricultural and Biological Engineers) 57(6):1741-1750

Moreno García, J. E., Martínez, L. A., Belalcázar Cerón, L. C., & Rojas, N. Y. (2018). Corporate carbon footprint of a palm oil mill. Tecciencia, 13(24), 1-10.

Nilsson, K., Flysjö, A., Davis, J., Sim, S., Unger, N., & Bell, S. (2010). Comparative life cycle assessment of margarine and butter consumed in the UK, Germany and France. The International Journal of Life Cycle Assessment, 15(9), 916-926.

Ntiamoah A. and Afrane G. (2008). Environmental impacts of cocoa production and processing in Ghana: life cycle assessment approach. Journal of Cleaner Production 16, 1735-1740.

Ogunsina, B. S., M. A. Adeyemi, T. A. Morakinyo, O. J. Aremu, and A. I. Bamgboye. (2017). Direct energy utilization in the processing of cocoa beans into powder. Agricultural Engineering International: CIGR Journal, 19(3): 213–218

Parente, L., Witjes, M., Hengl, T., Landa, M., & Brodsky, L. (2021). *Continental Europe land cover mapping at 30m resolution based CORINE and LUCAS on samples (Version v0.1) [Dataset]*. Published March 1, 2021. https://zenodo.org/records/4725429.

Parente, L., Sloat, L., Mesquita, V., Consoli, D., Stanimirova, R., Hengl, T., Bonannella, C., Teles, N., Wheeler, I., Ehrmann, S., Hunter, M., Ferreira, L., Mattos, A. P., Oliveira, B., Meyer, C., Şahin, M., Witjes, M., Fritz, S., Malek, Ž., & Stolle, F. (2024). Annual 30-m maps of global grassland class and extent (2000–2022) based on spatiotemporal Machine Learning. Springer Science and Business Media LLC. https://doi.org/10.21203/rs.3.rs-4514820/v3.

Poggio, L., de Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., and Rossiter, D. (2021) SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty, SOIL, 7, 217–240.

Potapov P, Turubanova S, Hansen MC, Tyukavina A, Zalles V, Khan A, Song X-P, Pickens A, Shen Q, Cortez J. (2021) Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. Nature Food. https://doi.org/10.1038/s43016-021-00429-z.

Ramos, N. P., Folegatti, M. I. da S., Bayma, G., Novaes, R. M. L., Morandi, M. A. B., Pighinelli, A. L. M. T., Mendes, N. C., Savioli, J. P. P. das D., Debiasi, H., & Balbinot Junior, A. A. (2023). Regionalização dos perfis "típicos" da produção de soja para uso no RenovaBio. Embrapa Meio Ambiente.

Ramos, N. P., Mendes, N. C., Folegatti, M. I. da S., Bayma, G., Novaes, R. M. L., Pighinelli, A. L. M. T., Morandi, M. A. B., Savioli, J. P. P. das D., Miranda, R. A. de, & da Silva, A. F. (2024, August). *Agricultural corn profiles for Brazilian states – Reference I for the RenovaBio policy*. Embrapa Environment.

Ramos, N. P., Mendes, N. C., Folegatti, M. I. da S., Bayma, G., Pighinelli, A. L. M. T., Novaes, R. M. L., Morandi, M. A. B., Savioli, J. P. P. das D., & Buffon, V. B. (2024, June). *Regionalization of "typical" sugarcane production profiles for use in RenovaBio*. Embrapa Environment.

Rodrigues Viana, L., Dessureault, P. L., Marty, C., Boucher, J. F., & Paré, M. C. (2023). Life cycle assessment of oat flake production with two end-of-life options for agro-industrial residue management. Sustainability, 15(6), 5124.

Saswattecha, K., Kroeze, C., Jawjit, W., & Hein, L. (2015). Assessing the environmental impact of palm oil produced in Thailand. Journal of cleaner production, 100, 150-169.

Schmidt, J., De Rosa, M. (2020). Certified palm oil reduces greenhouse gas emissions compared to non-certified. Journal of Cleaner Production, 277, 124045.

Taylor C, Maroccia J, Masterson M and Rosentrater KA (2023) Comprehensive life cycle assessment of the corn wet milling industry in the United States. Front. Energy Res. 11:1023561. doi: 10.3389/fenrg.2023.1023561

Vercalsteren, A., Boonen, K., Asscherickx, L., Peeters, K., De Smet, S., 2022. LCA of starch products for the European starch industry association: Summary report: https://starch.eu/wp-content/uploads/2022/04/LCA-2022-Summary-Report-Starch-Europe-FINAL-130422.pdf.

Vancutsem C, Achard F, Pekel J-F, Vieilledent G, Carboni S, Simonetti D, Gallego J, Aragão LEOC, Nasi R. (2021) Long-term (1990-2019) monitoring of forest cover changes in the humid tropics. Science Advances.

Vasanthan, T., & Hoover, R. (2009). Barley starch: production, properties, modification and uses. In Starch (pp. 601-628). Academic press.

Vira-Sawmy M., Stoklosa J., Ebeling J. (2015): A probabilistic scenario approach for developing improved Reduced Emissions from Deforestation and Degradation (REDD+) baselines. Global Ecology and Conservation, Volume 4, P. 602-613.

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., and Weidema, B., (2016). The ecoinvent database version 3 (part I): overview and methodology. The International Journal of Life Cycle Assessment, [online] 21(9), pp.1218–1230. Available at: http://link.springer.com/10.1007/s11367-016-1087-8. Accessed 03.06.2024.

World Cocoa Foundation (2025) GHG Accounting Manual for Cocoa: A step by step GHG Accounting methodology for Land Use Change, Land Management and Removals. Version 1.0, January 2025.

Xu J, Morris PJ, Liu J, Holden J. (2018) PEATMAP: Refining estimates of global peatland distribution based on a meta-analysis, CATENA, Volume 160, 2018, Pages 134-140, ISSN 0341-8162.

Zimbres B, et al. (2021). Mapping the stock and spatial distribution of aboveground woody biomass in the native vegetation of the Brazilian Cerrado biome. Forest Ecology and Management. Volume 499, 1 November 2021, 119615.