LANDGRIFFON

LANDGRIFFON METHODOLOGY. TECHNICAL NOTE

Agricultural supply chain impact and risk assessment

Technical note

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Prepared by

Mike Harfoot
Elena Palao
Francis Gassert

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SUMMARY

LandGriffon is a software service that helps companies to assess environmental risks and impacts from agricultural production in their supply chains and to analyze possible futures.

Inspired by the need to move beyond current approaches, LandGriffon uses satellite data and modeling approaches to *spatialize* company supply chain information to enable companies to take action now with the information they have. It addresses the challenge of a lack of traceability by providing a framework for companies to understand the spatial dimensions of their agricultural supply chains and to evaluate impacts as accurately as possible.

LandGriffon provides a holistic picture of company agricultural supply chain impacts so companies can answer questions such as:

- *What materials, business units, or suppliers are the largest sources of impacts?*
- *Where are the most significant opportunities to reduce impacts and risks?*
- *Are we making progress against our targets?*

Every company has unique aspirations, environmental reporting needs, and supply chain visibility. LandGriffon provides a flexible framework with a baseline set of indicators that can be customized for individual companies and evolve over time.

LandGriffon is a commercial service designed to provide companies with cutting edge science data and analysis. However, the LandGriffon methodology and software source code are published openly to foster trust, collaboration, and continued innovation across the sector. This document describes in detail the current methodology Landgriffon uses to assess impact and risk, and highlights limitations and areas for improvement. We will continue evolving and improving LandGriffon in an open and collaborative way. We welcome collaborations and will work with the community to coordinate and develop the knowledge and tools necessary to reduce agricultural production's environmental impacts.

This version 0.2 of the LandGriffon methodology introduces updated water, land, and natural ecosystem conversion and biodiversity indicators in accordance with 2023 guidance from the Science Based Targets Network.

BACKGROUND

Our global population continues to grow, placing increasing demand on land for agricultural products. At the same time, we urgently need to avoid dangerous climate change and reverse the worsening state of nature. Finding sustainable solutions will require significant changes to many aspects of society. Agriculture, forestry, and land use change account for 22% of global greenhouse gas emissions (IPCC). Agriculture, deforestation and land degradation are dominant drivers of biodiversity decline on land (IPBES 2019). In 2019, agricultural land covered 37% of the global land surface area, approximately one-third of which was croplands and two-thirds were used for raising livestock (FAO 2021). This shows that one of this century's foremost challenges is meeting growing food needs while simultaneously reducing the environmental impacts of agriculture (Searchinger et al. 2019).

Companies with agricultural commodities in their supply chains play a key role in mitigating environmental and social impacts, as well as contributing to nature-based climate solutions. There is an increasingly strong business case for companies to identify and reduce these impacts. In part, this is due to enhanced environmental regulation. For example, in 2023 the European Commission brought into force a **Corporate Sustainability Reporting Directive** and a **regulation on deforestation-free products**. The UK recently adopted the Environment Act, Schedule 17, focussing on deforestation risks from commodities linked to commercial activities. The U.S. is also considering **legislation to minimize the environmental impacts of international trade**.

Despite the urgent sustainability challenge, there is limited availability of generally applicable, accurate and practical tools for assessing the environmental impacts of agricultural supply. Life Cycle Assessment (LCA) approaches are essential for assessing the potential environmental impacts of products and services (Hellweg and Milà i Canals 2014). Recently, LCA approaches have been used to create a consolidated and standardized dataset of typical environmental impacts (greenhouse gas emissions, pollution) for a range of agricultural products (Poore and Nemecek 2018) and the LCA approach is now a standard resource for footprinting analysis (e.g. **Foundation Earth**). The LCA approach provides information on characteristic environmental impacts associated with a particular production system in a specific geography, such as a particular country.

Despite the strengths of the LCA approach, environmental impacts can be very sensitive to precisely where and how a raw material is produced (Godar et al. 2016; Lathuillière et al. 2021). For example, Poore and Nemecek (2018) estimate the range of greenhouse gas emissions associated with agricultural products and find huge variability across producers and products. The emissions arising from 100g of beef protein from a beef herd range from around 20 to 105 kg-CO_2 equivalents. For some impacts, their context-specific nature is more pronounced than others. For land use change, water use and biodiversity, it really matters where the impacts occur. In the case of water, for some watersheds and some locations within them, there is already scarcity, so further water withdrawals are likely to have a greater impact than elsewhere (Gleick and Palaniappan 2010). Likewise for land use change, the negative impact on biodiversity is greater from the loss of intact tropical forest ecosystems than forestry plantations (Newbold et al. 2015).

To address the importance of context, tools have been developed that use more precise, spatially explicit information on production and the supply chain links to consumption. For instance, the platform **Trase** compiles and links production and trade data with transportation cost-optimization to trace commodity flows back to production landscapes. For Brazilian soy, Trase combines municipally reported soy production statistics with supply chain, logistics and international trade data to identify the footprint of consumption in other countries (Godar et al. 2016; Green et al. 2019). Developments in remote sensing and cloud computing are transforming capabilities to observe deforestation or other environmental impacts (Taylor et al. 2020). For example, the **Global Forest Watch Pro** tool uses these techniques to help companies identify deforestation events or risks, in and around the supply areas of the mills, silos or slaughterhouses from which they source (Amaral and Lloyd 2019).

The scale of our agricultural footprint and the diversity of its production systems and supply chains indicate the urgent need for new and comprehensive tools for assessing the impacts of supply chains. For instance, Trase can only provide detailed, high-quality traceability information for a subset of commodities and countries. Global Forest Watch Pro provides detailed information about deforestation impacts, but does not provide information on supply chains and souring locations beyond a known set of concessions and palm oil mills. These gaps arise primarily because of the uncertainties and time lags in global agricultural supply chain and production data. In such a data-limited field, the LandGriffon framework enables agricultural supply chain companies to evaluate, plan, and mitigate impacts arising from their diverse supply chains.

The LandGriffon approach

The LandGriffon methodology starts by assuming that many agricultural supply chains are difficult to track and manage. Some companies have direct relationships with the farms and processors that produce their raw materials. In many cases, though, they only have a rough idea of who and where their materials are ultimately sourced from. This is mostly due to the aggregation of resources, geographic distance, and processing steps involved in raw material production (zu Ermgassen et al. 2022). Although this lack of knowledge is mainly the case for companies furthest downstream in the supply chain, it is frequently true for manufacturers, traders and other intermediaries. Nonetheless, the need remains for companies to make important decisions about the environmental impacts in their supply chain despite the imperfect information they may currently possess.

The past decade has seen an explosion in global, high-resolution environmental monitoring products derived from satellite remote sensing and global modeling approaches. These data are particularly relevant to managing impacts and risks associated with agricultural production, yet they are not widely used by companies seeking to improve their environmental performance. This is partly because of the difficulty of tracing where materials are ultimately sourced from (Patterson et al. 2022).

LandGriffon is inspired by the need to move beyond life-cycle assessment approaches to provide spatially explicit information on agricultural supply chain impacts. It addresses the challenge of a lack of traceability by providing a framework for companies to understand the spatial dimensions of their agricultural supply chain information and to evaluate impacts as accurately as possible. We estimate supply chain impacts using a hierarchical approach. When information is limited, we use a probabilistic approach to identify likely sourcing regions and estimate impacts. When companies know more about their suppliers and sourcing locations, this information is used to improve the quality and accuracy of estimates. When field-level impact assessments are available, these data can supersede LandGriffon estimates.

For companies with agricultural supply chains, tools are needed that can be applied globally to agricultural commodities, integrate with current supply chain systems, and help explore pathways towards reduced impacts and risks. LandGriffon addresses that need through its capabilities:

1. It can integrate with diverse company supply chain data and systems;
2. It adopts a spatially explicit approach;
3. It can be used to understand all agricultural commodities at global scale;
4. It is extendable so that it works with currently available data but can readily incorporate newer data and indicators as these become available;
5. It allows companies to explore various pathways towards reduced impacts by evaluating the effects of actions such as changing recipes or sourcing locations, or reducing the environmental impacts of producers;
6. It promotes greater precision in supply chain traceability by rewarding this with more accurate impact estimates;
7. It aligns with the guidelines proposed by the Science Based Targets Network (Science Based Targets Network 2023b; 2023a) and the Taskforce on Nature-related Financial Disclosures (TNFD 2023) through its features and impact indicators.

Given the urgent need for companies to evaluate, plan, and mitigate environmental impacts, the LandGriffon framework fills an essential gap in enabling companies to take action even with limited information.

METHODS

The LandGriffon methodology is comprised of four elements (**Figure 1**):

1. importing supply chain data
2. modeling spatial sourcing
3. evaluating impacts
4. exploring pathways to reduce impacts

We use these elements to structure the methodological description below.

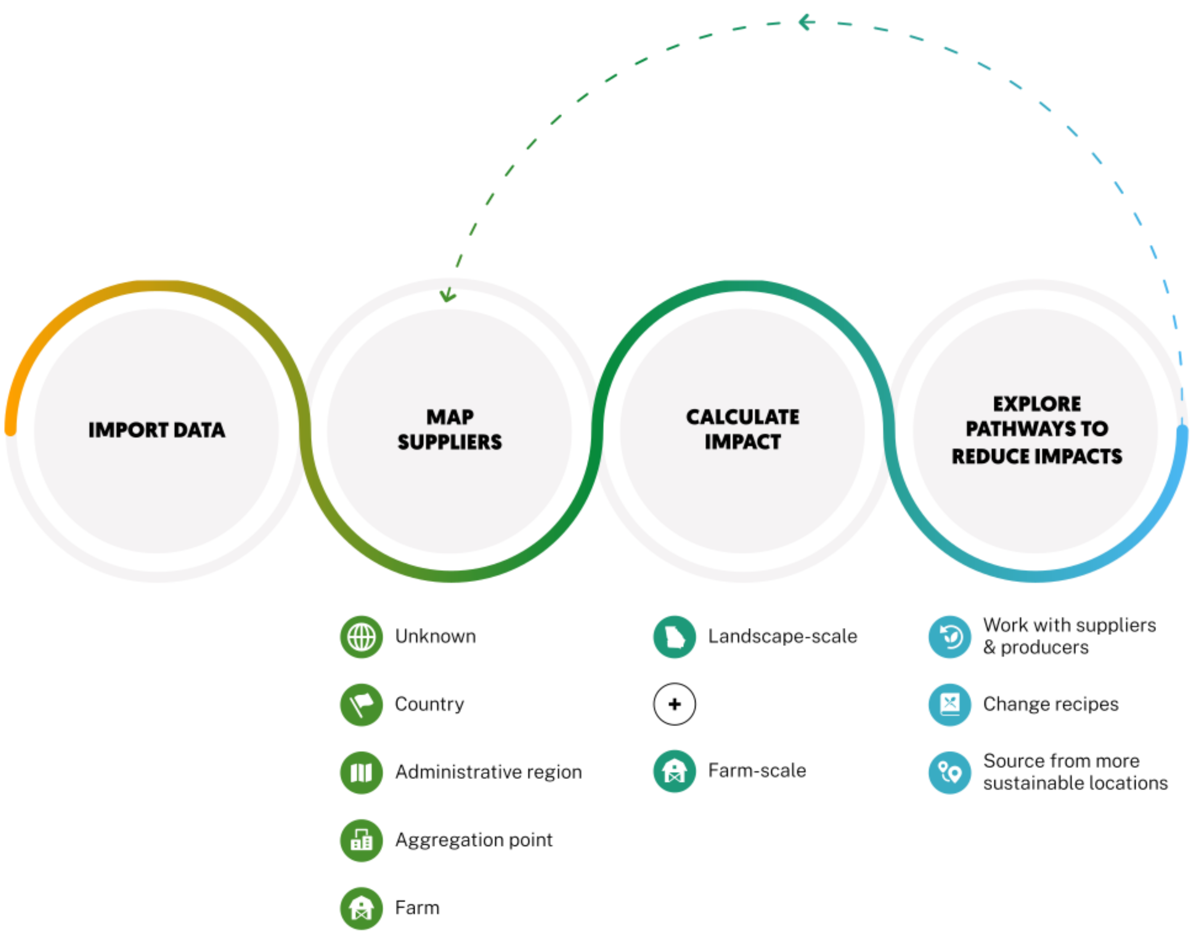


Figure 1. Schematic representation of the LandGriffon v0.2 methodology.

Importing supply chain data

LandGriffon users import company data on the agricultural materials they use to estimate their impacts (**Figure 2**). At a minimum, companies must provide the volume of each raw material used each year. Companies can report on their suppliers' details and the countries, regions, or exact farm locations from which materials are sourced to improve the precision of sourcing locations.

The information companies have on the production of their raw materials will vary in detail. Sometimes they know the exact farm that grows the product, and at other times, they purchase commodities on an open market or only know the address of a supplier that, in turn, purchases from a group of producers. This means that the procurement information that companies import provides varying degrees of precision on where in the world each material was sourced from.

A	B	C	D	E	F	G	H	I	J	K	L	M	N
Material	**Business unit**	**Suppliers**		**Sourcing location**					**Tonnage**				
Material	The business unit for which these materials were supplied	The company from which the materials were purchased	The company that produced the raw materials. (farm, cooperative, local aggregator etc.)	The level on information you have on where the raw materials were produced. One of: - Point of production (farm, ranch, plantation, etc.) - Aggregation point (warehouse, silo, mill etc.) - Country of production - Unknown	The country where the material was produced. If unknown, enter the country where the material was delivered.	Location of the producer. State, province, county, district, city, town, address etc. Leave blank if GPS coordinates are known. This will be geocoded with Google Maps.	GPS coordinates of producer, if known	GPS coordinates of producer, if known	Metric tonnes of the material purchased each year				
Required	**Required**			**Required**	**Required**	**Required for "Aggregation point" and "Point of production"**			**Required**				
Material	Business unit	Tier 1 Supplier	Producer	Location Type	Country	Address	Latitude (°N)	Longitude (°E)	2010 tons	2011 tons	2012 tons	2013 tons	2014 tons
40 Rubber and	Accessories	Cargill	Moll	Unknown	Lebanon				2400	2424	2448	2472	2497
40 Rubber and	Accessories		Moll	Unknown	Malaysia				1300	1313	1326	1339	1352
40 Rubber and	Accessories		Moll	Unknown	United States of /				1000	1010	1020	1030	1040
40 Rubber and	Accessories		Moll	Unknown	Japan				730	737	744	751	759
40 Rubber and	Accessories		Moll	Unknown	India				490	495	500	505	510
40 Rubber and	Accessories		Moll	Country of production	Thailand				3100	3131	3162	3194	3226
40 Rubber and	Accessories		Moll	Country of production	Indonesia				2600	2626	2652	2679	2706
40 Rubber and	Accessories		Moll	Country of production	Cote D'Ivoire				1100	1111	1122	1133	1144
40 Rubber and	Accessories		Moll	Country of production	Vietnam				810	818	826	834	842
40 Rubber and	Accessories		Moll	Country of production	Malaysia				740	747	754	762	770
40 Rubber and	Accessories			Aggregation point (warehouse, :	Liberia	Margibi			2300	2323	2346	2369	2393
40 Rubber and	[illegible]			Aggregation point (warehouse, si	India	Kerala			1200	1212	1224	1236	1248
40 Rubber and	[illegible]			Aggregation point (warehouse, :	Thailand	Nakhon Si Thammarat			1000	1010	1020	1030	1040

Figure 2. Example of the spreadsheet template for supplier data ingestion. The basic information that needs to be provided is the material and volume purchased. The user can also provide information regarding the sourcing location.

Given this variability in the spatial precision of sourcing location, we analyze sourcing data using a hierarchical structure, listed below in order of increasingly precise location type:

- **Unknown:** The material is sourced on a global market. No information is available on where it is produced.
- **Country of delivery:** The country the material was delivered to is known, but not the country in which it was produced.
- **Country of production:** The material is known to be produced in a country, but no other information is available.
- **Administrative region:** The material can be traced to production in a sub-national administrative region.
- **Production aggregation point:** The material can be traced to a specific aggregation point (using an address or coordinates), such as a mill, silo, warehouse, or another facility that receives product from producers in the local area.
- **Point of production:** The material can be traced to production on a specific farm or another point of production (using an address or coordinates).

Commodity standardization

We use an extension of the World Customs Organization's hierarchical Harmonized System (HS) codes to identify materials and commodity types (**Figure 3**). This allows us to include more detailed information for specific materials and fall back on generic estimates where data for the specific material is unavailable. Where necessary, volumes of derived or processed materials sourced by companies are standardized to the volumes of the raw material produced using tonnage ratios (Poore and Nemecek 2018; FAO n.d.). This material classification is extensible to allow the definition of additional types of raw materials within the hierarchy.

A	B	C	D
name	**hs_2017_co**	**short name**	**description**
01 Animals; live	01	Live animals	Animals; live
01.01 Horses, asses, mules and hinnies; live	0101	Horses, asses, r	Horses, asses, mules and hinnies; live
01.02 Bovine animals; live	0102	Bovine animals,	Bovine animals; live
01.03 Swine; live	0103	Swine, live	Swine; live
01.04 Sheep and goats; live	0104	Sheep and goat:	Sheep and goats; live
01.05 Poultry; live, fowls of the species Gallus domesticus, ducks, geese, tu	0105	Poultry, live	Poultry; live, fowls of the species Gallus domesticus, ducks, geese, turkeys and guinea fowls
01.06 Animals; live, n.e.c. in chapter 01	0106	Other animals, li	Animals; live, n.e.c. in chapter 01
02 Meat and edible meat offal	02	Meat	Meat and edible meat offal
02.01 Meat of bovine animals; fresh or chilled	0201	Bovine animals,	Meat of bovine animals; fresh or chilled
02.02 Meat of bovine animals; frozen	0202	Bovine animals,	Meat of bovine animals; frozen
02.03 Meat of swine; fresh, chilled or frozen	0203	Swine, fresh, chi	Meat of swine; fresh, chilled or frozen
02.04 Meat of sheep or goats; fresh, chilled or frozen	0204	Sheep and goat:	Meat of sheep or goats; fresh, chilled or frozen
02.05 Meat; of horses, asses, mules or hinnies, fresh, chilled or frozen	0205	Horses, asses, r	Meat; of horses, asses, mules or hinnies, fresh, chilled or frozen
02.06 Edible offal of bovine animals, swine, sheep, goats, horses, asses, m	0206	Edible offal of bc	Edible offal of bovine animals, swine, sheep, goats, horses, asses, mules or hinnies; fresh, chilled or frozen
02.07 Meat and edible offal of poultry; of the poultry of heading no. 0105, (i.	0207	Poultry meat anc	Meat and edible offal of poultry; of the poultry of heading no. 0105, (i.e. fowls of the species Gallus domesticu
02.08 Meat and edible meat offal, n.e.c. in chapter 2; fresh, chilled or frozer	0208	Other edible offa	Meat and edible meat offal, n.e.c. in chapter 2; fresh, chilled or frozen
02.09 Pig fat, free of lean meat, and poultry fat, not rendered or otherwise e	0209	Pig and poultry f	Pig fat, free of lean meat, and poultry fat, not rendered or otherwise extracted, fresh, chilled, frozen, salted, in
02.10 Meat and edible meat offal; salted, in brine, dried or smoked; edible fl	0210	Meat and edible	Meat and edible meat offal; salted, in brine, dried or smoked; edible flours and meals of meat or meat offal
04 Dairy produce; birds' eggs; natural honey; edible products of animal orig	04	Dairy, eggs and	Dairy produce; birds' eggs; natural honey; edible products of animal origin, not elsewhere specified or include
04.01 Milk and cream; not concentrated, not containing added sugar or othe	0401	Milk and cream r	Milk and cream; not concentrated, not containing added sugar or other sweetening matter
04.02 Milk and cream; concentrated or containing added sugar or other swe	0402	Milk and cream r	Milk and cream; concentrated or containing added sugar or other sweetening matter

Figure 3. Screenshot of the commodities included as part of the LandGriffon methodology with the World Customs Organization's hierarchical Harmonized System (HS) terminology. The full list can be found **here**.

Enriching supplier data with open access supply chain data

For specific raw materials, there is substantial open access data that can help inform the likely locations that companies are sourcing from. For example, **Trase** identifies the regions and producers that major commodity traders purchase from for soy, palm oil, beef, shrimp, cocoa, coffee, corn, wood pulp, chicken, cotton, sugar cane, and pork. For palm oil, universal mill lists and land concession data can be used to more accurately pinpoint company sourcing regions.

As these datasets continue to evolve and do not currently provide complete global coverage, we do not use them automatically in version 0.2 of LandGriffon. The LandGriffon team can assist users in manually incorporating these and other data.

Modeling spatial sourcing

The spatial sourcing model lies at the core of the LandGriffon methodology. The model identifies likely areas where materials are sourced from. It then attributes impacts in those areas to the sourcing of those materials.

When the exact production location is not known, we assume that the raw material is sourced from all locations producing within a given area (as defined in **Table 1**). Where the location type is the country of delivery, we assume that the material has been produced in that country or in any country exporting the material to the given country (identified using Multi-Regional Input-Output databases e.g. **EXIOBASE 3**).

The closest matching gridded production dataset for each material is identified to spatially allocate sourcing within the sourcing region. MapSPAM (International Food Policy Research Institute 2019) is used for crop production (**Figure 4**), and Gridded Livestock of the World v3 (GLWv3) (Gilbert et al. 2018) is used for estimating impacts from livestock production. MapSPAM and GLWv3 are the latest publicly available datasets but are representative of the year 2010. It is essential to acknowledge that, given the dynamic nature of livestock production and pasture commodities, livestock impact estimates are currently experimental.

Materials are matched using the extended HS commodity codes. Where there is no exact match, the closest parent in the hierarchical system will be used. For example, “Apples, Pears, and Quinces” (HS 0808), is matched to the MapSPAM dataset for Temperate Fruit crops. Materials with no close match, such as rubber or acacia, are analyzed on a case-by-case basis using specific additional datasets. More material is assumed to be sourced from locations with greater production. So, a higher probability of impact is associated with areas of high production.

There can be under- or overestimation of the impact associated with a raw material with this approach. If the weighted average impact across the whole sourcing area is lower than in the location or locations where the material was produced there will be an underestimation. If the raw material came from a production area with a low impact, there will be an overestimation.

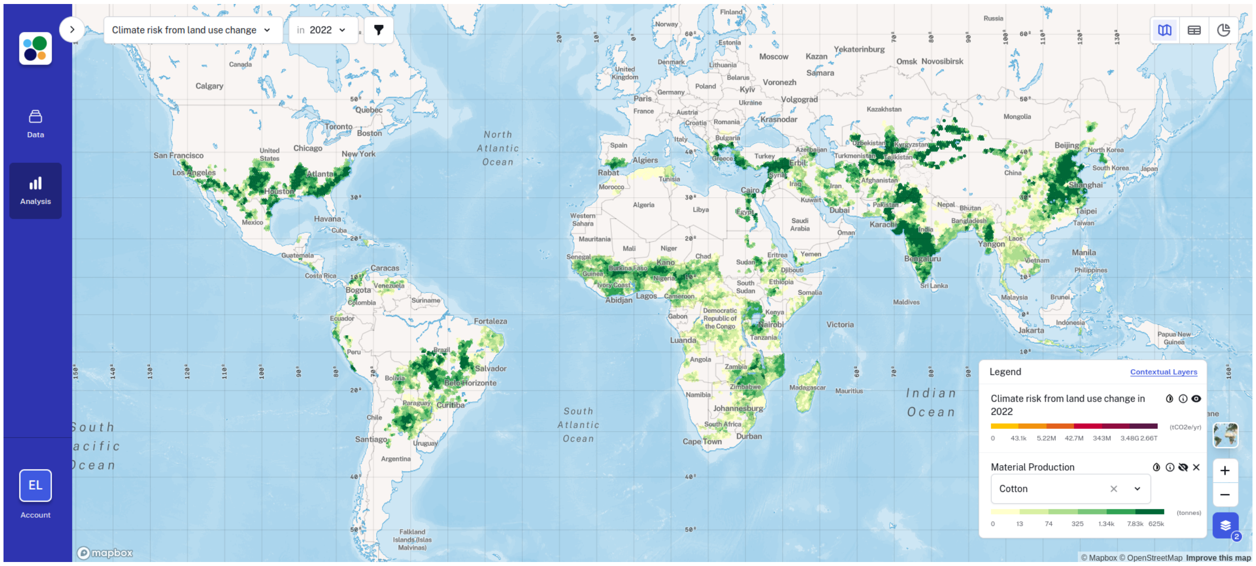


Figure 4. Distribution of cotton production (in tonnes) from MapSPAM data. The raw material production datasets are used in order to distribute the purchased volume across the sourcing location type identified. More material will be assumed to be sourced from locations in which there is greater production.

Understanding spatial sourcing at a sub-national level is critically important for reducing uncertainties in impact estimation. Future LandGriffon development will focus on using additional supply chain information to infer the likely agricultural supply chain of companies. This can be based on the sourcing profile of a country in which that company is based, or using company specific information on supply chains. For example, trader information for palm oil or cacao can be enriched with Trase data on supply chains. Ultimately, if companies are able to collect it, full knowledge of sourcing locations can be incorporated, which removes the need to model that information.

Spatial representation

Each sourcing location is geolocated depending on its associated location type (**Figures 5 and 6**). LandGriffon uses the H3 format for geospatial data processing. H3 has the benefit of computationally efficient visualization and calculation, limited distortion at high latitudes, and appealing aesthetics for visualization. This allows for low-latency calculations and visualizations that update rapidly and are enjoyable to explore.

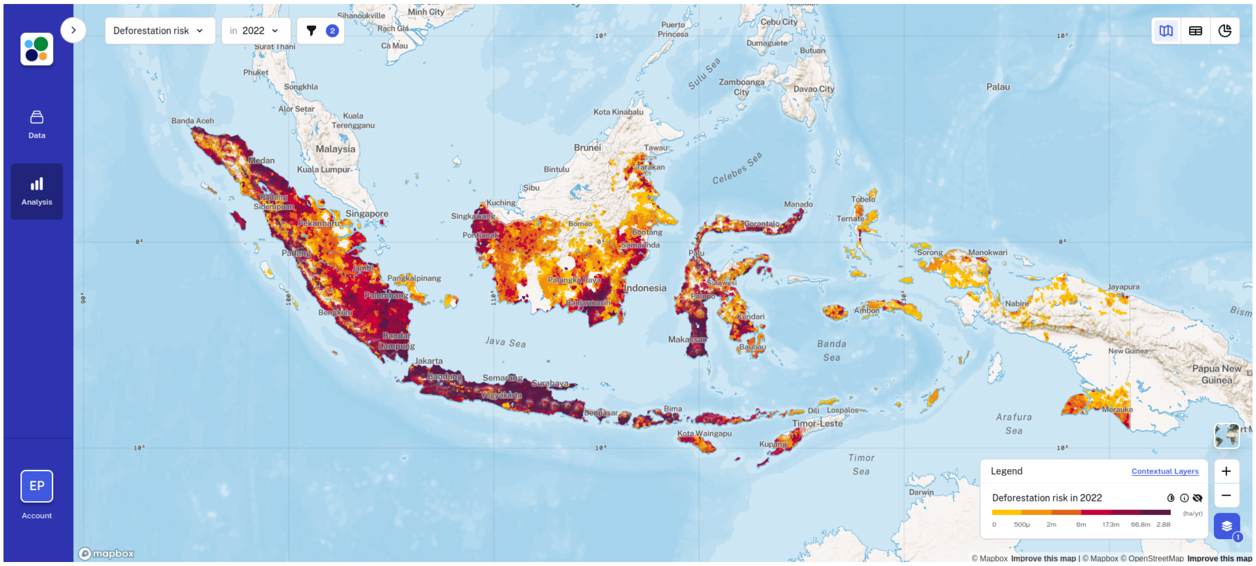


Figure 5. Geolocation of a country of production, showing the distribution of deforestation footprint associated with sourcing palm oil from Indonesia. We model the purchased volume as being produced across all areas of palm oil production in Indonesia.

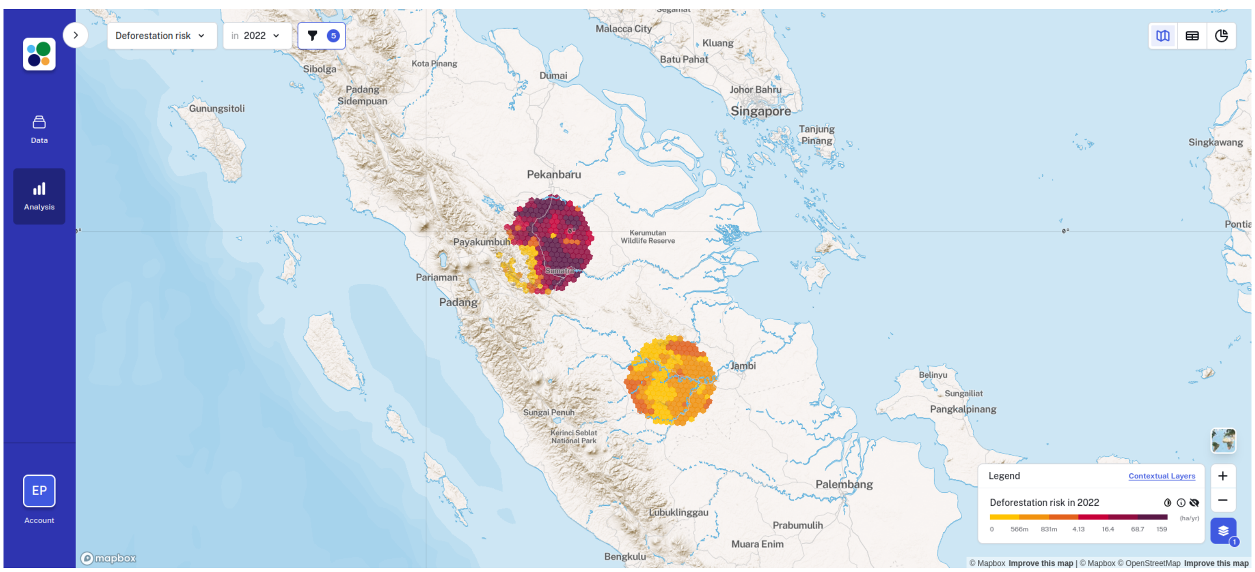


Figure 6. Geolocation of a supplier's aggregation point (50 km radius buffer), showing deforestation risk of palm oil around aggregation points in Indonesia. We model the purchased volume as being produced across all areas of palm oil production inside supplier aggregation points.

Table 1. Description of the location types, spatial sourcing assumptions and their implications.

Location type	Description	Spatial sourcing assumption(s)	Sourcing region	Implication(s)
Unknown	No information about the location of the raw material is known.	The raw material has been produced globally, in all locations producing that raw material, and sourced in proportion to the production in any location.	Assumed to be the whole world	Large uncertainties in the form of under- or over-estimation of impact compared to known sub-national location of production.
Country of delivery	The country in which the raw material is received is known, but not the country in which it is produced.	The raw material has been produced globally, in all locations exporting the material to the given country, and sourced in proportion to the production in any location.	Global map weighted using international trade data	As above
Country of production	The raw material is known to be sourced from a given country.	The raw material has been produced across the entire country, in all locations producing that raw material, and sourced in proportion to the production in any location.	Mapped to the respective country boundary	Moderate uncertainties in the form of under- or over-estimation of impact compared to the case when the point of production is known.
Administrative region of production	The raw material is known to be sourced from a given administrative region.	The raw material has been produced across the entire administrative region, in all locations producing that raw material, and sourced in proportion to the production in any location.	Mapped to the respective region boundary	Moderate uncertainties in the form of under- or over-estimation of impact compared to the case when the point of production is known.

Production aggregation point	The raw material is purchased from a specific supplier, and the facility that receives materials from local producers is known.	The raw material has been produced within a buffered area around the aggregation point provided, in all the areas with production of that material. The buffer is a rough estimation of the maximum distance of local material transport and should vary with raw material type but defaults to 50 km in this version.	Geocoded as a 50km aggregation circle around the aggregation point, under the assumption that the circle radius reflects the distance that local producers will transport commodities to the aggregator	Buffer may not be an accurate representation of the supply area and so may miss impacts arising outside this buffer and/or under-/overestimate impact within it. Where the amounts sourced from different facilities are unknown, impacts can be disproportionate to the locations of production.
Point of production	The farm or other production sites where the raw materials are produced is known.	The raw materials have been produced in that exact location.	Geocoded as points	The entire extent of that production might not be accounted for, if no spatial footprint for the farm or production unit is available. At present, the resolution of analysis is limited by the data available for impact calculation, which for raw material production is approximately 10km x 10km. With finer resolution data, future development will allow for finer-scale analysis for point of production polygons

Impact indicator calculation

Version 0.2 of LandGriffon includes indicators of environmental impacts for water use, water quality, land use, greenhouse gas emissions, natural ecosystems conversion and biodiversity (**Annex 1**).

Once sourcing areas are identified, we calculate indicators of impact of the materials sourced. All indicators are calculated as the quantity of a raw material multiplied by an *impact factor*, which is the average impact per ton of the raw material produced across the sourcing region. The impact, $I_{c,g}$, associated with raw material, *c*, and sourcing region, *g*, is calculated as:

$$I_{c,g} = IF_{c,g} * S_{c,g} \qquad \text{(Eq. 1)}$$

where $IF_{c,g}$ is the *impact per ton of raw material produced,* and $S_{c,g}$ is the total quantity of the raw material sourced from that region in *tons*.

The calculation of impacts and impact factors depends on the specific indicator and available data (**Annex 1**). For example, spatial maps of crop production exist, as do maps of the state of and pressures on water resources and deforestation. However, for many within-farm-gate impacts there is a need to use national or administrative level data such as those derived from generic life cycle assessments.

National and administrative data

For indicators derived from national or administrative-level data (e.g. from generic life cycle assessment or footprint analysis), the closest matching impact factor for the material and administrative region is identified:

- Materials are matched using an extension of the World Customs Organization's hierarchical Harmonized System (HS) commodity codes. Where there is no exact match, the closest parent in the materials and administrative regions hierarchy is used. For example, if the impact factor table does not include a record for a given country it will use a global average impact factor.

- Matches in the material hierarchy are selected over matches in the administrative hierarchy. E.g. For organic cotton from Burkina Faso, a global impact factor for organic cotton will be preferred to a Burkina Faso-specific impact factor for generic cotton.

Spatially explicit data

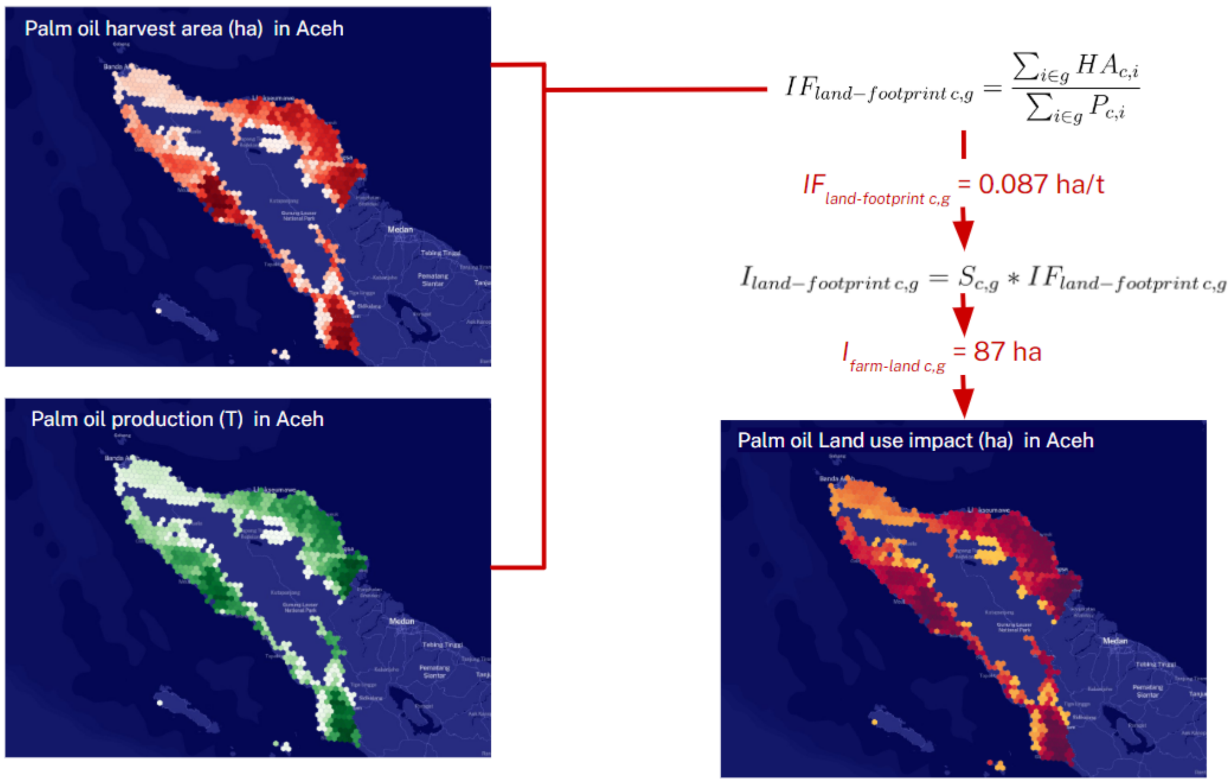
For indicators derived from spatial datasets, the method used to derive the impact factor depends on the *location type* and whether the indicator measures farm-level impacts or land use change impacts.

- Farm-level indicators aim to capture those impacts that occur or can be attributed to activities within the farm gate, i.e. the current footprint of agricultural production.
- Land use change indicators represent the impact of raw materials at the landscape-level. We calculate land use change impacts using a Statistical Land Use Change (sLUC) approach for a 50km radius around the location(s) in which the material is produced. This recognizes that commodity-driven land use change occurs outside of existing farms, and that land use adjacent to the land use change boundary adds to the land pressure that is driving land conversion.

Materials are assumed to be sourced in proportion to the amount of production occurring in each location within the sourcing region, such that locations that produce more are counted more heavily. In general, we achieve this by computing a *production weighted average impact factor,* $IF_{c,g}$, derived by multiplying the impact factor at each point, $IF_{c,i}$, by the production at each point, $P_{c,i}$, within the sourcing region, *g*, and then dividing by the sum of the production for the whole region:

$$IF_{c,g} = \frac{\sum_{i \in g} IF_{c,i} * P_{c,i}}{\sum_{i \in g} P_{c,i}} \quad \text{(Eq. 2)}$$

The production weighted average impact factor is a close analogy to the Commodity Supply Mix developed for Life Cycle Assessment (Lathuillière et al. 2021).



H3 index (i)	Production($P_{c,i}$, t)	Harvest area ($HA_{c,i}$, ha)
866576777ffffff	44219.7	3072.5
866576757ffffff	44219.7	3072.5
866576677ffffff	44031.5	2981.0
8665095afffffff	40154.8	2200.1
…	…	…

$$I_{land-footprint\,c,i} = IF_{land-footprint\,c,g} * S_{c,g} * \frac{P_{c,i}}{\sum_{j \in g} P_{c,j}}$$

Spatial allocation of land footprint ($I_{land-footprint\,c,i}$, ha)
0.757
0.757
0.754
0.687
…

5094544.7 t — 444220.2 ha → 0.087 ha/t

$IF_{land-footprint\,c,g}$

$$IF_{land-footprint\,c,g} = \frac{\sum_{i \in g} HA_{c,i}}{\sum_{i \in g} P_{c,i}}$$

Figure 7. (Top) Illustrative description of the impact factor calculation procedure for land use related to sourcing of palm oil from a sub-national region (Aceh, Indonesia). (Bottom) Detailed diagram of the impact factor calculation for a given raw material, *c* (in this case oil palm), and sourcing region, *g* (in this case Aceh). For the set of H3 points, *i*, in the sourcing region g, the production, $P_{c,i}$, and harvest area, $HA_{c,i}$, are combined to calculate the production weighted land footprint for that raw material. This footprint can be allocated spatially, in this case assuming 1000 t of palm oil is sourced from Aceh.

Farm-level impacts

Farm-level impact indicators (e.g. **Figure 7**) are calculated as follows:

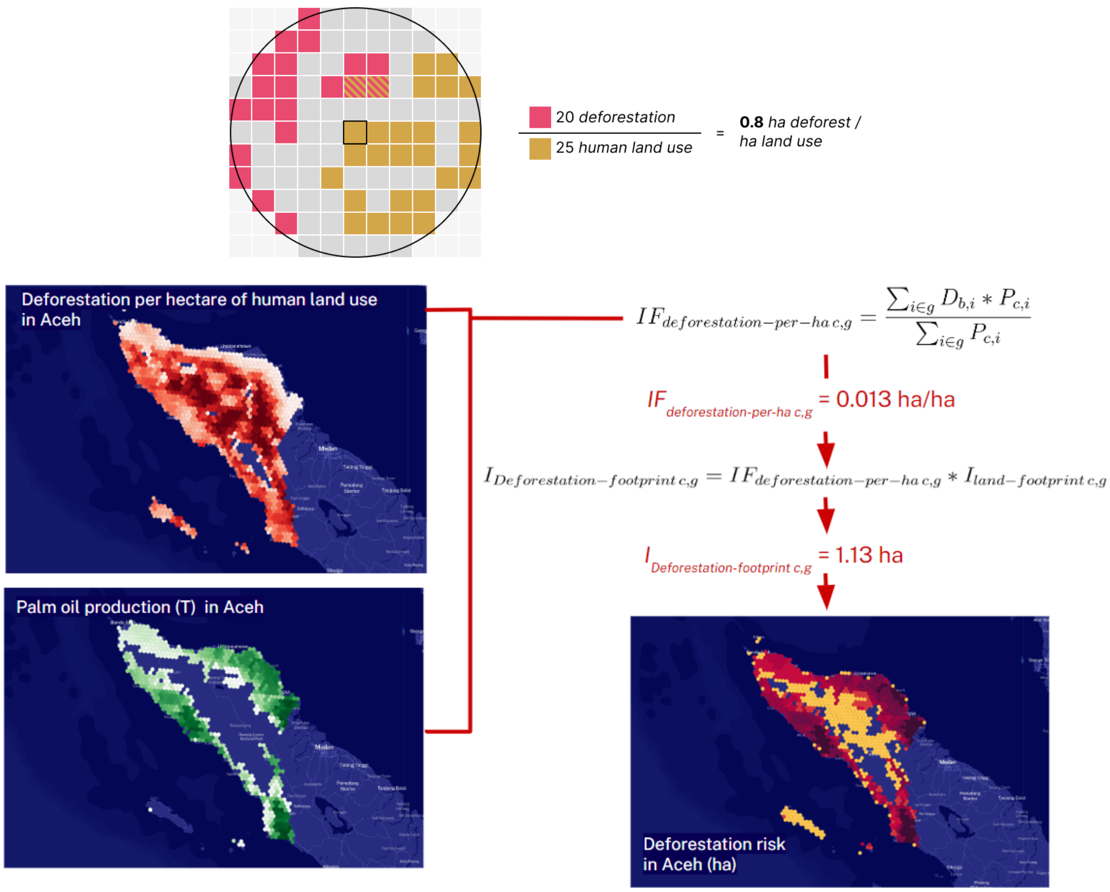
- The impact factor is calculated as the production weighted average within the sourcing region.
- If there is no overlap between the production map and the sourcing region, the impact factor is calculated as the area average for the sourcing region.

Land use change impacts

Land use change impact indicators (e.g. **Figure 8**) are calculated and allocated using a spatial adaptation of the statistical land use change (sLUC) proportional allocation based on land occupation approach (Greenhouse Gas Protocol 2022). In particular, instead of allocating responsibility for land use change to all human land uses across a jurisdiction, we allocate over the local area using a kernel radius, such that areas immediately adjacent to land use change receive more responsibility than areas that are far away, as follows:

- For each pixel in the sourcing region, the total impact, such as area of deforestation or natural ecosystem conversion, are calculated within a 50km radius of the pixel.
- This total impact is then divided by the total area of non-natural land use within the same radius.
- This yields a per-pixel statistical land use change impact factor expressed as the impact per area of land use (**Figure 8**).
- An impact factor for the sourcing region is calculated as the production weighted average for the sourcing region.
- Total impact is calculated by multiplying the land footprint of the raw material by this impact factor.

We selected a 50km distance in version 0.2 of LandGriffon as a conservative estimate of attributable impact distance (Sonter et al. 2017).



H3 index	Production(T) - $P_{c,i}$	Deforestation per hectare of human land use (ha/ha) - $D_{b,i}$	$Dg_{b,i}$ * $P_{c,i}$	Cell deforestation risk (ha) - $I_{deforestation\text{-}risk\ c,i}$
866576777ffffff	44219.7	0.014344	634.266460	0.010
866576757ffffff	44219.7	0.014344	634.266460	0.010
866576677ffffff	44031.5	0.015975	703.408445	0.010
8665095afffffff	40154.8	0.000081	3.259192	0.009
...	...	...	...	...

$I_{deforestation-footprint\ c,i} = IF_{deforestation-per-ha\ c,g} * I_{land-footprint\ c,i}$

1.13 ha

$IF_{deforestation-per-ha\ c,g} = \frac{\sum_{i \in g} D_{b,i} * P_{c,i}}{\sum_{i \in g} P_{c,i}}$

5094544.7 t

0.013 ha /ha

$I_{Deforestation-footprint\ c,g} = IF_{deforestation-per-ha\ c,g} * I_{land-footprint\ c,g}$

$I_{land-footprint\ c,g}$

87 ha

Figure 8. (Top) Illustration of the calculation of the deforestation rate per hectare of human land use $D_{b,i}$. (Middle) Illustrative description of the impact calculation procedure for deforestation footprint for sourcing 1000 t of palm oil from the Aceh sub-national region of Indonesia, with a land footprint, $I_{land\text{-}footprint\ c,g}$ of 87 ha. (Bottom) Detailed diagram of the impact factor calculation for sourcing this volume of palm oil. For the set of H3 points i, in the sourcing location g, the production, $P_{c,i}$, harvest area, $HA_{c,i}$, and deforestation per unit area of human land use in the buffered region b around the point, $D_{b,i}$, are combined to calculate the production weighted mean deforestation per unit of human land use across Aceh.

Impact calculations

Impact calculations are implemented in a modular way within the LandGriffon software such that new indicators can easily be added to the calculation framework. Version 0.2 of LandGriffon includes a default set of impact indicators following draft guidance from SBTN (**Table 2**). Further descriptions of indicators objectives, calculations, limitations, and next steps are provided in **Annex 1**.

Table 2. Impact indicators included by default LandGriffon v0.2.

Impact type category	Indicator	Short description
Water quantity	Water use	The volume of surface or groundwater that is consumed in the production of the raw material sourced.
	Unsustainable water use	The volume by which the water consumption associated with the production of the raw material sourced must be decreased to reduce pressure on nature.
Water quality	Nutrient load	The annual average water volume required to assimilate the nutrient load added by the raw material sourced.
	Excess nutrient load	The volume by which nutrient load associated with the raw material sourced must be decreased to achieve the desired instream nutrient concentration.
Land use	Land footprint	The total land area required to produce the raw material sourced.
Climate	GHGs (farm management)	The amount of greenhouse gas (GHG) emissions, including CO_2, N_2O and CH_4, arising from farm-management of the raw material sourced.
	GHGs (deforestation, sLUC)	The annual average emissions of greenhouse gas (GHG) associated with deforestation within a 50km radius attributable to the raw material sourced.
Natural ecosystem conversion	Deforestation footprint (sLUC)	The annual average area of deforestation within a 50km radius attributable to the raw material sourced.
	Net cropland expansion	The annual average area of cropland expansion into natural ecosystems occuring within a 50km radius attributable to the raw material sourced.

Biodiversity	Forest Landscape Integrity loss	The average forest landscape integrity score of natural ecosystems that have been converted to cropland within a 50km radius attributable to the raw material sourced.
	Biodiversity intactness loss	The average biodiversity intactness score of natural ecosystems that have been converted to cropland within a 50km radius attributable to the raw material sourced.

These indicators are currently focused on production impacts, as opposed to lifecycle impacts. Though LandGriffon has taken some inspiration from Life Cycle Assessment (LCA), there will be implicit impacts associated with the sourcing of raw materials that are not captured by production-focused indicators.

Scenario evaluation and pathway identification

LandGriffon performs impact calculations automatically on imported data. We provide tools for visual and quantitative analysis, exporting data, and creating forecasts or future scenarios simulating changes in procurement and impacts.

Scenario analysis involves exploring a range of futures to anticipate impacts and plan actions. LandGriffon allows the user to develop a portfolio of future actions or changes to operations and evaluates the resulting outcomes for the range of impact indicators in the tool. Scenarios can be compared, and actions identified that are likely to form a pathway to achieve a desired future state.

Companies can develop scenarios in which they can change elements of their supply chain. A user may identify the product or business area that generates the largest impact and assess how this impact could be reduced relative to the other areas.

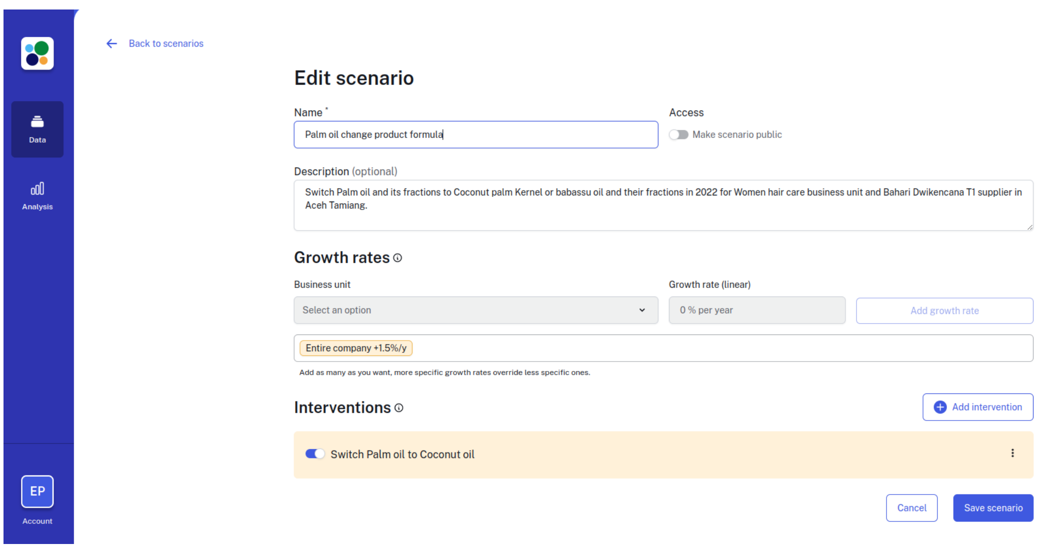


Figure 9. Example of the creation of a scenario with one intervention using the LandGriffon platform. The scenario includes just an intervention for changing palm oil. In the creation of a scenario the user can also set different growth rates directly through the platform.

Users can define future scenarios through a combination of *growth rates* and *interventions*. Growth rates set the expectations of how purchases of raw materials will change. In version 0.2 of LandGriffon, users can set growth rates for the entire company or for specific business units. The default growth rate is an annual linear growth of 1.5% across the whole company.

Interventions allow users to simulate changes and alternatives in sourcing. The broad action types available in version 0.2 of LandGriffon include:

- working with producers to reduce environmental impact and increase yield,
- changing recipes or switching to new materials,
- sourcing the same materials from another producer with a lower environmental footprint.

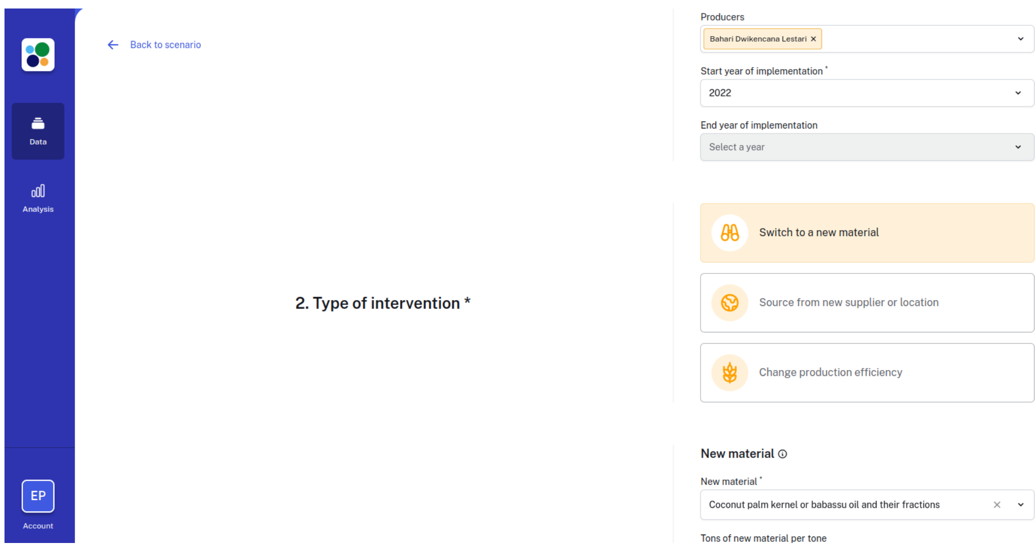


Figure 10. Types of interventions contemplated in the creation of a scenario.

Once a set of actions making up a future scenario has been defined, LandGriffon then calculates the change in impacts arising from this set of actions, which can be compared to a reference case, other scenarios, and company targets.

EXAMPLE ANALYSIS AND RESULTS

Usage of LandGriffon requires data about company procurement that is typically closely guarded. We provide an example analysis of using LandGriffon to analyze the impact of a hypothetical sourcing of 1000 tonnes of palm oil in Aceh, Indonesia with different levels of spatial sourcing precision, and exploration of scenarios.

Ingestion of company data

Supply chain data information regarding purchased raw materials for a given company is ingested into the LandGriffon platform as an initial step. This information is inputted using a template spreadsheet and uploaded directly to the platform.

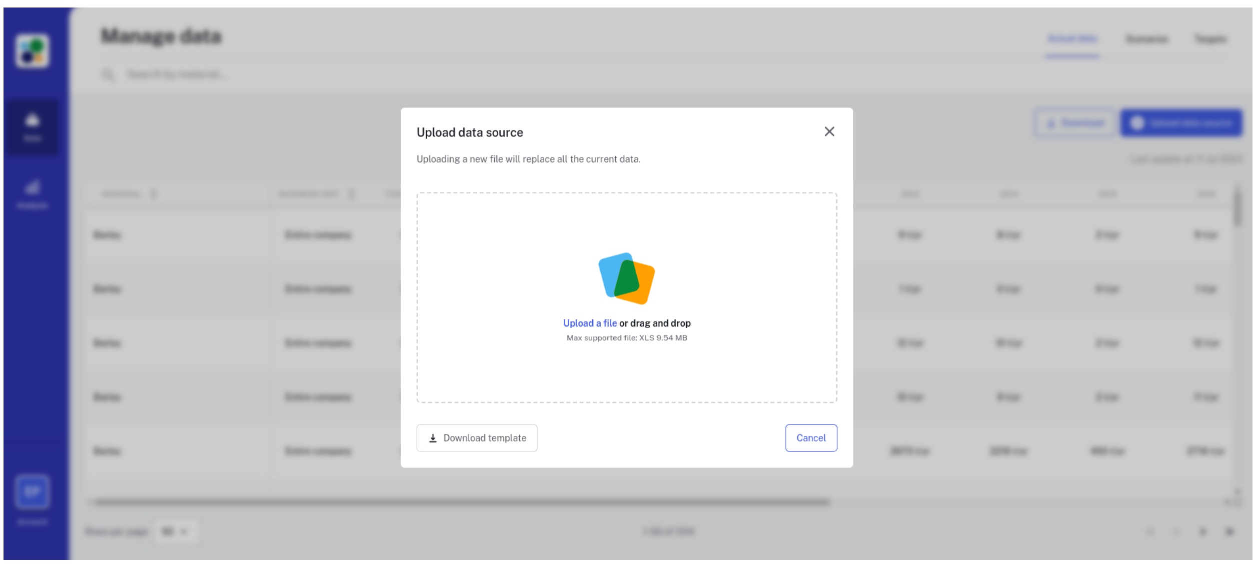
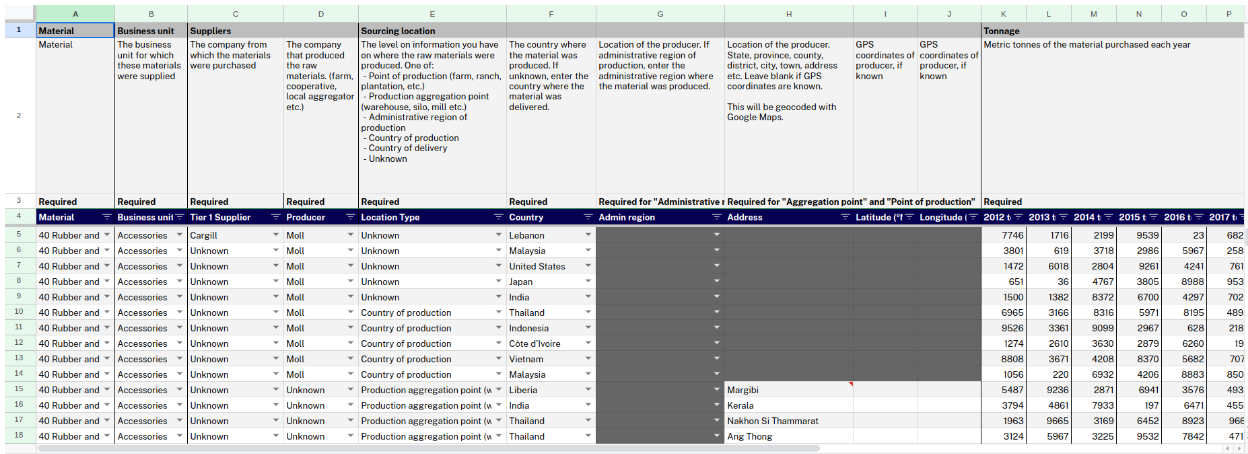


Figure 11. Ingestion of company data into LandGriffon.

During this preparation, as a minimum requirement, the user must provide the yearly purchased volume for each raw material. Additionally, the spreadsheet can also incorporate information regarding business units, suppliers, and sourcing locations.

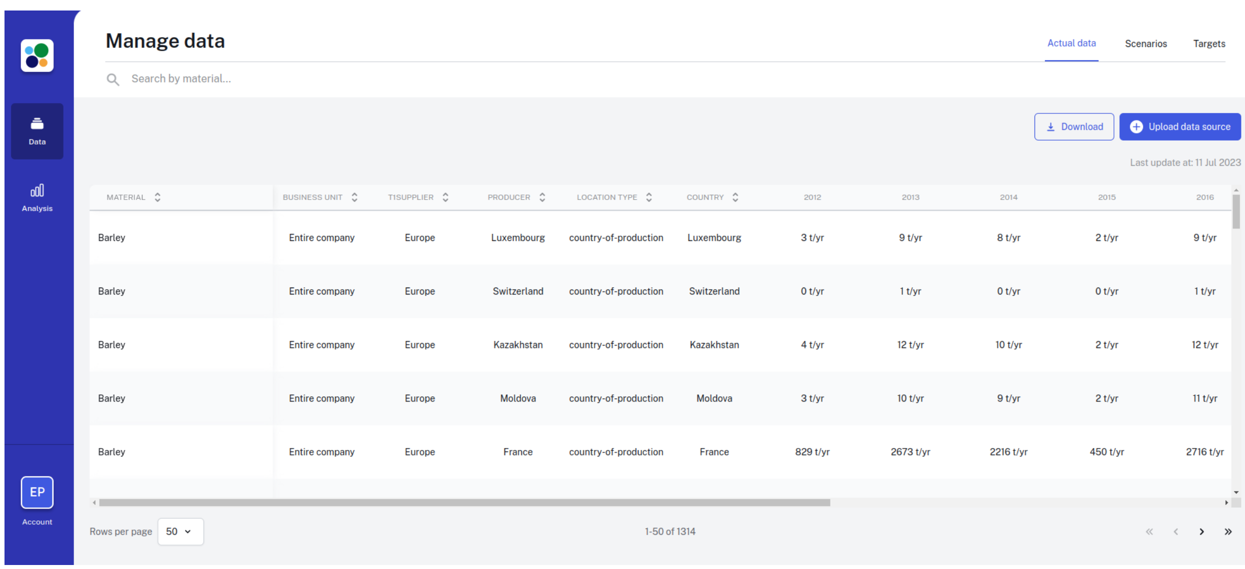
We understand that the level of information regarding the supply chain raw materials can vary significantly across companies, tiers, or business units, so the data ingestion in LandGriffon v0.2 is purposely designed to accommodate varying levels of detail. While populating this information, we can also help identify any third-party data sources that can enrich the company supply chain profile.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	**Material**	**Business unit**	**Suppliers**		**Sourcing location**						**Tonnage**					
2	Material	The business unit for which these materials were supplied	The company from which the materials were purchased	The company that produced the raw materials. (farm, cooperative, local aggregator etc.)	The level on information you have on where the raw materials were produced. One of: - Point of production (farm, ranch, plantation, etc.) - Production aggregation point (warehouse, silo, mill etc.) - Administrative region of production - Country of production - Country of delivery - Unknown	The country where the material was produced. If unknown, enter the country where the material was delivered.	Location of the producer. If administrative region of production, enter the administrative region where the material was produced.	Location of the producer. State, province, county, district, city, town, address etc. Leave blank if GPS coordinates are known. This will be geocoded with Google Maps.	GPS coordinates of producer, if known	GPS coordinates of producer, if known	Metric tonnes of the material purchased each year					
3	**Required**	**Required**	**Required**	**Required**	**Required**	**Required**	**Required for "Administrative r**	**Required for "Aggregation point" and "Point of production"**			**Required**					
4	**Material**	**Business unit**	**Tier 1 Supplier**	**Producer**	**Location Type**	**Country**	**Admin region**	**Address**	**Latitude (°I**	**Longitude (**	**2012 t**	**2013 t**	**2014 t**	**2015 t**	**2016 t**	**2017 t**
5	40 Rubber and	Accessories	Cargill	Moll	Unknown	Lebanon					7746	1716	2199	9539	23	682
6	40 Rubber and	Accessories	Unknown	Moll	Unknown	Malaysia					3801	619	3718	2986	5967	258
7	40 Rubber and	Accessories	Unknown	Moll	Unknown	United States					1472	6018	2804	9261	4241	761
8	40 Rubber and	Accessories	Unknown	Moll	Unknown	Japan					651	36	4767	3805	8988	953
9	40 Rubber and	Accessories	Unknown	Moll	Unknown	India					1500	1382	8372	6700	4297	702
10	40 Rubber and	Accessories	Unknown	Moll	Country of production	Thailand					6965	3166	8316	5971	8195	489
11	40 Rubber and	Accessories	Unknown	Moll	Country of production	Indonesia					9526	3361	9099	2967	628	218
12	40 Rubber and	Accessories	Unknown	Moll	Country of production	Côte d'Ivoire					1274	2610	3630	2879	6260	19
13	40 Rubber and	Accessories	Unknown	Moll	Country of production	Vietnam					8808	3671	4208	8370	5682	707
14	40 Rubber and	Accessories	Unknown	Moll	Country of production	Malaysia					1056	220	6932	4206	8883	850
15	40 Rubber and	Accessories	Unknown	Unknown	Production aggregation point (w	Liberia		Margibi			5487	9236	2871	6941	3576	493
16	40 Rubber and	Accessories	Unknown	Unknown	Production aggregation point (w	India		Kerala			3794	4861	7933	197	6471	455
17	40 Rubber and	Accessories	Unknown	Unknown	Production aggregation point (w	Thailand		Nakhon Si Thammarat			1963	9665	3169	6452	8923	966
18	40 Rubber and	Accessories	Unknown	Unknown	Production aggregation point (w	Thailand		Ang Thong			3124	5967	3225	9532	7842	471

Figure 12. Example of the spreadsheet template for supplier data ingestion. The basic information that needs to be provided is the material and volume purchased. The user can also provide information regarding the sourcing location.

Data is validated during ingestion (see **Annex 2**), and locations are geolocated. The results of the ingestion can be viewed in the LandGriffon platform under the admin tab. This allows quick exploration and editing of the supply chain data through the user interface.



MATERIAL	BUSINESS UNIT	T1SUPPLIER	PRODUCER	LOCATION TYPE	COUNTRY	2012	2013	2014	2015	2016
Barley	Entire company	Europe	Luxembourg	country-of-production	Luxembourg	3 t/yr	9 t/yr	8 t/yr	2 t/yr	9 t/yr
Barley	Entire company	Europe	Switzerland	country-of-production	Switzerland	0 t/yr	1 t/yr	0 t/yr	0 t/yr	1 t/yr
Barley	Entire company	Europe	Kazakhstan	country-of-production	Kazakhstan	4 t/yr	12 t/yr	10 t/yr	2 t/yr	12 t/yr
Barley	Entire company	Europe	Moldova	country-of-production	Moldova	3 t/yr	10 t/yr	9 t/yr	2 t/yr	11 t/yr
Barley	Entire company	Europe	France	country-of-production	France	829 t/yr	2673 t/yr	2216 t/yr	450 t/yr	2716 t/yr

Figure 13. Example of ingested data in the LandGriffon platform.

Impact calculation

The impact associated with each indicator and the company supply chain data is calculated during the ingestion process.

To calculate indicators we follow different approaches depending on the location type, as explained previously (see **Modeling spatial sourcing** and **Impact indicator calculation**). In this section, we aim to represent how impact estimates may vary depending on the location type by selecting a use case in Aceh, Indonesia.

For this use case, we are considering that a company is buying 1000 tonnes of palm oil in Aceh, Indonesia in a) a geolocated point of production; b) an aggregation point using the same coordinates (using a 50km buffer); and, c) an administrative area (Aceh, Indonesia).

We compute **land** and **deforestation** footprints as indicators and use data of the 2020 forest loss in Indonesia and 2010 palm oil production and harvested area from MapsSPAM.

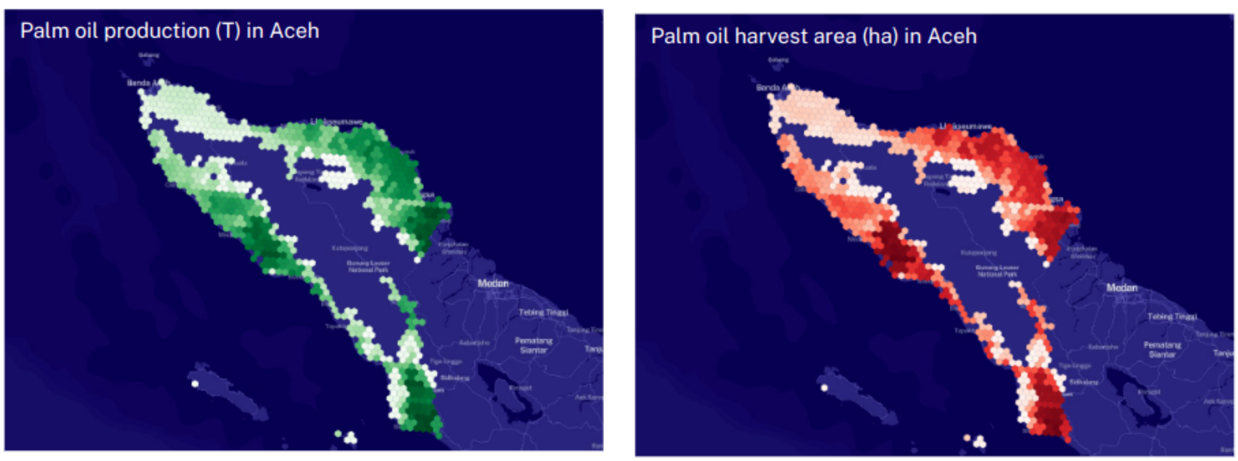


Figure 14. Palm oil production (t) and palm oil harvest area (h). Data based in Aceh, Indonesia on MapSPAM.

The land use indicator indicates the total land area required to produce 1000 tonnes of palm oil in each location type. The impact factor is the average impact in each pixel within the sourcing region, weighted by the production in each pixel.

Deforestation footprint is calculated by allocating deforestation to all human land use within a radius kernel before calculating the deforestation footprint of the specific raw material. The impact factor is then calculated as the production weighted average within the sourcing region using the palm oil production map.

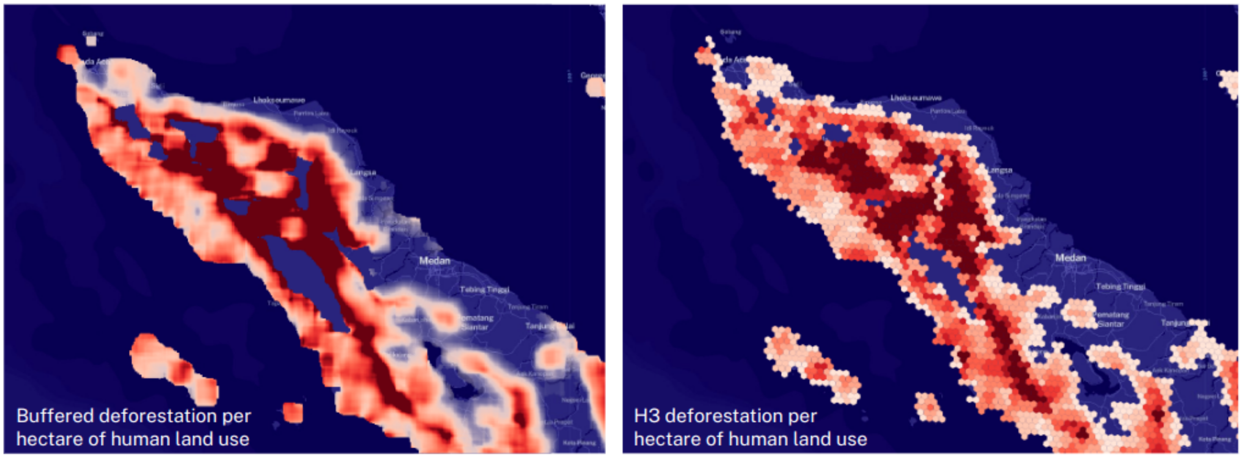


Figure 15. Deforestation per hectare of human land use calculated with a 50km kernel in raster and h3 format.

Table 3 and **Figure 16** show the calculated impacts for three different precisions of sourcing location in Aceh, Indonesia. The estimate of land area used to produce the 1000 tonnes of palm oil sourced varies from 103 ha for a point of production location to 86 ha for a colocated supply aggregation point and 87 ha for the region of Aceh. For deforestation, the example results show greater variation in reported impacts based on the precision of sourcing location. When the point of production was known there was a risk that this sourcing contributed to 0.25 ha of deforestation, compared with risks of 0.53 ha for the example supplier aggregation point or 1.15 ha when sourcing was only resolved to the Aceh region.

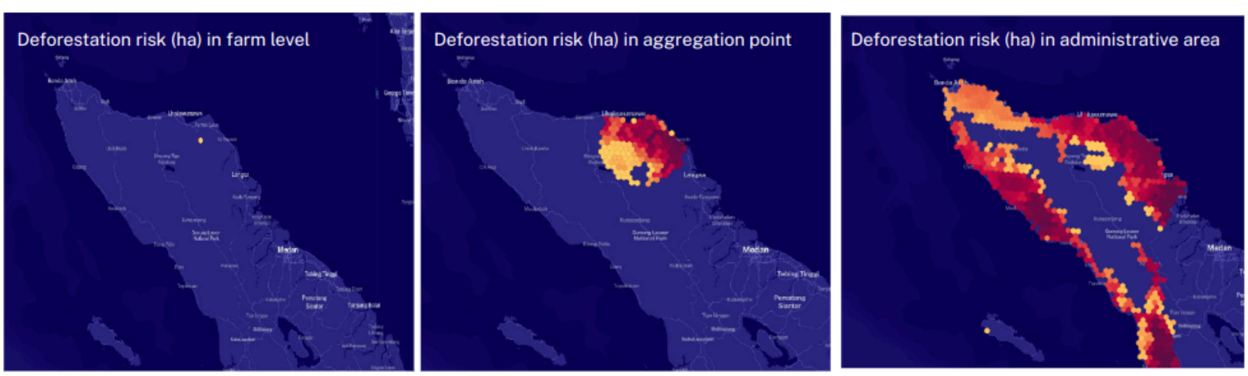


Figure 16. Distribution of deforestation risk (ha) impact across the location types based on palm oil production. Higher impact is associated with higher palm oil production.

Table 3. Summary of land use (ha) and deforestation footprint (ha) for purchasing 1000 tonnes of palm oil in different location types in Aceh, Indonesia.

Location type	Assumptions	Land footprint [ha]	Land footprint relative to point of production [%]	Defores-tation (sLUC) [ha]	Deforestation (sLUC) relative to point of production [%]
Point of production impact	The location will be a point of production. Impact calculated using the containing pixel values	102.75	-	0.25	-
Suppliers aggregation impact	The material has been produced in a 50 km buffer to the point provided.	86.30	83.99	0.53	210.32
Administrative region impact	The raw material has been produced across the entire administrative region, in all locations producing palm oil, and sourced in proportion to the production in Aceh, Indonesia.	87.20	84.86	1.15	454.37

LandGriffon v0.2 assumes that the impact is distributed across the areas of raw material production. So, higher probability of impact is associated with areas of high production and vice versa.

Across the whole Aceh landscape, the land footprint for each individual point ranges from 53 ha/1000 tonnes to 207 ha/1000 tonnes. Comparing these point of production estimates for land impact to those for the administrative region (87 ha/1000 tonnes) demonstrates the degree of over or underestimation that could result from lower accuracy supply chain data. Using estimates for the administrative region could overestimate the land use by 165% if the palm oil was actually produced from the most productive locations in Aceh. Meanwhile if the palm oil was produced in the least productive location, the regional estimate would represent 42% of the point of production land area.

Scenario analysis

After ingesting the data and calculating the impacts, the user can also explore mitigation of impacts through scenario planning directly through LandGriffon. This aligns with the prepare to respond element of the LEAP approach proposed by the Taskforce for Nature Related Financial Disclosure's beta framework (TNFD 2023).

To create a scenario the user needs to set the company's forecasted growth rates and add the impact mitigation actions that could be implemented. Mitigation actions are added through the creation of interventions.

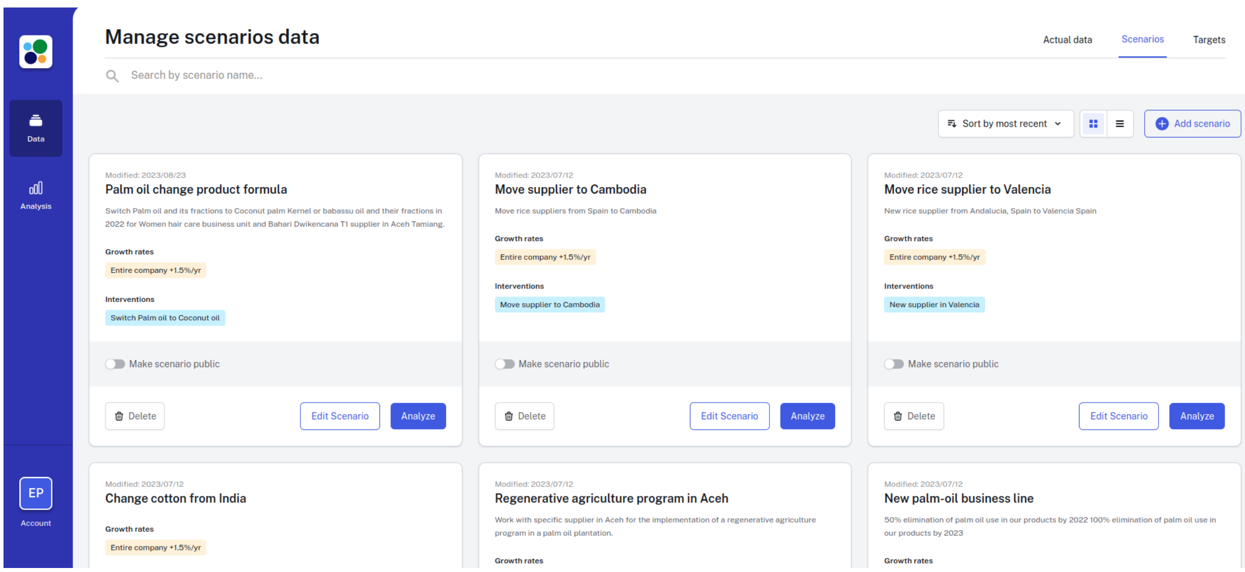


Figure 17. LandGriffon platform showing a set of scenarios created with the associated interventions.

In this example we create a scenario with a single intervention to explore how changing the volume of palm oil purchased in a supplier's location may reduce impacts given a default growth rate of 1.5% per year.

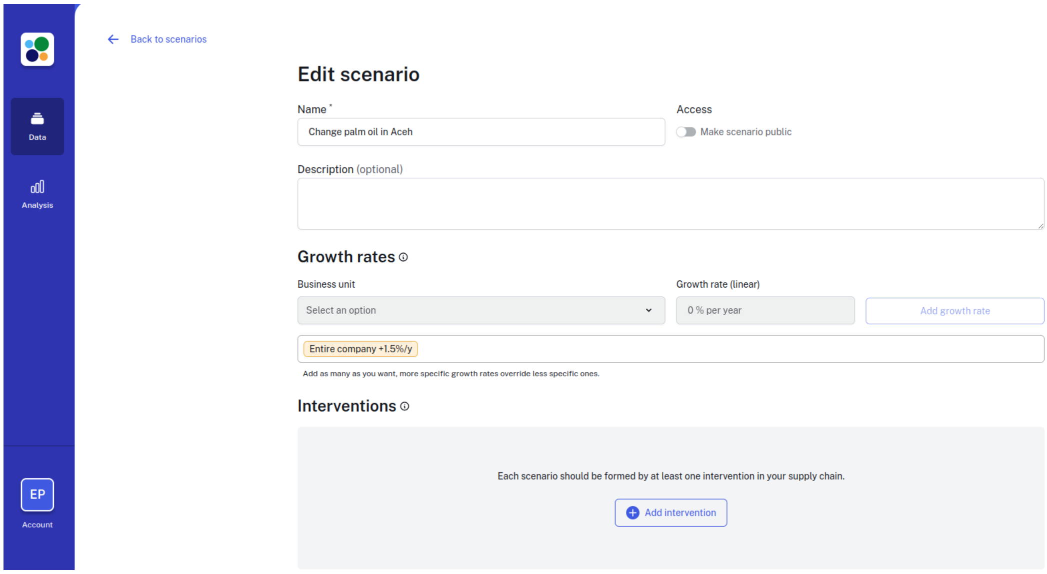


Figure 18. Creation of a scenario with the default linear growth rate of 1.5% for the entire company and no interventions.

We apply the intervention to 50% of the total volume purchased by the company in an aggregation point location in Aceh, Indonesia. See **Figure 19** for detailed information selected for the application of the intervention.

To this first selection, the user is able to apply different types of interventions. We describe the results of different types of interventions in the sections below.

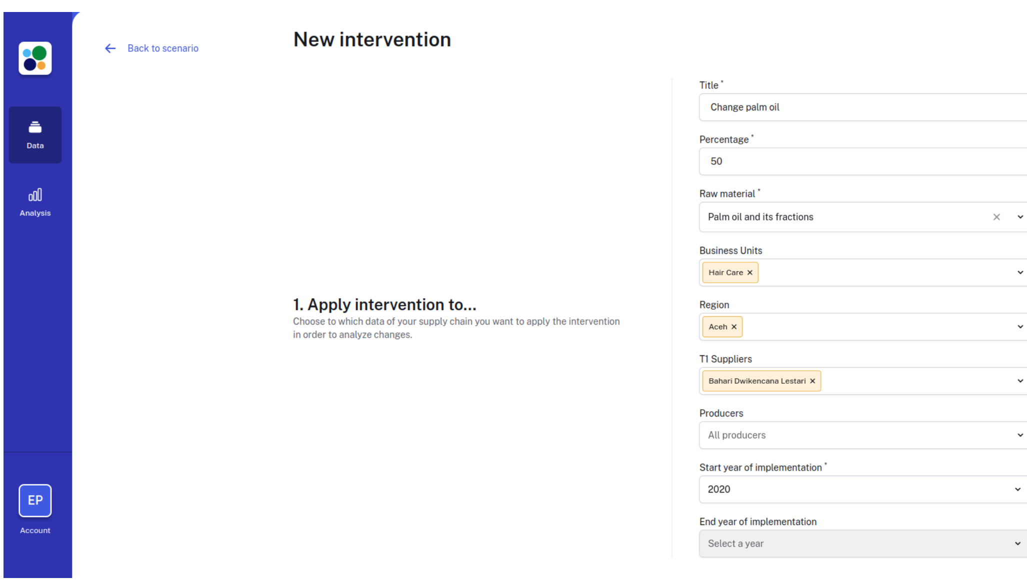


Figure 19. Initial filtering in the creation of an intervention. The image shows the selection of the 50% of total volume purchased of palm oil and its fractions for the entire company, as a business unit. The region selected is Aceh, Indonesia and the supplier selected is Bahari Dwikencana Lestari. The year of implementation is 2020.

Switch to a new material

We apply an intervention to change to a new material to evaluate the effect of a change of the recipe, which will result in the change of raw material composition in the company's supply chain.

In this intervention, the user has to specify the material they want to change the initial selection to and the new location where they will source this new material. The location can also be the same as the initial selection. Additionally, the user can select a new supplier, if needed, or provide custom impact factors for the new material to compute the calculations.

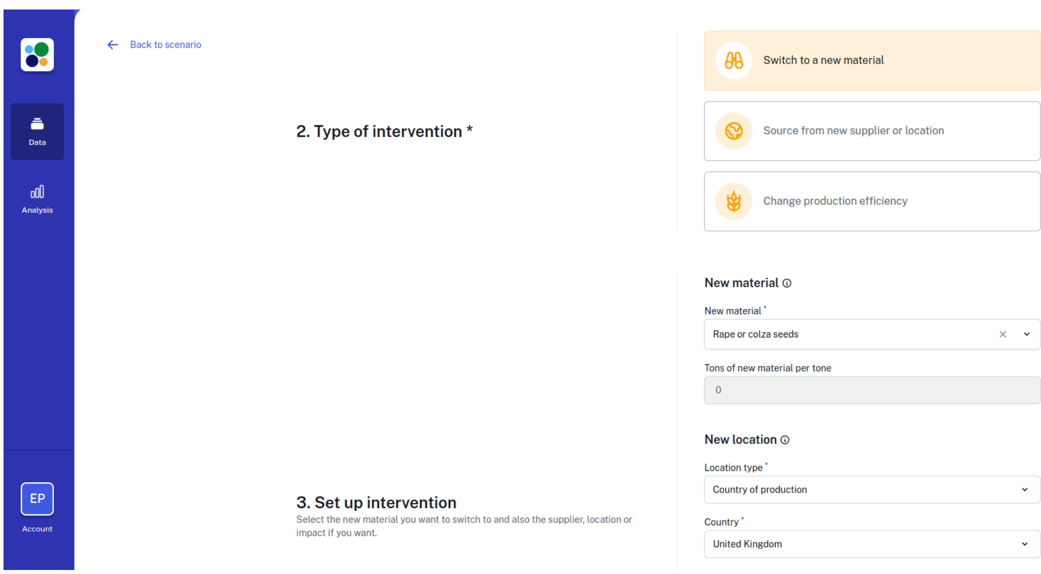


Figure 20. Change product formula by replacing the 50% of palm oil with rape seed oil, sourced from the United Kingdom.

Source from a new supplier or location

An alternative intervention is related to sourcing the same raw material from another producer with a lower environmental footprint. In this particular case we add an intervention for sourcing 50% of the palm oil purchased from a supplier in Aceh, Indonesia, from a different supplier located in the same region. To this end we need to add the location of the new supplier. The user can again provide custom impact factors instead of the LandGriffon default estimates to compute the impacts.

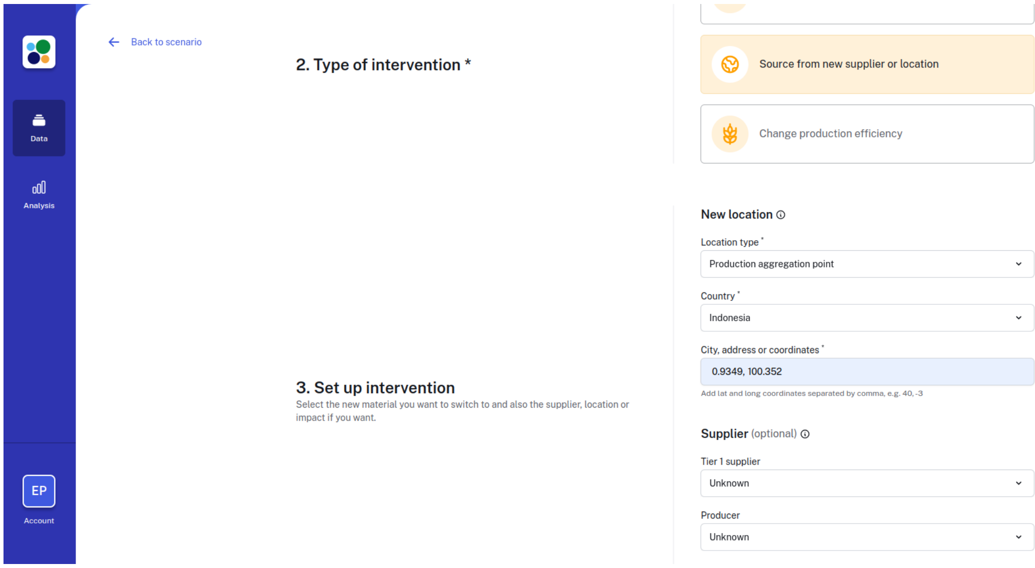


Figure 21. Source from a new supplier or location by moving the 50% of the palm oil purchased volume to a different supplier in Aceh, Indonesia.

Change production efficiency

As another alternative, LandGriffon also evaluates an intervention option for examining how impacts may be reduced and yield can increase by working with farmers. The user can test this by changing production efficiency. In this intervention we need to set the impact factor for each indicator that we want to recompute.

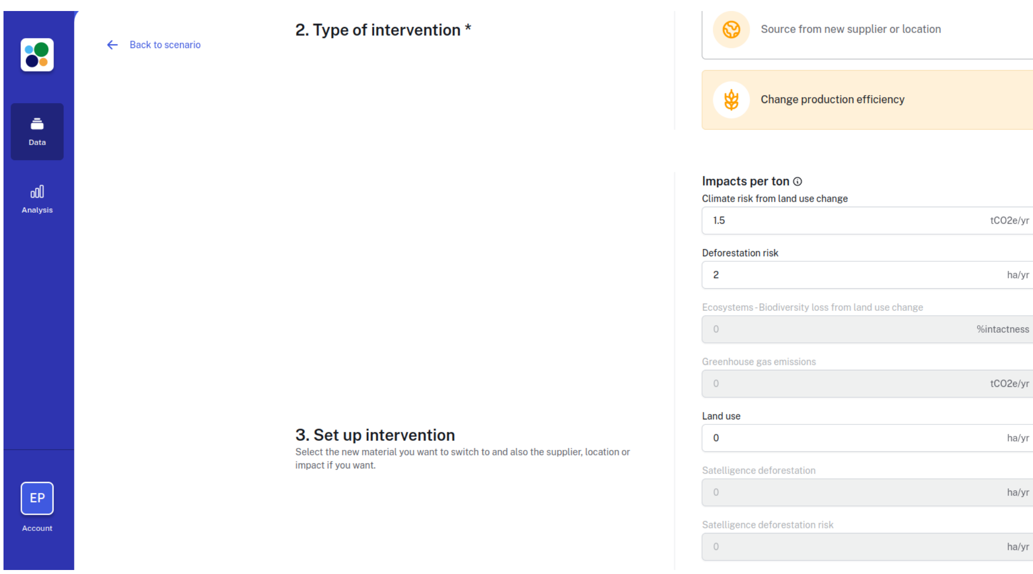


Figure 22. Change production efficiency for the 50% volume of palm oil purchased from a location in Aceh, Indonesia.

Scenario outputs and data comparison

Once we have compiled a scenario to be evaluated, consisting of a set of intervention actions, we can save the scenario and analyze the results. Similar to the analysis performed with the company's data during the ingestion process, the various interventions are analyzed and the output is presented in a table, chart and map view, showing the impacts estimated in each scenario.

The interventions can be compared against the original data ingested by the company. This in turn can be compared against company targets to check how measures can mitigate environmental impacts and help construct a pathway of actions to achieve sustainability goals.

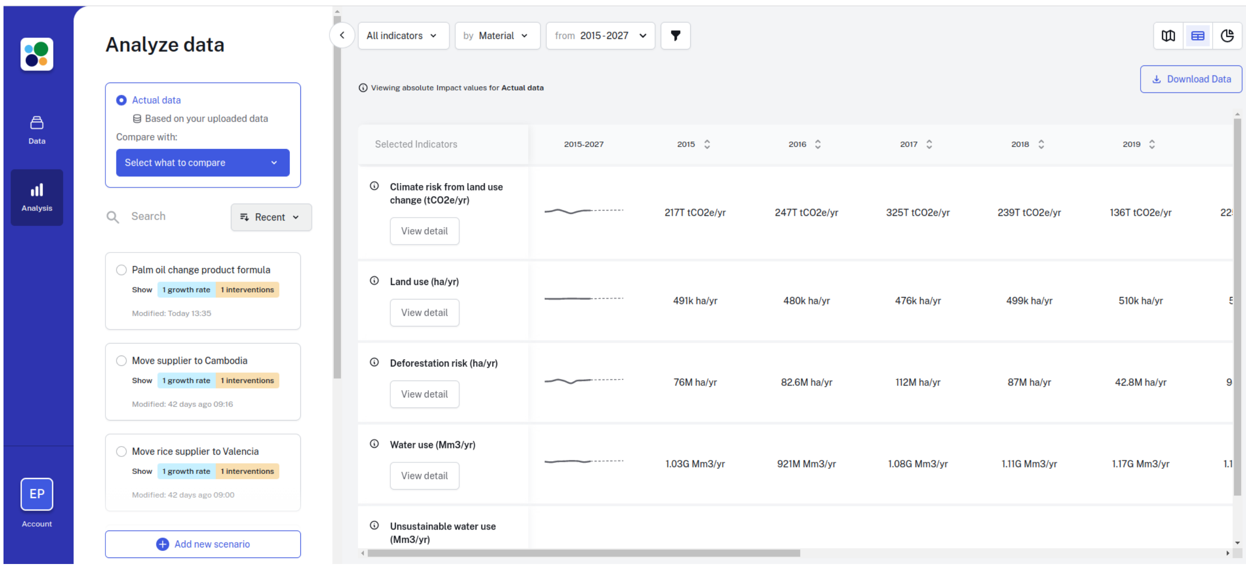


Figure 23. Table view of the various impacts of scenarios each composed of a set of interventions.

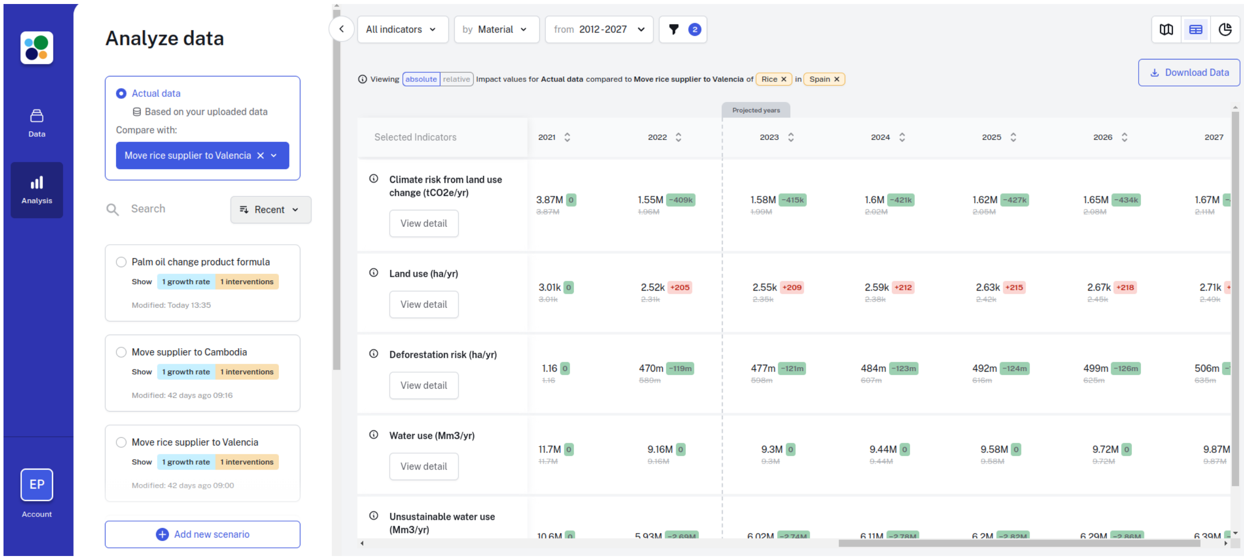


Figure 24. Table view of impact comparison between actual data and a test scenario. Numbers in red show an increase in impact while numbers in green show reduction in the impact produced.

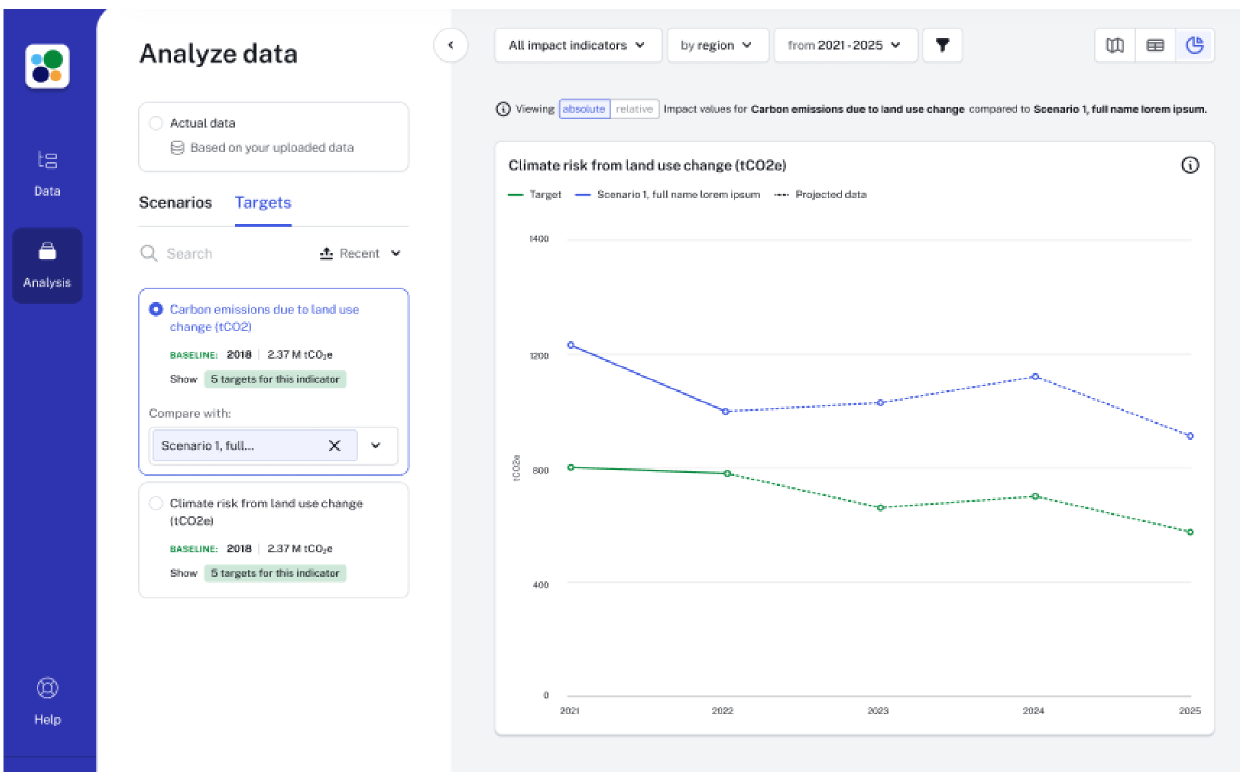


Figure 25. Chart view of the comparison produced between the actual data (area chart in green), a test scenario (line in dark green) and a company's target (dotted line) for each selected indicator.

DISCUSSION

LandGriffon is a novel tool that addresses a critical need for agricultural supply chain companies by providing a holistic evaluation of their supply chain production impacts. The tool has multiple parallel and often synergistic uses, including:

- Help companies with internal decision-making to reduce environmental impacts associated with their agricultural supply chains. For many companies, knowing where and what action to take first is a major challenge. LandGriffon can help companies prioritize sustainability investments.

- Communicating internally or externally to demonstrate the company's credentials to customers, suppliers or regulators and to advocate for collective action in critical landscapes that companies source from but are not 100% responsible for.

- Compiling sustainability disclosures, reporting and targets - LandGriffon can be set up to produce risk and impact estimates that comply with sustainability reporting frameworks such as **CDP**, the Global Reporting Initiative (**GRI**), the Science Based Targets Network (**SBTN**) or the Taskforce for Nature-related Financial Disclosure (**TNFD**).

- Prioritize which suppliers to audit, engage with, invest in or divest from, or identify which communities or landscapes deserve investment in local-scale assessment and action.

Data currently available to inform LandGriffon is top-down in nature meaning that it is inherently uncertain. The included indicators serve primarily as a prioritization and macro-scale planning tool, which can and should be supplemented by local engagement and analysis. Data gathered from such exercises and use cases can be incorporated back into the tool, feeding a cycle of progress and continuous improvement.

Ingestion of company data

The ingestion of whole company agricultural raw material supply chain data is itself an involved data collation and analysis exercise, requiring a number of validation steps. It is an important component of the framework because inputting accurate data is essential to the accurate evaluation of supply chain impacts.

Impact calculations

The range of default impact indicators included in the tool reflects key environmental impacts identified by organizations such as SBTN (Science Based Targets Network 2023b; 2023a) and TNFD (TNFD 2023) and implemented using currently available data and algorithms. The description of these indicator calculations includes some recommendations for improvements that could be made to them. The LandGriffon framework is customizable to incorporate other impact indicators and meet the needs of companies or initiatives.

We illustrated the implications that spatial precision of supply chain information can have on impacts. Lack of supply chain accuracy can introduce substantial uncertainty to impact calculations. This presents a huge opportunity for companies to identify and reduce supply chain uncertainty (discussed further below). However, from the tool perspective, there is also the potential to indicate this uncertainty by presenting conservative estimates of impact as well as a best estimate. Conservative estimates might bias towards the worst case, e.g. 90th percentile, for the sourcing region. We are in the process of comparing Landgriffon against independent impact estimates. Communicating the results of these comparisons and uncertainties arising from the methodology will be a focus for Landgriffon in the near-future.

Scenarios

The scenario analysis features in LandGriffon v0.2 provide a means for companies to explore targets against their current impacts and compare pathways of actions to achieve those goals.

In addition to implementing scenarios in the LandGriffon tool, designing them requires users to gather information on how to reduce impacts. The tool estimates impacts from the current supply chain and provides essential information for this process, for example, highlighting the business processes or commodities contributing the most impact. However, scenarios also benefit from information on the impact mitigation actions. This will involve working internally across business units and also externally with suppliers and scientists, amongst others, to identify feasible options for change.

Priority gaps and improvements

The introduction to this document identified some of the challenges associated with the development of LandGriffon v0.2 and in particular limitations in data to accurately evaluate impacts. It is critically important to be transparent about limitations in current data, whether that is detailing the company's supply chain or calculating impact, so that these can be taken into account in decision making and so the community can address them.

The philosophy behind the tool architecture has been to develop a framework that has the flexibility to allow customization with new data, impact indicator calculations and approaches, in line with improvements in scientific knowledge and data availability. The following presents a list of improvements that the agricultural supply chain community could prioritize:

- Issues of historical and static maps of raw material production represent major limitations. There is great potential for Earth Observation to improve crop maps and move this area towards continuously updated maps of production. Current imagery has been shown to be useful in upscaling field data on crop production (Karlson et al. 2020) and new hyperspectral sensors such the EnMAP (Guanter et al. 2016) and NASA's SBG mission (NASA JPL n.d.) will increase possibilities by generating more spectrally-detailed earth observation data in the coming years. However, the availability of representative field observations of crop types and production is a barrier that needs to be overcome to make use of the abundance of earth observation data.

- The current methodology of informing the probabilistic spatial allocation of production location (where sourcing location is uncertain) using only raw material production could be improved by making use of our understanding of national level supply chains to improve the accuracy with which the production locations can be inferred. Given the country where the sourcing company is based, bilateral trade matrices and multi-region input-output models can identify which countries imported commodities are likely to have been sourced from. This data hasn't been included in an automated manner in LandGriffon v0.2, but it could be in the future. In addition, information on sub-national sourcing locations of particular companies, including that provided by Trase could be integrated into LandGriffon to reduce uncertainty in sourcing regions where production locations supplying a given company are unknown.

- The tool has the potential to help companies identify their key supply chain uncertainties, which if reduced would contribute most to their understanding of impact. The information in the tool could be adapted to show what commodities, business operations or supply chain elements contribute most to uncertainty around supply chain impacts.

- Impact calculations included in the tool represent only a small number of impacts, which often co-occur and interact (Harfoot et al. 2021). This raises the potential issue that by missing important impacts the tool might fail to capture trade-offs between impacts and possible interventions to reduce impacts. For example, agricultural intensification in a production landscape could produce greater yields and hence reduce overall land footprint, but could result in more pollution, which is currently not included in impact calculations.

- An important category of impacts that is not yet included in the tool are those related to social impacts, such as gender issues, health consequences, and human or social capital (FAO 2020). As the agricultural sector changes and companies look to reduce their environmental impacts, it is important that the tool develops capabilities for companies also to understand the consequences of their supply chains for social issues.

- Environmental and social impacts in production landscapes arise from multiple cumulative causes, including the agricultural supply chains of multiple companies or impacts from other economic sectors with land use footprints, such as extractive industries (Whitehead, Kujala, and Wintle 2017). Transforming landscapes towards greater future sustainability requires coordination across these cumulative impacts. Tools such as LandGriffon allow coordination across companies and sectors to make effective and integrated decisions.

- For companies to make robust decisions to mitigate their supply chain impacts, information should be available for them on interventions that might be beneficial for a given raw material and production location. At present, some data and analysis exist to inform these decisions (Conservation Evidence 2022; Deborah Bossio, et al. 2021), but there is a great need to consolidate this into a more usable form to inform a company's decision-making.

- Future scenarios could be improved by incorporating projections for future impacts due to global demands for land and pressures such as climate change, and assessment of risks to the company.

- The availability of near real time data on land use change and deforestation could be incorporated in the tool to provide alerts and operational land use relevant information. For example, the tool could present information on deforestation in the proximity of current sourcing locations or where habitat loss is occurring within critically important habitats.

Concluding remarks

LandGriffon establishes a framework that can be applied to agricultural commodities globally, integrated with a company's current supply chain systems, evaluate impacts in a customizable way and help explore pathways to reduce impacts. Given the scale and complexity of agricultural supply chains, there are considerable uncertainties associated with data and methods. We aim to be open about these and so stimulate a community of practice to improve our capabilities in a coordinated way, because collaboration and openness will be critical to achieving real improvements in the sustainability of agricultural supply chains. We hope that LandGriffon v0.2 and future iterative improvements to the framework can achieve this and help drive more positive futures for society and nature.

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ANNEX 1: IMPACT INDICATORS

This section describes the impact indicator calculations according to a template with the following elements:

- Short description
- Source datasets
- Interpretation: what impact the indicator is aiming to represent
- Method: the calculation methodology
- Comments: caveats and possible future developments for the indicator

The **Table A1** shows the baseline set of impact indicators included as part of the LandGriffon Methodology v0.2.

Table A1. Impact indicators in LandGriffon v0.2.

Impact type category	Indicator	Short description
Water quantity	**Water use**	The volume of surface or groundwater that is consumed in the production of the raw material sourced.
	Unsustainable water use	The volume by which the water consumption associated with the production of the raw material sourced must be decreased to reduce pressure on nature.
Water quality	**Nutrient load**	The annual average water volume required to assimilate the nutrient load added by the raw material sourced.
	Excess nutrient load	The volume by which nutrient load associated with the raw material sourced must be decreased to achieve the desired instream nutrient concentration.
Land use	**Land footprint**	The total land area required to produce the raw material sourced.
Climate	**GHGs (farm management)**	The amount of greenhouse gas (GHG) emissions, including CO_2, N_2O and CH_4, arising from farm-management of the raw material sourced.
	GHGs (deforestation, sLUC)	The annual average emissions of greenhouse gas (GHG) associated with deforestation within a 50km radius attributable to the raw material sourced.
Natural ecosystem conversion	**Deforestation footprint (sLUC)**	The annual average area of deforestation within a 50km radius attributable to the raw material sourced.
	Net cropland expansion	The annual average area of cropland expansion into natural ecosystems occuring within a 50km radius attributable to the raw material sourced.
Biodiversity	**Forest Landscape Integrity loss**	The average forest landscape integrity score of natural ecosystems that have been converted to cropland within a 50km radius attributable to the raw material sourced.
	Biodiversity intactness loss	The average biodiversity intactness score of natural ecosystems that have been converted to cropland within a 50km radius attributable to the raw material sourced.

Water quantity

Water use

Short description

The volume of water that is consumed in the production of the raw material sourced.

Source datasets

- Mekonnen, M.M. & Hoekstra, A.Y. (2010) The green, blue and grey water footprint of farm crops and derived crop products. Value of Water, 47.
- Mekonnen, M.M. & Hoekstra, A.Y. (2010) The green, blue and grey water footprint of farm animals and animal products. Value of Water, 48.

Interpretation

The water use indicator describes the average volume of water consumed in the production of raw materials in a given country context. It is intended to align with the Science Based Targets Network (SBTN) water quantity target indicator (Science Based Targets Network 2023b) and the water use impact driver indicator of the Taskforce on Nature Related Financial Disclosures (TNFD 2023).

Method

We estimate water use as the average blue-water footprint (BWF) of crops and their derived products at both the global and subnational levels, along with the average blue water footprint of animals and their products (Mekonnen and Hoekstra 2010a; 2010b). Blue-water footprint is water that has been sourced from surface or groundwater resources and is either evaporated, incorporated into a product or taken from one body of water and returned to another, or returned at a different time.

To calculate water use, we look up the blue water footprint per ton of raw material, c, and sourcing region, g, ($BWF_{c,g}$), and multiply by the tons of the raw material sourced from that sourcing region ($S_{c,g}$):

$$I_{water-use\,c,g} = BWF_{c,g} * S_{c,g} \quad \text{(Eq. i1)}$$

Comments

- Blue-water footprint data is estimated for the period of 1996 to 2005, and is an average value for the raw material and administrative region. Changes or improvements in irrigation technology and patterns are likely to have occurred in the intervening period.
- The Water Footprint Network is expected to publish an updated dataset of crop and animal product water footprints in the coming months at **https://tools.waterfootprint.org/sbtn-water-targets/**. We will update this indicator correspondingly.

Water quantity

Unsustainable water use

Short description

The volume by which the water consumption associated with the production of the raw material sourced must be decreased to reduce pressure on nature.

Source datasets

- *Water use indicator*
- Kuzma, S., M.F.P. Bierkens, S.Lakshman, T. Luo, L. Saccoccia, E. H. Sutanudjaja, and R. Van Beek. 2023. "Aqueduct 4.0: Updated decision-relevant global water risk indicators." Technical Note. Washington, DC: World Resources Institute. Available online at: doi.org/10.46830/writn.23.00061.

Interpretation

The unsustainable water use indicator shows the amount by which water use would need to be reduced in order to reduce pressure on local watersheds and return them to a maximum allowable level of basin-wide withdrawals, according to the Science Based Targets Network (SBTN) water quantity target approach (Science Based Targets Network 2023b). It aligns with the core impact driver indicator on water use from areas of water scarcity of the Taskforce for Nature-Related Financial Disclosures (TNFD) (TNFD 2023). Unsustainable water use is measured as a proportion of total water use.

Method

We calculate unsustainable water use by calculating the proportion by which water use would have to be decreased by all actors to reduce the water stress of each river basin to below a high-stress threshold.

We use Baseline Water Stress (BWS) from **Aqueduct v4.0** (Kuzma et al. 2023) to identify the proportion by which water use must be reduced. Baseline water stress measures the ratio of total water withdrawals to available renewable surface and groundwater supplies. Water withdrawals include domestic, industrial, irrigation, and livestock consumptive and nonconsumptive uses. This measure is similar to other measures of water stress per river basin, such as the Water Use in Life Cycle Assessment (WULCA) characterization factors (Boulay et al. 2018). A high-stress threshold of 0.4 (Gassert et al. 2015), is used to determine maximum basin-wide level of water withdrawals. We calculate the required reduction in water use to bring each basin (b) below the high stress threshold as:

$$Propn_{water-use-reduction\ ,b} = \frac{BWS_b - 0.4}{BWS_b},\ \text{if}\ \ BWS_b > 0.4 \qquad \text{(Eq. i2)}$$

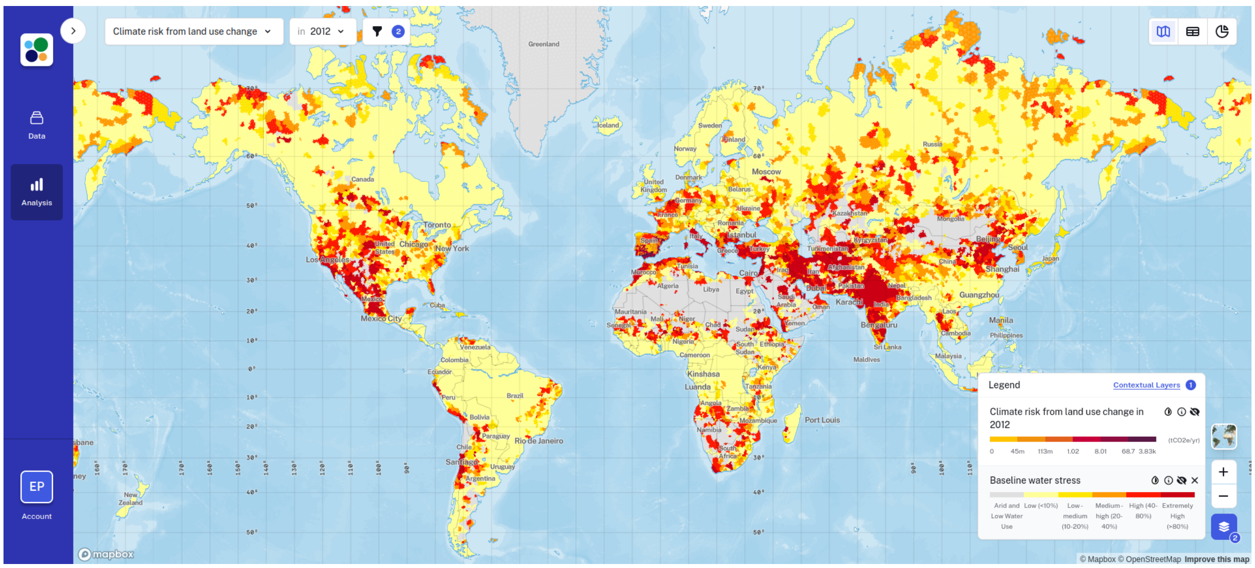

Figure A1. Baseline Water Stress (Kuzma et al. 2023) as shown in LandGriffon.

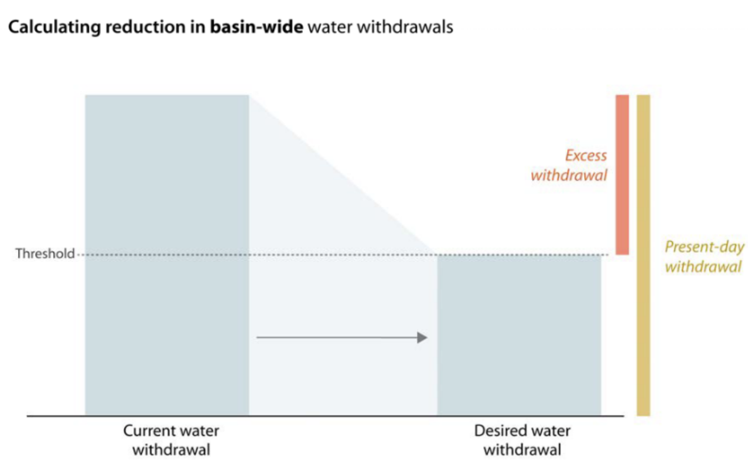

Figure A2: Illustration of how unsustainable "excess" water use is calculated. Adapted from (Science Based Targets Network 2023b).

Water use in basins with a water stress ratio below 0.4 is considered to be below the maximum allowable basin-wide water use and does not count towards the unsustainable water use indicator.

For each sourcing region, we generate a weighted average proportion to reduce for based on gridded datasets of material production (MAPSPAM, GLW3). Specifically, for each point (i) of the n points within the sourcing region (g) we multiply the production of the raw material ($P_{c,i}$) by the proportion to reduce, and divide the total by the total production across the entire sourcing region.

$$Propn_{water-use-reduction\,c,g} = \frac{\sum_{i \in g} Propn_{water-use-reduction,i} * P_{c,i}}{\sum_{i \in g} P_{c,i}} \qquad \text{(Eq. i3)}$$

Unsustainable water use is then the total water use as computed for the water use indicator multiplied by the weighted average proportion to reduce for the sourcing region.

$$I_{unsustainable-water-use\,c,g} = I_{water-use\,c,g} * Propn_{water-use-reduction\,c,g} \qquad \text{(Eq. i4)}$$

This is equivalent to distributing water use across the sourcing region according to the production of the raw material, and calculating the required reduction at each point, and summing the total across the sourcing region.

Comments

- Water use (Blue-water footprint) data is estimated for the period of 1996 to 2005, and is an average value for the raw material and administrative region. Changes or improvements in irrigation technology and patterns are likely to have occurred in the intervening period.
- Aqueduct is not explicitly recommended as a source for calculation of maximum basin-wide water use in current draft SBTN guidance (Science Based Targets Network 2023b), but recommended by other sources for setting enterprise water targets (e.g. Reig et al. 2021).

- The Water Footprint Network is expected to publish an updated dataset of crop and animal product water footprints in the coming months at https://tools.waterfootprint.org/sbtn-water-targets/. We will update this indicator correspondingly.

Water quality

Nutrient load

Short description

The annual average water volume required to assimilate the nutrient load added by the raw material sourced.

Source datasets

- Mekonnen, M.M. & Hoekstra, A.Y. (2010) The green, blue and grey water footprint of farm crops and derived crop products. Value of Water, 47.
- Mekonnen, M.M. & Hoekstra, A.Y. (2010) The green, blue and grey water footprint of farm animals and animal products. Value of Water, 48.

Interpretation

The nutrient load indicator describes the average volume of freshwater required to absorb the nutrient load created by production of the raw material. It is intended to align with the Science Based Targets Network (SBTN) water quality target indicator (Science Based Targets Network 2023b) and the Taskforce on Nature-related Financial Disclosure's (TNFD) water pollution impact driver (TNFD 2023).

Method

We estimate nutrient loading as the average grey-water footprint (GWF) of crops and their derived products at both the global and subnational levels, along with the average gray water footprint of animals and their products (Mekonnen and Hoekstra 2010a; 2010b). In the context of crop production, the grey-water footprint is the amount of water necessary to assimilate the nutrients that ultimately reach either ground or surface water, and serves as an indicator of the volume of freshwater pollution. The leaching of nutrients from agricultural fields constitutes a primary cause of nonpoint source pollution in water bodies.

To calculate nutrient load for each raw material, *c*, and sourcing region, *g*, we look up the grey-water footprint, $GWF_{c,g}$, and multiply by the tons of the raw material sourced from that region, $S_{c,g}$:

$$I_{nutrient-load\,c,g} = GWF_{c,g} * S_{c,g} \quad \text{(Eq. i5)}$$

Comments

- Grey-water footprint data is estimated for the period of 1996 to 2005, and is an average value for the raw material and administrative region. Changes in farm management practices and patterns are likely to have occurred in the intervening period.
- The Water Footprint Network is expected to publish an updated dataset of crop and animal product water footprints in the coming months at **https://tools.waterfootprint.org/sbtn-water-targets/**. We will update this indicator correspondingly.

Water quality

Excess nutrient load

Short description

The volume by which nutrient load associated with the raw material sourced must be decreased to achieve the desired instream nutrient concentration.

Source datasets

- *Nutrient load indicator*
- McDowell, R. W., A. Noble, P. Pletnyakov, B. E. Haggard, and L. M. Mosley. 2020. ‘Global Mapping of Freshwater Nutrient Enrichment and Periphyton Growth Potential’. Scientific Reports 10 (1): 3568. **https://doi.org/10.1038/s41598-020-60279-w**.
- McDowell, R. W., Alasdair Noble, Peter Pletnyakov, and Luke M. Mosley. 2020. ‘Global Database of Diffuse Riverine Nitrogen and Phosphorus Loads and Yields’. Geoscience Data Journal 8 (2): 132–43. https://doi.org/10.1002/gdj3.111.

Interpretation

The excess nutrient load indicator describes the extent to which nutrient loads must be reduced to meet the desired nutrient concentration following the Science Based Targets Network (SBTN) water quality target indicator approach (Science Based Targets Network 2023b). The reduction is measured as a proportion of the total nutrient load indicator and expressed in terms of the volume of freshwater required to absorb the excess pollutants.

Method

We calculate excess nutrient load by calculating the proportion by which nutrient loads would have to be decreased by all actors to reduce the nutrient loading below maximum allowable basin-wide load.

We use modeled nutrient concentrations from McDowell et al.(McDowell, Noble, Pletnyakov, and Mosley 2020; McDowell, Noble, Pletnyakov, Haggard, et al. 2020) to determine if the limiting nutrient is nitrogen (N) or phosphorus (P) and calculate the proportion by which nutrient loads must be reduced in each river basin. Following SBTN guidance (Science Based Targets Network 2023b), we use global concentration threshold values representing acceptable levels of algal growth for total N (*TN*) of 0.70 mg/L and total P (*TP*) of 0.046 mg/L. We calculate the required reduction in basin-wide nutrient load for each basin (*b*) as:

$$required\_reduction_b = \begin{cases} \frac{\mathrm{TN}_b - 0.7}{\mathrm{TN}_b}, & \text{if N-limited} \\ \frac{\mathrm{TP}_b - 0.046}{\mathrm{TP}_b}, & \text{if P-limited} \end{cases} \quad \text{(Eq. i6)}$$

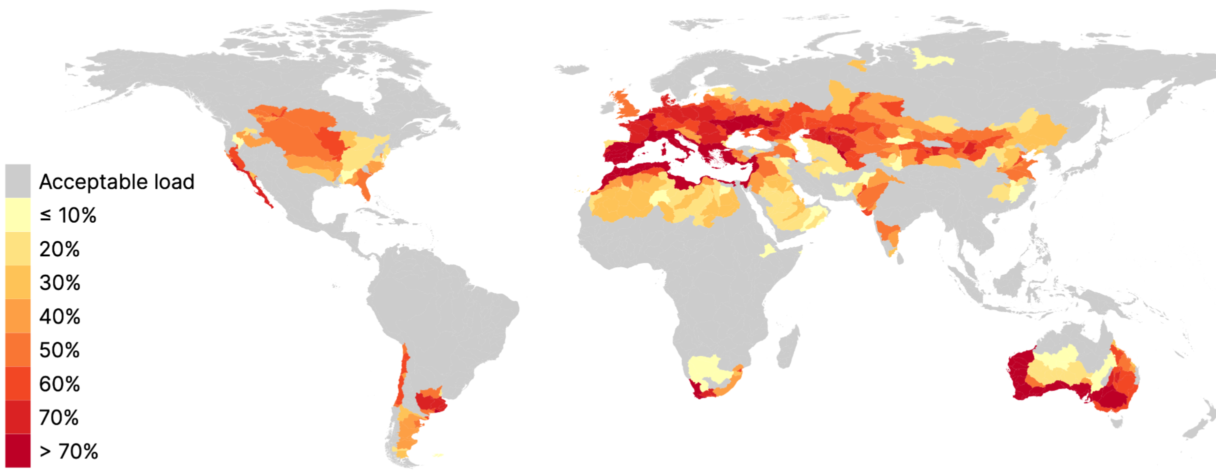

Figure A1. Required reduction in basin wide nutrient load, derived from McDowell et al. (McDowell, Noble, Pletnyakov, and Mosley 2020; McDowell, Noble, Pletnyakov, Haggard, et al. 2020)

To compute the excess nutrient load, $I_{excess-nutrient-load\ c,g}$, for each raw material, c, and sourcing region, g, we generate a weighted average required reduction in nutrient load for the sourcing region based on gridded datasets of material production (MapSPAM, GLWv3). Specifically for each point, i, within the sourcing region, g, we multiply the required reduction in nutrient load by the production of the raw material, $P_{c,i}$, and divide by the sum by the total production across the entire sourcing region.

$$required\_reduction_{c,g} = \frac{\sum_{i \in g} required\_reduction_i * P_{c,i}}{\sum_{i \in g} P_{c,i}} \quad \text{(Eq. i7)}$$

The excess nutrient load is then the Nutrient Load indicator, $I_{nutrient-load\ c,g}$, multiplied by the required reduction for the sourcing region.

$$I_{excess-nutrient-load\ c,g} = I_{nutrient-load\ c,g} * required\_reduction_{c,g} \quad \text{(Eq. i8)}$$

This is equivalent to distributing the nutrient load across the sourcing region according to the production of the raw material, and calculating the required reduction at each point, and summing the total across the sourcing region.

Comments

- Grey-water footprint data is estimated for the period of 1996 to 2005, and is an average value for the raw material and administrative region. Changes in farm management practices and patterns are likely to have occurred in the intervening period.
- The Water Footprint Network is expected to publish an updated dataset of crop and animal product water footprints in the coming months at **https://tools.waterfootprint.org/sbtn-water-targets/**. We will update this indicator correspondingly.
- Where possible, more detailed data on the state of nutrient pollution in local watersheds, and employment of best management practices (BMPs) aimed at reducing nutrient inputs from various sources such as precision agriculture, cover cropping, controlled-release fertilizers, and improved manure management techniques should be preferred to globally modeled indicators.

Land use

Land footprint

Short description

The total land area required to produce the raw material sourced.

Source datasets

- International Food Policy Research Institute. 2019. 'Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 2.0'. Harvard Dataverse. https://doi.org/10.7910/DVN/PRFF8V.

Interpretation

The land footprint indicator describes the total area of land required to produce the quantity of a raw material sourced. It is designed to align with the Science Based Targets Network's (SBTN) land footprint reduction target (Science Based Targets Network 2023a) and the Taskforce for Nature-related Financial Disclosure's (TNFD) land use change impact driver indicator (TNFD 2023).

Method

We calculate the land footprint of crops as the inverse of crop yield, based on gridded crop yield data from MapSPAM (International Food Policy Research Institute 2019). The average land footprint, $IF_{land-footprint\ c,g}$, per ton of raw material, *c*, within sourcing region, *g*, is derived is computed as a production-weighted average of the inverse of crop yield $y_{c,i}$, for each point *i* within the sourcing region, *g*, which gives:

$$IF_{land-footprint\,c,g} = \frac{\sum_{i\in g} \frac{1}{y_{c,i}} * P_{c,i}}{\sum_{i\in g} P_{c,i}} = \frac{\sum_{i\in g} HA_{c,i}}{\sum_{i\in g} P_{c,i}} \qquad \text{(Eq. i9)}$$

where $P_{c,i}$ is the production of raw material; and, $HA_{c,i}$ is the planted area.

The total land footprint is then this per-ton land footprint multiplied by the total tonnage of raw materials sourced, $S_{c,g}$:

$$I_{land-footprint\,c,g} = S_{c,g} * IF_{land-footprint\,c,g} \qquad \text{(Eq. i10)}$$

The land use indicator represents the area of agricultural land associated with the production of the crop, and does not account for loss of habitat associated either directly with agricultural expansion or indirectly, for example, to create new roads to accommodate better supply and transport or to build villages for the agricultural workforce.

Comments

- The cropland production and yield data from MapSPAM are representative of the year 2010. Changes in cropping patterns and crop yield are likely to have occurred.
- The MapSPAM team is in the process of producing updated cropland maps. We will update this indicator correspondingly when the new data is released.
- The current land footprint does not incorporate the land areas implicit in production of commodities. For example, livestock production often involves the use of feed, which itself requires land area to produce. It is important to incorporate this impact component because in some cases this implicit impact is likely to be significant relative to the direct land area of the production unit.

Climate

GHGs (farm management)

Short description

The amount of greenhouse gas (GHG) emissions, including CO_2, N_2O and CH_4, arising from farm-management of the raw material sourced.

Data sources

- Halpern, Benjamin S., Melanie Frazier, Juliette Verstaen, Paul-Eric Rayner, Gage Clawson, Julia L. Blanchard, Richard S. Cottrell, et al. 2022. 'The Environmental Footprint of Global Food Production'. Nature Sustainability 5 (12): 1027–39. https://doi.org/10.1038/s41893-022-00965-x.

Interpretation

Estimates the emissions of greenhouse gasses (CO_2, N_2O and CH_4 expressed in terms of CO2 equivalent global warming potential) arising from farm management practices in the production of agricultural commodities. It is intended to align with the guidance for calculating within farm gate emissions from the land sector (Greenhouse Gas Protocol 2022).

Method

Emissions are calculated using outputs from a geospatial analysis of environmental pressures arising the within-farm-gate from production of foods (Halpern et al. 2022). The analysis includes emissions of CO_2, CH_4 or N_2O arising from: burning or volatilization of crop residues; pumping irrigation water; machinery used for field operations; production and transport of fertilizer; fertilizer application; pesticide production; enteric fermentation; and manure management. These emissions are better characterized for more intensive agricultural production systems than for low input or subsistence farming systems. Importantly emissions from land use conversion are not included in this metric, since these, by definition, occur outside of the farm-gate.

Emissions are mapped to the location of production. For crops, production is based on MAPSPAM and FAOSTAT data, whilst livestock production uses the Gridded Livestock of the World (GLWv3). Since emissions are calculated for the year 2017, we converted absolute emissions into an emission rate, or $IF_{farm\text{-}GHG}$, by dividing emissions in each crop type and pixel by the mass of production of each crop type in each pixel. Emissions were reprojected from their original Gall-Peter equal area coordinate system to align with the MAPSPAM grid. Where Halpern et al. (2022) had aggregated MAPSPAM crops into super categories, we disaggregated emissions using the grid cell relative production of the crops in the super category.

The farm-level GHG impact factor for a raw material *c* sourced from region *g* is the mean impact factor over the points, *i*, within the sourcing region, weighted by the production $P_{c,i}$:

$$IF_{farm-GHG\,c,g} = \frac{\sum_{i\in g} P_{c,i} * IF_{farm-GHG\,c,i}}{\sum_{i\in g} P_{c,i}} \quad \text{(Eq. i11)}$$

Where *i* is a point within the sourcing region, *g*, $P_{c,i}$ is the total production of raw material *c* at point *i*, where production is currently taken from MAPSPAM and is representative of the year 2010 (International Food Policy Research Institute 2019).

GHG emissions associated with the production of $S_{c,g}$ the quantity of raw material *c* that is sourced from region *g*, is then calculated as follows:

$$I_{farm-GHG\,c,g} = S_{c,g} * IF_{farm-GHG\,c,g} \quad \text{(Eq. i12)}$$

An indicator of emissions associated with land-use change in the areas adjoining production landscapes is described below (**GHGs (deforestation, sLUC)**).

Comments

- At present, emissions associated with livestock production exclude emissions associated with the production of feed for those livestock. Future work should address this limitation.
- The MAPSPAM and GLWv3 data on crop and livestock production are representative of the year 2010. These and other data used in the estimation of GHG emissions from agricultural commodities should be replaced with more recent data on crop and livestock production locations and production systems, where this is available.

Climate

GHGs (deforestation, sLUC)

Short description

The annual average emissions of greenhouse gas (GHG) associated with deforestation within a 50km radius attributable to the raw material sourced.

Data sources

- *Land footprint* indicator
- *Deforestation footprint (sLUC)* indicator
- Noon, Monica L., Allie Goldstein, Juan Carlos Ledezma, Patrick R. Roehrdanz, Susan C. Cook-Patton, Seth A. Spawn-Lee, Timothy Maxwell Wright, et al. 2021. ‘Mapping the Irrecoverable Carbon in Earth’s Ecosystems’. Nature Sustainability 5 (1): 37–46. **https://doi.org/10.1038/s41893-021-00803-6**.
- ESA. 2017. ‘Land Cover CCI Product User Guide Version 2. Technical Report’. maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf.

Interpretation

An estimate of the annual average greenhouse gas emissions arising from deforestation events over the previous 20 years, within a 50km proximity of where a raw material was sourced and attributable to that raw material using a statistical land use change (sLUC) approach. Emissions are calculated as the vulnerable carbon (the amount of biomass and soil carbon that would be lost in a land use change event typical for the location) associated with areas of deforestation. It is intended for use in reporting land use change related emissions in alignment with the Greenhouse Gas Protocol (GHGP) FLAG Guidance (Greenhouse Gas Protocol 2022) and Science Based Targets Initiative (SBTI).

Method

We estimate the amount of emissions associated with deforestation that can be attributed to the production of a raw material using a statistical land use change (sLUC) accounting methodology. It measures the amount of carbon loss due to deforestation that occurs nearby to the areas where raw materials are produced within a supply shed.

The sLUC method means that exact farm locations do not need to be known. Rather all farms within 50km of deforested land will be assigned a proportion of the related carbon loss based on their land footprint. This recognizes that A: deforestation by definition always takes place outside of existing cropland, and B: raw material crop production often drives deforestation indirectly, by displacing ranchers and smallholders rather than converting forests directly into cropland.

Estimating deforestation carbon loss

Greenhouse gas emissions from deforestation is the amount of carbon emissions that can be associated with a deforestation event. We estimate forest carbon loss due to deforestation by combining deforestation extent (see **Deforestation footprint (sLUC)**) with maps of vulnerable carbon (Noon et al. 2021) in those same areas. Vulnerable carbon, the amount of biomass and soil carbon that would be lost in a land use change event, is reported globally for 2010 at a 300m resolution.

For areas that were deforested between 2000 and 2010, we estimate year-2000 vulnerable carbon by filling gaps in forest carbon in the 2010 data using the following methodology:

- We select pixels that are classified as forests in 2010 in the ESA CCI Land Cover time series v2.0.7 dataset (ESA 2017), which was used as an input to generate the vulnerable carbon data, and compute mean vulnerable carbon for forests in the local area using a 10km kernel.
- We assign the mean vulnerable carbon values for forest to pixels that are classified as forests in the year 2000 by Hansen et al. (2013), but not classified as forests in 2010 by ESA.

This ensures that all pixels that may be identified as deforested have a carbon value that is reflective of the local area.

Deforestation carbon loss per hectare of land use

Responsibility for greenhouse gas emissions from deforestation is allocated on a per-pixel basis to all human land uses within a 50km radius in alignment with the Greenhouse Gas Protocol (GHGP) draft guidance Statistical Land Use Change (sLUC) proportional allocation method. In particular, for each pixel, we compute the total carbon value of deforested areas within 50km and divide it by the total area of non-natural land use (Mazur et al. 2023) within 50km, to get a ratio of tons of carbon per hectare of land use. Areas of open water and built areas are considered unavailable to agriculture and are excluded.

In areas where the ratio of deforestation to human land use exceeds 1.0 (i.e. there is more forest loss than land use), we reduce carbon loss by a proportional amount such that a single hectare of human land use cannot be responsible for more than one hectare of forest loss and its associated carbon. Finally, we divide the total area of deforestation over the previous 20 year period by 20 and multiply by 3.66 to convert tons of carbon to annualized emissions tons of carbon dioxide. The result is a global, high resolution map of tons of carbon dioxide per year from deforestation per hectare of human land use.

Greenhouse gas emissions from deforestation

The greenhouse gas emissions from deforestation for each raw material, c, and sourcing region, g, is computed by multiplying the average emissions per hectare of human land use, $IF_{carbon-loss-per-ha_{c,g}}$, by the land footprint of the raw material sourced, $I_{land-footprint\,c,g}$, as calculated for the land footprint indicator:

$$I_{deforestation-GHG\,c,g} = IF_{carbon-loss-per-ha\,c,g} * I_{land-footprint\,c,g} \quad \text{(Eq. i17)}$$

The average carbon loss per hectare of human land use is calculated as follows:

$$IF_{carbon-loss-per-ha\,c,g} = \frac{\sum_{i \in g} L_{b,i} * P_{c,i}}{\sum_{i \in g} P_{c,i}} \quad \text{(Eq. i18)}$$

Where $L_{b,i}$ is the annual carbon loss per hectare of human land use in the 50km radius buffered region, *b*, around point *i*. This rate is weighted by the raw material production ($P_{c,i}$) to account more for the areas where it is produced.

Comments

- Attribution to raw materials could be improved in line with the developments proposed for the landscape-level deforestation impacts.

Natural ecosystems conversion

Deforestation footprint (sLUC)

Short description

The annual average area of deforestation within a 50km radius attributable to the raw material sourced.

Data sources

- *Land footprint* indicator
- Tyukavina, Alexandra, Peter Potapov, Matthew C. Hansen, Amy H. Pickens, Stephen V. Stehman, Svetlana Turubanova, Diana Parker, et al. 2022. 'Global Trends of Forest Loss Due to Fire From 2001 to 2019'. Frontiers in Remote Sensing 3. **https://www.frontiersin.org/articles/10.3389/frsen.2022.825190**
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- Potapov, Peter, Matthew C. Hansen, Amy Pickens, Andres Hernandez-Serna, Alexandra Tyukavina, Svetlana Turubanova, Viviana Zalles, et al. 2022. 'The Global 2000-2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results'. Frontiers in Remote Sensing 3 (April): 856903. **https://doi.org/10.3389/frsen.2022.856903**.

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Interpretation

Deforestation footprint estimates the area of deforestation occurring within a 50km radius that is attributable to the quantity of raw material sourced using a statistical land use change (sLUC) approach. The indicator assumes that deforestation is driven by demand for land area, and is intended to assist companies in prioritizing sourcing regions in alignment with Zero Deforestation commitments, such as the **Accountability Framework Initiative (AFI)** and the Science Based Targets Network (SBTN) Zero Natural Land Conversion target. It also aligns with the Taskforce for Natural Related Financial Disclosure's (TNFD) land use change indicator (TNFD 2023).

Method

The deforestation indicator estimates the extent of deforestation that can be attributed to the production of a raw material. Importantly, this deforestation indicator uses a statistical land use change (sLUC) accounting methodology, meaning that exact farm locations do not need to be known. Rather all farms within 50km (the maximum distance assumed in our analysis to have some attributable relationship to agricultural land demands of deforested land will be assigned a proportion of that deforestation based on their land footprint. This recognizes that A: deforestation by definition always takes place outside of existing cropland, and B: raw material crop production often drives deforestation indirectly, by displacing ranchers and smallholders rather than converting forests directly into cropland.

Estimating deforestation extent

Deforestation is the conversion of forested areas to non-forest land use such as arable land, urban use, logged area or wasteland (FAO 2023). We estimate the extent of deforestation by looking first at all areas of tree cover loss over the past 20 years (Hansen et al. 2013), and then exclude the following areas where tree cover loss is unlikely to be a change in land use:

1. Loss of non-natural tree cover (Mazur et al. 2023) outside of areas classified as intact forests in 2000. Specifically, intact forests, as identified using Intact Forest Landscapes (Potapov et al. 2017), and Primary Humid Tropical Forests (Turubanova et al. 2018), and Mazur et al. uses the Spatial Database on Planted Trees (Richter et al. in review) to classify tree crops (c.2010-2020) as non-natural. This is intended to exclude harvesting within plantation woodlots and changes in tree cropping patterns.

2. Forest disturbance (Potapov et al. 2022) outside of areas classified as intact forests in 2000. Forest disturbance identifies areas with trees of >5m in height in both 2000 and 2020, but experienced significant disturbance in the intervening period. This is intended to exclude long-standing land use patterns of rotational logging and shifting agriculture, as well as natural forest disturbances (wildfire, blowdown) in secondary forests.

3. Tree loss that corresponds with burned areas outside of tropical and subtropical biomes (Tyukavina et al. 2022). This is intended to exclude tree cover loss due to wildfire in biomes where fire is a frequent natural occurrence.

This methodology is likely to misclassify tree loss as not being deforestation the following cases:

- where secondary forests are converted to woodlots or tree crops.
- Conversion of non-tropical intact forests where land-clearing was associated with fire, for example in regions of natural gas flaring.

On the contrary, it will also likely misclassify tree loss as deforestation in the following areas:

- Recent rotational logging of secondary forests where the area had not regrown as of 2020.
- Recent natural disturbances of secondary forests where the area had not regrown as of 2020.
- Natural forest disturbances in Primary Humid Tropical Forests.

We do not attempt to offset tree cover losses with tree cover gain outside of forest disturbance pixels.

Though these adjustments provide a better estimate of deforestation than raw forest loss data, overall this continues to overstate deforestation risk in areas of long standing rotational logging and frequent wildfire, and may underestimate the conversion of secondary forests to woodlots or tree crops, in particular, outside of the humid tropics.

Deforestation per hectare of land use

Responsibility for deforestation is allocated on a per-pixel basis to all human land uses within a 50km radius in alignment with the Greenhouse Gas Protocol (GHGP) draft guidance Statistical Land Use Change (sLUC) proportional allocation method (WRI and WBCSD 2022). In particular, for each pixel, we compute the total area of deforestation within 50km and divide it by the total area of non-natural land use within 50km, to get a ratio of hectares of deforestation per hectare of land use (**Figure A4**). Areas of open water and built areas are considered unavailable to agriculture and are excluded.

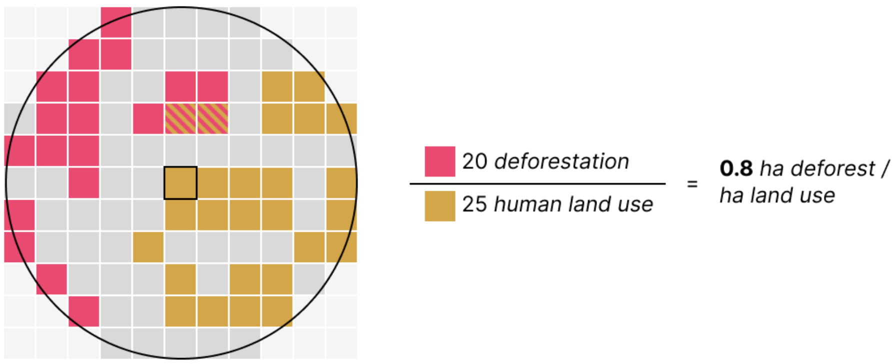

Figure A4. Illustration of proportional allocation method using a radius around a pixel. Land use produces direct or indirect pressure for land expansion in the surrounding area. For each pixel, we compute the total area of deforestation within a given radius and divide by the total area of human land use to allocate responsibility for deforestation. The result is that land use in close proximity to land expansion boundary receives a greater responsibility for deforestation.

If this ratio exceeds 1.0 (i.e. there is more forest loss than land use) it is capped at 1, such that a single hectare of human land use cannot be responsible for more than one hectare of forest loss over the analysis period. Finally, we divide the total area of deforestation over the previous 20 year period by 20 to get an annualized loss value. The result is a global, high resolution map of hectares of deforestation per hectare of human land use (**Figure A4**).

Deforestation risk

For each raw material, the deforestation risk is computed by multiplying the average deforestation per hectare of human land use by the crop production (MapSPAM 2010) and multiply by the land use in hectares as shown below:

$$I_{Deforestation-footprint\,c,g} = IF_{deforestation-per-ha\,c,g} * I_{land-footprint\,c,g} \qquad \text{(Eq. i13)}$$

Where $IF_{deforestation-per-ha\,c,g}$ is the average deforestation per hectare of human land use for a raw material, c, in a sourcing region, g. $I_{land-footprint\,c,g}$ corresponds to the land use impact of sourcing a raw material, c, in a sourcing region, g, and it is calculated using Eq. i10.

The average deforestation per hectare of human land use is calculated as follows:

$$IF_{deforestation-per-ha\,c,g} = \frac{\sum_{i \in g} D_{b,i} * P_{c,i}}{\sum_{i \in g} P_{c,i}} \quad \text{(Eq. i14)}$$

Where $D_{b,i}$ is the annual deforestation per hectare of human land use in the 50km radius buffered region, *b*, around point *i*. This rate is weighted by the raw material production ($P_{c,i}$) to account more for the areas where the raw material is grown.

Comments

Future work should incorporate more direct attribution of deforestation and information about what replaced the forest loss. Causes of forest loss have been attributed to broad economic sectors (Curtis et al. 2018) but more resolved information on drivers could be implemented. For example, Pendrill et al., (2019) use a land-balance model to allocate remotely sensed deforestation to raw material production (Pendrill et al. 2019).

Natural ecosystems conversion

Net cropland expansion

Short description

The annual average area of cropland expansion into natural ecosystems occuring within a 50km radius attributable to the raw material sourced.

Data sources

- *Land footprint* indicator
- Mazur, Elise, Michelle Sims, Elizabeth Goldman, Martina Schneider, Fred Stolle, Marco Daldoss Pirri, and Craig Beatty. 2023. 'SBTN Natural Lands Map: Technical Documentation'. SBTN. **https://sciencebasedtargetsnetwork.org/wp-content/uploads/2023/05/Technical-Guidance-2023-Step3-Land-v0.3-Natural-Lands-Map.pdf**.
- Karra, Krishna, Caitlin Kontgis, Zoe Statman-Weil, Joseph C. Mazzariello, Mark Mathis, and Steven P. Brumby. 2021. 'Global Land Use / Land Cover with Sentinel 2 and Deep Learning'. In 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, 4704–7. Brussels, Belgium: IEEE. https://doi.org/10.1109/IGARSS47720.2021.9553499.

Interpretation

An estimate of the annual net area of cropland expansion into natural ecosystems since 2020 within a 50km radius that is attributable to the quantity of raw material sourced using a statistical land use change (sLUC) approach. This indicator assumes that land conversion is driven by demand for land in the local area. Because it only measures conversion to cropland, it can be considered a conservative estimate (lower bound) of the amount of natural ecosystems that are lost. It is intended to assist companies in prioritizing sourcing areas in alignment with Zero Deforestation and Zero Land Conversion commitments, such as the Accountability Framework Initiative (AFI) and the Science Based Targets Network (SBTN) Zero Natural Land Conversion target. It also aligns with the Taskforce for Natural Related Financial Disclosure's (TNFD) land use change indicator (TNFD 2023).

Method

Estimating natural ecosystems conversion

The methodology employed to identify the risk that raw material sourcing is contributing to the conversion of natural ecosystems commences with the identification of natural lands and the determination of their distribution. The concept of natural ecosystem can be defined as one that closely resembles the original state of a given area, in terms of its species composition, structural attributes, and ecological functions, without significant human-induced alterations. This encompasses both managed ecosystems and ecosystems that have suffered degradation but are anticipated to recover, either through natural processes or active management (AFI, 2019).

Due to limitations in remotely sensed data on sparse human land uses such as logging and pasturing, we use a conservative approach evaluating only the conversion of natural ecosystems directly to cropland, using the SBTN Natural Lands dataset (Mazur et al. 2023).

We assess cropland expansion using the **Esri LC 10m** cropland class (Karra et al. 2021). We consider any area that is classified as cropland in one any of the previous three years to be cropland to account for temporal variations (i.e. fallowing) and minimize inaccuracies. E.g. such that any cropland between 2017 and 2020 is considered cropland for the year 2020.

To identify natural ecosystem conversion to cropland, we first identify the total land area that is considered to be cropland in 2022 but not in 2020, filtered to regions that are classified as natural in SBTN Natural Lands dataset. We also identify cropland reduction as areas that are cropland in 2020 but not in 2022.

Natural ecosystems conversion per hectare of land use

Responsibility for crop conversion in natural ecosystems is allocated on a per-pixel-basis to all human land uses within a 50km radius in alignment with the Greenhouse Gas Protocol (GHGP) draft guidance Statistical Land Use Change (sLUC) proportional allocation method (WRI and WBCSD, 2022).

In particular, for each pixel, we compute the total area of crop expansion in natural ecosystems within 50km, and the total area of cropland reduction in natural ecosystems within 50km. We compute net cropland expansion in natural ecosystems as expansion minus reduction, excluding areas with more reduction than expansion.

Finally we divide net cropland expansion by the total area of non-natural land use within 50km, to get a ratio of hectares of cropland expansion in natural ecosystems per hectare of land use. Areas of open water and built up areas are considered unavailable to agriculture and are excluded.

Net cropland expansion in natural ecosystems

For each raw material and sourcing region, the net cropland expansion in natural ecosystems indicator is computed by multiplying the net crop expansion per hectare of human land use by the land footprint of the raw material sourced:

$$I_{net-cropland-expansion\,c,g} = IF_{natural-crop-conversion-per-ha\,c,g} * I_{land-footprint\,c,g} \quad \text{(Eq. i15)}$$

Where $IF_{natural-crop-conversion-per-ha\,c,g}$ is the net cropland expansion in natural ecosystems per hectare of human land use for raw material, *c*, in sourcing region, *g*. $I_{land-footprint\,c,g}$ corresponds to the land use impact of sourcing the same raw material from that region (see Eq. i10).

The net cropland expansion in natural ecosystems per hectare of human land use is calculated as follows:

$$IF_{natural-crop-conversion-per-ha\,c,g} = \frac{\sum_{i \in g} C_{b,i} * P_{c,i}}{\sum_{i \in g} P_{c,i}} \quad \text{(Eq. i16)}$$

Where $C_{b,i}$ is the net cropland expansion in natural ecosystems across the buffered region *b*, per hectare of human land use in the same region, centered on location *i*. This rate is weighted by the raw material production ($P_{c,i}$) to account more for the areas where the raw material is grown.

Comments

- In many regions, patchwork cycles of land use changes persist, characterized by irregularities. The Potapov methodology (Potapov et al. 2022), used in the SBTN natural lands layer (Mazur et al. 2023), accommodates up to four years for observations, with potential cycles extending to five years. However, discrepancies between the Potapov dataset and the Esri land cover used here may lead to biases when our estimates of conversion are integrated with the SBTN natural lands dataset.

- Extending the analysis using Dynamic World data (Brown et al. 2022) could yield notable improvements. Leveraging this higher cadence time series has the potential to enhance classification consistency. The increased frequency of data capture provided by Dynamic World data offers a finer-grained perspective on land use dynamics. By incorporating this data source, the accuracy and reliability of classification could be heightened, contributing to a more comprehensive and robust assessment of land use changes and their implications.

Biodiversity

Forest landscape integrity loss

Short description

The average forest landscape integrity score of natural ecosystems that have been converted to cropland within a 50km radius attributable to the raw material sourced.

Data sources

- *Net cropland expansion* indicator
- Grantham, H. S., A. Duncan, T. D. Evans, K. R. Jones, H. L. Beyer, R. Schuster, J. Walston, et al. 2020. 'Anthropogenic Modification of Forests Means Only 40% of Remaining Forests Have High Ecosystem Integrity'. Nature Communications 11 (1): 5978. https://doi.org/10.1038/s41467-020-19493-3.

Interpretation

Quantifies the biodiversity importance of natural ecosystems that have been converted to cropland within a 50km radius of raw material sourced following a statistical land use change (sLUC) approach. Biodiversity importance is measured here as the Forest Landscape Integrity Index, which represents how ecologically intact forest ecosystems are. Higher values indicate that more intact forest landscapes, those with greater ecological importance, have been lost. As only areas which have been converted to cropland are considered, this may be considered a conservative estimate (lower bound) of loss. This indicator aligns with the Taskforce for Nature-related Financial Disclosures' (TNFD) ecosystem condition indicator (TNFD 2023).

Method

There are many facets of biodiversity that vary in importance for different stakeholders. For this reason several biodiversity risk indicators are proposed reflecting these different aspects. To align with previous analysis and with guidance from the SBTN, two categories of indicator are often proposed, one focussed on species and the other on ecosystems. Here we specifically use an ecosystem focussed indicator.

To capture the naturalness or integrity of ecosystems, accounting for composition, structure and function, we use the published estimates of forested ecosystem intactness using the Forest Landscape Integrity Index (FLII) (Grantham et al. 2020). FLII expresses the degree of intactness of forest ecosystems based on the spatial structure of the forest habitat and on the degree of human modification to the ecosystem. This indicator expresses the forest ecosystem integrity of natural ecosystem loss that can be attributed to sourcing of a raw material.

We use FLII as a weighting to scale natural ecosystem conversion since 2020 by to indicate a biodiversity value associated with its loss. So the impact factor for sourcing a raw material *c* from region g would be calculated as:

$$IF_{FLII-conversion-per-ha\,c,g} = \frac{\sum_{i \in g} B_{b,i} * P_{c,i}}{\sum_{i \in g} P_{c,i}} \quad \text{(Eq. i19)}$$

Where $B_{b,i}$ is the FLII score of natural land conversion events occurring in the buffered region *b* around each point *i* in the sourcing region *g*, per unit area of non-natural land use, given by:

$$B_{b,i} = \frac{\sum_{j \in b} FLII_j * C_j}{\sum_{j \in b} N_j} \quad \text{(Eq. i20)}$$

Where *j* is the set of points inside the buffered region *b* around point *i*. C_j is the area of cropland expansion into natural ecosystems, $FLII_j$ is the FLII score and N_j is the area of non-natural land use, all at point *j*.

And the FLII impact is then calculated as the product of the FLII impact factor and the annual average net cropland expansion into natural ecosystems (from eq. 15):

$$I_{FLII-cropland-expansion\,c,g} = IF_{FLII-conversion-per-ha\,c,g} * I_{net-cropland-expansion\,c,g} \quad \text{(Eq. i21)}$$

Comments

- There are multiple biodiversity variables and this ecosystem focussed indicator would be complemented by a species focussed variable. One of the simplest metrics that could be considered is the total number of mapped species whose area of habitat in the year 2020 is reduced by natural land conversion occurring within the buffered sourcing region.

  Species count indicators can be modified to reflect the importance of the habitat being lost for the species occurring in that location by weighting the area of land cover change by the rarity-weighted richness of the pixels lost. Rarity weighted richness combines species richness with the endemism of the species occurring in a given grid cell.

- There are alternative measures that can be used to indicate the ecosystem level importance of land use change. For example, the Biodiversity Intactness Index (see the following section).

Biodiversity

Biodiversity intactness loss

Short description

The average biodiversity intactness index of natural ecosystems that have been converted to cropland within a 50km radius attributable to the raw material sourced.

Data sources

- *Net cropland expansion* indicator
- Gassert, Francis, Joe Mazzarello, and Sam Hyde. 2022. 'Global 100m Projections of Biodiversity Intactness for the Years 2017 - 2020'. Technical White Paper. **https://ai4edatasetspublicassets.blob.core.windows.net/assets/pdfs/io-biodiversity/Biodiversity_Intactness_whitepaper.pdf**

Interpretation

Quantifies the biodiversity importance of natural ecosystems that have been converted to cropland within a 50km radius of raw material sourced following a statistical land use change (sLUC) approach. Biodiversity importance is measured here as the biodiversity intactness index (BII), which estimates how much of a terrestrial site's original biodiversity remains in the face of human land use and related pressures. Higher values indicate that more intact ecological communities, those with greater ecological importance, have been lost. BII focuses on the local biodiversity across ecosystem types as compared to FLII, which reflects the pressures on the structure of forest landscapes. As only areas which have been converted to cropland are considered, this may be considered a conservative estimate (lower bound) of loss. This indicator aligns with the Taskforce for Nature-related Financial Disclosures' (TNFD) ecosystem condition indicator (TNFD 2023).

Method

To capture the compositional intactness of ecosystems, we use published estimates of biodiversity intactness using the biodiversity intactness index (BII) (Gassert, Mazzarello, and Hyde 2022; Newbold 2016; Hill et al. 2018; Scholes and Biggs 2005). This indicator expresses the intactness of the ecological communities in natural ecosystem loss that can be attributed to sourcing of a raw material.

The methodology is analogous to that for forest landscape integrity loss except that we use BII instead of FLII as a weighting to scale natural ecosystem conversion since 2020 by to indicate a biodiversity value associated with its loss. So the impact factor for sourcing a raw material *c* from region g would be calculated as:

$$IF_{BII-conversion-per-ha\,c,g} = \frac{\sum_{i \in g} B_{b,i} * P_{c,i}}{\sum_{i \in g} P_{c,i}} \quad \text{(Eq. i22)}$$

Where $B_{b,i}$ is the BII score of natural land conversion events occurring in the buffered region *b* around each point *i* in the sourcing region *g*, per unit area of non-natural land use, given by:

$$B_{b,i} = \frac{\sum_{j \in b} BII_j * C_j}{\sum_{j \in b} N_j} \quad \text{(Eq. i23)}$$

Where *j* is the set of points inside the buffered region *b* around point *i*. C_j is the area of cropland expansion into natural ecosystems, BII_j is the BII score and N_j is the area of non-natural land use, all at point *j*.

And the BII impact is then calculated as the product of the BII impact factor and the annual average net cropland expansion into natural ecosystems (from eq. 15):

$$I_{BII-cropland-expansion\,c,g} = IF_{BII-conversion-per-ha\,c,g} * I_{net-cropland-expansion\,c,g} \quad \text{(Eq. i24)}$$

Comments

- Other biodiversity metrics can be considered to indicate the ecosystem level importance of land use change. For example the proposed Ecological Integrity Index (Hill et al. 2022), which estimates the ecological integrity of all locations; or the biodiversity habitat index (BHI) estimates each cell in a global grid, the proportion of habitat remaining across all other cells that are ecologically similar to this cell of interest (Hoskins et al. 2020). EII_j or BHI_j could be inserted instead of BII_j into equation i23 to calculate this indicator.

- Explore the threats to species as a result of land use expansion reducing the area of habitat available to them.

- Explore the calculation of loss of important habitat in Key Biodiversity Areas and/or Protected Areas, as a result of raw material sourcing.

- Better understand the biodiversity implications of intervention measures.

ANNEX 2: VALIDATING INGESTED DATA

Two types of checks are performed on the ingested data; a) validation prior ingestion and; b) validation during ingestion.

Prior to ingestion, checks are made that the data provided by the user is consistent with the data in the LandGriffon platform for:

- raw material types: do the user-supplied raw materials belong to one of the 175 commodities included in the commodity dataset (see: Commodity standardization)?
- business unit: are tier 1 supplier and producer fields consistent with the information provided by the user?
- purchased volumes: are the provided values equal to or greater than 0?

A different validation is performed during ingestion. Apart from validation of the types ingested, we perform a validation of the geolocation process. The Location type provided should belong to one of the categories covered above (unknown, country of delivery, country of production, administrative region, supplier aggregation point or point of production). The country or administrative area provided for a sourcing location that is either unknown, country of delivery, country of production or administrative area, should correspond to one of the GADM (version 3.6) admin level 0 or level 1 locations. Either latitude, longitude or detailed address information should be provided (along with country information) for a point of production or aggregation point. The resulting point from geolocating the latitude-longitude or address information should belong to the country specified. The latitude and longitude should be provided in EPSG:4326 -WGS 84 coordinate system.

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