LANDGRIFFON

LANDGRIFFON METHODOLOGY.

Agricultural supply chain impact and risk assessment.

Technical note

Version 0.1

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CONTENTS

SUMMARY

LandGriffon is a software service that helps companies assess risks and impacts from agricultural production in their supply chains and analyze possible futures. 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. As LandGriffon provides a holistic picture of company agricultural supply chain impacts, 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.

Although LandGriffon is a commercial service, 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 methodological approach to impact and risk assessment within LandGriffon, as well as known limitations and areas for improvement. We aim to continue the evolution of LandGriffon openly and collaboratively. We therefore welcome comments and feedback from the community and will work with others to coordinate and develop the knowledge and tools necessary to reduce agricultural production's environmental impacts.

BACKGROUND

In the context of growing global population and increasing demand for agricultural products, the joint goals of avoiding dangerous climate change and reversing the ongoing decline in the state of nature will require significant changes to many aspects of society. Agriculture, forestry, and land use change account for 22% of global greenhouse gas emissions (IPCC), while pressure from agriculture, deforestation, and land degradation is a dominant driver of biodiversity decline on land (IPBES). Agricultural land covered 37% of the global land surface area in 2019. Of this area, approximately one-third were croplands and two-thirds used for raising livestock (FAO 2021). This suggests that meeting growing food needs while reducing the environmental impacts of agriculture is one of the foremost challenges of the 21st century (Tim Searchinger et al. 2019).

Companies with agricultural commodities in their supply chains play a key role in mitigating environmental and social impacts and in contributing to nature-based climate solutions. The business case for companies to identify and reduce these impacts is growing. In part, this stems from regulation. For example, in 2021 the European Commission proposed **regulation on deforestation-free products** and in 2022 proposed a **Directive on corporate sustainability due diligence in company value chains**. The UK has also adopted the Environment Act, Schedule 17, which focuses on deforestation risks from commodities linked to commercial activities. While the U.S. is also considering **legislation to minimize the environmental impacts of international trade**.

Despite the urgency of the sustainability challenge, the availability of generally applicable, accurate, and practical tools for assessing the environmental impacts of agricultural supply chains remains limited. Life Cycle Assessment (LCA) approaches have been critical for assessing a product's or service's potential environmental impacts (Hellweg and Milà i Canals 2014). A recent consolidated and standardized dataset of typical environmental impacts (greenhouse gas emissions, pollution) for a range of agricultural products has been derived using LCA approaches (Poore and Nemecek 2018) and has become a standard resource for footprinting analysis (e.g. **Foundation Earth**). This LCA approach provides information on characteristic environmental impacts associated with a particular production system in a specific geography, such as nations.

However, environmental impacts can be very sensitive to precisely where and how a commodity 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 across products. The emissions arising from 100g of beef protein sourced from a beef herd range from around 20 up to 105 kg-CO2 equivalents (these are values for the 10th and 90th percentiles so exclude extreme low and high emission estimates). The context dependency of impacts is amplified for land use change, water use and biodiversity, for which it really matters where the impacts occur. In the case of water, for some watersheds and locations within them, there is already scarcity, so further water withdrawals are likely more impactful than elsewhere (Gleick and Palaniappan 2010). Likewise for land use change, loss of intact tropic forest ecosystems can have a much more detrimental biodiversity impact than loss of plantation forestry ecosystems in the northern hemisphere (Newbold et al. 2015).

In response, tools have been developed that use more precise spatially explicit information on production and the supply chain links to consumption. The platform 'Trase' for instance 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 agriculture’s 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, whilst Trase provides excellent, detailed traceability information this is for a specific subset of commodities and countries. Global Forest Watch Pro provides detailed information about deforestation impacts but does not provide information about supply chains or sourcing locations. These gaps arise primarily because of the uncertainties and time lags in global agricultural supply chain and production data. In this environment of limited information, the LandGriffon framework enables agricultural supply chain companies to evaluate, plan, and mitigate impacts arising from diverse supply chains.

The LandGriffon approach

The LandGriffon methodology starts from the presumption that many supply chains are difficult to track and manage. While some companies within agricultural supply chains have direct relationships with the farms and processors that produce their raw materials, in many cases 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 from commodity production (zu Ermgassen et al. 2022). Although this lack of supply chain knowledge is particularly 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 decisions 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 remain minimally used by companies seeking to improve their environmental performance, partly because of the difficulty of tracing where materials are ultimately sourced from (David Patterson et al. 2022).

LandGriffon is inspired by the need to move beyond life-cycle assessment approaches and 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 spatialize agricultural supply chain information and evaluate impacts as accurately as possible. We estimate supply chain impacts using a hierarchical approach. When little information is available, we use a probabilistic model 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.

Given the urgent need for companies to take action to evaluate, plan, and mitigate environmental impacts, we believe that the LandGriffon framework fills an essential gap in enabling companies to act in environments of limited information.

For companies with agricultural supply chains, we believe there is currently a gap in tools that can be applied globally to agricultural commodities, integrate with current supply chain systems, and help explore pathways to reduce impacts and associated risks to their businesses. LandGriffon aims to address these and other gaps by having the following properties:

1. ability to integrate with diverse company supply chain data and systems,
2. spatially explicit,
3. generally applicable for all agricultural commodities at global scale,
4. extendable so that it works with currently available data but can readily incorporate newer data and indicators as these become available,
5. allows companies to explore various pathways to reduce impacts by evaluating the effects of actions such as changing recipes or sourcing locations, or reducing environmental impacts of producers.
6. promotes greater precision in supply chain traceability by rewarding this with more accurate impact estimates.
7. aligns with the needs of companies in implementing the draft guidelines proposed by the Science Based Targets Network (**SBTN**) and the Taskforce on Nature-related Financial Disclosures (TNFD, (TNFD 2022). This is manifested in the features and baseline impact indicators already implemented and under development in the tool.

METHODS

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

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

And we use these elements to structure the methodological description below.

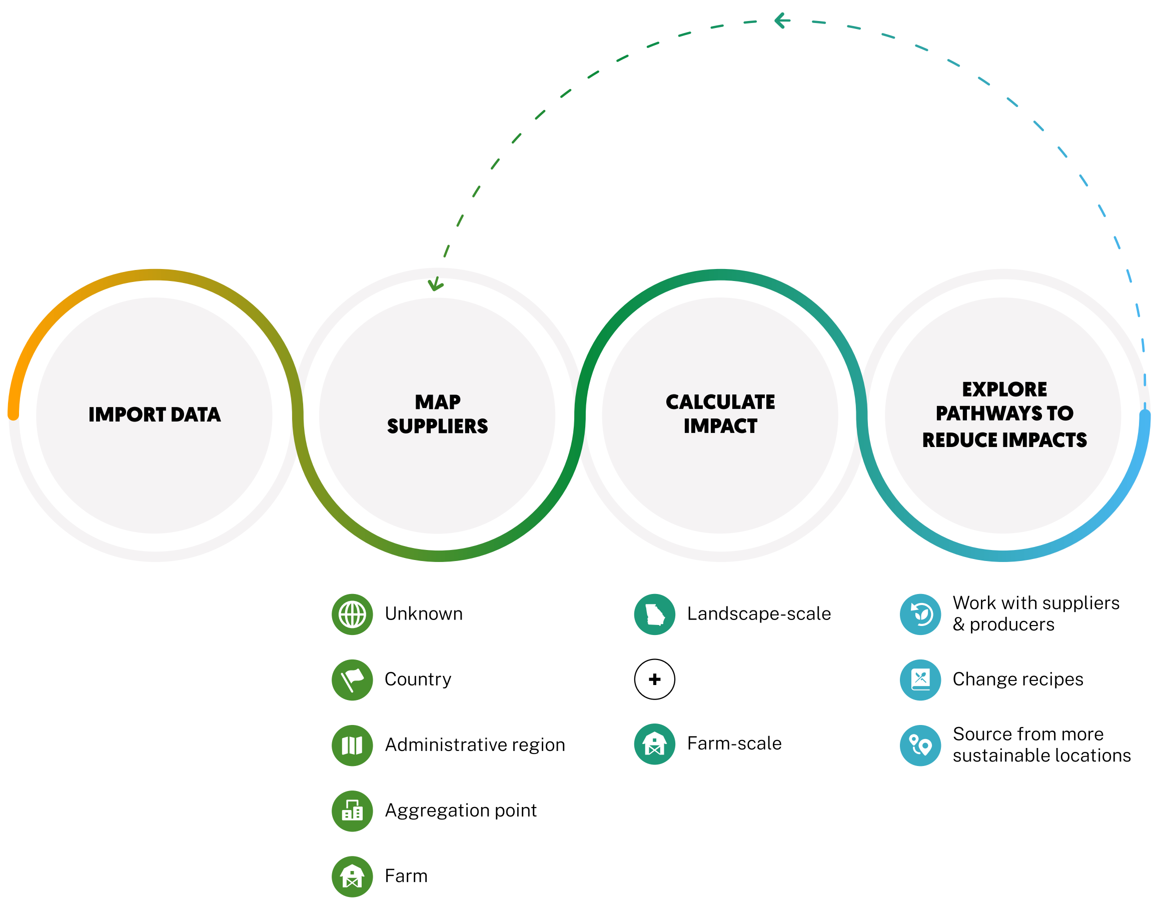


Figure 1. *Schematic representation of the LandGriffon v0.1 methodology with example impacts represented. Image credits: Sustainable Agriculture by Abdulloh Fauzan, Recipe by myiconfinder, Change Location by iconik, Line Graph by Elisabeta, Global by Delwar Hossain, Country by ibrandify, Seoul by PTWIZ, Mill by Muhammad Atiq, Farm by Symbolon, Grande Region by clemsi, French Region Map by Rahe (all from NounProject.com).*

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 location.

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 the procurement information companies can 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				
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	[redacted]	[redacted]	[redacted]	2400	2424	2448	2472	2497
40 Rubber and	Accessories		Moll	Unknown	Malaysia	[redacted]	[redacted]	[redacted]	1300	1313	1326	1339	1352
40 Rubber and	Accessories		Moll	Unknown	United States of /	[redacted]	[redacted]	[redacted]	1000	1010	1020	1030	1040
40 Rubber and	Accessories		Moll	Unknown	Japan	[redacted]	[redacted]	[redacted]	730	737	744	751	759
40 Rubber and	Accessories		Moll	Unknown	India	[redacted]	[redacted]	[redacted]	490	495	500	505	510
40 Rubber and	Accessories		Moll	Country of production	Thailand	[redacted]	[redacted]	[redacted]	3100	3131	3162	3194	3226
40 Rubber and	Accessories		Moll	Country of production	Indonesia	[redacted]	[redacted]	[redacted]	2600	2626	2652	2679	2706
40 Rubber and	Accessories		Moll	Country of production	Cote D'Ivoire	[redacted]	[redacted]	[redacted]	1100	1111	1122	1133	1144
40 Rubber and	Accessories		Moll	Country of production	Vietnam	[redacted]	[redacted]	[redacted]	810	818	826	834	842
40 Rubber and	Accessories		Moll	Country of production	Malaysia	[redacted]	[redacted]	[redacted]	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 it 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** - It is known which country the material was delivered to, 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 material 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 commodities sourced by companies will be standardized to the volumes of the raw commodity produced using tonnage ratios (Poore and Nemecek 2018; FAO n.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, tı	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 oth	0401	Milk and cream ı	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 sw	0402	Milk and cream ı	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 commodities, there is substantial open access data that can help inform the likely locations they are sourcing from. For example, for companies sourcing soy, palm oil, beef, shrimp, cocoa, coffee, corn, wood pulp, chicken, cotton, sugar cane, and pork, **Trase** identifies the regions and producers that major commodity traders purchase from for key producing countries. 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 have opted not to automate their use in version 0.1 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 material sourcing areas. It then attributes impacts in those areas to the sourcing of those materials.

Where the location type is unknown or is only known at the scale of the country or region of production, we assume that the commodity is sourced from all locations producing that material within the relevant spatial extent (**Table 1**).Where the location type is known as the country of delivery, we assume that the material has been produced globally, in all locations exporting the material to the given country (identified using Multi-Regional Input-Output databases e.g. **EXIOBASE 3**), and sourced in proportion to the production in any location.

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 livestock production. MapSPAM and GLWv3 are the latest publicly available datasets but are representative of the year 2010. Materials are matched using the extended HS commodity codes but where there is no exact match, the closest parent in the hierarchical system will be used. For example, “Apples, Pears, and Quinces” (HS 0808), will be matched to the MapSPAM dataset for Temperate Fruit crops. Commodities with no close match, such as rubber or acacia, will be analyzed on a case-by-case basis using specific additional datasets. More material will be assumed to be sourced from locations with greater production. So, a higher probability of impact is associated with areas of high production and vice versa.

This implies that LandGriffon could underestimate or overestimate the impact associated with a commodity. If the weighted average impact across the whole sourcing area is lower than in the location or locations where the material was produced there is an underestimation. If the commodity came from a production area with a low impact, there is an overestimation.

Figure 4. *Distribution of Cotton production (Tonnes) from Mapsmap data. The commodity 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.*

Sub-national understanding of spatial sourcing is critically important for reducing uncertainties in impact estimation and is the focus of tools such as Trase. Future LandGriffon development will focus on using additional supply chain information to infer the likely sourcing profiles of companies. These profiles 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, palm oil or cacao trader information can be extended with Trase data on supply chains. Ultimately, full knowledge of sourcing location, when this data has been collected, can be incorporated and removes the need for modelling.

Spatial representation

Each sourcing location is geolocated depending on its associated location type (**Figures 5 and 6**). LandGriffon v0.1 uses the H3 format for geospatial data and processing. **H3 has the benefit of having efficient hash table matrix math performance, high-speed resampling for visualization or 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.

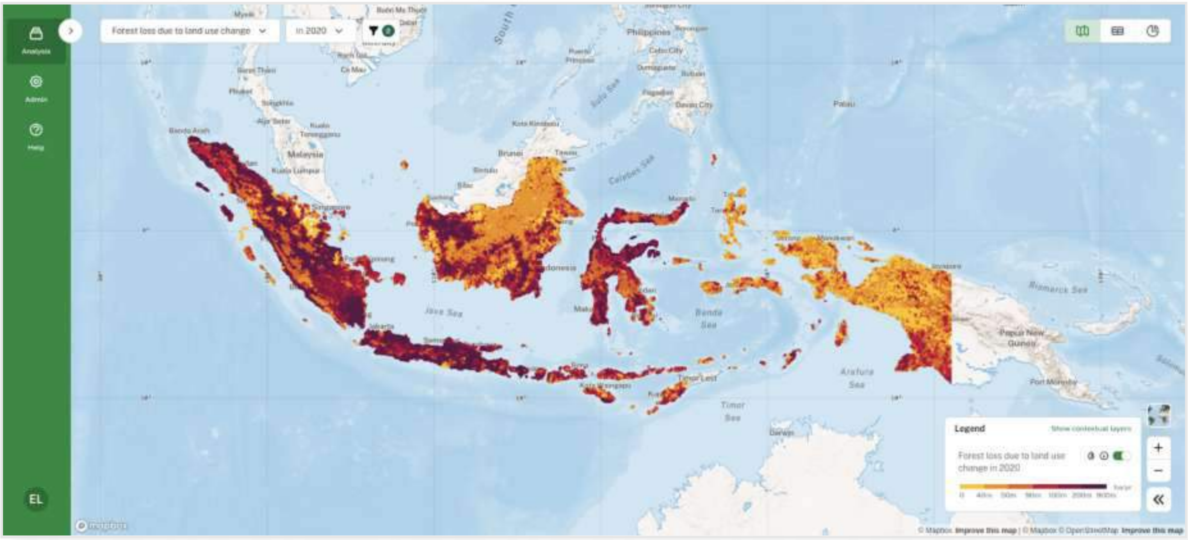


Figure 5. *Geolocation of a country of production, showing the distribution of deforestation risk associated with sourcing palm oil from Indonesia. We model the purchased volume as being produced across all areas of palm oil production in Indonesia.*

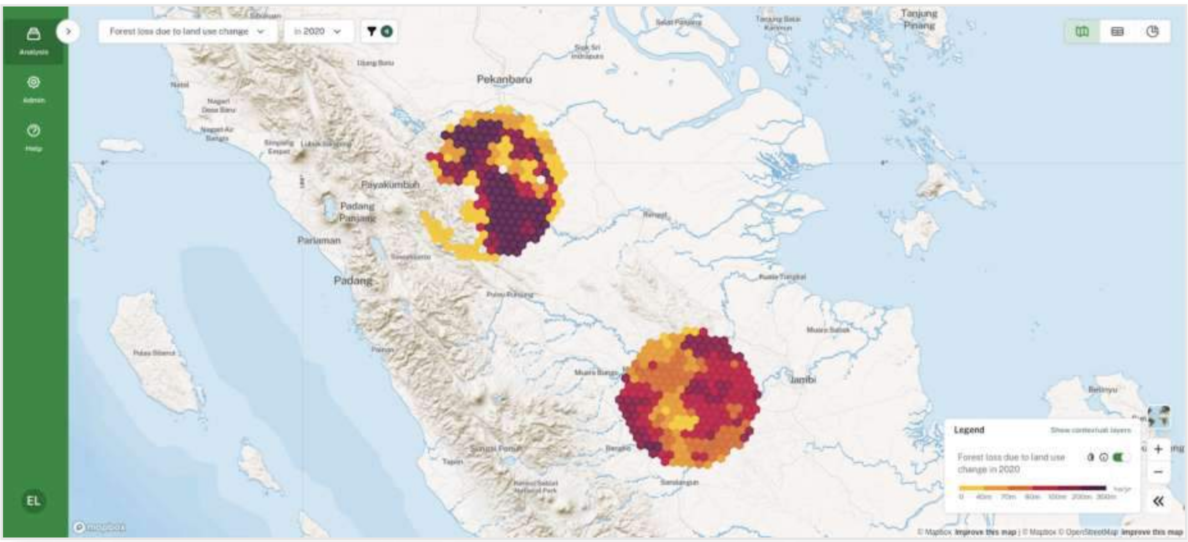


Figure 6. *Geolocation of a supplier's aggregation point (50 km radius buffer), showing deforestation risk of palm oil around aggregation points in Indonesia. We model the purchased volume as being produced across all areas of palm oil production inside supplier aggregation points.*

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

Location type	Description	Spatial sourcing assumption(s)	Geolocation	Implication(s)
Unknown	The raw materials are purchased on an open market and the company does not know the country where it receives the material.	The material has been produced globally, in all locations producing that commodity, 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 the case when the sub-national location of production information is known.
Country of delivery	The raw materials are purchased on an open market, but the company does know the country from which it receives the material	The 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 materials are purchased on an open market, but known to be sourced from a given country.	The material has been produced across the entire country, in all locations producing that commodity, and sourced in proportion to the production in any location.	Mapped to their respective boundaries.	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 materials are purchased on an open market, but known to be sourced from a given administrative region.	The material has been produced across the entire administrative region, in all locations producing that commodity, and sourced in proportion to the production in any location.	Mapped to their respective boundaries.	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 material has been produced in a buffer to the 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 commodity 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- or overestimate impact within it. Where the amounts sourced from different facilities are unknown, then 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 commodity 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 0.1 of LandGriffon includes baseline indicators (**Annex 1**) of environmental impacts such as water use, land use, deforestation, greenhouse gas emissions, and biodiversity loss associated with agricultural production.

Once the data is geolocated, we compute indicators, denoted by the symbol I, of the materials sourced. All indicators are calculated as the quantity of a commodity sourced multiplied by an impact factor, which represents the average impact per ton of the commodity produced across the sourcing geometry. So, the impacts, $I_{c,g}$, associated with commodity, *c*, and geometry, *g*, can be calculated as:

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

where: $IF_{c,g}$ is the Impact Factor for the commodity, *c*, across sourcing geometry, *g*, in *impact per ton of commodity produced*; and $S_{c,g}$ is the total quantity of commodity *c* sourced from geometry *g* in *tons*.

Impact indicators calculation depends on available data, which varies across impacts. For example, spatial maps of crop production exist, as do maps of water use and deforestation. However, spatially explicit information on greenhouse gas (GHG) emissions from agricultural commodity production is not generally available. So, impact calculation of GHG emissions will rely on life cycle assessment or footprinting impact factors.

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 is a farm-level or landscape-level indicator.

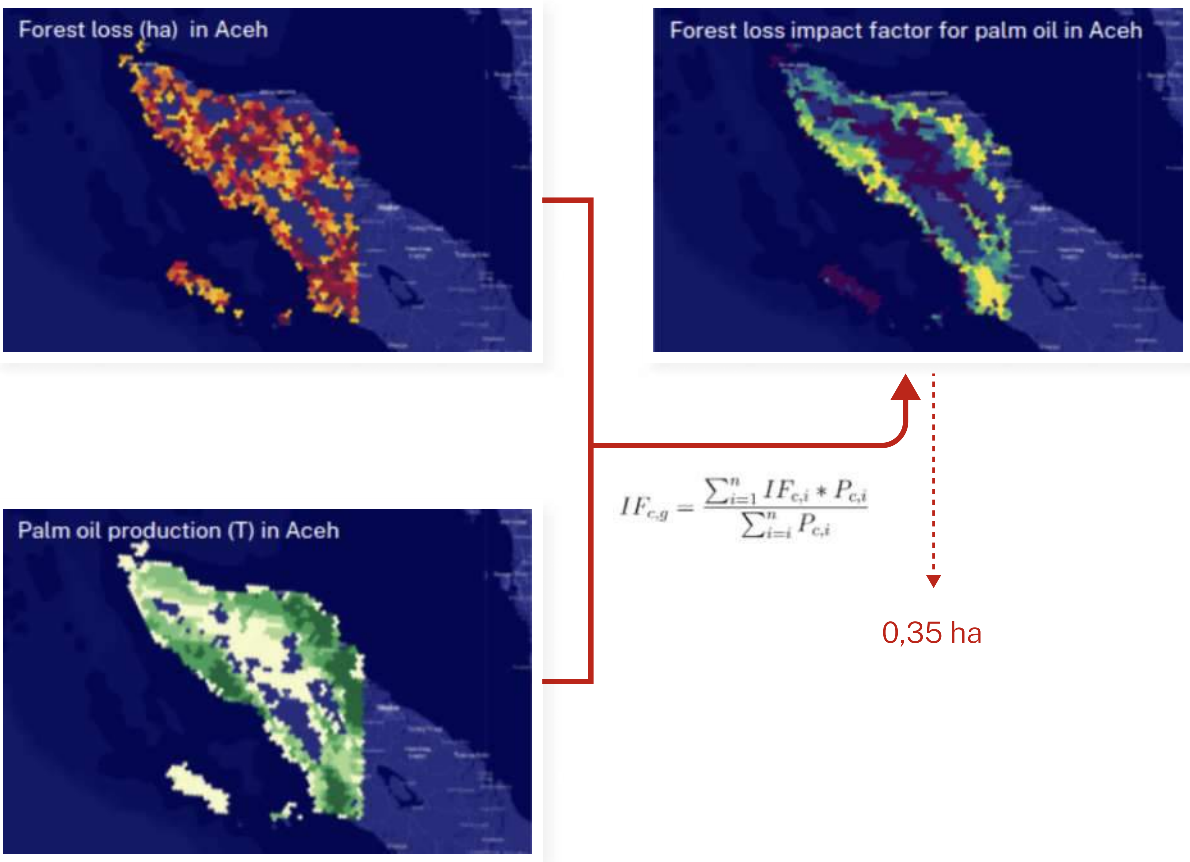
- Farm-level indicators aim to capture those impacts that occur within the current footprint of agricultural production.

- Landscape-level indicators represent the potential impact of commodities at the landscape-level including areas surrounding production areas under the assumption that commodity-driven land cover change occurs in the proximity of existing farms. At a macro-scale, using land for one commodity sourced into a supply chain presents a land opportunity cost in relation to using land for the production of another crop. Land area sourced into a company's supply chain adds to the cumulative pressure for land in the proximal area and so contributes indirectly to land use change there.

Materials are assumed to be sourced in proportion to the amount of production in any given location, such that areas that produce more are counted more heavily. For each material and location, we compute a production weighted average impact factor, defined as the sum of the spatial dataset multiplied by the production for each grid location within the sourcing geometry, divided by the sum of the production over the entire sourcing geometry:

$$IF_{c,g} = \frac{\sum_{i=1}^{n} IF_{c,i} * P_{c,i}}{\sum_{i=i}^{n} P_{c,i}} \qquad \textit{(Eq. 2)}$$

Where $IF_{c,i}$ represents the spatially varying impact over each pixel or other spatial unit i of the n such units within the sourcing geometry *g*, and, $P_{c,i}$, is the production of the commodity c across those spatial units (tons). The production weighted average impact factor is a close analogy to the Commodity Supply Mix developed for Life Cycle Assessment (Lathuillière et al. 2021).



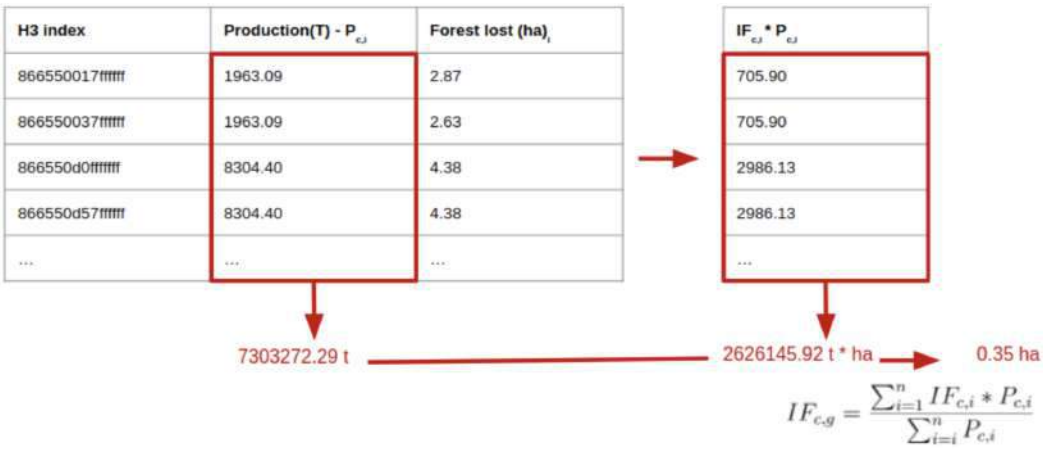


Figure 7. *(Top) Illustrative description of the weighted average impact factor calculation procedure for forest loss for palm oil in a sub-national region.(Bottom). Detailed description of the weighted average impact factor calculation for a given commodity and geolocation.*

Farm-level impacts

Farm-level impact indicators (e.g. **Figure 8**) are calculated as follows:

- The impact factor is calculated as the production weighted average of the spatial dataset within the sourcing geometry.
- If there is no overlap between the production map and the sourcing geometry, the impact factor is calculated as the area average for the sourcing geometry.
- For farm-level impacts associated with supplier aggregation points, a buffer is applied around the aggregation point. In version 0.1 of LandGriffon this buffer defaults to 50km radius, as is commonly used for palm oil mills.

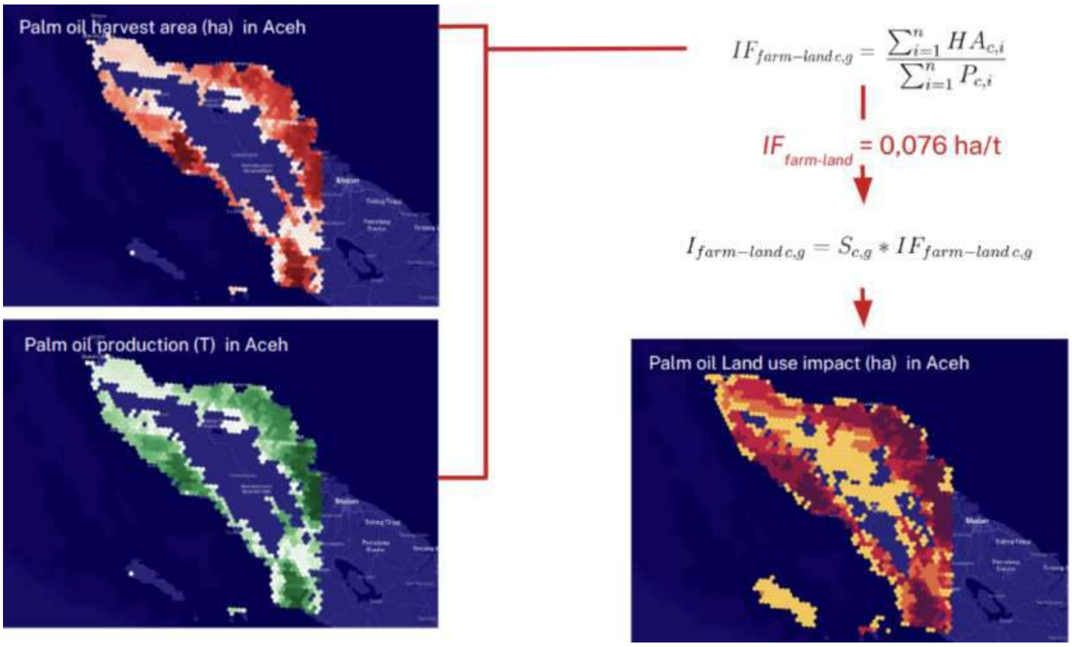


Figure 8. *Example of a farm level impact calculation. Calculation of the land use impact for purchasing palm oil, the crop (denoted by c in the equations), from the region g, which here is Aceh, Indonesia. Where,* $HA_{c,i}$ *represents the harvest area of palm oil per pixel, i, in hectares;* $P_{c,i}$ *is the production of palm oil in each pixel in tonnes; and* $S_{c,g}$ *is the amount of palm oil sourced from the Aceh region in tonnes.*

Landscape-level impacts

Landscape-level impact indicators (e.g. **Figure 9**) are calculated in the following way:

- For unknown, country, administrative region or aggregation point location types, the production map is buffered using a radius kernel prior to using it as the weighting layer, in order to capture areas nearby to producing regions.
- The impact factor is calculated as the production weighted average within the sourcing geometry using the buffered production map (if there is no overlap between the production map and the sourcing geometry, the impact factor is calculated as the area average for the sourcing geometry).
- To avoid double counting proximal landscape-level impacts, the impact is distributed across all the crops produced in the sourcing geometry, and impacts are allocated in proportion to each crop's area footprint.

The choice of buffer size by which to analyze impacts in the proximity of production systems for landscape level indicators defaults to 50km in version 0.1 of LandGriffon. Future developments may implement a more complex approach to distances, for example, varying with the material, the characteristics of the production landscape, and/or the administrative region.

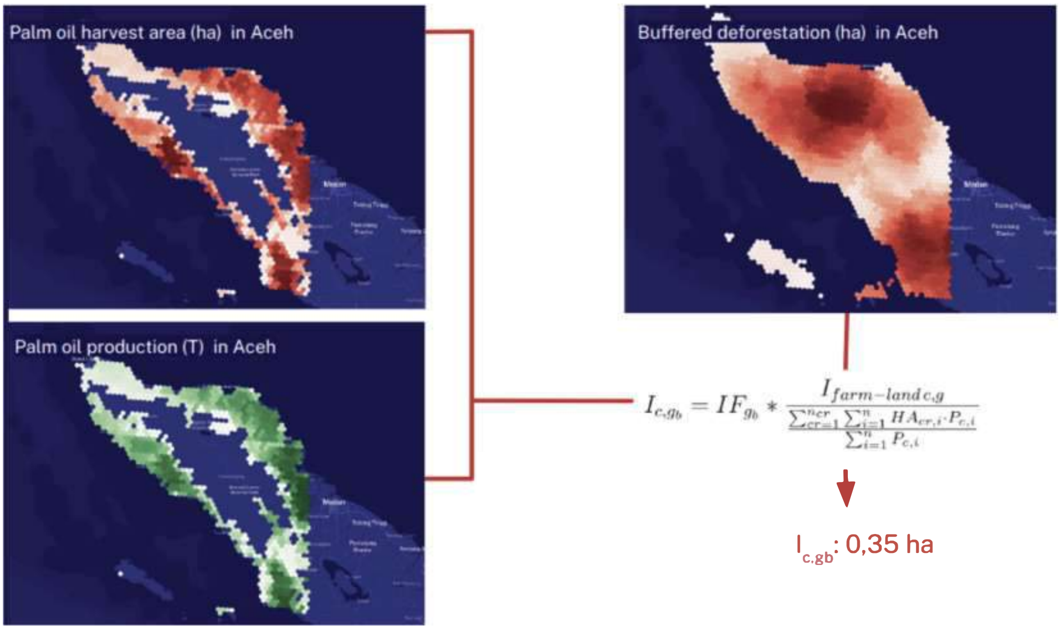


Figure 9. *Example of a landscape-level impact calculation of the weighted deforestation risk calculation for purchasing 1 ton of Palm oil sourced from Aceh, Indonesia.*

Impact calculations

In LandGriffon, farm-and landscape-level impact calculations are implemented in a modular way so that it is easy to integrate new indicators with supply chain ingestion and spatial geolocation framework. Version 0.1 of LandGriffon includes a baseline set of impact indicators (**Table 2**). Further descriptions of indicators objectives, calculations, limitations, and next steps are provided in Annex 1.

Table 2. *Impact indicators either fully implemented or progressing to implementation in LandGriffon v0.1.*

Impact indicator level	Implemented	In progress
Unknown	• **Water use** • **Unsustainable water use** • **Land use**	• **Greenhouse gas emissions**
Country of delivery	• **Deforestation risk** • **Climate risk from land use change**	• **Biodiversity risk from land use change**

These indicators are currently focused on production impacts, as opposed to lifecycle impacts. So, although LandGriffon has taken some inspiration from Life Cycle Assessment (LCA), there will be implicit impacts associated 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.

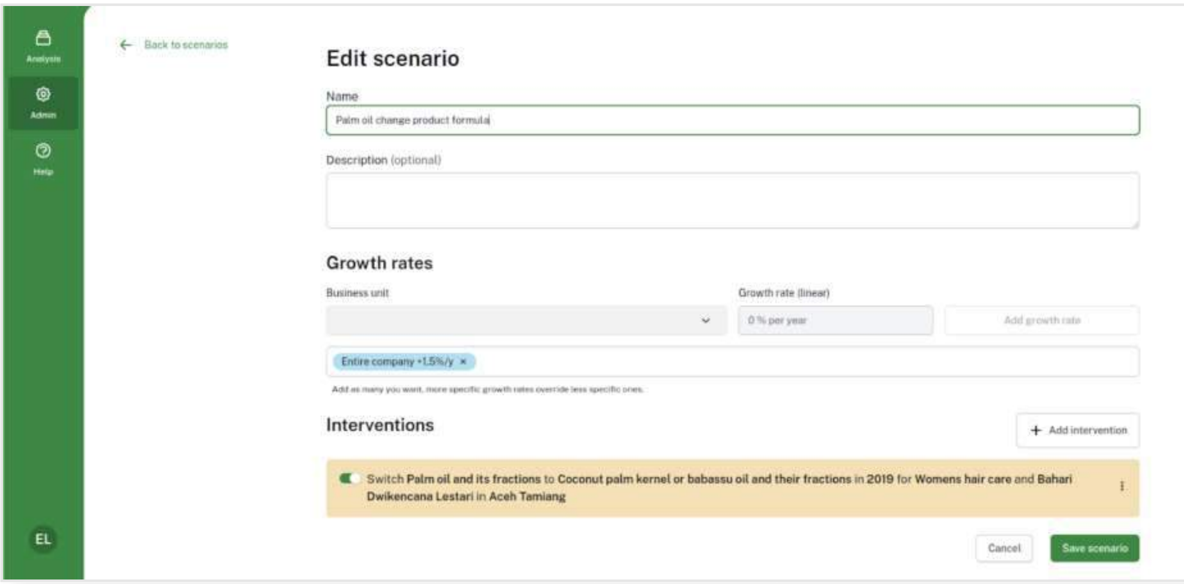


Figure 10. *Example of the creation of a scenario with one intervention using the LandGriffon platform. The scenario includes just an intervention for changing palm oil. In the creation of a scenario the user can also set different growth rates directly through the platform.*

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 0.1 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 0.1 of LandGriffon include:

- Working with farmers 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.

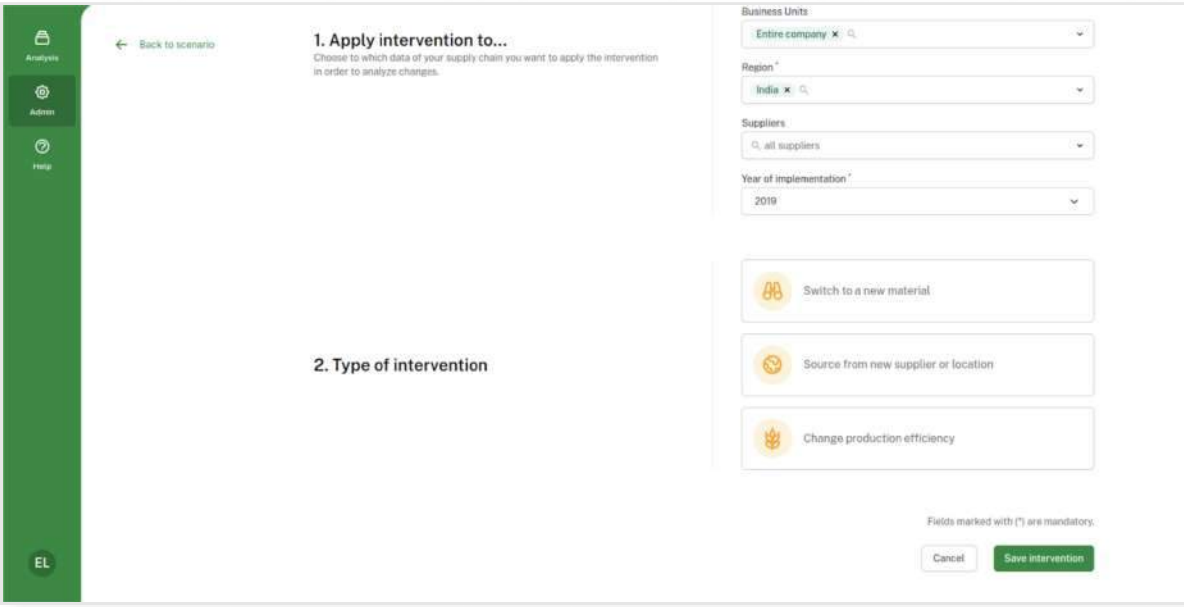


Figure 11. *Types of interventions contemplated in the creation of a scenario.*
Once a set of actions making up a future scenario has been defined, LandGriffon then calculates the change in impacts arising from this set of actions, which can be compared to a reference case, other scenarios, and company 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 purchasing commodities for a given company needs to be ingested into the LandGriffon platform as an initial step. This information is ingested using a template spreadsheet directly through the platform.

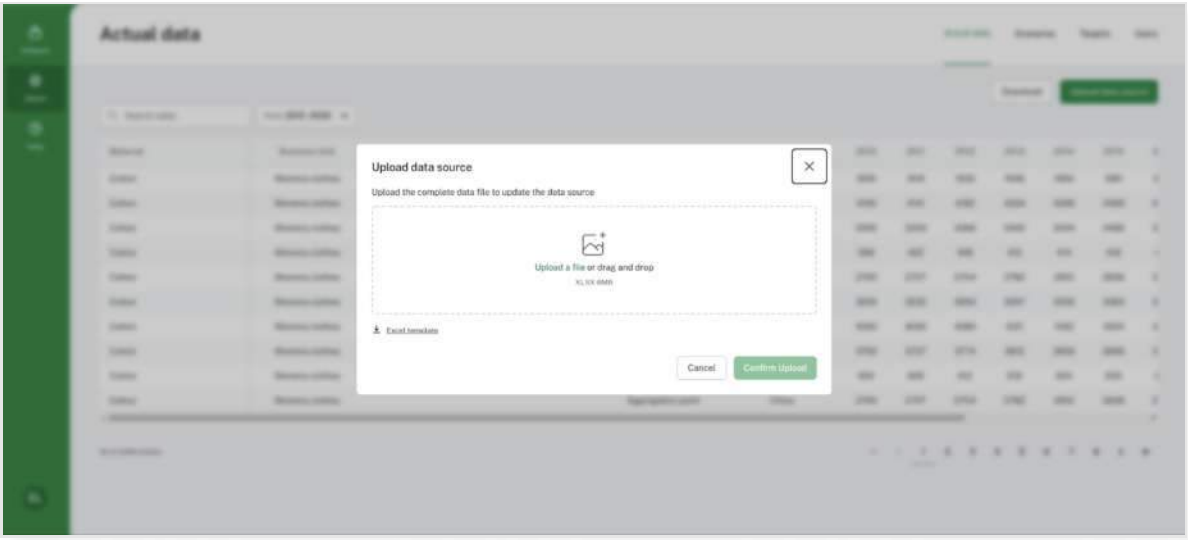


Figure 12. *Ingestion of company data into LandGriffon.*

During this preparation, as a minimum requirement, we need to provide the yearly purchased supply chain volumes for any given commodity. Additionally, the spreadsheet can also incorporate information regarding business units, suppliers, and location types.

We understand that the level of information regarding the supply chain commodities can vary significantly across companies, tiers, or business units, so the data ingestion in LandGriffon v0.1 is purposely designed to fit these discrepancies using the different location types. 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
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 13. *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**), locations are geolocated.

The outputs of the ingestion are visible at all times in the LandGriffon platform under the admin tab. This allows quick exploration and editing through the user interface of the company data ingested.

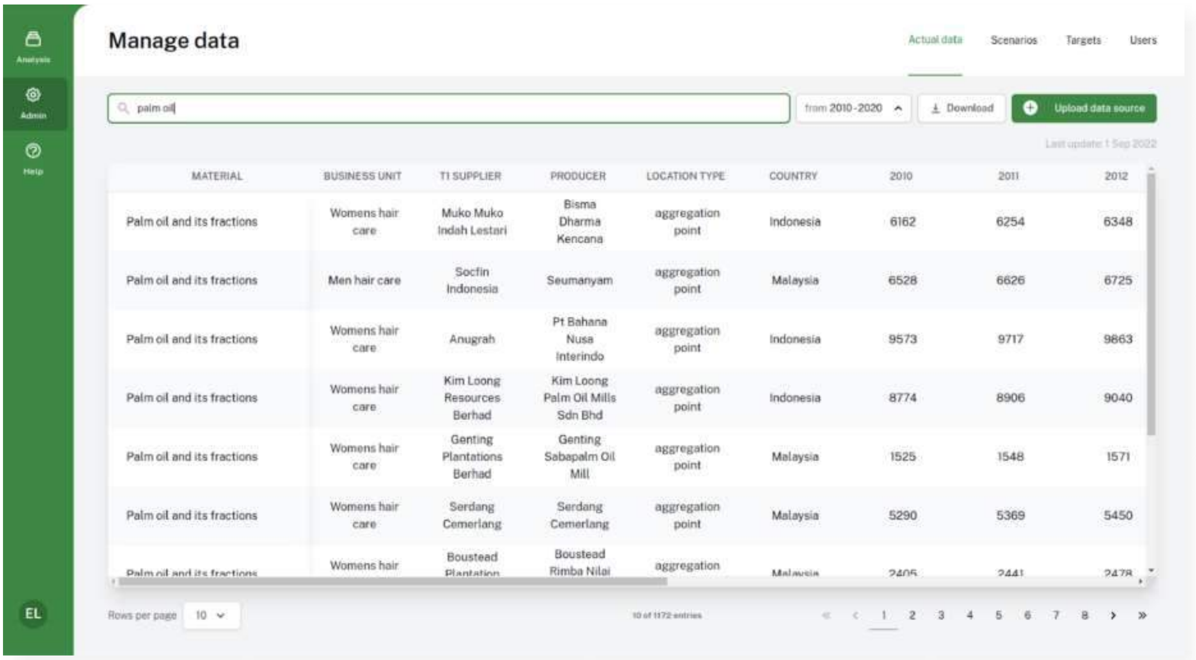


__Figure 14.__ Example of ingested data in the LandGriffon platform.

Impact calculation

The impact associated with a particular 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 use** (farm level indicator) and **deforestation risk** (landscape-level indicator) as indicators and use data of the 2021 forest loss in Indonesia (Satelligence) and 2010 palm oil production and harvest area from MapsSPAM.

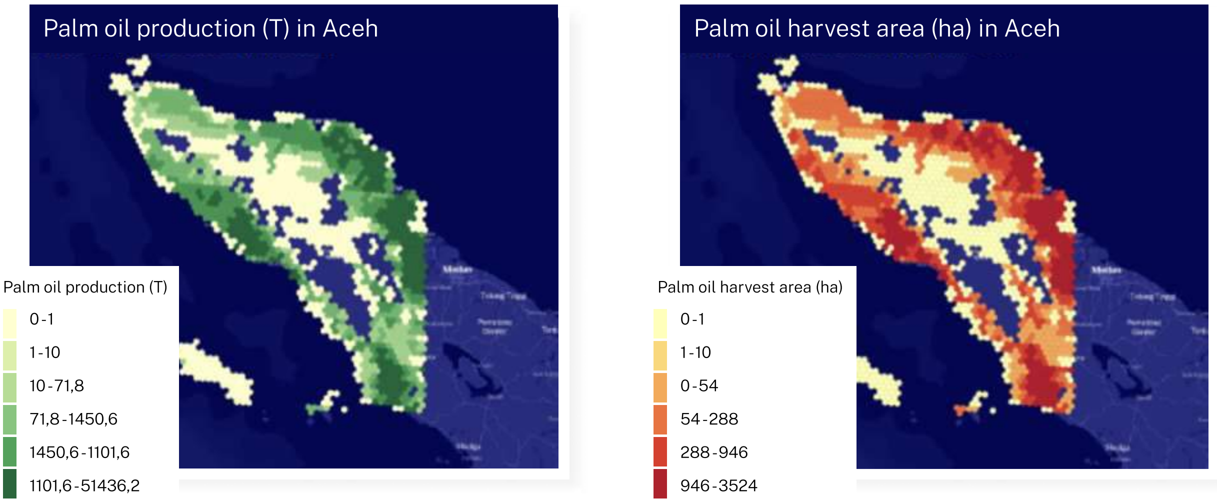


Figure 15. *Palm oil production (t) and palm oil harvest area (ha) in Aceh, Indonesia. Data based on MapSPAM.*

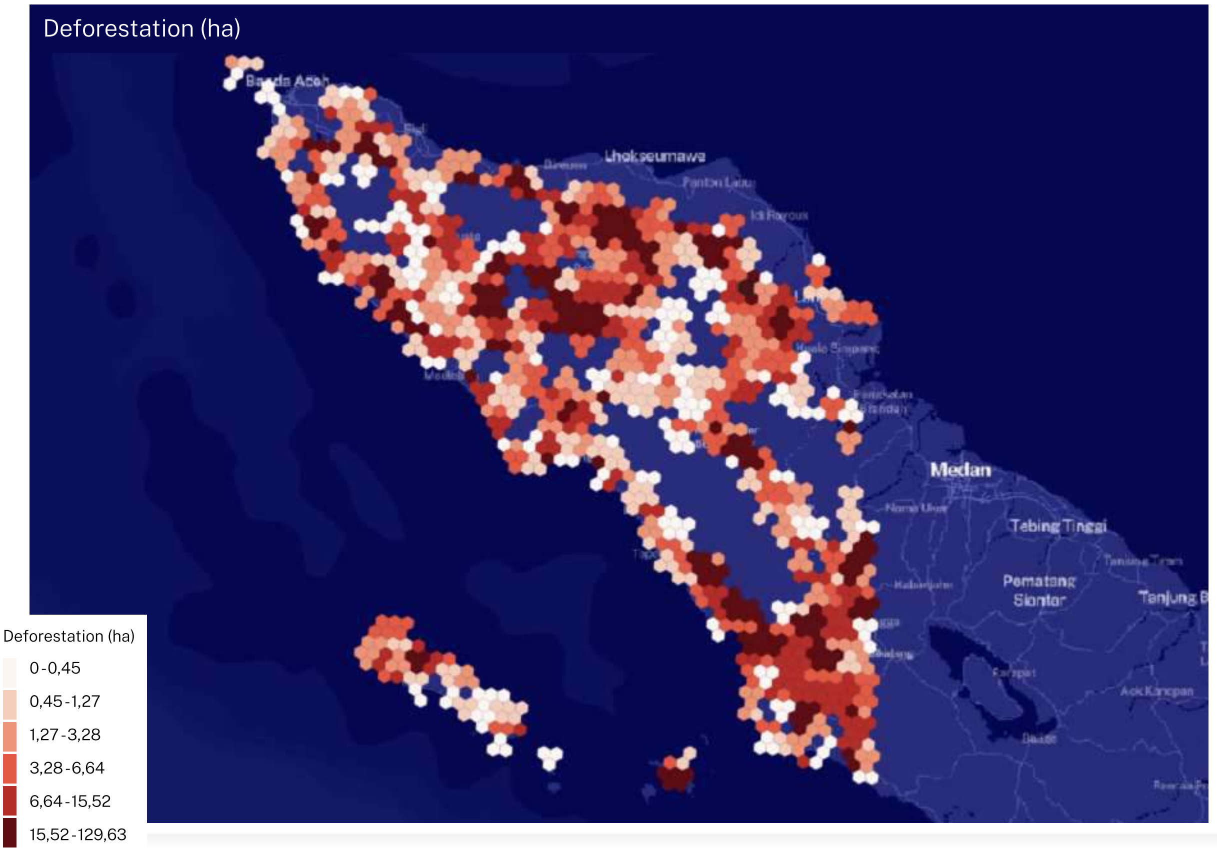


Figure 16. *Deforestation (ha) that is taking place in Aceh, Indonesia in 2021 based on Satelligence dataset.*

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 geometry, weighted by the production in each pixel.

Deforestation risk is classified as a landscape-level indicator, therefore, we follow the methodology previously presented in the **Landscape-level impacts** section to account for land expansion. For landscape-level impacts, the production map is buffered using a radius kernel before using it as the weighted layer, to capture areas near production regions. The impact factor is calculated as the production weighted average within the sourcing geometry using the buffered production map.

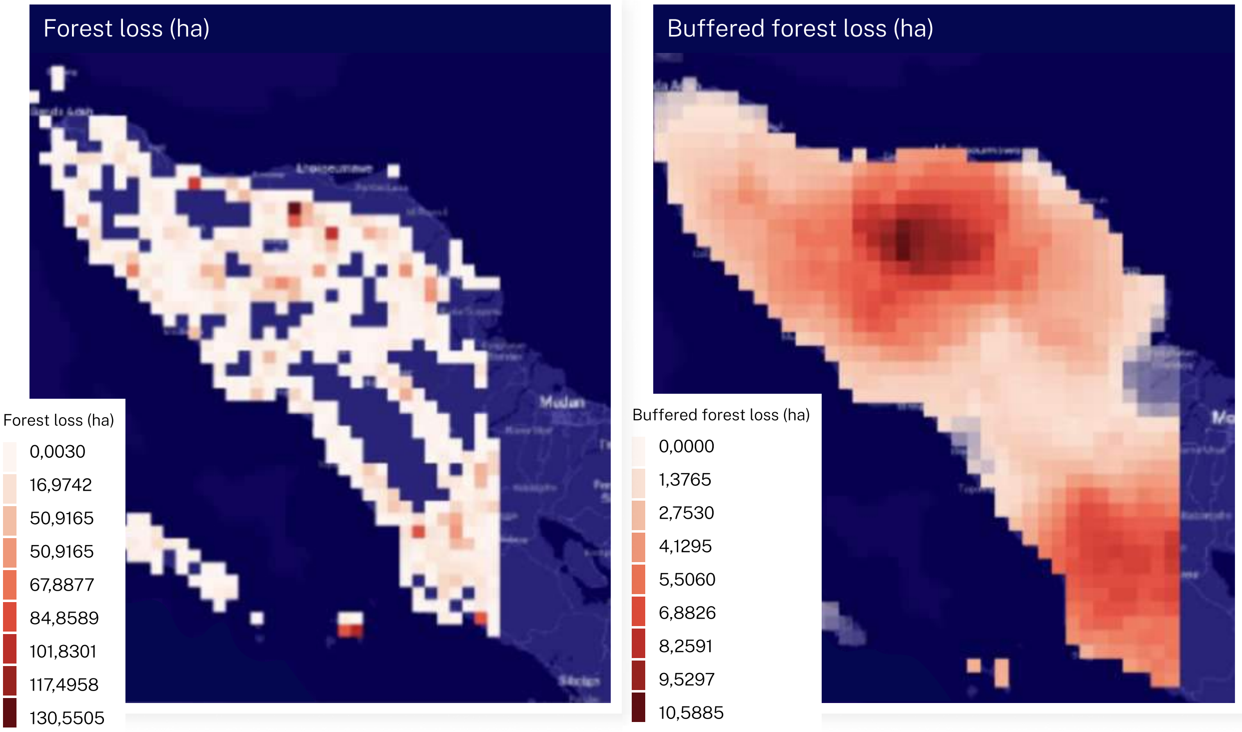


Figure 17. *50 km^2 buffer kernel applied in the deforestation raster.*

The table below summarizes the results for the land use and deforestation risk calculations for each location type:

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

Location type	Assumptions	Land use (ha)	Land use relative to point of production (%)	Deforestation risk (ha)	Deforestation risk relative to point of production (%)
Farm level impact	The location will be a point of production. Impact calculated using the containing pixel values	63.152	-	0.082	-
Suppliers aggregation impact	The material has been produced in a 50 km buffer to the point provided.	71.721	113.57	0.063	76.8
Administrative region impact	The commodity has been produced across the entire administrative region, in all locations producing palm oil, and sourced in proportion to the production in Aceh, Indonesia.	87.195	138.07	0.084	100.2

LandGriffon v0.1 assumes that the impact is distributed across the areas of commodity production. So, higher probability of impact is associated with areas of high production and vice versa. The image below shows the result of distributing the impact calculated previously:

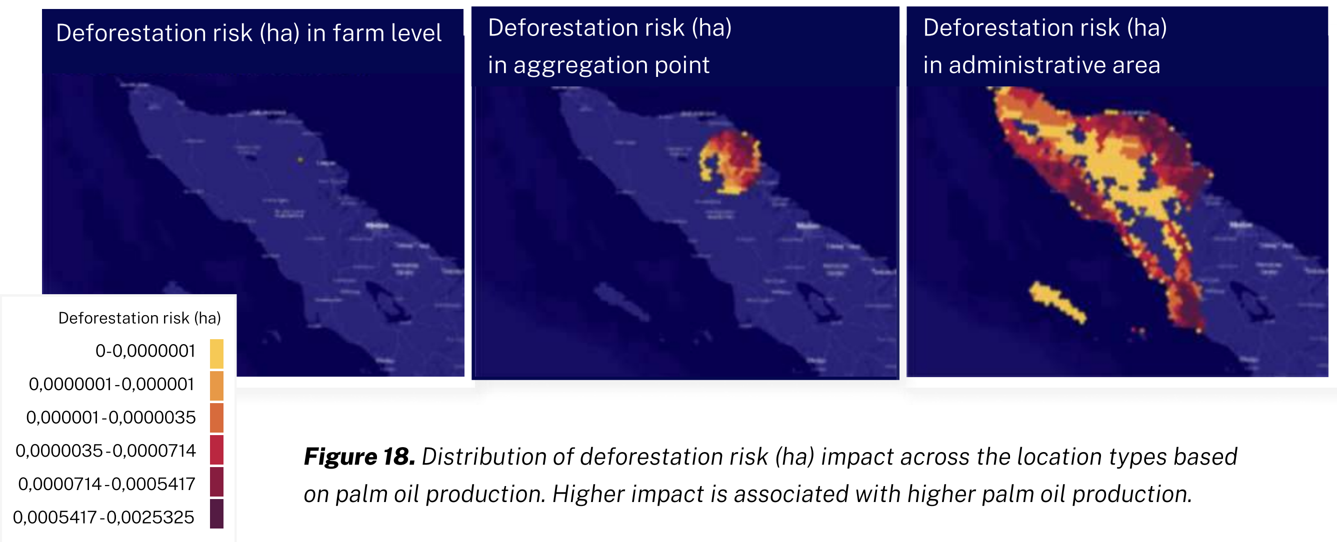


Figure 18. *Distribution of deforestation risk (ha) impact across the location types based on palm oil production. Higher impact is associated with higher palm oil production.*

The impact indicators in table 3 show that depending on the precision of the sourcing information, the estimate of farm-level land area used to produce the 1000 tonnes of palm oil sourced varies from 63 ha for a point of production location to 87 ha if the sourcing was only known to come from the Aceh region. For deforestation, the example results show that there is a risk that this sourcing contributed to 0.082 ha of deforestation, when the point of production was known, 0.063 ha for the example supplier aggregation point or 0.084 ha when sourcing was only resolved to the Aceh region.

Across the whole Aceh landscape, the land impact for each individual point ranges from 31 ha/1000 tonnes to 1000 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 farm-level land use by 280% 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 only 8.7% 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 2022).

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.

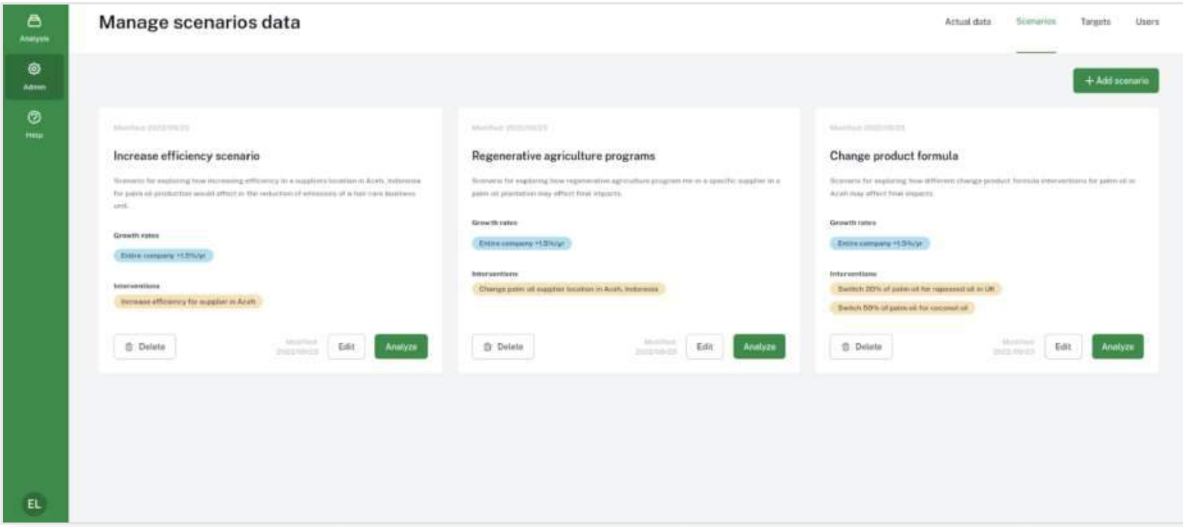


Figure 19. *LandGriffon platform showing a set of scenarios created with the associated interventions.*

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.

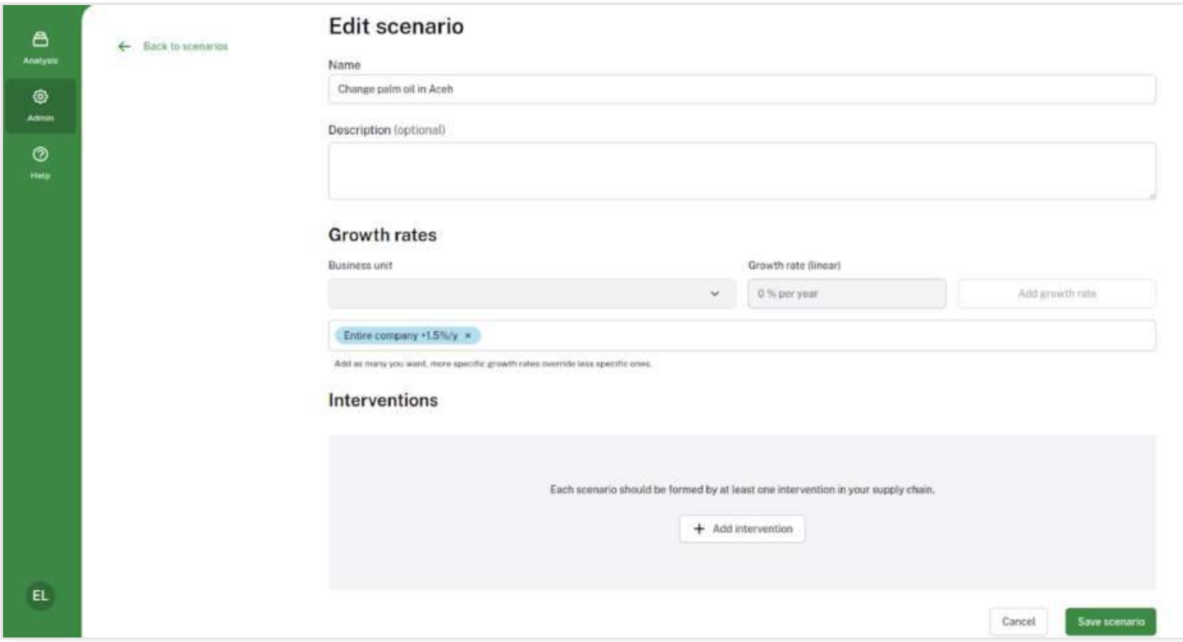


Figure 20. *Creation of a scenario with the default linear growth rate of 1.5% for the entire company and no interventions.*

We apply the intervention to 50% of the total volume purchased by the company in an aggregation point location in Aceh, Indonesia. See **Figure 21** 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.

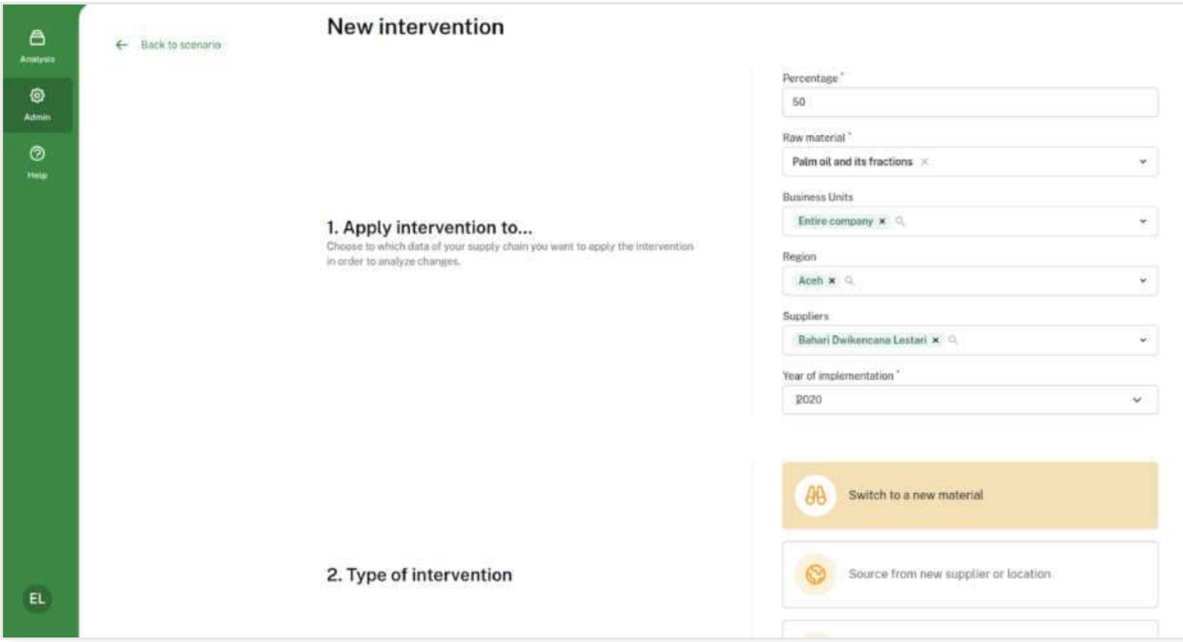


Figure 21. *Initial filtering in the creation of an intervention. The image shows the selection of the 50% of total volume purchased of palm oil and its fractions for the entire company, as a business unit. The region selected is Aceh, Indonesia and the supplier selected is Bahari Dwikencana Lestari. 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 commodity 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.

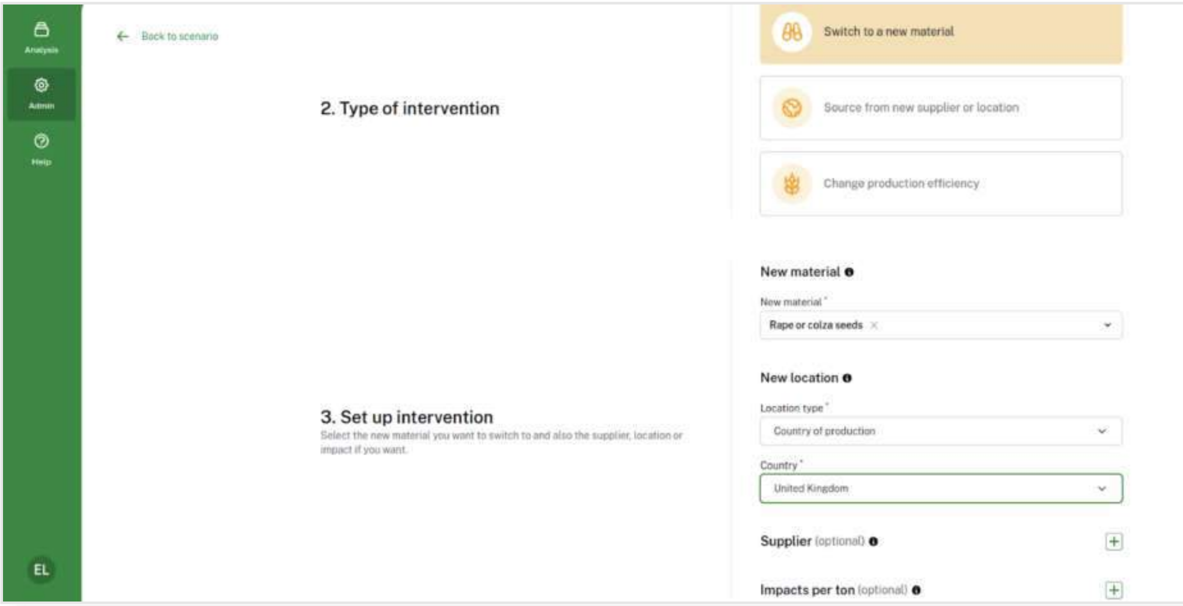


Figure 22. *Change product formula by replacing the 50% of palm oil with rape seed oil, sourced from the United Kingdom.*

Source from a new supplier or location

An alternative intervention is related to sourcing the same commodity 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.

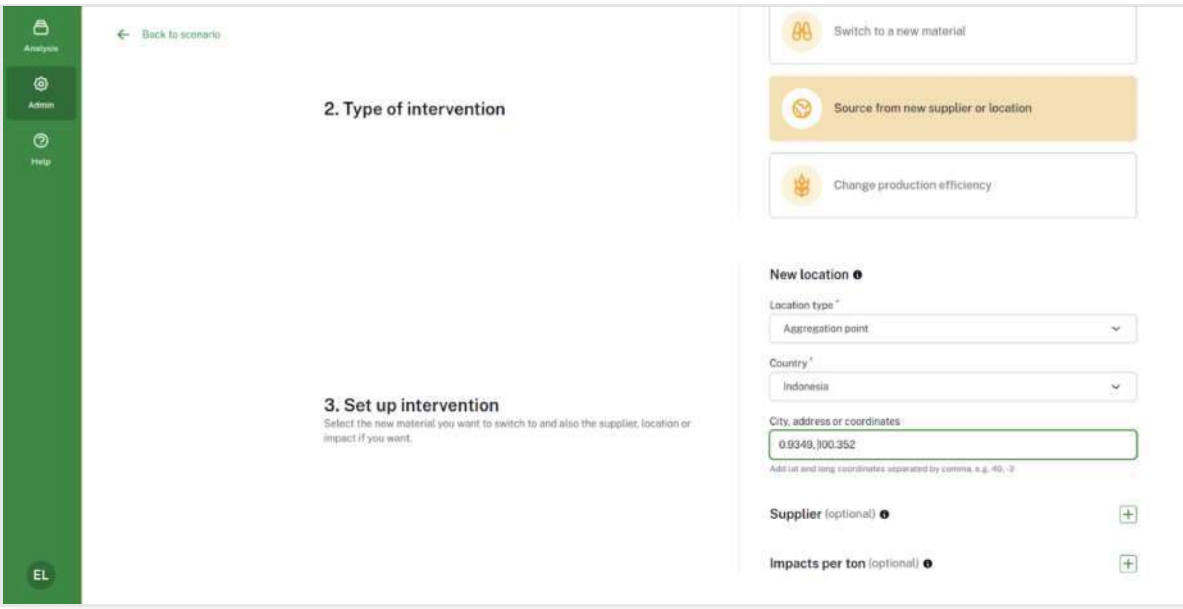


Figure 23. *Source from a new supplier or location by moving the 50% of the palm oil purchased volume to a different supplier in Aceh, Indonesia.*

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.

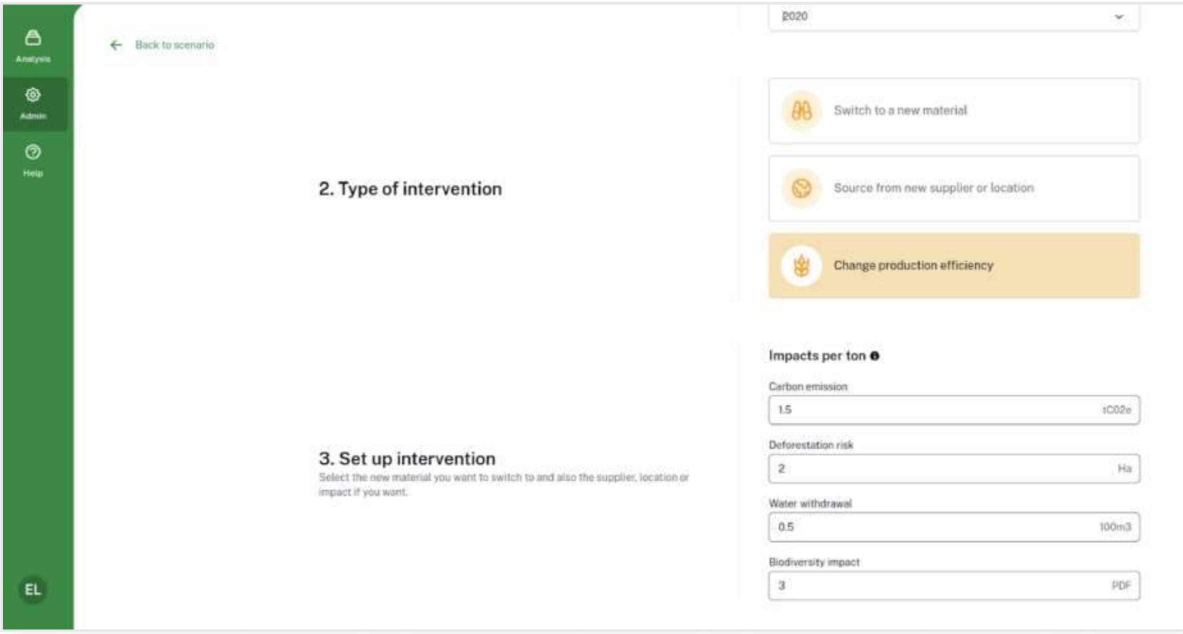


Figure 24. *Change production efficiency for the 50% volume of palm oil purchased from a location in Aceh, Indonesia.*

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.

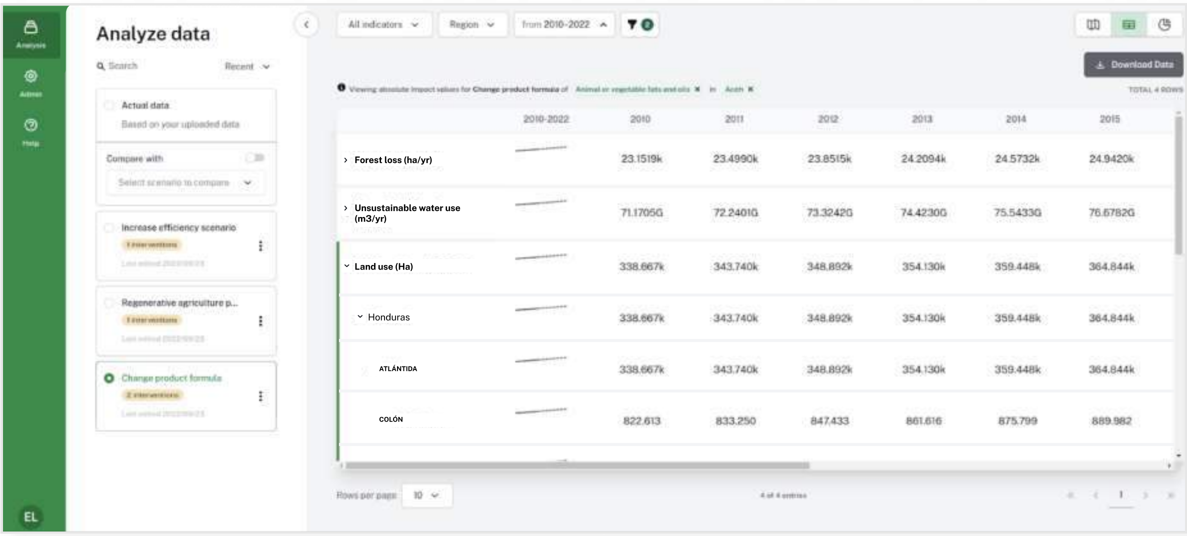


Figure 25. *Table view of the various impacts of scenarios each composed of a set of interventions.*

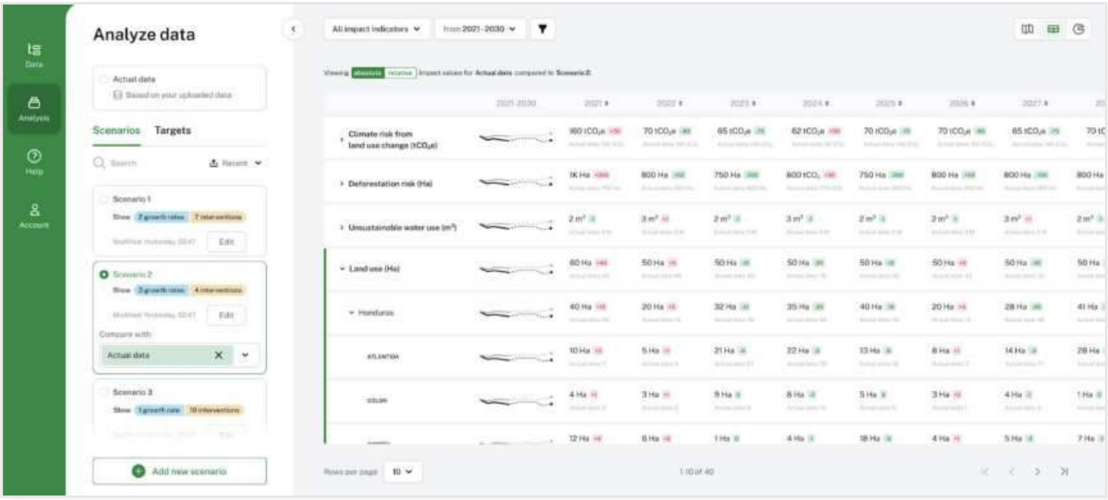


Figure 26. *Table view of impact comparison between actual data and a test scenario. Numbers in red show an increase in impact while numbers in green show reduction in the impact produced.*

Figure 27. *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 in financial reporting - LandGriffon can be set up to produce risk and impact estimates that comply with sustainability reporting frameworks such as **CDP** or the Global Reporting Initiative (**GRI**).

- 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 baseline 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 commodity 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 the Science Based Targets Network (**SBTN**) 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 take a value close to the worst case, e.g. 90th percentile, for the sourcing geometry. The communication of uncertainty and options for reducing it will be a focus as LandGriffon develops.

Scenarios

The scenario analysis features in LandGriffon v0.1 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 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 v0.1 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 commodity 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 show 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 commodity 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 v0.1, 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 Land Griffon 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 2020a). 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 commodity 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 v0.1 and future iterative improvements to the framework can achieve this and help drive more positive futures for society and nature.

ACKNOWLEDGEMENTS

We are grateful for comments on earlier versions of this methodology from collaborators at the Stockholm Environment Initiative - Toby Gardner, Shirish Bhattarai, Chris West, Jonathan Green, Vivian Ribeiro, Michael Lathuillière.

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ANNEX 1: IMPACT INDICATORS

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

- **Status:** whether the indicator is implemented in LandGriffon v0.1
- **Objective:** what impact the indicator is aiming to represent
- **Method:** the calculation methodology
- **Future Development:** possible future developments of the indicator and, where possible, organizations that are well placed to make those developments.

Water use

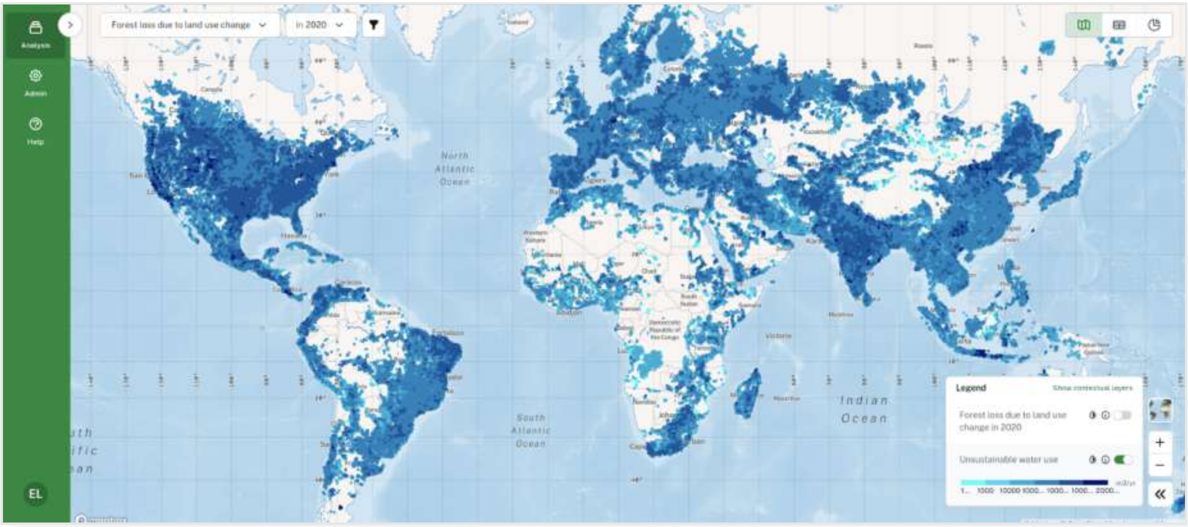
Status: Implemented.

Objective:

To estimate the surface or groundwater water resources used to produce the commodity sourced.

Method:

To compute the water use, we use the **blue water footprint in the period 1996-2005** related to agricultural production (**Figure A1**). Blue water footprint (BWF) 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. Irrigated agriculture, industry and domestic water use can each have a blue water footprint. Therefore, the blue water footprint is an indicator of direct and indirect appropriation of freshwater resources.



A1. *Blue Water Footprint in H3 format. Source:* ***Water footprint network.***

The Impact factor in this case is the **blue water footprint per ton of crop**, *c*, and nation, *n*, ($BWF_{c,n}$, units $m^3\ t^{-1}$).

Where a commodity, *c*, is sourced with an unknown location or country of delivery, a global sourcing geometry, *g*,is used and the volume sourced is given by $S_{c,g}$, and a global average blue water footprint (BWF) is calculated as:

$$I_{farm-water\,c,g} = S_{c,g} * \frac{\sum_{i=1}^{n} BWF_{c,i} * P_{c,i}}{\sum_{i=i}^{n} P_{c,i}} \qquad \textit{(Eq. i1)}$$

Where *i* is one of the n countries producing commodity *c*; and, $P_{c,i}$ is the production of commodity *c* in country *i*.

The BWF is only available for each crop at the national level. For administrative region, production aggregation point and production point sourcing geometries at or within a country, n_g, the water use is therefore calculated as:

$$I_{farm-water\,c,g} = BWF_{c,n_g} * S_{c,g} \qquad \textit{(Eq. i2)}$$

Future developments:

Exploration of the satellite remote sensing of water productivity, for example applying the methods developed in the Water Productivity through open access of remotely sensed derived data products (FAO 2020b).

Unsustainable water use

Status: Implemented.

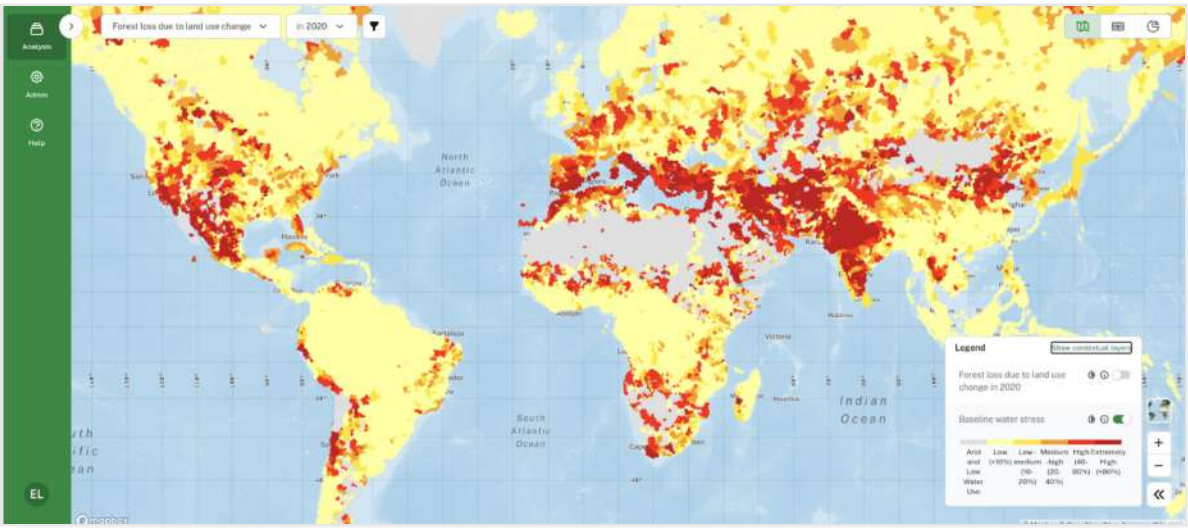
Objective:

To calculate the impact of water used in regions of water stress.

Method:

We calculate unsustainable water use by looking at water use taking place in water stressed regions where the raw material is grown. As a water stress layer we use Baseline Water Stress (BWS) from **Aqueduct**.

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).



A2. *Baseline Water Stress. Source:* ***Aqueduct***

We calculate the water use (blue water footprint, BWF) associated with the quantity of commodity c sourced from water stressed areas, defined as those areas, x, inside the sourcing geometry, g, where BWF ≥ 0.4. This threshold has been used to indicate high risk of unsustainable water use (Gassert et al. 2015).

The proportion of water used that can be classed as unsustainable water use is calculated as:

$$\frac{\sum_{s\in x} BWF_{c,s}}{\sum_{i=1}^{n} BWF_{c,i}} \qquad \textit{(Eq. i3)}$$

The unsustainable water use indicator is then given as the product of the water used in the production of commodity c from sourcing geometry, *g*, and this proportion of unsustainable water use in *g*:

$$I_{farm-waterstress\,c,g} = I_{farm-water\,c,g} * \frac{\sum_{s\in x} BWF_{c,s}}{\sum_{i=1} nBWF_{c,i}} \qquad \textit{(Eq. i4)}$$

Future development:

Future development of this indicator should focus on updated estimates of water availability and use in catchments, so that water stress can be calculated dynamically and closer to real time

Land use

Status: Implemented.

Objective:

To indicate the total land area required to produce the quantity of each commodity sourced.

Method:

The farm-level land use Impact factor is derived from yield for crop *c* in pixel *i*, $Y_{c,i}$, scaled by production volumes, which gives:

$$IF_{farm-land\,c,g} = \frac{\sum_{i=1}^{n} \frac{1}{y_{c,i}} * P_{c,i}}{\sum_{i=1}^{n} P_{c,i}} = \frac{\sum_{i=1}^{n} \frac{HA_{c,i}}{P_{c,i}} * P_{c,i}}{\sum_{i=1}^{n} P_{c,i}} = \frac{\sum_{i=1}^{n} HA_{c,i}}{\sum_{i=1}^{n} P_{c,i}} \qquad \text{(Eq. i5)}$$

Where i is one of the n pixels from which that crop is sourced in the sourcing geometry, *g*, $P_{c,i}$ is the total production of commodity *c* in pixel *i*, and $HA_{c,i}$ is the production area of crop *c* in pixel *i*, where production is currently taken from MAPSPAM and is representative of the year 2010 (International Food Policy Research Institute 2019).

The land use required to produce $S_{c,g}$ the quantity of commodity *c* that is sourced from geometry *g*, is then calculated as follows:

$$I_{farm-land\,c,g} = S_{c,g} * IF_{farm-land\,c,g} = S_{c,g} * \frac{\sum_{i=1}^{n} HA_{c,i}}{\sum_{i=1}^{n} P_{c,i}} \qquad \text{(Eq. i6)}$$

The land use indicator represents the area of agricultural land associated with the production of the crop. At the farm-level this indicator is not taking into account any 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.

Future development:

- The primary focus of development is improving the crop production and area maps, because they are representative of the year 2010 and, therefore, outdated.
- Incorporation of 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. So, its omission is likely to lead to biased outcomes.

Greenhouse gas emissions

Status: In progress

Objective:

To indicate the amount of greenhouse gas (GHG) emissions, including CO_2, N_20 and CH_4, arising from the production and transport of commodities and their supply chains.

Method:

The method is being developed in alignment with the draft GHG Protocol guidance for the land sector (**Greenhouse Gas Protocol 2022**). Emissions are being calculated using emission factors from life cycle assessment analysis (e.g. **openLCA**), and emissions associated with observations of land use change occurring within 20 years or more inside production landscapes.

GHG impacts are calculated in one of two ways:

- for commodity sourcing that requires a single impact factor (e.g. the point of production is known, or the impact factor does not vary across space within a country), Equation 1 in the main text is used,
- where the impact factor varies within the sourcing geometry, equation 2 in the main text is used.

A land-scape GHG emission risk indicator, which also takes into account land-use change in the area adjoining production landscapes is described below (**Climate risk from land use change**).

Future development:

Models of carbon stock dynamics within production landscapes can be integrated into the analysis to more accurately evaluate emissions or removals of greenhouse gasses.

Deforestation risk

Status: Implemented.

Objective:

To quantify deforestation occurring in the proximity of commodity production areas and allocate this to the quantity of commodity sourced. The term 'risk' is applied to this indicator since it is accounting for deforestation happening within the proximity of the sourcing location. The cause of the deforestation is unknown but since it is happening close to a sourcing location, there is a risk of that sourcing contributing to the deforestation.

Method:

This indicator captures landscape-level impacts and is derived from Eq. 1. but also takes into account the buffered spatial extent and that multiple crops might be growing within the landscape. Generally, for landscape-level indicators, impacts are expressed relative to how much of the total harvested area across all crops is accounted for by the commodity sourced from that location.

First the land use footprint (ha) of commodity *c* within sourcing geo $I_{farm-land\,c,g}$ is calculated according to equation i6.

Then the deforestation occurring within a buffered region around the sourcing geometry, (referred to as the buffered sourcing geometry, g_b) is then calculated as follows taking into account the n_{cr} crops being harvested in the buffered region:

$$I_{c,g_b} = IF_{g_b} * \frac{I_{farm-land\,c,g}}{\frac{\sum_{cr=1}^{ncr}\sum_{i=1}^{n} HA_{cr,i} \cdot P_{c,i}}{\sum_{i=1}^{n} P_{c,i}}} \qquad \textit{(Eq. i7)}$$

Where IF_{g_b} is the impact factor associated with the buffered sourcing geometry *gb*; $HA_{cr,i}$ is the harvested area (ha) of crop cr in spatial unit i of the n units of the buffered sourcing location gb; and, $P_{c,i}$ is the production of the sourced crop c in spatial unit i. At present, the buffer size used defaults to 50km.

For deforestation risk, we calculate IF_{g_b} within the buffered sourcing location using remote sensing imagery to give the cumulative area of pixels that move from a forested to a non-forested state. A machine learning algorithm is trained to classify forested or bare pixels, and classify areas that were forest before and appear bare now as deforestation patches. The algorithm is sensor-agnostic and uses optical (Landsat, Sentinel-2) and radar (Sentinel-1) imagery.

We calculate the area of loss over a 5 year period in order to account for recent land expansion associated with current commodity production. The loss is expressed as a mean annual rate over the five year period to avoid issues allocating the forest loss in time to the commodities sourced.

The impact factor IF_{g_b} then becomes the annual rate of deforestation D_{g_b} (ha/yr) across sourcing location g_b and the indicator of risk is given by substituting into Eq. i7:

$$I_{deforest\, c,g_b} = D_{g_b} * \frac{I_{farm-land\, c,g}}{\frac{\sum_{cr=1}^{ncr}\sum_{i=1}^{n} HA_{cr,i} \cdot P_{c,i}}{\sum_{i=1}^{n} P_{c,i}}} \qquad \textit{(Eq. i8)}$$

Deforestation can be associated with loss of forest from plantations or from naturally regenerating forests, and these events have very different interpretations especially for biodiversity outcomes. The data we use from Satelligence differentiates deforestation of natural forest from that in plantations.

Future development:

- An extension of this analysis is to limit the deforestation impacts to those locations where natural or naturally regenerating forest is the likely forest being lost using an existing global forest management dataset, available for the year 2015 (Lesiv et al. 2022) and using timescale of plantations to allocate deforestation impacts (Du et al. 2022).
- The current default time horizon for deforestation quantification of 5 years is reasonable for crops but could be too short to capture the impacts of agricultural production systems with a long lifetime, such as livestock production or rubber plantations. So, it could be valuable to use longer deforestation timescales for those commodities that have a longer time from conversion to production. This time horizon could be altered to 20 years to align with draft guidance on emissions calculations(**Greenhouse Gas Protocol 2022**).
- More direct attribution of deforestation and 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 commodity production (Pendrill et al. 2019).

Climate risk from land use change

Status: Implemented.

Objective:

Quantify the GHGs associated with deforestation of the landscape proximal to agricultural production.

Method:

Terrestrial vegetation globally absorbs approximately 30% of the anthropogenic CO2 emissions on average. Although there is uncertainty in the regional distribution of the global terrestrial carbon sink, there is evidence that the majority of carbon sequestered by the terrestrial biosphere has been accumulated in forest ecosystems, primarily in the tropics. The major carbon stock on land is soil carbon and other ecosystems including wetlands, grasslands and some croplands can be important for accumulation of soil carbon.

Global estimates of deforestation related emissions arising from changes in carbon stocks contained in above-and below-ground plant biomass, soil organic carbon, deadwood and litter pools, form the basis of landscape-level related greenhouse gas risk indicator (Harris et al. 2021). We used the general equation for landscape-level impacts (Eq. i7) substituting in the mean annual gross emissions of GHGs associated with forest change over the period 2001-2019 across the buffered sourcing geometry g_b (t CO_2-eq/yr) as the impact factor.

$$I_{emiss\,c,g_b} = E_{g_b} * \frac{I_{farm-land\,c,g}}{\frac{\sum_{cr=1}^{n_{cr}} \sum_{i=1}^{n} HA_{cr,i} \cdot P_{c,i}}{\sum_{i=1}^{n} P_{c,i}}} \qquad \text{(Eq. i9)}$$

As in equation i6, HA_{g_b} is the harvested area (ha) of crop cr in the buffered sourcing location g_b, and $I_{land-area\,c,g}$ is the land area used to produce the quantity of commodity *c* sourced and given by equation i6.

E_{gb} is calculated as the sum of forest greenhouse gas emissions across g_b. Therefore this method indicates the potential that deforestation associated with the commodity sourced from *g* contributed to greenhouse gas emissions.

In addition to giving rise to emissions resulting from the loss of carbon stocks, deforestation results in the removal of greenhouse gas sequestration as carbon is stored in vegetation biomass or sequestered below ground.

$$I_{remov\,c,g_b} = R_{g_b} * \frac{I_{farm-land\,c,g}}{\frac{\sum_{cr=1}^{ncr} \sum_{i=1}^{n} HA_{cr,i} \cdot P_{c,i}}{\sum_{i=1}^{n} P_{c,i}}} \quad \text{(Eq. i10)}$$

Where R_{gb} is change in the mean annual gross removals of GHGs in forests associated with deforestation events occurring within the sourcing region g_b (t CO_2-eq/yr).

Future development:

- Adjusting the time period over which emissions are calculated to be consistent with the deforestation observations.
- Improving attribution, in line with the developments proposed for the landscape-level deforestation impacts.

Biodiversity risk from land use change

Status: In progress

Objective:

To indicate the potential impact that sourcing a given quantity of a commodity could have on biodiversity.

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, we propose two categories of indicator, one focussed on species and the other on ecosystems.

Species:
One of the simplest metrics that could be considered is the total number of mapped species whose area of habitat is reduced by land use change occurring within the buffered sourcing geometry, g_b.

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, and measures how important a given pixel is for the overall ranges of the species occurring in that pixel. So we can use rarity weighted richness as a weighting to scale land use by to indicate the significance of its loss. So the impact factor for the buffered sourcing geometry, g_b, would be calculated as:

$$IF_{RWR_{g_b}} = \sum_{i=1}^{n} D_i * RWR_i \qquad \text{(Eq. i11)}$$

Where RWR_i is the rarity weighted richness of pixel i of n pixels within buffered sourcing geometry, g_b. RWR_i is normalised across ecoregions, so that importance is not biased by global patterns of naturally occurring species richness (Leclère et al. 2020).This impact factor indicates the biodiversity-scaled deforestation area in the buffered sourcing geometry, g_b.

The species based impact is then calculated as:

$$I_{bd-species\,c,g_b} = IF_{RWR\,g_b} * \frac{I_{farm-land\,c,g}}{\frac{\sum_{cr=1}^{ncr}\sum_{i=1}^{n} HA_{cr,i} \cdot P_{c,i}}{\sum_{i=1}^{n} P_{c,i}}} \qquad \text{(Eq. i12)}$$

Ecosystem:
We calculate an indicator of the change in ecosystem quality and structure. This indicator expresses the change in ecosystem integrity that can be attributed to sourcing of a commodity.

This indicator could express the average degree of intactness of habitat lost as a result of deforestation, for example using an inverse function of the Human Footprint Index of human impacts (Venter et al. 2016) as in the ecosystem intactness approach (Beyer et al. 2020).

A more sophisticated measure might attempt to calculate the change in ecosystem structure as a result of deforestation, taking into account a change in habitat quality and its configuration. to calculate the integrity value of habitat loss or an ecosystem intactness approach (Beyer et al. 2020) to recalculate the integrity layer including the habitat change to give a change in integrity.

Future development:

- Explore an alternative measure of habitat importance taking into account the difference in species composition in different locations. 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. BHI_i could be inserted instead of RWR_i into equation i12 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 commodity sourcing.
- Incorporate more ecologically informed measures of ecological intactness such as the Forest Landscape Integrity Index (FLII) (Grantham et al. 2020) or ecosystem integrity (Hansen et al. 2021).
- 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:

- commodity types - do the user-supplied commodity belong to one of the 175 commodities included in the commodity dataset (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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