September 2024

# SEI-PCS Indonesia palm oil v1.2.2 supply chain map: Data sources and methods

Trase maps supply chains for agricultural commodities, making it possible to link products and supply chain actors with specific areas of production and associated deforestation exposure. It uses a generalised supply chain mapping approach called Spatially Explicit Information on Production to Consumption Systems (SEI-PCS) as the basis for this work.

This document describes the data and methods that Trase used to map the supply chain for Indonesian palm oil using a model version called 'SEI-PCS Indonesia palm oil v1.2.2'. This model represents a collaboration between experts at the Stockholm Environment Institute, Global Canopy, Auriga, TheTreeMap/Nusantara Atlas and the Conservation Economics Lab at the University of California, Santa Barbara (UCSB).

For all palm oil exports, this method attempts to identify the likely fresh fruit bunches (FFB) units of production, the intermediate mills and refineries producing crude and refined palm oil (CPO and RPO respectively), as well as the traders involved in the supply chain (see Figure 1). The method uses trade and production data, as well as information on company mill/refinery-ownership, company traceability reports and road networks together with an optimisation model to establish supply chain connections and link districts of production to countries of import. Table 1 provides an overview of key statistics for the industry for 2018–2022.

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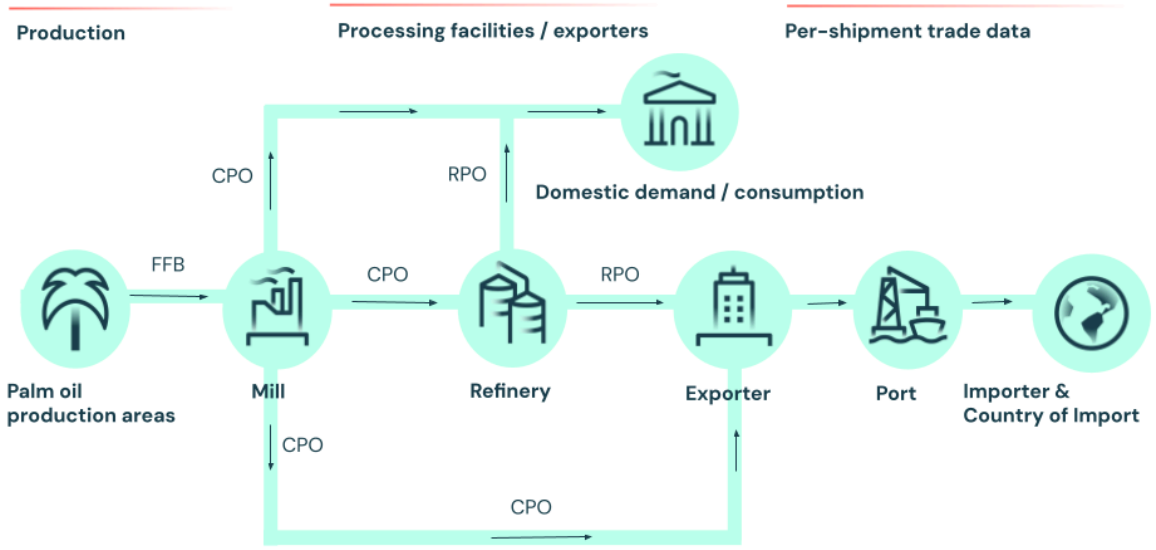



Figure 1. Outline of supply chain modelled by SEI-PCS Indonesian palm oil v1.2.2.

## Table 1: Summary statistics for Indonesia's palm oil industry, 2018–2022

| | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|
| Total refined palm oil (RPO) and crude palm oil (CPO) production (CPO equivalents***, million tonnes*) | 42.9 | 47.1 | 44.8 | 45.1 | 46.8 |
| Total RPO and CPO exports (CPO equivalents, million tonnes*) | 29.0 | 29.3 | 26.9 | 26.8 | 26.1 |
| Number of mills | 1,125 | 1,171 | 1,218 | 1278 | 1318 |
| Number of exporting companies | 188 | 226 | 198 | 150 | 112 |
| Number of exporting groups | 83 | 109 | 103 | 38 | 31 |
| Number of importing countries | 137 | 145 | 135 | 137 | 138 |
| Percentage of palm oil consumed and processed domestically (%) ** | 32 | 38 | 40 | 41 | 44 |

** = metric tonnes*

*** Percentage of palm oil production processed domestically is an estimate calculated by subtracting reported exports from total production.*

**** Production is in CPO equivalents and for refined palm oil (RPO), this is equivalent to 1.095 tonnes of crude palm oil (CPO)*

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Trase integrates its supply chain model with a variety of indicators to detail the environmental, social and economic impacts of commodity trade. These indicators are detailed in Table 2.

### Table 2: Summary of indicators, 2018–2022

| | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|
| Oil palm area (million ha) | 15.6 | 15.9 | 16.1 | 16.3 | 16.5 |
| Oil palm yield (CPO equivalent tonnes/ha) (annual average) | 2.6 | 2.8 | 2.6 | 2.6 | 2.7 |
| Annual deforestation for industrial oil palm (ha) | 55,209 | 41,270 | 28,769 | 16,894 | 19,889 |
| Annual deforestation for smallholder oil palm (ha) | 1,464 | 449 | NA | NA | NA |
| Territorial deforestation (ha) | 301,282 | 337,680 | 223,071 | 174,670 | 208,231 |
| Industrial oil palm deforestation exposure (million ha)* | 1.59** | 1.52** | 1.45** | 1.31 | 1.17 |
| Share of palm oil traded under zero-deforestation commitment (%) | 87 | 87 | 80 | 78 | 57 |
| Oil palm planted on peat (million ha) | 2.13 | 2.16 | 2.19 | 2.21 | 2.24 |
| Burned area (ha) | 571,665 | 1,765,472 | 332,011 | 411,170 | 246,284 |
| Palm oil tax revenue (trillion rupiah) | 14.9 | 8.07 | 3.32 | NA | NA |
| Remaining forest cover (million ha) | 88.1 | 87.8 | 87.6 | 87.4 | 87.2 |
| Palm oil production (CPO equivalent million tonnes) | 42.9 | 47.1 | 44.8 | 45.1 | 46.8 |
| Smallholder production (CPO equivalent million tonnes) | 14.3 | 13.8 | 13.4 | 14.8 | 15.7 |
| Gross emissions from territorial deforestation (million tonnes CO2eq) | 138.0 | 142.3 | 99.6 | 79.5 | 95.0 |
| Gross greenhouse gas emissions from industrial palm oil land conversion (million tonnes CO2eq) | 48.2 | 42.6 | 28.3 | 25.5 | 21.7 |
| Net greenhouse gas emissions from industrial palm oil land conversion (million tonnes CO2eq) | 18.7 | 16.4 | 10.9 | 8.9 | 9.3 |
| Greenhouse gas emissions from peat burning (million tonnes CO2eq) | 38.6 | 161.2 | 3.7 | 5.7 | 5.4 |
| Greenhouse gas emissions from peat subsidence (million tonnes CO2eq) | 142.3 | 144.0 | 145.5 | 146.7 | 147.4 |

*including a 10-year allocation and 3-year lag period (methods below); ** data referring to model 1.2.0.

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## Data version history

### Table 3: Version history for Indonesia palm oil supply chain

| Version | Publication date | Change |
|---|---|---|
| 1.2.2 | September 2024 | Spatial metrics on deforestation are now based on the Nusantara Atlas using data derived from Gaveau et al. (1). In the previous version 1.2, forest cover and territorial deforestation were derived from the Tropical Moist Forest (TMF) datasets provided by the Joint Research Center of the European Commission (JRC) (2). In version 1.2.2, we replaced these datasets with the newly available forest and deforestation data from the Nusantara Atlas (1). This version also adds new greenhouse gas (GHG) emission metrics: gross emissions from land conversion, total GHG emissions from palm oil, gross GHG emissions from industrial palm oil land conversion, carbon sequestration in new industrial oil palm plantations, net GHG emissions from industrial palm oil land use change, GHG emissions from peat burning and GHG emissions from peat subsidence. |
| 1.2.0 | September 2022 | Nearly complete revision of palm oil supply chain model as detailed in this document. Revisions include integration of mill-level production, expanded use of traceability reports, and improved linking of exporters to mills and refineries and concessions to mills. Addition of new indicators and datasets. Subnational model released for 2018–2020. |
| 1.1.0 | December 2019 | Integration of traceability report data, improvements to the mill and company data. Zero-deforestation commitments included for national years and improvement in the production indicators. Subnational model only released for 2015 exports. |
| 1.0 | July 2019 | First release |

## How to cite this document

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## How to cite the data

Benedict, J., Biddle, H., Gollnow, F., Heilmayr, R., Mueller, C., & Ribeiro, V. (2024). Indonesia palm oil (2021–2022) (Version 1.2.2) [Data set]. Trase. https://doi.org/10.48650/X83N-7M36

# Supply chain mapping data

## Trade data – International exports

The model uses per-shipment data (such as customs data, bills of lading and/or cargo manifests) for 2018–2022 covering all exports of crude palm oil (CPO) and refined palm oil (RPO) classified under the Harmonized System (HS) customs codes in Table 3. Products do not include palm kernel oil, biodiesel or palm oil derivatives. We used commodity-equivalence factors (see Table 4) to convert different products to a standard commodity equivalent, in this case crude palm oil. We confirmed the quality of the data by comparing it with yearly aggregated data of export volumes published by Indonesia's Central Statistics Agency or Badan Pusat Statistik, (BPS), the government statistics agency (3). We confirmed the consistency of the palm oil export data with data from BPS, as shown in Table 5.

### Table 4: Palm oil product HS codes and commodity-equivalence factors (to CPO equivalent)

| HS Code | Description | Commodity equivalence factor |
|---|---|---|
| 15111000 | Crude palm oil | 1.00 |
| 15119020 | Refined palm oil | 1.053 |
| 15119031 | Solid fractions of refined palm oil | 1.053 |
| 15119032 | Solid fractions of refined palm oil | 1.053 |
| 15119036 | Liquid fractions of refined palm oil | 1.053 |
| 15119037 | Liquid fractions of refined palm oil | 1.053 |
| 15119039 | Liquid fractions of refined palm oil | 1.053 |
| 15119041 | Solid fractions of unrefined palm oil | 1.00 |
| 15119042 | Solid fractions of unrefined palm oil | 1.00 |
| 15119049 | Solid fractions of unrefined palm oil | 1.00 |

From 2020–2022, the trade data reported significantly fewer exports than the official numbers published by BPS, as shown in Table 5. We have assumed that these deviations reflect missing export records in the trade data. To address this discrepancy, we appended 'unknown' shipments (a shipment for which a district of production could not be identified) for under-reported HS codes so that the trade data yearly volumes match the volumes published by BPS for that year.

## Table 5: Comparison of Indonesia palm oil export volumes from trade data with BPS reports, 2018-2022

| HS Code | Year | BPS (tonnes) | Trade data (tonnes) | Ratio |
|---|---|---|---|---|
| 1511000 | 2018 | 6,543,463 | 6,554,495 | 1.00 |
| | 2019 | 7,406,477 | 7,401,796 | 1.00 |
| | 2020 | 6,092,930 | 7,170,956 | 0.85 |
| | 2021 | 2,543,057 | 2,097,773 | 0.82 |
| | 2022 | 3,455,677 | 1,440,114 | 0.42 |
| 15119020 | 2018 | 5,655,821 | 5,752,413 | 0.98 |
| | 2019 | 4,428,638 | 4,423,283 | 1.00 |
| | 2020 | 5,304,535 | 5,613,660 | 0.95 |
| | 2021 | 7,997,060 | 7,424,044 | 0.93 |
| | 2022 | 7,348,502 | 5,373,430 | 0.73 |
| 15119031 | 2018 | 2,222,143 | 2,219,127 | 1.00 |
| | 2019 | 2,250,571 | 2,250,008 | 1.00 |
| | 2020 | 2,072,290 | 2,164,759 | 0.96 |
| | 2021 | 2,311,894 | 2,279,589 | 0.99 |
| | 2022 | 2,453,773 | 1,866,703 | 0.76 |
| 15119032 | 2018 | 872,485 | 882,515 | 0.99 |
| | 2019 | 906,964 | 915,007 | 0.99 |
| | 2020 | 521,649 | 536,660 | 0.97 |
| | 2021 | 557,212 | 476,747 | 0.86 |
| | 2022 | 284,889 | 155,734 | 0.55 |
| 15119036 | 2018 | 1,858,062 | 1,786,901 | 1.04 |

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| | | | | |
|---|---|---|---|---|
| | 2019 | 1,430,963 | 1,426,516 | 1.00 |
| | 2020 | 1,357,562 | 1,420,012 | 0.96 |
| | 2021 | 1,397,010 | 1,334,160 | 0.96 |
| | 2022 | 1,207,997 | 1,134,020 | 0.94 |
| 15119037 | 2018 | 10,535,053 | 10,262,134 | 1.03 |
| | 2019 | 10,320,822 | 10,368,285 | 1.00 |
| | 2020 | 7,938,044 | 8,515,316 | 0.93 |
| | 2021 | 11,712,067 | 10,453,514 | 0.89 |
| | 2022 | 11,053,428 | 7,785,638 | 0.70 |
| 15119039 | 2018 | 163,677 | 359,578 | 0.46 |
| | 2019 | 568,115 | 571,573 | 0.99 |
| | 2020 | 508,879 | 509,395 | 1.00 |
| | 2021 | 310,020 | 290,987 | 0.94 |
| | 2022 | 216,916 | 194,939 | 0.90 |
| 15119041 | 2018 | 16,849 | 20,849 | 0.80 |
| | 2019 | 112,802 | 112,802 | 1.00 |
| | 2020 | - | - | - |
| | 2021 | - | - | - |
| | 2022 | - | - | - |
| 15119042 | 2018 | - | - | - |
| | 2019 | 18,093 | 18,038 | 1.00 |
| | 2020 | 300 | 300 | 1.00 |
| | 2021 | - | - | - |
| | 2022 | - | - | - |
| 15119049 | 2018 | 60,862 | 60,862 | 1.00 |

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| | | | | |
|---|---|---|---|---|
| | 2019 | 792,042 | 792,044 | 1.00 |
| | 2020 | 470 | 4,199 | 0.11 |
| | 2021 | 10,202 | 10,202 | 1.00 |
| | 2022 | 97,021 | 3,350 | 0.03 |
| Total CPO equivalent | 2018 | 29,049,849 | 29,017,963 | 1.00 |
| | 2019 | 29,283,174 | 29,329,596 | 1.00 |
| | 2020 | 26,922,615 | 24,728,395 | 0.92 |
| | 2021 | 26,838,522 | 24,367,006 | 0.91 |
| | 2022 | 26,118,205 | 17,953,930 | 0.69 |

## Domestic demand

We estimated domestic demand for CPO and RPO by subtracting the total, annual volume of CPO and RPO exports from the total, annual volume of production, as reported by BPS. This "domestic demand" represents a combination of domestic consumption, as well as further, downstream processing including the domestic production of biofuels and oleochemicals, some of which are exported as downstream products.

## Supply chain data

### Asset data

Mills

We used an updated version of the Universal Mill List (UML) that is currently maintained by the Conservation Economics Lab at UCSB (4). The mill dataset includes verified locations and information on ownership and mill capacity. We used the 1,318 mills that were known to be in operation in 2022 (Figure 1).

We obtained mill capacity values through reports from provincial plantation agencies (Dinas Perkebunan), the initial SIPERIBUN (Plantation Licensing Information System) results, and data from the Roundtable on Sustainable Palm Oil (RSPO) and the Indonesian Sustainable Palm Oil system (ISPO). There were 28 mills for which we could not find a capacity value. For these mills, we used a spatial interpolation at the district (kabupaten) or province level (depending on the availability of other mills).

### Refineries

We used refinery data from AidEnvironment and Auriga's desk-based research. This dataset includes ownership and location information about each refinery, which enables us to link individual refineries to exporters that appear in the trade data (see section on supply chain mapping method). The dataset does not yet include comprehensive information on capacities.

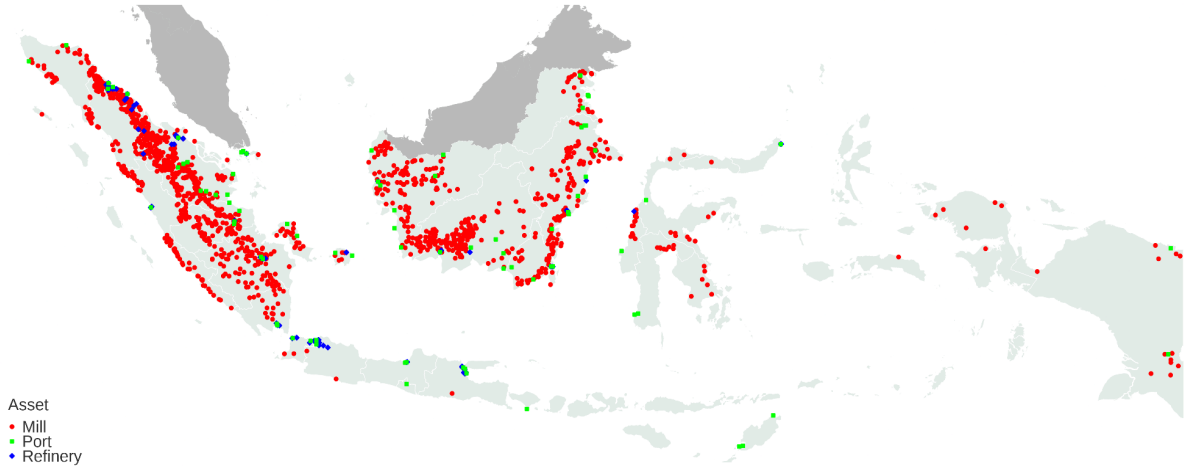



Figure 2: Location of palm oil mills, ports and refineries

### Traceability reports

To link exporters, palm oil refineries and bulking facilities with their supplier mills, we used traceability reports, which are corporate self-declarations detailing sourcing patterns. The share of exports going through refineries with traceability reports are shown in Table 6. We linked these processing facilities to ports of export on the basis of proximity and ownership. Although traceability reports typically do not contain volumetric information, we were able to use the known connections detailed in the reports to constrain allocation in the optimisation procedure (see supply chain mapping method section). This procedure ensures that, within the Trase model results, refineries are linked to exactly the same set of mills as declared in the refinery's traceability report.

**Table 6: Number of refineries and mills included in traceability reports**

| Year | No of refineries | No of mills | Share of exports linked to refinery traceability report (%) | Share of exports linked to group level traceability report (%) |
|---|---|---|---|---|
| 2018 | 45 | 916 | 76.1 | 0.5 |
| 2019 | 41 | 932 | 73.6 | 0.4 |
| 2020 | 43 | 958 | 68.1* | 0.8 |

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| | | | | |
|---|---|---|---|---|
| 2021 | 49 | 1035 | 75.6* | 0.06 |
| 2022 | 45 | 992 | 54.4* | 0.01 |

** Approximately 2.2 million of CPO equivalent tonnes (8.2% of exports) were missing from the 2020 export data, 2.4 million of CPO equivalent tonnes (9.1% of exports) from the 2021 export data and 8.2 million of CPO equivalent tonnes (31.5% of exports) from the 2022 export data. This is detailed in the section on trade data.*

### Oil palm concessions

We used spatially explicit data on oil palm concession licences (e.g HGU, IUP and Izin Lokasi) to determine the location and control of oil palm concessions. We used the oil palm concessions to determine the possible sourcing areas of the mills. This data was compiled by the Carlson Lab at New York University (5). It is not comprehensive, however, and has limited information on smallholder managed concessions linked to companies (plasma).

### Transportation data

We used road network data from Indonesia's geospatial agency (Badan Informasi Geospasial; BIG) to determine the cost of transport between logistics hubs (ports, refineries and mills) and between mills and FFB areas of production. This data was only available for Sumatra, Kalimantan, Sulawesi, Java, Maluku and Papua. As such, the quality varies across the country. In some locations, such as Riau Islands Province, we could not access the data and so we used straight-line distances. To include fresh fruit bunches (FFB) produced on small islands or remote regions on islands, we added known connections via sea or rivers to the road network to allow for the transportation of FFB.

### Company data

We generated a unified dictionary of company names and parent groups in order to align and connect exporting companies, domestic traders and asset owners. We drew parent group information from Indonesian corporate research (by CDMI Consulting Research), company groups' websites and annual reports, and company filings (AHUs, by their Indonesian abbreviation).

### Geographic boundaries

We used jurisdictional boundaries for districts (kabupaten) and provinces, as defined by the Indonesian Geospatial Agency (BIG) in 2016. We paired each jurisdiction with geocodes provided by BPS to give a standard identifier for each area. We also used the sub-district jurisdictional boundaries (kecamatan) from BIG from 2019.

## Production

### Province-level CPO production

We compiled data on palm oil production for 2018–2022 from the province-level statistics on crude palm oil production provided by the Directorate General of Estate Crops via the government statistics agency (BPS) (6).

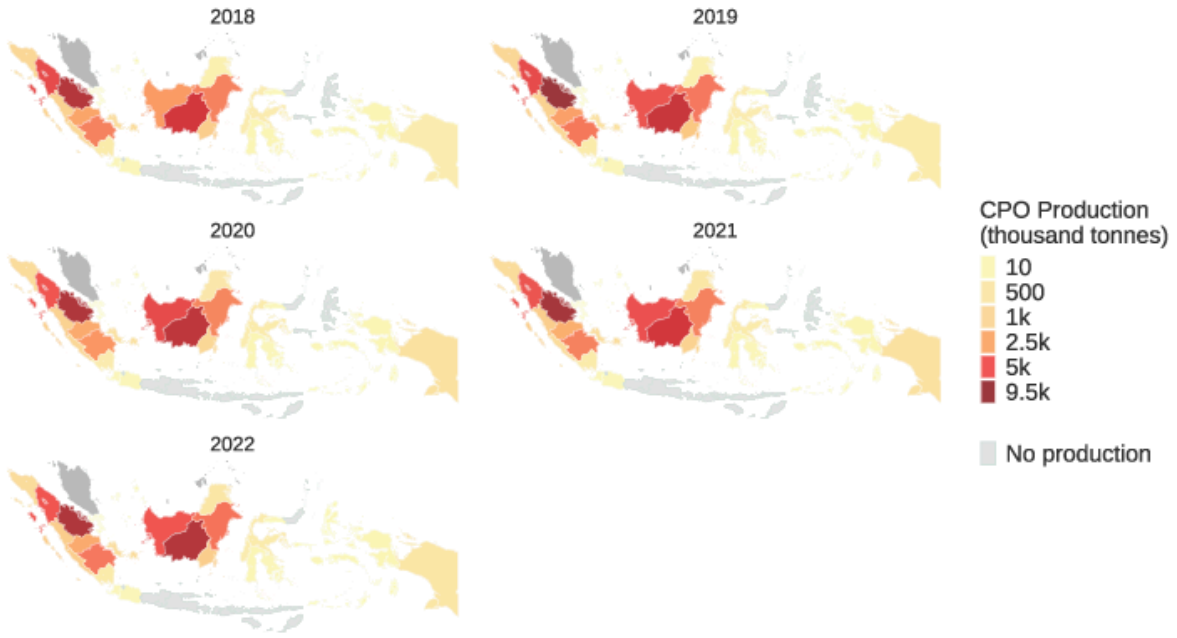



Figure 3: BPS reported province-level production (2018–2022)

## Mill production

Annual, mill-level production was estimated based on a number of sources (Table 7). For a portion of these mills, we were able to assign specific production numbers using publicly reported production volumes. These production numbers come mainly from RSPO certification reports, company self-reported greenhouse gas emission reports to the Directorate of Air Pollution Control under the Ministry of Environment and Forestry, company annual reports or the provincial plantation agency (Dinas Perkebunan) statistics reports. For the remainder of the mills, we used a production 'capacity factor' that is calculated based on known provincial production volumes and mill capacities using the following equation

$$\text{capacity factor}_{\text{province}} = \text{total production}_{\text{province}} / \text{total capacity}_{\text{province}}$$

This factor then allows us to estimate mill-level production based on each mill's capacity as follows:

$$\text{estimated production}_{\text{mill}} = \text{capacity factor}_{\text{province}} \times \text{capacity}_{\text{mil}}$$

Estimated production values for each mill were compared against each mill's known exports as reported in the trade data. If CPO exported from a mill exceeded that mill's estimated production, we updated that mill's production to match its total exports. To ensure that total,

province-level production remained unchanged after this adjustment, we then removed the adjusted mills' total exports and mill capacities from the province's remaining production and capacity. We then iterated this procedure multiple times until we reached stable production numbers for all mills. This approach generated estimates of the total production for each mill based on a) trade data, b) reported production volumes and c) estimates based on mill capacity and provincial production figures. This gave us the estimated supply of CPO leaving each mill, which underpins our supply chain mapping method by simultaneously determining the amount of CPO supplied by each mill, as well as the amount of FFB demanded by each mill.

### Table 7: Share of mill production (%) by source type

| Source of mill production | Year | Share of mill production (%) |
|---|---|---|
| Trade data | 2018 | 2 |
| | 2019 | 3 |
| | 2020 | 3 |
| | 2021 | 1 |
| | 2022 | 0.3 |
| Publicly reported production volumes (RSPO certification reports, company reports/websites, provincial plantation agency statistics reports) | 2018 | 13 |
| | 2019 | 18 |
| | 2020 | 8 |
| | 2021 | 39 |
| | 2022 | 47.7 |
| Estimated based on mill capacity and provincial production | 2018 | 85 |
| | 2019 | 87 |
| | 2020 | 89 |
| | 2021 | 60 |
| | 2022 | 52 |

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### Production from FFB (fresh-fruit bunches) production units

We next sought to estimate the volume of FFB being produced in specific "FFB production units" (ffb_prod_units) distributed across Indonesia. Oil palm is grown across a variety of locations in Indonesia, including documented concessions, undocumented concessions, and private land holdings outside of concessions. To track production from all of these sources, we divided the entirety of Indonesia's land mass into unique "FFB production units." Specifically, we combined data on the spatial boundaries of kecamatan (sub-district) and concessions so that each FFB production unit represents either a known concession, or the area of land within a kecamatan falling outside of any known oil palm concession.

Next, we estimated the palm oil production for industrial plantations and smallholders within each FFB production unit. The oil palm areas were determined from the areas cleared for palm planting as defined by Gaveau et al (1) with a 3-year lag that assumes that the cleared areas are planted with palm and become productive 3 years after planting. We multiplied the estimated oil palm oil area (ha) by the CPO productivity (tonne/ha) published by BPS for smallholders and industrial plantations at the (6).

$$\text{production}_{\text{ffb_production_units}} = (\text{industrial oil palm area}_{\text{ffb_production_units}} \times \text{industrial plantations cpo productivity}_{\text{province}}) + (\text{smallholder oil palm area}_{\text{ffb_production_units}} \times \text{smallholder cpo productivity}_{\text{province}})$$

This gave us the estimated production (tonnes of CPO equivalent) for each of the FFB units of production that contained planted palm. The overall production numbers calculated through this approach was on average 1.3 times higher than the production reported by BPS, possibly because the palm planted areas from Gaveau et al. (1) include failed palm plantations.

To get a more accurate estimate of FFB production, we used an island level 'deflation factor' based on the ratio between the BPS reported production and the oil palm area estimated production.

$$\text{deflation factor}_{\text{island}} = \text{BPS reported production}_{\text{island}} / \text{area estimated production}_{\text{island}}$$

The deflation factor was then multiplied with each area of production to get a normalised production value.

$$\text{normalised production}_{\text{ffb_prod_units}} = \text{deflation factor}_{\text{island}} \times \text{production}_{\text{ffb_prod_units}}$$

For ease of display and visualisation on the Trase platform, we aggregated production to the kabupaten and province-level.

# Supply chain mapping method

We used two, interconnected, logic-based decision trees to (1) trace exports back to refineries and mills and (2) trace the resulting demand for FFB from mills back to FFB production units. Figure 4 provides an overview of each branch of the decision tree, while the narrative below describes each step of the model in more detail.

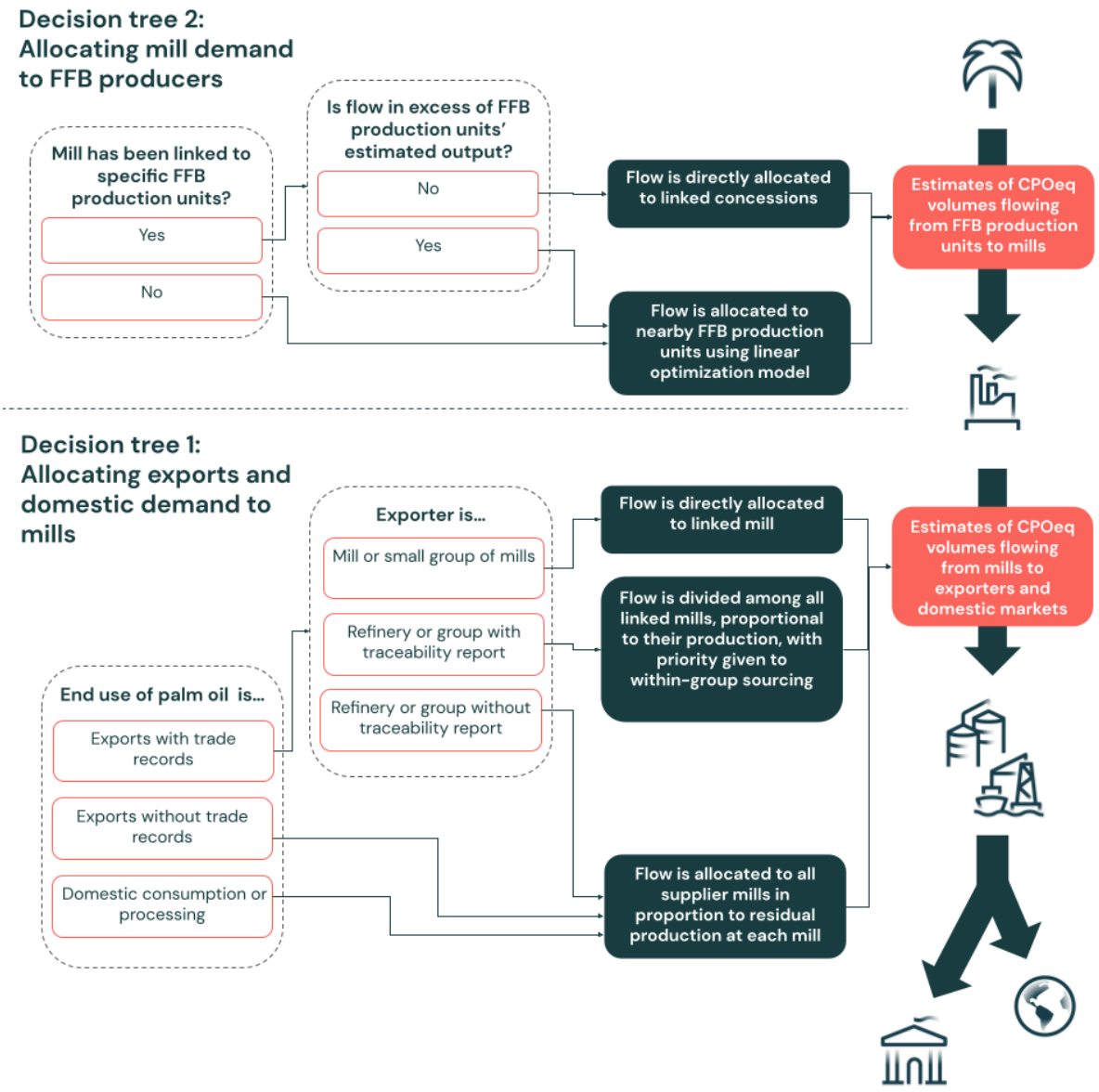



Figure 4: Detailed outline of **SEI-PCS Indonesian palm oil v1.2.2 model.**

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## Allocating exports and domestic demand to mills

### Separating exports and domestic demand

The first step of our model combined trade data with Indonesian oil palm production statistics to separate total Indonesian CPO and RPO production into three broad categories of end use: (a) exports with trade records; (b) exports without trade records; and (c) domestic consumption and downstream processing. Given that branches (b) and (c) did not have any reliable information on the location of sourcing, these flows were set aside, and allocated evenly to all mills with excess production left over after branch (a) was fully allocated.

### Matching exporters with refineries and mills

For exports with trade records, our first step was to identify the exporter listed in each shipment record. Exporters in the trade data are typically companies that are affiliated with specific mills and/or refineries. As a result, we sought to match exporters to the mills or refinery they represent. Exporters were matched to refineries based upon their respective company names and the closest port of export to the refinery. For approximately 11–15% of exports, exporters in the trade data could be matched directly to specific mills based on their respective company names (Table 8). For a small number of exporters, we linked them to specific mills or refineries if the exporters' name matched a refinery or mill's affiliated traders or plantation companies.

### Linking refineries to mills

For the large majority of refineries that released traceability reports, we constrained all of the refineries' sourcing to come from the mills listed in their traceability report. For refineries that did not release traceability reports, we were unable to identify the set of possible mills supplying CPO. In these cases, we included all possible mills as potential suppliers, but labelled the resulting flows as "unknown" in the results. As a result, "known" flows that are fully tracked include all exports with trade records that were either linked to a refinery with traceability reports, or that were linked directly to mills. These flows represent the large share of all exports, as well as a majority of total production in most years (Table 8).

### Table 8: Share of total volume that is linked directly to refinery with traceability report or mill(s)

| Exporter is | Flow labelled as | Year | Share of total production (%) | Share of total exports (%) |
|---|---|---|---|---|
| Known mill(s) | Known | 2018 | 8.7 | 12.9 |

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| | | | | |
|---|---|---|---|---|
| | | 2019 | 9.4 | 15.1 |
| | | 2020 | 7.0 | 11.7 |
| | | 2021 | 2.7 | 4.5 |
| | | 2022 | 1.2 | 2.2 |
| Known refinery with traceability report / group level traceability report | Known | 2018 | 52.1 | 77.0 |
| | | 2019 | 46.3 | 74.5 |
| | | 2020 | 41.8 | 69.6 |
| | | 2021 | 45.0 | 76.0 |
| | | 2022 | 34.8 | 54.1 |
| Known refinery without traceability report | Unknown | 2018 | 6.3 | 9.3 |
| | | 2019 | 5.7 | 9.3 |
| | | 2020 | 3.9 | 6.5 |
| | | 2021 | 6.0 | 10 |
| | | 2022 | 6.3 | 11.2 |
| Unmatched exporter | Unknown | 2018 | 0.6 | 0.8 |
| | | 2019 | 0.7 | 1.1 |
| | | 2020 | 2.4 | 4.0 |
| | | 2021 | 0.2 | 0.4 |
| | | 2022 | 0.2 | 0.4 |
| Domestic consumption and processing | Unknown | 2018 | 32.3 | - |
| | | 2019 | 37.9 | - |
| | | 2020 | 39.9 | - |
| | | 2021 | 40.6 | - |
| | | 2022 | 44.2 | - |
| Unreported exports | Unknown | 2018 | 0 | 0 |

Trase. (2024). SEI-PCS Indonesia palm oil v1.2.2 supply chain map: Data sources and methods. Trase. https://doi.org/10.48650/ZY8Z-F795

| | | |
|---|---|---|
| 2019 | 0 | 0 |
| 2020 | 4.9 | 8.2 |
| 2021 | 5.4 | 9.1 |
| 2022 | 17.5 | 31.5 |

## Assigning flows

After linking exporters to refineries and mills, we assigned the CPO equivalent embedded in each export shipment back to individual mills. The process for these allocations followed the three branches detailed in Figure 4:

- For exporters who were matched to specific mills, all exports were directly allocated to the associated mill. If export shipments assigned to these mills exceeded our initial estimates of mill-level production, we adjusted the mill's production to accommodate these flows, as detailed in the earlier section on mill production.
- For exporters who were matched to refineries with traceability reports, exports were split between all of the refinery's known supplying mills in proportion to the mills' production volume. Mills that were owned by the same group as the exporter received a higher share of the linked exports than mills that were owned by a different group. This was done by shifting 30% of the linked exports that would be allocated to mills not owned by the group back to mills owned by the group. The 30% value was selected as appropriate for this parameter since it minimised the root mean square error across a set of refineries for which we had more detailed data describing the share of purchases being made from within-group mills. When a mill was linked to an exporter through multiple refineries, the exported volume was split evenly between refineries since we did not have access to refinery-level capacities to weight this division. When the combined demand of linked exporters exceeded a mill's production, the excess fraction of the demand was iteratively reallocated to other mills in the refinery's supplier list. For a small share of flows (~2–3%), an exporters' total demand for CPO equivalent exceeded the estimated production volumes of linked mills. In these cases we evenly increased all linked mills' production estimates to accommodate this excess demand, while decreasing the production of other mills to ensure that total, province-level production continued to match official production estimates from BPS.
- We were unable to accurately constrain the location of sourcing for three branches in our decision tree, representing CPO and RPO that was fated for either (i) domestic consumption or processing, (ii) exports that were not recorded in trade data, or (iii) exports by refineries without traceability reporting. We aggregated all of these volumes, and then assigned them equally across all of the mills with unassigned

production that remained after assigning all exports as detailed in the previous two bullets. Given the high uncertainty of any specific link in this branch, all flows between individual mills and exporters have been obscured on the Trase platform. Nevertheless, the allocation procedure above ensures that deforestation rates assigned to these flows are all equal, and match the average deforestation rate associated with production by mills that are not "claimed" by other producers with traceability reporting.

## Allocating mill demand to FFB production units

### Linking mills to concessions

We first sought to link mills to concessions that might serve as their preferred FFB production units using a combination of approximate string matching between the names of concession owners, and the names of local mill companies and corporate groups. For some RSPO certified mills, we also had information on the set of concessions that served as their declared "supply base" based on data that was digitised and compiled from RSPO certification reports by the Carlson Lab and the Conservation Economics Lab.

### Table 9: Share of total volume by mill-concession link types

| Link type | Year | Share of total production (%) |
|---|---|---|
| Location or name of company / corporate group | 2018 | 23 |
| | 2019 | 25 |
| | 2020 | 26 |
| | 2021 | 38 |
| | 2022 | 37 |
| Supply base reporting (e.g. RSPO reports) | 2018 | 8 |
| | 2019 | 8 |
| | 2020 | 7 |
| | 2021 | 9 |
| | 2022 | 9 |
| Not linked to any concession | 2018 | 69 |

Trase. (2024). SEI-PCS Indonesia palm oil v1.2.2 supply chain map: Data sources and methods. Trase. https://doi.org/10.48650/ZY8Z-F795

| | | |
|---|---|---|
| | 2019 | 67 |
| | 2020 | 67 |
| | 2021 | 53 |
| | 2022 | 54 |

### Assigning flows

We used a combination of direct allocation and linear programming-based optimisation (LP) to assign volumetric flows between FFB production units and mills following the two branches detailed in Figure 4:

- When a mill was linked to specific FFB production units, the mill's demand for FFB was allocated directly to those production units. If the combined demand assigned to a production unit exceeded its estimated production, the excess fraction of the demand was passed on to the LP detailed in the next bullet point.
- For FFB demanded by any mills that were not connected to specific suppliers, FFB sourcing was predicted using an LP model. The LP assigned FFB sourcing by minimising total transportation costs between the FFB production unit and the mill, while prioritising purchases from a corporate group's own plantations. The within-group prioritisation was achieved by setting the transportation cost to zero when the supplying concession is controlled by the group.

# Sustainability indicators

## Oil palm planted area

Oil palm planted area is the annual extent of productive oil palm, accounting for both industrial and smallholder plantings. It was calculated using data provided by Gaveau et al. (1), who mapped the year in which oil palm is first planted in a given location. This dataset can be viewed at Nusantara Atlas. Oil palms were assumed to start producing FFB in their third year after planting and continue to produce for up to 30 years. Based on these assumptions, the productive oil palm planted area assigned to a target year is the total area planted up to three years before the target year. For example, the productive oil palm planted area in 2018 was represented by the total area mapped as oil palm plantation in 2015 by Gaveau et. al. (1). The metric, aggregated at provincial and kabupaten-level, is available at the map section and embedded into supply chain flows on the Trase website.

## Palm oil production

We estimated local fresh fruit bunch (FFB) production by combining provincial statistics on palm oil production with maps of local oil palm planted areas, both under industrial and smallholder management. The full details of these calculations are provided in the previous section "Production from FFB production units." Palm oil production is estimated in tonnes of CPO equivalent and aggregated to the level of individual kabupaten or provinces. The metric, aggregated at provincial and kabupaten-level, is available at the map section and embedded into supply chain flows on the Trase website.

## Smallholder production

Smallholder palm oil production is calculated in the same way as the palm oil production indicator above, but is confined to smallholder oil palm plantings derived from Gaveau et al.(1). It is important to note that the Gaveau et al. maps of industrial and smallholder oil palm include tied and plasma smallholders in their maps of industrial plantings (1). As a result, our smallholder production indicator can be best interpreted as an estimate of production by smallholders that are not directly tied to industrial operations. The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

## Palm oil yield

This metric estimates local palm oil yields in tonnes/ha by FFB production unit. It is calculated by dividing the annual palm oil production (industrial and smallholder) by the annual oil palm planted area (industrial and smallholder). The values are subsequently averaged by kabupaten and province levels to be available as regional indicators. The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

## Forest cover

Forest cover is  the total area of remaining forest derived from Gaveau et al.(1) within the selected jurisdiction, i.e., kabupaten or province. Gaveau et al. (1) combines two forest maps: one published for Indonesia (7), and the other for Indonesian New Guinea (8). These datasets were created using Landsat imagery and computer models trained on the spectral characteristics of primary evergreen forests, which have lower albedo and higher spectral variability than forest regrowth and surrounding agricultural lands, due to the presence of emergent trees, and high species diversity. This definition of 'forest' excludes young regenerating forests, agroforests, scrublands, tree plantations, agricultural lands, grasslands, and non-vegetated areas (1). The metric, aggregated at provincial and kabupaten-level, is available at the Map section on the Trase website.

'Forest' includes both intact primary (or old-growth) forests and primary forest that have been selectively logged during the 1970s, 1980s and 1990s. Intact forests have not been severely disturbed by humans in recent decades. Selectively logged forests have been impacted by both artisanal tree cutting as well as by more extensive mechanised timber cutting and extraction, and experienced regrowth after logging. Both intact and selectively logged forests typically have high carbon stocks. A comparison against above ground biomass (9) and tree height (10) maps for year 2020 indicates a mean above ground carbon of 116 Mg C/Ha and mean tree height of 28 metres for forests.

## Deforestation

Four separate indicators describe the deforestation dynamics in the region of interest and/or associated with the palm oil supply chain: territorial deforestation, annual deforestation for industrial palm oil, and industrial palm oil deforestation (map view) and deforestation exposure (flow view).

### Territorial deforestation

This metric represents the total deforestation of forests (defined above) occurring in a single year. To calculate territorial deforestation, Gaveau et al.(1) combines forest cover as identified above with the annual tree cover loss dataset developed at University of Maryland (19). The tree cover loss dataset measures the removal of trees (tree height >5 m) if the canopy cover falls below 30%. It does not distinguish between removal of natural forests and planted trees. To reduce any error resulting from this ambiguity, Gaveau et al.(1) only included tree loss pixels inside areas identified as forest as defined above. The same data sources are used on The TreeMap's mapping platform The Nusantara Atlas (20). The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

### Annual deforestation for industrial oil palm and deforestation exposure

Annual deforestation for industrial oil palm is a subset of the territorial deforestation, and shows the total area deforested in the target year that will be subsequently converted to industrial oil palm plantations. This metric was calculated based on deforestation and industrial palm oil plantations as detected by Gaveau et al.(1). Following the estimation of annual oil palm deforestation in each FFB production unit, annual industrial oil palm deforestation exposure is calculated based on the share of local production sourced by the actor (trader, country) in each FFB production unit and year. A detailed description on how Trase calculates commodity deforestation and commodity deforestation exposure can be found here: Commodity deforestation exposure and carbon emissions assessment (Trase 2022 (11)). The metric is embedded into Trase's supply chain flows. The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

## Industrial oil palm deforestation and deforestation exposure

This metric estimates how much deforestation is associated with industrial palm oil plantations and the palm oil supply chain. This includes the full plantation cycle, from establishment, planting and harvest in a particular year. To estimate the deforestation associated with industrial oil palm production in a specific year, we used a three-year lag between deforestation for oil palm and the first harvest, and aggregated deforestation at the location of oil palm production across 10 years. By setting these parameters we are assuming that oil palms will start to produce, and consequently start to contribute to the volume traded in a given year, in the third year after the deforestation event for new plantations. These trees will continue to produce for around 30 years; however, here we are accounting only for the first ten years of production. For example, the total area of land that was classified as forest in 2007, but had been converted to oil palm plantations by 2017, would be considered as areas of deforestation contributing to industrial oil palm deforestation in 2020 trade (Figure 5). Following the estimation of industrial oil palm deforestation in each FFB production unit, industrial oil palm deforestation exposure is calculated based on the share of local production sourced by the actor (trader, country) in each FFB production unit and year. A detailed description on how Trase calculates commodity deforestation and commodity deforestation exposure can be found here: Commodity deforestation exposure and carbon emissions assessment (Trase 2022 (11)). The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

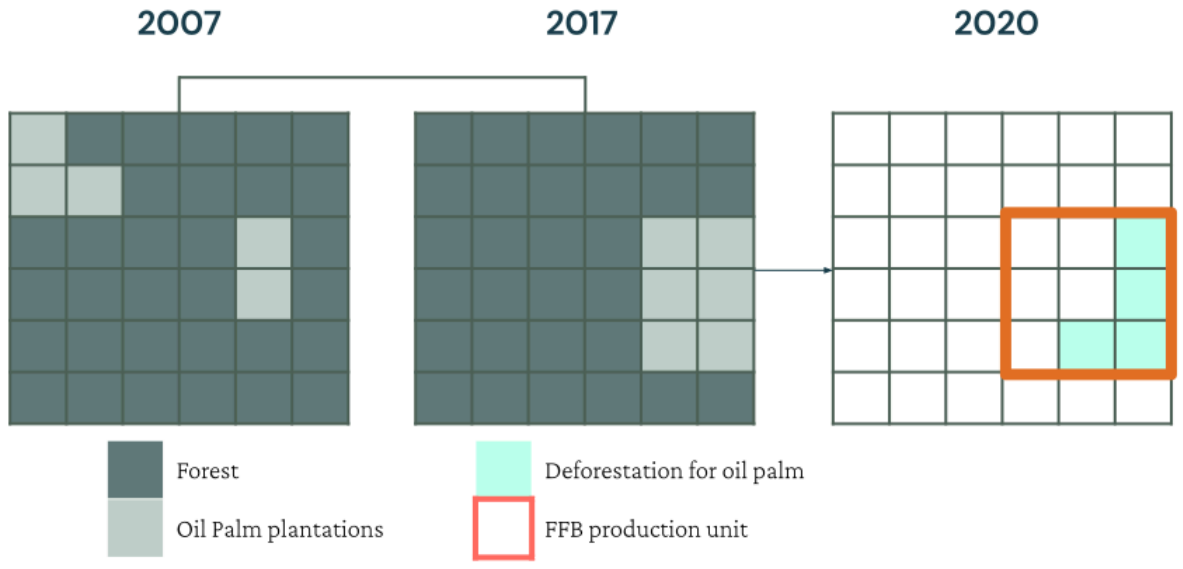



Figure 5: Illustration of the spatial assignment of deforestation for oil palm plantations in a given FFB production unit.

### Peat area

Peat area is the total amount of peatland in each kabupaten and/or province. Peatland areas were derived using Indonesia's official peat map, which was produced by the Indonesian Center for Agricultural Land Resources Research and Development within the Ministry of Agriculture 2019 (13). The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

### Burned areas

To estimate the area burned within each FFB production unit, we relied upon the official burned area dataset from Indonesia's Ministry of Environment and Forestry (MoEF, (15)). The dataset has been published yearly since 2015 by MoEF and is mapped at 1:250,000 scale on a monthly basis by visual interpretation of the extent of forest and land fires from Landsat-8, Landsat-9 and Sentinel-2 satellite imagery. The visually identified burned areas are then validated by experts using hotspot data from the Terra-Aqua MODIS Satellite, NOAA 20, S-NPP and Landsat-8 as well as field reports. It is worth noting that recent research indicates that this data might underestimate the total burned area. For example, Gaveau et al., 2021 (16), present evidence that the 2019 burned area was 90% greater than the area reported by MoEF. The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

## Fire on peatlands

Fires on peatlands quantifies the peat areas (defined above) that have been identified with fire-events based on the burned areas dataset defined above. The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

### Oil palm on peatlands

Oil palm on peatlands refers to the total amount of oil palm (4) planted on peat (17). Peatland areas were derived from Indonesia's official peatland map, which was published by the Indonesian Center for Agricultural Land Resources Research and Development within the Ministry of Agriculture in 2019 (17). The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

# Greenhouse gas emissions

## Gross emissions from territorial deforestation

Gross greenhouse gas emissions from territorial deforestation (tonnes of $CO_2$-eq) were calculated by estimating the maximum $CO_2$-eq potentially emitted due to the full removal of the biomass as a result of territorial deforestation (more details above), estimated in a given year. This metric is calculated by multiplying the area of territorial deforestation by an estimate of the carbon stock contained in each hectare of converted land. Carbon stocks represent the total carbon stored in above and below-ground biomass, but does not include carbon stocks in the soil. We create local estimates of above-ground woody biomass density (carbon stocks per hectare) using data from Harris et al., (6). Below-ground biomass density was estimated based on Harris et al. (6)'s above-ground biomass density and the ratio of below-ground to above-ground biomass derived from Spawn et al. (7). To convert biomass to carbon density, we used conversion factors of 0.47 t C $t^{-1}$ for above ground and 0.39 t C $^{-1}$ for below ground, respectively (Diop et al. (8)). Carbon is converted into $CO_2$-eq emissions by multiplying by a factor of 44/12 (or 3.67), based on the ratio between the molecular weight of C and $CO_2$ following IPCC (2014)(9). The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website.

## Gross greenhouse gas emissions from industrial palm oil land conversion

GHG emissions from industrial palm oil conversion (tonnes of $CO_2$-eq) were calculated within a given year and FFB by estimating all of the $CO_2$-eq potentially emitted due to annual oil palm land use change, including both from natural forest and non-forest land covers (as defined in Gaveau et al. (1)). This metric is calculated by multiplying the area converted each year to palm oil by an estimate of the carbon stock contained in each hectare of converted land independent of the fact whether than converted land was before forest or non-forest as we assumed that the carbon stock density map will account for the difference in carbon stocks between forest and non-forest. Carbon stocks represent the total carbon stored in above and below-ground biomass, but does not include carbon stocks in the soil. We created local estimates of above-ground woody biomass density (carbon stocks per hectare) using data from Harris et al., (7). Below-ground biomass density was estimated based on Harris et al. (7)'s above-ground biomass density and the ratio of below-ground to above-ground biomass derived from Spawn et al.(8). To convert biomass to carbon density, we used conversion factors of 0.47 t C $t^{-1}$ for aboveground and 0.39 t C $^{-1}$ for belowground, respectively (Diop et al. (9)). Carbon is converted into $CO_2$-eq emissions by multiplying by a factor of 44/12 (or 3.67), based on the ratio between the molecular weight of C and $CO_2$ following IPCC (2014)(10). The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website and embedded into Trase's supply chain flows based on the market share of each actor (trader, country) in each FFB production unit and year (see Trase 2022 (11)).

## Carbon sequestration in new industrial oil palm plantations

We estimate carbon sequestration resulting from the expansion of industrial oil palm plantations. To calculate this, we first estimate the total area of all new industrial oil palm plantations in the target year. We then multiply this area by the biomass carbon stock of industrial oil palm plantations. For above-ground biomass carbon we adopted the time-averaged values over the rotation period provided by Khasanah et al. (15) of 40.03 t C $ha^{-1}$ for plantations on peat and 42.07 t C $ha^{-1}$ for plantations on mineral soils in Indonesia. To account for below-ground biomass, we used the root-to-shoot ratio of 1:4 reported for oil palm plantations by Guillaume et al. (16) to estimate the total above and below-ground carbon for industrial plantations on peat as 50.38 t C $ha^{-1}$ and 53.38 t C $ha^{-1}$ . Using time-averaged carbon stocks over the rotation period reflects the fact that perennial plantation systems are cyclical – while the plantation will contain lesser or greater stocks of carbon in individual years, the average across the full rotation can serve as a useful estimate of the carbon impact of land use change into the long-term use as oil palm plantation.

Carbon is then converted into $CO_2$-eq emissions by multiplying by a factor of 44/12 (or 3.67), based on the ratio between the molecular weight of C and $CO_2$ following IPCC, (2014) (14). This equation calculates only the amount of carbon stored in the standing biomass within an oil palm plantation. The metric is embedded in the net greenhouse gas emissions from land use change indicator (see below) and is available on the Trase website.

## Net greenhouse gas emissions from industrial palm oil land use change

We calculate net greenhouse gas emissions from land use change as the difference between gross emissions from industrial palm oil conversion and carbon sequestration from new industrial palm oil plantations. The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website and embedded into Trase's supply chain flows based on the market share of each actor (trader, country) in each FFB production unit and year (see Trase 2022 (18)).

## Greenhouse gas emissions from peat burning

This metric represents the GHG emissions from fires on peat soils (tonnes of$CO_2$-eq) in a single year allocated to industrial palm oil within each FFB production unit. The emissions are calculated based on the area of overlap between the burned areas and peat areas (more details above) multiplied by 824 tonnes of $CO_2$-eq following the average emission factor estimates provided by Rodríguez Vásquez et al., (17). The value represents an average amount of $CO_2$-eq per hectare that is released into the atmosphere in a unique event of fire on peat. Rodríguez Vásquez et al., (17) based their estimate on other studies from peatland sites in Kalimantan,

Sumatra and Malaysia where depth of burn, bulk density and average emissions factors were measured. However, peat fires may be caused by a variety of land uses including, but not limited to, palm oil. To assign emissions to the oil palm sector, we multiply total emissions from peat burning by the proportion of modified peatlands that are covered by oil palm within the FFB production unit. We define modified peatlands as peat soils that are covered by either rice paddy, oil palm, pulpwood plantations, aquaculture and other agriculture as identified by MapBiomas Indonesia Collection 2 (18). This choice reflects the fact that fire is often used as land management to clear the land before it is used agriculturally and might then spread to neighbouring areas (Purnomo et al. 2019, (19)), whereas fires in intact peatland forests are uncommon (Marlier et al. 2015, (20)).

The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website and embedded into Trase's supply chain flows based on the market share of each actor (trader, country) in each FFB production unit and year (see Trase 2022 (18)).

## Greenhouse gas emissions from peat subsidence

The metric represents the GHG emissions from peat subsidence (tonnes of $CO_2$-eq) in a single year, assigned to the target year. The emissions are calculated based on the area of oil palm plantations on peat (more details above) within the FFB production area for the target year. This area is multiplied by an emission factor of 90 t $CO_2$-eq $ha^{-1}$ $yr^{-1}$ (averaged over the 30-year oil palm plantation cycle) accounting for methane, nitrous oxide and carbon dioxide GHG emissions due to subsidence after peat drainage, as described by Cooper et al., (19). Please note that this emission factor is higher than previous estimates which did not consider emissions from nitrous oxide or methane.

We note, however, that recent research by Deshmukh et al (20) provides evidence that these standard emissions factors are larger than what is measured from eddy covariance towers located in pulp plantations on tropical peatlands. We also note that our calculations only quantify emissions from peat subsidence occurring within oil palm plantations, and do not reflect subsidence in natural forests occurring as a result of changes in local and regional hydrology. The causal impact of plantation management on total peat emissions will depend upon the aggregate impacts that plantation management have on the local distribution of land cover and associated groundwater levels.

The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website and embedded into Trase's supply chain flows based on the market share of each actor (trader, country) in each FFB production unit and year (see Trase 2022 (18)).

## Total greenhouse gas emissions from palm oil

This metric estimates the major sources of GHG emissions from palm oil plantations in Indonesia: subsidence on drained peatlands, fire on peatlands, and land use change, i.e., the clearing of vegetation to establish oil palm plantations. The GHG sequestration from new plantations was also estimated and incorporated into the net GHG emissions reported by Trase.

For each FFB production unit area, the greenhouse gas emissions are summed up in each year (T) as:

$$GHG_{Total_{FFB,T}} = GHG_{Net\ LUC_{FFB,T}} + GHG_{Peat\ fire_{FFB,T}} + GHG_{Sub_{FFB,T}}$$

where the net greenhouse gas emissions from land use change are defined as:

$$GHG_{Net\ LUC_{FFB,T}} = (GHG_{Gross\ LUC_{FFB,T}} - C\ Sequestration_{Oil\ Palm_{FFB,T}})$$

$GHG_{Gross\ LUC}$ = GHG emissions from biomass carbon stock change during the transition from forest or non-forest vegetation to industrial oil palm plantation (t $CO_2$-eq $ha^{-1}year^{-1}$)
$GHG_{Peat\ Fire}$ = GHG emissions due to fires on peat (t $CO_2$-eq $ha^{-1}year^{-1}$)
$GHG_{Sub}$ = the yearly GHG emissions due to peat subsidence (t $CO_2$-eq $ha^{-1}$ $year^{-1}$)

## Certification

Certification information includes Indonesian Sustainable Palm Oil (ISPO) and Roundtable on Sustainable Palm Oil (RSPO) certification status of mills. The RSPO certification status was based on the mill certification status as shown on the GeoRSPO platform (21) and also RSPO certification reports compiled by the Carlson Lab. The ISPO certification status of mills was compiled and provided by Auriga. We report the number of ISPO and RSPO certified mills by kabupaten and province in the map section on the Trase website.

## Zero-deforestation commitments

Zero-deforestation commitments (ZDC) are obtained by Global Canopy's annual assessment which determines whether an exporter trader group has a commitment to zero deforestation or to "no deforestation, no peat and no exploitation" (NDPE). ZDCs as either net or gross deforestation are acceptable. A commitment is accepted as zero deforestation if the exporter

trader (or exporter group) explicitly uses the phrases "zero deforestation", "zero conversion" or "NDPE" in their sustainability goals or current policies, or has a policy (or target) for 100% certification where the certification is equivalent to a zero-deforestation standard. ZDC are reported as “NDPE commitment” if the commitment clearly states “no deforestation, no peat and no exploitation” (NDPE), “company commitment” if the specific company is committed to zero deforestation, or zero conversion, “none” if the company does not have a ZDC), or “unknown” if the company’s ZDC position was not checked. Typically, Global Canopy’s assessment focuses on the top companies that together trade 90% of the commodity volume in a given year. The metric is available at the map section on the Trase website as ZDC percent, aggregated at provincial and kabupaten-level, and embedded into Trase’s supply chain flows based on the exporter group.

## Forest 500

The Forest 500 indicator scores companies’ deforestation commitments according to Global Canopy’s Forest 500 assessments (https://forest500.org/). Global Canopy’s Forest 500 project identifies the 500 companies and financial institutions with the greatest influence on tropical deforestation, and, each year, assesses them on the strength and implementation of their publicly available commitments on deforestation, conversion, and associated human rights abuses (Forest 500) (22).

The Forest 500 value represents the commodity-specific score categorised in groups where 0 is none, 1: >0% to <20%, 2: 20% to <40%, 3: 40% to <60%, 4: 60% to <80% and 5: 80% to 100% of the assessed criteria. The metric is embedded into Trase’s supply chain flows based on the Exporter Group.

## Palm oil tax revenue

Palm oil tax revenue is available for the 2018–2020 period at the kabupaten level. This data was obtained through the Indonesian Ministry of Finance (Kementerian Keuangan). The data shows the income tax revenue by the kabupaten in a given year in Indonesian Rupiah (IDR). The number is calculated by the sum of PPh Pasal 22, PPh Pasal 25/29, PBB, and PPN for the KLU (Klasifikasi Lapangan Usaha or Indonesia Standard Industrial Classification) number 01262 Perkebunan Kelapa Sawit (Oil Palm Plantations) and 10431 Industri Minyak Makan Kelapa Sawit (Crude Palm Oil). Negative tax revenue values in some kabupaten are due to tax refunds that are returned for excess payments made by taxpayers or tax payments that should not be owed (tax restitution). The metric, aggregated at provincial and kabupaten-level, is available at the map section on the Trase website and is embedded into Trase’s supply chain flows.

## Limitations

We believe that SEI-PCS Indonesia palm oil v1.2.2 model represents the most consistent and complete representation of Indonesian palm oil supply chains that is currently available to the public. Nevertheless, several important limitations are worth highlighting to encourage effective use of the data and underscore opportunities for future improvements:

- Uncertainty of volumetric flows: Widespread traceability reporting within the palm oil sector enables us to describe binary links between refineries and mills with a high degree of accuracy. However, these traceability reports almost never include data specifying the volumes of crude palm oil sourced from specific mills. As a result, we allocate volumes by dividing CPO purchases proportionally across suppliers. This provides a rough estimate of volumetric flows between mills and refineries, but the accuracy of these estimates is low. Users of Trase are advised that more qualitative descriptions of the set of mills included in a supply chain will generally be much more accurate than more quantitative assessments of specific volumes flowing between mills and refineries. Uncertainty in volumes will translate into uncertainty in levels of exposure of supply chain actors to deforestation and other impacts. However, the traceability reporting provides a high level of confidence as to whether a given buyer is connected to a given hotspot of deforestation, via the supply sheds of known mill suppliers, even though uncertainty remains as to the level of exposure. Greater disclosure of volumes in traceability reporting would also allow a much more accurate assessment of exposure.
- Exports by refineries without traceability reports: Given the important role that traceability reports play in constraining the Trase model's allocations, supply chains ending in exports by refineries without traceability reports are inherently less well-understood. As a result, we treat these flows as if they were composed of an equal mix of production from all FFB producers who have excess capacity left after more certain supply chains are allocated. We believe this provides a reasonable estimate of the relative deforestation intensity of these flows, especially when compared to supply chains measured with greater confidence. Nevertheless, due to this uncertainty we have obscured upper nodes in these supply chains (e.g. FFB production units, mills) as "unknown". However, the underlying unobscured dataset can be made available upon request.
- Domestic consumption and manufacturing: Export records represent an important dataset constraining the Trase model. However, volumes of CPO and RPO that are used or further processed within Indonesia are not recorded in export data. As a result, our ability to accurately represent the supply chains supplying domestic markets are entirely determined by our estimates of production that remains after accounting for all exports. However, since we also lack information detailing the total production of

each refinery or mill, we are unable to link this production to specific mills or refineries. As a result, the Trase model labels the upper nodes (e.g. FFB production units, mills) of supply chains serving domestic markets as “unknown.”

- Missing exports data: Trase has labelled the difference between the per-shipment export records and the official exported volumes by BPS as “unknown” in the flows. These missing shipments have been growing steadily since 2020 and represent 17.5% of total production and 31.5% of total exports in CPO equivalent tonnes in 2022 (more details on this in Table 1). This has hindered our ability to link exporters that are affected by these missing exports to any known exporting refineries or mills and subsequently properly determining their export share and metrics such as deforestation exposure.

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