CODEX PLANETARIUS

A Validation Framework for Supply Chain Environmental Metrics

Epoch

About *Codex Planetarius*

Codex Planetarius is a proposed system of minimum environmental performance standards for producing globally traded food. It is modeled on the *Codex Alimentarius*, a set of minimum mandatory health and safety standards for globally traded food. The goal of *Codex Planetarius* is to measure and manage the key environmental impacts of food production, acknowledging that while some resources may be renewable, they may be consumed at a faster rate than the planet can renew them.

The global production of food has had the largest impact of any human activity on the planet. Continuing increases in population and per capita income, accompanied by dietary shifts, are putting even more pressure on the planet and its ability to regenerate renewable resources. We need to reduce food production's key impacts.

The impacts of food production are not spread evenly among producers. Data across commodities suggest that the bottom 10-20% of producers account for 60-80% of the impacts associated globally with producing any commodity, even though they produce only 5-10% of the product. We need to focus on the bottom.

Once approved, *Codex Planetarius* will provide governments and trade authorities with a baseline for environmental performance in the global trade of food and soft commodities. It won't replace what governments already do. Rather, it will help build consensus about key impacts, how to measure them, and what minimum acceptable performance should be for global trade. We need a common escalator of continuous improvement.

These papers are part of a multiyear proof of concept to answer questions and explore issues, launch an informed discussion, and help create a pathway to assess the overall viability of *Codex Planetarius*. We believe *Codex Planetarius* would improve food production and reduce its environmental impact on the planet.

This proof-of-concept research and analysis is funded by the Gordon and Betty Moore Foundation and led by World Wildlife Fund in collaboration with a number of global organizations and experts.

For more information, visit www.codexplanetarius.org

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1 Executive Summary

The global food system is at a critical juncture. Agricultural production accounts for approximately 70% of global freshwater withdrawals (FAO AQUASTAT, 2024), drives an estimated 70% of terrestrial biodiversity loss (IPBES, 2019), and is responsible for roughly 23% of total anthropogenic greenhouse gas emissions – including CO_2 from deforestation and land degradation, methane from rice paddies and livestock, and nitrous oxide from fertilizer application (IPCC, 2019). The expansion of soft commodity production – palm oil, soy, cocoa, rubber, coffee, cattle, and timber – is the dominant proximate cause of tropical deforestation, releasing an estimated 4.8 Gt CO_2 per year from forest conversion alone (Global Forest Review, WRI, 2024). Beyond carbon, this expansion degrades soil fertility through progressive organic carbon depletion, disrupts hydrological cycles by replacing deep-rooted forest with shallow-rooted monocultures, fragments habitat corridors that sustain species dispersal and gene flow, and destabilizes the livelihoods of millions of smallholder producers who depend on functioning ecosystem services. The ***Codex Planetarius*** initiative aims to shift from voluntary sustainability standards to mandatory minimum performance levels, particularly targeting the bottom tier of producers who generate a disproportionate share of these environmental externalities. By reliably linking first-mile environmental impacts to downstream buyers, the framework creates an accountability structure that spans the full supply chain – from production landscape to end market.

The "Palm in Paradise" pilot study on Indonesian palm oil successfully mapped the "first mile" of the supply chain, linking 1,290 mills to their sourcing areas. The key finding was that **the bottom 5% of facilities are linked to over 73% of post-2020 deforestation and nearly 78% of total Land Use Change (LUC) emissions.** This concentration of risk provides a clear mandate for a targeted approach focused on the worst performers.

To operationalize *Codex Planetarius* as a global, credible standard, the underlying data must be accredited with a high degree of confidence. This report outlines a comprehensive **Validation Framework** designed to establish that credibility. The work asks four questions: Are the model's scientific foundations sound – and where do they diverge from field evidence? Which input variables have the greatest impact on facility-level risk rankings, and therefore where should validation effort be concentrated? What does a practical, cost-effective field validation strategy look like at scale? And to what extent can a framework built for Indonesian palm oil extend to the other six EUDR-regulated commodities?

The sensitivity analysis produced quantitative results across all five tested scenarios, computed directly against the live 1,290-supply-shed Indonesian palm oil dataset: peat soil misclassification emerged as the structurally highest-impact driver (16.9% of bottom-5% facilities are displaced when 20% of peat-classified supply sheds are misclassified as mineral, based on PEATGRIDS 1 km raster intersection with supply shed geometries, noting that the pilot treats peat as a binary flag; differentiating by thickness and drainage intensity would likely increase this sensitivity further); estate/smallholder classification is the highest-impact, immediately executable driver (14.5% classification shift when tenure type is swapped); travel time sensitivity at 60-minute and 120-minute variants (vs. 90-minute baseline) showed 3.2% classification shifts; and deforestation detection agreement analysis revealed 36.8% multi-method concordance globally – producing a 35.5% emission ranking shift but 0% EUDR compliance ranking change, confirming that the worst deforesters are consistently identified across all detection methods even when single-method detections are discounted. This dual result supports a two-layer detection framework: a high-sensitivity union of all methods for EUDR compliance flagging, and a high-confidence intersection (≥2 methods agreeing) for GHG emission accounting.

By rigorously defining the scientific "ground truth" and isolating the most critical, high-leverage input variables, this project establishes a defensible, science-based protocol for validating environmental performance at scale. The framework concludes with a two-tiered sampling strategy – Tier 1 for lightweight screening validation and Tier 2 for quantitative field validation – to ensure an efficient and statistically sound approach to deployment. While the framework was developed and validated using Indonesian palm oil as the pilot commodity, a commodity generalizability assessment (Section 3.4, pg 31) demonstrates that the core architecture extends with low adaptation effort to soy, cocoa, rubber, and coffee, establishing a pathway toward a universal first-mile monitoring standard.

2 Comprehensive Literature Review & External Benchmarking

This section synthesizes existing, peer-reviewed literature on palm oil environmental impacts to benchmark model assumptions against established scientific data. This review is essential for establishing the "external validity" of the *Codex Planetarius* metrics, incorporating key findings across Greenhouse Gas Emissions, Hydrology and Ecosystem Services, and Biodiversity.

2.1 Greenhouse Gas Emissions & Carbon Dynamics

The literature confirms that **soil type (peat vs. mineral) and plantation age are the dominant drivers of environmental impact.** The primary emissions source is conversion of natural forests and peat drainage (LUC), but cultivation practices also contribute to the overall carbon balance (non-LUC).

2.1.1 Land Use Change (LUC) Emissions and High-Leverage Risk Drivers

LUC emissions – from deforestation and peat drainage – are the most significant sources in the palm oil sector. The literature confirms their dominance and aligns with the model's prioritization.

- **Peat Drainage is Critical:** Oil palm on drained peatlands are massive net carbon sources. Two variables govern the magnitude: peat deposit thickness determines the total carbon stock vulnerable to oxidation, while drainage depth (water table drawdown) controls the rate of release – carbon loss scales linearly with water table depth, reaching ~20 tC ha^{-1} yr^{-1} at a typical plantation drainage depth of 70 cm (Carlson et al., 2015). Meijide et al. (2020) found ecosystem GWPnet (integrating CO_2, CH_4, and N_2O fluxes) of 46.0 ± 11.5 tCO_2e ha^{-1} yr^{-1} for mature plantations on peat, versus 6.9 ± 3.5 tCO_2e ha^{-1} yr^{-1} on mineral soils – approximately seven times larger. Peat extent and thickness are mapped globally by PEATGRIDS (Widyastuti et al., 2025; 1 km continuous thickness in cm, with uncertainty), with finer-resolution extent from Miettinen et al. (2016) at 30 m. Drainage depth is not directly observable from optical remote sensing; InSAR-derived subsidence rates offer the most promising proxy – Hooijer et al. (2012) established a linear relationship between subsidence and water table depth, and Hoyt et al. (2020) demonstrated landscape-scale mapping across 2.7 Mha of Southeast Asian peatlands at 90 m (data archived at Zenodo), though coverage is partial and the baseline (2007–2011) predates recent expansion. The current pilot treats peat intersection as a binary risk flag; incorporating thickness and drainage intensity is a priority refinement discussed in Section 3.1.2, pg 16.
- **Deforestation & Conversion Emissions:** Forest-to-plantation conversion produces a massive emission spike from **(1) biomass clearance** (all cleared carbon conservatively counted as lost) and **(2) peat drainage** oxidation. McCalmont et al. (2021) measured early conversion emissions of **137.8 Mg CO_2 ha^{-1} yr^{-1}**, dropping to **17.5 Mg CO_2 ha^{-1} yr^{-1}** at maturity. Deforestation is detected at 30 m via GLAD (Hansen et al., 2013) and Tropical Moist Forest (Vancutsem et al., 2021) products. The GHG Protocol Land Sector and Removals Standard (Requirement 10) requires LUC emissions to be allocated using linear discounting over an assessment period of 20 years or the cultivation cycle, whichever is longer – for oil palm (~25-year rotation), the crop cycle applies (GHG Protocol, 2024, p. 40). Linear discounting weights years closer to conversion more heavily, partially capturing the front-loaded flux profile. Plantation age – the key variable for positioning each supply shed within the amortization window – is mapped at 30 m by Descals et al. (2024) (RMSE 2.02 years for estates, 4.89 for smallholders).

Table 1: LUC emissions – literature benchmark alignment

Study	Risk Driver / Indicator	Key Finding on Emissions & Soil	Benchmark Alignment
Meijide et al. (2020)	Peatland extent delineation; peat-to-plantation conversion	Oil palm on peat are massive net carbon sources, with ecosystem net warming potential (GWPnet) approximately seven times larger for mature plantations on peat (GWPnet = 46.0 ± 11.5 tCO_2e ha^{-1} yr^{-1}) than for mineral soils (GWPnet = 6.9 ± 3.5 tCO_2e ha^{-1} yr^{-1}). GWPnet integrates all three GHGs (CO_2, CH_4, N_2O); CO_2 dominates the on-site budget. Confirmed that mineral plantations may also be a net carbon source when harvest export is included.	**High Alignment:** Validates the model's high emission factor applied when a supply shed intersects with peat soil.
McCalmont et al. (2021)	Plantation age; peat conversion timing	Eddy covariance measurements (net ecosystem CO_2 exchange only – not including CH_4 or N_2O) of oil palm on peatland show early conversion period emissions of 137.8 Mg CO_2 ha^{-1} $year^{-1}$, dropping to 17.5 Mg CO_2 ha^{-1} $year^{-1}$ in the mature phase. The CO_2 flux profile is strongly non-linear – front-loaded in years 1–5 post-conversion. Note: this describes the measured CO_2 flux trajectory, not the total emission liability; peat oxidation continues for as long as the peat remains drained (potentially centuries), with the mature-phase rate (17.5 Mg CO_2 ha^{-1} yr^{-1}) representing an ongoing baseline, not a cessation of emissions.	**Moderate Alignment:** The model follows GHG Protocol rules, allocating the total LUC carbon stock change over the cultivation cycle (~25 years for oil palm) using linear discounting, which weights earlier years more heavily. This partially captures the front-loaded flux profile. Plantation age is therefore a critical input.
IPCC (1997, 2000)	Drained tropical peat soil; peat under palm	Older benchmark figures are 20 tC/ha/yr for drained tropical peat soil (~73.4 tCO_2e/ha/yr) and 5 tC/ha/yr (~18.35 tCO_2e/ha/yr) for tropical peat under palm.	**High Alignment:** The 20 tC/ha/yr figure is consistent with the model's indicative LUC on peatland range of 20–80 tCO_2e/ha/yr. The 5 tC/ha/yr figure aligns closely with the measured mature-phase emission (17.5 Mg CO_2 ha^{-1} yr^{-1}) and the model's ongoing peat oxidation factor (5–15 tCO_2/ha/yr).
Carlson et al. (2015)	Drainage depth; water table drawdown	Linear relationship between water table depth and carbon loss in SE Asian plantations: ~20 tC ha^{-1} yr^{-1} at 70 cm drainage depth, with heterotrophic respiration accounting for ~82% of total soil CO_2 flux.	**High Alignment:** Quantifies the emission-rate-controlling variable (drainage depth) that the pilot's binary peat flag does not capture. Supports the priority refinement of scaling emission factors by drainage intensity.
Hooijer et al. (2012)	Peat subsidence; drainage–emission relationship	Established linear relationship between subsidence rate and water table depth in drained tropical peatlands, enabling InSAR-derived subsidence as a proxy for drainage intensity.	**High Alignment:** Provides the mechanistic link between remotely observable subsidence and the emission-controlling variable (drainage depth).
Hoyt et al. (2020)	Landscape-scale peat subsidence mapping	InSAR-derived subsidence mapped at 90 m across 2.7 Mha of SE Asian peatlands (2007–2011, ALOS PALSAR-1). Data archived at Zenodo (doi:10.5281/zenodo.3694667).	**Moderate Alignment:** Demonstrates feasibility of landscape-scale drainage intensity characterization from RS, but coverage is partial (2.7 Mha of ~25 Mha total SE Asian peatland) and baseline predates recent expansion and restoration activity.

2.1.2 Non-LUC Emissions and Cultivation Practices

Non-LUC emissions arise from ongoing management practices and soil degradation. All plantations are net carbon emitters when all ecosystem components are considered.

- **Soil Carbon Depletion:** The primary ongoing emission driver is **progressive SOC loss** – not plantation age per se, but the cumulative depletion of soil organic matter under monoculture. Rahman et al. (2018) documented a **42% drop in SOC stocks in the top 30 cm** after 29 years. Management practices (cover crops, frond stacking) can reduce SOC loss, and within-plantation variability is significant. Global baseline SOC is mapped by **OpenLandMap-soildb** (Hengl et al., 2026; 30 m, 2000–2022), but the dataset does not extend beyond 2022, so **plantation age remains the operational proxy** for SOC depletion trajectory, with Tier 2 field-measured soil cores required for calibration.

- **Estate vs. Smallholder Classification:** The estate/smallholder distinction determines non-LUC emission factor selection: estates typically apply higher fertiliser rates (Euler et al., 2017; Woittiez et al., 2017) and operate POME infrastructure; smallholders have lower input intensity but often lack effluent management. These are sector-wide generalizations – actual emissions depend on individual farm management practices, which are not observable from remote sensing; the estate/smallholder classification therefore serves as the best available proxy for emission factor stratification at scale, not as a deterministic predictor of any individual facility's emissions. The Tier 2 field validation protocol (Section 3.3, pg 27) is designed to collect actual management practice data at sampled plots to calibrate and refine these emission factor assignments. Descals et al. (2021) produced a 10 m Sentinel-2-based global classification using plot morphology rather than arbitrary size thresholds, making the second-ranked sensitivity driver directly monitorable from space. The applicability of this classification axis varies by commodity (Section 3.4, pg 31).

Table 2: Non-LUC emissions – literature benchmark alignment

Study	Risk Driver / Indicator	Key Finding on Emissions & Soil	Benchmark Alignment
Rahman et al. (2018)	SOC depletion; management practice differentiation	Significant decline in Soil Organic Carbon (SOC) stocks, with a **42% drop in SOC stocks in the top 30 cm of soil** after 29 years of cultivation compared to forest baselines. Significant within-plantation variability exists, with SOC highest in frond stacks (FS), followed by weeded circles (WC), and lowest between palms (BP).	**High Alignment:** Reinforces the necessity of the framework's planned soil respiration rate measurement for validation and highlights the importance of management practices.

2.2 Hydrology, Ecosystem Services, and Erosion

Forest-to-monoculture conversion fundamentally alters the water cycle and degrades ecosystem services – water regulation, soil fertility, aquatic biodiversity, and flood/drought buffering. These losses directly threaten the long-term productivity and resilience of the commodity system.

- **Water Scarcity & Runoff:** Merten et al. (2016) found that lower soil infiltration in oil palm landscapes produces up to **two-fold higher peak flows** and reduced groundwater recharge. Kristanto et al. (2021) reinforced the necessity of erosion potential metrics. Sabajo et al. (2017) found Land Surface Temperature (LST) increased by up to **10.1°C** between forest and clear-cut land, while Stiegler et al. (2019) confirmed that oil palm's high transpiration rate makes it prone to drought stress.
- **Planned Water Risk Assessment:** A **Standardized Water Stress Index (SWSI)** is under development – a composite metric computed from water deficit (P – ET, using ERA5 and MODIS MOD16A2), storage depletion (accounting for streamflow), and a WRI Aqueduct regional modifier, locally weighted against a 10-year baseline to capture anomalous stress. Not yet implemented for the pilot.
- **Erosion Risk and Riparian Buffers:** Riparian buffers and terracing substantially reduce erosion risk. Buffer integrity is assessable from **HydroRIVERS** stream networks (Lehner et al., 2008), the Google DeepMind / WRI 10 m canopy height map (Tolan et al., 2024), and Epoch's biomass stock change model – enabling annual monitoring of riparian vegetation conditions across all supply sheds.

Table 3: Hydrology and ecosystem services – literature benchmark alignment

Study	Risk Driver / Indicator	Key Finding on Hydrology & Ecosystem Services	Benchmark Alignment
Merten et al. (2016)	Soil infiltration; peak flow regulation	Lower soil infiltration capacities in oil palm plantations (Jambi, Sumatra) compared to forest are consistent with the observed strong decline of soil quality. This may explain the **two-fold higher relative peak flows (flash floods)** and reduced groundwater recharge.	**High Alignment:** Directly validates the Water Stress indicator's focus on soil moisture percentile and the degradation of water regulation ecosystem services.
Kristanto et al. (2021)	Erosion potential; sediment yield	High runoff associated with oil palm expansion is obvious due to low infiltration. Surface runoff is a primary driving factor for water regulation services assessments.	**High Alignment:** Reinforces the use of Sediment Yield/Erosion Potential, validating the necessity for DEM and precipitation-based metrics.
Sabajo et al. (2017)	Land Surface Temperature (LST); micro-climate regulation	Conversion of forest causes a local warming effect, with LST increasing by up to 10.1°C between forest and clear-cut land.	**High Alignment:** Confirms the link between land cover change and micro-climate stress. LST is a directly reportable indicator of ecosystem service degradation.
Stiegler et al. (2019)	Evapotranspiration anomaly; drought vulnerability	Oil palm's high photosynthetic efficiency makes it prone to water and heat stress, directly affecting photosynthesis and evapotranspiration (ET). Oil palm plantations have a strong potential to further amplify air heating during droughts.	**High Alignment:** Supports the use of ET anomaly as a key indicator to flag potential soil degradation or drainage-induced stress.

2.3 Biodiversity and Landscape Integrity

The literature supports a shift beyond canopy presence to structural integrity and landscape connectivity as the core biodiversity assessment.

- **Conservation Schemes and Primary Forest Loss:** HCS/HCV schemes lack a global dataset, reinforcing reliance on RS proxies: TMF (Vancutsem et al., 2021) and GLAD (Hansen et al., 2013) at 30 m. Fitzherbert et al. (2008) found **54-67% species richness loss** from conversion to oil palm. Gibson et al. (2011) showed that even logged forests retain irreplaceable biodiversity – complete clearance, not degradation, drives the steepest losses.
- **Landscape Connectivity:** Remnant forest patches (hillslopes, riparian corridors, forest islands) function as refugia and dispersal steppingstones. Connectivity – not just patch area – determines species persistence (Fitzherbert et al., 2008). Annual connectivity trends are derivable from the Google DeepMind / WRI forest layer (Tolan et al., 2024; 10 m) and TMF, with resistance-based connectivity modelling (McRae et al., 2008; Anantharaman et al., 2020) providing an updatable index per supply shed.
- **Riparian Buffer Integrity: Riparian reserves (≥30 m under RSPO P&C) serve as linear connectivity corridors and provide** ecosystem services. Buffer condition is monitorable via **HydroRIVERS** (Lehner et al., 2008) stream networks combined with forest cover layers and Epoch's biomass stock change model. Year-on-year change in buffer continuity index tracks restoration or degradation.

Table 4: Biodiversity and landscape integrity – literature benchmark alignment

Study	Risk Driver / Indicator	Key Finding on Biodiversity	Benchmark Alignment
Fitzherbert et al. (2008)	Species richness loss; habitat conversion irreversibility	Oil palm supports dramatically fewer species than the habitats it replaces: estimated **54-67% species richness loss** relative to primary forest.	**High Alignment:** Confirms primary forest conversion as the top-ranked biodiversity risk.
Gibson et al. (2011)	Intact forest irreplaceability; degradation vs. clearance	Even heavily logged forests retain irreplaceable biodiversity – complete clearance, not degradation, drives the steepest species losses.	**High Alignment:** Supports using primary/intact forest extent as the primary biodiversity indicator.
Pirker et al. (2016)	HCS/HCV area mapping; conservation scheme coverage	High Carbon Stock (HCS) and High Conservation Value (HCV) schemes are widely used. HCV is a local concept and no global dataset exists.	**High Alignment:** Validates the model's focus on high carbon/conservation value areas as biodiversity proxies.

3 Methodology: First-Mile Mapping, Validation, and Sensitivity

3.0 Key Definitions

The supply shed framework relies on three spatial units that nest hierarchically. Understanding their relationship is essential for interpreting the metrics and validation results that follow.

- **Facility (Mill):** The aggregation point – the physical processing facility (palm oil mill, soy crusher, cocoa fermentation unit) to which commodity is delivered and where traceability is established. Each facility is georeferenced and attributed to a parent company. In the Indonesian palm oil pilot, 1,290 mills were mapped using the TRASE dataset.
- **Supply Shed:** The geographic sourcing area of a single facility, delineated as a travel-time isochrone from the mill along the road network. For palm oil, the baseline isochrone is 90 minutes (~50 km radius), reflecting the 24–48 hour milling constraint for Fresh Fruit Bunches (FAO & Cramb, 2015). The supply shed defines the spatial boundary within which all environmental metrics are computed and attributed to that facility. Supply sheds of neighboring mills overlap in dense production regions, creating shared accountability zones. It is important to note that the supply shed is a probabilistic catchment area, not a confirmed supply chain: the isochrone identifies all plots that could deliver to a given mill based on travel-time accessibility, but does not establish that any specific plot actually does. The actual sourcing relationship depends on contractual arrangements, market prices, and producer decisions that are not observable from remote sensing. A further limitation is that the current isochrone is defined solely by travel time and does not account for mill processing capacity: a large mill (e.g., 60 t FFB/hr) draws from a wider effective sourcing radius than a small mill (e.g., 20 t/hr), even at the same travel-time threshold, because it must absorb more of the surrounding production to operate at capacity. Incorporating mill throughput into the supply shed delineation – effectively scaling the isochrone by demand – is a planned refinement discussed in Section 4.1 (pg 34). This distinction is addressed further in Section 4.1, and Tier 1 validation (Section 3.3, pg 27) includes structured sourcing-link interviews to empirically test the predicted mill-plot relationship.
- **Commodity Plot:** An individual production unit (plantation block, smallholder parcel) within the supply shed where the target commodity is cultivated. Plots are mapped at 30 m resolution from the Forest Data Partnership commodity classification layer and, for palm oil, further classified as estate or smallholder using Descals et al. (2021) 10 m Sentinel-2 imagery. All per-hectare environmental metrics (emissions, deforestation, biodiversity) are computed at the plot level and aggregated to the supply shed for facility-level reporting.

The nesting is: **plots** sit within a **supply shed**, which is attributed to a **facility**. Validation (Section 3.3, pg 27) operates at the plot level within sampled supply sheds, while reporting and ranking operate at the facility level.

Table 5: Acronyms and abbreviations

Acronym	Definition
AGB	Above-Ground Biomass
CCDC	Continuous Change Detection and Classification (multi-sensor ensemble)
CHM	Canopy Height Model
CI	Confidence Interval
CSDDD	Corporate Sustainability Due Diligence Directive (EU)
CSRD	Corporate Sustainability Reporting Directive (EU)
DBH	Diameter at Breast Height
DEM	Digital Elevation Model
ESRS	European Sustainability Reporting Standards
ET	Evapotranspiration
EUDR	EU Deforestation Regulation (2023/1115)
FDP	Forest Data Partnership
FFB	Fresh Fruit Bunches
FHD	Foliage Height Diversity
GEDI	Global Ecosystem Dynamics Investigation (NASA spaceborne lidar)
GHG	Greenhouse Gas
GLAD	Global Land Analysis and Discovery (Hansen et al., 2013)
HCS	High Carbon Stock

Acronym	Definition
HCV	High Conservation Value
InSAR	Interferometric Synthetic Aperture Radar
ISPO	Indonesian Sustainable Palm Oil
LST	Land Surface Temperature
LUC	Land Use Change
MSPO	Malaysian Sustainable Palm Oil Standard
NDPE	No Deforestation, No Peat, No Exploitation (trader policies)
NISAR	NASA-ISRO Synthetic Aperture Radar (L-band + S-band SAR satellite, launched 2024)
PAI	Plant Area Index
POME	Palm Oil Mill Effluent
RS	Remote Sensing
RSPO	Roundtable on Sustainable Palm Oil
SAR	Synthetic Aperture Radar
SBTi FLAG	Science Based Targets initiative – Forest, Land and Agriculture
SFDR	Sustainable Finance Disclosure Regulation (EU)
SOC	Soil Organic Carbon
SWSI	Standardized Water Stress Index
TMF	Tropical Moist Forest (Vancutsem et al., 2021)

The pilot study successfully linked 1,290 mills to their sourcing areas using the approach described in the *Codex Planetarius* "Palm in Paradise" supply shed analysis report (Epoch Blue, 2025). While the pilot study focused on carrying out this analysis for palm oil across the whole of Indonesia (with applicability to other commodities discussed in Section 3.4, pg 31), this Validation Framework aims to put into perspective what are the most material risk drivers for the oil palm value chain in terms of environmental impact – as revealed by the literature review – and to reconcile these indicators from most to least material, assessing where the supply shed analysis approach can support this assessment and with what level of accuracy and rigor.

3.1 Risk Driver Prioritization

3.1.1 Ranked Risk Drivers by Environmental Impact Category

The literature review and pilot study results converge on a clear hierarchy of environmental risk drivers. Ranking these drivers quantitatively is essential for defining what the monitoring system must detect with precision, what can be estimated reliably from remote sensing, and what requires on-the-ground validation. Risk drivers are ranked below within each of the three primary impact categories measured by the model.

Category 1: Greenhouse Gas Emissions ($tCO_2e\ ha^{-1}\ yr^{-1}$)

The magnitude of emissions per unit area provides the most objective basis for prioritization. The literature establishes clearly ordered emission ranges:

Rank	Risk Driver	Indicative Emission Range ($tCO_2e\ ha^{-1}\ yr^{-1}$)	Indicator	Key Source
1	LUC on peatland (deforestation + drainage)	20 - 80	Land use change emissions rate + soil organic carbon emissions rate	Meijide et al. (2020): GWPnet ~7× mineral; McCalmont et al. (2021): 137.8 in first years post-conversion, dropping to 17.5 at maturity
2	LUC on primary forest – mineral soil	5-25 (amortized over 20 years; actual flux is front-loaded in years 1-5 post-conversion, then declines as regrowth offsets decomposition)	Land use change emissions rate + plantation above-ground biomass trend	McCalmont et al. (2021); GHG Protocol Land Sector and Removals Standard 20-year linear amortization
3	SOC depletion from long-term cultivation	1-5	Soil organic carbon emissions rate	Rahman et al. (2018): 42% drop in top 30 cm after 29 years – progressive, cumulative, and only partially recoverable. Note: SOC depletion is accounted separately from LUC emissions; the LUC estimate captures above-ground biomass stock change and, on peatland, peat oxidation from drainage, while this row addresses the additional, slower SOC loss from cultivation of mineral and organic soils that continues beyond the 20-year LUC amortization window
4	Non-LUC: on-farm practices (fertilizer N_2O, mill processing, energy)	1-5	Non-LUC production emissions rate	Scales with estate vs. smallholder classification and fertilizer intensity; estate/smallholder distinction mappable from RS via Descals et al. (2021) global Sentinel-2-based plantation type map
5	AGB loss in natural patches within commodity landscape	0.5-3	Plantation and remnant forest above-ground biomass trend	Tracked via GEDI AGB time series; applies to degradation of forest remnants, riparian corridors, and hillslope patches within the supply shed – not to plantation monoculture biomass cycling, which is approximately carbon-neutral over harvest cycles

The peat-LUC interaction is the single largest emissions driver by an order of magnitude. The sensitivity analysis (Section 3.2, pg 26) confirms this quantitatively: a 20% peat misclassification rate produces a 1**6.9% classification shift**, while estate/smallholder swap produces 14.5% and travel time variation only **3.2%.**

Category 2: Biodiversity (Ecological Function & Ecosystem Services)

Unlike emissions, biodiversity impact does not reduce to a single numeric unit; ecosystem service loss is multi-dimensional. The ranking here uses a composite assessment of irreversibility, spatial extent, and ecological function affected:

Rank	Risk Driver	Ecological Function Affected	Epoch Annual Indicator (State + Trend)	RS Trend Detectability
1	Primary/intact forest cover (HCS/HCV) – annual state	Species richness, gene pool, carbon storage – condition is monitored annually; both improvement (natural regrowth) and deterioration (ongoing deforestation) are captured	Annual primary forest area per supply shed; post-2020 deforestation area percentage (net deforestation rate in year t); year-on-year change tracks whether the supply shed is improving or worsening	**High** – TMF primary forest flag + GLAD annual loss layer; deforestation trend expressed as ha yr^{-1} and updated annually
2	Landscape connectivity (patch size distribution, isolation) – annual state	Species movement, gene flow, predator-prey dynamics; connectivity can degrade with new clearing or recover with regrowth; supply shed resilience depends on the current patch configuration	Not directly computed in current pipeline; derivable annually from GLAD/TMF forest cover: patch area distribution, mean nearest-neighbor distance, and resistance-based connectivity index – all computable from annual rasters	**Partial** – patch geometry metrics fully derivable from GLAD/TMF raster stack each year; resistance-based connectivity index (McRae et al., 2008) tracks improving/worsening trend
3	Canopy structural heterogeneity (FHD/PAI) – annual state	Microhabitat diversity, pest/disease resilience; a supply shed with recovering structural complexity signals reduced monoculture vulnerability (e.g., Ganoderma, bagworm)	Canopy structural diversity score (Rao's Q entropy on foliage height diversity and plant area index), recomputed annually from GEDI; trend direction (increasing = recovering structural diversity; decreasing = homogenisation) is directly interpretable as a resilience signal	**High** – GEDI covers equatorial tropics at 25 m footprint; annual update enables trend detection over time
4	Riparian buffer integrity – annual state	Aquatic habitat, water quality, flood regulation, HCV4 connectivity; buffers can be cleared (worsening) or recover (planted/regenerated) – annual monitoring captures this dynamic	Not directly computed in current pipeline; derivable annually: HydroRIVERS drainage network (Lehner et al., 2008) + Google DeepMind / WRI natural forest layer (Tolan et al., 2024) + Epoch biomass stock change model→ buffer width and continuity index; year-on-year delta tracks restoration vs. clearance	**Medium** – HydroRIVERS stream network + 10 m forest overlay; narrow buffers (<30 m) at limit of MMU but trend detectable via multi-year time series

Two critical points: (1) the biodiversity assessment is inherently temporal – the Epoch platform recomputes indicators annually, tracking whether each supply shed is improving or deteriorating; and (2) the current canopy height heterogeneity metric cannot distinguish intact forest from fragmented patches of equivalent area – a limitation addressed by the field validation framework (Section 3.3, pg 27).

Category 3: Water & Hydrological Functioning (Runoff/Drought Contribution)

Water impacts from oil palm expansion operate at the catchment scale. The ranking reflects the directness and magnitude of the hydrological disruption:

Rank	Risk Driver	Hydrological Mechanism	Proxy Indicator	RS Detectability
1	Peatland drainage	Subsidence, fire risk, irreversible alteration of peat hydrology; drainage canals disconnect the natural water sponge	Soil organic carbon emissions rate (partial proxy for drainage status)	**Low** – InSAR subsidence baseline exists for a subset of SE Asian peatlands (Hoyt et al., 2020) but coverage is partial; drainage depth requires field measurement. NISAR (launched 2024) will improve coverage
2	Watershed-scale deforestation rate	2× higher peak flows (Merten 2016), reduced groundwater recharge, amplified flood and drought cycles	Watershed-scale annual deforestation rate (ha yr^{-1}, aggregated at catchment level)	**High** – TMF/GLAD at watershed scale
3	Evapotranspiration reduction	Reduced evaporative cooling → +10.1°C LST (Sabajo 2017); amplified drought during El Niño events (Stiegler 2019)	Water stress index (SWSI – evapotranspiration anomaly component)	**High** – ERA5 + MODIS ET at 500 m
4	Erosion/sediment yield	Surface runoff-driven soil loss → silting of waterways, reduced water quality	Not directly computed in current pipeline	**Medium** – DEM slope + deforestation overlay

Category 4: Regulatory and Compliance Risk Landscape

Regulatory compliance creates a prioritization axis that is structurally independent from the three environmental impact categories above: it is **rule-based and binary**, applied uniformly regardless of emission magnitude, ecosystem type, or soil condition. The oil palm sector currently faces an overlapping stack of mandatory and de facto mandatory compliance requirements, each with distinct market access, financial, and legal consequences. Table 6 below provides a comprehensive overview of the frameworks material to the Indonesian and Malaysian palm oil sectors, their environmental obligations, and their monitorability from remote sensing.

A key design principle of the Epoch supply shed approach relevant to all compliance frameworks is **"reporting in excess"**: the isochrone-based sourcing radius is deliberately conservative, capturing all land within travel-time reach of the mill regardless of whether individual plots are formally registered or documented. This means the supply shed probabilistically over-reports the sourcing footprint rather than under-reporting it – a high-confidence, defensible approach for due diligence purposes precisely because it excludes the risk of false negatives. Regulators and auditors can be shown that the entire possible sourcing area has been screened, not just the formally declared supply base. Operators sourcing exclusively from within a supply shed with zero flagged deforestation can demonstrate compliance conservatively and systematically, without requiring plot-level GPS records for every smallholder in the supply chain.

Table 6: Regulatory and compliance framework overview – palm oil sector

Framework	Jurisdiction	Status	Key Environmental Obligation	Consequence of Non-Compliance	Key RS-Monitorable Indicator	Epoch Supply Shed Metric
EUDR (EU Deforestation Regulation 2023/1115)	EU – applies to any operator placing palm oil (and 6 other commodities) on the EU market	**Legally binding** – enforcement for large operators: 30 Dec 2025; SMEs: 30 Jun 2026	No deforestation or forest degradation on production land post-31-Dec-2020; operator must provide geolocated plot-level due diligence statements	EU market access barred; fines up to 4% of annual EU turnover or proportional to environmental damage value; products seized and destroyed	Post-2020 deforestation – GLAD+TMF+CCDC ensemble; multi-method agreement flag. The supply shed probabilistic sourcing radius provides the due diligence boundary: screening the entire isochrone at 30 m resolution is the "reporting in excess" approach most defensible under EUDR Article 9 (due diligence obligations)	Post-2020 deforestation area (% of supply shed)
UK FRCDD (Forest Risk Commodity Due Diligence – Environment Act 2021, s.27)	United Kingdom	**Legally binding** – secondary legislation in development; large operators targeted first	Due diligence that forest-risk commodities (incl. palm oil) produced legally with respect to local forest law	Fines up to £250,000 per violation; public naming of non-compliant businesses	Deforestation detection (GLAD/TMF); legal concession boundary compliance	Post-2020 deforestation area (% of supply shed)
ISPO (Indonesian Sustainable Palm Oil, Perpres 44/2020)	Indonesia	**Mandatory** for all Indonesian palm oil estates, mills, and smallholders	Legal land title; no conversion of HCV areas or peat regardless of depth; environmental management plan; traceability to mill	Loss of export license; ineligibility for state bank financing; exclusion from supply chains of ISPO-requiring buyers	Peat extent (Miettinen et al., 2016) + deforestation detection; drainage canal density (Park et al., 2020)	Soil organic carbon emissions rate (peat proxy) + post-2020 deforestation area (%)
MSPO (Malaysian Sustainable Palm Oil Standard, mandatory since 2020)	Malaysia	**Mandatory** for all Malaysian palm oil producers	Legal compliance; no deforestation of HCV; riparian buffer maintenance; no new peat development	Loss of MSPO certificate; exclusion from markets requiring certified sustainable palm oil (EU, retail chains)	Deforestation detection; riparian buffer integrity (HydroRIVERS + DeepMind/WRI forest layer)	Post-2020 deforestation area (%) + riparian buffer index

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Table 6 (continued): Regulatory and compliance framework overview – palm oil sector

Framework	Jurisdiction	Status	Key Environmental Obligation	Consequence of Non-Compliance	Key RS-Monitorable Indicator	Epoch Supply Shed Metric
Indonesian Primary Forest & Peatland Moratorium (Presidential Instruction 6/2019 and predecessors)	Indonesia	**Legally binding** – applies to primary forest and peatlands in the Indicative Map of Primary Forest and Concessions (PIPPIB)	No new concession issuance or conversion of primary forest and peatland areas; restoration obligations in priority peat hydrological units (KHG)	Regulatory action; concession revocation; criminal liability	Primary forest layer (TMF/Vancutsem et al., 2021); peat extent (Miettinen et al., 2016); drainage canal detection for restoration compliance	Post-2020 deforestation area (%) + peat drainage canal density
RSPO P&C 2018 (Roundtable on Sustainable Palm Oil, 2018 Principles & Criteria)	Global	**Voluntary** but de facto mandatory for access to EU, UK, US, and major Asian retail markets; increasingly required by financial institutions	No new development on HCV or HCS areas; no development on peat regardless of depth; mandatory riparian buffers; full supply chain traceability; no burning	Suspension or revocation of RSPO certificate; delistment from certified supply chains; loss of RSPO premium price	HCS/HCV: TMF primary forest + GLAD; peat drainage canals (Park et al., 2020); riparian buffer continuity (HydroRIVERS + DeepMind/WRI forest layer)	Post-2020 deforestation area (%) + riparian buffer index + peat drainage metric
NDPE Policies (No Deforestation, No Peat, No Exploitation – Wilmar, Cargill, ADM, Golden Agri-Resources, Musim Mas, et al.)	Global – major commodity traders and refiners	**Trader-level commitments**, legally binding in trader contracts; covers the majority of globally traded palm oil volumes	No sourcing from areas with post-cutoff deforestation or peat development; traceability to mill (and increasingly to plantation) required	Delistment from trader/ refiner supply chains; immediate suspension of sourcing contracts – effectively a market ban for unlisted suppliers	Deforestation detection (GLAD/TMF, High); peat drainage canal density (Park et al., 2020, Medium)	Post-2020 deforestation area (%) + peat drainage proxy
CSRD + ESRS (EU Corporate Sustainability Reporting Directive 2022/2464 + European Sustainability Reporting Standards)	EU – applies to large companies and their supply chains	**Legally binding** for large EU companies from FY2024; extends to non-EU companies supplying EU markets	Mandatory disclosure of material nature-related impacts and dependencies; deforestation, biodiversity, and land-use change must be reported under ESRS E4 (biodiversity) and E1 (climate)	Regulatory fines; investor divestment; ESG rating downgrades; cost of capital increases. Under the **EU Sustainable Finance Disclosure Regulation (SFDR)**, Article 8 products that promote environmental or social characteristics require underlying supply chain data on deforestation and land-use impacts – creating a direct demand signal from asset managers for supply-shed-level metrics	RS-derived metrics (deforestation rate, LUC emissions, water stress, biodiversity score) directly feed ESRS-compliant disclosures and SFDR Article 8/9 product reporting	All supply shed indicators feed CSRD/ ESRS/SFDR disclosure package

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Table 6 (continued): Regulatory and compliance framework overview – palm oil sector

Framework	Jurisdiction	Status	Key Environmental Obligation	Consequence of Non-Compliance	Key RS-Monitorable Indicator	Epoch Supply Shed Metric
CSDDD (EU Corporate Sustainability Due Diligence Directive 2024/1760, as amended by the EU Omnibus Simplification Package)	EU – applies to companies >5,000 employees and >€1.5B net worldwide turnover (or >€1.5B EU turnover for non-EU companies), including their upstream supply chains	**Legally binding** – transposition by Member States by 2026; phased application from 2027. The EU Omnibus narrowed the scope by raising applicability thresholds from the original >1,000 employees/ >€450M turnover	Mandatory supply chain due diligence on environmental and human rights impacts; includes deforestation, biodiversity loss, climate impacts	Fines up to 5% of global net turnover; civil liability for damages	Supply shed deforestation and biodiversity metrics support CSDDD-required supply chain risk assessment	All supply shed indicators support CSDDD audit trail
SBTi FLAG (Science Based Targets initiative – Forest, Land and Agriculture guidance, 2022)	Global – investor- and lender-required for companies with FLAG sector exposure	**Voluntary** but effectively mandatory for companies seeking climate-aligned finance; endorsed by TCFD, TNFD, GFANZ	No-deforestation targets aligned with 1.5°C pathways; absolute emissions reduction targets for land sector; FLAG emissions must be reported separately	Ineligibility for green finance instruments; breach of lender sustainability-linked loan covenants; SBTi label revocation	Annual deforestation rate (GLAD/TMF); LUC emissions time series; total GHG emissions rate trend	Land use change emissions rate; total GHG emissions rate; post-2020 deforestation area (%) – all tracked as annual trends

These frameworks have **different cutoff dates, geographic scope, and definitional thresholds** – a facility can be compliant with one while in breach of another. The most consequential divergence: EUDR uses a post-31-Dec-2020 cutoff while RSPO/NDPE typically use 2013–2016 HCS cutoffs. The Epoch framework tracks deforestation at annual resolution from 1990 to present, enabling simultaneous compliance assessment under multiple cutoff dates.

A facility can rank in the bottom 5% on regulatory compliance while acceptable on environmental impact, or vice versa. Both axes are required: the sensitivity analysis (Section 3.2, pg 26) runs on both GHG emissions rate (environmental) and post-2020 deforestation area (compliance) as co-equal outputs.

3.1.2 Remote Sensing Monitoring Feasibility Assessment

The value of the Epoch supply shed approach lies precisely in its ability to monitor the highest-impact risk drivers systematically and at scale using satellite and airborne data. Table 7 below provides a comprehensive assessment of monitoring feasibility for each identified risk driver.

Impact tier methodology: The impact rating is a composite across three axes: (1) GHG emissions magnitude, (2) ecosystem service loss, and (3) supply chain resilience. Drivers scoring high across multiple axes compound to a higher tier – the Critical tier is reserved for drivers where impacts co-occur across GHG, ecosystem, and supply chain dimensions.

Table 7: Risk driver × monitoring feasibility matrix

Risk Driver	Impact Tier	RS/Global Data Available?	Key Dataset(s)	Confidence Level	Limiting Factor
LUC on primary forest	Critical	High	Pre-2017: GLAD GLCLU2020 land cover transitions (30 m) + IPCC conversion factors. Post-2017: GEDI L4A annual AGB stock change (25 m) + biome root:shoot ratios for BGB. SOC tracked separately via OpenLandMap (30 m, 2015–2022)	High	Plot boundary precision; cloud cover
LUC on peatland	Critical	Partial	PEATGRIDS peat thickness + C-stock (Widyastuti et al., 2025; 1 km) + GLAD/ TMF deforestation	Medium	PEATGRIDS provides continuous peat thickness (cm) and carbon stock (Mg C m^{-2}) at 1 km with uncertainty bands, enabling differentiation of deep vs. shallow deposits, but resolution is coarse relative to plot boundaries. Current pilot uses binary peat intersection only; scaling by thickness is a planned refinement
Peatland drainage status	Critical	Low	Hoyt et al. (2020) InSAR subsidence baseline (ALOS PALSAR-1, 90 m, 2007-2011, 2.7 Mha coverage; Zenodo); NISAR (L-band, launched 2024) will enable updated wider-coverage baseline	Low	Existing subsidence baseline covers a subset of SE Asian peatlands and predates recent expansion/restoration. Drainage depth (water table drawdown) – the emission-rate-controlling variable – requires Tier 2 field measurement (piezometer transects) for calibration
Primary forest conversion (biodiversity)0)	Critical	High	TMF primary forest layer, AGB magnitude	High	Species-level data absent
Biogenic AGB degradation	High	High	GEDI AGB annual time series (2017-2025)	Medium-High	Cloud cover in equatorial belt; GEDI coverage gaps
EUDR compliance (binary)	High	High	GLAD + TMF + CCDC deforestation ensemble	High	Access to legal concession/HGU boundaries
Landscape connectivity	High	Partial	Derivable from deforestation patch geometry; resistance-based connectivity modelling (McRae et al., 2008; Anantharaman et al., 2020)	Low-Medium	Requires dedicated landscape metrics computation

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Table 7 (continued): Risk driver × monitoring feasibility matrix

Risk Driver	Impact Tier	RS/Global Data Available?	Key Dataset(s)	Confidence Level	Limiting Factor
Canopy heterogeneity (FHD/PAI)	High	High	GEDI foliage height diversity + plant area index bands	Medium-High	GEDI coverage; cloud gaps
Riparian buffer integrity	High	Medium	HydroRIVERS stream network (Lehner et al., 2008) + Google DeepMind / WRI natural forest layer (Tolan et al., 2024) + Epoch biomass stock change model	Medium	Narrow buffers (<30 m) below minimum mapping unit of 10 m forest layer
SOC depletion	High	Medium	Open Land Map – soildb (Hengl et al., 2026; 30 m, 2000–2022; SOC at depth intervals 0–15, 15–30, 30–60, 60–100, 100–200 cm. Framework uses 0–30 cm for mineral soil SOC depletion per Rahman et al. (2018); peat SOC loss is accounted separately via the peat oxidation EF (Table 9)) + plantation age proxy for post-2022 trajectory	Medium	Annual data ends 2022; plantation age is operational monitoring proxy beyond that
Non-LUC emissions	Medium	Partial	Emission factor lookup; Descals et al. (2021) estate/smallholder classification (Sentinel-2, 10 m)	Medium	Sub-farm practice data not observable; classification uncertainty
Water stress / drought (SWSI)	High†	High	SWSI: ERA5 P + MOD16A2 ET (Mu et al., 2011)→ water deficit; streamflow Q→ storage depletion; WRI Aqueduct groundwater modifier	Medium	Streamflow Q data latency; groundwater trends coarse at sub-watershed scale
Erosion / sediment yield	Medium	Medium	Copernicus GLO-30 DEM slope + HydroRIVERS drainage network (Lehner et al., 2008)	Medium	Not computed in the current pipeline; requires additional pipeline step

† Water stress is rated High under the composite methodology: while its direct GHG contribution is low in Indonesia's high-rainfall palm oil regions (where drained peatlands account for ~92% of the sector's GHG budget; ICCT, 2016), it scores High on both ecosystem services (watershed deregulation, downstream flooding, freshwater habitat loss) and supply chain resilience (drought-induced water and heat stress materially reduce FFB yield and oil content, a direct business continuity risk). The stacking of these two High-scoring axes warrants a High composite rating. In water-stressed geographies – Cerrado soy, Ethiopian coffee, Central Asian cotton – all three axes would score High or Critical, making this driver Critical in those contexts.

Key insight: The highest-impact drivers are predominantly detectable from existing RS datasets. **The critical uncertainty lies in classification accuracy for two inputs:** (1) the peat soil layer (PEATGRIDS, 1 km – coarse relative to plot boundaries), and (2) the estate/smallholder classification (Descals et al., 2021, 10 m – uncertain in mosaic landscapes). These are precisely the top two sensitivity analysis findings (Section 3.2, pg 26).

Figure 1: Each risk driver is plotted by composite impact tier (y-axis: GHG emissions + ecosystem service loss + supply chain resilience, stacked) and RS monitoring confidence (x-axis). Pie colors indicate which metric domains a driver affects – split colors denote multi-domain drivers whose impacts compound. Dashed rings = not yet computed in the current pipeline. Quadrant upper-right = high impact, high observability ("Monitor Now"); upper-left = high impact, low observability ("Field Validation Priority" – the target of Section 3.3, pg 27); lower-right = monitorable at low incremental cost; lower-left = deprioritized.

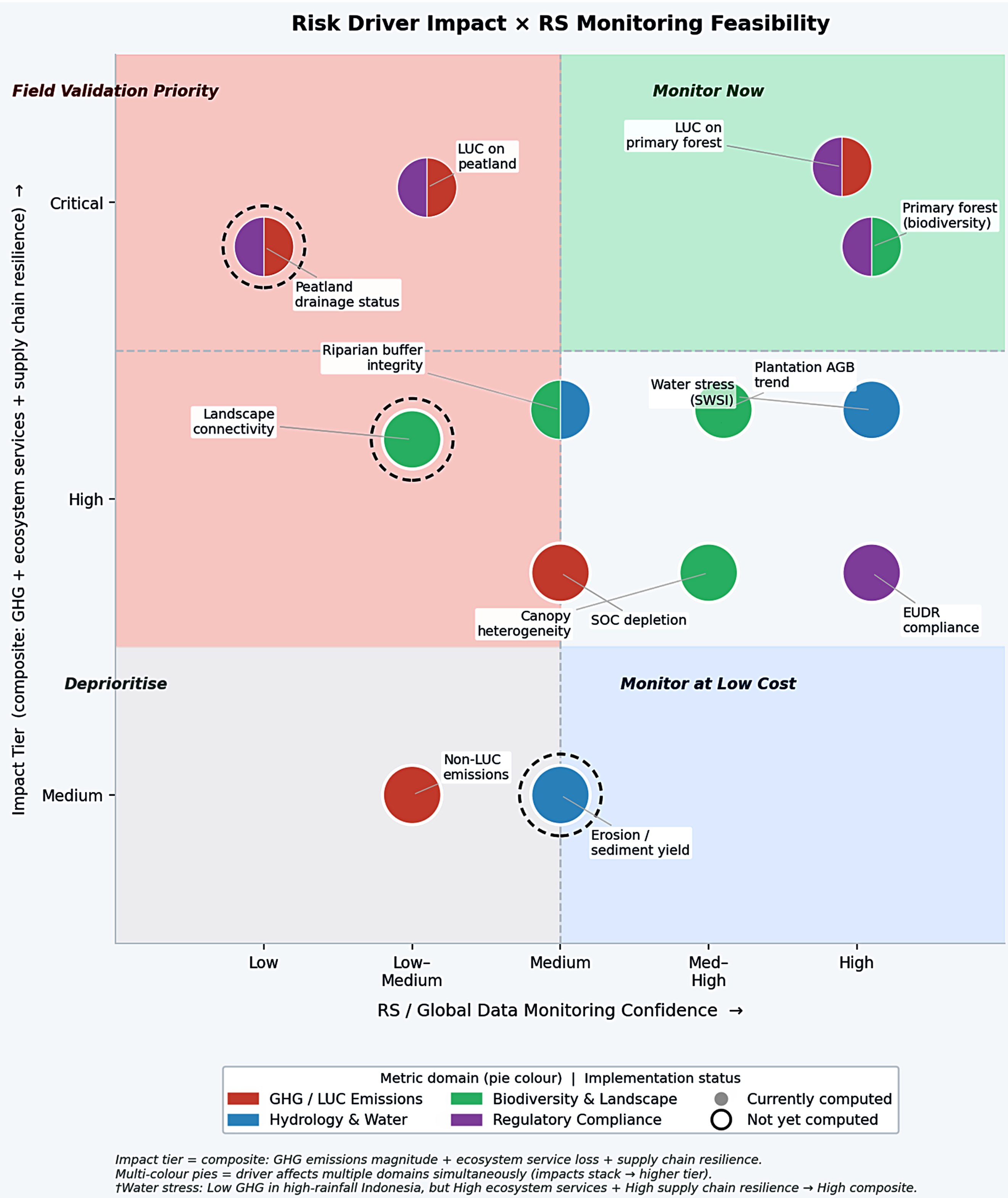
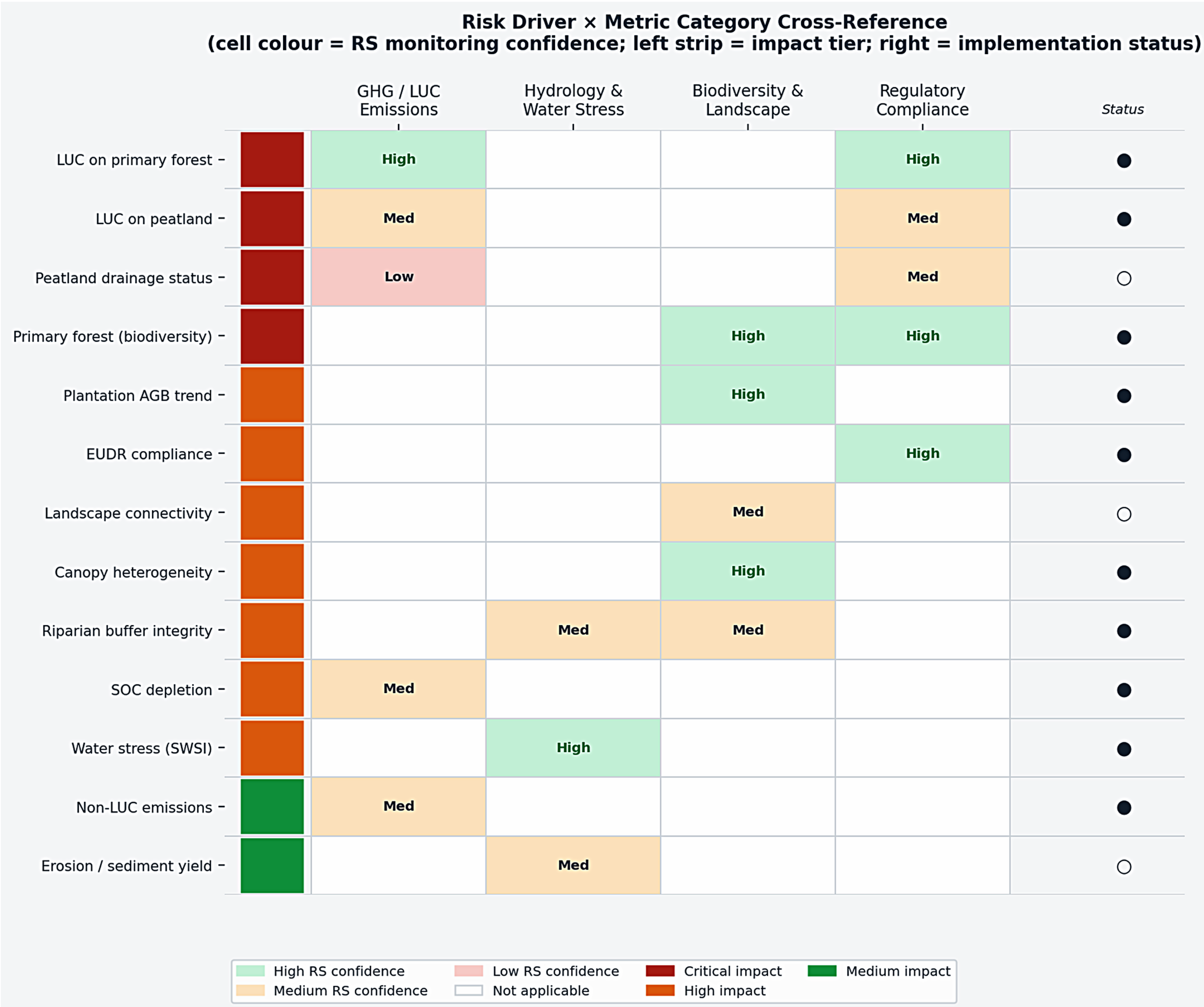


Figure 2: Cell color indicates RS monitoring confidence for each risk driver–domain combination (green = High, amber = Medium, red = Low). Left strip = impact tier (red = Critical, orange = High, green = Medium). Right column = implementation status (filled circle = computed; open circle = not yet computed).



3.1.3 Annual Indicator Set: Named, Attributed, and Computable

Table 8 below defines the **normative annual indicator set** – the minimum set of metrics that any supply shed analysis conforming to the *Codex Planetarius* standard should produce for every screened facility on an annual basis. This is the ideal monitoring target, independent of what was computed in the pilot study. The current pipeline implements the majority of these indicators; those not yet operational are flagged in Table 7 (pg 16) and represent the near-term development roadmap. The indicators are attributed to a named mill and its parent company, transforming landscape-level environmental statistics into company-specific, auditable performance data that can be compared across the entire sector on a like-for-like basis.

Table 8: Annual indicator set – *Codex Planetarius* palm oil monitoring

Category	Indicator	Definition	Unit	Reporting Frequency	Remote Sensing Source	Data Quality Standard (from Section 3.3, pg 27)
LUC Emissions	LUC Emissions Rate	Net land-use change emissions per hectare of commodity area within the supply shed	$tCO_2e\ ha^{-1}\ yr^{-1}$	Annual	GLAD+TMF+CCDC deforestation ensemble + GEDI above-ground biomass	**Tier 2:** field AGB inventory, 95% CI per TSC-BioCR (5% estates, 10% smallholders)
Non-LUC Emissions	Non-LUC Production Emissions	Ongoing production emissions (fertilizer, POME, machinery) scaled by estate/ smallholder emission factor	$tCO_2e\ ha^{-1}\ yr^{-1}$	Annual	Emission factor lookup (region and system type)	**Tier 1:** tenure/size field verification, ≥80% classification accuracy
Total Emissions	Total GHG Emissions Rate	Sum of LUC + non-LUC + SOC emissions, net of carbon removals, per hectare. Biogenic AGB cycling is excluded: within mature plantation systems, above-ground biomass turnover is approximately carbon-neutral over multi-year cycles under GHG Protocol accounting, and is tracked separately as a plantation condition indicator	$tCO_2e\ ha^{-1}\ yr^{-1}$	Annual	Composite of above	Composite of above
Regulatory Compliance	Post-2020 Deforestation Area	Percentage of commodity area with detected deforestation after 31 December 2020 (EUDR reference date)	%	Annual	GLAD + TMF deforestation ensemble	**Tier 1:** reference site visits for disputed plots, binary confirmation
Biodiversity	Canopy Structural Diversity	Canopy height heterogeneity index across the supply shed (Rao's Q entropy from foliage height diversity and plant area index)	0–1	Annual	GEDI foliage height diversity + plant area index bands	**Tier 2:** forest structure inventory (basal area, species richness)
Biodiversity	Mean Canopy Height	Mean canopy height across commodity area within the supply shed	m	Annual	GEDI canopy height model	**Tier 2:** field canopy height measurement

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Table 8 (continued): Annual Indicator Set – *Codex Planetarius* palm oil monitoring

Category	Indicator	Definition	Unit	Reporting Frequency	Remote Sensing Source	Data Quality Standard (from Section 3.3, pg 27)
Biodiversity	Remnant Vegetation AGB Trend	Net year-on-year change in above-ground biomass stock within natural patches, riparian corridors, and hillslope forest remnants inside the supply shed (excluding commodity monoculture, which cycles approximately carbon-neutral over harvest rotations): a landscape degradation and recovery signal	$tCO_2e\ ha^{-1}\ yr^{-1}$	Annual	GEDI AGB annual time series (2017–present) + Google DeepMind / WRI natural forest mask to isolate non-commodity vegetation	**Tier 2:** vegetation transect at sampled remnant forest plots
Water Stress	Water Stress Index	Standardized Water Stress Index (SWSI): water deficit (P − ET), storage depletion (P − ET − Q), and regional groundwater modifier (WRI Aqueduct)	0–1	Annual	ERA5 precipitation + MODIS ET + WRI Aqueduct groundwater	**Tier 2:** soil moisture probes at ≥3 locations, 90% confidence interval
GHG Intensity	Emissions Intensity	Total GHG emissions per tonne of commodity produced	$tCO_2e\ tonne^{-1}$	Annual	Composite emissions + reported mill production volume	Annual production data from mill operator

These indicators constitute a proposal for a **minimum normative monitoring package** for *Codex Planetarius*. They are designed to be: (a) fully computable from satellite and global datasets without in-situ data; (b) updateable annually as new satellite observations become available; (c) validated at scale through the sampling framework in Section 3.3, pg 27; and (d) attributed to the named mill as the accountable economic actor. The emissions intensity indicator is the critical crosswalk to financial disclosure frameworks (TCFD, TNFD, SBTi FLAG) that normalize environmental impact by production volume. Note that watershed-scale deforestation – useful as a landscape health context indicator – is derivable from the same GLAD/TMF datasets used for the LUC emissions and EUDR compliance indicators, requiring no additional data collection.

3.1.4 Emission Factors and Known Gaps

The supply shed environmental metrics depend on emission factors (EFs) that translate remotely sensed land cover and classification inputs into quantitative GHG estimates. Understanding the EF structure – and where it relies on assumed rather than measured values – is essential context for interpreting the sensitivity analysis (Section 3.2, pg 26) and the validation protocol (Section 3.3, pg 27).

LUC Emission Factors

LUC emissions are computed as the difference in carbon stock between the pre-conversion land cover (primarily forest) and the post-conversion commodity system (oil palm), amortized linearly over 20 years per the GHG Protocol Land Sector and Removals Standard (2026).

The primary input is above-ground biomass (AGB) at conversion, derived from the GEDI L4A footprint-level AGB product and aggregated to supply shed scale. For deforestation events detected during the GEDI operational period (2019–present), the AGB value at or near thew time of conversion is used directly. For historical events (pre-2019), the approach uses GEDI-derived AGB measurements of comparable intact forest within the same supply shed as a proxy for the pre-conversion stock, on the assumption that forest in the same landscape and soil type would have had similar biomass density prior to clearance. This is a reasonable approximation for recent decades but becomes less precise for older conversion events where the surrounding forest may itself have been degraded. For the Indonesian palm oil pilot, forest AGB values range from approximately 100 to 250 Mg/ha depending on forest type and degradation state.

Where a plot overlaps with peat soils (PEATGRIDS, 1 km), an additional peat SOC premium is applied reflecting the aerobic decomposition of exposed peat. The premium is derived from the difference in carbon stock between tropical peat (approximately 600 tC/ha) and mineral soil (approximately 80 tC/ha), amortized over 20 years with C-to-CO_2 conversion

(×44/12), yielding approximately 95.3 tCO_2e/ha/yr at full peat depth. This is weighted by the actual peat area fraction within each supply shed. In the Palm in Paradise pilot, PEATGRIDS raster values were intersected with all 1,290 supply shed geometries and applied as a peat adjustment factor to the GHG ranking. The sensitivity analysis (Scenario 1) quantifies the impact of misclassification error in this layer.

A regional LUC modifier of ±13–14% is applied based on regional forest type and peat presence, reflecting the higher biomass density of peat swamp forests relative to lowland dipterocarp forests on mineral soils.

Non-LUC Emission Factors

Non-LUC emissions represent ongoing production-phase GHG sources that are not directly observable from satellite imagery. They are assigned via a lookup table structured by production system type (estate vs. smallholder) and region.

The largest non-LUC component is fertilizer-derived N_2O. Synthetic nitrogen application rates differ substantially between production systems. Estate plantations in Indonesia typically apply 150–260 kg N/ha/yr (Corley & Tinker, 2016; estate survey data report 230–260 kg N/ha/yr as common practice). Independent smallholders show much wider variability: Woittiez et al. (2017) surveyed over 300 smallholders across Sumatra and Kalimantan and found a mean of 166 kg N/ha/yr, but with large regional variation, from 40–75 kg N/ha/yr for plasma smallholders in Riau to rates matching estates in Sintang. Many independent smallholders apply no synthetic fertilizer at all (Euler et al., 2017). N_2O emission factors currently follow IPCC Tier 1 defaults (1% of applied N emitted as N_2O-N, with a GWP_{100} of 265), though the 2019 IPCC Refinement provides a higher disaggregated factor for wet tropical climates (see EF Source Table below). The estate/smallholder differential in fertilizer intensity is the largest single component of the non-LUC EF gap.

Palm Oil Mill Effluent (POME) is the second major non-LUC source. Anaerobic decomposition of POME produces CH_4. Estates with captive mills typically have POME treatment infrastructure, reducing emissions by 50–80%, while smallholder fruit sold to third-party mills may or may not benefit from methane capture at the receiving mill. The EF is assigned at the mill level based on known infrastructure, but coverage is incomplete.

Fuel and energy emissions from harvesting, transport, and processing machinery are a smaller component. Estate operations typically have higher mechanization and energy use per hectare but also higher energy efficiency per tonne of product. Default values are drawn from RSPO GHG calculators and Indonesian national inventory submissions.

Carbon removals from above-ground biomass accumulation in maturing palms are tracked annually from the GEDI time series and credited against gross emissions. Within mature plantation systems (>8 years), AGB turnover is approximately carbon-neutral over multi-year harvest cycles, so the net removal credit is primarily relevant for young replanted stands.

SOC Depletion Factors

SOC loss under continuous cultivation is modelled as a time-dependent depletion curve, with plantation age (derived from Descals et al., 2024 planting year maps) serving as the proxy for cumulative soil carbon loss. The baseline SOC stock is taken from OpenLandMap-soildb (30 m, Hengl et al., 2026) for the pre-conversion state, and a progressive depletion trajectory is calibrated against the Rahman et al. (2018) finding of approximately 42% SOC loss in the top 30 cm after 29 years of cultivation. This trajectory is the least empirically constrained component of the emission factor structure; the sensitivity analysis (Section 3.2, pg 26) treats progressive SOC refinement as a high-priority structural improvement.

Emission Factor Source Table and Critical Assessment

The following table documents the specific EF values, their sources, and an assessment of whether they represent best-available practice.

Table 9: Emission Factor Source Assessment. The framework's total tCO_2e is the sum of: LUC biomass and SOC stock change (CO_2), peat oxidation (CO_2), fertilizer N_2O, and POME CH_4 – each computed via separate emission factor components (Table 9 below). Individual components are CO_2-only; full three-gas coverage is achieved through the composite total.

Component	EF Value (tCO_2e/ha/yr unless noted)	Source	Assessment	Notes
LUC – AGB loss at conversion	18–46 tCO_2e/ha/yr (amortized over 20 years from 100–250 Mg/ha forest AGB, ×0.47 C fraction, ×3.67 CO_2 conversion)	GEDI L4A footprint-level AGB (Dubayah et al., 2022); GHG Protocol 20-year amortization	Best-in-class. GEDI is the only spaceborne lidar providing direct AGB measurements at pantropical scale.	Spatial coverage gaps near the equator due to ISS orbit; gap-filled with Sentinel-2/ALOS-2 fusion where needed.
LUC – Peat SOC loss at conversion	~95 tCO_2e/ha/yr (amortized; from the differential between tropical peat ~600 tC/ha and mineral soil ~80 tC/ha, ×3.67, over 20 years)	PEATGRIDS (Widyastuti et al., 2025); IPCC Wetlands Supplement (2013)	Partially. PEATGRIDS is the best available global product but at 1 km resolution is coarse relative to supply shed boundaries. Peat C stock values are IPCC defaults, not site-specific.	Regional products (Miettinen et al., 2016, 30 m for SE Asia) offer better spatial precision. Site-specific peat depth measurements during Tier 1 would improve accuracy.
LUC – Amortization	20-year linear	GHG Protocol Land Sector and Removals Standard (2026)	Best-in-class. This is the normative standard for corporate GHG accounting.	Conservative: underestimates early-period flux, overestimates mature-phase flux (see Section 2.1.1, pg 3). Plantation age from Descals et al. (2024) positions each shed within the amortization window.
Fertilizer N_2O	Currently applied: 1% of N input as N_2O-N (GWP_{100} = 265), yielding 0.4–0.9 tCO_2e/ha/yr for estates, 0.1–0.3 for smallholders	IPCC 2006 Tier 1 default	Not best-in-class. The 2019 IPCC Refinement disaggregated EF1 by climate and fertilizer type: 1.6% for synthetic fertilizer in wet tropical climates (95% CI 1.3–1.9%), vs. 0.5% in dry climates (Hergoualc'h et al., 2022). Indonesian palm oil falls in the wet tropical category, meaning the 1% default underestimates N_2O by approximately 60%. **External benchmarking confirms this:** the Hestia platform (hestia.earth) aggregated Indonesian oil palm emission data (2010–2025) applies the 1.6% EF and reports 0.89 tCO_2eq/ha/yr from inorganic fertilizer N_2O at 141 kg N/ha – compared to 0.60 tCO_2eq/ha/yr under the 1% default for the same application rate (Hestia, 2025).	Field-measured N_2O flux from Indonesian oil palm (Oktarita et al., 2017) reported 2.4–2.7% of applied N, suggesting the true emission may be 2–3× the current default.
Fertilizer application rate	Estates: 150–260 kg N/ha/yr; Smallholders: 40–166 kg N/ha/yr (highly variable)	Corley & Tinker (2016); Woittiez et al. (2017); Euler et al. (2017)	Partially. Estate rates well-documented through RSPO reporting (230–260 kg N/ha/yr common). Smallholder rates poorly constrained: regional variation from 40–75 kg N/ha/yr (Riau plasma) to rates matching estates (Sintang). Many independent smallholders apply no synthetic fertilizer.	Second-highest sensitivity driver (14.5% classification shift). Tier 1 management practice interviews would improve this.
POME CH_4	0.6–2.0 tCO_2e/t FFB (varies by treatment)	RSPO PalmGHG Calculator v4; Stichnothe & Schuchardt (2011)	Acceptable. PalmGHG is the industry standard but methane capture status is incompletely mapped. Field measurements report ~12.4 kg CH_4 per tonne POME from open ponds (Yacob et al., 2006). POME contributes approximately 66.5% of total mill-level emissions (Franco et al., 2013).	Mills with biogas capture reduce POME emissions by 50–80%. Capturing methane at Indonesia's ~850 mills could abate ~41 Mt CO_2e/yr.

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Table 9 (continued): Emission Factor Source Assessment. The framework's total tCO_2e is the sum of: LUC biomass and SOC stock change (CO_2), peat oxidation (CO_2), fertiliser N_2O, and POME CH_4 – each computed via separate emission factor components (Table 9). Individual components are CO_2-only; full three-gas coverage is achieved through the composite total.

Component	EF Value (tCO_2/ha/yr unless noted)	Source	Assessment	Notes
Fuel and machinery	0.3–0.8 tCO_2e/ha/yr	RSPO PalmGHG Calculator; national energy statistics	Acceptable but low-impact. Fuel emissions are a small fraction of total supply shed GHG profile (<5%).	Low sensitivity; not a validation priority.
SOC depletion (mineral soils)	~1.4% of top-30-cm SOC lost per year (~42% cumulative over 29 years)	Rahman et al. (2018)	Limited evidence base. Single-site study (Sarawak, Malaysia). Depletion rates vary with soil type, drainage, management, and climate.	Additional field studies needed. OpenLandMap-soildb (30 m, Hengl et al., 2026) provides spatial SOC baseline but not temporal trajectory.
Peat oxidation (ongoing)	5–15 tCO_2/ha/yr (drainage-dependent)	IPCC Wetlands Supplement (2013); Hooijer et al. (2012)	Partially. IPCC default range is well-established for drained tropical peat, but actual rate depends on water table depth, not directly observable from space.	Drainage canal density (Open Research Question 2) would enable continuous rather than binary EF assignment.
Carbon removals (palm AGB accumulation)	2–8 tCO_2e/ha/yr (age-dependent)	GEDI annual AGB time series; Corley & Tinker (2016)	Best-in-class for the RS component. Allometric models well-established for oil palm.	Net credit is small relative to LUC and peat emissions. Primarily relevant for young replanted stands.
Allometric equations (AGB from DBH)	Species-specific pantropical models	Chave et al. (2014)	Best-in-class. Standard pantropical allometric reference used by GEDI, national forest inventories, and REDD+ MRV globally.	Local calibration during Tier 2 AGB inventory improves accuracy for specific forest types.

LUC emission factors are anchored in best-available datasets (GEDI, PEATGRIDS, GHG Protocol). The non-LUC factors are the weakest link: the N_2O fertilizer EF uses the 1% IPCC Tier 1 default when the 2019 Refinement provides 1.6% for wet tropical climates – a ~60% underestimate. Cross-referencing against the Hestia platform (hestia.earth) – an open-access harmonized database of agricultural environmental impacts aggregating LCA data across commodities and geographies (Hestia, 2025) – confirms alignment across all major EF components: Hestia's aggregated Indonesian oil palm profile (2010–2025, recalculated using IPCC 2019 methods) reports a total GWP_{100} of 52.3 tCO_2eq/ha/yr at 21.6 t FFB/ha yield, with LUC (AGB + BGB) at 32.9 tCO_2/ha/yr (within the report's 18–46 range), peat oxidation at 17.2 tCO_2/ha/yr (national average across all soil types), fertilizer N_2O at 0.89 tCO_2eq/ha/yr using the 1.6% EF, and fuel + inputs at 0.64 tCO_2/ha/yr – all within or consistent with the ranges documented in Table 9. Crucially, Hestia independently applies the 2019 IPCC Refinement N_2O EF (1.6%) rather than the 1% Tier 1 default, providing external validation that the current pipeline should adopt this higher factor.

Known Gaps and Limitations

The emission factor structure has several acknowledged limitations that the validation framework is designed to address.

Table 10: Known gaps and limitations in the emission factor structure

Gap	Impact	Mitigation
Non-LUC EFs are assigned by production system type, not measured per facility	Facilities with atypical management (e.g., a smallholder cooperative with high fertilizer use) are mischaracterized	Tier 1 field verification of management practices; Tier 2 measurement where resources allow
POME methane capture status is incompletely mapped	Mills with methane capture receive the same default EF as those without. The TRASE/Universal Mill List dataset records mill locations and parent companies but does not include POME treatment infrastructure attributes; RSPO PalmGHG submissions contain this data but cover only ~19% of global production	Mill-level infrastructure survey during Tier 1 visits; potential for RS-based detection of covered vs. open settling ponds from high-resolution imagery
SOC depletion trajectory assumes a single curve for all soil types	Mineral soils, shallow peats, and deep peats have different depletion dynamics	Tier 2 soil characterization; separate EF curves by soil class once field data supports it
Smallholder emission profiles are poorly constrained by literature	The estate/smallholder EF differential is partly assumed from RSPO defaults	Open Research Question 1 (Section 6, pg 36); systematic cross-system measurement campaigns; Hestia database benchmarking
Carbon removal credits assume standard allometric relationships	Actual biomass accumulation varies by cultivar, planting density, and management	Tier 2 AGB inventory provides direct calibration data
EFs are currently palm-specific	Extension to other commodities requires new EF structures (e.g., enteric CH_4 for cattle, shade-tree C stocks for coffee)	Commodity-specific EF development as part of the generalization roadmap (Section 3.4, pg 31)

This emission factor structure is deliberately conservative: where field data is unavailable, the framework uses IPCC Tier 1 defaults and documented literature values rather than proprietary or unverifiable assumptions. The sensitivity analysis (Section 3.2, pg 26) quantifies which EF components have the greatest impact on facility rankings, directing validation effort to where measurement would most improve the framework's credibility.

3.2 Sensitivity Analysis & Risk Driver Prioritization

The Sensitivity Analysis aims to isolate which model inputs are the "key levers" driving a high-risk (bottom 5%) classification. The analysis is conducted by computationally isolating and modifying one variable at a time on the current dataset, measuring its impact on a facility's classification.

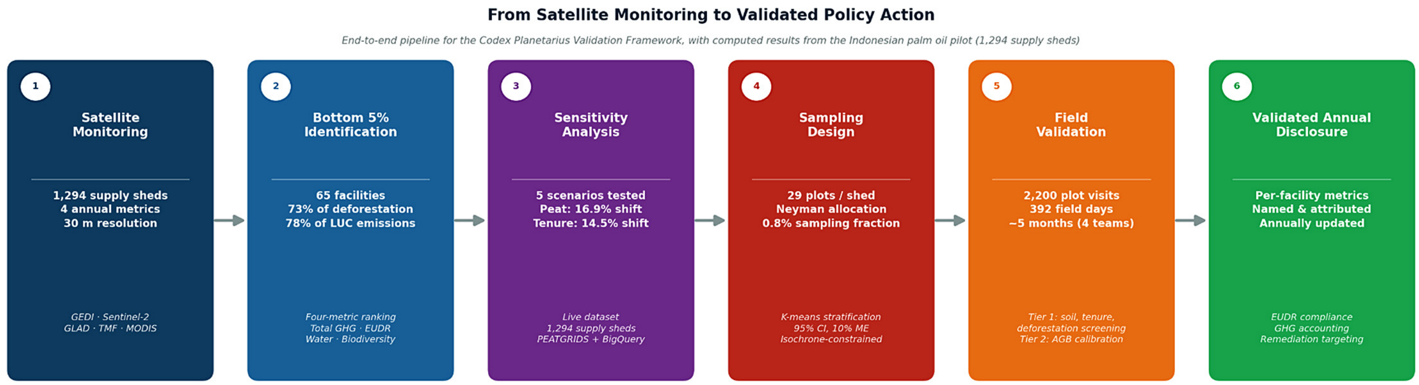
A risk classification sensitive to uncertain data layers is not a defensible basis for policy action until that uncertainty is bounded. The sensitivity analysis identifies which inputs most determine the bottom-5% outcome, directing validation effort where it is most consequential.

The model stores separate per-metric outputs, so the "bottom 5%" is defined independently on four parallel axes: (1) **Total GHG Emissions Rate** (LUC + non-LUC + SOC − removals, per hectare); (2) **Post-2020 Deforestation Area** (% of commodity area, EUDR compliance); (3) **Water Stress Index** (SWSI, 0–1); and (4) **Canopy Structural Diversity** (Rao's Q entropy, 0–1). A facility in the bottom 5% on any metric warrants validation. Scenarios 1, 2, 4, and 5 are executable from the existing dataset; Scenario 3 requires re-running the isochrone computation.

Table 11: Sensitivity analysis results – ranked input variables by impact on bottom 5% classification

Rank	Risk Driver / Input Variable	Scenario Tested	Impact on "Bottom 5%" Classification	Validation Priority
1	**Peat Map Sensitivity**	Simulate peat SOC operationalization using PEATGRIDS (Widyastuti et al., 2025; 1 km): peat ~600 tC/ha vs. mineral ~80 tC/ha ~95.3 tCO_2e/ha/yr premium. Three sub-scenarios: (1a) full premium weighted by actual peat area fraction per supply shed (avg ~29.8 tCO_2e/ha/yr); (1b) 20% peat misclassification; (1c) all peat reclassified as mineral.	**16.9% classification shift** (S1a vs S1b delta). Of 1,290 supply sheds, 1,170 have some peat overlap (median peat area fraction 21.4%, mean 29.9%). The high count reflects the 1 km raster coarseness – many have only marginal overlap. **Peat map accuracy is the structurally highest-impact driver.**	**Highest Priority.** Validation standard: ≥80% peat/mineral binary classification accuracy.
2	**Estate vs. Smallholder Classification**	Swap estate ↔ smallholder for all facilities; re-apply LUC (±14%), non-LUC (±19%), and SOC (±15%) emission factors. Classification from Descals et al. (2021) Sentinel-2 10 m.	**14.5% classification shift.** 9 of 62 bottom-5% facilities change classification. Tenure propagates through the entire EF structure. **Largest immediately executable scenario.**	**Highest Priority (executable now).** GPS-logged plot observations + structured interviews. Standard: ≥80% accuracy.
3	**Travel Time Sensitivity**	Supply shed delineation at 60 min (~40 km) and 120 min (~80 km) vs. 90-min baseline. Area scales with t^2.	**3.2% classification shift** at both variants. Only 2 of 62 bottom-5% facilities change. The worst emitters are high-emitters at their core — ranking is determined by conditions near the mill, not at the periphery.	**Moderate Priority.** Road network quality verification in high-risk supply sheds.
4	**Plot Boundary Fuzziness**	Apply −50 m, −10 m, +10 m, +50 m buffers to all plot boundaries.	**0% classification change** across all buffer sizes. Plot boundary uncertainty at ±50 m is non-material at supply-shed scale.	**Low Priority.** No dedicated validation required.
5	**Deforestation Detection Agreement**	Re-compute using only plots where ≥2 methods agree (GLAD, TMF, Dynamic World), discounting single-method detections.	**36.8% multi-method agreement globally.** Emission ranking: **35.5% shift** (single-method noise is material). EUDR compliance ranking: **0% shift** (worst deforesters consistently detected by all methods). Policy implication: use **union** of methods for EUDR compliance (maximize sensitivity) and **intersection** (≥2 methods) for GHG accounting (maximize accuracy).	**High Priority.** Ground-truth the 63.2% single-method-only fraction via high-resolution imagery review and field visits.

Figure 3: End-to-end pipeline from satellite monitoring to validated policy action, with computed results from the Indonesian palm oil pilot (1,290 supply sheds). Each stage feeds the next: satellite data produces environmental metrics for all supply sheds; bottom-5% identification concentrates attention on the 65 facilities linked to the majority of deforestation and emissions; sensitivity analysis quantifies which input variables most affect the classification; sampling design computes the field effort required (29 plots per supply shed via Neyman allocation); field validation confirms or refutes the classification over a 5-month campaign; and the validated metrics are published as an annually updated, facility-level disclosure and disclosed against the relevant geographical and jurisdictional regulations and voluntary standards.



3.3 Validation Framework: Standards & Calibration Strategy

The final framework synthesizes the findings from Sections 3.1 (pg 10) and 3.2 (pg 26) into a rulebook for validation. The framework is deliberately **method-agnostic:** it specifies required data quality standards rather than prescribed hardware, ensuring durability as technology evolves. Any field protocol – whether manual peat probe surveys today or drone-based hyperspectral mapping tomorrow – is accepted as long as it can statistically demonstrate it meets the established quality thresholds.

3.3.1 Performance-Based Method Specifications

Each risk driver requiring field validation is assigned a quantitative Data Quality Standard derived directly from the Sensitivity Analysis in Section 3.2 (pg 26). The standard specifies: (a) the required precision level, (b) the corresponding field indicator to measure, and (c) the validation tier. **Tier 1 (Screening Validation)** verifies the categorical inputs that drive the bottom-5% classification – binary classifications (peat/mineral, estate/smallholder) and supply shed linkage – using rapid, low-cost field methods (interviews, GPS observations, visual assessments). **Tier 2 (Field Validation)** verifies the continuous metric values (AGB magnitude, water stress level, biodiversity score) against field-measured equivalents at a subset of confirmed high-risk sites, providing calibration relationships between remote sensing indicators and ground truth. All field protocols are designed for scalability: lightweight, requiring no specialist laboratory equipment, and completable within 1–2 field days per supply shed.

Table 12: Performance-based method specifications

Risk Driver to Validate	Validation Standard (Required Precision)	Corresponding Field Indicator	Validation Tier
Peat Soil Type & Drainage	**≥80% accuracy** in peat vs. mineral binary classification at supply-shed scale (consistent with state-of-the-art tropical peatland maps; Miettinen et al., 2016)	GPS-logged soil observations at ≥5 locations per supply shed: peat auger/probe for soil type confirmation (fibric/hemic/sapric vs. mineral), peat depth measurement, and visual assessment of drainage indicators (canal presence, subsidence cracks, water table height relative to ground surface). No lab analysis required.	**Tier 1** (screening)
Estate vs. Smallholder Classification	**≥80% accuracy** in binary tenure classification (consistent with RS-derived land cover classification benchmarks; Descals et al., 2021 report 85% producer accuracy for Sentinel-2 smallholder/industrial classification)	GPS-logged plot boundary observations; structured interview with plantation manager or cooperative head on tenure status and management regime. Classification follows Descals et al. (2021) morphological criteria (plot size distribution, spatial regularity) rather than arbitrary fixed area thresholds.	**Tier 1** (screening)
Supply Shed Boundary / Sourcing Link	**≥80% accuracy** in predicted vs. actual sourcing link (proportion of sampled farmers confirmed to sell to predicted mill)	Structured interview with plantation managers and smallholders: "Do you sell to [mill name]?" Cross-referenced with road network completeness check at supply shed boundary.	**Tier 1** (screening)
LUC Emissions (AGB loss factor)	Field-verified AGB must align with remote sensing estimates within a **95% confidence interval** using stratified random sampling (per TSC-BioCR methodology: 5% margin for estates, 10% for smallholders at 95% CI)	Lightweight vegetation inventory at sampled plots: DBH and height measurements for all trees ≥10 cm DBH within 35×35 m plots. AGB calculated via pantropical allometric equations (Chave et al., 2014). Results compared to GEDI-derived AGB at coincident locations.	**Tier 2** (field validation)
Water Stress Index	Satellite-derived water stress indicators must be **directionally consistent** with ground-observable conditions (qualitative agreement, not point-value match)	Rapid visual stream health assessment using the USDA-NRCS Stream Visual Assessment Protocol (SVAP) – a 15-element visual scoring checklist of instream and riparian conditions completable in under 30 minutes per stream crossing with no specialist equipment (NRCS, 1998). Supplemented by visual observation of plantation water table indicators: canal water level, peat subsidence cracks, and oil palm frond condition (stress visible as yellowing and spear leaf closure). Optional single spot-check soil moisture reading for calibration.	**Tier 2** (field validation)
Biodiversity / Canopy Structure	Field-derived canopy structural metrics must show **directional agreement** with GEDI-derived FHD/PAI (qualitative ranking consistency rather than point-value precision)	Smartphone hemispherical photography: upward-facing fisheye images at ≥5 fixed points per supply shed provide leaf area index and canopy openness proxies – completable in under 1 minute per point using freely available apps (Bianchi et al., 2017). Visual rapid assessment of understory density, frond stacking status, under-canopy vegetation cover, and agroforestry presence using a structured observation checklist along a 100 m transect (<30 min). Riparian buffer continuity assessed visually at ≥2 stream crossings: buffer width, canopy continuity, and bank vegetation condition scored on a 4-point scale per RSPO HCV rapid assessment guidance.	**Tier 2** (field validation)
Deforestation Detection (Multi-Method Agreement)	**≤20% false-positive rate** among single-method deforestation detections in mosaic/edge landscapes (the 36.8% multi-method agreement rate in the current dataset, with 63.2% single-method-only, means the majority of flagged deforestation requires ground-truthing confirmation; however, the 0% EUDR ranking change confirms that the worst deforesters are consistently identified)	High-resolution imagery review (Planet/Sentinel-2 time series) at a stratified sample of single-method-flagged plots, supplemented by field visit confirmation at accessible sites. Binary assessment: deforestation confirmed (yes/no) per plot.	**Tier 1** (screening)

3.3.2 Two-Tiered Strategic Sampling & Alignment Plan

The framework defines two distinct phases for field validation to maximize cost-effectiveness. The order is not arbitrary: Tier 1 is always executed first, because its output (confirmation of the highest-leverage inputs) determines the exact focus and intensity of Tier 2 effort.

Tier 1: Screening Validation (Triage)

Objective: Verify if the model's "triage" is accurate – do the high-risk facilities identified remotely actually correlate with poor performance on the ground? This tier specifically validates the three highest-leverage input variables identified by the sensitivity analysis: soil type (Scenario 1), estate/smallholder classification (Scenario 2), and deforestation detection agreement (Scenario 5).

Method: Epoch's Optimized Sampling Design (Epoch Blue, 2025) is used to generate a statistically rigorous field visit plan. The design works as follows:

1. **Stratification:** The landscape within the supply shed is stratified into K-means clusters using the remote sensing covariates most correlated with the target variables: (a) the PEATGRIDS peat probability raster (Widyastuti et al., 2025) and OpenLandMap-soildb SOC density (Hengl et al., 2026) for soil type stratification, and (b) the commodity plot size distribution and regional palm concession map (for estate/smallholder stratification). This reduces within-stratum variance and maximizes the efficiency of sampling by concentrating observations in landscape zones of highest uncertainty.
2. **Sample Size Calculation (Neyman Allocation):** The required number of field visits is computed using the generalized Neyman Allocation formula:

$$\textbf{Total sample size:} \quad n = \frac{N \cdot t_{\mathrm{VAL}}^2 \left(\sum_i w_i s_i\right)^2}{N \cdot E^2 + t_{\mathrm{VAL}}^2 \sum_i w_i s_i^2}$$

$$\textbf{Per-stratum allocation:} \quad n_i = n \times \frac{w_i S_i}{\sum_i w_i S_i}$$

Where N = total number of commodity plots in the supply shed, t_VAL = 1.96 (95% confidence interval), E = margin of error (10% for AGB field validation per GHG Protocol guidelines), w_i = stratum area weight (stratum area / total area), and s_i = standard deviation of the target variable within stratum i. The per-stratum allocation then distributes the total sample optimally: n_i = n × (w_i s_i) / (Σ w_i s_i), concentrating samples in high-variance strata where additional observations contribute most to precision.

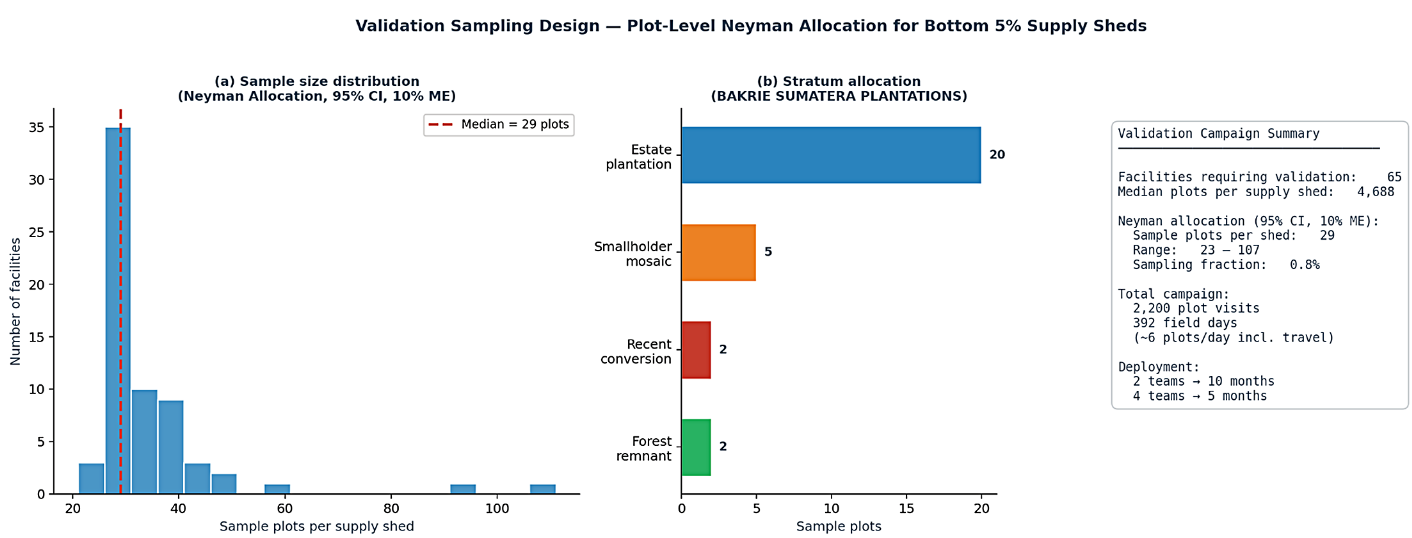
1. **Logistical Constraints:** Sampling locations are constrained to fall within 60-minute travel time from the mill using Dijkstra's least-cost routing on the Overture road network, matching the isochrone algorithm used for supply shed delineation. If a selected location is inaccessible, the field team can move to an alternative location within the same stratum, maintaining statistical integrity while accommodating field realities.
2. **Computed sampling design for the 65 bottom-5% supply sheds.** Applying the Neyman Allocation at plot level across all 65 bottom-5% facilities (using real commodity areas, plot counts, and composition from the live dataset), with K-means stratification into 3–4 strata per supply shed (estate plantation, smallholder mosaic, recent conversion, forest remnant), the computed sample sizes are (Table 13, next page):

Table 13: Computed sampling design for bottom-5% supply sheds

Parameter	Value
Facilities requiring validation	65
Median commodity plots per supply shed	4,688 (range 590–11,571)
Median sample plots per supply shed (Neyman)	29 (range 23–107)
Sampling fraction	0.8% of total plots
Field days per supply shed (~6 plots/day incl. travel)	5 (range 4–18)
Total campaign: sample plots	2,200
Total campaign: field days	392
Deployment with 2 parallel teams	~10 months
Deployment with 4 parallel teams	~5 months

For a representative facility (Bakrie Sumatera Plantations, 130,281 ha commodity area, 5,849 plots), the Neyman allocation produces: estate plantation stratum (113,626 ha, 5,102 plots) → 20 samples; smallholder mosaic (16,656 ha, 748 plots) → 5 samples; recent conversion and forest remnant → 2 samples each. Total: 29 plot visits over 5 field days, validating AGB at 95% CI with 10% margin of error. The sampling fraction is 0.5% of the total plot population, demonstrating that the stratification-based approach reduces field burden by an order of magnitude compared to simple random sampling while maintaining statistical rigor.

Figure 4: Plot-level Neyman Allocation results for the 65 bottom-5% supply sheds. (a) Distribution of per-facility sample sizes, with median of 29 plots. (b) Per-stratum allocation for a representative facility, showing how the Neyman weighting concentrates samples in high-variance strata (estate plantation, smallholder mosaic). (c) Campaign summary.



Key field protocol (no specialist equipment, 1–2 days per supply shed):

- **Mill link verification:** Structured interview – "Do you sell to [mill name]?" – GPS-logged.
- **Soil type verification:** GPS-logged observations at ≥5 locations: visual soil assessment, peat probe depth, drainage indicators (canal presence, subsidence cracks, water table height). No lab analysis.
- **Plot classification verification:** GPS-logged plot boundary observations; tenure confirmed via interview (land certificate, management regime).
- **Deforestation detection verification:** High-resolution imagery review (Planet NICFI, Sentinel-2) of single-method-flagged plots; field confirmation where accessible.
- **Biodiversity rapid assessment:** 100 m walking transect, smartphone canopy photos at 5 points, riparian buffer scored at ≥2 stream crossings.

Outcome: Statistical confirmation or refutation of bottom-5% classification. Where inputs are inaccurate, metrics are recalculated with field-verified data.

Tier 2: Field Validation (Ground-Truth)

Objective: Ensure that the quantitative metrics (LUC emission magnitudes, water stress levels, biodiversity scores) are actually capable of validating the specific, continuous risk drivers identified by the remote model. This tier is executed at a subset of Tier 1 sites – prioritizing locations where Tier 1 confirmed the classification AND where the model indicates unusually high metric values that warrant independent verification.

Method: Quantitative measurements at validated high-risk sites:

- **AGB inventory (35×35 m plots):** All trees ≥10 cm DBH measured; AGB via Chave et al. (2014) allometry; compared to GEDI at coincident locations. Per TSC-BioCR: 5% margin estates, 10% smallholders at 95% CI.
- **Soil characterization:** Hand-feel texture + moisture probe at ≥3 locations; peat probe where applicable. Lab SOC cores reserved for calibration subset.
- **Water stress:** SVAP visual stream health assessment; canal water levels and subsidence cracks as drainage proxies.
- **Biodiversity/structure:** Clinometer canopy height at ≥5 points; 100 m understorey transect; hemispherical canopy photos; riparian buffer width at stream crossings.

Outcome: Calibration relationships between RS indicators and field-measured equivalents – the data needed to move from "screening tool" to "credible performance standard."

3.4 Generalizability to Other Commodities

A critical question for the *Codex Planetarius* initiative is whether the validation framework developed for Indonesian palm oil represents a one-off, highly context-specific methodology, or the foundation for a universal first-mile monitoring standard. The answer is nuanced but fundamentally optimistic: **the core framework is highly generalizable, with commodity-specific adaptation effort being low to medium for the dominant soft commodity groups.**

The four-step lifecycle – (1) Identify aggregation facilities, (2) Derive supply sheds, (3) Identify commodity production areas, (4) Produce environmental metrics – requires different levels of adaptation for each commodity. Table 14 (next page) provides a systematic scorecard.

Table 14: Commodity Generalizability Scorecard

Framework Component	Palm Oil (Indonesia)	Soy (Brazil)	Cocoa (Ghana/ Côte d'Ivoire)	Rubber (Thailand/ Myanmar)	Coffee (Colombia/ Ethiopia)	Cattle (Brazil)	Timber / Wood Products
Facility identification	Green: Trase dataset available	Green: Grain silos/ crushers (TRASE)	Green: Cooperative/ export facilities	Amber: Processing factories	Amber: Wet mills	Amber: Slaughterhouses	Amber: Sawmills / pulp mills (Global Forest Watch concession registry)
Supply shed delineation	Green: 90-min isochrone (~50 km radius; FFB must be milled within 24–48h, FAO & Cramb, 2015)	Green: 120-min isochrone (~80 km)	Green: 90-min isochrone (~50 km; smallholders within ~22 km, Mighty Earth, 2020)	Green: 120-min isochrone (~80 km)	Green: 120-min isochrone (~80 km)	Amber: 180-min isochrone (~120 km; slaughterhouse buying zones 153–360 km, Imazon, 2017)	Red: Concession boundary replaces isochrone (legal harvest area, not travel-time catchment); economic haulage distance 60–100 km on unpaved logging roads
Commodity area mapping	Green: FDP models (30 m)	Green: GLAD soy planted area (Song et al. 2021)	Green: FDP cocoa models	Green: FDP rubber models	Green: FDP coffee models	Green: Global Pasture Watch GGC-30m (Parente et al., 2024) – 30 m cultivated/natural pasture classification, global coverage, already integrated in the Epoch pipeline	Amber: Plantation forests: Shimizu et al. (2025) 30 m tropical plantation map (arXiv 2602.17372) for Latin America; JRC Global Forest Cover forest types for managed forest globally; jurisdictional forest tenure and ownership maps for concession boundaries
Deforestation & degradation detection (EUDR)	Green: No change	Green: No change	Green: No change	Green: No change	Green: No change	Green: No change	Amber: EUDR covers both deforestation and forest degradation (Article 2(6)); selective logging must be distinguished from natural disturbance. Epoch's biomass stock change model detects degradation as AGB loss below a clearance threshold, complementing the GLAD/TMF deforestation ensemble
LUC emissions framework	Green: Verified	Green: Biome map replaces peat map as key lever (Cerrado vs. Amazon)	Green: Forest carbon stocks dominant lever	Green: Similar to palm (peat overlap in Kalimantan)	Amber: Shade-grown coffee under agroforestry retains substantial canopy cover – the LUC emission factor must account for partial rather than complete biomass loss, as shade coffee systems maintain 30–60% of original forest AGB (Tscharntke et al., 2011)	Amber: Methane (enteric) adds non-LUC component not observable from space; LUC framework for pasture conversion applies directly	Amber: Selective logging degradation emissions quantifiable via Epoch's biomass stock change model (AGB loss without complete canopy removal); conversion from natural forest to plantation is standard LUC. Long-rotation managed forests have different SOC dynamics than annual/perennial crops

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Table 14 (continued): Commodity Generalizability Scorecard

Framework Component	Palm Oil (Indonesia)	Soy (Brazil)	Cocoa (Ghana/ Côte d'Ivoire)	Rubber (Thailand/ Myanmar)	Coffee (Colombia/ Ethiopia)	Cattle (Brazil)	Timber / Wood Products
Biodiversity metric	● CHM/FHD works	▲ Cerrado/ savanna needs different structural metric	● Forest-based CHM metric applies	● Similar to palm	● Shade-grown coffee: high CHM relevant	▲ Grassland biodiversity not captured by CHM	● CHM/FHD directly applicable to logged vs. intact forest comparison
Water stress metric	● Verified	● No change needed	● No change needed	● No change needed	● No change needed	● No change needed	● No change needed
Sensitivity analysis leverage	● Peat map (#1), Estate/ Smallholder (#2)	● Biome map (#1), Deforestation baseline (#2)	● Forest baseline map (#1)	● Similar to palm (peat overlap in Kalimantan)	● Shade-grown vs. full-sun classification (#1) – determines whether partial or full AGB loss factor is applied	● Methane factors (#1), land use baseline (#2)	● Degradation vs. deforestation threshold (#1), Concession boundary accuracy (#2)
Ease of fit to palm oil model	**Baseline**	**High**	**High**	**High**	**Medium-High**	**Low-Medium**	**Low-Medium**

Legend: ● = direct transfer, no modification needed; ▲ = parameter or data source adaptation required; ● = significant new method development needed; ● = moderate adaptation, partially analogous to palm baseline.

Key generalizable components (transfer without modification): Supply shed delineation algorithm (travel time parameter is commodity-specific: palm 90 min, cocoa 90 min, soy/rubber/coffee 120 min, cattle/timber 180 min – reflecting documented commodity-specific logistics constraints); Deforestation and degradation detection methodology (GLAD + TMF + Epoch biomass stock change ensemble applies universally; EUDR covers both deforestation and degradation under Article 2(6)); LUC emissions framework structure (only emission factor JSON changes per commodity/region); EUDR compliance check (universal, post-31-Dec-2020 cutoff applies globally); Optimized Sampling Design methodology (K-means stratification + Neyman allocation transfers directly); Two-tiered validation strategy (Tier 1 screening + Tier 2 field validation)

Supply shed geometry varies by commodity perishability: palm 90 min (~50 km), soy/rubber/coffee 120 min (~80 km), cattle 180 min (~120 km, Imazon, 2017). Larger supply sheds dilute per-hectare metrics more, meaning the travel-time sensitivity (Scenario 3) would produce different magnitudes of shift per commodity.

Commodity-specific adaptation: **Soy (Brazil):** Biome map (Amazon vs. Cerrado) replaces peat map as the dominant sensitivity lever. **Cocoa (West Africa):** Primary adaptation is cooperative-level facility identification in fragmented smallholder systems. **Coffee (Colombia/Ethiopia):** Shade-grown agroforestry retains 30–60% of forest AGB (Tscharntke et al., 2011), requiring a partial biomass loss factor. Misclassifying shade-grown as full-sun would substantially overestimate LUC emissions. **Cattle (Brazil):** Most significant adaptation – enteric methane (not RS-observable) requires dedicated EF development. Supply shed geometry is much larger (180-min isochrone).

Cross-commodity emission factor benchmarking via Hestia. The Hestia platform (hestia.earth) – an open-access, harmonized database of agricultural environmental impacts developed by the University of Oxford's Martin School – provides aggregated LCA profiles for the top 15 most-produced crops across major producing countries, including several EUDR-relevant commodities (oil palm, soy, cocoa, coffee, and cattle products). All data are harmonized to a common schema and glossary, with gap-filling and recalculation using IPCC 2019 Refinement methods applied systematically (Hestia, 2025). As demonstrated in this report's palm oil benchmarking (Section 3.1.4, pg 21; Table 9, pg 23), Hestia's aggregated profiles can serve as independent cross-checks on the emission factors used within the supply shed framework – identifying where Tier 1 defaults diverge from best-available science (e.g., the N_2O EF gap) and confirming where current factors are well-calibrated (e.g., LUC, fuel + inputs). This benchmarking approach is directly transferable: as the framework extends to soy, cocoa, coffee, and cattle, Hestia's corresponding country-level aggregations can provide the same independent EF validation without requiring primary data collection. A caveat on data quality: Hestia's strength lies in its methodological harmonization and use of peer-reviewed source data, but aggregated profiles reflect national averages weighted by production volume (via FAOSTAT), not site-specific measurements. They are best suited as plausibility checks and gap-identification tools rather than as ground-truth calibration targets. Site-level field validation (Section 3.3, pg 27) remains essential for Tier 2 accuracy.

4 Operationalizing for Equity: The 1% Fund and Smallholders

A core objective of the *Codex Planetarius* initiative is to avoid the exclusion of smallholders from global commodity markets. The framework is designed to ensure that bottom-5% classification drives remediation and support, not market exclusion.

4.1 Addressing Smallholder Exclusion

- **RS-Based Classification (Not Arbitrary Size Thresholds):** The estate/smallholder distinction uses Descals et al. (2021) – 10 m Sentinel-2-based morphological classification rather than arbitrary area thresholds. The Sensitivity Analysis confirmed this as the highest-impact immediately executable variable (14.5% classification shift). Whether the assumed EF differential between estates and smallholders is empirically well-supported remains an open question – literature on Indonesian smallholder emission profiles is limited (Euler et al., 2017; Vermeulen & Goad, 2006), and Tier 2 field data should test this assumption.
- **Inclusion via Aggregation:** By mapping the Supply Shed rather than the individual farm, liability is shared by the **Mill/ Aggregator.** This forces large commercial mills to take responsibility for the environmental performance of their smallholder supply base, incentivizing them to distribute remediation support (e.g., for re-wetting drained peatlands or re-establishing riparian buffers) rather than cutting smallholders off.
- **Overlapping Supply Sheds and Metric Allocation:** In dense production regions (e.g., Riau, Jambi), multiple mill supply sheds overlap spatially – meaning the same commodity plots may fall within the sourcing area of several mills simultaneously. This overlap has different implications depending on the type of metric being reported.

Per-hectare intensity metrics (tCO_2e/ha/yr, deforestation rate %, biodiversity score) are overlap-immune: a plot's environmental performance is intrinsic and does not inflate when reported against multiple mills. These are the primary reporting unit.

Absolute metrics (total ha deforested, total tCO_2e) require allocation to avoid double-counting. The planned approach is probability-based plot-level disaggregation, where each plot is assigned a sourcing probability to each competing mill based on: (1) inverse travel time weighting; (2) mill processing capacity (larger mills exert greater "pull"); and (3) road connectivity quality. Probabilities normalize to 1.0, ensuring full allocation without inflation. This is not yet implemented – the pilot reports per-hectare metrics only. Tier 1 sourcing-link interviews (Section 3.3, pg 27) will calibrate these probability weights empirically.

4.2 The 1% Fund

The **1% Fund** is a proposed *Codex Planetarius* financial mechanism, first articulated by Jason Clay at WWF, that would channel a fraction of commodity trade value into targeted environmental restoration at the worst-performing supply sheds. The concept proposes a 1% environmental fee on the declared price of globally traded food commodities, internalizing environmental externalities that are currently absent from commodity pricing. The mechanism is not yet operational – it is in the proof-of-concept phase alongside the broader *Codex Planetarius* initiative – but it illustrates how the supply shed framework could be coupled with a remediation funding structure. The mechanism follows a "remediation-first" approach, consistent with the *Codex Planetarius* principle that producers in the bottom tier should receive support for improvement rather than market exclusion:

Table 15: 1% Fund mechanism

Mechanism	Description
Targeted Disbursement	The Supply Shed methodology identifies the "Bottom 5%" of producers (worst performers) on each metric. The fund is channeled specifically to validated high-risk supply sheds.
Actionable Support	Capital is directed towards specific interventions that address the validated risk drivers: financing peatland re-wetting and canal blocking, supporting riparian buffer restoration, providing inputs for intensification to reduce expansion pressure, enabling smallholder capacity building for improved management practices, and potentially buy-out compensation for lands taken out of production where restoration requires permanent land-use change.

The two-tiered validation framework is directly coupled to fund eligibility: **only supply sheds that complete Tier 1 validation and receive a confirmed high-risk classification** are eligible for remediation fund allocation. This ensures the fund is deployed where it will have the highest impact, and that the allocation decision is based on field-verified evidence, not just model output.

5 Conclusion

The "Palm in Paradise" pilot study established a single, decisive fact: **the bottom 5% of facilities are linked to over 73% of post-2020 deforestation and nearly 78% of total LUC emissions.** This concentration of environmental damage in a small tail of the supply chain is both the problem and the opportunity – it means that targeted intervention at fewer than 65 mills out of 1,290 can address the majority of the sector's deforestation and climate impact.

This Validation Framework converts that opportunity into a deployable, defensible standard through four contributions:

1. **Quantified sensitivity analysis** across five scenarios on the live 1,290-supply-shed dataset – identifying peat classification (16.9% shift) and estate/smallholder tenure (14.5% shift) as the highest-impact drivers, while confirming travel time (3.2%) and plot boundaries (0%) as secondary. Deforestation multi-method agreement (36.8%) supports a dual detection framework: union for EUDR compliance, intersection for GHG accounting.

2. **A lightweight, scalable validation protocol**: GPS observations, structured interviews, smartphone canopy photography – no lab analysis or specialist equipment. Two tiers: Tier 1 screens categorical inputs; Tier 2 calibrates continuous metrics.

3. **A commodity-generalizable architecture** that transfers to soy, cocoa, rubber, and coffee with low adaptation. Cattle and timber require more development.

4. **An equity-preserving design** attributing performance to the mill/aggregator, not the individual smallholder.

Path forward: Immediate: Tier 1 tenure validation for the 65 bottom-5% facilities – 2,200 plot visits, ~5 months with 4 teams. Near-term: SOC refinement with higher-resolution peat data; extension to soy (Brazil) and cocoa (West Africa). Structural: Annual monitoring and disclosure cycle – four-metric ranking updated from satellite data, validated, and attributed to named facilities.

The scientific foundations are sound for LUC factors (best-available global datasets) but weaker for non-LUC factors (IPCC Tier 1 defaults). The validation protocol is designed to close this gap. Open questions (Section 6, pg 36) concern EF empirical validation, continuous RS proxies to replace binary classifications, and whether the monitoring system can credibly track improvement over time.

6 Open Research Questions

The following questions surfaced directly from the issues identified in this report – the sensitivity analysis results, the emission factor gaps documented in Section 3.1.4 (pg 21), and the commodity generalization challenges in Section 3.4. (pg 31) They are ordered by urgency: the first three address structural weaknesses that limit the framework's credibility today; the remaining two address challenges that become material as the framework scales beyond the palm oil pilot.

1. **How well do production-system emission factor differentials hold up against field measurements?** The non-LUC emission factors – identified in Section 3.1.4 as the weakest link in the emission factor structure – rely on IPCC Tier 1 defaults and RSPO calculator assumptions that do not capture facility-level management variation. The estate/smallholder differential is the second-highest sensitivity driver (14.5% classification shift), yet direct field measurements of smallholder emission profiles are limited (Euler et al., 2017; Vermeulen & Goad, 2006). This is not palm-specific: soy EFs differ between mechanized Cerrado operations and smaller Amazonian clearings; cocoa emissions depend on full-sun vs. shade-grown management; cattle emissions vary dramatically between feedlot and extensive pasture. Systematic cross-commodity measurement campaigns comparing emission profiles across production systems would ground-truth the EF structures that drive facility rankings – and determine whether the current Tier 1 defaults are conservative, optimistic, or simply wrong.

2. **Can remotely sensed proxies replace binary geospatial classifications for the highest-impact inputs?** The sensitivity analysis identified peat map accuracy as the structurally highest-impact driver (16.9% classification shift), but the underlying problem is general: binary classifications (peat/mineral, forest/non-forest, Amazon/Cerrado biome boundary) create step-function discontinuities in emission factors at classification boundaries. A facility just inside a peat boundary receives the full SOC premium; one just outside receives nothing. Research into continuous remotely sensed proxies – drainage canal density for peat severity, biomass gradient for forest degradation, spectral mixture for biome transitions – would reduce sensitivity to classification thresholds across all commodity systems. This directly addresses the coarse-resolution problem documented for PEATGRIDS (1 km) and would improve the framework's defensibility for regulatory applications.

3. **What is the empirical false-positive rate of single-method deforestation detections in mosaic landscapes?** The sensitivity analysis found that 63.2% of detected deforestation is flagged by only one method (GLAD, TMF, or Dynamic World). The EUDR compliance metric depends on the accuracy of these detections, yet no systematic ground-truth dataset exists for single-method flags in tropical commodity mosaics. This ambiguity is likely worse in heterogeneous systems – shade-grown coffee, cocoa agroforestry, silvopastoral cattle – where the spectral boundary between "forest" and "commodity" is less distinct. Ground-truthing stratified samples of single-method detections would establish the calibration data needed to set defensible thresholds for the intersection vs. union detection framework.

4. **How do supply shed environmental metrics respond to remediation interventions, and over what timescale?** The 1% Fund (Section 4.2, pg 35) and the broader *Codex Planetarius* accountability structure assume that metrics will improve in response to targeted interventions – but the detectability and timescale of improvement have not been established. Can satellite monitoring detect the effect of peatland re-wetting within 2 years? Does riparian buffer replanting produce a measurable biodiversity signal within 3–5 years? Does rotational grazing on degraded pasture register in soil carbon metrics? Without this evidence, the framework can rank current performance but cannot credibly demonstrate that its remediation mechanism works. This is critical for funders and for the framework's long-term legitimacy.

5. **What biodiversity metrics are appropriate for non-forest commodity landscapes?** The current canopy height heterogeneity metric (Rao's Q entropy from GEDI) is well-suited to forest-to-plantation transitions but becomes less meaningful in savanna (Cerrado soy), grassland (cattle), or agroforestry (shade coffee, cocoa) systems where biodiversity does not correlate simply with canopy structure. As the framework extends to all seven EUDR-regulated commodities, research into RS-derivable biodiversity proxies for these biomes – functional diversity indices, spectral variability, phenological metrics, or integration with acoustic monitoring – becomes essential for maintaining the biodiversity ranking dimension across the commodity portfolio.

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