LATIN AMERICA COFFEE CARBON FOOTPRINT BASELINE STUDY

HUILA COLOMBIA

APRIL 2026

CONSERVATION INTERNATIONAL

SUSTAINABLE COFFEE CHALLENGE

meo CARBON SOLUTIONS

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACRONYMS

AGB	Above Ground Biomass
API	Application Programming Interface
BGB	Below Ground Biomass
BOD	Biological Oxygen Demand
COD	Chemical Oxygen Demand
CFA	Cool Farm Alliance
CFP	Cool Farm Platform
CI	Conservation International
CIRAD	Centre de Coopération Internationale en Recherche Agronomique pour le Développement – *(eng. French Agricultural Research Centre for International Development)*
DOM	Dead Organic Matter
EF	Emission Factor
GBE	Green Bean Equivalent
GHG	Greenhouse Gas
GHGP	Greenhouse Gas Protocol
GRAS	Global Risk Assessment Service
GWP	Global Warming Potential
IPCC	Intergovernmental Panel on Climate Change
IQR	Interquartile Range
LCA	Life Cycle Assessment
LUC	Land Use Change
MCS	Meo Carbon Solutions
MoE	Margin of Error
QC	Quality Control
SBTi	Science Based Target Initiative
SCC	Sustainable Coffee Challenge
SD	Standard Deviation
SE	Standard Error
SOC	Soil Organic Carbon
TSP	Technical Service Provider

ACKNOWLEDGEMENTS

We gratefully acknowledge the generous support and collaboration of the following organizations, whose contributions made this research possible.

The study was facilitated by Conservation International under the umbrella of the Sustainable Coffee Challenge. Meo Carbon Solutions served as the technical lead, designing and implementing the study based on collaboratively agreed parameters, with additional technical support from their sister companies Global Risk Assessment Services (GRAS) and 4C Services. Field data collection was carried out by Fundecafé (La Fundación para el Desarrollo Cafetero y Agropecuario).

The research included in this report was made possible through funding by the Walmart Foundation. It additionally leveraged the study design, governance, and third-party review of a larger companion study, the Latin America Coffee Carbon Footprint Baseline Study, supported by additional partners (Sustainable Coffee Challenge, 2026, p. 10). The findings, conclusions and recommendations presented in this report are those of the authors and do not necessarily reflect the opinions of Walmart Foundation or the endorsement of the results.

We extend our sincere appreciation to each of these organizations and to the hundreds of coffee farmers who agreed to be anonymously surveyed whose time, expertise and collaboration were essential to this research.

LATIN AMERICA COFFEE CARBON FOOTPRINT BASELINE STUDY

HUILA- COLOMBIA

EXECUTIVE SUMMARY

This study establishes a **farm-gate greenhouse gas (GHG) emissions baseline for Arabica coffee production in Huila, Colombia**, based on primary data collected from **388 representative farms** and calculated using a **harmonized carbon-accounting framework** consistent with a wider Latin America Coffee Carbon Footprint Baseline Study.

The average farm-gate carbon footprint of coffee produced in Huila **is 5.77 kg CO_2-eq per kg green bean equivalent (GBE)**, with a ±6% margin of error at a 95% confidence level. For context, a country-level footprint was calculated for Colombia at 5.59 kg CO_2-eq per kg GBE. The results provide a robust, region-specific reference point for understanding emission drivers, identifying mitigation priorities, and supporting climate action planning.

Emission Sources Breakdown of Huila Region

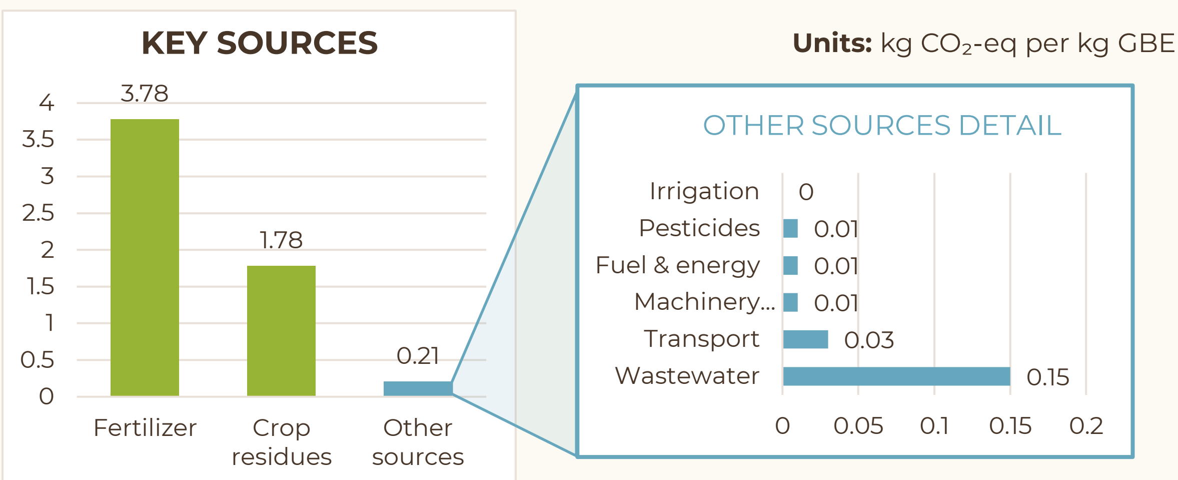


Figure 1: Emission Sources Breakdown of Huila Region

Emissions in Huila are **highly concentrated among a small number of sources**, with three categories accounting for virtually all (>99%) of total farm-gate emissions:

- **Fertilizer production and use** is the dominant source, contributing **3.78 kg CO_2-eq per kg GBE (~65%)**. Emissions are driven primarily by high mineral fertilizer application rates and associated soil nitrous oxide (N_2O) emissions, with upstream fertilizer production also making a substantial contribution.
- **Crop residue management** is the second largest source at **1.78 kg CO_2-eq per kg GBE (~31%)**. Emissions are dominated by N_2O from the decomposition of pruning residues, leaf litter, and coffee pulp left on the field, with smaller contributions from methane (CH_4) associated with burning or anaerobic handling.
- **Wastewater treatment** is negligible at the national level but contributes more visibly in Huila—**at 0.15 kg CO_2-eq per kg GBE (~3%)**—indicating a region-specific hotspot. Emissions are associated with on-farm wet processing and heterogeneous wastewater treatment pathways, some of which create anaerobic conditions conducive to methane formation.

All other sources, including fuel and energy use, transport, machinery operations, pesticides, and irrigation, each contribute **less than 1%** of total emissions at an aggregate level. **Non-crop biomass** was calculated using the CFP model; however, it is not included in the final emission value in accordance with GHG Protocol accounting principles.

Carbon Removals from Non-Crop Biomass

Non-crop woody vegetation (intercrops, shade trees, and hedges) provides a significant carbon storage benefit, estimated at **–1.47 kg CO_2-eq per kg GBE**. While this **represents baseline biomass stocks rather than measured sequestration over time**, it reflects the prominence of diversified and agroforestry-based systems in Huila relative to broader national patterns.

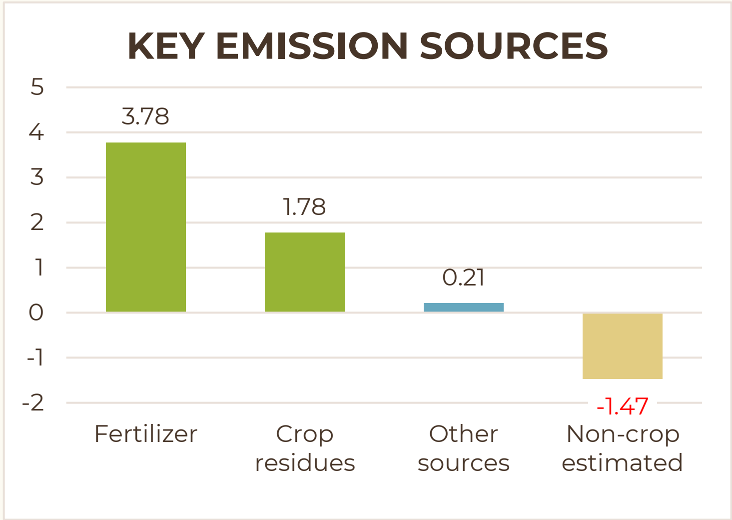


Figure 2: Carbon removals compared to emission sources

Implications for Climate Action

The Huila baseline demonstrates that **farm-gate coffee emissions on average are driven by a small set of management decisions**, particularly nutrient management, residue handling, and wastewater treatment. As a result, the most credible and scalable mitigation opportunities lie in:

- Improving **nitrogen-use efficiency** and avoiding **over-application of mineral fertilizers**,
- Refining **crop residue management practices to reduce N_2O and CH_4 formation**, and
- Upgrading **wastewater treatment systems** to limit anaerobic methane emissions.

Overall, this study provides a conservative, decision-useful regional baseline that complements the Colombia national reference value, providing deeper insight into one of the country's most important coffee-producing regions to support credible benchmarking, Scope 3 accounting, and region-level decarbonization planning when interpreted within its defined methodological boundaries

.

© CI LATAM STUDY Field Photos

1. INTRODUCTION

Coffee supply chains are under growing pressure to quantify and reduce greenhouse gas (GHG) emissions while maintaining producer livelihoods, supply security, and long-term resilience under climate change. In response to this need, Conservation International (CI), under the Sustainable Coffee Challenge and through broad industry support, led the Latin America Coffee Carbon Footprint Baseline Study (Sustainable Coffee Challenge, 2026[1]), henceforth the "LATAM Study," to establish robust, farm-gate GHG emission baselines for major coffee-producing origins in the region.

Implemented by Meo Carbon Solutions (MCS) in consortium with Global Risk Assessment Services (GRAS) and 4C Services, the study developed nationally representative baselines for Arabica coffee in Brazil, Colombia, Honduras, Mexico, and Peru, and for Robusta coffee in Brazil. The study was designed as a pre-competitive, sector-wide initiative to support harmonized carbon accounting, benchmarking, and climate action planning across coffee supply chains. It built upon a similar study conducted in Indonesia and Vietnam (Green Invest Asia and Pact, 2023[2]).

The LATAM Study was designed to produce country-level reference values with the initial intention of enabling sub-national analyses where survey coverage produced statistically significant regional samples. However, in practice, while nationally representative samples were still achieved, they had to be reduced due to resource and field constraints and were generally no longer conducive to representative sub-

Check here the
Latin America Coffee Carbon Footprint Baseline Study

Figure 3

1 Sustainable Coffee Challenge: Latin America Coffee Carbon Study: March 2026
2 Green Invest Asia and Pact: Establishing carbon footprint baselines for Robusta coffee production in two origins in Southeast Asia: Central Highlands, Vietnam and Southern Sumatra, Indonesia May 2023

national analyses. Although the national-level approach is appropriate for corporate GHG accounting and sector benchmarking, it may not provide sufficient granularity to serve as the core reference point for landscape-level planning and investment. Meanwhile, a need for more tailored insights arose among partners working in Huila, Colombia.

Huila is a key coffee landscape globally and the leading coffee-producing department in Colombia. Official Colombian sources have identified Huila as contributing about one-fifth of national coffee production, while the Federación Nacional de Cafeteros (FNC) describes the department's coffee sector as spanning 35 municipalities, covering the livelihood of more than 84,000 coffee-growing families, with 145,741 hectares of Arabica coffee (Federación Nacional de Cafeteros, 2026[3]).

Additionally, CI, alongside IDH, co-leads the Hylea Pact in Huila: a joint landscape initiative that brings together local governments, landowners, NGOs, and international companies aiming to strengthen governance and improve environmental and social conditions in Huila's coffee- and cocoa-producing communities. At the time of writing, initiative partners are also working to establish a collective sourcing-region decarbonization approach that can pool funding and support shared monitoring, reporting, and verification (MRV). For such a model to function credibly, a region-specific emissions baseline is required.

This Huila-specific study was therefore developed as an extension of the LATAM Study, using the same overall accounting logic, methodological boundaries, and analytical framework, while increasing the resolution of the analysis to the departmental level. The purpose is to generate a robust, regionally representative farm-gate carbon footprint baseline for Arabica coffee production in Huila that reflects the production systems, management practices, and processing arrangements specific to the department. In doing so, the study supports both continuity with the broader LATAM Study and greater relevance for local decision-making, climate investment design, and regional decarbonization planning.

---

3 Federación Nacional de Cafeteros

2. STUDY DESCRIPTION

2.1. STUDY DESIGN

This study was designed as a regional extension of the broader LATAM Study, with a specific focus on Arabica coffee production in Huila, Colombia. It applies the same core methodological approach as the LATAM Study, including a farm-gate system boundary, a functional unit of kg CO_2-eq per kg green bean equivalent (GBE), primary farm-level data collection, and carbon footprint calculations using the Cool Farm Platform (CFP) perennials module version 2.0. By maintaining methodological consistency with the broader LATAM Study, the Huila baseline enables direct comparison with the national Colombian baseline while providing greater geographic resolution for one of the country's most important coffee-producing regions.

The Huila study also builds on the recognition, already evident in the LATAM Study, that coffee production systems are heterogeneous and that this heterogeneity can materially influence emission profiles[4]. In the national-level baseline for Colombia, Huila was represented within the country sample, but only as one department among several included in the national aggregation. The dedicated Huila analysis expands this substantially by increasing the regional sample size to 371 farms. Of these, 137 surveys were completed during the LATAM Study, and a further 234 surveys were collected in a second data collection round between September and December 2025 in order to achieve the required sample size for the regional analysis. This expanded dataset improves statistical coverage of Huila's municipalities and strengthens the study's relevance for department-level interpretation and use.

The present report, therefore, serves two related functions. First, it documents the methodology and results of a regionally representative farm-gate carbon footprint baseline for Huila. Second, it demonstrates how the broader LATAM Study can be scaled from the national to the subnational level, where there is a clear intervention rationale, sufficient production significance, and a practical need for higher-resolution data. In this sense, the Huila study should be understood not as a separate methodological exercise, but as a targeted regional deepening of the same sector-aligned baseline architecture.

[4] The reference sources for the heterogeneity analysis are listed in the annex of the LATAM Study report.

2.2. PURPOSE AND OBJECTIVES OF THE STUDY

The primary purpose of this study is to establish a robust, regionally representative farm-gate GHG emission baseline for Arabica coffee production in Huila, Colombia. This baseline is intended to support credible accounting, benchmarking, and climate action planning at a scale that is relevant for both sourcing-region interventions and supply chain decision-making.

More specifically, the study has five interrelated objectives:

1. Quantify the average farm-gate carbon footprint of coffee produced in Huila using a harmonized methodology aligned with the broader LATAM Study.
2. Identify key sources and drivers of on-farm GHG emissions, including fertilizer use, crop residue and wastewater management, energy use, and transport.
3. Assess the relative contribution of different management practices to overall emission outcomes in Huila.
4. Explore opportunities for emission reduction by highlighting structural hotspots and variability within the production system.
5. Provide a transparent and standardized dataset that can support future methodological refinement, benchmarking exercises, and scenario analysis.
6. Contribute to industry learning and alignment by applying a shared accounting framework and openly documenting assumptions, limitations, and uncertainties.

This study was designed to generate an annualized carbon footprint baseline that can be used directly by coffee producers and supply chain actors for corporate GHG accounting, climate target setting, and decarbonization planning. Rather than serving as a full life-cycle assessment, it provides a practical inventory-based baseline aligned with GHGP and SBTi guidance. Results are calculated for a single reporting year so they can be integrated into annual corporate inventories, including Scope 3 Category 1 reporting, and used to support shared MRV and sourcing-region climate action in Huila.

For this reason, emissions are not averaged across multiple production years, since this would reduce consistency with corporate accounting practice and obscure year-specific emission patterns. The results, therefore, represent the emissions profile of the baseline year only. Although this approach does not fully capture inter-annual variability in yields or management intensity, it is appropriate for the study's objective of establishing a credible and decision-useful regional baseline. For future monitoring, a multi-year approach with separate annual assessments would further strengthen the reliability of inventories for perennial coffee systems, but this was beyond the scope of the present study.

2.3. SCOPE OF THE STUDY

2.3.1. SYSTEM BOUNDARY AND FUNCTIONAL UNIT

The system boundary for all analyses conducted in this study is defined at the farmgate level, consistent with internationally recognized carbon accounting standards and the methodological requirements of the CFP. This boundary encompasses all relevant activities occurring up to the point where a coffee product leaves the farm, expressed per functional unit of kg GBE. Within this boundary, the study includes:

- Coffee cultivation activities, including input application (e.g., fertilizers) and crop maintenance
- On-farm processing where applicable (e.g., wet processing, pulp or husk, and wastewater handling, wherever applicable);
- Upstream emissions associated with the production of agricultural inputs such as fertilizers, pesticides, fuel, and electricity;
- Farm-level energy use and machinery operations;
- On-farm residue and waste management practices;
- Transportation from the farm to the first point of sale or aggregation.

Activities occurring beyond the farm-gate, such as centralized milling, export logistics, roasting, packaging, retail, and consumption, fall outside the scope of this baseline study and are therefore not included in the analysis and reported results. The farm-gate boundary reflects both the study's analytical focus and practical considerations regarding data availability and comparability. It enables a consistent assessment across countries and Supplier Partners, while capturing the dominant emission sources in coffee production systems up to farm gate. The study boundary excludes processing outside the farm-gate, export, roasting, distribution, and retail stages. The results should therefore be interpreted as farm-gate baselines rather than comprehensive country-level carbon footprints of the entire coffee value chain.

2.3.2. PRODUCTION AND GEOGRAPHIC SCOPE

The study covers Arabica coffee production in the department of Huila, Colombia. Huila is an especially relevant geography for this type of analysis because of both its scale and its importance within Colombia's coffee sector. It is Colombia's leading coffee-producing department, accounts for roughly one-fifth of national coffee production according to official statistics and comprises a large and diverse coffee landscape distributed across 35 municipalities. The scale of production, number of farming families, and centrality of coffee to the regional economy make Huila a highly relevant unit for subnational baseline development.

The sampling framework for the Huila assessment was designed to provide regional representativeness across the department. The final target sample size was 371 farms (Section 3.2), allocated across municipalities in proportion to production significance. This expanded sample is materially larger than Huila's representation in the national Colombia sample of the LATAM Study, where Huila contributed 137 farms to the overall national dataset. The regional study therefore offers greater depth and specificity for Huila than was possible within the national baseline structure.

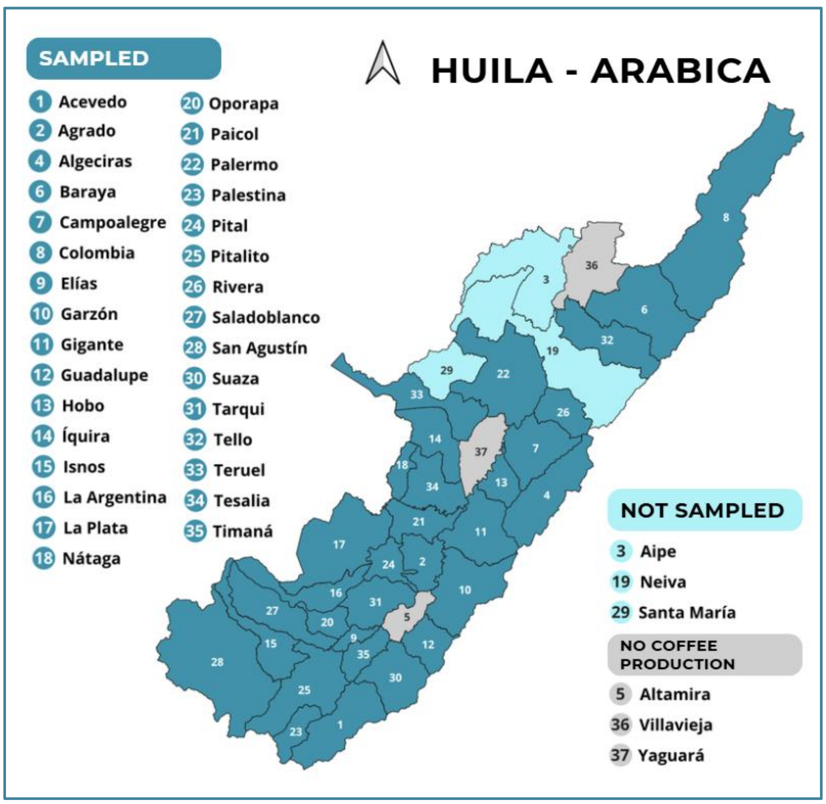


Figure 4: Map of Huila with included and excluded sampling areas

2.4. DATA, TOOL, AND IMPLEMENTATION BOUNDARIES

Several additional boundaries are inherent to the design and implementation of the Huila baseline and should be considered when interpreting the results. First, primary data collection relied on supplier-linked farm networks and trained enumerators to access producers and conduct farm surveys. Although a structured sampling and randomization approach (see Annex 2) was applied, farm access was not fully independent, as surveys could only be conducted within supply chains and local networks that were operationally accessible during implementation. As a result, the dataset primarily reflects coffee production systems connected to formal commercial channels and may underrepresent farms operating outside these networks. This limitation is important in the context of Huila, where production systems can be diverse and not all producers are equally integrated into organized supply chains.

Second, the study is bounded by the choice of calculation tools, the Cool Farm Platform perennial crop module version 2.0. The CFP tool was selected to ensure methodological consistency with the broader LATAM Study and because it provides a standardized, science-based framework aligned with IPCC methodologies and commonly applied in agricultural supply chains. As with all model-based calculators, results depend on a combination of primary farm data, default emission factors, and simplified representations of complex biological and management processes. These modelling characteristics influence absolute emission values and should be understood as an explicit boundary of the Huila baseline.

Third, certain carbon stock change components were intentionally excluded from the core baseline results. In line with the methodological approach applied in the LATAM Study, soil organic carbon (SOC) changes, reforestation and deforestation effects, and broader land-use change (LUC) emissions were kept out of scope due to methodological readiness, reporting limitations, and comparability considerations. At the time of implementation, these components could not be incorporated consistently enough to support a robust regional baseline for Huila. Only carbon captured in newly established non-crop woody biomass, such as shade trees, intercrops, and hedges, was included. These boundary choices were made to preserve transparency, consistency, and the decision-usefulness of the reported baseline, and are further explained in the methodology section (Chapter 0) of this report.

3. METHODOLOGY

Establishing a reliable carbon footprint baseline requires a methodology that is both scientifically robust and applicable across different coffee producing contexts. This chapter summarizes the methodological approach used to generate comparable and representative results.

3.1. OPERATIONAL BOUNDARIES AND DATA CATEGORIES

Data collection was confined to the farm-level. Emissions-related data from activities that took place beyond this boundary were excluded. The data points for analysis were selected based on the requirements of the CFP version 2.0 perennials module. Table 1: GHG calculation requirements under perennial module version 2.0 of the CFP tool summarizes the data categories that were included in the survey design, for eventual GHG calculations.

CATEGORY	SUB-CATEGORY	DETAILS
Inputs (Resources and materials used)	Farm-level characteristics	• Country • Climate • Temperatures
	Crop-level inputs	• Area • Age • Tree density • Plantation lifecycle duration • Crop type • Percentage of dead coffee trees • Production volume • Residues • Treatment of dead plants • Organic matter
	Pesticides	• Type • % active ingredient • Application rate
	Fertilizers	• Type • % formulation • Application rate • Origin
	Irrigation	• Type • Water source • Amount of water used • Source of power usage

	Energy	• Category (field and processing) • Source (fuel and electricity) • Usage (quantity)
	Machinery	• Type • Fuel type • Number of operations
Processes (Farm and crop management practices)	Waste management	• Seed • Waste fruit • Pruning waste • Leaf litter • Dead plant • Pulp or husk • Wastewater
	Logistics (transport)	• Mode • Weight carried • Distance
	Non-crop estimated	• Intercrop trees • Shade trees • Hedges
Outputs	Wastewater	• Quantity (m^3 or L) • Biological Oxygen Demand (BOD) or Chemical Oxygen Demand COD) value • Treatment type
Land Use Change (excluded from the CFP assessment)	Land use change	• Previous state • Year of change • Management inputs

Table 1: GHG calculation requirements under perennial module version 2.0 of the CFP tool

3.2. FUNDAMENTALS OF SYSTEMATIC ANALYSIS

The following subchapter includes short explanations of the standardized analytical tool of the analysis for emission calculation, structured sampling framework, harmonized data collection procedures through the survey questionaries, enumerator training, and data cleaning procedures ensuring consistent analysis across the entire Huila region. Each of these steps combined empirical rigor with practical execution, ensuring that the resulting baselines would be aligned with internationally recognized standards, while also being truly reflective of the diversity of coffee production systems. This approach allows for credible benchmarking, and insight into future emissions reduction strategies for the coffee sector.

Starting with the **emission calculation approach**, the main assessment tool applied for this baseline study is the Cool Farm Platform (CFP). The CFP, developed by the Cool

Farm Alliance, is a globally recognized tool for calculating carbon emissions and sequestration in agricultural systems. It provides standardized metrics for greenhouse gases, biodiversity, and water use, grounded in IPCC methodologies and empirical research. Designed for usability and scientific robustness, the platform enables farmers and supply chain actors to model "what-if" scenarios, identify emission hotspots, and develop tailored mitigation strategies. Inputs include crop yield, growing area, fertilizer type and rate, crop protection details, energy use, and optional transport data. Its interactive interface facilitates scenario analysis and supports decision-making for sustainable practices.

Next, the **sampling framework**, based on the LATAM Study, was initially developed to establish statistically robust and representative national carbon footprint baselines across five coffee producing countries. It captures variation in geography, farm types, and production practices while ensuring methodological consistency. To ensure statistical significance, Greenhouse Gas Protocol (2022[5]) recommends a minimum of 370 samples per country, based on homogeneous farm characteristics, a 95% confidence interval, a 5% margin of error, and a 0.5 population proportion. As such, the framework integrates GHG Protocol guidance, as well as 4C -filling ensuring coverage. Together, these elements support reliable, comparable, and nationally representative GHG estimates for coffee production, sampling principles, homogeneity analysis, department level stratification, sample allocation, and strict randomization to reflect the diversity of production systems. Sample sizes were adapted to agroecological and management variability, with departmental production data guiding allocation and targeted gap filling ensuring coverage. Together, these elements support reliable, comparable, and nationally representative GHG estimates for coffee production.

According to the sampling framework, the department-level sampling size for the Huila analysis was set to 388. 137 surveys were completed via the LATAM Study, so 251 additional surveys were collected in a second round in the period of September 2025 until December 2025.

DEPARTMENT	COFFEE TYPE	DEPARTMENT-LEVEL SAMPLE NUMBER	MUNICIPALITIES	MUNICIPALITY-LEVEL SAMPLE NUMBER
Huila Colombia	Arabica	388	Acevedo	37
			Agrado	5
			Algeciras	4
			Baraya	2

5 Greenhouse Gas Protocol. (2022). Appendix A. World Resources Institute & World Business Council for Sustainable Development.

			Campoalegre	2
			Colombia	6
			Elias	4
			Garzon	29
			Gigante	14
			Guadalupe	14
			Hobo	3
			Iquira	8
			Isnos	5
			La Argentina	8
			La Plata	51
			Nataga	8
			Oporapa	13
			Paicol	7
			Palermo	8
			Palestina	12
			Pital	13
			Pitalito	53
			Rivera	2
			Saladoblanco	10
			San Agustin	12
			Suaza	17
			Tarqui	11
			Tello	9
			Teruel	3
			Tesalia	3
			Timana	15

Table 2: Sample allocation at department and municipality levels

The **survey questionnaires** were developed to be concise, practical, and fully aligned with the data needs of the Cool Farm Platform (CFP) and the 4C Carbon Footprint Add-On to the LATAM Study, although the latter was not conducted for this Huila-specific analysis. The design process followed a structured sequence: defining all methodological data requirements, converting them into an Excel based master questionnaire, and deploying the tool digitally through the open-source survey software, KoboToolbox for efficient field implementation. The survey content was refined through multiple review rounds with technical auditors, supplier partners, and enumerators to ensure clarity, scientific accuracy, and operational practicality.

The survey instrument was developed with plain and accessible wording, translated and supported by a detailed enumerator guidance manual. Before full rollout, the questionnaire underwent a structured testing phase that identified and resolved ambiguities, cultural sensitivities, and weaknesses in skip logic or sequencing.

An **enumerator training** program ensured data quality and consistency by familiarizing participants with the survey objectives, KoboToolbox, questionnaire content, and practical field procedures through demonstrations, trial runs, and hands-on exercises. Ongoing support including training materials, recordings, written guidance, and country-specific WhatsApp groups enabled real-time troubleshooting and strengthened enumerators' capacity to collect accurate and reliable data throughout the fieldwork phase.

During implementation, trained enumerators conducted field visits to survey farmers. The use of KoboToolbox enabled offline data collection with built in validation checks to reduce errors. Standardized procedures, informed consent protocols, and continuous monitoring by MCS ensured reliable, verifiable, and consistent data across diverse farming contexts. This comprehensive survey development and implementation process provided a scientifically robust foundation for generating high quality data for the carbon footprint baseline study.

The **data cleaning and analysis** process followed a structured workflow that ensured accuracy, transparency, and reproducibility across all survey datasets. Raw data were systematically validated, translated, standardized, and aggregated, with extensive crosschecks and partner verification to remove incomplete, implausible, or inconsistent entries. Additional- derived variables, outlier detection, and standardized assumptions strengthened the analytical quality and supported integration into the CFP. After formatting, datasets were run through the CFP to generate farm level emission estimates-stage approach produced a clean, verified, and high-. This multistage approach produced a clean, verified, and high integrity dataset that provides a reliable foundation for all downstream aggregation, statistical analysis, and reporting.

Further in-depth details surrounding the methodology and data collection process may be found in the *LATAM Study, p.25-47.*

4. RESULTS

4.1. FINAL CARBON FOOTPRINT RESULT

The section below presents the carbon footprint results for coffee production, focusing on Arabica systems in Huila, Colombia.

All analyses in this report were conducted in line with the objectives and boundaries of the Huila baseline. Results are presented at the regional level, with additional breakdowns by emission source and analytical exploration of variability across farms. The study does not seek to rank farms or prescribe farm-specific mitigation actions. Instead, it provides aggregated insights into the main emission drivers and management patterns shaping coffee production in Huila, with the aim of informing broader regional decarbonization efforts.

It should be noted that the LATAM study underwent an independent third-party review conducted by CIRAD. While feedback and methodological recommendations from CIRAD's review were incorporated, to the extent possible, into the Huila baseline, no separate third-party review was conducted specifically for this regional analysis. In addition, the level of review and validation applied to this Huila report was more

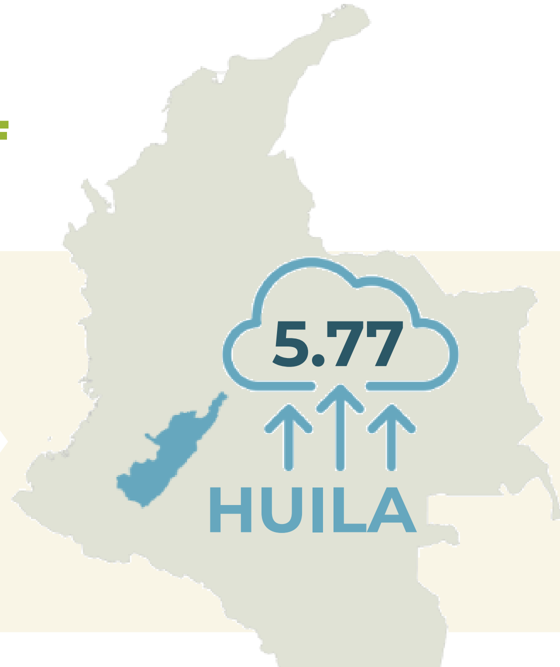
limited compared to the comprehensive review process undertaken for the full LATAM study. These differences should be considered when interpreting the results and their level of external verification

Methods such as Z-score-based hotspot identification and correlation- and factor-specific analysis are used to explore variability and contextualize averages, rather than to identify farms for exclusion or define statistically fixed archetypes. Details on Z-score analysis are provided in Section **Error! Reference source not found.**, while quality control (QC) and exclusion procedures are described further in the LATAM Study report.

The results should therefore be interpreted as standardized, internally consistent estimates suitable for benchmarking, learning, and strategic planning, rather than as precise measurements of emissions at individual farms. This framing helps balance scientific rigor, transparency, and practical applicability, while making clear the intended use and limitations of the Huila baseline.

4.1.1. GENERAL BREAKDOWN OF THE FINAL RESULTS

The baseline carbon footprint for coffee production in Huila, Colombia is **5.77 kg CO_2-eq per kg GBE** indicating the overall emission intensity of the region.



The system boundary for this analysis was defined at the farm-gate level encompassing primary cultivation activities, farm-level processing (where applicable), and upstream and downstream transportation. Transportation activities occurring within the farm were excluded from the system boundary due to the lack of reliable and consistent farm-level data. Based on discussions among Consortium and Supplier Partners, these internal transportation activities were assessed to have a negligible influence on final emission results.

Figure 5 showcases a further categorical breakdown of the results as an overview. It summarizes the key findings of the CFP assessments and offers insights into regional coffee production and associated emission patterns. The results show that emissions are primarily driven by fertilizer production and use, crop residue, and waste management (more detailed on Chapter 0).

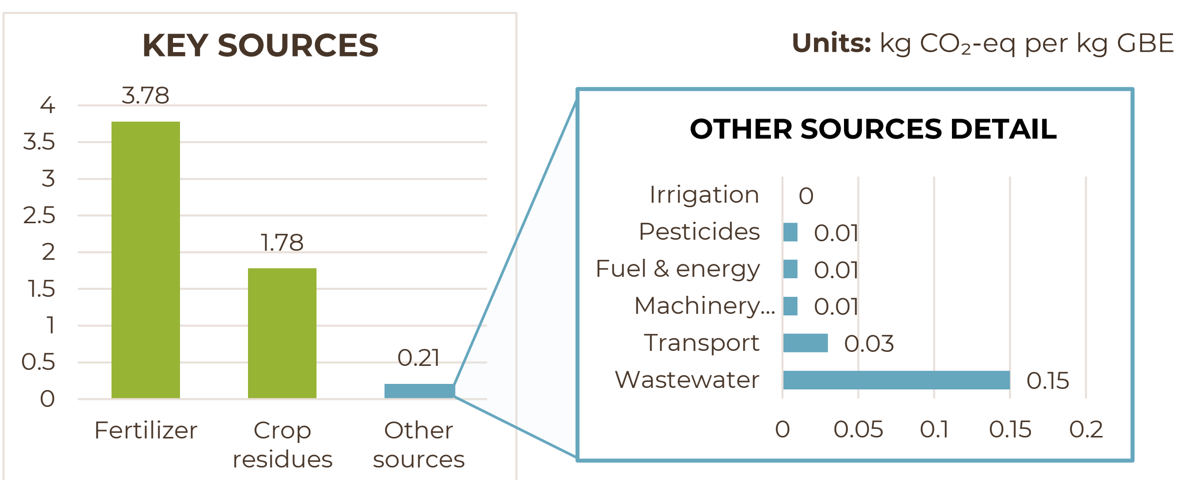


Figure 5: Emission breakdown of Huila Region (kg CO_2-eq per kg GBE)

It is important to contextualize that the values in Figure 5 represent a snapshot of emissions for the specific assessment year, reflecting production conditions and management practices at that time. Although such annualized results are suitable for GHG accounting and reporting, they do not capture interannual variability in yields, inputs, or climate. To strengthen climate action planning and greenhouse gas inventories, comparable data should therefore be collected over multiple consecutive years to capture variability and long-term trends.

Table 3 complements these findings by presenting yield metrics, including both average and median coffee yields across Huila. This provides additional context for interpreting emission intensities within the department's production systems. While the modelling framework calculates GHG emissions based on averaged data from participating farms, thereby reflecting regional mean values, the median yields reported in Table 3 highlight the influence of extreme yields on these averages.

The study's annualized approach, however, is in line with the GHG Protocol Corporate Accounting and Reporting Standard and the Corporate Value Chain (Scope 3) Standard principles, which state inventories must reflect conditions within the defined reporting period, and multi-year averaging would extend beyond the recommended temporal boundary. Thus, this study adopts a strict annual assessment approach while recommending multi-year assessments rather than cross-year averaging as the preferred method for developing realistic, consistent, and policy-relevant national GHG inventories over time. Further limitations, along with their implications for results interpretation and recommendations for future assessments, are discussed in Chapter 4 in this report, and with more detail, in the *LATAM Study, p.58-114.*

ASSESSMENT YEAR		PREVIOUS YEAR		MEAN YIELD (TWO YEARS) (KG/HA)
Median yield (kg/ha)	Average yield (kg/ha)	Median yield (kg/ha)	Average yield (kg/ha)	
1,196	1,267	1,068	1,160	1,213

Table 3: Average and median yield – Huila Region

4.1.2. DISAGGREGATION OF THE FINAL RESULTS AT THE REGIONAL LEVEL

After providing an aggregated overview of the results for Huila, a closer look at the municipalities and overall regional level is required to identify specific emission drivers. To interpret the regional-level input parameters, analyze their variability, and determine their relative influence on GHG emissions, an additional statistical approach was employed: the Z-score method.

The Z-score statistical method was applied independently across all emission categories (crop residues, transportation, fuel and energy, fertilizer, wastewater management, pesticide, machinery operations, non-crop biomass estimation, and irrigation energy) as well as for the corresponding input parameters associated with these individual categories. The Z-score standardizes individual data points relative to the mean and the dispersion of the dataset, allowing for comparability across different parameters.

It is calculated using the following formula:

$$Z = \frac{x_i - \bar{x}}{\sigma}$$

where:

- x_i= individual value of the parameter,
- $\bar{x}$= mean of the dataset,
- σ= standard deviation of the dataset.

The standard deviation (σ) is computed as:

$$\sigma = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}}$$

where:

- n= total number of observations.

After calculating the Z-score for each input parameter and the corresponding emission values, the results were interpreted based on statistical thresholds given by this statistical methodology. These are the following thresholds and their interpretations (McLeod et al., 2023[6]):

- $Z = 0$: value equals the mean,

6 McLeod, S. (2023, October 6). Z-score: Definition, formula, calculation & interpretation. Simply Psychology.

- $Z = \pm 1$: one standard deviation above or below the mean,
- $| Z | > 2$: value is unusual and often considered an outlier,
- $| Z | > 3$: value is highly unusual and typically considered an outlier.

It is important to highlight that the Z-score was chosen because it accounts for both the central tendency and the dispersion of the dataset, making it a more robust measure than simple percentage deviations. This approach enables the identification of extreme deviations (outliers) in input parameters or emission values, which may indicate emission hotspots or anomalies in agricultural practices. Such hotspots are critical for understanding variability and targeting mitigation strategies within coffee supply chains, and they give a full picture of the supply chain[7].

The Z-score is also inherently unitless, which makes it particularly suitable for analyzing input parameters that differ in units across categories. For example, wastewater may be expressed in litres, while the yield will be measured in kilograms or tons, but emissions are ultimately normalized to kilograms of CO_2-eq per kilogram of green bean equivalent (kg CO_2-eq per kg GBE). The Z-score's unitless property ensures comparability across diverse parameters and units without introducing bias from differing measurement scales. As the entire hotspot analysis of the main emissions and the Huila assessments is based on the functional unit kg CO_2-eq per kg GBE, ensuring methodological consistency in units of measure and other aspects is important, so that results can be interpreted correctly, and higher outliers in emissions can be identified. The subsequent sections present the final assessment results analyzed by the Z-score method and provide contextual interpretation for high-emission drivers.

Having now gained a detailed understanding of the methodological foundations of the Z-score analysis, this approach can be applied to disaggregate the study results. The following outcomes were derived from this analysis:

The average carbon footprint of the Huila coffee supply chain is 5.77 kg CO_2-eq per kg GBE, corresponding to total emissions of 4,949,717.45 kg CO_2-eq. Z-score analysis of yield confirms the robustness of this estimate, with only 14 farms (≈4%) exhibiting values above the mean, indicating that the national average is not driven by extreme production systems.

The Huila footprint is primarily shaped by input-intensive agronomic practices rather than downstream or processing-related activities. Fertilizer use is the dominant emission source, contributing 3.78 kg CO_2-eq per kg GBE (65%), reflecting both relatively high application rates and the combined impact of upstream fertilizer production and direct soil emissions. Crop residue management is the second largest

7 Z-score. (2008). In W. Kirch (Ed.), Encyclopedia of public health (p. 1484). Springer.

contributor at 1.78 kg CO_2-eq per kg GBE (31%), driven largely by pruning and leaf litter decomposition left on the field, which sustain nitrous oxide emissions through nitrogen mineralization processes. Methane emissions arise mainly from burning and limited anaerobic residue handling, resulting in an even split between N_2O and CH_4 within the residue category.

Wastewater management represents the third most relevant category which contribute 0.15 kg CO_2-eq per kg GBE (3%), reflecting the majority of the farms performing on-farm wet processing. In contrast, emissions from machinery operations, transport, fuel and energy use, irrigation energy, and pesticides are all marginal, each contributing less than 1%. This reflects limited mechanized operations, centralized aggregation structures, and relatively efficient logistics. Overall, Huila's footprint is characterized by high production efficiency but elevated input intensity, making fertilizer, residue management and wastewater management the dominant mitigation levers, collectively accounting for over 99% of total emissions.

4.2. ANALYSES PER EMISSION SOURCE

4.2.1. FERTILIZER PRODUCTION AND USE

Fertilizer production and use are widely recognized as major contributors to GHG emissions in agricultural systems and are consistently identified as a dominant source of emissions in coffee production at the farm level. Numerous life cycle assessment (LCA) studies have shown that mineral fertilizers, particularly nitrogen-based products, account for a substantial share of total farm-level emissions due to (1) a combination of upstream emissions from industrial manufacturing and (2) downstream emissions released after application to soils (Noponen et al., 2012[8]; Hergoualc'h et al., 2012[9]; Poore & Nemecek, 2018[10]). This dominance is further amplified by the fact that the principal GHG released from fertilized soils is N_2O, which has a global warming potential approximately 273 times higher than CO_2 over a 100-year time horizon, meaning that even relatively small quantities of N_2O emissions translate into substantial CO_2-equivalent impacts.

Upstream emissions associated with fertilizer production arise primarily from energy-intensive industrial processes, most notably the synthesis of nitrogen fertilizers via the Haber-Bosch process, which relies heavily on fossil fuels and generates significant CO_2 emissions (Brentrup et al., 2016[11]; IPCC, 2019[12]). These emissions vary substantially depending on the type of fertilizer produced, the efficiency of production technologies, and the regional energy mix used during manufacturing. As a result, emission factors for fertilizer production differ across countries and regions, introducing an inherent source of uncertainty when the precise origin of fertilizers is

8 Noponen, M. R. A., Edwards-Jones, G., Haggar, J. P., Soto, G., Attarzadeh, N., & Healey, J. R. (2012). Greenhouse gas emissions in coffee production systems: Case studies from Central America. Journal of Cleaner Production, 44, 1–10.

9 Hergoualc'h, K., Blanchart, E., Skiba, U., Hénault, C., & Harmand, J.-M. (2012). Greenhouse gas emissions from coffee systems: A review of field measurements and modelling. Agriculture, Ecosystems & Environment, 152, 83–94.

10 Poore, J., & Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. Science, 360(6392), 987–992.

11 Brentrup, F., Hoxha, A., & Christensen, B. (2016, October). Carbon footprint analysis of mineral fertilizer production in Europe and other world regions. In Proceedings of the 10th International Conference on Life Cycle Assessment of Food (LCA Food 2016).

12 Intergovernmental Panel on Climate Change. (2019). 2019 refinement to the 2006 IPCC guidelines for national greenhouse gas inventories. Institute for Global Environmental Strategies.

unknown or when compound fertilizers (e.g., NPK blends) are assembled in one location using nitrogen components produced elsewhere.

Fertilizer-related GHG emissions in coffee production systems are quantified using a lifecycle-based methodology aligned with the IPCC 2006 Guidelines, the 2019 IPCC Refinement, the GHG Protocol Land Sector and Removals Guidance, and ISO 14040/14044 principles.

65.5%

Fertilizer use is the foremost driver of GHG emissions in the Huila coffee supply chain. Fertilizer-related emissions amounted to **4,351,250.21 kg CO_2-eq**, which is equal to **3.78 kg CO_2-eq per kg GBE**, representing a **substantial share of the total farm-gate baseline with 65.5%**. When expressed per unit of land area, fertilizer emissions reached **4,748 kg CO_2-eq per ha**.

Fertilizer application rates in Huila coffee systems are significantly high, with an average use of 1,769 kg per ha. Input use is overwhelmingly dominated by mineral fertilizers, which are applied by 99% of farms, while only less than 1% report the use of organic fertilizers. This widespread and intensive use of synthetic fertilizers largely explain the prominence of fertilizer-related emissions in the Huila results. Of the total fertilizer-related emissions, approximately 43% are attributable to upstream fertilizer production and transport, while around 57% arise from on-field application, primarily driven by direct and indirect soil N_2O emissions. In absolute terms, this corresponds to approximately 1,643.44 kg CO_2-eq per ha from fertilizer production and 2,141.52 kg CO_2-eq per ha from on-field application, confirming that field-level nitrogen management is the dominant driver of fertilizer-related emissions in the Huila coffee supply chain.

Further Z-score analysis indicates the presence of a limited number of farms with comparatively high fertilizer-related emissions, reflecting a small proportion of producers applying substantially higher fertilizer inputs (6 farms with Z score > 2). When fertilizer emissions are expressed in terms of per ha and per kg GBE, 24 farms and 13 farms exhibit Z-scores more than 2 respectively, of which only 4 farms overlap. This limited overlap suggests that the fertilizer use alone is not the primary driver of high emission values across farms. Instead, variability in emission intensity is likely influenced by differences in yield and farm management practices, including relatively higher input intensity per hectare. While these higher-input systems should be considered when defining mitigation strategies, their limited number do not materially distort the aggregate emission results. Overall, the dataset provides a robust and representative picture of the Huila supply chain, while appropriately capturing underlying heterogeneity in fertilizer management practices.

4.2.2. FUEL AND ENERGY USE

In CFP, GHG emissions from fuel and energy use are calculated using a direct activity-based approach consistent with IPCC guidance and the GHG Protocol. Emissions are estimated based on the actual quantities of fuel and electricity consumed for field and farm operations.

Farmers report their consumption of energy carriers such as diesel, petrol, LPG, natural gas, electricity, and biofuels, either in physical units (litres, kilograms) or in energy units (kWh). CFP then applies fuel- and country-specific emission factors sourced primarily from internationally recognized datasets, including the UK Department for Environment, Food & Rural Affairs (DEFRA), the UK Department for Energy Security and Net Zero (DESNZ), and the International Energy Agency (IEA). These factors account for both combustion emissions and upstream well-to-tank emissions, ensuring a full fuel lifecycle perspective.

For electricity, CFP uses national grid emission factors that reflect the country-specific power generation mix. Bioenergy sources (such as fuel wood, biogas, biodiesel, and bioethanol blends) are treated in line with the GHG Protocol and IPCC conventions. Biogenic CO_2 emissions from combustion are reported separately as out-of-scope, while any fossil fuel component in blended fuels is included in the main footprint. Embedded emissions from the production of renewable electricity (e.g. wind, solar, hydropower) are included on a cradle-to-gate basis.

The methodology ensures that fuel and energy emissions in CFP represent a transparent, consistent, and comparable estimate of on-farm energy use across countries and production systems and captures both direct combustion emissions and upstream supply chain emissions associated with agricultural energy consumption.

0.2%

Fuel and energy use represented only a minor source of GHG emissions in the Huila coffee supply chain. According to the CFP analysis, total emissions from this category amounted to **11,919.93 kg CO_2-eq**, corresponding to **0.01 kg CO_2-eq per kg GBE**. This amount is representing **only a minor share of 0.2% of the total supply chain**.

The Z-score analysis shows that 24 out of 388 farms have Z-scores greater than 1, with 13 farms exhibiting exceptionally high values. Even though these farms account for 3% of the sample, fuel and energy emissions remain insignificant in relation to total supply chain emissions, as they represent just 0.18% of total farm-gate emissions.

Overall, the use of volume-based fuels such as petrol for on-farm processing remained limited within the sample, with most emissions in this category driven by grid electricity. Nearly 79% of the total assessed farms were reported to carry out processing activities, but their higher electricity demand resulted in a disproportionate contribution to total fuel and energy emissions within the category.

Z-score analysis shows that fuel and energy related emissions are heavily concentrated within a small subset of farms. When analyzing fuel used by volume, such as mineral petrol and gas, 3 farms display Z-scores greater than 2, while 22 farms exceed this threshold for electricity consumption alone. However, when emissions are expressed by output (kg CO_2-eq per kg GBE) and by land area (kg CO_2-eq per ha), only 4 farms with Z-scores greater than 2, overlaps. This indicates that their elevated total emissions are primarily driven by large production scales rather than inherently higher energy intensity. These farms are characterized and distinguished by substantially higher petrol use and electricity consumption in comparison to the rest of the sample.

4.2.3. PESTICIDE AND HERBICIDE USE

In CFP, pesticide-related GHG emissions are quantified using life-cycle emission factors sourced from the World Food LCA Database (WFLDB), following the methodology of Nemecek et al. (2019) and aligned with IPCC guidelines. Emissions are calculated based on the quantity of pesticide applied per hectare, the share of active ingredients in the product, and crop-specific emission factors that represent the cradle-to-gate production impacts of pesticide manufacture.

CFP distinguishes between pesticide categories (herbicides, insecticides, fungicides, and mixed formulations) and applies crop-specific emission factors where available. These factors capture emissions associated with raw material extraction, chemical synthesis, formulation, and packaging of pesticide products. Where an exact match between crop and product is not available in the database, CFP applies a conservative approach by selecting the most representative or highest available emission factor.

Only emissions associated with pesticide production are included in this category. Emissions from machinery used for pesticide application (e.g., sprayers, tractors) are accounted for separately under the fuel and energy use module. This ensures a consistent and transparent separation between chemical input emissions and operational energy emissions.

0.23%

Pesticide use contributed only marginally to the overall carbon footprint of the Huila coffee supply chain. Based on CFP calculations, total emissions associated with pesticide use amounted to **15,429.15 kg CO_2-eq**. This is corresponding to **0,01 kg CO_2-eq per kg GBE and approximately 0.23%** of total emissions when expressed per kg GBE. In absolute terms, pesticide-related emissions remain small when compared to dominant sources such as mineral fertilizers, crop residues management, and wastewater.

Z-score analysis shows that pesticide related emissions are concentrated within a small subset of farms. When emissions are assessed by the Z-score analysis based on per kilogram of GBE, only 3 farms display values above mean. On a per-hectare basis, 4 farms exhibit Z-scores greater than 2. The same farms consistently appear as outliers across both normalization methods, indicating genuinely higher pesticide intensity rather than effects driven by scale. In addition, sensitivity analysis demonstrates that excluding these farms changes total pesticide-related emissions by only about 0.2%, confirming that this category has a negligible influence on the overall carbon footprint.

4.2.4. CROP RESIDUE MANAGEMENT

In CFP, GHG emissions from crop residues in coffee production systems are modelled using a biomass-based, process-oriented framework that is consistent with IPCC guidance and life-cycle assessment principles. Crop residue management represents a major source of emissions in coffee systems and encompasses the handling and treatment of coffee fruit waste, dead plants, above-ground biomass (AGB), below-ground biomass (BGB), dead organic matter (DOM), pruning residues, and primary coffee processing by-products such as pulp and husk. The methodology is designed to reflect how biomass is generated throughout the coffee crop life cycle, how it is partitioned into distinct residue pools, and how each residue stream is subsequently managed at the farm level. Emissions are then quantified based on the physical and biochemical characteristics of each residue type and the management pathway applied by coffee producers.

Residue generation, management pathways, and associated greenhouse gas (GHG) emission calculations follow the same methodological approach described in the

LATAM Study. For a detailed explanation of biomass estimation, residue allocation, management pathways, and emission factors, refer to *LATAM Study, pp. 77–79.*

0.31%

In the Huila coffee supply chain, crop residue management is the second highest driver of GHG emissions at the farm gate. Based on CFP estimates, total emissions from crop residues amount to **2,049,903.98 kg CO_2-eq**, corresponding to **1.78 kg CO_2-eq per kg GBE** and representing approximately **31% of total supply-chain emissions**. Residue-related emissions are dominated by N_2O, which accounts for 71% of total crop residue emissions, while CH_4 contributes 29%.

This emission profile reflects the predominance of field-based residue decomposition processes, which sustain N_2O emissions through nitrogen mineralization, alongside a smaller but still relevant contribution from burning and anaerobic residue handling, which generate CH_4.

Z-score analysis indicates that crop residue emissions exhibit moderate heterogeneity, largely associated with pruning practices. When emissions are evaluated on a per-hectare basis, 13 farms exhibit elevated Z-scores greater than 2, increasing to 14 farms when emissions are normalized per kg GBE. Only 3 farms consistently appear across both normalization approaches, indicating the elevated total emissions are not driven by single structural factor, but rather reflect differences in farm scale, production efficiency and management practices. These higher values are systematically linked to leaf litter and coffee pulp & husks related emissions, confirming these two-management practices as the primary driver of emission within the residue category.

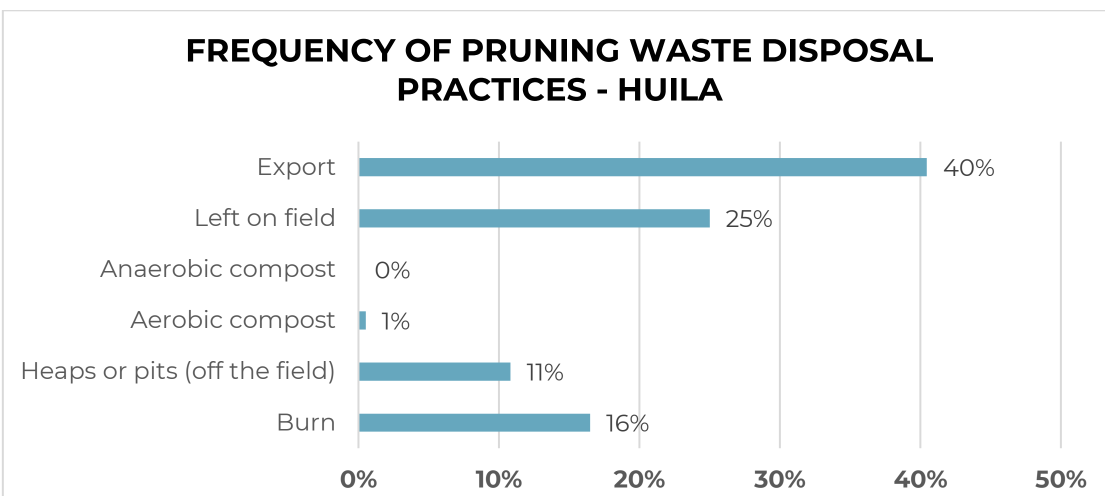


Figure 6: Frequency of Pruning Waste Disposal Practices - Huila

Reported residue management practices provide important context for these patterns. Pruning residues are predominantly exported, reported by 157 farms, while left on field and burning are the primary on-field emission pathways, reported by 97 and 64 farms respectively. Leaf litter management is also overwhelmingly field-based, with 383 farms reporting that litter is left on the soil surface. For coffee pulp and husk, the dominant practice remains field-based litter, reported by 244 farms, followed by aerobic compost and heaps or pits, reported by 120 farms and 82 farms respectively, and export of residues reported by only 1 farm, while anaerobic composting is reported by 4 farms. Together, these patterns indicate that residue management in Huila region is strongly characterized by low-intervention, field-based pathways, with limited adoption of controlled composting practices.

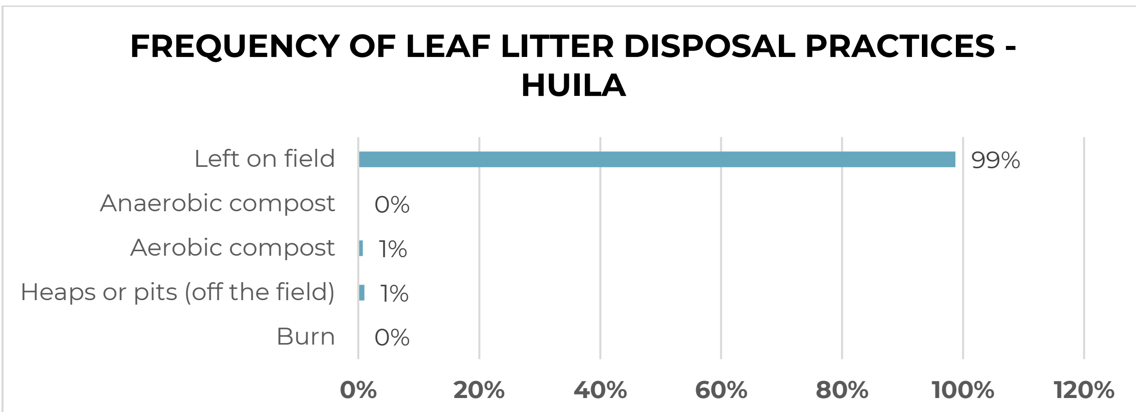


Figure 7: Frequency of Leaf Litter Disposal Practices - Huila

Overall, the magnitude and relative stability of crop residue emissions in Huila appear to be driven by high biomass volumes, the predominance of field-based residue management, and broadly consistent practices across farms, despite some variability linked to leaf-litter intensity and coffee pulp/husk handling. From a mitigation perspective, the results suggest that residue management, particularly processes influencing CH_4 formation under anaerobic conditions and N_2O emissions from residue mineralization represents a relevant area for further exploration. These findings should be interpreted in light of the underlying methodological assumptions and limitations of the CFP approach; for a detailed description, refer to the *LATAM Study, p. 95–97.*

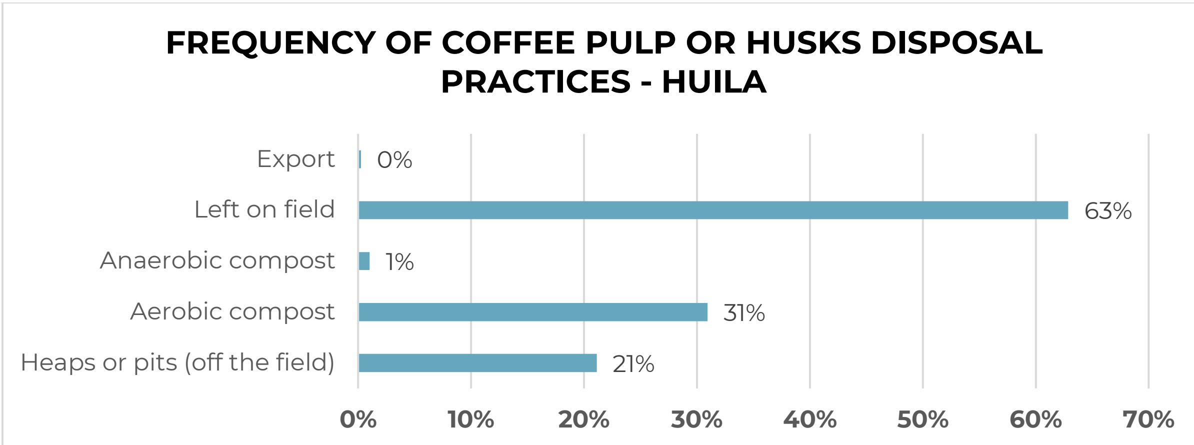


Figure 8: Frequency of Coffee Pulp or Husks Disposal Practices – Huila

4.2.4.1. CONCLUSIONS AND LIMITATIONS ON CROP RESIDUE MANAGEMENT

In Huila, crop residue management represents a relevant source of GHG emissions at the farm-gate, largely shaped by prevailing field-based practices and the handling of processing residues. Emissions are primarily driven by N_2O from decomposition of organic material, with CH_4 contributions arising where residues are stored or treated under aerobic conditions (e.g., heaps or pits). The analysis indicates that these emission patterns reflect common management practices across farms rather than being driven by a few extreme cases, highlighting residue management as an important area for potential mitigation in the region.

However, several methodological limitations should be considered when interpreting these results. Biomass and residue estimates are based on generalized functions within the CFP, which do not fully capture differences in coffee species, tree age distribution, or farm-specific management practices. In reality, coffee farms often consist of mixed-age trees and diverse systems, which can influence the volume of biomass and residues generated.

In addition, some residue streams are estimated based on yield-dependent assumptions. Given that coffee yields can vary significantly due to climatic and agronomic factors, these assumptions may not always accurately reflect actual residue generation in a given year. Similarly, the allocation of residues across different management pathways (e.g., composting, field application, heaps, or pits) is based on self-reported shares, which may simplify more complex and variable on-ground practices.

These factors introduce uncertainty and mean that the results should be interpreted as best-estimate, management-sensitive indicators rather than precise measurements. Despite these limitations, the analysis provides a robust and internally consistent basis for understanding emission drivers and identifying priority areas for improving residue management practices in Huila.

4.2.5. WASTEWATER

In CFP, GHG emissions from wastewater are estimated following the IPCC 2019 Guidelines for National GHG Inventories, with emissions attributed exclusively to CH_4 generated during wastewater treatment. The methodology links the volume of wastewater produced during coffee processing to its organic load, expressed through chemical oxygen demand (COD) or biochemical oxygen demand (BOD), which serve as proxies for the degradable organic matter available for methane formation. Emissions are calculated by combining wastewater volumes, organic content, and a methane conversion factor that reflects the treatment pathway and degree of anaerobic conditions. For coffee processing, CFP recommends using a default COD value of 9,000 mg per litre, consistent with IPCC guidance for coffee wastewater, which was used for the majority of farms assessed in this study in the absence of site-specific measurements. This approach ensures conservative and consistent estimation of wastewater-related emissions across countries, while allowing variability in results to be driven primarily by differences in processing intensity and treatment practices rather than by assumed organic load values.

2.5%

In Huila, wastewater treatment contributes a lower but clearly identifiable share of the total coffee carbon footprint. Total wastewater-related emissions are estimated at **166,944.15 kg CO_2-eq**, equivalent to **0.15 kg CO_2-eq per kg GBE** and representing approximately **2.5% of total supply-chain emissions**, being the third highest emission driver of the Huila assessment. These emissions are driven primarily by treatment system characteristics rather than by absolute wastewater volumes.

Among farms reporting on-farm wet processing, wastewater treatment practices are highly heterogeneous. The most frequently reported systems are constructed wetlands with vertical subsurface flow (171 farms), followed by centralized aerobic treatment plants (43 farms) and anaerobic reactors (36 farms). Sludge anaerobic digestion systems are reported by 9 farms, while horizontal subsurface flow constructed wetlands account for 10 farms and surface flow wetlands for 2 farms. A smaller number of farms report anaerobic lagoons, deeper than 2 m (19 farms). In addition, several farms report no formal treatment, discharging wastewater to unspecified aquatic environments (26 farms); fast-flowing sewers (36 farms); stagnant sewers (11 farms); outlets such as reservoirs, lakes and estuaries (8 farms); or other unmanaged outlets (17 farms).

Z-score analysis indicates that wastewater-related emissions are concentrated within a limited subset of farms, with 13 out of 388 farms exhibiting elevated total wastewater emissions on a per-hectare basis, and 30 farms on a yield-normalized basis. This suggests that the elevated total emissions are primarily driven by the large production scale rather than the structurally higher wastewater related emissions. In all cases, the affected farms represent a statistically negligible share of the sample, and elevated values are not consistently observed across normalization approaches.

Overall, wastewater treatment remains a minor contributor to the Huila coffee carbon footprint when compared with structurally dominant emission sources such as fertilizer use and crop residue management. While substantial farm-level heterogeneity in wastewater management systems exists, this variability does not materially influence national-level carbon footprint results.

Several methodological limitations should be made explicit when interpreting the wastewater results presented and generated with the CFP tool. These limitations primarily relate to the characterization of wastewater organic content, the representation of treatment pathways, and the practical constraints associated with farm-level data collection across diverse coffee-producing regions.

Wastewater-related greenhouse gas (GHG) emissions in this assessment are estimated using the CFP methodology, which follows the IPCC 2019 Guidelines and accounts for CH_4 emissions from anaerobic degradation of organic matter. While this approach ensures consistency with international reporting standards, it relies on simplified assumptions regarding wastewater characteristics and treatment conditions. A detailed discussion of the methodology, key assumptions, and associated limitations, including the use of default COD/BOD values, representation of treatment pathways, and temporal variability, are provided in the LATAM Study. For further information, refer to the *LATAM Study, p. 104–106.*

4.2.6. TRANSPORTATION

In CFP, transport-related GHG emissions are estimated based on the movement of coffee and associated materials off the farm boundary, including transport from farms to collection points, mills, or first buyers. Emissions are calculated as a function of the transported mass, the distance travelled, and the transport mode used. CFP applies default, mode-specific emission factors expressed per tonne-kilometre, which account for vehicle type and fuel use and include well-to-tank emissions. These emission factors are derived from authoritative sources, including DESNZ and DEFRA, ensuring consistency with internationally recognized life-cycle assessment practices. Where farm-specific fuel consumption data are unavailable, this distance- and mass-based approach provides a transparent and conservative estimate of transport emissions. Variability in transport emissions across farms, therefore, reflects differences in transported volumes, yields, distances, and logistics structures, rather than assumptions embedded in the methodology itself.

0.49%

In the Huila coffee supply chain, emissions from transportation are negligible relative to other emission sources. Total transportation emissions amount to **32,480.14 kg CO_2-eq**, corresponding to **0.03 kg CO_2-eq per kg GBE** and representing approximately **0.49% of total supply-chain emissions**.

Z-score analysis indicates that 21 farms exhibit transport emissions above the mean when expressed on per ha basis, representing approximately 3.35% of the sample. However, when emissions are normalized by production (kg GBE), 15 farms show an exceptionally high Z-score. This case is attributable to an extremely low reported yield, which disproportionately inflates transport emissions per unit of output. Overall, transportation emissions in Huila remain marginal and do not influence the representativeness of the dataset or the interpretation of key emission drivers.

4.3. UNCERTAINTY ASSESSMENT

An uncertainty assessment is a critical component of a carbon footprint analysis, as it enables transparent interpretation of results and provides context for understanding the reliability of estimated emissions. All results presented in this study should therefore be interpreted as indicative estimates rather than exact values, reflecting inherent variability in agricultural systems and limitations in data availability and modelling approaches. All carbon footprint estimates in this assessment are furthermore subjected to uncertainty arising from multiple sources, including:

- Sampling errors associated with using a subset of farms to represent a larger population
- Model-related assumptions embedded in the CFP
- Accuracy of farmer-reported data
- Data gaps or missing information required the use of default values.

Consistent with the approach adopted for the similar study conducted in Indonesia and Vietnam (Green Invest Asia and Pact, 2023), the uncertainty assessment presented here focuses primarily on sampling uncertainty, expressed as variability and margins of error derived from the sample. Other sources of uncertainty are acknowledged and discussed qualitatively but are not quantitatively incorporated into the margin of error.

It should be noted that the calculated Margin of Error (MoE) reflects only random sampling uncertainty. Systematic biases, such as consistent underreporting or misreporting of inputs, are not captured in the MoE and therefore are not reflected in the final emission values used for the assessments.

Further, as the baseline assessment is based on data collected for a single full harvesting season, additional uncertainty arises from year-to-year variability in coffee yields, fertilizer use, and climatic conditions. Given the perennial nature of coffee production, future assessments could reduce uncertainty by incorporating data from multiple coffee calendar years to better capture temporal variability. Further industry alignment around such an approach is recommended.

Uncertainty in this assessment arises from sampling variability, data collection and reporting constraints, and model-related assumptions embedded within the CFP and associated tools. While efforts were made to ensure representativeness and consistency across datasets, these sources of uncertainty should be considered when interpreting the results. A detailed discussion of uncertainty sources, including sampling design, data limitations, and model assumptions, is provided in the LATAM Study. For further information, refer to *LATAM Study, pp. 111–113.*

4.3.1. MARGIN OF ERROR CALCULATION

To quantify sampling uncertainty associated with the carbon footprint estimates, MoE was calculated at a 95% confidence level. This reflects uncertainty arising from sampling variability only and is intended to indicate the statistical precision of the estimated mean carbon footprint values. The calculation used followed standard statistical approaches for estimating confidence intervals from sample data and is consistent with the methodology applied in comparable carbon footprint assessments[13].

As mentioned, the farm samples used in this study were selected using a stratified sampling approach, where strata were defined at departmental levels, and sample sizes were allocated proportionally to production volumes. As a result, the aggregated sample already reflects the production-weighted structure of the underlying population. Because this weighting is embedded in the sampling design itself, no additional weighting factors were applied during the MoE calculation. Applying weights again at this stage would have constituted double weighting and would have distorted the estimation of sampling uncertainty. Therefore, the MoE was calculated directly from the observed variability within the final weighted sample.

MoE formula

The MoE[14] was calculated using the standard formula for the mean of a sample:

$$\mathrm{MoE} = \mathrm{SE} \times z_{\alpha}$$

$$\mathrm{SE} = \frac{s}{\sqrt{n}}$$

where:

- z_{α} is the z-score corresponding to a 95% confidence level (1.96),
- SE is the Standard Error,
- s is the sample standard deviation of the carbon footprint indicator (kg CO_2-eq per kg GBE),
- n is the effective sample size.

The MoE and confidence intervals at the regional level, based on CFP results, are provided in Table 4 below.

To ensure that the MoE reflects sampling variability rather than the influence of extreme observations, farms with Z-scores exceeding 2 were excluded from the MoE calculation. These farms were analyzed separately as part of an outlier assessment. This approach is consistent with the objective of estimating uncertainty around the mean for most of the farms and avoids distortion of confidence intervals due to a small number of atypical observations.

13 Walpole, R. E., Myers, R. H., Myers, S. L., & Ye, K. (2012). Probability and statistics for engineers and scientists (9th ed.). Pearson.
14 Triola, M. F. (2018). Elementary statistics (13th ed.). Pearson

Mean (kg CO_2-eq per kg GBE)	n	Coefficient of Variance (%)	Margin of Error (kg CO_2-eq per kg GBE)	Margin of Error (%)	95% Confidence Interval
5.31	388	71.6%	± 0.32	6%	[5.44 ; 6.09]

Table 4: MoE for CFP results for Huila - Colombia

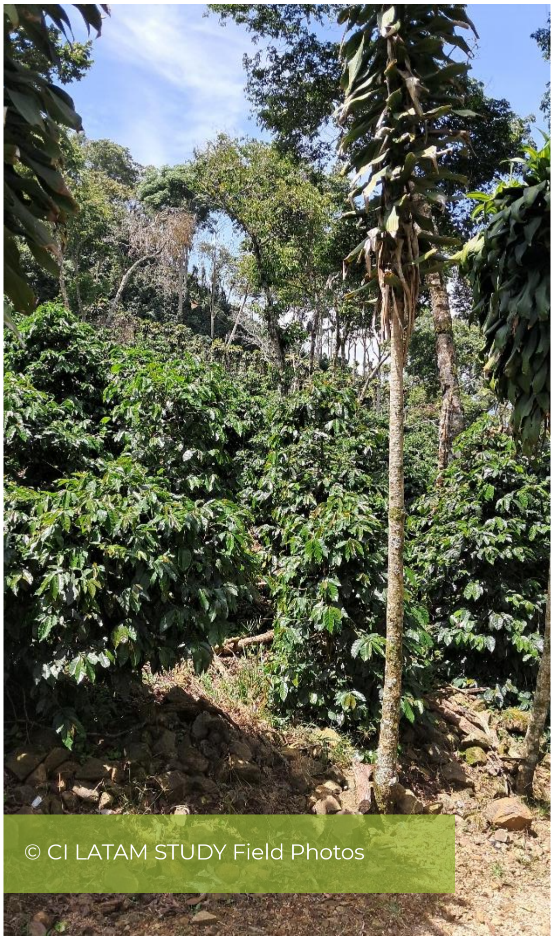
4.4. CARBON CAPTURED BY NON-CROP ESTIMATED BIOMASS

00Coffee production systems, particularly perennial systems, are inherently diverse and frequently extend beyond monocultural cropping. Intercrops, shade trees, and hedges are integral components of many coffee farms and can substantially influence the farm-level GHG balance.

Although these non-crop elements are typically associated with carbon sequestration through the accumulation of above-ground biomass, it is important to emphasize that the values presented here do not yet represent sequestration. At this stage, the data reflect only the baseline estimated biomass, which serves as an initial stock assessment prior to modelling any sequestration over time.

Non-crop components contribute to system productivity and resilience income streams, regulating microclimatic conditions, and protecting soils. In addition, they play a key role in agroecological functioning by enhancing nutrient cycling, reducing erosion, and supporting on-farm biodiversity. Excluding such co-products from the system boundary would therefore underestimate the carbon storage potential of coffee production systems and result in an incomplete representation of farm-gate emissions and removals. For this reason, non-crop plants, specifically intercrops, shade trees, and hedges, are included in the assessment wherever data availability and methodological coverage allow.

During primary data collection, farmers were asked to report the presence of co-products on their farms using an extensive predefined list of species (see Annex 1). This approach was applied consistently across all countries, enabling farmers to select species that most accurately reflected their on-farm conditions. Consequently, the dataset captures a broad diversity of non-crop species, reflecting the structural baseline of on-farm vegetation rather than sequestration outcomes. For each country, information was collected on the type of non-crop vegetation (intercrop, shade tree, or hedge), the species present, and key structural parameters, including plant density, the percentage of farm area occupied, and the average age of trees. These parameters establish the baseline of non-crop biomass against which future sequestration may be modelled.



Carbon storage from non-crop plants was estimated using the CFP, which applies a methodology for biomass changes in non-crop vegetation. The approach includes selected intercrop species, generic shade tree categories, such as tropical trees in wet or dry areas, and canopy or understory classes, and hedges based on species-specific or mixed parameters. However, CFP offers only a limited number of predefined species and generic categories for intercrops—namely, rubber, avocado, durian, jackfruit, and cashew, as well as shade trees, including tropical shade trees, temperate conifers, and shrubs. As a result, several species reported by farmers could not be directly mapped to available CFP categories and were therefore excluded from the CFP non-crop biomass calculation. The carbon capture estimate for non-crop plants derived from CFP is therefore conservative and does not fully reflect the diversity of species reported during data collection. This limitation arises from the availability of model parameters rather than from gaps in the primary data, and CFP-based estimates of carbon stored in non-crop biomass may underestimate total on-farm carbon stocks, particularly in highly diversified agroforestry systems.

Despite limitations, the results of the co-product assessment based on the CFP methodology are presented below. These values are excluded in the overall result by accounting them as removals or carbon sequestration from the system.

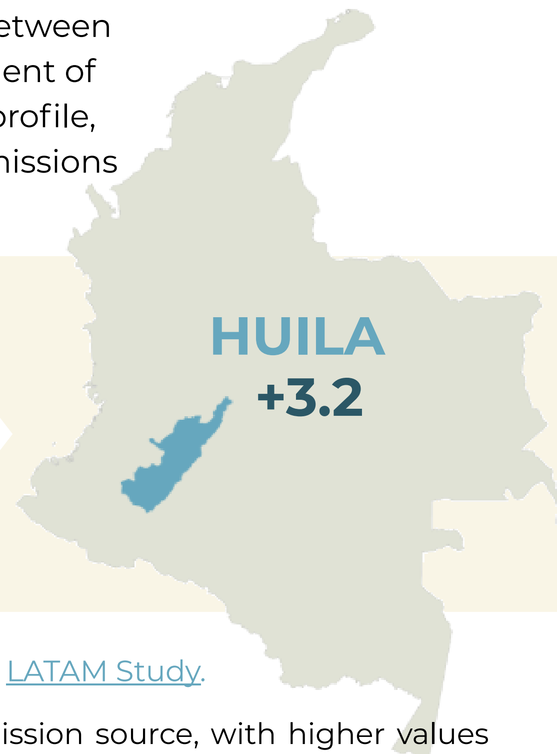
Non-crop biomass, estimated (kg CO_2-eq)	**Non-crop biomass, estimated** (kg CO_2-eq per ha)	**Non-crop biomass, estimated** (kg CO_2-eq per kg GBE)
-1,687,914.00	-1,841.72	-1.47

Table 5: Non-crop biomass estimates of Huila Region according to CFP

4.5. EMISSION BASED COMPARATIVE ANALYSIS WITH NATIONAL BASELINE

A comparative assessment of GHG emissions between Colombia at the national level and the department of Huila shows a broadly similar carbon footprint profile, with Huila exhibiting marginally higher total emissions per kilogram of green coffee bean equivalent.

The total emissions amount to **5.77 kg CO_2-eq per kg GBE in Huila compared to 5.59 kg CO_2-eq per kg GBE at the national level,** representing an increase of 3.2%.



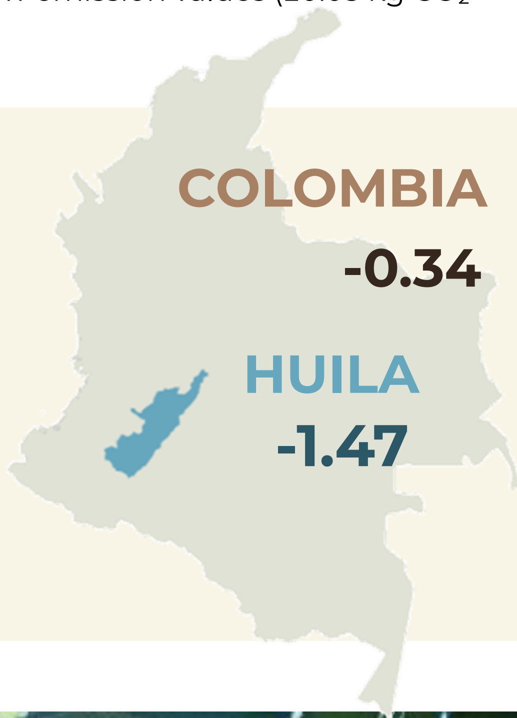
The values for this comparison are derived from the LATAM Study.

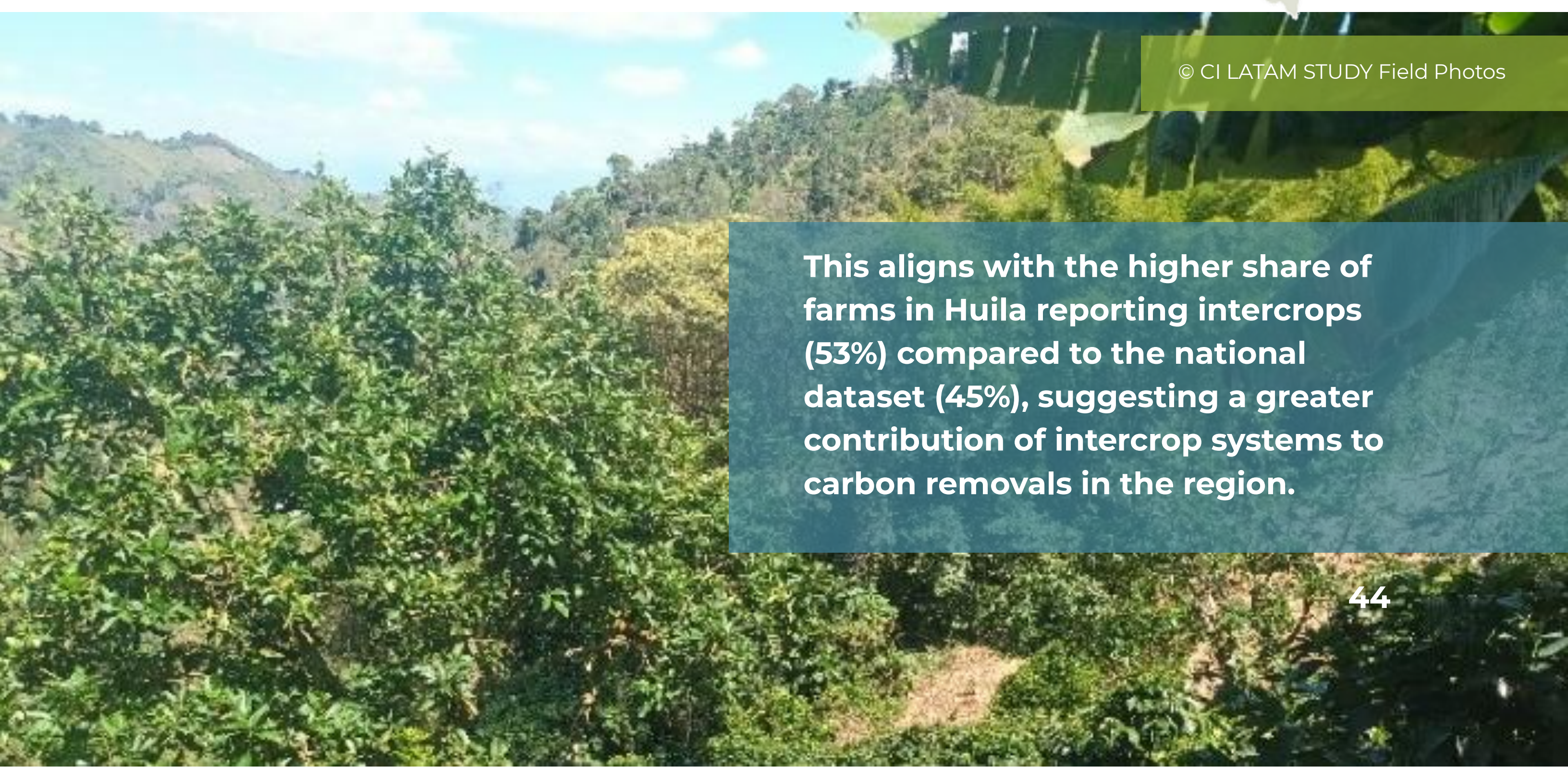
In both datasets, fertilizer use is the dominant emission source, with higher values observed in Huila (3.78 kg CO_2-eq per kg GBE) than at the national level (3.35 kg CO_2-eq per kg GBE), indicating that fertilizer-related emissions contribute more strongly to the overall footprint in the region. This difference is consistent with slightly higher average fertilizer application rates in Huila (1,795 kg/ha) compared to Colombia (1680 kg/ha). Crop residue emissions represent the second-largest category and are nearly identical across both cases (1.78 kg CO_2-eq per kg GBE in Huila and 1.82 kg CO_2-eq per kg GBE nationally), suggesting a comparable contribution of residue-related processes at both scales. In both datasets, residue emissions are dominated by field-based practices such as leaving residues (coffee husks and leaf litter) on the field, which drives similar N_2O-dominated emission profiles.

Clear differences are observed in several operational categories. Emissions from machinery operations are significantly lower in Huila (0.01 kg CO_2-eq per kg GBE) compared to the national average (0.30 kg CO_2-eq per kg GBE), due to reduced mechanized operations and more efficient field operations relative to national patterns. Emissions from fuel and energy use are also lower in Huila (0.01 kg CO_2-eq per kg GBE) than in Colombia overall (0.07 kg CO_2-eq per kg GBE). Although a higher share of farms in Huila report on-farm processing (79%), fuel and energy emissions remain lower, which is consistent with the dominant use of electricity in Huila compared to the greater reliance on coal and fuel wood in the national dataset, resulting in higher emission intensity.

In contrast, wastewater-related emissions are higher in Huila (0.15 kg CO_2-eq per kg GBE) than in Colombia overall (0.04 kg CO_2-eq per kg GBE), highlighting a comparatively greater contribution of wastewater management to total emissions in the region. This is consistent with higher average wastewater volumes reported in Huila (42,361L) compared to the national average (3,2151 L). Transport and pesticide emissions remain minor contributors in both datasets, with only marginal differences between the two, as reflected by their consistently low emission values (≤0.03 kg CO_2-eq per kg GBE).

A pronounced difference is observed in the non-crop vegetation category, where Huila exhibits substantially higher carbon removals compared to the national estimate, indicating a stronger contribution of this category to offsetting emissions at the regional level.





© CI LATAM STUDY Field Photos

This aligns with the higher share of farms in Huila reporting intercrops (53%) compared to the national dataset (45%), suggesting a greater contribution of intercrop systems to carbon removals in the region.

Overall, the slightly higher total emissions in Huila are primarily driven by a stronger contribution from fertilizer use and wastewater management, reflecting higher input intensity and greater wastewater generation within the regional system. These increases are partially offset by a substantially lower contribution from machinery operations and fuel and energy use, as well as a markedly stronger carbon sequestration effect from non-crop vegetation. Together, these patterns indicate that Huila's emission profile is shaped by input-driven emissions and wastewater dynamics, while operational emissions remain limited and carbon removals play a more significant role. This highlights clear regional differences in emission structure within Colombia and demonstrates the relevance of subnational assessments for identifying targeted mitigation priorities.

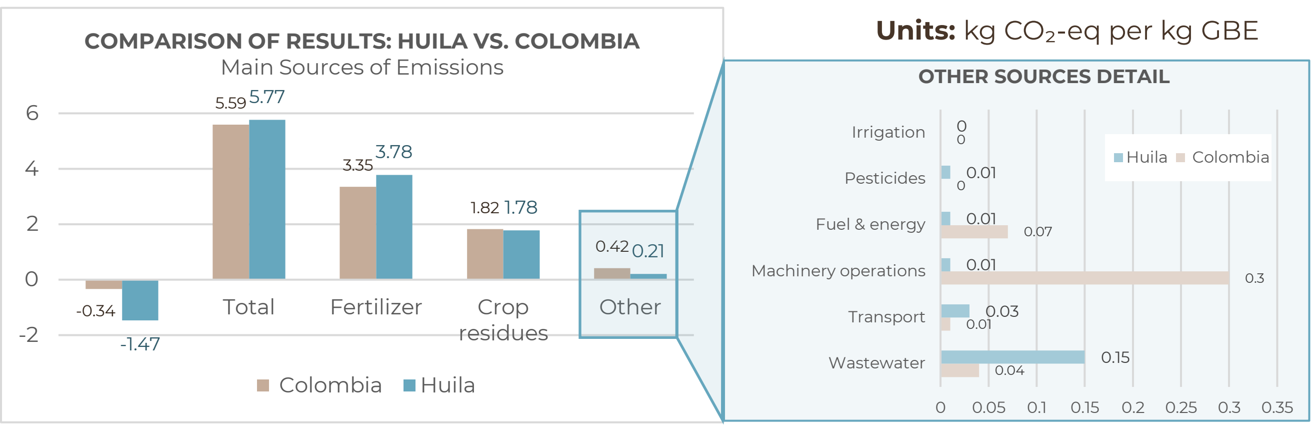


Figure 9: CFP results compared for Colombian and Huila Baseline

4.6. FACTOR SPECIFIC ANALYSIS

The factor-specific analysis applied in this section is conceptually distinct from the archetype framework used during the sampling design. In the sampling phase, archetypes were defined across seven varying factors to ensure that the dataset adequately reflected heterogeneity within national production systems. The primary objective of that approach was to safeguard representativeness and enable robust national-level comparisons.

In contrast, the factor-specific analysis presented here concentrates exclusively on variables that demonstrably influence farm-gate GHG emissions across countries.

Relevant factors for analysis were created if they had the following characteristics:

- Clearly related to emission levels,
- Reflective of farmer decisions or farm characteristics that could be easily understood, and
- Related to enough data points to allow reliable comparisons.

Factors that did not meet these criteria were excluded to avoid overly complex groupings, weak conclusions, or the highlighting of practice that were not truly meaningful in relation to GHG emissions. If farms were grouped using factors that had little impact on emissions, the resulting groups may have differed on paper, but not in actual emission outcomes which could make results harder to interpret and increase uncertainty.

Within this framework, two key factors were established: **fertilizer application intensity** and **certification status**. Fertilizer use is a decision made by farmers and is directly linked to major emission sources. It also varies enough across farms to support meaningful comparisons. Certification status, meanwhile, reflects a broader farm characteristic that is highly relevant to stakeholders, and helps describe differences in practices among farms.

While yield is related to emission intensity, it reflects the combined result of many interacting factors such as management practices, environmental conditions, and past decisions, rather than a single action under a farmer's control. As such, yield was not used as a primary grouping variable within the factor-specific analysis. Instead, the yield values are presented alongside fertilizer application intensity groups in tables below to contextualize emission outcomes across fertilizer-use categories, without implying a direct or uniform relationship between productivity and input intensity.

While the below analysis of fertilizer application intensity and certification status within this section aligns with the methodology used in the similar study conducted in Indonesia and Vietnam (Green Invest Asia and Pact, 2023[15]), it is important to note that grouping farms based on total fertilizer applied per hectare does not fully capture differences in nitrogen input. Mineral fertilizers vary widely in nitrogen content and emission profiles; for example, urea differs significantly from compound NPK fertilizers. As such, grouping farms only by the total mass of fertilizer applied hides important differences in nitrogen-related emissions.

A more detailed approach would require defining fertilizer categories in advance, based on agreed industry criteria for distinguishing fertilizers with different emission impacts. Such an approach would also require country-specific analysis of fertilizer use patterns to ensure that categories are meaningful, and enough farms would need to be included for reliable comparisons. As this level of detail was beyond the scope of the current study, the results analyzing fertilizer-based groups should be interpreted as general indicators of management intensity, rather than precise measures of nitrogen use and its impact. Future studies could improve accuracy by accounting for

15 Green Invest Asia and Pact: Establishing carbon footprint baselines for Robusta coffee production in two origins in Southeast Asia: Central Highlands, Vietnam and Southern Sumatra, Indonesia May 2023

differences in fertilizer composition and nitrogen content when defining farm groupings, using available data. Conducting an archetype analysis based on those that were previously established to define the heterogeneity of systems is further recommended and was specifically highlighted by the study's third-party reviewer.

4.6.1. FERTILIZER APPLICATION INTENSITY

Before classifying farms into fertilizer-use groups, the dataset was screened to identify unusually high fertilizer application rates that could distort the results. A Z-score analysis was used to flag extreme values. Farms with exceptionally high application rates were treated as outliers and excluded from the analysis to ensure that the resulting groups reflected typical farming practices rather than rare extremes.

The number of fertilizer-use groups was chosen to balance clarity with statistical reliability, and different options were tested. A two-group system was tested but considered too broad as it masked meaningful differences in fertilizer use and emissions. Systems with more than three groups resulted in categories with too few farms, making results unreliable and difficult to interpret. A three-group system—**low, medium, and high fertilizer use**—provided the best balance, as it preserved enough detail to show meaningful differences while ensuring reliable comparisons across countries. This approach was furthermore consistent with the similar study conducted in Indonesia and Vietnam (Green Invest Asia and Pact, 2023[16]), which reached a similar conclusion.

The thresholds separating the low, medium, and high fertilizer-use groups were determined using a data-driven method called **Jenks natural breaks**. This method identifies natural groupings in the data by placing boundaries where differences between farms are largest, and where similarities within groups are strongest. Using this approach avoids arbitrary cut-off points and ensures that farms are grouped in a way that reflects real patterns in fertilizer use.

Low input threshold (kg/ha)	Medium input threshold (kg/ha)	High input threshold (kg/ha)
< 1,050	1,050-2,100	>2,100

Table 6: Threshold for fertilizer input use – Huila Region

16 Green Invest Asia and Pact: Establishing carbon footprint baselines for Robusta coffee production in two origins in Southeast Asia: Central Highlands, Vietnam and Southern Sumatra, Indonesia May 2023

Analyses based on input intensity

Huila	Low input threshold	Medium input threshold	High input threshold
% of farm	30%	46%	24%
Median yield (kg/ha)	1,078.85	1,225.38	1,501.92
Average yield (kg/ha)	1,147.44	1,311.17	1,453.44
Average coffee plot size (ha)	2.20	2.44	2.41
Average emissions (kg CO_2-eq per kg GBE)	4.86	5.09	7.74

Table 7: Archetype analyses based on input threshold

As the above results show that fertilizer use, yield, and GHG emissions are not correlated in the same way across categories (e.g., higher input use does not always translate to higher yields, and lower input use does not always translate to reduced emissions), to further assess how these three variables relate to one another, three statistical measures were used: **correlation**, **explained variance (R^2)**, and the **fertilizer–yield slope**. These measures help describe how strongly variables are related, how much they help explain differences in emissions, and how yields tend to respond to fertilizer use. While they are used to describe patterns in the data, they do not imply cause-and-effect relationships.

- **Correlation** shows whether two variables tend to increase or decrease together. For example, it can indicate whether higher fertilizer-related emissions are associated with higher total farm emissions, or whether higher yields are linked to higher or lower emissions. Correlation helps identify relationships but does not prove that one factor causes another. Regardless, it may support farmer decision-making.
- **Explained variance (R^2)** shows how much of the difference in emission intensity across farms can be accounted for by a single factor, such as fertilizer-related emissions or yield. A higher R^2 value means that the factor helps explain a larger share of the observed variation between farms.
- The **fertilizer–yield slope** describes how yields change, on average, as fertilizer use increases. It provides an indication of how responsive yields are to additional fertilizer within the observed range of data; differences around this average

relationship reflect variations in farm management, environmental conditions, and production efficiency. For easier interpretation, fertilizer–yield responsiveness is grouped into three categories:

- **Low responsiveness (elasticity below 0.2)**: Yields change very little as fertilizer use increases.
- **Medium responsiveness (0.2–0.5)**: Yields respond somewhat to fertilizer, but results vary across farms.
- **High responsiveness (above 0.5)**: Yields increase strongly with additional fertilizer.

Together, these three measures help identify which factors are most useful for understanding emission patterns. They also help explain observed differences.

The factor-specific analysis based on synthetic fertilizer input demonstrates that fertilizer application intensity is a primary driver of farm-gate GHG emissions across Huila supply chain, typically accounting for 65.5% of the total carbon footprint. Using a data-driven three-group classification (low, medium, and high input), the results show that higher fertilizer intensity generally corresponds with higher emission intensity and increased input levels translate into proportional productivity gains. In Huila, yield responsiveness is high, indicating that yields increase with increase in fertilizer inputs. The high-input categories represent only a small share of farms (24%) yet exhibit disproportionately high emission intensities, indicating that these outcomes reflect specific management extremes rather than broader national production patterns. Overall, the findings highlight fertilizer management as a key emission lever, while underscoring the linear and context-dependent nature of its relationship with productivity.

Mitigation implications from the analysis suggests prioritizing nutrient-management strategies that improve nitrogen-use efficiency and reduce avoidable fertilizer-related emissions (e.g., better timing, and placement; avoiding over-application; and improving overall agronomic efficiency), alongside broader on-farm efficiency measures where feasible. However, these are general, data-informed indications rather than prescriptive interventions; real-world mitigation outcomes depend heavily on local biophysical conditions, farmer objectives, institutional support, and economic feasibility (costs, labour, risk, access to inputs and advisory services), and may differ substantially even between neighbouring farms.

Fertilizer emission share in total footprint	r	R^2	fertilizer–yield slope (ε)
66%	0.56	0.31	Medium

Table 8: Fertilizer-yield relationship

4.6.2. BASED ON CERTIFICATION

Certification status is frequently discussed as a potential pathway for improving environmental performance in coffee production because certification schemes may be associated with agronomic guidance, record keeping, and participation in structured support programs that can influence management practices (Franzen & Borgerhoff Mulder, 2007[17]; Blackman & Naranjo, 2012[18]). However, certification itself does not constitute a direct management input, and certification schemes differ widely in their objectives, requirements, and enforcement, such that observing differences between certified and non-certified farms does not imply that certification per se causes those differences (Irwandi et al., 2025[19]; DeFries et al., 2017[20]). In recognition of these methodological constraints and based on multiple partner feedback, certification is treated in this study as a descriptive attribute rather than as an explanatory variable for emission outcomes.

An exploratory comparison was conducted to examine whether certified and non-certified farms exhibit different distributions of farm-gate carbon footprint intensity (kg CO_2-eq per kg GBE) within the available dataset. This analysis was not designed to evaluate the impact or effectiveness of certification schemes, nor to attribute differences in emission intensity to certification status; rather, it is intended to describe observable associations in the context of the baseline dataset. Farms were classified into two categories based on self-reported certification status at the time of data collection, as scheme-level information was not consistently available. The results in Table 9 are presented solely as contextual associations and not as indicators of certification performance or mitigation effectiveness.

---

17 Franzen, M., & Borgerhoff Mulder, M. (2007). Ecological, economic and social perspectives on cocoa production worldwide. Biodiversity and Conservation, 16(13), 3835–3849.
18 Blackman, A., & Naranjo, M. A. (2012). Does eco-certification have environmental benefits? Organic coffee in Costa Rica. Ecological Economics, 83, 58–66.
19 Irwandi, Putra & Hasibuan, M. & Syah Putra, Hendris. (2025). THE IMPACT OF COFFEE FARMER CERTIFICATION ON FARMING SUSTAINABILITY (Bibliometric and Content Analysis)
20 DeFries, R. S., Fanzo, J., Mondal, P., Remans, R., & Wood, S. A. (2017). Is voluntary certification of tropical agricultural commodities achieving sustainability goals for small-scale producers? Environmental Research Letters, 12(3)

The analysis does not control for confounding variables or isolate the independent influence of certification, or its specifically recommended practices and it therefore does not support causal inference (Blackman & Naranjo, 2012[21]; McDermott, 2013[22]).

A robust assessment of the impacts of certification on farm-gate GHG emissions would be useful, but would require a dedicated study design that (1) incorporates scheme differentiation and practice differentiation by scheme into the data collection framework;(2) integrates certification criteria into the sampling framework; (3) and controls for key confounders such as farm size, fertilizer use, and production context. Such designs, including matched comparisons or longitudinal evaluations, have been advocated in the sustainability impacts literature and are necessary to distinguish scheme effects from correlated managerial and structural variables (Jena et al., 2012[23]; DeFries et al., 2017[24]). Certification is therefore identified as an important but methodologically complex dimension that warrants targeted investigation in future research, rather than as a variable that can be meaningfully interpreted within this baseline dataset.

Certification status	**% of farms**	**Average Carbon Footprint CFP** (kg CO_2-eq per kg GBE)
Certified	47%	5.68
Non-certified	53%	5.85

Table 9: Analysis of carbon footprint according to certification status

21 Blackman, A., & Naranjo, M. A. (2012). Does eco-certification have environmental benefits? Organic coffee in Costa Rica. Ecological Economics, 83, 58–66.
22 McDermott, J. H., Schemitsch, M., & Simoncelli, E. P. (2013). Summary statistics in auditory perception. Nature Neuroscience, 16(4), 493–498.
23 Jena, P. R., Stellmacher, T., & Grote, U. (2012). The impact of coffee certification on small-scale producers' livelihoods: A case study from the Jimma Zone, Ethiopia. Agricultural Economics, 43(4), 429–440.
24 DeFries, R. S., Fanzo, J., Mondal, P., Remans, R., & Wood, S. A. (2017). Is voluntary certification of tropical agricultural commodities achieving sustainability goals for small-scale producers? Environmental Research Letters, 12(3),

5. LESSONS LEARNED AND RECOMMENDATIONS

The LATAM Study represents one of the most comprehensive efforts to date to establish statistically robust, farm-gate carbon footprint baselines for coffee production across major Latin American origins. This assessment is conducted in the same time period and is fully aligned with the previously mentioned study.

By combining large-scale primary data collection, a heterogeneity-informed sampling framework, comparative analysis of results based on different frameworks, and explicit uncertainty assessment, both studies provide empirical insights into dominant emission drivers and practical lessons regarding current methodological and operational constraints.

A central lesson is that variability in reported carbon footprints is driven not only by differences in farm practices but also by ex-ante design choices related to survey structure, parameter definitions, modelling assumptions, and tool capabilities. As a result, several of the most influential emission sources, particularly fertilizer nitrogen inputs and crop residue management, cannot be treated as secondary technical details. Instead, they require early alignment at the study design stage to ensure that objectives, data collection, and the analytical scope are mutually consistent.

The recommendations below, therefore, address both data collection practices and methodological design, with a focus on strengthening the interpretability, robustness, and future usability of coffee carbon footprint baselines.

5.1. RECOMMENDATIONS FOR DATA COLLECTION AND SURVEY DESIGN

Several lessons emerged from the implementation and quality-control phases of data collection. First, survey timing was confirmed as a critical determinant of data quality. Surveys conducted during or immediately following the harvest period consistently produced more reliable information on yields, fertilizer application, residue handling, and processing practices. Future baseline updates should therefore explicitly align survey deployment with harvest calendars and avoid extended recall periods, particularly for parameters that directly influence emission calculations. Second, while the present study delivers statistically robust departmental baseline for Huila, a single-year assessments inherently limit interpretation. Annualized carbon footprints are suitable for corporate GHG accounting and benchmarking, but they do not capture interannual variability driven by climate, biennial bearing, or changing management intensity. Future studies should prioritize multi-year replication, enabling the construction of time series that distinguish structural mitigation progress from year-specific fluctuations. Third, the study highlights the importance of balancing data resolution with operational feasibility. Across all municipalities, emissions were concentrated in a limited number of sources, most notably fertilizer production and use, crop residue management, and wastewater treatment. Future surveys could therefore adopt a tiered approach, collecting high-resolution data for dominant emission drivers while sampling secondary parameters on a rotational or subsampled basis. Such an approach would reduce respondent burden while preserving analytical relevance. Finally, the iterative quality-control process demonstrated the value of strong enumerator training, validation protocols, and feedback loops, but also exposed the structural limits of farmer recall for technically complex parameters. Where feasible, future studies should increasingly complement survey data with farm records, cooperative-level information, or digital input tracking systems to reduce reliance on recall-based reporting.

5.2. METHODOLOGICAL AND MODELING RECOMMENDATIONS

The results of the Huila baseline are subject to several methodological and data-related limitations that should be considered when interpreting the findings. Many of these aspects are discussed in greater detail, including methodological and modeling recommendations, in the main LATAM study report. In this context, the points below highlight the most relevant caveats specific to the Huila assessment:

- Results are sensitive to modeling choices and emission-factor assumptions within the applied calculation tool, which can influence absolute values even when using consistent primary data.
- The sample is not fully statistically random, as farm selection was constrained by access through participating supply chains; results are therefore representative of these supply chains rather than the entire regional population.
- Residue management data are based on farmer-reported percentage allocations, which may simplify complex, variable practices and introduce uncertainty in emission estimates.
- Wastewater emissions are subject to high uncertainty due to variability in volumes, organic load (COD/BOD), and treatment pathways, and should be interpreted with caution.
- Fertilizer-related emissions depend on reported fertilizer types and default nitrogen content assumptions, which can introduce non-linear uncertainty in results.

- Land use change estimates rely on self-reported data and simplified approaches, limiting the robustness of historical land conversion assessment.
- Carbon sequestration and non-crop biomass are not fully integrated into final results due to current methodological and data constraints.

Overall, the results should be interpreted as standardized, best-estimate indicators suitable for understanding emission drivers and supporting regional benchmarking and strategic planning, rather than as precise measurements at the farm level.

6. CONCLUSION

This study establishes a robust, farm-gate carbon footprint baseline for Arabica coffee production in Huila, Colombia, providing a region-specific extension of the broader LATAM baseline framework. The results confirm that emissions in Huila are highly concentrated in a small number of sources, with fertilizer use, crop residue management, and wastewater treatment collectively accounting for virtually all farm-gate emissions.

A key insight specific to Huila is the high input intensity of production systems, particularly the widespread reliance on mineral fertilizers and relatively high application rates. This structurally drives the dominance of fertilizer-related emissions, with soil N_2O emissions representing the largest single contributor. At the same time, residue management practices in Huila are predominantly field-based, with limited intervention (e.g., controlled composting), leading to consistent N_2O emissions across farms and smaller but relevant CH_4 contributions.

In addition, the study highlights a region-specific wastewater signal, which is more pronounced in Huila than at the national level. This reflects the prevalence of on-farm wet processing and heterogeneous treatment systems, some of which create anaerobic conditions conducive to methane formation. While wastewater remains a smaller contributor overall, its relative importance in Huila indicates a localized emission hotspot that is not fully visible in national-level averages.

At the same time, the results suggest that emission patterns in Huila are structurally embedded rather than driven by a small number of extreme farms, as confirmed by Z-score analysis across key parameters. This reinforces that the identified emission profile reflects typical management practices across the region rather than outliers, strengthening the relevance of the baseline for regional benchmarking and planning.

However, several important caveats should be considered when interpreting the results. The baseline is derived from a model-based assessment (CFP) and relies on a combination of primary data, default emission factors, and simplified representations of biological processes. As a result:

- Absolute emission values are sensitive to methodological assumptions, particularly for fertilizer emission factors, residue modelling, and wastewater characterization.

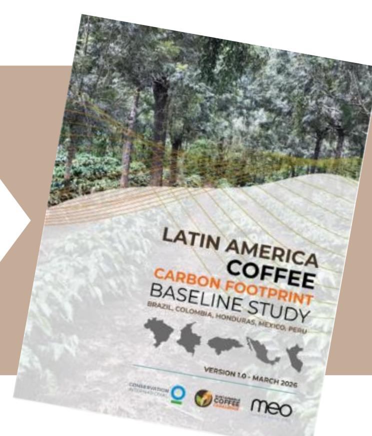
- Sampling is constrained by supply chain access, meaning results are representative of participating supply chains rather than the full population of farms in Huila.
- Key input data (e.g., fertilizer composition, residue handling, wastewater characteristics) are partly based on farmer-reported information and default values, introducing uncertainty.
- Residue and biomass estimates rely on generalized functions, which do not fully capture farm-level variability in tree age, pruning cycles, and system diversity.
- Wastewater emissions are subject to high uncertainty, particularly due to the use of default COD values and simplified treatment classifications.
- Carbon sequestration and land-use change are not fully integrated, meaning the results reflect a conservative, emissions-focused baseline rather than a full net carbon balance.

In addition, while the broader LATAM study underwent independent third-party review, the Huila baseline represents a regional extension with a more limited review process and without a dedicated third-party verification, which should be taken into account when considering the level of external validation.

Overall, the Huila baseline provides a robust, internally consistent, and decision-useful estimate of farm-gate emissions, suitable for benchmarking, Scope 3 accounting, and regional climate action planning. At the same time, results should be interpreted as best-estimate indicators of emission drivers and system dynamics, rather than precise measurements at individual farm level.

The study reinforces that meaningful emission reductions in Huila will depend primarily on addressing a small number of structurally dominant drivers, while continued improvements in data quality, methodological alignment, and multi-year monitoring will be essential to further strengthen the reliability and actionability of future assessments.

For further context, readers may refer to the broader **Latin America Coffee Carbon Footprint Baseline Study,** which covers five Latin American countries and applies the same methodological conditions.



7. REFERENCES

4C Services. (n.d.). *4C Services.* https://www.4c-services.org/

4C Services. (n.d.). *Carbon footprint add-on.* https://www.4c-services.org/4c-system/add-on-certifications/carbon-footprint-add-on/

Acharya, U., & Lal, R. (2021). *Carbon accounting for coffee-based farming systems.* CFAES Rattan Lal Center for Carbon Management and Sequestration, The Ohio State University; World Coffee Research. https://worldcoffeeresearch.org/resources/carbon-accounting-for-coffee-based-farming-systems

Arellano, C., & Hernández, C. (2023). Carbon footprint and carbon storing capacity of Arabica coffee plantations of Central America: A review. *Coffee Science, 18,* e182072. https://doi.org/10.25186/.v18i.2072

Brentrup, F., Hoxha, A., & Christensen, B. (2016, October). Carbon footprint analysis of mineral fertilizer production in Europe and other world regions. In *Proceedings of the 10th International Conference on Life Cycle Assessment of Food (LCA Food 2016)* (pp. 482–490). University College Dublin; Fertilizers Europe.

Chairany, N., Taufik, P. A., Nur, T., & Pawennari, A. (2024). Analysis of potential environmental impacts in the coffee supply chain using life cycle impact assessment. *Sustinere: Journal of Environment and Sustainability, 8(3),* 298 311. https://doi.org/10.22515/sustinere.jes.v8i3.404

Chéron-Bessou, J., Benoist, A., Colinet, G., & Achten, W. M. J. (2023). Carbon footprint of green coffee: A systematic review of life cycle assessment studies. *Journal of Cleaner Production, 389,* 136120. https://doi.org/10.1016/j.jclepro.2023.136120

Conservation International. (n.d.). *Conservation International.* https://www.conservation.org

Cool Farm Alliance. (2026). *Cool Farm Tool.* https://coolfarm.org

Cornelius, J. P., Hardy, F. W., & Harvey, C. A. (2025). Carbon footprints and CO_2 removal in primary production of coffee: A meta-analytical review. *Environmental Reviews, 33,* 1–15. https://doi.org/10.1139/er-2024-0079

Global Risk Assessment Services. (n.d.). *Global Risk Assessment Services.* https://www.gras-system.org

Goldman, E., Carter, S., & Sims, M. (2025). Fires drove record-breaking tropical primary forest loss in 2024. World Resources Institute; Global Forest Watch. https://www.globalforestwatch.org/blog/data-and-research/fires-drove-record-breaking-tropical-primary-forest-loss-in-2024/

Green Invest Asia & Pact. (2023). Establishing carbon footprint baselines for Robusta coffee production in two key origins: Central Highlands, Vietnam and southern Sumatra, Indonesia. https://docs.google.com/document/d/1gKls4gPqamQI3YAppofRysZ1_ceJ_R3y/edit

Green Invest Asia. (2026). *Green Invest Asia.* https://greeninvestasia.com

Greenhouse Gas Protocol. (2022). *Appendix A: Emission factors from cross-sector tools.* World Resources Institute. https://ghgprotocol.org/sites/default/files/2022-12/AppendixA.pdf

Harvey, C. A., Pritts, A. A., Zwetsloot, M. J., Valencia, V., Kettle, C. J., Milder, J. C., & Rice, R. A. (2021). Transformation of coffee-growing landscapes across Latin America: A review. *Agronomy for Sustainable Development, 41,* 62. https://doi.org/10.1007/s13593-021-00712-0

Hergoualc'h, K., Blanchart, E., Skiba, U., Hénault, C., & Harmand, J.-M. (2012). Greenhouse gas emissions from coffee systems: A review of field measurements and modelling. *Agriculture, Ecosystems & Environment, 152,* 83–94. https://doi.org/10.1016/j.agee.2012.02.014

Intergovernmental Panel on Climate Change. (2019). *2019 refinement to the 2006 IPCC guidelines for national greenhouse gas inventories.* Institute for Global Environmental Strategies. https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/

https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/Intergovernmental Panel on Climate Change. (2021). *Climate change 2021: The physical science basis (Working Group I contribution to the Sixth Assessment Report).* Cambridge University Press. https://www.ipcc.ch/report/ar6/wg1/

Intergovernmental Panel on Climate Change. (2023). Sections. In H. Lee & J. Romero (Eds.), Climate change 2023: Synthesis report. *Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 35–115). IPCC. https://doi.org/10.59327/IPCC/AR6-9789291691647

Irawan, A., & McLellan, B. C. (2024). A comparison of life cycle assessment (LCA) of Andungsari Arabica coffee processing technologies towards lower environmental impact. *Journal of Cleaner Production, 447,* 141561. https://doi.org/10.1016/j.jclepro.2024.141561

Ketterings, Q. M., Coe, R., Van Noordwijk, M., Ambagau', Y., & Palm, C. A. (2001). Reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests. Forest Ecology and Management, 146(1-3), 199-209. https://doi.org/10.1016/S0378-1127(00)00460-6

Ledo, A., Heathcote, R., Hastings, A., Smith, P., & Hillier, J. (2018). Perennial-GHG: A new generic allometric model to estimate biomass accumulation and greenhouse gas emissions in perennial food and bioenergy crops. *Environmental Modelling & Software, 102,* 292–305. https://doi.org/10.1016/j.envsoft.2017.12.005

McLeod, S. (2023, October 6). Z-score: Definition, formula, calculation & interpretation. Simply Psychology. https://www.simplypsychology.org/z-score.html

MEO Carbon Solutions. (2025). *MEO Carbon Solutions.* https://www.meo-carbon.com

Nab, C., & Maslin, M. (2020). Life cycle assessment synthesis of the carbon footprint of Arabica coffee: Case study of Brazil and Vietnam conventional and sustainable coffee production and export to the United Kingdom. *Geo: Geography and Environment, 7(2),* e00096. https://doi.org/10.1002/geo2.96

Noponen, M. R. A., Edwards-Jones, G., Haggar, J. P., Soto, G., Attarzadeh, N., & Healey, J. R. (2012). Greenhouse gas emissions in coffee production systems: Case studies from Central America. *Journal of Cleaner Production, 44,* 1–10. https://doi.org/10.1016/j.jclepro.2012.11.042

Poore, J., & Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. *Science, 360(6392),* 987–992. https://doi.org/10.1126/science.aaq0216

Sarmento dos Muchangos, L., Mejia, C., Gupta, R., Sadreghazi, S., & Kajikawa, Y. (2025). A systematic review of life cycle assessment and environmental footprint for the global coffee value chain. *Environmental Impact Assessment Review, 111,* 107740. https://doi.org/10.1016/j.eiar.2024.107740

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., & Kumar, P. (2007). Agriculture. In B. Metz, O. R. Davidson, P. R. Bosch, R. Dave, & L. A. Meyer (Eds.), *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 497–540). Cambridge University Press. https://www.ipcc.ch/report/ar4/wg3/

Solidaridad. (2024). Overview of the carbon balance in coffee production: Carbon footprint assessment of coffee farms in the Alta Mogiana region, Brazil (2022–2023). Solidaridad Network. https://www.solidaridadnetwork.org/wp-content/uploads/2024/09/Overview-of-the-carbon-balance-in-coffee-production_final.pdf

Sustainable Coffee Challenge. (n.d.). *Sustainable Coffee Challenge.* https://www.sustaincoffee.org

Triola, M. F. (2018). *Elementary statistics* (13th ed.). Pearson

Van Rikxoort, H., Schroth, G., Läderach, P., & Rodríguez-Sánchez, B. (2014). Carbon footprints and carbon stocks reveal climate-friendly coffee production. *Agronomy for Sustainable Development, 34*(4), 887–897. https://doi.org/10.1007/s13593-014-0223-8

Walpole, R. E., Myers, R. H., Myers, S. L., & Ye, K. (2012). *Probability and statistics for engineers and scientists* (9th ed.). Pearson.

Z-score. (2008). In W. Kirch (Ed.), *Encyclopedia of public health* (p. 1484). Springer. https://doi.org/10.1007/978-1-4020-5614-7_3826

8. ANNEXES

- Annex 1: INTERCROP TREE SPECIES LIST
- Annex 2: RANDOMIZATION PROTOCOL
- Annex 3: PESTICIDES LIST

ANNEX 1: INTERCROP TREE SPECIES LIST

No.	Tree species name
1	Acacia Acacia oraria/Acacia mangium
2	African teak Moraceae
3	African tulip tree Spathodea campanulata
4	Avocado Persea americana
5	Cashew Anacardium occidentale
6	Cassia Cassia fistula
7	Coconut palm Arecaceae
8	Conifer forests Default
9	Custard Apple Casimiroa tetrameria
10	Croton tree/Mukinduri Croton megalocarpus
11	Durian Durio zibethinus
12	Banana Musa spp.
13	Egyptian riverhemp Fabaceae
14	Ficus ovata Ficus padifolia
15	Fig-mulberry Ficus padifolia
16	Flame tree Erythrina abyssinica
17	Fruit Tree Default
18	Giant Lira Melia azedarach
19	greenheart tree Ocotea psychotrioides
20	Guava Psidium guajava
21	Hopea Hopea odorata
22	Inga species various
23	Jacaranda Jacaranda mimosifolia
24	Jackfruit Artocarpus
25	Kapok Ceiba pentandra
26	Lemon Citrus limon
27	Listea Litsea Lauraceae
28	Loquats Rosaceae

No.	Tree species name
29	Macadamia Proteaceae
30	Mango Mangifera indica L
31	midnight horror Oroxylum indicum
32	Moringa/Drumstick tree Moringa oleifera
33	Nile tulip Markhamia lutea
34	Oranges Citrus sinensis
35	Papaya Carica papaya
36	Parasol tree Malvaceae Firmiana colorata
37	Pepper Piperaceae Piper arthante
38	Pinus species Pinaceae Pinus sylvestris
39	Plantain Musa paradisiaca
40	Plantation teak/Common teak Tectona grandis
41	Quercus Species various
42	Quickstick Gliricidia sepium
43	Red Stinkwood Prunus Rosaceae Prunus arborea
44	Royal Poinciana/flame tree Delonix regia
45	Rubber Hevea brasiliensis
46	Southern Silky Oak Proteaceae
47	Spiked Powder Puff Leguminosa (Fabaceae)
48	Strangler Fig Moraceae Ficus
49	Sudan teak Boraginaceae Cordia (Various)
50	Tamarind Fabaceae
51	Umbrella tree Araliaceae Schefflera
52	Wild tamarind/red leucaena Fabaceae Leucaena leucocephala
53	Tropical trees (Dry)
54	Tropical trees (Moist)

ANNEX 2: RANDOMIZATION PROTOCOL

RANDOMIZATION PROTOCOL

This document provides comprehensive guidelines for supplier partners and enumerators to ensure the proper implementation of randomization principles during the data collection process.

Protocol Guidelines:

When visiting farms in the designated municipalities, adhere strictly to the following randomization protocols to maintain data integrity:

- *Diversify Farm Visits:* Prioritize visits to sparsely located farms to enhance the variety of the sample pool, which can help mitigate sampling bias.
- *Avoid Bias in Farm References:* While surveyed farms can serve as a useful reference for identifying other potential sampling locations, avoid using references where they share similar characteristics (e.g., familial relations). This practice reduces the risk of introducing bias into the sampling process.
- *Re-allocation of Samples:* If the required number of samples from a target municipality cannot be obtained, enumerators are allowed to re-allocate the missing samples to adjacent municipalities within their assigned areas. Such re-allocations must be documented and reported promptly.

Best Practice Guidelines (Applicable when practical):

Ensure Representation of Diverse Farm Types: To prevent sampling bias, avoid focusing exclusively on certified farms when there are both certified and non-certified farms in the supply chains. Include a random mix of certified and non-certified farms in your sample to ensure that the sample accurately reflects the entire population within the supply chain.

Importance of Adherence:

Strict adherence to these protocols is crucial to preserving the integrity and validity of the data collection process, ensuring that the findings are representative and reliable.

ANNEX 3: PESTICIDES LIST

PLANT PROTECTION (% OF ACTIVE INGREDIENT)

Name of active substance	Percentage of active ingredient	Name of active substance	Percentage of active ingredient
Abamectina	18	Dinotefuram; Flutriafol	36
Acetamiprid	20	DMA dicamba salt; 2,4-D amine salt	30
Acetamiprido; Bifentrina	50	Epoxiconazole	25
Azoxistrobina	50	Fipronil	20
Azoxistrobina; Cyproconazol	28	Flupiradifurona	20
Azoxistrobina; Difenoconazol	33	Glyphosate	48
Azoxystrobin	33	Imidacloprid	70
Boscalida	50	Imidacloprid; Bezacyfluthrin	30
Caldo	39	Imidacloprido;Triadimenol	42
Carbendazim	50	Indaziflam	50
Carbosulfan	30	Lufenrom	40
Cercobin (Tiofanato-metílico)	30	Maconzeb; Azoxistrobina;Tebuconazole	75
Chlorabtraniliprole; Thiamethoxam	30	Malathion	50
Chlorothalonil	72	Mancozeb	45
Chlorpyrifos	48	Manzozeb	48
Ciantraniliprole	10	Piraclostrrobina; Epixiconazol	18
Cletodim	24	Profenofos	72
Clorantraniliprole	35	Quinalphose	25
Clorpirifos	35	Tebuconazole	35
Cobre	69	Thiametoxam	25
Cooper oxychloride	50	Thiametoxam; Ciproconazol	50
Cypermethrin; Profenofos	45	Thiametoxam; Clorantraniliprole	30
Cyprocanazol	10	Trifloxistrobina; Ciproconazol	54
Cyproconazol; Tiametoxam	60	Trifloxistrobina; Tebuconazol	30
Dimethoate	29	Zapp	62

Source: https://www.epa.gov/ingredients-used-pesticide-products/brief-overviews-about-individual-pesticides