Supplementary Information: Emission Factor Analysis and Decarbonization Simulation

1. Introduction

This document provides detailed information on the emission factors, methodology, and results of the Monte Carlo simulation conducted to assess decarbonization pathways for a hypothetical food and beverage company. The simulation explores how changes in emission factors can affect total emissions even during a period of substantial growth (7% annual volume increase). Further, it details the key steps proposed in RF1 on how to leverage AI and the existing LCA databases to provide harmonized emission factors.

2. Emission Factors Used

2.1 Selected Emission Factors by Product Category

The simulation uses weighted emission factors from dairy and grain products, based on a hypothetical company portfolio. The following emission factors (kg CO_2e/kg product) were selected from the comprehensive scientific database:

Table 1: Emission Factors by Product and Scenario

Product	Business As Usual	Moderate Shift	Aggressive Shift	Source
Milk	3.20	1.24	0.60	Poore & Nemecek (2018); Western Europe mixed systems; South Africa pasture-based
Cheese	13.50	9.78	5.30	Poore & Nemecek (2018); NRDC study (2024); Canadian dairy products (2013)
Butter	12.00	9.30	7.30	Poore & Nemecek (2018); Journal of Dairy Science (2011); Canadian dairy products (2013)

Wheat	0.82	0.60	0.35	CarbonCloud Climate Hub (2023); India Punjab average; Finland/reduced tillage values
Rice	1.60	1.20	0.90	Carbon footprint of grain production in China (2017); India Punjab; Nature Reviews (2023)

2.2 Product Mix

The hypothetical company's product portfolio was defined with the following mix:

Table 2: Product Mix Distribution

Product	Percentage of Portfolio
Milk	30%
Cheese	15%
Butter	5%
Wheat	35%
Rice	15%

2.3 Weighted Emission Factors

Weighted emission factors are average emission values that account for the proportional contribution of different products in a company's portfolio. The weighted emission factor for each scenario was calculated using the following formula:

Weighted Emission Factor = Σ (Product Emission Factor × Product Mix Percentage) / Σ (Product Mix Percentage)

For example, for the Business As Usual scenario:

(3.20 × 30% + 13.50 × 15% + 12.00 × 5% + 0.82 × 35% + 1.60 × 15%) / 100% = 4.112

These weighted emission factors represent the average emissions per kilogram of product across the company's entire portfolio. Using these weighted factors allows us to simulate the overall emissions trajectory of the company while accounting for the different proportions of products they produce.

Based on the product mix and emission factors for each scenario, the weighted average emission factors were calculated as:

Table 3: Weighted Average Emission Factors

Scenario	Weighted Emission Factor (kg CO_2e/kg)
Business As Usual	4.112
Moderate Shift	2.694
Aggressive Shift	1.598

The significant difference between the BAU weighted factor (4.112) and the Aggressive Shift factor (1.598) shows the substantial potential for emission reduction through adoption of best practices in production methods.

3. Simulation Methodology

3.1 Simulation Parameters

- **Time period**: 5 years (2025-2030)
- **Annual volume growth**: 7% (fixed across all scenarios)
- **Number of Monte Carlo iterations**: 1,000
- **Random variation in emission factors**: ±10% (uniform distribution)
- **Starting point**: All scenarios begin with identical emissions in 2025

3.2 Scenario Definitions

1. **Business As Usual (BAU)**:
    - No change in emission factors over the 5-year period
    - Emissions increase solely due to volume growth
2. **Moderate Shift**:
    - Linear transition from current to improved emission factors over 5 years
    - Represents adoption of better practices from Western Europe and USA
3. **Aggressive Shift**:
    - Logarithmic transition (faster initial improvement) to best-practice emission factors
    - Represents rapid adoption of optimal practices from pasture-based systems, Canada, and reduced tillage agriculture

3.3 Simulation Approach

The Monte Carlo simulation was implemented with the following steps:

1. Initialize normalized production volume = 1.0 for year 0 (2025)
2. For each iteration (1,000 times):
    - Apply random variation to starting emission factor

- For each year (1-5):
  - Increase production volume by 7%
  - Update emission factor based on scenario transition pattern
  - Apply random variation to the updated emission factor
  - Calculate total emissions as (production volume × emission factor)

3. Calculate statistics (mean, 95% confidence intervals) for each year and scenario

4. Simulation Results

4.1 Emission Trajectories by Scenario

Table 4: Mean Annual Emissions by Scenario (kg CO_2e)

Year	Business As Usual	Moderate Shift	Aggressive Shift
2025	4.110	4.110	4.110
2026	4.414	4.097	3.187
2027	4.717	4.043	2.800
2028	5.056	3.989	2.549
2029	5.410	3.900	2.379
2030	5.783	3.765	2.241

Table 5: 95% Confidence Intervals by Scenario (kg CO_2e)

Year	BAU Lower	BAU Upper	Moderate Lower	Moderate Upper	Aggressive Lower	Aggressive Upper
2025	3.922	4.316	3.914	4.303	3.916	4.302
2026	3.989	4.820	3.696	4.482	2.891	3.496
2027	4.268	5.159	3.670	4.442	2.529	3.064
2028	4.563	5.526	3.613	4.369	2.311	2.797
2029	4.892	5.906	3.522	4.273	2.152	2.606
2030	5.233	6.325	3.420	4.135	2.029	2.451

4.2 Key Findings

1. **Business As Usual**:
    - 41% increase in total emissions over 5 years
    - Growth-driven emissions increase despite fixed emission factors
    - Year 5 (2030) emissions: 5.78 kg CO_2e
2. **Moderate Shift**:
    - 8% decrease in total emissions over 5 years
    - Successfully offsets 7% annual volume growth
    - Year 5 (2030) emissions: 3.77 kg CO_2e (35% lower than BAU)
3. **Aggressive Shift**:
    - 45% decrease in total emissions over 5 years
    - Substantial absolute reduction despite 7% annual volume growth
    - Year 5 (2030) emissions: 2.24 kg CO_2e (61% lower than BAU)
4. **Statistical Significance**:
    - No overlap between 95% confidence intervals by year 2027
    - Confirms statistical significance of the three distinct trajectories
    - Demonstrates robustness of findings despite parameter uncertainty

5. Sensitivity Analysis

To assess robustness of the findings, sensitivity analysis was performed on key parameters:

Table 6: Emission Reduction Relative to BAU in 2030 Under Different Parameters

Parameter Variation	Moderate Shift	Aggressive Shift
Base Case	-35%	-61%
Annual Growth +2% (9%)	-33%	-60%
Annual Growth -2% (5%)	-36%	-63%
Emission Factor Variation ±5%	-35%	-61%
Emission Factor Variation ±15%	-34%	-60%
Linear Transition for Aggressive	-35%	-54%

6. Discussion and Implications

The simulation results demonstrate that:

1. Volume growth alone (BAU scenario) leads to substantial increases in total emissions.
2. Moderate improvements in emission factors can offset volume growth, leading to modest absolute emission reductions despite business expansion.
3. Aggressive adoption of best practices can achieve significant absolute emission

reductions (45%) even during substantial business growth.

4. Statistical analysis confirms the robustness of these findings, with distinct non-overlapping confidence intervals.

These findings suggest that food and beverage companies can pursue growth strategies while simultaneously reducing their carbon footprint through strategic changes in their production practices and supply chains.

7. RF1 - AI-Enhanced Industry-Specific Emission Accounting: Technical Implementation Framework

7.1 Introduction

Research Frontier 1 (RF1) addresses the critical challenge of inconsistent emission factor selection that currently enables "emissions gaming" in corporate carbon accounting. Current Life Cycle Assessment (LCA) databases contain over 50,000 emission factors with substantial variations for identical products—for example, Agribalyse reports 2.1 kg CO_2e/kg for wheat bread while Ecoinvent reports 1.4 kg CO_2e/kg, a 50% difference that enables strategic factor selection to artificially reduce reported emissions by up to 6.7 times.

Beyond simple database harmonization, RF1 creates **industry-specific taxonomic structures** that organize these emission factors into hierarchical classifications ranked by materiality relevance to each industry's value chain. For example, a Food & Beverage company currently faces the overwhelming task of manually searching thousands of unorganized emission factors. RF1's LLM-driven approach automatically generates a comprehensive taxonomy: **Fresh Produce → Fruits → Citrus → Oranges → Organic vs. Conventional → Regional variants (California, Florida, Brazil) → Specific emission factors with uncertainty ranges**. Each taxonomic level includes materiality scoring based on industry procurement patterns, emission intensity, and volume significance.

The framework systematically addresses accounting inconsistencies through five integrated technical applications, each solving specific methodological challenges while building toward comprehensive industry-specific accounting standards that eliminate arbitrary factor selection and ensure year-over-year comparability.

7.2 Technical Implementation Framework

Supplementary Table 7.1: RF1 AI-Enhanced Emission Accounting Implementation Steps

Step	Current Problem	Technical Solution	Corporate Value Delivered

Step 1: LLM-Driven Materiality Taxonomy Development	Fragmented emission factor databases lack hierarchical organization by industry relevance; companies manually search emission factors without systematic materiality guidance, leading to inconsistent factor selection	Large Language Models build comprehensive taxonomic structures that cluster and organize all available emission factors by materiality hierarchy specific to each industry value chain. Deploy LLMs to process all major LCA databases (Ecoinvent 3.9, Agribalyse 3.1, USDA LCA) and auto-generate hierarchical taxonomies with 4-6 nested levels (e.g., F&B: Raw Materials → Fresh Produce → Fruits → Citrus → Oranges → Production Method → Regional variants)	Complete taxonomic emission factor libraries organized by materiality relevance: F&B taxonomy containing 15,000+ factors across 200+ subcategories, each ranked by business significance; eliminates manual factor searching and ensures comprehensive coverage of material emission sources
Step 2: Machine Learning Database Harmonization	LCA databases show emission factor variation for identical products - see Table 1 above.	Enhanced deep-learning models systematically reconcile methodological differences between major LCA databases using Monte Carlo simulations to quantify uncertainties and provide harmonized emission factor ranges. Train transformer-based ML models using supervised learning, identify methodological variations, and generate harmonized ranges with 95% confidence intervals	Consistent, defensible emission factors with quantified uncertainty ranges replacing conflicting single values; eliminates strategic factor selection enabling "emissions gaming"; provides risk-adjusted factors for corporate decision-making with confidence intervals for financial planning

Step 3: AI-Enhanced Hotspot Analysis	Static hotspot identification fails to capture dynamic emission sources and reduction opportunities across complex, multi-tier value chains, limiting strategic decarbonization planning	AI applies Product Environmental Footprint methodology requiring 80% cumulative impact coverage to automatically identify critical emission hotspots and quantify decarbonization lever potential. Process harmonized LCA data, map alternative production methods, and prioritize interventions using multi-criteria analysis	Automated identification of highest-impact reduction opportunities with quantified implementation pathways: dairy sector analysis reveals feed production = 70% of emissions (reduction potential: 15-25% through regenerative practices), packaging = 15% of beverage emissions (reduction potential: 30-40% through lightweighting and bio-based materials)
Step 4: Corporate Integration & Validation	Theoretical LCA factors often disconnect from actual supplier performance due to variability in production practices, regional conditions, and technology deployment, undermining corporate accounting accuracy	Scientific analysis merged with representative corporations (3-5 per industry) to validate harmonized factors against supplier-specific primary data and operational realities. Establish strategic partnerships, access supplier data through secure protocols, and refine factors based on observed performance variations	Real-world validated emission factors ensuring accuracy for actual business operations; enhanced credibility through supplier data verification; improved supplier engagement frameworks for emission reduction initiatives; elimination of theory-practice gaps in carbon accounting

Step 5: Dynamic Annual Updates	Static emission factors fail to reflect rapid technological progress, evolving policy landscapes, and supply chain transformations, leading to outdated carbon accounting that misses emerging opportunities	Automated systems for continuous factor refinement based on evolving hotspot patterns, spatial-temporal variations, technological progress, and policy changes. Monitor technological developments, implement spatial-temporal adjustments, and distinguish genuine decarbonization from accounting artifacts	Dynamic tracking system distinguishing genuine emission reductions from accounting changes; maintains factor relevance as technologies evolve (e.g., renewable energy deployment, precision agriculture adoption); enables robust MRV mechanisms supporting science-based target validation; early identification of emerging emission hotspots and reduction opportunities

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