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FarmCarbon AI: An AI-Based Framework for Carbon Mitigation and Financing in Central European Dairy Farms

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ABSTRACT:
Agriculture is a major source of greenhouse-gas (GHG) emissions, particularly through enteric fermentation and manure management in dairy farming. This paper presents FarmCarbon AI, an AI-assisted framework that combines deterministic IPCC Tier-2 calculations, mitigation-scenario screening, economic screening, and structured grant-draft generation for Central-European dairy farms. The evaluation uses 100 constrained synthetic farm profiles across eight country contexts; it is therefore a test of workflow behaviour under modeled inputs, not evidence of field performance or national representativeness. The calculation engine estimates enteric CH_4, manure CH_4, and manure N_2O, while the retrieval-augmented language-model component is limited to source-grounded explanation and draft documentation rather than numerical calculation. Under the specified scenario assumptions, modeled emission reductions were 8–19%. A one-way sensitivity analysis of the illustrative high-intensity profile shows that economic screening is highly dependent on the assumed low-carbon milk premium, co-financing rate, and operating costs; it should not be interpreted as a market forecast. The study contributes a transparent prototype and an explicit validation agenda for future testing with measured farm records, country-specific costs, expert review, and benchmark comparisons with established calculators and human workflows.

Keywords: sustainable agriculture; artificial intelligence; greenhouse gas emissions; dairy farming; IPCC Tier-2 methodology; carbon footprinting; climate finance; decision support; Central Europe; Common Agricultural Policy

1. Introduction

Approximately 12% of global anthropogenic greenhouse-gas (GHG) emissions derive from agriculture, particularly from enteric fermentation and manure management in dairy farms (IPCC, 2021; Hristov et al., 2013; Gerber et al., 2013). In dairy systems, enteric CH_4 remains the main source (≈ 70–80%), followed by manure CH_4 and N_2O (Hristov et al., 2013; Gerber et al., 2013; Thomassen et al., 2008; IPCC, 2019; Bronson & Knezevic, 2016). Mitigation strategies such as dietary lipid addition (Martin et al., 2010), 3-NOP feed additives (van Wesemael et al., 2019), seaweed supplementation (Roque et al., 2021), and improved manure management (Chadwick et al., 2011) may collectively reduce emissions by 20–40%. The European Green Deal and Farm-to-Fork Strategy set binding targets of 55% emission reduction by 2030 and climate neutrality by 2050 (European Commission, 2021), which requires scientifically rigorous farm-level tools (FAO, 2022).

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Most tools currently used by farmers remain overly complex, opaque, or reliant on manual data entry (Thomassen et al., 2008; IPCC, 2019; Bronson & Knezevic, 2016). Conventional Tier-1 calculators apply generic emission factors that ignore herd productivity, feeding systems, and manure-storage conditions (Hristov et al., 2013; Gerber et al., 2013), leading to biased results across farms and regions. By contrast, Tier-2 approaches improve precision by linking emissions to actual energy intake, feed composition, and manure management, as defined in the 2019 IPCC Refinement (IPCC, 2019). However, Tier-2 requires regional emission factors, detailed animal and environmental parameters, and multiple interlinked equations (Thomassen et al., 2008; IPCC, 2019; Bronson & Knezevic, 2016). For most Central- and Eastern-European farms, these computational and administrative demands limit adoption in climate-finance or sustainability-certification schemes (Bronson & Knezevic, 2016; GHG Protocol, 2014).

Adoption is also constrained by high investment costs (European Court of Auditors, 2021). To cover them, farmers must apply for public subsidies and blended-finance models under the EU Common Agricultural Policy (CAP) (Canadian Agri-Food Policy Institute, 2025; European Court of Auditors, 2021; Climate Policy Initiative, 2023). Yet preparing grant proposals demands substantial administrative effort and the ability to translate technical concepts into standardized reporting frameworks. Without adequate decision-support tools (Saro et al., 2024b) and accessible guidance (Saro et al., 2024a), many small and medium-sized farmers face significant barriers to participation. Further research is therefore needed to bridge the gap between scientific methods and usable farm-level tools.

With this goal in mind, we developed FarmCarbon AI as an AI-assisted decision-support prototype combining deterministic IPCC Tier-2 GHG calculations, mitigation-scenario simulation, economic screening, and structured grant-draft generation. The prototype was exercised on 100 synthetic farm profiles across eight country contexts. Accordingly, the results demonstrate the internal behaviour of the workflow under declared assumptions; they do not validate per-farm predictions, confirm eligibility for funding, or demonstrate realised adoption. The system combines structured data ingestion, a calculation layer based on IPCC equations and emission factors, scenario and cost–benefit modules, and an LLM-assisted layer for evidence-linked explanatory text and draft documentation. This framing distinguishes the deterministic calculation outputs from AI-generated language and sets an empirical validation agenda for subsequent work.

2. Data and Methods

SYSTEM OVERVIEW

FarmCarbon AI is an AI-assisted workflow for IPCC Tier-2 GHG calculations, mitigation-scenario evaluation, and structured grant-draft preparation. It combines (i) a prompt-driven interface with structured input templates, (ii) retrieval from a curated documentary corpus containing IPCC equations and selected policy/template material, (iii) a deterministic logic layer for enteric CH_4, manure CH_4, and manure N_2O, (iv) parameterized mitigation measures with size-scaled cost models, and (v) a document-generation layer. Numerical GHG and economic values are produced by the deterministic

engines; the LLM is not used as a calculator. All results should be read as scenario outputs conditional on the input data, intervention parameters, and financial assumptions.

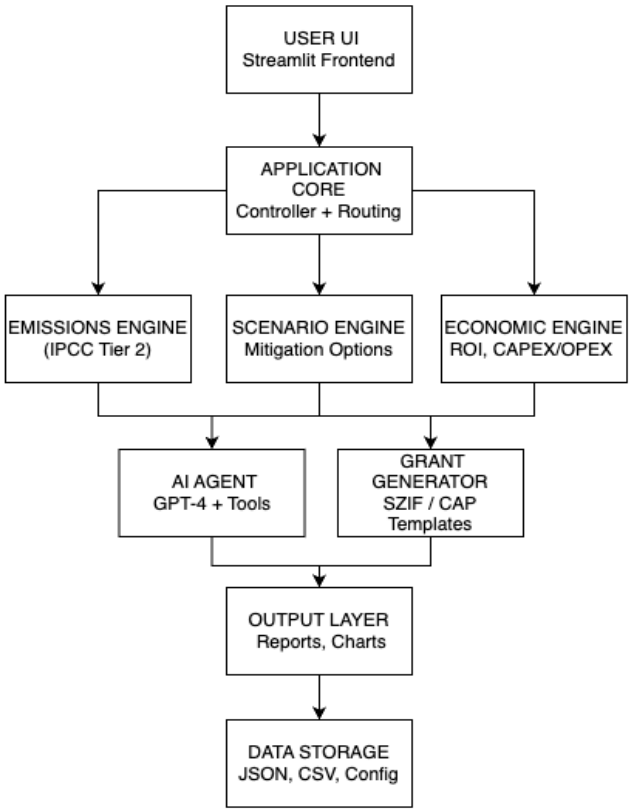

Figure 1. FarmCarbon AI integrates deterministic Tier-2 emissions accounting, mitigation scenarios, economic screening, and AI-assisted explanatory drafting in a single measure–report–verify–fund workflow. The Streamlit interface and Application Core route inputs to Emissions, Scenario, and Economic engines. Their structured outputs are supplied to a GPT-4-based retrieval-augmented drafting agent and a grant-draft generator; numerical calculations remain in the deterministic engines and outputs require human review before use.

SYNTHETIC FARM DATASET

To exercise the workflow, we constructed a synthetic dataset of 100 dairy-farm profiles spanning eight Central-European country contexts: Czech Republic, Slovakia, Poland, Germany, Austria, Hungary, Slovenia, and Croatia. The data were designed for coverage of plausible production and manure-management conditions, not to estimate country averages or to represent the distribution of operating farms. Each profile was generated by constrained draws within the ranges shown in Table 1. Structural consistency was enforced by constraining the number of lactating cows to 60–90% of herd size and calculating annual milk volume from lactating-cow numbers and milk yield. Manure-system category and storage duration were jointly constrained to avoid impossible combinations. No empirical joint distribution or country-specific covariance matrix was

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estimated from farm microdata; consequently, correlations beyond these structural constraints were not preserved. Country labels should therefore be interpreted as scenario contexts rather than representative national samples. This deliberate limitation preserves privacy while making external validity dependent on subsequent validation with measured farm records.

Table 1. Design ranges and structural constraints used to generate 100 synthetic Central-European dairy-farm profiles. The values are scenario-design inputs for workflow testing, not estimates of national farm distributions.

Input variable	Design range	Purpose in constrained profile generation
Herd size	50–1,500 cows	Coverage of small to large dairy operations
Milk yield	5,000–12,000 kg/cow/year	Combined with lactating-cow number to determine annual milk volume
Fat and protein	3.4–4.6% / 2.8–3.9%	Plausible milk-composition values for scenario inputs
Manure system	Slurry, lagoon, solid	Selects relevant manure-management parameters
Climate category	Cfb / Dfb	Provides climate context for scenario testing
Storage time	2–12 months	Constrained jointly with manure-system category

Figure 2. Distribution of selected design inputs in the synthetic profile set. The figure visualises the scenario coverage used for testing; it should not be interpreted as an empirical distribution for the eight countries.

AI-ASSISTED COMPONENT, CONTROLS AND REPRODUCIBILITY

The text-generation component was implemented as a GPT-4-based agent with retrieval-augmented prompting. The prompt template instructs the agent to use only supplied inputs and retrieved source excerpts, to state assumptions, to cite the retrieved source title/section in the generated draft, and to flag missing evidence rather than fill gaps

with unsupported text. A deterministic verifier receives the same structured inputs and provides the equation outputs that the agent may explain; the agent is not permitted to alter numerical values. A reproducible run should retain the input record, retrieved-document identifiers and versions, calculation outputs, prompt-template version, generated text, and human review decision. No formal retrieval-accuracy, hallucination-rate, or expert-agreement benchmark was conducted in the present synthetic evaluation. We therefore do not claim quantified LLM reliability or full legal/administrative compliance. The evaluation uses synthetic data only; deployment with real farms would require data-minimization, access controls, and an explicit decision on whether any farm data may leave the local environment.

IPCC TIER-2 CALCULATIONS

The system implements Tier-2 calculations for three sources: enteric CH_4, manure CH_4, and direct and indirect manure N_2O. Enteric CH_4 is derived from gross energy intake (GE), the conversion factor Ym, and the energy density of methane. Manure CH_4 is computed from volatile solids (VS), methane potential B_0, and the methane conversion factor (MCF). Manure N_2O is based on nitrogen excretion (Nex), volatilization, and leaching. All equations follow IPCC 2019 Volume 4, Chapter 10 (formulas 10.21–10.27) with AR6 GWP100 factors of 27.2 for CH_4 and 273 for N_2O.

SYSTEM BOUNDARY AND COMPARATIVE INTERPRETATION

The reported indicator is an operational farm-level emissions intensity expressed as kg CO_2eq per kg milk, calculated from the three modeled sources above. It is intended for within-workflow comparison of baseline and mitigation scenarios. It is not a full life-cycle assessment (LCA): upstream feed production, purchased energy, land-use change, capital equipment, allocation choices, and product-standardization procedures are outside the current boundary. For this reason, direct numerical comparison with published dairy LCAs is informative only when system boundary, functional unit, herd productivity, climate, emission factors, and GWP version are aligned.

MITIGATION MEASURES AND SCENARIOS

Seven mitigation measures were encoded as scenario parameters with literature-informed reduction ranges and cost assumptions, as summarized in Table 2. Four packages were then formed for exploratory comparison: Feed Optimization, Manure Management, Advanced Mitigation, and Comprehensive (Full Stack). The parameters are not measured treatment effects and should not be interpreted as universally attainable outcomes.

Table 2. Mitigation technologies represented in FarmCarbon AI. Reduction ranges and financial inputs are scenario assumptions used for exploratory comparison; they are not observed farm-level effects, quotations, or eligibility determinations.

Measure	Target	Reduction (%)	CAPEX (€)	OPEX/year (€)
Lipid addition	CH_4	18%	2,500	1,500
3-NOP feed additive	CH_4	25–40%	2,000	4,000
Seaweed supplement	CH_4	30–80%	1,500	6,000

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Measure	Target	Reduction (%)	CAPEX (€)	OPEX/year (€)
Slurry acidification	CH_4	40–60%	15,000	8,000
Covered slurry storage	CH_4	50–80%	10,000	1,500
Anaerobic digestion	CH_4	70–90%	25,000	10,000
Nitrification inhibitor	N_2O	50%	0	5,000

ECONOMIC MODEL AND SCALING

The economic module is a screening model rather than a forecast. It scales capital expenditure (CAPEX) and annual operating expenditure (OPEX) by the number of lactating cows using a square-root coefficient to approximate economies of scale. Because the cost, payment, and subsidy inputs vary by contract, country, technology, and time, all financial outputs are conditional on the declared assumptions and should be independently checked with farm-specific quotations and funding rules.

Investment and Operating Costs:

Each mitigation technology has a parameterized CAPEX and annual OPEX, scaled to herd size. The original reference case uses a 300-cow reference herd, for which a 50-cow farm has a coefficient of approximately 0.41 and a 600-cow farm approximately 1.41. These scaling factors are pragmatic assumptions; they do not replace supplier quotations, farm-engineering design, or country-specific eligibility checks.

Revenue Sources:

The reference case assumes annual efficiency gains equal to 5% of CAPEX, a low-carbon milk premium of €0.02 per kilogram of eligible milk, and carbon-credit revenue of €20 per tonne of CO_2eq avoided. These values are illustrative scenario inputs, not observed prices or guaranteed revenues. In particular, a premium may apply to only a defined volume, may require certification, and may not be available in a given market. The model therefore reports the contribution of each assumption separately and should not be used to infer a guaranteed investment return.

Payback Period:

For screening, annual net benefit is calculated as efficiency gain + low-carbon milk premium + carbon-credit revenue − annual OPEX. The reported payback is the farm-funded investment divided by annual net benefit when the net benefit is positive. The 10-year payback threshold and €1,000 net-benefit threshold are decision rules used by the prototype, not universal investment criteria. Scenarios with non-positive annual net benefit are classified as not viable under the stated assumptions.

SENSITIVITY ANALYSIS

To test the dependence of the illustrative economic output on uncertain assumptions, we performed a one-way sensitivity analysis for the high-intensity synthetic profile shown in Figures 3–5. The calculation used the stated 1,100 lactating cows, 5,769 kg milk/cow/year, €52,500 CAPEX, €21,000 annual OPEX, 577 kg CO_2eq/year modeled reduction, and the prototype formula above. We varied co-financing (0% and 60%), low-carbon milk premium (€0, €0.005, and €0.020/kg), and OPEX (base and +20%). This is a deterministic stress test of the declared formula, not a market simulation or field validation.

GRANT AUTOMATION

The LLM-assisted module can generate a structured draft containing an investment description, measure rationale, budget fields, and modeled climate-impact summary in approximately 3.2 seconds for the synthetic test record. The draft is aligned with selected SZIF and EU CAP template fields used in the prototype, but it is not a certification of compliance and must be checked by the applicant and the competent funding authority. No real grant submission, approval decision, or administrative time study was evaluated in this paper; the timing observation refers only to automated draft generation under the test configuration.

3. Results

For each synthetic profile, FarmCarbon AI produces a structured scenario output: modeled carbon-intensity indicator, source-level emission breakdown, mitigation-package comparison, economic-screening variables, and a grant-draft summary. These outputs help examine the internal consequences of the selected assumptions. They are not measurements from operating farms, evidence of technology adoption, or evidence that a financing application will be accepted.

SCENARIO COVERAGE IN THE SYNTHETIC TEST SET

The synthetic test set was constructed to exercise the four mitigation packages across varied herd sizes, milk yields, manure systems, climates, and storage durations. The earlier wording on "technology adoption across farms" has been removed because the profiles are synthetic and do not record observed technology adoption. Figure 2 remains the descriptive figure for the distribution of scenario inputs.

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Figure 3. Baseline and selected-scenario dashboard for an illustrative high-intensity synthetic profile labelled as Sachsen, Germany. The display shows the three modeled source categories (enteric CH_4, manure CH_4, and N_2O) in CO_2-equivalents using AR6 GWP100.

ILLUSTRATIVE HIGH-INTENSITY SYNTHETIC PROFILE

Figure 3 presents an illustrative profile with 1,222 cows, 1,100 lactating cows, and 5,769 kg milk/cow/year. The displayed carbon-intensity indicator is 0.96 kg CO_2eq/kg milk within the prototype boundary. The dashboard identifies manure methane as the largest modeled source, followed by enteric methane and a smaller N_2O contribution. Because the profile is synthetic and the boundary is partial, this value is not a field benchmark or an EU classification.

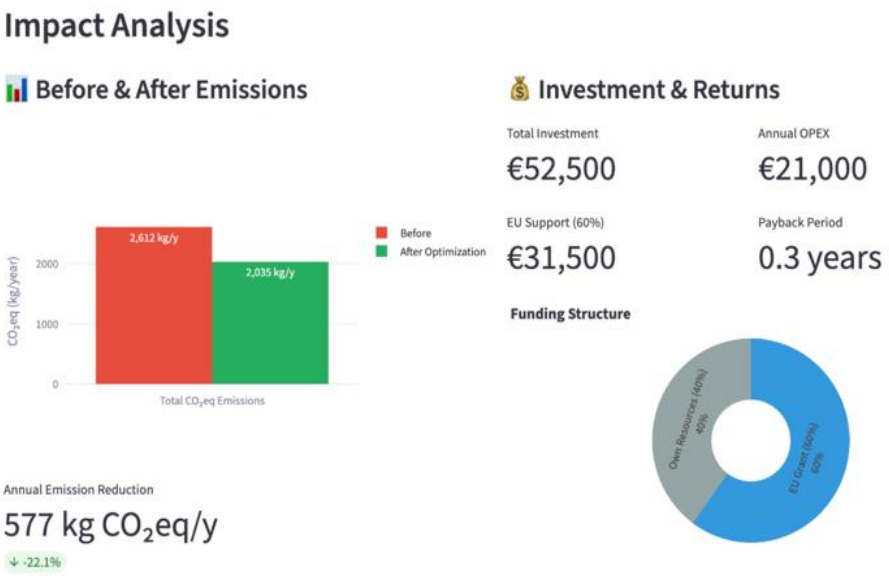

Figure 4. Baseline versus Comprehensive-scenario modeled emissions for the illustrative profile in Figure 3. The figure presents a within-model comparison of total CO_2-equivalent emissions across enteric CH_4, manure CH_4, and N_2O; it is not a field intervention result.

ILLUSTRATIVE EMISSIONS CHANGE AND ECONOMIC SCREENING

For the illustrative profile, the prototype output changes modeled annual emissions from 2,612 to 2,035 kg CO_2eq, a modeled reduction of 577 kg CO_2eq (22.1%). This reduction is a scenario output based on the selected package and its parameters, rather than a measured abatement result. The displayed €52,500 investment and €21,000 annual OPEX are inputs to the economic screen. Their financial interpretation changes substantially when payment and subsidy assumptions are varied, as shown below.

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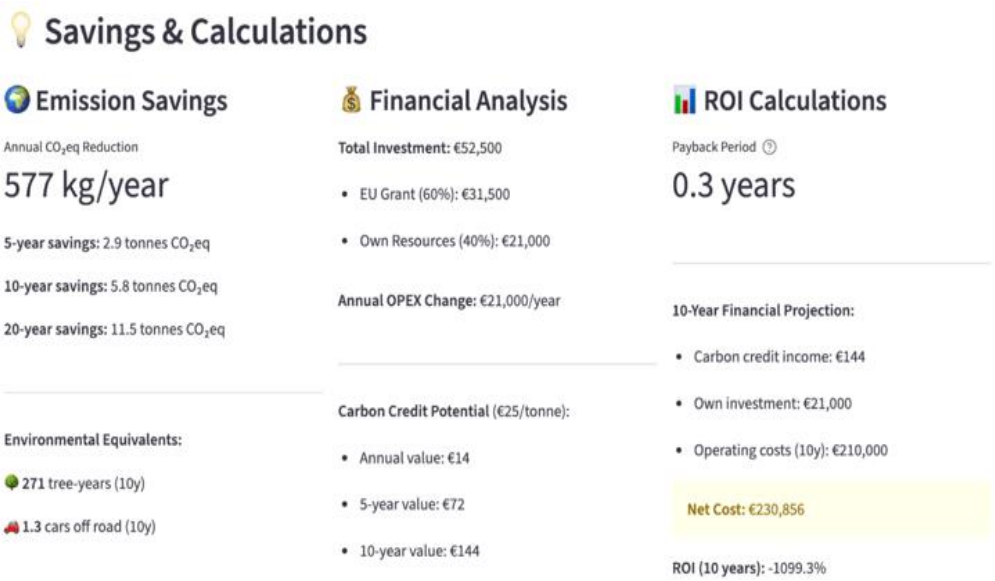

Figure 5. Economic-screening dashboard for the illustrative profile. Values are conditional on the prototype assumptions for CAPEX, OPEX, subsidy, milk premium, carbon-credit price, and annual emission reduction; they should not be interpreted as a verified investment appraisal.

SENSITIVITY OF THE ILLUSTRATIVE ECONOMIC SCREEN

Table 3 recalculates the illustrative profile using the economic formula stated in Methods. At the declared €0.020/kg premium, the premium dominates the annual net-benefit calculation; reducing the subsidy from 60% to 0% increases modeled payback from 0.19 to 0.48 years but does not reverse the result. By contrast, without a milk premium the annual net benefit is negative even with 60% co-financing. The result shows that the conclusion is more sensitive to a verified premium and OPEX than to the subsidy level under this formula. Carbon-price variation has little effect because the displayed annual avoided emissions are 0.577 t CO_2eq. These are arithmetic sensitivities of the prototype, not claims about farm profitability.

Table 3. One-way sensitivity analysis for the illustrative high-intensity synthetic profile. Annual net benefit = 0.05 × CAPEX + (milk premium × annual milk) + (carbon-credit price × modeled avoided emissions) − OPEX.

Scenario	Co-financing	Milk premium (€ / kg)	OPEX multiplier	Annual net benefit; payback
Reference case	60%	0.020	1.00	€108,555; 0.19 years
No subsidy	0%	0.020	1.00	€108,555; 0.48 years
Lower premium	60%	0.005	1.00	€13,366; 1.57 years
No premium	60%	0.000	1.00	−€18,363; not viable
Lower premium + OPEX +20%	60%	0.005	1.20	€9,166; 2.29 years

Note. Annual milk volume = 1,100 × 5,769 = 6,345,900 kg; efficiency gain = 5% of €52,500 CAPEX; carbon-credit price = €20/t CO_2eq; modeled avoided emissions = 0.577 t CO_2eq/year. Values are rounded and are conditional on the prototype formula.

LOW-CARBON FARM EXAMPLE

Figure 6 presents a second illustrative synthetic profile (CZ013, Plzeňský context) with a displayed carbon-intensity indicator of 0.23 kg CO_2eq/kg within the prototype boundary. The profile contains 742 cows and 8,591 tonnes of annual milk in the dashboard, and the modeled source breakdown is dominated by enteric methane (84.9%). This example illustrates how the workflow can direct attention to nutritional or genetic scenarios where enteric methane dominates; it does not establish that a real farm has achieved an "EU Excellent" classification.

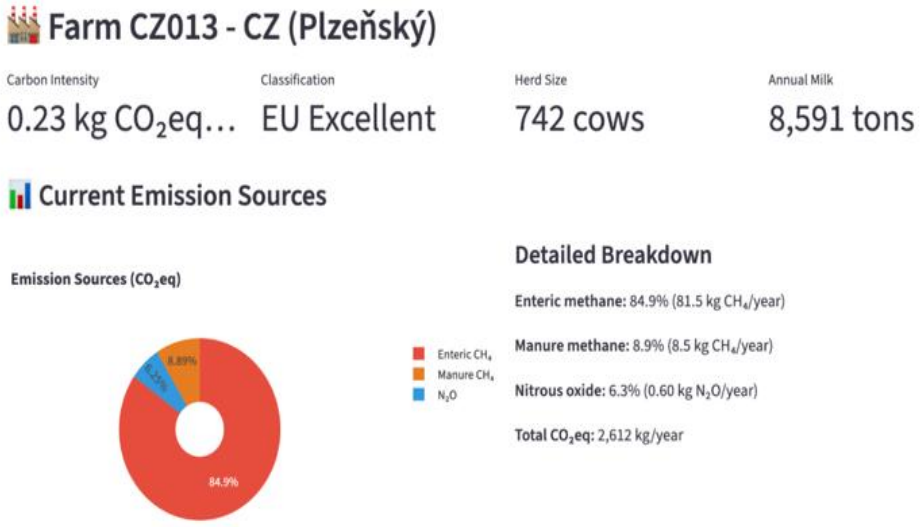

Figure 6. Modeled emissions profile for an illustrative low-carbon synthetic profile, showing enteric CH_4, manure CH_4, and N_2O per unit of milk as CO_2-equivalents (AR6 GWP100). This is a scenario display rather than a measured farm inventory.

4. Discussion

The synthetic scenario tests show how FarmCarbon AI links deterministic IPCC Tier-2 accounting with mitigation scenarios, an economic screen, and AI-assisted drafting. Within the prototype boundary, enteric and manure methane were the main modeled sources in the illustrative profiles, and combined feed and manure-management packages reduced the modeled total in selected scenarios. These outputs demonstrate workflow capability under declared inputs; they do not provide external evidence of real-farm abatement, financial adoption, or grant success.

The synthetic-set mean carbon-intensity indicator of 0.89 kg CO_2eq/kg milk is below the values cited for the Netherlands (1.13 kg CO_2eq/kg), Ireland (1.19 kg CO_2eq/kg), and Italy (1.32 kg CO_2eq/kg). The difference cannot be read as a performance advantage because the studies use different system boundaries, functional units, allocation rules, herd productivity, climates, emission factors, and possibly GWP versions. Our

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indicator includes only enteric CH_4, manure CH_4, and manure N_2O; it is therefore useful for internal scenario comparison but not directly comparable with full dairy LCAs. The modeled predominance of enteric CH_4 is consistent with the broad literature identifying enteric fermentation as a principal dairy GHG source (Hristov et al., 2013; Gerber et al., 2013; IPCC, 2019).

The modeled scenario reductions of 8–19% are parameter-dependent outputs rather than causal estimates. They are directionally consistent with literature reporting methane-reduction potential for feed additives and manure-management interventions, but direct comparison requires attention to dose, diet, animal response, baseline system, measurement period, leakage, and whether effects overlap when measures are combined. The approximately 22.1% change in the illustrative Comprehensive scenario should therefore be treated as an exploratory result of the prototype configuration, not as an estimate of maximum practical abatement.

The revised sensitivity analysis clarifies that economic rankings are not stable under all assumptions. Under the prototype formula, a verified €0.020/kg premium makes the illustrative high-investment case appear viable even without a subsidy, whereas the same case is not viable without a premium. This dependence should not be generalized: eligibility, qualifying milk volume, carbon-credit terms, OPEX, financing costs, taxes, depreciation, energy prices, and feed prices require farm- and country-specific validation. The economic module is therefore best viewed as a transparent screening tool that identifies assumptions requiring verification before investment, rather than as an investment recommendation.

Several limitations are central to interpretation. First, the evaluation uses synthetic profiles with structural constraints but without empirical country-specific covariance structures or measured farm outcomes; external validity remains unknown. Second, mitigation efficacy and cost inputs are literature-informed ranges and simplified scaling assumptions that may not capture farm-specific technical performance, financing, eligibility, volatility, or interactions among measures. Third, the reported boundary is not a full LCA. Fourth, the AI-assisted component was not evaluated through retrieval-accuracy, hallucination-rate, expert-agreement, or human-workflow studies. Findings should consequently be interpreted as evidence of prototype workflow behaviour, not as validated per-farm forecasts, funding advice, or administrative performance.

The framework supports traceability because its numerical layer is explicitly tied to IPCC Tier-2 equations and the revised workflow specifies the records that should be retained for each run. However, traceability is a design objective rather than a demonstrated guarantee in this study: no independent audit or formal reproducibility benchmark was conducted. Similarly, the RAG-LLM component is constrained to source-grounded explanation and draft generation, but the present paper does not quantify retrieval accuracy or hallucination risk. Human review remains mandatory for calculations, policy interpretation, and any funding submission.

Future research should validate FarmCarbon AI against measured records from operating farms across herd sizes, production systems, and national policy settings. A preregistered validation should compare modeled emissions and mitigation recommendations with established calculators, farm advisers, and specialist reviewers; report retrieval precision/recall, source-coverage, numerical-verification pass rate,

hallucination and failure cases, review burden, and data-governance controls; and test sensitivity to market and policy parameters. The mitigation library can then be extended to methane vaccines, precision feeding, selective breeding, and additional emissions sources within a clearly defined LCA boundary.

5. Conclusion

FarmCarbon AI is a transparent prototype that links deterministic IPCC Tier-2 calculations with mitigation-scenario screening, a conditional economic screen, and AI-assisted explanatory and grant-draft generation. Across 100 synthetic profiles, the workflow produced modeled emission reductions of 8–19% under the selected intervention parameters. The illustrative sensitivity analysis shows that financial outputs depend materially on the assumed milk premium, operating costs, and co-financing rate; they are not evidence of actual farm profitability or funding eligibility. The contribution is therefore a reproducible workflow specification and a testable validation agenda, not a claim of field-proven mitigation, auditability, or administrative impact. Validation with measured farm data, country-specific cost and policy inputs, formal AI-component evaluation, expert review, and comparison with established calculators is required before operational deployment.

References

Arla Foods. (2023). Climate Check report.

Baldini, C., Bava, L., Zucali, M., & Guarino, M. (2018). Milk production life cycle assessment: A comparison between estimated and measured emission inventory for manure handling. Science of the Total Environment, 625, 209–219.

Bronson, K., & Knezevic, I. (2016). Big data in food and agriculture. Big Data & Society, 3(1), 1–5.

Canadian Agri-Food Policy Institute. (2025). Digital agriculture and climate finance report.

Chadwick, D. R., Sommer, S. G., Thorman, R., Fangueiro, D., Cardenas, L. M., Amon, B., & Misselbrook, T. H. (2011). Manure management: Implications for greenhouse gas emissions. Animal Feed Science and Technology, 166–167, 514–531.

Climate Policy Initiative. (2023). Global landscape of climate finance 2023.

European Commission. (2021). 'Fit for 55': Delivering the EU's 2030 climate target on the way to climate neutrality (COM(2021) 550).

European Court of Auditors. (2021). Common Agricultural Policy and climate: Half of EU climate spending but farm emissions are not decreasing (Special Report No. 16/2021).

Food and Agriculture Organization of the United Nations. (2022). World food and agriculture: Statistical yearbook 2022.

Fonterra Co-operative. (2025). Low-emission farm bonus program.

Gerber, P. J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., & Tempio, G. (2013). Tackling climate change through livestock: A global assessment of emissions and mitigation opportunities.

GHG Protocol. (2014). Agricultural guidance: Measuring and reporting greenhouse gas emissions from agricultural operations.

Hristov, A. N., Oh, J., Firkins, J. L., Dijkstra, J., Kebreab, E., Waghorn, G., Makkar, H. P. S., Adesogan, A. T., Yang, W., Lee, C., Gerber, P. J., Henderson, B., & Tricarico, J. M. (2013). Mitigation of methane and nitrous oxide emissions from animal operations: I. A review of enteric methane mitigation options. Journal of Animal Science, 91(11), 5045–5069.

Intergovernmental Panel on Climate Change. (2019). 2019 refinement to the 2006 IPCC guidelines for national greenhouse gas inventories (Vol. 4).

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Intergovernmental Panel on Climate Change. (2021). Climate change 2021: The physical science basis.

Martin, C., Morgavi, D. P., & Doreau, M. (2010). Methane mitigation in ruminants: From microbe to the farm scale. Animal, 4(3), 351–365.

Moran, D., Macleod, M., Wall, E., Eory, V., McVittie, A., Barnes, A., Rees, R., Topp, C. F. E., & Moxey, A. (2011). Marginal abatement cost curves for UK agricultural greenhouse gas emissions. Journal of Agricultural Economics, 62(1), 93–118.

O'Brien, D., Shalloo, L., Patton, J., Buckley, F., Grainger, C., & Wallace, M. (2012). A life cycle assessment of seasonal grass-based and confinement dairy farms. Agricultural Systems, 107, 33–46.

Roque, B. M., Venegas, M., Kinley, R. D., de Nys, R., Duarte, T. L., Yang, X., & Kebreab, E. (2021). Red seaweed (Asparagopsis taxiformis) supplementation reduces enteric methane by over 80 percent in beef steers. PLOS ONE, 16(3), e0247820. https://doi.org/10.1371/journal.pone.0247820

Saro, J., Stádník, L., Bláhová, P., Huguet, S., Brožová, H., & Ducháček, J. (2024a). A decision support system based on disease scoring enables dairy farmers to proactively improve herd health. Czech Journal of Animal Science, 69(5), 165–177. https://doi.org/10.17221/53/2024-CJAS

Saro, J., Šubrt, T., Brožová, H., Hlavatý, R., Rydval, J., Ducháček, J., & Stádník, L. (2024b). A decision support system for herd health management for dairy farms. Czech Journal of Animal Science, 69(12), 502–515. https://doi.org/10.17221/178/2024-CJAS

Thomassen, M. A., van Calker, K. J., Smits, M. C. J., Iepema, G., & de Boer, I. J. M. (2008). Life cycle assessment of conventional and organic milk production in the Netherlands. Agricultural Systems, 96, 95–107.

UK Department for Environment, Food and Rural Affairs. (2023). Harmonisation of agricultural carbon calculators.

van Wesemael, D., Vandaele, L., Ampe, B., Cattrysse, H., Duval, S., Kindermann, M., Fievez, V., De Campeneere, S., & Peiren, N. (2019). Reducing enteric methane emissions from dairy cattle: Two ways to supplement 3-nitrooxypropanol. Journal of Dairy Science, 102(2), 1780–1787.