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Transdisciplinary model-based systems engineering in the development of the Ruminant Farm Systems model

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This study adopts a transdisciplinary model-based systems engineering (MBSE) approach to support the development of the Ruminant Farm Systems (RuFaS) model, an advanced on-farm decision support tool. Using the cloud-based MBSE platform Innoslate (SPEC Innovations, Manassas, VA), we identified key stakeholders, constructed use cases, defined system boundaries, refined stakeholder requirements, and outlined the system architecture and subsystem interfaces for RuFaS. To demonstrate RuFaS's ability to meet stakeholder requirements, we selected a specific use case focused on comparing whole farm impacts across different manure management scenarios. For the current case, we defined 12 scenarios from 4 manure management strategies and 3 diet-climate conditions based on U.S. regions. The scenarios included two bedding types (sawdust vs. sand), two storage methods [anaerobic digestion with lagoon (ADL) vs. slurry storage (SS)], and three regions (R1, R2, R3). RuFaS predictions were responsive to changes in scenario conditions, with whole farm greenhouse gas (GHG) emissions ranging from $1.23 \pm 4.64 \times 10^{-3}$ to $1.61 \pm 9.45 \times 10^{-3}$ kg CO_2-eq/kg fat-and protein-corrected milk (FPCM). Regional variations influenced whole herd enteric CH_4 intensity, with R2 scenarios showing the highest emissions ($0.472 \pm 3.65 \times 10^{-3}$ kg CO_2-eq/kg FPCM), followed by R1 ($0.458 \pm 4.19 \times 10^{-3}$ kg CO_2-eq/kg FPCM) and R3 ($0.449 \pm 3.45 \times 10^{-3}$ kg CO_2-eq/kg FPCM), driven by differences in dry matter intake, and milk production and composition. Manure storage methods also impacted emissions, with ADL scenarios producing 0.146 kg CO_2-eq/kg FPCM lower whole farm GHG emissions than SS scenarios, due to the combined effects of reduced manure storage CH_4 emissions associated with anaerobic digestion and associated increased NH_3 emissions and subsequent indirect N_2O emissions. These findings highlight the complex interactions among RuFaS model components and confirm its ability to support effective comparisons of manure management practices to meet specific stakeholder needs. Our transdisciplinary MBSE approach provides a robust framework for ongoing RuFaS evaluation, ensuring alignment with stakeholder requirements. This study represents a pioneering milestone in the application of MBSE to agricultural system model development, highlighting its potential to advance decision-making in sustainable dairy farm management.

KEYWORDS

model-based systems engineering, transdisciplinary engineering, sustainability, dairy, manure management, RuFaS

1 Introduction

Dairy farms are complex systems requiring coordinated management of livestock, manure, and feed. In recent decades, the U.S. dairy industry has consolidated into fewer, larger farms with a substantial number of cattle (Son et al., 2022). This shift, driven partly by advances in technology, particularly on larger farms, aims to improve production efficiency and reduce risks (Son et al., 2022). Although the industry assumes a critical role in global food production (Comerford et al., 2021), dairy producers and farm managers operate under narrow profit margins and are challenged to meet changing standards for environmental stewardship and animal welfare (McGarr-O'Brien et al., 2023; Phillips, 2024).

Within the U.S., the dairy industry accounts for between 1.9 to 2.5% of the country's total greenhouse gas (GHG) emissions (Place et al., 2022). In spite of recent efforts to reduce the carbon footprint of dairy production, GHG emissions from dairy farms in the U.S. are still on the rise. Between 1990 and 2019, total emissions grew 38%, primarily driven by a 90% rise in emissions from manure management (O'Hara, 2023). However, efforts to mitigate GHG emissions in dairy farming are ongoing and many GHG emission mitigation strategies are available to dairy producers. Nutritional approaches, such as monitoring the concentrate-to-forage ratio in diets and use of feed additives, have shown potential in reducing enteric CH_4 emissions (Hristov, 2023; Belanche et al., 2025). Similarly, several available manure management technologies can reduce GHG emissions, including anaerobic digestion, solid–liquid separation, manure composting, covered manure storage, compost-bedded packs, and weeping walls, among others (El Mashad et al., 2023; Fournel et al., 2019).

Although many GHG emission mitigation opportunities exist, the amount of avoided emissions and secondary effects on production vary on individual farms. Moreover, farmers' perspectives on these technologies are often mixed. A 2011 survey of Iowa farmers (Arbuckle et al., 2015) suggests that farmers often prioritize immediate, practical benefits over broader environmental concerns, underscoring a preference for profitability over sustainability. Further, the cost of implementation is often a barrier to adoption without a financial incentive from government programs, carbon markets, or other premium pricing programs that require quantification of the impact (Fournel et al., 2019). Thus, the next generation of farmers need tools that provide essential management data that distill information on both profitability and environmental outcomes.

Unlike traditional modeling tools that use life cycle assessment and empirical emission factors, whole farm models meet these needs through a process-based approach (Del Prado et al., 2013; Del Prado et al., 2025). They serve as multifunctional tools in production, research, and education, offering insights into costs and guiding farm management strategies in addition to quantifying GHG emissions (Rotz, 2018; Ahmed et al., 2020). Agricultural scientists have been developing whole farm models since the 1970s (Jones et al., 2017), but their applications beyond science and education remains limited. In recent years, there has been increased adoption of models such as COMET-Farm, Cool Farm Tool, Integrated Farm Systems Model (IFSM), and FARM-ES (Ahmed et al., 2020; Olivo et al., 2024; National Dairy FARM Program, https://nationaldairyfarm.com/dairy-farm-standards/environmental-stewardship/) to meet industry and/or research needs to quantify emissions from dairy farms under different management and environmental conditions. However, these models exhibit structural limitations: they rely on largely fixed modules, annual or monthly timesteps, and limited pathways for incorporating emerging technologies or management options (Hansen et al., 2021). The Ruminant Farm Systems (RuFaS) model[1] is under development and was designed to address these gaps. RuFaS is an open-source, modular, Python project on GitHub that simulates dairy operations continuously at a daily time step. The modern, modular code structure facilitates simulation of mass and nutrients flow between modules each day, creating dynamic feedback across the system. Users are encouraged to update any module as new science emerges, ensuring transparency, clarity, and adaptability to evolving dairy industry technologies (Hansen et al., 2021; Kebreab et al., 2019). The mission of the RuFaS project is not merely to quantify the environmental impacts of management decisions on dairy farms. Instead, we seek to build a supportive community where farmers can make effective use of the technologies and data they already have. By helping farmers harness this data for day-to-day management, RuFaS can provide valuable insights into the potential environmental impacts of current and proposed practices, thereby supporting more informed decision-making.

The RuFaS model framework integrates animal lifecycle, manure management, crop production, and feed storage into a unified, continuous simulation cycle (Reed, 2021; Supplementary Figure 1). The Animal Module simulates the life cycle of each animal from birth through culling or death, tracking daily activities and events (Reed, 2021). Data on manure excretion generated by the Animal Module is transferred to the Manure Module, which manages the manure processing chain—from collection in each pen to processing through methods like solid–liquid separation or anaerobic digestion, and ultimately, to storage (Reed, 2021). This module provides detailed information on the quantity and composition of manure, which is utilized by the Soil and Crop Module during the application of manure to fields (Reed, 2021). The Soil and Crop Module simulates crop production and supplies the Feed Management and Inventory Module with data on the composition and inventory of farm-grown feed at harvest (Reed, 2021). This information is combined with data on purchased feed by the Feed Management and Inventory Module to support diet formulation in the Animal Module, creating a continuous and interconnected cycle within the model (Reed, 2021).

Understanding the needs of all the stakeholders is essential to designing tools like RuFaS that are intuitive and practical for daily use. As Doidge et al. (2024) noted, agricultural technologies are often created in a top-down manner, with limited involvement of end-users during the preliminary stages of product development. This approach can result in technologies that are less aligned with the actual needs of stakeholders. These researchers further indicated that farmers tend to prefer technologies that offer convenience, support their knowledge and understanding of on-farm challenges, and enable self-reliance (Doidge et al., 2024). Moreover, it's crucial to recognize that farmers are just one group of stakeholders among many in the dairy supply chain. The Model-Based Systems Engineering (MBSE) approach offers an opportunity to map out all relevant stakeholders and their specific needs, which is fundamental for developing adaptable, user-friendly tools.

1 https://github.com/RuminantFarmSystems/RuFaS

MBSE represents a departure from traditional document-centric systems engineering approaches, emphasizing the utility of models across the life cycle of large and complex systems to support activities such as requirements collection, trade-off studies, design, analysis, verification and validation (Madni and Sievers, 2018; Shevchenko, 2020; Gough and Phojanamongkolkij, 2018). Documentation in MBSE is simplified via templates that automatically create documents from model content, saving time and reducing manual updates (Gough and Phojanamongkolkij, 2018). This process makes it easier for teams to focus on essential information while keeping documents current for easy sharing (Gough and Phojanamongkolkij, 2018). Other advantages offered by MBSE approaches include managing system intricacies, illustrating component interactions, early detection of potential defects, and ensuring the project stays within budget and on schedule (Hart, 2015).

In MBSE, diagrams are commonly used to represent various aspects of a system (Shevchenko, 2020). Asset diagrams, also known as block or physical block diagrams, illustrate the physical components of a system model (Lawrence and Herber, 2024), while hierarchy diagrams show the decomposition of system elements (Hettema, 2013). Use case diagrams identify core system functionalities and show interactions with external entities, such as users or other systems (Aquino et al., 2021). These foundational diagrams inform other MBSE tools, such as activity diagrams (Aquino et al., 2021; Rahim et al., 2015) and IDEF0 diagrams (Wang et al., 2009) which represent system functionalities, inputs, and outputs. Together, these standardized visual tools play a critical role in defining stakeholder requirements, improving the efficiency and accuracy of system development, and facilitating collaboration among developers.

MBSE methodologies have been applied across disciplines such as aerospace, defense, energy, and medical sectors, among others (Campo et al., 2023). In agriculture, MBSE has primarily been applied in the development of agricultural machinery and vehicles (Cichocki et al., 2022; Hossain et al., 2022). More recently, MBSE was integrated with life cycle assessment to model crop and field management practices and evaluate their environmental impacts (Pradel et al., 2024). Livestock rearing enterprises and the software that supports their management are also complex systems, yet, to the best of the authors' knowledge, MBSE approaches remain unexplored in these systems. This limited use in agriculture and livestock modeling likely stems from two main factors: unfamiliarity of MBSE tools and methods within the agricultural science community, and weak collaborations between systems engineers and agriculture scientists (Kragt et al., 2016; Henderson et al., 2024).

Lang et al. (2012) define transdisciplinarity as "a reflexive, integrative, method-driven scientific principle aiming at the solution or transition of societal problems and concurrently of related scientific problems by differentiating and integrating knowledge from various scientific and societal bodies of knowledge." In fact, systems engineering has long been inherently transdisciplinary. Pennotti et al. (2024) argue that the future impact of systems engineering relies on embracing this transdisciplinary essence and focusing on elegant problem-solving.

In this study, we employed a transdisciplinary MBSE approach that integrates knowledge and methods from systems engineering, dairy production, manure management, environmental sustainability, and software engineering, among other disciplines, to support RuFaS model development to ensure stakeholder needs are met and to provide transparency and adaptability. Our first objective was to formulate an MBSE framework that defines RuFaS while characterizing stakeholders, use cases, and system boundaries. Our second objective was to employ a specific use case to showcase the interaction among RuFaS components, demonstrating their collective role in generating production and environmental outcomes that address stakeholder needs. Collectively, we aim to implement a valuable systems engineering framework for future RuFaS model development.

2 Materials and methods

Using an MBSE approach, we first created diagrams to define system scope, external interactions, and RuFaS component links. We then documented stakeholder requirements based on their needs, which were organized and structured using these diagrams. Finally, we focused on a specific use case and performed simulations with the RuFaS model, varying management practices to address the stakeholder needs specific to the selected use case.

2.1 MBSE model development: diagramming and documentation in Innoslate

We used Innoslate (SPEC Innovations, Manassas, VA), a web-based MBSE platform, to define the hierarchical structure, use cases, system boundaries, stakeholder requirements, and component interfaces of the RuFaS model. Innoslate's support for Lifecycle and Systems Modeling Languages (Lawrence and Herber, 2024) offers a streamlined, visual approach to designing and analyzing complex systems. Its intuitive interface facilitates engagement with non-engineering users, such as animal scientists (Swafford and Parrish, 2020), while also supporting real-time collaboration and documentation management (Vaneman, 2016; Swafford and Parrish, 2020).

We developed the diagrams and documentation within the Innoslate model from existing publications (Kebreab et al., 2019; Hansen et al., 2021; Reed, 2021) and internal product records and design documentation. Under Innoslate's Diagrams section, we constructed an asset diagram (Figure 1) to represent the physical system context of the RuFaS model, two sets of hierarchy diagrams—physical diagrams (Figure 2) that map the RuFaS model within its physical context, and functional diagrams (Figure 3) that capture the RuFaS model's primary functions alongside those of related systems. The system of interest, RuFaS, was highlighted in yellow to indicate its significance. Additionally, we developed a use case diagram (Figure 4) and an activity diagram (Figure 5) based on a selected use case, which we detail further in Section 2.2. In the Documents section, we used Innoslate's Import Analyzer to incorporate a stakeholder requirements file (Table 1) originally compiled in Word with an established format for integration into the Innoslate environment.

2.2 Stakeholder needs and use cases

We identified six external and two internal stakeholder groups relevant to RuFaS (Figure 1). The external stakeholders, denoted as external components (EC), include farmers and consultants, scientists, dairy processors, regulatory agencies, non-governmental

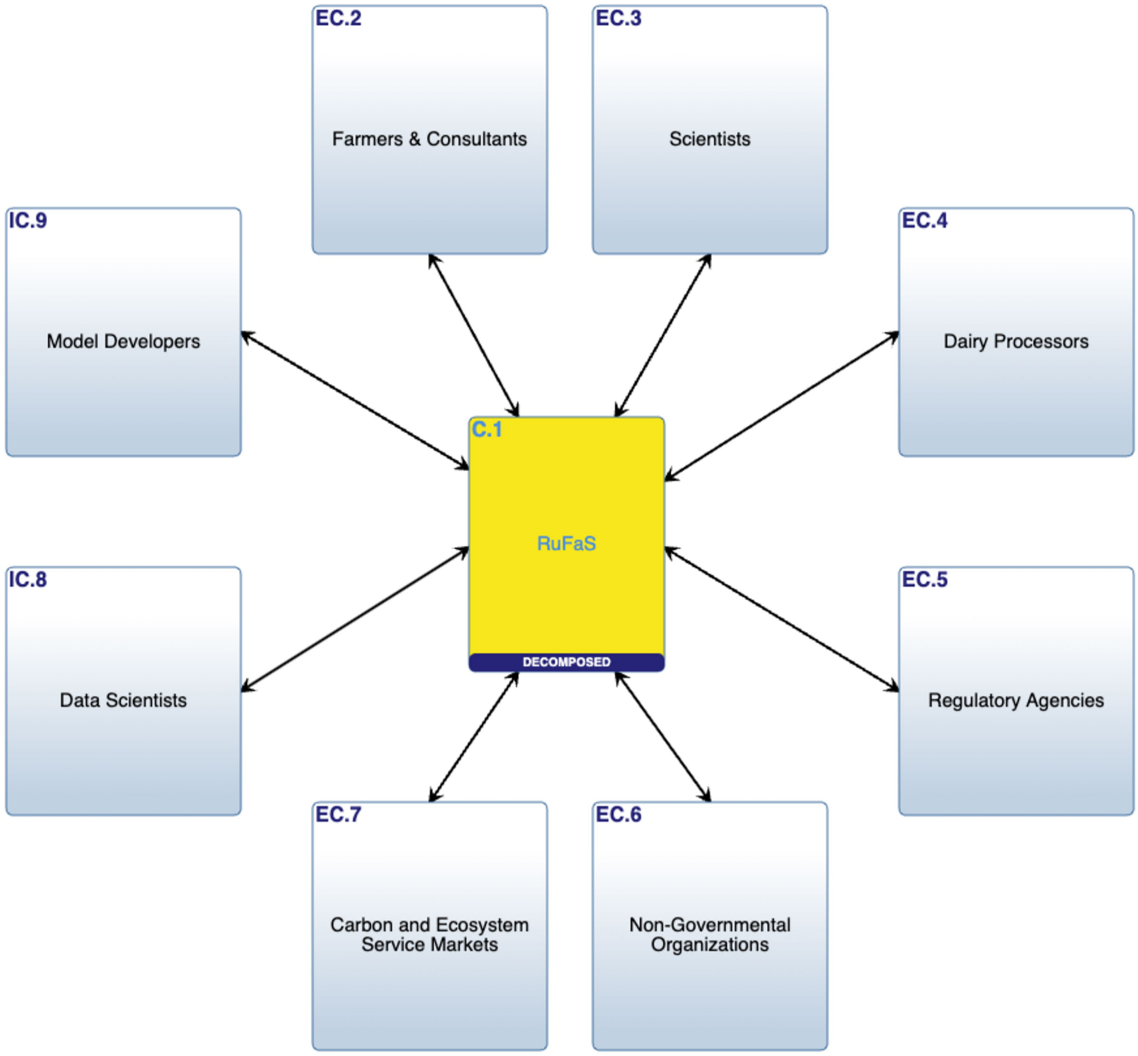

FIGURE 1
Asset diagram of the Ruminant Farm Systems (RuFaS) model, with external stakeholders represented as external components (EC) and internal stakeholders as internal components (IC). Source: Generated by Innoslate.

organizations, and carbon and ecosystem service markets. Internal stakeholders, denoted as internal components (IC), include model developers—comprising subject matter experts and software engineers—as well as data scientists, who provide key on-farm management data. Among the external stakeholders, the most active RuFaS users will likely be farmer consultants and dairy processors. The scientist group covers ecology, agronomy, soil science, and manure engineering. Data scientists consist of professionals working with platforms such as Dairy Brain (Ferris et al., 2020) and the Cornell Agricultural Systems Testbed and Demonstration Site (CAST; https://cals.cornell.edu/cast-farm-future) and on-farm management software, including DairyComp 305 (Valley Agricultural Software, Tulare, CA) and BoviSync (BoviSync LLC, Fond du Lac, WI).

We developed ten of the most representative use cases to address the diverse needs of these stakeholders and documented them in a use case diagram (Figure 4). We highlight two key use cases for farmers and consultants: "UC.1: Farmers & consultants track progress of different management practices and inform future decisions" and "UC.3: Farmers & consultants compare system impacts of proposed management practices before implementation." We then added specificity to UC.3 by identifying four specialized sub-cases (UC.3.A., UC.3.B., UC.3.C., and UC.3.D.) that pertain to specific areas of management on a dairy farm including manure, nutrition management, enteric CH_4 mitigation, and field management. Scientists have two dedicated use cases, and each remaining stakeholder—both external and internal—has a specific use case. These use cases collectively illustrate a wide range of applications for the RuFaS model. We further demonstrated the complex interactions of model components in predicting farm production and environmental outcomes with a single use case. For that demonstration, we selected UC.3.A., "Farmers & consultants compare system impacts of proposed manure management practices before implementation" because it targets our largest stakeholder group—farmers and consultants and utilizes two of the most complex modules within the RuFaS model, the Animal and Manure Modules.

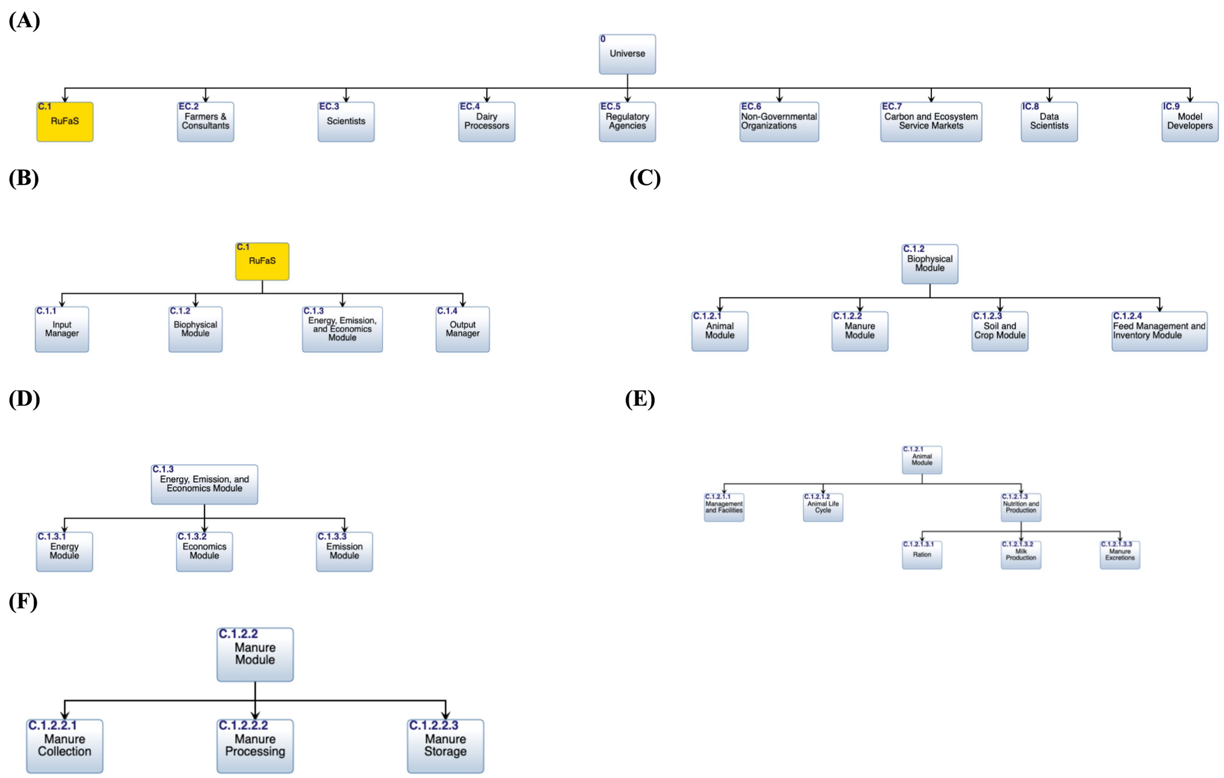

FIGURE 2
Physical hierarchy diagrams of the Ruminant Farm Systems (RuFaS) model and its subsystems, with external stakeholders represented as external components (EC) and internal stakeholders as internal components (IC): **(A)** top-level universe hierarchy diagram; **(B)** RuFaS physical hierarchy diagram; **(C)** biophysical module physical hierarchy diagram; **(D)** energy, emission, and economics module physical hierarchy diagram; **(E)** animal module physical hierarchy diagram; **(F)** manure module physical hierarchy diagram. Source: Generated by Innoslate.

2.3 RuFaS animal and manure modules

The Animal and Manure Modules in RuFaS work together to provide detailed predictions of GHG emissions, with flexible options for diet formulation and manure management—key elements relevant to our selected use case. The Animal Module predicts enteric CH_4 emissions accounting for both animal and diet-related factors (Niu et al., 2018). This module offers two methods for diet formulation: an automated approach using a nonlinear programming algorithm (Li J. et al., 2022) or a user-defined ration recipe, allowing it to accommodate various use case scenarios and user preferences. At each formulation interval, the module calculates nutrient requirements for individual animals within a pen, averages them at the pen level, and formulates diets using both farm-grown and purchased feeds, considering nutrient needs, feed availability, cost, and other constraints. The Manure Module addresses emissions related to manure management, predicting ammonia (NH_3) and CH_4 emissions from manure on the barn floor and NH_3, N_2O and CH_4 emissions during long-term storage. The Manure Module offers a range of management options, including five bedding materials (sand, straw, manure solids, sawdust, and compost bedded pack barns), five manure handling methods (alley scraper, flush system, manual scraping, tillage, and harrowing), two manure separation techniques (rotary screen and screw press), and seven manure treatment options (slurry storage underfloor, slurry storage outdoor, anaerobic digestion, anaerobic lagoon, compost bedded pack barns, composting, and open lots). This flexibility enables users to simulate diverse strategies.

2.4 Case study of RuFaS fulfillment of stakeholder use case

To demonstrate the ability of the RuFaS model to fulfill UC.3.A., we conducted simulations for 4 distinct manure management practices across 3 major dairy-producing regions, designated as R1, R2, and R3, using the RuFaS model, version 0.9.2, which is programmed in Python 3.11 (Python Software Foundation, https://www.python.org/). These regions were selected to represent diverse diets, weather conditions, and feed emission factors. Each scenario was simulated four times, modeling a 1,000-cow Holstein dairy farm. Our project did not involve animal or human subjects; hence the ethical clearance was not applicable.

Supplementary Table 1 shows animal input parameters based on the specifications outlined by Li et al. (2023). We set heifers' reproductive program to a Synch-Estrus Detection (Synch-ED) protocol and cows' program to a Timed-AI (TAI) protocol. Following the 17-day presynch in the Ovsynch program, we started the Ovsynch protocol at 67 days in milk (Dairy Cattle Reproduction Council, https://www.dcrcouncil.org/protocols/). Wood's lactation curve parameters were updated for each region, assuming a milking frequency of three times per day and based on 2016 data (Li M. et al.,

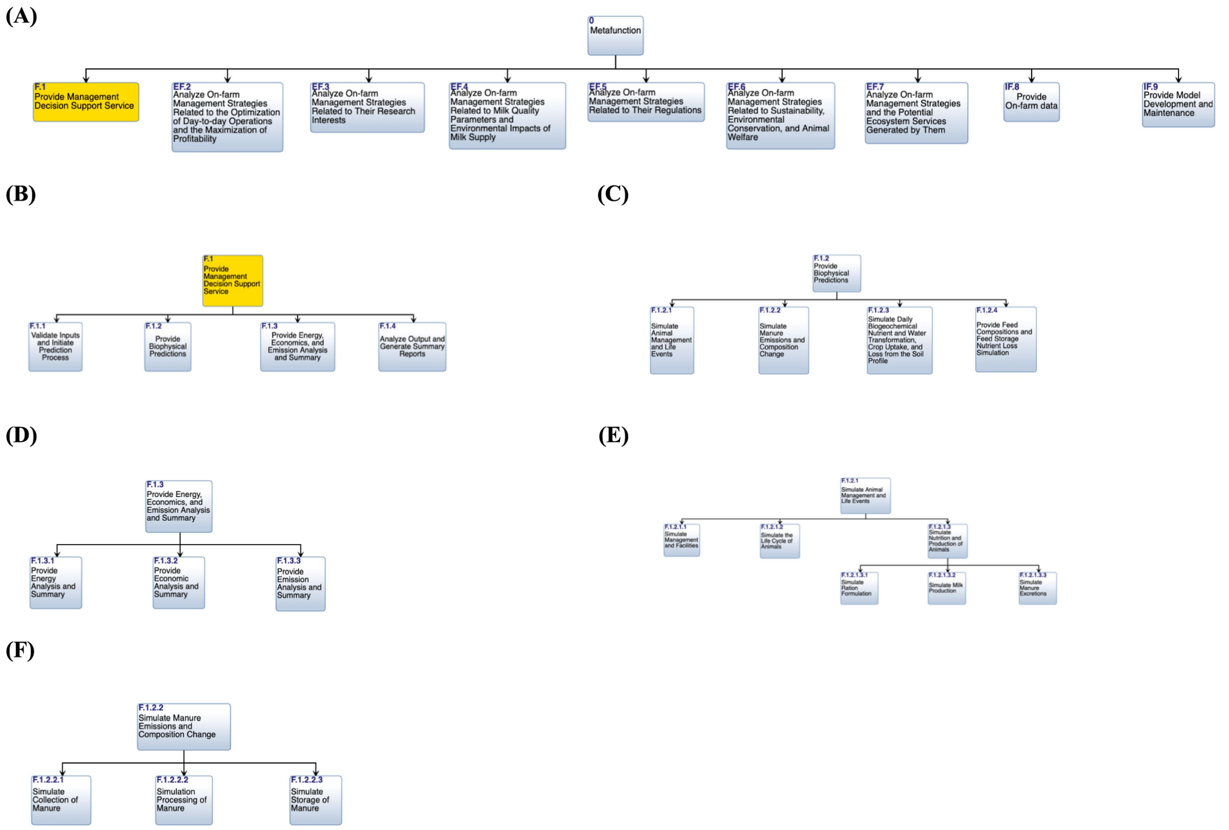

FIGURE 3
Functional hierarchy diagrams of the Ruminant Farm Systems (RuFaS) model and its subsystems, with functions of external stakeholders represented as external functions (EF) and those of internal stakeholders as internal functions (IF): **(A)** top-level metafunction hierarchy diagram; **(B)** RuFaS functional hierarchy diagram; **(C)** biophysical module functional hierarchy diagram; **(D)** energy, emission, and economics module functional hierarchy diagram; **(E)** animal module functional hierarchy diagram; **(F)** manure module functional hierarchy diagram. Source: Generated by Innoslate.

2022; Wood, 1967). Average milk protein and fat components for each region were sourced from the Council On Dairy Cattle Breeding (CDCB) website.[2] We applied region-specific diets based on forage and byproduct availability (Thoma et al., 2013; de Ondarza and Tricarico, 2021; Asselin-Balençon et al., 2013). Supplementary Table 2 provides a full list of the lactating cow diets. The RuFaS model provides multiple options for predicting enteric CH_4 and we applied the Niu et al. (2018) model, which considers dietary composition alongside animal dry matter intake (DMI), to predict enteric CH_4.

For manure management practices, we selected sand and sawdust as bedding materials, using a manual scraping method for sawdust scenarios and a flush system for sand scenarios. In sand scenarios, a sand lane separation method was automatically applied, while sawdust scenarios excluded separation. Finally, we employed the slurry storage outdoor (SS) and anaerobic digestion and lagoon (ADL) as the treatment methods. We set the storage duration of slurry storage to 180 days and the anaerobic lagoon to 365 days. Table 2 provides a summary of the manure management scenarios. For each simulation scenario, a single manure management practice is applied to manure from all pens on that farm. In addition to animal and manure management inputs, we also updated the weather profile according to each region.

In our assessment of environmental impacts, we focused on CH_4, N_2O, and NH_3 emission. CH_4 emissions were accounted for across multiple stages, including animal emissions, housing, and manure treatment and storage processes. The NH_3 and N_2O emissions, on the other hand, are predominantly associated with manure, originating from both housing and storage. Details on the equations and factors used for the estimation of these gas emissions are presented in Supplementary Table 3. A database of feed emissions factors was compiled from 3 sources. County-specific emissions factors for 7 of the most commonly used dairy feeds (Alfalfa hay, alfalfa haylage, corn grain, corn silage, DDGS, soybean meal, and wheat midds) were sourced from the Food System Supply-chain Sustainability (FoodS[3]) model (Pelton et al., 2021; Pelton et al., 2024)[3]. LEIF consulting,[4] in coordination with collaborators from the UMN FoodS[3] group, was commissioned to estimate regionally specific emission factors for 17 commonly fed by-products (Almond hulls, brewer's grains, canola meal, cereal waste, citrus pulp, corn cannery waste, wet corn distillers

2 https://webconnect.uscdcb.com/#/national-performance-metrics

3 https://foodscubed.umn.edu/

4 https://www.leifllc.com/

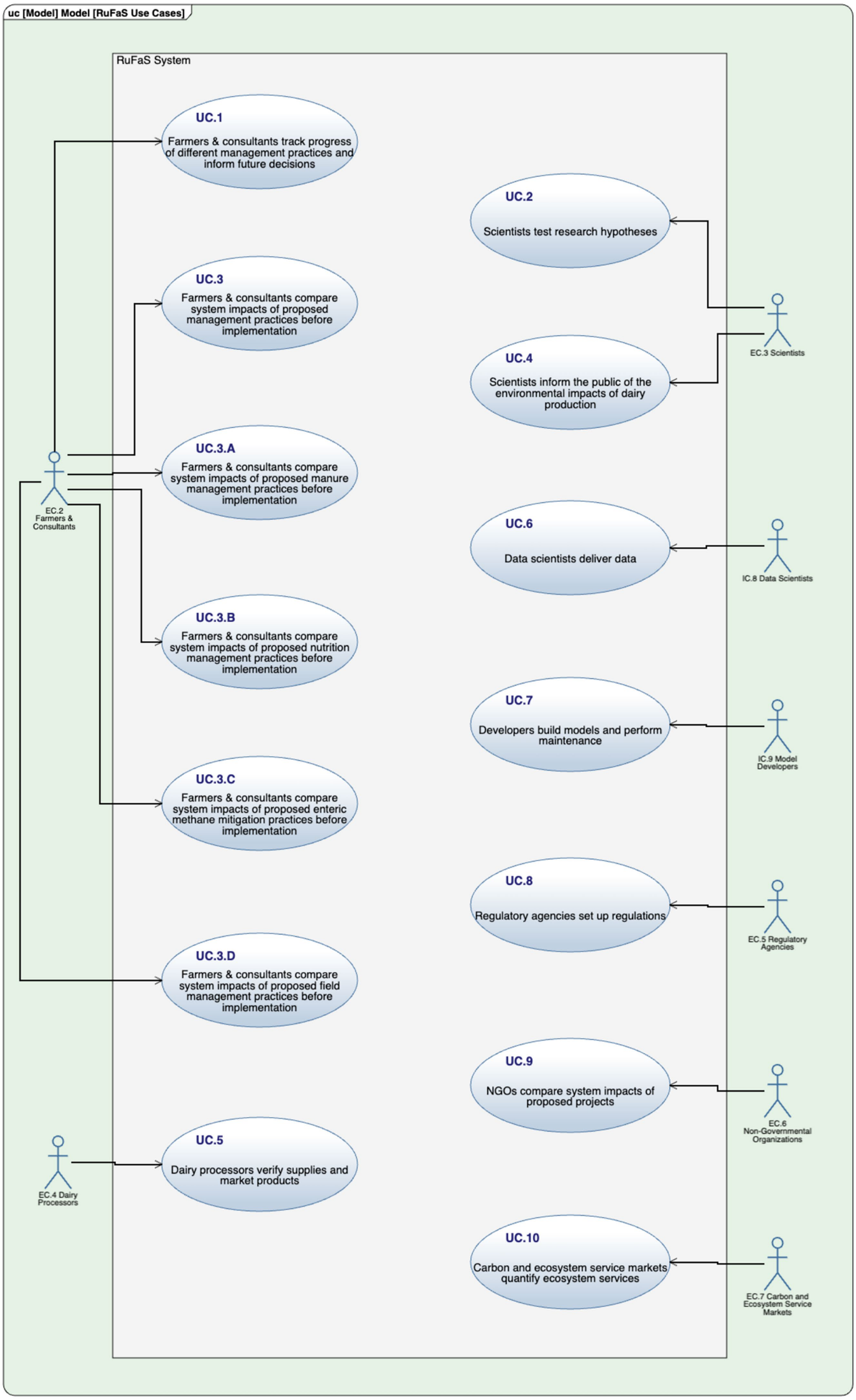

FIGURE 4
Use case diagram of most common and important use cases for the Ruminant Farm Systems (RuFaS) model, with use cases are denoted as UC. Source: Generated by Innoslate.

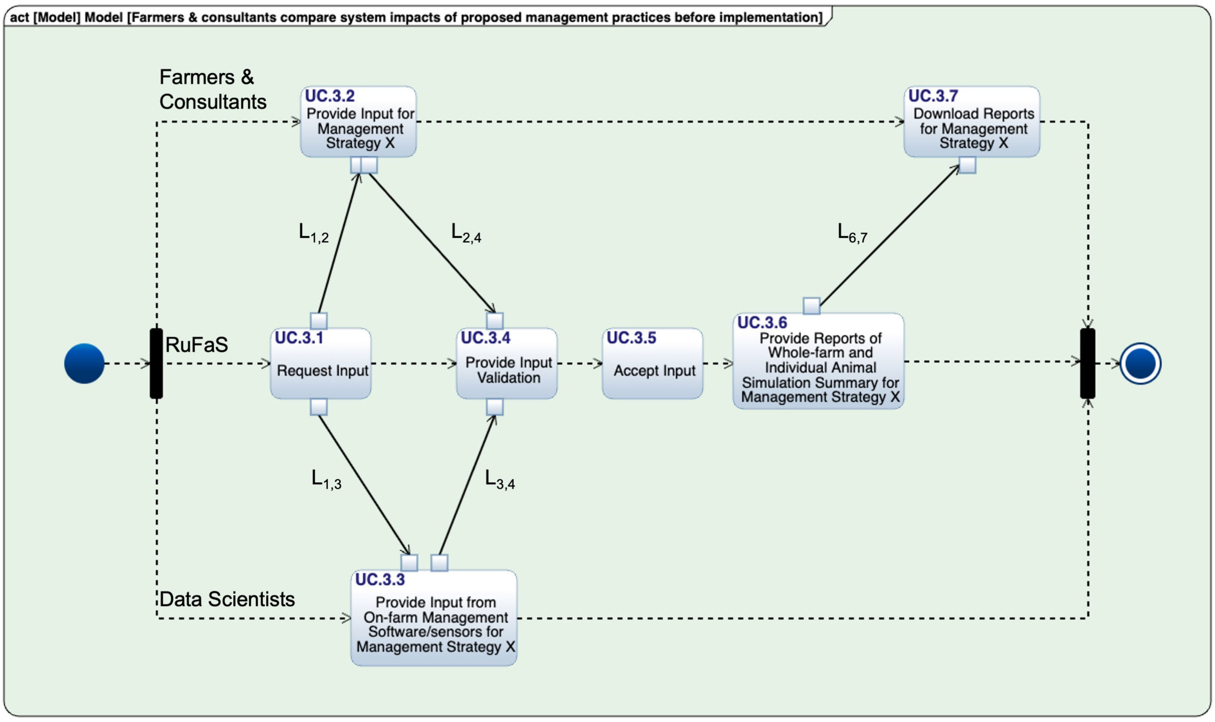

FIGURE 5
Activity diagram of "UC.3: farmers & consultants compare system impacts of proposed management practices before implementation". To enhance legibility, information-flow link ($L_{\#,\#}$) is denoted by a short identifier. Their full descriptions are: $L_{1,2}$—(request farmers & consultants for input); $L_{1,3}$—(request data scientists for input); $L_{2,4}$—(animal, manure, field, and soil data for management strategy X); $L_{3,4}$—(Weather profile, diet data for management strategy X); $L_{6,7}$—(whole-farm and individual animal simulation reports for management strategy X). Source: Generated by Innoslate.

grains, dry corn gluten feed, wet corn gluten feed, whole cottonseed, malt sprouts, cane molasses, soybean hulls, defatted soybean meal, acid whey, condensed whey, and powdered whey). National averages emissions factors for the remaining feeds were sourced from the Intergovernmental Panel on Climate Change (IPCC) (2023). The GHG emission results are expressed in the form of kg CO_2 equivalents (CO_2-eq)/kg fat-and protein-corrected milk (FPCM). FPCM is calculated using Equation 1 (Hall, 2023; Sjaunja et al., 1990):

$$FPCM\,(kg) = 0.25 \times Milk\,(kg) + 12.2 \times Milk\ Fat\,(kg) + 7.7 \times Milk\ Crude\ Protein\,(kg) \tag{1}$$

For the 100-year Global Warming Potential values, we used 27 for CH_4 and 273 for N_2O [Intergovernmental Panel on Climate Change (IPCC), 2023]. A biophysical allocation method was used to distribute emissions between milk and meat, based on the net energy required for lactation and growth (International Dairy Federation, 2022). The resulting milk allocation factor averaged 88.4% across all scenarios.

3 Results and discussions

3.1 MBSE approaches

While MBSE was not applied during early development, its later integration has already yielded clear benefits. When describing the RuFaS model in Innoslate, we presented the details to the third hierarchical level (Figures 2, 3). This allows both users and model developers without programming experience to easily grasp the model's structure and trace its components. This setup also enhances the efficiency of onboarding new RuFaS developers, improving team productivity and supporting future training efforts.

3.1.1 Users, use cases, and user needs

Our MBSE approach offers a structured method for identifying key stakeholders (Figure 1) and their use cases (Figure 4). Stakeholders from dairy production and processing sectors have actively contributed to every stage of RuFaS development and application. By engaging stakeholders throughout the model's development, we foster a shared understanding of the system and promote stakeholder ownership over the model outcomes. Their contributions, gathered during quarterly and annual meetings, provide valuable insights that guide the development of this next-generation decision-support tool for farm management. Developers also visit farms nationwide to inform model refinement through real-world practices.

We identified two major use cases (UC.1 and UC.3) for a subset of stakeholders—farmers & consultants (Figure 4). UC.1 encompasses the range of diverse practices on a farm, such as reproductive protocols, manure treatments, crop rotation schedules, and feed storage methods. In contrast, UC.3 focuses on assessing the impacts of these practices, including both production outcomes such as milk yield and dry matter intake, and environmental outcomes like GHG and NH_3 emissions. These use cases provide clear, scenario-based insights, guiding developers in stakeholder requirement development.

TABLE 1 Examples of the stakeholder requirements of the Ruminant Farm Systems (RuFaS) model related to UC.3.A.

Requirements
The system shall report production outcomes of the farm
The system shall simulate milk production and composition
The system shall simulate diet formulation
The system shall simulate dry matter intake
The system shall simulate feed efficiency
The system shall simulate animal manure excretions and composition
The system shall be able to represent the inherent variability of dairy herds
The system shall simulate individual cow culling, purchases, and sales
The system shall report environmental outcomes of the farm
The system shall simulate manure management practices
The system shall represent bedding materials
The system shall represent inorganic bedding materials
The system shall represent sand bedding
The system shall represent organic bedding materials
The system shall represent sawdust bedding
The system shall model handling methods
The system shall model manual scraping
The system shall model water flushing
The system shall model manure treatment methods
The system shall simulate anaerobic digester
The system shall model sand lane separation
The system shall model solid–liquid separation
The system shall model manure storage methods
The system shall simulate anaerobic lagoon
The system shall simulate slurry storage outdoor
The system shall simulate greenhouse gas emissions from the farm
The system shall simulate methane emissions
The system shall simulate carbon dioxide emissions
The system shall simulate nitrous oxide emissions
The system shall account for seasonable fluctuations in greenhouse gas emissions
The system shall simulate ammonia emission from the farm
The system shall account for seasonable fluctuations in ammonia emissions

3.1.2 Stakeholder requirements

MBSE supports developers in managing system complexity by modeling stakeholder requirements from Table 1. These requirements play a crucial role in guiding the development of RuFaS, ensuring it aligns with user needs. Table 1 illustrates examples of stakeholder requirements for both production and environmental outputs. These requirements directly informed the development of relevant functionalities within RuFaS, such as the estimation of GHG and NH_3 emissions, as detailed in Supplementary Table 3.

Furthermore, to address the requirement of representing the inherent variability of dairy herds, the RuFaS model was designed to simulate outcomes on a per-cow basis. This feature sets RuFaS apart from other whole-farm systems models and life cycle assessment tools. Simulating at the individual-animal level enables integration of genetic breeding values for individual animals, making it possible to simulate herds with varying genetic potential and assess their environmental impacts at the herd level (Hu et al., 2024; Briggs et al., 2024). Moreover, the RuFaS model simulates system processes on a daily timestep, a design choice driven by stakeholder requirements for detailed, high-resolution simulations. For example, with daily timesteps, RuFaS can fulfill the requirement to simulate individual animal culling, purchase, and sales, reflecting real-world dynamics more accurately. The daily timesteps also allow RuFaS to account for seasonal fluctuations in GHG and NH_3 emissions. The implementation of daily simulations is further facilitated by the use of Python as the programming language in RuFaS.

Among the stakeholder requirements specific to UC.3.A., the simulation of manure management practices is of critical importance. Table 1 outlines structural and functional requirements for each stage of the manure processing chain, including bedding materials, handling, treatment, and storage. This structured guidance ensures that RuFaS flexibly accommodates a wide range of manure management combinations and accounts for interactions in elements of the subsystems. For example, manure handling and treatment methods will influence the emissions produced in that part of the manure management chain and will also influence downstream GHG and NH_3 emission as a result of the changes in manure mass and composition in the upstream management practices. This flexibility positions RuFaS as a durable and versatile decision-support tool for dairy farm management, with the ability to evolve alongside advancements in agricultural practices.

Altogether, these stakeholder requirements work in harmony to meet user needs effectively, supporting the RuFaS project's mission to provide practical, adaptable tools for dairy farm management.

3.1.3 Data streams and subsystem interfaces

The MBSE approach also helped identify and clarify the connections between subsystems within the RuFaS model. Activity diagrams (Figure 5; Supplementary Figure 2) illustrate how the model's subsystems interact across multiple levels, tracking inputs and outputs for each subsystem. As shown in Figure 5, farm management input data, such as animal, manure, field, soil, and weather data, are collected from various sources. Validated by the Input Manager (Supplementary Figure 2), these inputs flow into the Biophysical Modules (Animal Module, Manure Module, Soil and Crop Module, and Feed Management and Inventory Module) for biological simulations and to the Output Manager for generating tailored outputs. The Biophysical Module conducts the biophysical process simulation. Within the Biophysical Module, data is exchanged between submodules on a daily timestep. Relevant to the use case explored here, manure mass and composition data generated by the Animal Module feeds into the Manure Module, influencing gas emission estimates from barn floors and during storage (Supplementary Figure 2). Intermediate simulation results from each module are routed through the Output Manager and subsequently integrated into the Energy, Emission, and Economics Module, where energy use, environmental impact, and production costs are calculated. The final outcomes are then compiled by the Output Manager to generate tailored reports (Supplementary Figure 2).

RuFaS integrates input streams from farm software, farmer interviews, published research, and experimental datasets (Figure 5). In this study, we focused on a few variable inputs across different

TABLE 2 Manure management scenario design for UC.3.A.

Bedding material	Manure handler	Manure separator	Manure treatment and storage	Manure storage length
Sawdust	Manual scraping	None	Anaerobic digestion and lagoon	365
Sawdust	Manual scraping	None	Slurry storage	180
Sand	Flush system	Sand lane	Anaerobic digestion and lagoon	365
Sand	Flush system	Sand lane	Slurry storage	180

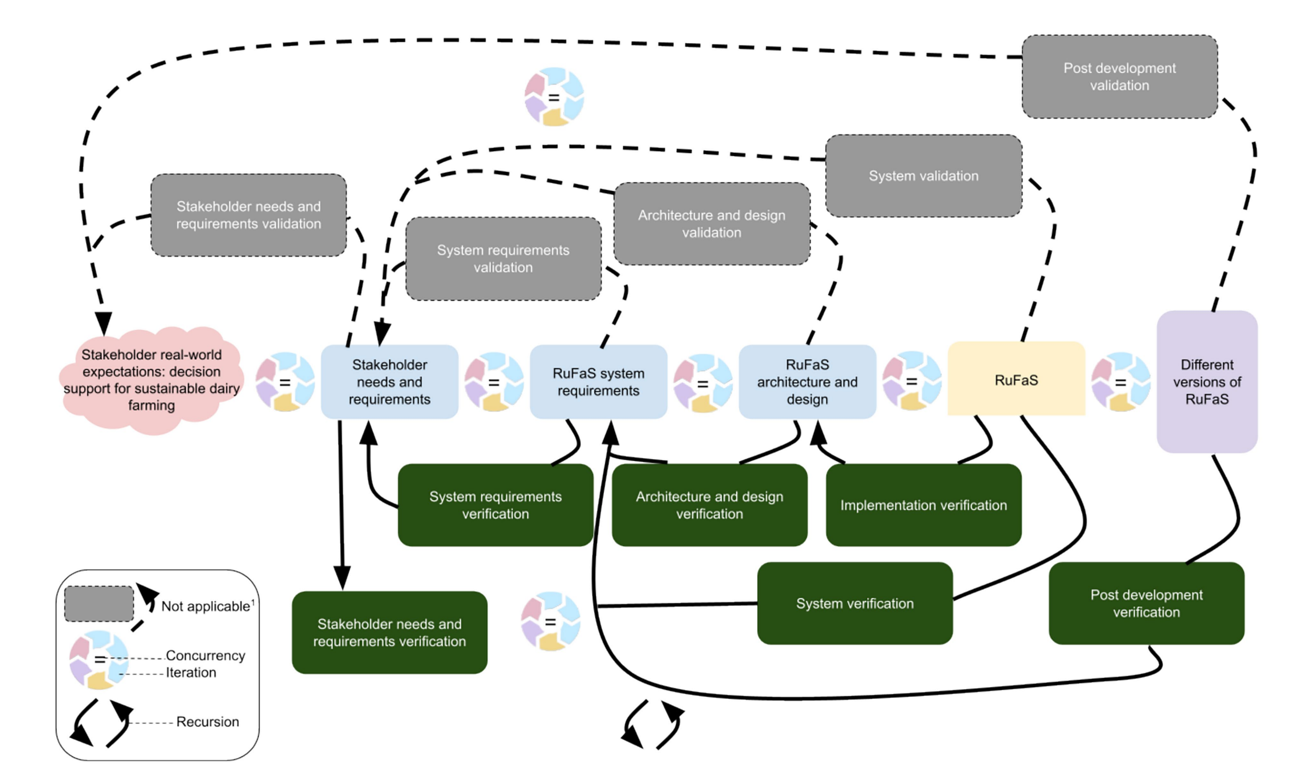

FIGURE 6
Technical processes of the model-based systems engineering (MBSE) approach to support the development of the Ruminant Farm Systems (RuFaS) model, adapted from INCOSE 5th edition (Walden and International Council on Systems Engineering, 2023). [1] Validation of the RuFaS model is not practical and therefore not the focus of the current study.

management practices, such as weather profiles, diets, lactation curve parameters, milk components, bedding types, and manure treatments. However, additional input data on metrics such as body weight, annual milk production, herd turnover rates, and reproductive protocols will enhance the model's fidelity to the farm or use-case of interest. The RuFaS model offers flexibility by allowing simulations with both industry-standard and, if available, farm-specific data, enabling meaningful comparisons across management practices.

3.1.4 Verification and validation

The INCOSE Systems Engineering Handbook (Walden and International Council on Systems Engineering, 2023) distinguishes verification from validation: verification ensures that a system is built correctly, while validation confirms that it is the right system for the intended purpose. We have illustrated this iterative technical process in Figure 6, adapted from the INCOSE handbook (Walden and International Council on Systems Engineering, 2023), to clarify its role in supporting the development of the RuFaS model.

This study emphasizes verification through a stakeholder-informed use case, ensuring alignment with specified requirements. In biological systems, it is impractical to validate all possible scenarios or to collect every real-world measurement. As model developers, our focus shifts toward evaluating the model's accuracy and functionality. Other ongoing efforts to assess the RuFaS model accuracy and functionality include sensitivity analyses, comparisons with experimental data, and pilot testing using data from commercial dairy farms.

3.2 RuFaS simulation outcomes

3.2.1 Production outcomes

Accurately simulating milk production at individual animal and herd levels is crucial for whole farm models. Production efficiency—the conversion of feed into milk—has major economic implications, while milk production is a driving factor in many environmental

TABLE 3 Production outcomes of simulations across regions by the Ruminant Farm Systems (RuFaS) model for UC.3.A.

Item	Regions					
	R1		R2		R3	
	Mean	SD	Mean	SD	Mean	SD
Herd demographics						
Number of total cows	996	2	996	3	995	2
Number of lactating cows	873	1	872	2	874	2
Number of heifers	930	28	937	25	920	19
Milk production and composition						
Annual milk production, kg/yr./cow	13,000	30.2	12,378	31.5	13,515	27.3
Daily milk production, kg/d/cow	40.6	0.07	38.7	0.06	42.2	0.11
Milk fat, %[a]	3.85	0.00	3.93	0.00	3.70	0.00
Milk protein, %[a]	3.08	0.00	3.08	0.00	3.11	0.00
Dry matter intake, kg/d/cow	24.0	0.05	23.6	0.03	24.2	0.04

[a]Milk fat and protein concentrations were sourced from the Council On Dairy Cattle Breeding (CDCB) website (https://webconnect.uscdcb.com/#/national-performance-metrics) and set as a constant in the version 0.9.2 of the RuFaS model.

outcomes due to its impact on feed intake (Gong et al., 2025). In the RuFaS simulations from this study, the annual milk production per cow varied by region as expected in response to changes in the lactation curve parameters and herd management inputs for each region (Supplementary Table 1). The resulting milk production estimates were 13,515 ± 27.3 kg/yr./cow for R3, followed by 13,000 ± 30.2 kg/yr./cow for R1, and 12,378 ± 31.5 kg/yr./cow for R2 (Table 3). These estimates align with those reported by Li M. et al. (2022) which were informed by a CDCB dataset and reflect the same regional hierarchy (R3 > R1 > R2; R3: 14,020, R1: 13,696, R2: 13,083 kg/yr./cow). Daily milk production per cow followed a similar pattern to annual per cow milk production (R3 at 42.2 ± 0.11 kg/d/cow, R1 at 40.6 ± 0.07 kg/d/cow, R2 at 38.7 ± 0.06 kg/d/cow; Table 3) due to the consistent number of lactating animals across scenarios (R3: 874 ± 2, R1: 873 ± 1, R2: 872 ± 2; Table 3).

Predicted daily DMI followed the regional milk production pattern, with the highest daily DMI in the R3 scenarios (24.2 ± 0.04 kg/d/cow), followed by the R1 (24.0 ± 0.05 kg/d/cow) and R2 (23.6 ± 0.03 kg/d/cow) (Table 3). The close relationship between milk production and DMI is expected due to the physiological relationships between milk production, nutrient requirements, and animal feed intake. RuFaS estimates DMI using the NASEM (National Academies of Sciences, Engineering, and Medicine) (2021) formula, which integrates milk energy output, days in milk, body weight, and parity, following de Souza et al. (2019). This provides a biologically grounded prediction mechanism that links productivity to intake. In their work, de Souza et al. (2019) highlighted that DMI of lactating dairy cows in North America is primarily driven by milk production and the energy needed for maintenance, both major energy expenditures for dairy cows.

3.2.2 Environmental outcomes

Enteric CH_4 and manure-related emissions (CH_4 and N_2O) are the two largest sources of GHG on U.S. dairy farms, together contributing nearly 70% of total GHG emissions (Rotz et al., 2021). Management practices such as diet formulation and manure handling significantly influence these emissions across production stages (Hristov, 2023; Rotz, 2018; Wattiaux et al., 2019). In our RuFaS simulations, total farm GHG emissions across 12 scenarios ranged from $1.23 \pm 4.64 \times 10^{-3}$ to $1.61 \pm 9.45 \times 10^{-3}$ kg CO_2-eq/kg FPCM, as shown in Figure 7. Regional variations in management are reflected in RuFaS estimates of total emission intensity, with R2 scenarios producing the highest emission intensity ($1.55 \pm 5.75 \times 10^{-2}$ kg CO_2-eq/kg FPCM), followed by R3 (1.50 ± 0.112 kg CO_2-eq/kg FPCM), while R1 scenarios had the lowest emission intensity ($1.29 \pm 5.98 \times 10^{-2}$ kg CO_2-eq/kg FPCM). Similarly, manure treatment methods also influenced total farm GHG intensities, with ADL scenarios (1.37 ± 0.109 kg CO_2-eq/kg FPCM) yielding lower intensities compared to SS scenarios (1.52 ± 0.123 kg CO_2-eq/kg FPCM): a difference of 0.146 kg CO_2-eq/kg FPCM. However, no numerical differences were observed between emissions intensity estimates from sand (1.44 ± 0.140 kg CO_2-eq/kg FPCM) and sawdust (1.45 ± 0.136 kg CO_2-eq/kg FPCM) bedding scenarios. Our results affirmed that enteric (32.0%) and manure (32.9%) emissions are the primary contributors to GHG emissions on the farm. These findings align with a recent IFSM model study, which reported a national GHG range of 0.65 to 1.67 kg CO_2-eq/kg FPCM for 2020 (Rotz et al., 2024).

Enteric CH_4 varied across regional scenarios in our simulations (Figures 8A,B). However, the estimated daily enteric CH_4 production per lactating cow in our simulations was similar across regions, ranging from $420 \pm 7.00 \times 10^{-4}$ g/d (R3) to $423 \pm 8.39 \times 10^{-4}$ g/d (R1). We also observed the expected correlation between enteric CH_4 production and DMI within each region (Figure 8A), which is in alignment with many findings in the literature [e.g., Marumo et al. (2023)] that DMI is the major driver for enteric CH_4 emissions. This is also reflected in the Niu et al. (2018) enteric CH_4 equation used in RuFaS (Supplementary Table 3). However, DMI is not the sole driver of enteric CH_4, as shown by variations in our predictions across regions despite similar DMI levels. This variation reflects additional factors influencing CH_4 output, such as dietary NDF content, bodyweight, and milk fat concentration, all of which are incorporated into the Niu et al. (2018) equation. In particular, among the simulated regions, R3 has a lower milk fat concentration (3.70%) compared to R1 (3.85%) and R2 (3.93%) (Table 3). The intensity of enteric CH_4 emissions reflects the combined influence of milk yield and composition on emissions. Our simulation results showed higher simulated whole herd enteric CH_4 intensity for R2 (0.472 ± 3.65 ×

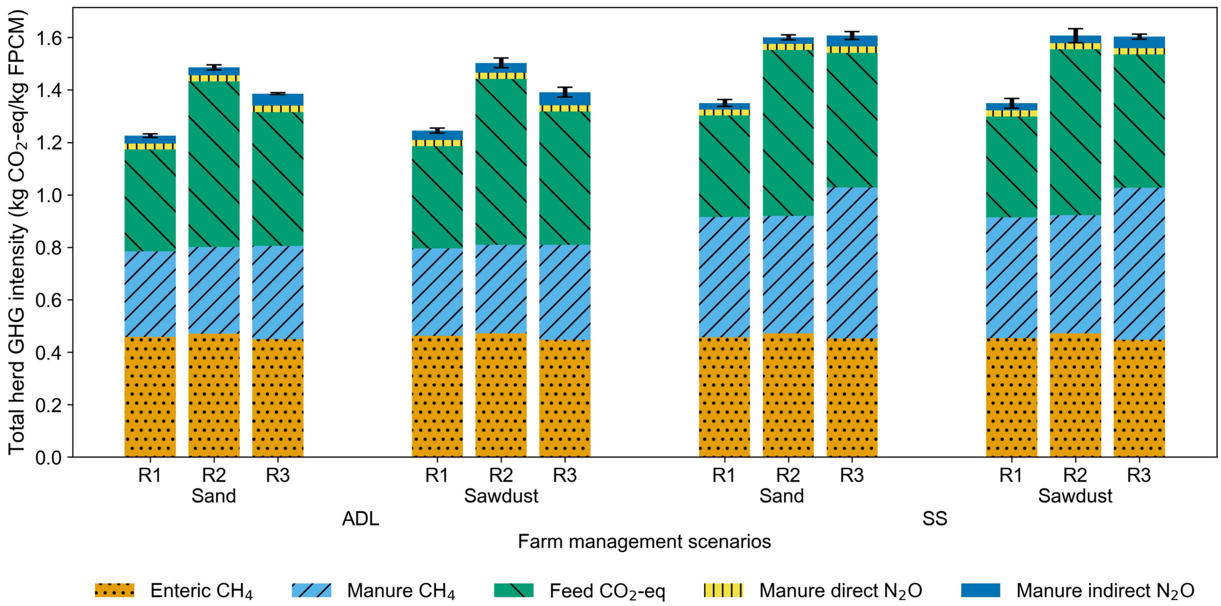

FIGURE 7
Average total herd greenhouse gas (GHG) intensity (kg CO_2-eq/kg FPCM) simulated by the Ruminant Farm Systems (RuFaS) model across all 12 scenarios, categorized by regions (R1, R2, R3), bedding materials (sand, sawdust), and manure treatment methods [anaerobic digestion and lagoon (ADL), slurry storage (SS)], based on 4 simulations, with error bars indicating 95% confidence intervals.

10^{-3} kg CO_2-eq/kg FPCM), followed by R1 ($0.458 \pm 4.19 \times 10^{-3}$ kg CO_2-eq/kg FPCM) and R3 ($0.449 \pm 3.45 \times 10^{-3}$ kg CO_2-eq/kg FPCM) (Figure 8B). These values are slightly higher than the U.S. average of 0.434 kg CO_2-eq/kg FPCM reported by Rotz et al. (2021) but remain below the 0.63 kg CO_2-eq/kg FPCM observed for Wisconsin Holsteins by Uddin et al. (2021).

Feed emissions also showed regional variation, as emission factors differ by location and typical regional diets. Our simulations showed that feed emissions for R2 scenarios were the highest ($0.633 \pm 4.43 \times 10^{-3}$ kg CO_2-eq/kg FPCM), followed by R3 scenarios ($0.510 \pm 3.32 \times 10^{-3}$ kg CO_2-eq/kg FPCM). Feed emissions for R1 scenarios were the lowest, at $0.388 \pm 2.82 \times 10^{-3}$ kg CO_2-eq/kg FPCM (Figure 8C). Emission results in our study were generally higher than those reported in previous literature, where feed emissions were estimated at 0.22 kg CO_2-eq/kg FPCM (Rotz et al., 2021; Uddin et al., 2021), largely due to the higher emission factors used in this study which include recent estimates of the emissions associated with land use change.

Manure CH_4 emissions arise from both barn floor and manure storage. Methane emissions from manure are largely dependent on manure volatile solid content (Møller et al., 2004). Our results showed that manure CH_4 emissions varied across manure treatment methods. Management of manure with ADL ($0.341 \pm 1.35 \times 10^{-2}$ kg CO_2-eq/kg FPCM) resulted in lower manure CH_4 emissions compared to SS ($0.495 \pm 5.99 \times 10^{-2}$ kg CO_2-eq/kg FPCM) (Figure 9A). This reduction occurs because anaerobic digestion breaks down volatile solids, converting them into biogas, which can be used for energy production (Møller et al., 2004). Consequently, the availability of volatile solids for CH_4 generation during manure storage is decreased and the total CH_4 emissions are reduced (Marañón et al., 2011). Manure CH_4 emissions were similar between sand bedding ($0.416 \pm 9.09 \times 10^{-2}$ kg CO_2-eq/kg FPCM) and sawdust bedding options ($0.421 \pm 8.89 \times 10^{-2}$ kg CO_2-eq/kg FPCM) (Figure 9A). Currently, the RuFaS model does not account for the contribution of organic bedding to manure volatile solids for the generation of CH_4 due to the lack of reliable, quantifiable methods to represent this process in the literature. For instance, one study (Le Riche et al., 2017) observed a 53% increase in CO_2-eq GHG emissions from wood bedding over sand bedding between April and December of 2014. Another study found that adding straw to manure increased CH_4 production by 10% for every kilogram of straw added to 100 kg of manure (Møller et al., 2004). As the effects of sawdust and other organic bedding materials on manure storage CH_4 are better understood, we will incorporate this factor into the RuFaS model.

The higher manure CH_4 emissions observed in our simulations, compared to those reported by Uddin et al. (2021) (0.28 kg CO_2-eq/kg FPCM) and Rotz et al. (2021) (0.19 kg CO_2-eq/kg FPCM), can be attributed to several factors. One explanation is that RuFaS uses more recent equations to calculate manure volatile solids for both lactating and dry cows (Appuhamy et al., 2014; Appuhamy et al., 2018), which may result in higher emission estimates. However, a direct comparison of manure volatile solid excretions is not possible, as these were not reported by Uddin et al. (2021) or Rotz et al. (2021). Another contributing factor is the inclusion of heifers in the simulated farms, which can also contribute to increased emissions. Uddin et al. (2021) did not include heifers when reporting manure CH_4 emissions. Even though Rotz et al. (2021) included heifers in their estimates, the ratio of heifers to cows in their study averaged 0.679, while the ratio of the average net number of heifers to cows in our simulated farms, when accounting for purchases and sales, was 0.865 (Table 3).

Most of manure nitrogen loss is in the form of NH_3 which indirectly contributes to N_2O emissions in the air and are thus included in whole farm models and life cycle assessments (Rotz et al., 2021; Aguirre-Villegas et al., 2024). Our simulation results indicated higher NH_3 emissions with ADL treatment (8.98 ± 1.762 g/kg FPCM) compared to SS (7.38 ± 1.873 g/kg FPCM) (Figure 9B). This increase in NH_3 emissions is due to increased ammoniacal nitrogen from the breakdown of organic nitrogen by the microbes inside the digester (Neerackal et al., 2015) which is represented in RuFaS by an conversion of non-ammoniacal N to ammoniacal nitrogen in the digestate leaving an anaerobic digester and entering the anaerobic lagoon. Our results are slightly lower than those reported by Aguirre-Villegas et al. (2024), who observed NH_3 emissions from slurry storage of 10.37, 9.56, 9.33 g/kg FPCM for confinement farms with 50, 200, and 1,000 cows, respectively. However, they are higher than the U.S. average annual emission of 6.5 g/kg FPCM reported by Rotz et al. (2021). Manure NH_3 emissions varied by bedding material, with sand (7.69 ± 1.931 g/kg FPCM) lower than sawdust (8.67 ± 1.927 g/kg FPCM) (Figure 9B), which is a result of the additional water added to the manure with the flushing method associated with sand bedding. This additional water increases the simulated manure volume and decreases NH_3 emissions estimates because manure volume enters the NH_3 emission equation

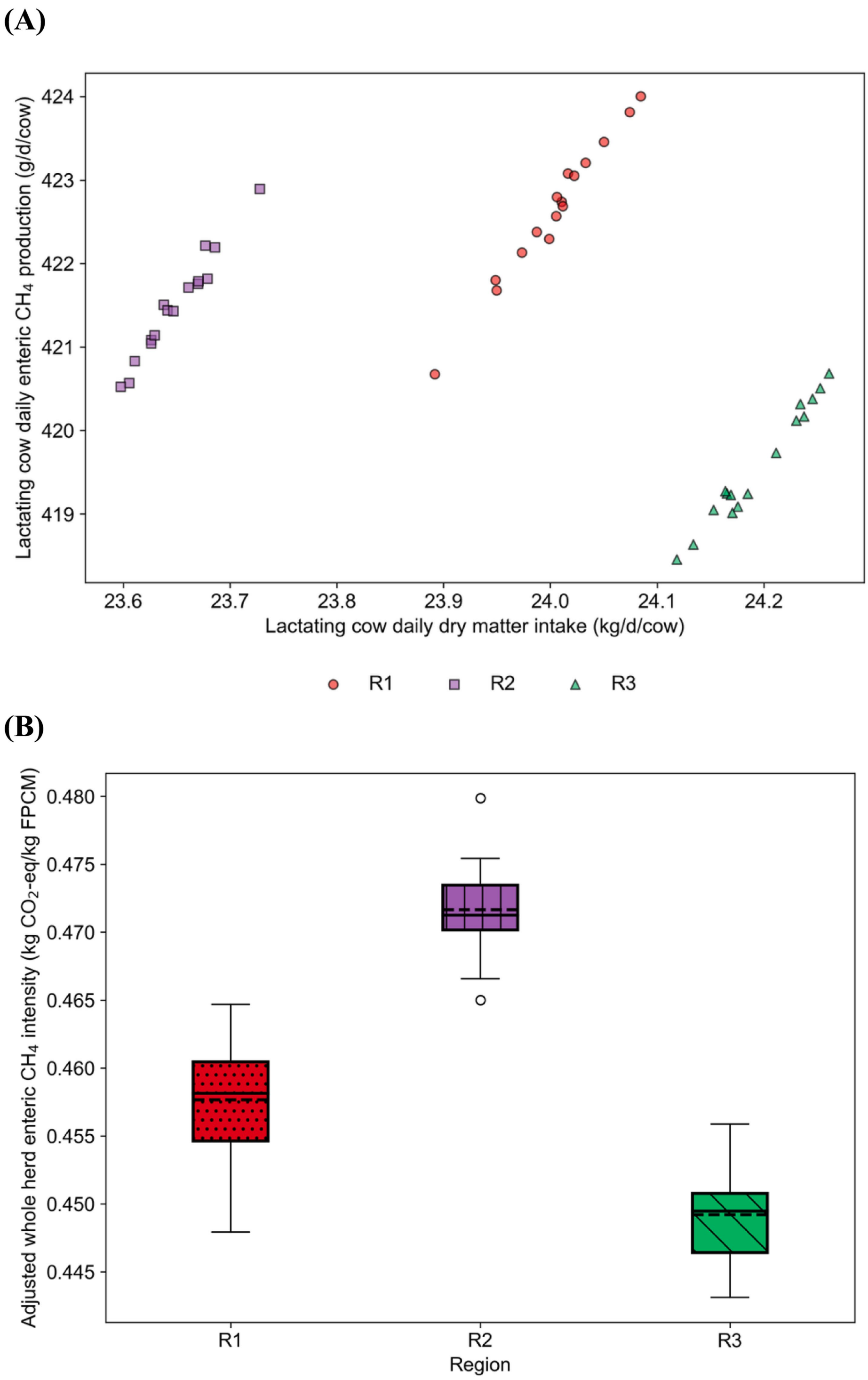

FIGURE 8 (Continued)

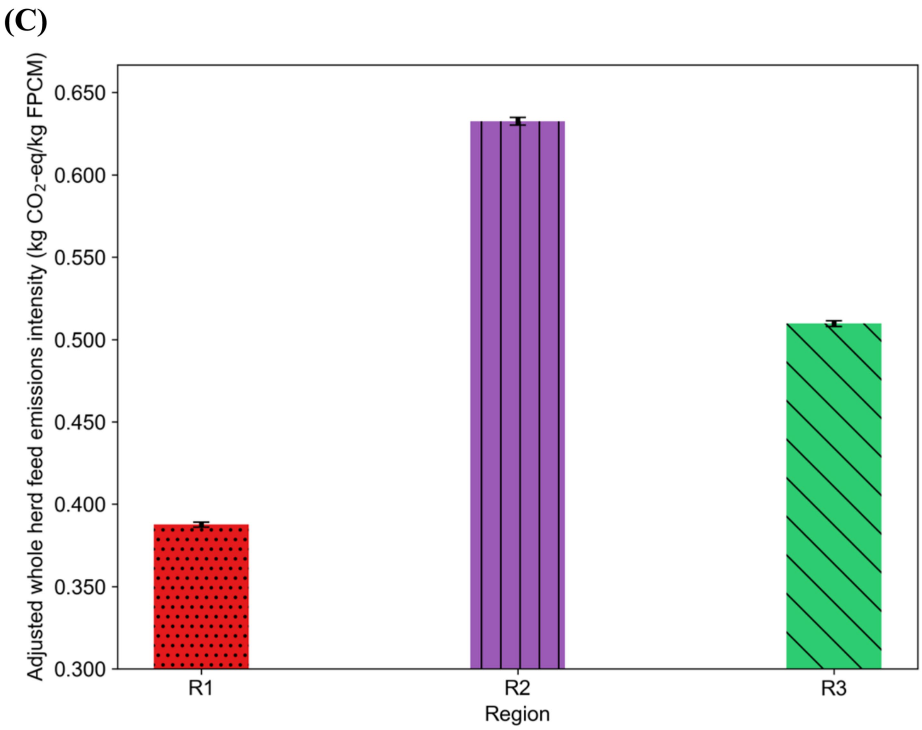

FIGURE 8
Simulated gas emissions from the Ruminant Farm Systems (RuFaS) model across regional scenarios: **(A)** daily enteric CH_4 production (g/d/cow) of lactating cows relative to daily dry matter intake (kg/d/cow); **(B)** whole herd CH_4 intensity (kg CO_2-eq/kg FPCM), with solid line representing the median, dashed line the mean, box edges marking the 25th and 75th percentiles, and whisker ends showing the minimum and maximum values; **(C)** whole herd feed emissions intensity (kg CO_2-eq/kg FPCM), with error bars indicating 95% confidence intervals.

proposed by Rotz and Oenema (2006) in the denominator and thus, increased volume decreases NH_3 emission estimates. There is relatively little information in the literature on methods for predicting NH_3 emissions from manure and future work should focus on improving our understanding of the relationships between manure volume, surface area, temperature and NH_3 emissions so that we can increase prediction accuracy and response to key management practices.

Nitrous oxide emissions originate from nitrogen in manure through sequential nitrification and denitrification processes (Schmithausen et al., 2018). In our simulations, we observed no numerical differences in N_2O levels between ADL scenarios ($1.06 \pm 5.07 \times 10^{-2}$ kg/yr./cow) and SS scenarios ($1.06 \pm 5.41 \times 10^{-2}$ kg/yr./cow) (Figure 9C). Similarly, there were no numerical differences in N_2O emissions between sand-bedded scenarios ($1.06 \pm 5.44 \times 10^{-2}$ kg/yr./cow) and sawdust-bedded scenarios ($1.06 \pm 5.02 \times 10^{-2}$ kg/yr./cow) (Figure 9C). The lack of difference between these methods is expected, as the impacts of these factors are not well understood and are not currently accounted for in the RuFaS model which uses a simple N_2O emissions factor based on total manure N entering the system. Our results align with findings from Rotz (2018), who reported N_2O emissions of 1.20 kg/yr./cow for a confinement farm in Pennsylvania with slurry manure storage.

3.3 Transdisciplinarity

This study applied MBSE to develop a computational tool supporting production and sustainable decision-making in dairy farming. It serves as an example of how systems engineering can facilitate collaborative problem-solving in non-engineering contexts to address global issues like sustainability through a transdisciplinary approach. This work integrates diverse disciplinary knowledge to create a tool that meets both practical and research needs.

In the context of production and sustainability decisions on dairy farms, people are central to the process. Lang et al. (2012) highlighted several challenges in transdisciplinary sustainability research, which includes achieving balanced stakeholder involvement, integrating diverse knowledge sources, and fostering ongoing participation. While stakeholder input has guided RuFaS development since its inception, these contributions were not previously captured in a structured, traceable format. Through MBSE, we established an effective framework for managing stakeholder engagement in the development of the RuFaS model, thus serving as both a documentation tool and a dynamic reference point, aligning ongoing development with evolving stakeholder priorities.

4 Implications, limitations, and future work

RuFaS enables comparative analysis of manure management strategies on environmental outcomes, directly addressing key stakeholder requirements. This research brings an innovative approach by incorporating MBSE methods into agricultural systems modeling, marking a transdisciplinary effort to promote sustainable management solutions for dairy farms. While MBSE has been widely applied in other sectors to develop complex systems, its use in agriculture remains limited. This transdisciplinary approach opens new avenues for systems-based innovation in sustainable agriculture.

The processes of identifying stakeholders, understanding their needs, and developing a system that aligns with these requirements

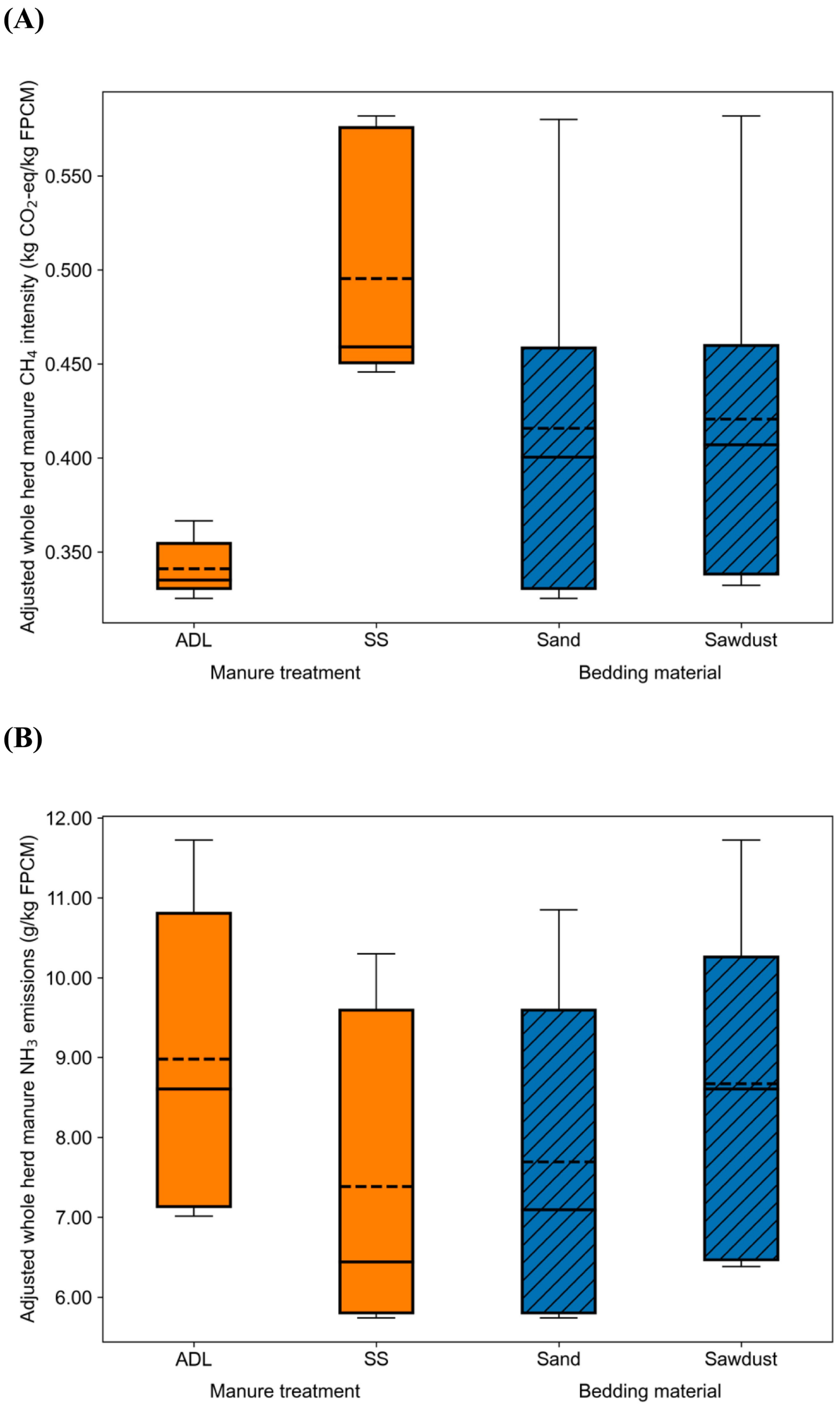

FIGURE 9 (Continued)

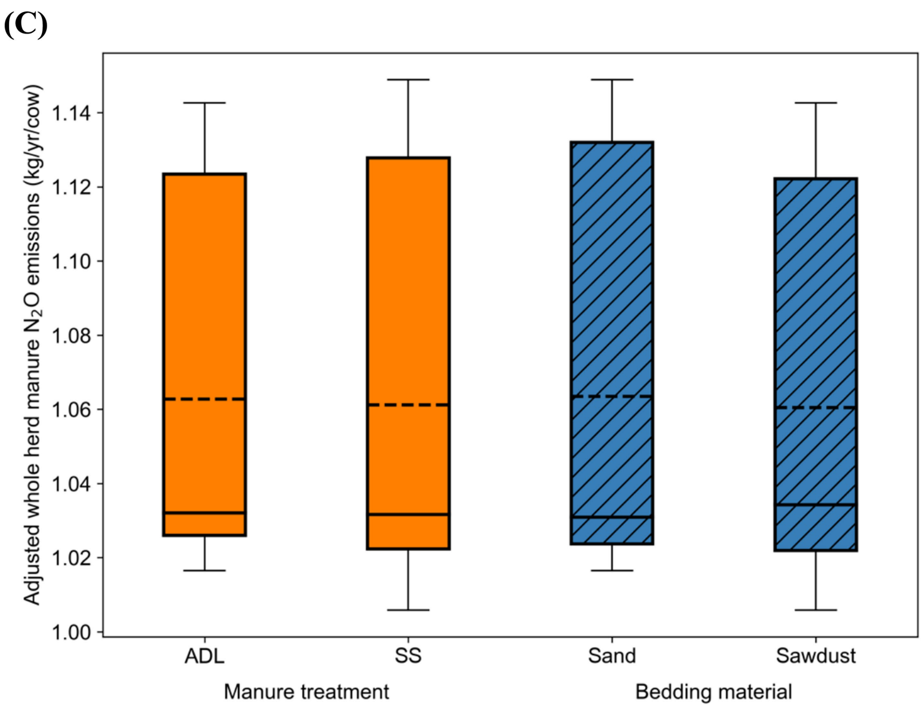

FIGURE 9
Simulated whole herd gas emissions from the Ruminant Farm Systems (RuFaS) model, categorized by manure treatment methods [anaerobic digestion and lagoon (ADL), slurry storage (SS)] and bedding materials (sand, sawdust): **(A)** manure CH_4 intensity (kg CO_2-eq/kg FPCM); **(B)** manure NH_3 emissions (g/kg FPCM); **(C)** manure N_2O emissions (kg/yr./cow). Solid line indicates median, while dashed line indicates mean. The solid line represents the median, the dashed line the mean, with box edges marking the 25th and 75th percentiles, and whisker ends showing the minimum and maximum values.

offer a practical framework that future model developers and researchers can easily adapt and expand upon. Currently, verification and validation steps are conducted manually, as RuFaS and the MBSE model are not yet programmatically integrated due to resource constraints. In other fields, the verification and validation can be automated to ensure continuous alignment of the system performance and requirements. Additionally, the use cases evaluated here focused only on GHG emissions from animals and manure management which is a subset of the environmental impacts associated with dairy production. Additional environmental modules—such as field-based GHG emissions, nutrient runoff, and air quality indicators—are supported by RuFaS but were not assessed in this study. Future development should prioritize integration of the MBSE model and simulation layers to enable automated verification and validation pipelines, improve traceability, and support adaptive management tools such as digital twins.

Although the MBSE approach was not implemented from the earliest stages of RuFaS model development, it offers significant benefits for future work. Adopting a systems perspective through MBSE not only enhances transparency and stakeholder alignment but also lays the groundwork for future integration of predictive, data-driven farm management systems.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HH: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. CW: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing. TP: Investigation, Writing – original draft, Writing – review & editing. KR: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Correction note

A correction has been made to this article. Details can be found at: 10.3389/frsus.2025.1693950.

Generative AI statement

The author(s) declare that Gen AI was used in the creation of this manuscript. The authors acknowledge that portions of the text in this manuscript were edited using generative AI technology, specifically ChatGPT-4. The author has reviewed and approved all content to ensure its accuracy, originality, and alignment with the scientific standards of the manuscript.

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frsus.2025.1561453/full#supplementary-material

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