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Review

Review of Sources of Uncertainty and Techniques Used in Uncertainty Quantification and Sensitivity Analysis to Estimate Greenhouse Gas Emissions from Ruminants

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Abstract: Uncertainty quantification and sensitivity analysis are essential for improving the modeling and estimation of greenhouse gas emissions in livestock farming to evaluate and reduce the impact of uncertainty in input parameters to model output. The present study is a comprehensive review of the sources of uncertainty and techniques used in uncertainty analysis, quantification, and sensitivity analysis. The search process involved rigorous selection criteria and articles retrieved from the Science Direct, Google Scholar, and Scopus databases and exported to RAYYAN for further screening. This review found that identifying the sources of uncertainty, implementing quantifying uncertainty, and analyzing sensitivity are of utmost importance in accurately estimating greenhouse gas emissions. This study proposes the development of an EcoPrecision framework for enhanced precision livestock farming, and estimation of emissions, to address the uncertainties in greenhouse gas emissions and climate change mitigation.

Keywords: greenhouse gas emission; ruminant livestock; uncertainty analysis; sensitivity analysis; methane; carbon dioxide; nitrous oxide; EcoPrecision framework

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1. Introduction

1.1. Uncertainty Quantification and Sensitivity Analysis

Uncertainty quantification and sensitivity analysis are essential for improving the modeling and estimation of greenhouse gas emissions in livestock farming to identify of the sources and the most significant input parameters and their impacts on the overall model output, thus minimizing errors [1–5]. Identifying the sources of uncertainty in modeling greenhouse gas emissions and analyzing their sensitivity can improve accuracy in modeling emissions and support the development of effective mitigation strategies for sustainable livestock production [1,6,7]. Different frameworks, methods, and approaches such as Monte Carlo simulations, contribution to variance analysis, global sensitivity methods, traditional matched filter methods, optimal estimation (OE) methods, integrated assessment models, model intercomparison studies, scenario analysis, and expert judgment have been used in analyzing the cause or source of uncertainties to perform uncertainty analysis and quantification and sensitivity analysis in greenhouse gas emissions from ruminants [5,8–11].

1.2. The Relationship between Livestock Formation, Greenhouse Gas Emissions, and Climate Change: Implications and Mitigation Strategies

Livestock, particularly ruminants, significantly contribute to global greenhouse gas emissions and climate change through manure management and the release of carbon dioxide, methane, and nitrous oxide through enteric fermentation [12–17]. The consequences of increasing emissions include a heightened greenhouse effect and global warming, which necessitates appropriate mitigation strategies to limit temperature rise [14,18]. The bidirectional interaction between ruminant livestock emissions and climate change forms a positive feedback loop, impacting livestock well-being, feed availability, and disease prevalence [19,20].

Addressing these challenges requires sustainable and adaptive livestock farming practices that consider technological innovations, policy interventions, and behavioral changes [21,22]. Effective sustainability strategies and policies, advanced technologies such as big data, artificial intelligence, internet of things (IoT)-based smart farming, remote sensing, and precision livestock farming (PLF), and good management practices such as manure management, feed optimization, breed selection interventions, and land-based carbon sequestration at the farm level, can reduce emissions, which is vital for reaching the temperature goal of the Paris Agreement [13,14,23–28]. Overall, the implementation of effective sustainability strategies, policies, and technological innovation can enhance the accuracy of results and analysis on climatic conditions, livestock, and carbon sequestration [29]. However, further research is needed to understand the complex interactions between ruminant livestock emissions, greenhouse gases, and climate change that will eventually contribute to the development of integrated mitigation strategies [13,27].

1.3. Emission Quantification Techniques and Estimation Approaches

Emissions of greenhouse gases can be quantified directly or indirectly [12,30]. Direct techniques demand that some instrumentation, such as remote sensing, directly measures emissions in the atmosphere. In contrast, the indirect approach often uses an estimation model, such as activity data and an emission factor [31]. Also, emissions can be estimated using bottom-up and top-down methods [32,33]. Activity data and emission features are used by bottom-up methods to calculate emissions by multiplying individual sources with their respective emissions [32,33]. The main goal of top-down estimates is to enhance bottom-up forecasts by providing information to connect emissions to processes, thus supporting climate action [34]. Top-down methods that use atmospheric methane observations to estimate emissions can improve bottom-up estimates [35,36]. Tiers 1, 2, and 3 are approaches used in calculating greenhouse gas emissions and removals by the Intergovernmental Panel on Climate Change (IPCC) [12,37,38]. Tier 3 is used nationally to create an emission inventory [12,37,39]. Also, the Life Cycle Assessment (LCA) framework is used to evaluate emission intensity and quantification through the production life cycle [40–42]. However, these techniques and approaches have uncertainties and can lead to conflicting forecasts [35,41].

1.4. Theoretical Frameworks for Modeling the Correlation between Greenhouse Gas Emissions in Livestock Farming

Life Cycle Assessment (LCA) is a framework that evaluates the environmental impacts of livestock production at various stages, such as enteric fermentation, feeding practices, and manure management [43,44]. The LCA framework also helps in identifying specific evaluation criteria for livestock-focused assessments, including transparency, reproducibility, completeness, fairness, and acceptability, and aids in developing tailored mitigation strategies for livestock farming [45]. However, the LCA framework has limitations like inaccuracies and robustness of sustainability in modeling greenhouse gas emissions from livestock [43,46]. Therefore, harmonization of LCA methods is needed, and uncertainty in input variables like milk yield affects emission estimates and the classification of farms [44,47]. Overall, reducing critical uncertainties is crucial for effective LCA use [48,49].

Integrated assessment models (IAMs) are comprehensive frameworks that help to understand the correlation between greenhouse gas emissions and livestock farming, and models to assess the impacts of different factors on emissions [50,51]. They combine knowledge from various domains, thus allowing for policy evaluation based on economic, climatic, and interdisciplinary components analyzing emissions from different stages, evaluating mitigation strategies, and simulating scenarios, thus providing insights into policy interventions [52–54]. However, IAMs are limited in modeling greenhouse gas emissions in livestock farming due to uncertainties and errors in input variables [54]. Classifying farms into adopters and non-adopters of mitigation measures is prone to errors and also fails to account for equity and fairness concepts, which are crucial for policy decisions [48].

Precision Agriculture (PA) frameworks are used to understand greenhouse gas emissions in livestock farming using IoT, sensors, and data analytics [55]. Future research should integrate multidisciplinary approaches, deep learning, machine learning, and intelligent technologies for sustainable development [56]. However, PA frameworks face challenges in modeling greenhouse gas emissions due to a lack of data and a gap between modeled scenarios and reality in the agricultural sector [48,57,58].

The utilization of Monte Carlo simulation and sensitivity analysis frameworks is essential in evaluating the uncertainty and sensitivity of emission estimates within models and for devising effective strategies to combat climate change, particularly in the context of reducing greenhouse gas emissions from livestock [3,59]. Nevertheless, Monte Carlo simulation and sensitivity analysis frameworks face challenges in modeling greenhouse gas emissions such as uncertainty in parameters and assumptions, and the need for accurate quantification of uncertainties [60]. The choice of sampling strategies and interpretation methods also affects the accuracy of results, necessitating further research and development [61].

A theoretical framework for modeling greenhouse gas emissions from ruminants is essential for understanding and mitigating their contribution to climate change. These frameworks play a crucial role in deciphering the primary contributors to emissions and pinpointing specific areas for targeted mitigation efforts.

Thus, this review aimed to (1) assess the source of uncertainties in the estimation of greenhouse gas emissions from ruminant livestock, (2) investigate the techniques used in uncertainty quantification and sensitivity analysis in the estimation of greenhouse gas emissions from ruminant livestock, and (3) propose the development of an EcoPrecision framework for enhanced precision livestock farming and emission estimation, to address the uncertainties in greenhouse gas emissions from livestock and climate change mitigation.

2. Materials and Methods

A comprehensive search strategy was devised and implemented to identify relevant articles on greenhouse gas emission modeling in the ScienceDirect, Google Scholar, and Scopus databases. Google Scholar serves as a comprehensive repository of citation data across various academic disciplines, providing users with direct access to pertinent sources. Scopus is an abstract and citation database that adheres to strict controls, complements the Web of Science, and grants access to exceptional author and affiliation identifiers. ScienceDirect, an expansive collection encompassing over 9.5 million articles and book chapters, presents a multitude of search options, allowing for refinement by content type, subject matter, or journal. Moreover, it permits users to customize their search ordering. These data sources provide researchers with comprehensive and exhaustive coverage. The following query was used: "uncertainty", "sensitivity analysis", "greenhouse gas emission", and "ruminant livestock" or beef or dairy or cattle or sheep or goat or livestock or ruminants. A search in Google Scholar generated 11,300 results. After a thorough review, only 316 of these results were deemed relevant and selected for further analysis. Pages 17 and 18 were inaccessible on Google Scholar during the article retrieval process. A search via ScienceDirect yielded 392 results, and only 298 were selected for analysis. A search on Scopus yielded 289 initial results. After a thorough evaluation, 112 relevant results were selected for further analysis.

Inclusion and Exclusion Criteria

Only studies that met the following criteria were included:

i. Greenhouse gas emissions from livestock or ruminants;
ii. Uncertainty analysis and sensitivity analysis;

iii. Articles published between 2019 and 2023 in English.

This study concentrated on the past five years to deliver the most current and relevant information, thus emphasizing recent developments in greenhouse gas emission estimation. The rationale for this was the aim to provide readers with the latest insights, considering the significant developments and changes observed in this field over the specified timeframe.

A set of exclusion criteria was formulated to narrow down the focus and maintain relevance. Studies not directly related to greenhouse gas emissions from livestock or ruminants, aligning with our selection of the specific scope of this research, were deliberately excluded in the review. Additionally, the exclusion of papers not written in English aimed to ensure linguistic consistency and facilitate a comprehensive understanding of the content. Furthermore, the exclusion of papers older than five years prioritized recent information, thus capturing the latest developments in the field. These exclusion criteria were thoughtfully designed to enhance the precision and topical relevance of the study, hence enabling a focused exploration of the recent and pertinent literature on greenhouse gas emissions from livestock farming.

All 726 search results were exported to RAYYAN for screening, and 75 duplicates were detected. After the removal of duplicates, title and abstract screening was performed, and 148 articles qualified for full-text screening. As a result of this extensive search effort, a total of 20 published articles were identified and included for further analysis in this review.

3. Results

Figure 1 illustrates the PRISMA flow diagram, showcasing the inclusion of 20 articles that met the predetermined criteria from a total pool of 1603 articles initially considered for this review. A summary of the articles can be found in Table 1.

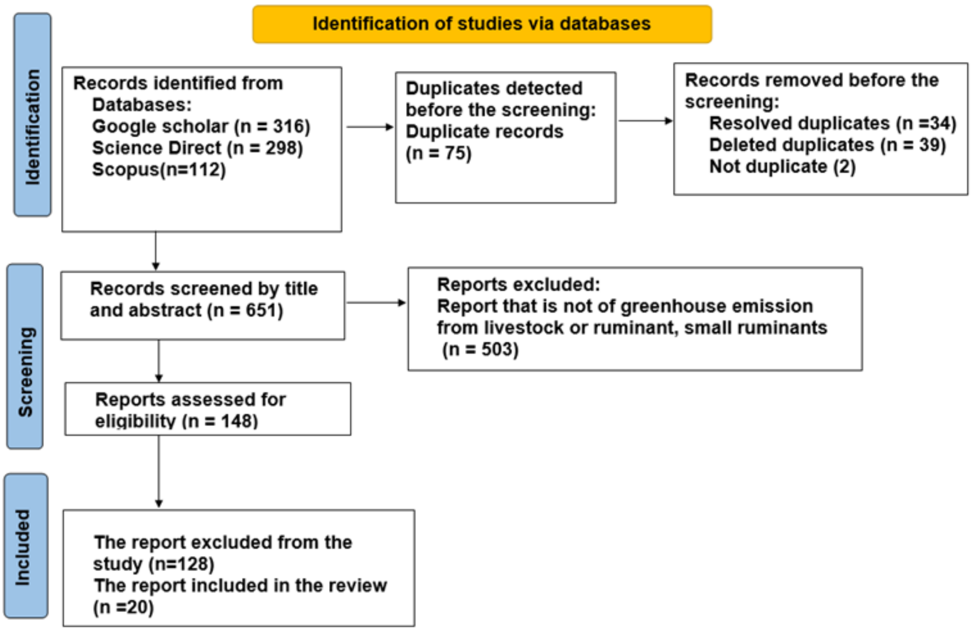

Figure 1. PRISMA flow diagram.

Table 1. Summary of reviewed articles.

Author	Objective and Results	Uncertainty and Sensitivity Analysis and Techniques Used	Source of Uncertainty
Ribeiro et al. [62]	The study aimed to construct a methane emissions database, formulate predictive models, and validate their accuracy using data from 38 studies.	Various prediction equations (54 in total) were assessed for methane production, revealing diverse approaches and potential uncertainty; cross-validation gauged accuracy and precision.	Nutrient intake, diet composition, methane emission measurement techniques, and use of different data collection methods introduce variability and uncertainty in the measurements.

Table 1. *Cont.*

Author	Objective and Results	Uncertainty and Sensitivity Analysis and Techniques Used	Source of Uncertainty
Xu et al. [63]	The study aimed to compile an up-to-date, high-resolution methane emission inventory to address uncertainty.	Existing inventories of methane emissions from China's livestock sector involve significant uncertainty.	N/A
Xu et al. [8]	The study develops a regional agricultural life cycle assessment database, revealing a mean greenhouse gas emission reduction of 179.10 kgCO2eq per USD 100 through Monte Carlo simulations, addressing previous limitations.	Monte Carlo simulations gauged Life Cycle Assessment uncertainty; sensitivity analysis confirmed input parameter changes insignificantly affected results, ensuring robustness with ≤3% variations.	Variability in input data, assumptions made in the Life Cycle Assessment model, and potential data collection and measurement errors.
Vinković et al. [64]	The study employed an Unmanned Aerial Vehicle-based system to measure dairy cow farm methane emissions, highlighting the necessity for additional research to refine estimates.	N/A	Variabilities in wind speed and the angle between the wind and the flight transect were the dominant sources of uncertainty in estimating methane emissions from dairy farms using Unmanned Aerial Vehicle-based measurements.
Kumari et al. [65]	The objective of the paper was to review methane measurement and estimation techniques, as well as mitigation approaches, for livestock farming.	N/A	Variations in animal diets, animal breeds, management practices, top-down and bottom-up approaches, sampling methods, and measurement equipment contribute to uncertainty in methane emission estimation.
Sykes et al. [9]	The study pinpoints key factors affecting model uncertainty in greenhouse gas accounting, suggesting refinement for enhanced accuracy and policy decision support.	Monte Carlo, simulation, and sensitivity analyses are methods used to assess and analyze uncertainty in greenhouse gas accounting models for livestock systems.	Variability in input data, model scope inherent in the modeling process, and allocation methods contribute to the uncertainties in greenhouse gas accounting models for livestock systems.
Bühler et al. [66]	The study compared methane emissions from dairy housings using the inverse dispersion method (IDM) and the in-house tracer ratio method (iTRM).	The study conducted an uncertainty analysis to determine the measurement duration required for the inverse dispersion method (IDM) to accurately determine methane emissions from dairy housings.	The spatial distribution of sources (animals, housing areas), variable air exchange, and inverse dispersion method (IDM) introduce uncertainties in determining gaseous emissions from stationary sources.
Thiruvenkatachari et al. [67]	The study aimed to estimate methane emissions from manure lagoons in two California dairies using dispersion models and compare results from two models, revealing significant differences in their emission rates.	Two dispersion models, numerical Eulerian (EN) and backward Lagrangian stochastic (bLS) models, were used to estimate emissions' uncertainty and sensitivity.	Differences in the formulation of dispersion models and variability in methane concentrations measured at the two dairies contribute to uncertainty in the emission estimates.
Park et al. [5]	The study successfully developed a method to analyze uncertainty in greenhouse gas emission models. It effectively addressed input variables contributing to model uncertainty, providing a valuable approach for greenhouse gas emission modeling.	Contribution to variance (CTV) analysis, data quality analysis, Monte Carlo simulation, and the global sensitivity method techniques were employed to assess and reduce uncertainty in the greenhouse gas emission model output.	Uncertainty in model output arises from technological, geographical, and time-related representativeness, as well as completeness, precision, and methodological appropriateness.
Ndao et al. [68]	The study evaluated input parameter uncertainty in estimating West African cattle methane emissions, identifying crucial factors and emphasizing research for accuracy improvement.	Uncertainty analysis methodologies were used to evaluate and quantify the uncertainty associated with estimating enteric methane emission.	The IPCC default input parameters, such as the coefficient for calculating net energy for maintenance (Cfi), digestible energy (DE), and the methane conversion rate (Ym), were found to be significant sources of uncertainty.

Table 1. *Cont.*

Author	Objective and Results	Uncertainty and Sensitivity Analysis and Techniques Used	Source of Uncertainty
Marklein et al. [7]	The research focuses on developing a dairy database to analyze methane emissions, employing sensitivity analysis for accuracy and emphasizing data resolution's crucial role in emissions management.	Sensitivity analysis was performed on each method used to estimate facility-scale manure emissions.	The uncertainty in facility-scale manure emissions is propagated using the sum of the squared partial derivatives of each variable's variance.
Harmsen et al. [69]	The study analyzed diverse models, comparing methane emission projections in deep mitigation scenarios, emphasizing uncertainties, particularly in agriculture emissions, necessitating further research for clarity.	Techniques used in uncertainty analysis were integrated assessment models, model intercomparison studies, literature review, sensitivity analysis, and scenario analysis to identify and quantify the uncertainties associated with different factors and emission assumptions.	The sources of uncertainty in methane emission projections include model-specific assumptions, the comparison of models' predictions to the literature, the effectiveness of different mitigation measures, and the increasing share of agriculture methane emissions.
Arceo-Castillo et al. [59]	The study investigates methane production in ruminants, assesses emission uncertainty, and develops mitigation strategies for accurately estimating dairy cattle production.	Statistical modeling, sensitivity analysis, and Monte Carlo simulations to assess and improve the accuracy of estimating methane emissions and to better understand the sources of uncertainty in dairy cattle production systems.	Factors such as diet composition, animal genetics, management practices, and the complexity of accurately quantifying and mitigating methane emissions were identified as sources of uncertainty.
Hempel et al. [70]	The study compared methane emission data between slatted and solid floor systems. It found that extreme emission values were more prevalent in the slatted floor system, suggesting slurry storage was a significant source of methane emissions.	N/A	The study also identified uncertainties related to sampling strategies and deviation between the two farm locations as the source of uncertainty.
Kumari et al. [71]	The study aimed to assess methane emissions from Indian livestock and their role in climate change using climate metrics.	GIS software for spatial mapping and continuous analysis of absolute global surface temperature change potential (AGTP) was used to assess uncertainty in methane emissions and their impact on surface temperature.	Livestock population database, emission factors, the choice of estimation methodology (tier 1, tier 2, or tier 3), and sampling methodology can introduce uncertainty in estimating methane emissions.
Jacob et al. [72]	This paper reviews the ability of current and scheduled satellite observations of atmospheric methane emissions from global-to-point sources.	N/A	Retrieval methods, instrument precision, inverse methods, detection thresholds, variable bias, and factors related to wind direction and surface reflectivity can introduce uncertainties in quantifying emissions.
Vechi et al. [73]	The study aimed to measure whole-farm methane emissions from cattle farms, finding discrepancies with IPCC guidelines and urging model improvements, particularly in enteric and manure emissions.	N/A	Temporal resolution, variation in dispersion pattern, atmospheric conditions, time of measurement of feeding and general cattle activity, type of fodder, amount of manure accumulated, and measurement uncertainty contribute to the delay in methane emission measurements.
Solazzo et al. [10]	The study aimed to assess structural uncertainty in the Emissions Database for Global Atmospheric Research (EDGAR) emission inventory.	Assumptions and reference cases played a significant role in uncertainty estimation.	Activity data (AD), emission factors (EFs), methodological choices, and assumption of complete correlation between subcategories and countries were identified as a significant source of uncertainty in the EDGAR inventory.

Table 1. *Cont.*

Author	Objective and Results	Uncertainty and Sensitivity Analysis and Techniques Used	Source of Uncertainty
Hempel et al. [6]	The study explores methane emissions, revealing parabolic temperature dependence—circadian rhythm affected by feeding and airflow and emission minima found at 10–15 °C.	The sensitivity of estimated regression coefficients on the selected training data indicates potential uncertainty in the modeling approach.	Variability in emissions, modeling approaches, and the influence of feeding strategies and herd compositions were identified as sources of uncertainty.
Huang et al. [11]	The study assessed aerosol scattering effects on methane retrieval, revealing biases influenced by surface albedo aerosol properties emphasizing methodological considerations for accuracy.	The traditional matched filter (MF) and optimal estimation (OE) methods were used in uncertainty quantification.	The sources of uncertainty in methane retrievals from airborne remote sensing measurements include aerosol scattering, surface albedo, aerosol optical depth, and the choice of retrieval method.

3.1. Sources of Uncertainty

3.1.1. Animal Parameters

Differences in diet composition and nutrient intake, as indicated by Ribeiro et al. [62], introduce uncertainties in predicting methane emissions. Furthermore, factors such as animal breeds, diets, and management practices contribute significantly to this uncertainty, as emphasized by Kumari et al. [71]. According to Arceo-Castillo et al. [59], the complexities associated with animal genetics, diet composition, and management practices, all contribute to variations in estimating methane emissions in different dairy cattle farming scenarios.

In the realm of modeling greenhouse emissions in livestock systems, Sykes et al. [9] identified sources of uncertainty, such as inconsistencies in input data, methane emissions from enteric fermentation, and feed production. Measurement uncertainties related to cattle activity, feed type, manure levels, and other factors have also been highlighted by Vechi et al. [73], emphasizing the need for precision in data collection methods. Additionally, Bühler et al. [66] encountered challenges in quantifying methane emissions due to spatial distribution and fluctuating air exchange in dairy housing facilities.

Variations in cattle breeds, feeding practices, and environmental conditions were identified as potential contributors to uncertainty in estimating enteric methane emissions [65]. This aligns with the findings of Hempel et al. [6], who established that feed intake is the most influential factor with uncertainty in predicting carbon dioxide emissions.

3.1.2. Data Sourcing Techniques or Data Collection Tools

The various data-sourcing techniques and data collection tools employed in studying GHG emissions reveal several challenges and uncertainties, ultimately influencing our understanding of the impact of climate change. Firstly, Ribeiro et al. [62] point out that methane emission measurements using techniques like SF6, Green Feed, and open-circuit respiratory chambers can introduce uncertainties. These uncertainties may arise from the inherent limitations and potential biases associated with each measurement method [62]. Similarly, Vinković et al. [64] draw attention to the uncertainties introduced in estimating methane emissions from dairy farms using unmanned aerial vehicles (UAVs) measurements. Variability in wind speed and angles between flight transects and wind are identified as sources of uncertainty, highlighting the importance of accounting for environmental factors in data collection. Xu et al. [8] emphasize the impact of variability in input parameters, errors in data collection tools, and model simulations on uncertainties in greenhouse gas emissions. This underlines the importance of rigorous data validation and accurate parameterization in emission models.

Bühler et al. [66] highlight the uncertainties introduced by the inverse dispersion method (IDM) when estimating greenhouse gas emissions from stationary sources. The choice of measurement methods can significantly affect the accuracy of emission estimations. Huang et al. [11] emphasize the uncertainties associated with using airborne remote sensing measurements for methane retrieval. Factors such as aerosol scattering, surface albedo, retrieval method choice, and aerosol types can introduce biases, impacting the reliability of methane data obtained through remote sensing [11]. According to Arceo-Castillo et al. [59], uncertainties in methane emission measurements arise from analyzing ducting efficiency, particularly in assessing flow within the duct connecting chambers to methane analyzers. This emphasizes the need for precision in the measurement setup. Jacob et al. [72] identify various sources of uncertainty in methane emission estimation from satellite observations, including retrieval methods, instrument precision, detection thresholds, and the influence of atmospheric conditions. These uncertainties collectively affect the reliability of methane emission estimates derived from satellite data.

The findings of Vechi et al. [73] indicate that measurement campaigns throughout the year may have limited temporal resolution, potentially introducing uncertainty in capturing short-term emission variations. Dispersion models' assumptions and variations in measuring methane concentrations can also contribute to uncertainties, as highlighted by Thiruvenkatachari et al. [67]. Moreover, Hempel et al. [70] point out uncertainties in artificial and natural tracer measurement approaches, which influence the observed differences in methane emissions between farm locations. Sampling strategies for determining indoor methane concentrations also contribute to uncertainties in emission estimates.

3.1.3. Quantification and Estimation Approaches and Techniques Used in Greenhouse Gas Emissions

Utilizing both top-down and bottom-up methods, as highlighted by Kumari et al. [71] and Vechi et al. [73], introduces complexities and uncertainties in assessing methane emissions. Additionally, the impact of assumptions in LCA and default parameters in IPCC Tier 2 methodology, emphasized by Xu et al. [63] and Ndao et al. [68], further contributes to the overall uncertainty in emission factor accuracy. Hempel et al. [70] draw attention to the limitations of livestock population databases and the potential overestimation of emissions using default factors, underscoring the need for improved data coverage and parameter refinement.

3.1.4. Environmental Factors

Vinković et al. [64] and Vechi et al. [73] emphasize the significance of environmental variables such as wind speed, flight transect angles, and turbulence intensity as sources of uncertainty. The variability in these atmospheric conditions introduces challenges in obtaining precise measurements and necessitates a nuanced understanding of how environmental factors influence emission estimates [64,73]. Bühler et al. [66] shed light on spatial challenges, indicating that the spatial distribution of emission sources (e.g., animals and housing areas), and the fluctuating air exchange in dairy housing facilities also contribute to uncertainties. This spatial dimension adds another layer of complexity to emission quantification, requiring methodologies that account for the dynamic nature of emissions within the farm environment [66]. Park et al. [3] identify sources of uncertainty in model outputs, including geographical, time-related, and technological representativeness, completeness, precision uncertainty, and methodological appropriateness and consistency, which underscore the importance of robust modeling practices for enhancing the accuracy of emission estimates.

3.1.5. Greenhouse Gas Inventories

Xu et al. [63] and Solazzo et al. [10] both highlight that uncertainties in activity data and emission factors significantly contribute to the overall uncertainty in greenhouse gas inventories. Activity data refers to the information on human activities that result in emissions, while emission factors represent the average emission rates per unit of activity [10,63]. The uncertainty in these components can arise from various sources, including discrepancies in spatial and temporal variability of emissions and the distribution of manure in different manure management systems [10]. These uncertainties have broader implications for understanding the increase or decrease in GHG emissions and their impact on climate change [10].

3.1.6. Other Sources

Harmsen et al. [69] identify several contributing factors to the variability and uncertainty in forecasting future methane emissions from livestock. Model-specific assumptions play a significant role, as different models may adopt varying assumptions, leading to divergent predictions [69]. The comparison of model projections to the existing literature introduces uncertainty, which emphasizes the need for consistency and accuracy in data and assumptions [69]. The efficacy of diverse mitigation measures further contributes to variability, since the effectiveness of these measures can vary based on factors like implementation and adoption rates [69]. The growing proportion of agricultural methane emissions adds another layer of complexity, reflecting the dynamic nature of emissions from this sector [69]. Sykes et al. [9] highlight inconsistencies in input data, allocation methods, and inherent uncertainties in the modeling process (epistemic uncertainty) as sources of uncertainty in estimating greenhouse gas emissions from livestock systems. The skewness in key modeling coefficients, particularly those related to nitrous oxide and methane emissions, significantly contributes to uncertainty [9]. Specific coefficients associated with methane emissions from enteric fermentation and feed production introduce variability and emphasize the importance of accurate parameterization in emission models [9].

3.2. Techniques Used in Uncertainty and Sensitivity Analysis

Xu et al. [8] utilized Monte Carlo simulations in LCA, revealing relatively low uncertainty with a low coefficient of variation. Their sensitivity analysis emphasized the robustness of the results, showcasing minimal effects from changes in input parameters. Sykes et al. [9] employed Monte Carlo simulation and sensitivity analysis in livestock systems and identified a notable 8.3% discrepancy attributable to skewness in key modeling coefficients. Park et al. [5] utilized analytical and stochastic approaches, including Monte Carlo simulation and variance-based methods to assess GHG emissions uncertainty. Thiruvenkatachari et al. [67] employed numerical models, obtained confidence intervals, and highlighted the impact of variability in methane concentrations, dispersion models, and measurement uncertainties. Bühler et al. [66] conducted relative uncertainty analysis for the inverse dispersion method, revealing uncertainties in measurements.

Ndao et al. [68] applied uncertainty analysis to enteric methane emission factors, determining the importance of each input parameter. Marklein et al. [7] employed a novel approach for facility-scale manure emissions, extending sensitivity analysis to the state level. Harmsen et al. [69] used integrated assessment models, inter-comparison studies, literature reviews, sensitivity analysis, and scenario analysis to identify and quantify uncertainties in methane emission projections. Huang et al. [11] discovered method-dependent biases in methane retrieval and emphasized the influence of aerosol optical depth and aerosol types. Kumari et al. [71] utilized geographical information systems (GIS) for spatial mapping and provided insights into uncertainty at different levels, while Solazzo et al. [10] performed sensitivity analysis and emphasized the impact of methodological choices on emission inventory uncertainty. Furthermore, Xu et al. [8] employed linear mixed models to assess emission variations from individual cows, feeding periods, and times of the day.

4. Discussion

The challenges associated with estimating GHG emissions from ruminant livestock reveal a complex interplay of interconnected factors, including diet, genetics, management practices, environmental conditions, modeling uncertainties, and measurement challenges [29,74–76]. This intricate web of elements contributes to the difficulties in accurately estimating emissions [29,74,75]. The identified uncertainties in animal parameters highlight the urgency of addressing the challenges to refine emission models and devise effective mitigation strategies [48,68,75]. The present study underscores the significance of improving precision in data collection, advancing modeling techniques, and cultivating a holistic understanding of the diverse factors influencing emissions [74].

In data sourcing and collection techniques, complexities and uncertainties significantly impact the accuracy of GHG emission estimations [30,48]. Therefore, addressing these uncertainties is crucial for refining emission models and gaining an enhanced understanding of their implications for climate change [74]. Similarly, continuous efforts are needed to improve data collection methods, refine emission models, and implement accurate parameters to comprehensively grasp the contribution of ruminants to greenhouse gas emissions [74]. The intricacies in estimating emissions from ruminants further underscore the challenges arising from multiple interconnected sources of uncertainty. Hence, advocating a holistic approach that considers environmental, spatial, and modeling dimensions becomes imperative [77]. The present study emphasizes the interdisciplinary efforts required to refine measurement techniques, improve modeling approaches, and advance the understanding of emissions from ruminants [30].

Accurate GHG inventories play an integral role in assessing sector contributions to emissions and formulating effective mitigation strategies [27,74,78]. However, uncertainties related to activity data and emission factors compromise the accuracy of these inventories, impacting climate change projections and mitigation policies [79,80]. Thus, continuous refinement in data collection methods, emission factor determinations, and overall inventory methodologies is essential for identifying, justifying, and adjudicating national-level mitigation commitments [74].

The collective impact of uncertainties on the accuracy of GHG emission predictions is highlighted, emphasizing the potential discrepancies arising from inaccuracies in model assumptions, comparisons to the existing literature, and modeling coefficients [11,66]. This discussion underscores the implications for decision-makers and policymakers in designing effective mitigation strategies [27,75,81] The identified uncertainties suggest variations and potential biases in our understanding of future emission trajectories, underscoring the importance of addressing these uncertainties for informed decision-making [82,83]. Diverse techniques, such as Monte Carlo simulations and sensitivity analysis, showcase the complexity of GHG emission estimation, emphasizing the need for a combination of methods for a comprehensive understanding [10,60].

This review significantly contributes to the field of GHG emissions estimation in livestock farming. It offers a comprehensive understanding of the multifaceted sources of uncertainty in estimating GHG emissions, covering animal parameters, data sourcing techniques, environmental factors, and quantification approaches. This study underscores the interconnected nature of these factors, advocating for a holistic approach to address uncertainties. This review has implications for developing effective mitigation strategies and influencing policy decisions, highlighting the need for continuous refinement in data collection methods and emission models. The importance of interdisciplinary collaboration is emphasized to tackle the complexity of uncertainties effectively. This work is crucial as it disseminates knowledge about greenhouse emissions challenges, contributes to the global understanding of livestock farming's impact in climate change, and offers practical solutions and innovations for sustainable agricultural practices and climate change management.

This review concludes with the proposition of an EcoPrecision framework for enhanced precision livestock farming, emission estimation, addressing uncertainties in GHG emissions from livestock, and climate change mitigation. The proposed framework draws inspiration from various existing frameworks and methodologies, such as PA frameworks, LCAs, IAMs, GIS-based approaches, Monte Carlo simulation, and sensitivity analysis. The proposed framework adds value by providing an integrated solution, emphasizing methodological choices, and guiding researchers and practitioners in decision-making. The framework aims to enhance the accuracy and reliability of emission estimates by focusing on capturing on-farm dynamics using real-time data for input variables rather than relying on fixed values. It promotes cross-disciplinary collaboration, establishes validation processes, and ensures the comparability and reliability of the greenhouse gas emission framework. Additionally, the framework prioritizes education and capacity building to empower stakeholders to implement best practices and contribute to improving livestock farming sustainability. Innovative strategies and advanced methodologies, such as Monte Carlo simulation and sensitivity analysis, are embraced within the proposed framework to address uncertainties effectively.

In the data collection stage, the framework will utilize remote sensing technology to gather real data from farms. These data will include animal-related metrics and geospatial information. All of the collected data will be integrated into a digital platform, where a machine learning model will analyze the vast amount of data and uncover hidden patterns in emission data. This will allow for the creation of more accurate and robust estimation models, enabling continuous monitoring and updating of emission estimations to improve precision. The framework will also employ Monte Carlo simulation to model uncertainties and perform sensitivity analysis to identify critical parameters that affect emission estimation. After conducting the uncertainty and sensitivity analysis, the model will evaluate and simulate the environmental impact, projecting the long-term effects on climate change mitigation strategies and different management practices within the entire livestock production system or processes. The framework will generate reports, visualizations, and recommendations for farms and decision-makers, providing insights for precision livestock farming, emission estimation, and climate change mitigation.

5. Conclusions

In addressing the complexities of estimating GHG emissions from livestock, this study underscores the critical need for a comprehensive approach that considers interconnected factors. It emphasizes refining emission models, improving data collection precision, and fostering holistic understanding as key strategies. By tackling uncertainties in data sourcing, collection techniques, and emissions estimation techniques, this research contributes to a greener environment. The proposed EcoPrecision framework integrates various methodologies and offers practical solutions that can guide decision-makers and practitioners in adopting sustainable agricultural practices for effective climate change mitigation. This study highlights the challenges in GHG inventories and the importance of continuous refinement in data collection methods. By addressing uncertainties related to activity data and emission factors, this research aimed to improve the accuracy of inventories and, consequently, inform more effective climate change policies. The emphasis on interdisciplinary collaboration and the proposed EcoPrecision framework signifies a commitment to advancing sustainable practices that can contribute to a greener and more environmentally conscious future.

The future will encompass the practical application of the proposed framework, specifically within ruminant livestock farms that employ a diverse range of management practices. Our objective is to adapt the framework to accommodate the varied management approaches utilized in ruminant farming, utilizing real-time data for input variables. This implementation phase seeks to validate the applicability and effectiveness of the proposed framework across a spectrum of management practices within ruminant livestock farms, contributing to the ongoing effort to improve sustainability practices in the broader livestock industry.

One potential limitation in the future could be the variability and complexity of management practices used on different ruminant livestock farms. Although the proposed framework is adaptable to various approaches, it may face challenges when dealing with highly unique or unconventional strategies. Some farming systems may have specialized practices that could make it difficult to seamlessly integrate the framework. Additionally, regional differences, farm size, and resource availability could also impact the effectiveness of implementation, potentially limiting the framework's universal applicability. To ensure practicality and success across a range of management practices on ruminant livestock farms, it will be important to address these variations and customize the framework accordingly.

Continuous refinement and customization may be necessary to overcome these potential limitations and improve the framework's adaptability to different farming scenarios.

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