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Big Data Management Within Multi-Objective Optimization Modeling for Sustainable Food Production

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This is to certify that the doctoral dissertation by

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Walden University
2025

Abstract

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Dissertation Submitted in Partial Fulfillment

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Doctor of Philosophy

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Abstract

Producing enough food to feed a growing human population without further degrading the environment through unsustainable natural resource use is a global issue. The purpose of this quantitative nonexperimental study was to examine the extent to which big data management of environmental impact sources, assessment methods, and allocation methods in multi-objective optimization (MOO) modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level. Representation theory, the theory of effective use of information systems, the dynamic capabilities view, and the natural resource-based view were used to describe the necessity of accurately representing and managing the real-world environmental impact of big data within information systems to increase sustainable food animal production. This study's secondary data sources included the U.S. Department of Agriculture. Nonparametric statistical tests were used to analyze broiler chicken, beef cattle, and swine feed formulations ($N = 111$) developed via MOO modeling. The results indicated that environmental impact source, assessment method, and allocation method significantly affected the consistency and predictability of sustainable feed formulation at the farm level. Not all predictor variables significantly affected all criterion variables, such as the assessment method: (a) number of ingredients ($p = .005$), (b) crude protein content ($p < .001$), (c) LO ($p < .001$), and (d) TAP ($p = .015$). The implications for positive social change include the potential for U.S. food animal producers to apply sustainable food animal feed formulations from environmental impact sources, assessment, and allocation method compatibilities to produce enough food for a growing human population.

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Dedication

This dissertation is dedicated to my husband, Greg Modica, and my daughter, Gemma Modica. Greg supported me during my entire postsecondary educational career spanning 10 years, and I would not have succeeded without all his efforts as a husband and a father to keep our family moving forward throughout this time. Gemma cheered me on alongside Greg and inspired me to see this journey to completion as she watched me balance work, school, and motherhood.

Additionally, I dedicate this dissertation to my first graduate advisor and committee chair, Dr. Mark Edwards. Dr. Edwards became an integral mentor after offering me my first research opportunity as an undergraduate, which grew into a passion for continual learning of, and developing solutions for, the animal nutrition industry. One of Dr. Edwards's most memorable lessons, inspired by his graduate advisor and mentor, Dr. Duane Ullrey, is that you cannot manage what you do not measure. This was a driver for my dissertation study, and I hope it resonates with future researchers.

Acknowledgments

First and foremost, I thank God and acknowledge His presence with me over the course of this dissertation. He gave me and my family an appreciation for the highs and the strength to persevere through the lows of this journey.

I sincerely thank my dissertation committee chair and methodology expert, Dr. Paul Frankenhauser, who consistently reached out to offer guidance, but more importantly to provide encouragement. His continual acknowledgement of my progress energized me to continue this journey. I also thank my second committee member and content expert, Dr. Christina Anastasia, who was instrumental in reviewing my dissertation during its development and at its completion. Her praise at my defense gave me confidence in my position as a researcher and expert in my field of study that carried me through to the end.

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Chapter 1: Introduction to the Study

Achieving increased food animal production with lowered environmental impacts requires developing better decision-making tools via big data management in information systems. Advances in information systems have generated copious amounts of agricultural data that can improve decision making (Zhai et al., 2020); however, translating these data into practical knowledge remains a challenge (Zhai et al., 2020). Leveraging existing environmental impact big data and developing an information systems approach that enables food production systems to predict optimal scenarios in which food production increases and environmental impacts decrease may lead to better informed agricultural decision making. Furthermore, the results of the current study may lead to positive social change by contributing to three of the United Nations sustainable development goals including zero hunger, responsible consumption and production, and climate action by improving sustainable agriculture, identifying climate change impacts in food production, and mitigating future effects on the ecosystem through employing big data management techniques. This first chapter includes the background of the study, problem statement, purpose of the study, research question and hypotheses, theoretical foundation and framework, nature of the study, definitions, assumptions, scope and delimitations, limitations, significance of the study, and a summary.

Background of the Study

The purpose of this study was to examine the extent to which big data management of environmental impact sources, assessment methods, and allocation methods within multi-objective optimization (MOO) modeling affected the consistency and predictability of sustainable food animal feed management practices at the farm level. Big data analytics have been implemented across the agricultural industry to promote concepts such as precision agriculture and smart farming, both aimed at more efficient food production (Astill et al., 2020; Baierle et al., 2022; Jayashankar et al., 2020; K. Sharma et al., 2022; Lioutas & Charatsari, 2020). Efficient food production, defined as practices that use the least amounts of natural resources to maintain food integrity, is an immediate problem. In the United States in 2022, 12.8% of the population (17 million people) dealt with food insecurity, which was defined as “uncertain of having or unable to acquire enough food to meet the needs of all their members” (U.S. Department of Agriculture [USDA], 2023c). Although there are known political aspects related to food insecurity, they were not the focus of the current study and were not discussed. Efficient food production is critical to feed the global human population, the associated global pet population, and the food animals used to feed humans and their pets.

Efficient food production will need to be one of many solutions to achieve food security. The criticality of employing big data and other digital tools within the agricultural industry for developing solutions to food security has been demonstrated. Using regression analysis, Popkova (2023) found a significant relationship between artificial intelligence, big data, and robotics, and sustainable development of food and consumer goods mass production. With the projected human population growth of two billion people over the next 25 years, efficiency of food production has been further focused on increasing the amount of food produced while reducing associated environmental impacts, particularly climate change factors (Astill et al., 2020; Chojnacka et al., 2021; Mekonnen & Gerbens-Leenes, 2020; United Nations, n.d.-a). There is a clear intent to apply digital technologies to efficient food production practices. With the added necessity of not only minimizing natural resource use but also reducing environmental impacts, efficient food production must shift to sustainable food production.

In contrast to efficient food production, sustainable food production also accounts for upstream and downstream effects of natural resource use. Sustainability efforts have been focused on shifting human dietary recommendations to more sustainable choices (e.g., less red meat consumption; Cardador et al., 2022). Researchers have yet to adequately address the diets of food animals (livestock), which are a large source of greenhouse gas emissions and other environmental impacts along the human food production chain (Cardador et al., 2022). Furthermore, the greatest environmental impacts of any food animal production system are associated with animal feed inputs because feed ingredients add the burden of compounded impacts coming from their own production (Benavides et al., 2020; Méda et al., 2021). This explains why the development of sustainable feed management has been identified as a critical priority in the agriculture industry (Benavides et al., 2020). Identifying sustainable food production solutions requiring further development is the first step, but this must be followed by research aimed at qualifying those solutions. A strategy aimed at mitigating the environmental impacts of food animal diets may have a greater impact on reducing environmental impacts along the human food chain than changing human dietary habits alone.

There have been published research efforts to develop such strategies. Garcia-Launay et al. (2018) developed a MOO model based on linear programming and constraints. Garcia-Launay et al. designed their MOO model to optimize food animal feeding practices for nutritional requirements, low cost, and low environmental impacts with a focus on climate change (CC; kg CO_2-e/kg feed ingredient), nonrenewable energy demand (NED; MJ/kg feed ingredient), land occupation (LO; m^2year/kg feed ingredient), terrestrial acidification potential (TAP; mol H^+-e/kg feed ingredient), phosphorus demand (PD; kg P/kg feed ingredient), and freshwater eutrophication potential (FEP; kg PO_4^{3-}-e/kg feed ingredient) impact categories. From the results, Garcia-Launay et al. demonstrated the ability of the MOO model to report feed formulations across traditional French broiler chicken, bull calf, and pig operations that fit nutritional requirements with up to 48% reduced environmental impacts and low to moderate cost increases of 1%–7%. MOO modeling shows promise as a management tool to balance cost and environmental impacts of food animal feeding practices. With this new technique, there was a need for additional studies to build on the foundational research.

Further examinations using the MOO modeling technique with food animal feeding practices have demonstrated varying results. Méda et al. (2021) were the first to employ Garcia-Launay et al.'s (2018) MOO model process of optimizing nutritional requirements, low cost, and low environmental impacts (with consideration of the same six impact categories) of food animal feed formulation with the additional variable of phase feeding type for French pig production (classic 2-phase, 2-phase with lower net energy content, and multiphase), and French broiler chicken production (classic 3-phase and 3-phase with higher digestible amino acid contents and lower metabolizable energy content). Méda et al.’s results showed that the environmental impact values of feed formulation type were affected by phase feeding type. In turn, the feed formulations affected cost and gross margin of food animal production, demonstrating the downstream effects of optimized environmental impacts. This effect of an additional variable suggests the importance of further examining data management for MOO model scenarios aimed at lowering environmental impacts. Data management techniques for MOO modeling of environmental impacts may also benefit environmental impact information systems more broadly.

Considerations of data management for MOO modeling of environmental impacts have been supported by subsequent studies. de Quelen et al. (2021) employed the same MOO model process and impact categories as Garcia-Launay et al. (2018) with the added variables of French pig production performance (body weight and carcass characteristics) and locally versus nonlocally sourced ingredients. de Quelen et al. were the first to feed the diet formulations developed through the MOO model process to food animals to examine the efficacy of low environmental impact diets on actual food animal production. de Quelen et al.’s MOO model formulations lowered four of the six environmental impacts of interest, and the low environmental impact diets resulted in comparable food animal performance to traditional low-cost diets. Testing the effects of environmentally optimized feed formulations (diets) is a necessary step to ensure these diets can support current food production rates. The potential to maintain food animal performance with diets that have lower environmental impacts than traditional diets is promising.

Similar results were achieved with MOO modeling for low-cost, low environmental impact rainbow trout feed management. Wilfart et al. (2023) followed de Quelen et al.'s (2021) process and developed MOO model feed formulations for French rainbow trout production, then performed a feeding study to test the effects of low environmental impact diets on fish growth and resulting potential food production. Wilfart et al. considered two additional impact categories of water use (m^3) and net primary production use (carbon, kg) along with the six previously researched impact categories of Garcia-Launay et al. The MOO model results demonstrated a lower cost and lower environmental impact diet compared to baseline with similar fish performance over the 12-week feeding study; however, growth curves indicated potentially lower growth over longer feeding periods when fed with the low environmental impact diet, which could have critical impacts on food animal production. Although research supported the use of MOO modeling for low environmental impact food animal production, diet changes must be carefully reviewed and considered from a practical feed management perspective. There are additional variables of food animal feed management that require research attention.

The literature gap addressed in the current study was Ahmad et al.'s (2021) recommendation to quantitatively examine sustainability optimization modeling with more robust environmental impact big data because these data may significantly change sustainability optimization results and affect downstream decision making. The purpose of the current study was not only to address this gap in the literature but also to work toward improving sustainable food production. Shrivastava et al. (2020) identified the need to integrate social sciences with environmental sustainability research, which has traditionally been dominated by the natural sciences. Approaching environmental science from a transdisciplinary viewpoint may increase the amount of data available to be used for modeling and decision making. Based on the literature gap and the research on MOO modeling for low environmental impacts of French food animal production, the current study aimed to extend the focus of research to the United States and expand environmental impact values from a single data source to two sources that allowed for examination of the effects of big data source, assessment method, and allocation method.

Problem Statement

The issue that prompted me to search the literature was the need to understand how to integrate and manage data inputs for sustainability optimization and simulation modeling at the firm level (see Bayu et al., 2022). Although researchers had investigated this issue, the extent to which environmental impact big data sources and calculation methods affect the consistency of food animal feed formulation prediction at the farm level had not been examined. Ahmad et al. (2021) recommended that future studies quantitatively examine sustainability optimization modeling and include more robust environmental impact data (i.e., CC) because these data may significantly change sustainability optimization results and affect decision making; however, reliability of comparability among published environmental impact data was unknown. The research problem I addressed in this study was the need to examine the extent to which big data management of environmental impact sources, assessment methods, and allocation methods within MOO modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

Purpose of the Study

The purpose of this quantitative nonexperimental study was to examine the extent to which big data management of environmental impact sources, assessment methods, and allocation methods in MOO modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level. The predictor (independent) variables related to big data management were environmental impact database source (Global Feed LCA Institute [GFLI] 2.0 and ECOALIM V1 by Agribalyse, hereafter referred to as Agribalyse), assessment method (Environmental Footprint 3.0 [EF] and ReCiPe), and allocation method (economic, energy, and mass). The criterion (dependent) variables related to sustainability performance from the MOO model output were number of ingredients, cost, crude protein content, and environmental impacts (CC, LO, FEP, and TAP) of food animal (broiler chicken, beef cattle, and swine) feed formulation. The predictor variables were generally defined as the ways in which environmental impact values are derived and stored for individual feed ingredients. Sustainability performance of food animal feed formulation was generally defined as the simultaneous achievement of meeting traditional significant factors in food animal production (ingredient composition, nutrient composition, and cost) and reducing environmental impacts of the production. The traditional factors are well known for their effects on farm level decision making, while environmental impact values have been garnering attention from researchers over the past few years regarding their role as an upcoming significant factor (de Quelen et al., 2021; Méda et al., 2021; Wilfart et al., 2023). However, the extent of consistency and predictability of sustainable feed formulation across environmental impact database source, assessment method, and allocation method had not been examined.

Research Question and Hypotheses

The research question and hypotheses guiding this quantitative study were as follows:

RQ: To what extent do environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level?

H_0: Environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling do not affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

H_a: Environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

MOO modeling and statistical analysis were used to answer this research question. The MOO method requires inputs in the form of at least one constraint and at least two objectives. The constraint was minimum nutrient requirements of broiler chicken, beef cattle, and swine during starter, grower, and finisher feeding phases (see Table 1). The first model objective was to achieve low-cost formulations, and the second model objective was to achieve low environmental impact formulations, including CC, LO, FEP, and TAP. An additional required input to develop the formulation against constraints and objectives was nutrient composition of the feed ingredients chosen for potential inclusion in the model. Sustainability performance was defined as ingredient composition (number of ingredients), crude protein content, cost, and environmental impact values of the resulting MOO model formulations for each species at each feeding phase using environmental impact values from different sources, assessment methods, and allocation methods.

Table 1

Feeding Phases of Broiler Chickens (Defined by Age in Days), Beef Cattle (Defined by Time Spent in Feeding Phase in Months), and Swine (Defined by Weight in kg)

Species	Feeding phase		
	Starter	Grower	Finisher
Broiler chicken	1–21 days	22–42 days	43–56 days
Beef cattle	None	2–3 months	3–10 months
Swine	7–23 kg	24–100 kg	101–200 kg

Note. Broiler chicken data were adapted from "Nutrient Requirements of Poultry (9th ed.)," by National Research Council, 1994, National Academies Press. Copyright 2022 by the authors. Beef cattle data were adapted from "Sector at a Glance – Beef Cattle," by U.S. Department of Agriculture, 2023a, (USDA ERS - Sector at a Glance). Beef cattle do not have a starter phase because they spend 3 to 7 months nursing and are then moved into the grower phase. The grower phase represents the average time of three commonly used grower feeding phase methods (USDA, 2023a). Swine data were adapted from "Too Much of a Good Thing: Rethinking Feed Formulation and Feeding Practices for Zinc in Swine Diets to Achieve One Health and Environmental Sustainability," by G. C. Shurson, P. E. Urriola, and Y.-T. Hung, 2022, *Animals*, *12*, Article 3374 (https://doi.org/10.3390/ani122333374). Copyright 2022 by the authors.

All input data were secondary data collected from recently published literature and freely accessible databases (peer-reviewed research, governmental databases, and nongovernmental organizational databases). I collected nutrient requirements for each food animal species at each feeding phase from the National Research Council's (NRC; 1994, 2000, 2012) published collection of nutrient requirements. I determined feeding phases from the NRC (1994, 2000, 2012) and other published data (Moritz et al., 2022; Shurson et al., 2022; USDA, 2023a). I collected feed ingredient costs from the USDA (n.d.-a). I also used this data source to collect feed ingredient nutritional composition and supplemented with data from the National Animal Nutrition Program (NANP; 2023).

Lastly, I collected environmental impact values for feed ingredients from two freely accessible databases: the 2022 GFLI (2023a) and Agribalyse (n.d.). The GFLI database provided environmental impact data derived from two assessment methods (EF and ReCiPe) and three allocation methods (economic, energy, and mass; GFLI, 2023a). The Agribalyse database provided environmental impact data derived from one assessment method (EF) and allocated in a single way (economic; Agribalyse, n.d.).

Theoretical Foundation

The theories and concepts that grounded this study included the dynamic capabilities view (DCV; Teece et al., 1997), representation theory (Wand & Weber, 1988), the theory of effective use of information systems (TEU; Burton-Jones & Grange, 2013), and the natural resource-based view (NRBV; Hart, 1994). DCV asserts that organizations can leverage their "managerial and organizational processes" (Teece et al., 1997, p. 5), known as dynamic capabilities, to adapt to changing conditions through resource modification (Bayu et al., 2022). The key constructs of this theory are innovative responses to assets and strategic management of changing environments (Teece et al., 1997). This theory was used in the current study to identify and describe strategic management of agricultural sustainability information systems as a dynamic capability. Farm managers require skills and tools designed for adaptation to changes in food production aimed at decreasing environmental impacts.

Strategic management of sustainability information systems requires that the systems be designed accurately. The origin of representation theory is attributed to Frobenius's work in 1896 but was first applied to the discipline of information systems in the late 1980s (Recker et al., 2019; Wand & Weber, 1988). Wand and Weber asserted that the design of an information system should accurately represent real-world phenomena. The key constructs of this theory, as defined by Wand and Weber, are interaction, mapping, tracking, reporting, and sequencing. This theory was used in the current study to describe the necessity of accurately representing current food production processes and sustainable alternatives. Lack of accurate representation is a critical impediment to the development of information systems for sustainable food production.

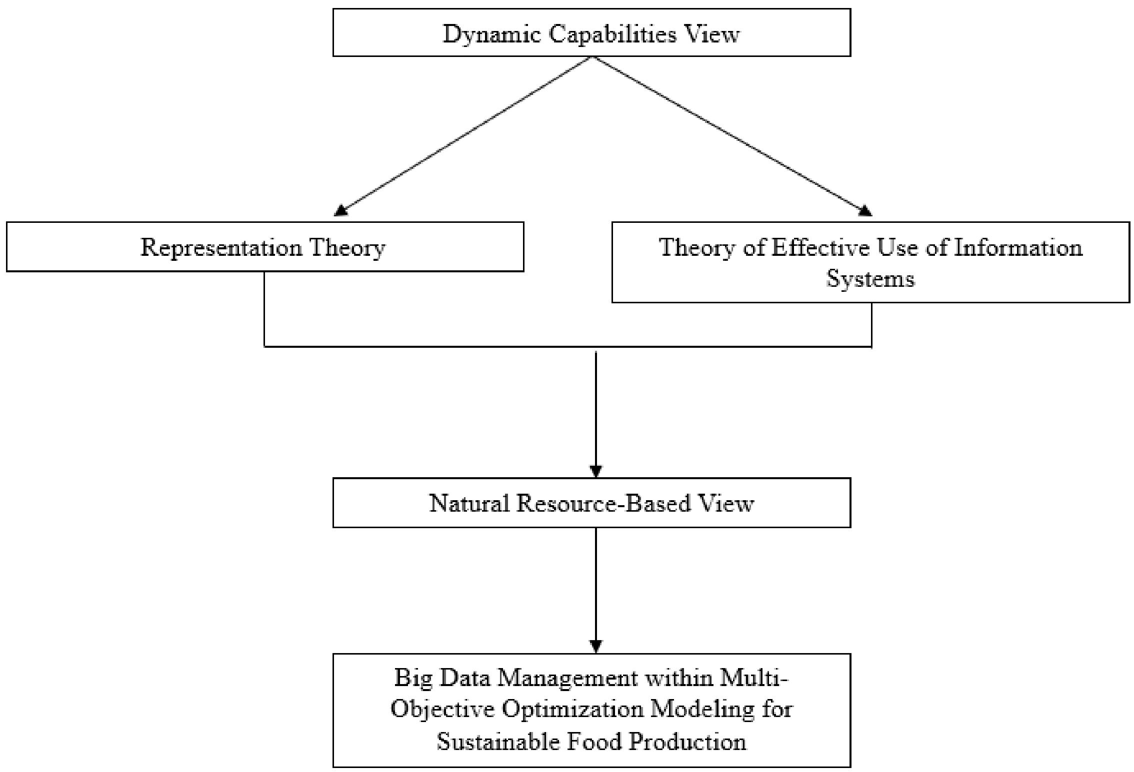
Accurate representation by an information system must be coupled with ease of access and implementation by the user. The TEU is a contemporary extension of representation theory developed by Burton-Jones and Grange (2013). Burton-Jones and Grange posited that information systems are only beneficial when used effectively. This theory was developed from an understanding of effective use of information systems as a use that increases the likelihood of attaining goals (Burton-Jones & Grange, 2013; Surbakti et al., 2020). The key constructs of this theory are transparent interaction, representational fidelity, and informed action. Burton-Jones and Grange asserted that a user must be able to identify accurate representations that allow for informed decisions (i.e., effective use). An information system should include accurate data that facilitates strategic management of current processes and change implementation. Farm managers must be able to easily model such management and implementation for sustainable food production.

Lastly, the intended output or purpose of an information system must be plausible within the system design. Hart (1994) considered the NRBV to be an organization's ability to consider problems related to natural resources and the environment as a competitive advantage. This theory is an extension of the resource-based view by Wernerfelt (1984) who posited that unique organizational resources allow for competitive advantage. The NRBV theory is built on three key constructs of pollution prevention, product stewardship, and sustainable development, which have an associated environmental driving force (key resource and capability) and strategic logic (Hart, 1994). Within an information system designed to facilitate sustainable food production, an alternative solution to current practices must be feasible. Environmental considerations as competitive advantage are natural next steps for the food production industry because farm managers will need to balance increased food production without increasing natural resource depletion.

These theories and concepts were integrated in the current study to examine the extent to which big data management of environmental impacts within MOO modeling can affect consistency and predictability of sustainable food animal feed management practices at the farm level (see Figure 1). Strategic management of agricultural sustainability platforms requires that the use of environmental big data (a) accurately represents current food production, (b) includes easy access and implementation, and (c) features sustainable development as a plausible outcome. Maintaining each of these improvements for sustainable food production information system development requires more detailed attention than was achievable in the current study; however, the results may provide direction for future studies focused on continued development of one or more of these theories. Chapter 2 provides a more detailed discussion of each theory.

Figure 1

Theoretical Framework Integrating Dynamic Capabilities View, Representation Theory, Theory of Effective Use of Information Systems, and Natural Resource-Based View



Nature of the Study

The nature of this study was a quantitative nonexperimental design using MOO modeling. In MOO modeling, multiple objective functions are simultaneously optimized to fit a constraint, resulting in a single optimal solution from many potential scenarios (Wang et al., 2011). This type of modeling originated in the early 1990s and extended traditional linear programming originally developed for poultry feed formulation in the 1950s (Hutton et al., 1958; Wang et al., 2011). This method was further developed and validated for use with optimizing cost and environmental impacts of food animal feed formulation with nutritional requirements as the constraint (de Quelen et al., 2021; Garcia-Launay et al., 2018; Méda et al., 2021; Wilfart et al., 2023). Quantitative methodology was appropriate for the current study because I examined the extent to which big data management may affect sustainable food animal feed formulation consistency and predictability using numerical data and statistical analysis.

The MOO model constraints of this study were nutritional requirements of broiler chickens, beef cattle, and swine. A MOO model was developed for each species at each of two or three life stages (starter, grower, and finisher) because nutrient requirements change with life stage (see Table 1). The MOO model objectives of this research were least cost and lowest environmental impacts. The least cost objective considered how the cost of each potential ingredient affected the cost of each complete formulation developed from the model. The lowest environmental impact objective considered how CC, LO, FEP, and TAP values of each ingredient affected the respective impact values of each complete formulation.

In the current study, I examined the extent to which the source and calculation methods of environmental impact values affected food animal feed formulations developed using MOO modeling. I derived the environmental impact values from two databases (GFLI 2.0 and Agribalyse), two assessment methods (EF and ReCiPe), and three allocation methods (economic, mass, and energy). I analyzed the formulations for differences among the number of ingredients, crude protein content, cost, and environmental impacts (CC, LO, FEP, and TAP). I collected secondary data, including nutrient requirements of broiler chicken, beef cattle, and swine at three life stages (starter, grower, and finisher), common ingredients employed in U.S. food animal production, ingredient nutrient composition, ingredient cost, and ingredient environmental impact values.

Definitions

The following terms defined in the context of environmental sustainability were used throughout the study:

Acidification: Reduction of pH to a more acidic state (molecular H+ *or* kg SO_2-e/functional unit; Agribalyse, n.d.; GFLI, 2023a; U.S. Environmental Protection Agency, 2023).

Allocation method: “The method of allocating emissions to a specific category” (GFLI, 2023b, p. 4). Economic allocation bases environmental impacts on the economic value of products leaving a system, energy allocation is based on caloric value of products leaving a system, and mass allocation is based on the quantitative mass of products leaving a process (GFLI, 2023a).

Assessment method: “The measurement of [environmental] emissions through a specific method” (GFLI, 2023b, p. 2).

Big data: An extremely large and complex data set from a variety of sources requiring “advanced techniques for storage, management, analysis, and visualization” (Oesterreich et al., 2022, p. 128).

Climate change: A collective measure of greenhouse gases (carbon dioxide, methane, nitrous oxide) in which the global warming potential (GWP) of each gas is converted to the same unit of measure for harmonization, referred to as carbon dioxide equivalents (kg CO_2-e/kg functional unit; GFLI, 2023a; U.S. Environmental Protection Agency, 2023).

Environmental impact: An adverse or beneficial change to the environment "wholly or partially resulting from an organization's environmental aspects" (U.S. Environmental Protection Agency, 2023, Safety, Health, and Environmental Management System Terms and Definitions section).

Environmental sustainability: Conserving natural resources and minimizing waste creation and release (Bayu et al., 2022).

Eutrophication: Adverse effects in aquatic environments such as algal blooms, reduced oxygen, and death of aquatic life due to increasing nutrient loads of surrounding terrestrial environments. Phosphorus (freshwater) and nitrogen (marine) are of traditional concern (kg P-e/functional unit; GFLI, 2023a; Morelli et al., 2018).

Functional unit: "Unit of comparison that assures that the products being compared provide an equivalent level of function or service" (U.S. Environmental Protection Agency, 2023, Lifecycle Assessment Principles and Practices Glossary section).

Land occupation: Human use of land including agricultural, residential, industrial, and other activities (m^2a crop-e/functional unit; GFLI, 2023a; U.S. Environmental Protection Agency, 2023).

Multi-objective optimization (MOO) modeling: A quantitative and analytical model that establishes the trade-offs among multiple objectives and constraints of a system (Ahmad et al., 2021).

Nonrenewable energy: Fossil fuels sourced from nonrenewable (limited) materials such as coal or natural gas (MJ *or* kg oil-e/functional unit; GFLI, 2023a; González-Quintero et al., 2021).

Water use: Water consumption and "user deprivation potential" (m^3/functional unit; GFLI, 2023b, p. 9).

Assumptions

In the current study, I assumed that U.S. food animal producers are aware of the increasing emphasis placed on environmental sustainability, particularly environmental impact data, as a decision-making tool for agricultural production. Dias et al. (2021) quantitatively examined the role of dynamic capabilities and natural resources on agricultural entrepreneurship and demonstrated that Portuguese farmers (representing 160 small fruit farms) could gain competitive advantage by mitigating environmental effects. Research and development of new agricultural products or processes should be considered dynamic capabilities that allow farms to add resources, update competencies, and create new value (Dias et al., 2021). Furthermore, the known advantage of big data analytics to improve organizational capabilities has been applied to agriculture in the form of contract farming (Lin et al., 2022). Big data improved farm business and operations decisions, including predicting future situations (Lin et al., 2022). Such capabilities could allow food animal producers to develop feed formulations based on potential future ingredient availability, cost, and environmental impacts under the assumption that they are willing to embrace natural resources as dynamic capabilities.

I also made assumptions about the secondary data I employed. First, I assumed that the feed ingredients and diet phases I identified were commonly employed in food animal (broiler chicken, beef cattle, and swine) production in the United States at the time of this study. Rajala et al. (2021) reported that science-based evidence developed from agricultural studies is not often translated into practical applications due to a lack of coordinated efforts among researchers, farmers, and other stakeholders despite positive benefits of integrating new technologies and innovations at the farm level. Without detailed reporting on practical applications, I employed research applications in the current study.

Lastly, I assumed that most U.S. food animal producers are aware of environmental impact values and their free accessibility for implementation in farm practices from the two databases I employed in this study. Prokopy et al. (2019) reported that U.S. farmers' awareness of agricultural impacts on the environment positively affected their adoption of sustainability programs or practices in 11% of cases but was not a significant factor. However, Prokopy et al. identified knowledge of specific sustainability programs and practices as being significantly and positively associated with respective adoption by U.S. farmers in 22% of cases. Adoption of sustainable practices by food producers may be improved with education on how to use environmental impact data rather than mere awareness of these data and their respective sources. I considered implementation and effective use of accurate data within sustainable food production information systems within the theoretical framework of this study.

Scope and Delimitations

Common food animals produced for human consumption products in the United States include chickens, cattle, bison, swine, sheep, goats, and turkeys (USDA, n.d.-b). Of these species, only cattle, chickens, and swine were part of the top 10 current agricultural commodities (based on cash receipt) in the United States at the time of the current study (USDA, 2023b). Therefore, I collected data on these species and further specified cattle and chickens as beef and broiler types. The intended environmental impact values serving as sustainable performance predictors were CC (kg CO_2-e/kg feed ingredient), LO (m^2a/kg feed ingredient), FEP (kg P/kg feed ingredient), and TAP (kg SO_2/kg feed ingredient). These impacts were the focus of recent studies and allowed for comparison with existing published data and recommendations (see de Quelen et al., 2021; Méda et al., 2021; Wilfart et al., 2023). Furthermore, I collected these data from two publicly available databases, one of which had been employed in similar research and one that had yet to be studied from this perspective.

The data I collected on food animal species were delimited to the U.S. region except for environmental impact values, which were sourced from two publicly available databases with global inputs because comprehensive regional data were lacking at the time of this study. I obtained nutritional composition data of commonly used feed ingredients and food animal feeding phases within the United States (as determined by published literature) from the past 5 years, while feed ingredient costs were obtained from 2022 through 2024. Therefore, results are generalizable to U.S. broiler chicken, beef cattle, and swine producers using the same ingredients and feeding phases as I identified in this study. No human subjects were required for this study because I collected only secondary data.

A common theory grounding contemporary studies on big data management and analytics is information processing theory originally developed in 1956 by George Miller (P. Sharma et al., 2022; Rosnov & Roberts, 2005; Song et al., 2020; Yu et al., 2021). Researchers using this theory in the context of big data have posited that an organization requires an exchange of information with its surroundings to address uncertainty (P. Sharma, et al., 2022; Song et al., 2020; Yu et al., 2021). The focus of the theory is on the uncertainty of information (data) inputs and how an organization can manage internal processes to handle this type of uncertainty (Song et al., 2020). In the current study, my focus was not on uncertainty of data inputs but on the uncertainty of data outputs based on data developed and managed differently. Therefore, information processing theory was deemed to be misaligned with the purpose and nature of this study.

Limitations

A potential challenge with any retrospective study is collecting current data. I did not foresee this being an issue in this study because the most difficult data to obtain (environmental impact values) were freely available online; however, these data were not available for every ingredient commonly used in food animal diets in the United States. Environmental impact values of feed additives (e.g., dicalcium phosphate, synthetic amino acids) were largely unavailable. Because this has also been an issue in practical employment of environmental impact big data, I considered that to be a strength of this study because I was able to demonstrate what can be achieved with currently available data and report on what big data remain to be developed within the information systems and agriculture industries. Another limitation of my study was the scope of two publicly available environmental impact databases: GFLI 2.0 and Agribalyse. A plethora of databases are available reporting individual feed ingredient environmental impact values, but it was not practical for a single study to employ them all. Lastly, with the most recent environmental impact methodology developed in 2006, some information published more than 5 years prior to this study was required.

Significance of the Study

This study may be significant in that I aimed to contribute to three United Nations sustainable development goals through improving big data management of sustainable food production: (a) zero hunger, (b) responsible consumption and production, and (c) climate action. With the estimated increase in the global human population of two billion people by the year 2050 comes an estimated need to double the current amount of animal-based protein over the same timeline (Sagues et al., 2020; United Nations, n.d.-a). Protein is a critical component of human and animal diets but is also the most environmentally demanding and expensive nutrient to produce (Acuff et al., 2021). To shift toward more sustainable food production methods, the agricultural industry should begin with the most resource-intensive systems: feed management practices of food animals (i.e., livestock). Employing improved environmental impact big data management practices in food animal production systems may help food animal production managers make better informed decisions regarding sustainable food production.

Global food security is an increasing problem with the expected addition of two billion people requiring food by 2050. The United Nations sustainable development goal of zero hunger aims to create positive social change through ending world hunger by 2030 (United Nations, n.d.-d). This is a critical task considering there will be an estimated 600 million people dealing with hunger by 2030 (United Nations, n.d.-d). Two actions to mitigate food security risks are greater investments in sustainable agriculture and food system transformation (United Nations, n.d.-d). Mehrabi et al. (2022) cited high-quality data as the foundation for forecasting, identifying, and reacting to global food security risks; however, farm level data are severely lacking worldwide. Therefore, examining the extent to which big data management affects consistent sustainable predictability at the farm level is an important step toward mitigating global food security.

For lasting impact, sustainable food production also requires sustainable food consumption. The United Nations sustainable development goal of responsible consumption and production aims to ensure positive social change through global adoption of sustainable consumption and production patterns to protect current and future generations (United Nations, n.d.-c). The United Nations (n.d.-c) has a goal of reducing per capita global food waste by half by the year 2030, which will require a significant shift in natural resource use and conservation. Vázquez-Burguete et al. (2023) asserted that natural resources are inextricably linked to the world economy through consumption and production. The criticality of unveiling ways to manage sustainable food animal production and consumption to reach the United Nations's aggressive food waste reduction goal is evident. A possible solution is improvement in big data management for environmental impacts of food production.

One of the most common indicators of sustainable practices is the measurement of GWP. GWP is defined differently by international standards for measuring environmental impacts than by the United Nations, which studies the drivers and potential outcomes of global warming (U.S. Environmental Protection Agency, 2024). The United Nations sustainable development goal of climate action aims to achieve positive social change through preventing global warming from reaching 1.5ºC above preindustrial levels by 2050 (United Nations, n.d.-b). Although human efforts to reduce climate impact are listed as one of the United Nations's (n.d.-b) targets, information systems and digital technologies can be critical components of human-induced climate change action (Dwivedi et al., 2022). Big data analytics have been used to predict the effects of climate change (i.e., GWP) on aspects of food production (e.g., soil carbon status for crop production) and to predict the effects of food production components (e.g., food transportation) on climate change (Hinge et al., 2021; Li et al., 2022). The circularity of food production effects on climate change and climate change effects on food production exemplifies the challenges of developing solutions for sustainable food production. A necessary component for combatting climate change is consistent predictability of the likely environmental impacts related to food production systems through big data management.

Significance to Theory

In this study, I considered aspects of big data management, sustainability management, data modeling and analytics, and information systems that can affect the future of sustainable food production. The original contribution I made with this study was to add perspective on how big data management of environmental impact sources, assessment methods, and allocation methods affect the consistency and predictability of sustainable food animal feed formulation modeling scenarios. The employment of environmental impact values from different databases and developed from different assessment or allocation methods within a single sustainable food production modeling scenario may increase the accuracy of predictions. The outcome of this study may support the perspective of integrating information systems theories into practical food animal feed formulation processes. This may further enable a connection between traditional agriculture and digital transformation to aid in fighting world hunger, promoting sustainable production, and mitigating climate change.

Significance to Practice

My research may support professional management of environmental impact big data through understanding the consistency to which databases, assessment methods, and allocation methods predict feed formulation characteristics. Although significant differences in environmental impact values based on source and development methods are known, the effects of source and development methods on other aspects of sustainable food animal production modeling require further research. Additionally, sustainable food animal feed formulation processes can be improved by enhancing the practical employment of big data via improved big data management. My study results may clarify some of the farm-level ambiguity associated with practical employment of environmental impact big data and may aid food animal production managers in making better informed decisions related to producing enough food to support the United Nations's goals of zero world hunger, responsible production and consumption, and decreased climate change.

Significance to Social Change

In this study, I aimed to contribute to the social problem of a lack of understanding of how to integrate and manage data inputs for sustainability optimization and simulation modeling at the firm level (see Bayu et al., 2022). My findings may promote positive social change through developing a big data and information systems management approach that enables consistent results of the predicted environmental costs of food animal feed formulation processes and predicts optimal scenarios in which food production increases and environmental impacts decrease. U.S. food animal producers may better understand how to implement and interpret environmental impact big data at the farm level to contribute more sustainably produced animal-derived food products for the growing human population. Findings may also support the United Nations's goals of zero world hunger, responsible production and consumption, and decreased climate change.

Summary

In this study, I examined the extent to which big data management of environmental impact sources, assessment methods, and allocation methods within MOO modeling can affect the consistency and predictability of sustainable food animal feed management practices at the farm level. Accessibility of big data within the agricultural industry is critical for developing solutions to food security problems (Hinge et al., 2021). With the projected human population growth of two billion people over the next 25 years, food production will need to increase, which will increase associated environmental impacts (Astill et al., 2020; Chojnacka et al., 2021; United Nations, n.d.-a). At the time of the current study, there was a lack of knowledge regarding practical implementation of environmental impact big data within food production systems, which is a critical component of food security and sustainability. My study may improve the way environmental impact big data are managed and implemented within food animal feed management practices to improve sustainable food production.

Chapter 2 provides a review of recent (within the previous 5 years when possible) literature relevant to the topic of big data management and the research question focused on environmental impact big data in MOO modeling. The literature review was intended to provide food animal producers in the United States with an understanding of the benefits of shifting toward more sustainable feed management practices of food animals (i.e., livestock) through the implementation of practical environmental impact big data management.

Chapter 2: Literature Review

The problem addressed by this study was a lack of understanding of how to integrate and manage data inputs for sustainability optimization and simulation modeling at the firm level through quantitative optimization modeling with more robust environmental impact big data (see Ahmad et al., 2021; Bayu et al., 2022). The purpose of this quantitative nonexperimental study was to examine the extent to which big data management of environmental impacts within MOO modeling can improve consistent sustainable performance of food animal feed management practices at the farm level. The United Nations is working toward global goals of zero hunger, responsible production and consumption, and decreased climate change, all of which intersect at sustainable food production. Big data can be integral in meeting these goals because big data has been deemed a critical element of developing solutions for food security problems (Popkova, 2023). This second chapter includes a description of the literature search strategy, a review of the theoretical foundation and integration of theories, and a comprehensive review on the literature on big data management, dynamic capabilities, sustainable food production, and optimized information systems. The chapter concludes with a summary.

Literature Search Strategy

This study was developed using existing knowledge from literature and data published within the past 5 years. I used seminal works as supporting literature for theoretical and methodological choices, while contemporary peer-reviewed research (2020–2024 focus) and organizational data (governmental, such as the USDA, and nongovernmental, such as GFLI) made up the bulk of data and information forming the background of the study and status of the discipline with respect to the research problem. Because much of the environmental impact optimization modeling work within the food animal industry has been performed in recent years, published literature beyond 5 years was employed when necessary to develop an exhaustive narrative on the topic. I employed the following databases in my search strategy to identify existing published literature on big data (management, predictive analytics, and decision making), information systems, environmental impacts, sustainable food production, predictive and optimization modeling, and statistical analysis: Walden Library (formerly Thoreau), Google Scholar, Agricola, SAGE Journals, and ScienceDirect. I searched the following keywords: *big data management*, *big data predictive analytics*, *big data decision making, information system optimization, environmental impact management*, *environmental footprint management*, *sustainability management*, *sustainable food production*, *predictive modeling*, *sustainability modeling*, and *sensitivity analysis*. Only literature for which full publications were accessible were used.

Theoretical Foundation

The theoretical framework for this study included the DCV, representation theory, the TEU, and the NRBV. At the convergence of these theories was the ability to study the extent to which big data management of environmental impact sources and calculation methods affect the consistency of food animal feed formulation predictability within MOO modeling at the farm level.

DCV

Most organizations seek competitive advantage, which positions one organization as superior to another in at least one unique organizational characteristic. As an answer to the question of how organizations obtain and maintain competitive advantage, Teece et al. (1997) developed the DCV. This approach was centered on competitive advantage in the context of strategic management during times of accelerated change (Teece et al., 1997). Strategic management refers to the ways in which an organization develops, uses, and maintains resources and capabilities to achieve competitive advantage (Henry, 2021). Teece et al. built the DCV on existing related approaches including the competitive forces approach (Porter, 1980), strategic conflict approach (Shapiro, 1989), and a collection of corporate strength and weakness approaches referred to as resource-based perspectives. At the time of its development, the DCV differed from previous strategic management theories that assumed organizational environments were highly static.

A static organizational environment disregards the continual evolution of business environments. Teece et al. (1997) acknowledged the shifting nature of organizations, particularly evident in the technological advances of the late 20th century. Teece et al. asserted that organizations must identify combinations of internal and external resources (nonreplicable organizational assets) and competencies (capabilities that define an organization's fundamental business core), collectively referred to as dynamic capabilities. Key constructs of the DCV include innovative (dynamic) responses to assets and strategic management (capabilities) of changing environments. Teece et al. identified that these key constructs refer to an organization's ability to revitalize their resources quickly and efficiently through their unique capabilities to match changing business landscapes. Organizational and business environment changes are inevitable, whether positive or negative. An organization's ability to respond is the best defense to survive or thrive during such changes.

Organizational responses can be proactive or reactive. An innovative response, a type of proactive behavior, refers to an organization's ability to capitalize on specialized knowledge, technology, and other resources that are difficult to trade (Teece et al., 1997). This response is toward the change in an organizational asset, identified by Teece et al. as complementary, financial, institutional, market, reputational, structural, and technological. Complementary assets are related resources that help an organization to obtain or maintain any of the other six assets (Teece et al., 1997). Financial assets are an organization's cash flow and ability to use this as leverage for positive performance (Teece et al., 1997). Institutional assets concern an organization's business environment, which can be used as resources and capabilities and may include regulatory, external culture (e.g., geographic location of the organization), internal culture, and more (Teece et al., 1997). Although financial assets and responses to changes of these assets are often closely related to organizational success, institutional assets and related responses may be less obvious.

Organizational performance is also considered among assets. Market assets are an organization's market share; however, Teece et al. (1997) asserted that an organization's competences and capabilities that result in firm performance should be included in an organizational market share strategy to achieve long-term success. Reputational assets are an intangible resource concerning the responses of competitors, customers, and suppliers to an organization (Teece et al., 1997). Structural assets are the internal governance of an organization and any direct external influences (e.g., parent organizations; Teece et al., 1997). Last, technological assets are technology or intellectual property that differentiate an organization (Teece et al., 1997). Possession of these assets is not enough to ensure organizational success. An organization's ability to survive changing environments also requires tactful and purposeful management.

Organizational success is dependent on effective management in any environment, but changing environments require additional flexibility and speed that are achievable through strategic management. Teece et al. (1997) identified three roles of organizational and managerial processes necessary for strategic management, which are coordination and integration, learning, and reconfiguration and transformation. Coordination and integration are an organization's management of internal and external activities (Teece et al., 1997). The strategies behind coordination and integration include developing alliances, technological collaboration, and buyer–supplier relationships (Teece et al., 1997). These strategies highlight the importance of organizations operating outside of silos. Although organizations should protect specialized assets, they should not ignore the benefits of mutuality.

Strategic management processes are not innate to organizations but require practice and intentionality. Learning is the process of experimentation and repetition that leads to greater organizational efficiency (Teece et al., 1997). For learning to be strategic, management must understand (a) the benefits of individual and organizational skills, (b) the social nature of learning, (c) the requirements of coordination and communication, and (d) the importance of organizational routine (Teece et al., 1997). Lastly, reconfiguration and transformation refer to management's ability to identify and adapt to changing conditions, both internally and externally (Teece et al., 1997). Teece et al. identified benchmarking as a strategic tool to achieve reconfiguration and transformation because this requires implementation of an organized process. Strategic management is not a single static action but a series of ongoing processes. This multifaceted concept should be a significant consideration when organizations look to develop competitive advantage.

The question of how big data can support competitive advantage through information systems processes has been raised. In an empirical study in which information technology executives from 500 of Norway's largest organizations were surveyed, Mikalef et al. (2020) found that organizational competitive advantage can be mediated through big data analytics. This result demonstrated the importance of the utilization of big data within organizations, not only its existence. Furthermore, in a quantitative analysis of the dynamic capabilities associated with organizations implementing a circular economy model focused on lowering environmental impacts, Scarpellini et al. (2020) found significant competences of corporate social responsibility and environmental accounting practices. Scarpellini et al. asserted that more circular economy quantitative studies should utilize the DCV. This may help identify dynamic capabilities that promote organizational adoption and implementation of actions oriented toward environmental protection. As environmental perspectives become more necessary within business contexts, organizations can leverage competitive advantage through such dynamic capabilities.

Representation Theory

A potential complication with any information system is translation into practical use. Frobenius is credited for developing representation theory in 1896, and asserted that a system should accurately represent real-world phenomena (Recker et al., 2019; Wand & Weber, 1988). Representation theory was originally applied to mathematics, but in the late 1980s this theory was applied to information systems (Wand & Weber, 1988). A critical assertion of this theory by Wand and Weber related to information systems is that representation equates to individual human perception of the real world. Therefore, Wand and Weber's view of representation theory (of information systems) excludes benefits, costs, efficiency, and value because these are related to the purpose of a representation rather than the perception of a representation. However, consensus on the real-world phenomena of interest is important to reduce the potential for considerable differences across individual human perceptions. The expectations of an information system designed to accurately represent the real world should be defined to achieve this consensus.

One way to define expectations is through the key constructs of representation theory. The key constructs as explained by Wand and Weber (1988) are interaction, mapping, tracking, reporting, and sequencing. Each construct is used to explain a critical way in which the information system and the real world must be linked to define what makes an information system an accurate representation. The first construct of interaction assumes that the real-world system can affect change within the information system by which it is represented (Wand & Weber, 1988). For this to be true, Wand and Weber (1988, 1990) asserted that an information system must be designed to describe two types of real-world change: static (defined as the state) and dynamic (defined as the behavior). The interaction construct of environmental sustainability information systems could be modeled after life cycle assessment processes in which there may be a known state of existence with the assumption of no change, or a state of flux in which a change is compared to a baseline scenario. The challenge of describing static states and dynamic behaviors within an environmental sustainability information system may be describing both simultaneously.

To effectively capture the interaction of an information system, the states reflected within the system must mirror those of the real world. The second construct of mapping requires that each static state of the real system has a matching static state within the information system (Wand & Weber, 1988). This construct is not defined for dynamic behaviors. Furthermore, the real system must feed into the respective information system (Wand & Weber, 1990). Within an environmental sustainability information system, this would mean that the environmental impact big data are static values that match the current state of environmental impacts for a given material in which the data exist (e.g., already developed and validated data). To achieve this, the information system would need to be linked to the real-world system in such a way that governs the data collection process.

In addition to affecting change and matching states within an information system, there must be consensus on system boundaries (information and real-world). The third construct of tracking requires that the laws of the information system and the real-world system be the same (Wand & Weber, 1988, 1990). According to Wand and Weber (1988), laws are meant to return systems to a stable state and are only activated when a deviation occurs. Therefore, laws of a real-world system are what drive changes within an information system. The accuracy of representation of real-world laws in an information system is critical to ensure deviations are recognized and appropriately managed.

To achieve representational accuracy, the information system must include as much information as possible from the real-world system. The fourth and fifth constructs are reporting and sequencing, respectively. Reporting requires that the information system reflects every event that happens in the real system (Wand & Weber, 1988). Reporting specifically concerns external events which happen outside of the immediate real-world environment (Wand & Weber, 1988). Sequencing requires that a sequence of events in the real system are mirrored by a corresponding sequence of events in the information system (Wand & Weber, 1988). Event reporting and sequencing are important constructs, as one event can trigger or otherwise affect another. Together, the five key constructs define the ways in which an information system should be linked to, and accurately represent, its real-world counterpart.

As information systems are becoming more prevalent across disciplines, representation theory is continually being applied to new professional fields. Although focused on repurposing personal technology for work tasks, Burleson et al. (2021) used representation theory (along with the TEU described below) to guide their quantitative study on behavioral intentions related to technology adaptation and perceived usefulness. Burleson et al.'s findings may be applicable to the adaptation of technology to new tasks, which is related to the current study. Although food animal producers are continually including new technologies developed for their processes into their systems, adapting existing technologies for alternative uses can be more difficult. Based on literature searches from the past 5 years using the search engines mentioned previously, this study appeared to be the first to apply representation theory to information systems of environmental impact data.

TEU

Although accurate representation of the real world within an information system is critical, there also needs to be appropriate use of the information system. Burton-Jones and Grange (2013) developed a contemporary extension of representation theory called the theory of effective use of information systems (TEU). Burton-Jones and Grange explained that accurate representation of real-world phenomena is only one half of an information system, with the other half concerning effective use of the system. Although there is a plethora of research aimed at when and why systems are used, little research concerns what constitutes effective use of a system (Burton-Jones & Grange, 2013). Burton-Jones and Grange asserted that filling this gap was important for understanding how to use an information system to attain a relevant goal. The scope of TEU is the individual use of an information system to obtain a goal that has objective qualities (Burton-Jones & Grange, 2013). In relation to the current study, a food animal producer was an individual user, and the goal of the information system was to achieve environmentally sustainable animal feed formulations. Objective qualities were least cost, meeting nutritional requirements, and minimizing environmental impacts.

There are three actions a user must fulfill within an information system to obtain a goal with objective qualities. As previously identified, the key constructs of TEU include transparent interaction, representational fidelity, and informed action (Burton-Jones & Grange, 2013). The general framework for TEU is based on Weiner’s (1948) basic cybernetic control framework, systems theory of which Laszlo and Krippner (1998) identified at least a dozen originations, and Frobenius’ origination of representation theory. In their theory, Burton-Jones and Grange included the basic cybernetic control framework of user actions, consequences, perceptions, and goals along with the notions of uncontrollable and unpredictable system disturbances. Together, these concepts drive the development and basic use of a dynamically representative information system. TEU highlights that basic use of an information system does not necessarily equate to intended or effective use.

An accurately representative information system may still be underutilized or misused if the system is not user friendly. The first construct of transparent interaction is defined as “the extent to which a user is accessing the system’s representations unimpeded by its surface and physical structures” (Burton-Jones & Grange, 2013, p. 642). Surface and physical structure are both elements of information systems defined by Wand and Weber (1998) in representation theory. Surface structure is the elements that facilitate user interaction with the system and physical structure is the physical elements that house the system (Wand & Weber, 1998). Thus, transparent interaction concerns a user’s ability to access the representation afforded by an information system. An information system is only as useful as the accessibility of the data and information.

The data and information of the system should continually be updated for improved accuracy and user experience. The second construct of representational fidelity refers to the fallibility of the representation of a system (Burton-Jones & Grange, 2013). This construct requires acknowledgement of deep structure, the third element of information systems described by Wand and Weber (1988). Deep structure is what the system holds or entails (Wand & Weber, 1988). Lastly, the construct of informed action is what the user does with the representation obtained from the system (Burton-Jones &

Grange, 2013). Burton-Jones and Grange stated that this action includes how the user is leveraging the representation to complete a specific task.

Recently, Namvar et al. (2023) demonstrated that in current digital environments of machine learning, effective use (as defined by TEU) should be implemented alongside wise reasoning. Wise reasoning (or wisdom) is a human ability to deal with multiple conflicting demands and expectations through considering and balancing multiple perspectives (Namvar et al., 2023). Namvar et al. recognized that machine learning is fundamentally different from information systems because there is greater autonomy, deeper learning capabilities, and inscrutability. Therefore, there is a need to consider wise reasoning of information systems by the user as defined by representation theory and TEU.

NRBV

In 1994, Dr. Stuart Hart proposed a new theory about an organization's strategic management capabilities based on the organization's relationship with the natural environment. Hart (1994) called this theory the natural resource-based view (NRBV). This was an extension of Wernerfelt's (1984) theory concerning organizational analysis from an internal resource perspective rather than a product perspective, which Wernerfelt called the resource-based view (RBV). In the NRBV, the natural environment is considered an external resource in addition to internal organizational resources as defined in the RBV. Hart (1994, 1995) asserted that both external and internal resources are required to adequately address organizational competitive advantage. Such organizational advantage can be achieved through two sequential steps. First, organizations must understand their current relationship with the natural environment, and second, organizations must improve this relationship (for the better of the natural environment) over the long-term.

Both steps require interaction with the key concepts of pollution prevention, product stewardship, and sustainable development (Hart, 1994, 1995). Each of these concepts has associated environmental drivers, key resources and capabilities, and strategic logic (i.e., competitive advantage; Hart, 1994). As the first concept name implies, pollution prevention is focused on stopping the occurrence of pollution before it begins (proactive approach) rather than after (reactive approach). The environmental driver of pollution is organizational emissions of hazardous chemicals (Hart, 1994). Hart identified proactiveness via people, materials, and processes as the key resources and capabilities of this concept because prevention costs less than mitigation. Furthermore, strategic logic follows as significant cost savings (Hart, 1994). Although there has been massive improvement in pollution management (reactive approach) over time, pollution prevention (proactive approach) still requires further development.

The key concept of product stewardship means that a product system should aim to "achieve low life cycle environmental costs" (Hart, 1994, p. 7). Such costs are measured via life cycle analysis (LCA), which assesses the production stages of a system for their respective environmental impacts (Hart, 1994; Zhang et al., 2020). The environmental driver of product stewardship is environmental responsibility. The key resources and capabilities of product stewardship are external stakeholders (via input for product processes) and design for environment, which includes an environmental perspective into product processes (Hart, 1994). The strategic logic behind product stewardship is the development of low environmental impact products (Hart, 1994). Case (2023) recently reported for the National Retail Federation that 78% of U.S. consumers want to buy from environmentally friendly companies, indicating the potential competitive advantage of product stewardship.

The last key concept of sustainable development is fulfilling the needs of existing and emerging markets using technologies, processes, and products “within the planet’s ecological means” (Hart, 1994, p. 10). Ecologically sustainable economic and social development are the environmental drivers of sustainable development (Hart, 1994). According to the United Nations (2022), sustainable development is only successful long-term when a country’s economic growth is greater than its population growth, but this achievement is very difficult for developing countries. As economies develop and populations grow, there are associated increases in environmental impacts including resource depletion, waste production, and fossil fuel use (Hart, 1994). Shared vision aimed at environmental sustainability supported by strong leadership and strategic management are the key resources and capabilities for organizations to work toward sustainable development (Hart, 1994). Lastly, Hart described the transformation of environmentally harmful practices to environmentally protective practices as strategic logic of sustainable development.

The NRBV has been employed in several studies about environmental (or green) performance at the organization level. Using the NRBV as a foundation, Bresciani et al. (2022) demonstrated a positive relationship between environmental management control systems, green dynamic capabilities (i.e., green innovation), and investment in environmental management (i.e., environmentally friendly packages) with green performance (defined as a reduction in pollutants and cost). Similarly, Appannan et al. (2023) used the NRBV and DCV as foundations for their quantitative study. Appannan et al. demonstrated that the effects of pollution prevention and clean technology strategies on environmental performance were mediated by environmental management accounting.

Integration of Theories

Representation theory, TEU, DCV, and NRBV converge to describe the necessity of accurate representation and management of real-world environmental impact big data within information systems to increase food animal production with lowered environmental impacts. There is a clear lack of real-world representation afforded by information systems housing environmental impact big data. This decreases the effective use of such systems. The benefits that organizations receive from information systems are dependent upon effective use (Trieu et al., 2022). The trend of unsustainable food production may be mitigated through effective management and use of big data in information systems. Representation theory and TEU may help mitigate the first concerns.

Along the line of inquiry into representative information systems, DCV asserts that big data capabilities should be context specific. This further supports development of the effective use of environmental impact big data. In a recent review and synthesis of DCV research studies performed in the discipline of information systems (IS), Steininger et al. (2022) concluded that a greater number of DCV studies exist within the strategic management discipline than in IS, leading to their recommendation of future research to emphasize DCV in the IS discipline. The implementation of DCV into the current study framework aimed to benefit both the study and continued development of the theory.

Lastly, competitive advantage can be attained with the NRBV lens by strategically managing natural resource constraints through environmental sustainability (Danso et al., 2019). Hart's (1994) recognition that organizations must "alter the nature of economic activity or risk irreversible damage to the planet's basic ecological systems" (p. 2) is even more relevant today than at its conception. Hart identified concerns with consumption rates and atmospheric composition (i.e., climate change), which are two topics covered by the United Nations sustainable development goals. Hart argued that organizations required updated models that placed the natural environment and its preservation at the center of business activities. An implication of the NRBV is that production managers of food animal systems cannot remain competitive in the sustainable food production industry if they cannot adequately manage environmental impact big data within their information systems. According to the outcome of a recent Deloitte (2022) survey on U.S. organizational sustainability disclosure and preparedness, 51% of the respondents anticipated greater trust with stakeholders when enhancing their sustainability actions and reporting, indicating further potential organizational benefits of embracing sustainable development.

Literature Review

Environmental Impacts of Food Production

Food related big data are constantly increasing and should be leveraged to benefit the entirety of the food industry worldwide (Tao et al., 2020). Within food production, the agriculture industry accounts for the greatest environmental impacts including 50% of global land occupation, 70% of global freshwater withdrawals, and 26% of total human induced greenhouse gas emissions (Kucukvar et al., 2019; Castonguay et al., 2023). Multiple benefits of big data management and implementation within agriculture have recently been identified. Lassoued et al. (2021) asserted that agricultural big data can highlight previously unidentified or unacknowledged patterns that can lead to productivity gains. Lioutas and Charatsari (2020) reported that big data can help identify and decrease agricultural environmental footprints, particularly through increasing natural resource use efficiency. A critical component of these data is environmental impacts.

Environmental impacts are adverse changes to the environment from energy and natural resource use, and waste creation (U.S. Environmental Protection Agency, 2023). Common examples include pollution, land degradation, and water depletion. In the current study, the environmental impacts of concern were CC (kg CO_2-e/ functional unit), LO (m^2a/functional unit), FEP (kg P/functional unit), and TAP (kg SO_2/functional unit). Each environmental impact has an associated value calculated via LCA. The International Organization for Standardization (ISO) authored standards for LCA methods in 2006 after new applications of historical LCA methodologies (e.g., products, energy, waste) highlighted the need for updated reference information (Finkbeiner et al., 2006). The ISO standard 14040:2006 provides LCA principles and framework, while ISO standard 14044:2006 provides LCA process requirements (International Organization for Standardization, 2006a, 2006b).

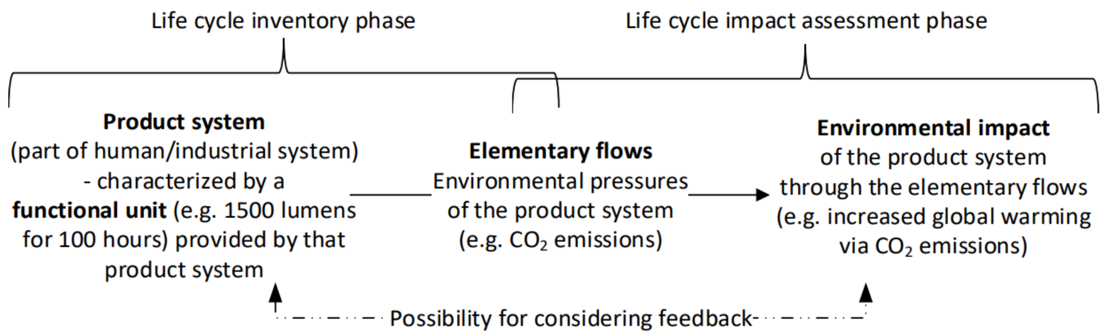
LCA

The goal of a LCA is to identify areas of improvement regarding environmental impacts and natural resource use mitigation. All LCAs should include four phases of (a) objective and scope, (b) system inputs and outputs (referred to as a life cycle inventory), (c) impact assessment (i.e., value calculation), and (d) evaluation of the results (see Fig. 2; International Organization for Standardization, 2006a, 2006b). Each phase concerns the environment, defined as three key areas of ecosystems, natural resources, and human health (Schaubroeck et al., 2021). Within the ISO standards, there are elements of the methodology that require the researcher to make choices among alternatives (Dekker et al., 2020). These are the boundary of inquiry, assessment method, and allocation method. These choices determine whether the LCA is consequential (describes state of change in a production system, typically against a baseline scenario) or attributional (describes current state with assumption of no change in a production system), although

Schaubroeck et al. argued there remains too much ambiguity around these definitions. Regardless of type, all LCAs provide the means to determine a single environmental impact value per product at a single timepoint.

Figure 2

Basic Requirements of Life Cycle Assessment as Defined by ISO 14040:14044



Note. From "Attributional & Consequential Life Cycle Assessment: Definitions, Conceptual Characteristics and Modelling Restrictions," by T. Schaubroeck, S. Schaubroeck, R. Heijungs, A. Zamagni, M. Brandão, and E. Benetto, 2021, *Sustainability*, *13*, 7386 (https://doi.org/10.3390/su13137386). Copyright 2021 by the authors.

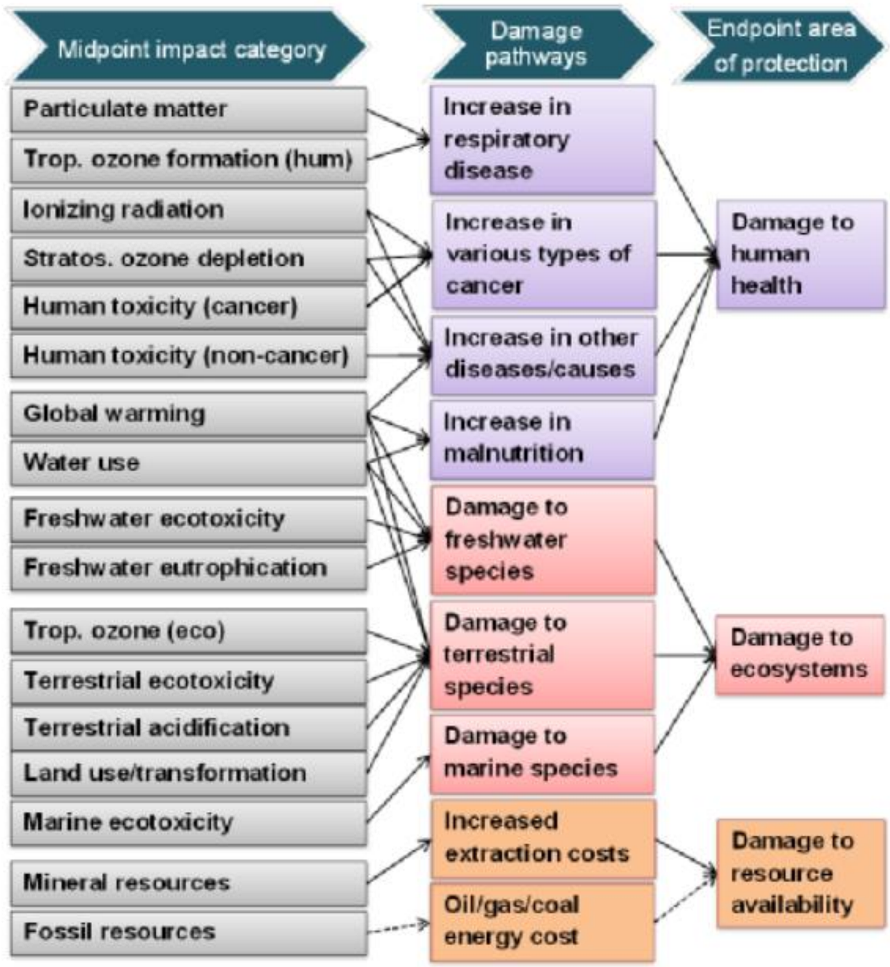
The boundary of inquiry includes boundaries of the system for time, geography, life cycle of intended product and related products, production of capital goods, and the boundary between technological and natural occurrences which must match the purpose of the LCA (Li et al., 2014; Tillman et al., 1994). The researcher must choose what processes are in and out of scope for the LCA. This includes determining if the system of interest is cradle-to-grave, cradle-to-gate, gate-to-gate, or gate-to-grave. A cradle-to-grave boundary is considered a full LCA by considering all aspects of a product's life cycle, such as product design, development, production, distribution, use, and end of life disposition (Jacquemin et al., 2012). All other boundaries consider portions of a product's life cycle. Cradle-to-gate considers aspects from product design to production, gate-to-gate considers distribution, and gate-to-grave considers distribution, use, and end of life disposition.

Within assessment options, the researcher must choose among methods that differ in their impact category rules (e.g., the classification of environmental impact). The most pertinent assessment methods to the current study are discussed. The first assessment method is the product environmental footprint (PEF), developed and implemented by the European Commission. This method is based on ISO LCA standard principles but includes product environmental footprint category rules (PEFCR) aimed at standardizing LCA principles for products within the same category (European Commission, 2021). PEFCR provides a level of comparability across similar products with similar processes (e.g., comparability of meat-type products), but is only relevant for European products (European Commission, 2018).

The second assessment method, ReCiPe, was developed commensally between two European universities and two private European organizations focused on sustainability software development. Also based on ISO LCA standard principles, this method includes characterization factors that aggregate global scale individual environmental impact categories into broader categories of potential damages (Dekker et al., 2020; Huijbregts et al., 2017). These broader categories consist of midpoints (called damage pathways), which include human health conditions (e.g., respiratory issues, cancer, etc.), damage to different animal species and environments (e.g., freshwater, marine, and terrestrial), and mineral and fossil damage (e.g., extraction and energy costs) (Dekker et al., 2020; Huijbregts et al., 2017). There are also endpoints (called area of protection), including ecosystem, human health, and resource scarcity (Dekker et al., 2020; Huijbregts et al., 2017). The categories and aggregation are demonstrated below (see Fig. 3). Within ReCiPe methodology, environmental impact categories funnel into midpoints which further funnel into endpoints, providing users with information about consequences of environmental impacts in addition to impact values.

Figure 3

Diagram of ReCiPe Environmental Impact Aggregation in Midpoints and Endpoints



Note. From "ReCiPe2016: A Harmonised Life Cycle Impact Assessment Method at Midpoint and Endpoint Level," by M. A. J. Huijbregts, Z. J. N. Steinmann, P. M. F. Elshout, G. Stam, F. Verones, M. Vieira, M. Zijp, A. Hollander, A., and R. van Zelm, 2017, *International Journal of Life Cycle Assessment*, *22*, 138–147 (https://doi.org/10.1007/s11367-016-1246-y). Copyright 2016 by Springer-Verlag Berlin Heidelberg.

Within allocation options, the researcher must choose among methods that differ in how the environmental impacts (burdens) are attributed along the system. In systems where main products and downstream products coexist, the researcher must decide how to divide environmental impacts among all products, if at all (Wilfart et al., 2021). Although this option exists, ISO LCA standards recommend avoiding allocation where each product and coproduct are associated with their own respective systems of inputs and outputs (International Organization for Standardization, 2006a; Wilfart et al., 2021). This review focused on the allocation methods most critical to the current study. These methods are economic-, energy-, and mass-based allocation.

Economic allocation allocates the highest environmental impact to the product with the highest economic value (GFLI, 2023b; Wilfart et al., 2021). For example, human grade products are of higher dollar value, and therefore environmental impact, than pet food grade products. Energy allocation allocates higher environmental impact based on caloric value (GFLI, 2023b). For example, fats and oils are more calorically, and therefore more environmentally impactful, than dried meal products. Lastly, mass allocation allocates higher environmental impact based on quantifiable physical conditions, such as mass or weight (GFLI, 2023b; Wilfart et al., 2021). For example, by-products constitute a higher mass of food animals, and therefore environmental impact, than human grade products.

Environmental Impact Big Data Management

LCAs are the most common methodology used to evaluate the environmental impacts of agricultural production (van der Werf et al., 2020). The myriads of choices required by a researcher to complete a LCA are evidence of the difficulty in measuring and developing comparable environmental impacts across organizations and industries. Along with measurability and comparability, integration of environmental impact big data into organizational decision making has also been reported as a current challenge of environmental impact data management (Frieberg et al., 2021; Kharel et al., 2022; Macci et al., 2022). Antecedents of environmental sustainability big data decision making for Chinese hospitals were reported as (a) organizational culture focused on technology and big data, (b) talent management, and (c) leadership focus (Nisar et al., 2020). Interestingly, these antecedents were also identified as big data management challenges (Nisar et al., 2020). Talent management and the lack of comparability (e.g., standardization and governance) have also been reported as challenges to big data management in the European agriculture industry (Osinga et al., 2022). These data indicated the need to develop better and more efficient big data management tools.

Despite apparent challenges, farmers and organizations across the agriculture industry are investigating big data and technology driven solutions to food security and climate change. Solutions include smart farming and precision agriculture aimed at more efficient production through remote sensing (Astill et al., 2020; Jayashankar et al., 2020; K. Sharma et al., 2022; Torky & Hassanein, 2020; Vicente, 2022). Other solutions are aimed at managing the data collected from such technologies. For example, the Agricultural Research Service (ARS) of the USDA has been working on a database solution for collecting and storing high quality big data in real time (Kharel et al., 2022). Furthermore, in a quantitative analysis, Baierle et al. (2022) identified big data management (collection, processing, and analysis) as one of the top five digital technologies currently used among the Brazilian food industry. Therefore, further development in the use of big data databases was warranted.

Over recent years, there have been multiple efforts to aggregate environmental impact data into a single database. Cabernard and Pfister (2021) stated that although difficult to obtain a definition of the ideal system, efforts toward this goal have resulted in numerous databases with varying degrees of efficacy due to variations in data availability, consistency, and quality. The most common databases have been developed directly from LCA derived data, but Sacchi et al. (2022) argued that these databases are too static, representing a single point in time. Therefore, new types of dynamic databases are being evaluated, such as prospective LCA inventory (pLCA) and multi-regional input-output (MRIO) databases.

At the time of the current study, the pLCA process had only been recently proposed by Arvidsson et al. (2018), defined as a LCA performed on an emerging technology that is in early phase development but modeled for a future state of further development. The ability to evaluate scenario ranges and predictive scenarios are two benefits of pLCAs compared to conventional LCAs (either consequential or attributional)

(Arvidsson et al., 2018). Given the rise in emerging technologies, pLCA has received a great deal of attention from the research community. For example, Sacchi et al. (2022) evaluated the use of a new tool called the prospective environmental impact assessment (or *premise*) to streamline pLCA database development through integrated assessment models (IAM). Sacchi et al. concluded that *premise* could highlight the effects of uncertainty on LCI database development through comparisons of numerous scenario specific databases. Using pLCA to estimate current and future environmental impacts of Brazilian agricultural commodities based on current and future proposed technologies, Lucas et al. (2023) determined that future technologies could significantly reduce environmental impacts by over 50%, depending on region and commodity.

MRIO databases aggregate global environmental impact data across the value chain and across a specified time frame (Cabernard & Pfister, 2021). The benefits of MRIO are identifying production distribution and sector interdependence across and within economies (Abbood et al., 2023). Using MRIO analysis, Abbood et al. determined that across 41 countries, the U.S. is responsible for 81.73% of the total carbon footprint and 84% of the total energy footprint. Furthermore, the U.S. agriculture sector (which includes hunting, fishing, and forestry) accounts for 22% of the overall U.S. carbon footprint (Abbood et al., 2023). However, of the seven MRIO databases in existence, only two (EXIOBASE3 and Eora26) were publicly available at the time of the current study (Cabernard & Pfister, 2021). This demonstrated the difficulty of accessing and implementing the same environmental impact data across studies or organizational processes to achieve comparable and meaningful results.

Agribalyse and Global Food LCA Institute

Of the existing LCA databases, I used Agribalyse and the Global Food LCA Institute 2.0 (GFLI). Both databases house environmental impact data for feed ingredients used in food animal production but differ in their approach. Agribalyse is a collective program co-piloted by two French environmental organizations (ADEME and INRAE) where environmental impacts of French feed ingredients are calculated via LCA based methodology (Agribalyse, n.d.; Wilfart et al., 2016). This database, first published in 2014, reports environmental impact values of 200 agricultural products (and 2500 food products) calculated using the cradle to gate approach (cultivated feed ingredients), EF assessment method, and economic allocation (Agribalyse, n.d.).

The GFLI is a global collaborative effort where environmental impacts of global feed ingredients are also calculated via LCA based methodology (GFLI, 2023b). In contrast to Agribalyse, GFLI offers environmental impact values calculated using both a cradle to gate and cradle to plant (processed feed ingredients) approach with the organization's own two collective assessment methods. The first, EF, is derived from PEF, PEFCR, and livestock environmental assessment and performance (LEAP), and offers values for three allocation methods of economic, energy, and mass (GFLI, 2023b). The second, ReCiPe 2016, is a LCA derived method (developed between two universities, a national institute, and a private organization partnership) and offers values for the same three allocation methods (National Institute for Public Health and the Environment, 2018).

Sustainable Food Production

As previously described, food security is a contemporary concern with 17 million people in the U.S. experiencing food insecurity in 2022 (USDA, 2023c). Furthermore, amid food insecurity, the expected global population increase of two billion persons over the next 25 years is additionally concerning (Astill et al., 2020; Castonguay et al., 2023; Chojnacka, et al., 2021; United Nations, n.d.-a). The agriculture industry has a greater impact on poverty and food security than any other sector of the economy, yet this industry is also the most susceptible to environmental changes (Abbass et al., 2022; Pawlak & Kołodziejczak, 2020; Sarkar et al., 2020). Therefore, the development of sustainable food production is critical and will work toward achieving three of the United Nations sustainable development goals including zero hunger, responsible consumption and production, and climate action.

There are multiple reasons why traditional food production processes are considered environmentally unsustainable. First, traditional food production requires the use of natural resources, much of which has been overexploited (Namany et al., 2020; Vicente, 2022). Second, production and consumption cycles operate at low efficiency, resulting in high food waste (Krishnan et al., 2020; Osinga et al., 2022; Read et al., 2020). Third, the inherent variability of living organisms and environmental conditions lead to a consistent level of uncertainty in agricultural production (Namany et al., 2020;

Osinga et al., 2022). Fourth, traditional food production must operate within the bounds of reproduction and growth cycles (Osinga et al., 2022). To achieve global food security, these challenges must be addressed.

Utilizing environmental impact big data in decision making is a potential solution to unlock sustainable food production. Consumers want to know about the environmental impacts of their food choices and often take these into consideration when making food choices (Clark et al., 2022). Recent consumer research demonstrated that numeric sustainability labeling information, such as carbon emission values, strengthens consumers' choices in sustainable food products (Stillman et al., 2023). Unfortunately, there are multiple ways to calculate carbon emissions and other environmental impact values of food processes and products, making it difficult to know if advertised values can be compared. Baierle et al. (2022) declared that digital transformation is an upcoming enabler for agriculture and the food industry. Using a quantitative agent-based model to compare scenarios of tomato crop production, crop water requirement, and trade market flows in Qatar over a 5-year period, Namany et al. (2020) demonstrated that sustainable tomato production should include the purchase of imports to reduce annual water use from the estimated 4.9 billion m^3. These data indicated that agriculture digital transformation should include leveraging existing environmental impact big data and developing an information systems approach.

MOO Modeling for Sustainable Food Production

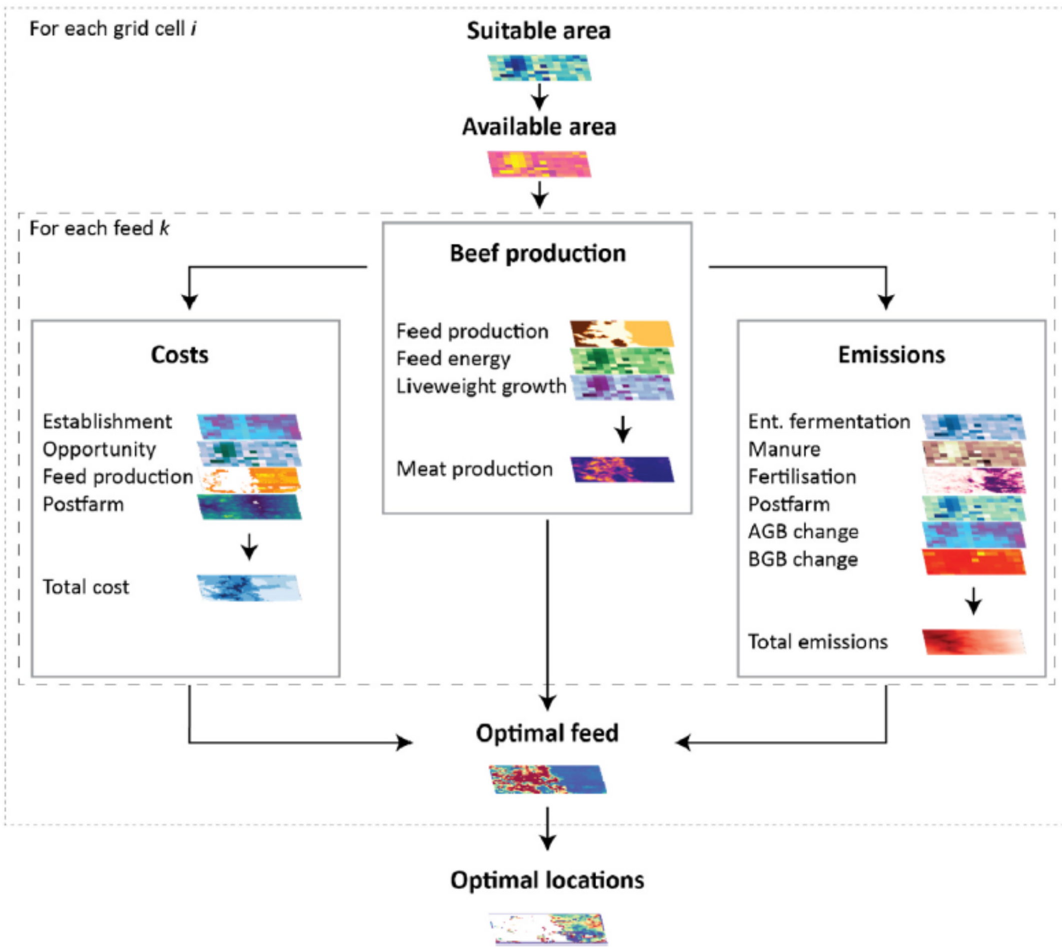
MOO modeling is a mathematical solution for trade-off situations and a form of multicriteria decision making (Deb, 2011). The process is based on the premise that in nature, most problems have multiple goals (objectives) that must be fulfilled simultaneously. Within MOO modeling, there is one constraint (requirement) that must be fulfilled and multiple objectives (additional goals) that a researcher aims to achieve concurrently. Each objective is maximized or minimized with the possibility of having objectives in opposing directions (e.g., increase protein content and decrease carbon emissions; Shafiee et al., 2021). While MOO modeling can be used to optimize many types of objectives, this review focused on MOO modeling for environmental impact optimization within food production. Over the past 5 years, MOO modeling had been employed worldwide to optimize environmental impacts related to agriculture and food production; however, published studies focused on agriculture and food production in the U.S. were scarce.

U.S. MOO Modeling in Agriculture

One of the few studies to employ MOO modeling for U.S. agriculture was a national assessment and comparison of U.S. and Argentinian beef cattle production optimization. Castonguay et al. (2023) aimed to find the most efficient beef cattle diets and geographies within these two countries (10 km resolution) to minimize greenhouse gas emissions and production costs. The researchers developed a MOO modeling approach called MOO-GAPS (multi-objective optimization model of global animal production and sustainability) to optimize greenhouse gas emissions and production costs of scenarios varying in feed practices (grazing, grazing and grain, grazing and stover, grain and stover, current feed) and location (U.S. and Argentina) (Castonguay et al., 2023). The MOO-GAPS approach was unique in that each optimization factor was considered spatially as individual 10 km areas of land layered together, allowing for multi-dimensional analysis (see Fig. 4; Castonguay et al., 2023). This type of analysis allowed for plots of land to be considered as best fit with sustainable agriculture practices.

Figure 4

Multi-Dimensional Spatial Analysis of the Multi-Objective Optimization Model of Global Animal Production and Sustainability



Note. From "MOO-GAPS: A multi-objective optimization model for global animal production and sustainability," by A. C. Castonguay, S. Polasky, M. H. Holden, M. Herrero, J. Chang, D. Mason-D'Croz, C. Godde, K. Lee, B. A. Bryan, J. Gerber, E. T. Game, and E. McDonald-Madden, 2023, *Journal of Cleaner Production*, *396*, 136440 (https://doi.org/10.1016/j.jclepro.2023.136440). Copyright 2023 by the authors.

Within each 10 km spatial plot, Castonguay et al. (2023) calculated the greenhouse gas emissions, economic cost of production, and amount of meat production for each feed practice option within each location. Using weighted sum optimization, Castonguay et al. identified the optimal feeding practice (defined as low cost, low emissions) within each spatial plot, and the plots in which the optimal feeding practice would meet beef cattle production and meat demand for the respective geographic area. The MOO-GAPS results for U.S. beef cattle production indicated that greater greenhouse gas reductions are associated with higher production costs; however, the results also highlighted current inefficiencies that, if solved, could result in cost savings while maintaining current emissions (Castonguay et al., 2023). The optimal feed type for U.S. beef production was identified as a mix of grass and grain (approximately 65% and 20%, respectively), and stover (15%) with changes to proportions. Castonguay et al. demonstrated that increasing grass inclusion to approximately 75% with a simultaneous reduction in stover (no change to grain) would optimize least cost while decreasing grass inclusion to approximately 50% and increasing grain to approximately 35% (no change to stover) would optimize lowered emissions. These results exemplified the challenges of developing sustainable agricultural practices.

Cost is often a significant factor in sustainable agriculture practices. Over recent years, commodities used to feed food animals for meat production (e.g., corn, soybean, wheat) in the U.S. have increased in cost. From 2020 to the height of inflation in 2023, feed grain prices doubled (National Agriculture Statistics Service, 2023a, 2023b, 2023c).

As of the beginning of 2024, these prices had not been restored to 2020 values (National Agriculture Statistics Service, 2023a, 2023b, 2023c). Therefore, environmental impact optimization in food animal feeding practices is a potential solution to develop different scenarios where cost and environmental impacts are optimized to varying degrees until a practical solution is identified. Data lacking from Castonguay et al.'s (2023) study that are a consideration in the current study include feeding phases and additional food animal species that cannot utilize grass (i.e., grazing) as a feed input.

Non-U.S. MOO Modeling in Agriculture

Globally, there have been numerous environmental optimization evaluations of crops and food animals. In Brazil, Esteves et al. (2021) used MOO modeling to identify the best combination of corn, soybean, and beef cattle production on the same farm to optimize cost, environmental impacts, and biomass available for biofuel production. An outcome of the study was Esteves et al.'s conclusion on the importance of allocation method on MOO model results. However, only a single source of environmental impact data was used so it was unclear whether similar allocation methods across data sources pose a concern, particularly for comparative purposes. This was addressed in the current study. In another example, Sun et al. (2022) optimized energy consumption and environmental impacts of pig production in China through data envelopment analysis (DEA) an optimization approach focused on input and output efficiencies. Sun et al. defined the inputs as feed, water, coal, electricity, diesel, labor, and piglets with grown (harvest weight) pigs as the output. The optimization results demonstrated a 2.22 kg CO_2-

e/pig greenhouse gas emissions reduction with very little to no change in other environmental impacts. Additionally, electricity use per pig could be mitigated to the greatest extent with 18.96 MJ/pig saved after optimization. Although energy consumption was not considered in the current study, this environmental impact may be important to include in future studies due to the relationship between energy consumption and environmental impacts.

In Germany, Buschbeck et al. (2020) used MOO modeling to optimize agricultural food production and associated environmental impacts within five regions of the state of Baden-Württemberg. With consideration of production type (conventional and organic) and demand scenarios (typical German diet, vegetarian, and vegan), Buschbeck et al. demonstrated the optimal solution to be 40–80% organic food production and 50–60% non-regional food (e.g., food produced in neighboring regions) to decrease environmental impacts. Although Buschbeck et al.'s study focused on human diets, the ECOALIM environmental impact database by Agribalyse was employed, indicating potential comparative use of these data and results with the current study. With a focus on mushroom production in Iran, Taherzadeh-Shalmaei et al. (2023) used MOO modeling and DEA to compare optimization scenarios of energy consumption and environmental impacts. Taherzadeh-Shalmaei et al. indicated that converting mushroom greenhouses to more efficient practices could reduce energy consumption and associated environmental impacts without decreasing production volume. Furthermore, the MOO model results outperformed the DEA results by optimizing energy consumption at

11125.94 MJ/m^2 compared to 1022537.82 MJ/m^2 (Taherzadeh-Shalmaei et al., 2023). The results supported the use of MOO modeling as the optimization process for the current study.

Also focused on Iran, Shafiee et al. (2021) applied MOO modeling to the dairy industry supply chain network to optimize costs, environmental impacts, and societal impacts (defined qualitatively from very optimistic to very pessimistic) based on demand. Shafiee et al. demonstrated that as demand increases (+40%), not only do costs (+53%) and environmental impacts (+54%), but social impacts also increase (+81%). The indication is that although products may cost more with increasing demand, consumers still had a positive outlook on the product and the respective industry, which had positive implications for the cost increases commonly associated with environmental impact mitigation. In another dairy cattle example, Notte et al. (2020) used MOO modeling to demonstrate that optimizing feed inputs by increasing feed grains and decreasing feed roughage for dairy cattle could allow for higher stocking density, thereby increasing milk production in Uruguay. Notte et al. indicated the ability of optimized feed input to positively affect food animal production, which is a potential solution to food security. Unfortunately, Notte et al. did not consider environmental impacts of the feed inputs which were considered in the current study.

Only a few of the published studies examining ways to optimize environmental impacts from agricultural production have considered how environmental impact big data can improve sustainable feed formulation for food animal production. Garcia-Launay et al.'s (2018) study involving the use of MOO modeling at the farm level to optimize nutritional requirements, low cost, and low environmental impacts of broiler chicken, bull calf, and pig operations in France is the foundation for incorporating environmental impact big data into food animal feeding practices as a solution to sustainable food production. Garcia-Launay et al. aimed to develop a formulation method that could simultaneously optimize nutrition, cost, and the environmental impacts of CC, NED, LO, TAP, PD, and FEP. The requirements of the method included linear programming (Garcia-Launay et al., 2018). Linear programming has been used in food animal feed formulations since the 1950s (Hutton et al., 1958). This type of modeling differs from MOO modeling in that there is only one constraint (nutrient requirements) and one optimization (cost).

Garcia-Launay et al. (2018) included linear programming to encourage adoption by food animal production managers. Osinga et al. (2022) reported that agricultural stakeholders' main concerns with the adoption of big data technologies were cost, user friendliness, and the ability to embed the technologies within their current work processes. Garcia-Launay et al. successfully developed a MOO modeling approach using Microsoft Excel and Python statistical software to optimize feed formulations across traditional French broiler chicken, bull calf, and pig operations that fit nutritional requirements (MOO model constraint) with up to 48% reduced environmental impacts (using values from the ECOALIM by Agribalyse database) and low to moderate cost increases of 1–7%. From a survey on 645 grain growers in China, Li et al. (2020)

demonstrated the highest direct effect on farmers' intent to implement agricultural green practices was perceived value (0.364) followed by perceived benefits (0.270), which both outweighed the negative impact of perceived risk (-0.190). Therefore, Garcia-Launay et al.'s reduction in environmental impacts (demonstrated benefit) should encourage French farmers' choice to adopt MOO model feeding practices despite the potential cost increase (demonstrated risk). The use of Agribalyse environmental impact values renders the data from Garcia-Launay et al.'s study useful for comparison to the current study.

Méda et al. (2021) were the first to employ Garcia-Launay et al.'s (2018) MOO modeling process of optimizing nutritional requirements, low cost, and low environmental impacts (CC, NED, LO, TAP, PD, and FEP derived from the ECOALIM by Agribalyse database) of food animal feed formulation. An additional consideration by Méda et al. was the added variable of phase feeding type for French pig production (classic 2-phase, 2-phase with lower net energy content, and multiphase), and French broiler chicken production (classic 3-phase and 3-phase with higher digestible amino acid contents and lower metabolizable energy content). This additional variable allowed Méda et al. to examine the efficacy of MOO model feeding practices across multiple contemporary production scenarios. Feeding phases are often employed to match nutrient provisions with stages of food animal growth and development (NRC, 1994, 2000, 2012). Méda et al. used traditional linear programming to develop a baseline diet and MOO modeling to develop optimized diets. The same approach was used in the current study.

The MOO model was performed with nutritional requirements and production scenario as constraints, and environmental impacts, feed cost, and gross margin as optimizations (Méda et al., 2021). The ingredient list for each production and animal scenario combination demonstrated that each baseline formulation averaged one ingredient more (19.6) than each optimized formulation (18.5) (Méda et al., 2021). Méda et al. demonstrated the importance of further examining data management for MOO modeling scenarios, as the environmental impact values of feed formulation types were affected by phase feeding type (production scenario). Furthermore, this affected feed cost and gross margin of food animal production, which are important considerations for food security solutions. Méda et al.'s optimization results indicated reductions across all production scenarios for the environmental impacts of CC, NED, and LO with negligible reductions in the remaining impacts (see Table 2). Additionally, feed costs and gross margins both increased with the use of optimized (non-baseline) production scenarios (see Table 2).

MOO modeling reduced environmental impacts to a greater extent for pigs and broilers fed their respective classic production scenario compared to the alternative scenarios (Méda et al., 2021). For example, CC was reduced by an additional 19 and 45 kg CO_2-e/ton feed in the classic pig scenario (2-phase) compared to the alternative 2-phase (2-phase plus) and multiphase scenarios, respectively (see Table 2). For broilers, CC was reduced by 30 kg CO_2-e/ton feed in the classic scenario (3-phase) compared to the alternative 3-phase (3-phase plus; see Table 2). Méda et al. demonstrated that food animal production scenarios can affect the extent to which environmental impacts can be optimized alongside feed costs when nutrient requirements are considered as a constraint. The use of Agribalyse environmental impact values rendered the data from Méda et al.'s study useful for comparison to the current study.

Table 2

Differences in Environmental Impact Values of Pig and Broiler Diets Between Baseline and Optimized Production Scenarios

Environmental impact (per ton of feed)	Pig production scenario			Broiler production scenario	
	2-phase	2-phase plus	Multiphase	3-phase	3-phase plus
Climate change (kg CO_2-e)	71	50	26	100	70
Acidification (mol H+-eq)	1.0	0.6	0.1	0.4	0.5
Eutrophication (kg PO_4^{3-}-eq)	0.4	0.5	0.2	0.3	0.3
Nonrenewable energy demand (MJ)	695	260	-6	1395	744
Land occupation (m^2/yr)	181	248	76	-59	10
Phosphorous demand (kg P)	0.2	0.4	0.4	0.8	0.8
Feed cost (€)	4,0	7,0	3,0	10,0	6,0
Gross margin (€)	6,0	18,0	5,0	16,0	10,0

Note. Adapted from "Reducing environmental impacts of feed using multiobjective formulation: What benefits at the farm gate for pig and broiler production?," by B. Méda, F. Garcia-Launay, L. Dusart, P. Ponchant, S. Espagnol, and A. Wilfart, 2021, *Animal*, *15*, 100024 (https://doi.org/10.1016/j.animal.2020.100024). Copyright 2020 by the authors.

Around the same time, de Quelen et al. (2021) performed a study employing the MOO modeling process developed by Garcia-Launay et al. (2018) with the added variables of French pig production performance (body weight and carcass characteristics) and locally versus non-locally sourced ingredients. de Quelen et al. considered the same six environmental impacts of CC, NED, LO, TAP, PD, and FEP derived from the same Agribalyse database. de Quelen et al. used traditional linear programming to develop a baseline diet and MOO modeling to develop optimized diets. de Quelen et al. were the first to feed the diet formulations developed through the MOO model process to food animals to examine the efficacy of low environmental impact diets on actual food animal production.

MOO modeling was performed with nutritional requirements as the constraint, and environmental impacts and ingredient source as optimizations (de Quelen et al., 2021). The ingredient list showed the highest average number of ingredients were included in the baseline diet (18.5), followed by the optimized local diet (15.5), and the optimized non-local diet (13.5; de Quelen et al., 2021). The optimization results using non-locally sourced ingredients showed a significant reduction in five of the environmental impacts compared to baseline (see Table 3). The only nonsignificant result was for LO, which was still numerically reduced through optimization. Interestingly, the optimization results for the locally sourced ingredient diet reduced some, but not all, environmental impacts (see Table 3). In fact, some impacts increased when locally sourced ingredients were used, such as FEP and LO. This is likely due to inefficiencies in some of the local ingredient processes compared to non-local processes and provides local ingredient manufacturers with areas to improve.

Table 3

Differences in Environmental Impact Values of Pig Production Between Baseline Diet and Optimized Diets with Non-Locally (Eco Diet) Versus Locally (Local Diet) Sourced Ingredients

Environmental impact (per kg body weight)	Eco diet	Local diet
Climate change (kg CO_2-e)	0.23[a]	0.29[a]
Acidification (mol H+-eq)	0.005[a]	0.002
Eutrophication (kg PO_4^{3-}-eq)	12[a]	-5
Nonrenewable energy demand (MJ)	1.15[a]	4.07[a]
Land occupation (m^2year)	0.05	-0.66[a]
Phosphorous demand (kg P)	27[a]	12[a]

Note. Adapted from "Eco-friendly feed formulation and on-farm feed production as ways to reduce the environmental impacts of pig production without consequences on animal performance," by F. de Quelen, L. Brossard, A. Wilfart, J.-Y. Dourmad, and F. Garcia-Launay, 2021, *Frontiers in Veterinary Science, 8*, 689012 (https://doi.org/10.3389/fvets.2021.689012). Copyright 2021 by the authors.

[a]Significant difference from baseline diet at $p < 0.05$.

de Quelen et al. (2021) indicated from the feeding studies that the optimized diets resulted in comparable pig production performance to baseline body weight and carcass characteristics. A single performance measure of feed conversion ratio was significantly greater for pigs fed the locally sourced ingredient diet compared to the non-locally sourced ingredient diet, but was not significantly different from pigs fed the baseline diet (de Quelen et al., 2021). These results demonstrated the efficacy of pig feed formulations optimized for environmental impacts in achieving typical production performance. This supports the need to maintain (at minimum) food animal production as organizations work toward achieving global food security. Unfortunately, feed costs were not considered by de Quelen et al., and feed costs may affect the ability of food animal production managers to implement sustainable feed formulations into current practices. The use of Agribalyse environmental impact values rendered the data from de Quelen et al.'s study useful for comparison to the current study.

Lastly, Wilfart et al. (2023) followed de Quelen et al.'s (2021) process and developed MOO model feed formulations derived from Garcia-Launay et al. (2018) for a food animal feeding study. Wilfart et al. examined the effect of low environmental impact diets on French rainbow trout growth and resulting potential food animal production. In contrast to the prior studies, Wilfart et al. considered two additional environmental impacts of water dependence (m^3) and net primary production demand (kg C) along with the six impacts previously studied. All environmental impact values were derived from the same Agribalyse database except for water dependence and net primary production demand, which the researchers calculated specifically for their study. Wilfart et al. used traditional linear programming to develop a baseline diet and MOO modeling to optimize a diet for environmental impacts.

MOO modeling was performed with nutritional requirements and feed ingredient inclusion rates as constraints, and environmental impacts as optimizations (Wilfart et al., 2023). The ingredient list differed between the two diets with the baseline diet including less ingredients (16) compared to the optimized diet (23) (Wilfart et al., 2023). The optimized diet resulted in reduced environmental impacts across all categories compared to baseline, although some reductions can be considered negligible, such as FEP (0.002 kg PO_4^{3-}-eq) and PD (0.001 kg P) (see Table 4). Like de Quelen et al. (2021), Wilfart et al. demonstrated no significant difference in fish final body weight or composition but did note a trend of slower growth in fish fed the optimized diet. This means that long-term feeding of optimized diets may not equate to greater food animal production. An implication is difficulty attaining the amount of food animal production (at lowered environmental impacts) necessary to achieve global food security.

Table 4

Differences in Environmental Impact Values of Trout Baseline Diet and Optimized Diet

Environmental impact (per kg of feed)	Difference
Climate change (kg CO_2-e)	0.64
Acidification (mol H+-eq)	0.005
Eutrophication (kg PO_4^{3-}-eq)	0.002
Nonrenewable energy demand (MJ)	6.3
Land occupation (m^2year)	0.39
Phosphorous demand (kg P)	0.001
Water dependency (m^3)	4.5
Net primary production demand (kg C)	9.4

Note. Adapted from “A step towards sustainable aquaculture: Multiobjective feed formulation reduces environmental impacts at feed and farm levels for rainbow trout,” by A. Wilfart, F. Garcia-Launay, F. Terrier, E. Soudé, P. Aguirre, and S. Skiba-Cassy, 2023, *Aquaculture*, *562*, 738826 (https://doi.org/10.1016/j.aquaculture.2022.738826). Copyright 2022 by the authors.

Additionally, Wilfart et al. (2023) considered the effect of environmental impact optimization on feed costs and found the optimized diet to cost 105,40 €/ton less than the baseline diet. This cost reduction opposed optimized feed cost results from Garcia-Launay et al. (2018) and Méda et al. (2021). This may be due to the greater number of plant-based ingredients in the optimized diet compared to the baseline diet, which consisted of more animal-based ingredients. Animal-based commodities tend to cost more than plant-based commodities due to greater required inputs for production (National Agricultural Statistics Service, 2023a, 2023b, 2024a, 2024b). For example, in the U.S. at the time of the current study, poultry cost $0.70/lb. while soybeans cost $0.22/lb. (National Agricultural Statistics Service, 2023b, 2024b). As with the prior studies, the use of Agribalyse environmental impact values rendered the data from Wilfart et al.'s study useful for comparison to the current study.

Summary and Conclusions

As evidenced by current literature, there was a lack of understanding how to integrate and manage data inputs from multiple sources for sustainability optimization and simulation modeling at the firm level. This was due to a clear lack of real-world representation afforded by information systems housing environmental impact big data which decreases effective use of such systems. In this his study, I aimed to mitigate this issue through DCV and TEU. Additionally, representation theory and NRBV were included to examine the context-specificity of environmental impact big data and ways in which food animal production managers can use representative big data and information systems to remain competitive in the sustainable food production industry.

The MOO model approach developed by Garcia-Launay et al. (2018) and further evaluated by Méda et al. (2021), de Quelen et al. (2021), and Wilfart et al. (2023)

demonstrated positive effects of environmental impact optimization for feeding practices of food animal production. Using MOO modeling, environmental impacts (CC, NED, LO, TAP, PD, and FEP) were reduced by nearly half that of the baseline impacts. However, none of the evaluations considered the effects of different environmental impact value sources, assessment methods, or allocation methods on optimization efficacy. Beltran-Peña et al. (2020) asserted that optimization and minimizing resource use inefficiencies are promising solutions to food security with the help of digital technologies. I addressed this gap, as identified by Ahmad et al. (2021), in the current study. The following chapter describes the methodology that addressed the research question focused on environmental impact big data in multi-objective optimization modeling. The chapter includes detailed discussions of the research design and rationale, methodology, data analysis plan, and validity.

Chapter 3: Research Method

The purpose of this quantitative nonexperimental study was to examine the extent to which environmental impact sources, assessment methods, and allocation methods within MOO modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level. To address this gap, I employed MOO modeling (nonlinear programming) and intended to use the statistical approach of multivariate analysis of variance (MANOVA) to analyze secondary data from sources including the NRC (1994, 2000, 2012), USDA (n.d.-a), NANP (2023), GFLI (2023a), and Agribalyse (n.d.). This chapter includes detailed discussions of the research design and rationale, methodology, data analysis plan, and validity.

Research Design and Rationale

The design of this quantitative study was nonexperimental. This design was appropriate because I analyzed secondary data that had been measured but not manipulated (see Cox, 2020). I collected published food animal (broiler chicken, beef cattle, and swine) nutrient requirements and feeding phases (starter, grower, and finisher) from the NRC (1994, 2000, 2012), USDA (2023a), and other peer-reviewed publications including Moritz et al. (2022) and Shurson et al. (2022). I collected feed ingredient costs (USD/kg) and nutritional composition data from the USDA (n.d.-a) and NANP (2023). Lastly, I collected environmental impact values (CC, LO, FEP, and TAP) for feed ingredients from the GFLI 2.0 database (GFLI; 2023a) and Agribalyse database (n.d.).

These data were optimized via MOO modeling using Microsoft Excel Solver and statistically analyzed using the Statistical Package for Social Sciences (SPSS) to examine the extent to which environmental impacts via source, assessment method, and allocation method within MOO modeling affect the number of ingredients, cost, crude protein content, and environmental impacts of sustainable food animal feed management practices at the farm level. I intended to use a MANOVA to examine the effect of multiple categorical independent variables on multiple continuous criterion variables (see Randolph, 2020). The predictor (independent) variables relating to big data management were environmental impact database source (GFLI and Agribalyse), assessment method (EF and ReCiPe), and allocation method (economic, energy, and mass). The criterion (dependent) variables relating to sustainability performance from the MOO model output were number of ingredients, cost, crude protein content, and environmental impacts (CC, LO, FEP, and TAP) of food animal (broiler chicken, beef cattle, and swine) feed formulation. The first MOO model for optimizing environmental impacts within food animal feed formulations was developed using Microsoft Excel Solver (Garcia-Launay et al., 2018). This program had also been used to perform MOO modeling in other industries such as environmental remediation and chemical engineering (Briones et al., 2020; Suwannahong et al., 2021).

Nonexperimental research is the predominant design of social science studies (Reio, 2016). This design allows for observational, correlational, or predictive research because data are analyzed as is and are not manipulated. Without manipulation, causation cannot be determined via nonexperimental designs (Price et al., 2017). In the current study, I did not determine the causation of differences in the criterion variables based on predictor variables, but rather examined whether statistical differences were present. The method chosen for this nonexperimental study was correlational because I was interested in examining statistical associations between the predictor and criterion variables. This study was a meta-analysis, which was developed in the 1970s by social scientists and statisticians to analyze data from individual studies in a single integrated study (Guzzo et al., 1987; O'Rourke, 2007). The research design was consistent with the need to quantitatively advance knowledge on the topic of environmental impact big data management. Nonexperimental research techniques for food animal feed formulation optimization had been developed in recent years, and this study was a continuation of the way quantitative data are employed in optimization modeling.

Methodology

According to Ahmad et al. (2021), quantitative optimization modeling is an effective technique to "identify, assess, and summarize critical factors" (p. 2) that facilitates informed decision making. Although the research design in the current study was nonexperimental and causation was not addressed, the presence or absence of statistical differences in the MOO model output demonstrated whether environmental impact inputs from different sources, assessment methods, and allocation methods affect the number of ingredients, cost, crude protein content, and environmental impacts (CC, LO, FEP, and TAP) of food animal (broiler chicken, beef cattle, and swine) feed formulation. The results may be used as a decision-making tool for agricultural production.

Population

Because I employed secondary data and no human subjects were used, there was no target population from which primary data were collected.

Sampling and Sampling Procedures

I used purposive sampling in this study to collect secondary data on broiler chicken, beef cattle, and swine nutrient requirements, common feed ingredient nutritional profiles and costs, and ingredient environmental impact values. I collected published food animal (broiler chicken, beef cattle, and swine) nutrient requirements and feeding phases (starter, grower, and finisher) from the NRC (1994, 2000, 2012), USDA (2023a), and other peer-reviewed publications including Moritz et al. (2022) and Shurson et al. (2022). I collected feed ingredient costs and nutritional composition data from the USDA (n.d.-a) and NANP (2023). I also collected environmental impact values (CC, LO, FEP, and TAP) for feed ingredients from the GFLI 2.0 (2023a) and Agribalyse (n.d.). No human subjects were used for this research.

Archival Data

All inputs were secondary data collected from recently published literature (peer-reviewed research, governmental databases, and nongovernmental organizational databases) and freely accessible databases. Nutrient requirements for each food animal species at each feeding phase were collected from the NRC's (1994, 2000, 2012) published collection of nutrient requirements. Feeding phases were determined from the NRC (1994, 2000, 2012) and other published data (Moritz et al., 2022; Shurson et al., 2022; USDA, 2023a). Feed ingredient costs were collected from the USDA (n.d.-a). This data source was also used to collect feed ingredient nutritional composition and supplemented with data from the NANP (2023).

In addition, environmental impact values for feed ingredients were collected from two freely accessible databases, the GFLI (2023a) and Agribalyse (n.d.). The GFLI database provided environmental impact data derived from two different assessment methods (EF and ReCiPe) and three different allocation methods (economic, energy, and mass). The Agribalyse database provided environmental impact data derived from one assessment method (EF) and one allocation method (economic). TAP data from the Agribalyse database were converted from H^+ to kg SO_2 units to align with GFLI data.

Data Analysis Plan

The research question and hypotheses guiding this quantitative study were as follows:

RQ: To what extent do environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level?

H_0: Environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling do not affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

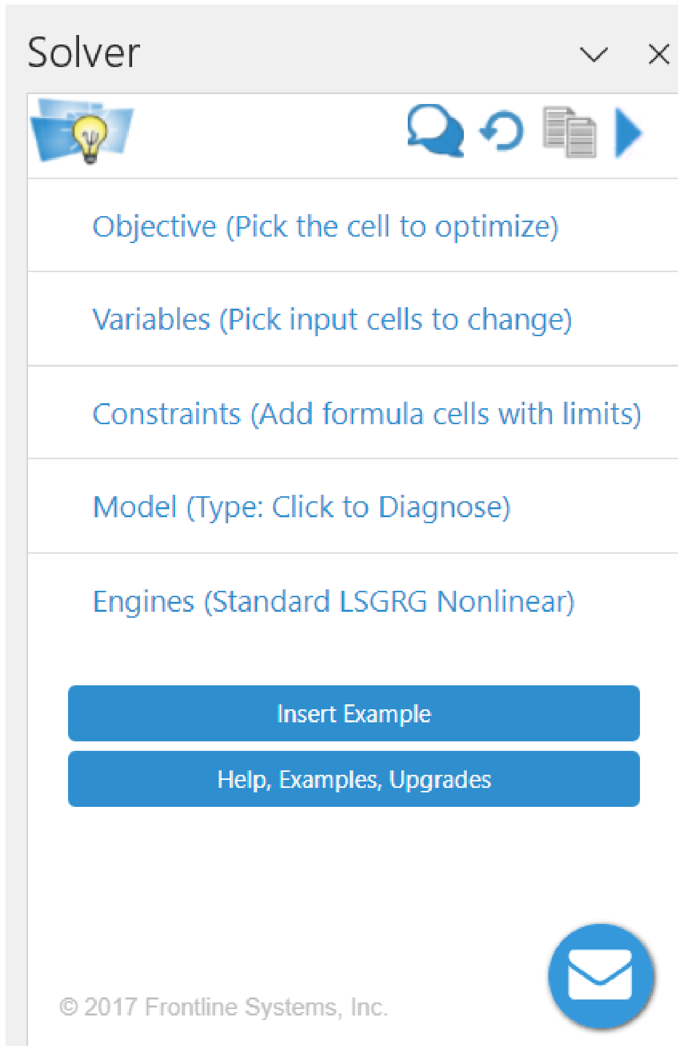
H_a: Environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

Microsoft Excel Solver was used to employ a MOO model as developed by Garcia-Launay et al. (2018). MOO modeling is based on linear programming for poultry feed formulation (Hutton et al., 1958). In linear programming, one objective function is optimized to fit a constraint. Hutton et al. explained that linear programming is a way to work with quantitative information from which thousands of possible solutions exist. MOO modeling builds on linear programming by optimizing multiple objective functions to fit one or more constraints. In the current study, the first model objective was to achieve low-cost formulations, and the second model objective was to achieve low environmental impact formulations including CC, LO, FEP, and TAP. The least cost objective considered how the cost of each potential ingredient affected the cost of each complete formulation developed from the model. The lowest environmental impact objective considered how CC, LO, FEP, and TAP values of each ingredient affected the respective impact values of each complete formulation. The constraints were minimum nutrient requirements of broiler chicken, beef cattle, and swine during starter, grower, and finisher feeding phases (see Table 1).

Microsoft Excel Solver is a five-step process (see Figure 5). The first step is to identify the cell to be optimized, which is referred to as the *objective* in Solver. Optimizations can be identified as maximum, minimum, or that of a specified value. The second step is to identify the variable data from which the optimizations are to be made and are added to the *variables* box. The third step is to identify the constraints which are added to the *constraints* box. Constraints can be identified as less than or equal to, equal to, greater than or equal to, integer, binary, or alldifferent (ordering or sequencing constraints). The fourth step is to diagnose the model type (automatically performed by the Solver function when prompted by the user) that determines the number of variables, functions, bounds, and integers (as applicable). Lastly, the solving method should be chosen from within the *engines* box based on intended solution type (e.g., local best solution, simplex algorithm, or global best solution). Clicking the right-facing arrow at the top of the dialogue box initiates the optimization modeling process, and a box appears at the bottom of the Solver screen to indicate that the process is complete.

Figure 5

Dialogue Box for Microsoft Excel Solver

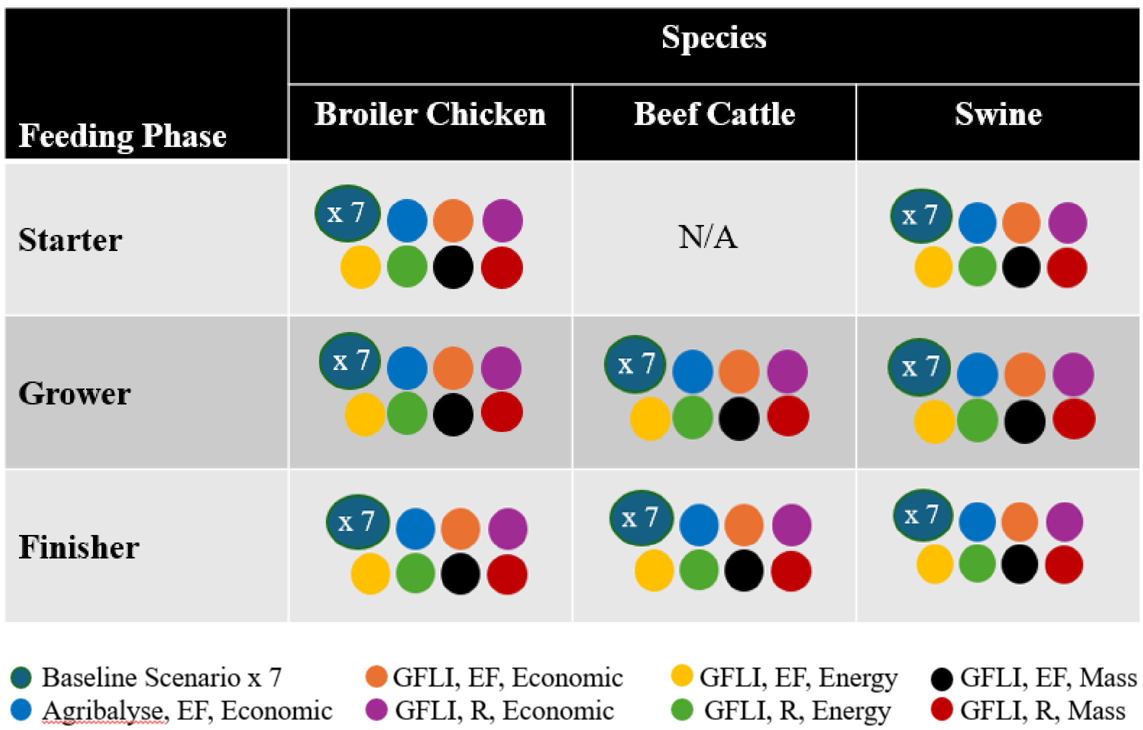


The results of the optimization were a feed formulation that best satisfied both optimizations within the constraints (either least-cost only in baseline scenarios, or least cost and low environmental impacts in optimized scenarios). The optimization process was followed for each species (broiler chicken, beef cattle, and swine) at each feeding phase (starter, grower, and finisher), as applicable, for a total of 112 optimizations (see

Figure 6). The optimization process was repeated 14 times for each species and feeding phase combination so that environmental impact values from two database sources, two assessment methods, and three allocation methods could be examined. The optimization process was also performed for each species and feeding phase combination without optimizing the environmental impact values to serve as baseline scenarios.

Figure 6

Matrix of Optimization Processes Based on Species, Feeding Phase, and Environmental Impact Variables



Note. Environmental impact variables are listed by database (Agribalyse, GFLI = Global Feed LCA Institute), assessment method (EF = Environmental Footprint 3.0, R = ReCiPe), and allocation method (Economic, Energy, Mass). Baseline scenario excludes environmental impact values from the optimization but includes them as outputs.

SPSS was used with the intent to perform a MANOVA on the MOO model output. The criterion variables of interest were the number of ingredients in each optimized feed formulation, cost of each feed formulation, crude protein content of each feed formulation, and environmental impacts of each feed formulation. A MANOVA is appropriate when there are two or more predictor variables and two or more criterion variables (Randolph, 2020). Randolph reported that the variables can be of any type (e.g., continuous, categorical, etc.) while Salkind (2010) reported that predictor variables should be categorical, and criterion variables should be continuous and moderately correlated. In the current study, the predictor and criterion variables fit Salkind's requirements. The MANOVA was intended to examine H_a, which states that environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

For the MANOVA, I planned an alpha level of 0.5 (95% confidence interval), meaning that I had a 5% chance of committing a Type I error (falsely rejecting H_0). The benefits of using MANOVA are that this test (a) controls for "experiment-wide error rate" unlike using multiple single or univariate analysis of variance (ANOVA) tests which increase Type I error, (b) reduces Type II error (falsely accepting H_0), and (c) controls for correlations among multiple criterion variables (Salkind, 2010). The challenges of using MANOVA are that the test results can be more complex to interpret, and there are more assumptions that must be met than required to perform a univariate ANOVA (Salkind, 2010). If any of the predictor variables were found to be significantly correlated to any of the criterion variables with a 95% confidence interval, the null hypothesis would be rejected.

Threats to Validity

With any study, the validity of the research must be considered. Validity provides confidence in the quality of the research study (Stewart & Hitchcock, 2020). In quantitative research, this ensures that the potential effects on study outcomes unrelated to the variables are addressed so that the results truly and accurately represent the study phenomenon.

External Validity

External validity refers to the extent to which research findings hold true across different contexts (Stewart & Hitchcock, 2020). There are five potential threats to external validity: (a) treatment variations, (b) context-dependent mediation, (c) types of outcome measures, (d) interactions of causal relationships with sample units, and (e) settings in which treatments are delivered (Stewart & Hitchcock, 2020). For the current study, treatment variations and settings in which treatments are delivered were not concerns, because I used a nonexperimental research design and employed secondary data without manipulation. Furthermore, as explained by Stewart and Hitchcock, external validity concerns can be mitigated by building on previous research studies to appropriately narrow the study focus and allow for comparison of existing related results. Because the current study was built on prior research and employed the same MOO modeling method and data from one of the same sources, external validity concerns were addressed.

Internal Validity

Internal validity refers to how truthful conclusions are that a predictor variable is responsible for a change in a criterion variable (Stewart & Hitchcock, 2020). Price et al. (2017) reported that internal validity is higher with experimental designs than nonexperimental designs due to the comparison of a treatment group to a control group. Because this nonexperimental study could only examine correlation and not causation, internal validity was low. To address internal validity, baseline data were included so correlational results could be compared to MOO modeling performed without the predictor variables.

Construct Validity

Construct validity refers to the extent to which the underlying concepts of a research study are accurately represented and examined (Stewart & Hitchcock, 2020). In quantitative research, construct validity can also be considered from the perspective of statistical conclusions (Stewart & Hitchcock, 2020). For the current study, construct validity was addressed by identifying secondary data that directly reflected the underlying concept of environmental impact big data management. Additionally, the intention to employ secondary data through a MANOVA was the most appropriate statistical examination for determining correlation without inferring causation.

Ethical Procedures

I employed secondary data from published literature and freely accessible databases. Data sources included Moritz et al. (2022), Shurson et al. (2022), NRC, USDA, NANP, GFLI, and Agribalyse. At the time of the current study, I did not work with any of the organizations from which I obtained secondary data, so there was no conflict of interest. No human participants were required, so there were no concerns regarding the ethical treatment of human subjects. I received Walden University Institutional Review Board (IRB) approval (06-07-24-1114805) for the use of all secondary data.

Summary

The purpose of this quantitative nonexperimental study was to examine the extent to which environmental impact sources, assessment methods, and allocation methods within MOO modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level. The research question was answered by optimizing secondary data in MOO modeling and statistically analyzing the output for the presence or absence of correlations. I narrowed the study focus based on prior related research and employed some of the same secondary data and optimization modeling as prior studies. These attributes addressed study validity and increased confidence in the research output. The following chapter describes the study results, including MOO model and statistical outputs.

Chapter 4: Results

The purpose of this quantitative nonexperimental study was to answer the following research question and confirm one of the following hypotheses:

RQ: To what extent do environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level?

H_0: Environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling do not affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

H_a: Environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

To answer the research question, I collected secondary data from sources including the NRC (1994, 2000, 2012), USDA (n.d.-a), NANP (2023), GFLI (2023a), and Agribalyse (n.d.). I also employed MOO modeling (nonlinear programming) and performed a statistical analysis. This chapter includes detailed discussions of data collection and study results.

Data Collection

I collected secondary data consisting of broiler chicken, beef cattle, and swine nutrient requirements per identified feeding phase (see Table 1), feed ingredient nutrient profiles, and feed ingredient environmental impact values from reputable sources that included the NRC (1994, 2000, 2012), USDA (n.d.-a), NANP (2023), GFLI 2.0 database (2023a), and Agribalyse database (n.d.). The data were manually entered into a Microsoft Excel spreadsheet over a period of 7 days.

To run MOO modeling within Microsoft Excel Solver, the researcher must organize data inputs. Within the Excel spreadsheet, I organized the data as a table with up to 29 feed ingredients (28 for broiler chickens and swine, and 29 for beef cattle) organized as rows, and 48 nutrients (e.g., crude protein, amino acids, crude fat, fatty acids, etc.) organized as columns (see Table 5). The table for beef cattle included one additional feed ingredient of bluestem grass as a roughage component, which is crucial for beef cattle but not appropriate for broiler chickens or swine. I also organized the species and feeding phases as rows with the respective nutrient requirements organized into the same columns as the feed ingredient nutrients. Lastly, I organized feed ingredient cost and each of the four environmental impacts as individual columns. The environmental impacts columns were repeated for each combination of source, assessment method, and allocation method. I converted the TAP data sourced from the Agribalyse database from kg H^+ to kg SO_2 units to align with GFLI data. Using the known equivalent of 1.31 kg H^+ = 1 kg SO_2, the following formula was used (The International EPD System, n.d.): TAP (kg H^+) / 1.31 = TAP (kg SO_2).

Table 5

Sample Secondary Data Table Organization for Use with Microsoft Excel Solver

Variable	Crude protein[a]	Linoleic acid[a]	Calcium[a]	Cost[b]	Climate change[c]
Feed ingredient					
Barley, grain	12.94	0.98	0.07	0.27	0.59
Bloodmeal	84.50	0.13	0.33	1.00	1.99
Corn, whole	9.22	1.92	0.02	0.23	0.30
Species and life stage					
Broiler, starter	23.00	1.00	1.00		
Beef cattle, grower	15.00		0.31		
Swine, finisher		0.10	0.50		

Note. Blank cells indicate no requirement for that nutrient or environmental impact. [a]Reported as %. [b]Reported as USD/kg feed ingredient. [c]Reported as kg CO_2-e/kg feed ingredient.

As described in Chapter 3, Microsoft Excel Solver is a five-step process (see Figure 5). In the first step, I identified the cost cell to be minimized (baseline scenarios) or a cell identifying both environmental impacts and cost to be minimized (optimized scenarios). In the second step, I identified each feed ingredient amount cell as a variable for a total of 28 or 29 variables (beef cattle require a roughage source). In the third step, I identified 19 minimum nutrient requirements for broiler chickens and swine (consistent for both species), and 15 minimum nutrient requirements for beef cattle (consistent with the other species) as the constraints. As minimums, I included these constraints as greater than or equal to within Solver. I chose minimum nutrient requirements over maximum nutrient requirements because minimums are nonnegotiable. Additionally, most maximum nutrient requirements pertain to micronutrients (minerals and vitamins), which are largely supplied via supplements.

Although I included 11 micronutrient supplements as possible feed ingredients, premixed micronutrient supplements are commonly used in food animal production systems. Premix nutrient profiles are difficult to accurately replicate from a general perspective. Attempting to optimize for maximum nutrient requirements without the correlating feed ingredients available to model would hinder optimization. I also included the constraints of each feed ingredient amount cell to be between 0 and 100 (representing the exclusion of a feed ingredient [0%] up to inclusion of a single feed ingredient [100%] within the model), and the summed feed ingredient amount cell to be equal to 100 (i.e., all included feed ingredient amounts in the model should sum to 100%).

In the fourth step, I initiated Solver's diagnosis of the model type. Based on species and feeding phase combination, Solver identified 28 to 29 variables, 8 to 21 functions, 56 to 58 bounds, and no integers. Lastly, I chose the solving method of generalized reduced gradient for smooth nonlinear data. This method was developed during the 1970s to solve nonlinear computational problems (Lasdon et al., 1974, 1978). I collected the cost, number of ingredients, crude protein content, CC, LO, FEP, and TAP for all solved models into a separate spreadsheet that I uploaded to SPSS Version 29.0.2.0 and statistically analyzed.

Study Results

I attempted to perform 112 MOO models within Solver (see Figure 6) and achieved solutions for 111 models. Solver could not find a solution for the model considering broiler chickens at the finisher feeding phase using Agribalyse environmental impacts. Upon reviewing the MANOVA assumptions, I determined that none of the data were normally distributed (see Appendix). Therefore, the parametric MANOVA analysis was inappropriate. Nonparametric tests are used when data are not normally distributed so long as the data fit the assumptions of nonparametric tests. Although a MANOVA would have allowed me to test for significant differences among all seven criterion variables across all three predictor variables simultaneously, the nonparametric test only allowed me to test for significant differences among all seven criterion variables across one predictor variable at a time.

I chose the Kruskal-Wallis H test to examine whether significant differences existed among each criterion variable based on each predictor variable, individually. This test is the nonparametric equivalent to a one-way ANOVA (there is no equivalent for a MANOVA). This test had four assumptions: (a) The criterion variables were measured at ordinal or continuous level, (b) the predictor variables consisted of two or more categorical levels, (c) the samples were independent of one another, and (d) the criterion variable distribution shapes were determined to be similar or different. The last assumption was required to correctly interpret the test results. My data met the first three assumptions, and I determined the criterion variable distribution shapes to be different across all levels of each predictor variable. Different distribution shapes indicated the appropriateness to interpret the mean ranks of each Kruskal-Wallis H analysis result.

Three Kruskal-Wallis H tests were conducted, one analysis for each predictor variable. Descriptive statistics for all three analyses in which I tested for significant differences among the seven criterion variables across levels of each predictor variable were identical. These data are presented in Tables 6, 7, and 8 where *N* represents the number of MOO models from which the data were obtained. The mean number of ingredients across all optimized animal feed formulation models (*N* = 111) was 5.32 (maximum = 14, minimum = 3) with variation from the mean of approximately two ingredients. Mean crude protein content was 30.22% (maximum = 77.04%, minimum = 7.50%) with variation from the mean of 19.66%. Mean cost (USD/kg) of each optimized model was $0.83 (maximum = $2.34, minimum = $0.06) with variation from the mean of $0.73.

Mean CC (kg CO_2-e/kg feed) was 76.74 kg CO_2-e (maximum = 496.20 kg CO_2-e, minimum = 0) with a variation from the mean of 96.43 kg CO_2-e. Mean LO (m^2a/kg feed) was 3,487.51 m^2a (maximum = 30,602.48, minimum = 0) with a variation from the mean of 6,735.21 m^2a. Mean FEP (kg P/kg feed) was .03 kg P (maximum = .17 kg P, minimum = 0) with a variation from the mean of .035 kg P. Mean TAP (kg SO_2/kg feed) was .86 kg SO_2 (maximum = 9.88 kg SO_2, minimum = 0) with a variation from the mean of 1.51 kg SO_2.

Table 6

Descriptive Statistics for Kruskal-Wallis H Test of Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Impact Database

Variable	*N*	*M*	*SD*	Minimum	Maximum
# Ingred	111	5.32	1.98	3	14
CP, %	111	30.22	19.66	7.50	77.04
Cost, $/kg	111	0.83	0.73	0.06	2.34
CC/kg	111	76.74	96.43	0.00	496.20
LO/kg	111	3487.51	6735.21	0.00	30602.48
FEP/kg	111	0.03	0.035	0.00	0.17
TAP/kg	111	0.86	1.51	0.00	9.88
Coded database	111	1.14	0.34	1.00	2.00

Note. # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (m^2a/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

Table 7

Descriptive Statistics for Kruskal-Wallis H Test of Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Impact Assessment Method

Variable	*N*	*M*	*SD*	Minimum	Maximum
# Ingred	111	5.32	1.98	3	14
CP, %	111	30.22	19.66	7.50	77.04
Cost, $/kg	111	.83	.73	.06	2.34
CC/kg	111	76.74	96.43	.00	496.20
LO/kg	111	3487.51	6735.21	.00	30602.48
FEP/kg	111	.035	.035	.00	.17
TAP/kg	111	.86	1.5	.00	9.88
Coded assessment method	111	1.57	.50	1.00	2.00

Note. # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (m^2a/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

Table 8

Descriptive Statistics for Kruskal-Wallis H Test of Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Impact Allocation Method

Variable	*N*	*M*	*SD*	Minimum	Maximum
# Ingred	111	5.32	1.977	3	14
CP, %	111	30.22	19.66	7.50	77.04
Cost, $/kg	111	.83	.73	.06	2.34
CC/kg	111	76.74	96.43	.00	496.20
LO/kg	111	3487.55	6735.21	.00	30602.48
FEP/kg	111	.035	.035	.00	.17
TAP/kg	111	.86	1.51	.00	9.88
Coded allocation method	111	1.86	.84	1.00	3.00

Note. # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (m^2a/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

The Kruskal-Wallis H test showed a statistically significant difference at $\alpha = .05$ in mean ranks of optimized animal feed formulation model crude protein content (H(1) = 5.482, $p = .019$), CC (H(1) = 22.961, $p < .001$), LO (H(1) = 28.833, $p < .001$), and TAP (H(1) = 9.940, $p = .002$) between the different databases (see Table 9). Mean ranks for GFLI database ($n = 96$) and Agribalyse database ($n = 15$) were as follows: (a) crude protein content = 57.11 for GFLI and 74.07 for Agribalyse, (b) CC = 67.79 for GFLI and 18.97 for Agribalyse, (c) LO = 62.48 for GFLI and 14.50 for Agribalyse, and (d) TAP = 59.81 for GFLI and 31.63 for Agribalyse (see Table 10). There were no significant differences in number of ingredients (p = .344), cost (p = .993), or FEP (p = .555) (see Table 9).

Table 9

Kruskal-Wallis H Test Statistics for Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Impact Database

Parameter	# Ingred	CP, %	Cost, $/kg	CC/kg	LO/kg	FEP/kg	TAP/kg
Kruskal-Wallis H	.896	5.482	.000	22.961	28.833	.349	9.940
df	1	1	1	1	1	1	1
Asymp. Sig.	.344	.019	.993	< .001	< .001	.555	.002

Note. # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (m^2a/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

Table 10

Kruskal-Wallis H Mean Ranks for Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Impact Database

Variable	Coded database	*N*	Mean rank
# Ingred	1.00	96	57.11
	2.00	15	48.90
	Total	111	
CP, %	1.00	96	53.18
	2.00	15	74.07
	Total	111	
Cost, $/kg	1.00	96	56.01
	2.00	15	55.93
	Total	111	
CC/kg	1.00	96	61.79
	2.00	15	18.97
	Total	111	
LO/kg	1.00	96	62.48
	2.00	15	14.50
	Total	111	
FEP/kg	1.00	96	55.29
	2.00	15	60.57
	Total	111	
TAP/kg	1.00	96	59.81
	2.00	15	31.63
	Total	111	

Note. 1.00 = Global Feed LCA Institute 2.0 database; 2.00 = Agribalyse database; # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (m^2a/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

The Kruskal-Wallis H test showed a statistically significant difference at $\alpha = .05$ in mean ranks of optimized animal feed formulation model number of ingredients (H(1) =

7.723, $p = .005$), crude protein content (H(1) = 14.467, $p < .001$), LO (H(1) = 18.419, $p < .001$), and TAP (H(1) = 5.869, $p = .015$) between the different assessment methods (see Table 11). Mean ranks for ReCiPe assessment ($n = 48$) and EF ($n = 63$) were as follows: (a) number of ingredients = 65.44 for ReCiPe and 48.81 for EF, (b) crude protein content = 42.71 for ReCiPe and 74.07 for EF, (c) LO = 40.98 for ReCiPe and 67.44 for EF, and (d) TAP = 47.52 for ReCiPe and 62.46 for EF (see Table 12). There were no significant differences in cost ($p = .933$), CC ($p = .905$), or FEP ($p = .584$) (see Table 11).

Table 11

Kruskal-Wallis H Test Statistics for Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Impact Assessment Method

Parameter	# Ingred	CP, %	Cost, $/kg	CC/kg	LO/kg	FEP/kg	TAP/kg
Kruskal-Wallis H	7.723	14.467	.007	.014	18.419	.300	5.869
df	1	1	1	1	1	1	1
Asymp. Sig.	.005	< .001	.933	.905	< .001	.584	.015

Note. # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (m^2a/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

Table 12

Kruskal-Wallis H Mean Ranks for Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Assessment Method

Variable	Coded assessment method	*N*	Mean rank
# Ingred	1.00	48	65.44
	2.00	63	48.81
	Total	111	
CP, %	1.00	48	42.71
	2.00	63	66.13
	Total	111	
Cost, $/kg	1.00	48	56.29
	2.00	63	55.78
	Total	111	
CC/kg	1.00	48	56.42
	2.00	63	55.68
	Total	111	
LO/kg	1.00	48	40.98
	2.00	63	67.44
	Total	111	
FEP/kg	1.00	48	57.92
	2.00	63	54.54
	Total	111	
TAP/kg	1.00	48	47.52
	2.00	63	62.46
	Total	111	

Note. 1.00 = ReCiPe assessment method; 2.00 = Environmental Footprint 3.0 assessment method; # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (m^2a/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

The Kruskal-Wallis H test showed a statistically significant difference at $\alpha = .05$ in mean ranks of optimized animal feed formulation model CC ($H(2) = 29.937$, $p < .001$), LO (H(2) = 13.989, $p < .001$), and TAP (H(2) = 15.715, $p < .001$) between the different allocation methods (see Table 13). Mean ranks for economic allocation ($n = 47$), energy allocation ($n = 32$), and mass allocation ($n = 32$) were as follows: (a) CC = 36.54 for economic, 68.75 for energy, and 71.83 for mass, (b) LO = 42.67 for economic, 65.44 for energy, and 66.14 for mass, and (c) TAP = 41.88 for economic, 65.63 for energy, and 67.11 for mass (see Table 14). There were no significant differences in number of ingredients ($p = .985$), crude protein content ($p = .743$), cost ($p = .995$), or FEP ($p = .078$) (see Table 13).

Table 13

Kruskal-Wallis H Test Statistics for Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Impact Allocation Method

Parameter	# Ingred	CP, %	Cost, $/kg	CC/kg	LO/kg	FEP/kg	TAP/kg
Kruskal-Wallis H	.029	.595	.009	29.937	13.989	5.106	15.715
df	2	2	2	2	2	2	2
Asymp. Sig.	.985	.743	.995	< .001	< .001	.078	< .001

Note. # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (m^2a/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

Table 14

Kruskal-Wallis H Mean Ranks for Significant Differences in Optimized Animal Feed Formulation Variables Based on Environmental Allocation Method

Variable	Coded allocation method	*N*	Mean rank
# Ingred	1.00	47	56.31
	2.00	32	56.34
	3.00	32	55.20
	Total	111	
CP, %	1.00	47	58.71
	2.00	32	54.48
	3.00	32	53.53
	Total	111	
Cost, $/kg	1.00	47	56.33
	2.00	32	55.88
	3.00	32	55.64
	Total	111	
CC/kg	1.00	47	36.54
	2.00	32	68.75
	3.00	32	71.83
	Total	111	
LO/kg	1.00	47	42.67
	2.00	32	65.44
	3.00	32	66.14
	Total	111	
FEP/kg	1.00	47	48.00
	2.00	32	60.81
	3.00	32	62.94
	Total	111	
TAP/kg	1.00	47	41.88
	2.00	32	65.63
	3.00	32	67.11
	Total	111	

Note. 1.00 = economic allocation method; 2.00 = energy allocation method; 3.00 = mass allocation method; # Ingred = number of ingredients; CP = crude protein content (%); CC = climate change (kg CO_2-e/kg feed); LO = land occupation (ma2/kg feed); FEP = freshwater eutrophication potential (kg P/kg feed); TAP = terrestrial acidification potential (kg SO_2/kg feed).

Summary

Due to non-normally distributed data, I chose the nonparametric Kruskal-Wallis H test to analyze my data. An individual Kruskal-Wallis H test was required to analyze the seven criterion variables against each of the three predictor variables. The results demonstrated significant differences in three or four criterion variables with each test. Crude protein content (%), CC (kg CO_2-e/kg feed), LO (m^2a/kg feed), and TAP (kg SO_2/kg feed) were significantly different based on database. Number of ingredients, crude protein content, LO, and TAP were significantly different based on assessment method. CC, LO, and TAP were significantly different based on allocation method. In Chapter 5, I interpreted the results as reported in this chapter, recommended directions for future research studies, and discussed the positive social change, theoretical, and practical implications.

Chapter 5: Discussion, Conclusions, and Recommendations

The issue that prompted me to search the literature was the need to understand how to integrate and manage data inputs for sustainability optimization and simulation modeling at the firm level (see Bayu et al., 2022). The development of sustainable food animal feed management had been identified as a critical priority in the agriculture industry to support the expected human population growth of two billion people by 2050 (Benavides et al., 2020; United Nations, n.d.-a). Achieving increased food animal production with lowered environmental impacts requires developing better decision-making tools via big data management in information systems. The purpose of this quantitative nonexperimental study was to examine the extent to which big data management of environmental impact sources, assessment methods, and allocation methods within MOO modeling could affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

Key findings of this study were significant differences in mean ranks of three or four criterion variables related to optimized animal feed formulation across each predictor variable. Crude protein content, CC, LO, and TAP were significantly different based on database. Number of ingredients, crude protein content, LO, and TAP were significantly different based on assessment method. Lastly, CC, LO, and TAP were significantly different based on allocation method. This chapter includes an interpretation of the findings outlined in Chapter 4, discussion of the limitations of this study as outlined in Chapter 1, recommendations for further research, implications of the research results for positive social change, and a summary.

Interpretation of Findings

The research question and hypotheses of this study were the following:

RQ: To what extent do environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling affect the consistency and predictability of sustainable food animal feed management practices at the farm level?

H_0: Environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling do not affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

H_a: Environmental impact sources, assessment methods, and allocation methods within multi-objective optimization modeling significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

The predictor variables were environmental impact database (GFLI or Agribalyse), assessment method (ReCiPe or EF), and allocation method (economic, energy, or mass). The criterion variables were number of ingredients, cost (USD/kg), crude protein content (%), and four environmental impacts including CC (kg CO_2-e/kg), LO (m^2a/kg), FEP (kg P/kg), and TAP (kg SO_2/kg). The research question was addressed using a quantitative nonexperimental design. The Kruskal-Wallis H test, a nonparametric analysis, was used to test for statistical differences between the criterion variables and each predictor variable, individually.

The Kruskal-Wallis H tests found significant differences in mean ranks among each criterion variable based on each predictor variable. The results indicated that four criterion variable mean ranks were significantly different based on database: (a) crude protein content (p = .019), (b) CC (p < .001), (c) LO (p < .001), and (d) TAP (p = .002). The results indicated that four criterion variable mean ranks were significantly different based on assessment method: (a) number of ingredients (p = .005), (b) crude protein content (p < .001), (c) LO (p < .001), and (d) TAP (p = .015). Lastly, the results indicated that three criterion variable mean ranks were significantly different based on allocation method: (a) CC (p < .001), (b) LO (p < .001), and (c) TAP (p < .001). With significant differences resulting from each analysis, I rejected the null hypothesis that no significant differences exist and accepted the alternative hypothesis that environmental impact sources, assessment methods, and allocation methods within MOO modeling significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

Number of Ingredients

The number of ingredients mean ranks across optimized diets were significantly different based on assessment method (p = .005), but not database (p = .344) or allocation method (p = .985). There was a higher mean rank for the number of ingredients in MOO diets using environmental impact data from the ReCiPe assessment method (65.44) compared to the EF assessment method (48.81). Previous studies also found the number of ingredients of optimized feed formulations to differ. Méda et al. (2021) demonstrated that food animal diets optimized for environmental impacts were more consistent in the number of ingredients used than baseline diets. The largest change was four fewer ingredients in swine diets for the 2P-feeding phase. Wilfart et al. (2023) found that trout diets optimized for environmental impacts had more ingredients (23) than baseline trout diets (16). In the current study, the difference in the number of ingredients aligns with prior study results. Although significance in the numerical or magnitude difference in environmental impacts of this study were not investigated, the results indicate that CC values across differing databases and allocation methods can be simultaneously employed in food animal MOO modeling if they are developed by the same assessment method.

From a practical perspective, the number of ingredients in feed formulations may not be as considerable a factor for feed managers as which ingredients are included in feed formulations. Benefits of maintaining consistency in the number of ingredients may include logistical ease (ingredient ordering and storage) and cost maintenance. However, these benefits are assuming consistency in the ingredients themselves, which is not guaranteed. A challenge to maintaining the number of ingredients is decreased flexibility in formulation. Seasonal ingredient quality and cost associations may require feed managers to change the number of ingredients in food animal diets to maintain animal performance and bottom line. Restricting the number of ingredients would minimize this flexibility. In my data set, the number of ingredients generally doubled when using environmental impact data from the ReCiPe assessment method compared to the EF assessment method. The practical significance of this is likely low because the number of ingredients were low in either scenario (e.g., broiler grower diets generally increased from four to eight ingredients).

Crude Protein Content

The crude protein content mean ranks across optimized diets were significantly different based on database ($p = .019$) and assessment method ($p < .001$) but not on allocation method ($p = .743$). There was a higher mean rank for the crude protein content in MOO diets using environmental impact data from the Agribalyse database (74.07) and EF assessment method (66.13) compared to the GFLI database (53.18) and ReCiPe assessment method (42.71). Differences in crude protein content of optimized feed formulations were reported in one prior study.

Méda et al. (2021) reported changes in crude protein content of diets based on feeding phase strategy and optimization type. Crude protein content of broiler three-phase diets increased by 1%–2% in the enhanced strategy (3P+) compared to nonenhanced strategy (3P), but optimization type (baseline or MOO) did not affect crude protein content. Méda et al. expected increases based on enhanced or nonenhanced diets because enhanced diets included more highly digestible amino acids. Although I did not test for significant differences in crude protein content based on optimization type, my findings revealed that broiler chicken diet crude protein content decreased by up to 8% in MOO diets compared to baseline when environmental impacts from the ReCiPe assessment method were employed but increased by up to 68.8% when the EF assessment method was employed. These differences are partially attributable to the use of only minimum (and not also maximum) crude protein content constraints in the current study. From a practical perspective, because protein is more metabolically, environmentally, and monetarily expensive to produce than other nutrients, ensuring food animal diets do not include excess crude protein content should be an important consideration.

Cost

The cost mean ranks across optimized diets were not significantly different based on database (p = .993), assessment method (p = .933), or allocation method (p = .995). Costs were increased with MOO diets compared to baseline. Broiler chicken diets increased from 55%–89%, swine diets increased from 89%–92%, and beef cattle diets increased from 30%–97%. Although mixed results related to costs of food animal diets optimized for minimal environmental impacts have been demonstrated across prior studies, the changes were much lower than demonstrated in the current study (Garcia-Launay et al., 2018; Méda et al., 2021; Wilfart et al., 2023). Considering that the cost increases of the current study would result in a need to increase meat product costs for consumers, they are highly impractical.

Garcia-Launay et al. (2018) reported cost increases of 1%–7% across their multi-objective diets compared to baseline diets with higher costs associated with broiler chicken diets. Results of environmental impact index and price index plots demonstrated a trend for lower environmental indices to be associated with higher price indices irrespective of food animal species or feeding phase (Garcia-Launay et al., 2018). Méda et al. (2021) demonstrated average changes of 3%–4% in formulation cost with the greatest change being a 6% increase. Cost changes were based on feeding phase rather than MOO modeling (Méda et al., 2021). In contrast, Wilfart et al. (2023) found their MOO diet to cost less than their baseline diet (1171.50€ and 1276.90€, respectively), although the difference (105.40€) was unlikely to be of practical significance. In contrast, feed managers would not be able to afford such high increases in formulation costs as demonstrated in the current study without raising food prices in the human food supply chain. With known variability in ingredient costs based on freight, purchase volumes, inflation, and more, a practical conclusion is to consider the factor of cost on a case-by-case basis.

CC

The CC mean ranks across optimized diets were significantly different based on database ($p < .001$) and allocation method ($p < .001$), but not on assessment method ($p = .905$). There was a higher mean rank for CC of MOO diets using environmental impact data from the GFLI database (61.79) and mass allocation method (71.83) compared to the Agribalyse database (18.97) and economic or energy allocation methods (36.54 and 68.75, respectively). Significant differences were expected, because the allocation method is known to result in environmental impacts of different values. The current study data demonstrated both decreases and increases in CC of MOO diets compared to baseline. Numerically, across feeding phase from baseline to MOO diets, CC (a) decreased between 15.8% and 91% for broiler chickens, (b) decreased between 29.4% and 99.6% or increased up to 110% for swine, and (c) decreased between 11.9% and 100% or increased up to 30.9% for beef cattle.

Positive effects of MOO diets for food animals on CC had been reported in prior studies. Researchers demonstrated decreases of 5.1%–46% with no demonstrated increases (de Quelen et al., 2021; Garcia-Launay et al., 2018; Méda et al., 2021; Wilfart et al., 2023). Importantly, de Quelen et al. reported all environmental impacts per kg of body weight or body weight gain, which means the values cannot be directly compared; however, trends for decreases and increases can still be considered in relation to the current study. Additionally, although Méda et al. reported on environmental impacts per diet and per kg of food animal live weight (separately), only diet-related environmental impacts are discussed in this chapter.

CC increases demonstrated in the current study with swine and beef cattle MOO diets coincide with crude protein content increases of 71.7% and 41.4%, respectively. These data exemplify the environmental demands of crude protein content. However, CC did not increase from every baseline to MOO diet where crude protein content also increased, which supports the conclusion that other factors (database and allocation method) affect environmental impacts in MOO modeling. Although significance in the numerical or magnitude difference in environmental impacts of this study were not investigated, the results indicate that CC values across differing assessment methods can be simultaneously employed in food animal MOO modeling if they are sourced from the same database and calculated by the same allocation method. These differences further support the conclusion that environmental impact database and allocation method significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

LO

The LO mean ranks across optimized diets were significantly different based on database ($p < .001$), assessment method ($p < .001$), and allocation method ($p < .001$).

There was a higher mean rank for LO of MOO diets using environmental impact data from the GFLI database (62.48), EF assessment method (67.44), and mass allocation method (66.14) compared to the Agribalyse database (14.50), ReCiPe assessment method (40.98), and economic or energy allocation methods (42.67 and 65.44, respectively). Significant differences were expected, because the allocation method is known to result in environmental impacts of different values. Numerically, across feeding phase from baseline to MOO diets, LO decreased a) between 71% and 91.2% for broiler chickens, (b) between 69.8% and 97.3% for swine, and (c) by nearly 100% consistently for beef cattle.

Mixed effects of MOO diets for food animals on LO have been reported in prior studies. Garcia-Launay et al. (2018), de Quelen et al. (2021), and Méda et al. (2021) reported both decreases (1.2% to 26%) and increases (0.7% to 18%) in LO across species and feeding phases when comparing MOO diets to baseline, while Wilfart et al. (2023) reported a decrease (23.7%). Of importance, Wilfart et al. compared a single MOO diet to a single baseline diet while the other researchers compared multiple baseline and MOO diets, which was also the design of the current study. Based on the trends of prior studies, Wilfart et al. may have demonstrated both decreases and increases in LO had they included more diet considerations (e.g., feeding phases, limited ingredients, locally sourced ingredients, etc.).

The particularly high LO decreases for beef cattle reported from the current study are attributable to the bermudagrass hay ingredient included in beef cattle finisher diets, which is not an ingredient included in either database employed. Therefore, there were no

LO data associated with bermudagrass hay which led to the MOO model assuming this ingredient to be the most sustainable option. This exemplifies the importance of including environmental impact values from different sources to improve the accuracy of MOO modeling for sustainable food animal feed formulation practices at the farm level. Although the numerical or magnitude difference in environmental impacts of this study were not investigated, the results indicate that LO values across differing allocation methods can be simultaneously employed in food animal MOO modeling if they are sourced from the same database and developed from the same assessment method. These differences further support the conclusion that environmental impact database, assessment method, and allocation method significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

FEP

FEP mean ranks across optimized diets were not significantly different based on database (p = .555), assessment method (p = .584), or allocation method (p = .078). Significant differences were expected, because the allocation method is known to result in environmental impacts of different values; however, this was not demonstrated in the current study. These results insinuate similarity among FEP values across the databases, assessment methods, and allocation methods examined.

Mixed effects of MOO diets for food animals on FEP have been reported in prior studies. Garcia-Launay et al. (2018), Méda et al. (2021), and Wilfart et al. (2023) reported decreases (5.7% to 37%) in FEP across species and feeding phases when comparing MOO diets to baseline. Of note, Garcia-Launay et al. did not include FEP as an optimization criterion, so their reported decreases were artifacts from optimizing CC, LO, PD, NED, and cost. de Quelen et al. reported decreases (6% to 8%) and increases (2.5% to 3.4%) in FEP from baseline to MOO diets for swine. In the current study, FEP was numerically decreased from baseline to MOO diets across species and feeding phases from 41.7% up to nearly 100%; however, values were low in all scenarios (e.g., from 0.02 to 0.01). This likely explains the nonsignificant result in mean rank differences. Although the numerical or magnitude difference in environmental impacts of this study were not investigated, the results indicate that FEP values across differing databases, assessment methods, and allocation methods can be simultaneously employed in food animal MOO modeling.

TAP

TAP mean ranks across optimized diets were significantly different based on database (p = .002), assessment method (p = .015), and allocation method (p <.001). There was a higher mean rank for TAP of MOO diets using environmental impact data from the GFLI database (59.81), EF assessment method (62.46), and mass allocation method (67.11) compared to the Agribalyse database (31.63), ReCiPe assessment method (47.52), and economic or energy allocation methods (41.88 and 65.63, respectively). Significant differences were expected, because the allocation method is known to result in environmental impacts of different values. Numerically, across feeding phase from baseline to MOO diets, TAP decreased a) between 34.3% and 88.9% for broiler chickens, (b) between 35.6% and 99.8% for swine, and (c) between 25% and 100% for beef cattle.

Positive effects of MOO diets for food animals on TAP have been reported in prior studies. Garcia-Launay et al. (2018), de Quelen et al. (2021), Méda et al. (2021), and Wilfart et al. (2023) reported decreases (1% to 29.4%) in TAP when comparing MOO diets to baseline across species and feeding phases. Therefore, the trend of TAP decreasing from baseline to MOO diets is consistent between the current and prior studies. The 100% TAP decrease demonstrated with beef cattle in the current study is once again due to the high inclusion level of bermudagrass hay in finisher diets. Without reported environmental impacts, this ingredient appears to the MOO model as completely sustainable. In addition to exemplifying the benefits of including environmental impacts from different databases, assessment methods, and allocation methods within a single model, these data also demonstrate the importance of human interpretation within information systems.

Although the numerical or magnitude difference in environmental impacts of this study were not investigated, the results indicate that TAP values across differing databases, assessment methods, and allocation methods cannot be simultaneously employed in food animal MOO modeling. These differences further support the conclusion that environmental impact database, assessment method, and allocation method significantly affect the consistency and predictability of sustainable food animal feed management practices at the farm level.

Limitations of the Study

This study was a quantitative nonexperimental design in which I used non-manipulated secondary data. External validity threats were successfully minimized by the nonexperimental design and the foundation of prior studies that appropriately narrowed the focus of the current study and allowed for comparison with existing related results. One anticipated limitation was the lack of environmental impact data for feed additives. Although I included necessary feed additives for MOO modeling, these data did not have published associated environmental impacts. This resulted in any MOO models that used feed additives to be unavoidably skewed toward lower environmental impacts. However, this is also the case in real-world scenarios which rendered the results from the current study reflective of practical implementation.

A second anticipated limitation concerned the use of only two environmental impact databases. This limitation was unavoidable because it was not practical to include all potential databases in a single study but was mitigated by including a database used in prior studies. The last limitation was the use of a nonparametric statistical test rather than a MANOVA, which would have allowed me to determine correlation. Although my test results indicated significant differences, the Kruskal-Wallis H test is only able to analyze for significant differences across mean ranks rather than the actual value of each criterion variable.

Recommendations

The results of the current study indicated significant differences in MOO modeling outputs based on environmental impact database, assessment method, and allocation method. However, the sources of significant differences (e.g., database, assessment method, and allocation method) were not the same across the criterion variables (number of ingredients, crude protein content, cost, and four environmental impacts). This demonstrates a need for future research to investigate what is driving the differences. Additionally, because I had to perform a nonparametric test on each predictor variable separately, I was unable to examine if significant differences existed for predictor variable interactions. Considering that the predictor variables are linked (e.g., one set of data came from the Agribalyse database which was developed via the EF assessment method and economic allocation), it would be reasonable for a future research question to involve examination of these interactions.

The addition of environmental impact values sourced from other databases not employed in the current study would provide further support of the effect of database on the consistency and predictability of sustainable food animal feed management practices at the farm level. The possibility exists that specific databases are more compatible and could be recommended for use together to improve the accuracy of MOO modeling for sustainable food animal feed formulation, but this has yet to be extensively explored. The current study was the first, to my knowledge, to examine differences in MOO modeling outputs based on environmental impact value source (i.e., database).

Because I was unable to carry out the original research plan to analyze for statistical differences in the actual criterion variable values via a MANOVA to report on correlations, future researchers may also consider ways to successfully perform parametric tests. The MANOVA was inappropriate for the current study due to nonnormal data. Future researchers may successfully demonstrate normally distributed data if MOO model outputs are analyzed per food animal species and feeding phase rather than altogether. Food animal species have different nutritional requirements at each feeding phase, and these requirements determine most of the MOO model constraints. Although I used the same nutrient requirement categories (e.g., minimum crude protein) across species and feeding phase as MOO model constraints, the numerical value of each category differed by species and feeding phase. From a practical perspective, this allowed the MOO model to include or disregard ingredients by different criteria. Using normally distributed data would address the nonparametric test limitation of the current study.

Future researchers may also consider expanding the study scope to additional food animal species and alternative production operations. As identified in Chapter 1, the U.S. produces at least seven species of food animal, but the current study scope was delimited to broiler chickens, beef cattle, and swine. Within food animal species, there are also multiple types of production as specified in the current study. For example, I included broiler (meat) chickens and beef cattle but there are also layer (egg laying) hens and dairy cattle that could be examined. Furthermore, I delimited this study to specific feeding phases (see Table 1), but these are not the only phases employed across the U.S. food animal industry. Examining alternative feeding phases could change the nutritional requirements of the food animal species, which would affect MOO modeling.

Implications

Social Change Implications

Through improving big data management of sustainable food production, I aimed to contribute to three United Nations sustainable development goals of (a) zero hunger, (b) responsible consumption and production, and (c) climate action. The social change implication of reaching these goals is producing enough food to feed a growing human population without further degrading the environment through unsustainable natural resource use. The main contribution of the current study toward these goals is the ability to use environmental impact values across databases, assessment methods, and allocation methods to produce food animal feed formulations with lowered environmental impacts compared to baseline. Although I was unable to demonstrate comparability across all environmental impacts for each predictor variable, I was able to demonstrate some comparability which is an important step forward. For example, from the results I can infer that FEP values from either database (Agribalyse or GFLI), assessment method (ReCiPe or EF), or allocation method (economic, energy, or mass) examined can be used interchangeably within MOO modeling for food animal feed formulation. Using environmental impacts from across sources can allow food animal producers to develop more complete ingredient profiles, thus increasing the accuracy of sustainable feed formulation predictions. More sustainable feed formulations are a step toward more sustainable food animal production to feed a growing human population.

Theoretical Implications

The theoretical purpose of the current study was to consider aspects of big data management, sustainability management, data modeling and analytics, and information systems that could affect the future of sustainable food production. Specifically, I aimed to contribute knowledge related to the accuracy of sustainable food animal feed formulation modeling by expanding environmental impact value sourcing. To achieve this, I developed a theoretical foundation based on the integration of DCV, representation theory, TEU, and NRBV. Together, these theories describe the necessity of accurate representation and management of real-world environmental impact big data within information systems to increase food animal production with lowered environmental impacts.

The outcome of the current study supports the perspective of integrating information systems theories into practical food animal feed formulation processes targeted at sustainable production. However, continued research and improvements are necessary to further integrate the social science of information systems with the natural science of environmental sustainability. As previously discussed, strategic management of agricultural sustainability platforms requires that the use of environmental big data (a) accurately represent current food production, (b) include easy access and implementation, and (c) feature sustainable development as a plausible outcome. All three of these requirements were met to varying degrees in the current study.

Accurate representation of current food production was attempted in the current study by including environmental impacts from more than one database. The benefit of including these data was more complete environmental impact profiles for each feed ingredient (e.g., a value may be missing from one database but available in another). From a DCV perspective, more complete ingredient profiles could allow food animal producers to develop greater dynamic capabilities with more accurate predictions of sustainable feed formulations. The challenge of including these data was that the environmental impact values were based on specific types of ingredient production (e.g., Agribalyse values were derived from the French agricultural industry while GFLI values were derived from agricultural industries across several countries including the U.S., Brazil, Canada, the Netherlands, and others). From a representation theory perspective, this challenge may be mitigated if there are enough similarities between production processes for the environmental impact values to be considered representative of more than one country of production. This requires further consideration as to minimum acceptable similarities.

Easy access and implementation of data was also attempted in the current study by including environmental impact values from two databases, two assessment methods, and three allocation methods. The benefit of including these data was the simplicity afforded to request the MOO model to use a specific set of environmental impact values. The challenge was extracting the data from the sources, converting data where necessary, and organizing the data into the MOO model database (spreadsheet). From a TEU perspective, once the data were properly organized and stored in the MOO model database, the modeling process was easy to perform across data sets. However, the process of transferring the environmental impact data from their original databases took time and attention to detail. Not only are Agribalyse and GFLI not organized in the same way, but some of the environmental impacts are also reported in different units and require mathematical conversions to be used together. Constant review of separate databases for new or updated environmental impact values is not the most efficient process for food animal producers to include these data into their formulation modeling systems.

Lastly, sustainable development as a plausible outcome was achieved in the current study. The Kruskal-Wallis H test only examined the presence of significant differences across mean ranks of the criterion variables based on environmental impact database, assessment method, and allocation method rather than significant differences in the criterion variable values themselves; however, I identified numerical differences. Across MOO models, there were numerical increases and decreases in environmental impact values. The decreases indicated sustainable food animal feed formulations as a plausible outcome of the system. The degree to which the decrease is significant requires further investigation.

A conclusion regarding the theoretical implications is that although I included human use of the information system through TEU, I did not account for any further interactions between human users and the system. In the current study, I found that the MOO model was not able to distinguish between values of 0 and missing values. Missing values occurred most often within the environmental impact data sets (e.g., regarding bluestem grass) where environmental impacts did not exist. Distinction between the two required human interpretation of the results based on knowledge of the inputs. An extension of the theoretical framework to encompass greater portions of human-information system interactions may be beneficial.

Practical Implications

From the current study, I was able to identify two areas for consideration when implementing environmental impact values in food animal feed formulation modeling at the farm level. The first is big data management of environmental impact values. At the time of the current study, there were numerous databases (some freely accessible, some requiring a paid subscription) housing environmental impact values. There is an impracticality in expecting or assuming U.S. food animal producers will have the ability to access all databases and regularly review the databases for new or updated values. A potential solution is for U.S. food animal producers to choose specific databases from which to extract environmental impact values and monitor this small subset.

The second area for consideration is to ensure human interpretation of the feed formulation modeling results within the context of the farm. For example, in the current study I demonstrated that the number of ingredients within formulations across species and life stages doubled, on average, when using environmental impact values developed from the ReCiPe assessment method compared to the EF assessment method (there were no affects based on database or allocation method). However, a doubling of the number of ingredients in a feed formulation from four to eight may be interpreted differently than a doubling from 10 to 20. Additionally, this change requires interpretation in relation to other changes, such as cost, nutrient profile, and environmental impacts (e.g., trade-offs). A MOO modeling information system can identify trade-offs between scenarios, but the human user needs to interpret the practical implications and significance of those trade-offs and apply the results to decision making.

Conclusions

The purpose of this study was to examine if environmental impact sources (database), assessment methods, and allocation methods within MOO modeling significantly affected the resulting food animal feed formulation ingredient profile (number of ingredients), crude protein content, cost, and four environmental impact values. All but one criterion variable was significantly affected by one or more predictor variable. The results indicated that environmental impact source, assessment method, and allocation method significantly affect the consistency and predictability of sustainable feed formulation at the farm level. However, because not all predictor variables significantly affected all criterion variables, this also demonstrates some compatibilities in environmental impact values across the Agribalyse and GFLI databases, ReCiPe and EF assessment methods, and economic-, energy-, and mass-based allocation methods when used in MOO modeling for U.S. broiler chicken, beef cattle, and swine feed formulations.

Including environmental impact big data derived from multiple sources, assessment methods, and allocation methods into feed formulation information systems may increase the accuracy of ingredient profiles represented by the system. Increasing ingredient profile accuracy may lead to increased accuracy of sustainable feed formulation predictions. Understandably, multiple environmental impact values for a single ingredient will still exist due to ingredient specifics (e.g., locale of production, production processes). Considering the positive social change impact that sustainable food animal feed formulations may have, a solution is needed to reconcile environmental impact values into compatible databases and to standardize assessment and allocation methods that allow for consistent predictability of sustainable outcomes.

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Appendix: Criterion Variable Histograms

Figure 7

Histogram of Number of Ingredients

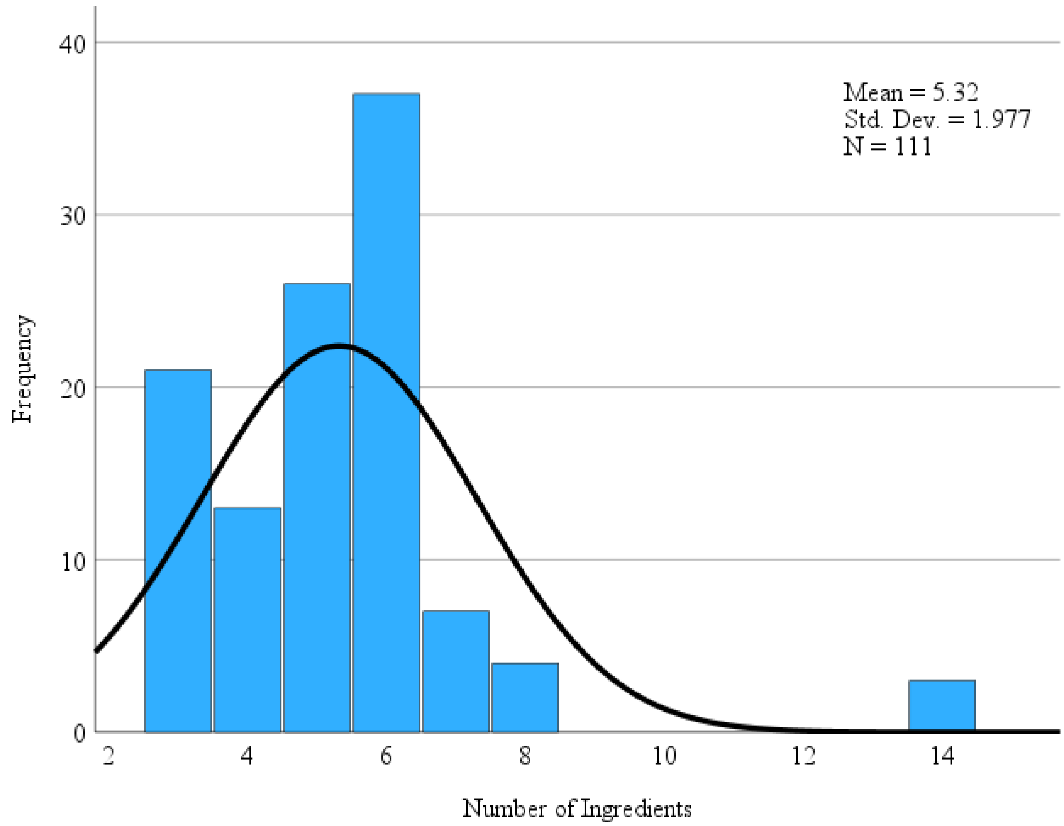

Figure 8

Histogram of Crude Protein Content (%)

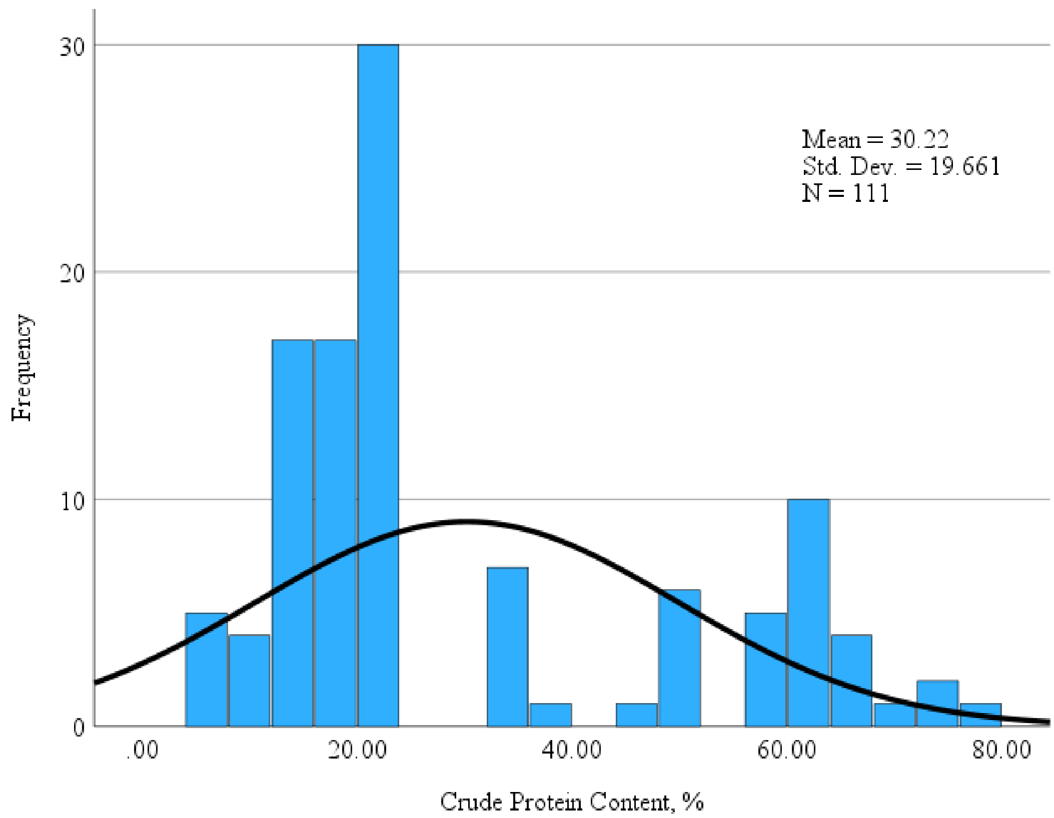

Figure 9

Histogram of Cost (USD/kg feed)

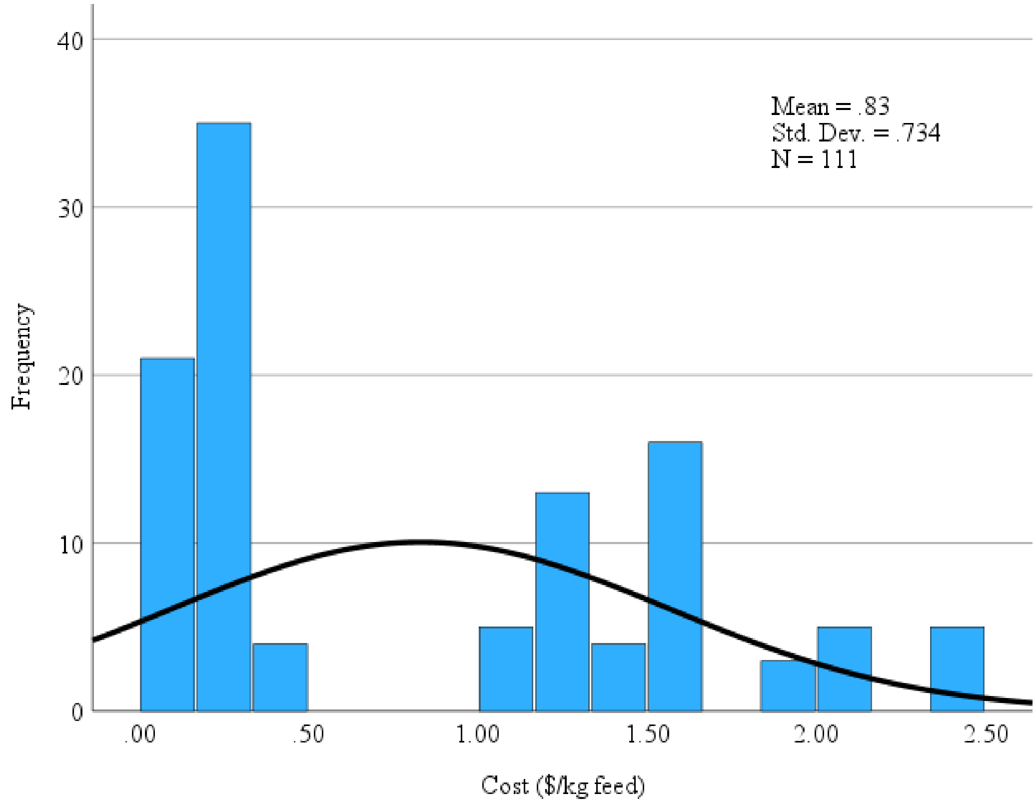

Figure 10

Histogram of Climate Change (kg CO_2-e/kg feed)

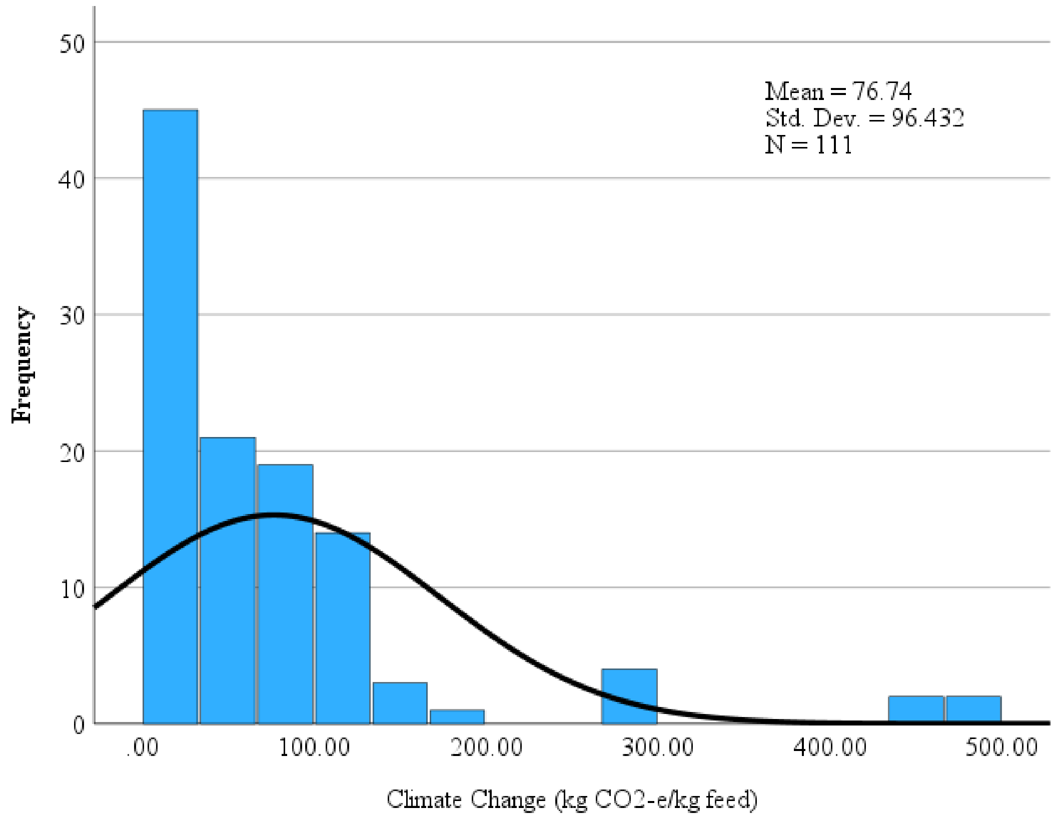

Figure 11

Histogram of Land Occupation (m^2a/kg feed)

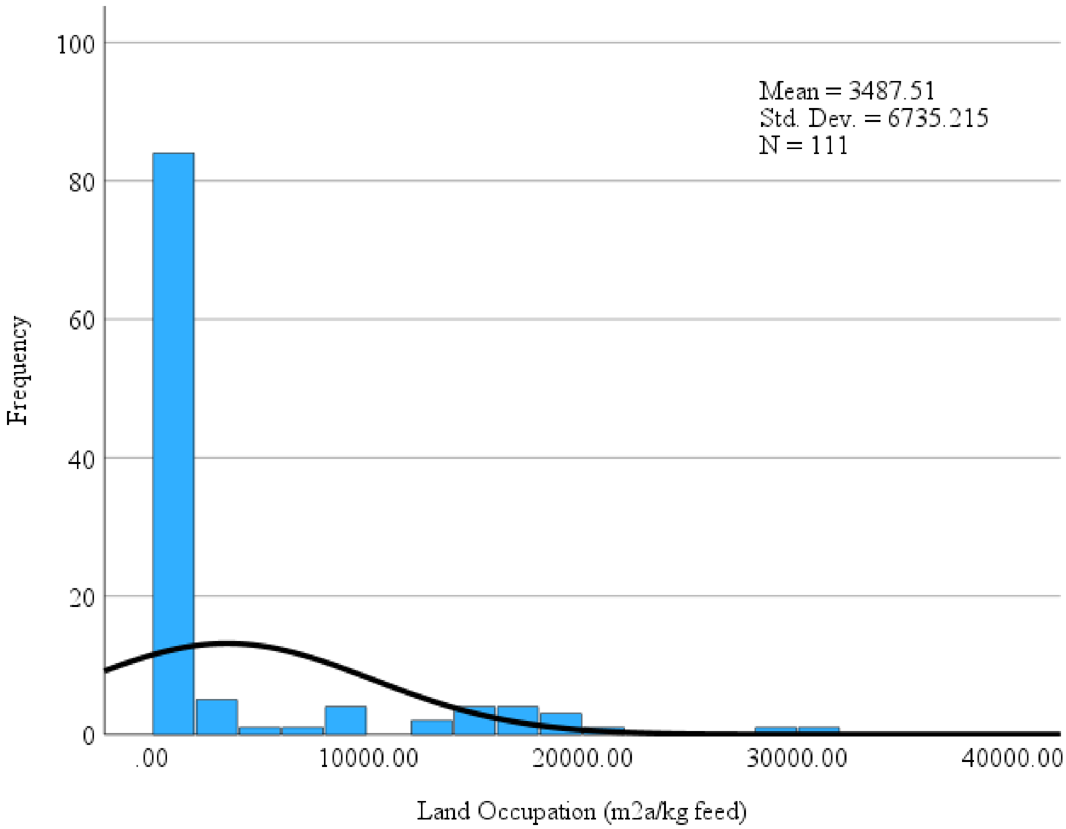

Figure 12

Histogram of Freshwater Eutrophication Potential (kg P/kg feed)

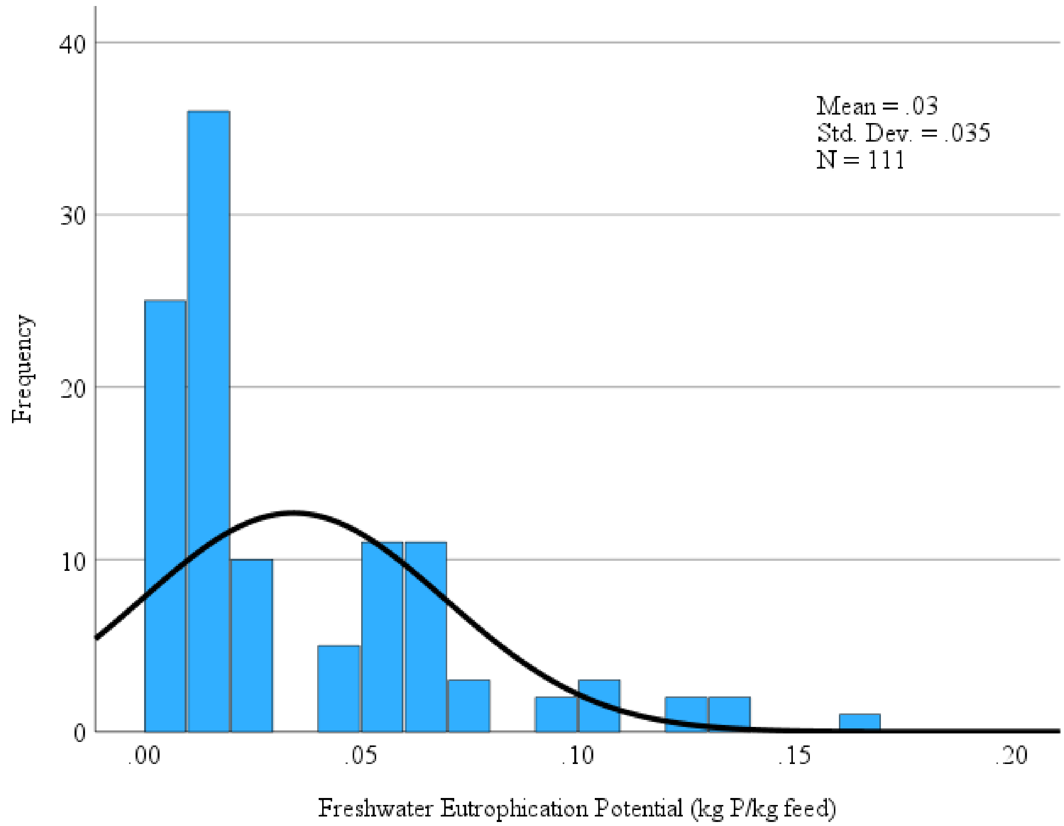

Figure 13

Histogram of Terrestrial Acidification Potential (SO_2/kg feed)