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Data-driven Decision Support Tools for Reducing GHG Emissions from Livestock Production Systems: Overview and Challenges

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***Abstract*— Livestock sector is known for its contribution to environmental pollution. A large portion of anthropogenic emissions is from livestock-related activities, such as animal feeding and manure management. According to the Food and Agriculture Organization of the United Nations, by 2050, 73% increase in livestock product consumption is anticipated. This poses an alarming threat to the environmental sustainability as a proportionate increase in greenhouse gases (GHG) emission is also expected. On the bright side, with the support of appropriate technologies and mitigation strategies, the livestock production sector is capable of achieving a substantial reduction in the level of emissions. A consistent quantitative analysis of emissions and related activities can help in identifying the sensitive areas to intervene. There are several data-driven decision support tools and practices available in literature that aim to help farmers contribute to sustainability. In this work, we provide an overview of the popular data-driven modelling techniques and decision support tools used to estimate GHG emissions from the various livestock farming-related sources. We also discuss the role of decision support tools in various management activities, such as analysing and designing farm systems trials and integrating environmental, technological and economic aspects. Finally, we discuss the challenges and opportunities in using data for decision support in reducing GHG emissions in livestock farming.**

Keywords*— *Livestock farming, greenhouse gases, modelling, decision support systems, sustainability.

I. Introduction

The livestock sector is closely related to the lives of millions in many ways, ranging from hunger eradication to social stability. The livestock food sector has an important role in global food security by providing food, employment and income, and contributing up to 20% of total agriculture in developing countries and 40% in developed countries [1]. Worldwide, 11% of the global population are reported to be undernourished and 45% of child death under the age of five are caused by severe acute malnutrition [2]. Protein energy nutritional value of animal source foods (ASFs), such as essential amino acids and micro-nutrients, present a great alternative option to population groups with limited access to a nutritious rich plant-based diet. Although the ASFs play a vital role in feeding the world, the livestock sector is also accounted for its harmful contribution to climate changes. Livestock farming has a significant impact on the earth as it contributes to a range of environmental issues, such as terrestrial biodiversity loss, soil acidification and air pollution, global warming and water pollution. As an important user of natural resources, it alters the carbon, nitrogen and phosphorus cycles (nutrient cycles), as well as the water cycle. It has been reported that Greenhouse gases (GHG) emitted from animal housing, yards, manure storage and treatment are responsible for 18% of the total anthropogenic GHG emission in worldwide [1]. This can also have a severe impact on human health, as well as animal health, giving rise to the need of a more sustainable livestock system. Although GHG emissions from livestock sector are massive, studies show that there is a large scope (up to 30%) to reduce GHG emissions from this sector [3]. GHG emissions mitigation can be achieved through several direct and indirect strategies, such as precision diet, vaccines, and selective breeding. Decisions of adopting the best management practices, in view of environmental pollution, are highly dependent on the economic benefits. A detailed understanding of the variables associated with, and their exact impact on the profitability, can help farm operators in various decision-making processes. With this aim, the concept of precision livestock farming (PLF), as the application of process engineering principles and techniques to livestock farming, can bring about innovativeness in sustainable livestock production through automatic monitoring, modelling and management of animal production or any GHG emission related livestock activities.

PLF uses IoT devices and data modelling techniques to continuously collect information from animals, and analyse it for making decisions, both related to the animals and to the environment. Previous studies indicate that PLF can be used to reduce the environmental damage caused by livestock farming [4, 5]. For instance, Peña Fernández et al. (2017) used PLF technologies to monitor chicken activities for modelling bio-aerosol concentration in poultry houses [6]. The use of PLF technologies in reproductive management and reduced GHG emission is also studied by Hristov et al. (2013) [7]. Nevertheless, there is no reference to PLF technology that is specifically developed to reduce the environmental load of livestock farming [8].

In recent days, use of PLF technologies in various processes, including the ones that give rise to greenhouse effect, such as feed efficiency and fertility management, are widely being accepted by the sector. For example, technologies for precision feeding not only improve animal welfare, but also reduce rumination time, which indicates less methane emission. Use of sensors in detecting animal illnesses at an early stage can also decrease the environmental burden through reduced use of antibiotics and blocking disease spread. Accurate management of fertility is another area where the IoT technologies are widely used. These technologies ensure successful and optimized animal reproduction by which a significant reduction of GHG emissions can be achieved. This increased interest in PLF technologies presents a strong possibility of enabling sustainable development by combining existing GHG emissions mitigation models and IoT devices.

In this paper, we investigate the role of data in decision support for reducing emissions of GHG from livestock by reviewing the already reported tools and literature. The rest of the paper is organised as follows. Section II presents an overview of the global status of livestock GHG emission and a brief introduction to emission estimation techniques. In Section III, components of decision support systems and their contribution to livestock farm management activities are discussed. Section IV discusses the various categories of modelling techniques used to estimate GHG emissions from individual sources. Rather than focusing on a single emission source, it is important to quantify the total emissions by considering the different processes in the whole livestock system and, hence, they are discussed separately in Section V. The data-driven decision support in livestock farming is associated with many practical challenges, such as data scarcity and model complexity, and these aspects are discussed in Section VI. Finally, in Section VII, we conclude the paper.

II. GHG Emissions from the Livestock Sector

The livestock sector is known for its direct and indirect contribution to global climate change through the emission of gases such as Carbon Dioxide (CO_2), Methane (CH_4), Nitrous Oxide (N_2O) and Hydrofluorocarbons (HFCs) [3]. While direct GHG emissions are associated with activities that are close to the livestock farms, such as enteric fermentations and anaerobic digestion of animal manures, indirect emissions are related to off-farm processes, such as feed crop production and product supply chain. Several techniques, like the Intergovernmental Panel on Climate Change (IPCC) equations, Life cycle assessment (LCA) and whole-farm models, for livestock GHG emission estimation are reported in literature [10].

IPCC guidelines consider the photosynthesis process to assume that the net CO_2 from livestock is zero and focus only on CH_4 and N_2O emissions from activities that are connected to farms, such as enteric fermentation and manure management [9]. GHG emissions estimation guidelines of IPCC are based on a three-tier hierarchy concept, in which Tier 1 uses basic livestock characterisation data, such as species and annual population, and Tier 2 uses more detailed information, such as livestock subcategories and feed intake. Tier 3 uses more sophisticated parameters like the detailed feed intake, regional trends, seasonal variations in livestock population, quality of animal food and nutritional supplements. Though Tier 1 methods are easy to implement, their inability to consider finer geographical details, such as soil type and climate variations, can result in inaccurate estimates. Since Tier 1 methods use a number of default sets of values, these methods are good for calculating emissions from minor sources, such as CH_4 from manure management and collection yard. Conversely, higher tier methods are known for their complexity and computational intensity, and correspondingly more accurate results. For more specific emission estimation, IPCC recommends Tier 3 approach as the approach considers region-specific high-resolution activity details.

The livestock product life encompasses a number of activities, such as raw materials production and acquisition, energy needs, livestock rearing, product manufacturing and product transportation and distribution. Therefore, a life cycle assessment (LCA) approach would be more suitable for accurate measurement of the total carbon footprint associated with livestock activities. In the LCA approach, the different stages between the cradle to grave of the product can be analysed to gauge its environmental impact. The main steps associated in LCA are setting of goals and scope, identification of parameters associated with each stage, building a model to represent its environmental interaction and impact assessment. In order to deal with the modelling part, based on the individual lifetime activity, LCA applies methodologies, such as energy analysis and IPCC guidelines. Functional units (FUs) are the important concept in LCA and they measure the product function to identify the reference basis for environmental impact assessment. Product function refers to what the product meant to do such as satisfy the protein need of the human body. For example, to assess the emissions from dairy sector, UNFAO (2010) report considered fat-and-protein corrected milk (FPCM) as a product and the resulted emission per kilogram of fat/protein is the FU [11]. In other words, functional units are the quantitative measures of livestock products like meat, milk and eggs to cause the environmental impacts identified. Some of the common FUs used in livestock sector are emissions per *kg of product, kg of protein, average daily per person intake* [12]. Global GHG emissions are usually represented in gigatons CO_2 equivalent ($GtCO_2eq$) [11]; where CO_2eq is a comparison measure of the amount of a particular greenhouse gas and its equivalent weight of CO_2 that would need to warm the earth by the same degree of heat [9].

According to the Food and Agricultural Organization of the United Nations (FAO), annually 7.1 $GtCO_2eq$ greenhouse gasses are emitted from livestock related activities [3]. While CH_4 is the most emitted gas from the sector with a measure of 3.1 $GtCO_2eq$, N_2O and CO_2 are emitted in equal amounts, measuring 2 $GtCO_2eq$. FAO uses a combination of Tier 2 models from IPPC guidelines and LCA approach to calculate net emissions from the global livestock sector. If we look into the emission on the basis of species, 65% of the total emission is contributed by cattle and other livestock, such as pigs, while poultry and small ruminants share almost equal contributions, ranging 7-10%. On a whole-farm view, processes associated with animal feed, such as production and transport, cause 45% of emission, and another 40% is caused by ruminant fermentation, 10% from manure processing activities and almost 5% is from energy usage. In a regional view, Latin America and the Caribbean top by contributing 18% of the total global livestock emission. Although East Asia tops the livestock production, emission from the region is 1 $GtCO_2eq$, causing almost 14% of the sector's emission. North America, South Asia and West Europe share the third place with almost 8.5% of the GHGs. North African and Sub-Saharan African regions also act as a significant contributor of livestock emission with an annual average of 0.3 $GtCO_2eq$. Many strategies, such as reducing livestock production as a whole, and controlling the climate-sensitive activities, are reported in literature [14]. Improving feed quality, increasing digestibility, adding fatty acids to diet and lipid supplementation, are some reported procedures for reducing enteric fermentation related emissions [3]. According to several studies, with improved feed quality, up to 15% methane reduction can be achieved per unit of fat protein corrected milk [1]. Policies, such as keeping manure in a low temperature, frequently removing manure from the farms, solid-liquid separation and diet adjustments, are helpful in reducing N_2O emissions. Proper manure management can achieve a 55% reduction in CH_4 emission and 41% mitigation in N_2O emission. Planning feed production related activities, like timing and adopting best practices of fertilizer application, can also help farmers in achieving a sustainable livestock farming. Animal efficiency, in terms of higher productivity, can also help to reduce the global warming potential. An efficient animal needs less nutrients, and nitrogen in faeces and urine will also be less. In addition, good animal management practices, such as selective breeding and improved animal, have a powerful GHG emissions mitigating effect [14].

In summary, proper mitigation strategies and techniques can achieve a significant amount of emission reduction (up to 41%) from the livestock sector [3]. The procedure for developing good mitigation strategies includes identifying the main drivers of GHG sources, using appropriate modelling techniques to understand what are the outcomes for the different mitigation interventions, and assessing all available mitigation strategies in terms of both sustainability and profitability. I. e., a decision support system with appropriate modelling techniques can help practitioners and decision makers to achieve a great extent of mitigation potential.

III. Decision Support Systems in the Livestock Sector

Decision Support Systems (DSSs) are computer-based recommendation systems which use techniques, such as information gathering, analysis and extraction of hidden insights, to help organizations with their decision-making activities [15]. Broadly, DSSs consist of two components: *data warehouse* – to store and manage data and *analytical processing unit* – to build an appropriate model that accurately represents the management problem in hand. Effectiveness of DSSs depends solely on the structure of the problem [16]. Some situations are static, with definite problem statement and solution, and such problems are known as structured problems. If a specific level of uncertainty is involved in the situation, then the problem is termed as semi-structured, and if the situation is highly chaotic, then it is known as unstructured problem. DSSs work well with structured and semi structured problems as the underlying mathematical relations can easily be formulated and to a lesser extend with unstructured problems because of their intrinsic modelling complexity.

Modelling is an inevitable aspect of modern DSSs. It considers the problem-relevant parameters of the system of interest and identifies their mathematical relationships with output performance parameters, providing scenarios that explain the system’s behaviour. These mathematical relationships can have a number of forms, such as statistical approximations, differential equations or game theory approaches. In most cases, models are built either to achieve an optimal solution for the problems within the time and resource constraints, or to assess a given system by simulating the model with different sets of parameter values. In livestock sector modelling is reported to be a very relevant management tool for different aspects, such as animal management, sustainability and production in livestock farming.

Use of modelling techniques in describing animal systems started in the year 1914, when Wood and Yule (1914) established a mathematical association between diet with starch content and animal output [17]. Most of the models used in earlier time were focusing on the static animal growth models and nutrient requirements with some predefined input set [17,18]. With the advent of computers and information technologies, researchers started to use more complex techniques to model and simulate dynamic behaviours of animal systems. Models suggested by Whittemore (1983) and Black et al. (1986) use deterministic modelling technique with combination of several regression equations to monitor animal growth in response to variables like feed intake and nutrient supplements [19, 20].

Mechanistic approaches use mathematical equations to model causal relationships between input and output variables. For example, Baldwin et al. (1987) assumed solubility of nutrients in diet affects the ruminant digestion rate and used a fourth order Runge-Kutta method to model the ruminant digestion in lactating cows [21]. Cornell Net Carbohydrate and Protein System (CNCPS), developed by Fox et al. (2004), uses animal characteristics, environmental parameters and feed intake to estimate nutrient supply for cattle [22]. Ruminant Nutrition System suggested by Tedeschi and Fox (2018) is a modified version of CNCPS to model ruminant nutrition. There are many other ruminant models available in literature and a detailed review of the important mathematical models is done by Tedeschi (2019) [23].

Another important application of mathematical modelling in the livestock sector is herd management as it helps operators to plan the overall farm operations effectively. Herd management strategies are closely associated with activities like batch selection/replacement, selective breeding, feeding and marketing of animals. One of the earliest research works in this direction is done by Van Arendonk (1985), in which they used a linear programming approach with different lactation characteristics to identify the optimum batch replacement policy of dairy cows [24]. Jalvingh et al. (1992) demonstrated the applicability of Monte Carlo approach and Markov chain in simulating herd dynamics for reproduction and replacement and explaining the consequences of different scenarios [25]. Such models are further improved by researchers using a Bayesian updating approach of animal traits and estimation of parameters at herd level [26]. Use of artificial intelligence (AI) techniques in herd management related activities, such as efficient clustering of animals for slaughtering and improved accuracy in predicting calving time, can also be found in recent literature [27]. Performance of AI based techniques depends on the quality and quantity of the data used for training and model building. Since the parameters associated with livestock vary with geographical conditions, it is difficult to build a generalised AI model. In such case, it is necessary to separately train the models for each location to accommodate the specific spatial characteristics.

Infectious diseases of animals are a common problem faced by livestock farmers. It not only affects the herd health and welfare but also damages the farming business. Use of mathematical models in describing transmission dynamics of communicable diseases, such as bovine tuberculosis and bovine viral diarrhoea, helps farmers in deciding or adopting appropriate control and eradication programs. From simple susceptible infectious (SI) models to social network analysis tools, a wide range of modelling techniques can be found in literature to explain the disease spread [28].

Simulation and modelling techniques have also found their position in achieving environmental sustainability of livestock production [29]. From simple deterministic mathematical models to complex machine learning techniques, a wide range of modelling techniques are reported in literature and practice for modelling GHG emissions from the livestock sector. The following section presents a detailed review of the available livestock GHG emission modelling techniques.

IV. Review of Livestock GHG Emission Models

Based on the complexity of the modelling techniques, Rotz (2018) classified GHG emission models broadly into four categories: a) default emission factor-based models, b) process-based emission factor-based models, c) statistical models, and d) mechanistic models [10], as we elaborate in the following. The selection of suitable GHG emission estimation tools is based on the amount of available data.

Default emission factor-based models that conform to the IPCC Tier 1 guidelines are the simplest, and they use an already defined emission values for each animal population to represent the GHG emissions [10]. For example, the annual CH_4 emissions for a highly productive dairy cow with high quality feed and grain in North America could be quantified as 128 kg [9]. The only required information here is the animal category and the feeding quality.

If more information about the underlying process of the emission source is available, then Tier 2 guidelines of IPCC can be adopted. Such techniques, based on process-driven emission factors, constitute the second category of livestock GHG emission models. For example, the enteric CH_4 is represented as a function of gross energy intake of an animal with an equation

$$EF = \frac{365}{55.65} \times \frac{Y_m}{100} \times GE,$$

where Y_m is the methane conversion factor that defines the portion of methane-producing potential achieved for each type of manure management system, GE is the gross energy intake, and EF is the CH_4 emission factor per head in a year [9]. To estimate GE, we need more data, such as animal weight, amount of milk production (for dairy cows), and fat content of milk.

When a process is described as a linear or nonlinear function of multiple factors, including random variables, then it is referred to as a statistical model. Rotz (2018) considered statistical models, which assume empirical or statistical relationships between the process factors and emission outputs, as a third category of GHG emission models [10].

The popular mechanistic simulation models that describe processes by a series of equations, compose the fourth category. These are the most detailed models that use multiple relationships to represent dynamics within processes. Continuous simulation (CS), also known as System Dynamics, is the core of mechanistic simulation models. In the CS methodology, a problem or a system (e.g., ecosystem or a farming system) may be represented as a causal loop diagram [30]. Causal loop diagrams aid in visualizing a system's structure and behavior and analysing the system qualitatively (Figure 1). To perform a more detailed quantitative analysis, a causal loop diagram is transformed to a stock and flow diagram. In general, a stock is the term for any entity that accumulates or depletes over time (i.e. milk production, feed intake, manure production or GHG emission) and a flow is the rate of change in a stock, in terms of formulas or equations with stocks as the variables in the formula.

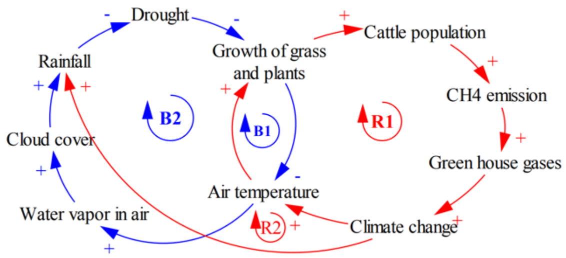

Figure 1: Example of causal loop diagrams for the interrelationships between cattle population and air temperature [60].

Apart from these four categories of GHG emissions models, recently, machine learning models have also been utilized to model livestock GHG emissions [31, 32]. We add and enlist these methods as a fifth category of GHG emission models. Machine learning models identify the complex nonlinear relations between predictors and outcomes from available data points. The last three categories of models (statistical, mechanistic, and machine learning) come under the IPCC Tier 3 approaches. Models in this category are usually highly complex, need more data input, and are less prone to uncertainty as they follow systematic modelling approaches.

As discussed earlier, the bulk of GHG emissions by livestock originates from four main categories of activities: enteric fermentation, manure management, feed production and energy consumption. IPCC has published clear guidelines for Tier 1 and Tier 2 methods to estimate the GHGs CH_4 and N_2O from these sources [9]. In the rest of the section we are discussing some instances of the Tier 2, and Tier 3 (statistical, mechanistic and machine learning) based models. Here, we mainly focus on the two sources that have received the most attention, i.e. enteric fermentation and manure emission.

A. *Modelling GHG Emissions From Enteric Fermentation*

Ruminants are large contributors of GHG emission as the byproduct of their digestive process is CH_4, which is more than twenty times as effective as CO_2 at trapping heat in the atmosphere. There are both linear and nonlinear models to model livestock enteric methane emissions, detailed as follows. Ellis et al. (2012) developed a mechanistic model with a set of linear equations to simulate the CH_4 emissions with changes in feeding strategies focused on varying sugar content in diet [33]. Using dairy farm data collected from different continents, Appuhamy et al. (2016) analysed the enteric CH_4 prediction capability of forty existent models [34]. They compared the results with error metrics like root mean square percentage error (RMSE), and concordance correlation coefficient (CCC), and argued that Tier 3 models are more suitable for North America and Australia, and Tier 2 models for Europe. Bell et al. (2016) used a multiple linear regression to model the functional relationship between feed intake and CH_4 emission of each animal [35]. However, using the variations of Mitscherlich equation-based regression model, Mills et al. (2003) demonstrated that the nonlinear functions are better capable of capturing the relationship between feed/nutrient intake and CH_4 emission [36]. The mathematical model developed by Dijekstra et al. (1992) to represent the complex interactions between the processes associated with enteric fermentation is one of the prominent works in this area and many of the later works build up on it [37].

B. Modelling GHG Emissions From Manure

Animal manure is another important source of carbon footprint and the total manure-related emissions depend on several factors, such as manure storage, handling and environmental conditions. Manure storage can be a slurry tank, liquid manure tank to store urine, compost heap or deep litter. Prominent gases generated from manure are CH_4, N_2O, and NH_3. Most of the reported manure GHG emission models are either based on the IPCC Tier 2 emission factors or an expansion of it. If we consider the animal housing, the emission factor is usually derived from the conditions such as how frequently the manure is removed and the environmental factors [38, 39]. In order to model the manure emission, Li et al. (2012) considered the detailed underlying biogeochemical process of producing GHG from manure and simulated it with varying values of relevant parameters, such as temperature, pH and moisture [38]. Sommer et al. (2004) proposed a model with nonlinear relationship between the GHG emissions and factors associated with slurry organic matter, such as water content, temperature and volatile solids contents [40]. In their earlier work, using the temperature, pH value, soil water content etc., a range of statistical models were developed to model the NH_3 emission from field applied manure [40]. NH_3 generated from the volatilization of land applied manure is an important source of N_2O and several studies are available in literature to model ammonia emissions from various livestock sources [40, 41]. A comprehensive list of articles that focus on modelling GHG emissions from a livestock source can be found in Table I.

V. WHOLE SYSTEM MODELS

The peculiarity of the above discussed models is that they focus on the emission sources, and do not consider the fact that complex interactions exist between the sources. Thus, there is a need for a holistic modelling of livestock related GHG emissions. Whole-farm models and LCA tools fall under this category since these methods examine all processes associated with an emission category. These tools also got wide acceptance in evaluating the environmental impact of livestock farming. We elaborate both categories in the following.

LCA assesses the different activities linked to livestock production, and it is reported that considering a single functional unit, rather than connecting multiple units, can yield simple and better modelling techniques [12]. Commonly used functional units in relation to livestock environmental impact are fat–protein corrected milk, energy corrected milk, live weight of animals, dead weight, bone–fat-free meat, kg egg and litter milk [12, 43]. Thomassen et al. (2008) discussed the concept of consequential and attributional LCA in livestock, where the consequential LCA (CLCA) refers to the emissions changes occurred by varying product demand, and attributional LCA (ALCA) focuses on the emissions contribution caused by a specific attribute [43]. With the help of several deterministic models they assessed both concept for ‘1 kg of fat and protein-corrected milk (FPCM) leaving the farm gate’ functional unit and concluded that though CLCA model is complex it is more powerful model compared to simple ALCA.

Cederberg and Mattsson (2000) used Tier 2 and Tier 3 models based life cycle assessment for ‘1000 kg energy corrected milk (ECM)’ functional unit and concluded that organic milk production can achieve significant reduction in Nitrogen emission [44]. Casey and Holden used process-oriented emission factor-based LCA to quantify GHG emissions from sucker-beef production in Ireland and the functional unit used in the study is ‘live weight per year’ [45]. Basset-Mens and Van der Werf (2005) used an LCA approach to assess the environmental impact of functional units ‘1 kg of pig produced’ and ‘1 ha of land surface used’, and observed distinct environmental impact intensity for each farming scenario [46]. Alvarez-Hess et al. (2019) used a partial LCA model to assess whole-farm activities and emissions, to conclude that 3-nitrooxypropanol additives in animal feed can contribute to significant reduction in GHG emissions [47]. A wide range of LCA-related studies indicate that a proper farm management strategy can lead to a remarkable emission mitigation can be achieved. Table II provides a list of several significant LCA approaches along with their functional units and scope descriptions.

Whole-farm models for estimation of livestock-related GHG emissions are an interdisciplinary approach, typically combining resource-based models, devised for emissions from specific sources, and LCA tools. Whole-farm models also incorporate factors, such as farm dimension, environmental parameters, species information, animal feed sources, etc. Some whole-farm representations are very complex and such models are usually used by scientific

TABLE I. SELECTED MODELLING TECHNIQUES FOR PREDICTING LIVESTOCK-RELATED GHG EMISSIONS

Literature	Methodology	Description
Sommer et al. (2001)	Statistical model	Compared several regression models and concluded that a hybrid mechanistic model would be more suitable for predicting livestock NH_3 emission [40].
Mills et al (2003)	Empirical model	Used Mitscherlich nonlinear regression model to successfully predict methane emission from United Kingdom dairy systems [36]
Sommer et al. (2004)	Empirical model	With help of several mathematical equations, proposed a deterministic model for dynamic prediction of CH4 and N2O emissions from liquid manure [40].
Ellis et al. (2011)	Empirical model	Analysed changes in CH_4 and N excretion patterns from cattle farm with different feeding strategies under controlled conditions [33]
Li et al. (2012)	Mechanistic model	Developed ManureDNDC a simulation tool which accommodates bio and geochemical processes associated with manure to predict the GHG emission [58]
Bell et al. (2016)	Statistical model	Used a multiple linear regression model to define the relation between feed intake and CH_4 yeild. The model is analysed for data from sheep, beef and dairy cattle [35].
Kolasa-Więcek, A. (2018).	Machine learning method	Modelling is done with a multi-layer perceptron neural network and identified cattle, buffalo, goat, sheep, afforestation and electricity consumption are the major contributors of livestock GHG [31].
Hempel et al (2020)	Machine learning method	With time, temperature, wind speed, and wind direction as independent variables NH_3 as dependent variable different machine learning algorithms are experimented. Gradient boosting and random forests provided the most accurate result [32].

TABLE II. SIGNIFICANT LCA TOOLS FOR MODELLING LIVESTOCK-RELATED GHG EMISSIONS

Literature	Functional Unit	Description
Cederberg & Mattsson (2000)	1000 kg energy corrected milk	Environmental benefits of organic milk production explained by assessing the life cycle of milk leaving the farm gate [44].
Basset-Mens, C., & Van der Werf, H. M. (2005)	1 kg of pig produced, and 1 ha of land surface used	Three contrasting pig production systems were analysed with in the boundaries of production and transport of feed ingredients and the farm gate to measure the global warming potential [46].
Casey & Holden (2006)	live weight per year	An LCA methodology suitable to check the GHG mitigation potential of a specific management strategy applied to Irish suckler-beef production [45].
Thomassen et al. (2008)	1 kg of fat and protein-corrected milk	Within the scope of cradle-to-farm gate, attributional and consequential LCA were implemented in SimaPro 7 tool [43].
Garcia-Launay et al. (2014)	1kg of pig live weight	By analysing cradle to gate activities of pig farms in France the role of feed practices in reducing the GHG emission. IPCC guidelines used for the LCA [48].
Kalhor et al. (2016)	one ton of live weight (LW) at farm gate and one ton of chicken meat at slaughterhouse gate	Cradle-to-slaughter house gate boundary is considered here and seasonal variations in GHG emissions are also studied [49].

community to understand the complicated interactions between the various farm components. One of the popular whole-farm models is the Global Livestock Environmental Assessment Model (GLEAM), developed by UNFAO [43]. GLEAM comprehensively assesses the pre- farm, on-farm and post-farm activities to estimate the total GHG emissions. GLEAM performs the estimation in terms of functional units.

Most of the popular whole-farm tools use a modular structure, where each module focuses on a particular farm-level process. For example, DairyMod simulation model, developed for the Australian pasture grazing system has separate modules for plant growth, water resources, animal management, farm management, fertiliser and nutrients [50]. $SIMS_{DAIRY}$ is another well-known whole-farm model, developed for the European region. The model is capable of accommodating the dynamic changes in farm-management decisions along with GHG emissions prediction [33]. Models like DairyMod and $SIMS_{DAIRY}$ are designed to capture the complex interactions between farms elements and, hence, they are more suitable for research purposes than industry applications. For GHG emissions calculation, AgRECalc and Cool Farm Tool are the two popular decision support tools in industry [10]. The implementations of these tools are based on Tier 1 and Tier 2 methodologies. Several other computer-based simulation tools are also available for GHG emissions, and we list some of the more significant ones in Table III.

VI. Challenges and Implications

Though data-driven decision support for reduction of GHG emissions could be of great use to livestock farmers for devising strategic sustainable farming decisions, several associated challenges makes it expensive and complex.

One of the essential challenges faced in modelling livestock-related GHG emissions is data support [10]. Many assumptions, such as the one that enteric N_2O has negligible contribution to carbon footprint, are based on limited information, and they need to be further confirmed by analysing appropriate data variables. Scarcity of data is for several reasons. For example, measuring CH_4 and N_2O relies on the livestock production model, which varies from country to country based on several factors such as prominent animal category and available feed type. Quantifications of these emissions generally consist of two steps: measuring gas concentration and assessing the air exchange rate. Larios et al. (2016), exhaustively analysed the techniques used for quantifying GHG emissions, and concluded that factors, such as the need of continuous measurement from several sampling sites, and highly complex farm models, make measuring livestock GHG emissions difficult. [57].

Another important limitation in estimating emissions accurately is the unavailability of a global cradle-to-grave simulation tool for the assessment of total GHG emission from individual livestock farms. Because of the numerous interdependent activities and interactions between the emission sources, most of the available tools work well within some specific scope, such as species, sources and farm models. Although there are several tools that attempt to capture these complexities, such models are more suitable for research purposes, than assisting farmers with their decision-making process. Another essential restriction associated with most of the whole-farm models is the difficulty in integrating new GHG emissions estimation modules or changing the existing one. Usually, the modules are interconnected and because of the large-scale interactions between them, incorporating even small changes may need huge rework in multiple modules. However, some tools like GLEAM focus

TABLE III. WHOLE-FARM BASED SIMULATION TOOLS FOR ANALYSING LIVESTOCK-RELATED GHG EMISSIONS.

Simulation Tool	Description
GLEAM	Tool covers cattle, buffalo, sheep, goats, pigs and chicken species. It is also capable of integrating with economic models to assess cost-effectiveness of GHG mitigation strategies [43].
DairyMod / EcoMod	Biophysical process simulation of the dairy pasture system [50].
MELODIE	Dynamic simulation of the flows of carbon, nitrogen, phosphorus, copper, zinc and water within animal, pasture, crop and manure components [52].
Holos	Process-based emission factors estimate all important direct and indirect sources of GHG emissions of livestock operations [51].
DairyWise	Combines already existing simulation models of specific subsystems into a whole farm model for use in interdisciplinary studies [54].
FarmAC	Process-related emission factors represent carbon and nitrogen flows on arable and livestock farms quantifying GHG, soil C sequestration, and N losses to the environment [55].
$SIMS_{DAIRY}$	Process simulation of the effects of management, climate and soil properties on nitrogen, phosphorus, and carbon losses along with profitability, biodiversity, soil quality, and animal welfare [32].
Cool Farm	An opensource software which uses Tier 3 models to estimate livestock GHG emission [56].
AgRECalc	An online simulation tool for calculating carbon footprint from dairy farm [10].

on the continuous improvement of both GHG calculation and utility in decision-making. Most of the tools are not easily accessible to farmers and need some level of technological knowledge to use them efficiently. Many of them present the estimation results in a scientific report form that is hard to understand by the common users. At present, only a very limited tools are available for livestock farmers to rely on for sustainable livestock farming practices. Nevertheless, technological advancements can contribute a great deal in improving the modelling approaches. PLF technologies are widely used for animal health and wellbeing, which eventually will contribute to low GHG emissions. Data, such as metabolic changes in lactating and pregnant cows, collected through PLF technologies, can also help in improving GHG emission models. Although many generic models are available, a more user-friendly and cost-effective simulation tool, with some level of recommendation options, will help livestock farmers to adapt optimized sustainable production strategies.

VII. Conclusions

We presented an overview of the data-driven decision support tools for quantifying livestock-related GHG emissions. The models that are used in these tools can be based on default emission factors, process-oriented emission factors, empirical/statistical models, mechanistic models or machine learning models. Most of the reported models consider enteric fermentation and manure management as emission sources. Such modelling techniques are not capable of presenting the overall emission estimation. However, whole-system models, such as LCA and whole-farm models, can incorporate the complex interaction between livestock components and hence such models are more preferred as decision support tool. These models use combination of different modelling techniques and they are built with in a specific scope. Consequently, we have also discussed the associated data collection and model complexity challenges and their impact on the performance of DSS tools. Finally, we see a great opportunity through the use of modern PLF technologies, to accurately record parameters that are critical for improving the livestock related GHG emissions estimation models. Thus, we expect to see more attention and tools in the livestock sector, related to tackling this very real global problem of the anticipated climate changes.

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