Science of the Total Environment 776 (2021) 145932

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Review

Modelling the effect of feeding management on greenhouse gas and nitrogen emissions in cattle farming systems

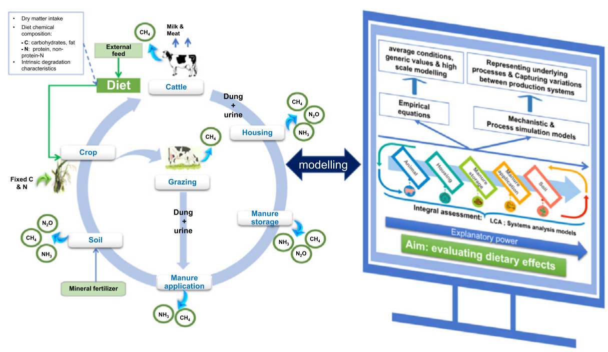
Latifa Ouatahar [a,b,*], André Bannink [c], Gary Lanigan [d], Barbara Amon [b,e]

[a] Institute for Animal Hygiene and Animal Health, Department of Veterinary Medicine, Freie Universität Berlin, Robert-von-Ostertag 7–13, 14163 Berlin, Germany
[b] Technology Assessment and Substance Cycles, Leibniz Institute for Agricultural Engineering and Bioeconomy – ATB, Max-Eyth-Allee 100, 14469 Potsdam, Germany
[c] Animal Nutrition, Wageningen University & Research, PO Box 338, 6700AH Wageningen, the Netherlands
[d] Environment, Soils and Land-Use, Teagasc, Johnstown Castle, Co. Wexford Y35 Y521, Ireland
[e] Faculty of Civil Engineering, Architecture and Environmental Engineering, University of Zielona Góra, Zielona Góra, Poland

HIGHLIGHTS

- Feed management decisions affect gaseous emission from cattle production systems
- Statistical and empirical models are practical in evaluating diets and inventories
- Mechanistic or Process-based models allow capturing variation in on-farm emissions
- Integral assessment approaches are preferred over isolating each emission source
- Combined use of process-based models for individual farm elements not used yet

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 28 September 2020
Received in revised form 31 January 2021
Accepted 10 February 2021
Available online 18 February 2021

Editor: Pavlos Kassomenos

Keywords:
Diet
Downstream emissions
Production system
Dairy
Beef
Life cycle assessment

ABSTRACT

Feed management decisions are an important element of managing greenhouse gas (GHG) and nitrogen (N) emissions in livestock farming systems. This review aims to a) discuss the impact of feed management practices on emissions in beef and dairy production systems and b) assess different modelling approaches used for quantifying the impact of these abatement measures at different stages of the feed and manure management chain. Statistical and empirical models are well-suited for practical applications when evaluating mitigation strategies, such as GHG calculator tools for farmers and for inventory purposes. Process-based simulation models are more likely to provide insights into the impact of biotic and abiotic drivers on GHG and N emissions. These models are based on equations which mathematically describe processes such as fermentation, aerobic and anaerobic respiration, denitrification, etc. and require a greater number of input parameters. Ultimately, the modelling approach used will be determined by a) the activity input data available, b) the temporal and spatial resolution required and c) the suite of emissions being studied. Simulation models are likely candidates to be able to better explain variation in on-farm GHG and N emissions, and predict with a higher accuracy for a specific mitigation measure under defined farming conditions, due to the fact that they better represent the underlying mechanisms causal for emissions. Integrated farm system models often make use of rather generic values or empirical models to quantify individual emissions sources, whereas combining a whole set of process-based models (or their results) that simulates the variation in GHG and N emissions and the associated whole farm budget has

* Corresponding author at: Max-Eyth-Allee 100, 14469 Potsdam, Germany.
E-mail addresses: latifati@zedat.fu-berlin.de, louatahar@atb-potsdam.de (L. Ouatahar), andre.bannink@wur.nl (A. Bannink), Gary.Lanigan@teagasc.ie (G. Lanigan), bamon@atb-potsdam.de (B. Amon).

https://doi.org/10.1016/j.scitotenv.2021.145932

not been used. The latter represents a valuable approach to delineate underlying processes and their drivers within the system and to evaluate the integral effect on GHG emissions with different mitigation options.

Contents

1. Introduction

Limiting global warming to below 1.5–2.0 °C, whilst feeding a population projected to increase to 10 billion by 2050 is a key global challenge with anthropogenic GHG emissions having already contributed to a mean 1 °C increase in global temperature above pre-industrial levels (Allen et al., 2018; FAO, 2018a).

Globally, agriculture is responsible for about 20–25% of total GHG emissions (IPCC, 2014) and for approximately 80%–90% of global anthropogenic ammonia (NH_3) emissions (European Environment Agency, 2019; Xu et al., 2019). Conversely, Agriculture, Forestry and Other Land Use (AFOLU) can play a key role mitigating further climate change (IPCC, 2014; Popp et al., 2017).

The livestock sector contributes approximately 14.5% to the global anthropogenic GHG emissions (FAO, 2017) and accounts for 64% of global NH_3 emissions mostly from deposited excreta and applied manure (FAO, 2006) which has increased considerably by about 70% from 1961 to 2014 (66 million to 113 million tonnes of N) (FAO, 2018b). Ruminant animals represent 75% of overall carbon dioxide equivalent (CO_2-eq) emissions from the livestock sector, with bovines comprising the bulk of these emissions (FAO, 2006; IPCC, 2019a).

Methane (CH_4) represents the main source of GHG emissions from ruminants, with the majority (80%) associated with enteric fermentation and the remainder due to manure management. Soil emissions, arising from animal feed production, comprise the second largest source of GHG emissions from dairy and beef systems. These emissions are dominated by nitrous oxide (N_2O) and CO_2, with N_2O arising from fertilization of fodder crops and pasture/range management, whilst CO_2 emissions arise from soil organic carbon (SOC) changes that are associated with land-use change (Gerber et al., 2013; Lesschen et al., 2011). Excesses of applied mineral fertilizers and livestock manure also generates reactive N emissions to air and water, principally NH_3 and nitrate (NO_3^-) emissions, which cause water and air pollution (FAO, 2018b). It is therefore essential to improve manure nutrient-use efficiency in order to optimize crop growth and minimize N losses (Leip et al., 2019). The extent of GHG and NH_3 vary considerably across different livestock production systems as they are influenced by animal type, feed, climate, soil type and management practices (Rotz et al., 2014). Most European regions have shown a marked decrease in CH_4 emissions and N inputs by nearly 22% and 50% from 1990 to present (FAO, 2018b). This decrease was principally driven by structural changes in the Common Agricultural Policy (CAP), by a reduction in animal numbers and fertilizer input as well as limits set under the European Union (EU) Climate and Energy Package (2009/29/EC) and Nitrates Directive (91/676/EEC) that aimed to reduce GHG emissions and NO_3^- leaching to watercourses respectively (European Commission-Environment, 2010). Indeed, in areas where livestock production has increased, GHG emissions have increased and air/water quality has almost always deteriorated (FAO, 2018b).

Currently, the EU is committed to a 40% reduction in GHG emissions by 2030 compared to 1990 baseline levels with a longer term target of net Carbon (C) Neutrality by 2050 (European Commission, 2013). This corresponds to commitments under the Paris agreement target to maintain the increase in temperature to well below 2 °C and keep it to 1.5 °C above pre-industrial levels (UNFCC, 2015).

Various mitigation strategies have been proposed in the agricultural sector to meet the GHG and N abatement targets while at the same time maintaining sustainable production (Rogelj et al., 2018; Weiske and Petersen, 2006). Various mitigation options have been developed to tackle the impact of cattle production systems on GHG emissions (IPCC, 2014; Montes et al., 2013; Sejian et al., 2015). Studies tend to either focus on the impact of individual measures on GHG and/or NH_3 losses or on assessing suites of measures that could be adopted at a global scale, continental or national scale. In particular, cost-benefit studies of mitigation tend to be top-down and disregard different farm typologies and regional variation (Eory et al., 2018; Gerber et al., 2013; Lanigan et al., 2018). Yet, management decisions are generally made at the farm scale in the context of local farming conditions. Indeed, studies on farm-level GHG emissions have shown that farm to farm variation can be greater than that between different countries (Crosson et al., 2011). This can be challenging as local variations in biotic drivers (animal type/breed, forage type, etc.) and abiotic drivers (such as climate, soil type) can greatly influence GHG emissions and add a layer of complexity when assessing appropriate mitigation options (Amon et al., 2006; Del Prado et al., 2013; Rotz, 2018), and accounting for individual farm differences when generating a farm-specific integral assessment.

Conducting experiments at the animal, field, or whole-farm level, that involve direct measurements of GHG and/or NH_3 in air or N losses to groundwater/waterways, according to appropriate measurement protocols, can be expensive, time consuming and sometimes technically difficult (Hill et al., 2016; Smith et al., 2020). In the case of developing nations, this level of measurement is both impractical and unfeasible. Furthermore, there are significant differences across agro-ecological zones (e.g. feeding habits, climatic conditions) that impact the amount of GHG and N emissions produced, which results in such measurements not being representative for all farming types and conditions.

Mathematical modelling, based on empirical measurements, can play a major role in understanding the impact of management on farm GHG and reactive N emissions. This approach can be particularly useful for assessing individual measures, or more importantly, combinations of measures and can aid in the development and optimization of sustainable production systems (Jose et al., 2016; Kipling et al., 2014). They can also be particularly useful in assessing the synergies and trade-offs of combinations of mitigation options on various components of farm C and N cycling (Khalil et al., 2016). This can assist policy makers and farmers to predict emissions and take management decisions from economic, environmental and social angles (Kipling et al., 2016). Various models have been developed and used to quantify the farm budget of GHG and N emissions and to evaluate different mitigation strategies (Del Prado et al., 2013). For cattle farming systems, the complexity of these models ranges from basic inventory models where activity data is multiplied by emission factors (EF's) to more complex mechanistic or statistical representations of the emissions (Rotz, 2018), to dynamic models capturing the kinetic features of the processes underlying these emissions (Bannink et al., 2011; Kebreab et al., 2008; Li et al., 2012; Parton et al., 1998; Smith et al., 2010) .

Among many farm management aspects, feed management decisions are especially crucial as they strongly affect both GHG and N emissions from ruminant production systems as well as involving the highest costs of farming operations. Dietary intervention altering CH_4 emissions produced by ruminant activities is not only environmentally sustainable but also important to improve production efficiency. Enteric CH_4 emissions represent a loss of feed energy which has been measured to be between 2 and 11% of total gross energy intake by the animal (Blaxter and Clapperton, 1965; Lassey et al., 1997; Liu et al., 2017), and a higher emission yield may go along with a lower feed conversion (Mills et al., 2001). Attempts to reduce GHG in dairy and beef production systems are often considered to improve production efficiency and reduce economic losses due to emissions (Jose et al., 2016; Swain et al., 2018). As such, feed management decisions and their impacts across whole farm C and N cycling need to be considered when assessing GHG emissions and modelling mitigation strategies from ruminant production at farm, regional and global scale systems. On the question of scale, different modelling approaches may need to be employed depending on whether assessments are being made at a global, national or farm-scale. An inventory-based approach may be appropriate at a national level, where activity levels will dominate total emissions, whereas at the farm level, local differences in biotic and abiotic factors, such as feed quality, soil type, N input type and climate will be the principal drivers for variations in GHG emissions. As a result, process-based models that can simulate emissions based on these drivers may have to be utilized. With respect to animal feeding management, there is rather little information on the current limitations and requirements of different models and model typologies required to achieve sufficient specificity and consistency for integral GHG and N emission assessment. The present review therefore aims (i) to provide an overview on the impact of diet composition and diet quality on downstream GHG and N emissions as an important element to be captured with modelling, (ii) to discuss the relevance of different modelling approaches to evaluate GHG and N emissions from dairy and beef cattle farming systems, and (iii) to summarize and complement existing reviews of modelling frameworks to assess on-farm GHG from dairy and beef cattle production systems.

2. Typologies of dairy and beef cattle production systems

Modelling livestock systems is complex as it requires (multi) functional relationships between influencing biotic and abiotic factors for a variety of distinct but interconnected sources (animals, housing, manure pits and fields) to drive the models, and various climatic, physio-chemical, biological and management data may be required as input parameters depending on the type of modelling approach and system boundary (Kipling et al., 2014).

Ruminant production systems vary greatly across regions and it is challenging to develop typologies of these production systems as it requires identifying the main relevant parameters that impact gaseous emissions quantitatively and qualitatively. A range of farming characteristics can be used to categorize production systems based on animal type and/or herd size, commodity type (beef, milk, etc.), housing system (confinement or pastoral-based), manure management practices, cropping system and the agro-ecological situation (Table 1.).

Leip et al. (2010) developed a regional zoning of the main livestock production systems in Europe including dairy and beef cattle systems. Attempts have been made to classify different typologies using CAPRI, a model which assesses the impact of trade policy on agricultural activity, in order to describe these systems from a set of variables that include mainly feeding strategy, productivity and intensification level, housing system, dependency on external feedstuff supplies and the relative economic importance of the livestock sector. The results showed substantial diversity between livestock farming systems in Europe. Lesschen et al. (2011) derived data from CAPRI, FAO and IPCC to feed an inventory-based emissions model, MITERRA-Europe, and reported large variations in GHG emissions per unit of product among EU countries, which are mainly related to variations in the type of animal production systems, feed types and nutrient use efficiencies. Beef cattle showed the highest emission (22.6 kg CO_2 eq. kg^{-1} product) compared to dairy cattle (1.3 kg CO_2 eq. kg^{-1} product). Using a static life cycle assessment (LCA) approach, Gerber et al. (2010) estimated emissions at

Table 1
Main typologies of dairy and beef production systems.

Type	Characteristics	Emissions
Intensive confinement	– High stocking rates – Higher DMI and milk/meat production per animal – Mixture of forages cultivated on-farm – Larger proportion of concentrate and arable crops (eg. Maize) in diet – Animals housed for the majority of the year	– CH_4 (and total GHG) per unit product tends to be lower – Higher manure management (CH_4 and NH_3) emissions – Higher SOC loss due to larger proportion of cropland – High absolute emissions per farm
Extensive pastoral	– Comparatively low stocking rates with lower DMI and production per animal – Diet mainly grass or grass silage-based with low proportion of concentrates – Animals spend majority of time grazing – housing or out--wintering periods are comparatively short	– CH_4 (and total GHG) tends to be higher – Lower manure management emissions – High field N_2O emissions – Higher SOC levels on permanent pasture systems – Lower absolute emissions per farm

CH_4: methane, N_2O: nitrous oxide, NH_3: ammonia, GHG: greenhouse gas, SOC: soil organic carbon, DMI: dry matter intake.

global, regional and farming system levels and provided a typology of dairy farming systems based upon feed base and agroecological conditions. This study reported large variations between regions at global scale (1.3 to 7.5 kg CO_2 eq. kg^{-1} FPCM (±26%)) and grassland systems had the largest GHG emissions (2.7 kg CO_2 eq. kg^{-1} FPCM (±26%)) with respect to the mixed farming systems (1.8 kg CO_2 eq. kg^{-1} FPCM (±26%)).

Notwithstanding the importance of these studies to make statements about emission intensities and compare types of farming systems, it is worth noting that using generic approaches does not allow evaluating on-farm measures to be taken and their tradeoffs. More detailed approaches that quantify the farm emission processes are more suitable for such purpose as recommended by IPCC and referred to as Tier 3 approaches (IPCC, 2006). Accordingly, in order to capture all these variations between farming systems, especially feeding strategies and their downstream effect on other farm components (housing, manure and soil), each farm element or GHG and N emission source needs to be broken down into the underlying processes involved. This allows EF's to be generated in relation to the C and N cycling within the farming system. Excellent reviews on C cycling are given by Berner (2009) and Chapin et al. (2006) and on N cycling by Fowler et al. (2013), Kuypers et al. (2018) and Lehnert et al. (2015).

Altered diets may also alter the C and N composition of excreta, and impact on the entire C and N cascade, this affecting downstream farm emissions either in terms of manure management and/or soil-based emissions (Leip et al., 2011). Therefore, modelling approaches to obtain an integral assessment of the GHG emissions and to derive a GHG farm budget and C footprint of animal production starts from modelling the feeding management and its downstream effect on other farm components (i.e. housing, grazing, manure handling and soils). The following section reviews research on the dietary effects on GHG and N emissions to represent digestion and enteric fermentation in cattle, and downstream impacts of feeding strategies on GHG and N emissions.

3. Quantifying dietary effects on animal and downstream GHG and N emission

The use of dietary manipulation to reduce GHG and N emissions in livestock has been studied extensively. Diverse parameters influence GHG formation in the digestive tract or downstream effects in the farming system, such as digestibility, chemical composition of the diet and presence of functional additives in the ration. An overview of examples of studies is presented in supplementary materials, Table S1.

Knapp et al. (2014) reviewed and quantified different abatement opportunities in dairy cattle and reported that various feeding and nutrition-based mitigation approaches can reduce enteric CH_4 by 3% up to 15%. Similarly, Kumar et al. (2014) summarized different mitigation measures to reduce enteric CH_4 from ruminants. These mitigation measures included changing nutrient composition (e.g. shifting towards concentrate based diets, use of forages at an earlier stage of maturity), feed additives containing plant secondary compounds (tannins, phenolic monomers, saponins), feeding dietary lipids, addition of organic acids (malic and fumaric) and the use of halogenated compounds (red-seaweed *Asparagopsis taxiformis*; bromoform, chloroform, BES) and ionophores (monensin, lasalocid, salinomycin, avoparcin). Likewise, different mitigation options to reduce CH_4 and N_2O emissions from enteric fermentation and manure management have been reviewed and summarized by Hristov et al. (2013) and Montes et al. (2013). It is evident from all these studies that nutritional management and diet manipulation is an effective way of reducing GHG and N emissions from ruminants in confinement production systems. The most promising feeding strategies were including lipids in the diet, improving forage quality, NO_3^- supplementation and supplementing CH_4 inhibitors. Table 2 presents the abatement potential of different feeding management mitigation options on GHG and NH_3 emissions. Although not part of the present review, it is noted here that integrating economic with environmental aspects and comparing cost effectiveness abatement options within and between production systems is essential to confirm the effectiveness and wide applicability of the proposed abatement measures (Moraes et al., 2015; Pierer et al., 2016).

In addition to experimental studies, also modelling studies have been carried out to simulate and evaluate the effect of nutritional management strategies on GHG emissions and N losses at different levels of the manure management chain. Some examples are indicated in Table 3, extending to GHG accounting methods and LCA. Most of these studies are conducted in dairy cattle and they focus mainly on enteric CH_4 and N_2O from manure management using empirical models, LCA analysis and mechanistic dynamic approaches, or a combination of these approaches to simulate the impact of dietary strategies on overall GHG emissions at the farm level. However, no study has used a set of process-based simulation models at the whole farm scale to investigate the impact of different feeding strategies on on-farm GHG emissions.

In the following sub-sections, dietary factors which are drivers for emissions will be discussed in more detail, followed by a discussion on downstream impact of feeding strategies on GHG and N emissions, and modelling studies at the production system level.

3.1. Effect of feeding level/animal productivity

Given the positive relationship between animal size as well as production or growth rates and feed intake, CH_4 emissions are expected to increase with increasing feed intake (IPCC, 2019a). The available energy to be fermented and partly be converted into CH_4 increases with feeding level. Moreover, the efficiency of ruminal fermentation of feed decreases with increases in feed intake. This can result in a reduced amount of energy released in the form of CH_4 per kg of feed dry matter (DM) by the rumen (Kataria, 2016). Therefore, the same kg feed DM delivers less CH_4 at a higher level of feed intake (Warner et al., 2017).

Table 2
Overview of feasible feeding management mitigation measures and their potential of greenhouse gases (methane (CH_4), nitrous oxide (N_2O) and ammonia (NH_3) abatement in dairy and beef cattle (excluding potential synergies or trade-offs).

Measure	Nature of measure	Reported mitigation potential (% abatement)			Reference
		Enteric CH_4	N_2O	NH_3	
N-use efficiency	Production efficiency		60		(Lanigan et al., 2018)
Adding fatty acids to dairy diets	Feeding practices	10.3			(Lanigan et al., 2018)
Nitrates	Feed additives	18–30			(Hristov et al., 2013)
Ionophores	Feed additives	≤10			(Hristov et al., 2013; Kumar et al., 2014)
Plant bioactive compounds (tannins)	Feed additives	10–30			(Gerber et al., 2013; Kumar et al., 2014)
Dietary lipids	Feed additives	10–30			(Hristov et al., 2013; Jayasundara et al., 2016; Kumar et al., 2014)
Concentrate inclusion in ration	Feeding practices	10–30			(Hristov et al., 2013; Kumar et al., 2014)
Forage quality and management	Feeding practices	10–30			(Hristov et al., 2013; van Gastelen et al., 2019)
Reduced dietary crude protein	Feeding practices		10–30	4–73	(Hristov et al., 2013; Sajeev et al., 2017, 2018)
3-Nitrooxypropanol	Feed additives	0–60			(Dijkstra et al., 2018a, 2018b)

Table 3
Modelling of the effect of diet on greenhouse gas (GHG) and nitrogen (N) emissions from beef and dairy cattle production systems.

Category of animals	Purpose of study	Modelling approach	Modelled GHG and N source	Reference
Beef cattle	Investigation of the effect of varying levels of DMI digestibility, total digestible nutrients, and CP on GHG emissions under different scenarios	Life cycle assessment methodology	Enteric CH_4, CH_4 manure, N_2O manure, N fertilizer	(Ruviaro et al., 2015)
Dairy cattle	Simulation of the effect of dietary concentrate and protein levels in silage-based diets on CH_4 emissions and N and phosphorus excretion in dairy bulls	Dynamic and mechanistic Karoline model	Enteric CH_4, N and P in excreta	(Huhtanen and Huuskonen, 2019)
Dairy cattle	Evaluation of various nutritional strategies to mitigate GHG emissions	Empirical model based on fiber and CP content in the diet and IPCC tier 1 approach	Enteric CH_4, N_2O manure	(Rendon-Huerta et al., 2018)
Dairy cattle	Evaluation via optimization of the effect of different dietary strategies on milk yield and N losses	NCYCLE model	N flows in soil, plant, rumen, and excreta	(del Prado et al., 2006)
Dairy cattle	Evaluation of cost effectiveness of dietary supplementation of extruded linseed product and NO_3^- source, and reducing the maturity stage of grass and grass silage	Mechanistic model for enteric CH_4 production and LCA approach	Enteric CH_4, N_2O manure, N_2O-N application	(Van Middelaar et al., 2014)
Dairy cattle	Analyzing various feeding strategies to reduce GHG according to differences between forage: concentrate ratio and CP content	Empirical model based on fiber and CP content and IPCC methodology	Enteric CH_4, N_2O manure	(Rendon-Huerta et al., 2018)

CP: crude protein, P: phosphorus, DMI: Dry Matter Intake, LCA: Life Cycle Assessment, IPCC: Intergovernmental Panel on Climate Change, CH_4: methane, N_2O: nitrous oxide, NH_3: ammonia, NO_3^-: nitrate.

By using a dynamic mechanistic model of whole-rumen function, Mills et al. (2001) predicted that the loss of feed energy due to CH_4 reduces with increasing dietary energy intake. The modelling effort also demonstrated that limiting the ratio of lipogenic to glucogenic volatile fatty acids (VFA) in the rumen and hindgut (which is a consequence of higher feed intake as well) can reduce methanogenesis, comparable to replacing soluble sugars with starch or shifting from corn silage to grass silage.

Varying feed intake does not always affect average ruminal pH, and hence ruminal acidity, but increased rate of fermentation generally is associated with increased rumen concentration of VFA and acidity. Therefore, changing feed intake. For example, by shifting from a forage-based diet to more concentrate-based may impact ruminal acidity (Nagaraja and Titgemeyer, 2010), and thereby the fermentation profile and formation of CH_4 (Brask et al., 2015).

3.2. Effect of digestibility

The calculation of emissions from enteric fermentation depends on the accurate estimation of diet digestibility. According to IPCC (2019a), an increase in 10% digestibility in feed leads to a reduction of approximately 12–20% in enteric CH_4 yield. Furthermore, Shibata et al. (1993) reported that when animals are fed more digestible feed types such as concentrate, CH_4 production per dry matter intake (DMI) is reduced, whereas increasing DMI of less digestible feed like forages had little effect on CH_4 production per DMI. Increasing the concentrate proportion in the diet generally increases the proportion of propionic acid formed with rumen fermentation and decease CH_4 yield (Coppock et al., 1964). Therefore, manipulating the diet through feeding highly digestible feedstuffs can be an effective way of reducing CH_4 emission (Bell and Eckard, 2012).

In a meta-analysis based on 497 dietary treatments in 92 studies with dairy cows the impact of dietary forage and concentrate parameters on apparent total diet digestibility was investigated (Nousiainen et al., 2009). The results suggest that feeding concentrate improved total diet organic matter (OM) digestibility and increasing crude protein (CP) in concentrates also improved production level and OM digestibility in cows. In a recent meta-analysis of in vivo studies with ruminants, van Gastelen et al. (2019) concluded that management practices to improve roughage quality (including digestibility as a characteristic) are a potent mitigation strategy to reduce enteric CH_4 per unit of feed fed to ruminants, and that the implications of this have to be addressed when assessing GHG emissions. Appuhamy et al. (2018) furthermore suggested that the accurate estimation of energy digestibility of feed allows for more accurate estimates of the volatile solids (VS) outputs from dairy cow's manure using empirical models compared to IPCC Tier 2 approach. Evaluating at the level of the whole production system, Ruviaro et al. (2015) modelled the effect of variation in the parameters DMI digestibility, total digestible nutrients, and dietary CP in beef cattle operations on emissions of enteric CH_4, of CH_4 and N_2O from manure, and of N_2O from N-fertilizer application. The results showed that increased digestibility generates a lower CH_4 and N_2O emission per unit of animal product.

3.3. Effect of dietary chemical composition

Forage type has an impact on enteric CH_4 production, NH_3 concentration and VFA production (Meale et al., 2012). For example, in a mixed grass legume-based diet, the presence of condensed tannin activity in sainfoin decreased NH_3-N production in the rumen up to 67% and CH_4 up to 7% in vitro (Niderkorn et al., 2011). However, it had a negative impact on fiber digestion. On the other hand, other legume species such as white clover, red clover and alfalfa, when associated with grass based diets, increased NH_3-N production up to 28% (Niderkorn et al., 2011). A more recent study showed that feeding forages rich in N (e.g. alfalfa silage and grass hay) to Holstein steers resulted in a higher proportion of both CH_4 and N_2O in the rumen compared to animals that consumed corn silage, and forages rich in NO_3^- (alfalfa silage) in a higher proportion of N_2O (Gerlach et al., 2018).

Bannink et al. (2010) used a dynamic mechanistic model to simulate the impact of type and quality of grass forage by distinguishing two N fertilization rates and two stages of grass maturity, next DMI and dietary content of concentrates, on CH_4 emissions in dairy cows. Rate of N fertilization as well as level of maturity of grass herbage and grass silage at harvesting both had an impact on CH_4 emission. Further modelling studies by Ellis et al. (2011) investigated the effect of high sugar grasses on CH_4 emission. The results suggested that high water-soluble carbohydrates in grass may increase CH_4 production, although it is considered as a strategy to mitigate N emissions. Other insights indicate a high fraction of water-soluble carbohydrates and their rapid fermentation might lead to less CH_4. In order to study the changes in enteric CH_4 production in relation to passage rate, pH, feed type and inhibitors on methanogenesis, Janssen (2010) presented a model based on methanogen growth kinetics . The model suggests that thermodynamics of rumen fermentation are influenced by H_2 concentration. Lower H_2 concentrations favors fermentation pathways and less propionate formation and therefore more enteric CH_4 production in the rumen, whilst high H_2 concentration lead to less H_2 formation, more propionate and less enteric CH_4 emissions. Following a similar but more detailed thermodynamical approach, van Lingen et al. (2019) performed a

Bayesian mechanistic modelling study to represent the mechanisms driving VFA and H_2 production in the rumen and predict enteric CH_4 emission. The model simulates the thermodynamic control of H_2 partial pressure on VFA fermentation pathways via NAD+ to NADH ratio in fermentative microbes and methanogenesis in cattle. The simulation results indicated that parameters affecting impact of fractional passage rate and NADH oxidation explain 86% of variation in predicted CH_4 production. Such modelling approaches may be useful tools to further elucidate the causal factors involved with the effect of variation in chemical composition and rate of rumen fermentation on enteric CH_4.

3.4. Effect of feeding dietary additives

Apart from diet composition, also dietary additives may affect emissions. Kataria (2016) reviewed the use of different feed additives as a strategy to reduce CH_4 emissions. These mitigation options include organic acids, NO_3^-, and sulfates, bacteriocins and ionophores, saponins, tannins, probiotics and prebiotics, and fat and oil supplementation. Three promising additives for which there is general agreement of a persistent mitigating effect on enteric CH_4 are NO_3^- salts, 3-nitrooxypropanol (3-NOP) and fats.

Dietary NO_3^- supplementation can reduce CH_4 emissions up to 30% (Jayasundara et al., 2016). van Wyngaard et al. (2018) evaluated the impact of three levels of dietary NO_3^- supplementation on enteric CH_4 emissions under grazing conditions and showed that increasing dietary NO_3^- decreased linearly CH_4 production. Only the high levels of dietary NO_3^- supplementation tended to decrease milk yield due to decreased concentrate DMI, but not the lower levels (<2% of dietary DM). In a study by Veneman et al. (2015) it was concluded that NO_3^- supplementation has a minor effect on the general functioning of the rumen and its microbial population.

Recently, it was concluded that CH_4 inhibitors, such as 3-NOP, have demonstrated to successfully reduce CH_4 from dairy and beef cattle by circa. 30% (Kumar et al., 2014). In a recent meta-analysis on the effect of 3-NOP, Dijkstra et al. (2018a, b) showed that the response depends on dietary fiber content, the dose and the category of cattle involved (the effect being stronger in dairy than in beef cattle). Nevertheless, the mitigation potential indeed appears to be invariably high across all conditions.

The impact of dietary fat composition on CH_4 emissions in dairy cows was evaluated by Giger-Reverdin et al. (2003) using a regression approach on a literature dataset on dietary fats inclusion. They concluded that the supplementation with unsaturated fats might decrease CH_4 production. This is consistent with the study of Grainger and Beauchemin (2011), who reported a high potential for all fatty acids and for crude fat to lower enteric CH_4 emissions from ruminants from 1.7 up 6.7% for each 10 g fat added to the diet/kg DM.

3.5. Downstream impacts of feeding strategies

Dietary manipulation not only impacts on enteric CH_4 but also composition and amount of cattle excreta, which directly affects downstream manure management and field-based emissions. The process of the release of GHG and N from manure (its OM also referred to as VS) involves all stages, starting from excretion in barns or in other areas of the farm, through storage and manure management systems, until manure application and incorporation into soils (Fig. 1).

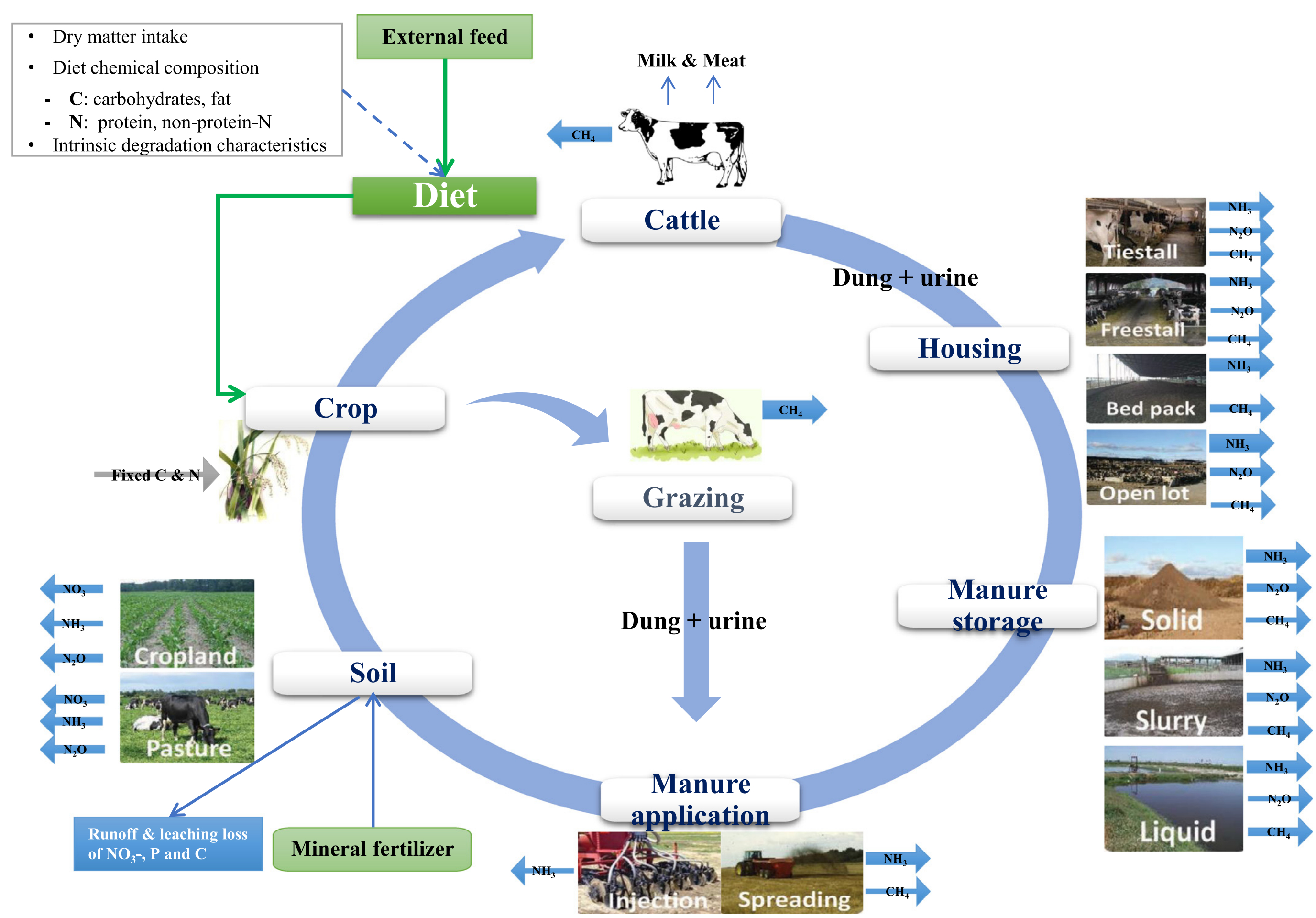


Fig. 1. Farm elements involved with direct and indirect greenhouse gas emissions. The differently sized arrows indicate the relative contribution of these emissions (adapted from Del Prado et al., 2013; Rotz, 2018), CH_4: methane, CO_2: carbon dioxide, N_2O: nitrous oxide, NH_3: ammonia, NO_3^-: nitrate, C: carbon, N: nitrogen, P: phosphorus.

Several processes take place: decomposition, hydrolysis, nitrification (i.e. oxidation of ammonium (NH_4^+) to NO_3^- via nitrite (NO_2^-), denitrification (i.e. reduction of NO_3^- to N_2O and N_2), and fermentation, affecting emissions of CO_2, CH_4, N_2O as well as NH_3 and leaching of NO_3^- (Li et al., 2012).

The principal dietary impact is associated with reducing CP content which influences the N content of excreta and the relationship between N excreted with urine and with faeces. A meta-analysis of manure management measures by Hou et al. (2015) assessed 24 studies investigating the impact of reducing CP content of animal feed. Reductions in NH_3 emissions of between 24% and 65% were observed with significant linear relationship**s** between dietary CP content and manure pH, manure N content, amount of urine-N excreted, and amount of total N excreted. This is consistent with the findings of the study of Sajeev et al. (2017) that reported a decrease in NH_3 and N_2O emissions by 42% and 30% respectively when animals were fed a reduced dietary CP. Sajeev et al. (2017) also found that there is still a substantial potential for reduction on N excretion by optimized cattle diets. Moreover, the reduction of dietary N intake or increase of energy content decreases urinary N excretion and urea N in cattle (Dijkstra et al., 2013). This has been demonstrated reduced manure N excretion and N_2O and NH_3 emission per tonne milk produced upon maize silage (low N, high starch) supplementation in grass-based systems (Luo et al., 2008). However, increased manure CH_4 emissions could partially offset these reductions. Sajeev et al. (2017) observed a 71% increase in manure CH_4 associated with increased carbohydrate content, while Massé et al. (2016) reported increased manure CH_4 of 39%–79% was also associated with the incorporation of 50 and 100% corn silage into alfalfa-based dairy diets in Canada.

In terms of pastoral systems, plantain has been shown to reduce urine N content but also reduce the N_2O EF associated with urine deposition (de Klein et al., 2020). It is hypothesized that the urine N may be reduced via either diuretic properties of plantain or levels of condensed tannins (Cheng et al., 2017; O'Connell et al., 2016). However, there is growing evidence that root exudates from plantain along with Brassicas contain compounds that inhibit nitrification (de Klein et al., 2020; Subbarao et al., 2006). There are also indications that inclusion of plantain along with clover will also increase SOC sequestration (Whitehead et al., 2018).

Using a dynamic mechanistic model of enteric fermentation and digestion, Dijkstra et al. (2018a) simulated compositional details of dairy cow faces and urine in relation to dietary changes. Results showed the greatest urinary N excretion was associated with diets with high fertilization rates and early cut grass silage whereas enteric CH_4 emission was lowest, compared to low fertilized diets and late cut grass silages. Upon inclusion of maize silage at the expense of grass silage both N excretion and enteric CH_4 emission were reduced.

There is currently no direct evidence that the feed-driven compositional changes in manures enhance C sequestration. However, the linear correlation between C content of manure and increased SOC has been established in numerous studies with a 0.12–0.23 tC increase in SOC per tonne manure C added (Fornara et al., 2020; Guo et al., 2007; Ludwig et al., 2011; Maillard and Angers, 2014). Therefore, increasing C content of slurry via feed strategies should, in theory, enhance SOC, although the impact is likely to be minor. The main impact of feed strategies on SOC levels will be in terms of forage cultivation, with the primary impact of management associated with soil disturbance (ploughing) and/or vegetation type. Croplands tend to have lower SOC levels due to the fact that disturbance, such as ploughing breaks up aggregates, exposing long-term SOC to decomposition, while C input from crop growth tends to be limited to shorter periods than perennial systems (Six et al., 1998; Smith et al., 2010). Grasslands tend to have larger SOC levels due to lack of disturbance which leave aggregates undisturbed, year-long green cover, but also increases the proportion of fungi in the soil which aid in aggregate formation (Chambers et al., 2016; Ogle et al., 2005; Salvador et al., 2017; Soussana et al., 2010).

Modelling approaches to obtain an integral assessment of the GHG emissions and to derive a GHG farm budget and C footprint of animal product starts from modelling the feed management and its downstream effect on other farm components (i.e. housing, manure handling and soil). Indeed, the impacts on whole farm emissions have generally been restricted to modelling studies. Little et al. (2017) used the Holos model, a static farm system model that utilizes empirical relationships between feed, manure and soil characteristics to generate enteric and manure and soil emissions, to study alfalfa vs corn-based diets on farm. It also used a semi-empirical two-pool model (the ICBM model) to estimate soil C changes. Small differences were observed in terms of CH_4 and N_2O emissions, with slightly lower absolute emissions from the alfalfa systems, but lower emissions intensity for the corn system. However, SOC levels were projected to be almost 20 tC ha^{-1} higher in the alfalfa system, highlighting the need for a holistic approach.

Other studies on the impacts of oil, condensed tannin and/or NO_3^- supplementation highlighted the tradeoff between GHG emissions, liveweight gain and profit margins, with strategies that optimized finishing weight and held GHG constant estimated as being more profitable compared to strategies that decreased total GHG but maintained a constant finishing weight (Harrison et al., 2016; Herd et al., 2015; Rawnsley et al., 2018). These studies highlighted the strength of modelling approaches in the ability to combine various strategies into tailored production systems. They also highlight the dependency of the systems boundary utilized as Herd et al. (2015) concluded that the GHG benefit of supplementary lipid feeding was diminished once embedded energy extra diesel used in transporting the supplement were accounted.

3.6. Modelling studies on the impact of feeding strategies at the production system level

Instead of modelling the impact of diet on the emissions at the animal level, some studies extend the modelling efforts to allow evaluation of the downstream effect of diet on other GHG emissions and on N in manure management chain including grasslands and production of feed crops. Various N-flow models have been developed to assess the impact of grassland management and the evaluation of the effects of various dietary strategies and N intake on milk and N losses to air and water (del Prado et al., 2006; Hoekstra et al., 2020; Wheeler et al., 2008). These modelling results have been useful in terms of optimizing the ratio of milk yield to environmental N losses (i.e. CH_4, NO_3^- leaching, N_2O and NH_3 emissions). Using an empirical model based on fiber and CP content and IPCC methodology, Rendon-Huerta et al. (2018) analyzed the potential of feeding strategies to reduce CH_4 and N_2O emissions in dairy cattle operations. The results suggested that cows fed diets with a forage proportion of on average 50% of dietary DM and 16.7% CP in dietary DM generated 2.8 g less CH_4 per unit of milk (11.6 $g \cdot kg^{-1}$ milk) and had a 2.7% higher N utilization (27.8%), compared to diets with a forage proportion of >56% and lower CP content of 15.9%. Van Middelaar et al. (2014) studied the cost-effectiveness of NO_3^- supplementation, an altered grassland management and the dietary inclusion of linseed as enteric CH_4 mitigating feeding strategies in dairy cows to mitigate farm GHG emissions, using a dynamic mechanistic model for enteric fermentation and digestion in combination with an LCA method. Although NO_3^- supplementation largely reduced GHG emissions, in terms of cost-effectiveness, reducing the stage of maturity of grass harvested for ensiling was the option with lower cost and was indicated as most promising for application in practice.

These modelling studies demonstrate that for an assessment of the effect of dietary measures on whole farm GHG emission it is important to derive the integral effect on GHG emissions from the individual farm components, including the trade-offs or synergies between them. It also should be emphasized however that although assessments are generally made based on static EF's and empirical equations, for some details it appears necessary to represent underlying processes and their tradeoffs. Different modelling frameworks that have been developed to assess GHG an N emission from farm components (animal, housing and manure handling, and soil) using different modelling approaches (including process-based models that represent these underlying processes) are discussed next.

4. Inventory/assessment of GHG and nitrogen emissions from dairy and beef cattle production systems

4.1. Inventory/assessment of enteric CH_4 emissions

About 95% of enteric CH_4 is produced by ruminants (Mills, 2008), and the digestive system impacts the rate of CH_4 emissions as well as age, body weight and characteristics of feed consumed (IPCC, 2019a). The level of CH_4 emissions may also be associated with profitability of the herd as it is associated with feed conversion efficiency and cattle performance (Mills, 2008).

It has been argued that dynamic mechanistic approach is more suitable over empirical relationships for simulating the processes of digestion and rumen function in order to address environmental issues at the farm level (Bannink et al., 2006a). Various dynamic, mechanistic models of rumen fermentation have been developed that represent the degradation of feed substrates, their utilization by microorganisms and the production of end-products of fermentation. Some models only describe the rumen, some describe the whole gastrointestinal tract (Fig. 2) (Baldwin et al., 1987; Dijkstra et al., 1992; Ellis et al., 2014; Lescoat and Sauvant, 1995). Prediction of methanogenesis furthermore requires accurate prediction of the molar proportion of individual VFA as end-products of fermentation, determining H_2 production and its use by methanogens for CH_4 production(Benchaar et al., 1998; Mills et al., 2001). The prediction of VFA is generally unsatisfactory (Nagorcka et al., 2000) and mostly empirical estimates of stoichiometric coefficient for VFA production are used with rumen modelling (Bannink et al., 2006b), although recently also a more mechanistic approach has been adopted (van Lingen et al., 2019).

Nitrous oxide can also, in principle, be a byproduct of feeding or of enteric fermentation, although the overall contribution of this gas to enteric fermentation emissions is almost absent (Hamilton et al., 2010) unless the diet contains considerable amounts of NO_3^- (Petersen et al., 2015). Considering the global warming potential of N_2O that is 296 times greater than CO_2 (IPCC, 2001) the trade-off of N_2O formed with NO_3^- feeding should be taken into account. According to Rotz et al. (2018) more research is needed on enteric N_2O, and they assumed an EF of 0.8 g N_2O kg^{-1} of N intake to predict enteric N_2O emission from dairy cattle and 2.2 g N_2O kg^{-1} of N intake from beef cattle, in Integrated Farm System Model (IFSM) at the farm scale.

Using a multivariate Bayesian model, Reed et al. (2014) showed that increasing diet metabolizable energy content increases the efficiency with which feed N is converted to milk N, and therefore reducing N losses and improving dairy production efficiency. Having good estimates of N losses, in particular with urine, is very important to quantify N emissions from the animal excreta and the whole production chain (Rotz et al., 2014). Modelling N excretion in cattle could be represented as a function of different animal and dietary variables, such as N intake and N digestibility (Dong et al., 2014), or through more dynamic and mechanistic models representing the processes of digestion in the gastrointestinal tract (Bannink et al., 2018).

In terms of reporting GHG emissions, the IPCC classifies the methodologies into three distinct Tiers, according to the quantity of information required, and the degree of complexity of the applied models (Fig. 3). The IPCC provides default Tier 1 estimates of the amount of CH_4 generated by enteric fermentation, with EF's between 73 and 138 (kg CH_4 $head^{-1}$ $year^{-1}$) for dairy cattle and between 46 and 64 for other cattle categories (i.e. mature females, mature males, steers, heifers and calves) depending on regional characteristics, animal categories and the level of productivity). When gross energy intake data is available based on diet description and energy feed evaluation systems, a more advanced Tier 2 approach can be adopted involving the use of CH_4 conversion factor (i.e. the percentage of gross energy intake converted to CH_4 energy). There is a substantial opportunity to further increase the accuracy of Tier 2 predictions by capturing the variation in factors that impact feed requirements and consumption (e.g. level of feed intake, diet composition, digestibility, genotype of animal, heat stress effect on feed intake and maintenance requirements). These estimates can be improved even further for country specific circumstances

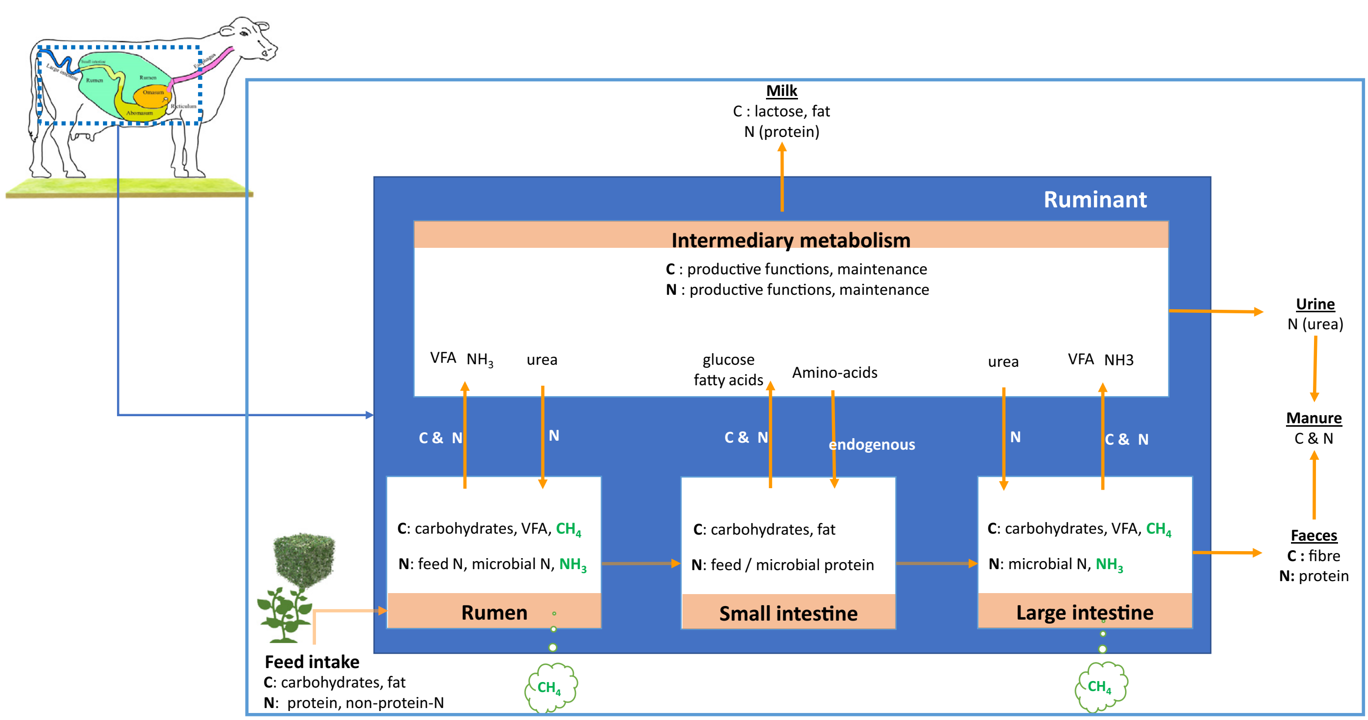


Fig. 2. Simplified scheme model representation of the main routes of nitrogen (N) and carbon (C) in the gastrointestinal tract in ruminants (adapted from Dijkstra et al. (2011)), CH_4: methane, NH_3: ammonia, VFA: volatile fatty acids.

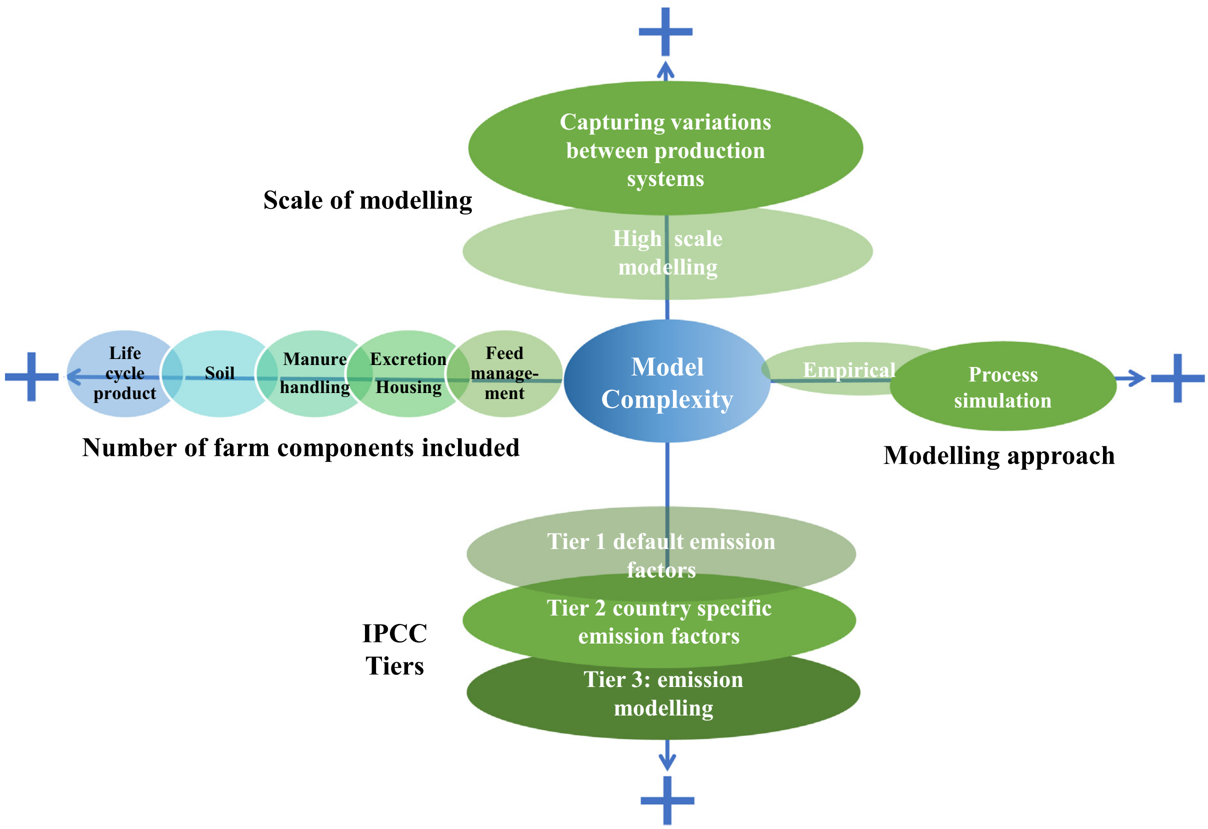


Fig. 3. Schematic diagram of the group of models associated with assessment of greenhouse gas and nitrogen emissions from cattle production systems and their level of complexity with respect to number of farm components included, adopted Intergovernmental Panel on Climate Change (IPCC) approach, modelling approach, and scale of modelling.

with Tier 3 methodology (IPCC, 2019a), either by an experimental/empirical or by a mechanistic modelling approach.

Enteric CH_4 emissions have been predicted using empirical relationships which are relatively simple to use because the input variables used are commonly available in many cases (Bell and Eckard, 2012; Jentsch et al., 2007; Van Gastelen et al., 2017; Wilkerson et al., 1995). A recent review by Hristov et al. (2018) highlighted the main uncertainties in predicting enteric CH_4 using these empirical models, especially in inventories. The accuracy of these models could be increased if they are developed from robust and numerous datasets encompassing different types of diets in different production systems across the world. Using both mechanistic and empirical regression approaches to predict CH_4 emissions in dairy cattle, Benchaar et al. (1998) concluded that prediction accuracy was higher with the mechanistic models compared to regression models when there is a large variation in diet composition. Therefore, the use of dynamic, mechanistic models that simulate the digestion and methanogenesis in the rumen can be a suitable way to improve prediction accuracy because they are more sensitive to dietary changes over empirical models. Sufficient data should be available to generate model inputs, however. In line with this, Kebreab et al. (2008) compared two empirical and two mechanistic models to assess enteric CH_4 emissions and also concluded mechanistic models provide better predictions and assessment of the potential of mitigation options, and recommended their use for inventory purposes.

Indeed, more advanced Tier 3 models have been developed to predict enteric CH_4 from ruminants and to be applied in national inventories (Table 4). Nevertheless, the models that have been referred to with the term "Tier 3" appear to involve a wide range of models; from empirical models (Eugène et al., 2019; Jo et al., 2016), to static, mechanistic models (Herrero et al., 2008), to dynamic, mechanistic models also referred to as 'process-based' models (Bannink et al., 2011). The Tier 3 models that have been reported adopt very different approaches to capture the dietary effects on enteric CH_4 (and downstream GHG emissions). They must be documented in a transparent way and the inventories complied must undergo detailed external review before their results are accepted, regardless of the tier approach used. Bannink et al. (2011) developed a Tier 3 from an extant dynamic, mechanistic model of digestion and fermentation to estimate enteric CH_4 in dairy cows. This model has been used also in Dutch national GHG inventories since 2005 and was recently updated to improve prediction of apparent fecal N digestion in support of Dutch NH_3 inventory (Bannink et al., 2018) while leaving predicted enteric CH_4 unaffected. Karoline is a Nordic, dynamic and mechanistic model that describes digestion and has modules for predicting enteric CH_4 emissions in dairy cows (Huhtanen

Table 4
Modelling frameworks for assessment of enteric CH_4 emissions according to IPCC Tier 3 methodology.

Model	Applicable to:	Country	Model approach	Diet components model inputs	Reference
Danish Tier 3 method	Dairy cows	Denmark, Norway, and Sweden	Empirical equations	DMI, fatty acids and NDF	(Nielsen et al., 2013)
Dutch tier 3 method	Dairy cows	Netherlands	Dynamic and mechanistic	DMI, chemical composition of the diet, intrinsic rumen degradation characteristics	(Bannink et al., 2011)
French Tier 3 method	Ruminants	France	Empirical equations	DMI, digestible organic matter intake, dietary proportion of concentrate	(Eugène et al., 2019)
Japanese tier 3 method	Beef cattle	Japan	Empirical equations	DMI	(Jo et al., 2016)

DMI = dry matter intake, NDF = neutral detergent fiber, IPCC: Intergovernmental Panel on Climate Change.

et al., 2015). However, this model is not used as Tier 3 method in CH_4 inventory in any of these countries, as they still use simple empirical equations. Indeed, Nielsen et al. (2013) proposed an equation to predict CH_4 based on input variables related to DMI, content of sugars, CP, and NDF (Neutral Detergent Fiber) as implemented in the Nordic feed evaluation system. More recently, Eugène et al. (2019) proposed a more generic Tier 3 method by an empirical equation based on feeding level and dietary proportion of concentrate to predict enteric CH_4 to be applied in French GHG inventory.

4.2. Inventory/assessment of emissions from animal housing and manure handling

The CH_4 emission from livestock manure (i.e., faeces and urine) can also be estimated by various tiers (IPCC, 2019a). The Tier 1 and the advanced Tier 1a approach provide default EF's based on the amount of VS excreted by animals in each type of manure management system (between 6.0 and 18.2 g CH_4 kg^{-1} VS for dairy cows, and between 7.6 and 14.1 g CH_4 kg^{-1} VS for other cattle). Following IPCC Tier 2 guidelines, predicting CH_4 emissions from manure relies on the amount of VS in manure (i.e. biodegradable and non-biodegradable fractions of OM in manure), which can be modelled based on feed intake and dietary nutrient characteristics and digestibility and B_0, the CH_4 production potential from the degradation of these compounds (IPCC, 2019a). A recent study suggested however an empirical model that estimates VS outputs as a function of OM intake and dietary nutrient composition (NDF, CP) from dairy cows with higher accuracy compared to the default IPCC Tier 2 guidelines (Appuhamy et al., 2018), indicating that there is room for improved prediction accuracy by further model development.

The prediction of the amount of N loss in manure management systems and the partitioning of N between urinary N and fecal N is important in order to determine the quantity of N available as well as the N formed in the soil after manure application. Petersen (2018) argued that more dynamic and consistent methods (process-based non-static approach) are needed to accurately estimate emissions from manure management. Yet, estimating N_2O emissions from livestock systems with higher Tier 3 method would require herd structure, annual populations and feed intake and feed characterization as inputs (IPCC, 2019a). It is worth noting that the IPCC recommends considering emissions that occur at the farm site only (i.e. on-farm storage of the input materials for manure digestion and pre-digestion, leakage during the digestion process and emissions from the storage and application of digestate to agricultural fields) and not emissions that result from combustion when the manure is used for biogas production.

A mechanistic approach or more process level simulation of NH_3 production would be required to estimate emissions under different production systems and evaluating the best mitigation strategies (Hristov et al., 2011), and an overview of the elements required for this have been reviewed by Sommer et al. (2006). Using such a mechanistic model, the effect of N excretion, herd and barn characteristics on NH_3 emission was predicted by Monteny et al. (2002). The NH_3 emission could be predicted accurately for a wide range of diets and barn conditions. A similar approach has been taken by Zhang et al. (2005) in the development of the animal housing sub-model of their Farm Emissions Model (FEM). Similar to Monteny et al. (1998), it uses a mass balance model to calculate the ammoniacal N concentration in the housing air, and a ventilation model is used to calculate ventilation rate. A meta-analysis of the impacts of nutrition and environmental effects on NH_3 emissions from US dairy housing revealed that milk yield was negatively correlated with NH_3 while outside air temperature, CP and DMI positively impacted NH_3 emissions (Bougouin et al., 2016). Floor type also had a significant effect with emissions from slatted floors four times lower compared to open-lot systems. In a more integral approach, Rotz et al. (2014) integrated an NH_3 emission model, which simulates the process of NH_3 formation and estimates the whole farm emission, with the Integrated farm system model (IFSM). Recently, another process-based model that simulates the whole emissions including CO_2, CH_4, N_2O and NH_3 as well as the corresponding C and N losses from cattle manure compost has been incorporated to the IFSM (Bonifacio et al., 2017). GAG is another process simulation model that estimate NH_3, total ammoniacal nitrogen (TAN) and soil pH from urine patches in grazing conditions (Móring et al., 2015). Other models allow assessing the overall emissions from manure management starting from the point of excretion by the animal till the field application. For example, Manure DNDC developed by Li et al. (2012) is a process-based model based on biogeochemical concepts that simulates the reactions that occur in manure and considers the environmental factors that drive the processes of emissions from livestock manure. The model allows the construct of customized virtual farm by incorporating the farm characteristics and adopted management practices, and it computes the main on-farm GHG emissions (CO_2, CH_4, N_2O) and NH_3 and NO_3^- leaching. The model allows to evaluate dietary effects by considering both feed intake (kg DM $head^{-1}$ day^{-1}) and %CP in dietary DM as inputs (Table 5).

4.3. Inventory/assessment of soil emissions

The characterization and modelling choice for soil C stock change and soil C and N emissions is highly scale dependent. At the farm and field levels, a range of biotic and abiotic parameters (including N and C inputs, vegetation type, climate, grazing intensity and duration and a range of soil characteristics) are important in order to accurately simulate C and N cycling and thus quantify management impacts on soil C stocks and N losses to air and water (Oertel et al., 2016). This is made more challenging due to the temporal asynchrony between SOC sequestration (which changes over decadal timescales) and soil C and N emissions (which vary diurnally and seasonally).

At the national/regional scale, inventory-based approaches may be satisfactory as the principal drivers are the amount and type of N and C inputs and soil texture. In terms of N_2O, the IPCC inventory approach calculates emissions based on the amount of N within a category multiplied by the relevant EF. The IPCC applies a Tier 1 EF of 1% of applied N for EF_1 (the EF for direct N inputs), and 0.4% for EF_3 (the EF for deposited N during grazing, termed pasture, range and paddock).These EF's may be lower or higher depending on climatic zone and N type applied (IPCC, 2019b). For this reason, some countries such as Canada, Netherlands, New Zealand and Ireland use a Tier 2 EF's with N

Table 5
Process-based modelling frameworks for assessment of greenhouse and nitrogen emissions from animal housing and manure management.

Model	Country	Summary description of the model	Reference
Ammonia emission model	Netherlands	A model consisting in floor and slurry pit modules to predict NH_3 emission from dairy cow barns with cubicles (free stall)	(Monteny et al., 1998)
Ammonia emission model	USA	A sub model incorporated into Integrated Farm System Model for whole assessment of NH_3 emissions	(Rotz et al., 2014)
Manure DNDC	USA	A model based on biogeochemical concepts that simulate the reactions that occur in manure and consider the environmental factors that drive the processes of emissions.	(Li et al., 2012)
GAG model	UK	Process simulation model that estimate NH_3, TAN and soil pH from urine patches in grazing conditions	(Móring et al., 2015)
FAM	USA	Predictive model for estimating NH_3 emissions from confinement animal feeding operations	(Zhang et al., 2005)

NH_3: ammonia, TAN: total ammoniacal nitrogen.

disaggregated based on N type: EF_1 is typically disaggregated into urea N, ammonium nitrate and organic N (either liquid-applied or solid-applied), while EF_3 is disaggregated between dung and urine N (Harty et al., 2016; Krol et al., 2016; Metivier et al., 2009; Van der Weerden et al., 2011). Further disaggregation of all EF's can be performed for inclusion in static models based on soil type or land-use for modelling at smaller scales (Van der Weerden et al., 2011). This can be supplemented with either static EF's or empirical equations/response functions to account for leached and volatilized N (Hoekstra et al., 2020; Webb and Misselbrook, 2004). Disaggregation of EF's is based on measurements of N_2O emissions across the range of N types and soil types in order to generate the EF's and this research tends to be a) labour intensive and b) very expensive. The alternative approach is to develop mechanistic models and validate outputs against a subset of empirical data.

In terms of relative changes in SOC stocks, the inventory-based approach uses static land-use factors which quantify the annual rate of change in SOC based on default (Tier 1) land-use category (grassland, cropland, forestry, wetland), climatic zone and soil type — either mineral or organic soil, with mineral soil further disaggregated between sandy, low-activity clay and high activity clay soils (Ogle et al., 2004, 2005). Land-management factors can subsequently be utilized to further distinguish between different management with each land-use category. For instance, grassland has four management factors — improved, nominal, moderate degradation, and severe degradation (IPCC, 2006). These categories are generic – improved grassland for instance can account for higher fertilization, more productive species, or irrigation – all have the same land management accrual factor. The inventory approach also only accounts for the top 30 cm of soil (as this is the depth to which most anthropogenic impacts occur). In addition, the change in SOC is considered to be linear over a defined 30-year period, after which a new SOC equilibrium is assumed. This is a gross simplification as studies have indicated that upon land use or land management change that it can take over 100 years to reach a new SOC equilibrium (Johnson et al., 2008; Poeplau et al., 2011, 2015).

Sommer and Hutchings (2001) reviewed empirical models that predict NH_3 emissions from surface applied livestock manure (e.g. ALFAM model (Søgaard et al., 2002), that was upgraded to semi-empirical recently (Hafner et al., 2019). They highlighted that these models do not account for interactions between factors (e.g. interaction between climate and slurry DM) and hence cannot predict accurately. Therefore, instead of basing Tier 2 on empirical evidence, a mathematical representation of the processes involved in GHG emissions in soils can be adopted by an IPCC Tier 3 approach. This practice allows for the spatial and temporal variability of emissions to be captured, as well as the tradeoffs of changes in land use and management practices, and it may serve to further improve inventories (Metivier et al., 2009). In this respect, various process-based models have been developed. Nevertheless, Heinen (2006) reviewed fifty simplified process-based models for denitrification and reported that the representation of microbial reduction of nitrogenous compounds differs broadly between models. Furthermore, parameters of the water content dependent function for microbial reduction and water content need to be estimated with great accuracy for reliable emission predictions. Indeed, simultaneous C and N modelling requires robust modelling of the hydrological cycle, as C and N uptake and release are tightly coupled to plant and soil water relations and poor characterization of hydrological cycling through the soil/plant continuum remains a major source of uncertainty.

Other major abiotic drivers include climate (temperature, precipitation, relative humidity), soil parameters (soil C and N at various depths, texture, cation exchange capacity, water filled pore space (WFPS), vegetation parameters (shoot/root ratio, potential yield, water and nutrient demand). Finally, management data is required, including vegetation sowing/harvest dates, fertilizer type, amount and date of application, land preparation (ploughing, weed control, etc.), animal stocking rate and duration. Different process-based models may be sensitive to different inputs due to inherent bias within the individual model structure. Ensemble approaches may be advantageous in that this approach to assesses the sensitivity of different models to changes in input variables and generate an expanded envelope of possible systemic outputs (Guest et al., 2017; Sulman et al., 2018; Zimmermann et al., 2018).

Process-based dynamic models need to account for a myriad of biotic and abiotic drivers to simulate soil C and N cycling. These models may only simulate one loss pathway (NH_3 volatilization, NO_3^- leaching), focus on soil processes and/or individual C or N cycling or simulate whole ecosystem C and N cycling. Examples are listed in Table 6.

Century is a process-based model that simulates the dynamics of grassland and agricultural crop systems, especially the dynamics of C, N, phosphorus (P), and sulfur (S) for various plant-soil systems on monthly time step (Parton, 1996). Dellar et al. (2019) applied this model to model yields and N content of European grassland along with series of regression equation. They concluded that the dynamic modelling approach is more suitable over empirical modelling at the local level if site-specific analysis is required, whereas regression equations are more suitable to consider general trends. The process-based model DayCent represents an improved version of the Century model

Table 6
Process-based modelling frameworks for assessment of greenhouse gas and nitrogen emissions from soil.

Model	Country	Summary description of the model	Reference
Century	USA	Simulate the dynamics of grassland and agricultural crop systems, especially the dynamics of C, N, P, and S for various plant-soil systems	(Parton, 1996)
DayCent	USA	Daily step version of Century model	(Necpálová et al., 2015; Parton et al., 1998)
DNDC	USA	simulate the soil fluxes of N_2O, CO_2, CH_4 as well as NH_3 volatilization and NO_3^- leaching	(Giltrap et al., 2010; Li et al., 1992a, 1992b)
Ecosse	UK	Simulate C and N cycling and predict GHG emissions from organic soils in response to changes in land use and management practices	(Scottish Executive Environment and Rural Affairs Environmental Research, 2007)
Ecosys	Canada	simulate the fluxes of heat, water, C, O_2, N, P, and ionic solutes in natural and managed ecosystems	(Metivier et al., 2009)
PaSim	France	Simulate the fluxes of C, N, water, and energy at the interface between soil, vegetation, animals, and atmosphere in grassland ecosystems	(Riedo et al., 1998, 2002)
Volt'Air	France	mechanistic NH_3 volatilization models, that describe the pedo-climatic conditions of a soil surface at the required time and space resolution	(Garcia et al., 2011)
MERLIN	UK, Norway, the Netherlands, USA	Model of linked biotic and abiotic processes of N cycling in ecosystems to simulate leaching losses of inorganic N (NO_3^- and NH_4)	(Cosby et al., 1997)
HJA-N	USA	A model capturing temporal variation in the N and C budgets at a monthly time step	(Vaché et al., 2015)
SUNDIAL	UK	Simulates N dynamics in arable land	(Smith et al., 1996)
Roth C	UK	A monthly time step model to calculate the turnover of organic C in non-waterlogged soils	(Coleman and Jenkinson, 1996)
ICBM	Sweden	A model estimating dynamics of agricultural soil C pools	(Andrén et al., 2004)
CANDY	Germany	simulates temperature, moisture content, and C and N dynamics in soil	(Franko et al., 1995)
C-TOOL	Denmark	Simulates whole profile C storage in the profile of temperate agricultural soils	(Taghizadeh-Toosi et al., 2014)

C: carbon, N: nitrogen, P: phosphorus, N_2O: nitrous oxide, NH_3: ammonia, CO_2: carbon dioxide, NO_3^-: nitrate, NH_4: ammonium.

and it simulates soil N_2O, NO_x, and CH_4 fluxes among the atmosphere, the vegetation, and soil on a daily step (Parton et al., 1998). The pasture simulation model PaSim is a mechanistic biogeochemical model that simulates the fluxes of C, N, water, and energy at the interface between soil, vegetation, animals, and atmosphere in grassland ecosystems. It was originally developed by Riedo et al. (1998) and has been reviewed several times since, to include several changes among which the incorporation of a NH_3 exchange resistance model (Riedo et al., 2002). A further, widely used, process-based model is DNDC which simulates the soil fluxes of N_2O, CO_2, CH_4 as well as NH_3 volatilization and NO_3^- leaching. Originally, it was developed by Li et al. (1992a) with only 3 sub-models consisting of a thermal-hydraulic, a decomposition, and a denitrification sub-model. A more recent version includes two more sub-models which are fermentation and plant growth, and it accounts for the different management practices among which the practice of fertilizer and manure application (Giltrap et al., 2010). Soil emissions heavily depend on climate- and site-specific conditions as exemplified by various modelling efforts across countries. Recently, Kasper et al. (2019) modelled the effect of crop rotation, manure application, and climate- and site-specific conditions on N_2O emissions from Austrian soils. For application to Canadian conditions, the Metivier et al. (2009) developed the Ecosys model to simulate the fluxes of heat, water, C, O_2, N, P and ionic solutes in natural and managed ecosystems. The model represents the key biological processes and oxidation/reduction reactions that generate N_2O soil emissions. For organic soils, the Ecosse model was developed by the Scottish Executive Environment and Rural Affairs Environmental Research (2007) based on components of the single-point models DNDC, Century, Sundial and Rothc models. The model simulates GHG emissions from the soil/plant system and predicts C and N cycling in response to changes in land use and management practices.

4.4. Implications for inventory, whole-farm integral assessment and life cycle analysis

The IPCC Tier methodologies are applicable for national inventory purposes, but they lack the on-farm level resolution for a detailed analysis of emissions for a specific case of production system. Therefore, a more holistic approach is required to accurately assess GHG and N emissions in these systems. At the systems case level, LCA and so-called systems analysis models represent the main categories of whole farm GHG models (Crosson et al., 2011). In ruminant livestock farming systems, the use of domestic roughage produced on site and the return of manure to the soil crop system is what defines a whole farm approach and differentiates it from the intensive non-ruminant production systems for poultry and pig where feeds are imported and animals and excreta are exported (Schils et al., 2007b).

Several LCA studies have been carried out in beef and dairy cattle production systems (de Vries et al., 2015; de Vries and de Boer, 2010). According to McClelland et al. (2018), beef and dairy production systems are frequently evaluated using LCA methodology compared to other livestock species and 98% of studies include climate change as an impact category. In a study based on 44 milk LCA studies, Baldini et al. (2017) performed a critical review and highlighted that these studies need to be harmonized among practitioners because of their potential as a decision tool, and include a clear description of system boundaries as well as sensitivity analysis to consider the uncertainties related to the input data. However, Ellis et al. (2010) evaluated nine empirical equations for enteric CH_4 emission in cattle as they are incorporated into whole farm system models and reported that, generally, prediction accuracy of these empirical equations is poor. They concluded that their use may lead to an erroneous integral GHG assessment or inventory or lead to an incorrect evaluation of the effect of mitigation strategies. Furthermore, on a basis of a literature review of 31 published whole farm modelling studies in dairy and beef cattle, Crosson et al. (2011) reported substantial differences between models in terms of the EF's applied, the boundaries assumed, the approach of co-product allocation and the quality of input data. In itself, these differences limit a direct comparison between studies reported in literature. Furthermore, the modelling of soil C fluxes which represent an important sink and source for C in grassland-based production system, was either simplified or absent in most studies.

Despite the differences between whole farm models, they represent a very useful tool to assess the cycling of C and N within the farm and test different mitigation options in response to climatic drivers and management strategies. Indeed, the most complex whole farm simulation models try to link the underlying processes between the different components of the farming system and predict the GHG outputs (Del Prado et al., 2013). Various whole farm models (although based on different modelling approaches) have been developed in different countries to be implemented in beef and/or dairy cattle production systems. Some recent studies reviewed the whole farm system models found in literature to assess the GHG and N emissions from cattle production systems (Del Prado et al., 2013; Jose et al., 2016; Rotz, 2018). Table 7 summarizes and complements the list of the main models used in these reviews. Some of these models include mechanistic representations of the underlying processes (e.g. DairyGEM, IFSM), others models are based on empirical equations entirely, or they combine empirical and dynamic modelling approaches (e.g. SimSDairy).

The choice of a modelling framework that is based on a certain modelling approach depends mainly on the modelling objectives and the activity data that is available to feed the model. An overview on the modelling approaches separated into hierarchies and families with their capacities and limitations is presented in Table 8. The following sections reviews some modelling studies using different modelling approaches, that evaluated different management strategies for mitigating GHG and N emissions in cattle farming systems.

5. Modelling objectives and evaluation of management strategies

Mitigating CH_4, N_2O and NH_3 emissions from manure handling includes the whole chain of the production process: dietary manipulation and nutrient balance, housing and manure storage and treatment, and grazing management, crop and roughage production, and manure application.

The effect of mitigation strategies is generally modelled by analyzing the projections under a baseline scenario and under alternative scenarios that include changes in management practices towards reducing emissions at the farm or large-scale levels. The mitigation potential (in %) of each scenario is estimated by comparing the overall emissions between the baseline scenario and the mitigation scenario. In this light, several studies have analyzed future scenarios for agriculture and livestock and implications for GHG and N emissions from ruminant systems.

Donnellan et al. (2018) and Lanigan et al. (2018) projected and discussed different scenarios in Irish agriculture, where bovine agriculture is the most principal source of GHG and NH_3 emissions using a combined economic (FAPRI model) (Donnellan and Hanrahan, 2006) with an inventory emissions model. They proceeded to generate marginal abatement cost curves for a range of abatement options that either reduced CH_4/N_2O, increased SOC or displaced fossil fuel emissions. Furthermore, Garnsworthy (2004) proposed a model that relates changes in fertility parameters on predicted total gas emissions at the herd level and suggested that improvements in fertility, which means better production efficiency, is expected to reduce CH_4 emissions and NH_3 emissions up to 24% and 17% respectively. Common frameworks have been proposed for the implementation of these assessments of the cost-benefit of abatement measures which also incorporate the impact of upstream and downstream emissions, other environmental synergies/antagonisms, and key uncertainties (Eory et al., 2018). van der Weerden et al. (2018) estimated that changing dairy cattle grazing based production systems in New Zealand towards more efficient production systems, will decrease the GHG footprints generating lower emission intensity of 6% to 13% compared to the current systems.

Table 7
Whole farm modelling frameworks for assessment of on-farm direct and indirect greenhouse gas emissions from dairy and beef cattle systems.

Model	Animal category	Focus region	Model approach	Direct and indirect GHG outputs	Economics	Reference	Comments
BeefGEM	Beef cattle	Ireland	Empirical static model	CH_4, N_2O and CO_2, NH_3, NO_3^-	Yes	(Foley et al., 2011)	Model developed in Microsoft excel
CAPRI	Ruminants & non-ruminants	EU	Model based on IPCC tier 1 and tier 2 methodology	CH_4, N_2O	Yes	(Britz and Witzke, 2014)	
Cool Farm Tool		–	Model based on empirical equations and IPCC tier 1 and tier 2 approaches	Computes GHG emissions based on CO_2-eq	No	(Hillier et al., 2011)	
DairyGEM	Dairy cattle	USA	Process simulation model	CH_4, N_2O, CO_2, NH_3, H_2S	No	(Rotz et al., 2015)	
DairyWise	Dairy cattle	Netherlands	Empirical model based on crop and animal experiments	CH_4, N_2O, CO_2	Yes	(Schils et al., 2007a, 2007b)	Applicability restricted to the NL
FarmAC	Ruminants & non-ruminants	Denmark	The model uses Tier 2 approach for livestock and manure management and Tier 3 for crops and soil	CH_4, N_2O and CO_2, NH_3, C sequestration	No	(http://www.farmac.dk/)	web-based interface
FarmGHG	Dairy cattle	Europe	Model based on empirical equations and IPCC tier 1 and tier 2 methodologies	CH_4, N_2O and CO_2, NH_3, NO_3^-	No	(Olesen et al., 2004, 2006)	
GLEAM	Ruminants & non-ruminants	–	Model based generally on IPCC tier 1 and tier 2 guidelines under a life cycle assessment approach	CH_4, N_2O, CO_2	No	(Gerber et al., 2013)	
Holos	Dairy cattle	Canada	Empirical model based on IPCC tier 2 and tier 3 methodologies adapted to Canadian conditions	CH_4, N_2O, CO_2 NH_3, NO_3^-	No	(Little et al., 2008; McGeough et al., 2012)	Algorithms adapted to Canadian farming practices
HolosNor	Beef and dairy cattle	Norway	Empirical model based on Holos model adapted to Norwegian conditions	CH_4, N_2O, CO_2 NH_3, NO_3^-	No	(Bonesmo et al., 2013)	
Hoofprint	Ruminants	New Zealand	Empirical model	CH_4, N_2O, CO_2, NH_3, NO_3^-	No	(Sise et al., 2011)	
IFSM	Beef and dairy cattle	USA	Process simulation model	CH_4, N_2O, CO_2, NH_3, NO_3^-	Yes	(Rotz et al., 2014, 2018)	
OVERSEER	Ruminants	New Zealand	Model based generally on empirical equations and IPCC methodology	CH_4, N_2O, CO_2, NO_3^-	No	(Wheeler et al., 2008)	Presents the results as CO_2 equivalents
REPRO	Ruminants and non-ruminants	Germany	Model based generally on empirical equations and IPCC methodology	CH_4, N_2O, CO_2	No	(Küstermann et al., 2008)	Computes the overall GHG emissions in CO_2-eq in organic farming systems
SimSDairy	Dairy cattle	UK	Semi mechanistic model that uses both empirical and dynamic approaches	CH_4, N_2O, CO_2, NH_3, NO_3^-	Yes	(Del Prado et al., 2011)	
WFM	Dairy cattle	New Zealand	Model based on empirical components (regression equations) and a mechanistic component	CH_4	No	(Beukes et al., 2011; Palliser and Woodward, 2002)	Computes the overall GHG emissions in CO2-eq

GLEAM: global livestock environmental assessment model; WFM: whole farm model, IFSM: integrated farm system model.

In addition, using a bio-economic model, Bell et al. (2013) and Pryce and Bell (2017) concluded that genetic selection for better production efficiency (e.g. reducing milk volume and increasing fat and protein content, increasing survival) of the Australian dairy herd result in a reduction of GHG per unit of product while improving the net income (1.1% reduction in CH_4 and N_2O of the average herd).

Besides improving genetic merit and health of the herd, better production efficiency measures involve lower herd replacement rates, N use efficiency, use off-paddock facilities to reduce the time spent on pasture and adopting some management practices in order to reduce CH_4 and NH_3 emissions from livestock such as using low emission slurry spreading and manipulation of the diets (Gerber et al., 2013; Wall et al., 2010).

Table. 8
Modelling approaches separated into hierarchies and families with their capacities and limitations.

Modelling approach	Description/capacities of the models	Limitations
Inventory-based and static LCA models	– The activity data is multiplied by emission factors, or the use of generic values or empirical models to quantify individual emissions sources – Suitable for high scale modelling and national inventories	Can be of limited value if the objective is to compare the variation between regions, production systems, or individual mitigation measures
Empirical and statistical models	– Well-suited for practical applications when evaluating mitigation strategies, – Could be used as GHG calculator tools for farmers and for inventory purposes – Require a smaller number of input parameters	Do not allow capturing the variation between different production systems in different climate zones
Process-based and mechanistic models	– Allow capturing the impact of biotic and abiotic drivers on GHG and N emissions, such as feed quality, soil type, N input – Simulates the variation in GHG and N emissions and the associated whole farm budget – Represent underlying processes and their drivers within the system and evaluate the integral effect on GHG emissions – Estimate on-farm emission with higher accuracy compared to inventory based and empirical models – Allow assessing the impact of individual or a combination of mitigation options at the whole farm level, or assess the impact of climate change over time	Require a greater number of input parameters

LCA: life cycle analysis, GHG: greenhouse gas, N: nitrogen.

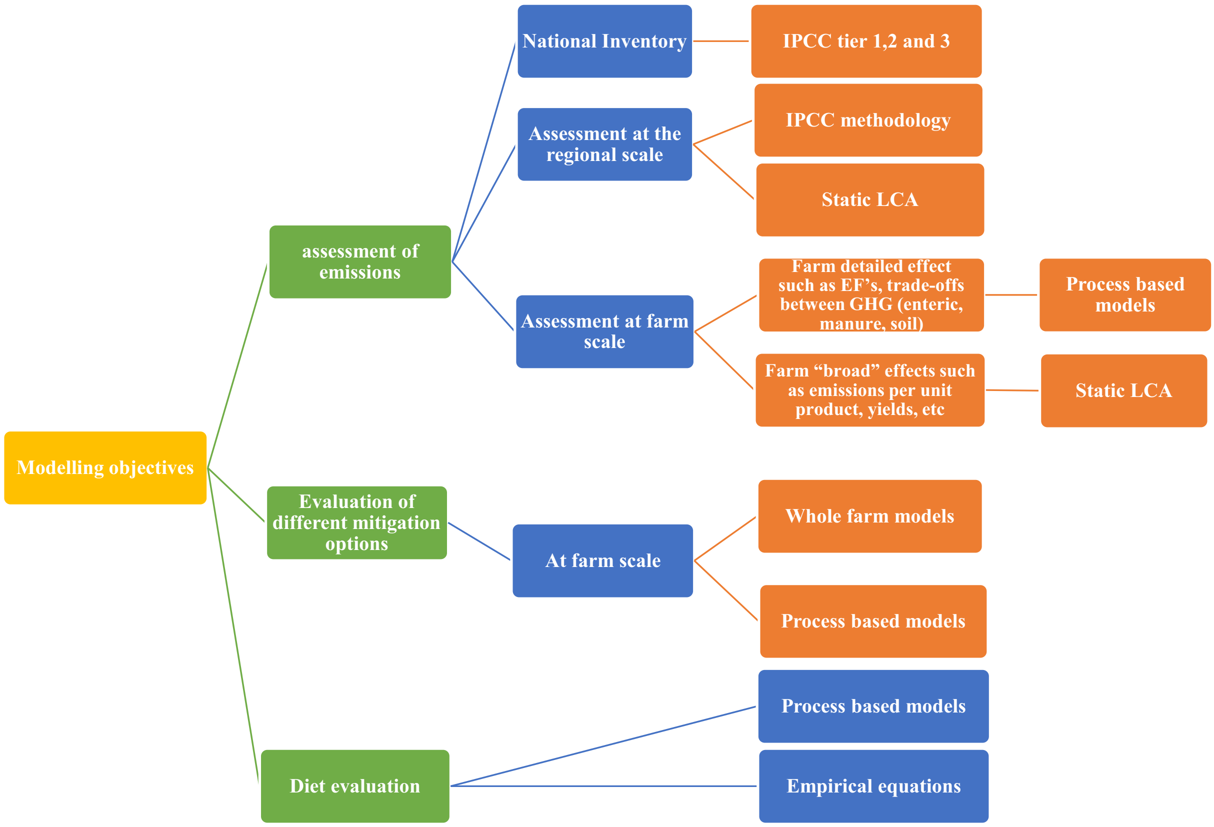


Fig. 4. Decision tree for the choice of the modelling approach to assess greenhouse gas and nitrogen emissions from cattle production systems depending on the objectives of modelling; LCA: life cycle assessment, IPCC: Intergovernmental Panel on Climate Change.

Furthermore, farm scale models were used to simulate GHG emissions and assess the environmental, economic, and technical implications of adopting alternative farm management strategies to reduce emissions. For example, Schils et al. (2007b) applied different whole farm models (i.e. DairyWise, FarmGHG, $SIMS_{DAIRY}$, and FarmSim) to estimate the impact of different mitigation options on on-farm GHG emissions such as anaerobic digestion or co-digestion of manure with residues, reduced grazing and increased use of maize crop and N use efficiency.

Hence, the modelling objectives define to a large extent what approach to be adopted, whether it is evaluating different mitigation options or assessing GHG and N emissions, depending on the scale (national, regional or farm level), or evaluation of diets and their relationships to gaseous emissions. Fig. 4 presents a decision tree for the choice of the modelling approach to assess GHG and N emissions from cattle production systems depending on the objectives of modelling.

6. Conclusions and recommendations

Various studies demonstrate the impact of dietary and livestock management decisions on whole-farm GHG and N emissions from beef and dairy production systems. The adoption of an integral assessment approach has to be preferred over isolating each emission source or farm component separately when evaluating GHG and N emissions and their drivers. This integrated approach allows for an overall estimate of direct as well as indirect GHG and N emissions including their trade-offs and synergies, and it allows comparisons between types of production systems and/or between different production conditions.

We recommend that any system model needs to balance a) the processes that the model is attempting to simulate, b) the mathematical approach that best represents those processes and c) the data required to parameterize and evaluate the model functioning. Process-based modelling approaches represent a reasonable alternative over experimental studies or modelling at a high scale (e.g. with farm LCA studies, or with inventory methods adopted at the farm scale). Representation at a high scale, while useful for national policy, can be of limited value if the objective is to compare the variation between regions, production systems, or individual mitigation measures. Static models using fixed values for EF's are essential tools when evaluating the impact of farm management strategies at fixed points in time, but cannot capture the spatial and temporal variation in processes and dynamics of C and N fluxes that are important when assessing spatial strategies or projecting emissions and productivity into the future. Process-based models may be promising tools to explore how assessment of GHG and N emissions can be improved beyond the current empirical models. Process-based models demonstrably cover a wider range of farming systems and conditions in terms of nutrition, manure management, soil fertilization and roughage/crop production. These models have an important advantage over adopting rather average estimates for GHG and N emissions, which may be suitable at the national scale, but which do not account for variations encountered on-farm. Therefore, it is our recommendation to make progress in prediction of GHG and N emissions by modelling studies delivering a precise definition of the aim and goal of the modelling effort, including a statement of the scale at which the model is expected to predict accurately, the type of mitigation measures the model is able to account for, including a clear presentation and definition of the underlying assumptions made. Implementation of these modelling systems do, however, require large amounts of activity data and depending on the temporal and spatial resolution required, these datasets may not be readily available. Deployment of process-based model systems will therefore (for some farm elements) also depend on the development of remote-sensing interpolation techniques or other proxies for these data.

Considering the relevance of feeding management strategies on on-farm GHG and N emissions, capturing the effect of dietary measures not only at the animal scale, but also downstream with farming activities through a process-based modelling approach appears a promising improvement over the adoption of average EF's. It allows for the assessment of how absolute GHG and N emissions as well as the emissions intensity of a product can be efficiently reduced.

Generally, the objective of process-based models is to investigate and explain variation in emissions factors and thereby deliver a process-based prediction of the direction of change in GHG emissions to be expected with changes in farm management. This is not necessarily the case with empirical models as they do not capture any mechanism behind the prediction variables in the model. Empirical models may very accurately represent the empirical evidence for a given situation or region and deliver a more accurate estimate of emissions/production for farms at that specific local or regional level. In this sense both types of modelling have their own value and can be used in support of each other.

The added value of modelling at the whole farm scale is their integral and overarching approach. However, they generally lack specificity and logicality in respect to representation of the underlying processes that give rise to GHG and N emissions because some parts are simplified and represented by empirical models. Further improvements could be made following an alternative approach by combining a set of process-based models to capture the dietary effects on GHG and N emissions at the animal scale as well as at different levels of manure management chain on the farm. Each modelled farm component delivers inputs for the other components, and in this way also process-based models can be used to generate an integral assessment of farm emissions.

In conclusion, if the objective is to compare the emissions between different countries or different food types at a high scale of modelling or a high systems level (e.g. meat and vegetables production), then simple models such as a static LCA approach or inventory-based approach with Tier 1 or Tier 2 EF's are adequate. However, if the modelling objective is to capture the variation between individual farm systems across a wide range of soil or climatic gradient or assess the synergy/antagonism between mitigation options and climate adaptation, we recommend that process-based models have important advantages in interpreting these interactions. Such an approach may have an important benefit over empirical approaches and in the fine-tuning and further improvement of whole farm scale models.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.145932.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This review was produced as part of the Capturing Effects of Diet on Emissions from Ruminant Systems (CEDERS) project, a FACCE ERA-GAS-funded project. ERA-GAS is the ERA-NET Cofund for monitoring & mitigation of Greenhouse gases from agri- and silvi-culture. The lead author is supported by the Teagasc Walsh Scholarship Fund and The Leibniz Institute for Agricultural Engineering and Bioeconomy-ATB Potsdam.

References

Allen, M., Pauline Dube, O., Solecki, W., Aragón-Durand, F., Cramer France, W., Humphreys, S., Kainuma, M., Kala, J., Mahowald, N., Mulugetta, Y., Perez, R., Wairiu, M., Zickfeld, K., 2018. 1. Framing and context. In: Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P.R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., Connors, S., Matthews, J.B.R., Chen, Y., Zhou, X., Gomis, M.I., Lonnoy, E., Maycock, T., Tignor, M., Waterfield, T. (Eds.), Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change. Press, p. 46.

Amon, B., Kryvoruchko, V., Amon, T., Zechmeister-Boltenstern, S., 2006. Methane, nitrous oxide and ammonia emissions during storage and after application of dairy cattle slurry and influence of slurry treatment. Agric. Ecosyst. Environ. 112, 153–162. https://doi.org/10.1016/j.agee.2005.08.030.

Andrén, O., Kätterer, T., Karlsson, T., 2004. ICBM regional model for estimations of dynamics of agricultural soil carbon pools. Nutr. Cycl. Agroecosyst., 231–239 https://doi.org/10.1023/B:FRES.0000048471.59164.ff.

Appuhamy, J.A.D.R.N., Moraes, L.E., Wagner-Riddle, C., Casper, D.P., Kebreab, E., 2018. Predicting manure volatile solid output of lactating dairy cows. J. Dairy Sci. 101, 820–829. https://doi.org/10.3168/jds.2017-12813.

Baldini, C., Gardoni, D., Guarino, M., 2017. A critical review of the recent evolution of Life Cycle Assessment applied to milk production. J. Clean. Prod. 140, 421–435. https://doi.org/10.1016/j.jclepro.2016.06.078.

Baldwin, R.L., Thornley, J.H.M., Beever, D.E., 1987. Metabolism of the lactating cow: II. Digestive elements of a mechanistic model. J. Dairy Res. 54, 107–131. https://doi.org/10.1017/s0022029900025231.

Bannink, A., Dijkstra, J., Kebreab, E., France, J., 2006a. Advantages of a dynamical approach to rumen function to help to resolve environmental issues. In: Kebreab, E., Dijkstra, J., Bannink, A., Gerrits, W.J.J., France, J. (Eds.), Nutrient Digestion and Utilization in Farm Animals Modelling Approaches. CABI Publishing, Wallingford, UK, pp. 281–298.

Bannink, A., Kogut, J., Dijkstra, J., France, J., Kebreab, E., Van Vuuren, A.M., Tamminga, S., 2006b. Estimation of the stoichiometry of volatile fatty acid production in the rumen of lactating cows. J. Theor. Biol. 238, 36–51. https://doi.org/10.1016/j.jtbi.2005.05.026.

Bannink, A., Smits, M.C.J., Kebreab, E., Mills, J.A.N., Ellis, J.L., Klop, A., France, J., Dijkstra, J., 2010. Simulating the effects of grassland management and grass ensiling on methane emission from lactating cows. J. Agric. Sci. 148, 55–72. https://doi.org/10.1017/S0021859609990499.

Bannink, A., van Schijndel, M.W., Dijkstra, J., 2011. A model of enteric fermentation in dairy cows to estimate methane emission for the Dutch National Inventory Report using the IPCC Tier 3 approach. Anim. Feed Sci. Technol. 166–167, 603–618. https://doi.org/10.1016/j.anifeedsci.2011.04.043.

Bannink, A., Spek, W.J., Dijkstra, J., Šebek, L.B.J., 2018. A tier 3 method for enteric methane in dairy cows applied for fecal N digestibility in the ammonia inventory. Front. Sustain. Food Syst. 2. https://doi.org/10.3389/fsufs.2018.00066.

Bell, M.J., Eckard, R.J., 2012. Reducing enteric methane losses from ruminant livestock – its measurement, prediction and the influence of diet. Livestock Production. InTech, p. 17 https://doi.org/10.5772/50394.

Bell, M.J., Eckard, R.J., Haile-Mariam, M., Pryce, J.E., 2013. The effect of changing cow production and fitness traits on net income and greenhouse gas emissions from Australian dairy systems. J. Dairy Sci. 96, 7918–7931. https://doi.org/10.3168/jds.2012-6289.

Benchaar, C., Rivest, J., Pomar, C., Chiquette, J., 1998. Prediction of methane production from dairy cows using existing mechanistic models and regression equations. J. Anim. Sci. 76, 617–627. https://doi.org/10.2527/1998.762617x.

Berner, R.A., 2009. A new look at the long-term carbon cycle. GSA Today 9, 2–6. https://doi.org/10.1130/1052-5173-19.1.40.

Beukes, P.C., Gregorini, P., Romera, A.J., 2011. Estimating greenhouse gas emissions from New Zealand dairy systems using a mechanistic whole farm model and inventory methodology. Anim. Feed Sci. Technol. 166–167, 708–720. https://doi.org/10.1016/j.anifeedsci.2011.04.050.

Blaxter, K.L., Clapperton, J.L., 1965. Prediction of the amount of methane produced by ruminants. Br. J. Nutr. 19, 511–522. https://doi.org/10.1079/bjn19650046.

Bonesmo, H., Beauchemin, K.A., Harstad, O.M., Skjelvåg, A.O., 2013. Greenhouse gas emission intensities of grass silage based dairy and beef production: a systems analysis of Norwegian farms. Livest. Sci. 152, 239–252. https://doi.org/10.1016/j.livsci.2012.12.016.

Bonifacio, H.F., Rotz, C.A., Richard, T.L., 2017. A process-based model for cattle manure compost windrows: part 1. Model Descr. Trans. ASABE 60, 877–892. https://doi.org/10.13031/trans.12057.

Bougouin, A., Leytem, A., Dijkstra, J., Dungan, R.S., Kebreab, E., 2016. Nutritional and environmental effects on ammonia emissions from dairy cattle housing: a meta-analysis. J. Environ. Qual. 45, 1123. https://doi.org/10.2134/jeq2015.07.0389.

Brask, M., Weisbjerg, M.R., Hellwing, A.L.F., Bannink, A., Lund, P., 2015. Methane production and diurnal variation measured in dairy cows and predicted from fermentation pattern and nutrient or carbon flow. Animal 9, 1795–1806. https://doi.org/10.1017/S1751731115001184.

Britz, W., Witzke, P., 2014. CAPRI Model Documentation.

Chambers, A., Lal, R., Paustian, K., 2016. Soil carbon sequestration potential of US croplands and grasslands: implementing the 4 per ThoUSAnd initiative. J. Soil Water Conserv. 71, 68A–74A. https://doi.org/10.2489/jswc.71.3.68A.

Chapin, F.S., Woodwell, G.M., Randerson, J.T., Rastetter, E.B., Lovett, G.M., Baldocchi, D.D., Clark, D.A., Harmon, M.E., Schimel, D.S., Valentini, R., Wirth, C., Aber, J.D., Cole, J.J., Goulden, M.L., Harden, J.W., Heimann, M., Howarth, R.W., Matson, P.A., McGuire, A.D., Melillo, J.M., Mooney, H.A., Neff, J.C., Houghton, R.A., Pace, M.L., Ryan, M.G., Running, S.W., Sala, O.E., Schlesinger, W.H., Schulze, E.D., 2006. Reconciling carbon-cycle concepts, terminology, and methods. Ecosystems. https://doi.org/10.1007/s10021-005-0105-7.

Cheng, L., McCormick, J., Hussein, A.N., Logan, C., Pacheco, D., Hodge, M.C., Edwards, G.R., 2017. Live weight gain, urinary nitrogen excretion and urination behaviour of dairy heifers grazing pasture, chicory and plantain. J. Agric. Sci. 155, 669–678. https://doi.org/10.1017/S0021859616001076.

Coleman, K., Jenkinson, D., 1996. A model for the turnover of carbon in soil. In: Powlson, D., Smith, P., Smith, J. (Eds.), Evaluation of Soil Organic Matter Models. Springer-Verlag, Berlin, pp. 237–246 https://doi.org/10.1007/978-3-642-61094-3_25.

Coppock, C.E., Flatt, W.P., Moore, L.A., Stewart, W.E., 1964. Relationships between end products of rumen fermentation and utilization of metabolizable energy for milk production. J. Dairy Sci. 47, 1359–1364. https://doi.org/10.3168/jds.S0022-0302(64)88918-9.

Cosby, B.J., Ferrier, R.C., Jenkins, A., Emmett, B.A., Wright, R.F., Tietema, A., 1997. Modelling the ecosystem effects of nitrogen deposition: Model of Ecosystem Retention and Loss of Inorganic Nitrogen (MERLIN). Hydrol. Earth Syst. Sci. https://doi.org/10.5194/hess-1-137-1997.

Crosson, P., Foley, P.A.A., Boland, T.M.M., Kenny, D.A.A., Shalloo, L., O'Brien, D., Lanigan, G.J.J., O'Brien, D., Lanigan, G.J.J., Foley, P.A.A., Boland, T.M.M., Kenny, D.A.A., 2011. A review of whole farm systems models of greenhouse gas emissions from beef and dairy cattle production systems. Anim. Feed Sci. Technol. 166–167, 29–45. https://doi.org/10.1016/j.anifeedsci.2011.04.001.

Del Prado, A., Misselbrook, T., Chadwick, D., Hopkins, A., Dewhurst, R.J., Davison, P., Butler, A., Schröder, J., Scholefield, D., 2011. SIMS DAIRY: a modelling framework to identify sustainable dairy farms in the UK. Framework description and test for organic systems and N fertiliser optimisation. Sci. Total Environ. 409, 3993–4009. https://doi.org/10.1016/j.scitotenv.2011.05.050.

Del Prado, A., Crosson, P., Olesen, J.E., Rotz, C.A., 2013. Whole-farm models to quantify greenhouse gas emissions and their potential use for linking climate change mitigation and adaptation in temperate grassland ruminant-based farming systems. Animal 7 (Suppl. 2), 373–385. https://doi.org/10.1017/S1751731113000748.

Dellar, M., Topp, C.F.E., Pardo, G., del Prado, A., Fitton, N., Holmes, D., Banos, G., Wall, E., 2019. Empirical and dynamic approaches for modelling the yield and N content of European grasslands. Manuscr. Subm. Publ. 122, 104562. https://doi.org/10.1016/j.envsoft.2019.104562.

Dijkstra, J., Neal, H., Beever, D.E., France, J., 1992. Simulation of nutrient digestion, absorption and outflow in the rumen: model description. J. Nutr 122, 2239–2256. https://doi.org/10.1093/jn/122.11.2239.

Dijkstra, J., Oenema, O., Bannink, A., 2011. Dietary strategies to reducing N excretion from cattle: implications for methane emissions. Curr. Opin. Environ. Sustain. 3, 414–422. https://doi.org/10.1016/j.cosust.2011.07.008.

Dijkstra, J., Oenema, O., van Groenigen, J.W., Spek, J.W., van Vuuren, A.M., Bannink, A., 2013. Diet effects on urine composition of cattle and N_2O emissions. Animal 7 (Suppl. 2), 292–302. https://doi.org/10.1017/S1751731113000578.

Dijkstra, J., Bannink, A., France, J., Kebreab, E., van Gastelen, S., 2018b. Short communication: antimethanogenic effects of 3-nitrooxypropanol depend on supplementation dose, dietary fiber content, and cattle type. J. Dairy Sci. 101, 9041–9047. https://doi.org/10.3168/jds.2018-14456.

Dijkstra, Jan, Bannink, A., Bosma, P.M., Lantinga, E.A., Reijs, J.W., 2018a. Modeling the effect of nutritional strategies for dairy cows on the composition of excreta nitrogen. Front. Sustain. Food Syst. 2. https://doi.org/10.3389/fsufs.2018.00063.

Dong, R.L., Zhao, G.Y., Chai, L.L., Beauchemin, K.A., 2014. Prediction of urinary and fecal nitrogen excretion by beef cattle. J. Anim. Sci. 92, 4669–4681. https://doi.org/10.2527/jas.2014-8000.

Donnellan, T., Hanrahan, K., 2006. The impact of potential WTO trade reform on greenhouse gas and ammonia emissions from agriculture: a case study of Ireland. In: Kaditi, E., Swinnen, J. (Eds.), Trade Agreements, Multifunctionality and EU Agriculture. Centre for European Policy Studies, Brussels, Belgium, p. 324.

Donnellan, T., Hanrahan, K., Lanigan, G., 2018. Future Scenarios for Irish Agriculture: Implications for Greenhouse Gas and Ammonia Emissions. Teagasc Irealand.

Ellis, J., Dijkstra, J., France, J., Parsons, A., Edwards, G., Rasmussen, S., Kebreab, E., Bannink, A., 2011. Effect of high-sugar grasses on methane emissions simulated using a dynamic model. J. Dairy Sci. 95, 272–285. https://doi.org/10.3168/jds.2011-4385.

Ellis, J.L., Bannink, A., France, J., Kebreab, E., Dijkstra, J., 2010. Evaluation of enteric methane prediction equations for dairy cows used in whole farm models. Glob. Chang. Biol. 16, 3246–3256. https://doi.org/10.1111/j.1365-2486.2010.02188.x.

Ellis, J.L., Dijkstra, J., Bannink, A., Kebreab, E., Archibeque, S., Benchaar, C., Beauchemin, K.A., Nkrumah, J.D., France, J., 2014. Improving the prediction of methane production and representation of rumen fermentation for finishing beef cattle within a mechanistic model. Can. J. Anim. Sci. 94, 509–524. https://doi.org/10.4141/CJAS2013-192.

Eory, V., Pellerin, S., Carmona Garcia, G., Lehtonen, H., Licite, I., Mattila, H., Lund-Sørensen, T., Muldowney, J., Popluga, D., Strandmark, L., Schulte, R., 2018. Marginal abatement cost curves for agricultural climate policy: state-of-the art, lessons learnt and future potential. J. Clean. Prod. 182, 705–716. https://doi.org/10.1016/j.jclepro.2018.01.252.

Eugène, M., Sauvant, D., Nozière, P., Viallard, D., Oueslati, K., Lherm, M., Mathias, E., Doreau, M., 2019. A new Tier 3 method to calculate methane emission inventory for ruminants. J. Environ. Manag. 231, 982–988. https://doi.org/10.1016/j.jenvman.2018.10.086.

European Commission, 2013. Green Paper — A 2030 Framework for Climate and Energy Policies, COM(2013) 169 Final. Brussels.

European Commission-Environment, 2010. The EU Nitrates Directive.

European Environment Agency, 2019. European Union Emission Inventory Report 1990–2017. https://doi.org/10.2800/78220.

FAO, 2006. Livestock's Long Shadow: Environmental Issues and Options Rome, Italy.

FAO, 2017. Livestock Solutions for Climate Change. Rome. https://doi.org/10.1109/CAMAP.2005.1574227.

FAO, 2018a. The Future of Food and Agriculture - Alternative Pathways to 2050. Summary Version Rome, Italy.

FAO, 2018b. Nitrogen inputs to agricultural soils from livestock manure. New statistics. Integrated Crop Management Rome.

Foley, P.A., Crosson, P., Lovett, D.K., Boland, T.M., O'Mara, F.P., Kenny, D.A., 2011. Whole-farm systems modelling of greenhouse gas emissions from pastoral suckler beef cow production systems. Agric. Ecosyst. Environ. 142, 222–230. https://doi.org/10.1016/j.agee.2011.05.010.

Fornara, D.A., Flynn, D., Caruso, T., 2020. Effects of nutrient fertilization on root decomposition and carbon accumulation in intensively managed grassland soils. Ecosphere 11. https://doi.org/10.1002/ecs2.3103.

Fowler, D., Coyle, M., Skiba, U., Sutton, M.A., Cape, J.N., Reis, S., Sheppard, L.J., Jenkins, A., Grizzetti, B., Galloway, J.N., Vitousek, P., Leach, A., Bouwman, A.F., Butterbach-Bahl, K., Dentener, F., Stevenson, D., Amann, M., Voss, M., 2013. The global nitrogen cycle in the twenty-first century. Philos. Trans. R. Soc. B Biol. Sci. 368. https://doi.org/10.1098/rstb.2013.0164.

Franko, U., Oelschlägel, B., Schenk, S., 1995. Simulation of temperature-, water- and nitrogen dynamics using the model CANDY. Ecol. Model. 81, 213–222. https://doi.org/10.1016/0304-3800(94)00172-E.

Garcia, L., Bedos, C., Génermont, S., Braud, I., Cellier, P., 2011. Assessing the ability of mechanistic volatilization models to simulate soil surface conditions. A study with the Volt'Air model. Sci. Total Environ. 409, 3980–3992. https://doi.org/10.1016/j.scitotenv.2011.05.003.

Garnsworthy, P.C., 2004. The environmental impact of fertility in dairy cows: a modelling approach to predict methane and ammonia emissions. Anim. Feed Sci. Technol. 112, 211–223. https://doi.org/10.1016/j.anifeedsci.2003.10.011.

van Gastelen, S., Dijkstra, J., Bannink, A., 2019. Are dietary strategies to mitigate enteric methane emission equally effective across dairy cattle, beef cattle, and sheep? J. Dairy Sci. 102, 6109–6130. https://doi.org/10.3168/jds.2018-15785.

Gerber, P., Vellinga, T., Opio, C., Henderson, B., Steinfeld, H., 2010. Greenhouse Gas Emissions from the Dairy Sector: A Life Cycle Assessment. FAO, Rome, Italy https://doi.org/10.1016/S0301-4215(01)00105-7.

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, G., 2013. Tackling Climate Change Through Livestock: A Global Assessment of Emissions and Mitigation Opportunities. Food and Agriculture Organization of the United Nations (FAO), Rome.

Gerlach, K., Schmithausen, A.J., Sommer, A.C.H., Trimborn, M., Büscher, W., Südekum, K.H., 2018. Cattle diets strongly affect nitrous oxide in the rumen. Sustain. 10, 1–13. https://doi.org/10.3390/su10103679.

Giger-Reverdin, S., Morand-Fehr, P., Tran, G., 2003. Literature survey of the influence of dietary fat composition on methane production in dairy cattle. Livest. Prod. Sci. 82, 73–79. https://doi.org/10.1016/S0301-6226(03)00002-2.

Giltrap, D.L., Li, C., Saggar, S., 2010. DNDC: a process-based model of greenhouse gas fluxes from agricultural soils. Agric. Ecosyst. Environ. 136, 292–300. https://doi.org/10.1016/j.agee.2009.06.014.

Grainger, C., Beauchemin, K.A., 2011. Can enteric methane emissions from ruminants be lowered without lowering their production? Anim. Feed Sci. Technol. 166–167, 308–320. https://doi.org/10.1016/j.anifeedsci.2011.04.021.

Guest, G., Kröbel, R., Grant, B., Smith, W., Sansoulet, J., Pattey, E., Desjardins, R., Jégo, G., Tremblay, N., Tremblay, G., 2017. Model comparison of soil processes in eastern Canada using DayCent, DNDC and STICS. Nutr. Cycl. Agroecosystems 109, 211–232. https://doi.org/10.1007/s10705-017-9880-8.

Guo, L., Falloon, P., Coleman, K., Zhou, B., Li, Y., Lin, E., Zhang, F., 2007. Application of the RothC model to the results of long-term experiments on typical upland soils in northern China. Soil Use Manag. 23, 63–70. https://doi.org/10.1111/j.1475-2743.2006.00056.x.

Hafner, S.D., Pacholski, A., Bittman, S., Carozzi, M., Chantigny, M., Génermont, S., Häni, C., Hansen, M.N., Huijsmans, J., Kupper, T., Misselbrook, T., Neftel, A., Nyord, T., Sommer, S.G., 2019. A flexible semi-empirical model for estimating ammonia volatilization from field-applied slurry. Atmos. Environ. 199, 474–484. https://doi.org/10.1016/j.atmosenv.2018.11.034.

Hamilton, S.W., DePeters, E.J., McGarvey, J.A., Lathrop, J., Mitloehner, F.M., 2010. Greenhouse gas, animal performance, and bacterial population structure responses to dietary monensin fed to dairy cows. J. Environ. Qual. 39, 106–114. https://doi.org/10.2134/jeq2009.0035.

Harrison, M.T., Cullen, B.R., Tomkins, N.W., McSweeney, C., Cohn, P., Eckard, R.J., 2016. The concordance between greenhouse gas emissions, livestock production and profitability of extensive beef farming systems. Anim. Prod. Sci. 56, 370–384. https://doi.org/10.1071/AN15515.

Harty, M.A., Forrestal, P.J., Watson, C.J., McGeough, K.L., Carolan, R., Elliot, C., Krol, D., Laughlin, R.J., Richards, K.G., Lanigan, G.J., 2016. Reducing nitrous oxide emissions by changing N fertiliser use from calcium ammonium nitrate (CAN) to urea based formulations. Sci. Total Environ. 563–564, 576–586. https://doi.org/10.1016/j.scitotenv.2016.04.120.

Heinen, M., 2006. Simplified denitrification models: overview and properties. Geoderma 133, 444–463. https://doi.org/10.1016/j.geoderma.2005.06.010.

Herd, R.M., Hutton Oddy, V., Bray, S., 2015. Baseline and greenhouse-gas emissions in extensive livestock enterprises, with a case study of feeding lipid to beef cattle. Anim. Prod. Sci. 55, 159–165. https://doi.org/10.1071/AN14222.

Herrero, M., Thornton, P.K., Kruska, R., Reid, R.S., 2008. Systems dynamics and the spatial distribution of methane emissions from African domestic ruminants to 2030. Agric. Ecosyst. Environ. 126, 122–137. https://doi.org/10.1016/j.agee.2008.01.017.

Hill, J., Redding, M., Pratt, C., 2016. A novel and effective technology for mitigating nitrous oxide emissions from land-applied manures. Animal Production Science. CSIRO, pp. 362–369 https://doi.org/10.1071/AN15519.

Hillier, J., Walter, C., Malin, D., Garcia-Suarez, T., Mila-i-Canals, L., Smith, P., 2011. A farm-focused calculator for emissions from crop and livestock production. Environ. Model. Softw. 26, 1070–1078. https://doi.org/10.1016/j.envsoft.2011.03.014.

Hoekstra, N.J., Schulte, R.P.O., Forrestal, P.J., Hennessy, D., Krol, D.J., Lanigan, G.J., Müller, C., Shalloo, L., Wall, D.P., Richards, K.G., 2020. Scenarios to limit environmental nitrogen losses from dairy expansion. Sci. Total Environ. 707, 134606. https://doi.org/10.1016/j.scitotenv.2019.134606.

Hou, Y., Velthof, G.L., Oenema, O., 2015. Mitigation of ammonia, nitrous oxide and methane emissions from manure management chains: a meta-analysis and integrated assessment. Glob. Chang. Biol. 21, 1293–1312. https://doi.org/10.1111/gcb.12767.

Hristov, A.N., Hanigan, M., Cole, A., Todd, R., McAllister, T.A., Ndegwa, P.M., Rotz, A., 2011. Review: ammonia emissions from dairy farms and beef feedlots. Can. J. Anim. Sci. 91, 1–35. https://doi.org/10.4141/CJAS10034.

Hristov, A.N., Oh, J., Firkins, J.L., Dijkstra, J., Kebreab, E., Waghorn, G., Makkar, H.P.S., Adesogan, A.T., Yang, W., Lee, C., Gerber, P.J., Henderson, B., Tricarico, J.M., 2013. Special topics — mitigation of methane and nitrous oxide emissions from animal operations: I. A review of enteric methane mitigation options. J. Anim. Sci. 91, 5045–5069. https://doi.org/10.2527/jas2013-6583.

Hristov, A.N., Kebreab, E., Niu, M., Oh, J., Bannink, A., Bayat, A.R., Boland, T.M., Brito, A.F., Casper, D.P., Crompton, L.A., Dijkstra, J., Eugène, M., Garnsworthy, P.C., Haque, N., Hellwing, A.L.F., Huhtanen, P., Kreuzer, M., Kuhla, B., Lund, P., Madsen, J., Martin, C., Moate, P.J., Muetzel, S., Muñoz, C., Peiren, N., Powell, J.M., Reynolds, C.K., Schwarm, A., Shingfield, K.J., Storlien, T.M., Weisbjerg, M.R., Yáñez-Ruiz, D.R., Yu, Z., 2018. Symposium review: uncertainties in enteric methane inventories, measurement techniques, and prediction models. J. Dairy Sci. 101, 6655–6674. https://doi.org/10.3168/jds.2017-13536.

Huhtanen, P., Huuskonen, A., 2019. Modelling effects of carcass weight, dietary concentrate and protein levels on the CH_4 emission, N and P excretion of dairy bulls. Livest. Sci. https://doi.org/10.1016/j.livsci.2019.103896.

Huhtanen, P., Ramin, M., Udén, P., 2015. Nordic dairy cow model Karoline in predicting methane emissions: 1. Model description and sensitivity analysis. Livest. Sci. 178, 71–80. https://doi.org/10.1016/j.livsci.2015.05.009.

IPCC, van der Linden, P.J., 2001. The scientific basis. In: Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., Dai, X., Maskell, K., Johnson, C.A. (Eds.), Climate Change 2001: Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press (CUP), Cambridge, United Kingdom and New York, NY, USA, p. 881 https://doi.org/10.1016/S1058-2746(02)86826-4.

IPCC, 2006. Vol 4. Agriculture, forestry and other land use. IPCC Guidelines for National Greenhouse Inventories. Hayama, Japan.

IPCC, 2014. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press (CUP), Cambridge, United Kingdom and New York, NY, USA.

IPCC, 2019a. Chapter 10: Emissions from livestock and manure management. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. IPCC, p. 225.

IPCC, 2019b. Chapter 11: N_2O emissions from managed soils, and CO_2 emissions from lime and urea application. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, pp. 11.1–11.54.

Janssen, P.H., 2010. Influence of hydrogen on rumen methane formation and fermentation balances through microbial growth kinetics and fermentation thermodynamics. Anim. Feed Sci. Technol. 160, 1–22. https://doi.org/10.1016/j.anifeedsci.2010.07.002.

Jayasundara, S., Ranga Niroshan Appuhamy, J.A.D., Kebreab, E., Wagner-Riddle, C., 2016. Methane and nitrous oxide emissions from Canadian dairy farms and mitigation options: an updated review. Can. J. Anim. Sci. 96, 306–331. https://doi.org/10.1139/cjas-2015-0111.

Jentsch, W., Schweigel, M., Weissbach, F., Scholze, H., Pitroff, W., Derno, M., 2007. Methane production in cattle calculated by the nutrient composition of the diet. Arch. Anim. Nutr. 61, 10–19. https://doi.org/10.1080/17450390601106580.

Jo, N., Kim, J., Seo, S., 2016. Comparison of models for estimating methane emission factor for enteric fermentation of growing-finishing Hanwoo steers. Springerplus 5. https://doi.org/10.1186/s40064-016-2889-7.

Johnson, I.R., Chapman, D.F., Snow, V.O., Eckard, R.J., Parsons, A.J., Lambert, M.G., Cullen, B.R., 2008. DairyMod and EcoMod: biophysical pasture-simulation models for Australia and New Zealand. Aust. J. Exp. Agric. 48, 621–631. https://doi.org/10.1071/EA07133.

Jose, V.S., Sejian, V., Bagath, M., Ratnakaran, A.P., Lees, A.M., Al-Hosni, Y.A.S., Sullivan, M., Bhatta, R., Gaughan, J.B., 2016. Modeling of greenhouse gas emission from livestock. Front. Environ. Sci. 4, 27. https://doi.org/10.3389/fenvs.2016.00027.

Kasper, M., Foldal, C., Kitzler, B., Haas, E., Strauss, P., Eder, A., Zechmeister-Boltenstern, S., Amon, B., 2019. N_2O emissions and NO_3^- leaching from two contrasting regions in Austria and influence of soil, crops and climate: a modelling approach. Nutr. Cycl. Agroecosyst. 113, 95–111. https://doi.org/10.1007/s10705-018-9965-z.

Kataria, R.P., 2016. Use of feed additives for reducing greenhouse gas emissions from dairy farms. Microbiol. Res. (Pavia) 6. https://doi.org/10.4081/mr.2015.6120.

Kebreab, E., Johnson, K.A., Archibeque, S.L., Pape, D., Wirth, T., 2008. Model for estimating enteric methane emissions from United States dairy and feedlot cattle. J. Anim. Sci. 86, 2738–2748. https://doi.org/10.2527/jas.2008-0960.

Khalil, T.M., Higgins, S.S., Ndegwa, P.M., Frear, C.S., Stöckle, C.O., 2016. Assessing the effect of different treatments on decomposition rate of dairy manure. J. Environ. Manag. 182, 230–237. https://doi.org/10.1016/j.jenvman.2016.07.056.

Kipling, R.P., Scollan, N.D., Bartley, D., Bellocchi, G., Hutchings, N.J., Dalgaard, T., Dasselaar, A.V.P., 2014. Modelling livestock and grassland systems under climate change. EGF at 50: The Future of European Grassland. Proceedings of the 25th General Meeting of the European Grassland Federation. Aberystwyth, Wales, 7–11 September 2014, pp. 97–99.

Kipling, R.P., Bannink, A., Bellocchi, G., Dalgaard, T., Fox, N.J., Hutchings, N.J., Kjeldsen, C., Lacetera, N., Sinabell, F., Topp, C.F.E., van Oijen, M., Virkajärvi, P., Scollan, N.D., 2016. Modeling European ruminant production systems: facing the challenges of climate change. Agric. Syst. 147, 24–37. https://doi.org/10.1016/j.agsy.2016.05.007.

de Klein, C.A.M., van der Weerden, T.J., Luo, J., Cameron, K.C., Di, H.J., 2020. A review of plant options for mitigating nitrous oxide emissions from pasture-based systems. N. Z. J. Agric. Res. 63, 29–43. https://doi.org/10.1080/00288233.2019.1614073.

Knapp, J.R., Laur, G.L., Vadas, P.A., Weiss, W.P., Tricarico, J.M., 2014. Invited review: enteric methane in dairy cattle production: quantifying the opportunities and impact of reducing emissions. J. Dairy Sci. 97, 3231–3261. https://doi.org/10.3168/jds.2013-7234.

Krol, D.J., Carolan, R., Minet, E., McGeough, K.L., Watson, C.J., Forrestal, P.J., Lanigan, G.J., Richards, K.G., 2016. Improving and disaggregating N_2O emission factors for ruminant excreta on temperate pasture soils. Sci. Total Environ. 568, 327–338. https://doi.org/10.1016/j.scitotenv.2016.06.016.

Kumar, S., Choudhury, P.K., Carro, M.D., Griffith, G.W., Dagar, S.S., Puniya, M., Calabro, S., Ravella, S.R., Dhewa, T., Upadhyay, R.C., Sirohi, S.K., Kundu, S.S., Wanapat, M., Puniya, A.K., 2014. New aspects and strategies for methane mitigation from ruminants. Appl. Microbiol. Biotechnol. https://doi.org/10.1007/s00253-013-5365-0.

Küstermann, B., Kainz, M., Hülsbergen, K.J., 2008. Modeling carbon cycles and estimation of greenhouse gas emissions from organic and conventional farming systems. Renew. Agric. Food Syst. 23, 38–52. https://doi.org/10.1017/S1742170507002062.

Kuypers, M.M.M., Marchant, H.K., Kartal, B., 2018. The microbial nitrogen-cycling network. Nat. Rev. Microbiol. 16, 263–276. https://doi.org/10.1038/nrmicro.2018.9.

Lanigan, G.J., Donnellan, T., Lanigan, G., Hanrahan, K., Paul, C., Shalloo, L., Krol, D., Forrestal, P., Farrelly, N., O'brien, D., Ryan, M., Murphy, P., Caslin, B., Spink, J., Finnan, J., Boland, A., Upton, J., Richards, K., 2018. An Analysis of Abatement Potential of Greenhouse Gas Emissions in Irish Agriculture 2021–2030 Prepared by the Teagasc Greenhouse Gas Working Group. Teagasc, Oak Park, Carlow.

Lassey, K.R., Ulyatt, M.J., Martin, R.J., Walker, C.F., Shelton, I.D., 1997. Methane emissions measured directly from grazing livestock in New Zealand. Atmos. Environ. 31, 2905–2914. https://doi.org/10.1016/S1352-2310(97)00123-4.

Lehnert, N., Coruzzi, G., Hegg, E., Seefeldt, L., Stein, L., 2015. NSF Workshop Report: Feeding the world in the 21st century : grand challenges in the nitrogen cycle. National Science Foundation, Arlington, VA.

Leip, A., Weiss, F., Wassenaar, T., Perez, I., Fellmann, T., Loudjani, P., Tubiello, F., Grandgirard, D., Monni, S., Biala, K., 2010. Evaluation of the Livestock Sector's Contribution to the EU Greenhouse Gas Emissions (GGELS) — Final Report. European Commission, Joint Research Centre.

Leip, A., Britz, W., Weiss, F., De Vries, W., 2011. Farm, land, and soil nitrogen budgets for agriculture in Europe calculated with CAPRI. Environ. Pollut. 159, 3243–3253. https://doi.org/10.1016/j.envpol.2011.01.040.

Leip, A., Ledgard, S., Uwizeye, A., Palhares, J.C.P., Aller, M.F., Amon, B., Binder, M., Cordovil, C.M.d.S., De Camillis, C., Dong, H., Fusi, A., Helin, J., Hörtenhuber, S., Hristov, A.N., Koelsch, R., Liu, C., Masso, C., Nkongolo, N.V., Patra, A.K., Redding, M.R., Rufino, M.C., Sakrabani, R., Thoma, G., Vertès, F., Wang, Y., 2019. The value of manure — manure as co-product in life cycle assessment. J. Environ. Manag. 241, 293–304. https://doi.org/10.1016/j.jenvman.2019.03.059.

Lescoat, P., Sauvant, D., 1995. Development of a mechanistic model for rumen digestion validated using the duodenal flux of amino acids. Reprod. Nutr. Dev. 35, 45–70. https://doi.org/10.1016/0926-5287(96)80180-8.

Lesschen, J.P., van den Berg, M., Westhoek, H.J., Witzke, H.P., Oenema, O., 2011. Greenhouse gas emission profiles of European livestock sectors. Anim. Feed Sci. Technol. 166–167, 16–28. https://doi.org/10.1016/j.anifeedsci.2011.04.058.

Li, C., Frolking, S., Frolking, T.A., 1992a. A model of nitrous oxide evolution from soil driven by rainfall events' 1. Model structure and sensitivity. J. Geophys. Res. 97, 9777–9783. https://doi.org/10.1029/92jd00510.

Li, C., Frolking, S., Frolking, T.A., Li, Changsheng, Frolking, S., Frolking, T.A., 1992b. A model of nitrous oxide evolution from soil driven by rainfall events: 2. Model applications. J. Geophys. Res. 97, 9777–9783. https://doi.org/10.1029/92jd00510.

Li, C., Salas, W., Zhang, R., Krauter, C., Rotz, A., Mitloehner, F., 2012. Manure-DNDC: a biogeochemical process model for quantifying greenhouse gas and ammonia emissions from livestock manure systems. Nutr. Cycl. Agroecosyst. 93, 163–200. https://doi.org/10.1007/s10705-012-9507-z.

van Lingen, H.J., Fadel, J.G., Moraes, L.E., Bannink, A., Dijkstra, J., 2019. Bayesian mechanistic modeling of thermodynamically controlled volatile fatty acid, hydrogen and methane production in the bovine rumen. J. Theor. Biol. 480, 150–165. https://doi.org/10.1016/j.jtbi.2019.08.008.

Little, S., Agriculture, C., Canada, A.-F., 2008. Holos, a Tool to Estimate and Reduce Greenhouse Gases from Farms: Methodology & Algorithms for Version 1.1. Publication. Agriculture and Agri-Food Canada, Canada Online.

Little, S.M., Benchaar, C., Janzen, H.H., Kröbel, R., McGeough, E.J., Beauchemin, K.A., 2017. Demonstrating the effect of forage source on the carbon footprint of a Canadian dairy farm using whole-systems analysis and the holos model: alfalfa silage vs. corn silage. Climate 5. https://doi.org/10.3390/cli5040087.

Liu, Z., Liu, Y., Shi, X., Wang, J., Murphy, J.P., Maghirang, R., Liu, Z., Member, A., Liu, Y., Student, G., Shi, X., Assistant, R., Wang, J., Murphy, J.P., Fellow, A., Maghirang, R., 2017. Enteric methane conversion factor for dairy and beef cattle: effects of feed digestibility and intake level. Trans. ASABE 60, 459–464. https://doi.org/10.13031/trans.11744.

Ludwig, B., Geisseler, D., Michel, K., Joergensen, R.G., Schulz, E., Merbach, I., Raupp, J., Rauber, R., Hu, K., Niu, L., Liu, X., 2011. Effects of fertilization and soil management on crop yields and carbon stabilization in soils. A review. Agron. Sustain. Dev. 31, 361–372. https://doi.org/10.1051/agro/2010030.

Luo, J., Saggar, S., Bhandral, R., Bolan, N., Ledgard, S., Lindsey, S., Sun, W., 2008. Effects of irrigating dairy-grazed grassland with farm dairy effluent on nitrous oxide emissions. Plant Soil 309, 119–130. https://doi.org/10.1007/s11104-008-9550-3.

Maillard, É., Angers, D.A., 2014. Animal manure application and soil organic carbon stocks: a meta-analysis. Glob. Chang. Biol. 20, 666–679. https://doi.org/10.1111/gcb.12438.

Massé, D.I., Jarret, G., Hassanat, F., Benchaar, C., Saady, N.M.C., 2016. Effect of increasing levels of corn silage in an alfalfa-based dairy cow diet and of manure management

practices on manure fugitive methane emissions. Agric. Ecosyst. Environ. 221, 109–114. https://doi.org/10.1016/j.agee.2016.01.018.
McClelland, S.C., Arndt, C., Gordon, D.R., Thoma, G., 2018. Type and number of environmental impact categories used in livestock life cycle assessment: a systematic review. Livest. Sci. 209, 39–45. https://doi.org/10.1016/j.livsci.2018.01.008.
McGeough, E.J., Little, S.M., Janzen, H.H., McAllister, T.A., McGinn, S.M., Beauchemin, K.A., 2012. Life-cycle assessment of greenhouse gas emissions from dairy production in Eastern Canada: a case study. J. Dairy Sci. 95, 5164–5175. https://doi.org/10.3168/jds.2011-5229.
Meale, S.J., Chaves, A.V., Baah, J., McAllister, T.A., 2012. Methane production of different forages in in vitro ruminal fermentation. Asian-Australasian. J. Anim. Sci. 25, 86–91. https://doi.org/10.5713/ajas.2011.11249.
Metivier, K.A., Pattey, E., Grant, R.F., 2009. Using the ecosys mathematical model to simulate temporal variability of nitrous oxide emissions from a fertilized agricultural soil. Soil Biol. Biochem. 41, 2370–2386. https://doi.org/10.1016/j.soilbio.2009.03.007.
Mills, J.A., Dijkstra, J., Bannink, A., Cammell, S.B., Kebreab, E., France, J., 2001. A mechanistic model of whole-tract digestion and methanogenesis in the lactating dairy cow: model development, evaluation, and application. J. Anim. Sci. 79, 1584–1597. https://doi.org/10.2527/2001.7961584x.
Mills, J.A.N., 2008. Modelling methane emissions from farm livestock. In: France, J., Kebreab, E. (Eds.), Mathematical Modelling in Animal Nutrition. CABI Publishing Series, p. 574 https://doi.org/10.1080/17508480009556350.
Monteny, G.J., Schulte, D.D., And, A.E., Lamaker, E.J.J., 1998. A conceptual mechanistic model for the ammonia emissions from free stall cubicle dairy cow houses, in: modelling of Ammonia emissions from dairy cow houses. Trans. ASAE 41 (1), 193–201.
Monteny, G.J., Smits, M.C.J., Van Duinkerken, G., Mollenhorst, H., De Boer, I.J.M., 2002. Prediction of ammonia emission from dairy barns using feed characteristics part II: relation between urinary urea concentration and ammonia emission. J. Dairy Sci. 85, 3389–3394. https://doi.org/10.3168/jds.S0022-0302(02)74426-3.
Montes, F., Meinen, R., Dell, C., Rotz, A., Hristov, A.N., Oh, J., Waghorn, G., Gerber, P.J., Henderson, B., Makkar, H.P.S., Dijkstra, J., 2013. Special topics — mitigation of methane and nitrous oxide emissions from animal operations: II. A review of manure management mitigation options. J. Anim. Sci. 91, 5070–5094. https://doi.org/10.2527/jas2013-6584.
Moraes, L.E., Fadel, J.G., Castillo, A.R., Casper, D.P., Tricarico, J.M., Kebreab, E., 2015. Modeling the trade-off between diet costs and methane emissions: a goal programming approach. J. Dairy Sci. 98, 5557–5571. https://doi.org/10.3168/jds.2014-9138.
Móring, A., Vieno, M., Doherty, R.M., Laubach, J., Taghizadeh-Toosi, A., Sutton, M.A., 2015. A process-based model for ammonia emission from urine patches, GAG (generation of ammonia from grazing): description, validation and sensitivity analysis. Biogeosci. Discuss. 12, 10059–10113. https://doi.org/10.5194/bgd-12-10059-2015.
Nagaraja, T.G., Titgemeyer, E.C., 2010. Ruminal acidosis in beef cattle: the current microbiological and nutritional outlook. J. Dairy Sci. 90, E17–E38. https://doi.org/10.3168/jds.2006-478.
Nagorcka, B.N., Gordon, G.L.R., Dynes, R.A., 2000. Towards a more accurate representation of fermentation in mathematical models of the rumen. In: McNamara, J.P., France, J., Beever, D.E. (Eds.), Modelling Nutrient Utilization in Farm Animals. CABI Publishing, p. 433 https://doi.org/10.1053/tvjl.2001.0576.
Necpálová, M., Anex, R.P., Fienen, M.N., Del Grosso, S.J., Castellano, M.J., Sawyer, J.E., Iqbal, J., Pantoja, J.L., Barker, D.W., 2015. Understanding the DayCent model: calibration, sensitivity, and identifiability through inverse modeling. Environ. Model. Softw. 66, 110–130. https://doi.org/10.1016/j.envsoft.2014.12.011.
Niderkorn, V., Baumont, R., le Morvan, A., Macheboeuf, D., 2011. Occurrence of associative effects between grasses and legumes in binary mixtures on in vitro rumen fermentation characteristics. J. Anim. Sci. 89, 1138–1145. https://doi.org/10.2527/jas.2010-2819.
Nielsen, N.I., Volden, H., Åkerlind, M., Brask, M., Hellwing, A.L.F., Storlien, T., Bertilsson, J., 2013. A prediction equation for enteric methane emission from dairy cows for use in NorFor. Acta Agric. Scand. A Anim. Sci. 63, 126–130. https://doi.org/10.1080/09064702.2013.851275.
Nousiainen, J., Rinne, M., Huhtanen, P., 2009. A meta-analysis of feed digestion in dairy cows. 1. The effects of forage and concentrate factors on total diet digestibility. J. Dairy Sci. 92, 5019–5030. https://doi.org/10.3168/jds.2008-1833.
O'Connell, C., Judson, H., Barrell, G., 2016. Sustained diuretic effect of plantain when ingested by sheep. 2016 Annu. Conf. New Zeal. Soc. Anim. Prod.
Oertel, C., Matschullat, J., Zurba, K., Zimmermann, F., Erasmi, S., 2016. Greenhouse gas emissions from soils—a review. Chem. Erde Geochem. https://doi.org/10.1016/j.chemer.2016.04.002.
Ogle, S.M., Conant, R.T., Paustian, K., 2004. Deriving Grassland Management Factors for a Carbon Accounting Method Developed by the Intergovernmental Panel on Climate Change. https://doi.org/10.1007/s00267-003-9105-6.
Ogle, S.M., Breidt, F.J., Paustian, K., 2005. Agricultural management impacts on soil organic carbon storage under moist and dry climatic conditions of temperate and tropical regions. Biogeochemistry 72, 87–121. https://doi.org/10.1007/s10533-004-0360-2.
Olesen, J.E., Weiske, A., Asman, W.A.H., Weisbjerg, M.R., Djurhuus, J., Schelde, K., 2004. FarmGHG. A model for estimating greenhouse gas emissions from livestock farms: documentation. Dan. Inst. Agric. Sci. 54.
Olesen, J.E., Schelde, K., Weiske, A., Weisbjerg, M.R., Asman, W.A.H., Djurhuus, J., 2006. Modelling greenhouse gas emissions from European conventional and organic dairy farms. Agric. Ecosyst. Environ. 112, 207–220. https://doi.org/10.1016/j.agee.2005.08.022.
Palliser, C.C., Woodward, S.L., 2002. Using Models to Predict Methane Reduction in Pasture Fed Dairy Cows.
Parton, W.J., 1996. The CENTURY model. In: Powlson, David S., Smith, P., Smith, J.U. (Eds.), Evaluation of Soil Organic Matter Models. Springer-Verlag, Berlin Heidelberg, pp. 283–291.
Parton, W.J., Hartman, M., Ojima, D., Schimel, D., 1998. DAYCENT and its land surface submodel: description and testing. Glob. Planet. Change 19, 35–48. https://doi.org/10.1016/S0921-8181(98)00040-X.
Petersen, S.O., 2018. Symposium review: greenhouse gas emissions from liquid dairy manure: prediction and mitigation. J. Dairy Sci. 101, 6642–6654. https://doi.org/10.3168/jds.2017-13301.
Petersen, S.O., Hellwing, A.L.F., Brask, M., Højberg, O., Poulsen, M., Zhu, Z., Baral, K.R., Lund, P., 2015. Dietary nitrate for methane mitigation leads to nitrous oxide emissions from dairy cows. J. Environ. Qual. 44, 1063–1070. https://doi.org/10.2134/jeq2015.02.0107.
Pierer, M., Amon, B., Winiwarter, W., 2016. Adapting feeding methods for less nitrogen pollution from pig and dairy cattle farming: abatement costs and uncertainties. Nutr. Cycl. Agroecosystems 104, 201–220. https://doi.org/10.1007/s10705-016-9767-0.
Poeplau, C., Don, A., Vesterdal, L., Leifeld, J., Van Wesemael, B., Schumacher, J., Gensior, A., 2011. Temporal dynamics of soil organic carbon after land-use change in the temperate zone — carbon response functions as a model approach. Glob. Chang. Biol. 17, 2415–2427. https://doi.org/10.1111/j.1365-2486.2011.02408.x.
Poeplau, C., Bolinder, M.A., Eriksson, J., Lundblad, M., Kätterer, T., 2015. Positive trends in organic carbon storage in Swedish agricultural soils due to unexpected socio-economic drivers. Biogeosciences 12, 3241–3251. https://doi.org/10.5194/bg-12-3241-2015.
Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B.L., Dietrich, J.P., Doelmann, J.C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., Kriegler, E., Lotze-Campen, H., Fricko, O., Riahi, K., Vuuren, D.P.va., 2017. Land-use futures in the shared socio-economic pathways. Glob. Environ. Chang. 42, 331–345. https://doi.org/10.1016/j.gloenvcha.2016.10.002.
del Prado, A., Scholefield, D., Brown, L., 2006. A model to simulate the effects of different dietary strategies on the sustainability of a dairy farm system. In: Kebreab, E., Dijkstra, J., Bannink, A., Gerrits, W.J.J., France, J. (Eds.), Nutrient Digestion and Utilization in Farm Animals Modelling Approaches. CABI Publishing, Wallingford, UK, pp. 275–280.
Pryce, J.E., Bell, M.J., 2017. The impact of genetic selection on greenhouse-gas emissions in Australian dairy cattle. Anim. Prod. Sci. 57, 1451–1456. https://doi.org/10.1071/AN16510.
Rawnsley, R., Dynes, R.A., Christie, K.M., Harrison, M.T., Doran-Browne, N.A., Vibart, R., Eckard, R., 2018. A review of whole farm-system analysis in evaluating greenhouse-gas mitigation strategies from livestock production systems. Anim. Prod. Sci. 58, 980–989. https://doi.org/10.1071/AN15632.
Reed, K.F., Moraes, L.E., Fadel, J.G., Casper, D.P., Dijkstra, J., France, J., Kebreab, E., 2014. Prediction of nitrogen use in dairy cattle: a multivariate Bayesian approach. Animal Production Science. CSIRO Publishing, pp. 1918–1926 https://doi.org/10.1071/AN14534.
Rendon-Huerta, J.A., Pinos-Rodríguez, J.M., Kebreab, E., 2018. Animal nutrition strategies to reduce greenhouse gas emissions in dairy cattle. Acta Univ. 28, 34–41. https://doi.org/10.15174/au.2018.1766.
Riedo, M., Grub, A., Rosset, M., Fuhrer, J., 1998. A pasture simulation model for dry matter production, and fluxes of carbon, nitrogen, water and energy. Ecol. Modell. 105, 141–183. https://doi.org/10.1016/S0304-3800(97)00110-5.
Riedo, M., Milford, C., Schmid, M., Sutton, M.A., 2002. Coupling soil-plant-atmosphere exchange of ammonia with ecosystem functioning in grasslands. Ecol. Model. 158, 83–110. https://doi.org/10.1016/S0304-3800(02)00169-2.
Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Kriegler, E., Mundaca, L., Seferian, R., Vilariño, M.V., 2018. Mitigation pathways compatible with 1.5 °C in the context of sustainable development. In: Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P.R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., Connors, S., Matthews, J.B.R., Chen, Y., Zhou, X., Gomis, M.I., Lonnoy, E., Maycock, T., Tignor, M., Waterfield, T. (Eds.), Global Warming of 1.5 °C. An IPCC Special Report on the Impacts of Global Warming of 1.5 °C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change. Press, p. 82.
Rotz, A.C., Chianese, D.S., Montes, F., Hafner, S., Bonifacio, H.F., 2015. Dairy Gas Emissions Model (DairyGEM). Ref. Man.
Rotz, C.A., 2018. Symposium review: modeling greenhouse gas emissions from dairy farms. J. Dairy Sci. 101, 6675–6690. https://doi.org/10.3168/jds.2017-13272.
Rotz, C.A., Montes, F., Hafner, S.D., Heber, A.J., Grant, R.H., 2014. Ammonia emission model for whole farm evaluation of dairy production systems. J. Environ. Qual. 43, 1143. https://doi.org/10.2134/jeq2013.04.0121.
Rotz, C.A., Corson, M.S., Chianese, D.S., Monte, F., Hafner, S.D., Bonifacio, H.F., Coiner, C.U., 2018. The Integrated Farm System Model — Reference Manual - Version 4.4.
Ruviaro, C.F., De Léis, C.M., Lampert, V. do N., Barcellos, J.O.J., Dewes, H., 2015. Carbon footprint in different beef production systems on a southern Brazilian farm: a case study. J. Clean. Prod. 96, 435–443. https://doi.org/10.1016/j.jclepro.2014.01.037.
Sajeev, E.P.M., Winiwarter, W., Amon, B., 2017. Greenhouse gas and ammonia emissions from different stages of liquid manure management chains: abatement options and emission interactions. J. Environ. Qual. 47, 30. https://doi.org/10.2134/jeq2017.05.0199.
Sajeev, E.P.M., Amon, B., Ammon, C., Zollitsch, W., Winiwarter, W., 2018. Evaluating the potential of dietary crude protein manipulation in reducing ammonia emissions from cattle and pig manure: a meta-analysis. Nutr. Cycl. Agroecosyst. 110, 161–175. https://doi.org/10.1007/s10705-017-9893-3.
Salvador, S., Corazzin, M., Romanzin, A., Bovolenta, S., 2017. Greenhouse gas balance of mountain dairy farms as affected by grassland carbon sequestration. J. Environ. Manag. 196, 644–650. https://doi.org/10.1016/j.jenvman.2017.03.052.
Schils, R., de Haan, M.H.A., Hemmer, J.G.A., van den Pol-van Dasselaar, A., de Boer, J.A., Evers, A.G., Holshof, G., van Middelkoop, J.C., Zom, R.L.G., 2007a. DairyWise, a

whole-farm dairy model. J. Dairy Sci. 90, 5334–5346. https://doi.org/10.3168/jds.2006-842.

Schils, R.L.M., Olesen, J.E., del Prado, A., Soussana, J.F., 2007b. A review of farm level modelling approaches for mitigating greenhouse gas emissions from ruminant livestock systems. Livest. Sci. 112, 240–251. https://doi.org/10.1016/j.livsci.2007.09.005.

Scottish Executive Environment and Rural Affairs Environmental Research, 2007. Ecosse-estimating Carbon in Organic Soils Sequestration and Emissions.

Sejian, V., Gaughan, J., Baumgard, L., Prasad, C., 2015. Climate Change Impact on Livestock: Adaptation and Mitigation. Springer India. MedCrave Group, LLC, London https://doi.org/10.1007/978-81-322-2265-1.

Shibata, M., Terada, F., Kurihara, M., Nishida, T., Iwasaki, K., 1993. Estimation of methane production in ruminants. Anim. Sci. Technol. 64, 790–796. https://doi.org/10.2508/chikusan.64.790.

Sise, J.A., Kerslake, J.I., Oliver, M.J., Glennie, S., Butler, D., Behrent, M., Fennessy, P.F., Campbell, A.W., 2011. Development of a software model to estimate daily greenhouse gas emissions of pasture-fed ruminant farming systems. Anim. Prod. Sci., 60–70 https://doi.org/10.1071/AN10072.

Six, J., Elliott, E.T., Paustian, K., Doran, J.W., 1998. Aggregation and soil organic matter accumulation in cultivated and native grassland soils. Soil Sci. Soc. Am. J. 62, 1367–1377. https://doi.org/10.2136/sssaj1998.03615995006200050032x.

Smith, J., Gottschalk, P., Bellarby, J., Richards, M., Nayak, D., Coleman, K., Hillier, J., Flynn, H., Wattenbach, M., Aitkenhead, M., Yeluripurti, J., Farmer, J., Smith, P., 2010. Model to Estimate Carbon in Organic Soils — Sequestration and Emissions (ECOSSE). User-Manual.

Smith, J.U., Bradbury, N.J., Addiscott, T.M., 1996. SUNDIAL: a PC-based system for simulating nitrogen dynamics in arable land. Agron. J. 88, 38–43. https://doi.org/10.2134/agronj1996.00021962008800010008x.

Smith, P., Soussana, J.F., Angers, D., Schipper, L., Chenu, C., Rasse, D.P., Batjes, N.H., van Egmond, F., McNeill, S., Kuhnert, M., Arias-Navarro, C., Olesen, J.E., Chirinda, N., Fornara, D., Wollenberg, E., Álvaro-Fuentes, J., Sanz-Cobena, A., Klumpp, K., 2020. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. Glob. Chang. Biol. 26, 219–241. https://doi.org/10.1111/gcb.14815.

Søgaard, H.T., Sommer, S.G., Hutchings, N.J., Huijsmans, J.F.M., Bussink, D.W., Nicholson, F., 2002. Ammonia volatilization from field-applied animal slurry-the ALFAM model. Atmos. Environ. 36, 3309–3319. https://doi.org/10.1016/S1352-2310(02)00300-X.

Sommer, S.G., Hutchings, N.J., 2001. Ammonia emission from field applied manure and its reduction — invited paper. Eur. J. Agron. 15, 1–15. https://doi.org/10.1016/S1161-0301(01)00112-5.

Sommer, S.G., Zhang, G.Q., Bannink, A., Chadwick, D., Misselbrook, T., Harrison, R., Hutchings, N.J., Menzi, H., Monteny, G.J., Ni, J.Q., Oenema, O., Webb, J., 2006. Algorithms determining ammonia emission from buildings housing cattle and pigs and from manure stores. Adv. Agron. 89, 261–335. https://doi.org/10.1016/S0065-2113(05)89006-6.

Soussana, J.F., Tallec, T., Blanfort, V., 2010. Mitigating the greenhouse gas balance of ruminant production systems through carbon sequestration in grasslands. Animal 4, 334–350. https://doi.org/10.1017/S1751731109990784.

Subbarao, G., Ito, O., Sahrawat, K., Berry, W., Nakahara, K., Ishikawa, T., Watanabe, T., Suenaga, K., Rondon, M., Rao, I., 2006. Scope and strategies for regulation of nitrification in agricultural systems — challenges and opportunities. CRC. Crit. Rev. Plant Sci. https://doi.org/10.1080/07352680600794232.

Sulman, B.N., Moore, J.A.M., Abramoff, R., Averill, C., Kivlin, S., Georgiou, K., Sridhar, B., Hartman, M.D., Wang, G., Wieder, W.R., Bradford, M.A., Luo, Y., Mayes, M.A., Morrison, E., Riley, W.J., Salazar, A., Schimel, J.P., Tang, J., Classen, A.T., 2018. Multiple models and experiments underscore large uncertainty in soil carbon dynamics. Biogeochemistry 141, 109–123. https://doi.org/10.1007/s10533-018-0509-z.

Swain, M., Blomqvist, L., McNamara, J., Ripple, W.J., 2018. Reducing the environmental impact of global diets. Sci. Total Environ. 610–611, 1207–1209. https://doi.org/10.1016/j.scitotenv.2017.08.125.

Taghizadeh-Toosi, A., Christensen, B.T., Hutchings, N.J., Vejlin, J., Kätterer, T., Glendining, M., Olesen, J.E., 2014. C-TOOL: a simple model for simulating whole-profile carbon storage in temperate agricultural soils. Ecol. Model. 292, 11–25. https://doi.org/10.1016/j.ecolmodel.2014.08.016.

UNFCC, 2015. Paris Agreement, Conference of the Parties on Its Twenty-first Session doi: FCCC/CP/2015/L.9.

Vaché, K., Breuer, L., Jones, J., Sollins, P., 2015. Catchment-scale modeling of nitrogen dynamics in a temperate forested watershed, Oregon. An interdisciplinary communication strategy. Water (Switzerland) https://doi.org/10.3390/w7105345.

Van der Weerden, T.J., Luo, J., de Klein, C.A.M., Hoogendoorn, C.J., Littlejohn, R.P., Rys, G.J., 2011. Disaggregating nitrous oxide emission factors for ruminant urine and dung deposited onto pastoral soils. Agric. Ecosyst. Environ. 141, 426–436. https://doi.org/10.1016/j.agee.2011.04.007.

Van Gastelen, S., Antunes-Fernandes, E.C., Hettinga, K.A., Dijkstra, J., 2017. Relationships between methane emission of Holstein Friesian dairy cows and fatty acids, volatile metabolites and non-volatile metabolites in milk. Animal 11, 1539–1548. https://doi.org/10.1017/S1751731117000295.

Van Middelaar, C.E., Dijkstra, J., Berentsen, P.B.M., De Boer, I.J.M., 2014. Cost-effectiveness of feeding strategies to reduce greenhouse gas emissions from dairy farming. J. Dairy Sci. 97, 2427–2439. https://doi.org/10.3168/jds.2013-7648.

Veneman, J.B., Muetzel, S., Hart, K.J., Faulkner, C.L., Moorby, J.M., Perdok, H.B., Newbold, C.J., 2015. Does dietary mitigation of enteric methane production affect rumen function and animal productivity in dairy cows? PLoS One 10, 1–18. https://doi.org/10.1371/journal.pone.0140282.

de Vries, M., de Boer, I.J.M., 2010. Comparing environmental impacts for livestock products: a review of life cycle assessments. Livest. Sci. 128, 1–11. https://doi.org/10.1016/j.livsci.2009.11.007.

de Vries, M., van Middelaar, C.E., de Boer, I.J.M., 2015. Comparing environmental impacts of beef production systems: a review of life cycle assessments. Livest. Sci. 178, 279–288. https://doi.org/10.1016/j.livsci.2015.06.020.

Wall, E., Simm, G., Moran, D., 2010. Developing breeding schemes to assist mitigation of greenhouse gas emissions. Animal 4, 366–376. https://doi.org/10.1017/S175173110999070X.

Warner, D., Bannink, A., Hatew, B., van Laar, H., Dijkstra, J., 2017. Effects of grass silage quality and level of feed intake on enteric methane production in lactating dairy cows. J. Anim. Sci. 95, 3687–3699. https://doi.org/10.2527/jas.2017.1459.

Webb, J., Misselbrook, T.H., 2004. A mass-flow model of ammonia emissions from UK livestock production. Atmos. Environ. 38, 2163–2176. https://doi.org/10.1016/j.atmosenv.2004.01.023.

van der Weerden, T., Beukes, P., de Klein, C., Hutchinson, K., Farrell, L., Stormink, T., Romera, A., Dalley, D., Monaghan, R., Chapman, D., Macdonald, K., Dynes, R., 2018. The effects of system changes in grazed dairy farmlet trials on greenhouse gas emissions. Animals 8, 1–20. https://doi.org/10.3390/ani8120234.

Weiske, A., Petersen, S.O., 2006. Mitigation of greenhouse gas emissions from livestock production. Agric. Ecosyst. Environ. 112, 105–106. https://doi.org/10.1016/j.agee.2005.08.009.

Wheeler, D.M., Ledgard, S.F., DeKlein, C.A.M., 2008. Using the OVERSEER nutrient budget model to estimate on-farm greenhouse gas emissions. Aust. J. Exp. Agric. 48, 99–103. https://doi.org/10.1071/EA07250.

Whitehead, D., Schipper, L.A., Pronger, J., Moinet, G.Y.K., Mudge, P.L., Calvelo Pereira, R., Kirschbaum, M.U.F., McNally, S.R., Beare, M.H., Camps-Arbestain, M., 2018. Management practices to reduce losses or increase soil carbon stocks in temperate grazed grasslands: New Zealand as a case study. Agric. Ecosyst. Environ. 265, 432–443. https://doi.org/10.1016/j.agee.2018.06.022.

Wilkerson, V.A., Casper, D.P., Mertens, D.R., 1995. The prediction of methane production of Holstein cows by several equations. J. Dairy Sci. 78, 2402–2414. https://doi.org/10.3168/jds.s0022-0302(95)76869-2.

van Wyngaard, J.D.V., Meeske, R., Erasmus, L.J., 2018. Effect of dietary nitrate on enteric methane emissions, production performance and rumen fermentation of dairy cows grazing kikuyu-dominant pasture during summer. Anim. Feed Sci. Technol. 244, 76–87. https://doi.org/10.1016/j.anifeedsci.2018.08.005.

Xu, R., Tian, H., Pan, S., Prior, S.A., Feng, Y., Batchelor, W.D., Chen, J., Yang, J., 2019. Global ammonia emissions from synthetic nitrogen fertilizer applications in agricultural systems: empirical and process-based estimates and uncertainty. Glob. Chang. Biol. 25, 314–326. https://doi.org/10.1111/gcb.14499.

Zhang, R., Rumsey, T.R., Fadel, J.G., Arogo, J., Wang, Z., Mansell, G.E., Xin, H., 2005. A Process-based Ammonia Emission Model for Confinement Animal Feeding Operations — Model Development. pp. 1–16.

Zimmermann, J., Carolan, R., Forrestal, P., Harty, M., Lanigan, G., Richards, K.G., Roche, L., Whitfield, M.G., Jones, M.B., 2018. Assessing the performance of three frequently used biogeochemical models when simulating N_2O emissions from a range of soil types and fertiliser treatments. Geoderma 331, 53–69. https://doi.org/10.1016/j.geoderma.2018.06.004.