The International Journal of Life Cycle Assessment
https://doi.org/10.1007/s11367-025-02529-5

CARBON FOOTPRINTING

Sensitivity analysis of parameters, emission factors, and coefficients for estimating animal emissions of ruminant species in the Global Livestock Environmental Assessment Model (GLEAM)

Armando Rivera Moncada[1] · Marie-Cécile Dupas[1,2] · Giuseppe Tempio[3] · Lydia Lanzoni[3] · Yushan Li[3] · Narindra Rakotovao[3] · Dominik Wisser[3] · Marius Gilbert[1]

Received: 29 April 2025 / Accepted: 5 August 2025

Abstract

Purpose Animal emissions account for nearly 60% of total greenhouse gas emissions from the livestock sector. To estimate these emissions, the Food and Agriculture Organization of the United Nations (FAO) developed a dedicated module within the Global Livestock Environmental Assessment Model (GLEAM). Although previous studies have explored selected inputs for specific animals and emission types, a comprehensive analysis of all 92 inputs (parameters and emission factors) had not been conducted. This study aimed to identify the most influential inputs affecting ruminant emissions in GLEAM.
Methods Using global data from GLEAM to build representative samples, a one-at-a-time (OAT) sensitivity analysis was conducted by varying each input individually while holding the others constant. Parameters-specific ranges were defined, and sensitivity was assessed using regression coefficients for methane, nitrous oxide, and their sum as total emissions.
Results Sensitivity was determined for 70 of the 92 inputs, based on a high R^2 between each input and the predicted emissions. Three parameters: gross energy of the diet, diet digestibility, and age at first calving, were the most influential with a negative correlation to animal emission, with diet digestibility emerging as the most sensitive. In contrast, parameters related to animal weight and two emissions factors: the methane producing capacity of manure (Bo) and urinary energy as a fraction of gross energy (UE), were the most influential with a positive correlation, mainly due to their impact on methane, which accounts for nearly 90% of total animal emissions. Nitrous oxide emissions were highly sensitive and positively correlated with the nitrogen content of the diet, while showing moderate sensitivity with a positive correlation to the emission factors for direct N_2O emissions from manure (EF3), for nitrogen volatilization and redeposition (EF4) and for N_2O from leaching/runoff (EF5). Regarding manure management systems, methane emissions were most affected and positively correlated with manure managed in liquid systems, while nitrous oxide emissions were most influenced with a positive correlation to manure managed as dry lot and deep litter. In contrast, changing manure management to compost, burned for fuel, or daily spreading showed the greatest potential to reduce animal emissions.
Conclusions The study identified the most and least influential parameters and emission factors based on individual effects but did not evaluate interactions between them. The findings support prioritizing data quality improvements for the most influential inputs while using default values for less influential ones, helping to improve the accuracy and efficiency of livestock emission assessments.

Keywords Livestock · Greenhouse gases · Model · Sensitivity · Emissions · GLEAM · Carbon footprint · Uncertainty

1 Introduction

The increase in greenhouse gas (GHG) emissions is causing temperatures to rise substantially worldwide, which is having serious effects on climate events. Livestock is widely recognized as a notable contributor to GHG emissions, accounting for approximately 12% of total anthropogenic emissions, when considering a life-cycle approach.

Communicated by Greg Thoma

Extended author information available on the last page of the article

Published online: 26 August 2025

Emissions directly related to animals, mainly from manure management and enteric fermentation, account for nearly 60% of livestock emissions.

To assess the environmental impact of the livestock sector and evaluate potential mitigation scenarios at national and global scale, the Global Livestock Environmental Assessment Model (GLEAM) serves as a primary analytical tool. Developed by the Food and Agriculture Organization of the United Nations (FAO), GLEAM incorporates methods, emission coefficients, and factors outlined by the Intergovernmental Panel on Climate Change (IPCC 2006, 2019), and simplifies the calculation process by reducing the complexity of required input parameters. Within its computational framework, GLEAM employs Life Cycle Assessment (LCA) and integrates spatial data that encompass animal production. The diverse data for the input parameters have been collected worldwide at various resolutions and from different sources, including surveys, literature, databases, and expert opinions. All of them are mapped onto a standardized grid with a spatial resolution of 10 km at the equator (FAO 2016).

All parameters and emission factors carry inherent uncertainties, which can lead to less accurate and less precise estimations of greenhouse gas emissions. To evaluate those impacts from individual parameters, sensitivity analysis has been identified as a key methodology, particularly when evaluating mitigation strategies in the livestock sector (Opio et al. 2013; Misra and Verma 2017). However, few studies have examined the sensitivity of parameters in the GLEAM model, and most specialized in specific greenhouse gas emissions or specific production systems. For instance, Uwizeye et al. (2017) conducted a sensitivity analysis on nitrogen flows through supply chains in dairy systems using GLEAM, with data collected from Rwanda and the Netherlands. Similarly, Opio et al. (2013) performed a sensitivity analysis to determine the most influential parameters and emission factors contributing to the uncertainty of emissions for dairy and beef systems in France and Paraguay.

A comprehensive evaluation of the model is essential to fully understand the sensitivity of all parameters and emission factors involved. Given that GLEAM is designed for global application, it is crucial to incorporate sensitivity analyses across all possible conditions to identify the most influential parameters and to help prioritize data collection and updating efforts. This study aims to analyse the impact of individual input parameters and emission factors used in GLEAM and similar models that follow IPCC guidelines. These models rely on a wide range of assumptions and variables, and understanding the contribution of each to the overall emission estimates is essential for accurately interpreting model results, especially when evaluating different scenarios.

A sensitivity analysis is particularly valuable as it enables researchers and policymakers to anticipate the effects of modifying specific input variables before applying changes in real-world scenarios. By identifying the parameters that most influence the results, we can better target interventions, improve model transparency, and enhance scenario analysis. Additionally, this study provides a foundation for future uncertainty assessments by highlighting the key inputs that should be prioritized when analysing emission variability, whether at the level of specific animal emission source or in a total animal emission estimate.

To establish an efficient sensitivity analysis method, it is essential to consider model complexity, the number of parameters, and the availability of input parameter ranges. Both model complexity and the number of parameters influence the computational cost of the analysis. To improve computational efficiency, techniques such as grouping parameters and defining samples have been developed (Saltelli et al. 2008). According to Pianosi et al. (2016), when the parameter range is available, testing sensitivity becomes simpler using a method referred to as Global Sensitivity Analysis. In contrast, if the range is unknown, assumptions must be made, such as defining a range around the mean value, which is the basis of Local Sensitivity Analysis.

One commonly used design in sensitivity analysis is the variation of one parameter at a time (OAT), characterized by its simplistic implementation without requiring any complex manipulation of the parameters data (Groen et al. 2016). Despite limitations in capturing the full impact of parameters, OAT is invaluable for screening low-impact parameters that might be excluded from more detailed analyses (Hamby 1994; Ferretti et al. 2016).

Several studies have employed an OAT design in sensitivity analysis to identify important parameters in emissions models that use the IPCC methodology. Most of these studies test models in specific countries, examining the uncertainty of default emission coefficients and factors from the IPCC. The primary outcome of these studies is the calculation of uncertainty transmission from these coefficients into emissions (Brown et al. 2001; Karimi-Zindashty et al. 2012).

In this paper, we conducted a sensitivity analysis of all parameters associated with the animal emission module, including their integration into all the preceding sequential modules (herd module and animal energy module) within the GLEAM model. Using data from four ruminant species, we applied a combined method of global and local sensitivity analysis, using an OAT (One-At-a-Time) design to determine the sensitivity of all the involved parameters.

2 Materials and methods.

The methodological framework of this study is based on, and fully aligned with, IPCC guidelines. We used GLEAM 3.0 (FAO 2022a), which incorporates the updated 2019 guidelines. However, its method for estimating nitrous oxide emissions is not fully in line with the IPCC methodology. To ensure alignment, the nitrous oxide component was adapted from GLEAM 2.0 (FAO 2016), which remains consistent with IPCC. In addition, the emission factors were updated according to the 2019 IPCC revisions. This approach allows the analysis to remain comparable with models based on the IPCC methodology.

The sensitivity analysis was performed using GLEAMS's global dataset from four ruminant species (cattle, buffalo, sheep and goats) (FAO 2022b), which is structured by production orientation and livestock production systems (see Appendix A for the list of the production systems). However, the sensitivity results are presented at the animal species level, as the IPCC guidelines estimate emissions at this scale, requiring a process of data aggregation. This paper includes numerous abbreviations for the parameters and emission factors analysed. For clarity, all abbreviations used throughout the manuscript are summarized in Table 1.

2.1 GLEAM model

GLEAM is structured into six sequential modules (FAO 2022a). The first, the herd module, categorizes the animal population into cohorts required by the IPCC to estimate emissions with a Tier 2 approach (see Appendix B for a list of the cohorts generated by GLEAM). It also provides additional outputs, such as average animal weight and growth rate. The second, the feed ratio and intake module, calculates animal energy requirements and estimates feed intake based on diet composition, also determining the nutritional composition of the feed ratio. The third, the animal emissions module, estimates emissions from animal production, including methane and nitrous oxide emissions from enteric fermentation and manure management. The fourth, the manure module, quantifies the amount of manure-nitrogen applied to crops after storage, or deposited on pastures by grazing animals. The fifth, the feed emissions module, assesses emissions from feed production, as carbon dioxide from energy consumption, methane from rice cultivation and nitrous oxide from nitrogen inputs to soils, including the manure-nitrogen calculated by the manure module. Finally, the allocation module distributes emissions among co-products generated throughout the supply chain.

This study evaluates the sensitivity of parameters associated with the animal emission module, which relies on outputs from the feed ratio and intake module. A total of 92 parameters, including inputs and emission factors, were identified across these two modules. However, some of these parameters also influence the herd module. To account for this, equations from the herd module that include these parameters were integrated, while fixed values, derived from the average of global datasets used in the analysis, were applied to the remaining parameters. The integration of the herd equations enabled the estimation of changes to the population structure in response to variation in input parameters, which were used to calculate a weighted average index to assess sensitivity at animal level. Additionally, since manure deposited on pasture is part of the manure management systems, the amount of manure-nitrogen on grassland, as estimated by the manure module, was integrated with emission factors from IPCC to calculate corresponding nitrous oxide emissions and evaluate the impact of variations in the fraction of this manure management system.

Figure 1 illustrates the structure of the GLEAM modules, Table 2. presents the processes and equations adopted from GLEAM, Table 3 details the average fixed values assigned to herd module parameters not included in the sensitivity analysis, and Fig. 2 illustrates the methodological process implemented in our study.

The model estimates four types of animal emissions: methane from enteric fermentation (CH_4_E), methane from manure (CH_4_M), nitrous oxide from manure management systems (N_2O_M) and nitrous oxide emitted from manure deposited on pastures (N_2O_MP). GLEAM applies a Global Warming Potential (GWP) factor to convert these emissions into CO_2-equivalent, enabling the calculation of total emissions. For this study, we used the GWP values from the AR5 assessment (FAO 2016): 34 for CH_4 and 298 for N_2O. This allowed for the assessment of the sensitivity of parameters and emission factors for each emission type, as well as their sensitivity effect on total emissions.

2.2 Classification of parameters tested in the sensitivity analysis

Due to the heterogeneous nature of the parameters involved, a classification was performed, based on the modules of GLEAM in which each parameter is used. This classification allows for defining a method and performing a sensitivity analysis for parameters with similar characteristics. Following the model description documentation (FAO 2016, 2022a), we established six groups of parameters. *Herd*: parameters related to animal growth and reproduction, *Feed*: parameters related to the nutritional values of feed, *Manure*: parameters associated to manure management systems. Additionally, we perform a detailed analysis of the equations, and we identify parameters whose complete range of values is integrated in the model. We group them in a fourth group called *Global Conditional* (See Appendix C).

Additionally, we identified the emission factors and coefficients (efc) used in the equations of the different modules in GLEAM, which were verified and updated following methods presented in Chapters 10 and 11 of the IPCC 2006 and 2019 guidelines (IPCC 2006, 2019). We explored these guidelines to extract the variability and uncertainty

Table 1 List of acronyms and abbreviations used throughout the paper

Abbreviation	Definition	Abbreviation	Definition
AF	Adult females	LINT	Lambing or kidding interval, period between two parturitions
afc	Age at first calving	litsize	Litter size, number of kids per parturition
afkg	Average live weight of adult female animals	MCF	CH_4 conversion factor for each mms
AM	Adult males	MF	Meat female animals
amkg	Average live weight of adult male animals	MFR	Ram to ewe (sheep) or does to bucks (goats) ratio
AR5	IPCC Fifth Assessment Report	mfskg	Live weight of female fattening animals at slaughter
bcr	Male to female ratio	milk_fat	Fat content of milk
BEF	Beef systems	milk_prot	Average fraction of protein in milk
BFL	Buffalo	milk_yield	Daily milk production
bo	Max CH_4 producing capacity for manure	MM	Meat male animals
Ca	Coefficient of animal's feeding situation	mms	Manure managed system (see appendix C)
CH_4	Methane emissions	mmskg	Live weight of male fattening animals at slaughter
CH_4_E	CH_4 from enteric fermentation	MXD	Mixed systems
CH_4_M	CH_4 from manure	N_2O	Nitrous oxide emissions
ckg	Live weight at birth	N_2O_M	N_2O from manure management systems
CO_2	Carbon dioxide	N_2O_MP	N_2O from manure deposited on pastures
CTL	Cattle	N_2Odirect	Direct N_2O from manure management
diet_di	Average digestibility of feed ration	N_2Oleach:	Indirect N_2O due to leaching from manure
diet_ge	Average gross energy content of feed ration	N_2Omanure	N_2O from manure
diet_n_cont	Average nitrogen content of feed ration	N_2Ovol	Indirect N_2O due to volatilization from manure
DMI	Dry matter intake	NEact	Net energy for activity
DR1	Death rate female calves, lambs or kids	NEfibre	Net energy for production of fibre
DR1M	Death rate male calves	NEgrow	Net energy for growth
DR2	Death rate other animals than calves, lambs or kids	NElact	Net energy for milk production
DRY	Dairy systems	NEmain	Net energy for maintenance
ef	Emission factor	NEpreg	Net energy for pregnancy
EF3	ef for direct N_2O emissions from mms	NEwork	Net energy for draught power
EF4	ef for nitrogen volatilization and redeposition	Nr	Nitrogen retention
EF5	ef for N_2O from leaching/runoff	Nx	Nitrogen excretion
efc	emission factors and coefficients	OAT	One-At-A-Time
FAO	Food and Agriculture Organization of United Nations	past_man_fra	Fraction of managed pastures
fr	fertility rate	prod_fibre	Annual production of fibre by animal
frac_leach_liquid	Proportion of manure nitrogen lost due to leaching from liquid manure	REG	Ratio of net energy available for growth in a diet to digestible energy consumed
frac_leach_solid	Proportion of manure nitrogen lost due to leaching from solid manure	REM	Ratio of net energy available in diet for maintenance to digestible energy consumed
frac_mlk	Fraction of milking adult females in the herd	RF	Replacement females
FracGasmPast	Fraction of nitrogen that volatilizes as NH_3 and NOx from manure	RFA	Replacement females in the midst of first year
FracLeachPast	Percentage nitrogen lost due to leaching/runoff from manure in pastures	RFB	Replacement females in the midst of the second year
FRRF	Rate of fertile replacement females	RM	Replacement males
GE	Total gross energy required	RMA	Replacement males in the midst of first year
GHG	Greenhouse emissions	RMB	Replacement males in the midst of the second year
GLEAM	Global Livestock Environmental Assessment Model	RRF	Replacement rate female animals
GRS	Grassland systems	RRF	Replacement rate female animals
GTS	Goats	SHP	Sheep
GWP	Global Warming Potential	temp	Average temperature Celsius
hours	Number of hours of work per day	UE	Urinary energy as fraction of gross energy

Table 1 (continued)

Abbreviation	Definition	Abbreviation	Definition
IPCC	Intergovernmental Panel on Climate Change	Vs	Daily volatile solids excreted by animal
lact	Duration of lactation period	ym	Percentage of gross energy converted to CH_4

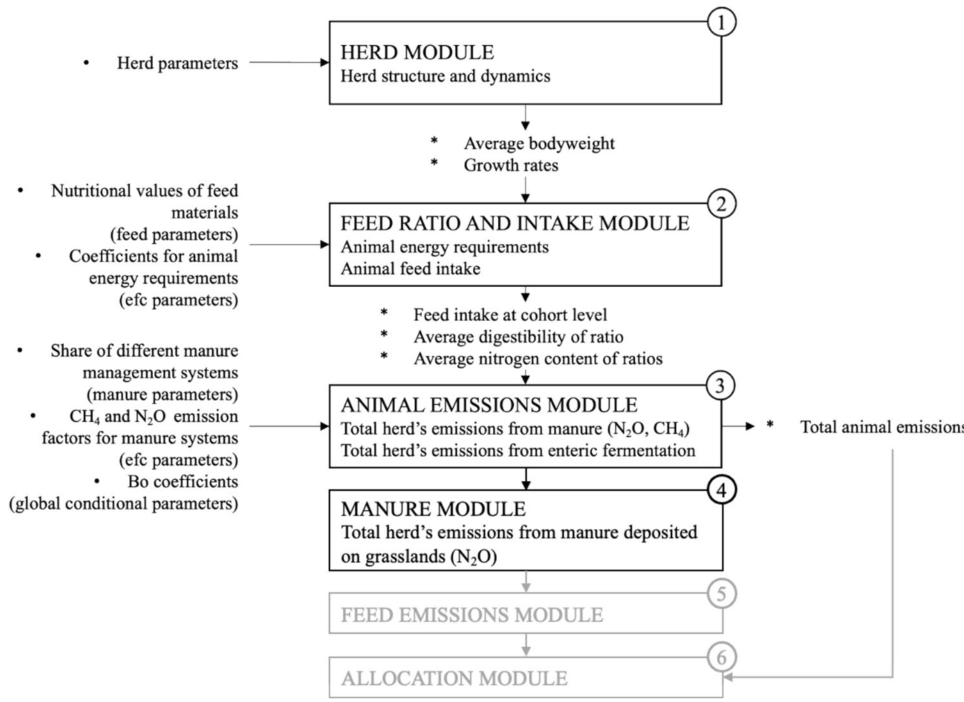

Fig. 1 GLEAM model structure adapted from FAO (2016, 2022a). The numbers represent the module number and calculation sequence. Modules 1, 2, 3, and 4 are part of this research

associated with each efc. With that information, we generated two additional groups: *Variability of emission factors and coefficients*: efc whose default values were derived from a range of values provided in the IPCC guidelines, *Uncertainty of emission factors and coefficients*: efc for which the IPCC guidelines provide uncertainty values (see Appendix D).

2.3 Parameters sample generation

A descriptive statistical assessment was conducted on the input parameters on each production system to evaluate data variability. Parameters related to feed nutritional values and manure management systems were identified with extremely low or null coefficients of variation, complicating the implementation of a sensitivity analysis based on data variability (see Appendix E). Moreover, the global datasets contain over 5 million records, which presented a major computational challenge for the sensitivity analysis process. To address this, a sample dataset was generated for each of the production systems to facilitate the evaluation of every parameter while simultaneously incorporating the complete variability of the *Global Conditional* parameters, whose full range is known. In each production system, following the sensitivity methodology approach by Pianosi et al. (2016), we established one fixed value for each parameter based on the characteristics of the parameter group, as described in Table 4.

Since our analysis tests the sensitivity of all parameters, we assign mean or mode values from other production systems to fill gaps or missing values. (see Appendix C and D for details on methods and values used on each parameter as fixed value). To assess sensitivity under all possible model conditions, we generated the sample dataset by creating unique combinations of global conditional parameters and incorporated the fixed values from the herd, feed, manure, emission factors and coefficient groups. For temperature, we only considered integer values, as GLEAM's conditions for this parameter are based on integer inputs. This approach reduced the size of the sample dataset and improved processing time.

2.4 Range definition for each parameter

To conduct the variation of one parameter at a time, a range was established on each parameter group. For the *Herd*

Table 2 Processes and subprocesses in GLEAM to estimate direct emissions

Process:	Source from GLEAM 3.0
Population proportion:	
BFL, CTL	Section 2.1.2
GTS, SHP	Section 2.2.2
Live weight and growth rates:	
BFL, CTL	Section 2.1.2.5
GTS, SHP	Section 2.2.2.4
Energy requirement – GE:	
NEmain: Net energy for maintenance	Equation 3.29
NEact: Net energy for activity	Equation 3.30–3.31
NEgrow: Net energy for growth	Equation 3.32–3.33
NElact: Net energy for milk production	Equation 3.34–3.35
NEwork: Net energy for draught power	Equation 3.36
NEfibre: Net energy for production of fibre	Equation 3.37
NEpreg: Net energy for pregnancy	Equation 3.38–3.39
REM: Ratio of net energy available in diet for maintenance to digestible energy consumed	Equation 3.40
REG: Ratio of net energy available for growth in a diet to digestible energy consumed	Equation 3.41
GE: Total gross energy	Equation 3.42
Dry matter intake estimation – DMI	Equation 3.53
Methane from enteric fermentation	
Ym: Percentage of gross energy converted to methane	Table 4.6
CH_4enteric	Equation 4.1
Methane from manure	
Vs: daily volatile solids excreted by animal	Equation 4.3
MCF: methane conversion factor for each manure management	Table 4.13[1]
CH_4manure	Equation 4.2
Nitrogen excretion – Nx	Equation 4.6
Nitrogen retention – Nr	Equation 4.7
Nitrogen oxide from manure management - N_2Omanure:	
N_2Odirect: Direct nitrous oxide from manure management	Equation 4.10[1]
N_2Ovol: Indirect nitrous oxide due to volatilization from manure management	Equation 4.11[1]
N_2Oleach: Indirect nitrous oxide due to leaching from manure management	Equation 4.12[1]
Nitrogen oxide from manure in pastures - $N_2O_{manure\ pasture}$	Equation 6.5a[1]

[1] Source from GLEAM 2.0, emission coefficients and factors updated to IPCC 2019 guidelines

Table 3 Fixed values used to estimate population proportion per pixel in the herd module for the parameters not included in the sensitivity analysis

Parameter:	Definition	Animal	Unit	Fixed value
AF	Adult females	BFL, CTL, GTS, SHP	Number	100
DR1	Death rate female calves	BFL, CTL	percentage	11.40
DR1	Death rate of lambs or kids	GTS, SHP	percentage	18.00
DR1M	Death rate male calves	BFL, CTL	percentage	11.40
DR2	Death rate other animals than calves	BFL, CTL	percentage	4.70
DR2	Death rate other animals than lambs or kids	GTS, SHP	percentage	8.00
FRRF	Rate of fertile replacement females	BFL, CTL, GTS, SHP	fraction	0.95
LINT	Lambing or kidding interval, period between two parturitions	GTS, SHP	days	240
MFR	Ram to ewe (sheep) or does to bucks (goats) ratio	GTS, SHP	ratio	0.05
RRF	Replacement rate female animals	BFL, CTL	percentage	14
RRF	Replacement rate female animals	GTS, SHP	percentage	28

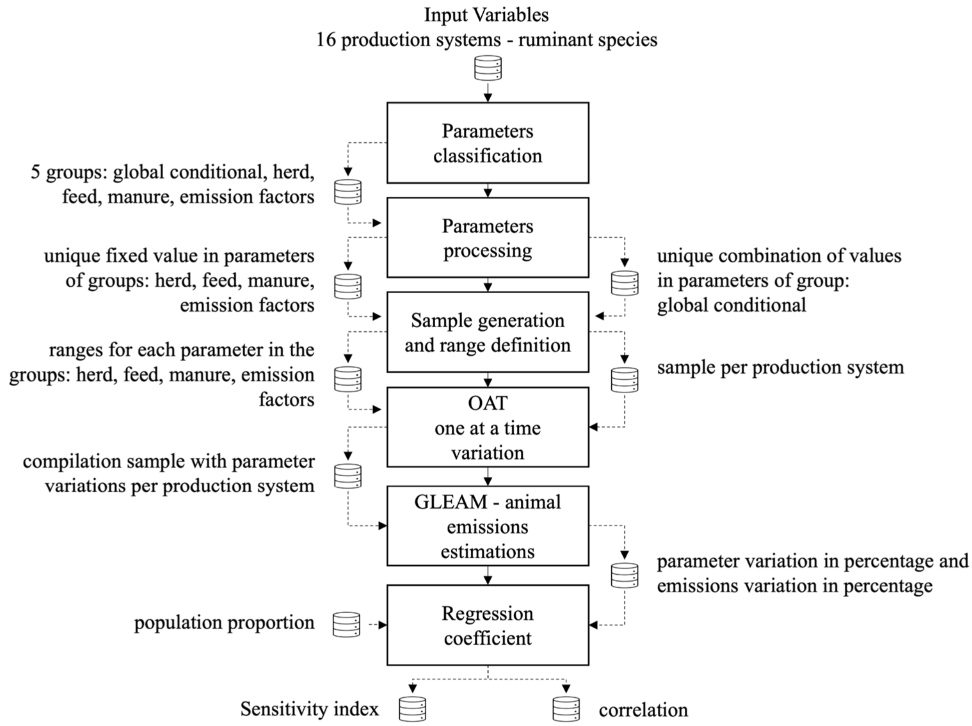

Fig. 2 Process to estimate sensitivity index of the variation of one-by-one input parameter to determine its impact on the estimation of greenhouse gas emissions using GLEAM

Table 4 Description of the methods used to define a fixed value per parameter, based on the characteristics of the parameter group

Parameter group	Method for the fixed value	Notes
herd	Mean value per cohort	Mean or mode values from other production systems are assigned in case of gaps or missing values. Our approach was to avoid having zeros as fixed values for the parameters
feed	Mean value per cohort	Mean or mode values from other production systems are assigned in case of gaps or missing values. Our approach was to avoid having zeros as fixed values for the parameters
manure	Fraction calculated by dividing 1 by the total number of manure systems per animal	Parameters in this group refer to manure management systems, which represents the share of manure on each system. In GLEAM these systems are expressed in fractions that must sum to 1 when combined
emission factors and coefficients	Default values from IPCC or method from GLEAM	Emission factors are derived from IPCC guidelines, except for the coefficient corresponding to animals feeding situation (Ca), emission factor for direct N_2O from manure (EF3) and the methane conversion factor from manure (Mcf) which are calculated using adapted methods described in GLEAM documentation
Global Conditional	All unique records	The data for these parameters are spatially structured. The unique records were extracted from each production system

and *Feed* group, where the parameter's range is unknown, a sequence was generated encompassing all possible values produced by varying between − 20% and + 20% from the fixed value, with an increment of 1% in the sequence. This percentage range was defined based on uncertainty values reported for parameters of these groups. According to IPCC (2006), uncertainty for parameters such as diet digestibility and animal weights ranges between 10 and 30%. To account for potential impacts overlooked when the selected range is insufficient (Norton 2015), additional limits (± 10% and ± 50%) were tested, but no notable changes were observed in the sensitivity results. Additionally, parameters expressed as fractions were adjusted to a maximum value of 1 when the selected range exceeded this limit.

For *Manure* group parameters which have a defined range from 0 to 1, the range was established as (0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1). However, to maintain the condition that all manure management systems must sum up to

1, a subtraction process was implemented (1—parameter), followed by dividing this result by the remaining manure management systems presented in the sample. For parameters in the *Global Conditional* group where the complete range of the parameter is known, all values were considered in the range. For the *Emission factor and coefficient* group, a range of 10 values was generated between the identified maximum and minimum limits for each parameter, including the fixed value assigned to the parameter.

By using specific ranges adapted to the characteristics of each parameter and by combining them with all possible conditional parameters, we addressed the limitations of parameter interactions under all possible conditions, which cannot be accounted for in a simple sensitivity analysis, as highlighted by Groen et al. (2016).

2.5 Sensitivity analysis technique

A One-At-A-Time (OAT) variation technique was implemented for all parameters, emission factors and coefficients. OAT is a simplistic technique that isolates the effect of individual parameters by varying one parameter at a time while keeping all other parameters fixed (Hamby 1994). This method is widely used in sensitivity analysis for models based on life cycle assessments (Groen et al. 2016). The OAT process was automated using R software, allowing the integration of the GLEAM model code in the process.

The sensitivity analysis method developed for this study is based on the standardized regression technique described by Hamby (1994) and Saltelli et al. (2008). This approach requires standardizing parameters' units before performing regression analysis to eliminate the unit-dependent effect. To achieve this, parameter variability was expressed as a percentage relative to the fixed value, while greenhouse gas emissions were expressed as a percentage relative to the emissions estimated from the fixed value. For parameters in the global conditional group, we standardized relative to the minimum value from the range, and specifically for temperature, we standardized relative to the mean temperature value.

The sensitivity of each parameter (sensitivity index) was calculated using the regression coefficient between the variability in percentage of the parameter and the variability in percentage of GHG emissions. This approach allowed for the observation of the correlation between the parameter and the type of emission, showing whether it is positive or negative, and the magnitude of change in GHG emissions after a one percent change in a given parameter from their fixed value. A sensitivity index close to zero indicates low sensitivity.

To generate a combined sensitivity index that includes all cohorts, we used a weighted average sensitivity index, utilizing the population proportion calculated for each cohort. For this paper, the sensitivity index is presented per animal. Therefore, we combine all production systems for each species before performing the regression analysis. Lastly, the coefficient of determination (R-square) was computed for each association used to calculate the sensitivity indexes to determine the linearity of our modelling. To visualize the results, heat maps were generated, which allowed for the distinction of four categories based on the parameter absolute index: high (index > 1), moderate (0.2–1), low (0.10–0.2), and extremely low (< 0.1). We calculated sensitivity per parameter for each of the four types of animal emissions, as well as for total emissions, which are the sum of all emission types.

3 Results

3.1 Population proportion

The population proportion was calculated using the herd module by varying only the parameters identified for estimating animal emissions, while keeping the rest of the parameters fixed, as detailed in Sect. 2.1. The cohort proportion remained relatively stable despite parameter variation. Since an average weight was used to calculate sensitivity at the animal level, the cohort proportions reflected the influence of each cohort on parameter sensitivity. The Adult females (AF) cohort was the primary contributor, with the greatest proportion across all species, ranging between 0.3 and 0.5. Meat animals (MM and MF), replacement females (RF), and replacement females in the first year (RFA) also contributed notably, with proportions varying between 0.1 and 0.3. The remaining cohorts maintained a proportion below 0.1 (see appendix F).

3.2 Sensitivity results

3.2.1 Influential parameters on animal emissions by animal species

Figures 3 and 4 present the most influential parameters for each type of animal emission, highlighting those with moderate to high sensitivity across all emission types (See Appendix G for a scheme illustrating the role of influential parameters for total emissions in the GLEAM processes and subprocesses).

For parameters with negative correlation, the results identified three as the most influential across all species. Diet digestibility (diet_di) stood out as the parameter with the greatest influence over all types of direct emissions, with absolute values exceeding 2.50. This parameter showed the greatest sensitivity among all parameters tested in this study, with values being 50% greater than the next most influential parameter.

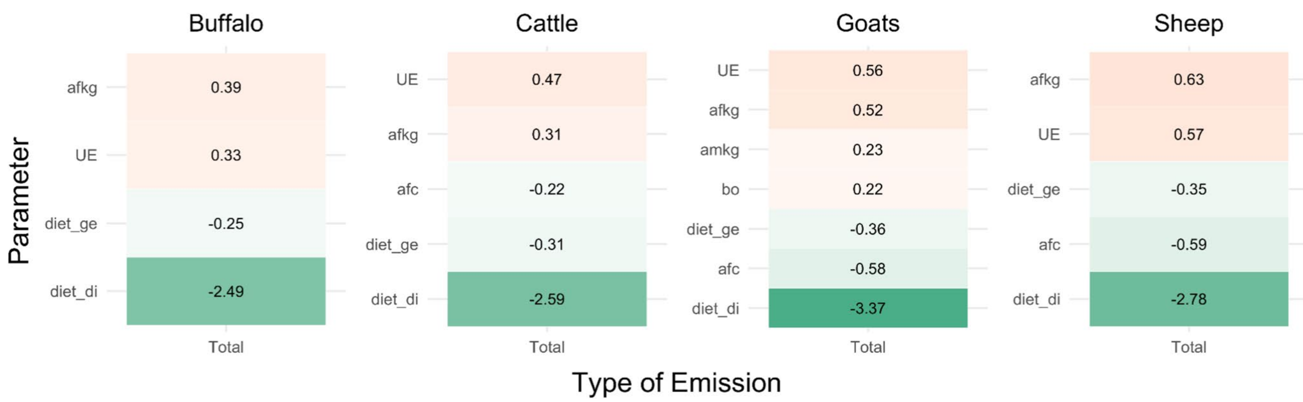

Fig. 3 Most influential parameters (sensitivity index ≥ 0.2) for total emissions (Total) in the GLEAM model for the ruminant species. Positive correlations are represented in red and negative correlations in green. The intensity of the colours indicates the strength of the sensitivity value

The second most influential parameter with a negative correlation, except for methane from enteric fermentation, was diet gross energy (diet_ge). Emissions were highly sensitive to this parameter, with absolute sensitivity values exceeding 1. The third parameter that stood out among those with a negative correlation was age at first calving (afc). Emissions showed moderate sensitivity to this parameter.

For parameters with positive correlation, total emissions did not exhibit high sensitivity to any parameter. However, they showed moderate sensitivity to three parameters: the urinary energy as a fraction of gross energy (UE) and the weight of adult females (afkg), both with sensitivity indexes close to 0.4. Additionally, in goats and sheep, total emissions showed moderate sensitivity to the maximum methane producing capacity of manure (Bo) and the weight of adult males (amkg), with sensitivity indexes close to 0.2 (Fig. 3).

Methane from enteric fermentation did not show high sensitivity to parameters with positive correlation. The only influential parameter with this type of correlation, but with moderate sensitivity, was the weight of adult females (afkg), with indexes close to 0.5 across all species (Fig. 4).

For methane emissions from manure, five parameters stood out as influential with positive correlation. These emissions were highly sensitive to the urinary energy as a fraction of gross energy (UE) and the maximum methane producing capacity of manure (Bo), both with sensitivity indexes exceeding 1. Additionally, these emissions showed moderate sensitivity to the weight of adult females (afkg), the proportion of manure managed as a lagoon (mmslagoon), and its methane conversion factor (Mcflagoon), each with sensitivity indexes ranging between 0.3 and 0.5 (Fig. 4).

Influential parameters with positive correlation to nitrous oxide emissions included two with high sensitivity: the nitrogen content of the diet (diet_n_content) and the manure deposited on pasture (mmspasture), both with indexes exceeding 1. These emissions also exhibited moderate sensitivity to the weight of adult animals (afkg and amkg), the emission factors for nitrogen volatilization and redeposition (EF4), and the manure managed as dry lot (mmsdrylot) and deep litter (mmsdeeplitt), along with their corresponding emission factors for direct N_2O emissions from manure (EF3drtylot and Ef3deeplitt). Additionally, for nitrous oxide emissions specifically from manure in pasture, the emission factor for N_2O from leaching (EF5), the emission factor for direct N_2O emissions from manure in pastures (EF3past), the percentage nitrogen lost due to leaching from manure in pastures (FracLeachpast) and the fraction of nitrogen that volatilizes from manure in pastures (FracGasmpast), stood out as influential, showing moderate sensitivity (Fig. 4).

3.2.2 Sensitivity analysis of the herd group parameter

In the herd group, none of the parameters exhibited high sensitivity in relation to any of the animal emissions. Two parameters exhibited moderate sensitivity across all species. Animal emissions showed moderate sensitivity with a positive correlation to the weight of adult females (afkg), with indexes around 0.4. In contrast, emissions demonstrated moderate sensitivity with a negative correlation to the age at first calving (afc), with indexes ranging between − 0.12 and − 0.59 for methane and total emissions.

Parameters with low sensitivity and positive correlation (sensitivity indexes between 0.10 and 0.20) included adult male weight (amkg) and weights of fattening animals at slaughter (mmskg and mfskg) across all species and milk yield in cattle. Specifically for nitrous oxide emissions, parameters with low sensitivity included the live weight at birth (ckg) in sheep and goats. In contrast, nitrous oxide emissions showed low sensitivity with a negative correlation to the age at first calving (afc) across all species and to milk protein content in cattle.

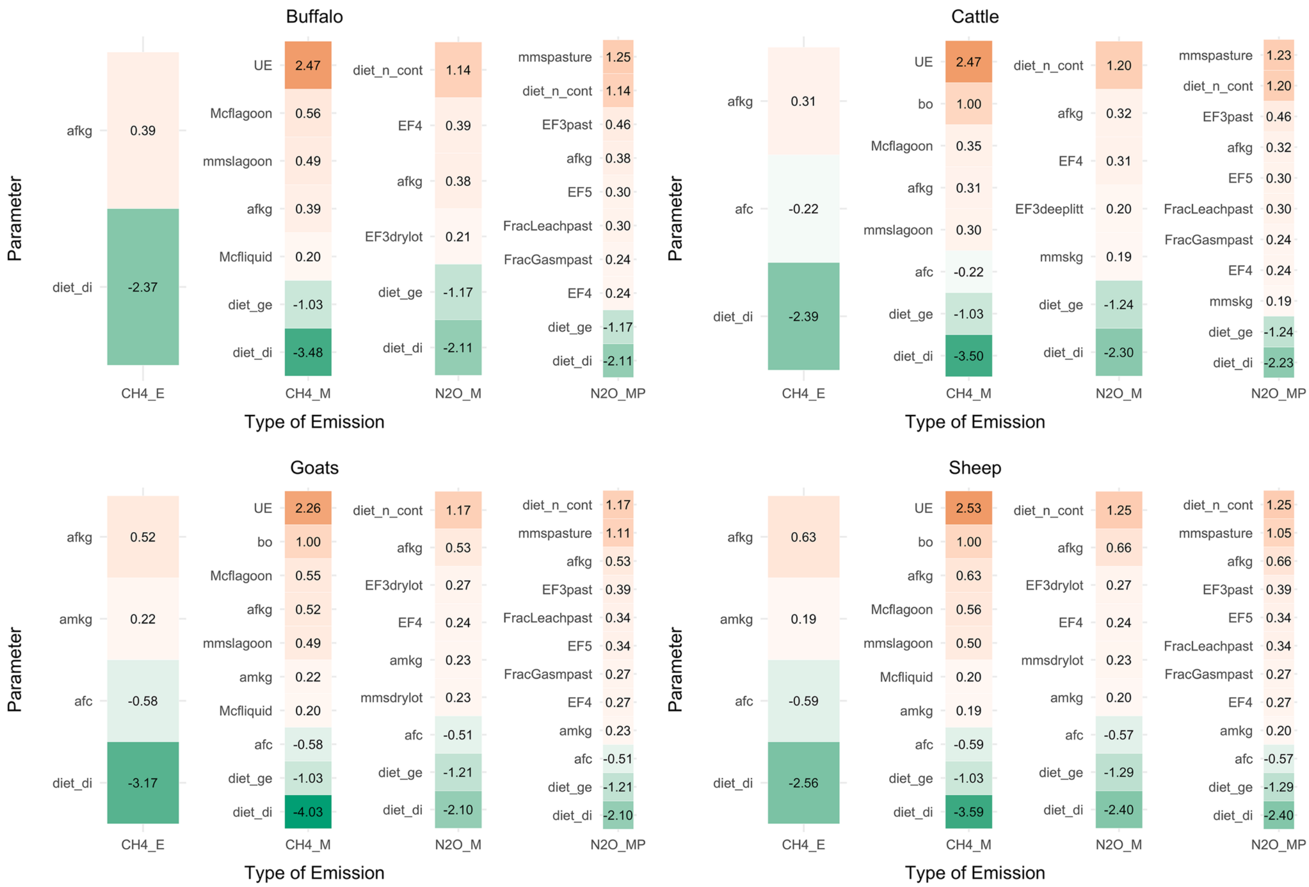

Fig. 4 Most influential parameters (sensitivity index ≥ 0.1) in the GLEAM model for the ruminant species, per type of direct emission: methane from enteric fermentation (CH_4_E) and from manure (CH_4_M), nitrous oxide from manure management systems (N_2O_M) and from manure in pastures (N_2O_MP). Positive correlations are represented in red and negative correlations in green. The intensity of the colours indicates the strength of the sensitivity value

Finally, parameters such as fertility rate (fr), litter size (litsize), number of hours of work by the animals (hours), fraction of managed pastures (past_man_fra), production of fibre (prod_fibre), male to female ratio (bcr) and lactation duration (lact) demonstrated extremely low sensitivity (SI integer value < 0.10) across all species and had minimal impact on the variability of daily emissions in this study (see Appendix H).

3.2.3 Sensitivity analysis of the feed group parameters

For the group of parameters associated with feed characteristics, all animal emissions were found to be highly sensitive to diet digestibility (diet_di), with a negative correlation observed in all species. Similarly, emissions from manure (CH_4_M, N_2O_M, and N_2O_MP) showed high sensitivity to diet gross energy (diet_ge), with a negative correlation across all species. In contrast, only nitrous oxide emissions exhibited high sensitivity with a positive correlation to the nitrogen content of the diet (diet_n_content) in all species (see Appendix I).

3.2.4 Sensitivity analysis of the manure group parameters.

The parameters in the manure group represent the impact on animal emissions when one manure management system increases while the rest decrease. For all the parameters in this group, it was important to explore the sensitivity analysis of each individual gas to determine if there was an amplification or attenuation of the total emission index. Some manure systems could have a positive relationship with methane production and a negative relationship with nitrous oxide, affecting the sensitivity index of total emissions.

Methane emissions from enteric fermentation (CH_4_E) showed no sensitivity to any manure management systems, except for manure in pastures (mmspasture). This parameter exhibited extremely low sensitivity with a positive correlation (maximum index of 0.03). The slight sensitivity was due to its role in calculating energy for activity, which affected dry matter intake and methane emissions.

Regarding methane emissions from manure (CH_4_M), these emissions showed moderate sensitivity with a positive correlation to manure stored as lagoon (mmslagoon) across all species, with a sensitivity index of approximately 0.40. The remaining manure systems exhibited low to very low sensitivity (absolute index < 0.13). Two parameters, mmsliqcrust and mmsbiogas, showed no linearity in the calculation of their sensitivity index, with R^2 values lower than 0.7.

Nitrous oxide emissions from manure (N_2O_M) exhibited low to moderate sensitivity with a positive correlation (indexes between 0.15 and 0.23) to deep litter systems (mmsdeeplitt) in cattle and dry lot systems (mmsdrylot) in buffalo, goats, and sheep. For all other manure systems, these emissions showed low to very low sensitivity (absolute index < 0.10).

Nitrous oxide emissions from manure in pastures (N_2O_MP) were found to be highly sensitive to manure deposited on pasture (mmspasture), exhibiting a positive correlation with a sensitivity index of approximately 1.15. Since GLEAM calculates nitrous oxide emissions from this manure system independently of other sources, mmspasture stood out as the only parameter with a high positive correlation with this greenhouse gas. In contrast, other manure management practices showed low to very low sensitivity with a negative correlation (see Appendix J).

3.2.5 Sensitivity analysis of the global conditional group parameters

The global conditional parameters included those that are spatially integrated within the GLEAM model and served as conditional factors in certain processes. All records of these parameters were used in the sensitivity analysis. Parameters in this group showed extreme low to no influence on methane from enteric fermentation (CH_4_E) and nitrous oxide in all species.

Methane emissions from manure (CH_4_M) and total emissions were found to be sensitive to the maximum methane producing capacity of manure (Bo) in cattle, sheep, and goats. CH_4_M exhibited high sensitivity with a positive correlation (sensitivity index = 1), while total emissions showed low to moderate sensitivity with a positive correlation (sensitivity index ranging from 0.15 to 0.22). The remaining parameters showed extremely low to no sensitivity.

The maximum methane producing capacity of manure (Bo) in buffalo and temperature in cattle did not demonstrate a linear relationship that could be explained by the sensitivity methods used in this study, as described in the descriptive statistics of parameters section (see Appendix K).

3.2.6 Sensitivity analysis of the emission factors and coefficients (efc) group

The sensitivity analysis of the emission factors and coefficients showed that all these parameters had a positive correlation with animal emissions. Total emissions were highly sensitive to the urinary energy as a fraction of gross energy (UE), with sensitivity indexes greater than 0.33 in all species. For the rest of the parameters, these emissions exhibited low to no sensitivity.

Methane emissions from enteric fermentation (CH_4_E) showed very low to no sensitivity to any emission factor included in this study. The gross energy converted to methane (ym), which directly influences methane emissions, was calculated based on diet digestibility in GLEAM. Therefore, their influence was accounted for within the sensitivity analysis of diet digestibility.

Methane emissions from manure (CH_4_M) were highly sensitive to the urinary energy as a fraction of gross energy (UE), with sensitivity indexes exceeding 2.20. Additionally, these emissions showed moderate sensitivity to the methane conversion factor for lagoons (Mcflagoon), with indexes ranging from 0.35 to 0.56 across all species, and exhibited low sensitivity (indexes between 0.05 and 0.20) to the methane conversion factors of manure as liquid crust (Mcfliqcrust), as liquid (Mcfliquid and Mcliqoth), as pit 2 (Mcfpit2), as deep litter (Mcfdeeplitt), and as biogas (Mcfbiogas). All remaining emission factors had extremely low or no influence on methane emissions from manure.

Nitrous oxide emissions from manure (N_2O_M) exhibited moderate sensitivity (indexes between 0.20 and 0.39) to emission factors for nitrogen volatilization and redeposition (EF4), to emission factors for direct N_2O emissions from manure in dry lots (EF3drylot) and from deep litter (EF3deeplitt). Additionally, these emissions showed low sensitivity (indexes between 0.10 and 0.20) to the emission factors for direct N_2O emissions from manure as solid (EF3solid) and the emission factor for N_2O from leaching (EF5). All other emission factors demonstrated very low to zero sensitivity indexes for these emissions.

Nitrous oxide from manure in pastures (N_2O_MP) was found to be moderately sensitive to emission factors for nitrogen volatilization and redeposition (EF4), emission factor for N_2O from leaching (EF5), emission factors for direct N_2O emissions from manure in pasture (EF3past), the percentage nitrogen lost due to leaching from manure in pastures (FracLeachpast) and the fraction of nitrogen that volatilizes from manure in pastures (FracGasmpast), with sensitivity indexes between 0.24 and 0.46 across all species. The rest of parameters showed extremely low to zero sensitivity for this type of emissions (see Appendix L and M).

3.3 Descriptive statistics of parameters and results

The coefficient of determination between parameters and greenhouse gas emission demonstrated linearity in 70 out of 92 parameters, with R^2 exceeding 0.70. This indicated that our sensitivity methodology, using regression coefficient, was robust enough to predict the sensitivity for most influential parameters, as suggested by (Saltelli et al. 2008). The nonlinearity of the remaining parameters was associated with location-specific conditional factors within certain cohorts (see Table 5). For these parameters, an alternative sensitivity method should be considered.

The distribution analysis of estimated greenhouse gas emissions resulting from parameter variation highlighted the proportional contribution of each emission type to total emissions, as total emissions represent the sum of the four greenhouse gas sources. Methane was the primary contributor across all ruminant species. Specifically, methane

Table 5 Parameters with an R-square lower than 0.7 per type of animal emission, animal species and cohort. For these parameters, the sensitivity analysis method is not reliable. This suggests that the variability in emissions is not well explained by changes in these parameters. Animal emissions: methane from enteric fermentation (CH_4_E) and from manure (CH_4_M), nitrous oxide from manure management systems (N_2O_M) and from manure in pastures (N_2O_MP), and their sum in total emissions (Total)

Parameter:	Animal	Cohort	Type of animal emission
afc	Goats	MF, MM	N_2O_M, N_2O_MP
afkg	Goats	MF	N_2O_M, N_2O_MP
amkg	Goats	MM, RMB	N_2O_M, N_2O_MP
bcr	Buffalo, Cattle	AM	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
bo	Buffalo	All	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
diet_ge	Buffalo	MM, RF, RM	CH_4_E
diet_ge	Cattle	AF	CH_4_E
diet_ge	Goats	AF, MM	CH_4_E
diet_ge	Sheep	AM	CH_4_E
fracGasmaerproc	Goats, Sheep	All	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
fracGasmbiogas	Buffalo, Cattle, Goats, Sheep	All	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
fracGasmburned	Cattle	All	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
fracGasmliqcrust	Goats, Sheep	All	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
fracGasmliquid	Goats, Sheep	All	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
fracGasmpasture	Buffalo, Cattle, Goats, Sheep	All	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
hours	Buffalo, Cattle	AM	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
mcfburned	Cattle	All	CH_4_M, Total
mcfdaily	Cattle	All	Total
milk_prot	Goats	AF	N_2O_M, N_2O_MP, Total
milk_yield	Goats	AF	CH_4_E, CH_4_M, N_2O_M, N_2O_MP, Total
mmsbiogas	Buffalo	All	CH_4_M
mmsbiogas	Cattle	All	CH_4_M, Total
mmsbiogas	Goats, Sheep	All	CH_4_M
mmsbiogas	Goats, Sheep	MF, MM	Total
mmscompost	Cattle, Goats	All	N_2O_M
mmscompost	Sheep	AF, MF, MM	N_2O_M
mmsdrylot	Buffalo, Cattle, Goats, Sheep	All	Total
mmsliqcrust	Buffalo, Cattle, Goats, Sheep	All	CH_4_M, Total
mmsliqoth	Cattle	All	Total
mmsliquid	Buffalo, Goats, Sheep	All	CH_4_M, Total
mmsliquid	Cattle	All	Total
mmspasture	Buffalo, Cattle	All	Total
mmspasture	Goats	AF, AM, RFB, RMB	Total
mmspasture	Sheep	RFA, RFB, RMA, RMB	Total
mmspit2	Cattle	All	Total
temp	Buffalo, Cattle	All	CH_4_M, Total
temp	Goats, Sheep	All	Total

from enteric fermentation accounted for nearly 70% of total emissions, followed by methane from manure, which contributed approximately 15% to 25%. Nitrous oxide represented the remaining 5% to 15% of total emissions (see Appendix N).

4 Discussion

The suggested sensitivity method implemented in GLEAM, which calculates cumulative sensitivity per animal by combining sensitivities across cohorts and production systems, successfully predicted the influence of 70 parameters involved in the model. This method was particularly effective for evaluating emission factors and parameters within the herd and feed groups, which are related to animal growth, reproduction, and feed composition (see Appendix H and I). However, this study did not account for the interactions between parameters. Its aim is to assess the individual impact of each parameter and be able to distinguish between influential and non-influential ones.

The results highlighted three parameters, with high and moderate sensitivity (absolute index > 0.20), that had a strong impact on reducing animal emissions (Fig. 3): diet digestibility (diet_di), gross energy of the diet (diet_ge) and age at first calving (afc).

In the context of animal emissions, improving diet digestibility is one of the most effective strategies for reducing greenhouse gas emissions, as shown by the results of the sensitivity analysis. Diet digestibility emerged as the most sensitive parameter in GLEAM's animal emissions estimates, with a sensitivity index close to − 3. This indicates that a 1% increase in diet digestibility results in an approximate 3% reduction in total animal emissions (Fig. 3). In addition, this parameter showed the same strong effect across all four sources of animal emissions. For methane and nitrous oxide emissions (Fig. 4), the absolute index value of this parameter was at least 1 percent greater than the following influential parameter. Furthermore, for total emissions, it was at least four times greater than the second most influential parameter. Numerous studies had identified the diet quality, and specifically the improvement of digestibility, as a technique with medium to high potential for mitigating greenhouse gas emissions, mainly methane emissions (Haque 2018), which can be reduced by 10 to 30% compared to baseline scenarios (Gerber et al. 2013; Mottet et al. 2017; Grossi et al. 2019). This effect is primarily due to the impact of diet digestibility on the energy available for maintenance (REM) and growth (REG), which directly influences the total energy requirements.

Additionally, diet digestibility plays a key role in methane emission factors (Liu and Liu 2018), particularly on the calculation of the percentage of gross energy to methane (ym) and the daily volatile solids excreted (Vs), both of which directly influence methane production. However, changing diet composition could impact processes that simultaneously influence the increase of emissions, potentially offsetting the mitigating effect. For instance, O'Mara et al. (2008) noted that while nutritional strategies may contribute to mitigating animal emissions, they could also influence emissions upstream, such as the ones associated with the production, processing and transport of feed. Similarly, Gerber et al. (2013) highlighted that the production of improved feed may be associated with land use change processes, potentially resulting in additional total emissions from the production chain.

In addition to diet digestibility, improving the gross energy content of the diet and reducing the age at first calving can also contribute to lowering greenhouse gas emissions from livestock. The gross energy of the diet exhibited high sensitivity, with an index near − 1, to methane and nitrous oxide emissions from manure, while age at first calving showed moderate sensitivity, with an index close to − 0.3, to all animal emissions (Fig. 4). These parameters are inversely correlated with dry matter intake and daily weight gain, respectively, which are positively correlated to greater animal emissions from enteric fermentation and manure management (Min et al. 2022). Specifically, a reduction in age at first calving is associated in the GLEAM model with animals reaching the adult stage at a younger age. The model adjusts and distributes the adult weight over a shorter period, resulting in greater daily energy requirements and, consequently, greater dry matter intake to meet those requirements. This highlights an additional factor to consider, particularly for slaughter animals, whose lifetime emissions decrease as they reach slaughter weight in a shorter time, a trend that can be observed in a full production system analysis (O'Mara et al. 2008).

In addition, three parameters were found to be highly influential for the increment of animal emissions (Fig. 3): the weight of adult females (afkg), the urinary energy as a fraction of gross energy (UE) and the maximum methane producing capacity from manure (Bo). All of them have moderate sensitivity between 0.20 and 0.50 to total emissions.

Among the input parameters evaluated in this study, animal weight, particularly the weight of adult females (afkg), emerged as the most influential parameter of increased greenhouse gas emissions. Heavier animals have greater maintenance and production energy requirements, which translates into higher feed intake and, consequently, elevated emissions from both enteric fermentation and manure management. This reinforces the importance of managing herd composition and size when aiming to reduce overall emissions in livestock systems. The weight of adult females stands out as the most influential parameter within the herd group, with a moderate sensitivity index close to 0.4 (see Appendix H). This indicates that a 1% change in adult female weight leads to an average increase of approximately 0.4% in any type of animal emissions. This parameter plays a direct role in estimating live weight per cohort and daily weight gain, which are critical inputs influencing energy requirements for growth, maintenance, and activity (see Appendix G). Additionally, in cattle, milk yield is identified as an influential parameter, particularly for methane emissions, as it is directly associated with the energy requirements for lactation. These energy requirements determine dry matter intake, which subsequently exhibit a positive correlation with methane and nitrous oxide emissions, especially in dairy systems (Jonker et al. 2016; Wolf et al. 2017; Starsmore et al. 2024).

The prominence of the weight of adult females over other parameters associated with animal weight can be attributed to the cumulative sensitivity method applied, specifically since this parameter is related to adult females (AF) cohort, whose population proportion represents almost 40% among all cohorts (see Appendix F).

The UE coefficient, which is the energy lost by ruminants in the urine, is the most influential parameter with positive correlation within the emission factors group. It contributes to calculating daily volatile solids excretion (Vs), which have a direct positive correlation with methane emissions from manure (Mangino et al. 2001). The IPCC (2019) guidelines recommend a default value of 0.04 for this parameter; however, the use of country-specific values is recommended. Although the estimation of UE is challenging, as it requires combustion-based analysis of urine samples, it can be estimated based on nitrogen content due to its direct relationship with it. Nitrogen content is a more commonly measured parameter in urine (Street et al. 1964; Morris et al. 2021).

The second most influential parameter from the emission factor group is the maximum methane-producing capacity from manure (Bo). This parameter is used to calculate the cumulative methane conversion factor across manure management systems and has a positive impact on methane emissions from manure (Mangino et al. 2001).

Additionally, the results by type of animal emission showed that the nitrogen content of the diet (diet_n_cont) is highly influential for nitrous oxide emissions, with a sensitivity index close to 1; it indicates a linear relationship with these emissions, as nitrogen excretion is directly linked to nitrogen availability in the diet. This is particularly important for monitoring the increase in nitrogen emissions resulting from high-protein diets and for evaluating potential mitigation through manure management practices (Külling et al. 2001; Oenema et al. 2005).

The sensitivity of manure management systems illustrates the impact on emissions when manure fraction increases in one system while decreasing in others (see Appendix J). In contrast, the sensitivity of the emission factors for methane from manure reflects the specific impact of modifying a single system (see Appendix L and M).

In general, manure stored in liquid systems without aerobic processes (mmslagoon, mmsliqcrust, mmsliquid, and mmspit2) have a notable impact on increasing methane emissions from manure, due to their high methane conversion factors. Among these systems, manure stored in lagoons (mmslagoon) is the most influential, with a moderate sensitivity index of approximately 0.50. Its methane conversion factor is the highest due to longer retention times. These factors are primarily influenced by temperature, resulting in considerable variability (IPCC 2006; Sommer et al. 2007; Opio et al. 2013). However, most of these manure systems have a negative correlation with nitrous oxide emissions, due to the low emission factor for direct N_2O emissions (EF3).

Increasing the proportion of manure managed through systems such as solid compost (mmscompost), solid burned as fuel (mmsburned), or daily spread (mmsdaily) can help reduce emissions from manure. This is mainly due to their low methane conversion factors and low emission factors for direct N_2O emissions (EF3), as noted in the IPCC guidelines, which explains their negative sensitivity in methane and nitrous oxide from manure. Moreover, raising their share in the overall manure management mix reduces the overall share of more emission-intensive systems like liquid storage, which are associated with higher methane emissions.

The analysis of emission factors for nitrous oxide emissions highlighted three factors with moderate sensitivity, with indexes close to 0.3. These include the emission factors for direct N_2O emissions from manure in deep litter (EF3deeplitt), solid dry lot (EF3drylot), and the emission factor for nitrogen volatilization and redeposition (EF4) (see Appendix L and M).

Focusing specifically on nitrous oxide from manure deposited on pastures, five emission factors exhibit moderate sensitivity, with indexes ranging from 0.24 to 0.50. Ranked in order of importance, these include: the emission factor for direct N_2O emissions from manure in pastures (EF3past), the emission factor for N_2O from leaching (EF5), the emission factor for nitrogen volatilization and redeposition (EF4), the percentage of nitrogen lost due to leaching/runoff from manure in pastures (FracLeachPast), and the fraction of nitrogen that volatilizes as NH_3 and NOx from manure in pastures (FracGasmPast).

These results align with previous studies identifying influential emission factors based on their uncertainty. Basset-Mens et al. (2009) used uncertainty analysis to assess the sensitivity of the same emission factors, ranking EF3, EF4, and EF5 in that order of importance for milk production farms in New Zealand. Similarly, Brown et al. (2001) highlighted EF3 from manure in pastures as particularly sensitive due to the high nitrogen production compared to other manure systems, followed by EF5 for its role in indirect nitrous oxide emissions, while considering EF4 insensitive.

Parameters related to manure systems were among the most challenging to predict in terms of their sensitivity, particularly for methane from manure. Some of these parameters exhibited insufficient linearity, with R^2 values below 0.7, which is the minimum recommendation by Saltelli et al. (2008) for applying the sensitivity index based on regression coefficients used in this study. This behaviour is driven by the cumulative sensitivity methodology utilized in this study. In this aspect, a non-cumulative analysis per cohort and production system is recommended to perform sensitivity from manure parameters.

Additional parameters that exhibited insufficient linearity in specific cohorts include the male to female ratio (bcr) and number of hours of work per day (hours). These parameters are interdependent in the calculation of energy for draught power. In GLEAM, this process starts with a minimum value of 0.10 for bcr, making linearity difficult to achieve for both parameters. However, their sensitivity is extremely low in the cumulative sensitivity analysis, as they mainly affect adult males, which constitute a small proportion of the population.

A similar issue arises with the age at first calving (afc), adult female weight (afkg), and adult male weight (amkg), where linearity was lacking in cohorts with low population proportions. The methane producing capacity for manure (Bo) in buffalo also showed low linearity, primarily because this parameter is represented by a single value in the original datasets. Another parameter with insufficient linearity is temperature, which is used in GLEAM for assigning methane conversion factors. These factors are calculated between two limits: 10 and 28 degrees Celsius. Outside this range, the limit values are applied, making it challenging to use linear regression for sensitivity analysis.

The sensitivity analysis of parameters associated with animal emissions in GLEAM identified several with extremely low sensitivity (indexes < 0.10). These include fertility rate (fr), number of hours of work per day (hours), male to female ratio (bcr), fraction of managed pastures (past_man_fra), fraction of milking adult females in the herd (frac_mlk), lactation period (lact), annual fibre production per animal (prod_fibre), litter size (litsize), temperature, most emission factors associated with non-liquid manure systems, proportion of manure nitrogen lost due to leaching in non-pasture manure systems (frac_leach), milk yield in small ruminants, and live weight at birth (ckg) in large ruminants. Additionally, the fraction of milk protein (milk_prot) shows extremely low sensitivity, except in cattle. While these parameters may have limited influence on animal emission estimates, some could still impact other emission sources.

The sensitivity analysis in this study was consolidated at animal level, requiring an aggregation of cohorts and herds. Conducting a sensitivity analysis at the level of individual cohorts, herds, or production systems could produce different results from those presented here.

Finally, this study focuses on the influence of independent parameters on emissions, without accounting for their interactions, which could be further explored through uncertainty analysis.

5. Conclusions.

The analysis of each parameter's influence on animal emissions estimation in GLEAM was successfully predicted and ranked using the sensitivity method proposed in this study. The results highlight the strong influence of feed quality and age at first calving in reducing emissions, while parameters related to animal weight were identified as influential to increase emissions. Additionally, emission factors such as urinary energy (UE) and the maximum methane producing capacity of manure (Bo) were found to have the greatest impact on increasing emissions as well.

The sensitivity analysis also identified 12 parameters from the herd group, three from the conditional parameters, and several emission factors associated with specific manure systems as having extremely low sensitivity. This distinction is crucial for optimizing data collection efforts by prioritizing parameters that have the greatest impact on results, particularly when resources are limited.

Furthermore, our methodology identifies the most influential parameters for individual animal emissions, making it particularly useful for studies focused on specific emission types, supporting potential mitigation strategies. However, since not all sensitivity indexes can be fully explained by this method, we provide a list of parameters for which sensitivity should be assessed using alternative sensitivity approaches or complemented with a herd-level sensitivity analysis. Finally, these findings can contribute to improving GLEAM's algorithms by incorporating default values for those with minimal influence.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11367-025-02529-5.

Author contribution Armando Rivera Moncada: conceptualisation, methodology, analysis, investigation, writing original draft, review and editing. Marie-Cécile Dupas: conceptualisation, methodology, writing original draft, review and editing. Giuseppe Tempio: conceptualisation, methodology, review and editing. Lydia Lanzoni: review and editing. Yushan Li: review and editing. Narindra Rakotovao: review and editing. Dominik Wisser: data curation, conceptualisation, methodology, analysis, investigation, project administration, funding acquisition, review and editing. Marius Gilbert: conceptualisation, methodology, analysis, investigation, project administration, funding acquisition, review and editing.

Funding This work was supported by AgResearch [grant numbers S3-SOW59].

Data availability The livestock data used to structure the samples for this study is sourced from GLEAMS's global dataset (FAO 2022b). This data is not publicly available, as FAO has not granted permission for researchers to share it. However, mean values for each parameter are accessible through the GLEAM dashboard, and additional data can be requested via the project email: info-GLEAM@fao.org. In addition, the values used in the samples are explained in Appendix C and D, allowing the results to be replicated.

Declarations

Competing interests The authors declare no competing interests.

References

Basset-Mens C, Kelliher FM, Ledgard S, Cox N (2009) Uncertainty of global warming potential for milk production on a New Zealand farm and implications for decision making. Int J Life Cycle Assess 14:630–638. https://doi.org/10.1007/s11367-009-0108-2

Brown L, Armstrong Brown S, Jarvis SC et al (2001) An inventory of nitrous oxide emissions from agriculture in the UK using the IPCC methodology: emission estimate, uncertainty and sensitivity analysis. Atmos Environ 35:1439–1449. https://doi.org/10.1016/S1352-2310(00)00361-7

FAO (2016) Global livestock environmental assessment model. Version 2

FAO (2022a) Global livestock environmental assessment model. Version 3

FAO (2022b) GLEAM 3 dashboard. In Shiny Apps. In: Shiny Apps. https://foodandagricultureorganization.shinyapps.io/GLEAMV3_Public/. Accessed 28 Apr 2025

Ferretti F, Saltelli A, Tarantola S (2016) Trends in sensitivity analysis practice in the last decade. Sci Total Environ 568:666–670. https://doi.org/10.1016/j.scitotenv.2016.02.133

Gerber PJ, Hristov AN, Henderson B et al (2013) Technical options for the mitigation of direct methane and nitrous oxide emissions from livestock: a review. Animal 7:220–234. https://doi.org/10.1017/S1751731113000876

Groen EA, van Zanten HHE, Heijungs R et al (2016) Sensitivity analysis of greenhouse gas emissions from a pork production chain. J Clean Prod 129:202–211. https://doi.org/10.1016/j.jclepro.2016.04.081

Grossi G, Goglio P, Vitali A, Williams AG (2019) Livestock and climate change: impact of livestock on climate and mitigation strategies. Anim Front 9:69–76. https://doi.org/10.1093/af/vfy034

Hamby DM (1994) A review of techniques for parameter sensitivity analysis of environmental models. Environ Monit Assess 32:135–154. https://doi.org/10.1007/BF00547132

Haque MN (2018) Dietary manipulation: a sustainable way to mitigate methane emissions from ruminants. J Anim Sci Technol 60:15. https://doi.org/10.1186/s40781-018-0175-7

IPCC (2019) 2019 refinement to the 2006 IPCC guidelines for national greenhouse gas inventories. In: Calvo Buendia E, Tanabe K, Kranjc A, Baasansuren J, Fukuda M, Ngarize S, Osako A, Pyrozhenko Y, Shermanau P, Federici S (eds) Published: IPCC, Switzerland

IPCC HS (2006) 2006 IPCC guidelines for national greenhouse gas inventories. In: Eggleston HS, Buendia L, Miwa K, Ngara T, Tanabe K (eds) Prepared by the national greenhouse gas inventories programme. Published: IGES, Japan

Jonker A, Molano G, Koolaard J, Muetzel S (2016) Methane emissions from lactating and non-lactating dairy cows and growing cattle fed fresh pasture. Anim Prod Sci 57:643–648. https://doi.org/10.1071/AN15656

Karimi-Zindashty Y, Macdonald JD, Desjardins RL et al (2012) Sources of uncertainty in the IPCC tier 2 Canadian livestock model. J Agric Sci 150:556–569. https://doi.org/10.1017/S002185961100092X

Külling DR, Menzi H, Kröber TF et al (2001) Emissions of ammonia, nitrous oxide and methane from different types of dairy manure during storage as affected by dietary protein content. J Agric Sci 137:235–250. https://doi.org/10.1017/S0021859601001186

Liu Z, Liu Y (2018) Mitigation of greenhouse gas emissions from animal production. Greenh Gases Sci Technol 8:627–638. https://doi.org/10.1002/ghg.1785

Mangino J, Bartram D, Brazy A (2001) Development of a methane conversion factor to estimate emissions from animal waste lagoons

Min B-R, Lee S, Jung H et al (2022) Enteric methane emissions and animal performance in dairy and beef cattle production: strategies, opportunities, and impact of reducing emissions. Animals 12:948. https://doi.org/10.3390/ani12080948

Misra AKK, Verma M (2017) Modeling the impact of mitigation options on abatement of methane emission from livestock. Nonlinear Anal Model Control 22:210–229. https://doi.org/10.15388/NA.2017.2.5

Morris DL, Firkins JL, Lee C et al (2021) Relationship between urinary energy and urinary nitrogen or carbon excretion in lactating Jersey cows. J Dairy Sci 104:6727–6738. https://doi.org/10.3168/jds.2020-19684

Mottet A, Henderson B, Opio C et al (2017) Climate change mitigation and productivity gains in livestock supply chains: insights from regional case studies. Reg Environ Change 17:129–141. https://doi.org/10.1007/s10113-016-0986-3

Norton J (2015) An introduction to sensitivity assessment of simulation models. Environ Model Softw 69:166–174. https://doi.org/10.1016/j.envsoft.2015.03.020

O'Mara FP, Beauchemin KA, Kreuzer M, McAllister TA (2008) Reduction of greenhouse gas emissions of ruminants through nutritional strategies. In: Rowlinson P, Steele M, Nefzaoui A (eds) Livestock and Global Climate Change. Proceedings of the International Conference, Hammamet, Tunisia, May 17–20, 2008. Cambridge University Press, Cambridge, UK, pp 40–43

Oenema O, Wrage N, Velthof GL et al (2005) Trends in global nitrous oxide emissions from animal production systems. Nutr Cycl Agroecosyst 72:51–65. https://doi.org/10.1007/s10705-004-7354-2

Opio C, Gerber P, Mottet A, Falcucci A, Tempio G, MacLeod M, Vellinga T, Henderson B, Steinfeld H (2013) Greenhouse gas emissions from ruminant supply chains – a global life cycle assessment. Food and Agriculture Organization of the United Nations, Rome, Italy

Pianosi F, Beven K, Freer J et al (2016) Sensitivity analysis of environmental models: a systematic review with practical workflow. Environ Model Softw 79:214–232. https://doi.org/10.1016/j.envsoft.2016.02.008

Saltelli A, Ratto M, Andres T, Campolongo F, Cariboni J, Gatelli D, Saisana M, Tarantola S (2008) Global sensitivity analysis: the primer. John Wiley & Sons, Chichester, UK

Sommer SG, Petersen SO, Sørensen P et al (2007) Methane and carbon dioxide emissions and nitrogen turnover during liquid manure storage. Nutr Cycl Agroecosyst 78:27–36. https://doi.org/10.1007/s10705-006-9072-4

Starsmore K, Lopez-Villalobos N, Shalloo L et al (2024) Animal factors that affect enteric methane production measured using the GreenFeed monitoring system in grazing dairy cows. J Dairy Sci 107:2930–2940. https://doi.org/10.3168/jds.2023-23915

Street JC, Butcher JE, Harris LE (1964) Estimating urine energy from urine nitrogen. J Anim Sci 23:1039–1041. https://doi.org/10.2527/jas1964.2341039x

Uwizeye A, Gerber PJ, Groen EA et al (2017) Selective improvement of global datasets for the computation of locally relevant environmental indicators: a method based on global sensitivity analysis. Environ Model Softw 96:58–67. https://doi.org/10.1016/j.envsoft.2017.06.041

Wolf P, Groen EA, Berg W et al (2017) Assessing greenhouse gas emissions of milk production: which parameters are essential? Int J Life Cycle Assess 22:441–455. https://doi.org/10.1007/s11367-016-1165-y

Authors and Affiliations

Armando Rivera Moncada[1] · Marie-Cécile Dupas[1,2] · Giuseppe Tempio[3] · Lydia Lanzoni[3] · Yushan Li[3] · Narindra Rakotovao[3] · Dominik Wisser[3] · Marius Gilbert[1]

✉ Armando Rivera Moncada
armando.rivera.moncada@ulb.be

Marie-Cécile Dupas
mariececile.dupas@ulb.be

Giuseppe Tempio
giuseppe.tempio@fao.org

Lydia Lanzoni
lydia.lanzoni@fao.org

Yushan Li
yushan.li@fao.org

Narindra Rakotovao
narindra.rakotovao@fao.org

Dominik Wisser
dominik.wisser@fao.org

Marius Gilbert
marius.gilbert@ulb.be

1 Universite Libre de Bruxelles, Brussels, Belgium

2 Data Science Institute, University of Hasselt, Hasselt, Belgium

3 Food and Agriculture Organization of United Nations FAO, Rome, Italy