Chapter

Analysis of Inputs Parameters Used to Estimate Enteric Methane Emission Factors Applying a Tier 2 Model: Case Study of Native Cattle in Senegal

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Abstract

In the context of the Paris Agreement, and considering the importance of methane emissions from cattle in West Africa, application of a Tier 2 method to estimate enteric methane emission factors is clearly pertinent. The current study has two purposes. Firstly, it aims to detect how much each input parameter contributes to the overall uncertainty of enteric methane emission factors for cattle. Secondly, it aims to identify which input parameters require additional research efforts for strengthening the evidence base, thus reducing the uncertainty of methane enteric emission factors. Uncertainty and sensitivity analysis methodologies were applied to input parameters in the calculation of enteric methane emission factors for lactating cows and adult male Senegalese native cattle using the IPCC Tier 2 model. The results show that the IPCC default input parameters, such as the coefficient for calculating net energy for maintenance (Cf_i), digestible energy (DE) and the methane conversion rate (Y_m) are the first, second and third most important input parameters, respectively, in terms of their contribution to uncertainty of the enteric methane emission factor. Sensitivity analysis demonstrated that future research in Senegal should prioritize the development of Y_m, Cf_i and DE in order to estimate enteric methane emission factors more accurately and to reduce the uncertainty of the national agricultural greenhouse gas inventory.

Keywords: uncertainty analysis, sensitivity analysis, Tier 2 model, native cattle, Senegal

1. Introduction

The important role of the livestock sector in food security is well understood [1]. At the same time, the sector plays a significant role in greenhouse gas emissions to the atmosphere [2, 3]. Among total agriculture sector emissions (5.4 Gt CO2e), 60% is due to livestock emission sources, mostly (63%) enteric fermentation [4].

Within the United Nations Framework Convention on Climate Change (UNFCCC), developing countries are presently required to submit national GHG inventory reports through National Communications. These reports are to be prepared following the Intergovernmental Panel on Climate Change (IPCC) Guidelines for GHG inventories [5]. The 2006 IPCC Guidelines set out three levels (or tiers) of increasing complexity (called Tiers 1–3) for use by a country. The purpose of the tiers is to provide unbiased and accurate estimates of national GHG emissions, and to enable inventory compilers to focus the use of resources on improving accuracy for key emission categories in the inventory. The Tier 1 method provides default values for GHG emissions per head of livestock and can reflect only variation in livestock numbers. The IPCC 2006 Tier 2 method for estimating enteric fermentation emissions from ruminants is based on net energy estimated using the National Research Council model [6]. This approach requires details on the characteristics of livestock sub-categories and their performance, for example, in terms of production (e.g., milk yield, daily weight gain) and reproduction (e.g., percentage of lactating cows).

At present, due to the scarcity of appropriate information on agricultural production in Sub-Saharan Africa (SSA), most countries in this region use the Tier 1 approach to quantify agricultural GHG emissions [7]. However, adopting the IPCC Tier 2 methodology can increase the accuracy of emission estimates [8]. In the SSA region [9, 10], provide enteric methane emission factors (EF) for cattle in South Africa and Benin, respectively, using the Tier 2 approach. A Tier 2 inventory for dairy cattle has also been produced by Kenya [11]. Since its second national communication in 2010, Senegal's national GHG inventory, prepared by the Ministry of Environment, has used EFs calculated using a Tier 2 approach.

However, caution is required when applying the IPCC Tier 2 method to livestock systems in Africa. A recent study reported that the Tier 2 model had low predictive ability when the quality of diet changes [12]. In addition, estimation of enteric methane through the IPCC Tier 2 model assumes that animal is reared in ad libitum conditions throughout the year. In extensive livestock systems such as in West Africa, feedstuffs from grazing resources are typically available in the wet season but is very scarce during the dry season [13–15].

In recent years, further methods have been developed which allow highly accurate determination of emissions [16–18]. However, for developing countries, these measurement techniques may be very expensive and require significant knowledge to implement [19, 20]. Despite its possible shortcomings, therefore, the 2006 IPCC Tier 2 method is a practical method to estimate enteric methane emissions from cattle with greater accuracy than the default Tier 1 method [5].

Implementing a detailed uncertainty and sensitivity analysis of the input parameters in the IPCC Tier 2 model can provide guidance for targeting future research efforts to improve enteric fermentation estimates, with which to inform national GHG inventories, Nationally Appropriate Mitigation Actions (NAMAs) and Nationally Determined Contributions (NDCs).

In this study, the first objective is to use uncertainty analysis (UA) to identify which input parameters contribute significantly to the overall uncertainty of enteric methane emission factors estimated using the IPCC Tier 2 model. The second purpose is to apply sensitivity analysis (SA) in order to identify which parameters, need additional research, thereby increasing the accuracy of enteric methane emission factors.

2. Materials and methods

2.1 Location and livestock grazing systems

Senegal is the most westerly country in Africa with a tropical climate. It covers a surface area of 196,712 square kilometers and has an estimated population of 15.7

million [21]. Approximately 77% of the working population are employed in the agricultural sector [22]. According to the latest population estimates for the year 2018, the rural population represents about 53% of the total population [21]. The estimated ruminant livestock numbers provided by the Senegalese Ministry of Livestock and Animal Production (MEPA) are 3.6 million cattle, 6.7 million sheep and 5.7 million goats [23].

Extensive livestock farming systems in Senegal are based on two native cattle breeds which are found in different agroecological zones. The zebu Gobra (*Bos indicus*) and the taurine Ndama (*Bos taurus*) are mostly raised in the Northern and the Southern parts of Senegal, respectively [24]. The less common Gobra x Ndama crossbreed, termed Djakoré cattle, is located in the Senegalese groundnut basin. To improve national dairy production in Senegal, local cattle breeds are crossed with exotic dairy breeds e.g., Montbelliard, Holstein, through public funded artificial insemination campaigns [25]. To our knowledge, the proportion of the cattle breeds in Senegal has not been officially documented. However, inspection of regional livestock data from MEPA and the distribution area of cattle, our approximations suggest that the zebu Gobra and the taurine Ndama represent 80–90% of the Senegalese cattle population. In this case study, the zebu Gobra and the taurine Ndama cattle, which are the two dominant domestic cattle breeds, are considered. Particularly, lactating cows and adult males are the studied cattle sub-categories.

2.2 Description of the used model

Our evaluation was implemented using the Tier 2 model recommended by IPCC [5]. This model (Eq. (1)) allows to approximate enteric methane emission factors (MEF, kg CH4/head/year) which is the output variable. To calculate gross energy intake (GE, MJ/d), net energy (NE, MJ/d) needed for different metabolic functions (i.e., maintenance, activity, growth, lactation, work and pregnancy) was predicted for each cattle subcategory using various formulas presented in the IPCC Guidelines. The output variable is calculated based on input parameters, such as average live body weight (LW, kg), average daily weight gain (ADG, kg/day), milk production (Milk, kg/day), feeding situation, and digestible energy (DE, %). Finally, these parameters together with the methane (CH4) conversion factor (Ym, %) enable calculation of net energy (NE, MJ/day), average daily feed intake (in terms of gross energy content, MJ/d) and the MEF (i.e., output) for each animal sub-category.

$$EF = \left[\left(GE * \left(Ym / 100\right) * 365\right) / 55.65\right] \tag{1}$$

where:

EF = emission factor, kg CH4 head/yr,

GE = gross energy intake, MJ head/yr,

Ym = methane conversion factor, per cent of gross energy in feed converted to methane.

The factor 55.65, (MJ/kg CH4) is the energy content of methane.

2.3 Sources of input data

The data for input parameters used derived mainly from two Livestock Research Centres (LRC) of the Senegalese Agricultural Research Institute (Institut Sénégalais de Recherches Agricoles, ISRA, see www.isra.sn): the Centre de Recherches

Parameters	Symbol	Unit	References	
			Gobra cattle	Ndama cattle
Coefficient for calculating Net energy for maintenance	Cf_i	MJ/d/kg	[5]	
Activity coefficient corresponding to animal's feed situation	C_a	MJ/d/kg	[5]	
Average live body weight	LW	Kg	CRZ-D database	CRZ-K database
Mature live body weight	MW	Kg	From expert opinion	From expert opinion
Average daily weight gain	ADG	kg/d	[26–28]	CRZ-K Research reports
Coefficient	C	dim.	[5]	
Average daily milk yield	Milk	kg/d	[24]	CRZ-K Research reports
Fat content of milk	Fat	%	[29]	CRZ-K Research reports
Number of hours of work	Hour	H	CRZ-D research reports	CRZ-K research reports
Pregnancy coefficient	C_p	dim.	[5]	
Methane conversion rates	Y_m	%	[5]	
Feed Digestibility	DE	%	[5]	

d: day; dim.: dimensionless; CRZ-D: Centre de Recherches Zootechniques de Dahra; CRZ-K: Centre de Recherches Zootechniques de Kolda.

Table 1.
Input parameters used to estimate enteric methane emission factors for Gobra and Ndama cattle using the Tier 2 methodology and their sources.

Zootechniques de Dahra (CRZ-D) and the Centre de Recherches Zootechniques de Kolda (CRZ-K). These LRCs are located in the Ferlo and the Casamance areas, respectively. The general focus of these LRCs is to disseminate bulls to Senegalese family farms, so as to maintain and improve the productivity (milk and meat) of indigenous cattle. CRZ-D and CRZ-K frequently collect data on reproductive (e.g., rank of calving, calving interval) and productive (e.g., LW, ADG, Milk) performance through surveys and direct measurements implemented as part of research programs conducted independently or in partnership with international research organizations (e.g., CIRAD, FAO).

For this study, research reports, theses, publications and data sourced from ISRA databases (http://intranet.isra.sn/aurifere/opac_css/) were examined for relevant information. Documents (e.g., annual reports) from the Senegalese Livestock Ministry (MEPA, http://www.elevage.gouv.sn/) and the National Agency for Statistics and Demography (ANSD, http://www.ansd.sn) were also consulted. When country-specific data was not available, values from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories was used. **Table 1** presents the data sources used to estimate emission factors for Senegalese cattle breeds.

2.4 Uncertainty and sensitivity analysis procedures

Authors from many scientific fields have described the application of uncertainty analysis (UA) and sensitivity analysis (SA) procedures to various modeling situations [30–32] and for a number of purposes [33]. For example, to achieve comprehensive uncertainty analysis, the 2006 IPCC Guidelines [5] recommend to use the Monte Carlo (MC) simulation method. The MC methodology is useful for dealing with great uncertainties, complex models and existing correlations between parameters [34, 35]. However, expanding the MC domain increases the requirements of the user, in terms of acquiring additional data and designing the analysis, and thus requires strong collaboration between experts [36]. For this present study, analysis of variance (ANOVA) and the standardized regression coefficient (SRC) were implemented for UA and SA, respectively.

Analysis was applied to emission factors for lactating cows (LC) and adult males (MA). The latest national communication indicates that these two animal classes are the largest emission sources among all cattle categories in Senegal [37]. For each of these animal categories, only the relevant parameters were estimated. For example, parameters such as milk yield (Milk, kg/day), fat content of milk (Fat, %) and the coefficient for pregnancy (Cp) were not estimated for MA, while number of hours of work (Hour, h/day) was not estimated for LC. Hence, 11 and 9 input parameters were considered for LC and MA, respectively. The number of simulations were 200,000 and 20,000 for LC and MA, respectively. These numbers were assumed to be satisfactory to stabilize the output. Indeed, a 3-level complete factorial design was defined [38] and considering the K dichotomous input parameters, the design requires 3 K simulations, i.e., 311 and 39 combinations of values for LC and MA, respectively [39].

2.4.1 Uncertainty analysis

Uncertainty analysis (UA) was applied to the enteric methane emission factors (MEF) of Senegalese native cattle derived using the IPCC Tier 2 method.

The input parameters characterized were from two main sources, i.e., parameters with values proposed by the 2006 IPCC Guidelines (PM) and parameters specific to extensive livestock farming systems in Senegal (PS).

The uncertainties of PM expressed in this study were those taken from the literature [5, 40]. The uncertainties of PS were not defined in the Senegalese NIR. Therefore, expert judgment was used to characterize the uncertainty of each PS. To do this, we proceeded as follows. The average value of each PS was estimated using livestock data reported from research conducted in Senegal. Then, these values were shared with national experts for assessment. These national specialists, who had worked previously on countrywide livestock research programs, suggested standard deviations around each mean values of PS, and these were used to represent relative uncertainties of each PS.

Consequently, an uncertainty of ±15% around the value of average live weight (LW, kg) and average daily gain (ADG, kg/day) were assumed. The fitted values of mature weight (MW, kg) had a relative uncertainty of ±25%. Milk production per lactating cow (Milk, kg/day) reported from the extensive livestock farming systems varies widely within and between Senegalese traditional farms, so an uncertainty range of ±20% was assumed, while the value of fat content of milk (Fat, %) was set to randomly fluctuate by ±2%. Regarding feed digestibility (DE, %), an uncertainty of ±15% is most commonly reported in the literature [40–42]. For this study, a value of ±20% was recommended by Senegalese experts, considering the extensive livestock farming systems, which are largely based on the use of rangeland forage resources. The probability density functions (PDFs) of all used input parameters is believed to be symmetrical.

The overall uncertainty in the estimated output is assumed to be normally distributed, with a 95% confidence interval of plus or minus the uncertainty of the assigned value for each input parameter. The **Tables 2** and **3** list the used values of the input parameters, for each breed and animal category.

To estimate the specific contribution of each parameter to overall uncertainty (i.e., uncertainty associated with calculation of enteric methane emission factors), the analysis of variance (ANOVA) procedure was applied. To do this, the uncertainty ranges related to the input parameters were used to define the maximum and minimum values of each input parameter. The distributions were defined as uniform (i.e., normal distributions). Then, using the "runif" instruction, input parameter values were randomly generated using R software [43]. To mimic the contributions of the generated values of each input parameter to output uncertainty, the equations proposed by the IPCC [5] were used. To rank the input parameters according to their effect on the output, the sums of the squares (Sum Sq) computed by the ANOVA procedure for each input parameter were divided by the total sums of squares. Therefore, the results were expressed as a proportion and ordered in terms of percentage contribution to output uncertainty, using the instruction order in the R software. The total uncertainty of enteric methane emission factors was calculated using Rule A [5], which is approximation approach based on first-order Taylor series expansion, often referred to as error propagations [44].

2.4.2 Sensitivity analysis

Some of the SA approach used in this study has been presented previously as a case study (see https://www.agmrv.org) for the Livestock Research Group of the Global Research Alliance for Agricultural Greenhouse Gases (https://globalresearchalliance.org).

A sensitivity package developed by [45] and implemented in R software was used to conduct a global sensitivity analysis procedure [46]. First, to generate values between a minimum and the maximum, we set a range of variation of ±20% around the allocated value of each input parameter, assuming a uniform distribution (with a 95% confidence interval). Second, these values were input into the 2006 IPCC Tier 2 model to generate a range of values for the output. Finally, the standardized

Symbol[1]	Unit	Used value[2]		Uncertainty (±%)	Sources of used uncertainties
		Gobra	Ndama		
ADG	kg/day	0.135	0.110	15	Expert opinion
C	dimensionless	0.8	0.8	30	[40]
C_a	MJ/day/kg	0.36	0.36	30	[40]
Cf_i	MJ/day/kg	0.386	0.386	30	[40]
C_p	dimensionless	0.10	0.10	10	[40]
DE	%	50	50	20	Expert opinion
Fat	%	4.7	4.24	2	Expert opinion
LW	kg	250	200	15	Expert opinion
Milk	kg/day	0.922	0.870	20	Expert opinion
MW	kg	200	180	25	Expert opinion
Y_m	%	6.5	6.5	15	[5]

[1]*For the definition of symbols, see* ***Table 1.***
[2]*For the sources of used values, see* ***Table 1.***

Table 2.
Assigned values of input parameters used in the Tier 2 model to assess enteric methane emission factors for Gobra and Ndama lactating cows.

Symbol[1]	Unit	Used value[2]		Uncertainty (±%)	Sources of used uncertainties
		Gobra	Ndama		
ADG	kg/day	0.135	0.110	15	Expert opinion
C	dimensionless	1.2	1.2	30	[40]
C_a	MJ/day/kg	0.36	0.36	30	[40]
Cf_i	MJ/day/kg	0.37	0.37	30	[40]
DE	%	50	50	20	Expert opinion
Hour	h/day	1.23	1.23	10	Expert opinion
LW	kg	300	250	15	Expert opinion
MW	kg	200	180	25	Expert opinion
Y_m	%	6.5	6.5	15	[5]

[1]*For the definition of symbols, see* ***Table 1.***
[2]*For the sources of used values, see* ***Table 1.***

Table 3.
Assigned values of input parameters used in the Tier 2 model to assess enteric methane emission factors for Gobra and Ndama adult male cattle.

regression coefficient (SRC) was used to obtain sensitivity indices for each input parameter [47]. The SRC reflects the change in the standard deviation of the MEF when all other input parameters are fixed and unchanged [48, 49].

3. Results

3.1 Contribution of input parameters to uncertainty

The estimated values of the effect of each input parameter on overall uncertainty are presented in **Tables 4** and **5** for lactating cows and adult males of the Gobra and Ndama cattle breeds, respectively.

The results show the effect of broad differences in the values for input parameters used in terms of their influence (expressed as a percentage, %) on overall uncertainty. The coefficient for maintenance (Cf_i) contributes more than 55% of the overall uncertainty. Digestibility (DE) and the methane conversion factor (Ym) were the second and third most significant input parameters, respectively. The contributions of the other parameters were less than 10%.

In general, these results were similar for each animal sub-category of each breed, although there was some difference in terms of the contribution of these parameters to overall uncertainty. For example, with respect to lactating cows, the effect of Cf_i on the total uncertainty of the enteric methane EF calculation was greater for Gobra (58.2%) compared to Ndama (54.4%). By comparison, the contribution of Cf_i for adult males was 57.0% and 56.3% for Ndama and Gobra, respectively.

3.2 Sensitivity of used input parameters

Figures 1 and **2** show the standardized regression coefficients (SRC) of each input parameter used to evaluate the enteric methane emission factors for lactating cows and adult males of Senegalese native cattle, respectively.

According to the linear regression method implemented, the methane conversion rate (Y_m) and the coefficient for calculating net energy for maintenance (Cf_i) are the parameters with the largest SRC. The results show also the importance of the digestibility of feed (DE%) and liveweight (LW). The rank order in terms

Species	Parameters	Sum sq	Mean sq	F value	Pr (>F)	Contribution (%)
Gobra	Cf_i	6302301	6302301	7319021	0.000	58.2
	DE	2064336	2064336	2397366	0.000	19.1
	Y_m	1823864	1823864	2118099	0.000	16.8
	C_a	350673	350673	407245	0.000	3.2
	LW	96244	96244	111770	0.000	0.9
	Milk	20210	20210	23470	0.000	0.2
	C_p	3330	3330	3867	0.000	0.0
	ADG	109	109	127	0.000	0.0
	Fat	83	83	96	0.000	0.0
	C	66	66	77	0.000	0.0
	MW	16	16	18	0.000	0.0
	Residuals	172207	1	NA	NA	1.6
Ndama	Cf_i	4509591	4509591	6005876	0.000	54.4
	DE	1438224	1438224	1915428	0.000	17.3
	Y_m	1293936	1293936	1723265	0.000	15.6
	LW	625802	625802	833444	0.000	7.5
	C_a	253737	253737	337927	0.000	3.1
	Milk	15579	15579	20748	0.000	0.2
	C_p	2938	2938	3913	0.000	0.0
	Fat	119	119	158	0.000	0.0
	MW	72	72	95	0.000	0.0
	C	68	68	90	0.000	0.0
	ADG	0	0	0	0.659	0.0
	Residuals	150164	1	NA	NA	1.8

NA: not applicable.

Table 4.
Contribution to the overall uncertainty of input parameters used to calculate enteric methane emission factors for lactating cows of Senegalese native cattle breeds.

Species	Parameters	Sum sq	Mean sq	F value	Pr (>F)	Contribution (%)
Gobra	Cf_i	760631	760631	605099	0.000	56.3
	DE	216733	216733	172416	0.000	16.0
	Y_m	195408	195408	155451	0.000	14.5
	LW	107049	107049	85160	0.000	7.9
	C_a	46181	46181	36738	0.000	3.4
	Hour	646	646	514	0.000	0.0
	ADG	8	8	6	0.014	0.0
	C	2	2	1	0.241	0.0
	MW	0	0	0	0.536	0.0
	Residuals	25128	1	NA	NA	1.9

Species	Parameters	Sum sq	Mean sq	F value	Pr (>F)	Contribution (%)
Ndama	Cf_i	595693	595693	611755	0.000	57.0
	DE	161026	161026	165368	0.000	15.4
	Y_m	148597	148597	152604	0.000	14.2
	LW	82999	82999	85237	0.000	7.9
	C_a	37722	37722	38739	0.000	3.6
	Hour	276	276	284	0.000	0.0
	MW	14	14	15	0.000	0.0
	C	1	1	1	0.273	0.0
	ADG	0	0	0	0.746	0.0
	Residuals	19465	1	NA	NA	1.9

NA: not applicable.

Table 5.
Contribution to the overall uncertainty of input parameters used to calculate enteric methane emission factors for adult male Senegalese native cattle breeds.

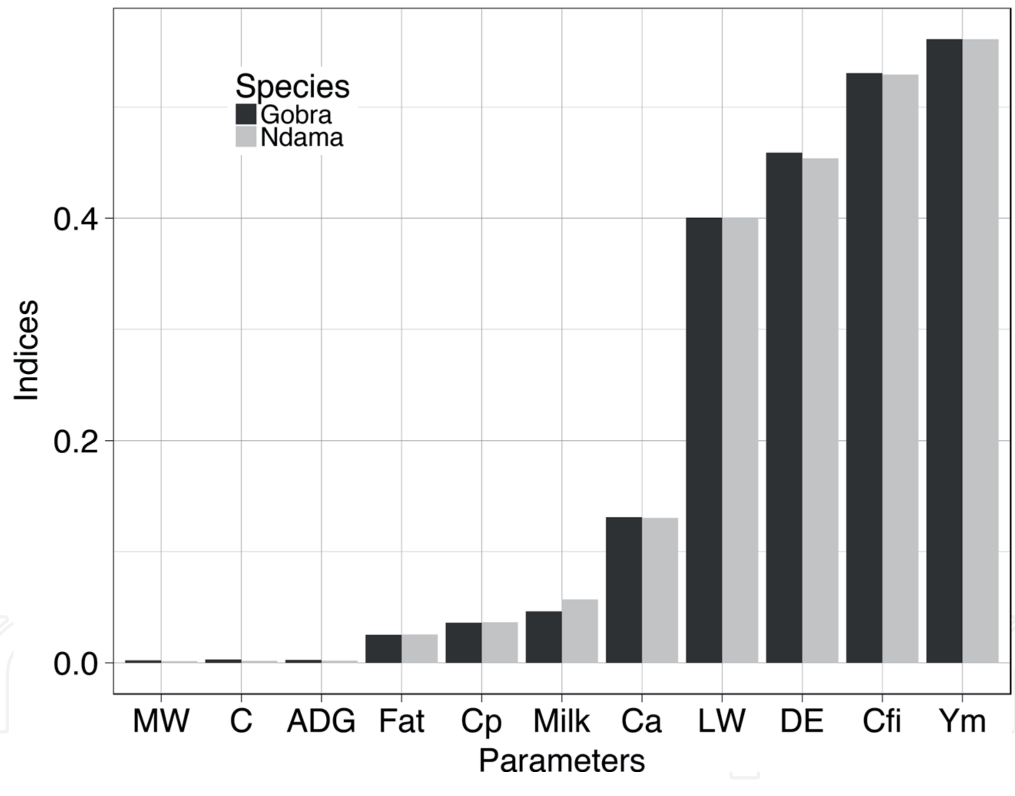

Figure 1.
Sensitivity indices based on standardized regression coefficients of input parameters used to calculate enteric methane emission factors for lactating cows of Senegalese native cattle breeds.

of sensitivity was identical for both cattle breeds and each animal sub-category. Moreover, our results reveal that among breeds, the SRC obtained for Ndama cattle was slightly larger. Differences were also observed between sub-categories. Compared to lactating cows, the SRC was higher for adult male Gobra cattle for parameters such as Y_m, Cf_i, and LW. For lactating cows, compared with adult males, Ym and DE showed more sensitivity for Ndama cattle. However, irrespective of breed or sub-category, the differences observed between SRC of input parameters did not exceed 8%.

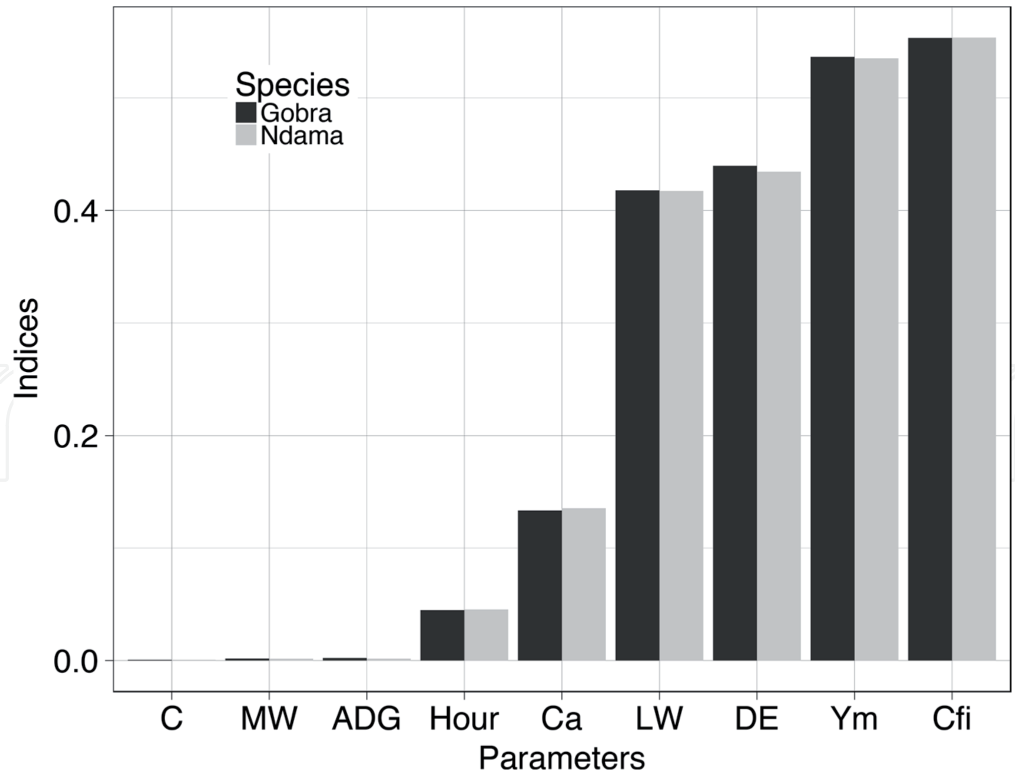

Figure 2.
Sensitivity indices based on standardized regression coefficients of input parameters used to calculate enteric methane emission factors for adult males of Senegalese native cattle breeds.

4. Discussion

4.1 Moving to a Tier 2 enteric methane emission factor

To date, because of the scarcity of relevant data in developing countries in the SSA region, the Tier 1 approach is most commonly used to evaluate enteric methane emission from livestock [50, 51]. Assessments at the regional level suggest that Africa has a higher uncertainty for each livestock product compared with Europe [52]. Additionally, [8] reported that only about one third of countries located in developing regions have conducted evaluation of uncertainty in their national GHG inventory. Considering the absence of reliable information on livestock in the SSA region, the IPCC Guidelines suggest that the uncertainty of enteric fermentation emission factors ranges from ±30% to ±50% for Tier 1 and ± 20% for Tier 2 approaches, respectively [5]. Hence, the use of a Tier 2 approach may enable a decrease in the uncertainty of predicted enteric methane emission factors used in national GHG inventories [53–55]. In Senegal, the third GHG emission inventory was submitted to the UNFCCC in 2015 (see https://unfccc.int/documents/89618). In that inventory, enteric methane emission of cattle was assessed using the Tier 2 methodology. Within the overall emissions from the agricultural sector, enteric methane was identified as a key source of emissions (accounting for 72% of total agricultural emissions). Cattle were responsible for 65% of total agricultural emissions. However, uncertainty analysis has not previously been performed on that national GHG inventory.

4.2 Importance of input parameters

Considering the results of both uncertainty and sensitivity analysis computed in this study, our calculations indicate that the coefficient of maintenance (Cf_i), the digestibility of feed (DE) and the methane conversion factor (Y_m) are the input parameters which require further research, because of their influence on the accuracy of enteric methane emission factors calculated using the 2006 IPCC Tier 2 approach.

The importance of Cf_i has been pointed out in previous research conducted in other regions [41, 42, 53]. The value of Cfi implemented in our assessment was sourced from the IPCC Guidelines. To our knowledge, studies focusing on this parameter are very few, particularly in developing countries, despite the dependence of this parameter on variation in temperature [5].

The composition of fodder consumed by ruminants is well documented in Senegal, and the profile of organic matter digestibility (OMd) is available [13–15, 54]. However, there is a need to determine at the national scale, an average value for OMd which takes into consideration seasonality. To date, the default value for feed digestibility (DE, %) from the IPCC Guidelines (i.e., 50 ± 5%) has always been applied in the Senegalese national GHG inventory. In general, estimation of DE is very complex, considering the various factors which need to be taken into consideration [56–58]. To estimate DE, robust formula needs to be developed based on numerous data which consider the diversity of diet [59]. For example, in West African livestock farming systems, the largest proportion of feed is from natural pastures [60–62]. Cattle herds in this region graze different types of feedstuffs (e.g., trees, crop residues, woody species, grasses). Throughout the seasons, the composition of the diet and the nutrient content of feedstuff both fluctuate [13, 63, 64]. Given the diversity of feedstuff and seasonal fluctuations in the West African context, determining an annual average value of DE is challenging. A fixed value for DE is reasonable as it is supposed to represent the annual average. Additionally, apart from the proposed values of DE in the 2006 IPCC Guidelines, reports of the value of DE are very limited in the literature, even in some developed countries. Indeed, with the lack of country-specific data related to the feeding system, Belgium applies DE values from the Netherlands, assuming that feed systems are comparable [65]. Slovenia uses a predicted equation sourced from INRA and German feeding tables [66]. In the national inventory of the UK, the DE values applied for dairy cattle were from tables of nutritive value and chemical composition of feeds, while for beef cattle values were based on expert opinion [67].

The methane conversion factor (Y_m, %) is the third parameter which needs to be better estimated when using the Tier 2 approach. Ym is defined as the percent of gross energy intake that is converted into methane (kg CH4/kg GEI). The appropriate value of Ym is the subject of considerable research by scientists [68]. Using a meta-analysis approach, [69] propose using 8.4 ± 0.4% (range 4.8% to 13.7%) for Y_m, while [70] suggest a value which varies from 5.0% to 7.2%. Several countries apply values for Y_m other than the default values suggested by the 2006 IPCC Guidelines. For example, Croatia calculated Y_m using a model reported by [56]. Denmark used a value for Y_m for dairy cattle (ranging from 5.98% to 6.13%) reported by [71].

Hence, in view of the diverse diet composition consumed by cattle over the course of the seasons in West Africa [72–74], determination of an appropriate value for Ym is clearly important for estimating the expected enteric methane emission factor using the IPCC 2006 Tier 2 approach.

In our case, we used expert judgment to characterize the uncertainties of input parameters. In addition, it is possible that the inputs parameters can be correlated. In Senegal, due to the scarcity of relevant reports related to the percentage of native cattle breeds in the total cattle herd, it is probable that uncertainty of activity data is actually higher than uncertainty of emission factors and should be a priority for GHG inventory improvement.

5. Conclusions

The purpose of conducting uncertainty and sensitivity analysis was to identify the most important factors driving emission factors in order to prioritize future data improvement and research efforts so as to improve livestock GHG emission estimates and reduce the uncertainty of inventory estimates for Senegal. Having applied analysis of variance and regression techniques for uncertainty analysis and sensitivity analysis, respectively, our results suggest that future research should focus on the estimates of the coefficient of maintenance, feed digestibility and the methane conversion factor.

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Conflict of interest

The author declares that no conflicts of interest have affected the conduct of the work proposed in this paper.

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