Atmospheric Environment 322 (2024) 120389

Contents lists available at ScienceDirect

Atmospheric Environment

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

Analysis of spatially distributed enteric methane emissions from cattle across the geo-climatic regions of Mexico and uncertainty assessment

Juan Carlos Angeles-Hernandez [a], Juan Carlos Ku-Vera [b], María Fernanda Vázquez-Carrillo [c], Sofía Viridiana Castelán-Jaime [d], Luisa T. Molina [e], Mohammed Benaouda [f], Ermias Kebreab [g], Manuel González-Ronquillo [i], Fernando Paz-Pellat [h], Hugo Daniel Montelongo-Pérez [i], Octavio Alonso Castelán-Ortega [i,*]

[a] *Instituto de Ciencias Agropecuarias Universidad Autónoma del Estado de Hidalgo Cd. Universitaria, Av. Universidad, Km.1, Ex-Hacienda de Aquetzalpa, C.P. 43600, Tulancingo, Hidalgo, Mexico*

[b] *Laboratory of Climate Change and Livestock Production, Department of Animal Nutrition, Faculty of Veterinary Medicine and Animal Science, Universidad Autónoma de Yucatán, Carretera Mérida-Xmatkuil Km. 15.5, C.P. 97285, Mérida, Yucatán, Mexico*

[c] *Departament of Animal Nutrition, Faculty of Veterinary Medicine and Animal Science, Universidad Nacional Autónoma de México, Mexico City, CP. 04510, Mexico*

[d] *Escuela Nacional de Estudios Superiores, León Unit. Universidad Nacional Autónoma de México. C.P. 37000, León, Guanajuato, Mexico*

[e] *Molina Center for Strategic Studies in Energy and the Environment, Boston, MA 02215, USA*

[f] *Institut Agro Dijon, 26 bd Docteur Petitjean, 21079 Dijon, France*

[g] *Department of Animal Science, University of California, Davis, 1103 Environmental Horticulture Bldg, One Shields Avenue, Davis, California, CA 95616, USA*

[h] *Colegio de Postgraduados de México, Montecillo, C.P. 56230 Montecillo, Estado de México, Mexico*

[i] *Laboratory for Research on Livestock, Environment and Renewable Energy, Faculty of Veterinary Medicine and Animal Science, Universidad Autónoma del Estado de México, Instituto Literario No. 100, Centro, C.P. 50000, Toluca, Mexico*

HIGHLIGHTS

- This is the first Tier 2 Inventory for enteric CH_4 emissions for Mexico.
- The inventory is 2039.21 ± 205 Gg CH_4 year^{-1} (uncertainty = −18.3 to +21.2. CI = 1666.3–2471.6) for 2018.
- Our method provides an accurate description of the inventory's uncertainty.
- As The accuracy of the inventory increases, the uncertainty expands.
- Gross energy intake is the primary source of uncertainty.

ARTICLE INFO

Keywords:
Enteric fermentation methane
Inventory
Cattle
Uncertainty analysis
Geo-climatic regions

ABSTRACT

The present work aims to calculate a bottom-up IPCC-Tier 2 inventory for enteric CH_4 emissions from cattle in Mexico, disaggregate the inventory into different geo-climatic regions to analyze the effect of the contrasting climates of Mexico on the inventory and identify the relevant sources of uncertainty associated with the inventory. Peer-reviewed country-specific emission factors (EF), activity data (AD) on animal characteristics, feeding management, and CH_4 conversion factors (*Ym*) were used in developing the emissions inventory. Monte Carlo simulation (MCS) was used to propagate the uncertainty throughout the Tier 2 model (T2model). Spearman-ranked correlation analysis (SRCA) was used to identify relevant input parameters (IPAs) for which CH_4 emissions variables were most sensitive. The estimated inventory for the year 2018 was 2039 Gg CH_4 year^{-1} with an uncertainty of −18.3 % to +21.2 %. The geo-climatic regions had an important influence on the inventory because emissions varied among regions, with the dry and tropical sub-humid geo-climatic regions being the highest CH_4 emitters due to their larger cattle populations and the effect of climate on cattle diets' quality, and in turn, the effect of diet on CH_4 emission. The IPAs associated with dry matter intake (DMI) and gross

* Corresponding author.
E-mail addresses: juan_angeles@uaeh.edu.mx (J.C. Angeles-Hernandez), kvera@correo.uady.mx (J.C. Ku-Vera), mafervc@comunidad.unam.mx (M.F. Vázquez-Carrillo), sofiavca0793@comunidad.unam.mx (S.V. Castelán-Jaime), ltmolina@mit.edu (L.T. Molina), mohammed.ben-aouda@agrosupdijon.fr (M. Benaouda), ekebreab@ucdavis.edu (E. Kebreab), mrg@uaemex.mx (M. González-Ronquillo), ferpazpel@gmail.com (F. Paz-Pellat), hmontelongop387@alumno.uaemex.mx (H.D. Montelongo-Pérez), oacastelano@uaemex.mx (O.A. Castelán-Ortega).

https://doi.org/10.1016/j.atmosenv.2024.120389
Received 15 June 2023; Received in revised form 26 January 2024; Accepted 1 February 2024
Available online 3 February 2024

energy intake (GEI) of cattle considerably impacted the uncertainty of enteric CH_4 emission estimates. This study concludes that implementing a bottom-up Tier 2 approach using disaggregated AD and country-specific EF allows a more accurate inventory estimation and assessment of its uncertainty than existing inventories. Future efforts to improve the quality of CH_4 inventories must focus on improving the accuracy of AD, like DMI, GEI, and country-specific EF.

1. Introduction

The United Nations Framework Convention on Climate Change (UNFCCC), through the 2015 Paris Agreement established the critical steps to respond to climate change (UNFCCC, 2015). The first step is to limit the global average temperature rise to well below 2 °C above pre-industrial levels. The most recent report released by the Intergovernmental Panel on Climate Change (IPCC) found that human activities are increasing greenhouse gas (GHG) emissions to record levels and that the world must cut GHG emissions by about 21 % by 2030 and 35 % by 2035 to keep warming within 2 °C above pre-industrial levels (IPCC, 2023a,b). Livestock production and rice cultivation are the most significant contributors to global emissions of non-CO_2 greenhouse gases like CH_4 and N_2O, accounting for 54 % of emissions of the agricultural sector (EPA, 2012). The annual global CH_4 emissions are ~570 million tonnes (Mt); this includes emissions from natural sources, around 40 % of emissions, and those originating from human activity, the 60 % remaining - known as anthropogenic emissions (IEA, 2020). The largest source of anthropogenic CH_4 emissions is agriculture, responsible for around a quarter of the total (145 Mt CH_4 or 3.62 Gt CO_2 eq^{-1}), closely followed by the energy sector, which includes emissions from coal, oil, natural gas and biofuels (IEA, 2020). Globally, cattle production systems dominate the agricultural sector CH_4 emissions with 64–78 % (2.3–2.8 Gt CO_2 eq^{-1}) (Herrero et al., 2016). However, these figures have considerable uncertainty depending on the study; for example, according to Beauchemin et al. (2008), CH_4 emissions from domestic ruminants account for ~28 % of the global anthropogenic emissions of this gas (~2.8 Gt CO_2 eq^{-1}), which is close to the figure reported by Herrero et al. (2016) but for cattle alone. During the UNFCCC 26th Conference of the Parties (COP26), the participating countries agreed to reduce anthropogenic CH_4 emissions by 30 % by 2030, compared with 2020 levels (UNEP, 2021), including cattle emissions. So, there is a need to generate more accurate and less uncertain national inventories to help design appropriate public policies to reduce CH_4 emissions from cattle production globally. Reducing CH_4 emissions from cattle initially requires an accurate estimation of the inventory of this GHG and its associated uncertainty. To estimate national enteric CH_4 emissions inventories, the IPCC proposes three "tiers" of complexity. Tier 1 is the most straightforward but the least accurate method. The Tier 2 approach is more accurate as it disaggregates the activity data (AD) and uses country-specific emission factors (EF). The Tier 3 method uses complex rumen kinetics models and highly disaggregated AD (Cersosimo and Wright, 2015). Only a few countries have developed Tier 3 inventories; for example, France proposed a new methodology to improve the French inventory's accuracy, which complies with IPCC (2014) rules for the Tier 3 method (Eugène et al., 2018). Thus, the estimations of the national inventories of CH_4 will always have a certain level of uncertainty. Non-CO_2 GHG emissions, like CH_4, originate from diverse sources and are much more uncertain to estimate than CO_2 emissions. The level of uncertainty of CH_4 inventories is of the order of 30 % or more, whereas for CO_2, this is only about ±5 % to ±10 % (PBL, 2020). Quantifying uncertainty is critical for describing and attributing effects derived from GHG emissions and climate change (Katz et al., 2013). Uncertainty refers to a lack of knowledge regarding the actual value of a quantity (Frey and Cullen, 1995). Therefore, the level of uncertainty in CH_4 emissions inventories depends on the level of the analyst's knowledge, the quality and quantity of AD, the parameters' uncertainty, and the understanding of the underlying process and inference methods (Tong et al., 2012). Emissions inventories are an essential input to air quality models and an important tool for policymakers to track progress towards mitigation targets and guide in defining the most cost-effective mitigation strategies and use in international treating reporting to the UNFCCC (Beauchemin and McGinn, 2005). Moreover, accurate calculations of national GHG inventories and the associated uncertainty are important to demonstrate that countries are taking action to meet their national climate targets under the Paris Agreement. Several approaches have been used to quantify how the uncertainty in the model inputs propagates throughout the model's output (Milne et al., 2014). The uncertainty and its propagation can be calculated using classical statistical methods, expert judgment and IPCC guidelines. However, when the assumption of normality of distribution of the AD is violated, the sample size is small, or when the relative range of uncertainty or standard deviation of the mean is large, like in inventory calculation for enteric CH_4 emissions from cattle, a non-parametric but computationally intensive method like bootstrapping (BOS) can be used to calculate the uncertainty of the relevant input parameters (IPAs) (Tong et al., 2012). In addition to BOS, Monte Carlo simulation (MCS) can be a valuable tool to assess the IPAs propagation through the model because it evaluates dependencies between IPAs and is more flexible than other methods. So, combining BOS and MCS can help to deal with complex CH_4 inventories calculation because production of this gas in the animal is affected by numerous sources of uncertainty including: animal characteristics, such as body weight, DMI, which is the primary variable determining the amount of enteric CH_4 produced by cattle (Castelán-Ortega et al., 2020), the chemical composition of the diet (Sejian et al., 2011), the diet's forage-to-concentrate ratio, the source of forage (Beauchemin and McGinn, 2005), cell walls content in forage plants, presence of plant's secondary metabolites known to possess anti-methanogenic properties, the digestibility of the diet (Benaouda et al., 2020). Moreover, regional differences in climate, temperature, rainfall, solar radiation, and nutrients are also associated with the variability in CH_4 inventories within a country because of their effects on plants' growth physiology. Thus, tropical regions are usually associated with taller, less nutritious, and fast-growing C4 grasses, which result in low digestibility, reduced DMI, high CH_4 yield (g CH_4 kg^{-1} DMI) and low daily emission (Thompson and Rowntree, 2020). In contrast, the greater nutritive value of C3 grasses native to temperate climate regions of the world is linked to higher digestibility and DMI (Lee et al., 2017), resulting in lower CH_4 yield (Moe and Tyrrell, 1979) but higher daily emission head^{-1}. Therefore, inventory calculation is challenging in countries where cattle production systems occur under different geo-climatic regions that range from tropical forests to arid and semi-arid regions. So, there is a considerable opportunity to improve CH_4 inventories if appropriate uncertainty analysis tools and geo-climatic region-specific information on EF, DMI, diets' digestibility and CH_4 conversion factor (*Ym*) are used in countries with contrasting climates and heterogeneous cattle production systems (Castelán-Ortega et al., 2020). However, none has conducted a Tier 2 inventory that includes all these sources of uncertainty. The livestock sector is Mexico's second largest anthropogenic source of CH_4 emissions, just behind the energy sector (SEMARNAT-INECC, 2018). Likewise, it is worth noting that all the previous official inventories for enteric CH_4 cattle emissions reported by the Mexican Ministry for the Environment (SEMARNAT) and the National Institute for Ecology and Climate Change (INECC) have been elaborated using the Tier 1 approach (SEMARNAT-INE, 2006). Furthermore, these inventories were associated with an inappropriate uncertainty assessment and the use of default uncertainty values defined by IPCC (2014). The approach used by SEMARNAT-INECC (2018) in Mexico to deal with uncertainty neither accounts for the lack of knowledge on CH_4 EF nor identifies potential sources of uncertainty from the AD, as recently pointed out by the UNFCCC concerning Mexico's last communication (UNFCCC, 2019). The present work aims to calculate a bottom-up IPCC-Tier 2 inventory for enteric CH_4 emissions from cattle in Mexico, disaggregate the inventory into the different geo-climatic regions to analyze the effect of the contrasting climates of Mexico on the inventory and identify the relevant sources of uncertainty associated with the inventory.

2. Materials and methods

The methodological approach used consisted of 1) geo-spatial disaggregation of the cattle population, 2) categorization of Mexico's cattle population and national survey application, 3) uncertainty analysis, 4) uncertainty propagation, and 5) sensitivity analysis. We used the *Ym* obtained from experiments conducted in open-circuit respiration chambers (OCRC) by our group (Arceo-Castillo et al., 2019; Canul-Solís et al., 2017; Castelán-Ortega et al., 2020; Hernández-Pineda et al., 2018; Ku-Vera et al., 2018; Valencia Salazar et al., 2018; Vázquez-Carrillo et al., 2020; Vázquez-Carrillo et al., 2021). We also used country-specific AD for Mexico on animal characteristics, feeding management and cattle population obtained from the literature and a national survey. We were aware that the T2model does not reflect all the complex interactions between the animal and the plants in the pastures, particularly in grazing systems, where DMI is strongly influenced by the sward structure and digestibility of the forage (Silva et al., 2013). However, this and other problems of the T2model were also acknowledged, as points for improvement, by the IPCC (2014) and its refined version (IPCC, 2019), but not solved until now. Developing a Tier 3 inventory that incorporates complex animal-plant interactions was not an option for us because of the lack of simulation models appropriate for Mexico.

2.1. Geo-spatial disaggregation of the cattle population

The geo-spatial disaggregation was conducted to analyze the effect of the contrasting geo-climatic regions of Mexico on enteric CH_4 emissions from cattle, as in Castelán-Ortega et al. (2014). We used geographical information systems (GIS) mapping tools consisted of dividing Mexico's territory into five geo-climatic regions using the Köppen climate classification (as in Chen and Chen, 2013): Dry (BS), Very Dry (BWh), Temperate (C), Tropical Humid (Am) and Tropical Sub-Humid regions (Aw); and then allocating the national cattle population of ~34.2 million heads for the year 2018 to each geo-climatic region (depending on their actual location), as shown in Fig. 1. The information used to conduct the geo-spatial disaggregation was obtained from the National Institute for Statistics and Geography (INEGI) and the National Water Commission (CNA), (CONAGUA., 2022). To determine the cattle number for each geo-climatic region, we used the cattle population in every one of the 2469 municipalities of Mexico and the individual municipality geographic location within one of the five geo-climatic regions. This information was captured in the GIS for analysis, which included calculating the geo-climatic region population obtained by adding the

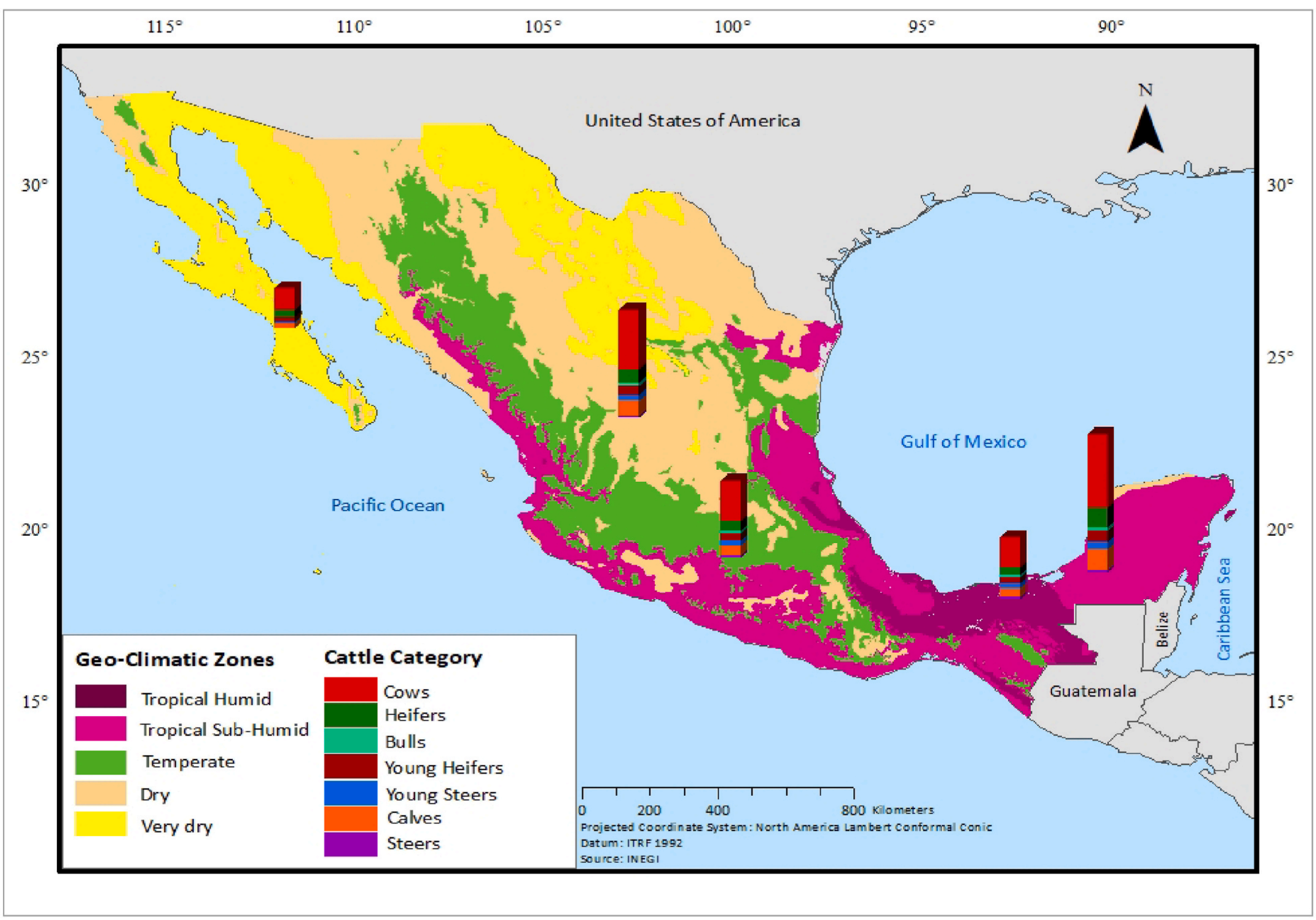

Fig. 1. Distribution of the Mexican cattle population disaggregated by categories in the five geo-climatic regions used for developing the national inventory for enteric methane emissions from cattle.

number of cattle heads in each municipality within a geoclimatic region. Fig. 1 shows the result of the approach used, and a detailed description of this process can be found in Castelán-Ortega and Ku-Vera (2019).

2.2. Categorization of Mexico's cattle population and national survey application

According to IPCC (2014), the stratification of the cattle population of a country into categories and sub-categories is necessary to conduct a Tier 2 national inventory. The categorization utilized in the present work was based on the classification used by the National Cattle Registry of Mexico (NCR) (SADER-SINIIGA, 2021) and the 2007 National Agricultural Census (INEGI, 2007). Thus, the Mexican cattle population of 34, 231, 567 heads was divided into nine categories: calves, young steers, young heifers, steer, heifers, dairy cows, beef cows, dual-purpose cows, and bulls (Fig. 1). By cows, we mean the mature female of cattle. The national survey consisted of 384 questionnaires proportionally applied to cattle farmers of the five geo-climatic regions shown in Fig. 1. Information on AD, such as cattle's productive purpose (milk, beef, and dual-purpose), milk yield, milk composition, daily body weight gain, herd size and herd structure in terms of the number of animals in each category, feeding systems (grazing, feedlot, cut and carry), dietary ingredients composition, DMI, concentrate supplementation, types of supplements inherent to each sub-category within the five geo-climatic regions, was collected.

The data was captured in an Excel database and analyzed using R codes developed for all analyses conducted in the present work. The mean, standard deviation and 95 % confidence intervals (CI) of each AD parameter used as an IPAs for the T2model were computed, and the output variables obtained were: daily net energy requirements (DNEreq), gross energy intake (GEI), DMI, among others, as shown in Table 1.

Typical diets for each geo-climatic region and cattle category were formulated using survey data on common feed ingredients, their inclusion levels, and specific cattle characteristics by geo-climatic region. A detailed description of the procedure to develop the diets can be found in Castelán-Ortega and Ku-Vera (2019). Subsequently, the diets were used in experiments conducted in OCRC to generate specific *Ym* and EF, as described in (Castelán-Ortega et al., 2018).

All Y*m* and EF were peer-reviewed before their use in the inventory. For example, the Y*m* factors for the Tropical Humid and Tropical Sub-Humid geo-climatic regions were taken from Canul-Solís et al. (2017), Piñeiro-Vázquez et al. (2017), Ku-Vera et al., 2018, Valencia Salazar et al. (2018), Arceo-Castillo et al. (2019). Similarly, the Y*m* factors for the Temperate, Dry and Very Dry regions were taken from Castelán-Ortega et al. (2018), Benaouda et al. (2020), Castelán-Ortega et al. (2020), Vázquez-Carrillo et al. (2020). The *Ym* factors for the Temperate region were published in Vázquez-Carrillo et al. (2021).

2.3. Uncertainty analysis

The equations shown in Table 1 were used to calculate the GEI for an average animal from each cattle category within geo-climatic regions. This set of equations is hereinafter referred to as the T2model. To compute the specific CH_4 EF to each geo-climatic region, the GEI was multiplied by the corresponding *Ym* factor in each animal category (Eq. 10.21; IPCC, 2014). A frequentist approach, based on empirical data, was used to make inferences for parameters of the distribution of the T2model inputs and assess propagation's effect on the IPAs' uncertainty. Thus, the uncertainty calculation comprised 1) a calculation of the uncertainty of the IPAs for the T2model; and 2) a calculation of the uncertainty of the IPCC (2014) T2model itself (Table 1).

2.3.1. Calculation of the uncertainty of the IPAs for the T2mode

This phase is comprised of a) Quantification of the variability of the activity and emissions data used as input to the T2model, b) choice of

Table 1
Input and output parameters used in the main method of the Tier 2 approach to calculate the inventory for enteric CH_4 emissions from cattle in Mexico.

Output variable	IPCC, 2014 equation	Input parameters	Source
Coefficient for calculating NEm (Cfi)	10.2	Winter temperature (°C)	(CONAGUA., 2022)
Net energy requirements for maintenance (NEm)	10.3		Eq. 10.2 (IPCC, 2014)
		Body weight (kg)	Survey
Net energy for activity (NEa)	10.4	NEm	Eq. 10.3 (IPCC, 2014)
Net energy for growth (NEg)	10.6	Live weight (kg)	Survey and scientific literature
		Mature live weight (kg)	
		Average daily weight gain (kg)	
Net energy for lactation (NEl)	10.8	Daily milk yield (kg d^{-1})	Survey
		Milk fat content (%)	Scientific literature
Net energy for pregnancy (NEp)	10.13	NEm	Eq. 10.3 (IPCC, 2014)
Ratio of net energy available in a diet for maintenance to digestible energy consumed (REM)	10.14	Digestible energy (%)	Experimental assays in OCRC
Ratio of net energy available for growth in a diet to digestible energy consumed (REG)	10.15	Digestible energy (%)	Experimental assays in OCRC
Gross energy requirements (GEI)	10.16	NEm	Eq. 10.3 (IPCC, 2014)
		NEa	Eq. 10.4 (IPCC, 2014)
		NEg	Eq. 10.6 (IPCC, 2014)
		NEl	Eq. 10.8 (IPCC, 2014)
		NEp	Eq. 10.13 (IPCC, 2014)
		REM	Eq. 10.14 (IPCC, 2014)
		REG	Eq. 10.15 (IPCC, 2014)
		Digestibility of energy	Experimental assays in OCRC
Dry matter intake (DMI)[a]	10.18 b	Body weight (kg)	Experimental assays in OCRC
		Digestibility energy	
Emission factor for each cattle category within a geo-climatic region (kg CH_4 $head^{-1}$ $year^{-1}$)[b]	10.21	GEI	Eq. 10.16 (IPCC, 2014)
		CH_4 conversion factor (*Ym*)	Experimental assays in OCRC
CH_4 emissions from a cattle category within a geo-climatic region (Gg CH_4 yr^{-1})	10.19	Emission factor	Eq. 10.21 (IPCC, 2014)
		Number of heads	INEGI, 2007; SADER-SINIIGA, 2021
Inventory (Gg CH_4 yr^{-1})	10.20	CH_4 category	Eq. 10.19 (IPCC, 2014)

[a] Equation used in tropical and sub-tropical geo-climatic regions that showed fed rations with low digestibility (45–55 %).
[b] Canul-Solís et al. (2017), Castelán-Ortega et al. (2018), Arceo-Castillo et al. (2019), Castelán-Ortega et al. (2020), Ku-Vera et al. (2018), Vázquez-Carrillo et al. (2020), Vázquez-Carrillo et al. (2021).

the appropriate probability density function (PDF), and c) Assessment of the uncertainty of the T2model IPAs according to their PDF. The most suitable PDFs were selected using graphical and statistical techniques. The selected PDF of the IPAs was used to estimate the coverage factor and expanded uncertainty using MCS analysis (JCGM, 2008a).

a) Quantification of the variability of the activity and emissions data used as input to the T2model: survey data, AD and data from experiments in OCRC were subjected to a depuration process, which consisted of the identification and management of outliers and missing values. Next, the median was used as a measure of the central trend because it is less sensitive to the presence of outliers (Kwak and Kim, 2017). The outliers were treated using a specific function developed in the R software (R Core Team, 2017) to carry out a random imputation of identified outliers to avoid introducing bias in the results.
b) Choice of the appropriate probability density function (PDF): First, empirical and cumulative distributions were plotted, which, together with descriptive statistics, helped to choose a candidate PDF that describes a set of likely parametric distributions. Skewness-kurtosis plots, as in Cullen and Frey (1999), were performed and helped to select the PDF that best fitted empirical data. Also, skewness and kurtosis values were plotted from the empirical data set's bootstrap samples (10^6 simulations).
c) Assessment of the uncertainty of the T2model IPAs according to their PDF: once the PDF was chosen for each IPAs, a parametric bootstrap approach was used to estimate their expected value, standard deviation, and 95 % CI as in Tong et al. (2012). Parametric bootstrap is a data-based simulation method for statistical inference where resamples of size *n* are randomly drawn from the selected PDF (Hesterberg, 2014). Out of these new sets of data, the CIs were calculated. Thus, 10^4 bootstraps resamples were considered appropriate, as in Tong et al. (2012). The uncertainty expressed as 95 % CI (bootstrapped) is hereinafter referred to as “expanded uncertainty” (JCGM, 2008b) and was expressed as a percentage (IPCC, 2014). For the AD of cattle population, neither the NCR nor the Livestock Census specifies the uncertainty associated with their estimates for the size of the Mexican cattle population. Therefore, a standard uncertainty of ±30 % was assumed across all categories in the five geo-climatic zones, which is within the range of the recommended uncertainty for a livestock population (IPCC, 2014).

2.3.2. Calculation of the uncertainty associated with the IPCC (2014) T2model

In this phase, we propagated the uncertainty of the IPAs and applied the sensitivity analysis to identify those IPAs that strongly influenced the uncertainty of the T2model. Thus, the mean and standard deviation of EF and AD were used as inputs to the T2model, while the MCS was used in the error propagation process to obtain the uncertainty of the enteric CH_4 estimations. The sensitivity analysis was conducted using the SRCA, which identified the principal IPAs that affected most the uncertainty of the CH_4 emission from the cattle. In the present work, we defined the uncertainty of the T2model as the uncertainty due to the combined effects of uncertainty of the model, IPAs, plus the uncertainty introduced by the model's structure itself (Frey and Cullen, 1995). Thus, the model's uncertainty was evaluated by propagating the bootstrap estimates across all the equations of the T2model. As shown in Table 1, the Tier 2 method estimates emissions of enteric CH_4 using the net energy system proposed by the National Research Council (NRC, 1984, 2001). This system uses a factorial approach by adding up the net energy requirements for maintenance, growth, lactation, pregnancy, activity and work using the equations and IPAs shown in Table 1. Similarly, the energy supplied by the typical diets from each geo-climatic region was assessed for uncertainty using their digestibility as the main attribute that describes the nutritional quality (Castelán-Ortega et al., 2018).

2.4. T2model's uncertainty propagation

The MCS technique (Hammersley and Handscomb, 1975; Lewis and Orav, 1989) quantified how the uncertainty of the IPAs and output variables propagated throughout the T2model because it can deal with complex models. The uncertainty propagation analysis aimed to determine the uncertainty in the output variables *U* (.), given the operations or equations g and the uncertainties in the IPAs Ai (.) (Heuvelink, 1998), as shown in Equation (1):

$$U(.) = g(\mathrm{A}_1(.), \ldots, \mathrm{A}_m(.)) \tag{1}$$

Where *U* (.) is an output variable of the T2model's equation *g* (.) on the *m* input parameter A_i (.).

The IPAs were considered random variables and were described by their PDF. The T2model's equations were run 10^6 times to obtain a set of output variables' values, which formed the probability distribution that described the IPAs' uncertainty. The uncertainty propagation analysis was conducted using the Propagate Package (Spiess, 2018) in R software throughout MCS; Taylor's first and second derivatives were also calculated. With *a priori* number of simulations defined, an adaptive methodology was carried out by increasing the number of simulations until reaching the stabilization of the values of the uncertainty of estimated output variables.

2.5. Sensitivity analysis

Spearman ranked correlation analysis (SRCA) was used to assess the sensitivity of the CH_4 EFs and the entire inventory to the uncertainty of the IPAs. The SRCA measures the strength of the association between the output variables of the T2model and their IPAs. Firstly, we calculated the SCRA between the CH_4 inventory and the IPAs of the T2model. Secondly, we calculated the SRCA between the IPAs of the T2model and the EF (kg CH_4 head^{-1} year^{-1}) because most of the uncertainty in the GHG inventories is primarily caused by the uncertainty associated with the EFs (Milne et al., 2014). Accordingly, we selected five IPAs with the highest association level with their respective EF. We then replaced the previously used IPAs with the new IPAs in the T2model and reran the model, but this time with half of the value of the standard deviation in order to identify the effect of reducing the input's uncertainty on the emission factor.

3. Results

3.1. Activity data

The cattle population of 34.2 million heads segregated by geo-climatic region, category and sub-category is shown in Table 2. It can be observed that the Mexican cattle herd is not heterogeneously distributed across the geo-climatic regions of the country. The largest population is located in the Tropical Sub-Humid region with 11.5 million heads, followed by the Dry climate region with 8.0 million heads. The smallest population is located in the Very Dry climate region. Cows (dairy, beef and dual-purpose) were the predominant categories in all geo-climatic regions with a population of 18.8 million heads, which represent ~ 55 % of total cattle inventory.

3.2. Enteric fermentation CH_4 emissions Tier 2 inventory

The inventory of CH_4 emissions from enteric fermentation of cattle was 2039 ± 205 Gg CH_4 year^{-1} (CI = 1666–2471) with an associated uncertainty of −18.2 % to +21.2 %. Fig. 2 shows the empirical distribution of the inventory, the mean emission and the 95 % CI. It can be observed that the empirical distribution is slightly skewed to the left due to the skewness shown by the EFs. Tables TA1 to TA5 in the Appendix show the PDF and their parameters, mean, standard deviation, 95 % CI

Table 2
Mexico's cattle population disaggregated by geo-climatic region, cattle category and sub-category for 2018 used for the IPCC (2014) enteric CH_4 inventory.

Category	Geo climatic region				
	Dry	Very Dry	Temperate	Tropical Humid	Tropical Sub-Humid
Dairy cows	1,257,368	541,047	1,047,499	–	–
Beef cows	2,063,011	770,973	1,135,665	1,795,571	3,578,483
Dual-purpose cows	957,790	315,324	708,868	1,595,340	3,101,697
Calves	1,348,161	363,766	692,236	299,039	500,567
Young steers	369,205	106,709	337,516	389,797	825,277
Young heifers	769,765	288,000	403,875	234,676	225,491
Steers	166,363	30,257	518,828	673,747	1,414,914
Heifers	946,316	447,640	146,115	123,137	271,229
Bulls	221,995	60,180	733,490	864,879	1,589,761
Total	8,099,974	2,923,896	5,724,092	5,976,186	11,507,419

and uncertainty of all IPAs used in the T2model for all cattle categories and geo-climatic regions, which were not included here due to space restrictions.

Fig. 3 shows the inventory for all geo-climatic regions of Mexico, and it can be observed that the Dry region is the main enteric CH_4 emitter with 607.2 Gg CH_4 year^{-1}. The second-largest emission was observed in the Tropical Sub-Humid region with 526.7 Gg CH^4 year^{-1}, the third-largest inventory was observed in the Temperate climate region, and the smallest regional inventory was observed in the Very Dry geo-climatic region, only 185.9 Gg CH_4 year^{-1}. Fig. 3 also shows differences in the 95 % CI, empirical distributions and spread of CH_4 estimations among geo-climatic regions. The emissions associated with each cattle category from the five geo-climatic regions are summarized in Table 3 This table shows the PDF, mean annual CH_4 emission, standard deviation, 95 % CI and uncertainty. It can be observed that CH_4 emission by category has several shapes of PDF, like generalized normal, skewed normal, and Johnson SU. These tables also show differences in uncertainties between regions and categories associated with various levels of uncertainty in the EF. For example, the Dry Climate geo-climatic region has the lowest uncertainty (−20.5 %, +22.2 %) with a generalized normal distribution (Table 3) and a small spread of their estimations (Fig. 3). Also, in this region, the lowest uncertainty was observed in the young heifer's category (−60.9 %,+72.4 %).

The 95 % CI of the CH_4 emissions differed more among the geo-climatic regions than among cattle categories within geo-climatic regions. The category steers showed the highest uncertainty level in most of the regions, except in the Temperate climate region. As shown in Table 3, the highest levels of uncertainty occurred in the Tropical Humid region with an expected value of 254.4 Gg CH_4 year^{-1} and 95 % CI that ranged from 153.6 to 402.5 Gg CH_4 year^{-1}. Dual-purpose cows and steers were the categories that contributed most to the uncertainty.

3.3. Sensitivity analysis

Fig. 4 shows the five IPAs, based on the SRCA, that affected most the uncertainty of the enteric CH_4 emissions. These parameters are GEI, *Ym* factor, milk fat content (MFC), daily milk yield (DMY) and DMI. It can be observed that the IPAs associated with the DMI and GEI have the most significant impact on the uncertainty on enteric fermentation CH_4 emissions, with values of SRCA of 0.87 and 0.86, respectively.

4. Discussion

The present work aimed to calculate a bottom-up IPCC-Tier 2 inventory for enteric CH_4 emissions from cattle in Mexico, disaggregate the inventory among the different Mexican geo-climatic regions to analyze the effect of contrasting climates on the inventory and identify the relevant sources of uncertainty associated with the inventory. The inventory obtained in the present work is 14 % higher than the last official inventory of 1790 Gg CH_4 year^{-1} for the year 2015 reported in the 6th National Communication (SEMARNAT-INECC, 2018) to the UNFCCC by the Mexican official institutions, SEMARNAT and INECC, responsible for communicating the national GHG inventories. But the official inventory is similar to the 2300 Gg CH_4 year^{-1} inventory for 2013, presented by Wolf et al. (2017) and the 2112 Gg CH_4 year^{-1} for 2015, presented by Scarpelli et al. (2020), also for Mexico. However, the Scarpelli et al. (2020) inventory includes manure management too. The

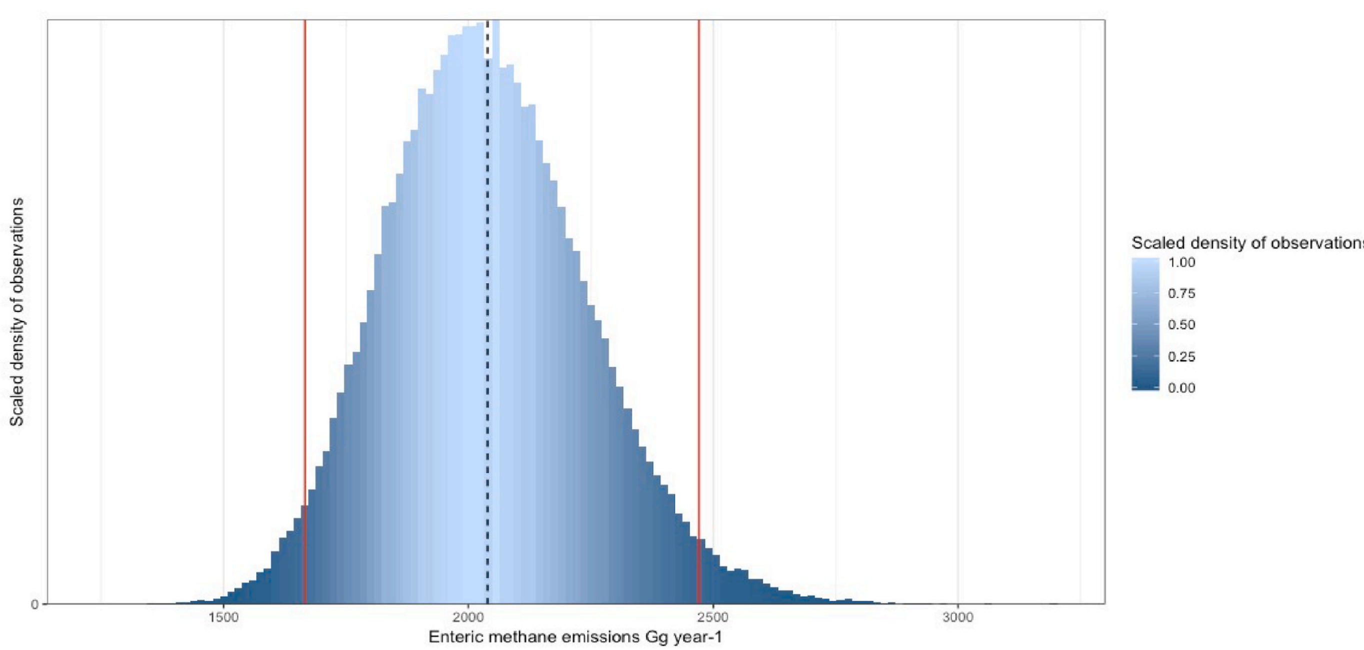

Fig. 2. Empirical distribution of the estimated enteric methane emissions inventory from the cattle of Mexico. Key: red lines represent a 95 % confidence interval, and the black dashed line is the mean of the enteric methane emission estimations.

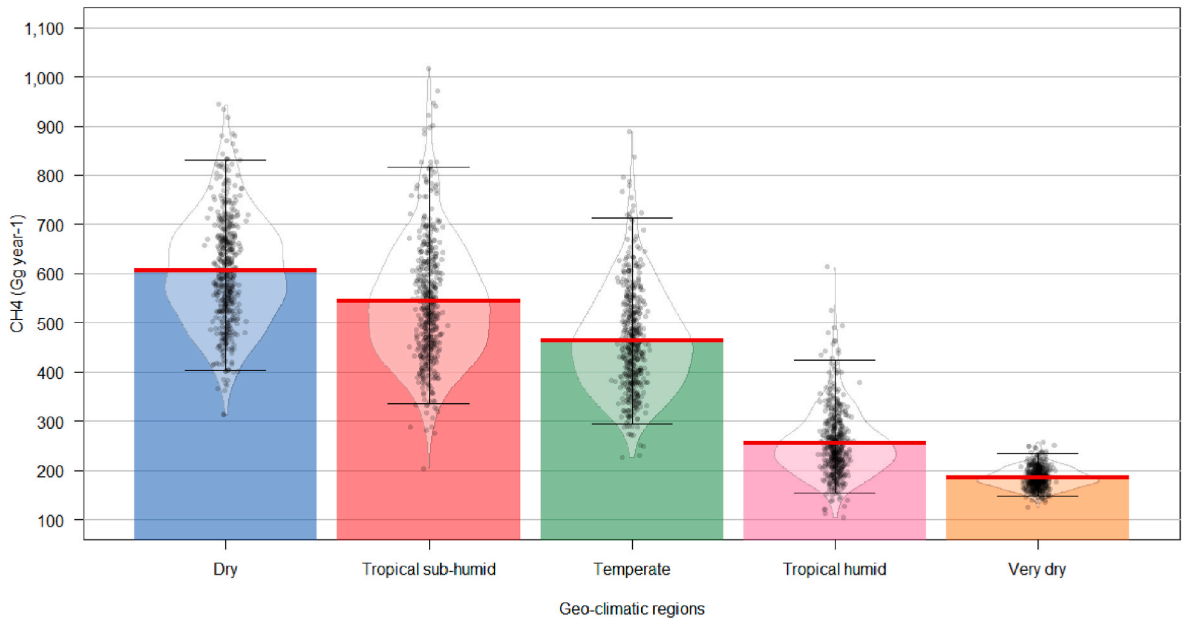

Fig. 3. A pirate plot of estimations of enteric methane emissions from cattle for the five geo-climatic regions of Mexico for 2018. Dots represent the raw data; the red horizontal line shows the mean of CH_4 emission; the beans represent the empirical probability distribution; and the upper and lower fence lines show the 95 % confidence interval.

discrepancy observed between our inventory, and SEMARNAT-INECC (2018) inventory can be partly attributed to the minor differences in the cattle population used for calculation, 34.2 million *vs* 33.8 million heads of cattle, respectively. However, most of the difference is attributed to the method for inventory calculation and the fact that the official inventory did not consider the different cattle categories, the productive purpose for cows, and their spatial distribution within the geo-climatic regions. Furthermore, the official inventory used the default IPCC (2014) EFs for non-dairy cattle of 56 kg CH_4 year^{-1} animal^{-1}, and 32 different EFs for dairy cattle, one for each state of the Mexican Republic, but the official inventory did not declare where these 32 EFs were taken as they are not mentioned in the IPCC (2014) guidelines nor in the national communication.

The underestimation of the inventories elaborated by SEMARNAT-INECC (2018) is also reported by Lu et al. (2021). These authors used a Tropospheric Monitoring Instrument (TROPOMI) to map and quantify CH_4 emissions from eastern Mexico. They found that the official inventories underestimate the anthropogenic CH_4 emissions of the oil and gas industry by up to 45 % and by ~21 % from the livestock sector. Likewise, Lu et al. (2021) reported an underestimation of 8.6 % of the SEMARNAT-INECC (2018) inventory for cattle enteric CH_4 emissions. The INEGI (2007) inventory reported in the 6th National Communication to the UNFCCC has an uncertainty of only 4.7 %, which is considerably lower than the uncertainty reported in the previous CH_4 inventories from the same institute and that of our study. For instance, the 2002 national inventory reported an emission of 1642 Gg of CH_4 with an associated uncertainty of 20 %, as shown in Table 4 (SEMARNAT-INE, 2006). However, the reduction in the uncertainty of the SEMARNAT-INECC (2018) inventory was not accompanied by an improved methodology for inventory calculation because both inventories used the Tier 1 method and the Tier 1 error propagation method to calculate the uncertainty. In contrast, our results suggest that uncertainty increment accompanies an improved inventory because it is well known that the Tier 2 and 3 approaches reveal additional complexity and critical sources of uncertainty that are not detected in the Tier 1 method (IPCC, 2014). Several developing countries also share the Tier 1 approach in reporting their official inventories to the UNFCCC, which is inadequate when appropriate methodologies and facilities are available, like in Mexico.

Our methodology represents progress in inventory uncertainty assessment because it reveals a more realistic understanding of the limitations of existing knowledge on enteric CH_4 emissions from cattle and their effect on inventory uncertainty. Our findings suggest that previous and recent approaches underestimated the size of the uncertainty of enteric CH_4 inventories, for example, Scarpelli et al. (2020) reported an uncertainty of only 10 %. In this sense, Katz et al. (2013) indicated that the magnitude of the uncertainty of inventories could increase when more rigorous approaches to GHG quantification are implemented because previously neglected sources of uncertainty are recognized and accounted for. Thus, the estimations of the national inventories of this gas will always have higher levels of uncertainty because CH_4 originates from many different sources and is much more uncertain than CO_2 emissions. The uncertainty of CH_4 inventories in a country and at a global level is of the order of 30 % or higher, as shown in Table 4, (PBL, 2020). So, although we did not reduce the inventory uncertainty compared with the official inventories, we obtained a more accurate estimate of the uncertainty's size, similar to that reported by (PBL, 2020), and other inventories reported in Table 4. This is explained because implementing Tier 2 and Tier 3 methods requires more detailed AD, but the resulting inventories are likely more accurate (Clark, 2017).

Table 4 compares our inventory and its uncertainty with other national inventories, and it can be observed that our inventory's uncertainty level is similar to those inventories using the Tier 2 approach, except for the Australian inventory (DEE, 2018), which assessed the uncertainty through the Tier 1 error propagation method, assigning an uncertainty default value of 51 %. Also, the USA's inventory developed by Hristov et al. (2017) shows a more considerable uncertainty (−32.0, +47.0) than that in the present study. These differences can be explained by the different methodologies used to estimate enteric CH_4 emissions. For instance, Hristov et al. (2017) assumed that DMI was the critical factor determining CH_4 emissions in their inventory because this variable showed significant variability in all cattle categories of the USA herd, which can partially explain the higher level of uncertainty of the USA inventory. However, independently of the Tier level used to estimate inventories, the present study and the national inventories in Table 4 showed high uncertainties (>10 %), derived mainly from the considerable uncertainty of the AD used, confirming Katz et al. (2013) asseveration. Our results also demonstrated that when the AD deviations

Table 3
Summary of the average annual enteric CH_4 emissions per cattle category and CH_4 inventory (Gg year^{-1}) for the different geo-climate geo-climatic regions of Mexico.

Category	PDF	Mean	Standard deviation	C.I. 95 % (expanded uncertainty)	Uncertainty, (% of mean)
Dry Climate geo-climatic region					
Dairy cows	Johnson SU	169.3	65.5	61.1–317.7	−63.9,+87.6
Beef cows	Johnson SU	196.2	73.5	72.2–358.8	−63.1,+82.8
Dual-purpose cows	Johnson SU	112.0	41.8	41.3–205.1	−63.0,+83.0
Calves	Johnson SU	10.3	4.2	3.61–19.9	−64.9,+93.
Young steers	GN	15.5	7.3	6.1–28.2	−60.3,+81.3
Young heifers	Johnson SU	31.1	10.5	12.1–53.7	−60.9,+72.3
Steers	Johnson SU	6.9	3.1	2.1–14.2	−68.8,+105.1
Heifers	Skewed normal	53.1	19.0	20.08–94.7	−62.2,+78.2
Bulls	Johnson SU	11.3	4.1	4.1–20.4	−63.5,+81.3
Inventory	GN	607.2	109.9	482.4–741.9	−20.5,+22.1
Very Dry climate geo-climatic region					
Dairy cows	GN	84.3	19.0	52.7–127.3	−37.5,+50.9
Beef cows	GN	41.4	7.3	28.5–57.1	−31.0,+37.9
Dual-purpose cows	Skewed normal	20.6	3.1	15.1–27.4	−26.9,+32.7
Calves	GN	1.8	0.6	0.8–3.2	−52.7,+77.1
Young steers	GN	2.3	0.7	1.1–3.9	−52.7,+77.1
Young heifers	Johnson SU	8.8	1.9	5.5–13.2	−37.1,+48.7
Steers	Johnson SU	1.04	0.4	0.4–1.9	−58.9,+86.4
Heifers	GN	17.1	3.6	10.9–25.0	−36.3,+45.9
Bulls	Johnson SU	6.2	1.6	3.6–10.1	−41.7,+60.6
Inventory	Johnson SU	185.9	21.0	149.6–231.9	−19.5,+24.7
Temperate climate geo-climatic region					
Dairy cows	GN	156.5	92.5	15.6–372.5	−90.0,+137.9
Beef cows	Johnson SU	78.1	26.9	30.1–135.7	−61.4,+73.6
Dual-purpose cows	Skewed normal	62.8	21.0	24.7–107.5	−60.5,+71.2
Calves	GN	15.1	7.4	3.0–31.6	−80.0,+109.7
Young steers	GN	18.0	8.1	5.6–36.9	−68.6,+105.2
Young heifers	Johnson SU	26.4	9.7	9.7–47.9	−63.0,+81.4
Steers	Johnson SU	32.4	11.2	12.0–57.8	−62.7,+78.5
Heifers	Johnson SU	11.4	4.4	4.1–21.4	−63.9,+87.1
Bulls	Skewed normal	64.1	21.9	24.6–110.8	−61.6,+72.7
Inventory	Johnson SU	466.7	104.5	296.4–706.4	−36.5,+51.3
Tropical Humid climate region					
Beef cows	Johnson SU	51.9	21.8	17.9–103.0	−65.5,+98.4
Dual-purpose cows	Johnson SU	125.7	56.5	42.0–262.6	−66.5,+108.8
Calves	GN	5.2	1.9	1.9–9.5	−63.3,+81.4
Young steers	Skewed normal	8.2	3.0	2.9–14.9	−63.6,+81.6
Young heifers	Johnson SU	13.0	5.9	4.0–27.1	−68.7,+108.2
Steers	Johnson SU	8.3	4.2	2.4–18.7	−71.0,+125.8
Heifers	Johnson SU	32.5	13.6	11.3–64.2	−65.1,+97.3
Bulls	Johnson SU	8.9	3.9	2.9–18.3	−66.4,+105.5
Inventory	Johnson SU	254.4	63.6	153.6–402.5	−39.6 + 58.2
Tropical Sub-Humid geo-climatic region					
Beef cows	Johnson SU	95.5	40.6	33.0–191.2	−65.4,+100.2
Dual-purpose cows	Johnson SU	279.8	110.6	101.2–532.8	−63.8,+90.4
Calves	Skewed normal	11.2	3.7	4.6–19.3	−59.1,+73.3
Young steers	Johnson SU	16.2	6.1	5.9–29.8	−63.3,+83.6
Young heifers	Johnson SU	27.3	12.4	8.5–56.7	−68.6,+107.8
Steers	Generalized normal	8.4	4.2	2.0–18.4	−75.7,+119.4
Heifers	Johnson SU	20.6	9.1	6.8–42.3	−66.7,+104.8
Bulls	Johnson SU	20.6	9.1	6.8–42.3	−66.7,+104.8
Inventory	Johnson SU	526.7	122.1	320.7–797.8	−39.1,+51.4

PDF = Probability density function, GN= Generalized normal.

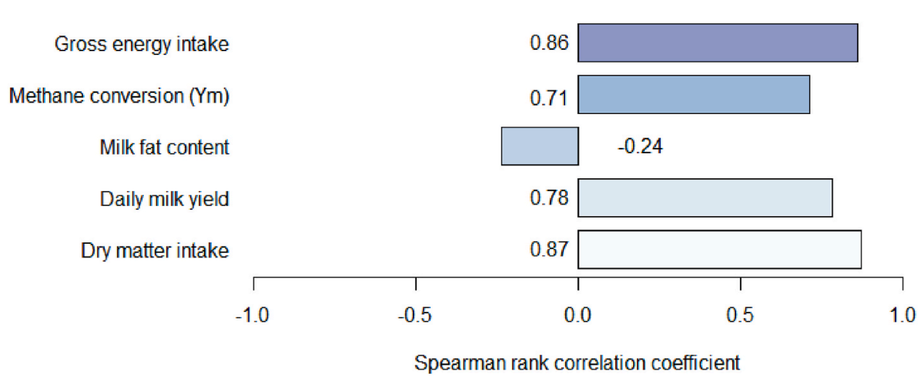

Fig. 4. Tornado plot of main inputs parameters that affect the uncertainty of T2model estimates of enteric fermentation CH_4 emissions for cattle in Mexico.

Table 4
Cattle enteric methane emission inventories and their associated uncertainty for several countries with a large cattle population.

Country	Year[a]	IPCC approach	Herd categorization[b]	Uncertainty approach[c]	CH_4 annual emission (Gg)	Uncertainty range %	Source
Mexico	2002	Tier I	DC, BC	Tier 1-EPM	1642.2	−20.0, +20.0	(SEMARNAT-INE, 2006)
Canada[d]	2008	Tier 2	Scw, Drcw, Mcw, DR, Hfed, YH, Sfed, YS, c, Bc, Bcw	MC	812.0	−22.0, +24.0[g] −19.0, +20.0[h]	Karimi-Zindashty et al. (2012)
Brazil	2010	NE	DC, BC	Tier 1-EPM	10,798.4	−34.0, +34.0[i]	MSTI (2016)
UK	2010	Tier 2	Dcw, Bcw, DH, BH, DR, Dc, Bc, Bbgc-2, B	MC	551.6	−17.4, +20.4	Milne et al. (2014)
USA	2012	CH_4 yield[e]	Bcw, Dcw, Mcw, Drcw, B, DR, DH, BH, H, ST, c	MC	6.201.0	−32.0,+40	Hristov et al. (2017)
Austria[f]	2014	Tier 2	DC, SC, YS, Bbgc-2, BH, OT-2	Tier 1-EPM	155.3	−22.4, +22.4	EAA (2016)
New Zealand	2015	Tier 2	Dcw, Bcw, DH, YH, MH, B, Bcw, Bbgc-1, Bbcg-2, Bbcg-3, BC, YS, BH, BS	MC	754.5	−16.0, +16.0	ME (2017)
Australia	2016	Tier 2	Dcw, YDH, DH, ST, B, Bbgc-1, Bbgc-2, Bbgc-3, Bcw, Bc, YS, BS	Tier 1- EPM	1512.5	−51.0, +51.0	DEE (2018)
Canada	2016	Tier 2	Dcw, DH, B, Bcw, BH, ST, c, Hs	MC	928.0	−19.0, +22.0[g] −16.0, +22.0[h]	(ECCC and C.C, 2018)
Germany	2016	Tier 2, Tier 3	Dcw, c, H, B, SC, OT-2	Tier 1-EPM	932.3	−20.4, +20.4	Haenel et al. (2018)
USA	2016	Tier 1, Tier 2	Dc, Bc, DR, YH, DH, Bc, Bcw, BH, BS, Sfed, Hfed, Bbgc-1, Bbgc-2	MC	6568.0	−11.0, +18.0	EPA (2012)
Mexico	2015	Tier 1	NE	NE	1790.0	−4.78, +4.7	SEMARNAT-INECC, 2018
Mexico	2017	Tier 2	Dcw, Bcw, DPcw, c, YH, YS, ST, H, B	MC, Bootstrap	2039.2	−18.3, +21.2	This study

[a] Year of CH_4 inventory according to available activity data of cattle population.
[b] Dairy cattle (DC); beef cattle (BC); dairy cows (Dcw); beef cows (Bcw); dual-purpose cows (DPcw); suckling cows (Scw); dry cows (Drcw); milking cows (Mcw); dairy replacements (DR); calves (c); dairy calves (Dc); beef calves (Bc); young heifers (YH); milking heifers (MH); young steers (YS); heifers (H); heifer for slaughter (Hs); dairy heifers (DH); young dairy heifer (YDH); beef heifers (BH); steers (ST); beef steers (BS); bulls (B); beef breeding growing cows 0–1 year (Bbgc-1); beef breeding growing cows 1–2 years (Bbgc-2); beef breeding growing cows 2–3 years (Bbgc-3); Steers feedlot (Sfed); heifers feedlot (Hfed); other cattle >2 years (OT-2).
[c] Monte Carlos simulation (MC); bootstrap simulation (Bootstrap); Tier 1 error propagation method (Tier 1-EPM); not specified (NE).
[d] Aditionally this inventory divided all the cow's categories into pregnant and non-pregnant.
[e] Enteric methane emissions were calculated as follows: CH_4 emission from enteric fermentation (Gg yr^{-1}) = cattle category-specific feed dry matter intake (DMI; kg $head^{-1}$ d^{-1}) × cattle category-specific methane emission factor (g kg^{-1} DMI) × 365 (d yr^{-1}) × county cattle population by category (head).
[f] This inventory disaggregates cattle CH_4 emissions by type of farming (conventional and organic).
[g] Non-dairy cattle.
[h] Dairy cattle.
[i] Beef cattle.

become pronounced, the model domain for using the Tier 1 error propagation method is not fulfilled. Therefore, using MCS was appropriately used to deal with CH_4 emission inventories that use the Tier 2 approach. It was also adequate to implement the disaggregation strategy because the Tier 2 MCS uncertainty analysis can manage significant IPAs' uncertainties and provide a more detailed and accurate assessment of all inherent uncertainties that influence a national inventory (Fauser et al., 2011).

It is well established that categorization of the national cattle population reduces the level of uncertainty of CH_4 emission inventories (IPCC, 2014); unfortunately, no previous Mexican enteric CH_4 inventories reported the uncertainty obtained using MCS, herd categorization nor the use of the Tier 2 method, making it difficult to evaluate if the categorization implemented in the present work contributed to improving the quality of our inventory. However, based on the other national inventories presented in Table 4, the inventories that used a detailed categorization of the countries' cattle population, e.g., the UK, New Zealand, Canada and the USA, showed the lowest uncertainty level ranging from 11 % to 24 %. These values are similar to our inventory, so it is possible to state that our approach reduced the inventory uncertainty from a hypothetical large uncertainty. Further uncertainty reduction will depend on the availability and quality of AD for Mexico's cattle population. For example, it is necessary to include the physiological state of cattle, seasonality, duration of productive stages, and annual changes in cattle population associated with exports of calves to the USA. It is also essential to integrate the temporality of emissions for each category and the development of critical IPAs to Tier 2 or Tier 3 approaches like the *Ym* factor and the digestibility information by cattle sub-category.

Our approach also reflected the effect of differences among Mexico's contrasting regions and cattle production systems on inventory size and uncertainty. For example, the highest regional inventory observed in the Dry climate region (Table 3) is attributed to relatively high Y*m* factors of more than 6.0 for high-yielding dairy cows, the second largest population of cattle heads of over 8.0 million, a large number of individuals of the cows' category (Fig. 1), and reasonably good quality pastures, mostly C3 types of grass like *Bouteloua gracilis* (Améndola-Massioti et al., 2005). Cattle intake of good-quality grasses increases daily CH_4 emissions per animal (Benaouda et al., 2020). On the other hand, the second-largest emission observed in the Tropical Sub-Humid region is explained by the largest cattle population (Fig. 1) of over 11.5 million heads (despite a low Y*m* factor of 4.64) and low-quality tropical pastures, primarily C4 grasses (Améndola-Massioti et al., 2005; Ku-Vera et al., 2018). On the other hand, the smallest cattle population in the Very Dry geo-climatic region of 2.9 million heads explains the smallest regional inventory, only 185.9 Gg CH_4 $year^{-1}$. In contrast, the augmented uncertainty of the inventories observed in Tropical regions can be attributed to the high uncertainty of the EFs, which are likely affected by the low DMI, rumen degradability and a longer retention time of digesta in the rumen of cattle grazing low-quality pastures. This results in lower CH_4 production day^{-1} $head^{-1}$ but a high CH_4 yield. Furthermore, there is a different category of cows in these regions, the dual-purpose cows, which are usually not considered in the temperate countries' inventories but constitute the majority of cattle in the world's warmer regions. Dual-purpose cows have larger DMI and CH_4 emissions than beef cows but lower than dairy cows (Castelán-Ortega and Ku-Vera, 2019).

This disaggregation approach aligns with Zhu et al. (2016), who pointed out that country and region-specific emission factors can reduce the uncertainty in GHG inventories for animal agriculture. Similarly, Karimi-Zindashty et al. (2012) found that applying IPCC (2014) default parameters, when used at the disaggregated provincial scale, reduced the overall uncertainty of the Canadian enteric fermentation CH_4 emissions inventory. Thus, the spatial distribution of the CH_4 emissions allowed us to assess specific geo-climatic regions that are likely to be more significant CH_4 emitters (Tropical Sub-Humid and Dry climate regions) and identify suitable mitigation strategies for each region (Piñeiro-Vázquez et al., 2017, Hernández-Pineda et al., 2018; Vázquez-Carrillo et al., 2020, Ku-Vera et al., 2018). The spatial distribution of the cattle population also provided a valuable guide to identifying potential locations for monitoring CH_4 emissions by comparing bottom-up CH_4 with top-down inventories to determine the relevance of AD and emission data used in the inventory. We also demonstrated that spatial disaggregation of the inventory data is a way to improve data quality and provide guidelines for identifying the most cost-effective approach for reducing uncertainty, as in Bun et al. (2010).

In this geo-climatic region of Mexico, smallholder and highly intensive cattle farming systems coexist (Castelán-Ortega et al., 2003, 2017). Thus, the high farm variability resulted in more considerable uncertainties for BW, DMI and DMY (Appendix). The histogram in Fig. 2 and pirate plot in Fig. 3 showed skewness to the left in the CH_4 emissions for the total inventory and the five geo-climatic regions, respectively, which determined the asymmetry of 95 % CI. These findings indicate that skewness of the IPAs propagated throughout the T2model (Appendix), which can lead to skewness in the uncertainty estimate of the expected value of CH_4 emissions. Therefore, the quality of AD is essential to get a good inventory. The skewness of the empirical distribution of the current CH_4 inventory and the asymmetry of 95 % CIs are in line with national inventories that used Tier 2 approach and MCS analysis to estimate CH_4 emissions and assess their uncertainty, respectively (ECCC and C.C, 2018; EPA, 2012; Hristov et al., 2017; Karimi-Zindashty et al., 2012; Milne et al., 2014), as shown inTable 4. However, an essential difference of the present study compared to CH_4 inventories in Table 4 is the use of bootstrap simulation to estimate the 95 % CI of IPAs, EFs and CH_4 inventory estimates. Bootstrap simulation has been used to quantify emission factors' uncertainty for censored data sets and applied to air toxic emissions (Zhao and Frey, 2004). However, few published inventories used bootstrap simulation to characterize the uncertainty of enteric fermentation CH_4 emissions from cattle. The bootstrap simulation was instrumental in the present study because most IPAs showed a certain level of skewness (Appendix). The primary assumption of bootstrap simulation is that the probability distribution estimated from the raw sample data best estimates the actual but unknown population distribution. Unfortunately, acquiring a larger sample size of regional-specific AD on *Ym* factors and feed digestibility to calculate EFs is complex due to technical and economic issues, e.g., the small number of laboratories with OCRC to measure CH_4 emissions in developing countries. Therefore, bootstrap simulation is an option to reduce the estimated bias from limited emission data (Tong et al., 2012).

Furthermore, as one of the primary sources of uncertainty in our inventory was that associated with the Efs (*Ym*), it is necessary to focus future research on minimizing the uncertainty of EFs (Wójcik-Gront and Gront, 2014). For example, the largest inventory levels of uncertainty observed in steers from Tropical climate regions implies that the information available to estimate CH_4 in this sub-category is less accurate. Therefore, future efforts should be directed toward generating more robust empirical EFs through specific experiments in these regions of Mexico. It was also evident that EFs' uncertainty was also derived from the propagation of the IPAs' uncertainty throughout the T2model. For this reason, we calculated the rank correlation coefficients between the EFs and IPAs as part of the sensitivity analysis. Similarly, GEI, DMI and daily milk yield greatly influenced uncertainty because these variables varies greatly across regions (see Appendix). This means that when we calculate and inventory we need to pay particular attention to the cows' category and the milk yield variable because it can be an important source of variation that needs to be considered.

Finally, Table 5 compares the mean *Ym* factors and their associated uncertainty disaggregated by geo-climatic region and cattle category used in the present study and the default *Ym* factors proposed by IPCC (2023b). The *Ym* factors' uncertainties in this table indicate that the current uncertainty of 5 % of the official Mexican inventory was underestimated because all uncertainties used in the present work and default values of the IPCC are above 5 % and 15 %, respectively. Furthermore, in Canada, Karimi-Zindashty et al. (2012) demonstrated that a large proportion of the uncertainty of their GHG inventory was associated with the use of globally applied IPCC (2014) default *Ym* values. The small uncertainty of our *Ym* factors compared to the IPCC (2014) factors is explained by the lower uncertainty achieved through *ex professo* experiments because IPCC recommends a $Ym = 6.5 \pm 1.0$ % (uncertainty −15.3 %, +15.3 %) for all categories of cattle, which are not in feedlots, and $Ym = 3.0 \pm 1.0$ % (uncertainty −33.3 %,+33.3 %) for feedlot cattle, as shown in Table 5.

Similarly, Hristov et al. (2018) demonstrated that using a constant value for the *Ym* factor is a major concern because the *Ym* factor can

Table 5
Comparison between the mean *Ym* factors and their associated uncertainty disaggregated by geo-climatic region and cattle category used in the present study and the default *Ym* factors proposed by (IPCC, 2006).

Zone	Categories	Ex-profeso experiments		(IPCC, 2006) guidelines	
		Mean	Uncertainty[a]	Mean	Uncertainty, %[a]
Very dry	Dcw	6.0	−5.9, +5.9	6.5	−15.3, +15.3
Very dry	Bcw, DPcw, c, YH, H, S	4.4	−11.6,+12.3	3.0	−33.3,+33.3
Very dry	YS	3.5	−5.7,+5.0	3.0	−33.3,+33.3
Very dry	B	6.4	−6.4,+6.2	6.5	−15.3, +15.3
Dry	Dcw	6.0	−5.9,+5.9	6.5	−15.3, +15.3
Dry	Bcw, DPcow	6.2	−7.8,+7.5	6.5	−15.3, +15.3
Dry	YH, YS, c	5.7	−2.6,+2.6	6.5	−15.3, +15.3
Dry	H	5.9	−8.2,+8.0	6.5	−15.3, +15.3
Dry	S	4.3	−4.0,+4.5	3.0	−33.3,+33.3
Dry	B	5.6	−5.3,+5.6	6.5	−15.3, +15.3
Temperate	Dcw	8.3	−15.8,+15.9	6.5	−15.3, +15.3
Temperate	Bcw, DPcow, YH, YS, ST, B	6.2	−3.7,+3.7	6.5	−15.3, +15.3
Temperate	Calves	6.2	−2.4,+2.1	6.5	−15.3, +15.3
Temperate	Heifers	7.9	−16.0,+13.0	6.5	−15.3, +15.3
Tropical humid and sub-humid	Bcw, DPcow, B, H	4.6	−6.3,+6.4	6.5	−15.3, +15.3
Tropical humid and sub-humid	C, YS,	4.7	−0.2,+0.2	6.5	−15.3, +15.3
Tropical humid and sub-humid	YH	5.4	−27.8,+38.0	6.5	−15.3, +15.3
Tropical humid and sub-humid	S	4.2	−9.8,+9.8	3.0	−33.3,+33.3

[a] Uncertanty expressed as a percentage. Dairy cows (Dcw); beef cows (Bcw); dual-purpose cows (DPcw); suckling cows (Scw); dry cows (Drcw); milking cows (Mcw); dairy replacements (DR); calves (c); dairy calves (Dc); beef calves (Bc); young heifers (YH); milking heifers (MH); young steers (YS); heifers (H); heifer for slaughter (Hs); dairy heifers (DH); young dairy heifer (YDH); beef heifers (BH); steers (ST); beef steers (BS); bulls (B); beef breeding growing cows 0–1 year (Bbgc-1); beef breeding growing cows 1–2 years (Bbgc-2); beef breeding growing cows 2–3 years (Bbgc-3); Steers feedlot (Sfed); heifers feedlot (Hfed); other cattle >2 years (OT-2).

show considerable variation due to factors such as feed quality, production level, DM digestibility, etc. Therefore, using one or two default *Ym* factors can result in significant uncertainty in CH_4 emissions estimates in countries like Mexico, with several geo-climatic regions and contrasting cattle production systems (Table 5). The sensitivity analysis allowed us to identify IPAs that strongly affected the uncertainty in our inventory; for example, the diet's *Ym* factor, GEI, DMI, DMY, and feed digestibility were crucial IPAs that affected the uncertainty of the EFs for cows and young animals. Therefore, special attention must be placed on these IPAs for future inventory preparation. Furthermore, our method explains the current inventory's critical sources of uncertainty with similar sources in other inventories that implemented the Tier 2 approach (Karimi-Zindashty et al., 2012; Milne et al., 2014). Likewise, our results of the sensitivity analysis are in agreement with another empirical model that estimates enteric CH_4 emissions, as described by Appuhamy et al. (2016), who listed 40 empirical models from several regions (Australia, North America, Europe and New Zealand), which all include a measure of intake as DMI, GEI or metabolizable energy (ME) intake.

4.1. Assumptions and limitations of the present study

In the present study, we assumed that the emissions registered in the OCRC also applied to grazing animals, which may not be a correct assumption. The OCRC technique has some limitations in measuring the CH_4 production of grazing animals (Goopy et al., 2016) because the capacity of animals to select the best quality forages cannot be replicated in the chambers where animals are offered a total mixed ration. Therefore, the DMI registered in chambers may not reflect that of grazing animals. Finally, our uncertainty assessment is based on MCS, considered the most efficient method for estimating uncertainty (Herrador et al., 2005). However, MCS presents some limitations, such as 1) the computer runtime can be long in complex cases, and 2) the selection of the proper PDF of IPAs can be difficult due to the inaccuracy of actual AD or the misunderstanding of the underlying biological process.

5. Conclusion

The Tier 2 approach implementation using disaggregated AD and country-specific emission factors allowed us to develop a better inventory of the enteric CH_4 emissions for cattle in Mexico and a more accurate estimation of the size of its uncertainty. To the best of our knowledge, the present study is one of the first attempts to merge the use of country-specific emission factors obtained from respiratory chamber measurements, disaggregation, and categorization of the cattle inventory among geo-climatic regions with a robust methodology for the propagation of uncertainty. Also, through the sensitivity analysis, we identified the primary sources of uncertainty, which allowed us to conclude that future efforts to increase the quality of CH_4 inventories must be focused on improving AD, particularly better EF for the different cattle categories in the Tropical climate regions.

CRediT authorship contribution statement

Juan Carlos Angeles-Hernandez: Data curation, Formal analysis. **Juan Carlos Ku-Vera:** Investigation, Methodology. **María Fernanda Vázquez-Carrillo:** Investigation. **Sofía Viridiana Castelán-Jaime:** Investigation, Methodology. **Luisa T. Molina:** Conceptualization, Funding acquisition. **Mohammed Benaouda:** Investigation. **Ermias Kebreab:** Investigation. **Manuel González-Ronquillo:** Investigation. **Fernando Paz-Pellat:** Data curation. **Hugo Daniel Montelongo-Pérez:** Investigation. **Octavio Alonso Castelán-Ortega:** Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Validation.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgements

The authors acknowledge the financial support from the Molina Center for Energy and the Environment (under UNEP Contract GFL-4C58), the Universidad Autónoma del Estado de México (Grant UAEM 3474/2013CHT), the National Council for Science and Technology of Mexico (Grant CONACYT-223418), and the UC MEXUS-CONACYT grant for the project Development of the enteric methane emissions inventory for cattle in Mexico through (*in vivo*) and (*in silico*) methodologies.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2024.120389.

References

Améndola-Massiotti, R., Castillo-Gallegos, E., Mrtínez Hernández, P., 2005. FAO Country Pasture/Forage Resource Profiles Mexico. https://www.researchgate.net/publication/288673431_Morphological_analysis_of_blue_grama_grass_Bouteloua_gracilis_Willd_ex_Kunth_Lag_ex_Griffiths_diversity_in_Chihuahua_Mexico.

Appuhamy, J.A.D.R.N., France, J., Kebreab, E., 2016. Models for predicting enteric methane emissions from dairy cows in North America, Europe, and Australia and New Zealand. Global Change Biol. 22, 3039–3056. https://doi.org/10.1111/gcb.13339.

Arceo-Castillo, J.I., Montoya-Flores, M.D., Molina-Botero, I.C., Piñeiro-Vázquez, A.T., Aguilar-Pérez, C.F., Ayala-Burgos, A.J., Solorio-Sánchez, F.J., Castelán-Ortega, O.A., Quintana-Owen, P., Ku-Vera, J.C., 2019. Effect of the volume of methane released into respiration chambers on full system methane recovery. Anim. Feed Sci. Technol. 249, 54–61. https://doi.org/10.1016/j.anifeedsci.2019.02.001.

Beauchemin, K.A., Kreuzer, M., O'Mara, F., McAllister, T.A., 2008. Nutritional management for enteric methane abatement: a review. Aust. J. Exp. Agric. 48, 21–27. https://doi.org/10.1071/EA07199.

Beauchemin, K.A., McGinn, S.M., 2005. Methane emissions from feedlot cattle fed barley or corn diets. J. Anim. Sci. 83, 653–661. https://doi.org/10.2527/2005.833653x.

Benaouda, M., González-Ronquillo, M., Appuhamy, J.A.D.R.N., Kebreab, E., Molina, L.T., Herrera-Camacho, J., Ku-Vera, J.C., Ángeles-Hernández, J.C., Castelán-Ortega, O.A., 2020. Development of mathematical models to predict enteric methane emission by cattle in Latin America. Livest. Sci. 241, 104177 https://doi.org/10.1016/j.livsci.2020.104177.

Bun, R., Hamal, Kh, Gusti, M., Bun, A., 2010. Spatial GHG inventory at the regional level: accounting for uncertainty. Climatic Change 103, 227–244. https://doi.org/10.1007/s10584-010-9907-5.

Canul-Solís, J.R., Vázquez, A.T.P., Castillo, J.I.A., Gamboa, J.A.A., Burgos, A.J.A., Pérez, C.F.A., Sánchez, F.J.S., Ortega, O.A.C., López, M.L., Owen, P.Q., Vera, J.C.K., 2017. Design and construction of low-cost respiration chambers for ruminal methane measurements in ruminants. Revista Mexicana de Ciencias Pecuarias 8, 185–191. https://doi.org/10.22319/rmcp.v8i2.4442.

Castelán-Ortega, O.A., Ku-Vera, J.C., 2019. Capítulo 22: ganadería. In: Estado Del Ciclo Del Carbono En México: Agenda Azul y Verde. Programa Mexicano del Carbono (PMC), Texcoco. Estado de México, México.

Castelán-Ortega, O.A., Fawcett, R.H., Arriaga-Jordán, C., Herrero, M., 2003. A Decision Support System for smallholder campesino maize–cattle production systems of the Toluca Valley in Central Mexico. Part I—integrating biological and socio-economic models into a holistic system. Agric. Syst. 75, 1–21. https://doi.org/10.1016/S0308-521X(01)00109-3.

Castelán-Ortega, O.A., Ku-Vera, J.C., Estrada-Flores, J.G., 2014. Modeling methane emissions and methane inventories for cattle production systems in Mexico. Atmósfera 27 (2), 185–191. http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S0187-62362014000200006&lng=es&tlng=en.

Castelán-Ortega, O.A., Mathewman, R., Martínez, E.G., García, R.B., Juárez, D. de la C., 2017. Caracterización y evaluación de los sistemas campesinos de producción de leche. El caso de dos comunidades del Valle de Toluca. Cienc. Ergo Sum. 4, 316–326.

Castelán-Ortega, O.A., Ku-Vera, J.C., Castelán-Jaime, S.V., Hernández-Pimeda, G.S., Mohammed, B., Ángeles-Hernández, J.C., Praga-Ayala, A.R., Montelongo-Pérez, H. D., 2018. Inventory of enteric methane emissions by cattle in the dry-land regions of México using the IPCC 2006 Tier 2 main method. In: Advances in Animal Biosciences. Cambridge University Press, Clermont-Ferrand, France, p. 739.

Castelán-Ortega, O.A., Pedraza Beltrán, P.E., Hernández Pineda, G.S., Benaouda, M., González Ronquillo, M., T Molina, L., Ku Vera, J.C., Montelongo Pérez, H.D., Vázquez Carrillo, M.F., 2020. Construction and operation of a respiration chamber of the head-box type for methane measurement from cattle. Animals 10, 227. https://doi.org/10.3390/ani10020227.

Cersosimo, L.M., Wright, A.G., 2015. Estimation methodologies for enteric methane emission in ruminants. In: Sejian, V. (Ed.), Climate Change Impact on Livestock: Adaptation and Mitigation. Springer India, pp. 209–220. https://doi.org/10.1007/978-81-322-2265-1.

Chen, D., Chen, H.W., 2013. Using the Köppen classification to quantify climate variation and change: An example for 1901–2010. Environ. Dev. 6, 69–79. https://doi.org/10.1016/j.envdev.2013.03.007.

Clark, H., 2017. The estimation and mitigation of agricultural greenhouse gas emissions from livestock. In: International Seminar on Livestock Production and Veterinary Technology, pp. 5–13. https://doi.org/10.14334/Proc.Intsem.LPVT-2016-p.5-13.

CONAGUA., 2022. Reporte del clima en México. Comisión Nacional del Agua 2022. Avenida Insurgentes Sur 2416, Col. Copilco El Bajo, Alcaldía Coyoacán, C.P. 04340, Ciudad de México. Mexico.

Cullen, AC, Frey, HC, 1999. Probabilistic Techniques in Exposure Assessment, 1st edition. Plenum Publishing Co. Springer, U.S.A.

DEE, 2018. National Inventory Report 2016 (Text No. Volume 1), the Australian Government Submission to the United Nations Framework Convention on Climate Change Australian National Greenhouse Accounts. Commonwealth of Australia. Department of Industry, Science, Energy and Resources (DEE), Australia.

EAA, 2016. Austria's National Inventory Report 2016. Submission under the United Nations Framework, Convention on Climate Change and under the Kyoto Protocol, vol. 5. Environment Agency Austria. Umweltbundesamt GmbH, Spittelauer Lände, Vienna/Austria, p. 1090.

ECCC, E., C C, C., 2018. National Inventory Report 1990-2016: Greenhouse Gas Sources and Sinks in Canada (Canada's Submission to the United Nations Framework Convention on Climate Change), Part 3. Gatineau, Quebec.

EPA, 2012. Global Anthropogenic Non-CO2 Greenhouse Gas Emissions: 1990-2030 [WWW Document]. https://cfpub.epa.gov/si/si_public_record_report.cfm?Lab=OAP&count=10000&dirEntryId=268252&searchall=&showcriteria=2&simplesearch=0&timstype=, 3.24.21.

Eugène, M., Sauvant, D., Noziere, P., Viallard, D., Oueslati, K., Lherm, M., Mathias, E., Doreau, M., 2018. Towards a Tier 3 Methodology to Calculate Methane Emission Inventory for Ruminants (Cattle). Cambridge University Press.

Fauser, P., Sørensen, P.B., Nielsen, M., Winther, M., Plejdrup, M.S., Hoffmann, L., Gyldenkærne, S., Mikkelsen, M.H., Albrektsen, R., Lyck, E., Thomsen, M., Hjelgaard, K., Nielsen, O.-K., 2011. Monte Carlo (Tier 2) uncertainty analysis of Danish Greenhouse gas emission inventory. Greenhouse Gas Measurement and Management 1, 145–160. https://doi.org/10.1080/20430779.2011.621949.

Frey, H., Cullen, A., 1995. Distribution development for probabilistic exposure assessment. In: Frey, H.C., Cullen, A.C. (Eds.), Annual Meeting of Air and Wste Management Association, pp. 1–16. San Antonio, TX.

Goopy, J.P., Robinson, D.L., Woodgate, R.T., Donaldson, A.J., Oddy, V.H., Vercoe, P.E., Hegarty, R.S., 2016. Estimates of repeatability and heritability of methane production in sheep using portable accumulation chambers. Anim. Prod. Sci. 56 (1), 116–122.

Haenel, H.-D., Rösemann, C., Dämmgen, U., Döring, U., Wulf, S., Brigitte, E.-M., Freibauer, A., Döhler, H., Schreiner, C., Osterburg, B., 2018. Calculations of Gaseous and Particulate Emissions from German Agriculture 1990-2016: Report on Methods and Data (RMD) Submission 2018 (Thünen Reports No. 57). Johann Heinrich von Thünen Institute, Federal Research Institute for Rural Areas, Forestry and Fisheries.

Hammersley, J.M., Handscomb, D.C., 1975. Monte Carlo Methods, Methuen's Monographs on Applied Probability and Statistics. Methuen & CO LTD, London, U.K.

Hernández-Pineda, G.S., Beltrán, P.E.P., Benaouda, M., García, J.M.P., Nova, F.A., Molina, L., Ortega, O.A.C., Pineda, G.S.H., Beltrán, P.E.P., Benaouda, M., García, J.M.P., Nova, F.A., Molina, L., Ortega, O.A.C., 2018. Pithecellobium dulce, Tagetes erecta and Cosmos bipinnatus on reducing enteric methane emission by dairy cows. Ciência Rural. 48 https://doi.org/10.1590/0103-8478cr20170484.

Herrador, M.Á., Asuero, A.G., González, A.G., 2005. Estimation of the uncertainty of indirect measurements from the propagation of distributions by using the Monte-Carlo method: An overview. Chemometr. Intell. Lab. Syst. 79, 115–122. https://doi.org/10.1016/j.chemolab.2005.04.010.

Herrero, M., Henderson, B., Havlík, P., Thornton, P.K., Conant, R.T., Smith, P., Wirsenius, S., Hristov, A.N., Gerber, P., Gill, M., 2016. Greenhouse gas mitigation potentials in the livestock sector. Nat. Clim. Change 1–10. https://doi.org/10.1038/NCLIMATE2925.

Hesterberg, T.. What Teachers Should Know about the Bootstrap: Resampling in the Undergraduate Statistics Curriculum. https://doi.org/10.48550/arXiv.1411.5279.

Heuvelink, G.B.M., 1998. Error Propagation in Environmental Modelling with GIS. CRC Press, London. https://doi.org/10.4324/9780203016114.

Hristov, A.N., Harper, M., Meinen, R., Day, R., Lopes, J., Ott, T., Venkatesh, A., Randles, C.A., 2017. Discrepancies and uncertainties in bottom-up gridded inventories of livestock methane emissions for the contiguous United States. Environ. Sci. Technol. 51, 13668–13677. https://doi.org/10.1021/acs.est.7b03332.

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

IEA, 2020. Methane Tracker 2020 – Analysis [WWW Document]. IEA. https://www.iea.org/reports/methane-tracker-2020 (accessed 6.9.23).

INEGI, 2007. Censo Agrícola, Ganadero Y Forestal 2007 [WWW Document]. URL. https://www.inegi.org.mx/programas/cagf/2007/, 8.13.21.

IPCC, 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme. Institute for Global Environmental Strategies, Hayama, Kanagawa, Japan.

IPCC, 2014. Climate Change 2013: the Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

IPCC, 2019. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories — IPCC. https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/ (accessed 2.6.24).

IPCC (Intergovernmental Panel on Climate Change), 2023a. Urgent Climate Action Can Secure a Liveable Future for All. IPCC press release. March 20, 2023, Interlaken, Switzerland. https://www.ipcc.ch/2023/03/20/press-release-ar6-synthesis-report/. (Accessed 20 March 2023).

IPCC (Intergovernmental Panel on Climate Change), 2023b. AR6 synthesis report summary for policymalers headline statements. https://www.ipcc.ch/report/ar6/syr/resources/spm-headline-statements. (Accessed 20 March 2023).

JCGM, 2008a. Evaluation of measurement data — guide to the expression of uncertainty in measurement., First. Joint Committee for Guides in Metrology (JCGM).

JCGM, 2008b. Evaluation of Measurement Data — Guide to the Expression of Uncertainty in Measurement.

Karimi-Zindashty, Y., Macdonald, J.D., Desjardins, R.L., Worth, D.E., Hutchinson, J.J., Vergé, X.P.C., 2012. Sources of uncertainty in the IPCC Tier 2 Canadian livestock model. J. Agric. Sci. 150, 556–569. https://doi.org/10.1017/S002185961100092X.

Katz, R.W., Craigmile, P.F., Guttorp, P., Haran, M., Sansó, B., Stein, M.L., 2013. Uncertainty analysis in climate change assessments. Nature Publishing Group 3, 769–771. https://doi.org/10.1038/nclimate1980.

Ku-Vera, J.C., Valencia-Salazar, S.S., Piñeiro-Vázquez, A.T., Molina-Botero, I.C., Arroyave-Jaramillo, J., Montoya-Flores, M.D., Lazos-Balbuena, F.J., Canul-Solís, J. R., Arceo-Castillo, J.I., Ramírez-Cancino, L., Escobar-Restrepo, C.S., Alayón-Gamboa, J.A., Jiménez-Ferrer, G., Zavala-Escalante, L.M., Castelán-Ortega, O.A., Quintana-Owen, P., Ayala-Burgos, A.J., Aguilar-Pérez, C.F., Solorio-Sánchez, F.J., 2018. Determination of methane yield in cattle fed tropical grasses as measured in open-circuit respiration chambers. Agricultural and Forest Meteorology, Greenhouse gas and ammonia emissions from livestock production 258, 3–7. https://doi.org/10.1016/j.agrformet.2018.01.008.

Kwak, S.K., Kim, J.H., 2017. Statistical data preparation: management of missing values and outliers. Korean Journal of Anesthesiology 70, 407–411.

Lee, M.A., Davis, A.P., Chagunda, M.G.G., Manning, P., 2017. Forage quality declines with rising temperatures, with implications for livestock production and methane emissions. Biogeosciences 14, 1403–1417. https://doi.org/10.5194/bg-14-1403-2017.

Lewis, P.A.W., Orav, E.J., 1989. Simulation Methodology for Statisticians, Operations Analysts, and Engineers, vol. 1. Wadsworth Publ. Co., USA.

Lu, S., Zavala-Araiza, D., Gautam, R., Omara, M., Scarpelli, T., Sheng, J., Sulprizio, M.P., Zhuang, J., Zhang, Y., Qu, Z., Lu, X., Hamburg, S.P., Jacob, D.J., 2021. Unravelling a large methane emission discrepancy in Mexico using satellite observations. Remote Sens. Environ. 260, 112461 https://doi.org/10.1016/j.rse.2021.112461.

Lu, X., Jacob, D.J., Wang, H., Maasakkers, J.D., Zhang, Y., Scarpelli, T.R., Shen, L., Qu, Z., Sulprizio, M.P., Nesser, H., Bloom, A.A., Ma, S., Worden, J.R., Fan, S., Parker, R.J., Boesch, H., Gautam, R., Gordon, D., Moran, M.D., Reuland, F., Villasana, C.A.O., 2021. Methane emissions in the United States, Canada, and Mexico: evaluation of national methane emission inventories and sectoral trends by inverse analysis of in situ (GLOBALVIEWplus CH4 ObsPack) and satellite (GOSAT) atmospheric observations. Atmos. Chem. Phys. Discuss. https://doi.org/10.5194/acp-2021-671 in review, 2021.

ME, 2017. New Zealand's Greenhouse Gas Inventory 1990–2015. Fulfilling Reporting Requirements under the United National Framework Convention on Climate Change and the Kyoto Protocol. Ministry for the Environment (ME)., Wellington, New Zealand.

Milne, A.E., Glendining, M.J., Bellamy, P., Misselbrook, T., Gilhespy, S., Rivas Casado, M., Hulin, A., van Oijen, M., Whitmore, A.P., 2014. Analysis of uncertainties in the estimates of nitrous oxide and methane emissions in the UK's greenhouse gas inventory for agriculture. Atmos. Environ. 82, 94–105. https://doi.org/10.1016/j.atmosenv.2013.10.012.

Moe, P.W., Tyrrell, H.F., 1979. Methane Production in Dairy Cows. J. Dairy Sci. 62, 1583–1586. https://doi.org/10.3168/jds.S0022-0302(79)83465-7.

MSTI, 2016. Third National Communication of Brazil to the United Nations Framework Convention on Climate Change - Volume III. Ministry of Science, Technology and Innovation, Secretariat of Policies and Programs of Research and Development, Brasilia, Brazil.

NRC, 1984. Nutrient Requirements of Beef Cattle, fifth ed. National Research Council. The National Academies Press, Washington, DC. https://doi.org/10.17226/19398.

NRC, N.R.C., 2001. Nutrient Requirements of Dairy Cattle, Seventh Revised Edition, seventh ed. National Research Council. The National Academies, Washington, DC. https://doi.org/10.17226/9825.

PBL, 2020. Trends in Global CO2 and Total Greenhouse Gas Emissions, 2019 report [WWW Document]. PBL Netherlands Environmental Assessment Agency. https://www.pbl.nl/en/publications/trends-in-global-co2-and-total-greenhouse-gas-emissions-2019-report, 8.12.21.

Piñeiro-Vázquez, A.T., Jiménez-Ferrer, G.O., Chay-Canul, A.J., Casanova-Lugo, F., Díaz-Echeverría, V.F., Ayala-Burgos, A.J., Solorio-Sánchez, F.J., Aguilar-Pérez, C.F., Ku-Vera, J.C., 2017. Intake, digestibility, nitrogen balance and energy utilization in

heifers fed low-quality forage and Leucaena leucocephala. Anim. Feed Sci. Technol. 228, 194–201. https://doi.org/10.1016/j.anifeedsci.2017.04.009.
R Core Team, 2017. R: the R project for statistical computing [WWW Document]. URL. https://www.r-project.org/, 8.23.21.
SADER-SINIIGA, 2021. SINIIGA. Sistema Nacional de Identificación Individual de Ganado [WWW Document]. URL. https://www.siniiga.org.mx/, 8.13.21.
Scarpelli, T.R., Jacob, D.J., Octaviano-Villasana, C.A., Ramírez-Hernández, I.F., Cárdenas-Moreno, P.R., Cortés-Alfaro, E.A., García-García, M.Á., Zavala-Araiza, D., 2020. A gridded inventory of anthropogenic methane emissions from Mexico based on Mexico's national inventory of greenhouse gases and compounds. Environ. Res. Lett. 15, 105015 https://doi.org/10.1088/1748-9326/abb42b.
Sejian, V., Lal, R., Lakritz, J., Ezeji, T., 2011. Measurement and prediction of enteric methane emission. Int. J. Biometeorol. 55, 1–16. https://doi.org/10.1007/s00484-010-0356-7.
SEMARNAT, INE., 2006. Inventario Nacional de Gases de Efecto Invernadero 2002. Secretaría del Medio Ambiente y Recursos Naturales-Instituto de Ecología, Mexico, City. Mexico. https://www.gob.mx/inecc/acciones-y-programas/inventario-nacional-de-emisiones-de-gases-y-compuestos-de-efecto-invernadero.
SEMARNAT, INECC., 2018. México, Sexta Comunicación Nacional y Segundo Informe Bienal de Actualización ante la Convención Marco de las Naciones Unidas sobre el Cambio Climático. Secretaría del Medio Ambiente y Recursos Naturales-Instituto Nacional de Ecología y Cambio Climático, Mexico, City. Mexico.
Silva, S.C.D., Gimenes, F.M.A., Sarmento, D.O.L., Sbrissia, A.F., Oliveira, D.E., Hernadez-Garay, A., Pires, A.V., 2013. Grazing behaviour, herbage intake and animal performance of beef cattle heifers on marandu palisade grass subjected to intensities of continuous stocking management. J. Agric. Sci. 151, 727–739. https://doi.org/10.1017/S0021859612000858.
Spiess, A.-N., 2018. Propagate: Propagation of Uncertainty.
Thompson, L.R., Rowntree, J.E., 2020. Invited Review: Methane sources, quantification, and mitigation in grazing beef systems. Appl. Anim. Sci. 36, 556–573. https://doi.org/10.15232/aas.2019-01951.
Tong, L.I., Chang, C.W., Jin, S.E., Saminathan, R., 2012. Quantifying uncertainty of emission estimates in National Greenhouse Gas Inventories using bootstrap confidence intervals. Atmos. Environ. 56, 80–87. https://doi.org/10.1016/j.atmosenv.2012.03.063.
UNEP, 2021. Updated climate commitments ahead of COP26 summit fall far short, but net-zero pledges provide hope [WWW Document]. UN Environment. URL http://www.unep.org/news-and-stories/press-release/updated-climate-commitments-ahead-cop26-summit-fall-far-short-net (accessed 2.6.24).
UNFCCC, 2015. Report of the Conference of the Parties on its Twenty-First Session, Held in Paris from 30 November to 13 December 2015. Addendum-Part Two: Action Taken by the Conference of the Parties 01194, vols. 1–36.
UNFCCC, 2019. Technical Analysis of the Second Biennial Update Report of Mexico Submitted on 28 November 2018. Summary Report by the Team of Technical Experts. UNFCCC. FCCC/SBI/ICA/2019/TASR.2/MEX [WWW Document]. https://unfccc.int/documents/203438, 8.13.21.
Valencia Salazar, S.S., Piñeiro Vázquez, A.T., Molina Botero, I.C., Lazos Balbuena, F.J., Uuh Narváez, J.J., Segura Campos, M.R., Ramírez Avilés, L., Solorio Sánchez, F.J., Ku Vera, J.C., 2018. Potential of Samanea saman pod meal for enteric methane mitigation in crossbred heifers fed low-quality tropical grass. Agricultural and Forest Meteorology, Greenhouse gas and ammonia emissions from livestock. Production 258, 108–116. https://doi.org/10.1016/j.agrformet.2017.12.262.
Vázquez-Carrillo, M.F., Montelongo-Pérez, H.D., González-Ronquillo, M., Castillo-Gallegos, E., Castelán-Ortega, O.A., 2020. Effects of three herbs on methane emissions from beef cattle. Animals 10, 1671. https://doi.org/10.3390/ani10091671.
Vázquez-Carrillo, M.F., Montelongo-Pérez, H.D., González-Ronquillo, M., Castillo-Gallegos, E., Castelán-Ortega, O.A., 2021. Partición de la energía bruta consumida y el aporte de energía metabolizable en bovinos F1: particion de la energía en bovinos. Ecosistemas y Recursos Agropecuarios 8. https://doi.org/10.19136/era.a8n2.2976.
Wójcik-Gront, E., Gront, D., 2014. Assessing uncertainty in the polish agricultural greenhouse gas emission inventory using Monte Carlo simulation. Outlook Agric. 43, 61–65. https://doi.org/10.5367/oa.2014.0155.
Wolf, J., Asrar, G.R., West, T.O., 2017. Revised methane emissions factors and spatially distributed annual carbon fluxes for global livestock. Carbon Bal. Manag. 12, 16. https://doi.org/10.1186/s13021-017-0084-y.
Zhao, Y., Frey, H.C., 2004. Quantification of variability and uncertainty for censored data sets and application to air toxic emission factors. Risk Anal. 24, 1019–1034. https://doi.org/10.1111/j.0272-4332.2004.00504.x.
Zhu, B., Kros, J., Lesschen, J.P., Staritsky, I.G., de Vries, W., 2016. Assessment of uncertainties in greenhouse gas emission profiles of livestock sectors in Africa, Latin America and Europe. Reg. Environ. Change 16, 1571–1582. https://doi.org/10.1007/s10113-015-0896-9.