Analysis of enteric methane emissions due to extreme variations in management practices of dairy-production systems

Tristan Senga Kiessé, Michael S. Corson, Maguy Eugène, Joël Aubin, Aurélie Wilfart

Analysis of enteric methane emissions due to extreme variations in management practices of dairy-production systems

Tristan SENGA KIESSE[1, *], Michael S. CORSON[1], Maguy EUGENE[2], Joël AUBIN[1], Aurélie WILFART[1]

[1]UMR SAS, INRA, AGROCAMPUS OUEST, 35000 Rennes, France

[2]UMR1213 Herbivores, INRA, 63122 Saint-Genès-Champanelle, France

[*]Corresponding author. *E-mail address:* tristan.senga-kiesse@inra.fr

Abstract

This study concerns variability in agrosystem inputs that affect greenhouse gas emissions at the farm scale, when management practices differ from average practices. Many studies of agrosystems assume average management practices. However, existence of a wide variety of farm-management practices may result in extreme variations in estimated environmental impacts. This large variation raises the need to use statistical tools to model extreme situations and their consequences on agrosystems. For instance, methane emissions generated by enteric fermentation in dairy cattle are particularly studied because they are important at a global scale. We investigated how extreme variations in feeding practices in dairy production affect predicted methane emissions, using a methane-emission model based on existing equations that is easy to apply at the farm scale. In this study, extreme variations in the time that cattle spent grazing were propagated through three different dairy-production systems. For an intensive dairy farm, predicted methane emissions decreased up to 15% (ca. 5% on average) and increased up to 11% (ca. 1% on average) under extremely long or short times spent grazing, respectively, compared to those from average variations in the time spent grazing. The range of variation in time spent grazing also reflects changes in feed rations. Farm-management practices require deep investigation to both evaluate and decrease risks of environmental impacts in dairy production.

Keywords: animal nutrition modeling; dairy-production system; extreme values; management practices; methane emissions

1. Introduction

Increasing the sustainability of livestock production systems is the subject of much research to evaluate and find mechanisms for reducing environmental impacts of these systems (Dollé et al., 2011). Both farm-management practices and environmental conditions are factors that influence environmental impacts of farming systems. Among other sources, the global livestock sector contributes significantly to greenhouse gas (GHG) emissions (methane (CH_4), nitrous oxide and carbon dioxide (CO_2)), representing 14.5% of human-induced GHG emissions (7.1 gigatons CO_2-eq per year in 2005) (Gerber et al., 2013). Within cattle-production systems, processing and transport of feed contribute 45% of total GHG emissions, followed by enteric fermentation (39% of GHG emissions) (Gerber et al., 2013), which is influenced by characteristics such as age and body weight, and the quality and quantity of feed consumed (Jouany and Thivend, 2008; Sauvant and Noziere, 2016). Dairy cattle are the livestock classes with the highest total GHG emissions, accounting for 1.4 gigatons CO_2-eq in 2007 (Gerber et al., 2013) (i.e., 67% of livestock sector emissions), as estimated by life cycle assessment (LCA, the leading framework for multicriteria environmental assessment of systems) (Gerber et al., 2011). These studies (Gerber et al., 2011; Gerber et al., 2013) investigated the relationship between milk production per cow and GHG emissions for dairy-production systems at a global scale (including African and Asian dairy cows).

Consequently, studies are increasingly interested in how changes in management practices and climate conditions influence environmental impacts of agrosystems, for instance, a study of environmental impacts of beef-production systems with contrasting grassland management (Morel et al., 2016). In the same way that environmental processes are subject to complex phenomena that are random and vary in time and space, changes in input variables affect predictions of agrosystem models. For instance, longer-than-normal droughts or rainfall periods affect management of both cattle and forages, yielding economic and environmental consequences. These reasons justify integrating statistical analysis tools with quantitative models of environmental processes to facilitate statistical analysis of these models. For instance, several sensitivity analysis (SA) methods applied to a simulation model of rice production were compared (Confalonieri et al., 2010). Likewise, SA of models of GHG emissions was performed at the farm level to evaluate the influence of input variables representing soil, vegetation and agricultural practices on predictions of nitrous oxide emissions (Drouet et al., 2011). Recently, SA of methane emission models was performed by changing variables describing feed intake, feed quality and animal liveweight of French

Mediterranean sheep farming systems, focusing on the use of diversified grazing resources (Mansard et al., 2018). However, in these and other agricultural studies, uncertainty in agricultural processes was analyzed primarily under average conditions (Cucurachi et al., 2016). Usual farm management practices and average climate conditions differ greatly from extreme practices and conditions, respectively, whose magnitudes can yield disproportionate responses in agrosystems. Thus, modeling and predicting consequences of extreme management practices are necessary for agrosystems at both theoretical and practical levels.

Studying extreme situations in agronomic systems raises several issues, such as which statistical tools to use to model probability distributions of extreme values. Agrosystem modeling can take advantage of statistical tools that analyze extreme variations as a way to complement uncertainty analysis. To this end, our study applied Extreme-Value Theory (EVT), recognized as the most popular approach to model extreme events. EVT is concerned with the stochastic nature of extremely large or extremely small values of a process (Embrechts et al., 1996; Charras-Garrido and Lezaud, 2013). EVT has been applied in finance (Embrechts et al., 1996), hydrology (Katz et al., 2002) and medicine (Chiu et al., 2016) but, to our knowledge, not yet in agronomy.

Our study integrated EVT into assessment of GHG emissions of agrosystems, to help stakeholders make decisions about dairy-cattle management and evaluate environmental impacts of their systems. The modeling approach was developed at an average annual scale based on French databases of dairy-production systems containing only average annual data, which are able, nonetheless, to describe agrosystem inputs that are affected by extreme variations. The time that cattle spend exclusively in farm buildings, exclusively on pasture, or transitioning from one to the other, is a key management variable that was used to propagate extreme variations in modeled agrosystems. Specifically, we investigated how extremely small or large amounts of grazing time (months/year) influenced predictions of enteric methane emissions from dairy cattle in different types of dairy-production systems.

2. Model and methods

2.1. Methane-emission model

Several models are available in the literature for predicting enteric methane emissions that depend on region- or country-specific data (Appuhamy et al., 2016). Smaller-scale mechanistic models also exist, such as the simulation model of dairy cattle digestion and fermentation (Bannink et al., 2011). Most models use measurable diet components as predictor variables, since it is recognized that feed intake is the main determinant for predicting methane emissions from ruminants (Ramin and Huhtanen, 2013). For instance, methane emissions have been predicted from digestible organic matter intake (DOMI), crude fat intake and energy intake above maintenance requirements for sheep, beef cattle and dairy cows (Bell et al., 2016). Although dry matter intake (DMI) of individual animals is not routinely measured on commercial farms, most models include it and estimate it from commonly available variables such as the quantity of milk produced. However, estimating DMI or any other predictor variable inevitably increases the residual error of predictions. Thus, we used an empirical model that predicts methane emissions (g CH_4/kg DM) per cow as a function of the quantity of DOMI (kg/cow/year) in the feed ration (Sauvant et al., 2011):

$$\mathrm{CH4_{cow}/DMI} = 7.14 + 0.22\mathrm{DOMI}(\%\mathrm{DM}) \qquad \text{Equation 1}$$

with DOMI (%DM) the percentage of DOMI in DMI, which equals OM%DMI $\times$ dOM, in which OM represents organic matter and dOM the digestibility coefficient.

The model was developed from 976 treatments in 170 experiments from the “Rumener” database, which contains published measurements of ruminants in calorimetric chambers (INRA, 2018a). The “Rumener” database contains information such as liveweight, feeding level (DMI expressed as a percentage of liveweight) and enteric methane emissions (Table S7, Supplementary Material). Using calibration data from the database, model predictions of methane emissions reached a coefficient of determination (R^2) = 0.81 and a residual standard deviation (RSD) = 2.7 g/kg DM (Sauvant et al., 2011). This RSD is similar to the ranges of RSD recently reported for a wide variety of methane prediction models (2.96-7.44 g/kg DM) (Niu et al., 2018) and for the 10 most accurate out of 40 methane prediction models for North America, Europe, Australia and New Zealand (2.93-3.45 g/kg DM) (Appuhamy et al., 2016).

Sample data were selected from a dataset of conventional dairy farms (n=43) in Brittany (France) collected previously for the LCA-based tool EDEN-E (van der Werf et al., 2009). Input data for each farm include parameters such as numbers of dairy cows, milk production, and fat and protein contents of milk (Table 1).

Table 1. Statistical description of observed data (number of dairy cows, milk produced, fat and protein contents) for input parameters from a sample of 43 farms in Brittany.

Input parameter	**Unit**	**Min.**	**Mean**	**Max.**	**Standard deviation**
No. of dairy cows	head	25.0	44.6	78.0	10.3
Quantity of milk produced	kg/cow/year	4500.0	7055.3	9217.0	1152.3
Milk fat content	g/kg	32.7	42.4	48.6	2.7
Milk protein content	g/kg	31.2	33.0	43.3	2.1

Total DMI and DOMI had not been measured on the farms; thus, we estimated them from the quantity of milk produced on each farm (Figure S1, Supplementary Material), as described in the next paragraph. Since the quantity of concentrate feed (e.g., soybean meal, rapeseed meal) purchased and stored by each farm was known, it was used to estimate the DMI, DOMI, and energy and protein contents of the concentrate feed fed. The quantity of milk produced (MilkProd, in kg/cow/year) depends on factors such as animal genetics and type of feed. We focused on the latter, specifically the quantities of grass, maize and concentrate feed required to meet cow requirements for energy (*dairy forage units*, $\mathrm{UFL/cow/year}$) and protein (*protein digestible in the intestine*, $\mathrm{PDI/cow/year}$). A dairy forage unit, defined as the net energy absorbed from 1 kg of barley (86% DM) during lactation, equals 1760 kcal according to a recent recalculation (INRA, 2018b). At the time of our study, however, it equaled 1700 kcal (Agabriel et al., 2007). Feed rations for dairy cows depend greatly on the physiological requirements that must be met. Energy and protein requirements needed to produce a given quantity of milk can be estimated (Faverdin et al., 2007).

Based on a cow's total UFL (g) and PDI (g) requirements, the DMI (kg) of the forages (grass grazed from pastures, preserved grass (hay) and maize silage) required to supplement the concentrate feed can be calculated from their UFL (/kg of dry matter) and PDI (g/kg of dry matter) contents (Table S1, Supplementary Material). Both protein (PDIN) and degradable nitrogen contribute to PDI. Protein requirements for maintenance and production requirements per day were based on PDIN:

$$\mathrm{PDI_{total/day}} = 3.25 \times \mathrm{LW}^{0.75} + 1.56 \times \mathrm{MilkProd_{/day}} \times \mathrm{PC} \qquad \text{Equation 2}$$

with LW the liveweight (assuming a mean of 650 kg) and PC the protein content of milk (g/kg).

Milk production for all cows was measured for a full 365-day period. In addition, energy requirements per day for maintenance and production requirements were calculated as:

$$\mathrm{UFL}_{\mathrm{total/day}} = (0.04 \times \mathrm{LW}^{0.75}) \times \mathrm{I}_{\mathrm{act}} + \mathrm{MilkProd}_{/\mathrm{day}} \times \left[0.44 + \left(0.0055 \times (\mathrm{FC} - 40)\right) + \left(0.0033 \times (\mathrm{PC} - 31)\right)\right] \quad \text{Equation 3}$$

with $\mathrm{I}_{\mathrm{act}}$ an activity index (assuming a mean value of 1.1) that influences feed intake capacity and FC the fat content of milk (g/kg).

From protein and energy requirements, DMI of each forage X_i was calculated as a function of the percentage of forage X_i in rations (by mass), and the protein and energy provided by the quantity of concentrate feed fed per year. Next, we decided to choose the quantity of DMI that met both protein and energy requirements to calculate the quantity of DOMI in the feed ration. Next, the DMI of each forage or feed was used to calculate the quantity of DOMI required in the feed ration for dairy cows to produce the desired quantity of milk. DOMI was calculated as the concentration of organic matter in a forage or feed (OM, in g/kg DM) multiplied by its coefficient of digestibility (dOM, in %) for a given feed X_i

$$\mathrm{DOMI}_{\mathrm{X_i}} = \mathrm{DMI}_{\mathrm{X_i}} \times \mathrm{OM}_{\mathrm{X_i}} \times \mathrm{dOM}_{\mathrm{X_i}} \quad \text{Equation 4}$$

Forage rations for cattle also depended on the time spent exclusively in farm buildings, exclusively on pasture (i.e., "only grazing"), or transitioning from one to the other during the year. The percentage of each type of forage $P_{j,j=1,2,3}$ in the annual ration was calculated from EDEN-E data as the sum of products of

(i) the number of fractional months $n_{i,i=1,2,3}$ that cattle spent exclusively in farm buildings, exclusively on pastures, or transitioning from one to the other during one year

and

(ii) the percentages $P_{i,j}$ of grazed grass, preserved grass and maize silage fed in each location during this time:

$$P_j = \sum_{i=1}^{3} n_i \times P_{ij} \quad \text{Equation 5}$$

with $\sum_{j=1}^{3} P_j = 1$, $\sum_{i=1}^{3} n_i = 12$ months and $\sum_{j=1}^{3} P_{ij} = 1$, with i the categories **1** = in buildings, **2** = on pasture, **3** = transitioning, and j the categories **1** = silage maize, **2** = grazed grass, **3** = preserved grass.

The Supplementary Material (Sections 1 and 2) provides more details on the calculation of DMI and DOMI, including relations between DMI, PDIN, UFL and P_j. It also provides statistical description of the number of months that cattle spent in each location per year and calculation of percentages of each type of forage in annual feed rations (Tables S2 and S3). In subsequent calculations, three farms with no concentrate feed recorded were excluded to avoid bias due to a lack of this information, leaving n=40 farms. Finally, DMI, DOMI and predicted methane emissions for each type of animal feed for the 40 farms studied were calculated (Figure 1).

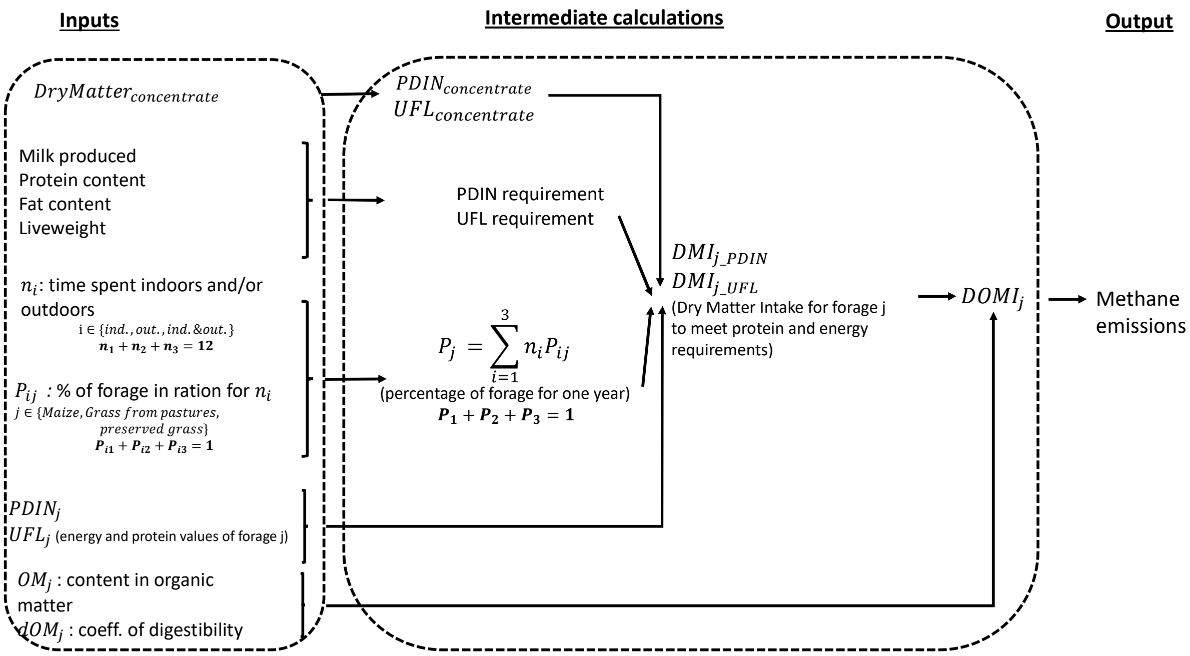

Figure 1. Conceptual model of calculation of enteric methane emissions (output) from average annual data (inputs) obtained from the EDEN-E dataset. All abbreviations are available in the main text.

Table 2. Statistical description of dry-matter intake (DMI) and digestible organic matter intake (DOMI) of feed rations of dairy cows (kg/cow/year) from 40 farms.

Component	**Parameter**	**Min.**	**Mean**	**Max.**	**Standard deviation**
Grazed grass	DMI	2245.9	3485.4	4293.1	525.1
	DOMI	1563.1	2425.8	2987.9	365.5
Preserved grass	DMI	0	329.4	2080.1	468.7
	DOMI	0	213.5	1347.9	303.7
Maize silage	DMI	0	1969.6	4484.2	1180.9
	DOMI	0	1507.1	3431.2	903.6
Concentrate feed	DMI	41.2	466.7	1041.6	298.1
	DOMI	35.1	371.8	861.2	243.8
Total	DMI	4897.2	6251.2	7646.9	727.5
	DOMI	3273.4	4518.2	5664.1	611.4

2.2. Extreme-Value Theory

Considering the independent input parameters $x_1, x_2, \ldots, x_d$, probability distributions of inputs affected by extreme variations can be identified using EVT. Applying EVT to agrosystems consists of extracting peak series, $z_1, z_2, \ldots, z_n$, which are values at which input parameters are considered extreme, then fitting the extracted peak series using appropriate probability distribution functions such as generalized extreme-value or generalized Pareto distributions (GPD) (Coles, 2001). For instance, the peak-over-threshold method consists of selecting a series of observations greater than a given threshold μ. In this context, the distribution of the excesses, $z = x - \mu$, extracted from observations x of the variable X is fitted by the GPD function with parameter θ=(σ, ε) defined by the empirical distribution function:

$$G_{\mu,\theta}(z) = 1 - \left[1 + \varepsilon\left(\frac{z(\mu)}{\sigma}\right)\right]^{-1/\varepsilon} \qquad \text{Equation 6}$$

for $\varepsilon \neq 0$ and $1 + \varepsilon\left(\frac{x-\mu}{\sigma}\right) > 0$, with $\sigma > 0$ and ε the scale and shape parameters, respectively.

Assuming independent maxima $z_1, z_2, \ldots, z_n$, obtained from random variable Z, the log likelihood function has the form

$$\mathcal{L}(\mu,\theta;\ z_1,z_2,\dots,z_n)=\sum_{i=1}^{n}\log\frac{dG_{\mu,\theta}}{dz}(z_i|\mu,\theta) \qquad \text{Equation 7}$$

Several methods are available to select the threshold μ, such as the use of quantiles (Chiu et al., 2016). The choice of the threshold requires a compromise between the bias and variance of estimators. Bias will likely result from a too-low threshold value, while large variance will likely result from a too-large threshold value. We used the weighted Hill estimator as a nonparametric approach to automatic select the threshold μ. The estimator $\hat{\theta}_{\mu}$ of parameter θ = (σ,ε) depending on threshold μ is obtained by maximizing a weighted quasi-log-likelihood function such that:

$$\hat{\theta}_{\mu}=\frac{1}{\hat{n}_{\mu}}\sum_{i=1}^{n}W_{z,h}(z_i)\log\frac{dG_{\mu,\theta}}{dz}(Z_i) \qquad \text{Equation 8}$$

where

$$\hat{n}_{\mu}=\sum_{i=1}^{n}W_{z,h}(z_i) \qquad \text{Equation 9}$$

is the weighted Hill estimator of the number of observations beyond the threshold μ. The set weights is defined as

$$W_{z,h}(z_i)=K\left(\frac{z_i-z}{h}\right) \qquad \text{Equation 10}$$

with $K(\cdot)$ a kernel function and $h>0$ a bandwidth parameter (Grama and Spokoiny, 2008; Durrieu et al., 2015).

A goodness-of-fit test was performed to test the null hypothesis that the tail was fitted by a GPD. In addition, a graphical test, the Pareto quantile plot, was performed from a scatter plot of points $(-\log(1-\mathrm{i}/(\mathrm{n}+1));\log(z_i))$, which are assumed to have a linear form with slope ε when the tail was fitted by a GPD. We used the 'evd' (Stephenson, 2002) and 'extremefit' (Durrieu et al., 2017) packages of R software (The Comprehensive R Archive Network: http://cran.r-project.org) to apply EVT. EVT was also applied to fit probability distribution functions of independent minima $t_1,t_2,\dots,t_n$ of fractional months that cattle spent only grazing using change variable $z_i^*=12-t_i$.

Based on data collected from agrosystems and experts opinion, our approach consisted of identifying variables that were directly affected by extreme variations in management practices. For instance, in systems with grazing, time spent exclusively in farm buildings, exclusively on pasture, or transitioning from one to the other is a component of farm management. EVT was applied to peak series of the time that cattle spent only grazing from EDEN-E data. Because each dairy farm had only one observation of the time spent only grazing, the final dataset to which EVT was applied contained only 40 observations. To simplify calculations without losing generality, once the time spent only grazing was set, the remaining time during the year was split evenly between the time spent exclusively in buildings and the time spent transitioning ($n_1 = n_2$), since they had relatively similar means in the EDEN-E dataset (2.4 and 3.0 months/year, respectively; Table S2). However, the percentages of each type of forage in annual feed rations during these two periods was not modified.

Extremely long and short values of time (months/year) that cattle spent only grazing were simulated under GPD and compared to average values simulated under a Gaussian distribution (Figure 2, for extremely long and average variations). We then simulated variations in mean annual DOMI and predicted methane emissions at the individual-animal scale (i.e., kg/cow/year) under extremely long, extremely short and average values of time that cattle spent only grazing.

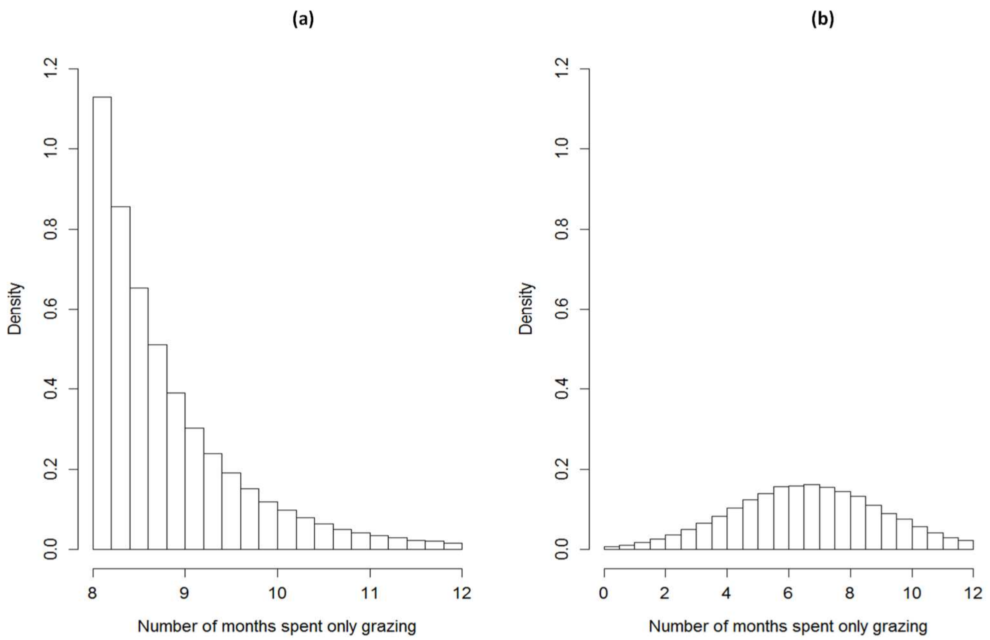

Figure 2. Time (months/year) that cattle spent only grazing simulated under (a) generalized Pareto distributions for extremely long variations and (b) Gaussian distributions for average variations

For the simulations, we selected one representative farm of each of three types of dairy farms from the EDEN-E dataset (Table 3):

(i) intensive (quantity of milk produced ≥ 8000 kg/cow/year)

(ii) semi-intensive (quantity of milk produced < 8000 kg/cow/year and percentage of forage area in maize ≥ 30%)

(iii) extensive (quantity of milk produced < 8000 kg/cow/year and percentage of forage area in maize < 30%)

For each type of dairy-production system, the time spent only grazing was assumed not to influence the mean quantity of concentrate feed fed, which was assumed to be related more to a system's milk-production goal per cow. Indeed, in the EDEN-E dataset, milk production per cow tended to increase as the quantity of concentrate feed fed per cow increased ($R^2 = 0.61$, data not shown).

Table 3.Characteristics of the representative farm selected from the EDEN-E dataset to represent each type of dairy-production system (intensive, semi-intensive and extensive). FA = forage area

			Months that cattle spent in each location per year			Annual distribution of forage intake (%) by mass		
Type	Milk produced (kg/cow/year)	Maize (% of FA)	Farm buildings only	Both farm buildings and pastures	Pastures only	Maize silage	Grazed grass	Preserved grass
intensive	8090	40	3.1	1.3	7.6	18.3	68.8	12.9
semi-intensive	6210	42	3.6	1.3	7.1	38.1	61.9	0.0
extensive	5500	5	1.3	2.7	8.0	5.4	77.9	16.7

Values of time that cattle spent only grazing were simulated for each farm in 100,000 replicates. In addition to descriptive statistics, we calculated *skewness* (the third standardized moment) and *kurtosis* (the fourth standardized moment), defined as

$$skewn(X) = \frac{m}{\sigma} = \frac{E\left[\left(X - mean(X)\right)^3\right]}{\left(E\left[\left(X - mean(X)\right)^2\right]\right)^{3/2}} \; and \; kurt(X) = \frac{E[(X-m)^4]}{(E[(X-m)^2])^2} \qquad \text{Equation 11}$$

with m the mean of X. These two statistics are useful to describe the shape of probability distribution functions.

Selecting the threshold μ requires a compromise between too-small and too-large values of μ. Setting μ too small increases the sample size of extremes and the bias of estimated parameters to the point that the fitted GPD may not approximate the tail well. Conversely, setting μ too large decreases the sample size of extremes, increasing the variance of estimated parameters. We tested three threshold values for the extremely long times: μ = 7.0, 7.5 and 8.0 months/year, corresponding to sample sizes n_μ of 23, 16, 11, respectively. We also tested three threshold values for the extremely short times: μ = 7.3, 7.0 and 6.5 months/year, corresponding to sample sizes n_μ of 25, 20, 14, respectively. For both extremes, the adequacy of the peak series was tested with three other extreme distributions (exponential, gamma and lognormal) useful for describing asymptotic distributions (Chiu et al., 2016). The Root Mean Squared Error (RMSE) was calculated to compare all fitted distributions.

3. Results

For extremely long times spent only grazing, the automatic selection procedure yielded the threshold value $\mu = 8.0$ months/year (Table 4, Figure 3). At μ = 8.0, the peak series had the smallest RMSE, and estimated parameters for the fitted GPD function were $\hat{\sigma} = 0.786$ and $\hat{\varepsilon} = 0.116$ (Table 4).

Table 4. Results of adequacy of observations above threshold μ of time (months/year) that cattle spent grazing, with generalized Pareto (GPD), exponential (EXP), gamma (GAM) and lognormal (LNO) distributions

GPD		**Estimated parameters for GPD**		**Root Mean Square Error**			
Threshold μ	n_μ	$\hat{\sigma}$	$\hat{\varepsilon}$	**GPD**	**EXP**	**GAM**	**LNO**
7.0	23	1.2	$-0.7\cdot 10^{-1}$	1.54	8.16	7.91	7.90
7.5	16	1.1	$-0.3\cdot 10^{-1}$	1.44	8.55	8.28	8.27
8.0	11	0.8	$1.2\cdot 10^{-1}$	1.35	8.91	8.63	8.62

The selected threshold μ is in bold. n_μ: sample size, $\hat{\sigma}$: estimated scale parameter of the GPD function, $\hat{\varepsilon}$: estimated shape parameter of the GPD function

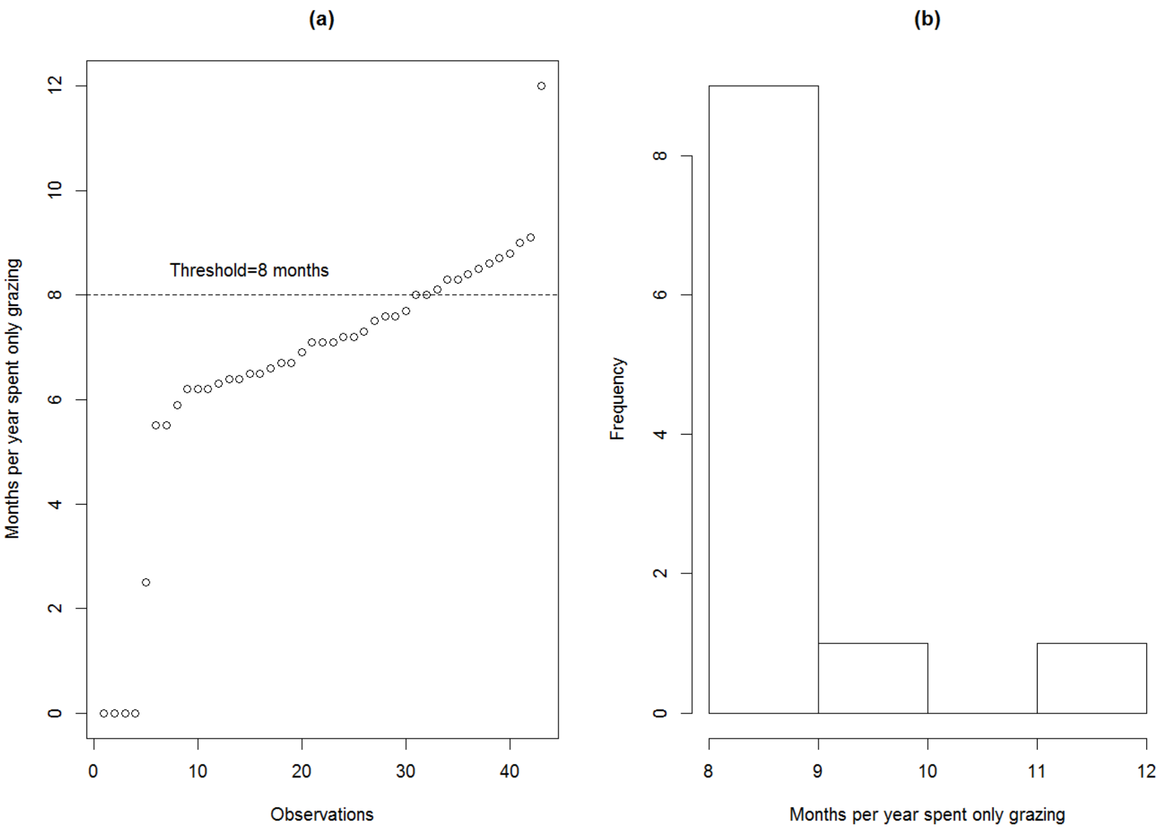

Figure 3. (a) Time (months/year) that cattle spent only grazing (with the dashed line representing the automatically selected threshold for the extremely long times, μ = 8 months/year) for n = 40 farms (sorted in ascending order) and (b) histogram of observations above the selected threshold μ = 8 months/year (sample size n_μ =11)

The Pareto quantile plot for threshold μ = 8.0 showed that scatter points $(-\log(1 - \mathrm{i}/(\mathrm{n} + 1)); \log(z_i))$ were approximated by a linear function with slope = $1.2 \cdot 10^{-1} \cong \hat{\varepsilon}$, intercept = 2.0, an R^2 = 0.80 and a residual standard error = $0.4 \cdot 10^{-1}$.

For the three types of dairy-production systems considered, distributions of the time that cattle spent only grazing, DOMI and predicted methane emissions under extremely long variations had an absolute value of skewness of 1.5 and kurtosis of 5.1 (Table 5). More precisely, distributions of extremely long variations of the simulated variables were skewed to the left (negative skewness) for time spent grazing and to the right (positive skewness) for DOMI and predicted methane emissions. Moreover, coefficients of variation of the distributions of the three variables simulated under extremely long variations were one-half of those simulated under average variations (Table 5). From the average to extremely long variations simulated, mean and maximum DOMI and predicted methane emissions decreased. For instance, for the intensive system, mean values of DOMI and predicted methane emissions decreased by 4.6% and 4.8%, respectively, while maximum values decreased by 16.8% and 14.9%, respectively. Minimum values of DOMI and methane emissions were the same for average and extremely long variations. For DOMI, 75% (the third quartile) of the simulated values were less than 4003 and 4284 kg/cow/year under extremely long and average variations, respectively. For predicted enteric methane emissions, 75% of the simulated values were less than 5013 and 5381 kg/cow/year under extremely long and average variations, respectively. Similar results were obtained for the two other types of dairy-production systems. More time spent only grazing decreased mean methane emissions (g CH_4) per cow and per kg of milk, the latter from 15.8 to 15.1 for the intensive system, 19.4 to 18.5 for the semi-intensive system and 19.0 to 18.5 for the extensive system (Table 5).

For extremely short times spent only grazing, the automatic selection procedure yielded the relatively high threshold μ = 7.3, with sample size n_μ = 25; estimated parameters for the fitted GPD function were $\hat{\sigma} = 1.255$ and $\hat{\varepsilon} = 0.295$ (Table S9, Supplementary Material). For the intensive system, from the average to extremely short variations simulated, mean values of DOMI and predicted methane emissions increased by 1.4% and 1.5%, respectively, while minimum values increased by 10.8% and 11.2%, respectively. Maximum values of both variables were the same for average and extremely short variations.

For the intensive system, two-sample Student's t-tests identified significant differences between mean DOMI (and thus methane emissions) simulated from extreme (extremely long and short) and average variations in time that cattle spent grazing (Tables S4 and S5, Supplementary Material). Simulated values of time that cattle spent only grazing, DOMI and methane emissions under the extreme and average variations differed, but results simulated under extremely short variations were the closest to those simulated under average variations (Figure 4, for the semi-intensive system).

Table 5. Descriptive statistics of the time spent only grazing simulated for all dairy-production systems under extremely long, extremely short and average variations, and its influence on digestible organic matter intake (DOMI) and predicted methane emissions for each type of system

Variables	**Variations simulated**	**1st Qu.**	**Mean**	**3rd Qu.**	**[Min.; Max.]**	**Standard deviation**
Time spent only grazing (months/year)	Extremely long	8.2	8.8	9.1	[8;12]	0.8
	Average	4.9	6.5	8.2	[0;12]	2.3
	Extremely short	5.2	5.8	6.9	[0;7.3]	1.5
Intensive system						
DOMI (kg/cow/year)	Extremely long	3925	3953	4003	[3683;4022]	66.5
	Average	4003	4146	4284	[3683;4700]	200.1
	Extremely short	4111	4205	4254	[4081;4700]	129.2
Methane emissions (kg/cow/year)	Extremely long	121.3	122.2	123.8	[113.5;124.4]	2.1
	Average	123.8	128.4	132.9	[113.5;146.3]	6.4
	Extremely short	127.3	130.3	131.9	[126.3;146.3]	4.2
Semi-intensive system						
DOMI (kg/cow/year)	Extremely long	3696	3722	3769	[3465;3787]	62.5
	Average	3769	3904	4036	[3465;4430]	190.1
	Extremely short	3872	3961	4007	[3843;4430]	122.0
Methane emissions (kg/cow/year)	Extremely long	114.2	115.1	116.5	[106.9;117.1]	1.9
	Average	116.5	120.8	125.0	[106.9;137.6]	6.0
	Extremely short	119.8	122.6	124.1	[118.9;137.6]	3.9
Extensive system						
DOMI (kg/cow/year)	Extremely long	3248	3256	3270	[3179;3276]	19.1
	Average	3271	3311	3351	[3179;3469]	57.1
	Extremely short	3301	3328	3342	[3293;3469]	36.8
Methane emissions (kg/cow/year)	Extremely long	100.9	101.2	101.7	[98.2;101.9]	0.7
	Average	101.7	103.2	104.7	[98.2;109.2]	2.1
	Extremely short	102.9	103.9	104.4	[102.5;109.2]	1.4
Extremely long: kurtosis =5.1, |skewness|=1.5 (>0 for DOMI and CH_4, and <0 for time spent grazing)						
Average: kurtosis =2.6, |skewness|=0.1 (>0 for DOMI and CH_4, and <0 for time spent grazing)						
Extremely short: kurtosis =2.1, |skewness|=1.6 (>0 for DOMI, and CH_4 and <0 for time spent grazing)						

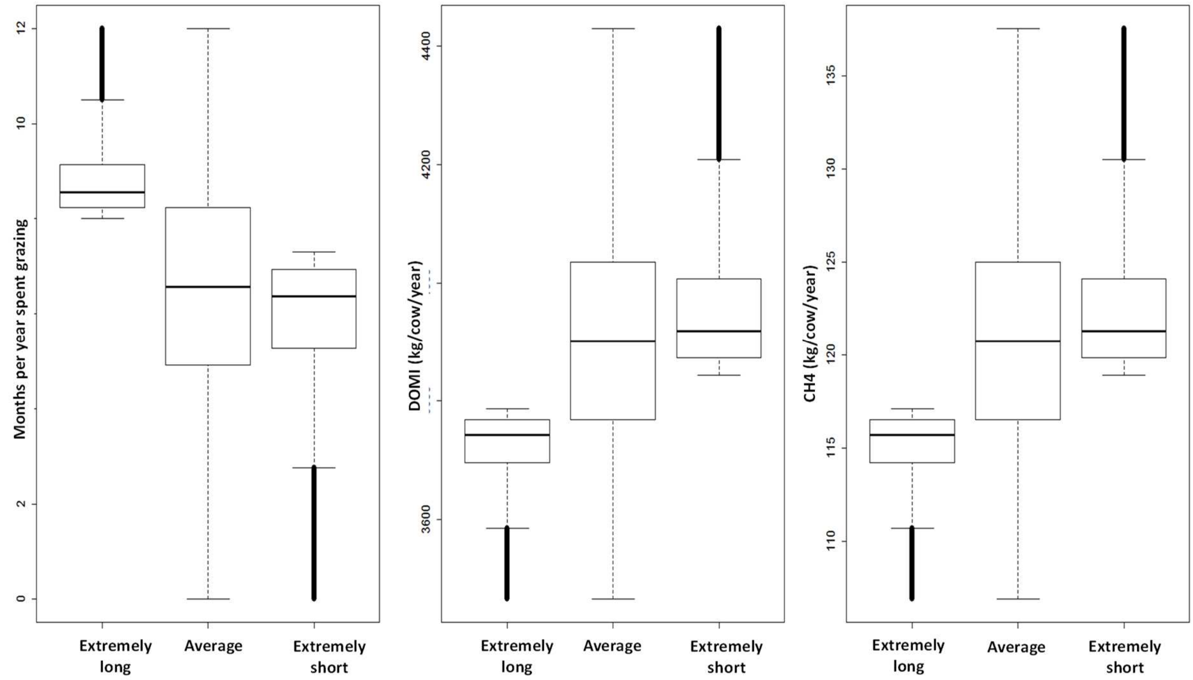

Figure 4. Boxplots of simulated time (months/year) spent only grazing, digestible organic matter intake (DOMI, kg/cow/year) and predicted methane emissions (CH4, kg/cow/year) under extremely long, extremely short and average simulated variations (100,000 replicates each) for the semi-intensive dairy-production system. Whiskers represent 1.5 times the interquartile range. Thick black lines are composed of strings of outliers.

4. Discussion

Variations in dry matter intake and enteric methane emissions

In this study, EVT was applied to average annual data, which are contained in most available databases of dairy-production systems. We assumed that extreme variations in the time that cattle spent only grazing reflected different management practices of dairy farms in Brittany. A constant mean annual quantity of concentrate feed fed was also assumed for all simulations. Simulating extremely long times that cattle spent only grazing was favorable for developing grass-based systems, which had lower mean annual DOMI (because their decrease in maize silage DOMI was larger than their increase in grass DOMI) and thus lower predicted enteric methane emissions per cow. The longer time that cattle spent only grazing implied an increase in the quantity of grazed grass and a decrease in quantities of the other types of forages (i.e., maize silage and preserved grass) in annual feed rations (detailed results in Table S6, Supplementary Material). Consequently, enteric methane emissions decreased when increasing the quantity of grazed grass (and decreasing the quantities of other types of forages).

Conversely, simulating extremely short times that cattle spent only grazing was unfavorable for developing grass-based systems. These short times both decreased the quantity of grazed grass and increased the quantities of maize silage and preserved grass in annual feed rations. For comparison, an 8-days experiment showed that daily herbage intake of dairy cows decreased (from 16.7 to 13.8 kg organic matter/cow/day) as daily herbage allowance decreased (from 46 to 19 organic matter/cow/day, respectively) (Peyraud et al., 1996). Furthermore, an increased DMI of silage and its increased passage rate, which reduces ruminal residence time, reduces enteric methane production (Haque, 2018). Simulated average feeding levels and predicted methane emissions in our study were found to lie within the ranges of variation in data of ruminants ingesting forages and concentrate feed (from the "Rumener" database) used to calibrate the methane-emission model in Equation 1, and within those of ruminants ingesting only forages (from the "Methafour" database) (Table S7 and S8, Supplementary Material) (INRA, 2018a). Longer- or shorter-than-average times that cattle spend only grazing may be influenced by climate conditions such as longer-than-normal droughts or rainfall periods. For instance, in regions north of the Alps whose landscape is dominated by grassland, even distribution of rainfall throughout the year and mild temperatures in winter favor grass growth (Thomet et al., 2011). This raises the issue of assessing the risk that uncommon environmental events will decrease the quantity of grass available for grazing.

Nutritional management strategies to mitigate GHG emissions

The range of variation in time spent grazing also reflects changes in feed rations and must be discussed when considering nutritional management strategies to mitigate enteric methane production. In our study, more time spent only grazing resulted in replacing maize silage and preserved grass with grazed grass (Table S6, Supplementary Material), which decreased mean methane emissions (g CH_4) per kg of milk and per cow. The type of pasture must be also considered when extending grazing time, since cattle grazing alfalfa emitted more methane than those grazing grass pastures, depending on sward maturity at grazing (Chaves et al., 2006; Archimède et al., 2011). Another nutritional strategy that may reduce enteric methane emissions consists of feeding maize and cereal silages instead of grass silage, since maize is already cultivated and fed to increase animal performance (Beauchemin et al., 2008). For instance, feeding grass silage instead of maize silage in a previous experiment decreased methane emissions per kg of milk by ca. 15%, from ca. 13 to ca. 11 g CH_4/kg of milk (Doreau et al., 2011). How replacement of maize or cereal silage by grass silage affects methane emissions should be further investigated in combination with the effects of more time spent grazing. Additional studies should focus on strategies to mitigate enteric methane emissions, such as supplementing diets with feed additives such as plant extracts (Wilfart et al., 2013) or enzymes. Nutrient composition (e.g., protein, fiber) should be investigated as well, since it is known to affect intake and therefore methane emissions (Doreau et al., 2011). However, no feed nutrient compositions were available in our study because they are not usually measured on commercial farms.

Differences in diet strategies do not affect other GHG emissions (e.g., CO_2) in the same way as enteric methane emissions. For instance, in a previous experiment, the type of pasture was found not to affect CO_2 production (Chaves et al., 2006). From experimental data of 67 lactating dairy cows, diets based on grass or on maize silage differed little in CO_2 emissions since internal use of nutrients (e.g., carbon) and the amount of carbon converted to CO_2 remained relatively constant when cows were fed according to requirements (Kirchgessner et al., 1991). Likewise, shifts in grass quality in another experiment were found to have no major effect on CO_2 production, following a GHG mitigation strategy in dairy systems that changed the diet from barley straw and protein concentrate to grazed grass (Lee et al., 2017). Note that the energy used (e.g., to produce silage) must also be considered in the mitigation strategies investigated (FAO, 2017). Increasing the time that cattle spend grazing would decrease the quantity of maize silage consumed, which would likely decrease quantities of maize silage produced or purchased, fertilizers applied, diesel used and electricity consumed. These positive and negative changes would influence overall environmental impacts.

Limitations of the study

This study has some limitations. First, the average annual scale of data limited the choice of models that predict methane emissions and the level of detail at which calculations were performed. The model used in our study was easy to apply as a function of the quantity of DOMI, and the EDEN-E data lay within the ranges of variation of the data used to develop and calibrate the model. However, the model needs to be tested with datasets other than those used to calibrate it. More detailed models that use factors such as the feeding level and the percentage of DOMI as concentrate feed to predict methane emissions (Sauvant and Noziere, 2016) would have required more information than that available in our study. Second, it ignores the sensitivity of dairy farms to inter-annual climate variation, since we did not have measurements over several years. For instance, for a group of dairy farms with known characteristics, one could apply EVT to the observed time that cattle spent only grazing in each of several years. The peaks extracted from these time series would also enable calculating the "return period", defined as the mean time before a random variable exceeds a given level over a long period. Knowing the return period of extreme values of time that cattle spent grazing could help farmers manage dairy farms. Although not including EVT, an interesting study examined the sensitivity of beef-production systems to climate conditions and the subsequent impacts on technico-economic results (Mosnier et al., 2012). This study simulated interannual variations in variables such as the purchase of forages, predicting that beef farms with lower stocking rates tended to have more stable incomes. Third, the small sample of dairy farms (n = 43), and thus the number of farms on which cattle grazed more than the upper threshold of μ = 8 months (n_{μ}=11) or less than the lower threshold of μ = 7.3 months (n_{μ} = 25), and the small difference between the two thresholds, limits the representativeness of results. To increase both the representativeness of data and the generality of results would require increasing the sample size of dairy farms. Fourth, applying EVT required extrapolating the models used. The data used to calibrate and validate variables in most models of agricultural systems contain few values in the tails of distributions (i.e., extremely small or extremely large). Applying EVT raises the issue of building models and collecting data specifically adapted to predict emissions under extreme variations.

Research prospects

Deeper investigation is required into the characteristics, management practices and environmental conditions of the group of farms considered to explain extreme variations in variables. These studies could help distinguish the influence among farms of factors such as management practices and environmental conditions on extreme variations in grass availability, which influences the time that cattle spend grazing. This could help consider and decrease risks due to these factors when assessing environmental impacts of dairy farms.

Another research prospect is to apply EVT directly to environmental factors by adding a submodel that generates environmental factors as input variables to models of dairy-production systems. For instance, predicted rainfall could be used as input for a grass growth model; for instance, predictions of the French climate model ARPEGE (Déqué et al., 1994) were used as input for the crop model STICS (Ruget et al., 2012). This would require additional data (e.g., soil quality, daily rainfall and temperature) and would raise the issue of combining data and models from average-annual and daily time scales. Moreover, EVT could be included in LCA studies to address risk and uncertainties in LCA modeling, perhaps even helping to inform public policies, since several studies have highlighted the need to integrate LCA and risk-analysis methods (Heijungs and Huijbregts, 2004).

5. Conclusion

Applying EVT enabled studying consequences of longer- and shorter-than-average times that cattle spent only grazing on DOMI and enteric methane emissions. Longer and shorter grazing times decreased and increased, respectively, both DOMI and predicted methane emissions of dairy farms. A future research prospect is to develop a framework to integrate EVT with LCA. Doing so would enable analyzing environmental impacts of agrosystems under extreme conditions and introducing the concept of risk into the design of new agrosystems. It also could help determine policy implications of risk analysis for the stakeholders concerned.

References

Agabriel, J., Pomiès, D., Nozières, M.-O., Faverdin, P., 2007. Alimentation des bovins, ovins et caprins. Besoin des animaux. Valeurs des aliments. Tables INRA. In: Quae (Ed.), Principes de rationnement des ruminants, Versailles, France.

Appuhamy, J.A., France, J., Kebreab, E., 2016. Models for predicting enteric methane emissions from dairy cows in North America, Europe, and Australia and New Zealand. Glob Chang Biol 22, 3039-3056.

Archimède, H., Eugène, M., Marie Magdeleine, C., Boval, M., Martin, C., Morgavi, D.P., Lecomte, P., Doreau, M., 2011. Comparison of methane production between C3 and C4 grasses and legumes. Animal Feed Science and Technology 166-167, 59-64.

Bannink, A., van Schijndel, M.W., Dijkstra, J., 2011. A model of enteric fermentation in dairy cows to estimate methane emission for the Dutch National Inventory Report using the IPCC Tier 3 approach. Animal Feed Science and Technology 166-167, 603-618.

Beauchemin, K.A., Kreuzer, M., O'Mara, F., McAllister, T.A., 2008. Nutritional management for enteric methane abatement: a review. Australian Journal of Experimental Agriculture 48, 21.

Bell, M., Eckard, R., Moate, P.J., Yan, T., 2016. Modelling the Effect of Diet Composition on Enteric Methane Emissions across Sheep, Beef Cattle and Dairy Cows. Animals : an open access journal from MDPI 6.

Charras-Garrido, M., Lezaud, P., 2013. Extreme Value Analysis : an Introduction. Journal de la Société Française de Statistique, Société Française de Statistique et Société Mathématique de France 154, 66-97.

Chaves, A.V., Thompson, L.C., Iwaasa, A.D., Scott, S.L., Olson, M.E., al., e., 2006. Effect of pasture type (alfalfa vs. grass) on methane and carbon dioxide production by yearling beef heifer. Canadian Journal of Animal Science 86, 409-418.

Chiu, Y., Chebana, F., Abdous, B., Belanger, D., Gosselin, P., 2016. Mortality and morbidity peaks modeling: An extreme value theory approach. Statistical methods in medical research.

Coles, S., 2001. An introduction to statistical modeling of extreme values. Springer, London.

Confalonieri, R., Bellocchi, G., Bregaglio, S., Donatelli, M., Acutis, M., 2010. Comparison of sensitivity analysis techniques: A case study with the rice model WARM. Ecological Modelling 221, 1897-1906.

Cucurachi, S., Borgonovo, E., Heijungs, R., 2016. A Protocol for the Global Sensitivity Analysis of Impact Assessment Models in Life Cycle Assessment. Risk analysis : an official publication of the Society for Risk Analysis 36, 357-377.

Déqué, M., Dreveton, C., Braun, A., Cariolle, D., 1994. The ARPEGE/IFS atmosphere model: a contribution to the French community climate modelling. Climate Dynamics 10, 249-266.

Dollé, J.-B., Agabriel, J., Peyraud, J.-L., Faverdin, P., Manneville, V., Raison, C., Gac, A., Le Gall, A., 2011. Les gaz à effet de serre en élevage bovin : évaluation et leviers d'action. In: Doreau M., B.R., Perez J.M. (Ed.), Gaz à effet de serre en élevage bovin : le méthane. Dossier, INRA Productions Animales, pp. 415-432.

Doreau, M., Martin, C., Eugène, M., Popova, M., Morgavi, D.P., 2011. Leviers d'action pour réduire la production de méthane entérique par les ruminants. In: Doreau M., B.R., Perez J.M. (Ed.), Gaz à effet de serre en élevage bovin : le méthane Dossier, INRA Productions Animales, pp. 461-474.

Drouet, J.L., Capian, N., Fiorelli, J.L., Blanfort, V., Capitaine, M., Duretz, S., Gabrielle, B., Martin, R., Lardy, R., Cellier, P., Soussana, J.F., 2011. Sensitivity analysis for models of greenhouse gas emissions at farm level. Case study of N(2)O emissions simulated by the CERES-EGC model. Environmental pollution 159, 3156-3161.

Durrieu, G., Grama, I., Jaunatre, K., Pham, Q.-K., Tricot, J.-M., 2017. extremefit: Estimation of Extreme Conditional Quantiles and Probabilities. R news.

Durrieu, G., Grama, I., Pham, Q.-K., Tricot, J.-M., 2015. Nonparametric adaptive estimation of conditional probabilities of rare events and extreme quantiles. Extremes 18, 437-478.

Embrechts, P., Klüppelberg, C., Mikosch, T., 1996. Modelling Extremal Events for Insurance and Finance. In: Rozovskii, B., Glynn, P.W. (Eds.), Stochastic Modelling and Applied Probability. Springer.

FAO, 2017. Global Livestock Environmental Assessment Model. Food and Agriculture Organization of the United Nations (FAO).

Faverdin, P., Delagarde, R., Delaby, L., Meschy, F., 2007. Alimentation des bovins, ovins et caprins. Besoin des animaux. Valeurs des aliments. Tables INRA. In: Quae (Ed.), Alimentation des vaches laitières, Versailles, France.

Gerber, P., Vellinga, T., Opio, C., Steinfeld, H., 2011. Productivity gains and greenhouse gas emissions intensity in dairy systems. Livestock Science 139, 100-108.

Gerber, P.J., Steinfeld, H., Henderson, B., Mootet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, A., 2013. Tackling climate change though livestock – A global assessment of Emissions and mitigation opportunities. Food and Agriculture Organization of the United Nations (FAO), Rome.

Grama, I., Spokoiny, V., 2008. Statistics of extremes by oracle estimation. The Annals of Statistics 36, 1619-1648.

Haque, M.N., 2018. Dietary manipulation: a sustainable way to mitigate methane emissions from ruminants. Journal of animal science and technology 60, 15.

Heijungs, R., Huijbregts, M.A.J., 2004. A Review of Approaches to Treat Uncertainty in LCA. iEMSs 2004 International Congress:"Complexity and Integrated Resources Management". International Environmental Modelling and Software Society, Osnabrueck, Germany.

INRA, 2018a. Databases and references. INRA feeding system for ruminants. Wageningen Academic Publishers, Wageningen, the Netherlands, pp. 529-593.

INRA, 2018b. INRA feeding system for ruminants. Wageningen Academic Publishers, Wageningen, the Netherlands.

Jouany, J.-P., Thivend, P., 2008. La production de méthane d'origine digestive chez les ruminants et son impact sur le réchauffement climatique. Management & Avenir 20, 259.

Katz, R.W., Parlange, M.B., Naveau, P., 2002. Statistics of extremes in hydrology. Advances in Water Resources 25, 1287-1304.

Kirchgessner, M., Windisch, W., Müller, H.L., Kreuzer, M., 1991. Release of methane and of carbon dioxide by dairy cattle. Agribiological Research 44.

Lee, M.A., Todd, A., Sutton, M.A., Chagunda, M.G.G., Roberts, D.J., Rees, R.M., Buggy, C., 2017. A time-series of methane and carbon dioxide production from dairy cows during a period of dietary transition. Cogent Environmental Science 3.

Mansard, L., Vigan, A., Meuret, M., Lasseur, J., Benoit, M., Lecomte, P., Eugène, M., 2018. An enteric methane emission calculator (DREEM) built to consider feed diversity: Case study of pastoral and sedentary farming systems. Small Ruminant Research 167, 6-15.

Morel, K., Farrié, J.-P., Renon, J., Manneville, V., Agabriel, J., Devun, J., 2016. Environmental impacts of cow-calf beef systems with contrasted grassland management and animal production strategies in the Massif Central, France. Agricultural Systems 144, 133-143.

Mosnier, C., Lherm, M., Agabriel, J., 2012. Parmi les systèmes bovin viande, ceux dont le chargement est plus faible sont-ils moins sensibles aux aléas climatiques ? Fourrages 212, 329-336.

Niu, M., Kebreab, E., Hristov, A.N., Oh, J., Arndt, C., Bannink, A., Bayat, A.R., Brito, A.F., Boland, T., Casper, D., Crompton, L.A., Dijkstra, J., Eugene, M.A., Garnsworthy, P.C., Haque, M.N., Hellwing, A.L.F., Huhtanen, P., Kreuzer, M., Kuhla, B., Lund, P., Madsen, J., Martin, C., McClelland, S.C., McGee, M., Moate, P.J., Muetzel, S., Munoz, C., O'Kiely, P., Peiren, N., Reynolds, C.K., Schwarm, A., Shingfield, K.J., Storlien, T.M., Weisbjerg, M.R., Yanez-Ruiz, D.R., Yu, Z., 2018. Prediction of enteric methane production, yield, and intensity in dairy cattle using an intercontinental database. Glob Chang Biol 24, 3368-3389.

Peyraud, J.L., Comeron, E., Wade, M., Lemaire, G., 1996. The effect of daily herbage allowance, herbage mass and animal factors upon herbage intake by grazing dairy cows. Annales de zootechnie 45, 201-217.

Ramin, M., Huhtanen, P., 2013. Development of equations for predicting methane emissions from ruminants. Journal of dairy science 96, 2476-2493.

Ruget, F., Clastre, P., Moreau, J.-C., Cloppet, E., Souverain, F., Lacroix, B., Lorgeou, J., 2012. Conséquences possibles des changements climatiques sur la production fourragère en France. I- Estimation par modélisation et analyse critique. Fourrages 210, 87-98.

Sauvant, D., Giger-Reverdin, S., Serment, A., Broudiscou, L., 2011. Influences des régimes et de leur fermentation dans le rumen sur la production de méthane par les ruminants. In: Doreau, M., Baumont, R., Perez, J.M. (Eds.), Gaz à effet de serre en élevage bovin : le méthane. Dossier, INRA Productions Animales, pp. 433-446.

Sauvant, D., Noziere, P., 2016. Quantification of the main digestive processes in ruminants: the equations involved in the renewed energy and protein feed evaluation systems. Animal : an international journal of animal bioscience 10, 755-770.

Stephenson, A.G., 2002. evd: Extreme Value Distributions. R news 2, 31-32.

Thomet, P., Cutullic, E., Bisig, W., Wuest, C., Elsaesser, M., Steinberger, S., Steinwiddr, A., 2011. Merits of full grazing systems as a sustainable and efficient milk production strategy. Grassland Science in Europe 16, 273-285.

van der Werf, H.M., Kanyarushoki, C., Corson, M.S., 2009. An operational method for the evaluation of resource use and environmental impacts of dairy farms by life cycle assessment. Journal of environmental management 90, 3643-3652.

Wilfart, A., Nguyen, V.T.N.G., Nguyen, T.T.H., Morgavi, D.P., Eugène, M., 2013. Environmental impacts of feed additives used in dairy production systems using a LCA approach. 20ème Rencontres Recherches Ruminants, Paris, France.