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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. *Agricultural Systems*, 2019, 173, pp.449-457. 10.1016/j.agsy.2019.03.024 . hal-02154622

HAL Id: hal-02154622

<https://hal.science/hal-02154622>

Submitted on 22 Oct 2021

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

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8 **Abstract**

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

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

28 **1. Introduction**

29 Increasing the sustainability of livestock production systems is the subject of much research to
30 evaluate and find mechanisms for reducing environmental impacts of these systems (Dollé et
31 al., 2011). Both farm-management practices and environmental conditions are factors that
32 influence environmental impacts of farming systems. Among other sources, the global
33 livestock sector contributes significantly to greenhouse gas (GHG) emissions (methane (CH₄),
34 nitrous oxide and carbon dioxide (CO₂)), representing 14.5% of human-induced GHG
35 emissions (7.1 gigatons CO₂-eq per year in 2005) (Gerber et al., 2013). Within cattle-
36 production systems, processing and transport of feed contribute 45% of total GHG emissions,
37 followed by enteric fermentation (39% of GHG emissions) (Gerber et al., 2013), which is
38 influenced by characteristics such as age and body weight, and the quality and quantity of
39 feed consumed (Jouany and Thivend, 2008; Sauvant and Noziere, 2016). Dairy cattle are the
40 livestock classes with the highest total GHG emissions, accounting for 1.4 gigatons CO₂-eq in
41 2007 (Gerber et al., 2013) (i.e., 67% of livestock sector emissions), as estimated by life cycle
42 assessment (LCA, the leading framework for multicriteria environmental assessment of
43 systems) (Gerber et al., 2011). These studies (Gerber et al., 2011; Gerber et al., 2013)
44 investigated the relationship between milk production per cow and GHG emissions for dairy-
45 production systems at a global scale (including African and Asian dairy cows).

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

61 Mediterranean sheep farming systems, focusing on the use of diversified grazing resources
62 (Mansard et al., 2018). However, in these and other agricultural studies, uncertainty in
63 agricultural processes was analyzed primarily under average conditions (Cucurachi et al.,
64 2016). Usual farm management practices and average climate conditions differ greatly from
65 extreme practices and conditions, respectively, whose magnitudes can yield disproportionate
66 responses in agrosystems. Thus, modeling and predicting consequences of extreme
67 management practices are necessary for agrosystems at both theoretical and practical levels.

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

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

87 **2. Model and methods**

88 **2.1. Methane-emission model**

89 Several models are available in the literature for predicting enteric methane emissions that
90 depend on region- or country-specific data (Appuhamy et al., 2016). Smaller-scale
91 mechanistic models also exist, such as the simulation model of dairy cattle digestion and
92 fermentation (Bannink et al., 2011). Most models use measurable diet components as

93 predictor variables, since it is recognized that feed intake is the main determinant for
94 predicting methane emissions from ruminants (Ramin and Huhtanen, 2013). For instance,
95 methane emissions have been predicted from digestible organic matter intake (DOMI), crude
96 fat intake and energy intake above maintenance requirements for sheep, beef cattle and dairy
97 cows (Bell et al., 2016). Although dry matter intake (DMI) of individual animals is not
98 routinely measured on commercial farms, most models include it and estimate it from
99 commonly available variables such as the quantity of milk produced. However, estimating
100 DMI or any other predictor variable inevitably increases the residual error of predictions.
101 Thus, we used an empirical model that predicts methane emissions (g CH₄/kg DM) per cow as
102 a function of the quantity of DOMI (kg/cow/year) in the feed ration (Sauvant et al., 2011):

$$\text{CH}_{4\text{cow}}/\text{DMI} = 7.14 + 0.22\text{DOMI}(\% \text{DM}) \quad \text{Equation 1}$$

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

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

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

119 *Table 1. Statistical description of observed data (number of dairy cows, milk produced, fat*
 120 *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 |

121

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

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

$$PDI_{\text{total/day}} = 3.25 \times LW^{0.75} + 1.56 \times \text{MilkProd}_{\text{day}} \times PC \quad \text{Equation 2}$$

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

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

$$\text{UFL}_{\text{total/day}} = (0.04 \times \text{LW}^{0.75}) \times \text{I}_{\text{act}} + \quad \text{Equation 3}$$

$$\text{MilkProd}_{\text{/day}} \times [0.44 + (0.0055 \times (\text{FC} - 40)) + (0.0033 \times (\text{PC} - 31))]$$

146 with I_{act} an activity index (assuming a mean value of 1.1) that influences feed intake capacity
 147 and FC the fat content of milk (g/kg).

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

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

156
 157
 158 Forage rations for cattle also depended on the time spent exclusively in farm buildings,
 159 exclusively on pasture (i.e., “only grazing”), or transitioning from one to the other during the
 160 year. The percentage of each type of forage $P_{j,j=1,2,3}$ in the annual ration was calculated from
 161 EDEN-E data as the sum of products of

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

165 and

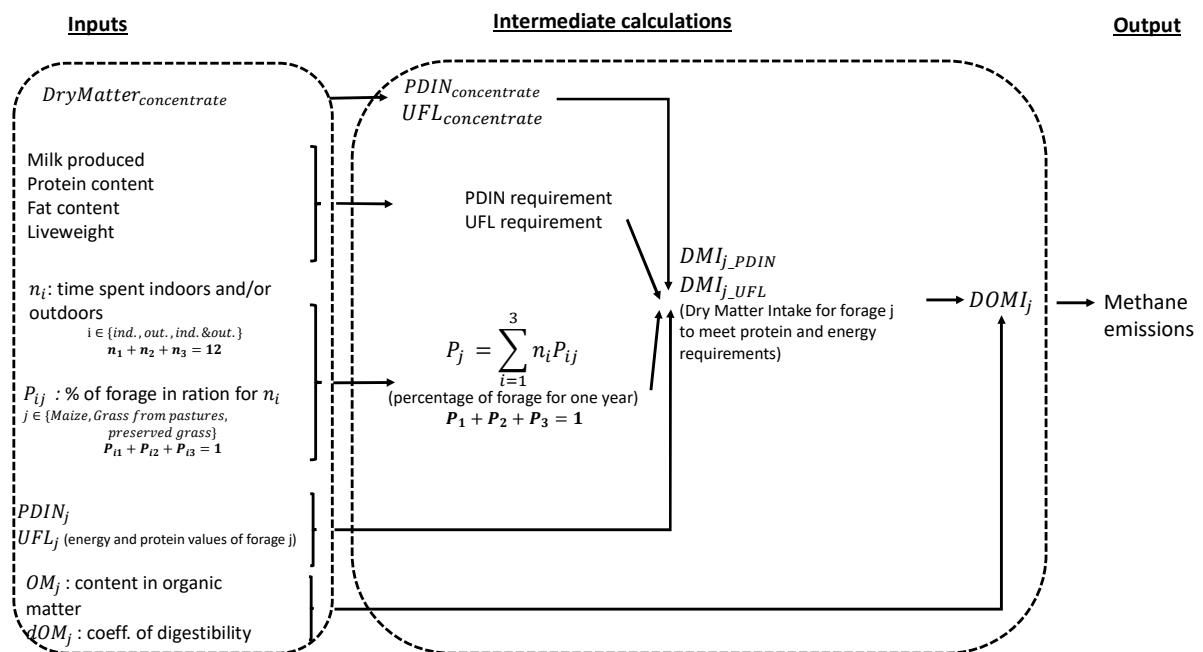
166 (ii) the percentages $P_{i,j}$ of grazed grass, preserved grass and maize silage fed in each
 167 location during this time:

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

168 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
 169 buildings, **2** = on pasture, **3** = transitioning, and j the categories **1** = silage maize, **2** = grazed
 170 grass, **3** = preserved grass.

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

179



180

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

184 *Table 2. Statistical description of dry-matter intake (DMI) and digestible organic matter*
 185 *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 |

186

187 **2.2. Extreme-Value Theory**

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

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

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

199 Assuming independent maxima z_1, z_2, \dots, z_n , obtained from random variable Z , the log
 200 likelihood function has the form

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

201 Several methods are available to select the threshold μ , such as the use of quantiles (Chiu et
 202 al., 2016). The choice of the threshold requires a compromise between the bias and variance
 203 of estimators. Bias will likely result from a too-low threshold value, while large variance will
 204 likely result from a too-large threshold value. We used the weighted Hill estimator as a
 205 nonparametric approach to automatic select the threshold μ . The estimator $\hat{\theta}_\mu$ of parameter θ
 206 $= (\sigma, \varepsilon)$ depending on threshold μ is obtained by maximizing a weighted quasi-log-likelihood
 207 function such that:

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

208 where

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

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

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

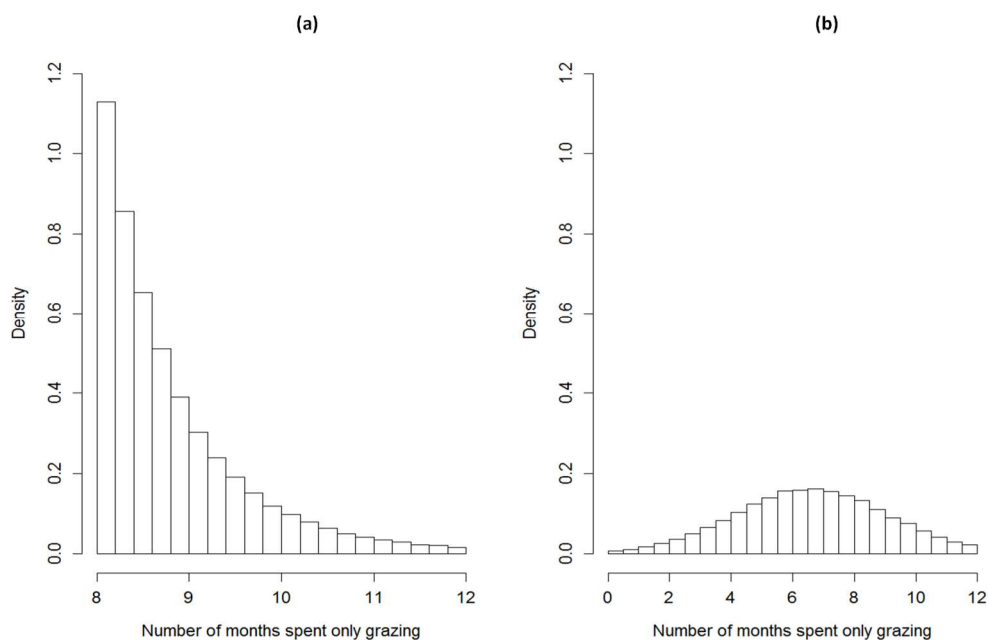
211 with $K(\cdot)$ a kernel function and $h > 0$ a bandwidth parameter (Grama and Spokoiny, 2008;
 212 Durrieu et al., 2015).

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

221 Based on data collected from agrosystems and experts opinion, our approach consisted of
 222 identifying variables that were directly affected by extreme variations in management
 223 practices. For instance, in systems with grazing, time spent exclusively in farm buildings,
 224 exclusively on pasture, or transitioning from one to the other is a component of farm

225 management. EVT was applied to peak series of the time that cattle spent only grazing from
226 EDEN-E data. Because each dairy farm had only one observation of the time spent only
227 grazing, the final dataset to which EVT was applied contained only 40 observations. To
228 simplify calculations without losing generality, once the time spent only grazing was set, the
229 remaining time during the year was split evenly between the time spent exclusively in
230 buildings and the time spent transitioning ($n_1 = n_2$), since they had relatively similar means in
231 the EDEN-E dataset (2.4 and 3.0 months/year, respectively; Table S2). However, the
232 percentages of each type of forage in annual feed rations during these two periods was not
233 modified.

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



240
241 *Figure 2. Time (months/year) that cattle spent only grazing simulated under (a) generalized*
242 *Pareto distributions for extremely long variations and (b) Gaussian distributions for average*
243 *variations*

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

- 246 (i) intensive (quantity of milk produced ≥ 8000 kg/cow/year)
- 247 (ii) semi-intensive (quantity of milk produced < 8000 kg/cow/year and percentage of
 248 forage area in maize $\geq 30\%$)
- 249 (iii) extensive (quantity of milk produced < 8000 kg/cow/year and percentage of forage
 250 area in maize $< 30\%$)

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

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

| Type | Milk produced (kg/cow/year) | Maize (% of FA) | Months that cattle spent in each location per year | | | Annual distribution of forage intake (%) by mass | | |
|----------------|-----------------------------|-----------------|--|----------------------------------|---------------|--|--------------|-----------------|
| | | | 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 |

259
 260 Values of time that cattle spent only grazing were simulated for each farm in 100,000
 261 replicates. In addition to descriptive statistics, we calculated *skewness* (the third standardized
 262 moment) and *kurtosis* (the fourth standardized moment), defined as

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

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

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

276 **3. Results**

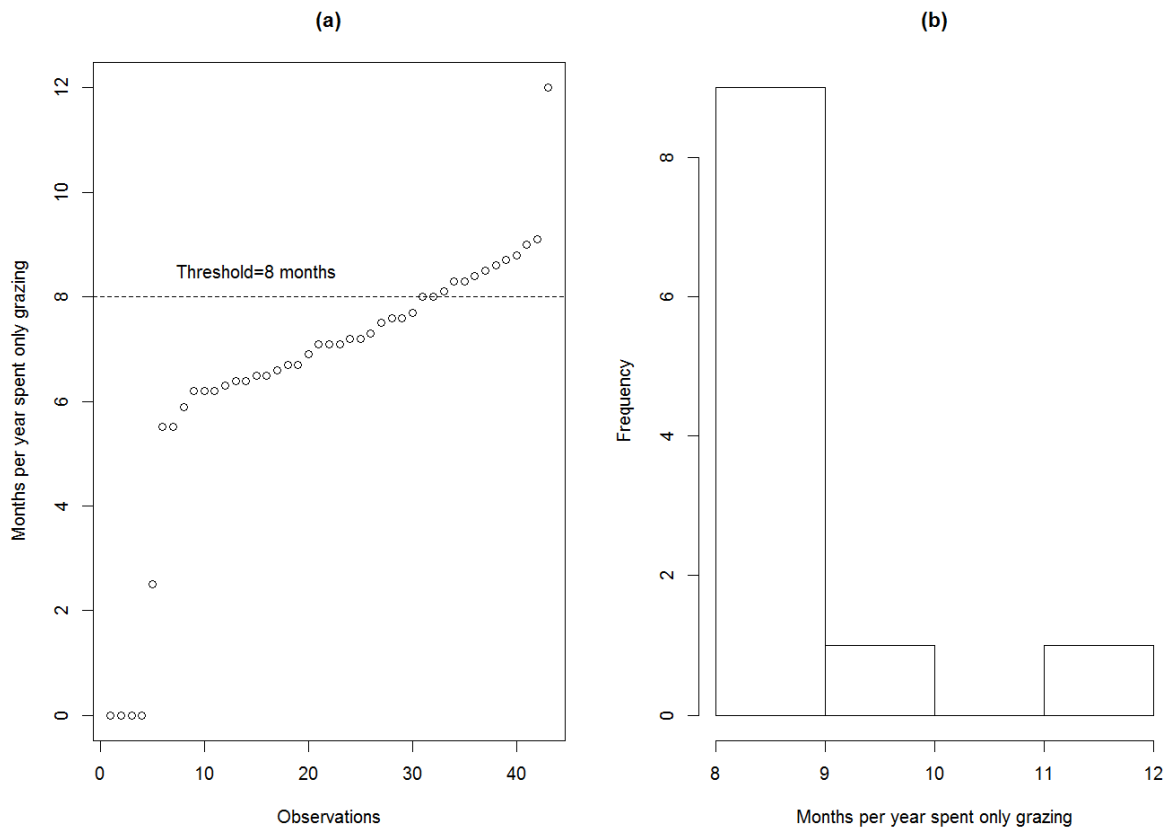
277 For extremely long times spent only grazing, the automatic selection procedure yielded the
278 threshold value $\mu = 8.0$ months/year (Table 4, Figure 3). At $\mu = 8.0$, the peak series had the
279 smallest RMSE, and estimated parameters for the fitted GPD function were $\hat{\sigma} = 0.786$
280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

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

| GPD Threshold μ | n_μ | Estimated parameters for GPD | | Root Mean Square Error | | | |
|------------------------|---------|---------------------------------|----------------------|------------------------|------|------|------|
| | | $\hat{\sigma}$ | $\hat{\varepsilon}$ | 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

284



285

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

290 The Pareto quantile plot for threshold $\mu = 8.0$ showed that scatter points ($-\log(1 - i/(n +$
291 $1)); \log(z_i)$) were approximated by a linear function with slope = $1.2 \cdot 10^{-1} \cong \hat{\varepsilon}$, intercept =
292 2.0 , an $R^2 = 0.80$ and a residual standard error = $0.4 \cdot 10^{-1}$.

293 For the three types of dairy-production systems considered, distributions of the time that cattle
294 spent only grazing, DOMI and predicted methane emissions under extremely long variations
295 had an absolute value of skewness of 1.5 and kurtosis of 5.1 (Table 5). More precisely,
296 distributions of extremely long variations of the simulated variables were skewed to the left
297 (negative skewness) for time spent grazing and to the right (positive skewness) for DOMI and
298 predicted methane emissions. Moreover, coefficients of variation of the distributions of the
299 three variables simulated under extremely long variations were one-half of those simulated
300 under average variations (Table 5). From the average to extremely long variations simulated,
301 mean and maximum DOMI and predicted methane emissions decreased. For instance, for the
302 intensive system, mean values of DOMI and predicted methane emissions decreased by 4.6%
303 and 4.8%, respectively, while maximum values decreased by 16.8% and 14.9%, respectively.
304 Minimum values of DOMI and methane emissions were the same for average and extremely
305 long variations. For DOMI, 75% (the third quartile) of the simulated values were less than
306 4003 and 4284 kg/cow/year under extremely long and average variations, respectively. For
307 predicted enteric methane emissions, 75% of the simulated values were less than 5013 and
308 5381 kg/cow/year under extremely long and average variations, respectively. Similar results
309 were obtained for the two other types of dairy-production systems. More time spent only
310 grazing decreased mean methane emissions (g CH₄) per cow and per kg of milk, the latter
311 from 15.8 to 15.1 for the intensive system, 19.4 to 18.5 for the semi-intensive system and 19.0
312 to 18.5 for the extensive system (Table 5).

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

320 For the intensive system, two-sample Student's t-tests identified significant differences
321 between mean DOMI (and thus methane emissions) simulated from extreme (extremely long

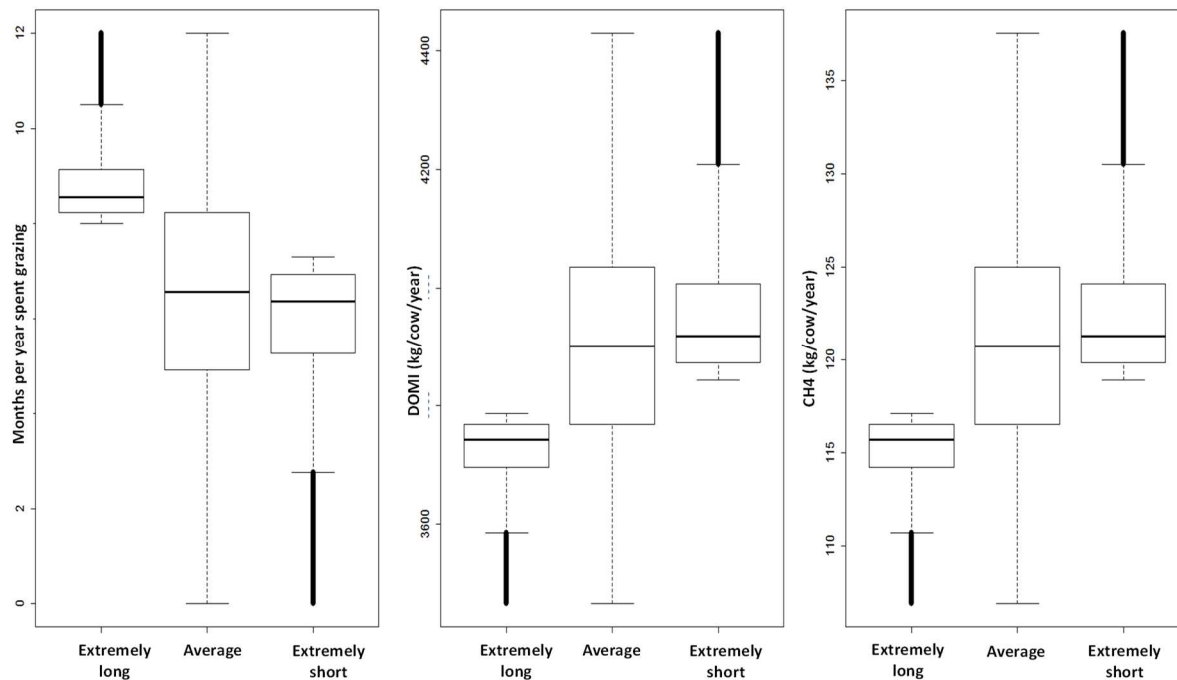
322 and short) and average variations in time that cattle spent grazing (Tables S4 and S5,
 323 Supplementary Material). Simulated values of time that cattle spent only grazing, DOMI and
 324 methane emissions under the extreme and average variations differed, but results simulated
 325 under extremely short variations were the closest to those simulated under average variations
 326 (Figure 4, for the semi-intensive system).

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

| Variables | Variations simulated | 1 st Qu. | Mean | 3 rd 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) | | | | | | |

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

339 4. Discussion

340 *Variations in dry matter intake and enteric methane emissions*

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

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

373 *Nutritional management strategies to mitigate GHG emissions*

374 The range of variation in time spent grazing also reflects changes in feed rations and must be
375 discussed when considering nutritional management strategies to mitigate enteric methane
376 production. In our study, more time spent only grazing resulted in replacing maize silage and
377 preserved grass with grazed grass (Table S6, Supplementary Material), which decreased mean
378 methane emissions (g CH₄) per kg of milk and per cow. The type of pasture must be also
379 considered when extending grazing time, since cattle grazing alfalfa emitted more methane
380 than those grazing grass pastures, depending on sward maturity at grazing (Chaves et al.,
381 2006; Archimède et al., 2011). Another nutritional strategy that may reduce enteric methane
382 emissions consists of feeding maize and cereal silages instead of grass silage, since maize is
383 already cultivated and fed to increase animal performance (Beauchemin et al., 2008). For
384 instance, feeding grass silage instead of maize silage in a previous experiment decreased
385 methane emissions per kg of milk by ca. 15%, from ca. 13 to ca. 11 g CH₄/kg of milk (Doreau
386 et al., 2011). How replacement of maize or cereal silage by grass silage affects methane

387 emissions should be further investigated in combination with the effects of more time spent
388 grazing. Additional studies should focus on strategies to mitigate enteric methane emissions,
389 such as supplementing diets with feed additives such as plant extracts (Wilfart et al., 2013) or
390 enzymes. Nutrient composition (e.g., protein, fiber) should be investigated as well, since it is
391 known to affect intake and therefore methane emissions (Doreau et al., 2011). However, no
392 feed nutrient compositions were available in our study because they are not usually measured
393 on commercial farms.

394 Differences in diet strategies do not affect other GHG emissions (e.g., CO₂) in the same way
395 as enteric methane emissions. For instance, in a previous experiment, the type of pasture was
396 found not to affect CO₂ production (Chaves et al., 2006). From experimental data of 67
397 lactating dairy cows, diets based on grass or on maize silage differed little in CO₂ emissions
398 since internal use of nutrients (e.g., carbon) and the amount of carbon converted to CO₂
399 remained relatively constant when cows were fed according to requirements (Kirchgeßner et
400 al., 1991). Likewise, shifts in grass quality in another experiment were found to have no major
401 effect on CO₂ production, following a GHG mitigation strategy in dairy systems that changed
402 the diet from barley straw and protein concentrate to grazed grass (Lee et al., 2017). Note that
403 the energy used (e.g., to produce silage) must also be considered in the mitigation strategies
404 investigated (FAO, 2017). Increasing the time that cattle spend grazing would decrease the
405 quantity of maize silage consumed, which would likely decrease quantities of maize silage
406 produced or purchased, fertilizers applied, diesel used and electricity consumed. These
407 positive and negative changes would influence overall environmental impacts.

408 *Limitations of the study*

409 This study has some limitations. First, the average annual scale of data limited the choice of
410 models that predict methane emissions and the level of detail at which calculations were
411 performed. The model used in our study was easy to apply as a function of the quantity of
412 DOMI, and the EDEN-E data lay within the ranges of variation of the data used to develop
413 and calibrate the model. However, the model needs to be tested with datasets other than those
414 used to calibrate it. More detailed models that use factors such as the feeding level and the
415 percentage of DOMI as concentrate feed to predict methane emissions (Sauvant and Noziere,
416 2016) would have required more information than that available in our study. Second, it
417 ignores the sensitivity of dairy farms to inter-annual climate variation, since we did not have
418 measurements over several years. For instance, for a group of dairy farms with known

419 characteristics, one could apply EVT to the observed time that cattle spent only grazing in
420 each of several years. The peaks extracted from these time series would also enable
421 calculating the “return period”, defined as the mean time before a random variable exceeds a
422 given level over a long period. Knowing the return period of extreme values of time that cattle
423 spent grazing could help farmers manage dairy farms. Although not including EVT, an
424 interesting study examined the sensitivity of beef-production systems to climate conditions
425 and the subsequent impacts on technico-economic results (Mosnier et al., 2012). This study
426 simulated interannual variations in variables such as the purchase of forages, predicting that
427 beef farms with lower stocking rates tended to have more stable incomes. Third, the small
428 sample of dairy farms ($n = 43$), and thus the number of farms on which cattle grazed more
429 than the upper threshold of $\mu = 8$ months ($n_{\mu}=11$) or less than the lower threshold of $\mu = 7.3$
430 months ($n_{\mu} = 25$), and the small difference between the two thresholds, limits the
431 representativeness of results. To increase both the representativeness of data and the
432 generality of results would require increasing the sample size of dairy farms. Fourth, applying
433 EVT required extrapolating the models used. The data used to calibrate and validate variables
434 in most models of agricultural systems contain few values in the tails of distributions (i.e.,
435 extremely small or extremely large). Applying EVT raises the issue of building models and
436 collecting data specifically adapted to predict emissions under extreme variations.

437 *Research prospects*

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

444 Another research prospect is to apply EVT directly to environmental factors by adding a
445 submodel that generates environmental factors as input variables to models of dairy-
446 production systems. For instance, predicted rainfall could be used as input for a grass growth
447 model; for instance, predictions of the French climate model ARPEGE (Déqué et al., 1994)
448 were used as input for the crop model STICS (Ruget et al., 2012). This would require
449 additional data (e.g., soil quality, daily rainfall and temperature) and would raise the issue of
450 combining data and models from average-annual and daily time scales. Moreover, EVT could

451 be included in LCA studies to address risk and uncertainties in LCA modeling, perhaps even
452 helping to inform public policies, since several studies have highlighted the need to integrate
453 LCA and risk-analysis methods (Heijungs and Huijbregts, 2004).

454 **5. Conclusion**

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

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