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1 **Sensitivity of greenhouse gas emissions to extreme differences in forage**
2 **production of dairy farms**

3 Tristan SENGA KIESSE*, Michael S. CORSON, Gwenola LE GALLUDEC, Aurélie
4 WILFART

5 UMR SAS, INRA, AGROCAMPUS OUEST, 35000 Rennes, France

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

7 **Abstract**

8 Dairy farms follow a wide variety of management practices depending on the economic and
9 environmental objectives that farmers target. Management practices are reflected, among
10 other things, by a wide variety of forage-production and animal-feeding strategies, which
11 influence productivity and greenhouse gas (GHG) emissions of dairy farms. Many studies
12 focus on agricultural systems with “average” characteristics to generalize results to a larger
13 percentage of existing systems. This approach, however, ignores systems with uncommon
14 characteristics, whose environmental impacts may be unusually large (e.g. due to
15 inefficiencies) or small (e.g. due to innovations). To address this issue, we used Extreme-
16 Value Theory (EVT) as a statistical tool to identify dairy farms with forage-related
17 characteristics that could be considered “extreme”. Application of EVT to a dataset of 78
18 dairy farms in Normandy (France) identified 15-20% of dairy farms with extreme minimum
19 amounts of dry matter (DM) of grass from pastures or maize silage and 10-15% of farms with
20 extreme maximum amounts of one or the other. Mean amounts of DM between the minimum
21 sample and maximum sample differed by a factor of ca. 3 for grass and a factor of 1.5 for
22 maize silage. Consequently, the maximum sample for grass or maize silage had mean
23 estimated gross GHG emissions (kg CO₂ eq) 13% lower or 25% higher, respectively, than
24 those of the minimum sample. Four strategies were identified for setting DM of grass and
25 maize silage at extreme levels, which influenced milk production and GHG emissions.
26 Extreme changes in the DM of one forage were generally compensated by changes in those of
27 the other forage and concentrated feed fed at non-extreme levels, which influenced enteric
28 methane emissions, manure management or the amount of feeds purchased.

29 **Keywords:** animal feeding, environmental impact, extreme value, forage production

30 **1. Introduction**

31 Management practices of dairy farms are widely studied due to their influence on farm inputs,
32 which in turn influence farm productivity and environmental impacts. Studying effects of
33 management changes on greenhouse gas (GHG) emissions and farm profitability is useful for
34 developing farm-level GHG mitigation strategies that could be financially viable (Lovett et
35 al., 2008). For instance, animal-feeding strategies directly influence enteric methane (CH₄)
36 emissions of dairy cattle, which contribute ca. 67% of GHG emissions of the global livestock
37 sector (Dollé et al., 2011; Gerber et al., 2011; Gerber et al., 2013). Thus, studies that predict
38 CH₄ emissions from dairy cattle often consider feed and forage intake as input variables
39 (Bannink et al., 2011). The quantities of inputs used to feed animals (either directly, such as
40 concentrated feed, or indirectly, such as fertilizers) vary greatly among farms, which may
41 cause these farms' environmental impacts (e.g. GHG emissions) to vary greatly as well. Many
42 studies of agricultural systems focus on "average" characteristics to generalize results to a
43 larger percentage of existing systems. This approach, however, ignores systems with
44 uncommon characteristics, whose environmental impacts may be unusually large (e.g. due to
45 inefficiencies) or small (e.g. due to innovations).

46 This study was concerned with modeling and predicting consequences of "extreme events"
47 (e.g., uncommon farm characteristics), which can help understand how variability in dairy
48 farm characteristics influences their environmental impacts. Dairy farms are confronted with
49 extreme climate events, financial instability and environmental concerns such as climate
50 change. In this context, farmers are developing various agricultural strategies to ensure food
51 production, and these strategies are reflected in a wide variety of farm characteristics. This
52 raises the issue of identifying dairy farm inputs with uncommon values, which affect their
53 productivity and GHG emissions. Extreme-Value Theory (EVT) is the most popular approach
54 to model extreme events. To analyze agricultural systems accurately, an increasing number of
55 studies combine statistical analysis with quantitative models of environmental processes. For
56 instance, statistics-based sensitivity analysis can be performed to assess the relative influence
57 of input variables on model outputs (Confalonieri et al., 2010; Drouet et al., 2011). Likewise,
58 uncertainty analysis is used to assess the robustness of predicted environmental impacts of
59 agricultural systems (Basset-Mens et al., 2009; Chen and Corson, 2014; Cucurachi et al.,
60 2016). However, statistical analyses have generally failed to study variables with accuracy
61 when these variables deviate from average trends. In contrast, EVT considers the stochastic
62 nature of maximum and minimum values of a process (Embrechts et al., 1996; Charras-

63 Garrido and Lezaud, 2013). Initially developed to study flood levels, EVT is now applied to
64 finance, insurance, meteorological events and environmental sciences. For instance, EVT was
65 applied to examine trends in hydrological extremes due to the anticipated intensification in the
66 hydrological cycle caused by climate change (Katz et al., 2002). Likewise, EVT was used to
67 model hospitalization and death peaks due to cardiovascular disease in Canada (Chiu et al.,
68 2016) and to assess water quality by analyzing marine biomarkers (Durrieu et al., 2016). EVT
69 increases the rigor of studies of extreme events by enabling one to statistically test and
70 identify threshold values and suitable probability distribution functions for modeling the tails
71 of distributions. To our knowledge, EVT has never been used to analyze dairy farms.

72 Based on a sample of dairy farms in Normandy (France), this study aimed to (1) identify those
73 with “extreme” forage-related characteristics and (2) compare their milk production and GHG
74 emissions. Groups of farms identified with extreme forage-related characteristics were also
75 compared according to other characteristics, such as their size (e.g. number of livestock units
76 (LU), utilized agricultural area (UAA)), areas of forage crops and sources of GHG emissions.

77

78 **2. Material and methods**

79 **2.1. Data**

80 The dataset consisted of 78 dairy farms in Normandy surveyed in 2014 by the French
81 Livestock Institute (IDELE). Annual data for a variety of annual farm inputs, characteristics
82 and outputs were collected for each farm: areas of pastures and silage maize in the forage
83 area, grass yield, number of LU, milk produced per cow, amount of concentrated feed fed,
84 estimated CH₄ emissions from dairy cows and heifers (Table 1). The main dairy cow breeds
85 were Holstein (minimum, mean and maximum of 45%, 89% and 100%, respectively) on 54
86 farms, Normande (61%, 89% and 100%, respectively) on 18 farms, and cross-breeds (50%,
87 63% and 100%, respectively) on 6 farms. GHG emissions (CH₄, nitrous oxide and carbon
88 dioxide) due to production and transport of purchased feeds, purchased fertilizers and on-farm
89 energy consumption were estimated. Milk production per cow was calculated as total milk
90 production per year divided by the number of dairy cows.

91 Table 1. Descriptive statistics of annual characteristics of 78 dairy farms in Normandy
 92 (France) in 2014. 1Q = 1st quartile, 3Q = 3rd quartile, CV = coefficient of variation, GHG =
 93 greenhouse gas

Characteristic	Min	1Q	Median	Mean	3Q	Max	CV (%)
Utilized Agricultural Area (UAA) (ha)	30.6	82.5	104.9	118.7	149.4	258.1	44
Main Forage Area (ha)	21.5	56.7	76.7	83.5	98.1	204.4	45
Area of pastures (ha)	13.8	35.4	45.4	55.8	73.2	161.5	59
Area of pastures in UAA (%)	15.2	34.6	44.9	48.1	59.0	100.0	40
Area of silage maize (ha)	0.0	18.2	24.7	27.1	36.1	59.6	48
Area of silage maize in UAA (%)	0.0	17.9	24.3	24.1	31.2	44.6	38
Number of livestock units	32	81	97	108	130	201	36
Replacement rate (%)	0.0	26.0	31.5	30.5	36.0	55.0	32
Grass yield (t DM/ha/year)	1.9	4.7	5.9	6.1	7.1	12.6	32
Concentrated feed fed (g/l milk)	0.0	144.5	184.0	184.8	16.8	319.0	35
Milk production per cow (l/year)	4271	6278	7387	7210	8283	9490	18
Gross GHG emissions (kg CO ₂ eq/farm/year)	3830	6173	6725	6618	7160	8118	12
Enteric CH ₄ emissions (kg CO ₂ eq/farm/year)	2537	3421	3576	3566	3729	4408	10

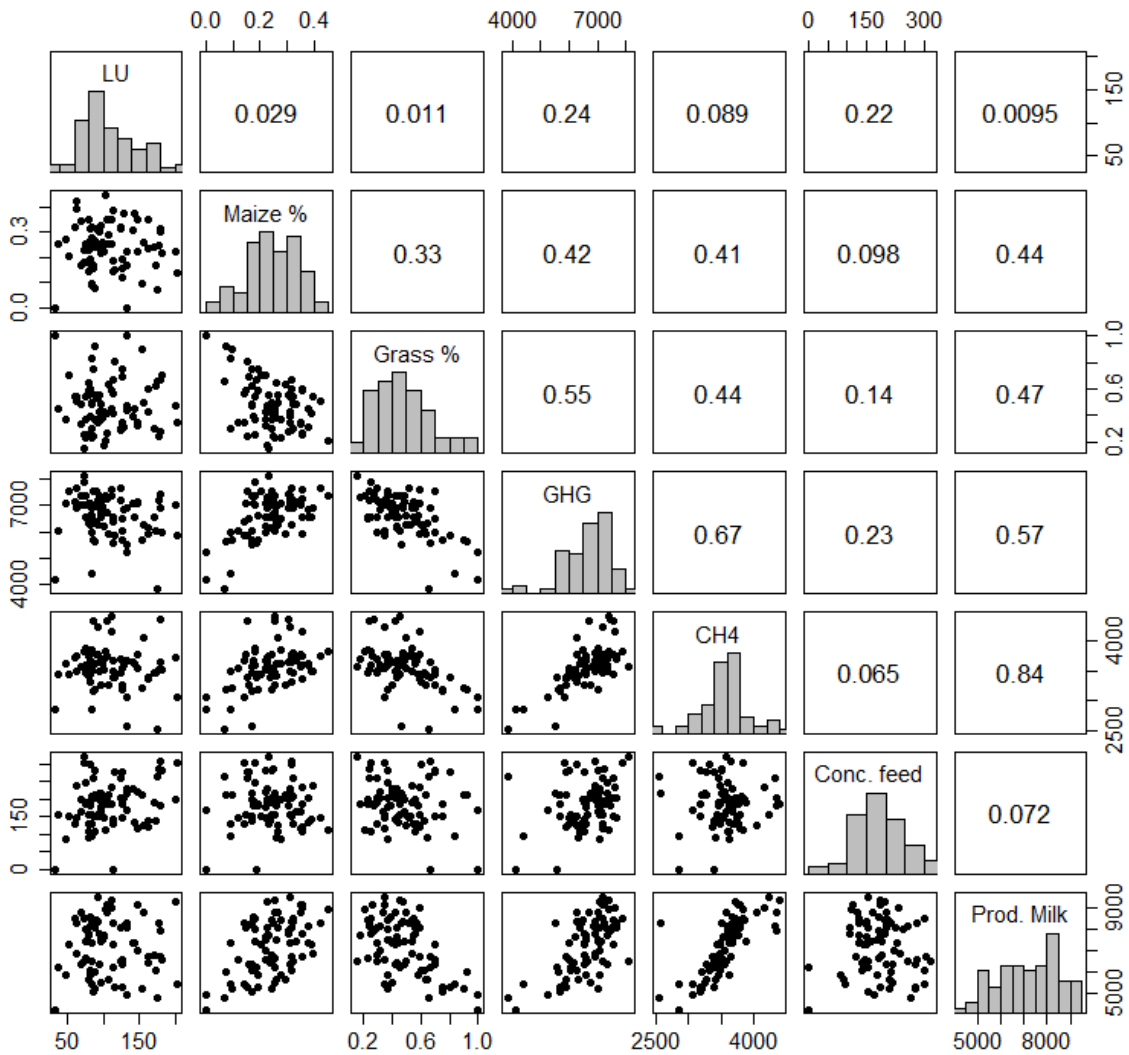
94

95 IPCC Tier 3 methodology (IPCC, 2006) was used to predict CH₄ emissions (g CH₄/kg of
 96 digestible organic matter) from dairy cows and heifers, based on an empirical model adapted
 97 to French national contexts that considers factors such as feeding levels and proportion of
 98 concentrated feed in the diet (Sauvant and Noziere, 2016). The main sources of GHG
 99 emissions were enteric fermentation from cattle (50%), manure storage and management
 100 (20%), organic and inorganic fertilization (9%), production and transport of inputs (e.g. feeds
 101 (12.5%), fertilizers (3%), and animals (<1%)), and on-farm energy consumption (5%)
 102 (Supplementary Table A1). Emissions were estimated from information provided by farmers.
 103 For instance, the amount of manure produced per year per farm was estimated from the type
 104 of animal housing, milk production (for dairy cows) and calving period (for suckler cows).
 105 Farmers also supplied additional information, such as the average duration of manure storage
 106 and amounts of off-farm effluents imported. Likewise, farmers provided amounts of mineral
 107 fertilizers and effluents applied per ha, feed purchased and total energy (electricity and diesel)
 108 consumed based on information in their bills and accounting books. GHG emissions from
 109 these sources were estimated using emission factors (e.g. kg CO₂ eq per kg of feed, kWh of

110 electricity or L of diesel purchased). Carbon sequestration (e.g. by pastures) was not
 111 considered. These contributions to GHG emissions led to a strong correlation between GHG
 112 (and enteric CH₄) emissions and milk produced per cow (Figure 1).

113

114



115

116 Figure 1. Pairwise scatter plots of areas of pastures and silage maize in UAA (%), number of
 117 livestock units (LU), concentrated feed fed (g/l of milk produced), milk production per cow
 118 (l), and estimated greenhouse gas (GHG) and enteric methane (CH₄) emissions (kg CO₂
 119 eq/farm/year) of 78 dairy farms in Normandy (France) in 2014, with Spearman's rho rank
 120 correlation coefficients ρ_n ($n=78$).

121 We calculated each farm's production of each forage per LU (kg dry matter (DM)/LU/year)
 122 by dividing the total DM of grass from pastures (DM_{Grass}) or maize silage (DM_{Maize}) (equal to
 123 area (ha) \times yield (t DM/ha)) by the number of LU. Since the yield of silage maize was not
 124 available for dairy farms in our dataset, we used the mean regional yield of 19.3 t DM/ha in
 125 2014 (ARVALIS-Institut du Végétal). DM_{Grass} and DM_{Maize} varied greatly among farms
 126 (coefficients of variation (CV) = 47% and 38%, respectively), but the variability in DM_{Maize}
 127 was due only to that of the area of silage maize, since we used the mean yield. Distributions
 128 of the amount of concentrated feed fed had similar characteristics as those of DM_{Grass} and
 129 DM_{Maize} (CV = 35%) (Table 1). Milk production per cow and estimated GHG and CH₄
 130 emissions, however, varied less (CV = 10-18%) (Table 1). Annual GHG and CH₄ emissions
 131 were analyzed according to two functional units: farm (kg CO₂ eq/farm/year) and l of milk
 132 produced (kg CO₂ eq/l/year).

133 2.2. Extreme-Value Theory

134 Consider a sequence of independent and identically distributed (iid) random variables (rv)
 135 X_1, X_2, \dots, X_n with realizations x_1, x_2, \dots, x_n , with its maximum sequence being denoted
 136 by Z_n . Within the EVT framework, limit laws for the (normalized and centered) Z_n of the iid
 137 inputs X_1, X_2, \dots, X_n belong to asymptotic distributions of type Fréchet, Weibull or Gumbel
 138 (Embrechts et al., 1996). EVT thus enables identification of probability distribution functions
 139 of inputs affected by extreme variations. Applying EVT to a dataset consists of extracting a
 140 maximum sequence, z_1, z_2, \dots, z_n , which contains values at maximum values of inputs, then
 141 fitting it using appropriate probability distribution functions such as the generalized Pareto
 142 distribution (GPD) (Coles, 2001). EVT also enables one to extract a minimum sequence and
 143 then fit it using extreme value distributions.

144 2.2.1. Generalized Pareto distribution

145 For a fixed threshold μ , consider the distribution of the excesses $z = x - \mu$ above μ , extracted
 146 from observations x of the rv X . The excess distribution function $P(X \leq x | X > \mu)$ above μ
 147 can be approximated by a GPD function, with parameter $\theta=(\sigma, \varepsilon)$, defined by the empirical
 148 distribution function

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

149 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
150 (Beirlant et al., 2004). GPD also enables one to approximate distribution function of values
151 below another fixed threshold μ extracted from observations x of the rv X .

152 **2.2.2. Threshold selection**

153 Selecting the threshold μ requires a compromise between selecting too-small and too-large
154 values of μ , which affects the bias and variance of the estimated GPD parameters. Setting μ
155 too small increases the sample size of extremes and the bias of estimated parameters to the
156 point that the fitted GPD may not approximate the tail well. Conversely, setting μ too large
157 decreases the sample size of extremes, increasing the variance in estimated parameters.
158 Finally, μ must be sufficiently large to ensure that the GPD is a reliable model (Scarrott and
159 MacDonald, 2012). Several methods are available to select μ , such as automatic selection of a
160 threshold based on the Hill estimator (Grama and Spokoiny, 2008; Durrieu et al., 2015) and
161 graphical assessment using a mean residual life function and threshold stability properties. We
162 chose to test four minimum and maximum extreme quantiles each and use them to calculate
163 the corresponding values of μ (Chiu et al., 2016).

164 **2.2.3. Statistical tests and root mean squared error**

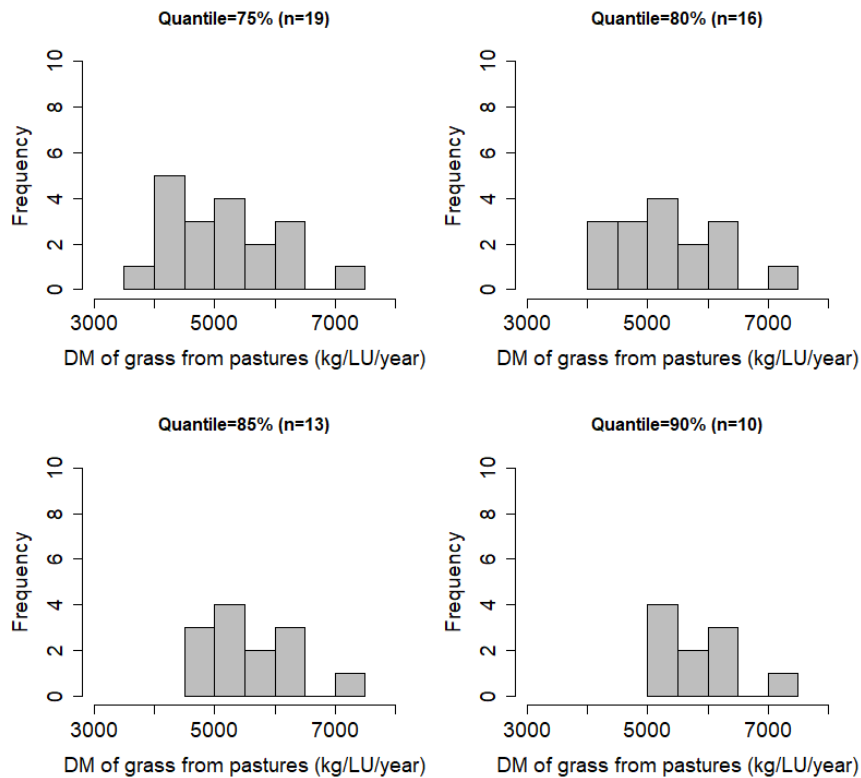
165 Once the minimum or maximum sample was extracted, the adequacy of its distribution to the
166 GPD was tested using the Kolmogorov-Smirnov (K-S) test. For the K-S test, the null
167 hypothesis H_0 was that the extracted sample followed a GPD, with results considered
168 significant at $\alpha=5\%$. For each quantile tested, the extracted sample was also compared to the
169 fitted GPD using the root mean squared error (RMSE). The Mann-Whitney (M-W) U test was
170 also performed to test differences in mean farm characteristics between the minimum and
171 maximum samples, with the differences considered significant at $\alpha=5\%$. For the M-W test,
172 the null hypothesis H_0 was that characteristics of farms in the minimum and maximum
173 samples followed the same distribution. We used the “evd” (Stephenson, 2002) and
174 “extremefit” (Durrieu et al., 2017) packages of R software (R Core Team, 2018) to apply
175 EVT.

176

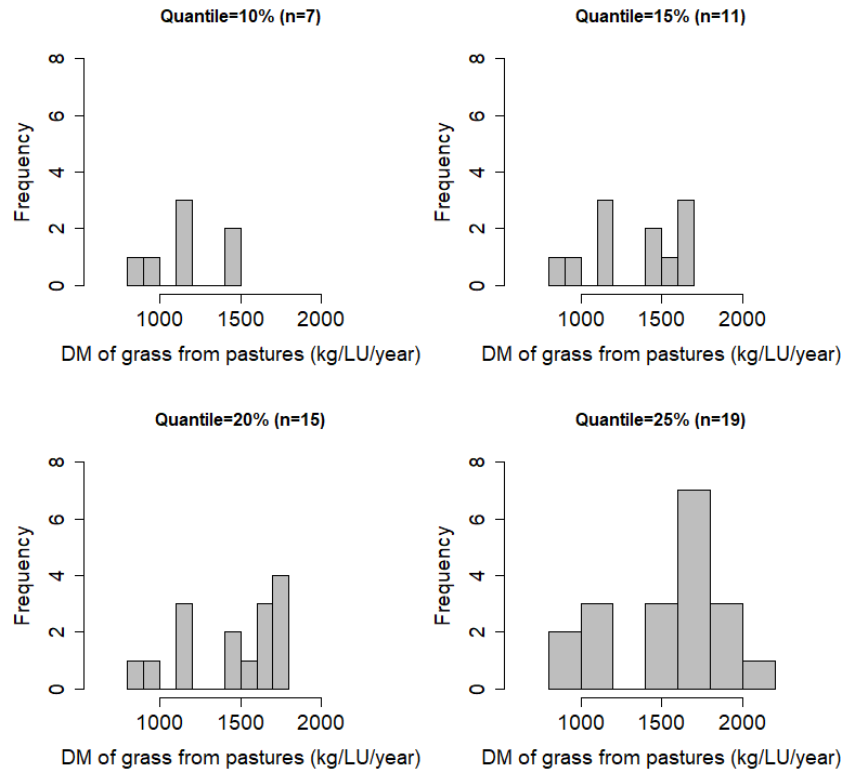
177 **3. Results**

178 **3.1. Extreme samples for dry matter of grass from pastures**

179 Quantiles of the entire dataset were tested as potential thresholds for the minimum (10%,
180 15%, 20% and 25%) and maximum (75%, 80%, 85% and 90%) samples (Table 2).
181 Distributions of extracted minimum and maximum samples changed as the quantile increased
182 (Figure 2 and Figure 3).



183
184 Figure 2. Distributions of the maximum sample of dry matter (DM) of grass from pastures
185 (kg/livestock unit (LU)/year) extracted as a function of dataset quantile (75%, 80%, 85% and
186 90%)
187



188

189 Figure 3. Distributions of the minimum sample of dry matter (DM) of grass from pastures
 190 (kg/livestock unit (LU)/year) extracted as a function of dataset quantile (10%, 15%, 20% and
 191 25%)

192

193 The K-S test did not reject the null hypothesis of the adequacy of the GPD for any of the
 194 quantiles considered. For the minimum sample (GrassMIN), the 10% and 15% quantiles had
 195 the smallest RMSE but did not have the largest p-values of the K-S test (Table 2). Because the
 196 sample size of the 10% quantile was 7, we selected the 15% quantile as the minimum
 197 threshold, corresponding to DM_{Grass} of 1708 kg/LU/year, to obtain a larger sample size of 11.
 198 For the maximum sample (GrassMAX), we selected the 90% quantile, which had the largest
 199 p-value, the smallest RMSE and sample size of 10, as the maximum threshold, corresponding
 200 to DM_{Grass} of 4946 kg/LU/year (Table 2). Other choices of thresholds were obviously
 201 possible.

202 Table 2. Results of applying Extreme-Value Theory to extract minimum (“MIN”) and
 203 maximum (“MAX”) samples of dry matter (DM) of grass from pastures (kg/livestock unit
 204 (LU)/year) as a function of multiple quantiles of the entire dataset of 78 farms in Normandy
 205 (France). Bold values indicate the quantiles retained as thresholds. RMSE = root mean
 206 squared error, K-S = Kolmogorov-Smirnov.

Sample	Quantile	DM of grass (kg/LU/year)	Sample size	Estimated shape $\hat{\epsilon}$	Estimated scale $\hat{\sigma}$	RMSE	K-S adequacy test (p-value)
MIN	10%	1586	7	-0.50	451.02	489.23	0.10
	15%	1708	11	-0.26	400.02	482.11	0.33
	20%	1868	15	-0.30	471.12	531.47	0.55
	25%	2088	19	-0.29	547.12	646.07	0.11
MAX	75%	3614	19	-0.28	1528.51	1790.08	0.23
	80%	4176	16	-0.20	1185.48	1458.05	0.62
	85%	4480	13	-0.22	1115.73	1356.73	0.66
	90%	4946	10	-0.18	919.31	1142.26	0.85

207

208 3.2. Extreme samples for dry matter of maize silage

209 EVT was also applied to observations of DM_{Maize} . Like for DM_{Grass} , the K-S test did not reject
 210 the null hypothesis (Table 3). Thus, to obtain sufficiently large sample sizes, minimum and
 211 maximum quantiles of 20% and 85%, respectively, were selected for minimum (MaizeMIN)
 212 and maximum samples (MaizeMAX) of DM of maize silage, respectively, corresponding to
 213 threshold values of 3647 and 6443 kg/LU/year, respectively.

214 Table 3. Results of applying Extreme-Value Theory to extract minimum (“MIN”) and
 215 maximum (“MAX”) samples of dry matter (DM) of maize silage (kg/livestock unit
 216 (LU)/year) as a function of multiple quantiles of the entire dataset of 78 farms in Normandy
 217 (France). Bold values indicate the quantiles retained as thresholds. RMSE = root mean
 218 squared error, K-S = Kolmogorov-Smirnov.

Sample	Quantile	DM of maize silage (kg/LU/year)	Sample size	Estimated shape $\hat{\epsilon}$	Estimated scale $\hat{\sigma}$	RMSE	K-S adequacy test (p-value)
MIN	10%	2860	5	-0.34	1517.92	1024.74	0.57
	15%	3439	9	-0.19	1457.39	1205.25	0.78
	20%	3647	13	-0.03	1237.25	1152.08	0.49
	25%	3811	17	0.03	1124.43	1120.97	0.34
MAX	75%	5872	19	0.01	1306.87	1863.52	0.90
	80%	6115	16	0.02	1282.16	1853.90	0.84
	85%	6443	13	0.06	1225.65	1820.91	0.67
	90%	6935	8	0.07	1318.36	1945.92	0.61

219

220 According to these thresholds, three farms were in both GrassMIN and MaizeMAX, five
 221 farms were in both GrassMAX and MaizeMIN, and one farm was in both GrassMAX and
 222 MaizeMAX (Figure 4).

223 3.3. Milk production and emissions by sample

224 On average, GrassMAX and GrassMIN produced less and more milk per cow (6269 and 7954
 225 l/cow/year, respectively) than the mean of the entire dataset (7210 l/cow/year) (Table 4).
 226 Similar differences in means were observed for annual GHG and enteric CH₄ emissions (kg
 227 CO₂ eq) per farm and per l of milk produced (Table 5). Amounts of concentrated feed fed for
 228 GrassMAX and GrassMIN were less than the dataset mean.

229 Conversely, MaizeMIN and MaizeMAX produced less and more milk per cow (5785 and
 230 7351 l/cow/year, respectively) than the dataset mean (7210 l/cow/year) (Table 4). Similar
 231 differences in means were observed for annual GHG and enteric CH₄ emissions per farm
 232 (Table 5). Per l of milk produced, annual GHG and enteric CH₄ emissions for MaizeMIN and
 233 MaizeMAX were generally slightly greater than or equal to, respectively, the dataset mean.
 234 Amounts of concentrated feed fed for MaizeMIN and MaizeMAX were less or slightly
 235 greater, respectively, than the dataset mean (Table 5).

236

237 Table 4. Mean and coefficient of variation (CV) of annual farm characteristics for the entire
 238 dataset and for farms in minimum (“MIN”) and maximum (“MAX”) samples of dry matter
 239 (DM) of grass and maize silage. % chg. = percentage increase from minimum to maximum
 240 sample. M-W p = p-value of Mann-Whitney test for the difference between minimum and
 241 maximum samples. UAA = Utilized Agricultural Area, MFA = Main Forage Area, LU =
 242 livestock unit

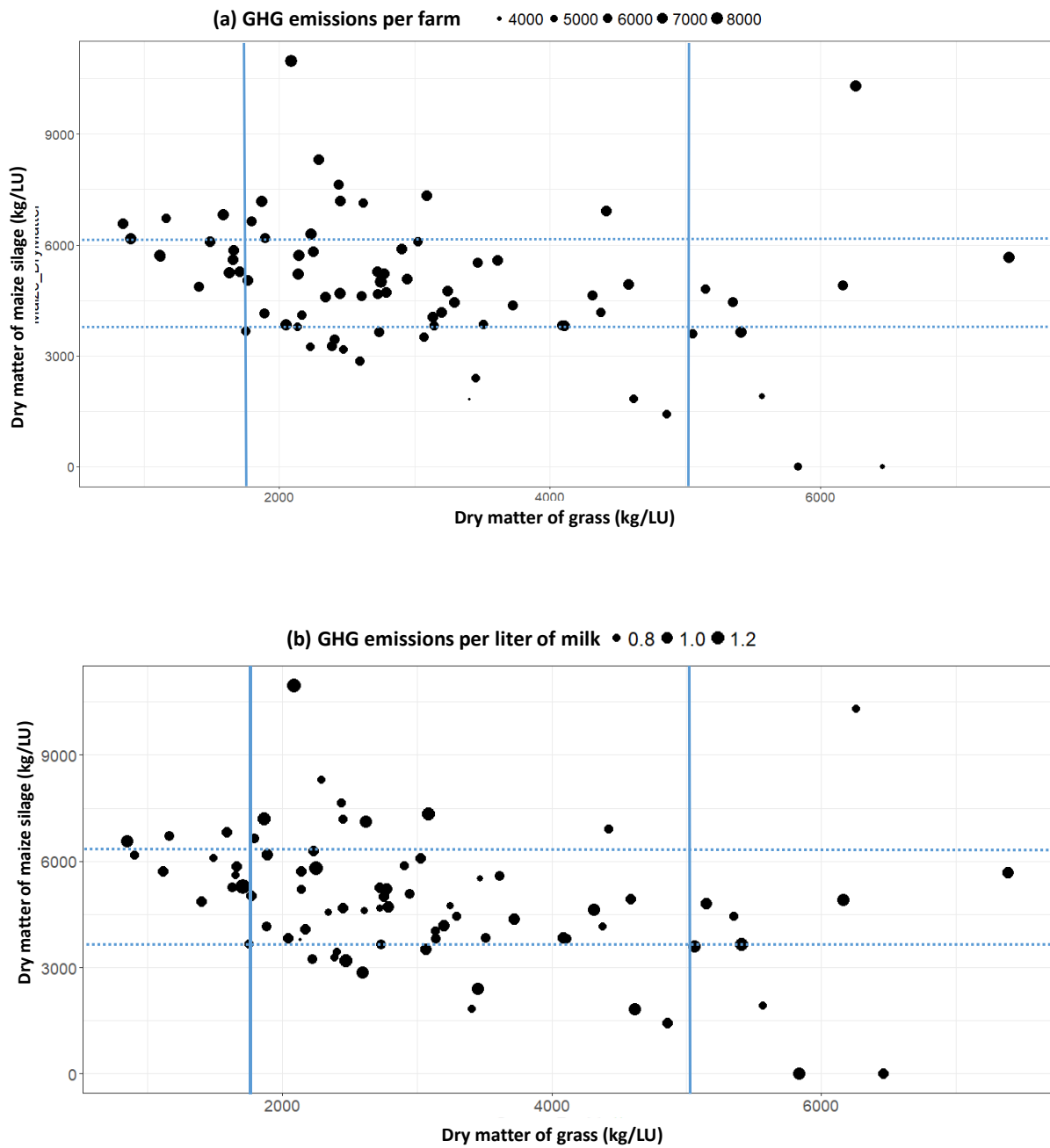
Variable	Statistic	Entire dataset	Grass DM sample			Maize silage DM sample				
			MIN sample	MAX sample	% chg.	M-W p	MIN sample	MAX sample	% chg.	M-W p
UAA (ha)	Mean	118.7	121.7	124.8	+3%	0.56	112.7	127.8	+13%	0.27
	CV	44%	26%	56%			51%	36%		
MFA (ha)	Mean	83.5	76.2	103.8	+36%	0.39	94.2	90	-5%	0.75
	CV	45%	39%	52%			45%	41%		
Grass DM (kg/LU/year)	Mean	3031	1325	5862	+342%	<0.001	3987	2531	-36%	0.07
	CV	47%	23%	12%			37%	56%		
Maize silage DM (kg/LU/year)	Mean	4836	5939	3931	-33%	0.02	2409	7669	+150%	<0.001
	CV	38%	10%	76%			51%	19%		
Number of LU	Mean	108	119	93	-21%	0.10	111	102	-8%	0.55
	CV	36%	24%	44%			39%	30%		
Concentrated feed fed (g/l milk prod./year)	Mean	185	177	153	-13%	0.39	173	186	+7%	0.85
	CV	35%	25%	47%			55%	34%		
Milk prod. per cow (l/year)	Mean	7210	7954	6269	-21%	0.04	5785	7351	+27%	<0.001
	CV	18%	12%	24%			19%	15%		

243

244 Table 5. Mean and coefficient of variation (CV) of annual gross greenhouse gas (GHG) and
 245 enteric methane (CH₄) emissions (kg CO₂ eq) by functional unit (FU) (per farm or per l of
 246 milk produced) for the entire dataset and for farms in minimum (“MIN”) and maximum
 247 (“MAX”) samples of dry matter (DM) of grass from pastures and maize silage. % chg. =
 248 percentage change from minimum to maximum sample. M-W p = p-value of Mann-Whitney
 249 test for the difference between emissions for farms in minimum and maximum extracted
 250 samples of DM of each forage.

FU	Variable	Statistic	Grass DM sample				Maize silage DM sample				
			Entire dataset	MIN sample	MAX sample	% chg.	M-W p	MIN sample	MAX sample	% chg.	M-W p
Farm	GHG emissions	Mean	6618	7044	6113	-13%	0.13	5549	6962	+25%	<0.001
		CV	12%	7%	20%			16%	9%		
	Enteric CH ₄ emissions	Mean	3566	3430	3667	-6%	0.05	3208	3616	+12%	0.001
		CV	10%	13%	4%			9%	8%		
l of milk produced	GHG emissions	Mean	0.93	0.89	0.99	+11%	0.03	0.98	0.97	-1%	0.93
		CV	14%	11%	13%			13%	17%		
	Enteric CH ₄ emissions	Mean	0.50	0.46	0.56	+21%	0.003	0.56	0.50	-11%	0.02
		CV	13%	8%	13%			11%	12%		

251



252 Figure 4. Bivariate plot of annual gross greenhouse gas (GHG) emissions (kg CO₂ eq) of
 253 farms (a) per farm and (b) per l of milk produced, as a function of annual dry matter (kg per
 254 livestock unit (LU) per year) of grass (with solid lines for maximum and minimum
 255 thresholds) and maize silage (with dashed lines for maximum and minimum thresholds)
 256

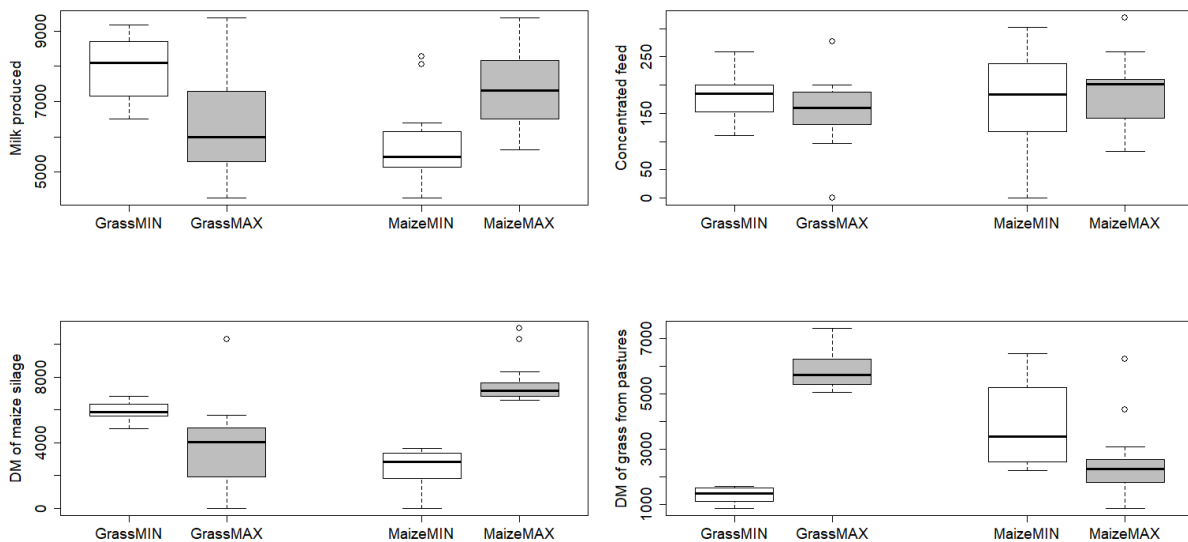
257 3.4. Sensitivity to extreme differences in DM of grass from pastures and maize silage

258 3.4.1. Milk production and farm sizes

259 GrassMAX had mean DM_{Grass} 3 times as high as GrassMIN, and its farms produced 21% less
260 milk per cow, had 33% less DM_{Maize} and fed 13% less concentrated feed per l of milk (Table
261 4, Figure 5). In contrast, MaizeMAX had mean DM_{Maize} 150% higher than that MaizeMIN,
262 and its farms produced 27% more milk per cow, had 36% less DM_{Grass} and fed 7% more
263 concentrated feed per l of milk (Table 4, Figure 5). The difference in the amount of milk
264 produced per cow between the minimum and maximum samples of DM_{Grass} or DM_{Maize} was
265 significant according to the M-W test (i.e. the null hypothesis was rejected) (Table 4).
266 Although MaizeMAX or GrassMIN produced more milk per cow than MaizeMIN or
267 GrassMAX, respectively, their farms did not differ significantly in mean size (e.g. number of
268 LU, UAA) (Table 4) or replacement rate (29-31% among the four extreme samples)
269 (Supplementary Table A2).

270 Cross-comparison of the same end of the distribution of each forage showed that GrassMIN
271 produced 27% more milk per cow than MaizeMIN (Table 4). Conversely, MaizeMAX
272 produced 17% more milk per cow than GrassMAX. Meanwhile, MaizeMAX fed 21% more
273 concentrated feed per l of milk than GrassMAX, while MaizeMIN fed 2% less concentrated
274 feed per l of milk than GrassMIN (Table 4).

275



276

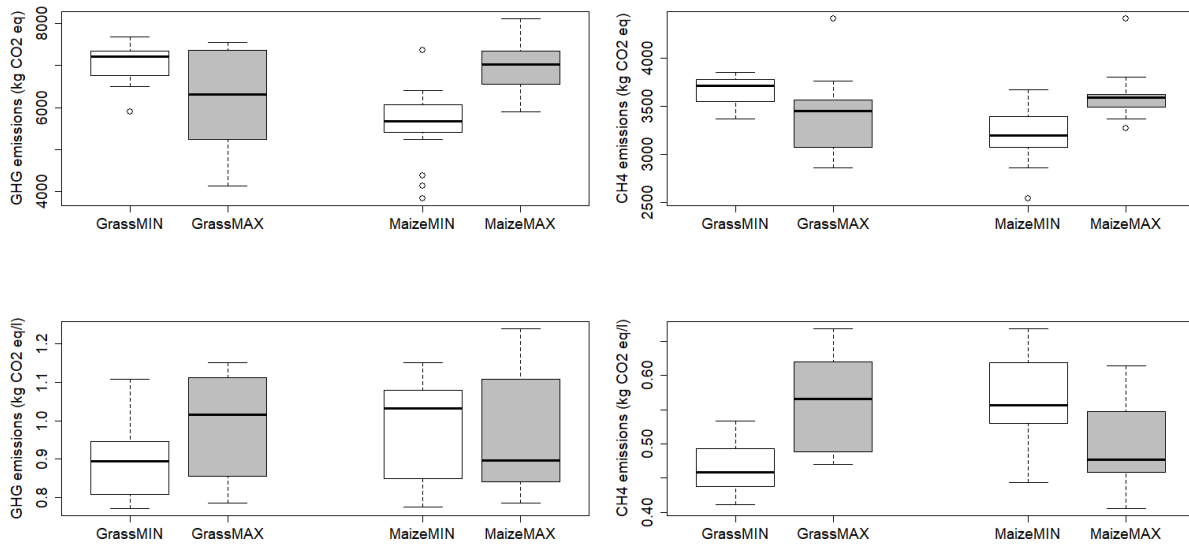
277 Figure 5. Boxplots of milk production per cow (l/cow/year), concentrated feed fed (g/l of milk
278 produced), grass from pastures and maize silage (kg dry matter (DM)/livestock unit/year) for

279 farms in minimum (“MIN”) and maximum (“MAX”) samples of DM of grass from pastures
280 and maize silage

281

282 **3.4.2. GHG and enteric methane emissions per farm**

283 Per farm, GrassMAX emitted 13% less gross GHGs than GrassMIN (non-significant), while
284 MaizeMAX emitted 25% more than MaizeMIN (significant) (Table 5, Figure 6). The same
285 trend was observed for enteric CH₄ emissions, which were the main source (48-54%) of GHG
286 emissions among the four extreme samples. The other sources – manure storage and
287 management, purchased feeds, organic and inorganic fertilization, energy consumption and
288 purchased fertilizers – contributed a mean of 18-21%, 9-14%, 8-10%, 5-6% and 2-3%,
289 respectively, among the four extreme samples. Compared to MaizeMIN, percentage
290 contributions to gross GHG emissions of enteric CH₄ emissions, manure storage and
291 management, and organic and inorganic fertilization for MaizeMAX differed significantly:
292 11% lower, 12% lower and 32% higher, respectively (Supplementary Table A2). The
293 percentage contribution of purchased feeds was also higher (by 37%), but not significantly so.
294 Compared to GrassMIN, percentage contributions of these sources for GrassMAX did not
295 differ significantly, except for that of purchased feeds, which was significantly lower. On-
296 farm energy consumption and purchased fertilizers did not differ significantly between
297 GrassMAX and GrassMIN or between MaizeMAX and MaizeMIN.



299

300 Figure 6. Distributions of annual gross GHG and enteric methane (CH₄) emissions (top) per
 301 farm per year (kg CO₂ eq/farm/year) and (bottom) per l of milk produced (kg CO₂ eq/l/year)
 302 for farms in minimum (“MIN”) and maximum (“MAX”) samples of dry matter (DM) of grass
 303 from pastures and maize silage

304

305 3.4.3. GHG and enteric methane emissions per l of milk produced

306 Per l of milk produced, GrassMAX emitted 17% more gross GHGs than GrassMIN
 307 (significant), while MaizeMAX emitted 1% less than MaizeMIN (non-significant) (Table 5,
 308 Figure 6). Enteric CH₄ emissions followed the same trend: 20% larger for GrassMAX than
 309 GrassMIN and 11% smaller for MaizeMAX than MaizeMIN (both significant). Cross-
 310 comparison of the same end of the distribution of each forage showed that GrassMIN emitted
 311 17% less GHGs than MaizeMIN, but GrassMAX emitted nearly the same amount of GHGs as
 312 MaizeMAX (1% difference). In comparison, GrassMIN emitted 21% less enteric CH₄ than
 313 MaizeMIN, but GrassMAX emitted 10% more enteric CH₄ than MaizeMAX.

314

315 **4. Discussion**

316 **4.1. Differences in forages and concentrated feed, milk production and cattle**
317 **management**

318 Extreme changes in the amount of DM of a given type of forage (grass or maize silage) were
319 generally compensated by changes in the other forage and concentrated feed fed at non-
320 extreme levels. To feed their animals, MaizeMAX maintained grass from pastures and
321 concentrated feed at levels similar to those of MaizeMIN. In contrast, GrassMAX fed less
322 maize silage than GrassMIN but maintained concentrated feed at a level similar to that of
323 GrassMIN. Meanwhile, an extreme increase in DM_{Maize} was associated with increased milk
324 production, since maize silage yields a large amount of DM and increases animal performance
325 when included in animal diets (Beauchemin et al., 2008). Although most farms had Holstein
326 cows (45-100% of cows on 69% of the farms), the prevalence of Normande cows (61-100%
327 of cows on 23% of the farms) may have increased variability around the relation between
328 DM_{Maize} and milk production. Management practices for cattle, in terms of replacement rate,
329 did not differ significantly between farms in minimum and maximum samples of each forage.
330 Meanwhile, the stocking rate (i.e. LU/ha Main Forage Area) decreased significantly from
331 GrassMIN to GrassMAX but not from MaizeMIN to MaizeMAX.

332 **4.2. Land management strategies**

333 As expected, significant differences in the percentage of UAA in pastures and maize silage
334 were found between farms in minimum and maximum samples of each forage
335 (Supplementary Table A2), since the area of each forage was used to calculate DM. On a 70
336 ha commercial farm in the Netherlands, Vellinga and Hoving (2010) studied effects of
337 increasing the proportion of maize silage in feed rations due to increasing the area of maize
338 silage grown. They examined several land-use scenarios, such as converting permanent
339 grasslands to silage maize, either in monoculture or in rotations with temporary grasslands.
340 For instance, increasing the silage maize area by 4 ha decreased GHG emission intensity by
341 11 g CO₂ eq/kg milk (Vellinga and Hoving, 2010). However, the practicality of changing
342 feeding strategies by changing land use depends on the size of the farm. Farms with small
343 total area or grassland area may have difficulty making certain changes. Maximizing DM_{Grass}
344 also requires future studies that investigate how land use and management influence other
345 services that grasslands provide besides forage production, such as modifying the quality (e.g.
346 fatty-acid contents) of milk and meat and mitigating GHG emissions by sequestering soil

347 organic carbon. Models have thus been developed to simulate farm systems, as well as
348 agronomic and environmental services provided by grasslands (Rotz, 2004; Graux et al.,
349 2013).

350 **4.3. Differences in GHG emissions by production strategy**

351 The results highlighted production strategies, reflected through the management of DM_{Grass}
352 and DM_{Maize} , that influenced both economic (milk production) and environmental (GHG and
353 enteric CH_4 emissions) outputs from dairy farms. Thus, the strategies for setting DM_{Grass} and
354 DM_{Maize} at extreme levels can be extrapolated, resulting in a change in annual GHG emissions
355 whose direction (decrease or increase) tends to depend on the FU chosen: gross emissions per
356 farm (kg CO_2 eq/farm/year) or emission intensity of milk (kg CO_2 eq/l milk). One strategy is
357 to minimize DM_{Maize} , which implies minimizing gross emissions but producing less milk than
358 the dataset mean, meaning that emission intensity increases. A second strategy is to minimize
359 DM_{Grass} , which keeps gross emissions nearly constant and maximizes milk production,
360 meaning that emission intensity decreases. A third strategy is to maximize DM_{Grass} , which
361 implies decreasing gross emissions and milk production (the former more than the latter),
362 meaning that emission intensity decreases. Finally, a fourth strategy is to maximize DM_{Maize} ,
363 which implies increasing gross emissions and milk production (the former more than the
364 latter), meaning that emission intensity increases. In these four strategies, CH_4 emissions
365 tended to vary in the same way as total GHG emissions, contributing approximately half of
366 the farms' GHG emissions.

367 These four strategies also reflected farmers' management practices. For instance, feed
368 purchases depend on a farm's degree of feed self-sufficiency (Coquil et al., 2013). The
369 contribution of purchased feed to gross GHG emissions was the smallest for GrassMAX and
370 largest for GrassMIN. Likewise, from MaizeMIN to MaizeMAX, the contribution of organic
371 and inorganic fertilization to gross GHG emissions increased but that of manure storage and
372 management decreased. Meanwhile, no strategies resulted in a significant change in on-farm
373 energy (diesel and electricity) consumption or amount of fertilizers purchased.

374 From a product-oriented viewpoint, decreasing GHG emissions per l of milk is a primary
375 objective, though debate continues over the total and per-ha impacts of the intensive dairy
376 farms required to reach such high levels of milk production and which functional unit(s) best
377 represent environmental impacts of dairy farms (Salou et al., 2017). In practice, management
378 changes to address both GHG emissions and farm profitability should be a compromise

379 between the four strategies highlighted to develop farm-level GHG mitigation strategies that
380 could be financially viable.

381 **4.4. EVT**

382 Applying EVT identified dairy farms with extremely low DM_{Grass} and DM_{Maize} . Hazards that
383 would further decrease DM_{Grass} and DM_{Maize} would have greater consequences on these
384 extreme minimum samples than on the other samples. Thus, one research perspective is to
385 assess the risks that dairy farms face if they already produce small amounts of forage, as well
386 as potential consequences of economic or climate perturbations on their productivity and
387 environmental impacts. One must consider, however, the sensitivity of threshold values to
388 various factors, such as a dairy farm's type (extensive, intensive) and geographic location.
389 Doing so would provide useful information about variability in threshold values and the
390 factors that influence it. Furthermore, sensitivity of a sample's GHG emissions to the choice
391 of threshold values should be studied further. For instance, a threshold that is too small (or
392 large) may lead to including (or excluding) values that are not (or are) extreme, affecting the
393 relevance of results. In our study, one main criterion for choosing threshold values was to
394 have a sufficiently large sample of dairy farms with extreme values of the inputs considered,
395 to ensure the representativeness of the minimum and maximum samples extracted.
396 Nonetheless, each extreme sample contained only 10-13 farms, which limited the
397 representativeness of farms with extreme differences in forages and influenced the
398 significance of statistical tests performed to assess differences between the samples. In a
399 sufficiently large dataset, testing the adequacy of fit of the extreme value distribution to the
400 GPD and measuring the error may be the only criteria needed to choose a threshold value.

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406

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487

488

489 **Supplementary Materials**

490 Table A1. Descriptive statistics of the percentage of total greenhouse gas (GHG) emissions
 491 due to methane emissions, manure storage and management, purchased feeds organic and
 492 inorganic fertilization, on-farm energy consumption and fertilizers used of 78 dairy farms in
 493 Normandy (France) in 2014. 1Q = 1st quartile, 3Q = 3rd quartile, CV = coefficient of variation

Characteristic	Min	1Q	Median	Mean	3Q	Max	CV (%)
Enteric methane emissions in total GHG (%)	41.0	47.0	49.0	49.6	53.0	66.0	9
Manure storage and management in total GHG (%)	12.0	19.0	20.0	19.5	21.0	23.0	10
Purchased feeds in total GHG (%)	0.0	10.0	13.0	12.5	15.0	21.0	33
Organic and inorganic fertilization in total GHG (%)	4.0	7.0	9.0	9.0	11.0	14.0	25
Energy consumption in total GHG (%)	3.0	4.0	5.0	5.3	6.0	12.0	27
Fertilizers in total GHG (%)	0.0	2.0	3.0	3.4	5.0	7.0	52

494

495 Table A2. Mean and coefficient of variation (CV) of additional farm characteristics for the
 496 entire dataset and for farms in minimum (“MIN”) and maximum (“MAX”) samples of dry
 497 matter (DM) of grass and maize silage. % chg. = percentage increase from minimum to
 498 maximum sample. M-W p = p-value of Mann-Whitney test for the difference between
 499 minimum and maximum samples. % chg. = percentage increase from minimum to maximum
 500 sample. UAA = Utilized Agricultural Area, LU=Livestock Unit, MFA=Main Forage Area,
 501 GHG = greenhouse gas

Variable	Statistic	Entire dataset	Grass DM sample				Maize silage DM sample			
			MIN sample	MAX sample	% chg.	M-W p	MIN sample	MAX sample	% chg.	M-W p
Area of pastures in UAA (%)	Mean	48.1	31.3	70.3	+124%	<0.001	72.3	38.5	-47%	<0.001
	CV	40%	36%	28%			26%	35%		
Area of silage maize in UAA (%)	Mean	24.1	30.7	14.5	-53%	<0.001	13.7	31.7	+131%	<0.001
	CV	38%	22%	60%			62%	14%		
Replacement rate (%)	Mean	30.5	29.5	31.1	+5%	0.36	29.2	29.9	+2%	0.91
	CV	33%	17%	29%			34.2%	25.6%		
Stocking rate (LU per ha of MFA)	Mean	1.4	1.6	0.9	-42%	<0.001	1.2	1.1	-8%	0.89
	CV	26%	19%	24%			31%	21%		
Enteric methane emissions in total GHG (%)	Mean	49.6	48.0	52.6	+10%	0.09	53.9	47.7	-11%	<0.001
	CV	9%	6%	14%			9%	7%		
Manure storage and management in total GHG (%)	Mean	19.5	19.2	19.8	+3%	0.54	20.7	18.2	-12%	0.02
	CV	10%	10%	9%			7%	17%		
Purchased feeds in total GHG (%)	Mean	12.5	15.4	8.8	-43%	<0.001	9.3	12.8	+37%	0.09
	CV	33%	16%	50%			48%	29%		
Organic and inorganic fertilization in total GHG (%)	Mean	9	8.9	8.9	-0.1%	1	7.7	10.1	+32%	0.02
	CV	25%	29%	25%			29%	25%		
Energy consumption in total GHG (%)	Mean	5.3	5.4	5.3	-3%	0.87	5.7	5.8	+3%	0.43
	CV	27%	12%	22%			39%	20%		
Fertilizers in total GHG (%)	Mean	3.4	3.5	3.4	-4%	1	2.5	3.0	+18%	0.54
	CV	52%	52%	69%	5		66%	67%		

502