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1 **Analysis of milk production and greenhouse gas emissions as a function of** 2 **extreme variations in forage production among French dairy farms**

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6 **Abstract**

7 Many studies that investigate mitigation strategies of greenhouse-gas (GHG) emissions from
8 farming systems often build farm typologies from average data from multiple farms. Results
9 from farm typologies are useful for general purposes but fail to represent variability in farm
10 characteristics due to management practices or climate conditions, particularly when
11 considering consequences of extreme environmental events. This limitation raises the issue of
12 better distinguishing, within datasets of farms, farms that have average characteristics from
13 those that deviate from average trends, in order to improve assessment of how climate
14 variability influences farm performance. We applied the statistical method called Extreme
15 Value Theory (EVT) to identify dairy farms that produced “extreme” amounts of forage.
16 Applying EVT to a dataset of dairy farms from Normandy, Lorraine and Nord-Pas-de-Calais
17 (France) identified subsamples of 10-30% of dairy farms with the smallest or largest amounts
18 of grass from pastures or maize silage in each region. Characteristics of farms with extreme
19 amounts of each forage often differed among regions due to the influence of geography and
20 climate. Farms with the largest amounts of grass or the smallest amounts of maize silage had a
21 variety of cow breeds in Normandy and Lorraine but had only Holstein cows in Nord-Pas-de-
22 Calais. Conversely, most farms with the smallest amounts of grass or the largest amounts of
23 maize silage had Holstein cows, regardless of region. The region also influenced whether farms
24 were oriented more toward producing milk with higher fat and protein contents (Normandy and
25 Lorraine) or toward producing larger amounts of milk (Nord-Pas-de-Calais). As the amount of
26 a given forage changed from smallest to largest, a significant increase or decrease in the amount
27 of milk produced usually changed GHG and enteric methane (CH₄) emissions per farm in the
28 same direction as the amount of milk produced. For instance, an extreme increase in the amount
29 of grass fed on farms (1314 vs. 5093 kg/livestock unit/year, respectively) in Normandy was
30 associated with decreased mean milk production (8236 vs. 5834 l/cow/year, respectively) and

31 GHG (7117 vs. 5587 kg CO₂ eq./farm/year) and enteric CH₄ (3870 vs. 3296 kg CO₂
32 eq./farm/year, respectively) emissions.

33

34 **Keywords:** environmental performance, extreme value theory, farm productivity, livestock
35 farming

36 Highlights

- 37 • Extreme Value Theory identified farms producing extreme amounts of forages in a region
- 38 • Most farms that fed more grass or less maize silage had a variety of cow breeds
- 39 • Most farms that fed less grass or more maize silage had Holstein cows
- 40 • Milk-production objectives varied as a function of region

41

42 1. Introduction

43 In the continuing context of human-induced climate change, the agriculture sector, particularly
44 livestock farming, is seeking ways to decrease its total greenhouse-gas (GHG) emissions
45 (Tubiello et al., 2021). Doing so requires analyzing current GHG emissions and also predicting
46 future emissions in response to changes in farming systems. Many analysis methods, especially
47 those at larger scales, construct hypothetical farm types from average data from multiple farms
48 (Avadí et al., 2018) or use data from real-world farms, but average these data over several years
49 to compensate for inter-annual variability (Tedesco et al., 2017). Both approaches yield results
50 that are useful for general purposes, but they are unable to represent explicitly farm
51 characteristics that display extreme values in response to high variability or extremes in the
52 environment (e.g., droughts, below-average temperatures).

53 High variability in the environment, such as heat waves that may decrease forage and crop
54 production (Tatsumi et al., 2011), influences livestock farming, including environmental and
55 economic performances of dairy farms. Likewise, droughts in New Zealand in recent decades
56 increased volatility of the price of milk on the global market and influenced profitability of
57 dairy farms (Pourzand et al., 2020). Simulations of future effects of climate change on Canadian
58 dairy farms also predicted higher emissions (e.g., ammonia, methane (CH₄), nitrate, phosphate)
59 to the environment than during the 1971-2000 reference period (Thivierge et al., 2017).
60 Nonetheless, consequences of extreme events on dairy farms vary as a function of their
61 characteristics. For instance, droughts that decrease crop yields influence farm performances

62 differently depending on farm characteristics, such as which crops are planted and the
63 percentage of farm area cropped (Lawes and Kingwell, 2012). Likewise, farms that depend
64 more on one single type of forage (e.g., grass) than an average farm does may be more
65 vulnerable to environmental extremes. This potential vulnerability raises the issue of better
66 distinguishing dairy farms that have average characteristics from those that deviate from
67 average trends, in order to improve assessment of how climate variability influences farm
68 performance.

69 Extreme-Value Theory (EVT) is a statistical approach for analyzing extreme events (Charras-
70 Garrido and Lezaud, 2013). EVT has been used to analyze the frequency of extreme
71 environmental events, especially floods (Quintela-del-Río and Francisco-Fernández, 2018), but
72 also droughts (Xu et al., 2011). EVT is thus useful for identifying atypical events that deviate
73 from average trends and for modeling their occurrence with appropriate statistical distributions
74 other than a normal distribution (Embrechts et al., 1996). The present study builds upon a
75 previous study (Senga Kiessé et al., 2020) that applied EVT to a sample of dairy farms in Lower
76 Normandy (hereafter, “Normandy”) (France), surveyed in 2014, (1) to identify subsamples of
77 farms with extremely high or low grass or maize silage production and then (2) to compare the
78 mean milk production, GHG emissions and other characteristics of these “extreme samples”.

79 In the present study, we analyzed data from a second sample of dairy farms, surveyed in 2013,
80 in Normandy and two additional regions of France: Lorraine and Nord-Pas-de-Calais. The
81 objectives of this study were to (1) identify farms with extreme forage production in the three
82 regions, (2) compare their characteristics and (3) explore the potential influence of differences
83 in geography and climate on results. Analyzing data from 2013 also allowed us to explore the
84 potential influence of differences in annual weather (2013 vs. 2014) on results for farms in
85 Normandy.

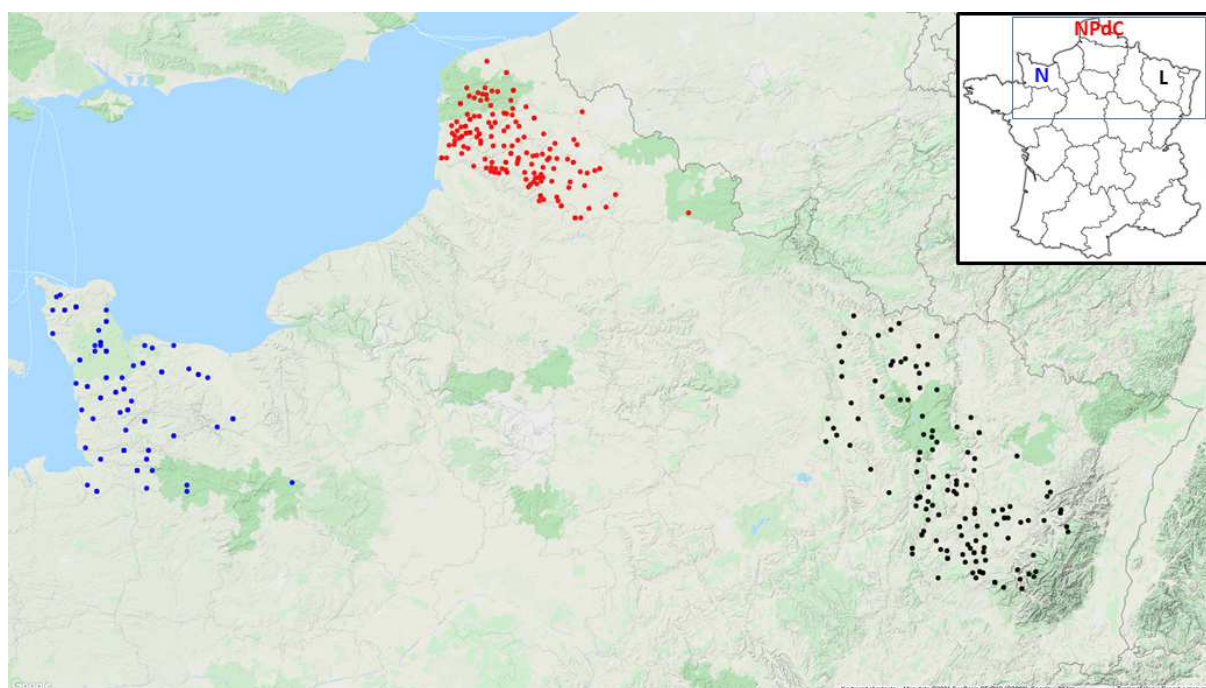
86

87 **2. Materials and methods**

88 **2.1. Data**

89 The French Livestock Institute (IDELE) surveyed 3135 conventional dairy farms from 11
90 regions of France over the period 2013-2015 (LIFE Carbon Dairy project, [www.carbon-](http://www.carbon-dairy.fr)
91 [dairy.fr](http://www.carbon-dairy.fr)). The dataset consisted of annual data surveyed in 2013 from dairy farms ($N = 390$) in
92 the Normandy (number of farms $n = 96$), Lorraine ($n = 140$) and Nord-Pas-de-Calais ($n =$

93 154) regions (Figure 1). Characteristics, inputs and outputs were collected for each farm, such
94 as areas of pastures and silage maize in the forage area, grass yield, number of livestock units
95 (LU), milk produced per cow, amount of concentrated feed fed and estimated CH₄ emissions
96 from dairy cows and heifers (Table 1). The dairy farms lay in a variety of geography, such as
97 lowlands in Normandy and Nord-Pas-de-Calais, and lowlands, foothills, mountains and “areas
98 facing natural or other specific constraints” (ANCs) (i.e., for which the European Union offers
99 payments for agricultural production) in Lorraine. All 390 dairy farms produced silage maize
100 except for 5 in Normandy (in lowlands) and 28 in Lorraine (10 in mountains, 8 in ANCs, 6 in
101 lowlands and 4 in foothills). The main dairy cow breed ($\geq 50\%$ of the herd) was Holstein on 63
102 farms in Normandy, 111 farms in Lorraine and 151 farms in Nord-Pas-de-Calais, followed by
103 Normande in Normandy and Montbeliarde in Lorraine (Supplementary Table S1).



104
105 Figure 1. Communes in which the 390 farms studied were located, in the French regions of
106 (Lower) Normandy (blue), Lorraine (black) and Nord-Pas-de-Calais (red) in 2013

107
108 Farm characteristics were collected or calculated from information provided by farmers. For
109 instance, milk production per cow was calculated by dividing annual milk production by the
110 number of dairy cows. Likewise, GHG (CH₄, nitrous oxide and carbon dioxide (CO₂))
111 emissions were estimated from information on production and transport of purchased feeds (i.e.,
112 concentrated feed, cereals and forages), purchased fertilizers and on-farm energy use. Soil

113 carbon dynamics, however, were not considered. For dairy cows and heifers, Tier 3
114 methodology of the Intergovernmental Panel on Climate Change (IPCC, 2006) was used to
115 predict enteric CH₄ emissions (g CH₄/kg of digestible organic matter), based on an empirical
116 model adapted to French national contexts that considers factors such as feeding levels and the
117 proportion of concentrated feed in the diet (Sauvant and Noziere, 2016). Enteric CH₄ emissions
118 were the main source (46-50%) of GHG emissions among the regions, followed by manure
119 storage and management (19-20%), purchased feeds (12-14%), organic and inorganic
120 fertilization (9-10%), energy consumption (5-6%) and purchased fertilizers (3-5%)
121 (Supplementary Figure S1). See the Supplementary Material for details of the equations used
122 to estimate GHG emissions. Estimated GHG emissions per farm and per l of milk produced in
123 Normandy, Lorraine and Nord-Pas-de-Calais (Table S3, Table S4 and Table S5) were in line
124 with those estimated in other regions of the world. For instance, mean GHG emissions per kg
125 of fat-and-protein-corrected milk at the farm gate were 0.962 and 1-2 kg CO₂ eq. for milk
126 produced on an average New Zealand farm (Basset-Mens et al., 2009) and in Europe (Gerber
127 et al., 2011), respectively.

128 Table 1. Descriptive statistics of annual characteristics of 390 dairy farms in 2013 in the three
 129 French regions studied (Normandy, Lorraine and Nord-Pas-de-Calais). CV = coefficient of
 130 variation, DM = dry matter, GHG = greenhouse gas, CO₂ = carbon dioxide, CH₄ = methane

Region	Characteristic	Min	Mean	Max	CV (%)
Normandy (n = 96)	Utilized Agricultural Area (UAA) (ha)	28	124	585	59
	Area of pastures in UAA (%)	12	55	100	35
	Area of silage maize in UAA (%)	0	26	52	39
	Number of livestock units	34	129	307	41
	Grass yield (t DM/ha/year)	1.9	6.5	14.6	34
	Concentrated feed fed (g/l milk)	73.0	190.9	394.0	34
	Milk production per cow (l/year)	3607	6983	10,368	21
	Gross GHG emissions (kg CO ₂ eq./farm/year)	3411	6486	10,946	19
	Enteric CH ₄ emissions (kg CO ₂ eq./farm/year)	1619	3531	4820	16
Lorraine (n = 140)	UAA (ha)	41	181	486	47
	Area of pastures in UAA (%)	12	59	100	41
	Area of silage maize in UAA (%)	0	11	37	71
	Number of livestock units	36	102	244	40
	Grass yield (t DM/ha/year)	1.8	5.4	11.3	29
	Concentrated feed fed (g/l milk)	0	212.8	429	33
	Milk production per cow (l/year)	4147	7462	11,462	18
	Gross GHG emissions (kg CO ₂ eq./farm/year)	4353	6626	9266	16
	Enteric CH ₄ emissions (kg CO ₂ eq./farm/year)	2903	3537	4773	10
Nord-Pas- de-Calais (n = 154)	UAA (ha)	34	109	274	43
	Area of pastures in UAA (%)	4	30	87	47
	Area of silage maize in UAA (%)	4	19	44	39
	Number of livestock units	26	84	283	43
	Grass yield (t DM/ha/year)	2.9	8.0	13.8	29
	Concentrated feed fed (g/l milk)	0	181.1	426.0	38
	Milk production per cow (l/year)	3789	8147	11,061	15
	Gross GHG emissions (kg CO ₂ eq./farm/year)	3411	6503	10,946	18
	Enteric CH ₄ emissions (kg CO ₂ eq./farm/year)	2858	3835	4570	7

131

132 Forage intake by cattle was not included in the survey; thus, on-farm forage production was
 133 used as a proxy of forage intake by assuming that each farm fed all of the forage it produced
 134 each year (and no more or no less) to its cattle. We estimated each farm's production of each
 135 forage per LU (kg DM/LU/year) by dividing the total DM of grass from pastures (DM_{Grass}) or
 136 maize silage (DM_{Maize}) (equal to area (ha) × yield (t DM/ha)) by the number of LU. The mean

137 yield of silage maize in each region in 2013 was used (18.6, 17.3 and 17.3 t DM/ha in
138 Normandy, Lorraine and Nord-Pas-de-Calais, respectively (Arvalis Institut du végétal, 2013,
139 2015)), since the dataset did not provide maize yield per farm.

140 **2.2. Extreme-Value Theory**

141 Applying EVT to a dataset of independent inputs x_1, x_2, \dots, x_n consists of extracting a
142 maximum sequence that contains maximum values of inputs, then fitting it using appropriate
143 probability distribution functions (Coles, 2001). EVT does not require assuming that inputs
144 follow a normal distribution. Within the EVT framework, limit laws for the maximum sequence
145 extracted of inputs x_1, x_2, \dots, x_n belong to asymptotic distributions of type Fréchet, Weibull or
146 Gumbel (Embrechts et al., 1996). For instance, consider the distribution of the excesses above
147 a fixed threshold μ , extracted from observations x of the rv X . The excess distribution function
148 $P(X \leq x | X > \mu)$ above μ can be approximated by a generalized Pareto distribution (GPD)
149 function, with parameter $\theta=(\sigma, \varepsilon)$, defined by the empirical distribution function

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

150 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
151 (Beirlant et al., 2004). EVT also enables one to extract a minimum sequence and then fit it using
152 extreme value distributions. Thus, the GPD also enables one to approximate the distribution
153 function of values below another fixed threshold μ extracted from observations x of the rv X .

154 *Threshold selection.* To select the threshold μ , we tested four minimum (10%, 15%, 20% and
155 25%) and four maximum (75%, 80%, 85% and 90%) extreme quantiles and used them to
156 calculate corresponding values of μ . The value of μ selected must not be too small or too large,
157 because the resulting sample size may make the bias or variance of the fitted GPD too large
158 (Scarrott and MacDonald, 2012). To help choose an adequate threshold, statistical tests were
159 performed and error was assessed.

160 *Statistical tests and root mean squared error.* The adequacy of distribution of extracted
161 minimum or maximum sample to the GPD was tested using the Kolmogorov-Smirnov (K-S)
162 test. The null hypothesis H_0 of K-S test was that the extracted sample followed a GPD.
163 Differences in mean farm characteristics between the minimum and maximum samples was
164 also tested by performing the Mann-Whitney (M-W) U test. The null hypothesis H_0 of the M-
165 W test was that characteristics of farms in the minimum and maximum samples followed the

166 same distribution. For K-S and M-W test results were considered significant at $\alpha=5\%$. In
167 addition, for each quantile tested, the extracted sample was also compared to the fitted GPD
168 using the root mean squared error (RMSE). We used the “evd” (Stephenson, 2002) and
169 “extremefit” (Durrieu et al., 2017) packages of R software (R Core Team, 2020) to apply EVT.

170

171 **3. Results**

172 **3.1. Extreme samples for dry matter of grass from pastures**

173 For DM_{Grass} , quantiles 15%, 10% and 10% were selected as the minimum thresholds, which
174 corresponded to 1764, 2862 and 1375 kg/LU/year, respectively, for farms in Normandy,
175 Lorraine and Nord-Pas-de-Calais, respectively (Figure 2, Table 2). Likewise, for farms in these
176 three regions, quantiles 85%, 70% and 90% were selected as the maximum thresholds, which
177 corresponded to DM_{Grass} of 4218, 5796 and 4881 kg/LU/year, respectively (Table 2). The K-S
178 test did not reject the null hypothesis of the adequacy of the GPD for the quantiles selected.
179 Nonetheless, the quantiles selected did not always have the smallest RMSE or largest p-value
180 of the K-S test. For instance, for the minimum sample (GrassMIN) of farms in Normandy, we
181 selected the 15% quantile to obtain a larger sample size of 14, because the sample size of the
182 10% quantile was 9 (Supplementary Table S2). Likewise, for the maximum sample
183 (GrassMAX) of farms in Normandy, we selected the 85% quantile to obtain a larger sample
184 size of 15, because the sample size of the 90% quantile was 10.

185

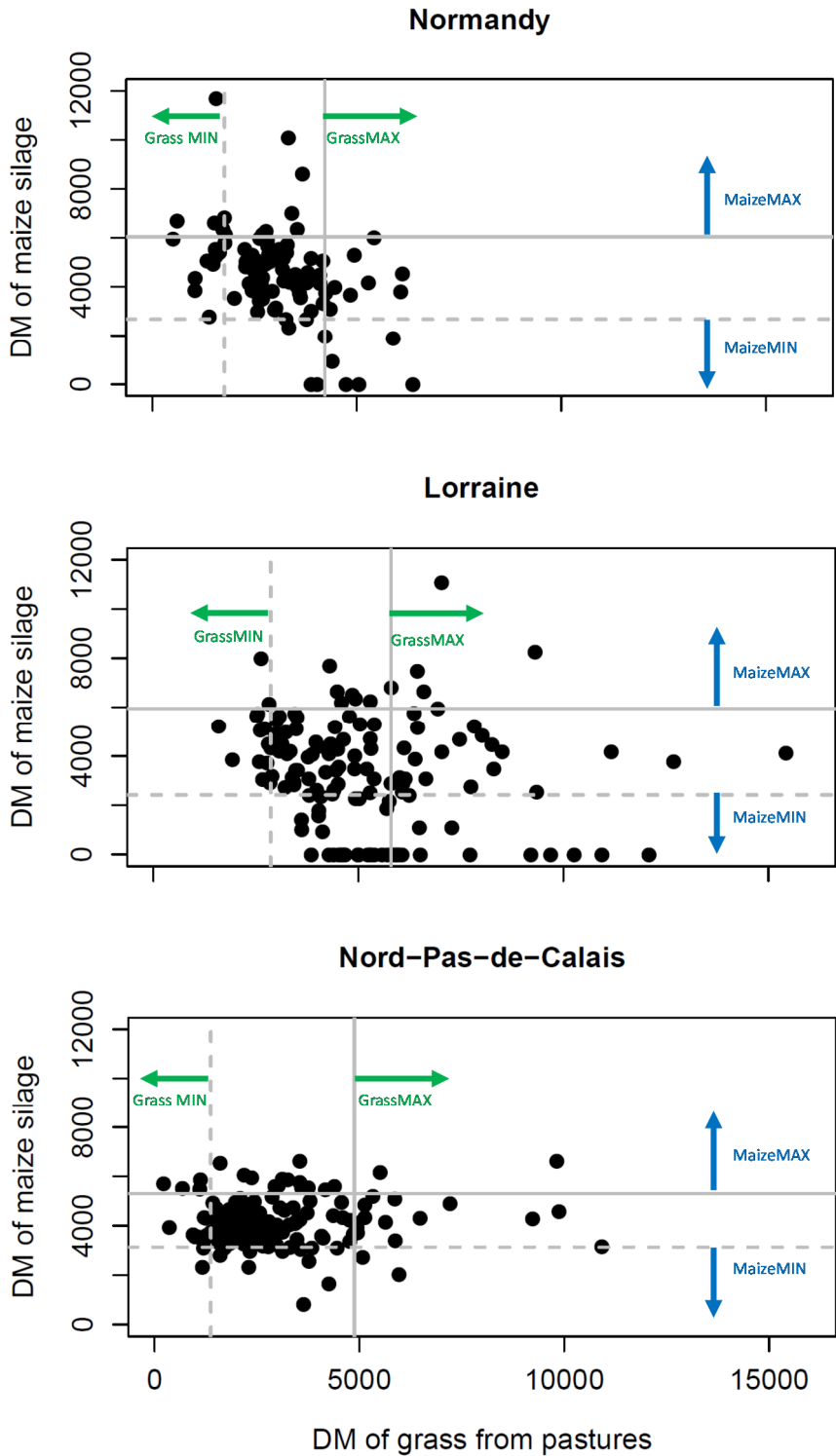
186 **3.2. Extreme samples for dry matter of maize silage**

187 For DM_{Maize} , quantiles 10%, 30% and 10% were selected as the minimum thresholds, which
188 corresponded to 2676, 2422 and 3134 kg/LU/year, respectively, for farms in Normandy,
189 Lorraine and Nord-Pas-de-Calais, respectively (Figure 2, Table 2). The quantile 30% was
190 selected to obtain a sufficiently large sample of farms in Lorraine, given the 28 farms there with
191 no DM_{Maize} . Likewise, for farms in these three regions, quantiles 85%, 90% and 90% were
192 selected as the maximum thresholds, which corresponded to DM_{Maize} of 6040, 5946 and 5309
193 kg/LU/year, respectively (Figure 2, Table 2). The K-S test did not reject the null hypothesis for
194 the selected quantiles.

195 Table 2. Results of applying Extreme-Value Theory to extract minimum (“MIN”) and
 196 maximum (“MAX”) samples of dry matter (DM) of grass from pastures (“Grass”) and maize
 197 silage (“Maize”) (kg/livestock unit/year) as a function of multiple quantiles of the entire dataset
 198 of farms in three French regions (Normandy, Lorraine and Nord-Pas-de-Calais) in 2013.

Sample	Region	Threshold of		Sample	
		DM (kg)	Quantile	size	Main breeds (number of farms)
GrassMIN	Normandy	1764	15%	14	Holstein (12), Normande (2)
	Lorraine	2862	10%	13	Holstein (13)
	Nord-Pas-de-Calais	1375	10%	15	Holstein (15)
GrassMAX	Normandy	4218	85%	15	Normande (9), Holstein (4), Jersey (2)
	Lorraine	5796	70%	42	Holstein (35), Montbeliarde (5), Jersey (1), Cross-breeds (1)
	Nord-Pas-de-Calais	4881	90%	18	Holstein (18)
MaizeMIN	Normandy	2676	10%	9	Normande (5), Holstein (2), Jersey (2)
	Lorraine	2422	30%	41	Holstein (23), Montbeliarde (14), Cross-breeds (2), Jersey (1), Vosgienne (1)
	Nord-Pas-de-Calais	3134	10%	15	Holstein (14), Bleue du Nord (1)
MaizeMAX	Normandy	6040	85%	13	Holstein (13)
	Lorraine	5946	90%	14	Holstein (14)
	Nord-Pas-de-Calais	5309	90%	19	Holstein (19)

199



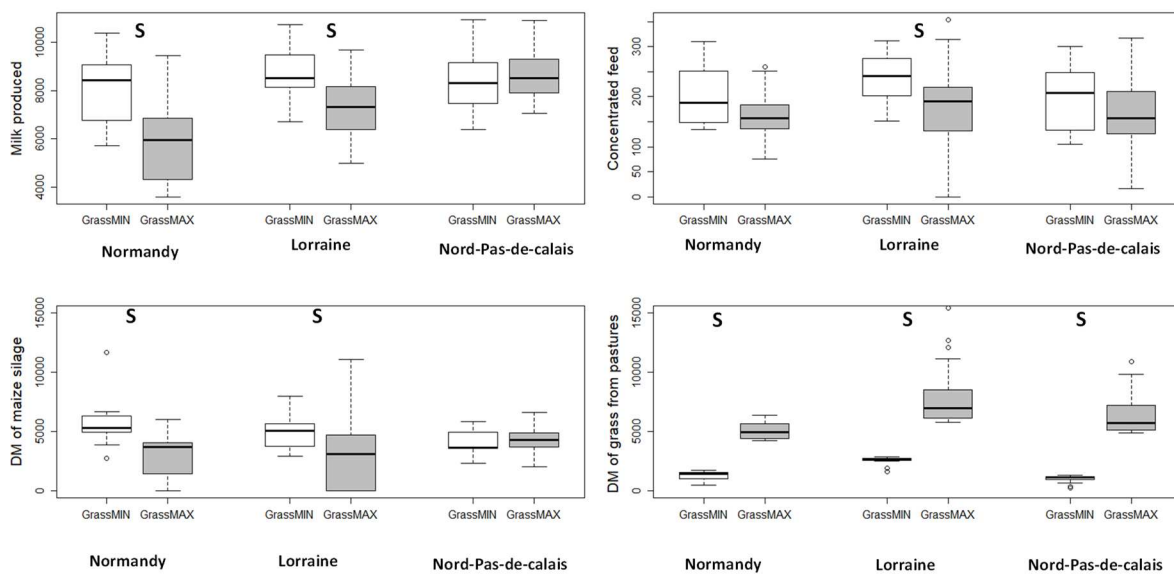
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202 Figure 2. Bivariate plot of farms in Normandy, Lorraine and Nord-Pas-de-Calais, as a function
203 of annual dry matter (DM) (kg/livestock unit/year) of grass (solid lines indicate maximum
204 thresholds, while dashed lines indicate minimum thresholds).

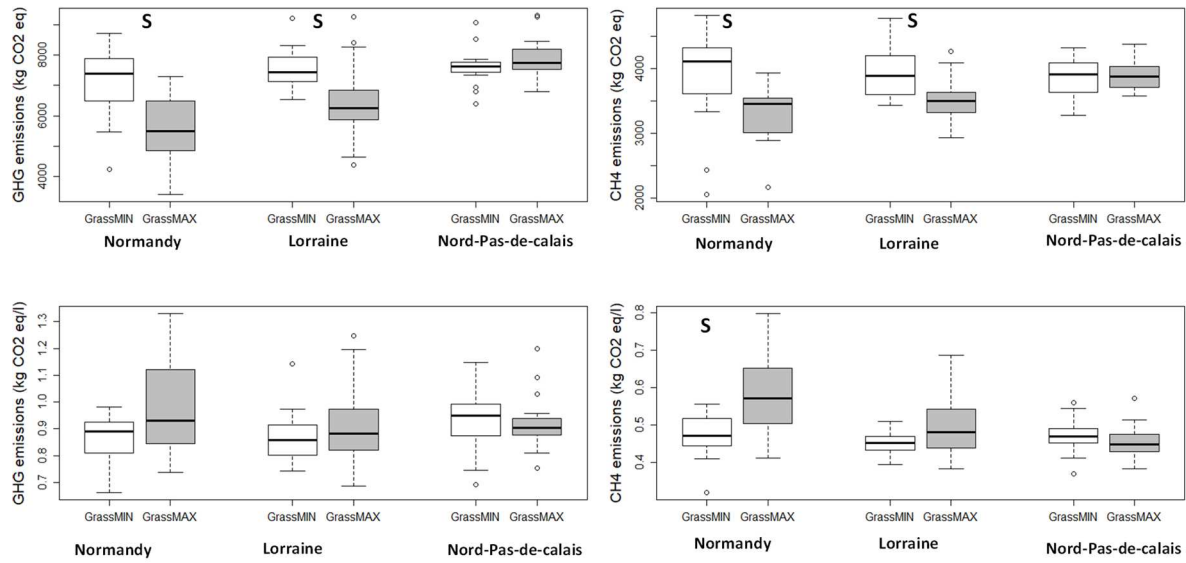
205 3.3. Forage production, milk production and emissions by sample

206 3.3.1. Normandy

207 *Extreme samples of DM_{Grass}*. In Normandy, mean milk production per cow in GrassMAX was
208 significantly smaller (-29%) than that in GrassMIN, due to feeding significantly more DM_{Grass}
209 (+288%), significantly less DM_{Maize} (-49%) and less concentrated feed (-21%, albeit non-
210 significant) (Figure 3, Table S3). The main breed on farms was Normande, Holstein and Jersey
211 in GrassMAX and Holstein and Normande in GrassMIN (Table 2). Likewise, mean GHG and
212 enteric CH₄ emissions per farm in GrassMAX were significantly lower (-21% and -15%,
213 respectively) than those in GrassMIN (Figure 4, Table S3), because producing grass emits less
214 GHGs (e.g., direct emissions of N₂O from fields, combustion of fossil fuels) than producing
215 maize silage. Conversely, mean enteric CH₄ emissions per l of milk produced were significantly
216 higher in GrassMAX (+26%) than those in GrassMIN (Figure 4, Table S3).



217
218 Figure 3. Distributions of milk production per cow (l/cow/year), concentrated feed fed (g/l of
219 milk produced), grass from pastures and maize silage (kg dry matter (DM)/ livestock unit/year)
220 for farms in minimum (“MIN”) and maximum (“MAX”) samples of DM of grass from pastures.
221 The letter “S” denotes significant differences between extreme samples of forage DM.



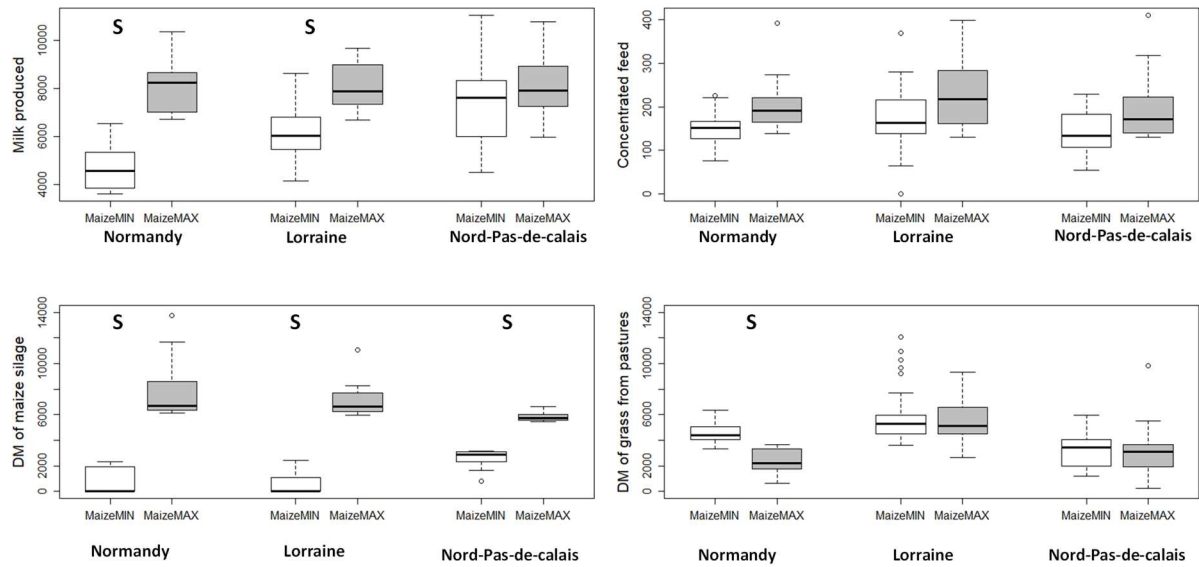
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223 Figure 4. Distributions of annual gross greenhouse gas (GHG) and enteric methane (CH₄)
 224 emissions (top) per farm per year (kg CO₂ eq./farm/year) and (bottom) per l of milk produced
 225 (kg CO₂ eq./l/year) for farms in minimum (“MIN”) and maximum (“MAX”) samples of dry
 226 matter (DM) of grass from pastures. The letter “S” denotes significant differences between
 227 extreme samples of forage DM.

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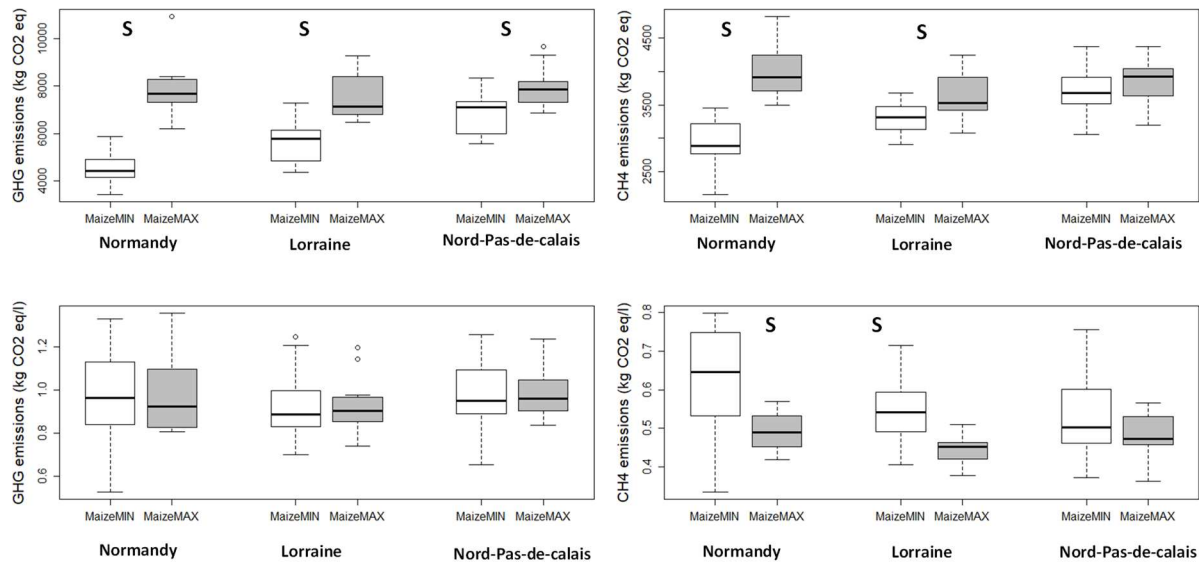
229 *Extreme samples of DM_{Maize}*. Unlike for DM_{Grass}, mean milk production per cow in MaizeMAX
 230 was significantly higher (+71%) than that in MaizeMIN (Figure 5, Table S3), due to feeding
 231 significantly more DM_{Maize} (+894%), significantly less DM_{Grass} (-49%) and more concentrated
 232 feed (+37%, albeit non-significant). The main breed on farms was Holstein in MaizeMAX and
 233 Normande, Holstein and Jersey in MaizeMIN (Table 2). Likewise, mean GHG and enteric CH₄
 234 emissions per farm were significantly higher in MaizeMAX (+75% and +39%, respectively)
 235 than those in MaizeMIN (Figure 6, Table S3). Conversely, mean enteric CH₄ emissions per l of
 236 milk produced were significantly lower in MaizeMAX (-21%) than those in MaizeMIN (Figure
 237 6, Table S3).

238



239

240 Figure 5. Distributions of milk production per cow (l/cow/year), concentrated feed fed (g/l of
 241 milk produced), grass from pastures and maize silage (kg dry matter (DM)/livestock unit/year)
 242 for farms in minimum (“MIN”) and maximum (“MAX”) samples of DM of maize silage. The
 243 letter “S” denotes significant differences between extreme samples of forage DM.



244

245 Figure 6. Distributions of annual gross greenhouse gas (GHG) and enteric methane (CH₄)
 246 emissions (top) per farm per year (kg CO₂ eq./farm/year) and (bottom) per l of milk produced
 247 (kg CO₂ eq./l/year) for farms in minimum (“MIN”) and maximum (“MAX”) samples of dry
 248 matter (DM) of maize silage. The letter “S” denotes significant differences between extreme
 249 samples of forage DM.

250 The ranking of sources of GHG emissions in Normandy did not change between farms in
251 extreme samples of DM_{Grass} or DM_{Maize} (Figure S2). Nonetheless, the extreme increase in
252 DM_{Grass} from GrassMIN to GrassMAX particularly increased the relative contribution of enteric
253 CH_4 emissions (45% vs. 55%, respectively) and decreased that of purchased feeds (17% vs.
254 9%, respectively) per farm. Likewise, the extreme increase in DM_{Maize} from MaizeMIN to
255 MaizeMAX particularly decreased the relative contribution of enteric CH_4 emissions (59% vs.
256 46%, respectively) and increased those of organic and inorganic fertilization (6% vs. 11%,
257 respectively) and purchased feeds (6% vs. 15%, respectively) per farm.

258 **3.3.2. Lorraine**

259 *Extreme samples of DM_{Grass} .* In Lorraine, mean milk production per cow in GrassMAX was
260 significantly smaller (-17%) than that in GrassMIN, due to feeding significantly more DM_{Grass}
261 (+206%) and significantly less DM_{Maize} (-34%) and concentrated feed (-22%) (Figure 3, Table
262 S4). The main breed on farms was usually Holstein and Montbeliarde in GrassMAX and
263 Holstein in GrassMIN (Table 2). Likewise, mean GHG and enteric CH_4 emissions per farm in
264 GrassMAX were significantly lower (-14% and -10%, respectively) than those in GrassMIN,
265 since less GHGs were emitted when producing grass (Figure 4, Table S4).

266 *Extreme samples of DM_{Maize} .* Unlike for DM_{Grass} , mean milk production per cow in MaizeMAX
267 was significantly higher (+30%) than that in MaizeMIN (Figure 5, Table S4), due to feeding
268 significantly more DM_{Maize} (+1214%) and concentrated feed (+31%). The main breed on farms
269 was Holstein in MaizeMAX and usually Holstein and Montbeliarde in MaizeMIN (Table 2).
270 Likewise, mean GHG and enteric CH_4 emissions per farm were significantly higher in
271 MaizeMAX (+33% and +9%, respectively) than those in MaizeMIN (Figure 6, Table S4).
272 Conversely, mean enteric CH_4 emissions per l of milk produced were significantly lower in
273 MaizeMAX (-18%) than those in MaizeMIN (Figure 6, Table S 4).

274 The ranking of sources of GHG emissions in Lorraine did not change between farms in extreme
275 samples of DM_{Grass} or DM_{Maize} (Figure S3). In addition, differences in the relative contributions
276 of sources to GHG emissions between farms in ForageMIN and ForageMAX were similar to
277 those in Normandy.

278 **3.3.3. Nord-Pas-de-Calais**

279 *Extreme samples of DM_{Grass} .* In Nord-Pas-de-Calais, mean milk production per cow did not
280 differ significantly between GrassMAX and GrassMIN; the former fed significantly more

281 DM_{Grass} (+549%) but also fed slightly more DM_{Maize} (+4%, non-significant) (Figure 3, Table S
282 5). Likewise, mean GHG and enteric CH_4 emissions per farm or per l of milk produced did not
283 differ significantly between GrassMAX and GrassMIN (Figure 4, Table S5). The main breed
284 on farms was Holstein in both GrassMAX and GrassMIN (Table 2).

285 *Extreme samples of DM_{Maize} .* Mean milk production per cow did not differ significantly between
286 MaizeMAX and MaizeMIN, even though the former fed significantly more DM_{Maize} (+125%)
287 and concentrated feed (+33%) (Figure 5, Table S5). The main breed on farms was Holstein in
288 MaizeMAX and Holstein and Bleue du Nord in MaizeMIN (Table 2). Among emissions, only
289 mean GHG emissions per farm were significantly higher in MaizeMAX (+15%) than in
290 MaizeMIN (Figure 6).

291 The ranking and relative contributions of sources of GHG emissions between farms in
292 ForageMIN and ForageMAX were generally similar to those in Normandy and Lorraine.
293 Nonetheless, the extreme increase in DM_{Grass} from GrassMIN to GrassMAX particularly
294 decreased the relative contribution of purchased feeds (17% vs. 13%, respectively) per farm but
295 had little influence on the contributions of other sources of GHG emissions (e.g., enteric CH_4
296 emissions were 45-47%, organic and inorganic fertilization was 20%) (Figure S4). The extreme
297 increase in DM_{Maize} from MaizeMIN to MaizeMAX particularly decreased the relative
298 contribution of enteric CH_4 emissions (49% vs. 44%, respectively) and increased that of
299 purchased feeds (11% vs. 15%, respectively) per farm.

300

301 **4. Discussion**

302 **4.1. Differences as a function of production strategy and region**

303 As in the previous study (Senga Kiessé et al., 2020), farms in the minimum and maximum
304 samples for a given forage were designed to differ significantly in mean forage production.
305 Although pastures and silage maize compete for a farm's agricultural land, relatively few farms
306 in an extreme maximum sample for one forage were in the extreme minimum sample for the
307 other forage. For instance, of the 14, 13 and 15 farms in GrassMIN in Normandy, Lorraine and
308 Nord-Pas-de-Calais, respectively, 4, 2 and 4 were also in MaizeMAX, respectively (Figure 2).
309 Likewise, in these three regions, of the 15, 42 and 18 farms in GrassMAX, 6, 13 and 2 were
310 also in MaizeMIN. Except in Nord-Pas-de-Calais, an extreme increase in DM_{Grass} was
311 associated with feeding less DM_{Maize} and concentrated feed (sometimes significantly so) and

312 producing significantly less milk per cow. Likewise, except in Nord-Pas-de-Calais, an extreme
313 increase in DM_{Maize} was associated with feeding less DM_{Grass} but more concentrated feed
314 (sometimes significantly so) and producing significantly more milk per cow. Most farms in
315 GrassMIN and MaizeMAX of all regions had Holstein cows, which is the breed with the highest
316 potential for milk production (Buckley et al., 2000). Conversely, cow breeds in GrassMAX and
317 MaizeMIN varied in Normandy and Lorraine, which may have increased the variability in the
318 relation between DM_{Maize} and milk production. In Nord-Pas-de-Calais, most farms in
319 GrassMAX had Holstein cows, which, in addition to feeding slightly more DM_{Maize} , avoided a
320 decrease in mean milk production per cow.

321 Varying mixed rations (e.g., maize silage with 30% concentrated feed, grass silage with 15%
322 concentrated feed) was shown to affect the lactation performance Normande and Holstein dairy
323 cows differently (Delaby et al., 2009). In the present study, farms in GrassMAX (and
324 MaizeMIN) fed more grass and tended to feed less concentrated feed; these grass-based systems
325 are less apt to express the genetic potential of cows that can produce large amounts of milk.
326 The performance of dairy cows in grass-based systems is related to their ability to convert
327 grazed grass to milk while receiving less concentrated feed. Nonetheless, the availability of a
328 sufficient amount of high-quality grass may enable dairy cows with high genetic potential to
329 produce large amounts of milk in grass-based systems (Buckley et al., 2000). In comparison,
330 farms in MaizeMAX (and GrassMIN) fed more maize silage and concentrated feed, which
331 increases animal performance in these extensive systems (Beauchemin et al., 2008).

332 Except in Nord-Pas-de-Calais, a significant change in mean milk production per cow
333 significantly changed mean GHG and enteric CH_4 emissions per farm in the same direction
334 (i.e., increase or decrease). Per l of milk produced, only mean enteric CH_4 emissions usually
335 changed significantly, due to the significant change in the amount of milk produced and
336 relatively larger enteric CH_4 emissions from digesting grass than from digesting maize silage
337 (Evans, 2018).

338 **4.2. Differences for farms in Normandy between 2013 and 2014**

339 Comparing results from the present study for Normandy (2013, 96 farms) to those of the
340 previous study (Senga Kiessé et al., 2020) (2014, 78 farms) revealed few significant differences.
341 Although the entire 2013 and 2014 samples did not necessarily contain the same farms, they
342 did not differ significantly in the mean values of farm characteristics analyzed or in GHG or
343 CH_4 emissions per farm or per l of milk produced. Among the four extreme samples, the largest

344 differences between the 2013 and 2014 samples were for the number of LU, which was 25-37%
345 larger in all four extreme samples from 2013. Consequently, the MaizeMIN sample had
346 significantly less DM_{Maize} in 2013 than in 2014 (794 vs. 2409 kg/LU/year, respectively), also
347 due in part to its smaller sample size (9 vs. 13, respectively), which increased its CV (126% vs.
348 51%, respectively). GHG emissions per farm of MaizeMIN were 19% lower in 2013 than in
349 2014, but GHG or CH_4 emissions for the other three extreme samples differed by no more than
350 13% between years. Similarly, GHG or CH_4 emissions per l of milk produced for all four
351 extreme samples differed by no more than 10% between years. Thus, differences in weather in
352 Normandy between 2013 (relatively cold and wet spring, relatively warm and dry summer) and
353 2014 (relatively warm spring, extremely wet summer) had relatively little influence on GHG
354 and CH_4 emissions. This can be explained in part by the fact that empirical coefficients used to
355 estimate GHG emissions following the Tier 3 approach (based on IPCC (2006)
356 recommendations, Supplementary Material) are less sensitive to weather conditions, unlike
357 process-based models. Nonetheless, the methane conversion factor used to estimate methane
358 emissions from manure storage and management (Eq. S3) depends on the mean annual
359 temperature, among other factors. Likewise, in a study of organic dairy farms in the northwest
360 lowland plains and central mountains of France (Bouttes et al., 2018), differences in weather
361 between two successive years had little influence on farm productivity or economic efficiency,
362 unlike differences in farmers' management practices. That study found no notable relationships
363 between climatic variability and variables related to farm management. Nonetheless,
364 comparison of annual data for only two years is not sufficient to highlight a significant influence
365 of weather conditions.

366

367 **4.3. Influence of geography and climate**

368 Characteristics of farms clearly differed in Lorraine, which had a wider variety of dairy cow
369 breeds on farms in extreme samples than the other two regions did. This increase in variety is
370 due mainly to Lorraine's mountainous terrain, which renders agricultural land more suitable for
371 producing pasture than for producing silage maize. Breeds in Lorraine are thus selected more
372 often to produce milk with higher fat and protein contents rather than large amounts of milk. In
373 contrast, farms in Nord-Pas-de-Calais are oriented more toward producing large amounts of
374 milk, which explains why 66 of the 67 farms in the extreme samples from that region had a
375 majority of Holstein cows.

376 Due to their proximity to the English Channel, farms in Normandy and Nord-Pas-de-Calais
377 experience an oceanic climate, and those closest to the coast have the highest annual rainfall,
378 which promotes development of grass-based systems. In comparison, farms in Lorraine
379 experience more of a continental climate, whose wider temperature range promotes production
380 of silage maize in lowlands. The lower temperatures in the mountains and foothills of Lorraine,
381 however, promotes development of grass-based systems. Nonetheless, climate conditions can
382 have less influence on the production (e.g., crop yields) or profitability (e.g., income) of farm
383 systems when farmers are able to adapt their practices (e.g., crop rotations, inputs) to them
384 (Reidsma et al., 2010).

385 **4.4. Limitations of the study**

386 Our need to assume that each farm fed all of the forage it produced each year (and no more or
387 no less) to its cattle was relatively strong, but in line with standard strategies of French dairy
388 farmers, who tend to set potential forage production to the size and composition of the cattle
389 herd. We purposely selected quantiles for thresholds that avoided overly large subsample sizes,
390 which could have increased the bias of the estimated GPD parameters to the point that the GPD
391 did not fit each tail well. Applying this approach to the sample of 96 farms in Normandy,
392 however, yielded small subsample sizes of only 9-15 farms, which limited the
393 representativeness and generality of our results. Since the GPD models only the tails of
394 distributions, a larger farm sample would be necessary to yield subsamples sufficiently large to
395 be able to draw more general conclusions (e.g., 350 farms could yield extreme subsamples of
396 ca. 50 farms each). For more extensive analysis, EVT should be applied to all farms in the
397 dataset to consider additional French regions. This analysis may help highlight features (e.g.,
398 geography, management strategies, cow breeds) of regions that influence dairy farm systems.

399 **4.5. Extreme-Value Theory**

400 Applying EVT allowed us to identify that a non-negligible proportion of dairy farms in a dataset
401 can have characteristics that differ significantly from average farms. Farms identified with
402 atypical forage production were thus studied as a function of environmental and economic
403 performances. EVT is not limited by the need to assume that variables follow a normal
404 distribution, unlike traditional modeling approaches, and it provides specific probability

405 distribution functions that model the behavior of extremely low and high values of variables in
406 the tails of distributions.

407 One research perspective is to perform bivariate extreme value analysis of farm characteristics
408 to identify situations in which two variables are simultaneously extremely low or high.
409 Applying EVT to time series data of farms would also enable us to analyze temporal dynamics
410 of extreme values of farm characteristics.

411 Identifying dairy farms that produce relatively little forage could help policymakers assess
412 problems that these farms may encounter if extreme conditions decrease forage production
413 further, since economic or climate fluctuations may influence their productivity or
414 environmental impacts more than those of other farms. A policy of diversifying the types of
415 forage produced could be considered to mitigate effects of these fluctuations.

416

417 **5. Conclusion**

418 We analyzed dairy farms that produced extreme amounts of forages in three French regions, as
419 influenced by geography and climate. EVT was revealed to be a useful approach for
420 distinguishing dairy farms that have average characteristics from those that deviate from
421 average trends. Distinguishing farms as a function of extreme amounts of forages also identified
422 farm management practices related to the main breed of cows, because milk-production goals
423 depended on the region. Potential changes in factors such as climate conditions, the economic
424 context and farm productivity should also be investigated to assess differences in vulnerability
425 to extreme weather events between “average” and “extreme” farms. These results could inform
426 stakeholders and policy decision makers about potential consequences of impacts due to more
427 frequent climatic extremes.

428 **Authorship contribution statement**

429 Michael S. CORSON: Writing - review & editing, Tristan SENGA KIESSE: Methodology,
430 Writing - original draft. Aurélie WILFART: Supervision, Writing - original draft.

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