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Abstract

Dairy farms follow a wide variety of management practices depending on the economic and environmental objectives that farmers target. Management practices are reflected, among other things, by a wide variety of forage-production and animal-feeding strategies, which influence productivity and greenhouse gas (GHG) emissions of dairy farms. Many studies focus on agricultural systems with "average" characteristics to generalize results to a larger percentage of existing systems. This approach, however, ignores systems with uncommon characteristics, whose environmental impacts may be unusually large (e.g. due to inefficiencies) or small (e.g. due to innovations). To address this issue, we used Extreme-Value Theory (EVT) as a statistical tool to identify dairy farms with forage-related characteristics that could be considered "extreme". Application of EVT to a dataset of 78 dairy farms in Normandy (France) identified 15-20% of dairy farms with extreme minimum amounts of dry matter (DM) of grass from pastures or maize silage and 10-15% of farms with extreme maximum amounts of one or the other. Mean amounts of DM between the minimum sample and maximum sample differed by a factor of ca. 3 for grass and a factor of 1.5 for maize silage. Consequently, the maximum sample for grass or maize silage had mean estimated gross GHG emissions (kg CO_2 eq) 13% lower or 25% higher, respectively, than those of the minimum sample. Four strategies were identified for setting DM of grass and maize silage at extreme levels, which influenced milk production and GHG emissions. Extreme changes in the DM of one forage were generally compensated by changes in those of the other forage and concentrated feed fed at non-extreme levels, which influenced enteric methane emissions, manure management or the amount of feeds purchased.

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

1. Introduction

Management practices of dairy farms are widely studied due to their influence on farm inputs, which in turn influence farm productivity and environmental impacts. Studying effects of management changes on greenhouse gas (GHG) emissions and farm profitability is useful for developing farm-level GHG mitigation strategies that could be financially viable (Lovett et al., 2008). For instance, animal-feeding strategies directly influence enteric methane (CH_4) emissions of dairy cattle, which contribute ca. 67% of GHG emissions of the global livestock sector (Dollé et al., 2011; Gerber et al., 2011; Gerber et al., 2013). Thus, studies that predict CH_4 emissions from dairy cattle often consider feed and forage intake as input variables (Bannink et al., 2011). The quantities of inputs used to feed animals (either directly, such as concentrated feed, or indirectly, such as fertilizers) vary greatly among farms, which may cause these farms' environmental impacts (e.g. GHG emissions) to vary greatly as well. Many studies of agricultural systems focus on "average" characteristics to generalize results to a larger percentage of existing systems. This approach, however, ignores systems with uncommon characteristics, whose environmental impacts may be unusually large (e.g. due to inefficiencies) or small (e.g. due to innovations).

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

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

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

2. Material and methods

2.1. Data

The dataset consisted of 78 dairy farms in Normandy surveyed in 2014 by the French Livestock Institute (IDELE). Annual data for a variety of annual farm inputs, characteristics and outputs were collected for each farm: areas of pastures and silage maize in the forage area, grass yield, number of LU, milk produced per cow, amount of concentrated feed fed, estimated CH_4 emissions from dairy cows and heifers (Table 1). The main dairy cow breeds were Holstein (minimum, mean and maximum of 45%, 89% and 100%, respectively) on 54 farms, Normande (61%, 89% and 100%, respectively) on 18 farms, and cross-breeds (50%, 63% and 100%, respectively) on 6 farms. GHG emissions (CH_4, nitrous oxide and carbon dioxide) due to production and transport of purchased feeds, purchased fertilizers and on-farm energy consumption were estimated. Milk production per cow was calculated as total milk production per year divided by the number of dairy cows.

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

IPCC Tier 3 methodology (IPCC, 2006) was used to predict CH_4 emissions (g CH_4/kg of digestible organic matter) from dairy cows and heifers, based on an empirical model adapted to French national contexts that considers factors such as feeding levels and proportion of concentrated feed in the diet (Sauvant and Noziere, 2016). The main sources of GHG emissions were enteric fermentation from cattle (50%), manure storage and management (20%), organic and inorganic fertilization (9%), production and transport of inputs (e.g. feeds (12.5%), fertilizers (3%), and animals (<1%)), and on-farm energy consumption (5%) (Supplementary Table A1). Emissions were estimated from information provided by farmers. For instance, the amount of manure produced per year per farm was estimated from the type of animal housing, milk production (for dairy cows) and calving period (for suckler cows). Farmers also supplied additional information, such as the average duration of manure storage and amounts of off-farm effluents imported. Likewise, farmers provided amounts of mineral fertilizers and effluents applied per ha, feed purchased and total energy (electricity and diesel) consumed based on information in their bills and accounting books. GHG emissions from these sources were estimated using emission factors (e.g. kg CO_2 eq per kg of feed, kWh of

electricity or L of diesel purchased). Carbon sequestration (e.g. by pastures) was not considered. These contributions to GHG emissions led to a strong correlation between GHG (and enteric CH_4) emissions and milk produced per cow (Figure 1).

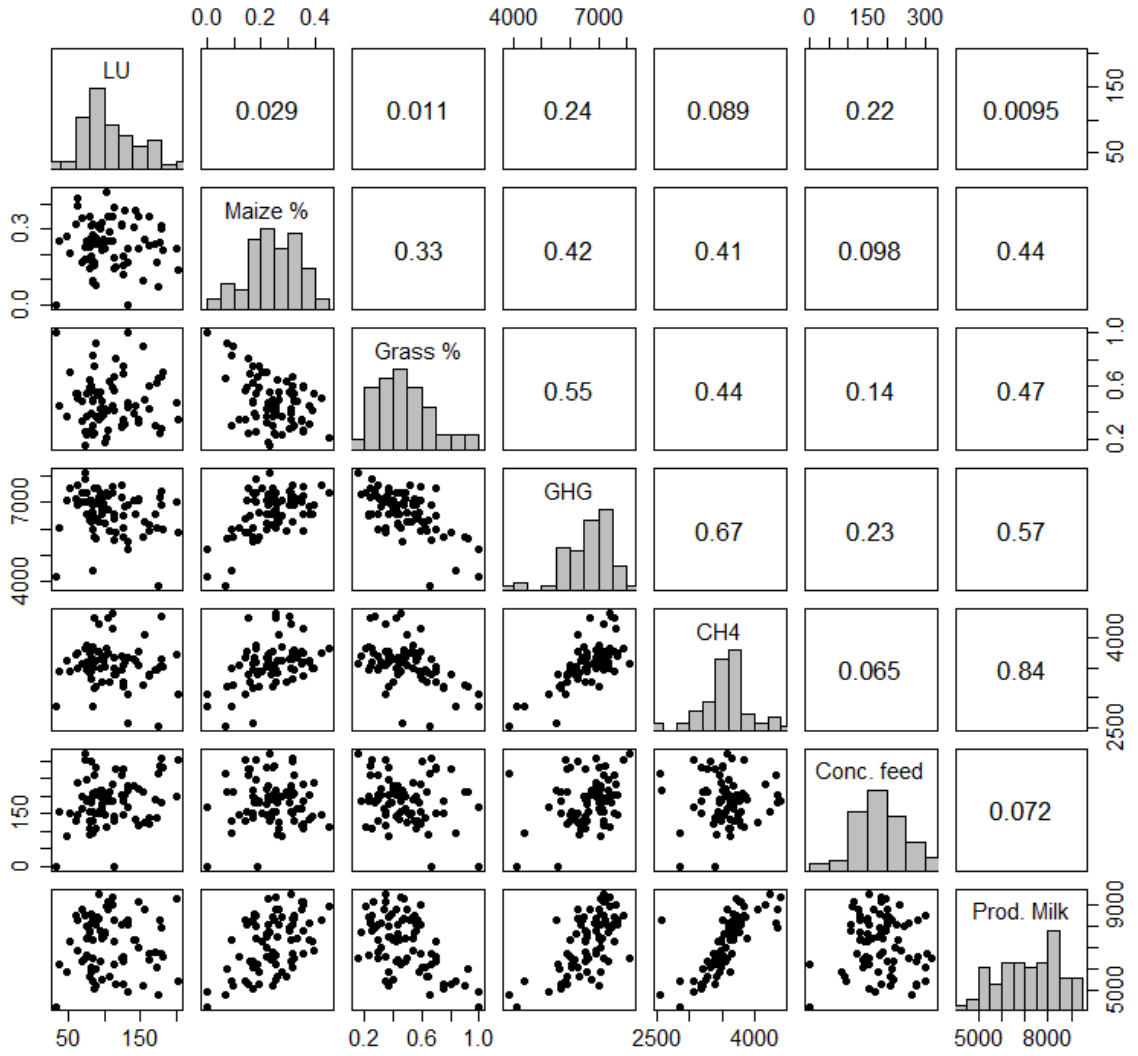


Figure 1. Pairwise scatter plots of areas of pastures and silage maize in UAA (%), number of livestock units (LU), concentrated feed fed (g/l of milk produced), milk production per cow (l), and estimated greenhouse gas (GHG) and enteric methane (CH_4) emissions (kg CO_2 eq/farm/year) of 78 dairy farms in Normandy (France) in 2014, with Spearman's rho rank correlation coefficients $\boldsymbol{\rho_n}$ ($\boldsymbol{n}$= 78).

We calculated each farm's production of each forage per LU (kg dry matter (DM)/LU/year) by dividing the total DM of grass from pastures (DM_{Grass}) or maize silage (DM_{Maize}) (equal to area (ha) × yield (t DM/ha)) by the number of LU. Since the yield of silage maize was not available for dairy farms in our dataset, we used the mean regional yield of 19.3 t DM/ha in 2014 (ARVALIS-Institut du Végétal). DM_{Grass} and DM_{Maize} varied greatly among farms (coefficients of variation (CV) = 47% and 38%, respectively), but the variability in DM_{Maize} was due only to that of the area of silage maize, since we used the mean yield. Distributions of the amount of concentrated feed fed had similar characteristics as those of DM_{Grass} and DM_{Maize} (CV = 35%) (Table 1). Milk production per cow and estimated GHG and CH_4 emissions, however, varied less (CV = 10-18%) (Table 1). Annual GHG and CH_4 emissions were analyzed according to two functional units: farm (kg CO_2 eq/farm/year) and l of milk produced (kg CO_2 eq/l/year).

2.2. Extreme-Value Theory

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

2.2.1. Generalized Pareto distribution

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

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

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

2.2.2. Threshold selection

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

2.2.3. Statistical tests and root mean squared error

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

3. Results

3.1. Extreme samples for dry matter of grass from pastures

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

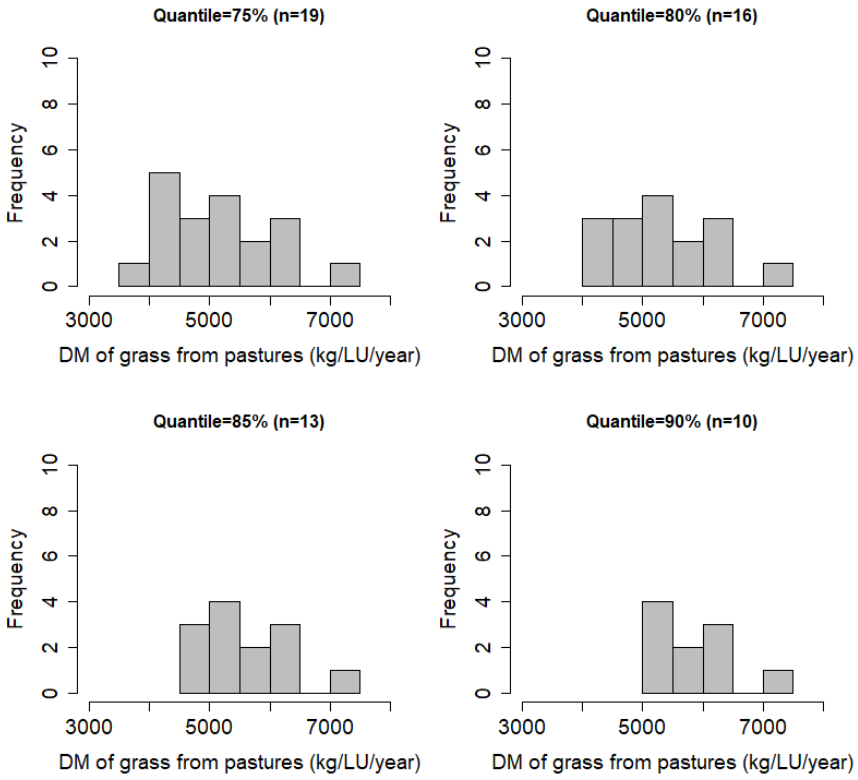


Figure 2. Distributions of the maximum sample of dry matter (DM) of grass from pastures (kg/livestock unit (LU)/year) extracted as a function of dataset quantile (75%, 80%, 85% and 90%)

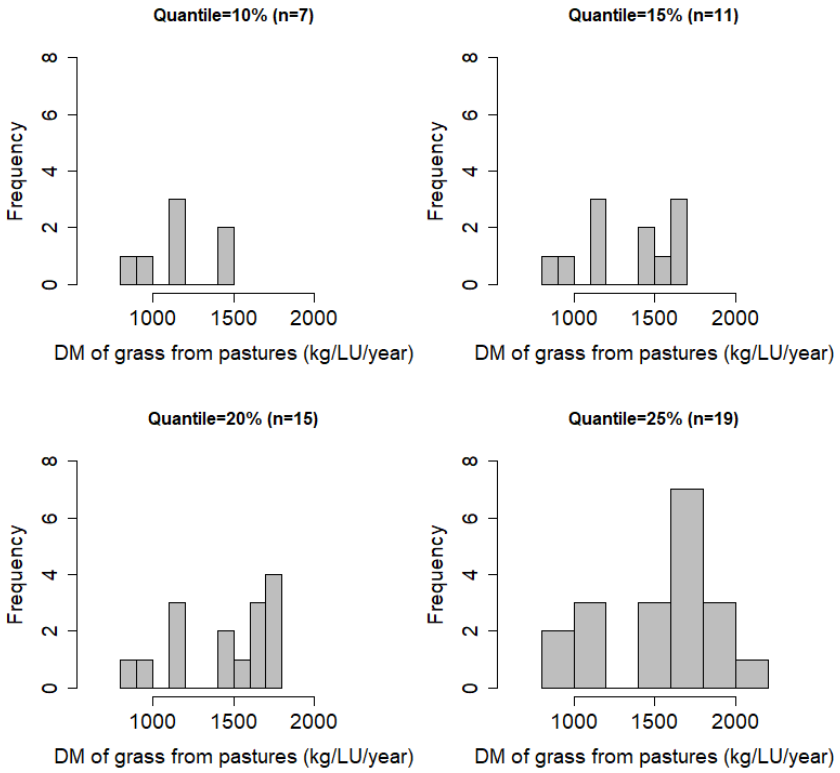


Figure 3. Distributions of the minimum sample of dry matter (DM) of grass from pastures (kg/livestock unit (LU)/year) extracted as a function of dataset quantile (10%, 15%, 20% and 25%)

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

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

Sample	Quantile	DM of grass (kg/LU/year)	Sample size	Estimated shape $\hat{\varepsilon}$	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**

3.2. Extreme samples for dry matter of maize silage

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

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

Sample	Quantile	DM of maize silage (kg/LU/year)	Sample size	Estimated shape $\hat{\varepsilon}$	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

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

3.3. Milk production and emissions by sample

On average, GrassMAX and GrassMIN produced less and more milk per cow (6269 and 7954 l/cow/year, respectively) than the mean of the entire dataset (7210 l/cow/year) (Table 4). Similar differences in means were observed for annual GHG and enteric CH_4 emissions (kg CO_2 eq) per farm and per l of milk produced (Table 5). Amounts of concentrated feed fed for GrassMAX and GrassMIN were less than the dataset mean.

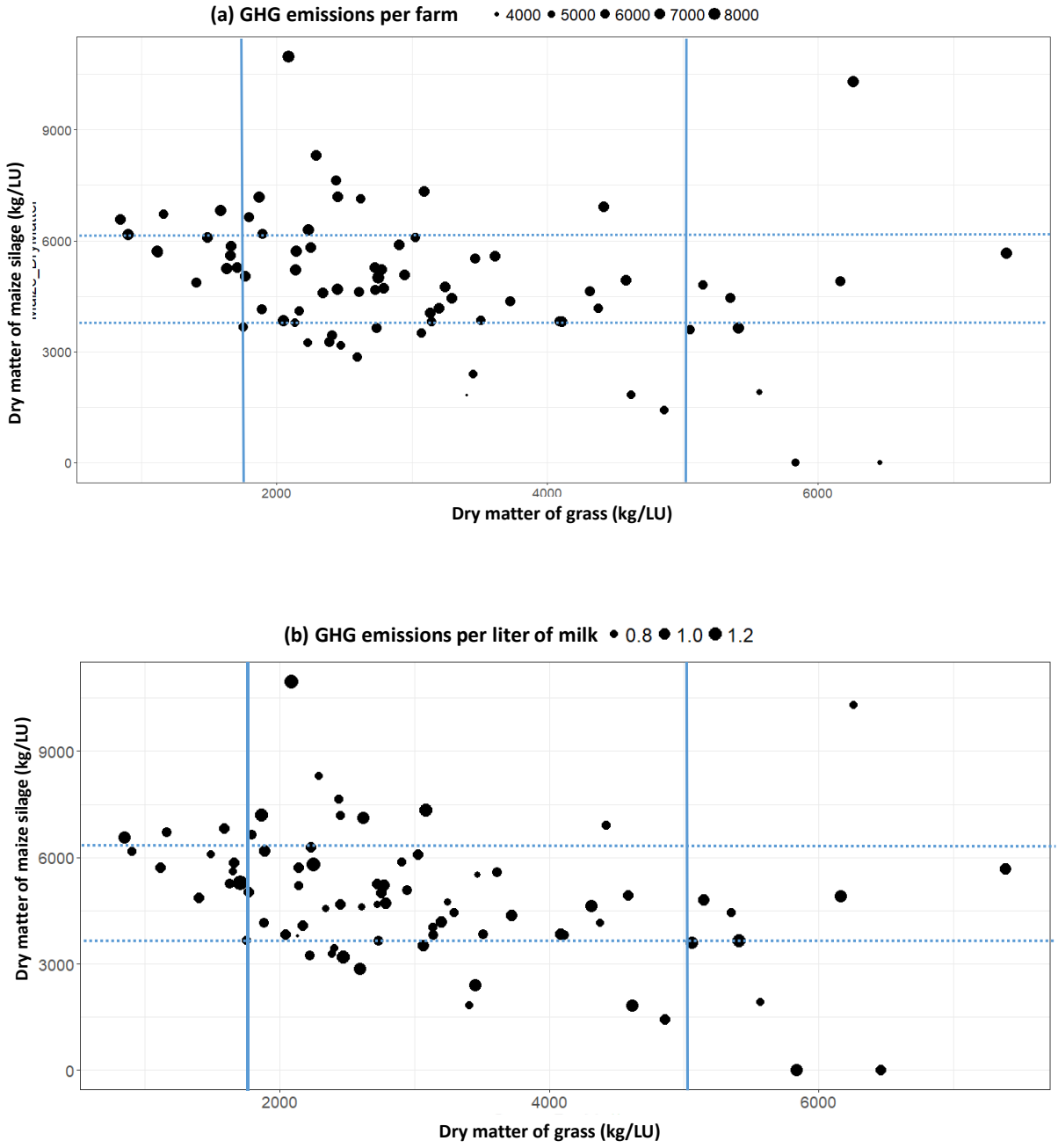
Conversely, MaizeMIN and MaizeMAX produced less and more milk per cow (5785 and 7351 l/cow/year, respectively) than the dataset mean (7210 l/cow/year) (Table 4). Similar differences in means were observed for annual GHG and enteric CH_4 emissions per farm (Table 5). Per l of milk produced, annual GHG and enteric CH_4 emissions for MaizeMIN and MaizeMAX were generally slightly greater than or equal to, respectively, the dataset mean. Amounts of concentrated feed fed for MaizeMIN and MaizeMAX were less or slightly greater, respectively, than the dataset mean (Table 5).

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

			Grass DM sample				Maize silage DM sample			
Variable	**Statistic**	**Entire dataset**	**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	Mean	3031	1325	5862	+342%	<0.001	3987	2531	-36%	0.07
(kg/LU/year)	CV	47%	23%	12%			37%	56%		
Maize silage	Mean	4836	5939	3931	-33%	0.02	2409	7669	+150%	<0.001
DM (kg/LU/	CV	38%	10%	76%			51%	19%		
year)										
Number of LU	Mean	108	119	93	-21%	0.10	111	102	-8%	0.55
	CV	36%	24%	44%			39%	30%		
Concentrated	Mean	185	177	153	-13%	0.39	173	186	+7%	0.85
feed fed (g/l	CV	35%	25%	47%			55%	34%		
milk prod./year)										
Milk prod. per	Mean	7210	7954	6269	-21%	0.04	5785	7351	+27%	<0.001
cow (l/year)	CV	18%	12%	24%			19%	15%		

Table 5. Mean and coefficient of variation (CV) of annual gross greenhouse gas (GHG) and enteric methane (CH_4) emissions (kg CO_2 eq) by functional unit (FU) (per farm or per l of milk produced) for the entire dataset and for farms in minimum ("MIN") and maximum ("MAX") samples of dry matter (DM) of grass from pastures and maize silage. % chg. = percentage change from minimum to maximum sample. M-W p = p-value of Mann-Whitney test for the difference between emissions for farms in minimum and maximum extracted samples of DM of each forage.

				Grass DM sample				Maize silage DM sample			
FU	**Variable**	**Statistic**	**Entire dataset**	**MIN sample**	**MAX sample**	**% chg.**	**M-W p**	**MIN sample**	**MAX sample**	**% chg.**	**M-W p**
Farm	GHG	Mean	6618	7044	6113	-13%	0.13	5549	6962	+25%	<0.001
	emissions	CV	12%	7%	20%			16%	9%		
	Enteric CH_4	Mean	3566	3430	3667	-6%	0.05	3208	3616	+12%	0.001
	emissions	CV	10%	13%	4%			9%	8%		
l of milk	GHG	Mean	0.93	0.89	0.99	+11%	0.03	0.98	0.97	-1%	0.93
produced	emissions	CV	14%	11%	13%			13%	17%		
	Enteric CH_4	Mean	0.50	0.46	0.56	+21%	0.003	0.56	0.50	-11%	0.02
	emissions	CV	13%	8%	13%			11%	12%		



252 Figure 4. Bivariate plot of annual gross greenhouse gas (GHG) emissions (kg CO_2 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

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

3.4.1. Milk production and farm sizes

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

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

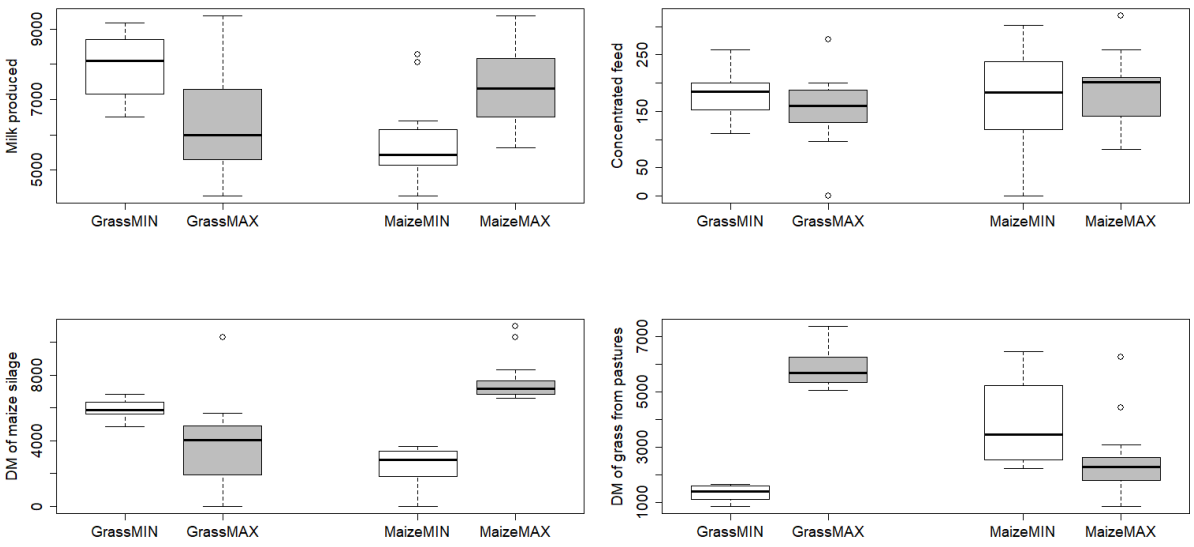


Figure 5. Boxplots of milk production per cow (l/cow/year), concentrated feed fed (g/l of milk produced), grass from pastures and maize silage (kg dry matter (DM)/livestock unit/year) for

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 CH_4 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 CH_4 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.

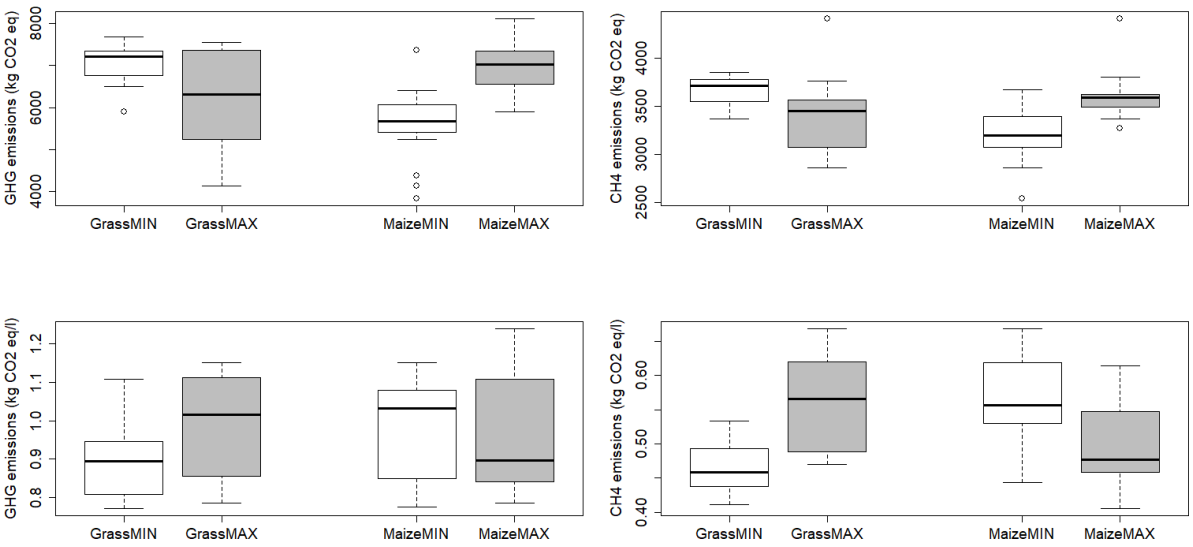


Figure 6. Distributions of annual gross GHG and enteric methane (CH_4) emissions (top) per farm per year (kg CO_2 eq/farm/year) and (bottom) per l of milk produced (kg CO_2 eq/l/year) for farms in minimum ("MIN") and maximum ("MAX") samples of dry matter (DM) of grass from pastures and maize silage

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

Per l of milk produced, GrassMAX emitted 17% more gross GHGs than GrassMIN (significant), while MaizeMAX emitted 1% less than MaizeMIN (non-significant) (Table 5, Figure 6). Enteric CH_4 emissions followed the same trend: 20% larger for GrassMAX than GrassMIN and 11% smaller for MaizeMAX than MaizeMIN (both significant). Cross-comparison of the same end of the distribution of each forage showed that GrassMIN emitted 17% less GHGs than MaizeMIN, but GrassMAX emitted nearly the same amount of GHGs as MaizeMAX (1% difference). In comparison, GrassMIN emitted 21% less enteric CH_4 than MaizeMIN, but GrassMAX emitted 10% more enteric CH_4 than MaizeMAX.

4. Discussion

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

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

4.2. Land management strategies

As expected, significant differences in the percentage of UAA in pastures and maize silage were found between farms in minimum and maximum samples of each forage (Supplementary Table A2), since the area of each forage was used to calculate DM. On a 70 ha commercial farm in the Netherlands, Vellinga and Hoving (2010) studied effects of increasing the proportion of maize silage in feed rations due to increasing the area of maize silage grown. They examined several land-use scenarios, such as converting permanent grasslands to silage maize, either in monoculture or in rotations with temporary grasslands. For instance, increasing the silage maize area by 4 ha decreased GHG emission intensity by 11 g CO_2 eq/kg milk (Vellinga and Hoving, 2010). However, the practicality of changing feeding strategies by changing land use depends on the size of the farm. Farms with small total area or grassland area may have difficulty making certain changes. Maximizing DM_{Grass} also requires future studies that investigate how land use and management influence other services that grasslands provide besides forage production, such as modifying the quality (e.g. fatty-acid contents) of milk and meat and mitigating GHG emissions by sequestering soil

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

4.3. Differences in GHG emissions by production strategy

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

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

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

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

4.4. EVT

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

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Supplementary Materials

Table A1. Descriptive statistics of the percentage of total greenhouse gas (GHG) emissions due to methane emissions, manure storage and management, purchased feeds organic and inorganic fertilization, on-farm energy consumption and fertilizers used of 78 dairy farms in 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

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

			Grass DM sample				Maize silage DM sample			
Variable	**Statistic**	**Entire dataset**	**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%		