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Modeling Production Efficiency and Greenhouse Gas Objectives as a Function of Forage Production of Dairy Farms Using Copula Models

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Abstract
Dairy farms are systems with multiple dependent variables whose practices influence their economic and environmental performances. Decisions made and actions taken to improve environmental performances of dairy farms carry the risk of decreasing farm profitability. Correlations among multiple variables must therefore be considered to reliably assess risks of improving environmental performances of farms. We applied copula models to a dataset of conventional dairy farms surveyed in France to decscribe relationships among their characteristics, such as forage dry matter (DM) production, milk production, and greenhouse gas (GHG) emissions. By modeling relationships among farm characteristics, copula models can identify the characteristics' joint distributions, unlike other statistical methods. For dairy farms, copula models are useful for estimating probabilities of reaching a milk production goal or not exceeding a regulatory emission limit as a function of forage production. For instance, when a farm produced at least 4,500 kg DM/livestock unit (LU)/year of maize silage, the probability of producing at least 7,000 l milk/cow/year was 75%, while the probability of emitting less than 7,000 kg CO_2 eq./LU/year (a value close to the mean of 6669 kg CO_2 eq./LU/year for all of the farms) was 48%. When the same amount of grass from pasture was produced, these probabilities changed to 48% and 78%, respectively (i.e., decreased probability of reaching a production goal, but increased probability of not exceeding an emission threshold). Farmers must make trade-offs, since increased milk production goals are likely to increase GHG emissions per LU and/or reduce GHG emission intensities per l of milk, but are less likely to be reached for a given amount of forage DM. By providing information about relationships among farm characteristics that other statistical approaches cannot, copula models are useful for investigating these trade-offs.

Keywords Animal feeding · Conditional probability · Environmental impact · Farm productivity · Joint distribution

1 Introduction

Agricultural systems involve variables that characterize farming practices, climate conditions, or the economic context. These variables influence economic and environmental performances of these systems. For instance, a French study investigated ten measures based on farming practices to improve environmental performances of dairy farms [1]. In this study, potential decreases and increases in greenhouse gas (GHG) emissions due to the measures were analyzed, as were trade-offs among them for farmers. When varying a farm input to decrease emissions, dependence between inputs must be considered to address indirect effects on dairy farms. For instance, farmers' animal-feeding strategies also influence enteric methane (CH_4) emissions of dairy cattle [2]. However, the composition of animal diets (e.g., amounts of concentrate feed and maize silage) also influences milk productivity. Likewise, increasing milk productivity (discussed as an alternative to reduce GHG emissions) did not reduce GHG emissions at a larger scale when considering other systems that milk productivity influenced indirectly, such as beef production [3]. Thus, there is practical interest in approaches that can consider dependence among variables of dairy farms in order to assess GHG-mitigation strategies.

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To address the issue raised by choosing among alternative solutions that contain trade-offs among multiple criteria, many studies have investigated methods of multicriteria decision analysis. For instance, life cycle assessment (LCA), which is recognized as the leading framework for multicriteria environmental assessment of systems [4], can benefit from multicriteria decision analysis to assess trade-offs among multiple criteria [5]. Likewise, to help choose an alternative based on comparative environmental assessments such as LCA, others have used stochastic multi-attribute analysis, which incorporates performance uncertainty into the assessment [6]. Sensitivity analysis methods have also been integrated into LCA steps to help stakeholders (e.g., farmers) in the decision-making process, by studying the contribution of each input parameter to the variance in output [7, 8]. However, the potential for dependence among input parameters is an additional complication in the environmental assessment of systems [9].

The present study was interested in analyzing indirect effects and potential trade-offs when farm characteristics are varied to improve environmental and economic performances of dairy farms. However, such analysis requires modeling relationships among variables of dairy farm characteristics. Regression models are traditionally used to relate variables that contribute to environmental impacts of dairy farms (e.g., enteric CH_4 emissions) to explanatory variables (e.g., dry matter (DM) intake of dairy cows), which describe farm characteristics [10]. However, traditional modeling approaches are often limited by the need to assume that variables are independent and follow a given distribution, usually normal. Traditional modeling approaches therefore encounter limits when the data contain extreme values (e.g., due to farms with uncommon characteristics) or when random variables exhibit tail dependence (i.e., stronger correlation as they move further into the tails of their distributions). A traditional regression model would not have been sufficient for our objectives, since it cannot identify tail dependence or generate explanatory and output variables simultaneously as a function of their respective probability distribution functions (pdfs).

Copulas are mathematical models useful for describing complex relationships between random variables [12, 13]. Copula models can construct joint distribution functions of variables from data and do not require the usual assumption that variables follow a normal distribution. They are also appropriate for measuring tail dependences for pairs of random variables [14, 15]. Copula models have been applied to a wide range of topics, including economics, risk management, and meteorological events. For instance, they have been used to characterize droughts based on the behavior of multiple variables, such as precipitation, soil moisture, and streamflow [16–18]. Likewise, copula models have been used for risk management in economics to investigate dependence between sources of risk [19]. Copula models have also been used in hydrology to estimate the risk of the occurrence of extreme events, by analyzing tail dependence between variables such as peak flow and volume [20, 21]. Copula models were recently applied in agriculture to consider dependencies among distributions of LCA impact indicators to analyze uncertainty in estimated impacts of two tomato production systems [22].

The present study aimed to assess the probability of reaching an economic production goal (e.g., a given milk production) or not exceeding an environmental regulatory limit (e.g., a threshold of GHG emissions) as a function of forage-related characteristics. On dairy farms, DM intake by dairy cows is identified as a major driver of milk production [23] and CH_4 production from enteric fermentation (the largest source of GHG emissions in ruminant production) [24, 25]. For instance, varying the ratios of grazed grass and maize silage in dairy cow diets influences milk production and GHG emissions. Thus, the main goal of our study was to build joint distribution functions of pairs of variables, which represented dependencies among forage-related characteristics (forage DM production), farm profitability (indirectly, via milk production), and environmental performance (GHG emissions) of dairy farms. To this end, relationships among DM of grass from pasture, DM of maize silage, milk production, and GHG emissions of dairy farms were modeled using a sample of dairy farms in Normandy (France). Environmental performances were also analyzed as a function of farm productivity.

2 Data and Methodology

2.1 Dataset

The dataset consisted of $\boldsymbol{n} = 76$ conventional dairy farms in Normandy surveyed in 2014 by the French Livestock Institute (IDELE). Annual data for a variety of farm inputs, characteristics, and outputs were collected for each farm: areas of pastures and silage maize in the forage area, grass yield, number of livestock units (LU), milk produced per cow, amount of concentrated feed fed and 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% of the herd, respectively) on 54 farms, Normande (61%, 89%, and 100%, respectively) on 17 farms, and crossbreeds (50%, 64%, and 100%, respectively) on 5 farms. Milk production per cow was calculated as total uncorrected milk production per year divided by the number of dairy cows. Although we could have used energy-corrected milk production, uncorrected milk production was sufficient for our goals. GHG emissions (CH_4, nitrous oxide,

Table 1 Descriptive statistics of annual characteristics of n = 76 dairy farms in Normandy (France) in 2014. *CV* coefficient of variation, *GHG* greenhouse gas

Characteristic	Min	Mean	Max	CV (%)
Utilized agricultural area (UAA) (ha)	30.6	119.4	258.1	43
Area of pastures in UAA (%)	15.2	46.7	92.0	37
Area of silage maize in UAA (%)	7.0	24.7	44.6	34
Number of livestock units (LU)	36	109	202	35
Grass yield (t dry matter/ha/year)	1.9	6.1	12.6	32
Concentrated feed fed (g/l milk)	0.0	187.4	319.0	33
Milk production per cow (l/year)	4819	7278	9490	17
Gross GHG emissions (kg CO_2 eq./LU/year)	3830	6669	8118	11
Enteric CH_4 emissions (kg CO_2 eq./LU/year)	2537	3581	4408	9

and carbon dioxide) due to production and transport of purchased feeds, purchased fertilizers, and on-farm energy use were estimated from the French project LIFE Carbon Dairy (www.carbon-dairy.fr). All GHG emissions were estimated from information provided by farmers. The main sources of GHG emissions were enteric fermentation from cattle, manure storage and management, organic and inorganic fertilization, and production and transport of inputs (e.g., feeds, fertilizers) (Supplementary Fig. S1). GHG emissions from these sources were estimated using emission factors (e.g., kg CO_2 eq./kg feed). Potential carbon sequestration (e.g., by pastures) was not considered. For dairy cows and heifers, IPCC Tier 3 methodology [26] was used to predict enteric CH_4 emissions (g CH_4/kg digestible organic matter), based on an empirical model adapted to French national contexts that considers factors such as feeding levels and the proportion of concentrated feed in the diet [27]. See the Supplementary Information for details about GHG estimation. The GHG emission intensity of milk ($GHG_{Emission\_intensity}$; kg CO_2 eq./l milk) was calculated by dividing gross GHG emissions per farm by total uncorrected milk production per year.

We calculated each farm's production of each forage per LU (kg DM/LU/year) by dividing the total DM of grass from pastures ($Grass_{DM}$) or maize silage ($Maize_{DM}$) (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 [28]. Consequently, the variability in $Maize_{DM}$ among farms was due only to that in their area of silage maize. Forage production served as a proxy of forage intake by cattle, which was not included in the survey. Forage production of dairy farms (e.g., areas and DM of forages) influenced both productivity (e.g., milk production per cow ($Milk_{Produced}$)) and environmental impacts (e.g., gross GHG emissions per farm ($GHG_{Emissions}$)), which led to correlation between them (Supplementary Fig. S2). Specifically, $Grass_{DM}$ was significantly and negatively correlated with $Milk_{Produced}$ (Spearman correlation coefficient ρ was −0.26, p = 0.02) and $GHG_{Emissions}$ ($\rho = -0.27$, p = 0.02). Conversely, $Maize_{DM}$ was significantly and positively correlated with $Milk_{Produced}$ ($\rho = 0.32$, p = 0.004) and $GHG_{Emissions}$ ($\rho = 0.54$, $p < 0.001$). These significant correlations highlighted the practical issue of examining their dependence in dairy farm systems in more detail, by considering the dependence between these and other characteristics throughout their respective distributions.

2.2 Copula Method

This section provides a simplified overview of the fundamental concepts of the copula method for modeling the dependence structure between only two variables. Unlike other statistical methods, the copula method offers many (bivariate) functions to represent how two variables vary simultaneously, which reveals the regions of their respective distributions in which the variables have the highest dependence. In an agricultural context, results of copula models are useful for estimating the probability of reaching a threshold (e.g., production goal) or not exceeding a threshold (e.g., regulatory limit) as a function of given farm characteristics. For more details, many articles review copulas comprehensively [29, 30]. We consider continuous random variables (rv) X and Y, whose univariate marginal cumulative distribution functions (cdf) are denoted by F_X and F_Y, and pdf are denoted by f_X and f_Y. Then, the pair of variables (X, Y) has a joint cdf and pdf denoted by $F_{X,Y}$ and $f_{X,Y}$, respectively. The cdfs F_X, F_Y, F_{XY} are unknown functions to estimate from data with the corresponding densities. We also denote the copula cdf by C_θ, with a univariate or bivariate parameter θ, and by c_θ, the copula density function.

2.2.1 Definition

Given realizations x, y of variables X, Y on $\mathbb{R}$ (the set of all real numbers), a copula is a bivariate function that associates the pair $(F_X(x), F_Y(x)) \in [0,1]^2$ of univariate marginal cdf to the joint cdf $F_{X,Y}(x,y) = \Pr(X \le x, Y \le y) \in [0,1]$ as follows [12]:

$$F_{X,Y}(x,y) = C_\theta\left(F_X(x), F_Y(y)\right), x, y \in \mathbb{R}. \tag{1}$$

By connecting $F_{X,Y}$ to F_X and F_Y, the copula function C_θ describes the dependence between X and Y.

Copula C_θ is estimated from the data, as detailed later (Sect. 2.2.3). Once the copula is estimated, the cdfs F_X and F_Y are also estimated to perform goodness-of-fit tests (Sect. 2.2.3).

2.2.2 Examples of Parametric Copulas

A variety of parametric copulas have been developed, which are grouped into main classes such as Archimedean, elliptical, and extreme-value copulas [29]. The variety of copulas enables one to model various structures of dependence between variables, such as positive or negative dependence and lower or upper tail dependence. In an agricultural context, modeling tail dependences is particularly useful since the occurrence of maximum (or minimum) values of one variable may be conditional on that of maximum (or minimum) values of another variable. As an illustration, we present the Archimedean copulas "Joe" [13] and "Frank"[30].

Example 1. The Joe copula ${C_\theta}^{Joe}$, with its parameter $\theta \geq 1$, is defined by

$$ {C_\theta}^{Joe}(u,v) = 1 - \left((1-u)^\theta + (1-v)^\theta - (1-u)^\theta(1-v)^\theta\right)^{1/\theta}. \tag{2} $$

The parameter $\theta \in [1, \infty)$ describes the degree of dependence between X and Y. Thus, $\theta = 1$ indicates an independence structure such that ${C_{\theta=1}}^{Joe}(u,v) = uv$. The Joe copula is appropriate for modeling only positive dependence structures. It is consistent with bivariate extreme analyses and can be used to model upper-tail-dependence structures. The upper-tail-dependence coefficient of the Joe copula can be calculated and expressed as a function of parameter θ, and it has a null lower tail-dependence coefficient.

Example 2. The Frank copula ${C_\theta}^{Frank}$, with its real parameter $\theta \neq 0$, is defined by

$$ {C_\theta}^{Frank}(u,v) = -\frac{1}{\theta}\ln\left(1 + \frac{(e^{-\theta u}-1)(e^{-\theta v}-1)}{e^{-\theta}-1}\right). \tag{3} $$

The value of parameter θ provides information about the structure of copula ${C_\theta}^{Frank}$. For instance, $\theta \to 1$ corresponds to independence, $0 < \theta < 1$ corresponds to positive dependence, and $\theta > 1$ corresponds to negative dependence. The Frank copula is not appropriate for modeling tail-dependence structure and has null lower and upper tail-dependence coefficients.

There also exist *rotated copulas* that consist of a simple rotation of existing copulas C_θ by 90°, 180°, and 270°. For instance, the 180°-rotated copula of C_θ, with the density function c_θ, is given by setting u to $1-u$ and v to $1-v$, which yields ${C_\theta}^{180_{rotated}}(u,v) = u + v - 1 + C_\theta(1-u, 1-v), u, v \in [0,1]$. Likewise, the 270°-rotated copula of C_θ is given by ${C_\theta}^{270_{rotated}}(u,v) = u - C_\theta(u, 1-v)$. The rotated copulas give more flexibility for using classes of copula that can display only one type of (tail) dependencies. For instance, a 270°-rotated Joe copula can fit negative dependencies, even though the non-rotated Joe copula (Example 1) fits only positive dependencies.

2.2.3 Copula Selection and Goodness-Of-Fit Tests

Given independent realizations $(x_i, y_i), i = 1, \ldots, n$, from the pair (X, Y) of continuous random variables with their marginal cdf F_X and F_Y. The selection procedure first consists of fitting several copulas from the main copula classes. For each copula C_θ considered, an estimate $\hat{\theta}_n$ of parameter θ is first calculated using the method of maximum likelihood such that $\hat{\theta}_n = \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^n \ln c_\theta(u_i, v_i)$, with c_θ the copula density and (u_i, v_i) the pairs are obtained by transforming realizations (x_i, y_i) to uniform margins on $[0,1]^2$. We then select the copula that minimizes the Akaike information criterion (AIC) given by $AIC_n = -2\sum_{i=1}^n \ln\left(c_{\hat{\theta}_n}(u_i, v_i)\right) + 2p$, with p being the number of parameters of the copula (e.g., $p = 2$ if θ has two components).

Once one copula $C_{\hat{\theta}_n}$ with the estimate $\hat{\theta}_n$ of its parameter was selected, we plotted two graphs to check the adequacy of $C_{\hat{\theta}_n}$ to the data [31]. The first graphical test consisted of plotting $N = 1{,}000$ random pairs $(U_j, V_j), j = 1, \ldots, N$, simulated using the Monte Carlo (MC) method from copula $C_{\hat{\theta}_n}$ along with pairs $(x_i, y_i), i = 1, \ldots, n$, of observations transformed to uniform margins on $[0,1]^2$ (n= 76 for the dataset of dairy farms). The MC method is well adapted for simulating relationships among multiple dependent variables [11], such as copulas, thus extrapolating the relatively small sample to a much larger one and increasing the robustness of the results obtained. The second graphical test first required that random pairs $(U_j, V_j), j = 1, \ldots, N$, simulated from copula $C_{\hat{\theta}_n}$ (and their margins) be transformed back into the original units of pairs $(x_i, y_i), i = 1, \ldots, n$, of observations. Then, the scatterplot of pairs $(\hat{F}_X^{-1}(U_j), \hat{F}_Y^{-1}(V_j))$ was compared to the pairs (x_i, y_i), where $\hat{F}_X$ and $\hat{F}_Y$ are the estimates of cdf F_X and F_Y. This is a simple way to simulate rv X with a (fitted) cdf $\hat{F}_X$, since we have $\hat{F}_X^{-1}(U) \sim \hat{F}_X$, for any random variable U uniformly distributed on $[0,1]$.

All analyses were performed in R software [32] using packages that applied the copula method, such as *VineCopula* [33] and *VC2copula* [34]. In particular, parametric copulas were chosen using the function "BiCopSelect" of the *VineCopula* package, which fits several copula classes, estimates parameters using the maximum likelihood method, and calculates AIC.

2.3 Application of the Copula Method

The copula selection procedure was first applied to model joint distribution functions of pairs of variables from the data. Using maximum likelihood estimation, we tested log-normal, gamma, Weibull, and normal pdfs to fit distributions of the variables. Based on the Kolmogorov–Smirnov test, distributions of $Grass_{DM}$ and $Maize_{DM}$ were ultimately fitted by lognormal pdfs, while those of $Milk_{Produced}$ and $GHG_{Emissions}$ were fitted by Weibull pdfs (Supplementary Figs. S3 and S4). Conditional probabilities of one variable exceeding or not exceeding a threshold given that another variable exceeded a given threshold were calculated (Supplementary Eq. S1). To this end, thresholds of milk production, GHG emissions, and DM of forages were predefined according to the variation range of variables from the dataset of 76 dairy farms, as detailed below. Conditional probabilities were calculated from the N = 1,000 points simulated from the selected copula using the MC method for the pairs of variables considered.

2.3.1 Milk Production or GHG Emissions as a Function of Forage DM

The probability of $Milk_{Produced}$ exceeding or $GHG_{Emissions}$ not exceeding given thresholds was calculated given that $Maize_{DM}$ or $Grass_{DM}$ exceeded given thresholds, based on values simulated from the chosen copula. For milk production, we considered the event $A = \{Milk_{Produced} \geq m\}$ of exceeding thresholds m > 0, given that the DM of each forage also exceeded thresholds f > 0 (Supplementary Eq. S1). For gross GHG emissions, we considered the event $B = \{GHG_{Emissions} \leq g\}$ of not exceeding thresholds g > 0, given that the DM of each forage also exceeded thresholds f > 0 (Supplementary Eq. S3). Thresholds m of $Milk_{Produced}$ were varied from 4,000 to 10,000 l/cow/year, with a step of 1,000. Thresholds g of $GHG_{Emissions}$ were varied from 4,000 to 9,000 kg CO_2 eq./LU/year, with a step of 1,000. Thresholds f of DM of each forage ($Maize_{DM}$ and $Grass_{DM}$) were varied from 1,500 to 7,500 kg/LU/year, with a step of 1,500.

2.3.2 GHG Emissions or Emission Intensity as a Function of Milk Production

The probability of $GHG_{Emissions}$ or $GHG_{Emission\_intensity}$ not exceeding given thresholds was calculated given that $Milk_{Produced}$ exceeded given thresholds, based on values simulated from the chosen copula. For gross GHG emissions, we considered the event $C = \{GHG_{Emissions} \leq g\}$ of not exceeding thresholds g > 0, given that $Milk_{Produced}$ exceeded thresholds m > 0 (Supplementary Eq. S4). For GHG emission intensities, we considered the event $D = \{GHG_{Emission\_intensity} \leq i\}$ of not exceeding thresholds i > 0, given that $Milk_{Produced}$ exceeded thresholds m > 0 (Supplementary Eq. S5). Thresholds g of $GHG_{Emissions}$ were varied from 4,000 to 9,000 kg CO_2 eq./LU/year, with a step of 1,000. Thresholds i of $GHG_{Emission\_intensity}$ were varied from 0.4 to 1.4 kg CO_2 eq./l of milk, with a step of 0.2. Thresholds m of $Milk_{Produced}$ were varied from 4,000 to 9,000 l/cow/year, with a step of 1,000.

3 Results

3.1 Milk Production as a Function of Forage DM

During the copula-selection procedure, a 180°-rotated Joe copula with $\hat{\theta}_n = 1.7$ (Example 1) and a Frank copula with $\hat{\theta}_n = -1.6$ (Example 2) best fit the dependence structure between $Milk_{Produced}$ and $Maize_{DM}$ and $Milk_{Produced}$ and $Grass_{DM}$, respectively (Fig. 1).

The graphical test generally indicated reasonably good adequacy of the scatterplot of n = 76 points from the dataset of dairy farms to that of N= 1,000 points simulated from the selected copula using the MC method, for the pairs $Milk_{Produced}$ and $Grass_{DM}$ and $Milk_{Produced}$ and $Maize_{DM}$ (Fig. 2). The scatterplots of points from the dataset and those simulated from selected copulas overlapped almost completely.

The conditional probability of $Milk_{Produced}$ exceeding a given threshold logically decreased as this threshold increased from 4,000 to 10,000 l/cow/year, given a constant threshold of forage DM ($Maize_{DM}$ or $Grass_{DM}$) (Fig. 3). For the minimum (or maximum) threshold of $Milk_{Produced}$, the probability of exceeding 4,000 (or 10,000) l/cow/year was 100% (or 0%), regardless of the threshold of $Maize_{DM}$ or $Grass_{DM}$. More specifically, the probability of exceeding a constant threshold of $Milk_{Produced}$ increased as the threshold of $Maize_{DM}$ increased. Conversely, the probability of $Milk_{Produced}$ exceeding a constant threshold generally decreased as the threshold of $Grass_{DM}$ increased. For instance, the probability of exceeding 7,000 l milk/cow/year increased from ca. 62% to 75% (or decreased from ca. 62% to 18%) as the threshold of $Maize_{DM}$ (or $Grass_{DM}$) increased from 1,500 to 7,500 kg/LU/year (Table S1). Then, for the same threshold of $Maize_{DM}$ and $Grass_{DM}$, the probability of $Milk_{Produced}$ exceeding a constant threshold was higher given $Maize_{DM}$ than $Grass_{DM}$. For instance, the probability of exceeding 7,000 l milk/cow/year was 75% (or 48%) given that $Maize_{DM}$ (or $Grass_{DM}$) exceeded 4,500 kg/LU/year. Finally, the rotated Joe copula modeled a lower tail dependence for $Maize_{DM}$ and $Milk_{Produced}$: producing a very small amount of milk was conditional on very low DM of maize silage.

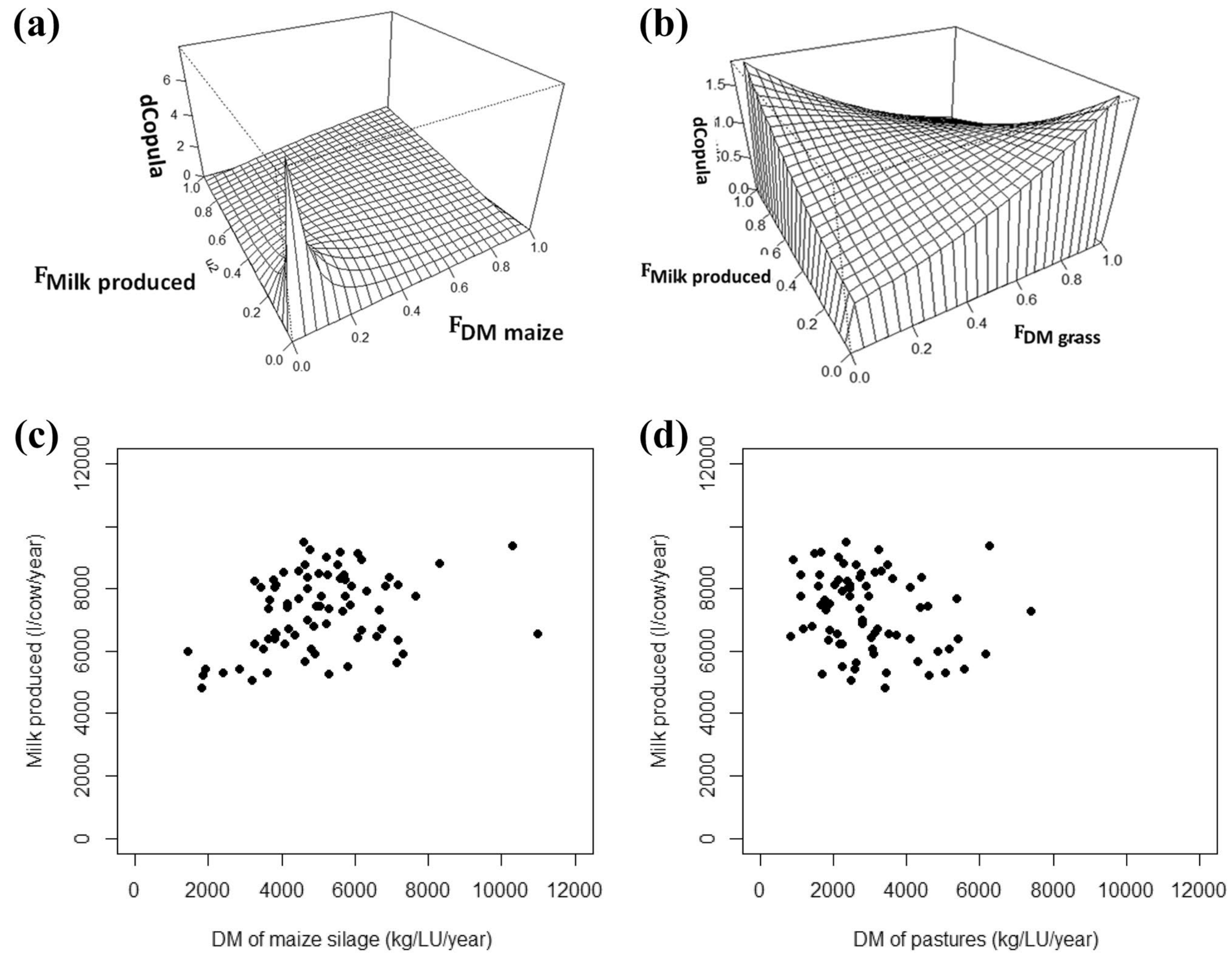

Fig. 1 Density functions of a (**a**) 180°-rotated Joe copula and (**b**) Frank copula selected to model the dependence structure between univariate marginal cumulative distribution functions of (**c**) milk production and dry matter (DM) of maize silage and (**d**) milk production and DM of grass from pastures

3.2 GHG Emissions as a Function of Forage DM

The 180°-rotated Joe copula with $\widehat{\theta}_n = 2.3$ and Frank copula with $\widehat{\theta}_n = 1.8$ best fit the dependence structures between $GHG_{Emissions}$ and $Maize_{DM}$ and $GHG_{Emissions}$ and $Grass_{DM}$, respectively. For each pair of variables, scatterplots of 76 points from the dataset and of 1,000 points simulated from the chosen copulas overlapped almost completely, which indicated that the chosen copulas represented the data satisfactorily (Supplementary Fig. S5).

Based on values simulated from the chosen copula, the probability of $GHG_{Emissions}$ not exceeding a given threshold logically increased as this threshold increased from 4,000 to 9,000 kg CO_2 eq./LU/year, given a constant threshold of $Maize_{DM}$ or $Grass_{DM}$ (Fig. 4). For the minimum (or maximum) threshold of $GHG_{Emissions}$, the probability of not exceeding 4,000 (or 9,000) kg CO_2 eq./LU/year was 0% (or 100%), regardless of the threshold of $Maize_{DM}$ or $Grass_{DM}$. The probability of $GHG_{Emissions}$ not exceeding a constant threshold decreased (or increased) as the threshold of $Maize_{DM}$ (or $Grass_{DM}$) increased. For instance, the probability of not exceeding 7,000 kg CO_2 eq./LU/year (a value close to the mean of 6669 kg CO_2 eq./LU/year for all of the farms (Table 1)) decreased from 65 to 36% (or increased from 66 to 83%) as the threshold of $Maize_{DM}$ (or $Grass_{DM}$) increased from 1,500 to 7,500 kg/LU/year (Table S1). Then, for the same threshold of $Maize_{DM}$ and $Grass_{DM}$, the probability of $GHG_{Emissions}$ not exceeding a constant threshold was lower given $Maize_{DM}$ than $Grass_{DM}$. For instance, the probability of not exceeding 7,000 kg CO_2 eq./LU/year was 48% (or 78%) when $Maize_{DM}$ (or $Grass_{DM}$) exceeded 4,500 kg/LU/year. Finally, the rotated Joe copula modeled a lower tail dependence for $Maize_{DM}$ and $GHG_{Emissions}$: emitting a very small amount of GHG was conditional on very

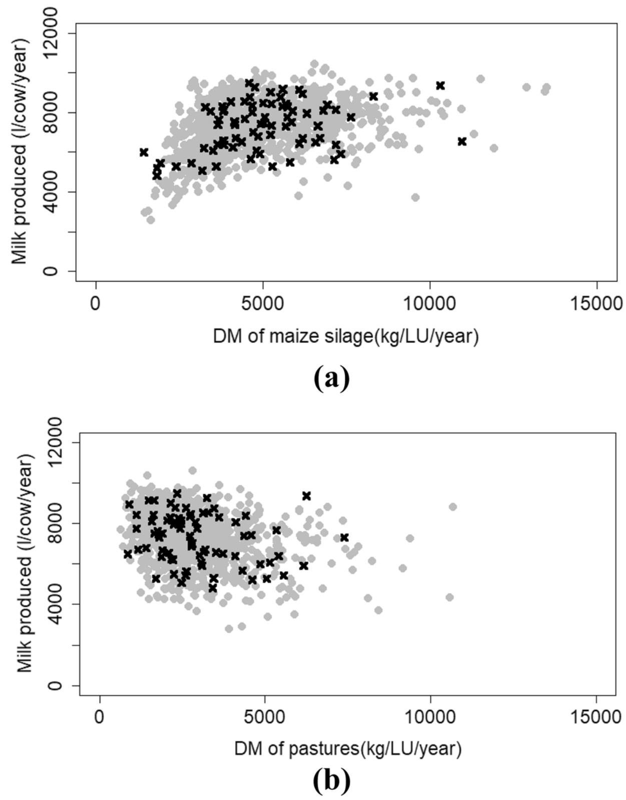

Fig. 2 Random sample (gray circles) of size $N = 1{,}000$ simulated from selected copulas using the Monte Carlo method to model dependence structures between milk production (l/cow/year) and dry matter (DM) of (**a**) maize silage and (**b**) grass from pastures (both in kg/livestock (LU)/year). Black crosses represent points from the dataset of $n = 76$ dairy farms

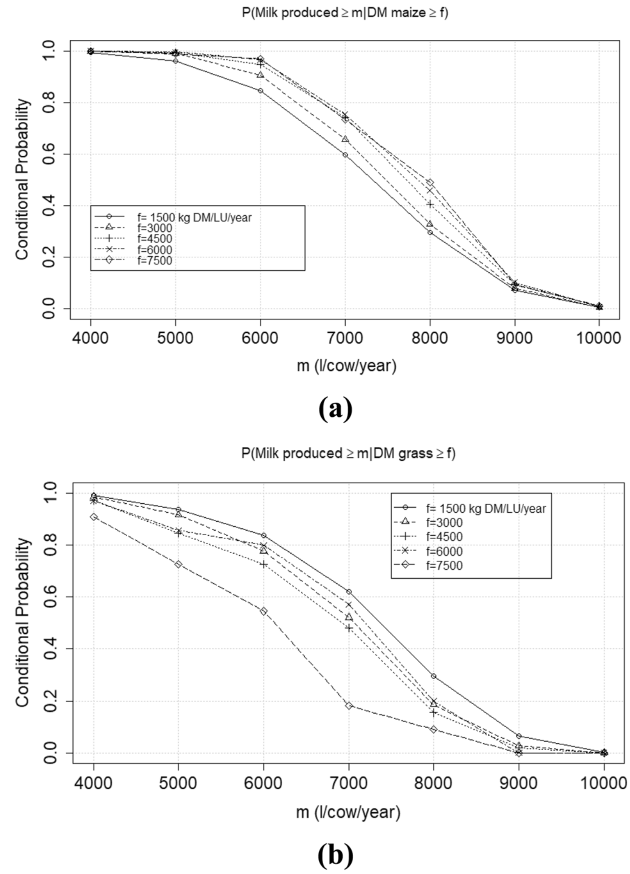

Fig. 3 Conditional probabilities of milk production (l/cow/year) exceeding given thresholds ("m") as a function of dry matter (DM) of (**a**) maize silage or (**b**) grass from pastures (both in kg DM/livestock unit (LU)/year) exceeding given thresholds ("f")

low DM of maize silage, like the relationship between milk production and maize silage.

3.3 GHG Emissions or Emission Intensities as a Function of Milk Production

A 180°-rotated Joe copula with $\widehat{\theta}_n = 2.1$ best fit the dependence structure between $GHG_{Emissions}$ and $Milk_{Produced}$. The graphical goodness-of-fit test was generally satisfactory, except for two points with the lowest $GHG_{Emissions}$ from the dataset of 76 dairy farms (Supplementary Fig. S6).

For the minimum (or maximum) threshold of $GHG_{Emissions}$, the probability of not exceeding 5,000 (or 8,000) kg CO_2 eq./LU/year was ca. 0% (or ca. 100%), regardless of the threshold of $Milk_{Produced}$ (Fig. 5a). The probability of not exceeding a constant threshold of $GHG_{Emissions}$ decreased as $Milk_{Produced}$ increased: emitting a very small amount of GHG was conditional on producing a very small amount of milk.

A Frank copula with $\widehat{\theta}_n = -7.7$ best fit the dependence structure between $GHG_{Emission\_intensity}$ and $Milk_{Produced}$ (Supplementary Fig. S6). Unlike $GHG_{Emissions}$, the probability of $GHG_{Emission\_intensity}$ not exceeding a constant threshold increased as $Milk_{Produced}$ increased (Fig. 5b). For instance, the probabilities of not exceeding 0.8 kg CO_2 eq./l were ca. 20% and 45% when $Milk_{Produced}$ exceeded thresholds of 6,000 and 8,000 l/cow/year, respectively.

4 Discussion

4.1 Potential to Reach Thresholds

4.1.1 GHG Regulatory Limit

To achieve certain objectives of environmental performances (e.g., not exceeding a given threshold of gross GHG emissions or emission intensities) raises the issue of which functional unit(s) best represent environmental impacts of dairy farms. Our results and the choice of functional unit are important when discussing targets for reducing GHG

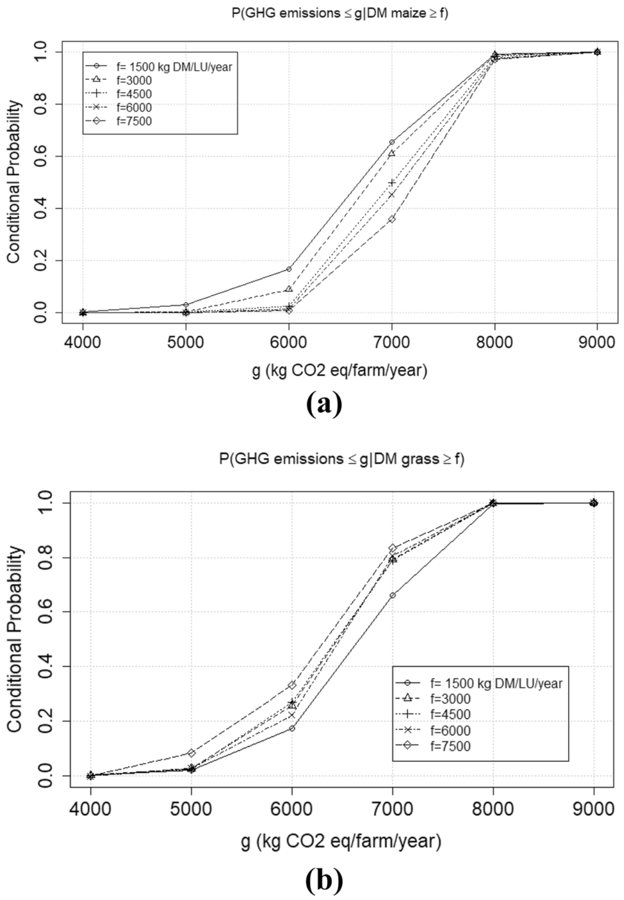

Fig. 4 Conditional probabilities of greenhouse gas (GHG) emissions (kg CO_2 eq./livestock unit/year) not exceeding given thresholds ("g") as a function of dry matter (DM) of (**a**) maize silage and (**b**) grass from pastures (both in kg/livestock unit (LU)/year) exceeding given thresholds ("f")

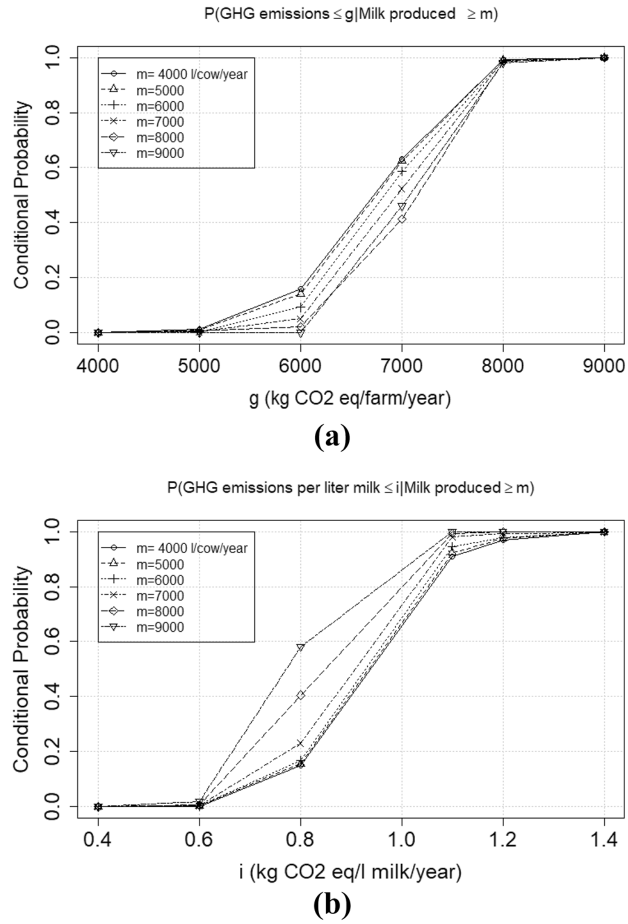

Fig. 5 Conditional probabilities of (**a**) gross greenhouse gas (GHG) emissions (kg CO_2 eq./livestock unit/year) and (**b**) GHG emission intensities (kg CO_2 eq./l milk/year) not exceeding given thresholds ("g" and "i", respectively) as a function of milk production (l/cow/year) exceeding given thresholds ("m")

emissions, and may change decisions about performances of dairy farms [35].

From a product-based approach, environmental impacts of milk are studied by calculating GHG emission intensity per l or kg of milk, among other impacts. $\text{Milk}_{\text{Produced}}$ is indeed one of the variables that influences $\text{GHG}_{\text{Emissions}}$ the most on dairy farms [36]. Dairy farms with high $\text{Milk}_{\text{Produced}}$ had lower $\text{GHG}_{\text{Emission\_intensity}}$. For instance, the probabilities of $\text{GHG}_{\text{Emission\_intensity}}$ not exceeding 1.1 kg CO_2 eq./l of milk produced (the median value from 75 estimates for fat-and-protein-corrected milk in the literature [37]) were ca. 94% and 99% when $\text{Milk}_{\text{Produced}}$ exceeded thresholds of 6,000 and 8,000 l/cow/year, respectively (Fig. 5). Similar results were found in a study of three hypothetical dairy farms in Germany with different milk yields — 6,000 (low-producing system), 8,000 (medium-producing system), and 10,000 (high-producing system) kg milk/cow/year — and different breeds [38]. In that study, based on probability distributions simulated using the MC method, the low-producing system had probabilities of 49% and 91% of generating lower GHG emission intensities per kg of milk than medium- and high-producing systems, respectively. However, recall that to reach a given threshold of GHG emission intensity, the probability of $\text{Milk}_{\text{Produced}}$ exceeding a given threshold depends on forage DM (Fig. 6).

Our results showed that unlike $\text{GHG}_{\text{Emission\_intensity}}$, extremely low $\text{GHG}_{\text{Emissions}}$ were conditional on extremely low $\text{Milk}_{\text{Produced}}$. Therefore, the lower the minimum threshold of $\text{Milk}_{\text{Produced}}$ (i.e., milk production goal) on dairy farms, the higher the probability of $\text{GHG}_{\text{Emissions}}$ not exceeding a given threshold. Conversely, increasing the minimum threshold of $\text{Milk}_{\text{Produced}}$ decreased the probability of $\text{GHG}_{\text{Emissions}}$ not exceeding a given threshold. For instance, when increasing the minimum threshold of $\text{Milk}_{\text{Produced}}$ from 4,000 to 6,000 l/cow/year, the probability of $\text{GHG}_{\text{Emissions}}$ not exceeding 7,000 kg CO_2 eq./LU/year decreased from ca. 62% to 58%, respectively (Fig. 5a).

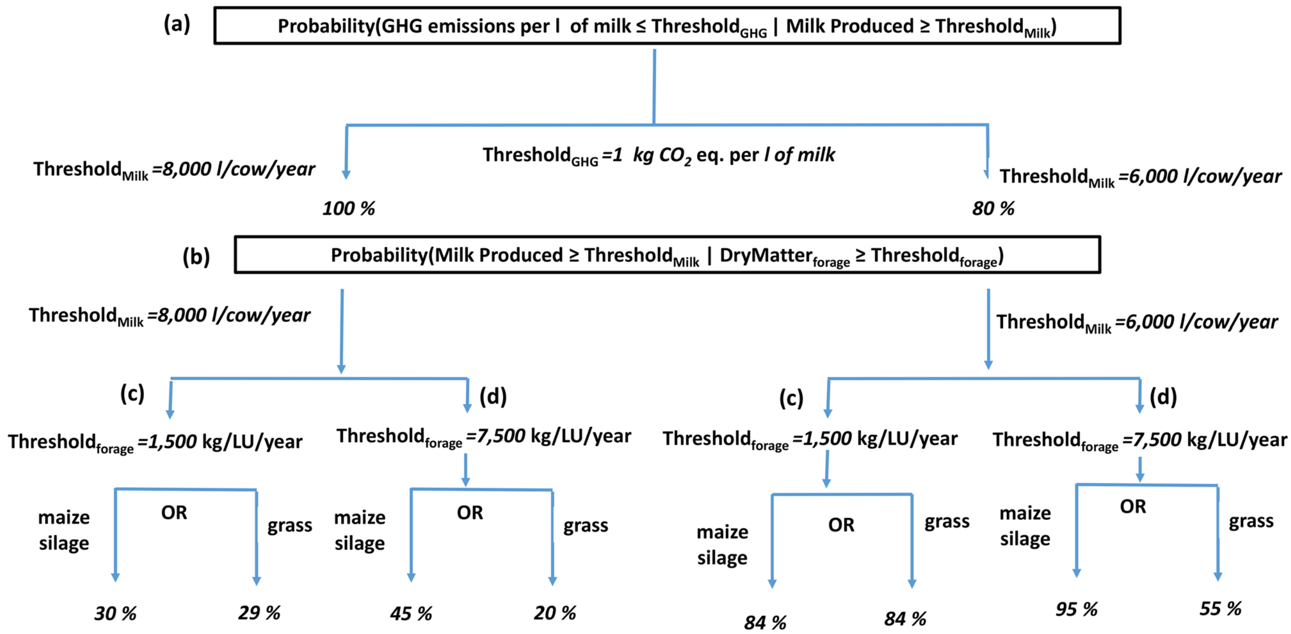

Fig. 6 (**a**) Conditional probabilities of greenhouse gas (GHG) emission intensities not exceeding a threshold of 1 kg CO_2 eq. per l of milk as a function of milk production (l/cow/year) and (**b**) conditional probabilities of milk production exceeding thresholds of 6,000 and 8,000 l/cow/year as a function of dry matter of maize silage and grass from pastures exceeding (**c**) 1,500 and (**d**) 7,500 kg/livestock unit (LU)/year

4.1.2 GHG Emissions as a Function of Forage DM

Farming practices to address $GHG_{Emissions}$ (and $Milk_{Produced}$) should consider compromises among proportions of $Maize_{DM}$, $Grass_{DM}$, and supplements in animal diets to reduce GHG emissions (while maintaining farm productivity). The contribution of animal feed to $GHG_{Emissions}$ must consider how feed ingredients are produced (i.e., grown, transported, and processed). A grass-based system would be expected to be more favorable for limiting $GHG_{Emissions}$ per LU per year. For instance, a high proportion of $Grass_{DM}$ in diets would imply a small contribution of purchased feed to $GHG_{Emissions}$, depending on a farm's degree of feed self-sufficiency [39]. Conversely, increasing $Maize_{DM}$ would also increase the contribution of fertilization to gross GHG emissions [40]. In our results, the higher the minimum threshold of $Maize_{DM}$ used on dairy farms, the lower the probability of $GHG_{Emissions}$ not exceeding a given threshold. Feed intake also contributes to enteric CH_4 emissions and direct and indirect nitrous oxide emissions [41]. In addition, feed production and manure handling were identified as the main GHG emission sources in studies of dairy farms in the USA [42, 43].

4.1.3 Milk Production Goal

When $Maize_{DM}$ or $Grass_{DM}$ exceeded a low threshold, $Milk_{Produced}$ had nearly the same probabilities of exceeding a given threshold of milk production for both $Maize_{DM}$ and $Grass_{DM}$. Our results also showed that extremely low $Milk_{Produced}$ was conditional on extremely low $Maize_{DM}$, which was not the case for $Milk_{Produced}$ and $Grass_{DM}$. However, increasing $Maize_{DM}$ increased the probabilities of $Milk_{Produced}$ exceeding thresholds more than increasing $Grass_{DM}$ did (Table 1). The proportion of $Maize_{DM}$ or $Grass_{DM}$ used in animal diets varies among dairy farms depending on geographic location, climatic conditions, and areas of pastures and silage maize in the total agricultural area. A high proportion of maize silage in diets is often used to obtain high milk production per cow. Conversely, a grass-based diet is usually less able to express the milk production potential of dairy cows [44]. For instance, North American Holstein–Friesian cows that grazed pasture, with no supplements (e.g., concentrates, feed additives), produced ca. 32% less milk per day (ca. 30 kg) than those fed a total mixed ration in confinement (ca. 44 kg) [45]. Among other reasons, grass-based diets supply less metabolizable energy for milk production. Effects of feeding strategies on milk production depend on the genetic potential of dairy cow breeds (e.g., Holstein, Normande) [46]. However, increasing levels of milk production raises the issue of potential negative effects on the reproductive performance of dairy cows, which is also a criterion of farm profitability [47].

4.1.4 Trade-offs Between Farm Profitability and Environmental Performances

Farmers must make trade-offs between the probability of GHG emission intensities not exceeding given thresholds as a function of milk production and the probability of milk production exceeding given thresholds as a function of forage DM (Fig. 6). In our results, the higher the milk production, the higher the probability of not exceeding a given threshold of GHG emission intensity. Moreover, a threshold of milk production was more likely to be exceeded when exceeding a certain threshold of DM of maize silage than the same threshold of DM of grass from pastures in dairy cow diets. It is useful to recall that grass production depends more on environmental conditions and less on fertilizer applications than maize production, which makes its yields more difficult to manage. For instance, impacts of climate change on grassland-based production systems have been studied due to the dependence of these systems on rain-fed feed production [48].

4.2 Limitations of the Study

The representativeness of this study's results is limited by the relatively restricted geographic distribution (Normandy) and small sample size of dairy farms ($n=76$), particularly its measures of tail dependence based on the number of farms with higher or lower milk production and GHG emissions as a function of forage production. Extrapolating joint pdfs using the MC method, however, did provide more robust estimates than the base sample alone would have provided, which makes extrapolation useful for the often small databases compiled for whole-farm assessments; nonetheless, a larger base sample would have increased the representativeness of the data and copula modeling. In addition, a validation dataset of dairy farms would have been useful for evaluating the probabilities of reaching the production goals and environmental performances that were calculated. For more extensive analysis, probabilities of reaching milk production goals and not exceeding GHG regulatory limits should be also investigated conditional on variables such as concentrated feed, which is often used to supplement dairy cow diets. An analysis based only on forage DM provides useful information, but it may not be sufficient for reliable risk assessment and decision making.

4.3 Copula Models

Applying copula models allowed us to build joint distribution functions of pairs of variables, which represented dependencies among $GHG_{Emissions}$, $Milk_{Produced}$, and DM of grass from pastures and maize silage of dairy farms. Correlated values of pairs of variables were thus generated according to their identified joint distribution function, which is an advantage of copula models compared to traditional approaches such as regression models. Unlike traditional regression approaches, the copula models did not predict an output variable as a function of input variables. Instead, copula models enabled a larger dataset of dairy farms to be simulated by extrapolating characteristics from the original sample.

One research perspective is to perform a full multidimensional analysis of economic and environmental performances of dairy farms, since $Milk_{Produced}$ and $GHG_{Emissions}$ depend on variables besides forage DM. Copula models can be applied to model multivariate distribution functions of variables that describe a highly dependent multivariate system by breaking the system into a cascade of pair copulas [49]. Copula models can thus be an approach for analyzing risk in environmental assessments of dairy farms by incorporating correlations between variables that are not necessarily normally distributed [9]. Based on information about the simultaneous occurrence of larger or smaller values of variables, copula models can be used to develop performance indicators of dairy farms, as an alternative to using highly complex models to describe these systems [50].

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Data Availability Not applicable.

Code Availability Not applicable.

Declarations

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

Conflict of Interest The authors declare no competing interests.

References

1. Pellerin, S., Bamiere, L., Angers, D., Béline, F., Benoit, M., Butault, J., et al. (2013). *How can French agriculture contribute to reducing greenhouse gas emissions? Abatement potential and cost of ten technical measures. Synopsis of the study report*. Paris.
2. Dollé, J.-B., Agabriel, J., Peyraud, J.-L., Faverdin, P., Manneville, V., Raison, C., et al. (2011). Les gaz à effet de serre en élevage bovin : évaluation et leviers d'action. In B. R. Doreau M., Perez J.M. (Ed.), *Gaz à effet de serre en élevage bovin : le méthane* (Vol. 24, pp. 415–432): Dossier, INRA Productions Animales.
3. Flysjö, A., Cederberg, C., Henriksson, M., & Ledgard, S. (2012). The interaction between milk and beef production and emissions from land use change–critical considerations in life cycle assessment and carbon footprint studies of milk. *Journal of Cleaner Production, 28*, 134–142.
4. Baumman, H., & Tillman, A. (2004). The hitch hiker's guide to LCA: An orientation in life cycle assessment methodology and application. *Studentlitteratur, Lund, Sweden*.
5. Rogers, K., Seager, T., & Linkov, I. (2008). Multicriteria Decision Analysis and Life Cycle Assessment. In *Dordrecht, 2008* (pp. 305–314, Real-Time and Deliberative Decision Making): Springer Netherlands.
6. Prado, V., & Heijungs, R. (2018). Implementation of stochastic multi attribute analysis (SMAA) in comparative environmental assessments. *Environmental Modelling & Software, 109*, 223–231. https://doi.org/10.1016/j.envsoft.2018.08.021
7. Cucurachi, S., Borgonovo, E., & Heijungs, R. (2016). A protocol for the global sensitivity analysis of impact assessment models in life cycle assessment. *Risk Analysis, 36*(2), 357–377. https://doi.org/10.1111/risa.12443
8. Ventura, A., Senga Kiessé, T., Cazacliu, B., Idir, R., & van der Werf, H. M. G. (2015). Sensitivity analysis of environmental process modeling in a life cycle context: A case study of hemp crop production. *Journal of Industrial Ecology, 19*(6), 978–993. https://doi.org/10.1111/jiec.12228.
9. Groen, E. A., & Heijungs, R. (2017). Ignoring correlation in uncertainty and sensitivity analysis in life cycle assessment: What is the risk? *Environmental Impact Assessment Review, 62*, 98–109. https://doi.org/10.1016/j.eiar.2016.10.006
10. Niu, M., Kebreab, E., Hristov, A. N., Oh, J., Arndt, C., Bannink, A., et al. (2018). Prediction of enteric methane production, yield, and intensity in dairy cattle using an intercontinental database. *Global Change Biology, 24*(8), 3368–3389. https://doi.org/10.1111/gcb.14094
11. Li, D.-Q., Jiang, S.-H., Wu, S.-B., Zhou, C.-B., & Zhang, L.-M. (2013). Modeling multivariate distributions using Monte Carlo simulation for structural reliability analysis with complex performance function. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 227*(2), 109–118. https://doi.org/10.1177/1748006x13476821
12. Sklar, A. (1959). Fonctions de répartition à n dimensions et leurs marges. *Publications de l'Institut de Statistique de l'Université de Paris, 8*, 229–231.
13. Joe, H. (1993). Parametric families of multivariate distributions with given margins. *Journal of Multivariate Analysis, 46*, 262–282.
14. Coles, S., Heffernan, J., & Tawn, J. (1999). Dependence measures for extreme values analyses. *Extremes, 24*, 339–365.
15. Embrechts, P., Mcneil, A., Straumann, D. (2002). Correlation and dependence in risk management: Properties and pitfalls. In *Risk Management: Value at Risk and Beyond* (pp. 176–223): Cambridge University Press.
16. Hao, Z., & AghaKouchak, A. (2013). Multivariate Standardized Drought Index: A parametric multi-index model. *Advances in Water Resources, 57*, 12–18. https://doi.org/10.1016/j.advwatres.2013.03.009
17. Kao, S.-C., & Govindaraju, R. S. (2010). A copula-based joint deficit for droughts. *Journal of Hydrology, 380*, 121–134. https://doi.org/10.1016/j.jhydrol.2009.10.029
18. Shiau, J.-T., Modarres, R., & Nadarajah, S. (2012). Assessing multi-site drought connections in Iran using empirical copula. *Environmental Modeling & Assessment, 17*(5), 469–482. https://doi.org/10.1007/s10666-012-9318-2
19. Patton, A. J. (2012). A review of copula models for economic time series. *Journal of Multivariate Analysis, 110*, 4–18. https://doi.org/10.1016/j.jmva.2012.02.021
20. Favre, A.-C., El Adlouni, S., Perreault, L., Thiémonge, N., & Bobée, B. (2004). Multivariate hydrological frequency analysis using copulas. *Water Resources Research, 40*(1). https://doi.org/10.1029/2003wr002456
21. Ilić, A., Prohaska, S., Radivojević, D., & Trajković, S. (2021). Multidimensional approaches to calculation of design floods at confluences—PROIL model and copulas. *Environmental Modeling & Assessment*. https://doi.org/10.1007/s10666-021-09748-8
22. Gil, R., Bojacá, C. R., & Schrevens, E. (2021). Accounting for correlational structures in stochastic comparative life cycle assessments through copula modeling. *The International Journal of Life Cycle Assessment, 26*(3), 604–615.
23. Opio, C., Gerber, P., Mottet, A., Falcucci, A., Tempio, G., MacLeod, M., et al. (2013). Greenhouse gas emissions from ruminant supply chains – A global life cycle assessment. Rome: Food and Agriculture Organization of the United Nations (FAO).
24. Sauvant, D., Giger-Reverdin, S., & Eugene, M. (2018). Enteric methane emissions. In D. Sauvant, L. Delaby, & P. Noziere (Eds.), *INRA feeding system for ruminants*. The Netherlands: Wageningen Academic Publishers.
25. Moraes, L. E., Strathe, A. B., Fadel, J. G., Casper, D. P., & Kebreab, E. (2014). Prediction of enteric methane emissions from cattle. *Global Change Biology, 20*(7), 2140–2148. https://doi.org/10.1111/gcb.12471
26. IPCC. (2006). Chapter 10: Emissions from livestock and manure management. In *Guidelines for National Greenhouse Gas Inventories*: International Panel on Climate Change.
27. Sauvant, D., & Noziere, P. (2016). Quantification of the main digestive processes in ruminants: The equations involved in the renewed energy and protein feed evaluation systems. *Animal, 10*(5), 755–770. https://doi.org/10.1017/S1751731115002670
28. Arvalis Institut du végétal. (2015, janvier 2015). Maïs et tournesol: Performances des variétés et conduite des cultures. *Aravalis-Cetiom Infos*.
29. Nadarajah, S., Afuecheta, E., & Chan, S. (2018). A compendium of copulas. *Statistica, 77*(4), 279–328.
30. Nagler, T. (2014). *Kernel methods for vine copula estimation*. Technische Universität München,
31. Genest, C., & Favre, A.-C. (2007). Everything you always wanted to know about copula modeling but where afraid to ask. *Journal of hydrologic engineering, 12*(4), 347–368. https://doi.org/10.1061//ASCE/1084-0699/2007/12:4/347
32. R Core Team. (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
33. Schepsmeier, U., Stoeber, J., Brechmann, EC., et al. (2015). VineCopula:Statistical Inference of Vine Copulas. *R package version 1.6–1*.

34. Nagler, T. (2019). VC2copula: Extend the 'copula' package with families and models from 'VineCopula'. *R package version 0.1.0*.
35. van der Werf, H. M. G., Knudsen, M. T., & Cederberg, C. (2020). Towards better representation of organic agriculture in life cycle assessment. *Nature Sustainability*. https://doi.org/10.1038/s41893-020-0489-6
36. Henriksson, M., Flysjö, A., Cederberg, C., & Swensson, C. (2011). Variation in carbon footprint of milk due to management differences between Swedish dairy farms. *Animal, 5*(9), 1474–1484. https://doi.org/10.1017/S1751731111000437
37. Baldini, C., Gardoni, D., & Guarino, M. (2017). A critical review of the recent evolution of Life Cycle Assessment applied to milk production. *Journal of Cleaner Production, 140*, 421–435.
38. Zehetmeier, M., Gandorfer, M., Hoffmann, H., Müller, U. K., de Boer, I. J. M., & Heißenhuber, A. (2014). The impact of uncertainties on predicted greenhouse gas emissions of dairy cow production systems. *Journal of Cleaner Production, 73*, 116–124. https://doi.org/10.1016/j.jclepro.2013.09.054
39. Coquil, X., Béguin, P., & Dedieu, B. (2013). Transition to self-sufficient mixed crop–dairy farming systems. *Renewable Agriculture and Food Systems, 29*(3), 195–205. https://doi.org/10.1017/S1742170513000458
40. Senga Kiessé, T., Corson, M. S., Le Galludec, G., & Wilfart, A. (2020). Sensitivity of greenhouse gas emissions to extreme differences in forage production of dairy farms. *Livestock Science, 232*, 103906. https://doi.org/10.1016/j.livsci.2019.103906
41. Gerber, P. J., Steinfeld, H., Henderson, B., Mootet, A., Opio, C., Dijkman, J., et al. (2013). Tackling climate change though livestock – A global assessment of emissions and mitigation opportunities. Rome: Food and Agriculture Organization of the United Nations (FAO).
42. Rotz, C. A., Montes, F., & Chianese, D. S. (2010). The carbon footprint of dairy production systems through partial life cycle assessment. *Journal of Dairy Science, 93*(3), 1266–1282. https://doi.org/10.3168/jds.2009-2162
43. Aguirre-Villegas, H. A., & Larson, R. A. (2017). Evaluating greenhouse gas emissions from dairy manure management practices using survey data and lifecycle tools. *Journal of Cleaner Production, 143*, 169–179. https://doi.org/10.1016/j.jclepro.2016.12.133
44. Delaby, L., Faverdin, P., Michel, G., Disenhaus, C., & Peyraud, J. L. (2009). Effect of different feeding strategies on lactation performance of Holstein and Normande dairy cows. *Animal, 3*(6), 891–905. https://doi.org/10.1017/S1751731109004212
45. Kolver, E. S. (2007). Nutritional limitations to increased production on pasture-based systems. *Proceedings of the Nutrition Society, 62*(2), 291–300. https://doi.org/10.1079/PNS2002200
46. Buckley, F., Dillon, P., Rath, M., & Veerkamp, R. F. (2018). The relationship between genetic merit for yield and live weight, condition score, and energy balance of spring calving Holstein-Friesian dairy cows on grass based systems of milk production. *BSAP Occasional Publication, 26*(2), 297–303. https://doi.org/10.1017/S0263967X00033814
47. Leblanc, S. (2010). Assessing the association of the level of milk production with reproductive performance in dairy cattle. *Journal of Reproduction and Development, 56*(S), S1-S7.
48. Ghahramani, A., Howden, S. M., del Prado, A., Thomas, D. T., Moore, A. D., Ji, B., et al. (2019). Climate change impact, adaptation, and mitigation in temperate grazing systems: A review. *Sustainability, 11*(24), 7224.
49. Aas, K., Czado, C., Frigessi, A., & Bakken, H. (2009). Pair-copula constructions of multiple dependence. *Insurance: Mathematics and Economics, 44*(2), 182–198.
50. Graux, A.-I., Gaurut, M., Agabriel, J., Baumont, R., Delagarde, R., Delaby, L., et al. (2011). Development of the pasture simulation model for assessing livestock production under climate change. *Agriculture, Ecosystems & Environment, 144*(1), 69–91.