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Using conditional Kendall's tau estimation to assess interactions among variables in dairy-cattle systems

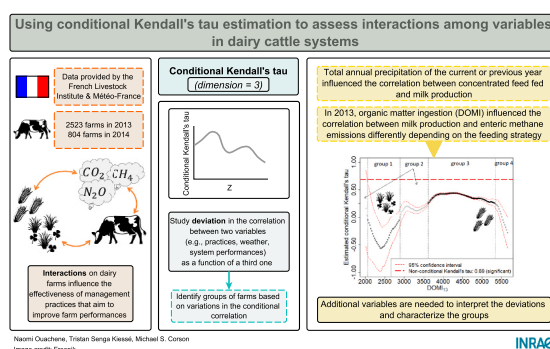
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HIGHLIGHTS

- Interactions on dairy farms influence the effectiveness of management practices that aim to improve farm performances.
- Conditional Kendall's tau assesses deviations in the correlation between two variables as a function of a third one.
- Digestible organic matter ingestion influenced the correlation between milk production and enteric methane emissions.
- Total annual precipitation influenced the correlation between concentrated feed fed and milk production.
- Additional variables are needed to interpret the deviations.

GRAPHICAL ABSTRACT



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ABSTRACT

Context: Understanding how multiple factors interact in complex systems is an important issue. In particular, agricultural production systems are based on biological and ecological processes that are influenced by environmental and human factors, all of which interact. When evaluating such systems statistically, these multiple dependences and interactions make it more difficult to model system performances as a function of management practices and weather.

Objective: Our objective was to assess interactions among management practices, weather and system performances. We aimed in particular to identify subsets of farms whose correlations for given pairs of variables as a function of another variable deviated greatly from the traditional correlation between the variables (i.e., atypical farms).

Methods: We investigated a measure of dependence that assesses whether (and if so, how) the correlation between two variables varies as a function of a third one: conditional Kendall's tau. We applied this measure to a set of variables that described management practices (e.g., concentrated feed fed), weather (e.g., precipitation) and performances (e.g., milk production, enteric methane emissions) for dairy-cattle systems in France in 2013 and 2014 (2523 and 804 farms, respectively).

Results and conclusions: In 2013, the amount of digestible organic matter in the ration ingested per cow influenced the correlation between milk production per cow and enteric methane emissions per livestock unit. In particular, the correlation was negative for a set of atypical farms whose ingested digestible organic matter was ≈ 2050 – 2900 kg.cow⁻¹. In addition, total annual precipitation in 2013 influenced the correlation between the amount of

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concentrated feed fed per cow and milk production per cow for farms surveyed in either year. In 2013 and 2014, the correlation began decreasing strongly beyond a certain threshold of precipitation (ca. 1400 and 1100 mm, respectively), which highlighted the need to adapt each farm's practices to its agricultural and weather context. *Significance:* Application of conditional Kendall's tau identified interactions that caused the effectiveness of management practices to vary and how they did so.

1. Introduction

Dairy-cattle farms are a source of several greenhouse gases (GHGs), such as methane (CH₄), nitrous oxide (N₂O) and carbon dioxide (CO₂) (Dumont et al., 2017). In the context of climate change, the environmental performances of dairy farms need to be improved, but certain social and economic objectives (e.g., food security, farm revenue) make doing so more difficult. To attempt to meet these multiple objectives, it is necessary to understand how management practices and environmental conditions interact to influence the interacting biological and ecological processes of farming systems. Changing a practice may improve the economic or environmental performance but also influence, sometimes indirectly, other characteristics of the farm. For instance, analyzing the effectiveness of on-farm measures to mitigate environmental impacts is complex, since the analysis should consider effects on all pollutant emissions of all production processes (Weiske et al., 2006). Likewise, sources of GHG emissions associated with milk production (e.g., enteric fermentation, manure management, agricultural soils, land-use change, energy consumption) are influenced by the rations of dairy cattle (Hawkins et al., 2015). Similarly, increasing the ration's starch content or changing manure management can reduce CH₄ emissions (Jayasundara et al., 2016). Multiple interactions among farm management practices and their agricultural contexts can influence the mitigation potential of changes in practices; for instance, manure deposited in grasslands cannot be used to feed biogas plants, and increasing the use of legume crops decreases the mitigation potential of decreasing fertilizer use (Pellerin et al., 2017). To help understand and model these multiple interactions, researchers use a variety of multi-criteria methods.

Complex simulation models (e.g., IFSM, DairyWise, FASSET) have been developed to model the dynamics of dairy farms as a whole (Jacobsen et al., 1998; Wastney et al., 2002; Schils et al., 2007; Vayssières et al., 2009; Rotz et al., 2012). Life cycle assessment (Baumann and Tillman, 2004) is also widely used to estimate and compare environmental impacts of farms based on the agricultural products they produce (Sieverding et al., 2020). In addition, statistical models are used for more specific objectives. For instance, multiple regressions based on several variable-selection procedures were used to quantify and compare the influence of several covariates on nitrogen-use efficiency at the farm level in Flanders (Ramírez and Reheul, 2009). Multiple regressions were also used to predict emissions of enteric CH₄ from lactating cows using different combinations of covariates at the farm level (Santiago-Juarez et al., 2016). To assess how agroecological, socio-territorial and economic sustainability interact to influence overall farm sustainability, principal component analysis (PCA), followed by ascending hierarchical classification, was applied to small dairy farms in northern Tunisia (Attia et al., 2022). Similarly, PCA was used to assess representative types of dairy-cattle and fodder-crop production systems at the regional scale in Europe (Díaz de Otálora et al., 2022).

In the present study, we used statistical models to help understand interactions that can render management practices, implemented to improve production or environmental performances, less effective. To this end, we investigated the conditional Kendall's tau coefficient, which measures the influence of at least one covariate on the dependence between two other covariates (Derumigny and Fermanian, 2019). The conditional Kendall's tau is based on copulas, which are functions that formalize the joint dependence structure among multiple variables regardless of the variables' distributions. The copula method has other

advantages, such as modeling many types of complex dependence structures (e.g., non-linear, among extreme values), due to the wide variety of copulas that exist (Genest and Favre, 2007; Nadarajah et al., 2017). Several agricultural studies (Chen et al., 2013; Madadgar and Moradkhani, 2013; Emmanouilides and Fousekis, 2015; Goodwin and Hungerford, 2015; Fousekis and Grigoriadis, 2017; Gaupp et al., 2017; de Almeida and Barbosa, 2020; Hasan and Abdullah, 2022) have used copulas, especially to estimate economic risks to farmers and social impacts as a function of crop yield and weather conditions. Recently, a copula-based local Kendall's tau was applied to study dependences in the tails of distributions of energy, agriculture and metal commodity markets over time (Albulescu et al., 2020).

Since the true value of conditional Kendall's tau remains unknown by construction, we investigated an estimator of conditional Kendall's tau which, to our knowledge, has not been used to help understand interactions among variables in agricultural systems to improve their environmental performances. It approximates the correlation between two variables as a function of another explanatory variable, unlike traditional correlation coefficients (e.g., Spearman's rho, Blomqvist's beta), which remain constant. It provides a good compromise between a traditional correlation coefficient and more complex methods (e.g., PCA) to study dependences among a set of variables. The main objective of this study was to examine how interactions can influence the effectiveness of management practices that aim to improve farm performances (i.e., the strength of the correlation between them) by using the conditional Kendall's tau. Consequently, conditional Kendall's tau was applied to assess correlations between farm production and environmental performances as a function of a management practice, as well as those between management practices and production performances as a function of weather conditions.

2. Materials and methods

2.1. Data

The data were extracted from the CAP'2ER database (<https://cap2er.eu/>) of the French Livestock Institute (IDELE). As part of IDELE's LIFE Carbon Dairy project, 2523 French farms were surveyed in 2013 and 804 potentially different farms were surveyed in 2014. The database provides more than 240 qualitative and quantitative variables that describe annual farm characteristics (e.g., cow breeds, percentage of grassland in the main forage area (MFA)), milk production, pollutant emissions (i.e., GHG emissions) and management strategies (e.g., amount of concentrated feed fed, percentage of maize silage or grazed grass in the ration). GHG emissions in the database were estimated by applying emissions equations and factors to sources of farm emissions (CAP'2ER Team, 2022). In particular, CH₄ emissions from enteric fermentation were estimated as a function of dry matter intake, proportion of concentrated feed in the ration, digestibility of the ration and, for dairy cows, addition of fats to the ration (Eq. S1 in Section S1 of the Supplementary Material) (Dong et al., 2006; Sauvart and Nozière, 2013; INRA, 2018).

In 2013 and 2014, the main cattle breed was Holstein (77.8% and 78.6% of farms, respectively), and the main region of France represented was Bretagne (77.4%) or Pays-de-la-Loire (68.3%), respectively. Farms were categorized into five types as a function of their geographic situation (i.e., mountain or plain) and their percentage of maize in the MFA (Table 1). The distribution of farm types differed significantly between

Table 1
Percentage of farms by type (geographic situation and dominance or percentage of grassland or maize silage in the main forage area) per survey year.

Farm type	2013	2014
Mountain/grass	2.8	0.4
Mountain/maize	0.6	4.2
Plain < 10% maize	2.2	1.0
Plain 10 – 30% maize	21.1	26.2
Plain > 30% maize	73.3	68.2

the two years ($p \leq 0.05$, chi-square test), with a higher percentage of mountain/grass farms in 2013 and mountain/maize farms in 2014.

To assess the influence of weather conditions, we downloaded daily temperature and precipitation data for 2012, 2013 and 2014 for mainland France (in an 8 km × 8 km grid) from the SAFRAN climate database, provided by Météo-France, via the SICLIMA platform developed by the AgroClim unit of INRAE. We used them to calculate annual precipitation (Table 2) and six other annual or growing-season meteorological indices (Table S1), which we associated with each farm by selecting the cell whose centroid lay closest to the centroid of the municipality to which the farm belonged (since exact farm locations were not available). For annual precipitation, we calculated the precipitation that each farm had received during the year it was surveyed, as well as that during the previous year, since surplus forage can be stored and fed to cows the following year (Wilkinson and Rinne, 2018).

2.2. Estimator of the conditional correlation

2.2.1. Conditional Kendall's tau

The conditional version of Kendall's tau is derived from its non-conditional version (τ), whose value (from -1 to 1) describes the

proportionality (i.e., positive correlation) or inverse proportionality (i.e., negative correlation) between two columns of ranked data (Kendall, 1938). In other words, Kendall's tau is a non-parametric association measure, which indicates a weak association between variables when close to zero. Kendall's tau depends on the bivariate function $C : [0, 1]^2 \rightarrow [0, 1]$ (a copula), which models the dependence structure between two continuous random variables, X and Y , such that (Nelsen, 2006):

$$\tau = 4 \int_{[0,1]^2} C(u, v) dC(u, v) - 1 \tag{1}$$

where (u, v) belongs to $[0, 1]^2$. Copula C is a function that connects the cumulative distribution functions (cdfs) F and G of X and Y , respectively, to the joint cdf H of the pair (X, Y) such that $H(x, y) = C(F(x), G(y))$ with $u = F(x)$ and $v = G(y)$ (Sklar, 1959).

To define conditional Kendall's tau, let X, Y and Z be continuous random variables. In addition, note $C_{X,Y|Z}$ the conditional copula that connects the cdfs $F_{X|Z}$ and $G_{Y|Z}$ of X and Y conditional on Z , respectively, and $H_{X,Y|Z}$, which is the joint conditional cdf of pair (X, Y) . Conditional Kendall's tau is defined by inserting the conditional copula into Eq. (1), such that:

$$\tau_{X,Y|Z} = 4 \int_{[0,1]^2} C_{X,Y|Z}(u, v) dC_{X,Y|Z}(u, v) - 1 := \tau(z) \tag{2}$$

Since $C_{X,Y|Z}$ and thus the true measure of $\tau_{X,Y|Z}$ are unknown, an estimator $\hat{\tau}(z)$ of conditional Kendall's tau is defined by replacing the conditional copula in Eq. (2) by its estimator $\hat{C}_{X,Y|Z}$. Both estimators $\hat{\tau}(z)$ and $\hat{C}_{X,Y|Z}$ were defined using a kernel-smoothing method weighted by covariate Z (Section S4). See Derumigny and Fermanian (2019) for the equation for the estimator $\hat{\tau}(z)$ and its associated theoretical properties.

Table 2

Descriptive statistics of the main variables analyzed for 2523 dairy farms surveyed in 2013 and 804 dairy farms surveyed in 2014. Shaded cells represent additional variables that were used to interpret the results. LU: livestock unit. Grass_{DM}: grazed grass dry matter. Maize_{DM}: maize dry matter. MFA: main forage area.

Year	Variable	Abbrev.	Unit	Min.	Mean	Max.
2013	Milk production	MILK ₁₃	l.cow ⁻¹	2276	7605	11,462
	Enteric methane emissions	CH4 ₁₃	t CO ₂ -eq.LU ⁻¹	1.452	3.368	4.252
	Digestible organic matter ingested	DOMI ₁₃	kg.cow ⁻¹	2021	4329	5651
	Quantity of concentrated feed	CONC ₁₃	kg.cow ⁻¹	0	1211	3541
	Precipitation in 2013	PRECIP _{13(F13)}	mm	586	1012	2162
	Precipitation in 2012	PRECIP _{12(F13)}	mm	697	1085	2039
	Percentage of Grass _{DM} in the ration	-	%	0	26	71
	Percentage of Maize _{DM} in the ration	-	%	0	65	100
	Percentage of grass in the MFA	-	%	1	62	100
	Percentage of maize in the MFA	-	%	0	37	99
2014	Milk production	MILK ₁₄	l.cow ⁻¹	2308	7618	11,447
	Enteric methane emissions ¹	CH4 ₁₄	t CO ₂ -eq.LU ⁻¹	2.004	3.363	4.361
	Digestible organic matter ingested ¹	DOMI ₁₄	kg.cow ⁻¹	2617	4288	5427
	Quantity of concentrated feed	CONC ₁₄	kg.cow ⁻¹	0	1429	5366
	Precipitation in 2014	PRECIP _{14(F14)}	mm	623	975	1656
	Precipitation in 2013	PRECIP _{13(F14)}	mm	588	921	1553
	Percentage of Grass _{DM} in the ration	-	%	0	19	62
	Percentage of Maize _{DM} in the ration ¹	-	%	5	58	99
	Percentage of grass in the MFA	-	%	14	61	98
	Percentage of maize in the MFA	-	%	2	39	86

¹Data were available only for 714 of the 804 farms.

2.2.2. Choosing the kernel and smoothing bandwidth

Applying estimator $\hat{\tau}(z)$ requires choosing a probability density function (i.e., a “kernel”) and a smoothing bandwidth h . The kernel (traditionally symmetric) is related to the weights attributed to the neighboring observations used to approximate each point of the estimate, while the smoothing bandwidth represents its size (Fig. S1). The smoothing bandwidth chosen is important since it influences the trade-off between bias and variance. A bandwidth that is too narrow will yield an erratic estimate of conditional Kendall’s tau, while a bandwidth that is too wide will yield an overly smooth estimate that can conceal potentially meaningful deviations.

We chose the optimal smoothing bandwidth h_{CV} using a cross-validation procedure with the “leave-one-out” method (i.e., calculate scores for multiple values of h and select the h with the lowest score) (Section S5). A recurrent issue when performing least squares cross-validation is the presence of multiple local minima (Hall and Marron, 1991; Savchuk et al., 2011). We addressed this issue by choosing the bandwidth that was the most consistent with the scale of the data (i.e., 10–30% of the range of variable Z). The Epanechnikov kernel (Tsybakov, 2004) was applied using the R package CondCopulas (Derumigny, 2022). To assess the uncertainty in the estimates, we calculated a 95% confidence interval (CI) by using a bootstrap sampling method.

2.3. Applying the conditional correlation coefficient

We applied conditional Kendall’s tau to the dataset to identify relations among variables for the dairy-cattle systems in 2013 and 2014. We selected 20 variables from the database (Tables 2 and S2) and the seven meteorological indices to explore the influence of one variable on correlations between two others. We first explored many combinations of conditional and conditioned variables for the farms surveyed in 2013 and ultimately selected the combinations with the largest variations in conditional Kendall’s tau. We then applied the conditional Kendall’s tau to these same combinations for the farms surveyed in 2014. In particular, we aimed to assess the influence of a management practice on the correlation between farm production and an environmental performance, as well as the influence of a weather condition on the correlation between a management practice and a production performance.

For example, we studied the correlation between milk production per cow and enteric CH₄ emissions per livestock unit (LU) as a function of the amount of digestible organic matter ingested (DOMI) per cow, since the ration directly influences milk production (Sanh et al., 2002) and enteric CH₄ emissions (Beauchemin et al., 2008). By representing the ration’s composition by its amount of DOMI, we investigated how a change in the ration, particularly in its digestibility, may have influenced the dependence of enteric CH₄ emissions on milk production, which can vary due to the ration’s influence on each of them individually.

We also studied the correlation between the amount of concentrated feed fed to cows and milk production per cow as a function of the precipitation of the same year or the previous year. Concentrated feed is often fed to cows, along with other forages (often produced on the farm), to stimulate their milk production (Sanh et al., 2002). The objective was to assess whether the environmental context (i.e., weather conditions) influenced the dependence of milk production per cow on concentrated feed.

2.3.1. Empirical conditional correlation and identification of sets of atypical farms

We first examined the empirical conditional Kendall’s tau of the sets of variables by grouping farms into subsamples that had the same interval of Z (chosen to optimize the number of subsamples along Z and the number of farms in each subsample) and then calculating the mean empirical Kendall’s tau of each subsample, which we compared to the estimated conditional Kendall’s tau ($\hat{\tau}$). We then identified groups of farms whose $\hat{\tau}$, for a given pair of conditioned variables and a

conditioning covariate Z , deviated greatly from the standard Kendall’s rank correlation coefficient between the conditioned variables (i.e., identified subsets of atypical farms). Covariates in the sets of variables (e.g., percentage of grazed grass dry matter in the ration, percentage of maize in the MFA) were then assessed to characterize the feeding strategies, resources and/or agricultural contexts of the farms in each group. Differences in medians of covariates were tested using the Mann-Whitney-Wilcoxon median comparison test and considered significant at $p \leq 0.05$.

3. Results

3.1. Influence of digestible organic matter ingested on the correlation between milk production and enteric methane emissions

One strong deviation in the conditional Kendall’s tau was observed for farms surveyed in 2013 between milk production per cow (MILK₁₃) and enteric CH₄ emissions per LU (CH₄₁₃) as a function of the amount of digestible organic matter ingested per cow (DOMI₁₃).

3.1.1. Estimated conditional Kendall’s tau

When examining the empirical conditional Kendall’s tau between MILK₁₃ and CH₄₁₃, the number of farms per subsample of DOMI₁₃ varied, and only 1.4% of the farms lay in the extremes (Fig. 1a). The mean empirical Kendall’s tau per subsample varied from ca. -1.00 to 0.25 . In comparison, the non-conditional Kendall’s tau between each pair of variables was strong and significant: 0.75 between CH₄₁₃ and DOMI₁₃, 0.89 between MILK₁₃ and DOMI₁₃, and 0.69 between MILK₁₃ and CH₄₁₃.

The optimal smoothing bandwidth (h_{CV}) was set to 380. The estimated conditional Kendall’s tau ($\hat{\tau}$) varied strongly as a function of DOMI₁₃ (Fig. 1b), and four groups of farms were identified:

- group 1: $\hat{\tau} < 0$, with DOMI₁₃ $\approx 2050\text{--}2900\text{ kg.cow}^{-1}$
- group 2: $\hat{\tau}$ in $[0, 0.25[$, with DOMI₁₃ $< 2050\text{ kg.cow}^{-1}$ and also $\approx 2900\text{--}3600\text{ kg.cow}^{-1}$
- group 3: $\hat{\tau} \geq 0.25$, with DOMI₁₃ $\approx 3600\text{--}5300\text{ kg.cow}^{-1}$
- group 4: $\hat{\tau} < 0.25$ and DOMI₁₃ $> 5300\text{ kg.cow}^{-1}$

Group 3 contained most (94.5%) of the farms surveyed in 2013, and its $\hat{\tau}$ ($0.26\text{--}0.44$) were the most similar to the non-conditional Kendall’s tau (0.69).

3.1.2. Characterization of farm groups

The feeding strategies of the groups of farms were characterized as a function of the percentages of maize dry matter (Maize_{DM}) and grazed grass dry matter (Grass_{DM}) in the ration. Farms in group 1 (i.e., negative $\hat{\tau}$ between MILK₁₃ and CH₄₁₃ and the smallest DOMI₁₃) had the lowest percentage of Maize_{DM} in the ration (median of 0%) (Fig. 2a). Conversely, farms in groups 3 (i.e., $\hat{\tau} \geq 0.25$) and group 4 had a high percentage of Maize_{DM} in the ration (median of 69% and 76%, respectively). Farms in group 2 had an intermediate correlation and percentage of Maize_{DM} in the ration (median of 23%). The median percentage of Maize_{DM} in the ration of groups 1 and 2 differed significantly from that in the ration of groups 3 and 4 (Fig. 2a).

The percentage of Grass_{DM} in the ration was the highest for farms in groups 1 and 2 (ca. 46% and 44%, respectively), which had the weakest (and sometimes negative) conditional correlations and the smallest DOMI₁₃ (Fig. 2b). Conversely, the percentage of Grass_{DM} in the ration was low (median of 25%) for farms in groups 3 (i.e., with the strongest conditional correlation) and 4 (i.e., with a weak or negative conditional correlation) (median of 15%). The median percentage of Grass_{DM} in the ration of farms in group 3 differed significantly from those of the farms in the other three groups (Fig. 2b). Similar results were obtained for the conditional correlation between MILK₁₄ and CH₄₁₄ as a function of

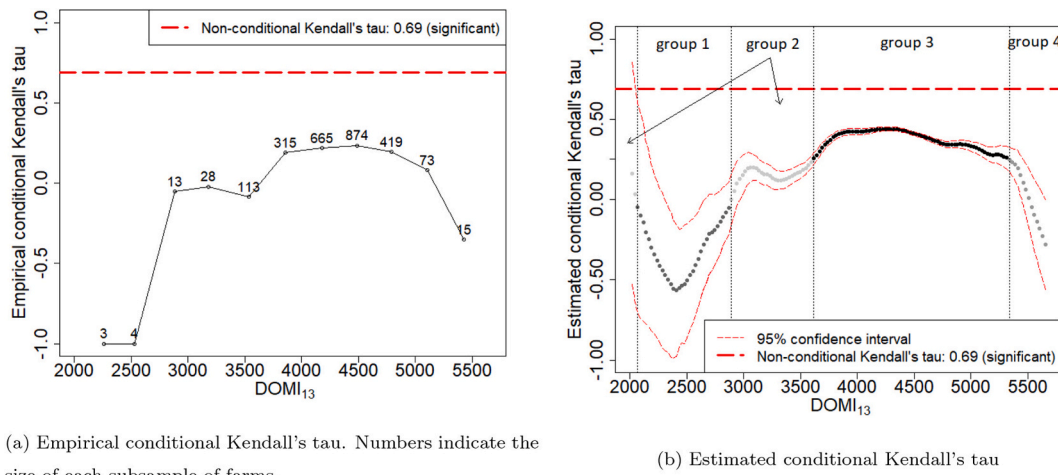


Fig. 1. Conditional Kendall's tau correlation between milk production per cow and enteric CH₄ emissions per livestock unit as a function of the amount of digestible organic matter ingested per cow (DOMI₁₃) for farms surveyed in 2013.

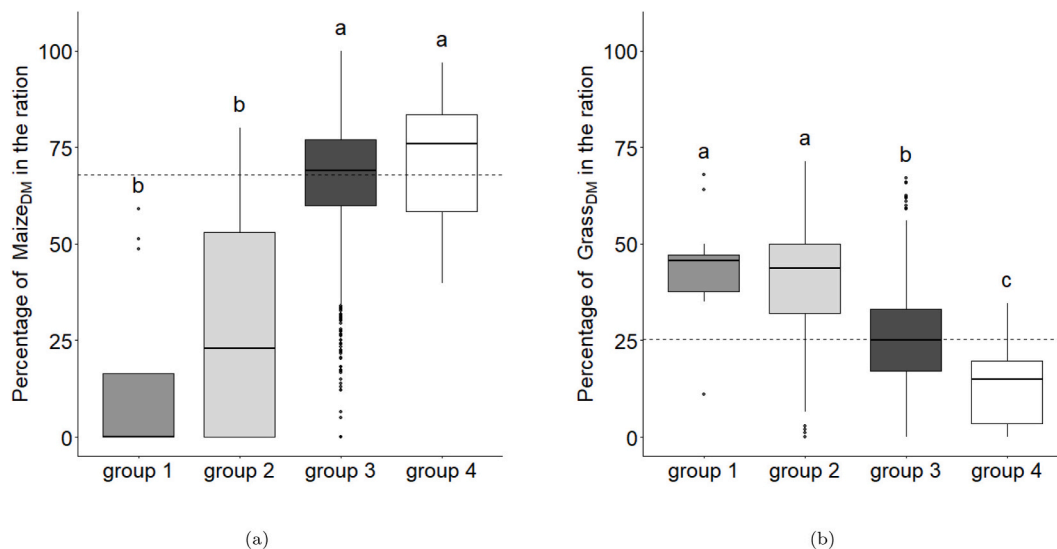


Fig. 2. Boxplots of percentages of (a) maize dry matter (Maize_{DM}) and (b) grazed grass dry matter (Grass_{DM}) in the ration of farms surveyed in 2013 as a function of farm groups 1–4 (digestible organic matter ingested \approx 2050-2900; < 2050 and also \approx 2900-3600; 3600-5300; and > 5300 kg.cow⁻¹, respectively). Different letters indicate significant differences between groups (*adj.p* < 0.05, Mann-Whitney-Wilcoxon median comparison test). Whiskers represent 1.5 times the interquartile range. The dotted horizontal line indicates the overall median of all groups combined.

DOMI₁₄ for the farms surveyed in 2014 (Section S6).

3.2. Influence of annual precipitation on the correlation between concentrated feed and milk production

Another strong deviation in the conditional Kendall's tau was observed for farms surveyed in 2013 and 2014 between the amount of concentrated feed fed to cows (CONC₁₃ and CONC₁₄, respectively) and milk production per cow (MILK₁₃ and MILK₁₄, respectively) as a function of the precipitation in 2013 (i.e. the same year (PRECIP_{13(F13)}) for farms surveyed in 2013 or the previous year (PRECIP_{13(F14)}) for farms surveyed in 2014).

3.2.1. Estimated conditional Kendall's tau

For the farms surveyed in 2013, empirical conditional Kendall's tau between CONC₁₃ and MILK₁₃ as a function of PRECIP_{13(F13)} (range of 580-2170 mm) differed little from the non-conditional Kendall's tau (0.42), except for precipitation of ca. 1400-1700 mm, for which it was –

0.07 (Fig. 3a). The non-conditional correlations between PRECIP_{13(F13)} and both MILK₁₃ and CONC₁₃ were weak but significant: –0.15 and –0.07, respectively. The optimal smoothing bandwidth (h_{CV}) was set to 320. The estimated conditional Kendall's tau between MILK₁₃ and CONC₁₃ as a function of PRECIP_{13(F13)} was consistent with the empirical version, except for precipitation of ca. 1400-1700 mm, when it decreased strongly to a minimum of ca. 0.16 (Fig. 3b). The 95% CI was narrowest for precipitation lower than 1400 mm, since this interval contained 96.2% of the farms. For the farms surveyed in 2013, three groups were identified:

- group 1: $\hat{\tau} \approx$ non-conditional τ , with PRECIP_{13(F13)} < 1400 mm
- group 2: $\hat{\tau} <$ non-conditional τ , with PRECIP_{13(F13)} \approx 1400-1700 mm
- group 3: $\hat{\tau} >$ non-conditional τ , with PRECIP_{13(F13)} > 1700 mm

In comparison, for the farms surveyed in 2014, the empirical conditional Kendall's tau between MILK₁₄ and CONC₁₄ as a function of PRECIP_{13(F14)} (range of 580-1560 mm) varied from ca. –0.33 to ca. 0.40

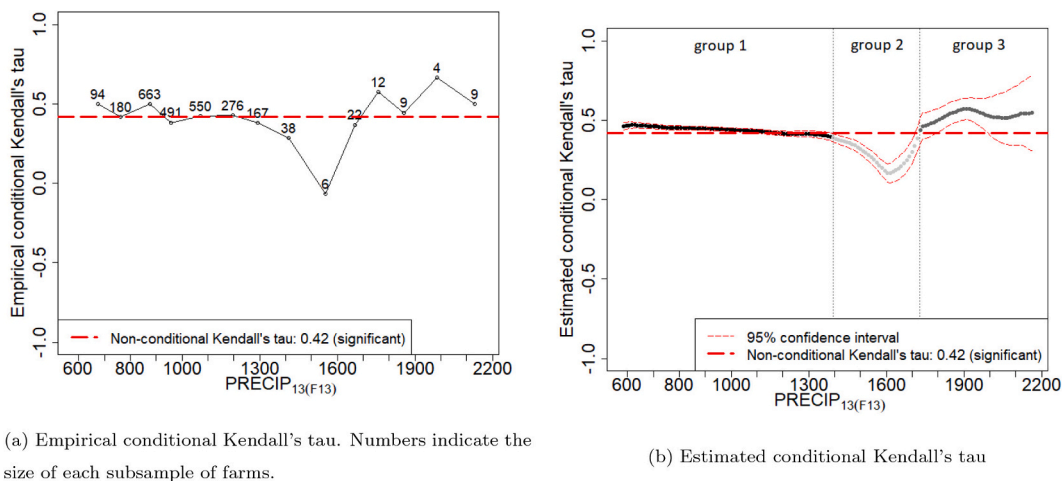


Fig. 3. Conditional Kendall's tau correlation between the amount of concentrated feed fed to cows and milk production per cow as a function of total precipitation received in 2013 for farms surveyed in 2013 (PRECIP_{13(F13)}).

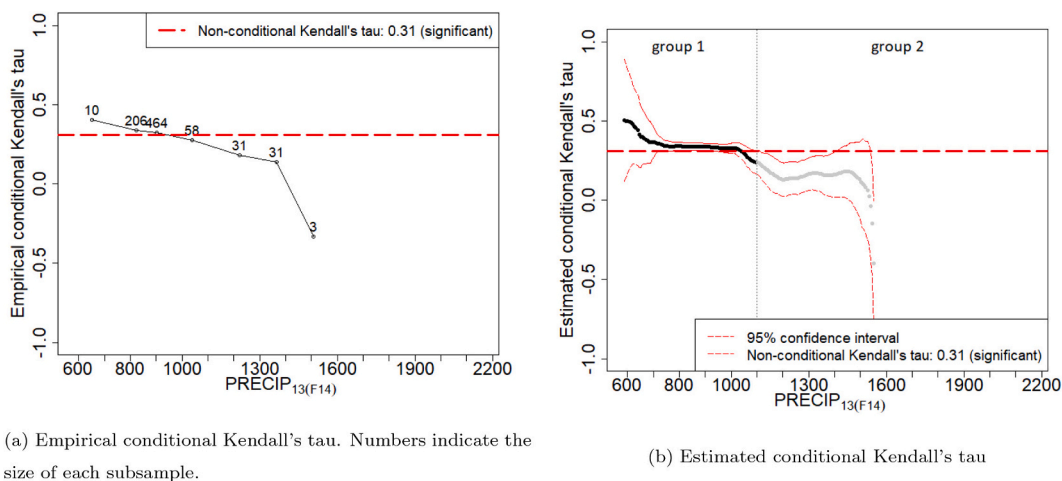


Fig. 4. Kendall's tau correlation between the amount of concentrated feed fed to cows and milk production per cow as a function of total precipitation received in 2013 by farms surveyed in 2014 (PRECIP_{13(F14)}).

(Fig. 4a). Each extreme of PRECIP_{13(F14)} contained few farms. Most farms had PRECIP_{13(F14)} of ca. 800-1100 mm, for which the empirical conditional Kendall's tau between MILK₁₄ and CONC₁₄ was similar to the non-conditional one (0.31). PRECIP_{13(F14)} was not correlated with either MILK₁₄ (− 0.03) or CONC₁₄ (− 0.01). For farms surveyed in 2014, the optimal bandwidth (h_{CV}) was set to 150. Like for the farms surveyed in 2013, the estimated conditional Kendall's tau decreased to a minimum (− 0.40), but this time from ca. 1100 mm of precipitation (Fig. 4b). The 95% CI was narrowest for precipitation lower than 1100 mm, since this interval contained 91.3% of the farms. For farms surveyed in 2014, two groups were identified:

- group 1: $\hat{\tau} \geq$ non-conditional τ , with PRECIP_{13(F14)} < 1100 mm
- group 2: $\hat{\tau} <$ non-conditional τ , with PRECIP_{13(F14)} \geq 1100 mm

Similar results were obtained for the conditional correlation between MILK₁₄ and CONC₁₄ as function of precipitation of the same year (PRECIP_{14(F14)}) for farms surveyed in 2014, and between MILK₁₃ and CONC₁₃ as function of precipitation of the previous year (PRECIP_{12(F13)}) for farms surveyed in 2013 (Sections S7 and S8, respectively).

3.2.2. Characterization of farm groups

The groups of farms were characterized as a function of the percentage of Grass_{DM} in the ration (to describe feeding strategies), the percentage of grass and maize in the MFA (to describe farm resources and the agricultural context), milk production per cow and the amount of concentrated feed fed to cows. For the farms surveyed in 2013, those in group 1, which had a nearly constant estimated conditional Kendall's tau (ca. 0.40), had a higher MILK₁₃ (median of 7734 l.cow^{−1}), higher percentage of maize in the MFA (median of 38%), but lower percentage of grass in the MFA (median of 60%) than those of farms in the other two groups (Table 3). Conversely, farms in group 3, which had the highest estimated conditional Kendall's tau (0.43-0.57), had median MILK₁₃ of 6176 l.cow^{−1} and 0% of maize in the MFA, since all of them were based on grasslands alone. Farms in group 2, which had the minimum estimated Kendall's tau (0.16), had median MILK₁₃ of 6909 l.cow^{−1}, a median percentage of maize in the MFA of 14% and an intermediate median percentage of grass in the MFA of 86%, all of which differed significantly from those of farms in the other two groups. Farms in groups 1 and 2 had a similar CONC₁₃ (median of 1161 and 1011 kg.cow^{−1}, respectively), which was significantly lower than that of farms in group 3 (1461 kg.cow^{−1}). Conversely, farms in groups 2 and 3 had the same percentage of Grass_{DM} in the ration (median of 39%), which was significantly higher than that of farms in group 1 (median of

Table 3

Median values of characteristics of farms surveyed in 2013 or 2014 in the groups defined as a function of deviation in estimated conditional Kendall's tau ($\hat{\tau}$). In 2013, groups 1–3 represent $\hat{\tau} \approx, <, \text{ or } >$ non-conditional τ , respectively, while in 2014, groups 1–2 represent $\hat{\tau} \geq \text{ or } <$ non-conditional τ , respectively. Different letters indicate significant differences ($p \leq 0.05$) for a given year according to the Mann-Whitney-Wilcoxon median comparison test. MFA: main forage area. Grass_{DM}: grazed grass dry matter.

Characteristic	2013		2014		
	Group 1	Group 2	Group 3	Group 1	Group 2
Milk production (l.cow ⁻¹)	7734 ^a	6906 ^b	6176 ^c	7722 ^a	7375 ^a
Amount of concentrated feed (kg.cow ⁻¹)	1161 ^b	1011 ^b	1461 ^a	1373 ^b	1634 ^a
Percentage of Grass _{DM} in the ration	25 ^b	39 ^a	39 ^a	18 ^a	16 ^b
Percentage of grass in the MFA	60 ^c	86 ^b	100 ^a	60 ^b	75 ^a
Percentage of maize in the MFA	38 ^a	14 ^b	0 ^c	39 ^a	25 ^b

25%).

For the farms surveyed in 2014, MILK₁₄ did not differ significantly between groups 1 and 2 (median of 7722 and 7375 l.cow⁻¹, respectively) (Table 3). However, farms in group 1 had significantly lower CONC₁₄ than those in group 2 (median of 1373 and 1634 kg.cow⁻¹, respectively), higher percentage of Grass_{DM} in the ration (median of 18% and 16%, respectively), lower percentage of grass in the MFA (median of 60% and 75%, respectively) and higher percentage of maize in the MFA (median of 39% and 25%, respectively).

4. Discussion

4.1. Influence of digestible organic matter ingested on the correlation between milk production and enteric methane emissions

For the farms surveyed in 2013, the negative conditional correlation between milk production and enteric methane emissions (CH₄₁₃) at the extremes of DOMI₁₃ (i.e., farms in group 1 and some farms in group 4) was unusual, given the strong positive non-conditional correlation between them and since increasing dry matter intake tends to increase both milk production and enteric CH₄ emissions per LU (Dall-Orsoletta et al., 2019). Nonetheless, enteric CH₄ emissions can be decreased by increasing the percentage of concentrated feed or maize silage in the ration (up to a certain percentage) (Beauchemin et al., 2008) or increasing the digestibility of fodder or grazed grass (O'Neill et al., 2011; Wims et al., 2010).

Since most farms in group 1 were based on grassland and thus fed a grass-based ration, the negative correlation could have been due to the increasing percentage of Maize_{DM} in the rations, which, by increasing their digestibility and energy content, thus decreased enteric CH₄ emissions while increasing milk production (i.e., creating a negative correlation). In comparison, group 2 contained farms with somewhat more maize in the MFA, while group 3 contained mainly conventional farms with more than 30% of maize in their MFA. An equivalent increase in the percentage of Maize_{DM} in their already maize-based rations may not have increased digestibility sufficiently to decrease enteric CH₄ emissions. For group 4, whose farms were the most intensive and had a low percentage of grass in the ration, the weak or negative correlation may have been due to a scale effect, since intensive farms produce more milk per cow but emit less enteric CH₄ per LU because they have more cattle.

Other studies have assessed relations among milk production, CH₄ emissions and the composition of cow rations (i.e., types and amounts of forages and concentrated feed). For instance, one study measured enteric CH₄ emissions of individual cows during milking on 21 com-

mercial dairy farms for three years (Bell et al., 2014). While CH₄ emissions increased for most farms as milk production increased, they decreased for certain farms due to differences in ration composition and energy use by cows. The rations on the farm with the largest negative relation included mainly maize silage, whole linseed meal and high-fat concentrated feed, all of which can decrease CH₄ emissions. Similarly, Wattiaux et al. (2019) highlighted how decreasing the ratio of forages (i.e., alfalfa and maize silage) to concentrated feed (i.e., high-moisture maize, ground maize grain, soybean by-products and cottonseed) can decrease CH₄ emissions without decreasing milk production. They also highlighted that cows fed legumes emit less CH₄ than those fed grass, perhaps because the fiber of legumes is less digestible and contains more hemicellulose than that of grass (Wattiaux et al., 2019). However, since maize silage contains more starch than other types of silage, replacing cereal or legume silage with it tends to decrease enteric CH₄ emissions while increasing milk production (Jayasundara et al., 2016; Eugène et al., 2021).

4.2. Influence of annual precipitation on the correlation between concentrated feed and milk production

Precipitation in 2013 (PRECIP_{13(F13)} and PRECIP_{13(F14)}) seemed to have a similar impact on the correlation between milk production per cow (MILK₁₃ and MILK₁₄) and the use of concentrated feed fed to cows (CONC₁₃ and CONC₁₄) whether farms were surveyed in 2013 or 2014. In both cases, the correlation reached a minimum beyond a certain threshold (ca. 1400 or 1100 mm for farms in group 2 surveyed in 2013 or 2014, respectively).

When considering feeding strategies, group 2 of farms surveyed in 2013 or 2014 had a high median percentage of grasslands in the MFA (86% and 75%, respectively). In 2013, group 2 had a higher median percentage of Grass_{DM} in the ration and fed a smaller median amount of concentrated feed per cow than did group 1 (i.e., with $\hat{\tau} \approx \text{ or } \geq$ non-conditional τ). In 2014, it was the opposite, since group 2 had a lower median percentage of Grass_{DM} in the ration and fed a larger median amount of concentrated feed per cow than did group 1. In addition, as mentioned, the distribution of farms among farm types differed slightly between 2013 and 2014.

Thus, similarities between the two curves of conditional Kendall's tau suggest an influence of precipitation beyond a certain threshold, which was stronger than those of the feeding strategy and farm type, for farms surveyed in both years. Beyond this threshold of precipitation during the current or previous year (depending on the feeding strategy), the weaker correlation between milk production per cow and concentrated feed fed per cow can be explained by decreased dependence on concentrated feed on farms (Dumont et al., 2022) due to a better environmental context for forage production. However, the influence of precipitation identified in the present study more likely represented differences in mean precipitation among regions of France than above-average precipitation received by the farms surveyed. Studying the same farms for multiple years would help to identify the influence of above-average precipitation. Examining the dependence of milk production on concentrated feed, studies have observed that replacing concentrated feed with high-quality forage and a sufficient amount of crude protein did not decrease milk production during late lactation (Hymøller et al., 2014). Similarly, Åby et al. (2019) observed that increasing the quality of grass silage (which depends in particular on the cutting frequency and weather conditions) decreases dependence on concentrated feed and can decrease GHG emissions per l of milk while maintaining milk production.

Farms in group 3 surveyed in 2013 that had received a large amount of precipitation (≥ 1700 mm) had a stronger correlation between MILK₁₃ and CONC₁₃. These farms were grassland farms, since 100% of their MFA was grasslands. The increased dependence of grassland farms on concentrated feed to produce milk reflected difficulties that they

encountered in feeding their cows when annual precipitation, which ranges from 500–2000 mm in France (1991–2020) (Météo-France, 2023), was high, which made them less resilient (Dumont et al., 2022; Bowen and Chudleigh, 2021). Along the same lines, an economic study assessed effects of weather conditions on milk production in Spain through their influence on cow productivity and forage production (Perez-Mendez et al., 2019). In particular, it observed that weather conditions that deviated from the average influenced forage production, which led to large changes in milk production and a maximum difference in profits of 10%. Qi et al. (2015) observed that weather conditions in Wisconsin, USA, influenced milk production differently depending on the season. While higher temperature in summer and autumn decreased milk production, it increased milk production in winter and spring; in comparison, higher precipitation always decreased milk production. Likewise, Roche et al. (2009) assessed the seasonal influence of weather conditions (e.g., temperature, relative humidity, evapotranspiration) in 18 farmlets of a farm in New Zealand on grass production, nutrient contents and mineral concentrations, and thus on animal production in grazing systems, helping to understand short-term changes in animal performance. Controlling for season and farmlet, weather conditions explained at most 14% of the variation in grass nutrient content. In particular, seasonal precipitation and grass-related variables (e.g., organic matter digestibility, metabolizable energy content) were moderately correlated.

4.3. Conditional Kendall's tau

Estimating conditional Kendall's tau is a useful approach for assessing more precisely the variation in the correlation between two variables as a function of another variable, unlike non-conditional Kendall's tau, which remains constant. It was particularly useful in the present study since cause-and-effect relations in agricultural systems (e.g., milk production and GHG emissions, feeding strategies and milk production) are influenced by other factors (e.g., management practices, weather conditions) (Pellerin et al., 2017). Ultimately, the best approach is to apply the method when the conditioned variables and conditioning variable(s) are specifically identified. Similarly, a copula-based estimator of conditional Spearman's rho (Gijbels et al., 2011) was used to assess correlations between yields and prices of wheat, maize and grapes as a function of weather conditions (Bousebata et al., 2020). However, the estimator we chose seems more robust, since its simpler equations ease calculations and increase confidence in the estimate.

Conversely, other methods such as PCA would not have helped study the variation in correlations, nor the dependence among such a small group of variables (Attia et al., 2022). Since the principal components in PCA are linear combinations of the original variables (Jolliffe and Cadima, 2016), non-linear dependences and potential correlations in the data are ignored, which may bias the results (Jiang and Eskridge, 2000). Associated tools such as the correlation circle represent the variables and their mutual correlation with the principal components, which describes the direction and degree to which variables are related to each other and which component(s) summarize their information. However, PCA does not describe how the correlation between two variables varies as a function of other variables. PCA is often followed by clustering (Díaz de Otálora et al., 2022) to identify and characterize groups of individuals as a function of the components (i.e., groups of variables). The conditional Kendall's tau goes further because it can identify groups of individuals (i.e., farms) differently, based not only on the variables, but on variations in the correlations between them. However, additional covariates are needed to characterize the groups of farms identified in more detail.

Confidence in the estimated conditional Kendall's tau decreased as the number of farms decreased. Because the number of farms was not uniformly distributed for each conditioning variable, the extremes of the curve usually contained few farms. Thus, deviations in the correlations and wide CIs at the extremes seemed due more to the few farms there

than to edge effects caused by the kernel-smoothing method, as shown by the wide 95% CI obtained by the bootstrap sampling method. Thus, results for the extremes need to be interpreted with caution. However, highlighting rare situations is sometimes interesting since extreme or unusual phenomena can occur (Senga Kiessé et al., 2022), but they are difficult to identify, model and understand.

Results of using the estimator of conditional Kendall's tau indicate that other variables should be investigated to try to characterize atypical groups of farms. This method has also been generalized for more than two conditioning variables, but it may be difficult to interpret its results in real-life applications (Derumigny and Fermanian, 2019). A natural next step would be to explore statistical methods that can assess more than three variables simultaneously and are useful for modeling multiple interactions without compromising the interpretation, such as vine copulas (Czado and Nagler, 2022).

5. Conclusion

The variable correlation observed between milk production and enteric CH₄ emissions as a function of the amount of digestible organic matter ingested supported observations that increasing the digestibility of cow rations can mitigate CH₄ emissions without decreasing milk production. In addition, the variable correlation observed between the amount of concentrated feed in the ration and milk production as a function of precipitation of the current or previous year confirmed that milk production depends less on concentrated feed when high-quality forages are available. Although additional variables were needed to interpret deviations in the conditional correlations, the study demonstrated the utility of using conditional Kendall's tau to assess a variable's influence on the dependence between two other variables.

CRedit authorship contribution statement

Naomi Ouachene: Writing – original draft, Investigation. **Tristan Senga Kiessé:** Writing – review & editing, Supervision. **Michael S. Corson:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

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