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METHANE EMISSIONS VARIATION AMONG NEW ZEALAND DAIRY FARMS AND HERDS

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SUMMARY

This study investigated the current animal-level and herd-level variation for enteric fermented methane emissions across pasture-based dairy farms in New Zealand. We used the DairyNZ core database consisting of 2,398 herds and 751,981 cows as the inputs, and inferred crucial but unknown variables including methane emissions per unit of feed from department of environment, food&rural affairs (DEFRA), and live weight from New Zealand animal evaluation limited database to predict methane emissions for individual dairy cows. Methane emissions were predicted using dry matter intake (DMI) with an Intergovernmental Panel on Climate Change tier 2 approach. While individual methane emissions (R^2 =0.29) were poorly predicted, but excellent predictability of herd average methane emissions were well predicted (R^2=0.95) based on variables including herd, age, replacement rate, DMI, live weight (LW) and milk solids. The results showed an advantage of predicting methane emissions at herd level than individual cow level. Based on the results, the NZ dairy industry should focus on new traits and breeding objectives, with the support of trait prioritisation, a monitoring plan, policy making and incentivisation for farmers.

INTRODUCTION

More than 95% of methane emissions in a life cycle of dairy production come from enteric fermentation (Fonterra co-operative group limited, 2017). There is variation in greenhouse gas emissions among dairy farms caused by variation in production practices, environment, and regional historical disparity (Latham 2010; Beukes *et al*. 2010). To facilitate farmers in compliant with the future regulation, it will be important to establish objective, data driven and, practical and easy-to-implement methods of monitoring emissions levels at an individual farm level.

Currently animal identification and performance recording in New Zealand dairy farms are generally not well linked, due to the difficulty in tracking large herds on seasonal pasture-based production system (Edge and Kavalali 2018), although many farms have some level of recording in place for the purpose of herd improvement (3.67 million out 4.95 million cows, LIC and DairyNZ 2019). For example, the national database such as New Zealand dairy core database (DairyNZ Hamilton, New Zealand) have performance records unlinked to animal ID, such as live weight. Additionally, the current techniques for measuring methane per unit of feed was difficult to apply on a large scale (DEFRA 2014). With the introduction of new data and IT systems, it would be possible to create a database infrastructure that would allow dairy cow GHG emissions to be predicted at the individual cow level and aggregated to individual farm level.

Due to aforementioned reason, the objectives of this study were 1) to combine multiple existing data sources to predict the variation among individuals and herds for dairy cattle enteric fermentation methane emissions for New Zealand dairy farms; 2) assess the requirement of future data infrastructure and technologies in order to monitor methane emissions at animal and herd level and; 3) infer the emission mitigation strategies enabling the adoption of future on-farm emission policies and technologies.

MATERIALS AND METHODS

Data. New Zealand dairy core database containing herd test and movement records of

27,288,426 cows from 1989 to 2014. Breeds included Jersey, Holstein-Friesian and crossbred. Records of cows calving between June 1st and October 1st, 2005 were extracted, and quality control such as removing cows with lactation length beyond 365 days was applied. 751,981 cows with records in 2,398 herds were obtained in the end.

General approach. DMI approach illustrated in the IPCC 2000 (Pickering *et al.* 2020; Clark *et al.* 2003) as $E = F \cdot \alpha$, where E is methane emissions/cow/year, F is the annual DMI (kg DMI/year) and α is the methane emissions per unit of feed (g CH4/kg DMI).

Estimation of live weight. Simulated from mean live weight by age and breed (Livestock Improvement Company 2008; DairyNZ 2019), a CV of 0.105 (Zhang *et al.* 2019), a phenotypic correlation of 0.15 between LW and milk yield during the first 240 days of lactation (Correa-Luna *et al*. 2018).

Prediction of total lactation milk yield from test day records. Obtained by fitting quantile splines to each lactating cow for their milk volume, protein and fat production during lactation using smooth.spline function in R(v3.5.3).

Prediction of DMI from live weight and energy requirements. First calculated the energy requirement following Nicol and Brookes (2007) and Clark *et al*. (2003) as the summation of maintenance, lactation, replacement and gestation energy requirement; then converted energy to DMI by multiplying the average diet energy.

Prediction of methane emissions from DMI. First obtained the mean and SD of methane emissions per unit of feed, α, from experiments (DEFRA 2014) by removing research institute, measuring method, diet type, breed, sex and physiological status effects. Then sample α from this distribution and assign it to each cow i, multiplied by their DMI to obtain the prediction of E.

Statistical analysis. The summary statistical tests were calculated for measured and predicted variables (results not shown). Pearson correlations between E and energy related traits were also calculated (results not shown). To access the variance of variables in relation to E, an OLS linear model was fitted with herd as random effect, and milk solids, live weight, survival of individual cows and the herd averages of all previous effects as covariates.

RESULTS AND DISCUSSION

The methane emissions per unit of feed was estimated as 20.72 ± 4.24 g CH_4/kg DM. Variances of each variable regressed on individual and herd average E are shown in Table 1. Factors including herd, milk solids per cow, cow live weight and survival could predict individual feed intake well (R^2=0.29) but not individual methane output (R^2=0.29). The reason is the substantial variation that exists in methane eructed per unit of feed consumed, which is also difficult to measure in practice (Beukes *et al*. 2010; Herrero *et al*. 2013; DEFRA 2014). Additionally, in practice, farmers are unlikely to mitigate emissions by reducing production. Therefore, new technologies such as e-collars that measure cow activity for the use of predicting DMI is also likely to be of limited use in practice.

Herd average milk solids and live weight were powerful in predicting herd average methane emissions (R^2=0.95), hence policy based on farm level rather than individual cow level could be more effective in reducing methane emissions on an industry wide basis.

Table 1. Model comparisons for dry matter intake (*DMI, kg*) and methane emissions (*E*, kg) during the lactation for each cow and for the herd average ($\overline{DMI}$ and $\overline{E}$)

Dependent variable[1]	Model formula[2]	R^2	R	Model variance	Total variance
$DMI_{a_{ij}}$	$\sim h_{ij}$	0.28	0.52	232,627	845,228
	$\sim \overline{MS_{i\cdot}}$	0.25	0.50	211,555	845,228
	$\sim \overline{LW_{i\cdot}}$	0.11	0.33	94,448	845,228
	$\sim \overline{SUR_{i\cdot}}$	0.01	0.09	6,943	845,228
	$\sim \overline{age_{i\cdot}}$	0.01	0.09	7,011	845,228
	$\sim h_{ij} + MS_{ij} + LW_{ij} + SUR_{ij}$	0.78	0.88	661,980	845,228
E_{ij}	$\sim h_{ij}$	0.10	0.32	100	985
	$\sim \overline{MS_{i\cdot}}$	0.09	0.30	91	985
	$\sim \overline{LW_{i\cdot}}$	0.04	0.20	41	985
	$\sim \overline{SUR_{i\cdot}}$	0.003	0.06	3.09	985
	$\sim \overline{age_{i\cdot}}$	0.003	0.06	3.02	985
	$\sim h_{ij} + MS_{ij} + LW_{ij} + SUR_{ij}$	0.29	0.54	285	985
$\overline{DMI_{a_{i\cdot}}}$	$\sim \overline{MS_{i\cdot}}$	0.89	0.94	198,896	224,645
	$\sim \overline{LW_{i\cdot}}$	0.41	0.64	92,298	224,645
	$\sim \overline{SUR_{i\cdot}}$	0.02	0.14	4,512	224,645
	$\sim \overline{age_{i\cdot}}$	0.01	0.10	2,411	224,645
	$\sim \overline{MS_{i\cdot}} + \overline{LW_{i\cdot}}$	0.97	0.99	218,726	224,645
$\overline{E_{i\cdot}}$	$\sim \overline{MS_{i\cdot}}$	0.86	0.93	85	98
	$\sim \overline{LW_{i\cdot}}$	0.40	0.63	39	98
	$\sim \overline{SUR_{i\cdot}}$	0.02	0.14	1.96	98
	$\sim \overline{age_{i\cdot}}$	0.01	0.11	1.27	98
	$\sim \overline{MS_{i\cdot}} + \overline{LW_{i\cdot}}$	0.95	0.97	93	98

[1] Calculated for fall 2005 to spring 2006 season. *i* indicates *i*-th herd and *j* indicates *j*-th animal. *DMI* and *E* are accumulated predictions across the whole lactation.
[2] Dependent variables were herd (h_{ij}), herd average accumulated milk solids ($\overline{MS_{i\cdot}}$, kg), herd average mean live weight ($\overline{LW_{i\cdot}}$, kg), herd average survival ($\overline{SUR_{i\cdot}}$, year), herd average age ($\overline{age}_{ij}$, year), accumulated milk solids (MS_{ij}, kg), mean live weight (LW_{ij}, kg) and survival (SUR_{ij}, year). Herd was fitted as a random effect and other effects were fitted as covariates.

CONCLUSIONS

This preliminary study identified a key antagonism between farmer desire for profitable utilisation of farm feed resources and a national need to moderate the overall methane emissions from the dairy industry. Technologies that only predict individual feed intake will have limited value for practical mitigation of enteric methane emissions. Rather, additional mechanisms would be required to effectively incentivise mitigation opportunities that reduce emissions per unit of feed. A well-linked comprehensive animal level database infrastructure could support effectively incentivising some levels of farm and animal level changes to reduce enteric methane emissions.

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