Phase 3 – Multivariate analysis of Greenhouse Gas Emissions from New Zealand Sheep and Beef farms

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April 2020



Report for New Zealand Agricultural Greenhouse Gas Research Centre (NZAGRC), The Pastoral Greenhouse Gas Research Consortium (PGgRc) and Beef + Lamb New Zealand (B+LNZ). 55093X01

Client report number: RE450/2020/027



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Contents

1.	Exe	ecutive Summary	1
2.	Bad	skground	3
3.	Me	thods	4
	3.1	Farm data sources	4
	3.2	Financial indicators	5
	3.2.1	Gross margin	5
	3.2.2	EBITRm	5
	3.3	Farm data clustering	5
	3.3.1	B+LNZ farm classes	5
	3.3.2	Farm type clusters	6
	3.3.3	Feed clusters	6
	3.3.4	Gross margin per effective hectare clusters	7
	3.3.5	Gross margin per stock unit clusters	8
4.	Res	sults and Discussion	9
	4.1	Absolute Greenhouse Gas Emissions from New Zealand sheep and bee farms	
	4.2	Greenhouse Gas Emissions and farm area	. 13
	4.3	Farm Clustering and Greenhouse Gas Emissions	. 14
	4.3.1	B+LNZ sheep and beef farm classes	. 15
	4.3.2	Data clusters: Feed clusters	. 16
	4.4	Multivariate Analysis	. 21
	4.4.1	Correlation matrix heatmap	. 21
	4.4.2	Principal component analysis	. 23
	4.5	Economic efficiency and greenhouse gas emissions	. 28
5.	Cor	nclusions	. 37
6.	Ack	nowledgements	. 39
7.	Ref	erences	. 40

1. Executive Summary

Agriculture was the single largest contributor (48%) to total greenhouse gas (GHG) emissions in New Zealand in 2017, according to New Zealand's National Inventory, and sheep and beef livestock systems contributed about 40% of these emissions. Despite its importance, there has been limited analysis of sheep and beef systems in NZ. A holistic assessment of the farm-scale drivers of GHG emissions is critical to identifying opportunities to reduce emissions. We used farm-scale model, Farmax, to estimate feed inventories, nutrient flows and GHG emissions for 170 sheep and beef farms throughout New Zealand. Greenhouse gas (GHG) emissions were then calculated from Farmax outputs using the Agricultural Inventory Method equations.

The objectives of this project were to a) develop a data set containing animal policies, productive and reproductive efficiencies, and GHG emissions for a large number of sheep and beef farms located throughout New Zealand (n = 170 farms); b) to examine the relationships between variables that describe farm management and farm physical constraints, and GHG emissions; and c) to understand if relationships exist between financial descriptors and GHG emissions. No attempt was made to evaluate alternative mitigating scenarios within each farm or group of farms as this was outside the scope of this project but remains an area for further work. Also, because of the short-term nature of the dataset (one farm, one year), caution is required when extrapolating the results to i) longer periods of time, ii) circumstances other than the ones captured in the current dataset (e.g. weather, market), and iii) all of New Zealand sheep and beef farms (n = 23,400 farms; Beef + Lamb New Zealand Economic Service, 2019). Notwithstanding these limitations, our work provides a holistic assessment of the farm-scale drivers of GHG emissions and a comprehensive current state of affairs or baseline from which future trends in farm-scale GHG emissions can be established.

The mean and range in annual biological GHG emissions (CH₄ + N₂O) from the modelled farms were 3,662 and 157 to 7,096 kg CO₂ equivalents per effective (grazing) hectare (kg CO₂-e/eff ha), with 50% of the farms falling between 2,878 and 4,542 kg CO₂-e/eff ha, demonstrating the diversity in production systems across the sheep and beef sector. As stocking rate, animal product (wool + net carcass weight) and live weight gain all per effective hectare increased, GHG emissions increased. However, there was considerable variability in the data, for example, farms with GHG emissions of approximately 4,000 kg CO₂-e/eff ha had an almost three-fold difference in animal product per effective hectare (from 129 to 360 kg). Both increases in lamb weaning percentage (number of lambs weaned per number of ewes mated) and ewe efficiency (total weight of lambs weaned per weight of ewes mated) tend to be associated with increasing GHG emission per effective hectare, but the data are highly variable and at any level of emissions, the distribution in lamb weaning percentage and ewe efficiency are large. Methane accounted for 80% of total emissions (CH₄ + N₂O). Because of the limited use of N fertiliser in these sheep and beef farms, which most likely reflects the sector as a whole, feed intake (and its associated N content) was also the main driver of nitrous oxide emissions.

To tease out the impact of selected explanatory variables on GHG emissions (per effective ha), a correlation matrix heatmap was used to highlight the degree of association between variables on a one-to-one basis. As expected, feed intake (kg Dry

Matter (DM)/effective ha) and stocking rate (stock units (1 SU = 550 kg DM intake calculated to be the requirement for a 55kg ewe weaning 1 lamb)/effective ha) were identified as the strongest drivers of GHG emissions per ha. To a slightly lesser extent, total animal product produced (meat and fibre/eff ha) and ewes carried at July 1st (open), are also drivers of emissions. Comparatively, lamb weaning percentage, ewe efficiency, proportion of cultivatable land and proportion of liveweight (LW) sold relative to LW wintered, and N fertiliser applied appear to have a lower (but positive) correlation with GHG emissions. With the exception of the proportion of cultivatable land, these efficiency indicators, are the result of management decisions on the farm system and are less correlated with feed intake. Of the variables selected, feed conversion efficiency (FCE) and total farm area were the only variables that showed a negative correlation with GHG emissions.

A single dimension or principal component explained 50% of the variation (PC1). Within the cluster of farms with the highest average stocking rate (feed cluster 5), total feed intake and stocking rate (highly interrelated) drove that dimension. The multivariate analysis also shows that the main option to reduce GHG emissions from sheep and beef farms is to reduce total feed eaten per hectare, particularly in view of the relatively low intensity with which most of these farms are managed. Viable and productive sheep and beef systems that balance utilisation of pasture and risks of seasonal variation and climatic extremes in pasture supply, have adapted their stocking rate to adequately balance the need to maintain productive and nutritive pastures over time and to harvest the sward efficiently. Pasture is the major component of feed eaten, therefore a reduction in stocking rate alone will not be an effective way of reducing feed intake. because the remaining stock may increase feed intake so that there is no decrease in GHG emissions or feed quality cannot be maintained resulting in reduced animal performance and efficiency (reduced lambing percentage, animal growth rates, longer time to finish animals) meaning animals remain on the farm for longer and the reduction in GHG emissions will be less than what would be expected from a given reduction in stocking rate. Thus, the most effective way to reduce total farm feed intake will be to maintain current production per ha on productive areas of the farm and retire either the highest (and most flexible for other land uses) or lowest performing (and potentially more suitable for carbon sequestration) areas growing pasture, reduce total livestock numbers and total emissions. This may provide opportunities for considering alternative land uses with the potential for new non-livestock-based income streams.

This report provides the first analysis of financial data from a subset of farms (n=105). Farm management decisions impact on farm efficiency metrics and better efficiency measures are associated with improved revenue. Some farms are already high performing with strong gross margins, however the variability both within and between biophysical as well as financial clusters suggest real opportunity for efficiency gains to drive increased gross margins (GM) for some farms. A focus on GM/SU of the animal system will allow farmers to optimise their farm efficiency to achieve a higher income from their animal system, while maintaining GHG emissions. Alternatively, optimising efficiency of the animal system could enable a reduction in GHG emissions while maintaining farm income. The bottom line is farmer decisions around how the feed consumed on-farm is utilised in terms of choice of enterprises, their configuration into farm system, and the way they are managed is known to have a major influence on financial performance.

2. Background

Farming is a business and so profitability is a major driver of farmer decision-making. Nutrient, sediment and pathogen emissions from farms to water are already regulated or proposed to be regulated in an increasing number of NZ regions through the National Policy Statements for Fresh Water (Ministry for the Environment, 2019a) and Indigenous Biodiversity (Ministry for the Environment, 2019b), and the Climate Change Response Amendment Act (Ministry for the Environment, 2019c), and are increasingly important across NZ due to public and consumer perceptions. Hence, any redesigned farm systems must have strong practical applicability, pay attention to impacts on profitability and nutrient emissions to water, as well as to GHG emissions.

The contribution of the sheep and beef sector to NZ agricultural emissions has declined in the last 30 years, associated with a reduction in sheep numbers (Beef + Lamb New Zealand Economic Service, 2019). Despite a 30% reduction in GHG emissions in absolute terms, the sector has maintained similar levels of production and has doubled the value of its exports, since 1990 (Beef + Lamb New Zealand, 2019). However, sheep and beef livestock contributed almost 50 and 35% of emissions from total enteric fermentation and the agricultural sector, respectively, in 2016 (Ministry for the Environment, 2020). Although NZ is a small contributor to GHG emissions on a global scale, it is a global food producer and has an opportunity to demonstrate leadership internationally through innovation in the agricultural sector. There is the potential for these innovations to have a much greater impact through uptake and application in other countries.

Sheep and beef farms are diverse and are located over a range of landscapes, where each farm has different natural and capital assets, due to climate, location, aspect, altitude, slope, soil type (natural assets), along with previous investment in fencing, stock water, capital fertiliser, pasture improvement and animal genetics (capital assets). Despite their significance, little information exists describing the impact of the range in on-farm natural and capital assets and management decisions, which are the key drivers of GHG emissions across these diverse businesses (Mackay *et al.*, 2008; Harrison *et al.*, 2016). The inherent differences between these critical factors across commercial sheep and beef farms means that a large dataset will be required to represent the diversity of these NZ systems.

The objectives of this project were to a) develop a data set containing animal policies, productive and reproductive efficiencies, and GHG emissions for a large number of sheep and beef farms located throughout New Zealand (n = 170 farms); b) to examine the relationships between variables that describe farm management and farm physical constraints, and GHG emissions; and c) to understand if relationships exist between financial descriptors and GHG emissions. In more general terms, the aim of this project was to develop a data set containing GHG emissions, animal numbers and performance, and productive and reproductive efficiencies, along with physical and financial descriptors for a large number of sheep and beef farms located throughout New Zealand to enable us to start to understand the drivers of GHG emissions from New Zealand sheep and beef farms and where opportunities for change may exist.

3. Methods

Key farm characteristics affecting GHG emissions were assessed on a total of 170 farms using Farmax (Science edition 7.2.2.46) modelling. Data were modelled for a single year for each farm, either 2015/2016 or 2016/2017. Before the process of selection of relevant farm characteristics, analysis was undertaken to confirm the mean and range in values was comparable in each year. In addition to animal policies (i.e., animal numbers, stocking rates) and animal performance (i.e., LW gains, reproductive performance), other metrics were calculated from Farmax outputs (e.g., livestock GM was calculated as the sum of GM from each individual livestock enterprise).

Annual biological GHG emissions per effective hectare (herein GHG emissions, in kg CO_2 -e/eff ha; methane + nitrous oxide) were calculated from Farmax outputs using the Agricultural Inventory Method equations (Ministry for Primary Industries, 2019) and was the main response variable of interest in this research. Sources of methane (enteric fermentation and manure CH_4) and nitrous oxide emissions (direct and indirect sources of N_2O) were calculated based on published emission factors used by New Zealand's National Inventory calculations (does not include April 2020 changes to emission factors for hill country N_2O emissions). Global warming potentials of these GHG (25 and 298 for CH_4 and N_2O , respectively) were used to convert CH_4 and N_2O emissions to CO_2 equivalents (CO_2 -e). Carbon dioxide emissions were not considered in this modelling exercise.

In the assessment of farm characteristics driving GHG emissions, a large number of explanatory variables were considered. Although closely related, these variables can broadly be categorised as those more closely associated with a farm's natural and capital assets (e.g., farm cultivatable areas as a proportion of total area) and those that are more management-driven (e.g., N fertiliser applied, animal performance). A systematic assessment of the effect of these variables on GHG emissions was conducted graphically using the statistical packages Genstat (VSN International, 2015) and R (R Core Team, 2013). Analysis of >150 explanatory variables was undertaken in Phase 2 of this research (n = 125 farms), including post-weaning mortality for sheep and cattle, product per kg of LW wintered, LW gain for all stock classes per effective hectare, and ratio of LW on farm that was in breeding and trading livestock classes. As a result of the Phase 2 analysis, we narrowed the search to <20 explanatory farm variables, to allow for both one-to-one relationships (one y, one x) and multivariate analyses (one y, several x).

The investigation of the extended dataset for Phase 3 (n = 170 farms) began by testing that the data ranges developed in Phase 2 remained valid with the extended dataset.

3.1 Farm data sources

Beef + Lamb New Zealand (B+LNZ) provided anonymised production and financial data from farms in its Sheep and Beef Farm Survey (B+LNZ; https://beeflambnz.com/data-tools/sheep-beef-farm-survey) and these data were used to model 105 sheep and beef farms throughout New Zealand. A further 65 anonymised farm models were provided without B+LNZ farm class assigned nor financial benchmarking data. The 170-farm data set was used in the analysis of the physical relationships of the farm system, whereas the 105-farm subset of the data was used in the analysis of financial relationships. The 105 farms with reliable financial data were selected to ensure that they were

representative of the range of NZ farm types by B+LNZ farm class (B+LNZ; https://beeflambnz.com/data-tools/farm-classes).

3.2 Financial indicators

Stakeholders (farmers and B+LNZ) pointed out the need for farmers to see data within the context of their own business. Metrics commonly used by farmers were essential so they could identify where in the analysis their business would fit. Several financial indicators were used in the analysis for financial benchmarking of data for 105 farms. Some of additional indicators were calculated from the benchmarked data.

3.2.1 Gross margin

Gross margin (GM) is an animal enterprise analysis, and it is calculated as the revenue that the stock will generate, less the direct costs of production (animal health and sheep shearing), less an opportunity cost of the value of the stock.

For this report an aggregated gross margin has been calculated by adding the gross margin of each animal enterprise, and assuming all other things are equal, was used to create a modified gross revenue that represents the livestock revenue for the farm.

GM is commonly reported as GM per stock unit and is used to calculate the marginal increase in profit received by increasing stocking rate while assuming that all non-animal related costs are consistent and can therefore be treated as overheads. GM has been reported as GM per effective hectare and GM per stock unit (GM/SU)

3.2.2 **EBITRm**

Earnings before interest, tax, rent and managerial costs (EBITRm) is an indicator of farm profitability that is currently promoted by B+LNZ and the Red Meat Profit Partnership (RMPP, 2018) as the best option for comparing "profit" between farms. For our data set this was most simply calculated as the profit before tax (all revenue less all expenses except tax) with rent, interest and management salary added back into earnings. EBITRm was reported on a per effective hectare basis. EBITRm effectively compares farms as if each was run by an owner-operator (no paid manager), was freehold (no lease costs), and debt-free (no interest or principal repayments).

3.3 Farm data clustering

3.3.1 B+LNZ farm classes

B+LNZ has developed a set of industry standard farm business clusters based on island location and business type (B+LNZ; https://beeflambnz.com/data-tools/farm-classes). A total of 148 farms had been identified by their B+LNZ farm class and were clustered accordingly. A further 22 farms were not identified by their farm class and were not easily assignable due to the anonymity surrounding farm information.

3.3.2 Farm type clusters

New Zealand sheep and beef farms vary from extensive, high country breeding systems to irrigated intensive finishing systems. Comparing such diverse farms reduced the ability to identify physical and efficiency indicators that may influence GHG emissions from the farm system. Therefore, clustering of farms based on inputs and physical properties was necessary to aid in understanding the impact of farm natural and capital assets and efficiency indicators on GHG emissions.

A number of parameters were assessed for clustering farms and their ability to separate the farms into distinct groups was tested. We used a quantitative approach to cluster farms based on either physical constraints or management attributes. We used a regression tree analysis to rank the variables based on their separation and magnitude of contribution to GHG emissions (see Phase 1 report). Histograms were then used to enable quantitative assessment of the highest-ranking variables and identify appropriate biological ranges for each grouping. Several steps were undertaken. Further details on the selection of variables for clustering are provided in the Phase 2 report. Briefly, variables that represented physical constraints of the farm (e.g. slope), climate and weather, and livestock performance were evaluated to develop 'farm type' clusters. However, none of the 'farm type' clusters based on combinations of physical constraints provided the separation in GHG emissions across the clusters that we were trying to achieve. This led us to focus on clustering based on feed intake and stocking rate (described in Section 3.3.3). The clusters were utilised to separate farms into groupings with similar GHG emissions and to aid in the interpretation of the complex relationships between GHG emissions, farm biophysical variables, farm management practices, and, ultimately, financial performance.

3.3.3 Feed clusters

Farm feed clusters were developed to allow for a clear separation of GHG emissions. Criteria for clustering included livestock stocking rate (stock units (1 SU = 550 kg DM intake calculated to be the requirement for a 55kg ewe weaning 1 lamb) per effective ha; <5, 5-10, >10 SU) and feed intake (kg DM/ha; <4500, 4500-6800, >6800). By combining these two variables, five feed clusters were formed, ranging from low stocking rate / low feed intake (Feed Cluster 1) to high stocking rate / high feed intake (Feed Cluster 5; Table 1).

Table 1: Feed clusters based on stocking rate (SU/effective ha) and feed intake (kg DM/effective ha) (n=170 farms).

Cluster		1	2	3	4	5
Stocking rate	SU/eff ha	<5	5-10	5-10	>10	>10
Feed intake	kg DM/ha	<4500	<4500	4500-6800	4500-6800	>6800
Farms	Number	19	30	38	42	41

Of the potential nine combinations (3 stocking rate x 3 feed intake groups) considered in the clustering process, all farms were either in the L-L (Cluster 1), M-L (Cluster 2), M-M (Cluster 3), H-M (Cluster 4) or H-H (Cluster 5) (stocking rate-feed intake, respectively) (Figure 1).

		Feed intake (kg DM/eff ha)			
		Low (<4500)	Medium (4500- 6800)	High (>6800)	
Stocking Rate	Low (<5)	19			
(SU/eff ha)	Medium (5-10)	30	38		
	High (>10)		42	41	

Figure 1: Number of sheep and beef farms in each feed cluster, a combination of stocking rate and feed intake on a per effective hectare basis (n = 170 farms).

3.3.4 Gross margin per effective hectare clusters

Farms were also clustered based on financial indicators. Grouping by gross margin (GM) clusters was used to understand how the relationships between GHG emissions and explanatory variables investigated, impacted on GM. GM cluster boundaries at \$450 and \$700 per effective hectare were selected as they resulted in three approximately equal-sized GM clusters (Table 2).

Table 2: Gross margin per effective hectare clusters for all farms with reliable financial data (n=105).

Cluster	Low	Mid	High
GM/eff ha	<\$450	\$450-\$700	>\$700
No. of farms	37	37	31

Clustering within a narrow GHG band (3,000 to 5,000 kg CO₂-e/ha) was utilised in the financial analysis to enable additional interpretation of a smaller number of farms to identify economic efficiency trends. GM clusters were applied to feed cluster 3 and 4 (medium stocking rate and medium feed intake) using GM boundaries of \$500 and \$650 GM/eff ha.

Table 3: Gross margin per effective hectare clusters for the farms in feed clusters 3 and 4 with reliable financial data (n=53).

Cluster	Low	Mid	High
GM/eff ha	<\$500	\$500-\$650	>\$650
No. of farms	16	13	24

3.3.5 Gross margin per stock unit clusters

Farms were grouped into three clusters according to gross margin per stock unit (GM/SU). Low, medium and high GM/SU clusters were introduced with boundaries at \$54 and \$69 GM/SU (Table 4).

Table 4: Gross margin per stock unit clusters for all farms with reliable financial data (n=105) and for feed cluster (FC) 3 and 4 farms with reliable financial data (n=53).

Cluster	Low	Mid	High
GM/SU	<\$54	\$54-\$69	>\$69
No. of farms	33	39	33
FC 3&4 only	17	20	16

4. Results and Discussion

The objectives of this project were to a) develop a data set containing animal policies, productive and reproductive efficiencies, financial descriptors, and GHG emissions for a large number of sheep and beef farms located throughout New Zealand (n = 170 farms), and b) to examine the relationships between variables that describe farm management and farm physical constraints, and GHG emissions. No attempt was made to evaluate alternative mitigating scenarios within each farm or group of farms. Also, the short-termed nature of the dataset collected (one farm, one year) implies that caution is required when extrapolating these results to i) longer periods of time, ii) circumstances other than the ones captured in the current dataset (weather, market or otherwise), and iii) all of New Zealand sheep and beef farms (n = 23,400 farms; Beef + Lamb New Zealand Economic Service, 2019). Notwithstanding these limitations, our work provides a holistic assessment of the farm-scale drivers of GHG emissions and a comprehensive current state of affairs or baseline from which future trends in farm-scale GHG emissions can be established.

4.1 Absolute Greenhouse Gas Emissions from New Zealand sheep and beef farms

The mean and range of annual biological GHG emissions ($CH_4 + N_2O$) from the modelled farms were 3,662 and 157 to 7,096 kg CO_2 equivalents per effective hectare (kg CO_2 -e/ha), with 50% of the farms falling between 2,878 and 4,542 kg CO_2 -e/ha, demonstrating the diversity in production systems across the sheep and beef sector. These values are consistent with previously reported GHG emissions ($CH_4 + N_2O$) from the sector in New Zealand (Reisinger *et al.*, 2017; Dynes *et al.*, 2019; New Zealand Agricultural Greenhouse Gas Research Centre, 2019).

Methane emissions from enteric fermentation and faeces accounted for up to 80% of total GHG emissions and were strongly correlated with total emissions (Figure 2). Methane is generated through ruminant digestion, and emissions are largely a function of total feed intake (Hammond *et al.*, 2009; Niu *et al.*, 2018). Most nitrous oxide is emitted from soils and is affected by urinary nitrogen (N) excretion, other sources of N (fertiliser, biological fixation), vegetation type and cover, and soil type (Di and Cameron, 2006; de Klein *et al.*, 2019). Given the low amounts of N fertiliser used, the strong relationship between methane and total emissions is expected for these sheep and beef systems.

The strong relationship between feed intake and GHG emissions (Figure 3) is well established in New Zealand and elsewhere and is used at a national level for GHG reporting (Ministry for Primary Industries, 2019). Feed intake is a consequence of animal feed demand and feed on offer. Feed demand is driven by physiological process taking place in the grazing animal and is estimated in Farmax as the sum of energy required for maintenance, pregnancy, lactation, growth and activity (CSIRO, 2007). Feed on offer is largely the result of the amount of herbage offered to the grazing animal, because livestock on these farms are not heavily supplemented, nor is N fertiliser used to increase pasture production. In addition to an expected diversity in herd composition and management, some variation in feed intake at a given GHG emission level is observed, which may indicate GHG efficiency gains on some farms. For the same GHG emissions, lower feed intake tended to be linked to farms with a higher proportion of

nitrous oxide emissions, particularly from land areas in fodder crops. This was often offset by higher animal growth rates and better animal efficiency with a higher quality feed. Making farms more efficient would require a focus on increasing individual animal performance, in conjunction with a decrease in the number of animals to maintain feed intake at the same level or lower. At very high animal performance levels the relationship between feed intake and methane emitted is slightly changed. Achieving this would require appropriate animal genetics and capacity to supply the quality and quantity of feed required throughout the year. Higher quality feed will increase N content in the diet and increase nitrous oxide emissions and can limit the advantages of reduced methane to total emissions. Modelling studies suggest a decrease in farm system emissions by <5% and would also introduce issues around maintenance of feed quality at the whole-farm level which would limit this effect (Smeaton *et al.*, 2011; Reisinger *et al.*, 2017).

Stocking rate (SU/eff ha) was highly correlated with increasing GHG emissions per effective hectare (Figure 4). Stock units are calculated from the energy intake of the animal enterprise and is therefore strongly linked to feed intake and a similar relationship with GHG is expected. Different numbers of animals per ha can have the same stocking rate (in SU/ha) depending on feed intake.

GHG emissions increase as meat and wool production per effective hectare increases (Figure 5), however the relationship has more variation than those with methane, stocking rate or feed intake. The greater variation likely reflects the impacts of differences in both natural and capital assets and perhaps more significantly, differences in farm management decisions such as class of animals, marketing decisions and emergent properties of the farming system, e.g. feed quality. Most of these farms carried sheep (164 of 170 farms). Of note, the report does not include analysis of the cattle system component of these farms, but it does include a variable that captures the sheep:cattle ratio based on total DM intake (overall mean 63:36). There were 99 farms that had cattle and the analyses undertaken to date did not identify explanatory variables related to cattle that had a relationship with GHG emissions beyond those relationships selected for sheep (i.e., adding value to the GHG story). We recognise the value of deeper analysis of the role of cattle, particularly in those farms where cattle account for a significant proportion of DM intake (e.g., Becoña López *et al.*, 2013; Becoña *et al.*, 2014; Rearte and Pordomingo, 2014).

It is clear that sheep and beef farmers can reduce GHG emissions of their farm through a reduction in feed intake. Reducing feed eaten, which will require a reduction in stock numbers, is difficult in most sheep and beef systems as pasture is the major component of feed eaten at 90% for the average of these farms with the remainder predominantly crops (4,885 ±162 and 542 ±49 kg DM intake per hectare from pasture and other sources, respectively). The most effective way to reduce total farm feed intake will be through retirement of grazing land with restricted grassland potential, consistent with previous literature (Reisinger *et al.*, 2017; Dynes *et al.*, 2018). A reduction in area grazed (and in total DM consumed) through retirement of land growing pasture will reduce the total emissions of the farm.

Cropping on sheep and beef farms is used to match feed demand and supply by moving feed quantity and quality between seasons and to facilitate pasture renewal. A reduction in cropping may not have a significant impact on feed intake per ha. Reducing fertiliser

use on grazing lands has the potential to reduce feed grown and feed intake. However, nitrogen fertiliser use is low on sheep and beef farms (12.4 kg N/eff ha on average on these farms including crop applications) and is generally used tactically in response to feed shortages (Lambert et al., 2012) or to grow crops, leaving little ability to reduce pasture growth. The major form of fertiliser used on sheep and beef farms is superphosphate. Capital fertiliser application is required to maintain soil fertility and stimulate clover growth and nitrogen fixation; otherwise, nutrients will be mined from the soil with removal of grazed pasture as animal product (Lambert et al., 2004). A reduction in the application of superphosphate will, over time because of lag effects due to the long term availability of nutrients, reduce pasture grown and feed availability resulting in a reduction in stocking rate (Mackay and Lambert, 2011). However, this strategy will lower soil fertility on sheep and beef farms (Mackay and Costall, 2016) making sustainable farm management problematic due to changes to lower quality pasture species (Lambert et al., 1990), more contracted seasonal growth profiles and lower stock pressure reducing the ability to maintain pasture quality through grazing management (Lambert et al., 2014) and lower animal performance (Lambert et al., 1990). Phosphate fertiliser application was not specifically addressed in the farm system modelling however the impact of soil fertility on feed supply is incorporated in animal performance data recorded for each farm.

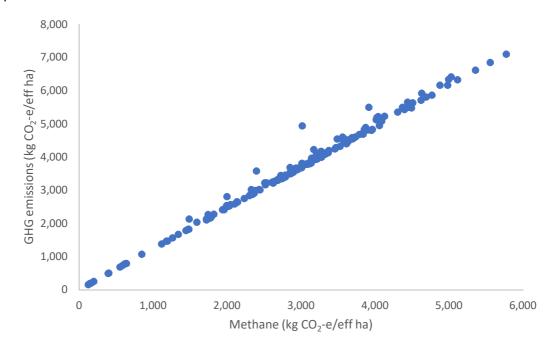


Figure 2 Greenhouse gas emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and methane (kg CO₂-e/effective hectare (eff ha)) for New Zealand sheep and beef farms (n=170 farms).

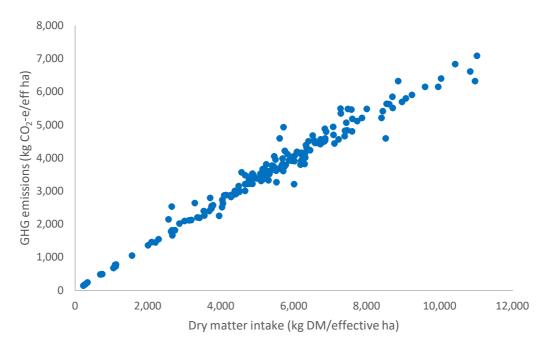


Figure 3: Greenhouse gas emissions (CH₄ and N_2O kg CO_2 -e/effective hectare (eff ha)) and feed intake (kg DM eaten/effective hectare (eff ha)) for New Zealand sheep and beef farms (n=170 farms).

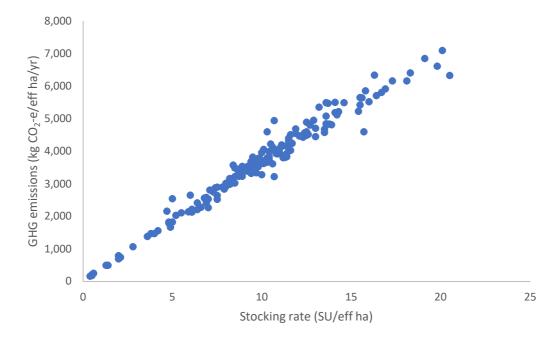


Figure 4: Greenhouse gas emissions (methane (CH₄) and nitrous oxide (N₂O) expressed as kilograms of carbon dioxide equivalents per effective hectare per year (kg CO₂-e/eff ha)) and stocking rate (stock units/effective hectare(SU/eff ha)) for New Zealand sheep and beef farms (n=170 farms).

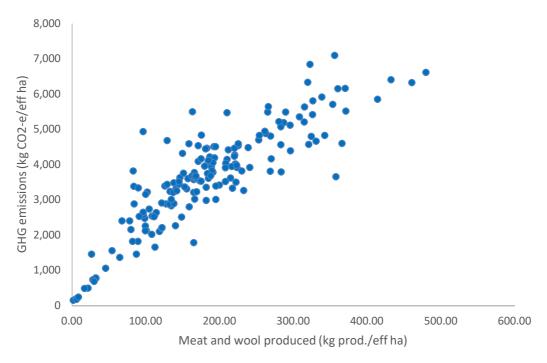


Figure 5: Greenhouse gas emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and animal product (meat and wool) per effective hectare (kg prod/eff ha) (n=170 farms).

4.2 Greenhouse Gas Emissions and farm area

GHG emissions per hectare are used to compare emissions between farms. The total farm area of the 170 modelled farms ranged from 82 ha to 13,443 ha. The proportion of the effective area, the area of the farm under grazing, ranged from 45% to 100% of the total farm area. It is common to use total area to report environmental emissions from the farm as this number is representative of the farm business. The effective (grazing) area is, however, the area from which biological GHG emissions are produced. Using total area added inconsistencies when comparing biological GHG between farms as two farms with identical animal systems would give different per total hectare results if significant non-grazing land is included.

Within the group of farms modelled, six farms had less than 60% of the total farm area under grazing. The description of these farms in terms of typical biophysical indicators such as stocking rate or feed intake as well as outputs such as GHG emission would differ markedly if they were considered on a total hectare (Figure 6) or effective hectare (Figure 7) basis. The relative position within the wider farm group changed more for these farms than for farms with a higher proportion of effective area. Using effective area is a more appropriate measurement to identify links between GHG emissions and area-specific biophysical indicators as well as non-area-specific efficiency indicators, e.g. feed conversion efficiency.

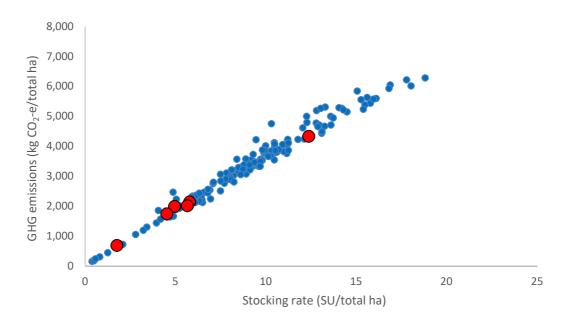


Figure 6: Impact of using total farm area on the relationship between greenhouse gas emissions (methane (CH_4) and nitrous oxide (N_2O) expressed as kilograms of carbon dioxide equivalents per total hectare per year (kg CO_2 -e/eff ha)) and stocking rate (stock units/total hectare(SU/eff ha)) for New Zealand sheep and beef farms (blue circles, n=170 farms). Showing farms with the lowest proportion of effective area (red dots, n=6 farms with between 45 and 60% effective area)

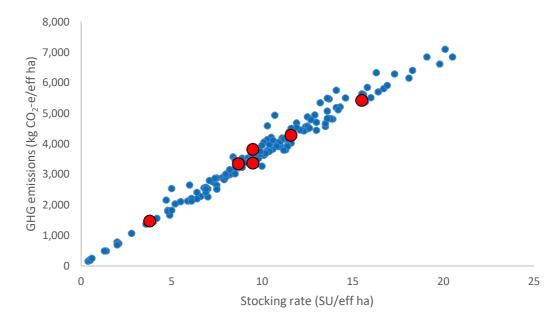


Figure 7: Impact of using effective farm area on the relationship between greenhouse gas emissions (methane (CH_4) and nitrous oxide (N_2O) expressed as kilograms of carbon dioxide equivalents per total hectare per year (kg CO_2e /eff ha)) and stocking rate (stock units/total hectare(SU/eff ha)) for New Zealand sheep and beef farms (blue circles, n=170 farms). Showing farms with the lowest proportion of effective area (red dots, n=6 farms with between 45 and 60% effective area)

4.3 Farm Clustering and Greenhouse Gas Emissions

To aid in understanding the impact of farm biophysical and efficiency indicators on GHG emissions several farm clusters were investigated, as described in Section 3.3.

4.3.1 B+LNZ sheep and beef farm classes

Significant overlap in absolute GHG emissions was observed between B+LNZ farm class ("Farm Class") clusters (Table 5 and Figure 8).

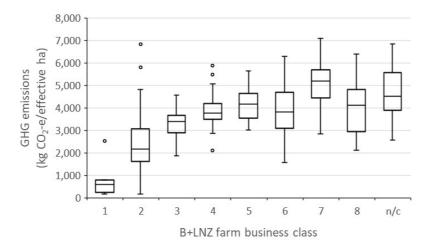


Figure 8. Greenhouse gas emissions (CH₄ and N₂O kg CO₂-e/effective hectare(eff ha)) and B+LNZ farm business class (1 South Island High country; 2 South Island Hill country; 3 North Island Hard hill country; 4 North Island Hill country; 5 North Island Intensive finishing; 6 South Island Finishing breeding; 7 South Island Intensive finishing; 8 South Island Mixed finishing) for New Zealand sheep and beef farms (n=170 farms).

Table 5: Average and range of absolute greenhouse gas emissions per effective ha (kg CO_2 -e/ha) and greenhouse gas emissions intensity (kg CO_2 -e/kg product) clustered by B+LNZ farm business class and the number of modelled farms in each farm class

Farm Class	GHG emissions per eff hectare mean (range)	GHG emissions intensity mean (range)	Number in cluster
1: SI High country	712 (157-2537)	31 (23-76)	10
2: SI Hill country	2588 (177-6845)	22 (11-55)	22
3: NI Hard Hill country	3292 (2157-4542)	28 (21-46)	19
4: NI Hill country	3886 (2103-5857)	21 (14-37)	30
5: NI Intensive finishing	4226 (3014-5646)	19 (14-29)	15
6: SI finishing/breeding	3751 (1559-6156)	20 (10-35)	33
7: SI Intensive finishing	5000 (2832-7096)	18 (13-25)	11
8: SI finishing/cropping	4037 (2126-6405)	24 (15-51)	8

Note: An additional 22 farms modelled did not have the B+LNZ farm class identified and are not included in Table 5.

The extent of the overlap in GHG emissions between B+LNZ farm business classes limited the potential to explore these classes as clusters with different emissions profiles.

As a result, other variables were assessed for use in forming clusters of farms with different GHG emissions profiles and to generate new insights.

4.3.2 Data clusters: Feed clusters

To reduce the overlap between clusters, feed clusters based on stocking rate and feed intake per effective hectare were developed (see section 3.3 for this process). Specific relationships of GHG emissions to biophysical and economic benchmarks were grouped by feed cluster to enable analysis of associations within and between clusters.

The boxplots (Figure 9) show (a) GHG emissions per total ha, (b) GHG emissions per effective ha, and (c) GHG emissions intensity (emissions per kg of meat and fibre) by feed cluster. When we look across feed clusters, from 1 to 5, both measures of emissions per ha increase linearly, whereas emissions intensity decreases linearly. The latter is most likely a reflection of the low carrying capacity of farms in feed cluster 1 $(27.9 \pm 3.4 \text{ kg CO}_2\text{-e per kg of meat}$ and fibre; mean \pm SE) versus upper-limit biological constraints in farms belonging to feed cluster 5 $(18.6 \pm 0.7 \text{ kg CO}_2\text{-e per kg of meat}$ and fibre), operating within the limits imposed by genetic gain and feed nutritive value. The position of the farms, belonging to these feed clusters, on a continuum from breeding to finishing systems can be implied by the ratio of total LW sold to total LW wintered (0.41, 0.58, 0.65, 0.73, 0.79 for feed clusters 1 to 5, respectively).

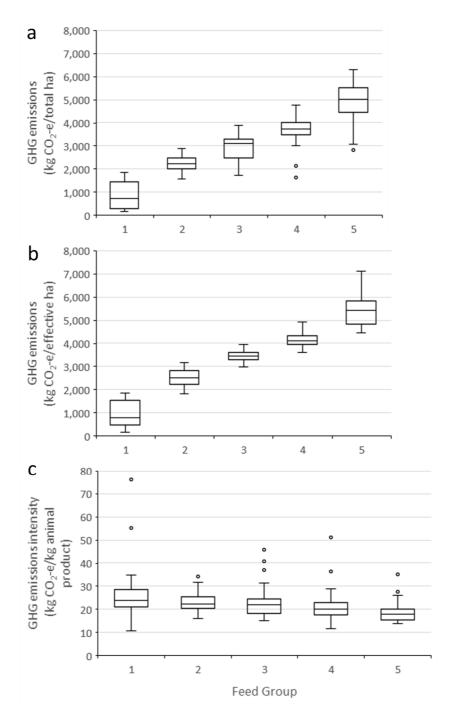


Figure 9. Greenhouse gas (GHG) emissions (CH₄ and N₂O; kg CO₂-e) a) per total hectare (ha), b) per effective ha, and c) GHG emissions intensity, and feed clusters (1 = <5 stock units (SU)/ha and <4.5 t feed intake (DM)/ha; 2 = 5-10 SU/ha and <4.5 t DM/ha; 3 = 5-10 SU/ha and 4.5-6.8 t DM/ha; 4 = >10 SU/ha and 4.5-6.8 t DM/ha; 5 = >10 SU/ha and >6.8 t DM/ha) for New Zealand sheep and beef farms (n=170)

A summary of key farm parameters for each of the feed clusters is shown in Table 6. As previously described, the clusters are based on both feed consumption and stocking rate per ha of effective area. Moving across the feed clusters from low to high intake and stocking rate, farm size, feed conversion efficiency and GHG emissions intensity tend to decrease (Table 6). GHG emissions, animal product per effective hectare, lamb weaning percentage and ewe efficiency all increase across the feed clusters. These relationships are explored further later in this report.

Table 6: Mean (± standard error) GHG emissions and selected farm variables by feed clusters based on stocking rate and total feed intake (see Table 1 for details on feed clusters) (n = 170 farms).

Farm biophysical or efficiency			Feed Clusters		
indicator	1	2	3	4	5
GHG emissions (kg CO ₂ -e/total ha)	897 (±136)	2242 (±46)	2938 (±87)	3671 (±82)	4916 (±131)
GHG emissions (kg CO ₂ -e/eff ha)	990 (±140)	2520 (±61)	3449 (±36)	4142 (±45)	5442 (±110)
GHG emissions intensity ¹	27.9 (±3.4)	23.2 (±0.9)	23.0 (±1.1)	21.1 (±1.0)	18.6 (±0.7)
Total farm area (ha)	5376 (±975)	952 (±139)	538 (±62)	453 (±64)	335 (±30)
Total animal product (kg/eff ha)²	48 (±10)	112 (±4)	159 (±6)	208 (±7)	305 (±11)
Stocking rate (SU/eff ha) ³	2.7 (±0.4)	6.8 (±0.2)	9.2 (±0.1)	11.1 (±0.1)	15.1 (±0.3)
Feed intake (kg DM/eff ha) ⁴	1454 (±207)	3709 (±94)	5021 (±48)	6086 (±57)	8225 (±191)
Cultivatable area (proportion of total)	0.36 (±0.09)	0.59 (±0.05)	0.57 (±0.05)	0.65 (±0.04)	0.80 (±0.03)
Lamb weaning percentage (%) ⁵	108 (±6)	124 (±4)	124 (±4)	135 (±4)	150 (±3)
Ewe efficiency (%) ^{5,6}	48 (±3)	55 (±2)	57 (±1)	60 (±2)	66 (±1)

¹kg CO₂-e/kg animal product (meat and fibre).

²Meat and fibre.

 $^{^{3}}$ 1 SU = 550 kg DM intake.

⁴Pasture + supplements (including feed on offer from fodder crops).

⁵Number of lambs weaned/number of ewes mated; n = 161 farms.

⁶[Total weight of lambs weaned (at weaning) ÷ total weight of ewes mated (at mating)] x 100

4.3.2.1 Efficiency

Since feed clusters represent different stocking rates and feed intake, and these directly drive methane emissions, average GHG emissions increase linearly from feed clusters 1 to 5. For many sheep and beef farmers, the natural and capital assets limit the capacity for these businesses to shift from one feed cluster to another. However, to what extent do land managers have opportunity to change or modify current systems or management to improve farm performance within their feed cluster, i.e. produce more product for the same emissions or maintain production while reducing emissions?

Ewe efficiency (kg of lamb weaned per kg of ewe mated) varies between 20 and 85% across the data set (Figure 10). As already described in section 4.3.2 and Figure 9b there is some separation between the feed clusters in GHG emissions, which reflects the relationship between feed intake and GHG emission, conversely the spread in ewe efficiency was similar across all the feed clusters. The extent to which the spread in data represents breed difference or differences in genetic merit was not explored in this report.

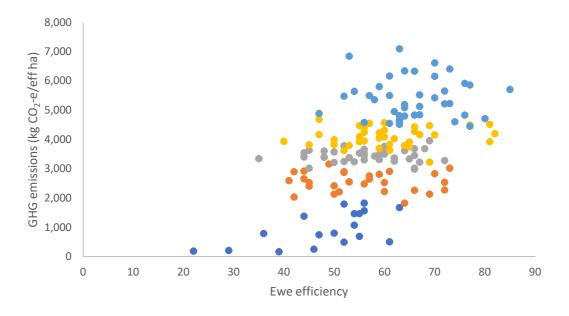


Figure 10 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and ewe efficiency ((%; total lamb weight weaned / total ewe weight mated) for New Zealand sheep and beef farms (n=170). Farm data points are coloured by feed cluster (\bullet = 1, \bullet = 2, \bullet = 3, \bullet = 4, \bullet = 5). See Table 1 for details on feed clusters.

Feed cluster 1 has the highest proportion of farms with ewe efficiency less than 50%, so further analysis of these data would be required to determine a link with mating weight and number of lambs weaned, where number of lambs weaned per ewe mated would likely negatively impact ewe efficiency. The farms in cluster 1 not only grow less feed, but they are farmed in a way to manage the particular risks inherent in the very large, extensive, hill and high-country properties and thus do not import feed supplements (in general). There are other logistic considerations with these properties. These are large properties, with few staff and are often relatively inaccessible, so options which are viable for other farm businesses are not practical and adoptable on these properties. Seasonal factors like summer/autumn drought further impact mating weight, while

management factors including selection of genetics will also impact on ewe efficiency. In addition, harsher climatic and topographical conditions would affect lamb survival having a flow-on effect to total lamb weight weaned. There is a lot of complexity left inside and between the clusters that need a much more detailed analysis to tease out underlying differences and causes. However, data were not available to undertake a more detailed analysis of such complexities.

Feed conversion efficiency was calculated as the kg of total feed intake per kg of animal product produced (meat and wool), a lower FCE value indicates greater return (in animal product) for every kg of total feed intake. Most farms had a feed conversion efficiency between 20 and 40 kg DM per kg of animal product (Figure 11) and there was a tendency for FCE to improve at higher feed clusters (feed clusters 4 and 5). However, the variation within most feed clusters was as large as the variation between clusters and indicates opportunities for farms with 'similar' natural and capital assets to benchmark efficiency indicators.

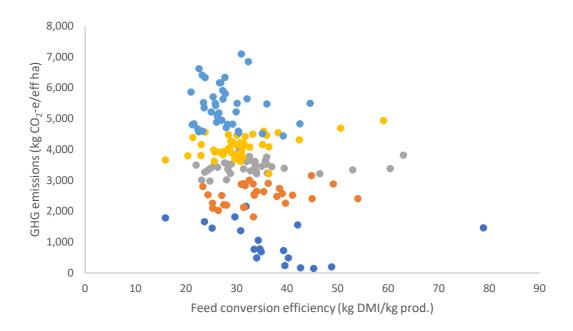


Figure 11 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and feed conversion efficiency (%; kg dry matter intake (DMI) per kg animal product) for New Zealand sheep and beef farms (n=170). Farm data points are coloured by feed cluster (\bullet = 1, \bullet = 2, \bullet = 3, \bullet = 4, \bullet = 5). See Table 1 for details on feed clusters.

Total animal product produced (kg of meat and wool per effective hectare) increases with increasing feed cluster. That is, as feed intake increases, so does animal product produced (Figure 12). However, again both within feed clusters and within a level of GHG emissions, there is substantial variation in the amount of animal product produced. For example, farms with emissions of approximately 4,000kg CO₂-e/eff ha have a range in animal product produced between ~100 and ~400kg meat and wool/eff ha. The differences between farms will in-part represent a different mix of enterprises within the farm systems, different management decision making and different natural and capital assets. However, as with other indicators of efficiency, farms in the same feed cluster have very different levels of production. This indicates that farms with 'similar' natural and capital assets could have practical and adoptable opportunities to increase animal

product produced. Further analysis is needed to determine the extent to which this would require a focus on increasing individual animal performance, in conjunction with a decrease in the number of animals to maintain feed intake at the same level. This type of analysis would be well suited to a co-development process with farmers, providing a strong 'shared' learning opportunity.

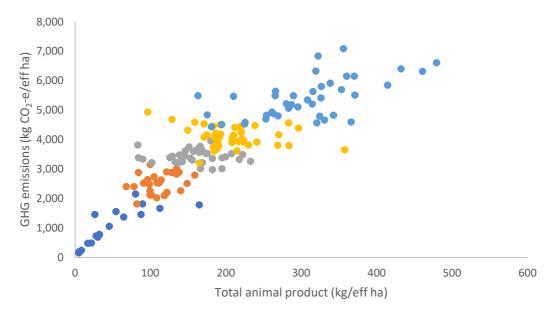


Figure 12 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and kilograms (kg) of total animal product (meat + wool) for New Zealand sheep and beef farms (n=170). Farm data points are coloured by feed cluster (\bullet = 1, \bullet = 2, \bullet = 3, \bullet = 4, \bullet = 5). See Table 1 for details on feed clusters.

4.4 Multivariate Analysis

4.4.1 Correlation matrix heatmap

In a pathway to tease out the impact of selected variables on GHG emissions (per effective ha), a correlation matrix heatmap was used to highlight the degree of association between variables on a one-to-one basis (Figure 13). Stocking rate (SU/effective ha) and total feed intake (kg DM/effective ha) were identified as the strongest drivers of GHG emissions per ha (darkest shade of red within the green box associated with Pearson correlation coefficients >0.75; Figure 13). This is expected, as the relationship between feed intake and methane emissions is well established (Ministry for Primary Industries, 2019). As stated above, methane accounted for 80% of total emissions (CH $_4$ + N $_2$ O). Because of the limited used of N fertiliser in these sheep and beef farms, which reflects the sector as a whole (Beef and Lamb New Zealand, 2019), feed intake (and its associated N content) is also the main driver of nitrous oxide emissions.

Feed intake continues to be the overarching factor driving GHG emissions (Waghorn *et al.*, 2002; Hammond *et al.*, 2013; Ministry for Primary Industries, 2019). To a slightly lesser extent, total animal product produced (meat and fibre/eff ha) and ewes carried at July 1st (open), are also drivers of emissions. In close association, viable and productive sheep and beef systems that balance utilisation of pasture and risks of seasonal variation and climatic extremes in pasture supply, have adapted their stocking rate to

adequately balance the need to maintain productive and nutritive pastures over time and to harvest the sward efficiently.

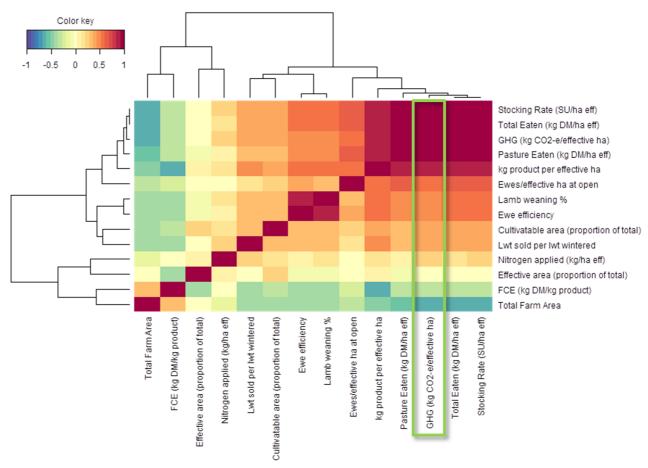


Figure 13 Heatmap to visualize hierarchical clustering of selected farm variables (13), as they relate to each other and to GHG emissions per ha (in the green box). The dendrograms along the sides show how the variables on rows and columns are independently clustered. The patterns on the heatmap show the degree of association (Pearson correlation) between variables; these range from -1 (dark blue; negative correlation) to 1 (dark red; positive correlation). Values closer to 0 indicate that there is no linear trend between the two variables (n = 170 farms).

Comparatively, lamb weaning percentage (131 \pm 2.0%), ewe efficiency (59 \pm 0.8%), proportion of cultivatable land (0.62 \pm 0.022), proportion of LW sold relative to LW wintered (0.66 \pm 0.022), and N fertiliser applied (8 \pm 1.3 kg N) appear to have a lower (but positive) correlation with GHG emissions (Pearson correlation coefficients 0.25 - 0.50; Figure 13). These efficiency indicators are the result of management decisions on the farm system and are less correlated with total feed intake.

Of the variables selected, feed conversion efficiency (FCE; kg DM intake required for one kg of meat + fibre production; 32.0 ± 0.66) and total farm area (1082 ± 162.4 ha) were the only variables that showed a negative correlation with GHG emissions. Feed conversion efficiency can be described by a number of metrics that combine measures of feed intake and desired animal production (Waghorn and Hegarty, 2011). Because of the metric chosen here, a lower number denotes less feed required per kg of animal product produced. A high FCE often dilutes the energy expenditure from the maintenance component relative to total energy expenditure (Grainger and Beauchemin, 2011). In other words, proportionally more energy is partitioned towards animal product in systems that have a lower FCE number leading to better product efficiency.

Total farm area is an interesting variable in the current dataset. It denotes the unique presence of extremely large farms with very low stocking rate (particularly in the South Island high and hill country) along with small farms with a high carrying capacity (Hutchinson et al., 2019). The extent to which this reflects a trend towards large corporate farms with negative economies of scale was not investigated.

4.4.2 Principal component analysis

A principal component analysis (PCA) followed (Figure 14). This data reduction technique allowed for a multivariate analysis using the same selected variables (one X, several Ys). Multivariate analysis often starts with data that involve a large number of correlated variables; the current dataset is no exception. Only a few of the selected variables could be considered 'independent' (i.e., having a low correlation; GHG emissions and proportion of total feed intake allotted to sheep, for example), but in farm systems analysis, even the most 'distant' variables are linked by either farm constraints. biological efficiencies, or farmer choices. To a certain extent, PCA analysis removes some of this lack of independence, and creates new dimensions (or principal components) that explain where the largest variability sits. In brief, PCA has been gaining popularity as a tool to highlight strong patterns within complex biological datasets, by capturing the essential relationships in a few principal components. These components convey the most variation in the dataset, reducing the overwhelming number of dimensions to those that explain most of the variation. A study, similar to the current work, of beef cow-calf grazing to systems in Uruguay used a correlation matrix and Principal Components Multivariate Analysis (n = 20 farms and ~26 explanatory variables) and found there is high potential to reduce cow-calf GHG emissions through improved grazing management (Becoña et al. 2014).

Given the variables chosen, two components (PC1 and PC2) captured most of the existing variance in the PCA. The loading biplot that resulted from this exercise covers two dimensions that explain most of the variation (i.e. PC1 explains 50% and PC2 explains 11% of the variation (Figure 14). The last step in this process was to add the feed clusters (and farms within) in the background behind the biplot. Feed clusters (Table 1 and Figure 1) have been added in the background and are represented by the coloured bubbles (orange to purple, matching feed cluster legend in Figure 14). Again, a number of key drivers of GHG emissions follow the same direction and extent as the big arrow in blue, denoting GHG emissions per effective ha (Figure 14). These key (and highly interrelated) variables include total feed intake and stocking rate (red dashed box; Figure 14). A single dimension or PC explains 50% of the variation (PC1). Within the 'purple' bubble (feed cluster 5), total DM eaten and stocking rate (highly interrelated) drive that dimension.

The group of variables that under expert evaluation were rated as 'intermediate correlation' (i.e. a much lower but positive correlation with GHG emissions) are also placed in the same right-hand side of Figure 14 (blue dashed box), but not in the same direction as the blue arrow. These variables include cultivatable area as a proportion of total area, N applied as fertiliser, LW sold per LW wintered, ewe efficiency and lamb weaning percentage. As mentioned above, these variables provide a measure of farm constraints, N inputs, a trading-to-breeding component, and reproductive efficiency (with underlying genetic and nutrition efficiencies). Changing some of these variables within a

given farm system might reduce GHG emissions (e.g., Cruickshank et al., 2009; Harrison et al., 2013), but when considered across a large number of sheep and beef farms, these variables do not reduce emissions on their own. It means that some variables have been considered important in terms of GHG abatement (e.g., shortening the half-life of the growing livestock) but for a snapshot (one year) across a large number of farms, this particular variable can become hidden or meaningless in terms of abatement. It wasn't until we did the 23-farm analysis over time that this particular variable became 'visible'. Previous work in this project in which GHG emission explanatory variables for the 1993/94 and 2015/16 seasons from 23 sheep and beef farms throughout New Zealand were compared (Rennie et al. 2019). The farm systems modelled were more efficient in the 2015/16 season than they were in 1993/94 with better utilisation of the feed grown (F pr. <0.001) and increased product per ha (F pr. 0.02). GHG emissions reduced by around 5%, in terms of both emissions per hectare and emissions intensity (emissions per kg of product), however this was not statistically significant. Using regression analysis, There are distinct slopes of LW gains (kg/head of stock, whole farm) for the 1993/94 and 2015/16 seasons when plotted against GHG emissions per ha (Figure 1). In addition to a steeper slope for LW gains > 25 kg/head, similar LW gains often resulted in greater GHG emissions in 1993/94 than in 2015/16, a reflection of the efficiency gains discussed in section 4.1. There were also different slopes for animal product (kg meat + fibre per ha) for the 1993/94 and 2015/16 seasons when plotted against GHG emissions per ha (Figure 2), similar animal product per ha often resulted in greater GHG emissions in 1993/94 than in 2015/16, a combined effect of feed conversion and reproductive efficiency gains (Rennie et al 2019). It was not possible to investigate these relationships in the current data set because the data was a snapshot of one year and no abatement strategies were applied to these farms. These data instead provide a comprehensive baseline from which trends could be identified if additional years were modelled for these farms.

Feed conversion efficiency and total farm area are clearly located in the opposing lefthand side within the black dashed box (Figure 14). The reasons these variables act as opposing forces have been discussed earlier (Section 4.4.1).

The shape and extent of the feed clusters in the background vary; a broader array of farms within feed cluster 1 is most likely a reflection of the broader range of values within each variable selected (Table 6). The feed cluster criteria were based on the main drivers of the vectors moving horizontally along PC1 (x axis), with variables such as stocking rate, feed consumption and animal produce explaining most of the variability in GHG emissions (Loadings in Figure15). Conversely, effective area (and to a lesser degree cultivatable area) as a proportion of total area and FCE explain most of the vertical variability along PC2 (y axis) (Figure 15). For these reasons, the shapes of the bubbles vary; feed clusters 2, 3 and 4 are narrower along PC1 but broad along PC2, which shows the variability of factors beyond those contemplated in PC1 within these feed clusters.

A number of variables have not been selected for the correlation matrix heatmap and PCA analysis. Response-type variables such as individual gases (methane and nitrous oxide) and emissions intensity (emissions per unit of animal product) were dropped from the final selection. Annual GHG emissions per effective hectare (methane + nitrous oxide) was the main response variable of interest for this report; variables beyond the one of main interest were considered out of scope for the current report.

Variables relating to the cattle enterprise were not in the final selection due to both a lower number of farms with significant numbers of breeding cattle (99 of 170 farms) and not contributing (as explanatory variables) to the GHG emissions story beyond the selected variables. On the former, there were too many missing data points relative to the total number of farms for a PCA analysis. On the latter, the alternative of providing a measure of combined reproductive efficiency for both ewes and cows was considered but subsequently dropped. Different sample sizes (i.e. number of farms with breeding ewes versus breeding cows) and the lack of a meaningful, unifying metric resulted in the decision against considering this variable further.

Difficulties in developing a meaningful breeding to finishing metric led to the inclusion of LW sold per LW wintered. Originally, ratios such as traded-to-breeding LW and net gained-to-breeding LW were also considered but dropped and replaced with the above mentioned LW sold per LW wintered. The addition of the two trading-to-breeding ratios did not add clarity to the picture, most likely a reflection of the short-term nature of the analysis. That is, the use of actual opening and closing animal numbers (rather than a theoretical steady state where the breeding livestock numbers are kept equal), and the broad diversity of animal categories considered, including the addition of dairy replacements in many farms. The short-term nature and the lack of a (theoretical) steady-state assumption also prevented us from including variables such as replacement rates (%) and mortality rates (%).

Although specific mitigation strategies are beyond the scope of this report, the multivariate analysis is consistent with earlier work showing that reducing feed intake is the main option for GHG abatement (Smeaton *et al.*, 2011; Reisinger *et al.*, 2017; Dynes *et al.*, 2018). However, the earlier analysis also highlights the variability in product per hectare suggesting the potential for increased efficiency to deliver to both animal product and gross margin. A focus on increasing animal product and profit for the same emissions will be required to give farmers the freedom to reduce feed intake.

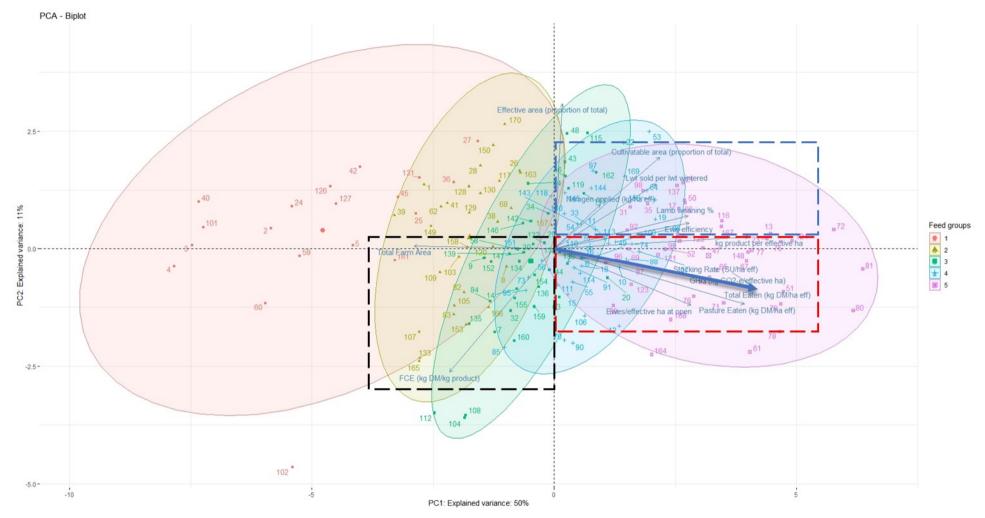


Figure 14 Principal component analysis biplot of selected farm variables (15) including GHG emissions per ha (larger blue arrow) (n = 170 farms).

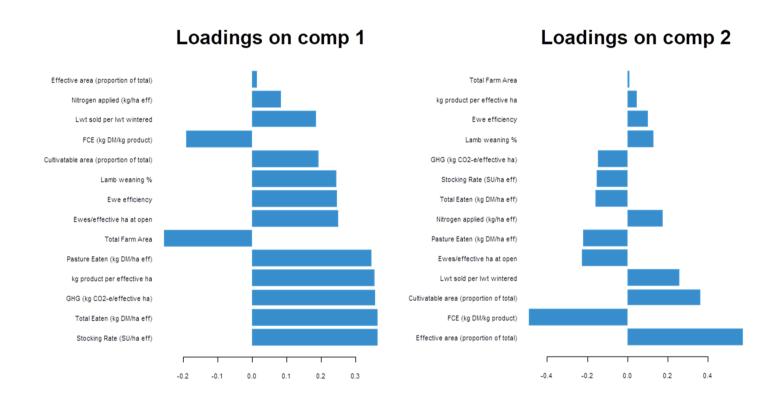


Figure 15 Loadings on Principal Component 1 (comp 1) and Principal Component 2 (comp 2) of selected farm variables (14) including GHG emissions per ha (n = 170 farms).

4.5 Economic efficiency and greenhouse gas emissions

Feed intake drives GHG emissions, so the key mitigation is reducing feed intake and likely livestock numbers. However, there are farms producing the same GHG emissions with very different gross margins per hectare and per stock unit. While these farms have few choices to reduce the output of GHG from their livestock systems, changing the gross margin enables choice with land use.

With the current dataset (170 farms modelled over a one-year period), biophysical mitigation was difficult to demonstrate unless the major drivers of GHG emissions such as feed intake were tackled. In much of the sheep and beef sector this would mean retiring land from grazing. Therefore, there is a need to look for economic efficiency indicators so that any planned changes to the enterprises within the farming system, for example the identification of land blocks for land use change or retirement from pastoral agriculture, considers the impact on revenue or profit of the farming business.

The relationship between profitability (EBITRm) and GHG emissions (Figure 15) showed wide variation within some GHG emission bands, which indicated there may be some opportunity to make efficiency gains. However, no direct relationship between biophysical parameters, efficiency metrics or expenses and GHG emissions could be identified. Simple relationships that allow direct business decisions to increase profitability while decreasing GHG emissions may not exist, although greater profitability at similar GHG emissions is already being achieved by some farm businesses in the dataset. A deeper analysis of farm expenses and potentially a new approach, which could include analysis of multiple years for each farm or 'averaging' expenditure like capital fertiliser to reduce the impact of a one-off large expenditure in a single year, may be required.

The calculation of profit necessarily looks at the expenses associated with the farm business. Some exclusions are made (such as interest, tax, rent and management costs in EBITRm) to ensure profit can be compared between farm businesses. Many of the expenses included in profit calculations, such as repairs and maintenance (R&M), vehicle costs, arise from business decisions rather than farm management decisions. These business expenses have minimal direct impact on the biological GHG emissions of the farm. Farm management decisions that impact animal performance have a more direct link to biological GHG emissions.

The aggregated (from each livestock enterprise) gross margin calculated for each farm is an indicator of the management decisions that influence the animal enterprises on farm and will therefore be more intrinsically linked to the biological GHG emissions of the farm.

GHG emissions per ha generally increase as GM per ha increased meaning that as farms increase revenue from their animal system the GHG emissions will also increase (Figure 16). This can be explained by considering that gross revenue from the animal system will usually increase on a per hectare basis as stocking rate increases (exceptions may include high value products such as low micron wool and velvet antler). Stocking rate, which has a strong relationship with feed intake, is highly correlated with GHG emissions per hectare, so this relationship with GM is expected.

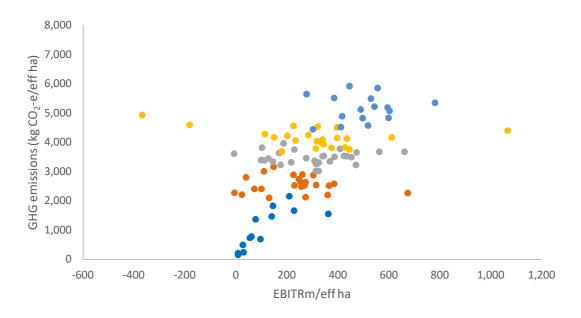


Figure 15 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and earnings before interest, tax, rent and managerial salaries (EBITRm) for New Zealand sheep and beef farms (n=105). Farm data points are coloured by feed cluster (\bullet = 1, \bullet = 2, \bullet = 3, \bullet = 4, \bullet = 5). See Table 1 for details on feed clusters.

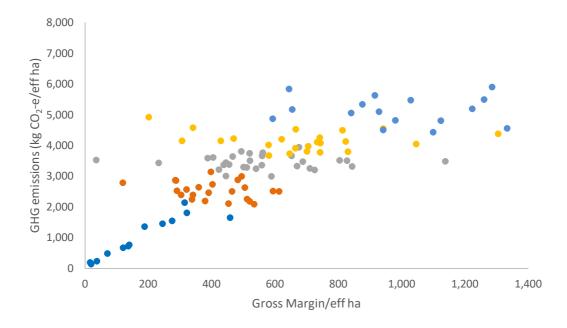


Figure 16 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and gross margin per effective ha for New Zealand sheep and beef farms (n=105). Farm data points are coloured by feed cluster (\bullet = 1, \bullet = 2, \bullet = 3, \bullet = 4, \bullet = 5). See Table 1 for details on feed clusters.

As discussed elsewhere, feed cluster 1 is predominantly made up of farms where temperature and rainfall provide biophysical constraints to productive potential and limit the ability of farm management decisions to impact gross revenue on a per ha basis; also noting, the total area of feed cluster 1 farms is on average five times larger than other feed clusters. In contrast, feed clusters 3 and 4 show a wide range in GM/ha for a relatively narrow band of GHG emissions.

At a high level it would seem that the relationship between GHG/ha and GM/ha, would mean that a farm business that reduces its GHG footprint, all other things being equal, it could expect to see a reduction in GM. However, the variation in the data indicates a need to better understand underlying drivers of these relationships. GM clusters were established to investigate if any biophysical parameters that are associated with decreased GHG emissions would have a negligible impact on GM and explain some of the variation seen in the GHG to GM relationship.

Biophysical indicators of the farm system with a high correlation to GHG emissions per ha (feed intake, Stocking rate, product) tended to correlate with gross margin similarly. Gross margin clusters were used to investigate these GM to biophysical indicator interactions (Figure 17 to Figure 20). Some overlap existed when GM and product varied for a given range of GHG emissions.

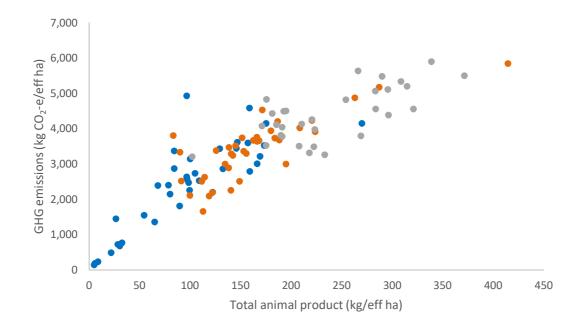


Figure 17 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha) and kilograms (kg) of total animal product (meat + wool) produced per effective ha for New Zealand sheep and beef farms (n=105). Farm data points are coloured by gross margin clusters (• = Low, • = Mid, • = High). See Table 2 for details of gross margin clusters.

Other indicators are often calculated to estimate the efficiency of the farm system. Feed conversion efficiency, lamb weaning percentage and ewe efficiency (Figure 18 to Figure 20) showed a tendency to have high GHG emissions in the higher GM clusters but with wider variation in the efficiency metric. Thus, while GM clusters applied to the full data set did not explain the variation with these efficiency metrics it was observed that for some farm groupings, particularly around 4,000 kg CO2-e/eff ha, there are large variations in GM, product produced per effective ha, ewe efficiency, lamb weaning percentage and ewe efficiency for very little change in GHG emissions.

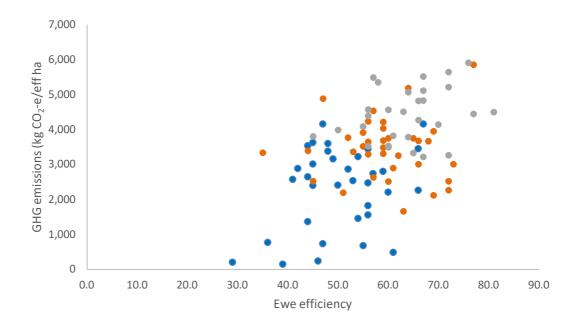


Figure 18 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and ewe efficiency (%; total lamb weight weaned / total ewe weight mated) for New Zealand sheep and beef farms (n=105) by gross margin clusters (\bullet = Low, \bullet = Mid, \bullet = High). See Table 2 for details of gross margin clusters.

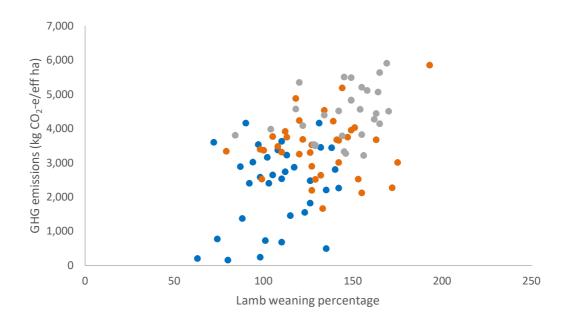


Figure 19 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and lamb weaning percentage (number of lambs weaned/number of ewes mated) for New Zealand sheep and beef farms (n=105). Farm data points are coloured by gross margin clusters (\bullet = Low, \bullet = Mid, \bullet = High). See Table 2 for details of gross margin clusters.

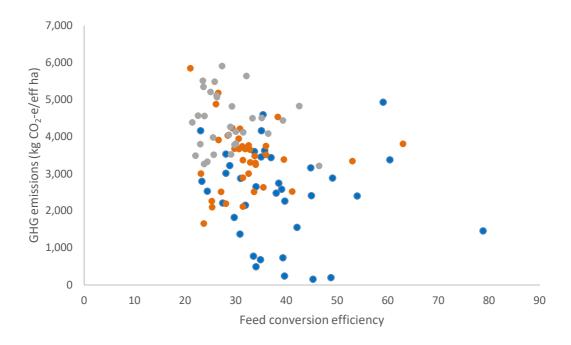


Figure 20 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and feed conversion efficiency (%; kg dry matter intake (DMI) per kg animal product) for New Zealand sheep and beef farms (n=105). Farm data points are coloured by gross margin clusters (\bullet = Low, \bullet = Mid, \bullet = High). See Table 2 for details of gross margin clusters.

A further analysis was undertaken to explore any underlying differences that impact on the clustering of both feed clusters and GM clusters. To reduce the variation in farm types the above analysis was confined to feed clusters 3 and 4. With a stocking rate greater than 5 SU/ha (feed cluster 3: 5-10 SU/ha; feed cluster 4: >10 SU/ha) and feed intake between 4500 and 6800 kg DM/eff ha, these farms were predominantly from B+LNZ farm classes 3, 4, 5 and 6, i.e. hill country farms. GHG emissions per ha were restricted to between 3000 and 5000 kg CO2-e/eff ha. Within this band there was no obvious relationship between GM or GM clusters and GHG emissions (Figure 21). A large variation in GM for the same GHG emissions suggested that some farms are able to gain more livestock revenue from similar GHG emissions.

Farm physical indicators (for example stocking rate, total feed intake, sheep:cattle ratio) showed no indication of any GM advantage for the given range of GHG emissions. An indication that farms in the high GM cluster produced more total animal product per ha (Figure 22) would confirm that increasing production leads to higher animal revenue. However, a slight increasing trend in GHG emissions per kg of product may be present; further, the analysis did not assess any business risk associated with intensification. Farm efficiency indicators gave some indication that farms could increase their GM as ewe efficiency increased (Figure 23), FCE (Figure 24) and lamb weaning percentage (Figure 25) showing some limited separation of the three GM clusters.

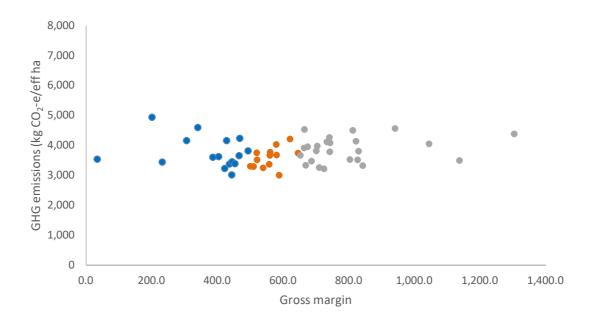


Figure 21 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and gross margin for New Zealand sheep and beef farms in feed cluster 3 and 4 (n=53) by gross margin clusters (\bullet = Low, \bullet = Mid, \bullet = High). See Table 3 for details of gross margin clusters.

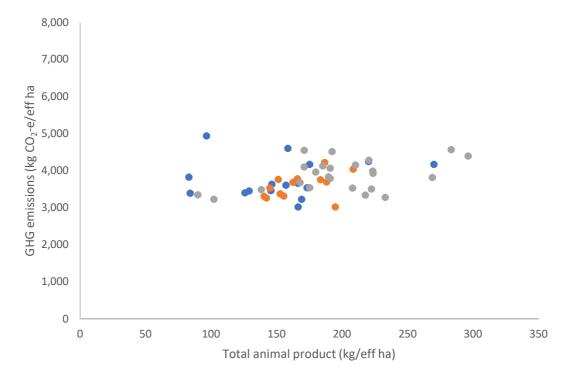


Figure 22 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and kilograms (kg) of total animal product (meat + wool) per effective hectare for New Zealand sheep and beef farms in feed cluster 3 and 4 (n=53) by gross margin clusters (\bullet = Low, \bullet = Mid, \bullet = High). See Table 3 for details of gross margin clusters.

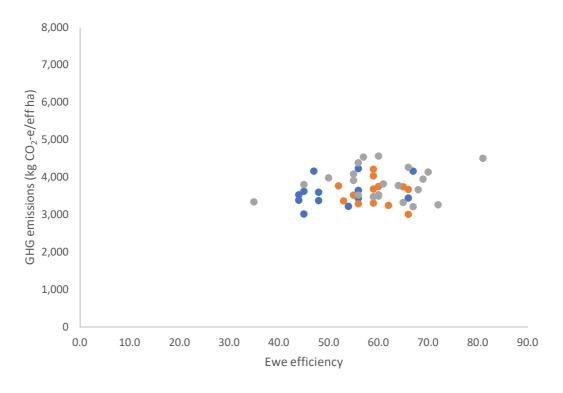


Figure 23 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and ewe efficiency (%; total lamb weight weaned / total ewe weight mated) for New Zealand sheep and beef farms in feed cluster 3 and 4 (n=53) by gross margin clusters (\bullet = Low, \bullet = Mid, \bullet = High). See Table 3 for details of gross margin clusters.

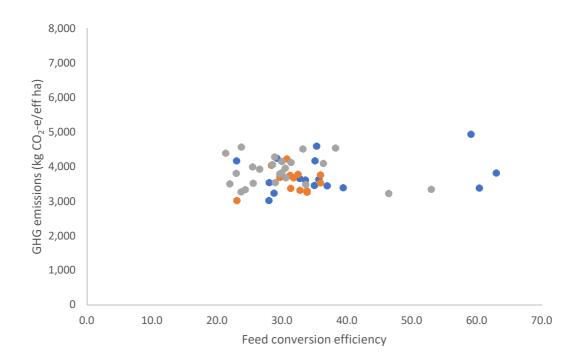


Figure 24 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and feed conversion efficiency (%; kg dry matter intake (DMI) per kg animal product) for New Zealand sheep and beef farms in feed cluster 3 and 4 (n=53) by gross margin clusters (\bullet = Low, \bullet = Mid, \bullet = High). See Table 3 for details of gross margin clusters.

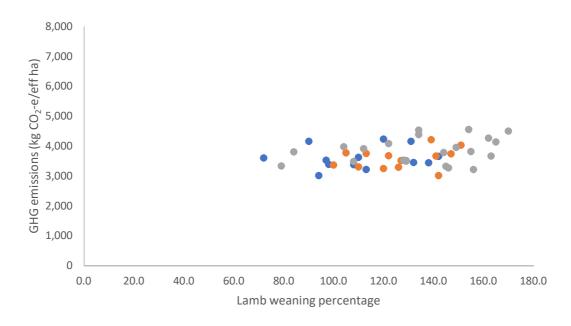


Figure 25 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and lamb weaning percentage (number of lambs weaned/number of ewes mated) for New Zealand sheep and beef farms in feed cluster 3 and 4 (n=53) by gross margin clusters (\bullet = Low, \bullet = Mid, \bullet = High). See Table 3 for details of gross margin clusters.

There is some difficulty and risk in the development of 'findings' or 'farmer actions' from minor trends in efficiency indicators. The interaction of farm management decisions, physical constraints and seasonal conditions contribute to variation within each cluster that does not give a clear relationship with GHG emissions. If specific physical constraints are suggested there may be more chance that farmers will disregard these as "my farm doesn't work like that" or "this *is* good for my farm". However, within this feed cluster, again there is significant variability between farm businesses with similar total feed intake; is this an opportunity for benchmarking?

A focus on higher level economic drivers will allow farm managers to focus on the best ways to achieve the advantage within their own constraints.

A continued focus on the aggregated gross margin as the base economic unit relatable to GHG emissions was required. Combining GM and non-animal expenses yielded no specific interaction. The magnitude of these expenses are predominantly business decisions and have minimal impact on animal production and consequently GHG emissions. Accordingly, GM clusters superimposed over the profit to GHG relationship did not yield any further interactions.

GM is commonly used to investigate per animal financial implications. Gross margin per stock unit (GM/SU) showed large variation within feed clusters (Figure 26) but no relationship to GHG emissions per ha.

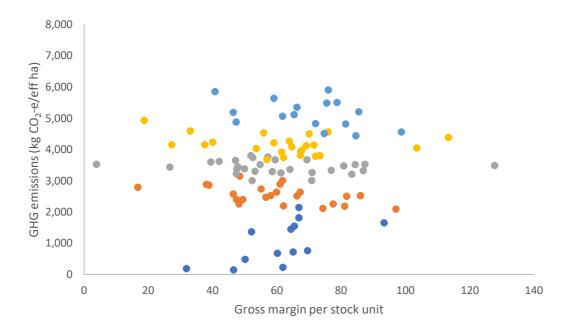


Figure 26 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and gross margin per stock unit (1 SU = 550 kg DM intake) for New Zealand sheep and beef farms (n=105) by feed cluster (\bullet = 1, \bullet = 2, \bullet = 3, \bullet = 4, \bullet = 5). See Table 1 for details on feed clusters.

Overlaying GM/SU clusters into the GHG to GM relationship (Figure 27) shows that farms with a higher GM/SU will have a higher GM/ha than others at the same GHG emissions. The relationship is highlighted when the farms are limited by feed cluster. Feed cluster 3 (Figure 28) shows clearly that increasing GM/SU will increase GM/ha without a substantial increase in GHG emissions. This relationship did not seem to be confounded by the feed cluster components, i.e. stocking rate or feed intake, both of which had a direct positive impact on GHG emissions.

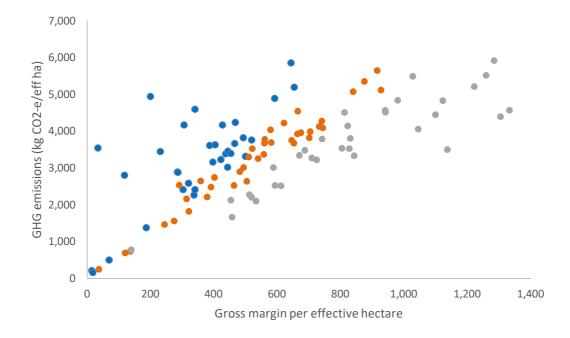


Figure 27 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and gross margin per effective hectare for New Zealand sheep and beef farms (n=105) clustered by gross margin per stock unit (1 SU = 550 kg DM intake; clusters: • = Low, • = Mid, • = High). See Table 4 for details of these clusters.

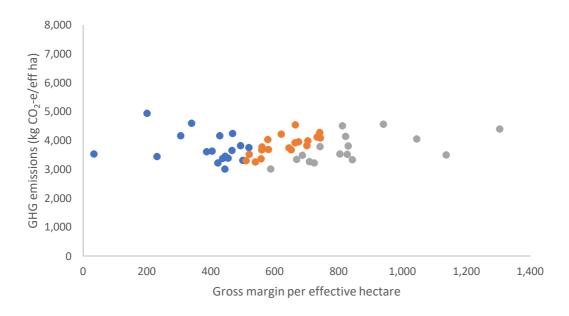


Figure 28 Greenhouse gas (GHG) emissions (CH₄ and N₂O kg CO₂-e/effective hectare (eff ha)) and gross margin per effective hectare for New Zealand sheep and beef farms in feed cluster 3 and 4 (n=53) by gross margin per stock unit (1 SU = 550 kg DM intake; Group clusters: \bullet = Low, \bullet = Mid, \bullet = High). See Table 4 for details of these clusters.

5. Conclusions

The most effective way to reduce absolute GHG emissions from sheep and beef farms is to reduce feed intake by reducing the area grazed and absolute stock numbers. This may offer the potential for new non-livestock-based income streams. The extent to which annual or perennial cropping, forestry or native vegetation are practical and adoptable options will be dependent on biophysical, market, regulatory and management drivers. While some farms are very efficient, many farm businesses have potential to increase gross margin per stock unit and give their business options to maintain financial viability and have real choices in how they configure their landscape.

The 170 farms in the data set were from across all B+LNZ farm classes and were selected to be representative of the NZ red meat sector. Analysis of 'real' farm businesses in this study has provided insight into complexity within and variability across sheep and beef farm systems.

Biological GHG emissions (methane and nitrous oxide) were highly correlated with feed intake. Methane emissions are directly related to total feed intake, while nitrous oxide emissions are driven by N intake, which is strongly correlated with feed eaten. The sector has very low use of N fertiliser. There are few, if any, opportunities for sheep and beef farmers to reduce nitrous oxide emissions through changes to fertiliser use. However, individual farms with significant amounts of cropping and N fertiliser use did have options for reducing nitrous oxide emissions. Opportunity exists for a re-analysis of the sheep and beef farm emissions once the changes to emissions factors for both sheep and cattle nitrous oxide emissions on hill country slopes have been implemented within an appropriate emissions calculator, e.g. Overseer.

Total feed production and feed intake on sheep and beef farms drives stocking rate and animal product per effective hectare, and these were highly correlated with GHG emissions per effective hectare. In contrast to many dairy systems, reducing feed offered to animal with no tactical use of N fertiliser, the reduction of pasture growth by changes in fertiliser application is complex and will impact production, profitability and the ability to manage a GHG efficient system. This again highlights the complexity and trade-offs faced by farmers in considering a future low carbon economy.

Farm management decisions impact on-farm efficiency metrics and increasing performance in these is associated with improved revenue. The variability both within and between biophysical and financial clusters suggests real opportunity for efficiency gains to drive increased gross margins for some farms. Some farms are already highly efficient and have little ability to increase, although others seem to have some ability to increase product and profit for their GHG emissions. This analysis focuses on individual farm business and does not consider the social consequences of the type of changes required to reduce agricultural GHG emissions, nor the competing priorities that drive farmer decision making. It is important to reflect that while there is evidence that some farms could become more efficient in either product or profit for the GHG emitted, there is little variation in the feed intake/GHG relationship and feed eaten must reduce to make significant reductions in GHG emissions within the constraints of the current farm systems that were modelled.

A focus on GM/SU of the animal system will allow farmers to optimise their farm efficiency to achieve a higher income from their animal system, with a possibility of maintaining GHG emissions. A benchmarking process, scenario testing and monitoring of GHG emissions, production, revenue and profitability would all be required for farmers to meet their GHG emissions and economic targets. The bottom line is farmer decisions around how the feed consumed on-farm is utilised in terms of choice of enterprises, their configuration into the farm system, and the way they are managed is highly variable and known to have a major influence on financial performance.

This dataset has highlighted that for the same GHG emissions there is significant variation in the many indicators of farm management decisions. In the future, the industry will require farm decision makers to understand the impact of their choices and goals on productivity, profitability *and* emissions through the use of measurement, monitoring and benchmarking. GHG emissions will be a consequence of the feed intake of the system, seasonally determined by the farm's natural and capital assets. A focus on improving animal system gross margins will allow the greatest income for those GHG emissions and give the most flexibility to reduce the feed intake if GHG emission reduction targets are a priority.

6. Acknowledgements

This research was funded by the New Zealand Agricultural Greenhouse Gas Research Centre and the Pastoral Greenhouse Gas Research Consortium (project number 17-IFS8.1-V1). We are proud of the efforts of the large team of researchers from AgResearch whose expertise developed the 170 farm models with strong support from the professionals at Farmax. We gratefully acknowledge the support from Beef + Lamb New Zealand for supplying data and expertise. Esther Meenken provided analysis and critical input into the design and approach to analysis of the data. Paul Maclean completed the multivariate analysis and Peter Green completed the initial multivariate analysis and the 'heat map' analysis. Dr Greg Lambert provided critical review of the analysis and report. Mark Aspin, Victoria Lamb, Brian Spiers and Rob Davison provided critical thinking in the design and analysis of the data.

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