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Reducing uncertainty of the enteric methane emissions inventory

Draft final report prepared for MAF

18 June 2009

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18 June 2009

Francis M. Kelliher, Harry Clark, Murray H. Smith, Keith R. Lassey, Richard Sedcole

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1. Executive Summary

Objectives

- Quantify the variability of methane (CH_4) yield, CH_4 emissions per unit of feed dry matter intake, of different animal types and the proportions attributable to CH_4 emissions measurement methods and the level of feed intake,
- Using the determined variability of CH_4 yield, and other parameters, re-assess uncertainty of the national enteric CH_4 emissions inventory,
- Compare the NZ inventory uncertainty analysis with those of Australia, Ireland and the USA and assess their uncertainty management processes to make recommendations for a New Zealand inventory process.

Recommendations

- For sheep divided by age into two classes, < 1 y old and > 1 y old and cattle, the mean CH_4 yields were statistically indistinguishable. Further, the mean CH_4 yields of sheep and cattle were statistically indistinguishable.
- Further research is needed to clarify the issue of emissions from young and old sheep. IPCC good practice guidelines, emanating from NZ studies, recommend using a lower methane yield value for young sheep but the analysis reported here suggests no clear link between age and CH_4 yield in sheep. This needs clarifying as a matter of urgency since it has implications for the national inventory and for IPCC best practice guidelines.
- To assess the uncertainty in the enteric CH_4 emissions inventory for sheep, the CV for CH_4 yield should be 3%. To potentially reduce this to 2%, it was estimated that nearly 400 additional measurements would be required in 5 experiments.
- Uncertainty of the enteric CH_4 emissions inventory should be expressed as a 95% confidence interval, ± 16%, and the basis of calculation explained clearly in the national inventory report. This uncertainty was broadly comparable to

that of the USA, while those of Australia (± 6%) and Ireland (± 2%) were inexplicably smaller.

- Further research is warranted to verify if CH_4 yield is inversely proportional to the level of feed intake. If so, this would warrant a changed inventory calculation method for determination of the CH_4 yield; it would be a function of the level of feed intake with respect to the maintenance requirement for animal types according to age and possibly physiological status.

2. Introduction

The current estimate of uncertainty in the national enteric methane (CH_4) emission inventory, expressed as a 95% confidence interval is ± 53%. This uncertainty is far greater than that determined by some other countries. For example, Ireland, the country nearest to New Zealand in the proportion of emissions arising from agriculture reported an uncertainty of only ± 2%, though the basis was unspecified. An important influence on uncertainty of the national enteric CH_4 emission inventory is uncertainty in the quantity of CH_4 produced per unit of feed consumed, called the CH_4 yield. Uncertainty of the CH_4 yield has been based on examination of CH_4 yield measurements and estimates undertaken in New Zealand between 1996 and 2002 (Clark et al. 2003), The calculated uncertainty, expressed as a coefficient of variation was ± 26%; this value was obtained in a very simple manner using a standard deviation derived by averaging the CH_4 yield values obtained from each of 50 experiments that covered a range of diets and management regimes for the animals (Kelliher et al. 2007). Since the Clark et al. (2003) study the number of CH_4 emissions and feed intake measurements undertaken in New Zealand has increased dramatically. Most significantly, anticipating the results, new calorimeter chamber facilities for more direct and precise measurement of CH_4 emissions have been constructed. The much larger pool of data available and the continuous need to improve the national enteric CH_4 emissions inventory and estimation of its uncertainty has prompted this review.

The objectives of this review were

- Quantify the variability of CH_4 yield, CH_4 emissions per unit of feed dry matter intake, of different animal types and the proportions attributable to the CH_4 emissions measurement method and the level of feed intake,

- Using the determined variability of CH_4 yield, and other parameters, re-assess uncertainty of the enteric CH_4 emissions inventory,
- Compare the NZ inventory uncertainty analysis with those of Australia, Ireland and the USA and assess their uncertainty management processes to make recommendations for a New Zealand inventory process.

3. Comparison of SF_6 and calorimeter methods to measure methane yield variation amongst animals

An objective was to quantify variation in the CH_4 yield (g CH_4 kg^{-1} DMI) amongst animals (that is, from one animal to another) when the CH_4 emissions were measured by two methods, sulphur hexafluoride (SF_6) tracer and calorimetry. Data were compiled for analysis from a number of experiments conducted over the past 13 years. There was a data record for each animal measured 5-day and 2-day arithmetic means for the SF_6 and calorimeter methods, respectively. In most experiments, the animals were repeatedly measured. Consequently, there were more records than animals. The SF_6 data included 3464 records from ? animals over the period 10 March 1996 – 3 April 2008. The calorimeter data included 529 records from ? animals over the period 20 August 2007 – 16 April 2009.

The data came from experiments including different animal types (for example, sheep or cattle or different aged animals) conducted for a number of purposes. The calorimeter experiments had a greater variety of purposes than the SF_6 experiments; many of the SF_6 experiments were conducted to obtain baseline data for the inventory whereas the more recent calorimetry experiments have involved dietary manipulations designed to test if different CH_4 yields were obtained. To fulfil the methods comparison objective, meta-analysis was required to quantify the variation in CH_4 yield amongst animals. It was realised that this variation could itself vary from one experiment to another. Thus, and separately, the analysis needed to account for 'consistency' of the variation in CH_4 yield amongst animals. To allow full description of the complex statistical methods and the results, the meta-analyses have been placed in an Appendix. However, as required to make this synopsis understandable, some brief descriptions and results will be reported here as well.

The data included experiments with a number of different feeds, but for application of results to the enteric CH_4 emissions inventory, the indoors data was confined to animals fed a diet typical of that consumed by the average New Zealand ruminant, i.e. cut and carried grass dominated pasture. For the indoors data, feed dry matter intake (DMI) had been accurately measured from daily weighing of feed offered and feed refused. For the indoors and outdoors data, we excluded records with extreme CH_4 yields < 10 g CH_4 kg^{-1} DMI or > 40 g CH_4 kg^{-1} DMI since these are outside the generally acknowledged physiological limits for enteric CH_4 emissions; values outside these limits are also in excess of three times the standard deviation which is a commonly used criterion for excluding experimental data.. Analyses were done for 3 animal classes; namely, sheep < 1 y old, sheep > 1 y old and cattle. Once quantified by analyses of the indoors data, the CH_4 yield variation amongst animals was compared to that determined for the outdoors data which was from grazing animal measurements by the SF_6 method. In these latter data DMI was estimated by a range of methods (e.g. faecal collection and back-energy calculations) rather than by direct measurement.

Sheep less than 1 year old

For sheep < 1 y old that were fed cut and carried grass indoors, there were 102 SF_6 method records including 32, 45 and 25 from the years 2004, 2005 and 2006, respectively. There were 6 experiments and 33 sheep measured, so 69 records were repeated measurements of the same animal. For the calorimeter method, there were 49 records including 35 and 14 from 2008 and 2009, respectively. There were 3 experiments and 34 sheep measured, so 15 records were repeated measurements of the same animal.

For the two methods, mean CH_4 yields were virtually indistinguishable, 23.9 and 24.0 g CH_4 kg^{-1} DMI for SF_6 and calorimeter, respectively. On this basis, the two methods were equally accurate. Within the experiments, measurements by the SF_6 method were more than twice as variable as the calorimeter method. This was quantified by within experiment standard deviations of log yield that were 0.210 and 0.099 (see Table 3 in the Appendix), indicating the variation amongst the animals (that is, from one animal to another). The comparison was based on different groups of animals for each method, but the groups were considered comparable based on them having virtually the same means. Thus, the higher standard deviation of the SF_6 method was deduced to have included the variation amongst the animals and additional variation attributed to the SF_6

method itself. In this way, the lower standard deviation of the calorimeter method was concluded to have been representative of the 'true' variation amongst the animals.

For sheep < 1 y old and grazing grass outdoors, there were 90 SF_6 method records including 51 and 39 from 1996 and 1997, respectively. There were 7 experiments and 67 sheep measured, so 23 records were repeated measurements of the same animal. Within the experiments, the standard deviation was 0.185, comparable to the value obtained indoors. For sheep < 1 y old and grazing grass outdoors, the typical New Zealand management regime, the percent standard error (%se) (CV, standard deviation as a percentage of the mean; the standard error was the standard deviation divided by the square root of the number of records) was 5.2%. For the enteric CH_4 emissions inventory, the %se is the statistic indicating the variation amongst animals. As stated, the calorimeter method was concluded to have been representative of the 'true' variation amongst the animals. However, the calorimeter method cannot be used outdoors for grazing animals. Therefore, based on the methods comparison indoors, the SF_6 method %se was reduced from 5.2% to 2.5% ([0.099/0.210]*5.2%). On this basis, we have suggested this %se should be associated with the CH_4 yield of sheep < 1 y old in the enteric CH_4 emissions inventory.

For sheep < 1 y old that were fed cut and carried grass indoors, the mean CH_4 yield was 45% larger than the corresponding mean for sheep < 1 y old and grazing grass outdoors (see Table 1 in the Appendix). The outdoors value, 16.5 g CH_4 kg^{-1} DMI, is currently used in the enteric CH_4 emissions inventory for sheep < 1 y old. While the difference between mean values from indoors and outdoors measurements by the SF_6 method was large, it was not statistically significant ($p = 0.05$, see section 2.3 of the Appendix).

Sheep more than 1 year old

For sheep > 1 y old that were fed cut and carried grass indoors, there were 123 SF_6 method records including 22, 24, 36, 11 and 30 from 2002, 2004, 2005, 2007 and 2008, respectively. There were 9 experiments and 64 sheep measured, so 59 records were repeated measurements of the same animal. For the calorimeter method, there were 182 records including 19 and 163 from 2007 and 2008, respectively. There were 3 experiments and 56 sheep measured, so 127 records were repeated measurements of the same animal.

For sheep > 1 y old, the two methods had mean CH_4 yields that were statistically indistinguishable (p =0.05), 23.7 and 22.2 g CH_4 kg^{-1} DMI for SF_6 and calorimeter, respectively. Within the experiments, measurements by the SF_6 method were nearly twice as variable as the calorimeter method. The corresponding within experiment standard deviations of log yield were 0.246 and 0.134.

For sheep > 1 y old and grazing grass outdoors, there were 123 SF_6 method records with 23, 21, 20, 14, 34 and 10 from 1997, 1998, 1999, 2000, 2001 and 2002, respectively. There were 13 experiments with 46 sheep measured, so 77 records were repeated measurements of the same sheep. Within the experiments, the standard deviation was 0.242, virtually identical to the value obtained indoors. Outdoors, for CH_4 yield, the SF_6 method CV was 5.1%. In the same manner as sheep < 1 y old, the SF_6 method CV was reduced to 2.8% ([0.134/0.246]*5.1%) to account for the additional variability attributable to the SF_6 method. This CV of 2.8% was only slightly larger than the 2.5% CV for sheep < 1 y old, 3% on average. Consequently, we have suggested a CV of 3% should be associated with the CH_4 yield of sheep of all ages in the enteric CH_4 emissions inventory.

For sheep > 1 y old that were fed cut and carried grass indoors and measured by the SF_6 method, the mean CH_4 yield was 23% larger than the corresponding mean for sheep > 1 y old and grazing grass outdoors (see Table 1 in the Appendix). However, the difference between mean values from indoors and outdoors measurements by the SF_6 method was not statistically significant (p = 0.05). Combining the indoors and outdoors means, the overall arithmetic mean CH_4 yield was identical to the value, 21.5 g CH_4 kg^{-1} DMI, currently used in the enteric CH_4 emissions inventory for sheep > 1 y old.

For sheep < 1 y and > 1 y old, indoors and outdoors, the two methods had mean CH_4 yields that were not statistically different (p = 0.05). Thus, despite some large differences between the mean CH_4 yields, the meta-analyses indicated no age distinction was warranted on a statistical basis. There has been one experiment conducted to quantify the difference between mean CH_4 yields of sheep < 1 y old and > 1 y old. The measurements used the SF_6 method and cut and carried grass DMI was measured daily for individuals ‘housed’ in crates, 14 mature ewes and 13 lambs at 13, 17, 25 and 35 weeks of age (Knight et al. 2008). At age 35 weeks, the lamb’s mean CH_4 yield was significantly less than that of the ewes (p = 0.05). However, for the three

earlier sets of measurements, the mean CH_4 yields were statistically indistinguishable. It would be advisable to further examine this important issue by another experiment using the calorimeter method.

Cattle

For cattle, analysis was confined to the SF_6 method since no data are yet available for cattle that have been fed grass based diets in the calorimeter chambers. A major experiment was completed June 2009 with cattle fed fresh grass and CH_4 emissions measured by the SF_6 and calorimeter methods. The final data were not available for inclusion in this report. However, a preliminary analysis of these data (Carlos Ramirez, personal communication) suggests that the mean CH_4 yields from young and old cattle were not statistically different, although these results await full statistical analysis before this can be stated conclusively.

For cattle that were fed cut and carried grass indoors, 200 SF_6 method records were analysed for this report including 70, 9 and 121 from 2003, 2004 and 2005, respectively. There were 5 experiments and 103 cattle measured, so 97 records were repeated measurements of the same animal. For cattle grazing grass outdoors, there were 1210 SF_6 method records including 1, 1, 2, 4, 2, 7, 7, 32, 29, 12 and 3% of these data from 1996, 1997, 1998, 2000, 2001, 2002, 2003, 2004, 2005, 2006, and 2007, respectively. There were 22 experiments and 984 cattle measured, so 226 records were repeated measurements of the same animal.

For cattle indoors and outdoors, the mean CH_4 yields were virtually identical at 21.7 g CH_4 kg^{-1} DMI. This mean CH_4 yield was statistically indistinguishable from those of the sheep ($p = 0.05$). Within the outdoors experiments, the cattle the within experimentstandard deviation of log yield was 0.151, very similar to the value of 0.159 obtained indoors. Indoors and outdoors, for the CH_4 yield of cattle, the SF_6 method CV was 7.0 and 3.6%. As previously stated there are no cattle data available from calorimeter measurements from which to ascertain the additional variation attributable to the SF_6 technique itself. Based on the available comparative results for sheep, an SF_6 method CV would be halved to give a ‘true’ representation of variation amongst the animals. For cattle, combining the indoors and outdoors CVs for the SF_6 method, the arithmetic mean CV was 5.2%. Halving this gave 2.6%, so we have suggested a CV of

3% should be associated with the CH_4 yield of cattle in the enteric CH_4 emissions inventory.

Recommendations –

(i) For sheep divided by age into two classes, < 1 y old and > 1 y old, the mean CH_4 yields were statistically indistinguishable.

(ii) The mean CH_4 yields of sheep and cattle were statistically indistinguishable.

(iii) To assess uncertainty of the enteric CH_4 emissions inventory, the CV for CH_4 yield should be 3%; this was the mean CV for sheep and cattle.

4. Uncertainty of the enteric CH_4 emissions inventory

The enteric CH_4 emissions inventory may be represented by an equation:

$$F_{CH4} = n\ R\ (1/e)\ m \qquad (1)$$

where the emissions have been expressed as a flux, F_{CH4}, mass of CH_4 per unit time. Variable n is the number of animals and variable R is the mean animal's 'metabolisable' energy (ME) requirement (MJ ME per unit time). The ME is equal to the gross energy (GE) minus the combined GE of the eructed CH_4 and the excreted urine and faeces. Thus, variable m, the mean CH_4 yield, is used in the conversion of term R from units of energy to the mass of CH_4. Internationally, variable R has been expressed on GE and ME bases. Here, variable e is the mean ME content of the feed dry matter (DM, MJ ME kg^{-1} DM) and variable m has been expressed in flux units of g CH_4 kg^{-1} DMI.

The variables in equation (1) are means based on sets of imperfect measurements or judgements. We can assess the uncertainty of each variable expressing it by the CV. Here we distinguish between two sources of uncertainty or variation. First, there is variability within a population that may be quantified by the standard deviation. Second, there is uncertainty about true population means, typically provided by sampling, so the uncertainty may be quantified by the standard error. In this report, we have expressed

the CV according to the standard error, the standard deviation of the distribution of the sample means.

In an earlier report to MAF, including the first assessment of uncertainty in the enteric CH_4 emissions inventory, Clark et al. (2003) expressed the CV according to the standard deviation and their CV for variable m was estimated to be 26%. The CV of Clark et al. (2003) was based on analysis of the arithmetic means of all available experiments (at that time) including all animal types and diets. Thus, their CV included any variance caused by the different diets studied. As stated, our analyses have been restricted to one diet, fresh grass. On the basis of the standard error, we have recommended CV = 3% for variable m.

Assuming each variable in equation (1) is independent and CVs < 10% (see Appendix 1), we may use a root mean square method to estimate a CV for F_{CH4} that may be written

$$CV(F_{CH4}) = [CV(n)^2 + CV(R)^2 + CV(e)^2 + CV(m)^2]^{0.5} \quad (2)$$

The CVs for variables n, R and e were 2, 5 and 5%, respectively, according to Kelliher et al. (2007). Determination of these CVs was described in their paper. As stated, we have recommended CV = 3% for variable m. Inserting these values into equation (2) gives $CV(F_{CH4}) = [CV(2\%)^2 + CV(5\%)^2 + CV(5\%)^2 + CV(3\%)^2]^{0.5} = 8\%$. The uncertainty of F_{CH4} may be expressed as a (±) 95% confidence interval by multiplying the CV by the t-statistic (= 1.96). Thus, we may be 95% certain that the inventory's true value is ± 16%.

For comparison with the uncertainty assessment of Clark et al. (2003), we can insert into equation (2) the same CVs for variables n, R and e but for variable m, CV = 26%. This yielded an uncertainty of F_{CH4} that was ± 53%, expressed as a 95% confidence interval.

Further comparisons were done based on the national enteric CH_4 emissions reports of Australian, USA and Ireland. The Australian national inventory report included a description of uncertainty analysis for their enteric CH_4 emissions inventory. This was done by Monte Carlo numerical simulation and expressed as a (±) 95% confidence interval. The interval was slightly asymmetrical about the mean; namely, – 5% and + 6%. Unfortunately, there was no other information was available; for example, there was

no CV for variable m. Thus we were unable to deduce what information used in the Monte Carlo analysis was based on expert judgement versus measurement. In contrast, for the New Zealand inventory, as stated, analytical assessment was based on a representative equation. Earlier, to assess the uncertainty of a change in New Zealand's enteric CH_4 emissions from one year to another, our analytical method had been subjected to peer review (Kelliher et al. 2007).

The USA national inventory report also indicated uncertainty analysis for their enteric CH_4 emissions inventory was done by Monte Carlo numerical simulation and expressed as a (±) 95% confidence interval. The interval was strongly asymmetrical about the mean; namely – 8% and + 19%. This seemed an unexpected result for biological variation, assuming it was not an artefact of the numerical simulation. For example, using the Monte Carlo software @Risk, one of us (FMK) found at least 5000 Latin hypercube algorithm sampling iterations were required to obtain consistent results (Bassett-Mens et al. 2009). However, an asymmetrical confidence interval may also have reflected a combination of complex calculations in the American inventory and/or an asymmetrical animal population structure. Regardless, informed comment was impossible because the required information had not been reported by the Americans.

The uncertainty assessment of Ireland's enteric CH_4 emissions inventory was reported as unspecified limits according to calculations following the Intergovernmental Panel on Climate Change (IPCC) "method". The interval was symmetrical and inexplicably minimal, ± 2%. It was puzzling that the national report also stated there was ± 15% uncertainty in the CH_4 yield for cattle, but the source of this statistic was not specified. Thus, we could not understand the Irish analysis due to the lack of information.

In 1990, the enteric CH_4 emissions from these four countries had a 64-fold range (452 to 28862 Gg, Table 1). The percentage changes over 16 years to 2006 were more consistent and relatively small (±11%). Thus, uncertainty assessment should have been considered very important. It was regrettable that lack of information in the national inventory reports prevented us from evaluating the other assessments. Given uncertainty of an enteric CH_4 emissions inventory depends on the CH_4 yield, we next consider the prospect of reducing uncertainty of the CH_4 yield in New Zealand's inventory.

Table 1 Enteric CH_4 emissions for 1990 and 2006 according to the national inventory reports of New Zealand, Australia, USA and Ireland.

Year	1990	2006	Change
Emissions	Gg CH_4	Gg CH_4	%
New Zealand	1039	1148	+11
Australia	3042	3323	+9
USA	28862	26443	-8
Ireland	452	438	-3

Recommendation – Uncertainty of the enteric CH_4 emissions inventory should be expressed as a 95% confidence interval, ± 16%, and the basis of calculation explained clearly in the national inventory report. This uncertainty was broadly comparable to that of the USA, while those of Australia (± 6%) and Ireland (± 2%) were inexplicably smaller.

5. Potential experimental requirements to reduce the uncertainty of methane yield

This section explores the potential number of grazing experiments required to reduce the uncertainty of CH_4 yield quantified by reducing the CV. For sheep > 1 y old, as stated, there were 123 SF6 method records including 13 experiments, 67 animals measured and 56 records repeated measurements of the same animals. Between and within the experiments, the log CH_4 yield standard deviations were 0.163 and 0.242 g CH_4 kg^{-1} DMI, respectively. For these animals, the unadjusted (see Table 1 in the Appendix) log CH_4 yield CV was 5.1%. For cattle, there were 1210 SF6 method records including 35 experiments, 109 animals measured and 116 records repeated measurements of the same animal. Between and within the experiments, the log CH_4 yield standard deviations were 0.207 and 0.151 g CH_4 kg-1 DMI, respectively. For these animals, the CH_4 yield CV was 3.6%. The lower CV reflected a larger number of experiments and records for the cattle.

We can analyse the above data to estimate the potential number of experiments and records required to reduce the sheep CH_4 yield CV to 4.0%. The analysis depends on the number of experiments and records. For example, 4 additional experiments would be required if the number of records increased to 1210, the number for the cattle data. Alternatively, if the number of records tripled to 369, 5 additional experiments should suffice.

By the SF_6 method, as stated, the CH_4 yield CV was twice that of the calorimeter method. Thus, reducing the CH_4 yield CV by the SF_6 method from 5.1% to 4% reduces the corresponding CV in the enteric CH_4 emissions inventory to 2%. The recommended CV was 3%, so 2% was 33% less. Inserting 2% into the calculation of a 95% confidence interval, the inventory's uncertainty became ± 15%, 6% less than when the CH_4 yield CV was 3%. This indicated there was little to be gained with respect to reducing uncertainty of the national enteric CH_4 inventory by simply conducting more animal measurements.

6. Methane yield and feed intake

On a daily average basis, for sheep fed grass in calorimeter chambers, enteric CH_4 emissions were proportional to the feed dry matter intake (Figure 1). The 143 records portrayed in Figure 1 came from two experiments denoted FLL and FLE for feed level lamb and feed level ewe, respectively. Results from the FLL experiment have been reported by Knight et al. (2008), while data from the FLL experiment are still undergoing quality assurance testing prior to final statistical analysis. The results quoted here for the FLL experiment should be considered preliminary although any changes are expected to be minor. For the 143 records, the arithmetic mean CH_4 yield was 23.8 ± 0.2 g CH_4/kg DMI (± standard error), statistically indistinguishable from the slope of the regression shown in Figure 1.

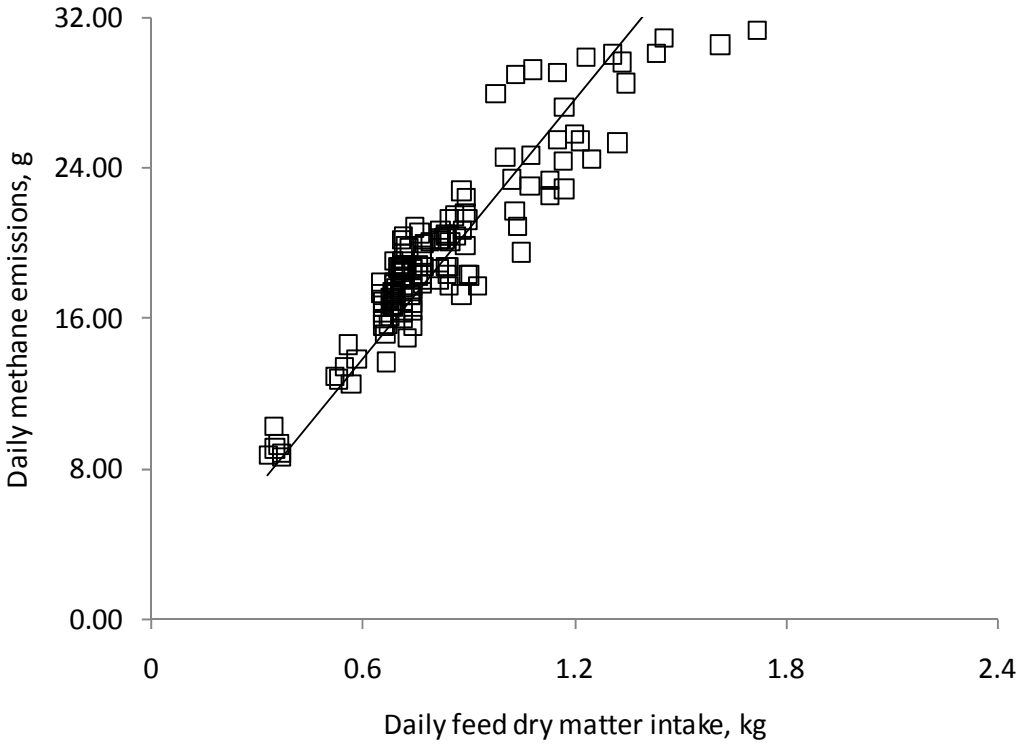

Figure 1 Relation between feed dry matter intake (DMI) and CH_4 emissions for 143 records of sheep fed grass in calorimeter chambers. Each data point was a 2-day average. Linear regression through the origin yielded a slope = 23.1 ± 0.2 (± standard error) g CH_4/kg DMI and 98% of the variance in CH_4 emissions was associated with feed DMI.

One interpretation of the consistent, linear relation portrayed in Figure 1 was the slope yielded a good estimate of the arithmetic mean CH_4 yield. However, to examine this further, we explored a relation between CH_4 yield and feed intake expressed as a proportion of the intake required for maintenance. Intake that met the maintenance requirement maintained the animal's live weight. The ME maintenance requirement was calculated following CSIRO (2007) as done in the enteric CH_4 emissions inventory.

While expression of the independent variable as a proportion of the maintenance ME requirement was different to feed intake, the feed intake was used to calculate it. Thus, the relation between CH_4 yield and feed intake as a proportion of the maintenance ME requirement was only explored, recognising the limitation of having both the independent and dependent variables determined using feed intake. Further, to refine the exploration, we did separate analyses for weaned lambs < 1 y old (denoted sheep <

1 y old), lactating ewes > 1 y old and dry and pregnant sheep > 1 y old. There were different relations for the different animal types, shown in Figures 2, 3 and 4 with the statistics provided in Table 2. Using the regression statistics, we quantified the sensitivities of CH_4 yield to feed intake level for each animal type in Table 3. For example, for the lactating ewes, increasing feed intake as a proportion of the maintenance requirement from 1 to 2 corresponded with a 33% reduction in the CH_4 yield. Though preliminary, these analyses were interpreted to have suggested a potential limitation of the current approach using an arithmetic mean value of CH_4 yield in the enteric CH_4 emissions inventory. The alternative approach to estimating CH_4 yield suggested by the relations in Figures 2, 3 and 4 could readily be incorporated into the enteric CH_4 emissions inventory. These analyses also suggested separating animals into types based on their age as well as physiological state may be necessary. Clearly, further research is warranted to verify these suggestions and the merit of an alternative approach for the enteric CH_4 emissions inventory. The alternative approach would be more complex than the current method but should give a more accurate estimate of the 'true' CH_4 emissions. This will make uncertainty assessment more complicated and the uncertainty may be increased.

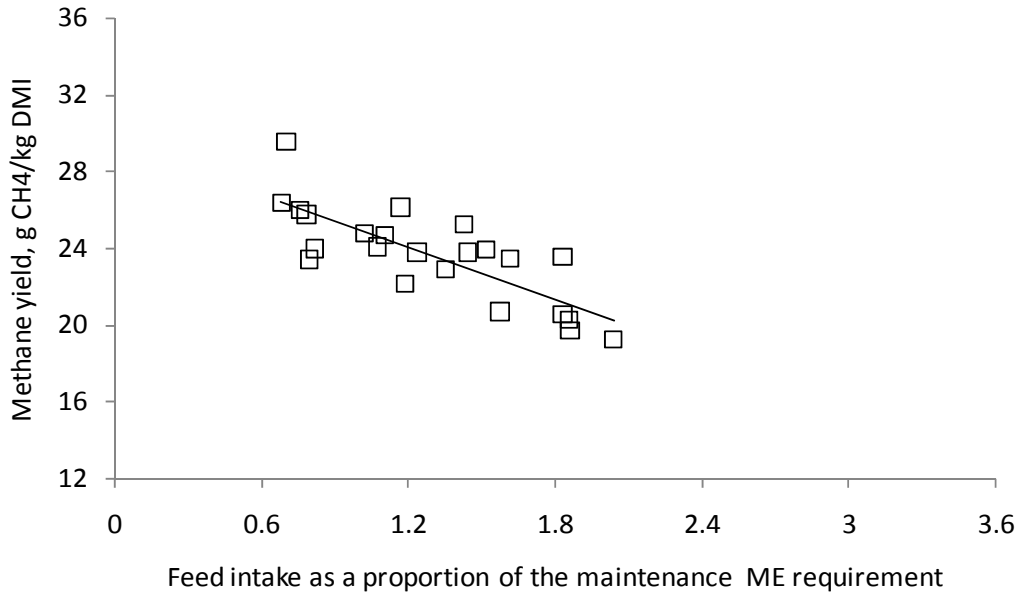

Figure 2 Relation between methane (CH_4) yield (g CH_4/kg DMI) and feed dry matter intake as a proportion of the maintenance (ME) requirement (independent variable) for sheep < 1 year old, including 23 records, that were fed grass in calorimeter chambers. Statistics for the regression line are given in Table 2.

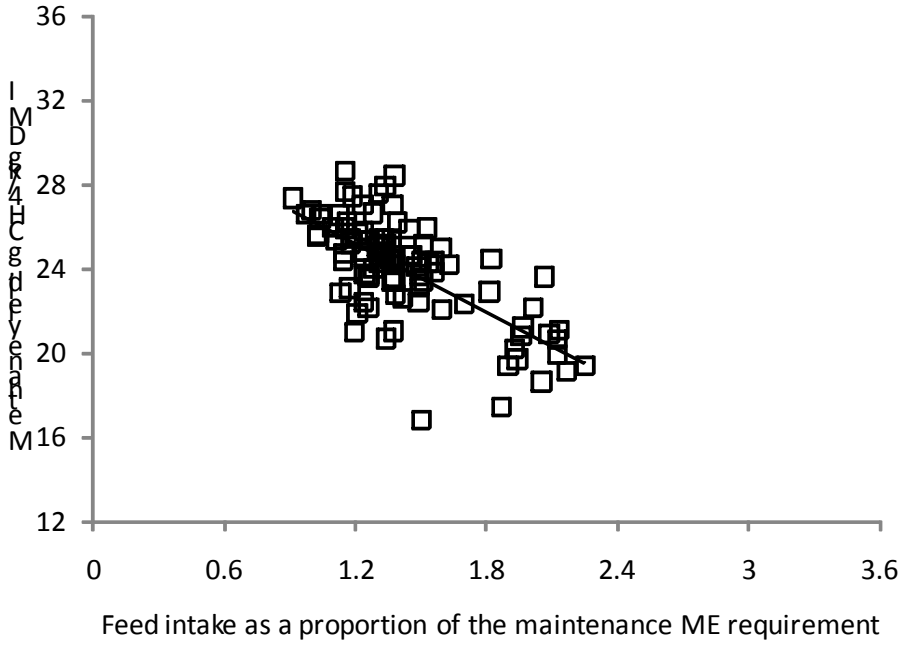

Figure 3 Relation between methane (CH_4) yield (g CH_4/kg DMI) and feed dry matter intake as a proportion of the maintenance (ME) requirement (independent variable) for sheep > 1 year old, including 27 records for pregnant ewes, that were fed grass in calorimeter chambers. Statistics for the regression line are given in Table 2.

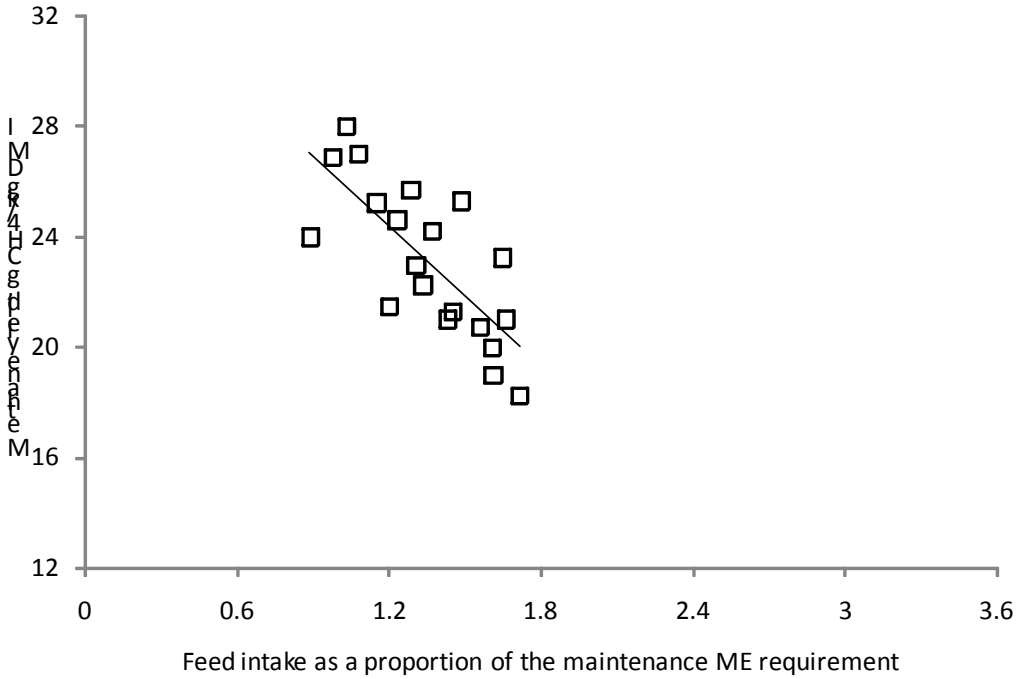

Figure 4 Relation between methane (CH_4) yield (g CH_4/kg DMI) and feed dry matter intake as a proportion of the maintenance (ME) requirement (independent variable) for 100 records based on sheep > 1 year old that were lactating and fed grass in calorimeter chambers. Statistics for the regression line are given in Table 2.

Table 2 Statistics for the regression lines shown in Figures 2, 3 and 4 including the coefficient of determination, R^2. Methane yield has been denoted (g CH_4/ kg DMI) and DMI was the dry matter intake.

Animal type	**Slope**	**Offset**	**R^2**	**Number of records**
	g CH_4/kg DMI	g CH_4/kg DMI		
Weaned lambs < 1 y old	-4.5 ± 0.8	29.5 ± 1.0	0.62	23
Dry and pregnant sheep > 1 y old	-5.4 ± 0.6	31.7 ± 0.8	0.57	100
Lactating sheep > 1 y old	-8.5 ± 1.7	34.6 ± 2.4	0.57	20

Table 3 Methane (CH_4) yields predicted by the regression statistics given in Table 1 for two levels of feed intake, the ME maintenance requirement and twice this level.

Animal type	**CH_4 yield when feed = the ME requirement**	**CH_4 yield when feed = twice the ME requirement**
	g CH_4/kg DMI	g CH_4/kg DMI
Weaned lambs < 1 y old	25.0	20.5
Dry and pregnant sheep > 1 y old	26.3	20.9
Lactating sheep > 1 y old	26.1	17.6

Recommendation – Further research is warranted to verify if CH_4 yield is inversely proportional to feed intake. If so, this would warrant a changed inventory structure for determination of the CH_4 yield as a function of feed intake with respect to the maintenance requirement for animal types according to age and physiological status.

7. Recommendations

- For sheep divided by age into two classes, < 1 y old and > 1 y old and cattle, the mean CH_4 yields were statistically indistinguishable. Further, the mean CH_4 yields of sheep and cattle were statistically indistinguishable.
- Further research is needed to clarify the issue of emissions from young and old sheep. IPCC good practice guidelines, emanating from NZ studies, recommend using a lower methane yield value for young sheep but the analysis reported here suggests no clear link between age and CH_4 yield in sheep. This needs clarifying as a matter of urgency since it has implications for the national inventory and for IPCC best practice guidelines.
- To assess the uncertainty of sheep in the enteric CH_4 emissions inventory, the CV for CH_4 yield should be 3%. To potentially reduce this to 2%, it was estimated that nearly 400 additional measurements would be required in 5 experiments.
- Uncertainty of the enteric CH_4 emissions inventory should be expressed as a 95% confidence interval, ± 16%, and the basis of calculation explained clearly in the national inventory report. This uncertainty was broadly comparable to that of the USA, while those of Australia (± 6%) and Ireland (± 2%) were inexplicably smaller.
- Further research is warranted to verify if CH_4 yield is inversely proportional to feed intake. If so, this would warrant a changed inventory structure for determination of the CH_4 yield as a function of feed intake with respect to the maintenance requirement for animal types according to age and physiological status.

8. Acknowledgements

We are grateful to Kirsty Hammond and Stefan Muetzel for helping us to compile the SF_6 and calorimeter data, respectively. German Molano and Grant Taylor kindly answered many questions about experimental details.

9. References

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10. Appendix 1 written by Murray H. Smith and Keith R. Lassey

Variation in methane emission yields from New Zealand ruminants.

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May 2009

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Variation in methane emission yields from New Zealand ruminants.

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Executive Summary

The task of obtaining an accurate estimate the total annual enteric methane emissions from ruminant animals in New Zealand (methane inventory) depends on obtaining accurate estimates of the various components that make up the estimate. Important components are the estimates of rates of methane emission per unit dry matter intake (methane yields) for the different species groups that make up the ruminant population. The most important species groups are sheep and cattle, which produce more than 90% of methane inventory.

Over the years, many experiments have been carried out with the aim of estimating methane yields for different species groups under different diet conditions and using different techniques for measuring the methane output and dry matter intake (DMI) for the individual animals over the duration of the experiment.

In this work we have developed an improved method for estimating the mean methane yield per unit dry matter intake (DMI) for different species groups of ruminants using data from multiple experiments. The method not only produces estimates which properly take into account the variation between experiments as well as variation between the individuals but also produces estimates of the associated standard errors (expressed as a percentage) which are realistic because they properly incorporate both sources of variation.

Only experiments where the basal diet was grass were used in the analysis and estimation of mean methane yields, because animals in the New Zealand inventory are for the most part grass fed. For analysis the experiments were grouped into three classes: SF_6 grazing (experiments carried out on grass pastures where methane emissions are measured by the SF_6 technique), SF_6 indoors (experiments where the animals are confined by stalls and their food intake measured directly, and their methane emissions measured by the SF6 technique), and chambers (experiments where the animals are confined to chambers where both the methane emissions and food intake are measured directly). The animal species were grouped into: sheep less than 1 year old, sheep 1 year old and greater, and cattle.

Estimates of the mean methane yields (all in units of g CH_4 per kg DMI) are obtained for each combination of species group and experiment class (except for cattle in chambers where no experiments on cattle with a grass basal diet have been carried out). For sheep < 1 year old, the estimated mean methane yields are 16.50, 23.87, and 24.04 for SF_6 grazing, SF_6 indoors, and chambers experiments, respectively. The difference between the estimated mean yields for SF_6 grazing and for SF_6 indoors is highly significant but the difference between estimated mean yields for SF_6 indoors and chambers is not significant. For sheep > 1 year the yield estimates are 19.24, 23.69, and 22.22 respectively, again the difference between the yields for SF_6 grazing and for SF_6 indoors is highly significant but the difference between estimated mean yields for SF_6 indoors and chambers is not significant. For cattle the estimated mean methane yields are 21.09 and 21.11 for SF_6 grazing and SF_6 indoors, respectively, and the difference is not significant. The standard error of the yield estimates vary between 3% and 9% of the yield.

It is apparent from the analyses that chambers experiments give yield estimates with smaller error. Not only are the variances of the yields between animals smaller in the chambers than for the other experiment classes but the between experiment variances are also smaller.

The highly significant difference between the methane yield estimates grazing and indoors (both using the SF_6 technique) for sheep > 1 year has implications for the methane inventory because it highlights the possibility of a systematic difference (at least in sheep) between the way the dry matter intake is measured when the methane yield is measured (direct measurement in crates or chambers) and the way it is estimated for the inventory (energy requirement based). Therefore there is a risk of systematic error in the inventory as it is currently calculated.

1. Introduction

New Zealand's profile of greenhouse gas (GHG) emissions is unusual among developed countries: approximately half of CO_2-equivalent emission is due to pastoral agriculture. Since agricultural emissions are of non-CO_2 gases (approximately 2/3 methane, 1/3 nitrous oxide), NZ also has an unusually high proportion of non-CO_2 gases—and methane in particular—when compared to other developed countries. Since non-CO_2 GHG emissions can be estimated only to limited precision when compared to CO_2 emissions (estimated at typically 20% uncertainty or higher versus less than 5%), NZ stands out, among developed countries, as having an emission inventory that carries unusually high uncertainty. We use the term (methane) *emission inventory* to mean the total annual methane emissions from ruminant animals.

The highly uncertain inventory puts NZ in a precarious position when engaging in international agreements to limit GHG emissions that have binding emission limitation targets, as well as when seeking agreements with the farming sector to introduce emission mitigation strategies. The largest single non-CO_2 component in the NZ inventory is methane (CH_4) generated by "enteric fermentation" in the gut of ruminant livestock. Enteric CH_4 accounts for almost all agricultural methane and one third of NZ's CO_2-equivalent emissions.

In a re-estimation of the NZ enteric CH_4 inventory for 1990 and for 2001, Clark et al. (2003) estimated the uncertainty in each of these two inventories at ±46% (95% confidence limits). The biggest single influence on this variation was the uncertainty in the amount of methane emitted per unit of feed intake, known as the *methane yield* and a common factor in each inventory component (at least for each animal species or cohort). It is apparent, however, that the wrong measure of uncertainty was used for the methane yield and this led to the inflated uncertainty. The appropriate estimate of the error associated with the methane yield, in any calculation of the methane inventory, is the standard error of the yield estimate, which can be expressed as a percentage of the mean, and referred to as the percent standard error. Any additional variation arising from between-animal variation in the yield becomes completely negligible in the inventory estimate because of the Law of Large Numbers, as methane emissions come from large numbers of animals.

The (inflated) uncertainty in the annual methane inventories as calculated by Clark et al. (2003) was so large that the 8.3% inventory increase over 1990–2001 could not be claimed as significantly different from zero. With the methane yield and a common multiplier of both inventories, the two inventory estimates are not independent of each other, a correlation that Clark et al. (2003) appeared not to take into account when noting that "the 95% confidence intervals for 1990 and all subsequent years overlap", which "indicates that from a purely statistical perspective we cannot be certain that emissions have actually increased since 1990". Overlapping of the two 95% confidence intervals does not guarantee that there is no significant difference ($P <$

0.05) between the two annual estimates, even if the two estimates were independent, especially if there is positive correlation in the errors of the two annual estimates.

This report provides a method for the estimation of methane yield, which has an associated uncertainty that takes into account the between-experiment variation as well as the between-record (a record is an individual yield measurement within an experiment) variation in the methane yields. It examines sources of error associated with the estimation of the methane yield and also comments on some of the implications of the results for the uncertainty in the calculations of the emission inventories and for making comparisons between years.

2. Estimation of the mean methane yields

The current method for the calculation of the annual methane emissions inventory scales the estimated total annual DMI (dry matter intake) for groups of ruminants by the CH_4 yield per unit of DMI. The total annual CH_4 emissions by animal group are aggregated over the groups to give the New Zealand emissions inventory. For this purpose it is important to have accurate estimates of the methane yields for the various animal groups. In this section we analyse the results from experiments directed at determining yields, with a view-point of highlighting possible sources of bias and of estimating components of variance that contribute to the variation in yield estimates.

The experiments that have been carried out to estimate CH_4 yield, CH_4 emissions per unit of DMI, fall into three broad classes:

SF_6 grazing	experiments using the SF_6 tracer technique with grazing animals outside
SF_6 indoors	experiments using the SF_6 tracer technique under controlled feeding conditions indoors or by other confinements.
Chambers	experiments using chambers under controlled feeding conditions.

The SF_6 tracer technique (Johnson et al., 1994) is uniquely suited for determining CH_4 emission rates by grazing animals, and has been used extensively in NZ, 1996–2000, for this purpose (e.g., see the review by Lassey 2007). A difficulty with deploying grazing animals is in determining the level (and quality) of feed intake, which can be determined only indirectly with limited confidence, leading to similarly limited confidence in estimates of the CH_4 yield. Consequently, the SF_6 technique has also been applied to animals housed in metabolic crates or similar confinement in which measured feed is delivered to the animal.

Most recently, the construction of chambers at AgResearch's Grasslands facility has enabled CH_4 emission as well as feed intake to be measured with unparalleled precision.

While the SF_6 technique measures only the CH_4 emitted at the mouth and nostrils, the chambers fully enclose the animal and detect CH_4 emissions from all orifices. It is believed that ~98% of the emission is through the nose or mouth, but this estimate is founded on very few experiments (Murray et al., 1976), and its variation with diet quality and quantity and among individual animals cannot be ruled out (indeed, may be expected). This and other factors lead to an uncertainty associated with the SF_6 technique itself. On the other hand, there are concerns about basing the national inventory estimate on measurements with non-grazing animals, because the NZ sheep flock and cattle herds graze essentially 100% of the time (albeit, sometimes accompanied by supplementary feeding).

The national inventory estimate follows a procedure not unlike that used with the SF_6 technique with grazing livestock. In the latter case, the feed intake (quantified as dry matter intake, DMI, or gross energy intake, GEI, the two being related through 18.4 MJ/kg(DMI) for a wide range of diets) is commonly estimated by applying an 'energy requirements model'. NZ has elected to adopt the model developed by CSIRO known as the 'CSIRO feeding standards model' (CSIRO 1990). Such a model applies energy balance: the energy required to maintain body condition plus that required to produce milk, meat, or a fleece; or to grow a foetus, is matched to the feed energy supply, taking account of the efficiencies of energy conversion (including the energy lost as CH_4). The same model is applied to the NZ inventory (in separate age and species groups): in effect, the energy requirements of maintenance and of productivity of the national herd and flock are estimated using the same CSIRO model and the requisite feed intake thereby assessed. The CH_4 emitted is deduced as a proportion of that intake given by the best available estimates of methane yield (Lassey, 2007, 2008).

Because special diets and supplements can affect methane output and, in New Zealand, almost all ruminants graze with minimal supplementation, our analysis was confined to the use of experimental records receiving grass basal diets in all three experiment classes. The three experiment classes have two different ways of measuring/estimating the methane emissions: the SF_6 technique in each of the two SF_6 experiment classes and the direct measurement in chambers. The classes have two distinct ways for measuring/estimating DMI: various estimation methods for the SF_6 grazing class of experiments, and direct measurement for both the SF_6 indoors and chambers experiment classes. The "various estimation methods" include: inert marker methods, energy requirement models (and where used in the data we analysed, the method may or may not have used the CSIRO feeding standards model), and, in the case of male lambs, the whole faeces collection method in which total faecal production and feed digestibility are both measured.

For each record, both quantities, the mean daily methane emissions per record (denoted ch4) and the mean daily DMI per record (denoted dmi), are measured with error (to a greater or lesser extent). In the SF_6 experiment classes, the ch4 is likely to have larger variance (than for the chambers class) and may also be measured with bias

(consistent under- or over-measurement) for reasons which may include, for example, that not all emissions are through the mouth and nose. In the SF_6 grazing class, the dmi may also be measured with bias because of the way it is estimated.

The fact that both the ch4 and the dmi, for each record, are measured with error is one of the reasons we did not adopt the approach of regressing ch4 on dmi to obtain an estimate of yield and to analyse the components of variance. When the covariate is subject to error, the slope estimate from a regression of ch4 on dmi depends on the magnitude of the variance in the measurement of the covariate (in this case dmi). When comparing the results from the different experiment classes it is important to minimise such a distortion and the estimation method we have adopted should help prevent the problem. Our approach treats the logarithm of the yield, the natural logarithim of ch4/dmi, as the difference between the log of the ch4 and the log of the dmi and, therefore, estimates the mean of the log yield as the difference of the means of two random quantities. The estimate of the mean of the log yield can then be back-transformed (using variance estimates as well) to get the estimate of the mean yield.

In Clark et al. (2003) the ruminant species was divided into the five groups: sheep < 1 year, sheep > 1 year, cattle, deer, and goats and used different yield estimates for each group. There are no data available for goats and only a small amount of SF_6 data available for deer. Therefore we have restricted our analysis to estimation of yields for the first three groups. They are

sheep < 1 year	sheep less than 1 year old
sheep > 1 year	sheep 1 year and older
cattle	all cattle.

2.1 Data used in the estimation of the yields

Two sets of data, in Excel spreadsheets, were obtained from Frank Kelliher and Harry Clark of AgResearch Ltd, one from grazing and indoor experiments using the SF_6 technique and the other from experiments in chambers. These data included mean (over the duration of the experiment) daily methane emissions (ch4) and mean daily DMI (dmi) for the records in the experiment. Variables relating to age, sex, species and diet (including any supplements) and others were also included. See Table A1 in the Appendix for the details of experiments and numbers of experimental records from the SF_6 data set. The chamber data included similar variables.

The original SF_6 data set consisted of 3463 experimental records (rows) from 56 trials involving 113 different experiments. 1884 of the records were cattle, 394 were deer, and 1185 were sheep. A data set of all grazing animals was prepared by first removing all records whose basal diet was not grass. Next records which received diet treatment or were part of CH_4 mitigation trials were removed (see Table A1). On advice,

estimates of methane yield for deer were not required from this analysis. Emissions by deer are a small proportion (approximately 5%) of the inventory (Clark et al. 2003) and also there is little experimental data, much of it repeat measures on the same animals, from which to estimate the methane yield. Consequently, all deer records were removed.

At this stage some data grooming was carried out, where missing age and season values were replaced by values deduced from the other variables. Also, a few corrections were made. Then all records with either ch4 or dmi missing were removed leaving 1427 records grazing and 462 records indoors.

Initially the chamber data comprised 528 records in 9 experiments and did not include any deer records. The ten records that had missing ch4 or dmi were removed leaving 518 records. Grass-based diets were identified by the first word in the diet comments variable. There were 360 records in 6 experiments with grass-based diets.

2.2 Estimation of mean yields

Some preliminary analyses were carried out on the SF_6 grazing data before our approach to the estimation of the mean yield was settled on.

2.2.1 Preliminary analysis of SF6 grazing data

Both ch4 and dmi are positive quantities which vary considerably with species, weight of animals, age, lactation/not, but the scatter plot of the two using all the data from the SF_6 grazing has a strong linear relationship. Despite the large ranges of the variables ch4 and dmi, the unimodality of the kernel density plots for the yields and the log yields shows that the ratio is relatively constant over the large range of intakes and over the different species (Figure 1). The kernel density plots of both the ch4 and dmi are bimodal and yet the kernel density plots of both the yields and log yields are unimodal. Note also that the kernel density plot of the log of the yield (lower right panel in Figure 1) is much less skewed than that for the yield (top right). The data plotted include different species, different experiments and different intake to maintenance ratios, all of which could add to the densities at different places along the axes.

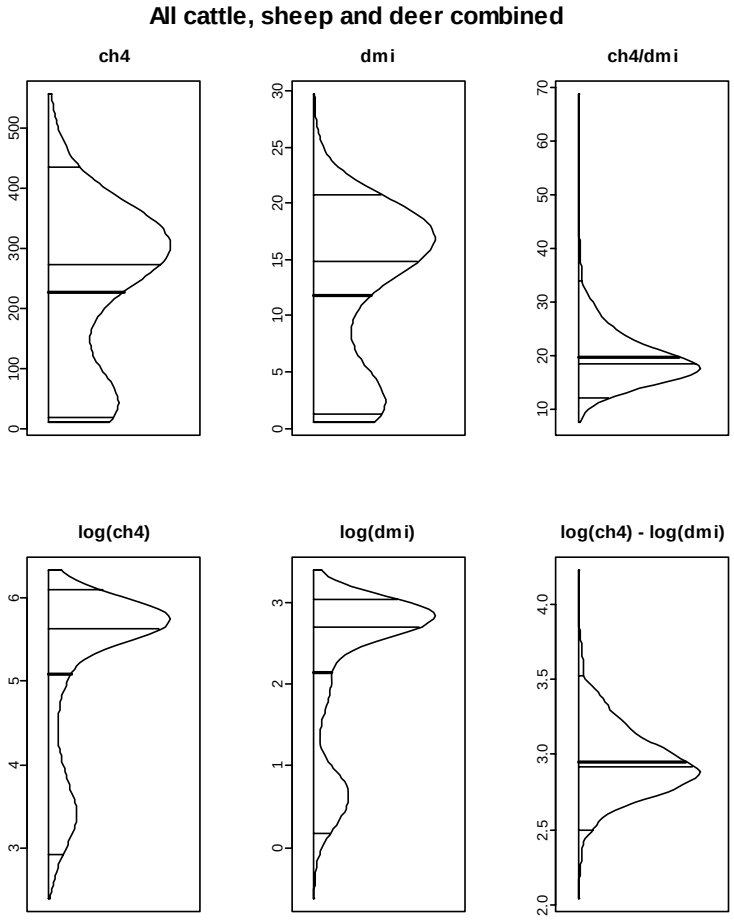

Figure 1: **Density plots of ch4 and dmi and the ratio for the grazing data. In the lower panels are the density plots of the logarithms.**

It is apparent that there is a strong linear relationship between ch4 and dmi that appears to pass close to the origin (left panel, Figure 2). There is also a strong relationship between their logarithms which has slope approximating 1, meaning their ratio is nearly constant and there is not a power law relationship between ch4 and dmi (right panel, Figure 2). The intercept of the line relates to the difference between the log ch4 and the log dmi and therefore to the log of the yields. Lines of constant yield would have slope 1 and the intercept would be log of the yield. The grey line in the right panel of Figure 2 is the line where yields are exp(2.978) = 19.65 (2.978 is the mean log yield for the data set used in the plots). The logarithms plot does not exhibit the increasing variance with increasing animal size (related to increasing ch4 and increasing dmi) that is apparent in the plot of the untransformed ch4 against dmi. That all this is apparent, despite the data set comprising different species and sizes of animal, confirms the straight line relationship between ch4 and dmi.

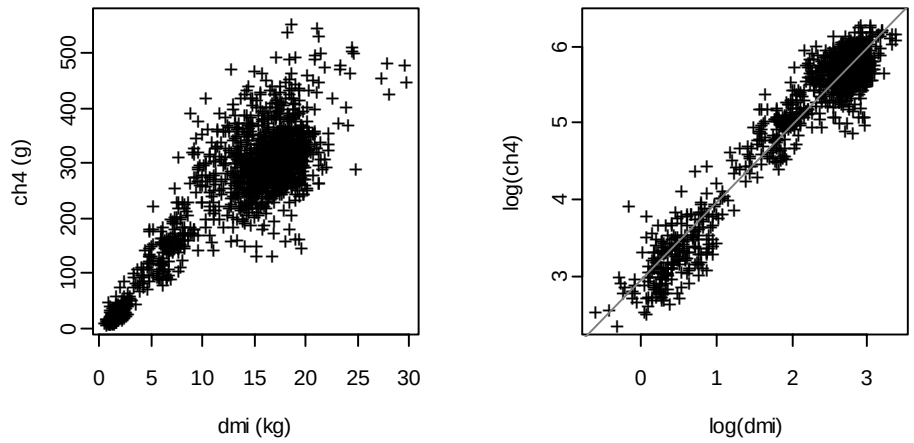

Figure 2: **Scatter plots of ch4 against dmi and log(ch4) against log(dmi) for all the SF_6 grazing data. The grey line in right panel has slope 1 and intercept 2.978.**

2.2.2 Model-based estimation of the mean yield

In this subsection we set up and fit models for the yield data for each of the species groups to data from each of three experiment classes. The method of "scaling up" an estimated ratio by a measurable total variable to get the population total is a widely used technique in survey sampling and there it is called the ratio estimator method. This is similar to the technique used to estimate the methane inventory where the estimated ratio is the estimated mean yield and the measurable total variable is the total DMI required (calculated from energy requirements). What is different about the survey sampling application is that the ratio is estimated from a random sample from the population, which is, therefore, representative of the population. For the estimation of the methane inventory, animal subjects for the experiments have not been chosen randomly from the whole population (of dairy cows, for example) and are not representative of the whole ruminant population. This is a very good reason to follow the Tier 2 IPCC method (IPCC 1997) that Clark et al. (2003) have used. The method for estimating the inventory rightly disaggregates the population into strata that have similar mean yields and for which energy requirements can be more easily calculated and converted to DMI. It then calculates the total DMI for each stratum, scales by the estimated yield for the stratum and sums over the strata. The method requires good estimates of the mean yield for the various strata, as well as good estimates of energy density per unit of DMI.

We are concerned with a method for obtaining good estimates of the mean yield in the species group and experiment class for which there are suitable data available. Our estimates are a combination of the results from each experiment within a class. We do not combine the results over the experiment classes because of the very different ways the ch4 and dmi are measured/estimated for the classes. We are also interested in the differences between the estimates from the different experiment classes. (The method

we use could easily be extended to obtain a combined estimate from all the classes for a species group but its value would be debatable.)

Our approach to integrating the different experiments within a species group and experiment class is similar to the standard meta-analysis approach that uses random effects (see, for example, Borenstein et al. 2009). Because different experiments were carried out under different conditions, each experiment has its own effect which acts on the overall mean yield (which is what we wish to estimate) to give the mean yield for the experiment. Using random rather than fixed experimental effects means that each experiment effect is assumed to have been chosen at random from a normal population of experiment effects. By setting up a model in this way the variation between experiments is included in the model as an additional component of variance in the same way as the between-subplot variance is included in a traditional split plot agricultural design, because the randomness of the experiment effect is like another layer of error. The data sets are highly unbalanced, in the sense that the numbers of records within the experiments can be very variable. Because of this, the traditional ANOVA approach to estimating variance components is not appropriate because the traditional ANOVA estimate is only efficient (and unique) in balanced designs. The maximum likelihood estimation method as applied to the random effects model is a way of obtaining efficient estimates of the mean yield and the variance components in the situation where the different experiments can have very different numbers of records (see McCulloch & Searle 2001).

We use a random effects model to obtain estimates of the yield for each experiment class and species group. The standard error of the yield estimate is expressed as a coefficient of variation (c.v.) of its sampling distribution. An estimate of each c.v. is not obtained directly from the fitted models but is obtained from simulations from the sampling distributions of the yield estimate.

Random effects model

There are good reasons for using a loglinear model for the methane yield, *Y*, in the model for each species group. It removes the problem of reweighting in the estimation procedure to allow for increasing variance with increasing dmi. Taking the response variable $y = \log(Y)$, to be the natural logarithm of the yield, means that errors and effects in the model act in a multiplicative way. An experiment random effect which is additive in the model for the log yield becomes multiplicative for the yield, so that the mean yield for a particular experiment is the product of the (overall) mean yield and a scaling effect for the experiment. We have also seen that the kernel density function of the log of the yields is more symmetric than the kernel density function for the raw yields (Figure 1) and this helps justify the normal error model (and the normal model for the experiment random effects).

Denoting the yield for record j in experiment i by Y_{ij}, the model for the log of the yields, $y_{ij} = \log\left(Y_{ij}\right)$, is

$$y_{ij} = \beta + b_i + e_{ij}$$

where β is the mean of the log yields, b_i is the random effect for experiment i, and e_{ij} is the error. The distributional assumptions are that the b_i are independent $\mathrm{N}\left(0, \sigma_b^2\right)$ random effects (normally distributed with mean 0 and variance σ_b^2) and the e_{ij} are independent $\mathrm{N}\left(0, \sigma^2\right)$ random errors. Thus, the distribution of each observation y_{ij} is $\mathrm{N}\left(\beta, \sigma_b^2 + \sigma^2\right)$. The experiment random effect induces a correlation between pairs of observations within an experiment. This is because all log yields in an experiment receive the same (random) b_i added to the mean β. For experiment i the correlation between the log yields for records j and j' ($j \neq j'$) is

$$\mathrm{Cor}\left(y_{ij}, y_{ij'}\right) = \frac{\sigma_b^2}{\sigma_b^2 + \sigma^2}.$$

Log yields in one experiment are independent of those in all the other experiments. The joint distribution of all log yields is multivariate normal. There are 3 parameters in the model, β, σ_b, and σ, which are the mean of the log yield, the experiment random effects standard deviation and the error standard deviation. Under the assumptions of this model, the yields Y_{ij}, have the lognormal distribution and their mean is given by

$$\mu = \mathrm{E}\left(Y_{ij}\right) = \exp\left(\beta + \frac{1}{2}\left(\sigma_b^2 + \sigma^2\right)\right). \qquad (1)$$

This reflects the right skewness of the lognormal distribution. While β is the mean of the log(yields), $\exp\left(\beta\right)$ is not the mean yield but is, in fact, the median yield. Because of right skewness the mean is larger than the median and it is given by Equation 1. The estimate of the mean yield is then obtained by substituting the parameter estimates from the fitted model into the above equation. Because of the complexity of the estimates of the 3 model parameters, there is no closed analytic expression for the standard error of the estimate of β, let alone for the standard error of the estimate of μ as given in Equation 1 (see McCulloch & Searle 2001).

In some experiment classes there were repeat measures on the same animal, identified by the same ear tag within an experiment. A correlation term for the repeat measures on the same animal was added to the model. In many cases the term made little difference, because the estimated correlation was close to zero or there were only a very few repeats, but it was important enough (by the likelihood ratio test comparing the model with correlation to the model without) to be retained in the SF_6 indoors class of experiments for both age groups of sheep. For the chambers class of experiments the correlation term had no effect for either sheep group.

Model fitting

Model fitting was carried out using the `lme` function from the `nlme` package in the statistical software R (R Development Core Team 2008). See Pinheiro & Bates (2000) for description of the mixed and random effects models and fitting methods. Models were fitted to each of the species classes for each of the experiment classes.

The fits of the models were assessed using residual plots. They appeared to confirm a good fit. The normal distribution assumption for the errors in the model was checked by normal quantile-quantile plots (Q-Q normal plots) of the residuals. In a Q-Q normal plot of a variable, the ordered values of the variable are plotted against the corresponding quantiles of the standard normal distribution. If the variable has a normal distribution then the points should lie close to a straight line (with intercept and slope equal to the mean and standard deviation of the variable, respectively). The Q-Q normal plots were also used to identify outliers, which were removed and the model refitted. All models appear to be consistent with the normal error assumption (Figure 3). The plots also show symmetric distributions for the residuals in the two SF_6 experiment classes. When the plots show a reverse S-shape (high top right and low bottom left relative to the line) then the residuals have thicker tails (larger kurtosis) than that for a normal distribution (Figure 3). For the chamber experiments the residuals follow the normal line closely for sheep < 1 year but not so closely for sheep > 1 year. Their distribution shows a slight left skewness (from the slight upside down U shape). The skewness could indicate the presence of some subgroups of sheep (within some experiments, because any consistent effect for an experiment would have been removed from the residuals via the experiment effect) which have differing mean yields, or it could have some other explanation. For each experiment class and species group the plots of the residuals against fitted values (the plots are not included in the report) were unremarkable and did not show any discernable trend of changes in variance. The latter helps confirm the assumption of the constant error variance σ in the models for the log yields. Models based on the raw yields would have non-constant variance (would be heteroscedastic) when this assumption is true.

The lack of skewness is the more important characteristic for the validity of the normal assumption of the model. Skewness in the error model has a bigger effect on the standard errors of the yield estimates than symmetric but thick-tailed errors. To account for any small amount of non-normality in the residuals we used a bootstrap sample of the residuals as part of the simulation required to calculate the coefficients of variation of the yield estimates.

For all combinations of experiment class and species group the model that included random experimental effects gave a significantly better fit than the corresponding model without experiment random effects. This was shown by a likelihood ratio test that compared the models with and without experiment random effects.

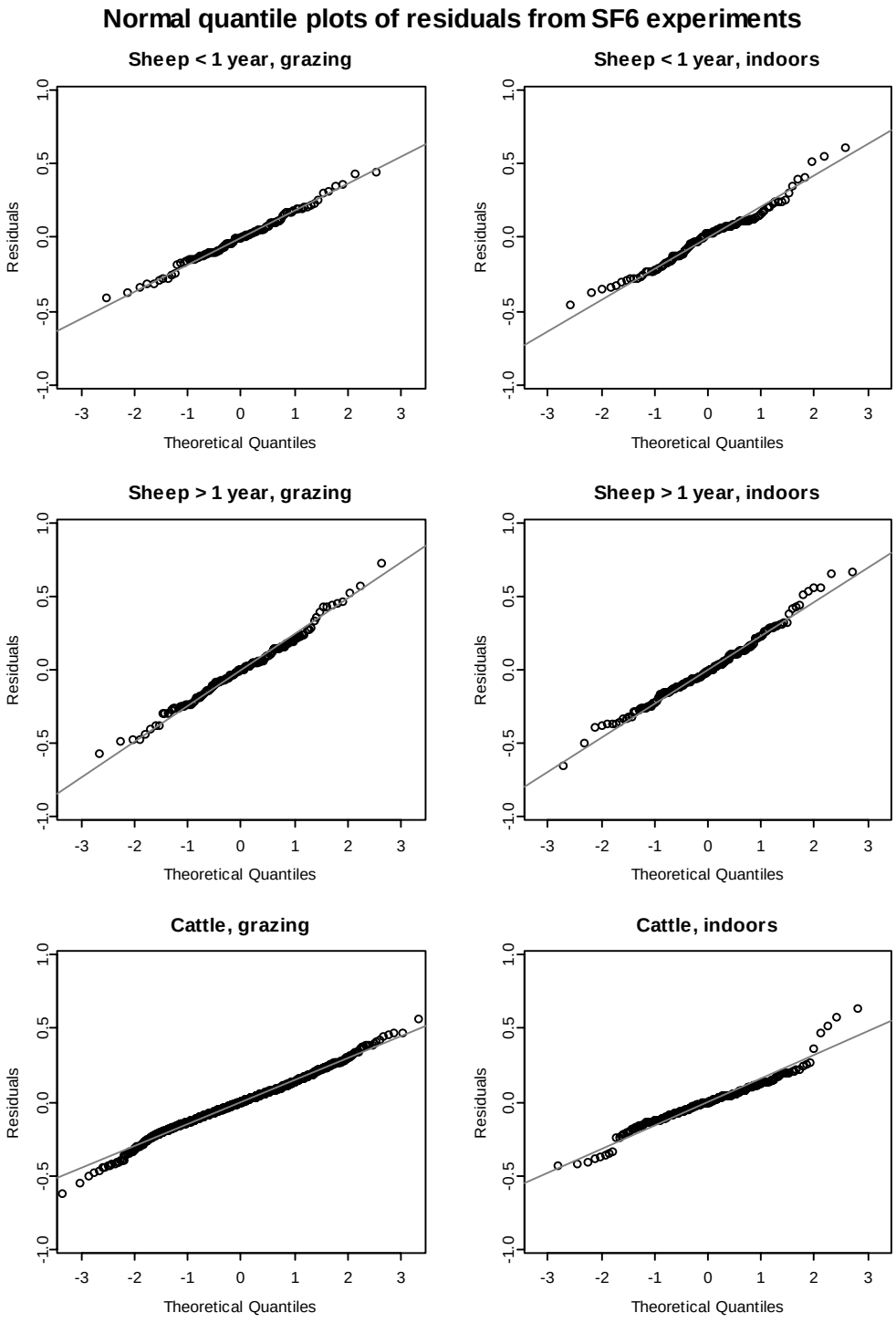

Figure 3: **Q-Q normal plots of residuals from the model fits by species groups for data from both SF_6 experiment classes.**

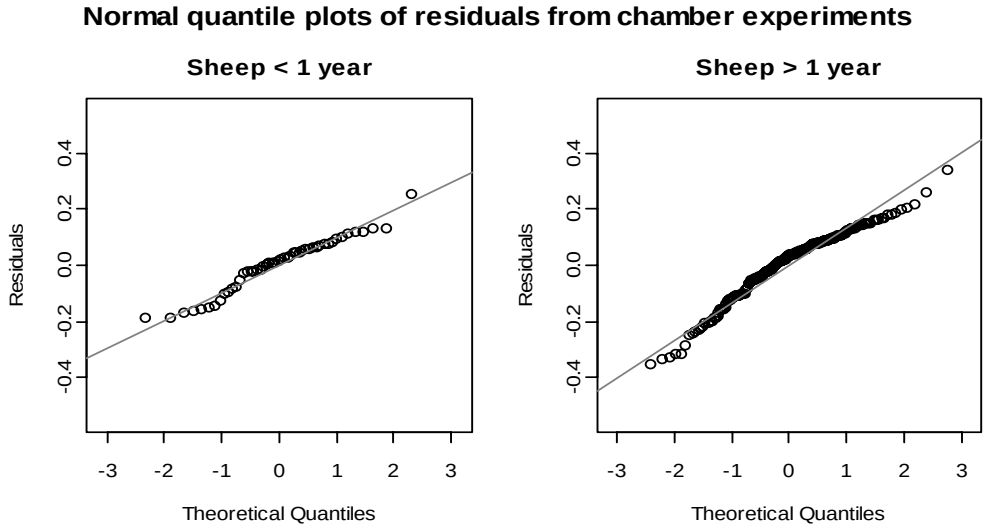

Figure 4: **Q-Q normal plots of residuals from the model fits by species groups for data from the chamber experiments.**

Estimation of the mean yields

The estimate of the mean yields is obtained by direct substitution of the parameter estimates from the fitted model into Equation 1. These estimates are efficient because they use the Maximum Likelihood estimates from each model. Estimation of the standard errors and coefficients of variation of the mean yield estimates is by simulation. The estimates of the mean yields together with their c.v.s are given in Table 1. The simulation for each species group starts with the fitted model for the group.

Table 1: **Sample sizes, n, and estimated mean yields for the animal groups by experiment class on grass-based diets. Coefficients of variation (%) of the sampling distributions of the estimates are in parentheses.**

	SF_6 grazing		SF_6 indoors		Chambers	
Species group	n	Est. mean	n	Est. mean	n	Est. mean
Sheep < 1 yr	90	16.50 (5.2)	102	23.87 (9.0)	49	24.04 (2.9)
Sheep > 1yr	123	19.24 (5.1)	153	23.69 (2.3)	182	22.22 (3.1)
Cattle	1210	21.09 (3.6)	200	21.11 (7.0)	0	–

The estimation procedure is complicated and it is not possible to calculate the coefficient of variation in an analytic way. Instead, the sampling distribution of the mean yield is simulated by generating a large number of sets of log yields, y_{ij}, from the model with parameter values equal to the fitted values from the model. We use 5000

sets of simulated log yields to obtain the estimates of the sample coefficient of variation. This was repeated for each experiment class and for each species class.

A single set of log yield data is obtained by first generating a set of experiment effects from the normal distribution with the standard deviation equal to the estimated σ_b. To theses are added the β estimate from the fitted model. These are assigned to the records according to the experiment. Finally errors are added by using a bootstrap sample (which allows replacement) from the fitted model residuals. The model is then fitted to the new data and the new parameter estimates are substituted into Equation 1 to get a single sample value from the sampling distribution of the mean yield estimate. After repeating 5000 times to get a sample from the sampling distribution of the mean yield estimate, the coefficient of variation is then calculated by dividing the sample standard deviation by the sample mean and converting to a percentage.

Unfortunately, there have been no experiments in chambers for cattle with grass-based diets and therefore, there is no estimate of the mean yield estimate for cattle in the chamber class of experiments. There have been two experiments in chambers with cattle that used non-grass-based diets, one used a diet of ryegrass chaffage and the other a diet of lucerne pellets.

There are a number of differences in the estimates (and c.v.s) between the different experiment classes for the same species groups. The differences between experiment classes occur in both the estimates and the coefficients of variation. The results from the model-based method can also be compared with the results from estimating the mean yield using a simple arithmetic mean of the yields for the same species group and experiment class. The arithmetic mean treats the differences between individual experiments as part of the overall variation and, consequently, will down-weight the experiment effects and ignores the varying numbers of records in each experiment, which leads to a different estimate. For the same reasons the associated c.v. of the sampling distribution of the arithmetic mean will generally be an underestimate of the true c.v.. The estimates from the arithmetic mean (Table 2) are given for comparison purposes with their associated c.v.s.

The arithmetic mean is the optimum estimator in conditions when the variances of the data are equal, there is no correlation structure and the error model is close to being normal, but it performs less well when there is heteroscedasticity in the data and when there is correlation. For yield, variance is likely to increase with size of the yield, so that larger values of yield have larger variance. This follows because there is little evidence of the variance of the log yields depending on size. Despite these remarks many of the arithmetic means estimates are close to the model-based estimates. Exceptions are for both experiment classes for cattle and for the sheep > 1 year in chambers. All c.v.s for the arithmetic means are much smaller than their model-based counterparts. Because likelihood ratio tests showed that experiment random effects were significant for every combination of species group and experiment class, to

ignore their existence and use the c.v.s associated with the arithmetic means would seriously underestimat uncertainties.

Table 2: **Sample sizes and sample arithmetic mean yields for the animal groups on grass based diets by experiment class. Coefficients of variation (%) of the sampling distributions of the arithmetic means are in parentheses.**

	SF_6 grazing		SF_6 indoors		Chambers	
Species group	n	Arith. mean	n	Arith. mean	n	Arith. mean
Sheep < 1 yr	90	16.49 (2.4)	102	23.87 (2.8)	49	24.07 (1.5)
Sheep > 1yr	123	19.55 (2.7)	153	23.67 (2.2)	182	22.91 (1.0)
Cattle	1210	19.89 (0.7)	200	19.65 (1.6)	0	–

2.3 Discussion of mean yield estimates

In this section we examine the differences between experiment groups in the estimates for the mean yields for each species class. As described earlier, the three experiment classes use different methods for estimating/measuring the denominator and numerator of the methane yield ratio, namely ch4 and dmi. The differences between experiment groups are likely to be related, in some way, to the different ways the ch4 and dmi were calculated.

The most striking differences are within the two sheep groups and the two experiment classes that use the SF_6 methane technique (top left 4 cells in Table 1). For the SF_6 indoors experiment class the yield estimates by age of sheep are very similar but for the SF_6 grazing experiment class the difference is large (but not significant, p-value = 0.061, using a comparison test for the means of the log yields, β). All four estimates used the SF_6 technique but there were differences between the groups in the way the dmi was calculated. The different ways of calculating dmi most likely account for some of the difference between the yield estimates for grazing sheep < 1 year and grazing sheep > 1 year. The same would be true for difference between yield estimates grazing and indoors for both sheep age groups. All the sheep < 1 year were males and the dmi was calculated using the whole faeces method. On the other hand, nearly 75% of the older sheep were ewes and most of the dmi calculations would have been based on energy requirements. In the SF_6 indoors class for both young and old sheep the dmi would have been calculated directly from the monitored feed intake. Differences between the yield estimates from the SF_6 indoors and the chambers experiment classes for young and old sheep (although not significant) may suggest that there are differences between the SF_6 technique and the direct measurement of methane in the chambers. However the differences are very small compared with their c.v.s and are definitely not significant.

There have been a number of reports in the literature (originating with Blaxter & Clapperton 1965) that the methane yield rate depends on the level of feed relative to maintenance. There is also good evidence of this in the data from both the grazing and the indoors SF_6 experiment classes in the plots of yield against food intake level relative to maintenance (Figure 5). Unfortunately the feed intake relative to maintenance variable was not available in the data from chamber experiment class, so no plots of yield against intake level relative to maintenance could be done.

The plots for all species groups whether indoors or grazing show a decreasing trend with intake relative to maintenance. In particular, the SF_6 grazing experiments for cattle show a strong downward trend. The cluster of points centred around a level above maintenance of 4 in the cattle grazing plot will mostly be lactating dairy cows, and these are centred on a yield of less than 20 g CH_4/kg DMI. The indoors data for sheep of both ages show a smaller trend but the range of level above maintenance is half that for the grazing sheep of both ages.

The cattle grazing indoors was broken down into dairy cows (female dairy breeds of age 2 years or more) and non-dairy cattle (all of which happen to be less than 2 years old) and the two groups plotted against level above maintenance.

The trend is also strong for cattle indoors, especially when it is noted that all the points (coloured gray) from a particular experiment appear in the bottom left corner, suggesting that there was something very unusual about the experiment. This experiment, which will have a relatively large negative experiment effect is very likely the reason for the large c.v. (7%) associated with the yield estimate for cattle SF_6 indoors. There is a hint of a flattening curve in the trends but the trends appear to be much more straight-line when the log yields are plotted against level above maintenance. The trend lines for the two plots would be quite similar (in slope and intercept) which suggests that level above maintenance is the more important variable and that age has much less influence on yield.

This result has implications for the calculation of total methane emissions because of the relatively large proportion of the total emissions coming from dairy cattle. It appears to be important to further disaggregate the inventory into separate species groups for dairy cows and non-dairy cattle and use separate estimated mean yields. Other analyses on grazing dairy cows showed increased yields in the autumn and winter months (not statistically significant, though) when their intakes above maintenance are reduced.

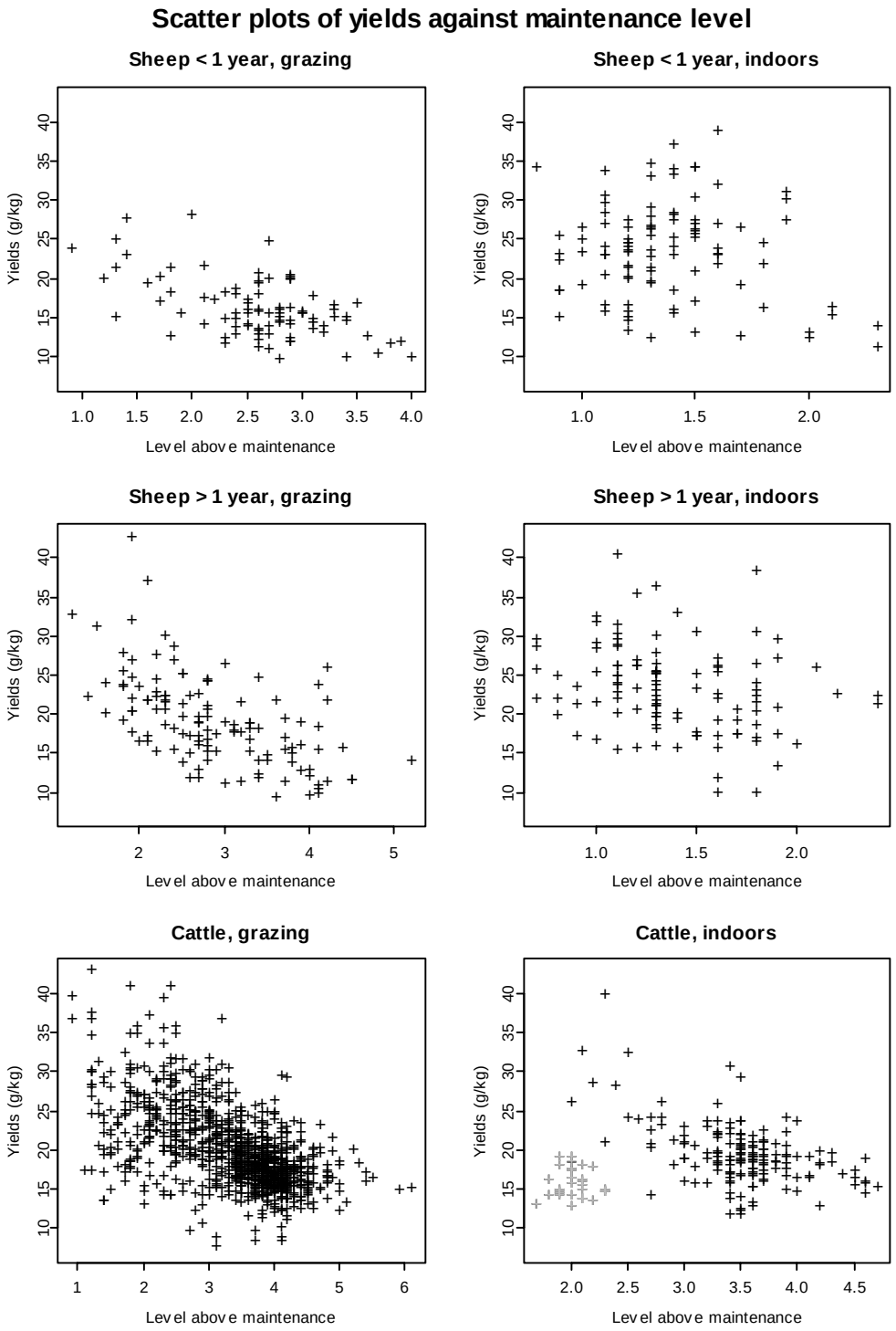

Figure 5: **Plots of yields against food intake relative to level above maintenance for the species groups using data from the SF6 grazing and SF6 indoors.**

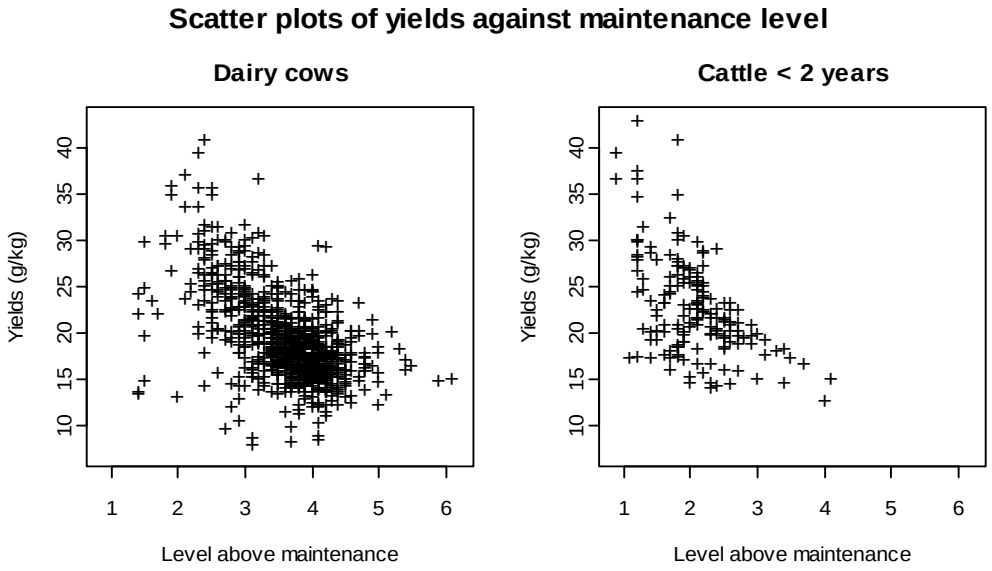

Figure 6: **Plots of yield against level above maintenance for dairy cows and other cattle**

It would be very useful to be able to check whether the same trend is there for experiments in chambers. It would appear that the time that food is in the rumen might be an explanation for the trend. However, the SF_6 technique only measures methane emissions from the mouth and nostrils and increased intake above maintenance may result in increased emissions from elsewhere.

In this section we have looked at some issues that might introduce bias in to the emissions inventory. In the next section we examine some of the sources of variation.

Discussion of variation contributing to uncertainty in the mean yield estimates

Each model fitted had two components of variance, between-experiment variance (the variance of the experiment random effects) and the within-experiment variance (the between-record variance within the same experiment). For each combination of species group and experiment class estimates of the two components of variance (expressed as the estimates of the standard deviations σ_b and σ) along with estimates of the mean log yield and its standard error are obtained from the fitted model. These estimates have been grouped together by species group so that differences between the experiment classes can be contrasted for each species group (Tables 3, 4, & 5).

Perhaps the first point to note is that the standard error of the estimate of β is immediately interpretable as the c.v. of the estimate of the median of the yields, $\exp(\beta)$, because of the relationship between the parameters of the normal distribution of the log yields and the parameters of the lognormal distribution of the yields. It can be seen that c.v.s of the estimated mean yields in Table 1 are almost exactly the same as the standard errors of the estimates of β (expressed as a percentage). The same c.v.

for the estimated mean yield as for the estimated median yield means that the standard error for the estimated mean yield is larger than that for the estimated median yield because the estimate is larger. It seems that the simulation method for estimating the c.v. of the estimated mean yield was unnecessary and the c.v.s could have been estimated directly from the approximate standard errors in the model fit output. The percent standard error of the estimated mean yield is then obtained directly from the standard error of the estimate of β via the relationship between the normal and lognormal parameters as follows:

$$\text{c.v.}(\text{mean yield}) = 100 \times \sqrt{\exp\left(\text{s.e.}(\beta)^2\right) - 1},$$

which closely approximates $100 \times \text{s.e.}(\beta)$ when the standard error (s.e.) is small.

Table 3: Number of experiments, number of experimental records, and parameter estimates for the sheep < 1 year models fitted to data from each experiment class. The Standard errors of the estimates of β are in parentheses.

Experiment class	Number of experi-ments	Number of records	Mean of log(yield), β. (s.e.)	Between experiment std dev., σ_b	Within experiment std dev., σ
SF_6 Grazing	7	90	2.778 (0.052)	0.127	0.185
SF_6 Indoors	6	102	3.129 (0.089)	0.211	0.210
Chambers	3	49	3.174(0.028)	0.040	0.099

Table 4: Number of experiments, number of experimental records, and parameter estimates for the sheep > 1 year models fitted to data from each experiment class. The Standard errors of the estimates of β are in parentheses.

Experiment class	Number of experi-ments	Number of records	Mean of log(yield), β. (s.e.)	Between experiment std dev., σ_b	Within experiment std dev., σ
SF_6 Grazing	13	123	2.915 (0.051)	0.163	0.242
SF_6 Indoors	9	153	3.134 (0.026)	0.045	0.246
Chambers	3	182	3.091 (0.031)	0.049	0.134

Table 5: **Number of experiments, number of experimental records, and parameter estimates for the cattle models fitted to data from each experiment class. The Standard errors of the estimates of β are in parentheses.**

Experiment class	Number of experi-ments	Number of records	Mean of log(yield), β. (s.e.)	Between experiment std dev., σ_b	Within experiment std dev., σ
SF_6 Grazing	35	1210	3..016 (0.036)	0.207	0.151
SF_6 Indoors	9	200	3.016 (0.071)	0.207	0.159

For the within-experiment variation, the standard deviations are quite similar for the SF_6 grazing and SF_6 indoors experiment classes. This is, perhaps, surprising as the indoors class uses direct measurement of dmi. For both age groups of sheep, the standard errors for the within experiment variation are smaller in chambers than for either of the SF_6 classes. This would be expected because of the direct measurement of both the ch4 and dmi variables.

For estimating between-experiment variation there were only a few experiments in some of the species group experiment class combinations. There were only 3 experiments in each of the sheep groups in chambers and this means that the between-experiment standard deviation estimates will have very large uncertainty. Nevertheless it does appear that the between-experiment variation is generally smaller for the chambers class of experiments than for the SF_6 technique experiments, although sheep > 1 year in SF_6 indoors experiments is an exception. In many cases the standard deviations of the between-experiment effects are comparable with the within-experiment standard deviations meaning that log yields for records within the same experiment have correlations ranging between 0.04 (for sheep > 1 year, indoors) and 0.65 (for cattle grazing). The larger correlations reduce the effective sample sizes of the experiments. The large between-experiment standard deviations for cattle and for sheep > 1 year, indoors may also reflect the different animal groups, such as dairy cows versus calves or lactating ewes versus dry sheep, that make up the records of different experiments.

Some attempt was made to estimate the between-record variance component for repeat measurements of yield on the same animal by fitting models with an extra random effect for each animal. The results were very variable, almost certainly because many experiments had a large number of records that were not repeat measurements, and no general conclusions could be drawn. Even fitting models to single experiments in which most measurements were repeats had widely differing standard deviations.

3. Discussion of the total inventory methane estimation procedure

This report concentrates primarily on the method of estimation of the mean methane yields for grass fed animals and on examining sources of variation in relation to the various methods of calculating daily methane production rate and the daily DMI rate. However, we also comment on the methodology that has been used to scale up the estimated mean yields to get the emission inventory (described in Clark et al. 2003).

In the procedure, ruminant species have been group into 5 species groups: sheep < 1 year old, sheep > 1 year old, cattle, deer, and goats. We believe the relationship between yield and intake level is reason to use separate estimates of yield for dairy cows and non-dairy cattle, especially in the months when milk production and hence intake requirements are greatest. The inventory methodology already disaggregates the energy calculations in an even finer way.

In calculating the emission inventory there is a disjunction between how the energy requirements of the ruminant population is calculated for conversion to total DMI and the way the methane yield is estimated. Firstly almost all New Zealand's ruminants graze, whereas many experiments are carried out indoors or in chambers where the food intake controlled. In some experiments (data from such experiments has not been used in this analysis) the animals have been fed processed food such as pellets and roughage. Secondly the method of calculation of the total DMI is based on energy requirements currently calculated using the CSIRO protocol (CSIRO 1990) which is then converted to DMI using energy densities for the food eaten adjusted to reflect the energy content at different times of the year. If a different protocol were used a different total DMI requirement would be calculated and yet, the estimates of yield based on measured DMI would not have changed in any way. It is because the yields do not relate directly to the variable (in this case estimated DMI) used to scale up to the total emissions that there is a strong risk of systematic error (or bias) in the total emissions estimate.

The real problem is that there is no obvious variable that could be used instead of the energy requirement-based variable currently used. It might be that a more directly related scaling variable could be found and used, which would then allow the regression of daily methane production on it as a predictor variable. It would also be important to use a variable for which it is possible to calculate values for the records in the methane yield experiments that have already been done. If such a variable could be used then the risk of bias in the inventory estimate would have been greatly reduced. Such a variable would likely result in larger c.v.s for the yield estimate (and a larger uncertainty in the inventory estimate) but this is a reasonable trade-off against the currently unacknowledged risk of unknown bias that might (or might not) be as large or larger than current c.v. of the inventory.

To assess the error of the estimated emission inventory we would recommend the use the lognormal distributions for the error distributions of multiplicative components that appear. This would simplify calculations and is a reasonable assumption because all the quantities are positive. It also affords a way to translate error bounds, often expressed as percentages, to means and variances for substitution into formulae or for use in simulations. It also is reasonable to assume the sampling distribution of the yield estimate would be well approximated by a lognormal distribution. In principle, there is then no need to do a simulation to obtain the error estimate for the estimated emission inventory, although it may still be the best approach in a practical sense. Kelliher et al. (2007) considered the problem of uncertainty in the product of the four quantities that comprise the total emissions for a species group. They considered the comparison of the inventory estimates for two different years but made unnecessary approximations to get their expressions for the variances of a product and the difference between two products with a common variable. In general, their variance estimate of the product will be an underestimate. However the size of the underestimate of the product variance and the size of the approximation error for the variance of the difference between the two products depend on how large the c.v.s of the components are.

We would adopt the following approach. If X_1 and Y are independent random variables with means μ_1 and μ and variances σ_1^2 and σ^2 respectively then it follows that the product, X_1Y, has mean $\mu_1\mu$ and variance

$$\mathrm{Var}\left(X_1Y\right) = \mu^2\sigma_1^2 + \mu_1^2\sigma^2 + \sigma_1^2\sigma^2. \qquad (2)$$

The expression for the variance is exact (as is that for the mean) for any two independent random variables. Therefore, it is better than the often-used first order approximation $\mu^2\sigma_1^2 + \mu_1^2\sigma^2$ (see Stuart & Ord 1987), which always underestimates the variance of the product. The above result can be repeatedly applied to get the mean and variance of the product of more than 2 independent random variables. If the additional assumption is made that X_1 and Y have lognormal distributions then the product will also have a lognormal distribution (as will the quotient of two random lognormal variables). In fact, if a set of variables have a multivariate lognormal distribution (with correlation) then the product of the variables (raised to any power, integer or real, positive or negative) will have a lognormal distribution.

For the comparison of the emission inventory for two years, the required variance of the difference can also be calculated directly. The two inventories comprise totals of methane emissions over strata into which the inventory has been disaggregated. The strata can be grouped together in groupings where there is a variable common between the two years (usually the yield of some species group, which then defines the stratum grouping). The basic form is that the emissions totals over the strata grouping for the two years under comparison, T_1 and T_2, can be written as $T_1 = X_1Y$ and $T_2 = X_2Y$, where X_1 and X_2 are products of the variables that are independent between the two

years (energy requirement or DMI) and Y is the part of the product where the variables are common to both years (the yield estimate and perhaps the average energy density). All three components, X_1, X_2, and Y are assumed to be independent. The difference between the stratum grouping totals can be written as $T_1 - T_2 = (X_1 - X_2)Y$, which is the product of two independent random variables: $X_1 - X_2$ with mean $\mu_1 - \mu_2$ and variance $\sigma_1^2 + \sigma_2^2$, and Y with mean μ and variance σ^2. Applying Equation 2 gives

$$\begin{aligned} \mathrm{Var}(T_1 - T_2) &= \mu^2\left(\sigma_1^2 + \sigma_2^2\right) + \left(\mu_1 - \mu_2\right)^2\sigma^2 + \sigma^2\left(\sigma_1^2 + \sigma_2^2\right) \\ &= \left(\mu_1 - \mu_2\right)^2\sigma^2 + \left(\mu^2 + \sigma^2\right)\left(\sigma_1^2 + \sigma_2^2\right). \end{aligned} \quad (3)$$

To get the variance of the difference between the total inventories for two different years the variances of the strata grouping differences (obtained using the expression in Equation 3) are summed. A test of significance of the difference between the inventories for the two different years can then be performed using this variance. It would be reasonable to assume a normal approximation to the distribution of difference because it is the difference of two distributions that are skewed the same way and therefore the difference is likely to be approximately symmetric.

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Appendix - Table A1: Details of the SF_6 data set used for analysing the CH4 yield.

Person running trial	Trial	Species	Sex	Location	Basal diet	Total	In/out	Total	Comments
Adrienne Cavanagh	LIC BoviQuest genetic variation	Cattle	Female	Grazing	Grass	296		296	
	LIC BoviQuest genetic variation trial 2	Cattle	Female	Grazing	Grass	385		385	
	Repeat LIC trial 2004	Cattle	Female	Grazing	Grass	30		30	
Ben Vlaming	Ben variance exp	Cattle	Female	Indoor	Lucerne silage	4	out	0	not grass
		Cattle	Female	Indoor	Tmr	4	out	0	not grass
	Ben's tube swapping	Cattle	Male	Indoor	Lucerne hay	24	out	0	not grass
	Vlaming sf6/cal comp	Cattle	Female	Indoor	Tmr	4	out	0	not grass
Carlos Raminez	Carlos Willow	Sheep	Male	Grazing	Grass	38	out	0	no DMI estimated
		Sheep	Male	Grazing	Willow	40	out	0	not grass
Cesar Pinares-Patino	Cesar bloat trial June 06	Cattle	Female	Grazing	Grass	48	out	0	special bloat treatment
	Cesar interspecies trial	Sheep	Male	Grazing	Grass	6		6	
		Sheep	Male	Indoor	Lucerne hay	6	out	0	not grass
	Cesar Trial	Sheep	Male	Grazing	Grass	38		38	
		Sheep	Male	Indoor	Lucerne hay	36	out	0	not grass
	Cesar Variation	Sheep	Male	Grazing	Grass	50		50	
		Sheep	Male	Indoor	Chaffage	96	out	0	not grass
		Sheep	Male	Indoor	Grass	24		24	
	Persistence indoors	Cattle	Female	Indoor	Lucerne hay	9	out	0	not grass
	Rumen digestion	Cattle	Female	Indoor	Grass	9		9	
	Tube swap June 05	Cattle	Male	Indoor	Chaffage	48	out	0	not grass
Eric Kolver	Kolver NZ vs OS Trial	Cattle	Female	Grazing	Grass	60		60	
Garry Waghorn	Agri-feeds Rumax Trial	Cattle	Female	Grazing	Grass	30		30	
	Monensin trial	Cattle	Female	Indoor	Grass	119		119	
	Ryegrass/Sulla	Cattle	Female	Grazing	Grass	7	out	0	special diet supplement
Garry Waghorn/	Pasture trial	Cattle	Female	Indoor	Grass	40		40	
Dave Clark		Cattle	Female	Indoor	Maize	24	out	0	not grass
	Twin Trial	Cattle	Female	Indoor	Grass	30		30	
German Molano	Aussie vaccine trial	Sheep	Female	Indoor	Lucerne hay	123	out	0	not grass
	Ballantrae calf trial	Cattle	Male	Grazing	Grass	72		72	
	Fumaric acid trial	Sheep	Male	Indoor	Lucerne hay	35	out	0	not grass
	Lamb ewe trial	Sheep	Female	Indoor	Grass	117		117	
		Sheep	Male	Indoor	Grass	39		39	
	Landcare March 2002	Cattle	Female	Grazing	Grass	20		20	
	Landcare Wards farm	Cattle	Female	Grazing	Grass	32		32	
	Level of Feeding	Sheep	Female	Indoor	Grass	32		32	

Person running trial	Trial	Species	Sex	Location	Basal diet	Total	In/out	Total	Comments
Frank Kelliher	Landcare January 2002	Cattle	Female	Grazing	Grass	20		20	
	Landcare Lincoln whole-herd trial	Cattle	Female	Grazing	Grass	20		20	
Harry Clark	Clark lactating ewe trial	Sheep	Female	Grazing	Grass	46		46	
Mark Ulyatt	Lassey sheep trial	Sheep	Male	Grazing	Grass	51		51	
	Ulyatt Aorangi sheep trial	Sheep	Male	Grazing	Grass	10		10	
	Ulyatt Ballantrae sheep trial	Sheep	Male	Grazing	Grass	10		10	
	Ulyatt BOP cow trial	Cattle	Female	Grazing	Grass	8		8	
	Ulyatt cow season trial	Cattle	Female	Grazing	Grass	39		39	
	Ulyatt Kikuyu cow trial	Cattle	Female	Grazing	Grass	9		9	
	Ulyatt Kikuyu sheep trial	Sheep	Male	Grazing	Grass	10		10	
	Ulyatt Massey cow trial	Cattle	Female	Grazing	Grass	10		10	
	Ulyatt sheep season trial	Sheep	Female	Grazing	Grass	44		44	
Natasha Swainson	Krause indoor hind trial	Deer	Female	Indoor	Grass	12	out	0	deer
	MAF CC13 Deer trial	Deer	Female	Grazing	Grass	38	out	0	deer
		Deer	Male	Grazing	Grass	8	out	0	deer
	Massey deer indoors	Deer	Male	Indoor	Grass	6	out	0	deer
	Massey inventory	Deer	Male	Grazing	Grass	70	out	0	deer
	Natasha Comparative trial	Cattle	Female	Indoor	Chaffage	88	out	0	not grass
		Deer	Male	Indoor	Chaffage	100	out	0	not grass
		Sheep	Male	Indoor	Chaffage	99	out	0	not grass
	Natasha Sheep Mitigation	Sheep	Male	Indoor	Chicory	60	out	0	not grass
		Sheep	Male	Indoor	Grass	60	*	24	special diet supplement
	Natasha Weaner deer	Deer	Male	Grazing	Grass	160	out	0	deer
Norm Thomson	Norms Oils	Cattle	Female	Grazing	Grass	30	out	0	special diet supplement
	Supplementing dairy cows with oils	Cattle	Female	Grazing	Grass	30	out	0	special diet supplement
Sharon Woodward	Cow-calf Trial	Cattle	Female	Grazing	Grass	79		79	
Terry Knight	BLCS trial	Cattle	Female	Grazing	Grass	58	*	28	30 out, with BLCS diet treatment
	Caucasian clover	Sheep	Male	Indoor	Caucasian clov	24	out	0	not grass
		Sheep	Male	Indoor	Clover	24	out	0	not grass
		Sheep	Male	Indoor	Grass	28		28	
	Chloroform trial	Cattle	Female	Indoor	Chaffage	72	out	0	not grass
	Fibre intake trial	Sheep	Male	Indoor	Grass	39	out	0	special diet supplement
Terry Knight/Frank Kell	Aorangi Landcare Trial	Cattle	Male	Grazing	Grass	58		58	
–	Pasture and Lotus	Cattle	Female	Grazing	Grass	16		16	
	Pasture and lotus silage	Cattle	Female	Indoor	Grass	6		6	
	Swap Latin square	Cattle	Male	Indoor	Lucerne hay	46	out	0	not grass
* some but not all units removed						3463		1945	