Ministry for Primary Industries
Manatū Ahu Matua

Statistical analysis to determine a nationally representative pasture quality sampling programme

Final Report

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Project Overview

The aims of this project were to (a) collate and analyse available pasture quality data to determine whether the data are statistically robust enough to provide nationally representative values for the key livestock classes on a monthly basis, (b) statistically derive the number of samples required to represent the seasonal and spatial variations of metabolisable energy (ME) and crude protein (CP) in each region; and (c) make clear recommendations for the establishment of a national pasture sampling programme. This work was grouped into two parts.

Part 1 consisted of the collation and analysis of existing pasture quality data. The results of Part 1 are included in a separate report (Upsdell et al. 2016).

Part 2 focused on the statistical design and recommendations for a national pasture sampling programme. The results of part 2 are described in this report.

Executive Summary

The aims of this study were to (a) collate and analyse available pasture quality data to determine whether the data are statistically robust enough to provide nationally representative values for the key livestock classes on a monthly basis, (b) statistically derive the number of samples required to represent the seasonal and spatial variations of metabolisable energy (ME) and crude protein (CP) in each region; and (c) make clear recommendations for the establishment of a national pasture sampling programme. The collation and analysis of existing pasture quality data are included in a separate report (Upsdell et al. 2016), while this report focuses on the statistical design of a national pasture sampling programme.

A major problem with the existing dataset is that the data were collected for other purposes and may not be representative of New Zealand pastures as a whole. For the sampling programme we focused on a stratified sampling design. Stratified sampling has the advantage that it ensures that each category is sampled, which improves representativeness. Our stratification scheme consisted of animal type (dairy, sheep/beef, deer), region, season, and slope (low, medium, high; not included for dairy).

For each animal type we calculated the optimal sampling allocation by region and season for ME and CP. This is the allocation that minimises the overall uncertainty for a given number of samples. There were insufficient data on the variability of ME and CP by slope class.

For this exercise it was assumed that there was no prior knowledge about the ME and CP distributions. Therefore, in order to use the assumption that the sample mean followed a normal distribution, we required that a sufficiently large number of samples were taken (≥30) so that the Central Limit Theorem could be applied. The 95% confidence interval was then calculated assuming the mean followed a normal distribution. In many cases the minimum number of samples required to achieve a precision of ±10% could be less than 30 if the data were known to be normally distributed.

In order to get the ME and CP within ±10% for each region, season and slope class would require 5760 samples for each species (16 × 4 × 3 × 30). This assumes that the ME and CP are calculated independently for each region/season/slope combination. However, if the requirement is simply that the national/annual mean ME and CP be within ±10%, then only 32–34 samples across representative sites would be needed for each species. In practice, it might be possible to achieve a given level of precision with fewer samples, but this is difficult to predict in advance. However, once data collection has begun, bootstrapping methods could be used to estimate the distribution of the (weighted) sample mean and hence derive a 95% confidence interval. In addition, the number of samples could be reduced if inferences about (e.g.) seasonal patterns could be applied across multiple categories. Upsdell et al. (2016) gives one example of this.

There are alternative stratifications that could result in lower within-stratum variances and result in better representativeness. One of these was the LENZ classification that classifies land according to environmental and climate similarities, as opposed to “region” which is an administrative unit. The current stratification also did not include any accounting for management practices. However, Beef + Lamb New Zealand and Dairy NZ both have farm type classifications which group farms of similar intensities. These alternative classifications would require some additional changes to the inventory in order to identify the proportion of animals in each category, but could result in more representative estimates of ME and CP.

1 Introduction

New Zealand’s national inventory uses a Tier 2 methodology to calculate enteric methane (CH_4) emissions from the four major grazed livestock species. This model also calculates the amount of N excreted as urine and faeces that feeds into the calculation of nitrous oxide (N_2O) emissions from agricultural soils. These calculations require information about pasture quality. For enteric fermentation, the metabolisable energy (ME) of pasture (along with digestibility) is used to determine the amount of dry matter intake (DMI) each animal requires to meet its energy needs. The N intake (which is proportional to the crude protein (CP) content of the pasture) is used to calculate the amount of N excreted in urine and faeces after a proportion of consumed N is used for growth, pregnancy, and milk, meat and wool production. This excreted N is then used to determine the N_2O emissions.

Therefore accurate estimates of ME and CP at a national (or regional) scale are needed to calculate New Zealand's greenhouse gas emissions.

Both ME and CP can vary according to a number of factors including climate, slope, season, pasture species and time since grazing. Currently the New Zealand national inventory uses monthly ME contents for dairy and deer, seasonal ME contents for sheep/beef and yearly N content (proportional to CP) estimates for dairy, sheep/beef, and deer (Pickering & Wear 2013).

Ensuring that the mean ME and CP values used are truly representative over all of New Zealand's pasture systems is a major challenge. A series of studies were conducted to relate pasture ME and CP to satellite spectral data (Ausseil et al. 2009, 2010a-b, 2011, 2012). Such methods have the advantage of enabling measurements across the whole of New Zealand but issues were found, particularly for N%. From these studies, relationships were found for ME and N content with residual standard errors of 0.95 and 0.65 respectively. However, for the N content there was a saturation issue with the satellite measurements when N levels were above 3% N (equivalent to 18.75% CP), which limited the ability to use this method for high N contents.

Bown et al. (2013) collated a database of ME and N content samples collected from 1996 to 2011, which they analysed using ANOVA for each region and farm type (dairy and sheep/beef). However, their conclusion was that the data from the collated database were not sufficient to provide scientifically validated estimates of monthly ME or N content on either a regional or New Zealand wide basis for dairy, sheep/beef or deer farms, and recommended that a nationwide survey of dairy and sheep/beef pastures be biometrically designed and conducted.

This study consists of two parts. The first part involves a reassessment of ME and CP values by region, season and pasture type using more recent data and statistical methods. The second part looks at designing a stratified sampling design for ME and CP that could be used to collect future pasture quality data.

2 Objectives

The 3 objectives of this study were:

1. Collate and analyse available data (metabolisable energy and crude protein) to determine whether the data are statistically robust enough to provide nationally representative values of pasture quality for the key livestock classes on a monthly basis, as used in the agricultural greenhouse gas inventory.
2. Statistically derive the number of samples required to represent the seasonal and spatial variations in each region (based on ME and crude protein), in a nationwide cost-effective pasture sampling programme at contrasting levels of variability.
3. Make clear recommendations for the establishment of a national pasture sampling programme, including locations of samples.

The first objective is covered in Section 3 and the accompanying report Upsdell et al. (2016). Objectives 2 and 3 are covered in Section 4.

3 Analysing Existing Data

3.1 Reassessment of metabolisable energy and crude protein in New Zealand pastures

A reassessment of the metabolisable energy and crude protein content in New Zealand pastures was performed by Upsdell et al. (2016). The data from Bown et al. (2013) were expanded with an additional 2,071 metabolisable energy and 976 crude protein datasets and this expanded data set was used to develop statistical models of ME and CP. Smoothing models were used to mitigate the effects of missing data and the non-balanced nature of the data set. The models had the form Season*(Stock type + Region + Site) where season was a curve repeating every 365 days. This exercise is explained in more detail in a separate report (Upsdell et al. 2016)

Table 1 and 2 show the regional estimates for ME and CP respectively. For further results of the statistical analysis refer to accompanying report (Upsdell et al. 2016)

Table 1: Estimates of metabolisable energy (MJME/kg DM) by season and stock type. Source: Upsdell et al. (2016)

Season	Dairy	Sheep / Beef	Deer
January	10.95	10.05	10.05
February	10.76	9.80	9.94
March	11.00	9.84	10.05
April	11.37	10.29	10.24
May	11.63	10.78	10.42
June	11.82	10.86	10.54
July	11.86	10.90	10.61
August	11.90	11.11	10.71
September	11.87	11.20	10.85
October	11.73	11.21	10.94
November	11.43	10.84	10.8
December	11.19	10.38	10.42
Standard Error of Estimate	**0.15**	**0.11**	**0.61**
Relative Standard Error	**1.3%**	**1.0%**	**5.8%**

Table 2: Estimates of crude protein (% DM) by season and stock type. Source: Upsdell et al. (2016)

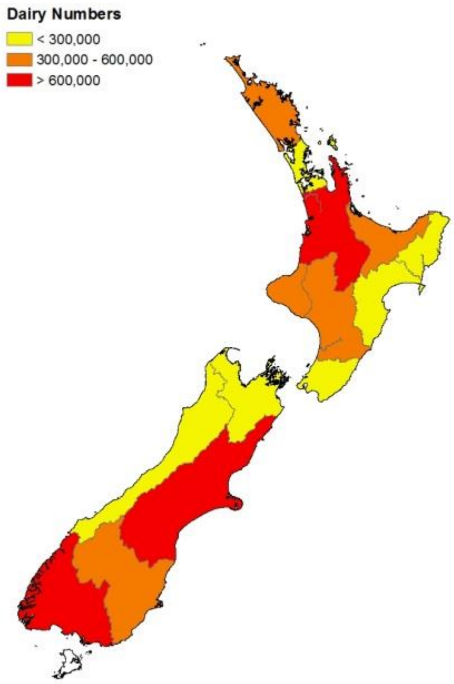
Season	Dairy	Sheep / Beef	Deer
January	20.28	17.60	18.23
February	20.94	16.37	18.61
March	23.2	16.47	18.85
April	24.26	18.20	19.29
May	24.02	22.27	19.83
June	22.06	21.49	20.46
July	21.50	22.07	20.05
August	21.22	22.29	19.98
September	22.13	22.53	20.68
October	22.24	20.62	20.47
November	20.48	16.95	18.97
December	20.28	17.89	18.90
Standard Error of Estimate	**0.72**	**0.86**	**2.84**
Relative Standard Error	**3.3%**	**4.4%**	**14.6%**

3.2 Data coverage

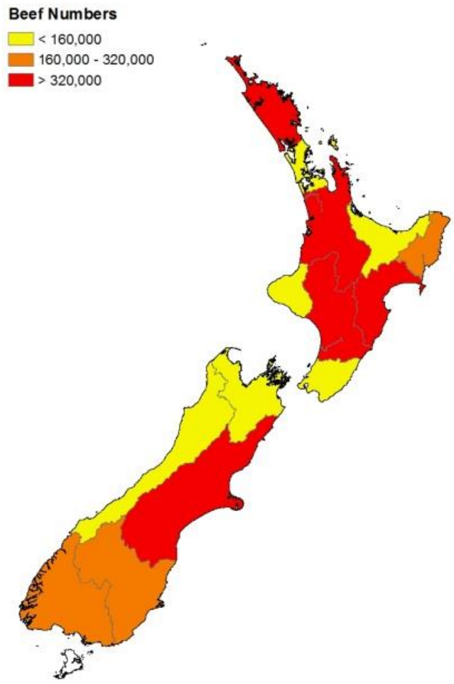
Figure 1(a)–(d) shows the number of animals by region according to the 2015 agricultural production survey (Statistics New Zealand). The number of available datasets by region and pasture type (dairy, sheep/beef, and deer) used in Upsdell et al. (2016) is given in Figure 2. Upsdell et al. (2016) separated the additional regional data: Wairarapa (59 sheep/beef, 205 unknown); Central North Island (48 sheep/beef); and Volcanic Plateau (244 sheep/beef, 65 unknown). These additional sites are not included in Figure 2.

However, for a subset of these data more precise location information is available. Figure 3 shows the location of the data used in Ausseil et al. (2011). This dataset includes some points specifically measured to provide a good spatial coverage of New Zealand pasture quality for developing and testing a model based on satellite data.

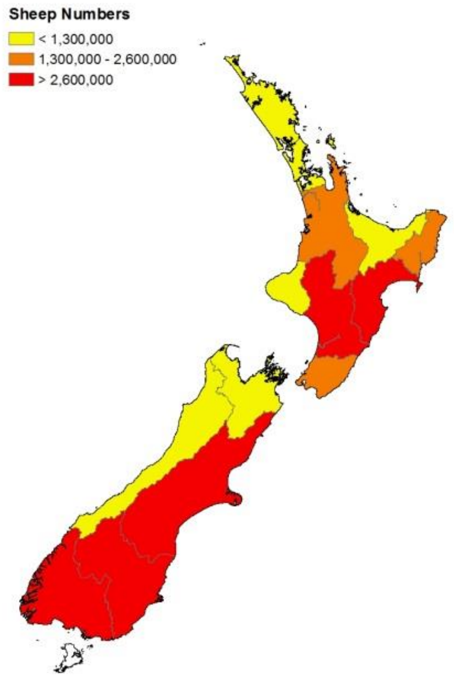
Figure 1: Number of animals by region as of 30 June 2015: (a) dairy cattle, (b) beef cattle, (c) sheep, (d) deer. Data Source: Statistics New Zealand.



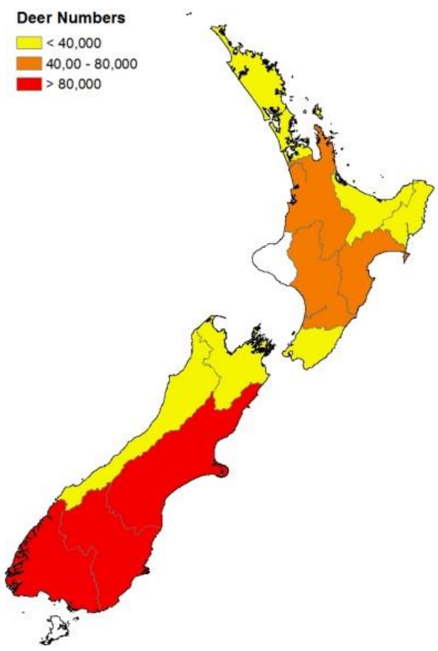
(a)



(b)

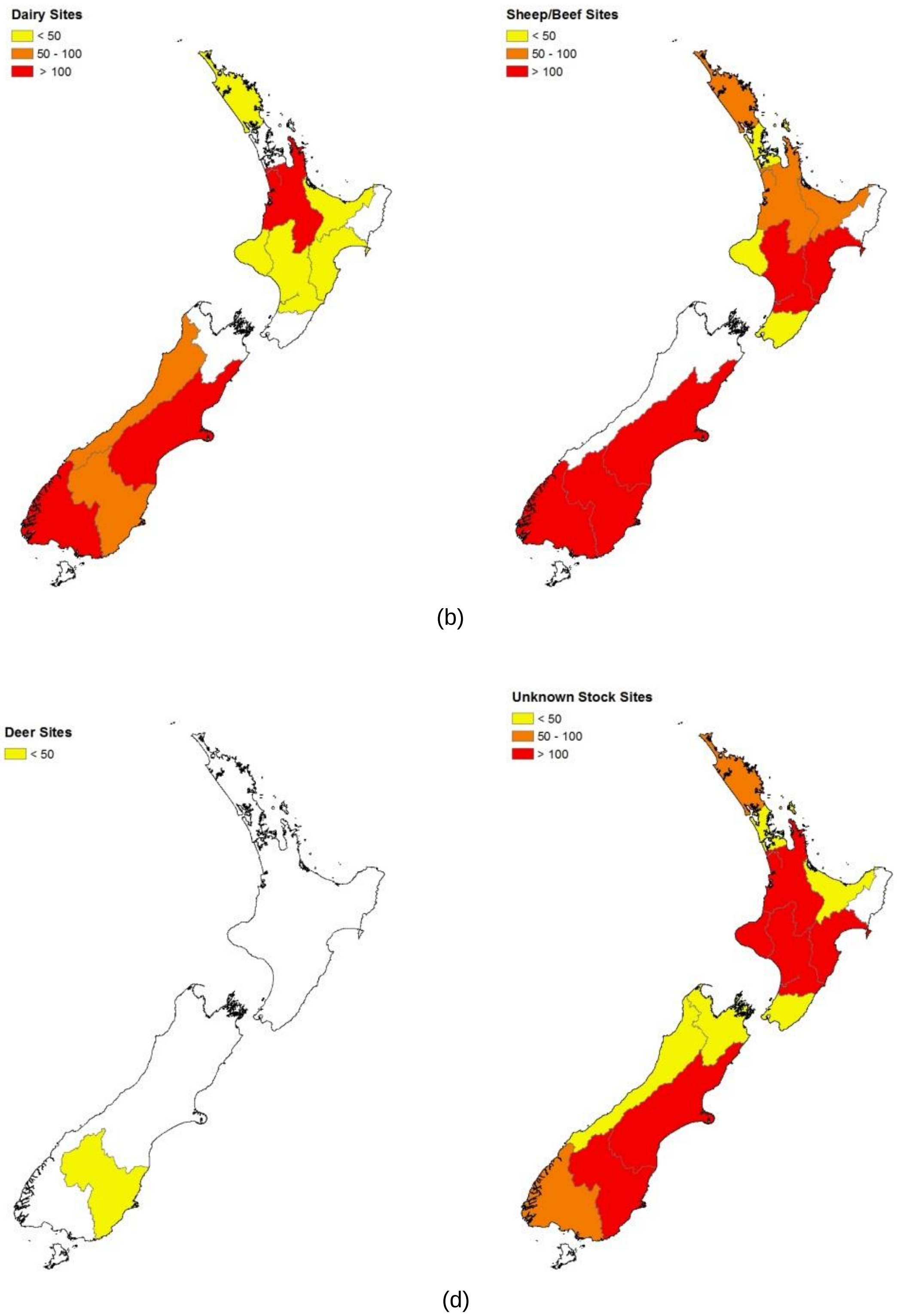


(c)



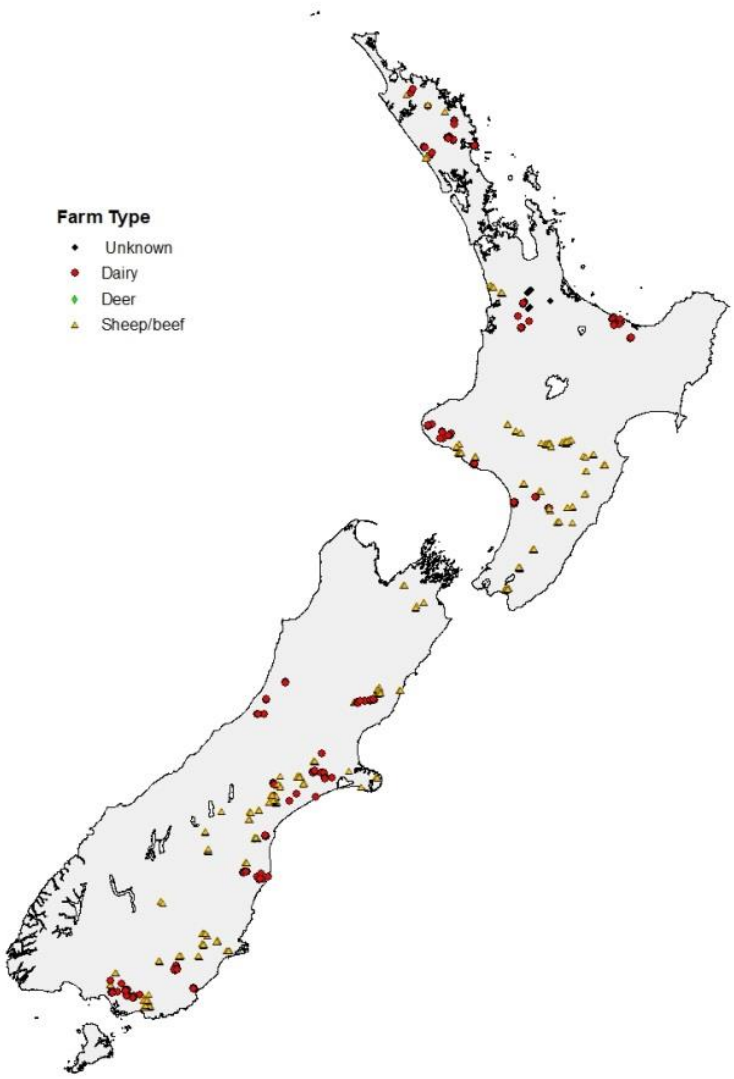
(d)

Figure 2: Number of datasets by region for (a) dairy, (b) sheep/beef, (c) deer, and (d) unspecified stock type pastures. Data from Upsdell et al. (2016).



(a) (b) (c) (d)

Figure 3: Location of pasture sampling sites 2000-2011 used in Ausseil et al. (2011).



4 Future sampling strategies

The recommendation of Bown et al. (2013) was that a nationwide survey of dairy, sheep and beef, and deer pastures be designed to provide representative pasture quality data. The recommended method was a stratified random survey using optimal statistical design.

In this section we investigate potential stratification schemes and assess how many samples would be required to obtain ME and CP estimates within ±5 or 10% of the true values. We then consider some alternatives that might be able to reduce the sampling requirement.

It should be noted that truly random sampling would be fraught with difficulty. Completely randomly selected sites could have access issues (e.g. land-owners refuse consent for sampling, site is physically difficult to get to), and a high rate of non-sampled sites could also introduce bias. Instead, the usual method is to aim for a selected, but representative, sample. Therefore it is important to develop a stratification scheme that will ensure sampling occurs over the range of factors likely to affect pasture quality, thereby ensuring a representative dataset and reducing the risk of bias.

4.1 Stratified Sampling

Stratified random sampling breaks the population of interest into groups (strata) and selects a random sample from within each of these groups. Breaking the population into strata helps ensure a representative mix of units is selected from the population and enough sample is allocated to groups about which we wish to form estimates. For instance, we wish to stratify by region to ensure a good mix of geographical areas is selected, or to help produce estimates for different regional areas.

In an optimised stratified sampling the number of samples within each stratum should be proportional to both the population and the standard deviation within the stratum. To optimise within a given cost the number of samples should also be inversely proportional to the square root of the cost. However, we have assumed that the collection costs are the same for each stratum (in reality it may be more expensive to sample from remote locations).

4.2 Factors affecting pasture quality

4.2.1 Stock type

The National Inventory model currently uses different ME and CP values for the different animal species. This reflects the differences in the types of pastures used to graze different animal types. Upsdell et al. (2016) found significant differences in ME and CP between stock types. However, for 44% of sites, stock type had not been recorded.

Within a stock type it is likely that there will be differences between different management systems (e.g. intensive vs extensive). Information on animal numbers in different farm systems is currently not available at national scale. However, the farm classifications as used by Beef + Lamb NZ's farm monitoring programme separates the more intensive lamb systems from the less intensive lamb systems. On dairy farms the range of farm types is smaller and is currently identified through the data collected by Dairy NZ.

4.2.2 Season

There are strong seasonal effects in ME and CP (Upsdell et al. 2016; Bown et al. 2013). The National Inventory model is capable of using monthly CP and ME values. Currently, for ME monthly values are used for dairy and deer while sheep and beef values are seasonal. For N content (proportional to CP) the value is constant for the whole year for all species (Pickering & Wear 2013). This may have a large effect on the inventory output as total feed consumption varies markedly with season, although this can be accounted for by using an appropriately weighted annual average value for each species.

4.2.3 Region

Pasture quality is affected by climate, and therefore it would be expected that pasture quality varies between regions. However, Upsdell et al. (2016) found region had little effect on ME and CP (with the CP differences not being significant at the 95% confidence level). This was surprising, but there are a number of possible explanations. Topography and pasture productivity are strong determinants of the type of stock grazed. Therefore it could be that accounting for differences in stock type explains most of the regional differences. Also, the regional boundaries used were defined for administrative purposes[1] and contain a diversity of geographic and climatic conditions. The model did not include any underlying climatic variables (e.g. latitude, temperature and rainfall) that might contribute to regional differences. It is also possible that the apparent lack of regional variability was due to non-representativeness of the dataset,[2] and an independent confirmation of these results would be advised.

However, there are factors that vary between regions (e.g. species grown, temperature profiles, rainfall patterns, soil fertility, intensity of production, slope and type of stock grazed) that can affect pasture quality and thus the pasture quality profile. For example, a pasture grown in Northland and a pasture grown in Southland, the SI High Country or Hawke's Bay will vary relative to each other during the year, even if grazed by the same stock type. When planning farm trials, this sort of knowledge has to be taken into account. For example, Litherland and Lambert (2007) showed strong differences in seasonal patterns when they separated their data in to three regions. Lack of regional effects may be due to the lack of data collected at the appropriate times in some of these regions.

The National Inventory model, however, only has complete activity data at regional scale for dairy; for other species only national-level data are available for data such as animal size and live weight gain. National values for ME and CP are currently used for all species including dairy. Animal numbers vary by species and region. Therefore, assuming that there are significant regional differences, it is important that these national values reflect a weighted value by their importance in terms of animal numbers (and feed requirements) in different regions.

4.2.4 Slope and Aspect

Slope information has not been recorded for the samples in the pasture quality database, but it is likely that the majority of samples were collected from flat or low slope land due to accessibility. Given that ~35% of New Zealand's grassland area is hill country (Saggar et al. 2015), slope effect could be important; however, the proportion of pasture consumed from sloping land relative to the total animal intake will be different from the relative area of sloping land. This is addressed in sections 4.5.2 and 4.5.3.

Not much work has been done on the slope effect on pasture quality. Bown et al. (2013) presented slope information from Ledgard et al. (2002) as well as pasture N data from Waikato and Hawke's Bay. These data suggested a difference in N content between pastures growing on easy and steep slopes (with higher quality pasture on the easier slopes). The following analysis used data from a study that measured pasture N content from four farmlets at Ballantrae, each with 3 aspects and slope classes over 3 seasons (Mackay et al. 1995).

We found that aspect had no statistically significant effect on N content, so a 2-way ANOVA on slope, season, and their interaction was applied (Table 3). The significant differences were calculated using the Tukey method at a 95% confidence interval. There was a significant effect of slope on N content between medium and high slopes, but not between low and medium slopes. While these results are from a single study and ME was not measured, changes in N levels are strongly suggestive of a change in both feed quality and ME values.

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[1] Although some geographically similar areas had been separated out.

[2] Although the method of Upsdell et al. (2016) can handle unbalanced data with respect to for factors included in the model, there is no mechanism to account for factors (e.g. slope, fertility) that are not included in the model.

Table 3: Pasture N content by slope class and season. Values with the same superscripts are not significantly different at 95% confidence level. Data from Mackay et al. (1995)

Slope	Summer	Autumn	Winter
Low	2.75[d]	4.04[ab]	4.45[f]
Medium	2.56[d]	3.91[a]	4.40[ef]
High	2.09[c]	3.52[g]	4.18[be]

4.2.5 Long term trends

Changes in farming practice, farm location and size, and climate change could all have long-term effects on pasture quality at both regional and national scale. Upsdell et al. (2016) could not find any long-term changes with time over the two decades from 1996 to 2015, but this is not to say that changes might not occur in the future due to changes in climate or management practices. The "stock" effect in the existing model incorporates the effects of both current management practices and the type of land where that stock class is grazed. Repeated measurements over time would be required to detect long term pasture quality trends.

4.3 Stratified sampling scheme

For this exercise we assume that we are designing a pasture quality sampling programme from scratch, and thus determining how many pasture samples would be needed to provide estimates within a specified precision (expressed in percent) of the true value.

MPI wish to know the size of the sampling problem for a given precision requirement. At the moment only dairy farming has regional level data available, so the sampling requirements for pooled (national) estimates make sense. It is also worthwhile, however, considering the additional sampling effort required to attain a specified precision for regional strata.

Our approach was to design a stratified sampling system using regional animal numbers, metabolisable energy (ME) requirement per animal per month (provided by MPI from the national inventory model), and to use the existing pasture quality data set to estimate variability within strata. In the first instance, we considered the sampling requirements for precision within ±5 or 10% for ME and crude protein (CP). The sampling stratification was:

- Animal type (Dairy, Beef, Sheep, Deer),
- Region (Regional councils excluding Chatham and other islands),
- Season (Sept/Nov, Dec/Feb, Mar/May, Jun/Aug),
- Slope (<15°, 16–24°, >25°). Slope class not included for dairy.

Although this stratification was selected because it closely matches the current inventory structure, it is not necessarily the best possible stratification. The relevant "population" for determining regional/national ME and CP was not simply the number of animals, as this would not account for seasonal difference in animal energy requirements. Instead, the appropriate "population" measure would be dry matter intake. As shown in Upsdell et al. (2016), however, the dry matter intake is itself dependent on the pasture ME content. Instead, we used the total animal ME demand per stratum, which can be calculated without prior knowledge of the pasture ME content. This will lead to a slight underestimation of the number of samples required in low ME regions where animals need to consume more dry matter to meet their requirements, and a slight overestimation of sampling in high ME regions. The ME requirements per head by month and animal stock sub-category from the National Inventory model were multiplied by the number of animals in that month and sub-category (data provided by MPI). These were then aggregated into national ME demands per season by stock type. The seasonal values were then disaggregated to the regional level using the relative stock number in each region from the 2015 Agricultural Production Survey (Statistics New Zealand).

For the slope stratification, we used GIS to intersect an animal stocking rate layer with the slope classes in the New Zealand Land Resources Inventory (NZLRI, Newsome et al. 2008). The animal stocking rate layers had been developed based on land use and carrying capacity for an earlier project (Giltrap et al. 2013), and so are several years out of date. However, the stocking rates were scaled so that the regional animal numbers matched those from the 2015 Agricultural Production Survey (Statistics New Zealand). The NZLRI slope classes were reclassified as low (0–15°), medium (16–24°), and high (>25°). Note that this is slightly different from the slope classifications proposed for the hill country N_2O inventory (Saggar et al. 2015). The ME requirements were then split according to the relative proportion of animals in each region and slope class.

4.4 Calculation Methodology

The objective was to obtain a good estimate of θ, the mean level ME or CP, using a randomly selected sample of the population. Here, the sampling frame consists of the land area of New Zealand, and the samples are drawn from this area. We want the estimate of θ with some specified precision ρ (say, 10%) of the true figure, which means that the standard error of θ, σ_θ, is expressed as $\sigma_\theta/\theta \leq 0.10$ for a desired precision of 10%. Here we call σ_θ/θ the relative standard error (RSE).

Calculations were performed using the R statistical software package. The code used for the calculations is included in Appendix 1.

The variance (or squared standard deviation) is not known precisely. Instead, we obtained estimates for the variance by species, region, season, and slope from the existing dataset. While estimates of variances based on small samples can be erratic, it is the only information we had on which to base a conventional sampling analysis. Where the variance of the ME and CP were not known for a given season in a region, we estimated the corresponding value by using the pooled estimate from all regions. This assumes that the pooled value does not depend on the region, which we suspect is not true, but have little evidence to make a better estimate. Then we estimated the sampling effort to gain refined estimates of the mean values of ME and CP within some specified precision (e.g. 10%) of the true figure.

The basis of the method is that if we know the variance (σ^2) of the quantity of interest (ME or CP) then the variance of the sampling effort with N samples is σ^2/N. The upper and lower 95% confidence intervals of the data can then be calculated, using the standard deviation $\sqrt{\sigma^2/N}$, yielding the 95% confidence interval $[\mu - \alpha, \mu + \alpha]$, for the mean μ and $\alpha/\mu = \rho/100$ for some specified precision ρ in percent. The sampling distribution for the mean is a Student-T distribution with N degrees of freedom, which will be very much like a Gaussian distribution when N is large (say, over 30 samples). The complication in these computations is that the samples can be stratified by region (or pooled in a national average), and also stratified by season and slope class.

We created a function to estimate the sample size for estimating the mean of ME (or CP) based on an unknown population standard deviation using an *estimate* of the variance from existing data, as well as a specified precision of the estimated mean (as a proportion such as 0.1 for 10%) at a specified confidence level (as a proportion of the mean such as 0.95 for 95%). The code for this calculation is included in Appendix 1.

The issue of small estimated group sizes arises frequently, so in all subsequent estimates of sample sizes it was assumed that when the estimated sample size is small, the sample size should be increased to 30 since we cannot make an assumption of normally distributed data otherwise.

There are a number of cautions that should be attached to the estimates of the number of samples required for sampling the ME and CP for each animal type:

- The estimates are based on pilot estimates of ME and CP mean and variance, which in turn depend on the available data. The integrity of the estimates will depend greatly on the randomness of the original data, or the lack thereof.
- In theory, while the distribution of the estimates of the pilot mean and variance also needs to be taken into account, insufficient information was available to account for this issue.

If available, this information would give lower and upper bounds for the number of required samples. However, since many of the sample size estimates are at least 30, this would be unlikely to change the lower level of the estimates.

- Where stratum estimates of mean and variance were not available, a pooled value was used, either a pooled national value (where no stratum estimate was available), or a value estimated from the pooled stratum.

4.5 Results

4.5.1 Dairy

Nationally pooled estimates

We first estimated the number of samples for dairy to achieve a ±5 or 10% precision of ME and CP at the 95% confidence interval, for the national average over the country. The initial precision level of ±5% was essentially arbitrary, but is roughly the estimated CV of metabolisable energy (Kelliher et al. 2007). The methodology from section 4.4 was applied using the spreadsheet to estimate the mean ME and CP for dairy (11.74 MJ/kg DM and 22.50% respectively), and the corresponding estimated variances (0.9140 and 21.49 respectively[3]). Therefore, the required number of samples for ME and CP for pooled data were 4 and 19 respectively for ±10% precision, and 13 and 68 for ±5% precision. For the sample size estimates less than 30, it would be advisable to increase the required sample size values to at least 30, since we are not assuming the means are normally distributed. Therefore, in the case of national pooled data, at least 30 samples would be required for both ME and CP at ±10%. This number of samples would also be sufficient to estimate ME at ±5%, but 68 samples would be required to estimate CP at this precision.

For optimal allocation, the allocation over regions should be done relative to the product of the animal population and the standard deviation of ME or CP for each region. The allocation proportions (based on 2015 census data from Statistics New Zealand) are given in Table 4. In some regions there were large differences in the relative variability of ME and CP leading to different recommended numbers of samples for ME and CP. If the number of samples from each region was taken to be the larger of the number of ME and CP then a total of 34 samples would need to be collected at ±10% precision and 67 samples for ±5% precision.

[3] The units of the variances are the squares of the units of the corresponding means

Table 4: Relative allocation of ME and CP samples for dairy pastures by region to obtain a nationally pooled average. Number of samples based on estimating ME and CP at ±5 and 10% precision

Region	%ME samples	%CP samples	±5% precision			±10% precision		
			#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples
Northland	9.4%	5.0%	3	3	3	3	2	3
Auckland	1.9%	1.8%	1	1	1	1	1	1
Waikato	37.8%	27.1%	11	18	18	11	8	11
Bay of Plenty	1.2%	4.0%	0	3	3	0	1	1
Gisborne	0.2%	0.1%	0	0	0	0	0	0
Hawke's Bay	1.2%	1.2%	0	1	1	0	0	0
Taranaki	8.4%	7.9%	3	5	5	3	2	3
Manawatu-Whanganui	7.2%	5.4%	2	4	4	2	2	2
Wellington	1.7%	1.6%	0	1	1	0	0	0
Tasman	1.2%	1.1%	0	1	1	0	0	0
Nelson	0.1%	0.1%	0	0	0	0	0	0
Marlborough	0.4%	0.4%	0	0	0	0	0	0
West Coast	1.3%	2.1%	0	1	1	0	1	1
Canterbury	14.3%	24.4%	4	17	17	4	7	7
Otago	4.1%	6.2%	1	4	4	1	2	2
Southland	9.7%	11.3%	3	8	8	3	3	3

Table 5 shows a similar table for the seasonal allocation of samples. As the animal ME requirement varies by season, the total animal ME requirement (as provided by MPI from the national inventory model) was used in place of population.

Table 5: Relative allocation of ME and CP samples for dairy pastures by season to obtain a nationally pooled average. Number of samples based on estimating ME and CP at ±5 and 10% precision

Region	%ME samples	%CP samples	±5% precision			±10% precision		
			#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples
Summer	32%	30%	9	20	20	9	9	9
Autumn	25%	21%	8	14	14	8	6	8
Winter	12%	14%	4	9	9	4	4	4
Spring	31%	35%	9	24	24	9	11	11

Stratification by season

We then estimated the number of samples needed to produce an average national estimate for each season. The sample calculations were performed on the data aimed to have ±5 or 10% precision for each season (Table 6). For ±10% precision and for ME at ±5% precision the sample size was determined by the requirement that each season should have a minimum of 30 samples, resulting in a minimum requirement of 120 samples for both ME and CP. To estimate CP at ±5% for each season required a total for 236 samples. Table 6 shows the distribution of samples required for each season.

Table 6: Relative allocation of ME and CP samples for dairy pastures by season to ME and CP at ±5 and 10% precision for each season

Region	±5% precision			±10% precision		
	#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples
Summer	30	77	77	30	30	30
Autumn	30	45	45	30	30	30
Winter	30	40	40	30	30	30
Spring	30	74	74	30	30	30

Stratification by region and season

We estimated the number of samples for each season and for each region required to get each region/season value within ±10%. Again the figures were adjusted so that the minimum number of estimated samples in each category was at least 30 (i.e. a total of 1920 across all categories). For a precision requirement of ±10% for each region/season the minimum number of samples required was 1920 for ME, and 1923 for CP (Northland/spring required 33 samples). In this case the major determinant of the number of samples was the need for 30 samples in each category. However, going to ±5% precision required 1927 and 2584 samples for ME and CP respectively.

4.5.2 Sheep and Beef

Pooled data nationally

We first determined the number of samples for sheep and beef to achieve a ±5 and 10% precision of ME and CP at the 95% confidence interval at the national level. The methodology from section 4.4 was applied using the spreadsheet to estimate the mean (10.68 MJ/kg DM and 21.30%) and variances[4] (1.340 and 23.48) for ME and CP respectively. Therefore, the required number of samples for ME and CP for pooled data were 7 and 23 respectively at ±10% precision and 21 and 82 at ±5% precision. For those sample size estimates less than 30, it would be advisable to increase the required sample size values to at least 30, since we were not assuming normally distributed data.

Table 7 shows the recommended sampling allocation by region based on the animal ME requirements and variability of ME or CP by region. Again there were some differences in the recommended numbers of ME and CP samples by region. Taking the larger of the ME or CP samples in each region results in a total of 32 samples for ±10% precision and 80 for ±5% precision.

Table 7: Relative allocation of ME and CP samples for sheep and beef pastures by region to obtain a nationally pooled average. Number of samples based on estimating ME and CP to within ±5% or ±10% precision

Region	%ME samples	%CP samples	±5% precision			±10% precision		
			#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples
Northland	4.7%	2.4%	1	2	2	1	1	1
Auckland	2.0%	1.6%	1	1	1	1	0	1
Waikato	10.8%	10.3%	3	8	8	3	3	3
Bay of Plenty	0.9%	1.5%	0	1	1	0	0	0

[4] The variances are expressed in terms of the units of the mean squared

Gisborne	5.8%	5.6%	2	5	5	2	2	2
Hawke's Bay	10.8%	8.8%	3	7	7	3	3	3
Taranaki	2.1%	0.9%	1	1	1	1	0	1
Manawatu-Whanganui	17.1%	17.0%	5	14	14	5	5	5
Wellington	4.5%	5.2%	1	4	4	1	2	2
Tasman	1.2%	1.2%	0	1	1	0	0	0
Nelson	0.0%	0.0%	0	0	0	0	0	0
Marlborough	1.6%	1.5%	0	1	1	0	0	0
West Coast	0.4%	0.4%	0	0	0	0	0	0
Canterbury	17.9%	15.1%	5	12	12	5	5	5
Otago	12.8%	15.1%	4	12	12	4	5	5
Southland	7.2%	13.2%	2	11	11	2	4	4

Table 8 shows the sample allocation by season.

Table 8: Relative allocation of ME and CP samples for sheep and beef pastures by season to obtain a pooled average. Number of samples based on estimating ME and CP to within ±5% or ±10% precision

Region	%ME samples	%CP samples	±5% precision			±10% precision		
			#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples
Summer	35%	29%	11	24	24	11	9	11
Autumn	28%	26%	8	21	21	8	8	8
Winter	19%	20%	6	17	17	6	6	6
Spring	18%	24%	5	20	20	5	7	7

At this stage there is little information on the variability of ME and CP for different slope classes. However, based on a GIS analysis of animal stocking rates and slopes classes (see section 4.3) we estimated that nationally the beef population meets 49% of its ME requirement from low slopes, 40% from medium slope, and 11% from high slopes, while the sheep population obtains 53% of its ME from low slope, 36% from medium slope, and 10% from high slopes. Combining these on a total ME basis suggests a weighting of 52%, 38%, and 11% for low, medium, and high slopes for sheep and beef pastures.

Stratification by season

As for dairy, the minimum number of samples required to estimate national, seasonal ME, and CP at ±10% precision was 120. This was due to the requirement that the minimum number of samples was at least 30 in each category in order to use the normal approximation to calculate the 95% confidence interval. However, for a precision of ±5% for each season, 120 ME and 281 CP samples would be required. Table 9 shows the number of samples required for each season at each level of precision. These samples should be allocated across regions according to Table 7.

Table 9: Relative allocation of ME and CP samples for sheep and beef pastures by season to ME and CP at ±5 and 10% precision for each season

Region	±5% precision			±10% precision		
	#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples

Summer	30	95	95	30	30	30
Autumn	30	68	68	30	30	30
Winter	30	77	77	30	30	30
Spring	30	41	41	30	30	30

Stratification by region and season

We estimated the number of samples for each season and for each region required to get each region/season value within ±5% and 10% for sheep and beef. Again the figures were adjusted so that the minimum number of estimated samples in each category was at least 30 (i.e. a total of 1920 across all categories). For ±10% precisions the minimum number of samples required was1920 for ME and 2106 for CP. For ±5% precision a minimum of 1920 samples were required for ME and 5243 for CP.

Stratification by region, season, and slope

We estimated the number of samples required to estimate ME and CP for each season, slope, and region. This was done in a similar manner to the dairy case. As before, the figures were adjusted so that the minimum number of estimated samples is at least 30. However, as we have also introduced 3 slope classes, the minimum number of samples increased to 5760. The required number of samples was calculated for precision requirements of ±5, 10, and 20%. These estimates are summarised in Table 10.

Table 10: Number of samples required to estimate ME and CP within ±10 or 20% (with 95% confidence) for sheep and beef pastures using stratification by region, season and slope

Precision at 95% confidence interval	ME samples	CP samples
±5%	5808	15791
±10%	5760	6342
±20%	5760	5760

To get CP estimates within ±10% at a 95% confidence interval would require 6342 samples. However, the minimum 5760 samples would get ME within ±10% and CP within ±20%.

4.5.3 Deer

Pooled data nationally

The number of samples necessary for deer pasture to achieve a ±5 or 10% precision of ME and CP at the 95% confidence interval at the national level was calculated using the same method as for dairy and sheep and beef above. The spreadsheet for deer gave an estimated mean for ME and CP of 9.68 MJ/kg and 14.60% respectively, and the estimated variances were 0.6349 and 4.434. However, as these data come from a single site, the variances are likely underestimated. The required number of samples for ME and CP for pooled data were 4 and 11 respectively for ±10% precision. For ±5% precision the required number of samples increases to 13 and 35. For the sample size estimates that were less than 30, it would be advisable to increase the required sample size values to at least 30, since we do not have any evidence to suggest that the means are normally distributed.

Table 11 shows the recommended sampling allocation by region based on the animal ME requirements. As deer pasture quality measurements have only been made in one region we have assumed that the variability of ME and CP are the same across all regions. Hence the recommended number of ME and CP samples are the same.

Table 11: Relative allocation of ME and CP samples for deer pastures by region to obtain a nationally pooled average. Number of samples based on collecting 30 ME and CP samples

Region	%ME samples	%CP samples	±5% precision			±10% precision		
			#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples
Northland	0.6%	0.6%	0	0	0	0	0	0
Auckland	1.0%	1.0%	0	0	0	0	0	0
Waikato	7.8%	7.8%	2	3	3	2	2	2
Bay of Plenty	3.7%	3.7%	1	1	1	1	1	1
Gisborne	1.4%	1.4%	0	1	1	0	0	0
Hawke's Bay	7.7%	7.7%	2	3	3	2	2	2
Taranaki	0.0%	0.0%	0	0	0	0	0	0
Manawatu-Whanganui	6.9%	6.9%	2	2	2	2	2	2
Wellington	2.2%	2.2%	1	1	1	1	1	1
Tasman	1.4%	1.4%	0	1	1	0	0	0
Nelson	0.0%	0.0%	0	0	0	0	0	0
Marlborough	0.8%	0.8%	0	0	0	0	0	0
West Coast	3.2%	3.2%	1	1	1	1	1	1
Canterbury	27.1%	27.1%	8	9	9	8	8	8
Otago	14.0%	14.0%	4	5	5	4	4	4
Southland	22.1%	22.1%	7	8	8	7	7	7

Table 12 shows the sample allocation by season.

Table 12: Relative allocation of ME and CP samples for deer pastures by season to obtain a pooled average. Number of samples based on collecting 30 ME and CP samples

Region	%ME samples	%CP samples	#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples
Summer	35%	29%	11	10	11	11	9	11
Autumn	20%	20%	6	7	7	6	6	6
Winter	22%	22%	6	8	8	6	6	6
Spring	24%	29%	7	10	10	7	9	9

While we have little information on the variability of ME and CP in different slope classes, based on GIS analysis (see section 4.3) we estimated that nationally deer obtain 73% of their ME requirement from low slopes, 23% from medium slopes, and 4% from high slopes.

Stratification by season

We estimated the number of samples required to estimate national average values for ME and CP for each season. The sample calculation was performed for ±5 and 10% precision, with the requirement that the minimum number of samples was at least 30 in each category. This resulted in a minimum total of 120 samples for ME and CP at ±10% precision and ME at ±5% precision. CP required 163 samples to obtain ±5% precision. Table 13 shows the number of samples required for each season at each level of precision. These samples should be allocated across regions according to Table 11.

Table 13: Number of ME and CP samples for deer pastures by season to estimate ME and CP at ±5 and 10% precision for each season

Region	±5% precision			±10% precision		
	#ME Samples	#CP Samples	Combined samples	#ME Samples	#CP Samples	Combined samples
Summer	30	42	42	30	30	30
Autumn	30	39	39	30	30	30
Winter	30	41	41	30	30	30
Spring	30	41	41	30	30	30

Stratification by region and season

We estimated the number of samples for each season and for each region required to get each region/season value within ±5 and 10% for deer. Again the figures were adjusted so that the minimum number of estimated samples in each category was at least 30 (i.e. a total of 1920 across all categories). At ±10% precision, the minimum number of samples required were 1920 for ME and CP. It was the requirement to have 30 samples in each category that was the major determinant of the number of samples required. At ±5% precision, the minimum number of ME samples was still 1920, but the number of CP samples increased to 2609.

Stratification by region, season, and slope

The number of samples for each season, slope and region were estimated in a similar manner to dairy. As before, the figures were adjusted so that the minimum number of estimated samples was at least 30. The required number of samples calculated for precision of ±10% within each stratum was 5760, i.e. the minimum 30 samples from each stratum. For ±5% precision, 5760 ME and 7825 CP samples are required.

4.5.4 Summary

Table 14 shows the total number of samples needed for different levels of precision and stratification.

Table 14: Number of ME and CP samples for dairy, sheep and beef, and deer pastures by season to estimate ME and CP at ±5 and 10% precision[5] for different levels of stratification

	±5% precision		±10% precision	
	#ME Samples	#CP Samples	#ME Samples	#CP Samples
Dairy				
National	30	68	30	30
Seasonal	120	236	120	120
Season + Region	1927	2584	1920	1923
Sheep and Beef				
National	30	82	30	30
Seasonal	120	281	120	120
Season + Region	1920	5243	1920	2106
Season + Region + Slope	5808	15791	5760	6342

[5] Note that the level of precision applies to every category in the stratification, e.g. at regional stratification a precision of ±10% applies to each region.

Deer				
National	30	35	30	30
Seasonal	120	163	120	120
Season + Region	1920	2609	1920	1920
Season + Region + Slope	5760	7825	5760	5760

Much pasture quality data has already been collected, but these data were collected for other purposes and do not necessarily constitute a representative sample. In addition, many of these samples lack important information (e.g. location, stock type). However, there is a subset of these data (e.g. that used in Ausseil et al. 2009, 2010b) for which accurate GPS co-ordinates and other supporting information are available. Therefore some data might be able to be used in a representative dataset, supplemented with additional sampling where required.

4.6 Alternative stratifications

In general, increasing the number of strata increases the number of samples required to achieve a given level of precision within each stratum. The use of stratification can also improve the precision of the pooled estimate, although it is difficult to quantify this improvement without knowing the distribution of the quantity within each stratum. More important for our purposes, however, stratification may help mitigate the problems of non-randomness in sampling by ensuring the samples cover the full range of the driving factors. For this purpose it is desirable to select a stratification with low within-strata variability. This reduces the effect of non-random sample selection on the overall estimate. In this section we propose a couple of alternative stratifications that could be considered. These would require some additional work to estimate the population (and production) within each stratum, but could potentially reduce the within stratum variability.

Beef + Lamb New Zealand classify (sheep and beef) farms into 8 classes (based on management) and 5 geographic regions with a total of 17 combinations of region and farm class. This is roughly the same as the current number of regions (16 excluding the Chatham Islands). It would be reasonable to expect that the variability within a regional farm class (e.g. Taranaki-Manawatu Intensive Finishing) would be less than the variability across an administrative region (e.g. all sheep and beef in Manawatu-Whanganui). The same samples could be used to estimate pasture quality for beef cattle and sheep, with different weightings applied according to the proportion of each species in each category. Data would need to be sourced on the numbers of sheep and beef cattle in each class. Further complications could arise if animals were transferred between different farm classes within a year. However, the need to trace the end product (i.e. meat) back to region makes establishing regional models for sheep, beef and deer difficult. Still, a weighted value for ME and CP could be established based on where most of each stock class are carried for the whole of New Zealand

Dairy NZ have a similar farm classification scheme (production systems 1–5, DairyNZ 2012). The DairyNZ production systems are defined by the percentage of imported feed fed to the animals, and therefore have the potential to incorporate the effects of imported feed into the national inventory model.

As mentioned earlier, the regions have administrative boundaries that do not necessarily group areas that are climatically and geographically similar. The Land Environments of New Zealand (LENZ) is an environmental classification designed to provide a framework for addressing a range of conservation and resource management issues (Leathwick et al. 2002). The classifications were determined by grouping areas with similar climate, slope and soil properties. At level 1 LENZ has 20 categories. However, some of these (e.g. Southern Alps, Permanent Ice and Snow) are not relevant to grazed pasture and so the total number of classes is similar to the number of regions. Figure 4 shows the LENZ level 1 boundaries compared with the region boundaries. While we do not have information on the variability of pasture quality within regions and LENZ classes, we can compare the variability of some of the underlying drivers. As an example, we took the mean annual temperature at 100-m resolution across all New Zealand grasslands (as identified in LCDBv4.1, Landcare Research) and looked at the standard deviations within each region compared with the standard deviations by LENZ class. The boxplot of the standard deviations (Fig. 5) shows that the standard deviations (of the mean annual temperature) within classes tends to be lower within LENZ classes than regions. This indicates there could be some benefit in stratifying by LENZ class, although additional work would be required to estimate the animal numbers in each LENZ class.

Figure 4: Boundaries for (a) LENZ level1 classes and (b) regional authorities in New Zealand

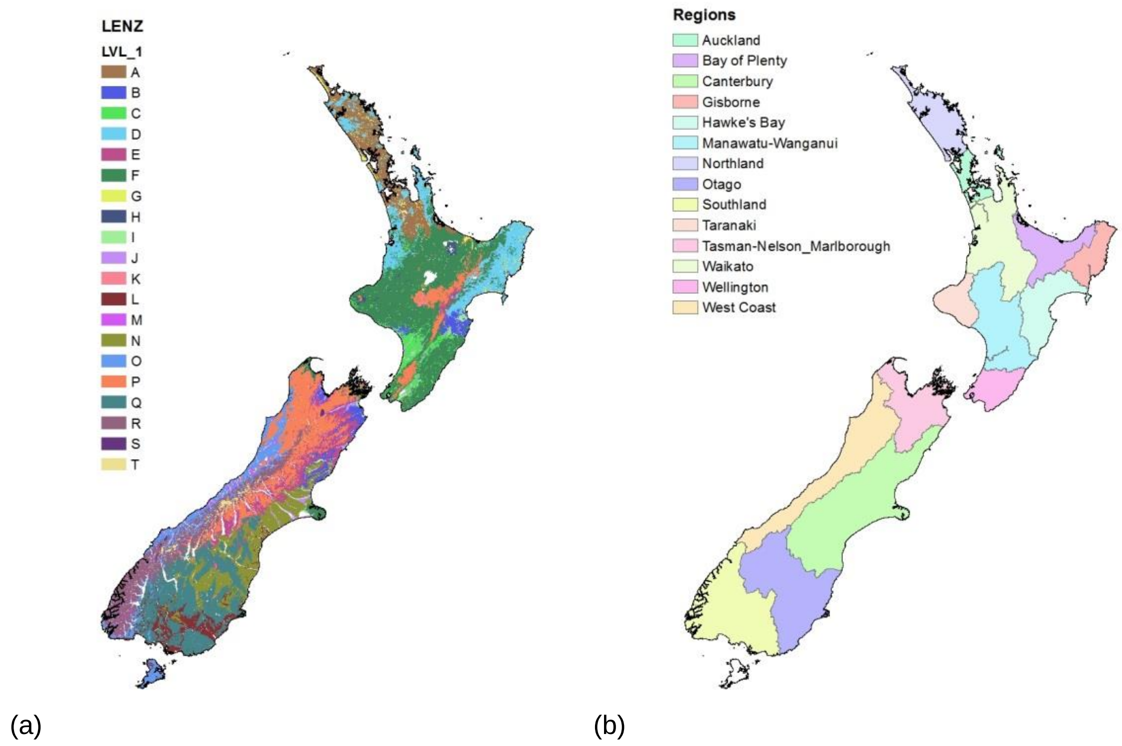
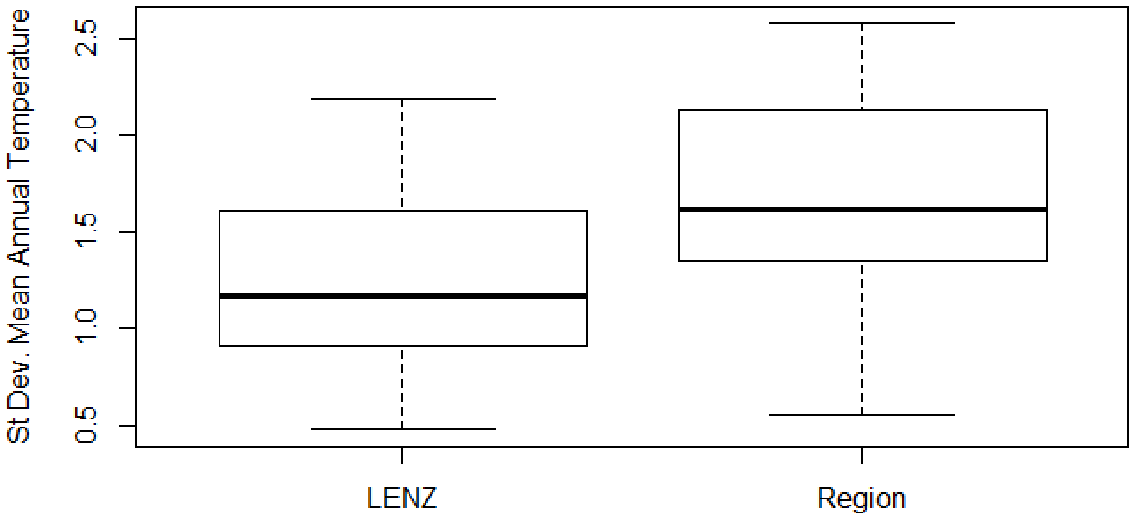


Figure 5: Standard deviation of mean annual temperature in grasslands within LENZ level 1 classes and regional boundaries



5 Discussion

Much of the field of statistics is built on the assumption of random sampling, but truly random sampling of pasture quality over the entirety of New Zealand is not feasible. Instead the focus needs to be on building a representative sample. This requires obtaining data over the range of factors that influence pasture quality and correctly weighting these to get appropriate averages at the desired level of aggregation (e.g. regional, national). Failure to account for important factors can lead to biased estimates.

A large amount of pasture quality data has been obtained from research and commercial sources. However, these data were collected for other purposes and do not necessarily constitute a representative sample. There is a risk that the data have some selection bias. For example, research samples might have been grown under atypical management systems while there could be a tendency for certain types of farm to be more likely to seek commercial pasture testing (e.g. because the pasture is being highly managed, or because there is a problem with the pasture growth). The existing dataset also had a problem with missing data, for example, some samples did not include location or animal species information. The smoothing model method of Upsdell et al. (2016) is able to handle unbalanced and missing data, but it cannot correct for unknown biases in the data or account for factors (e.g. slope, management, temperature, rainfall, plant cultivars, plant species, soil fertility) not included in the model. This is a limitation of the available data rather than of the model itself. The key question, then, is to determine what effort would be required to provide a model, such as that due to Upsdell et al. (2016), with data that are representative of the various controlling factors for ME and CP, while still satisfying UNFCCC reporting requirements. The strategies presented in this report represent one approach, which is sampling intensive.

More information is available, however, in a subset of the existing data. In particular, Ausseil et al. (2009, 2010b) collected 408 pasture samples to help build a model to predict pasture quality, so these samples had accurate GPS coordinates and covered a broad geographic range. There was also additional information (e.g. pasture species, grazing status, slope) recorded for many of the samples. Therefore some of these data might be able to be used in a representative dataset with additional samples collected to fill in gaps in the existing data.

We assessed the number of samples required to estimate the ME and CP within ±10% with 95% confidence. In order to assess the 95% confidence interval for these estimates we had to make some assumptions about the underlying distributions. To make these assessments we estimated the variances of ME and CP from the existing dataset. However, as we did not know that the distributions were normal we had to require that each category had at least 30 samples so that the sample mean could be assumed to be normally distributed. This requirement actually had more influence on the minimum number of samples than the required level of precision. In order to get the ME and CP within the desired precision for each region, season and slope class would require 5760 samples ($16 \times 4 \times 3 \times 30$) for each animal species. In practice, it would probably be possible to achieve a given level of precision with fewer samples, but this is difficult to predict in advance. Once data collection has begun, however, bootstrapping methods could be used to estimate the distribution of the (weighted) sample mean and hence derive a 95% confidence interval.

Tables 4, 7, and 11 show how samples should be allocated across regions in order to minimise overall uncertainty (based on total animal ME requirements and our current estimates of variability within each region). Tables 5, 8, and 12 do the same for the allocation by season. It should be noted that these values are not the same as the weightings that should be applied to obtain a national/annual estimate (these should be weighted by total animal ME requirements). At present we do not have information on the variability of ME and CP within slope classes.

While our assessment looked at stratifying by (administrative) region, grazing species, season and slope, there are other stratifications that might better group similar pasture types. For example, the LENZ level 1 classification groups environments with similar climate and soil properties, whereas the administrative regions may contain more diverse environments. Replacing “region” with “LENZ level 1” would not make much difference to the total number of categories. Beef + Lamb New Zealand and Dairy NZ both have their own farm classifications based on the intensity of management. Using these classifications would capture management differences not captured simply by looking at grazing species. However, all these alternative classifications would require some addition work to allocate the animal numbers into the new categories.

Data from Mackay et al. (1995) suggest there can be significant differences in pasture N content between high slopes and low to medium slopes (although this difference is less apparent in winter). We estimated about 11% of the ME consumed by sheep and beef cattle comes from high slope. Further studies to confirm this result (and to assess the effect of slope on ME) would therefore be worthwhile.

Remote sensing is an alternative method for assessing pasture ME and CP across the whole country. It requires a relationship between ME (or CP) and available satellite bands to be developed. A series of earlier studies (Ausseil et al. 2009, 2010a, b, 2011, 2012) investigated this possibility and found relationships for ME and N content with residual standard errors of 0.95 and 0.65 respectively. Although there did not appear to be any bias in the ME relationship, there was a saturation issue for the N content, which meant the satellites could not effectively measure above 3% N (equivalent to 18.75% CP). However, these relationships (at least for ME) could still be used to estimate the spatial and temporal patterns of pasture quality. This could be used as an independent check for bias in a dataset (or a model such as that of Upsdell et al. 2016). It might also be the easiest way to monitor for long-term trends in pasture quality. It would be worth investigating whether new satellite products are now available that might be capable of measuring pasture N contents >3%. In addition, the possibility of using hyperspectral imaging from a plane is being investigated (Alice Ryan, MPI, pers. comm.)

An alternative would be to collect some focused data sets in regions where the amount or quality of the data is poor or unknown to assess whether model produced by Upsdell et al. (2016) incorporates all the important factors. Differences due to slope or region are likely to be most apparent mainly under certain conditions. For example, drops in soil moistures result in earlier declines in feed quality due to the pasture going into a reproductive state. Poorer quality species are found under more extensive systems or lower fertility (e.g. steeper slopes), and decreases in feed quality occur sooner in grasses produced from more modern plant breeding schemes. In Northland, hotter temperatures result in more C4 grasses which tend to have a lower pasture quality.

6 Conclusions

There is a large amount of pasture quality data currently available. However, the problem is that it is difficult to ascertain how representative of New Zealand pastures this dataset is. A method such as that presented by Upsdell et al. (2016) could be used to enhance the estimate of ME and CP with additional data once all the drivers of pasture ME and CP have been accounted for. However, this method is not able to correct for unidentified sources of biases.

We investigated sampling strategies based on stratification by animal species (dairy, sheep/beef, deer), region, season and slope (sheep/beef and deer only). In order to estimate a 95% confidence interval for the ME and CP estimates, without prior knowledge of their distribution, we needed to assume there were at least 30 samples for each estimated value. This finally determined the minimum number of samples required in many cases. In practice, it would be possible to use bootstrapping methods to assess the 95% confidence interval as the data were collected, and the actual number of samples required might be less.

We were able to calculate the optimal sampling allocation by region and by season for each animal species. These allocations were calculated based on the total animal ME and the standard deviation of the ME and CP as estimated from the existing dataset in each category.

There are alternative stratifications that could result in lower within-stratum variances and result in better representativeness. One of these was the LENZ classification, which classifies land according to environmental and climate similarities, as opposed to “region”, which is an administrative unit. The current stratification does not include any accounting for management practices. However, Beef + Lamb New Zealand and Dairy NZ both have farm type classifications that group farms of similar intensities. These alternative classifications would require some additional work in order to identify the proportion of animals in each category.

We found some evidence (based on one study, but also confirmed in Bown et al. (2013) that pasture CP is lower in high slope land compared with low to medium slopes. Further work is needed to confirm this.

7 Recommendations

- Construct (and assess) a representative database of ME and CP values. This database should include a precise site location and sufficient additional information (e.g. sampling date, animal species, soil type, slope, management history) to assess the overall representativeness. Existing data that meet the quality criteria could be used as the basis for the database with gaps filled by new sampling. The new dataset could also be assessed for coverage over some of the alternative classifications suggested (e.g. LENZ level 1 classes, Beef + Lamb New Zealand farm types)
- Estimates of ME and CP at the required level of aggregation (e.g. national or regional, annual, seasonal or monthly) should be calculated as a weighted average. The weighting factor would be total animal ME requirements as this accounts for both the different feed demand at different times of the year and different animal numbers in different regions.
- Tables 4, 6, and 9 give the optimal sample allocations across regions in order to minimise overall uncertainty for a given number of samples. Tables 5, 7, and 10 do the same for the allocation by season. These tables may need revising as better estimates of the variability of ME and CP by region and season become available.
- Use bootstrapping to assess the 95% confidence interval of ME and CP estimates as new samples are collected.
- Investigate the feasibility of using LENZ classifications and/or the Beef + Lamb New Zealand and Dairy NZ farm classifications to ensure the dataset covers all the major management practices and environments and whether such alternative classification would result in a significant improvement in either the accuracy or precision of ME and CP estimates.
- Investigate the feasibility of using existing remote sensing methods to assess the representativeness of the pasture quality dataset and/or model results.

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Appendix 1 – R code used in section 4

Data

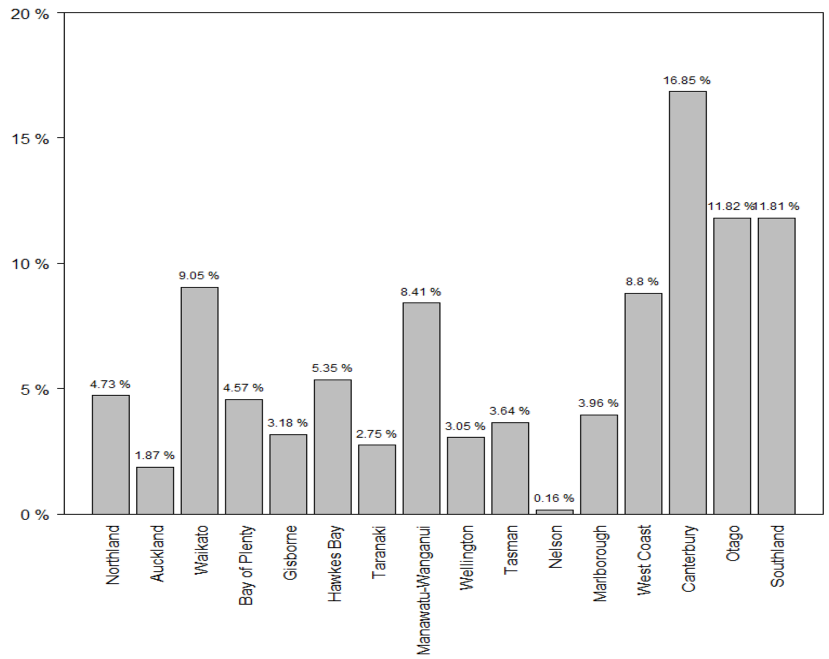
The range of animal types and seasons are well defined, as shown below. The slope classes are "low" (<15°), "medium" (16 to 24°), and "high" (> 24°).

```
Animal <- c("Dairy","Beef","Sheep","Deer")
Season <- c("Spring","Summer","Autumn","Winter")
Slope <- c("Low","Medium","High")
```

The regions, which exclude off-shore islands like the Chatham Islands, are somewhat arbitrary. Upsdell et al. (2016) used a region breakdown that effectively included a component of the climate. The region definition used here uses the term in an administrative sense.

```
region <- c("Northland","Auckland","Waikato","Bay of Plenty","Gisborne","H
awkes Bay",
            "Taranaki","Manawatu-Wanganui","Wellington","Tasman","Nelson",
"Marlborough",
            "West Coast","Canterbury","Otago","Southland")
region.area <- c(12498,4940,23900,12071,8386,14137,7254,22221,8049,9616,42
4,
                 10458,23244,44508,31209,31195)
area.nz <- sum(region.area)
```

A barplot of the area of each region as a percentage of the total area of New Zealand shows considerable imbalance between regions, which will be important in allocating the sampling units.



Data preparation

Animal numbers by region, season, and slope (if available) are needed in order to estimate the required stratified samples in a sampling effort. In this section, we read the animal numbers and associated stratification labels, as well as the data that forms the basis of the estimated ME and CP variance.

Dairy

We read the dairy data from an Excel spreadsheet.

```
library(readxl)
filename <- "../data/Dairy.xlsx"
d.dairy <- read_excel(filename,sheet=1)
```

The dairy data needed to be manipulated to fill rows in a few of the columns, and then the column with percentage of the national herd has to be coerced into a proportion. Finally, the factors are defined.

```
for(i in 1:nrow(d.dairy)) {
  if(!is.na(d.dairy$Region[i])) {
    region_name <- d.dairy$Region[i]
  } else {
    d.dairy$Region[i] <- region_name
  }
  if(!is.na(d.dairy$`% of National Dairy`[i])) {
    percent_national <- d.dairy$`% of National Dairy`[i]
  } else {
    d.dairy$`% of National Dairy`[i] <- percent_national
  }
}
d.dairy$`% of National Dairy` <- as.numeric(sub("%$","",d.dairy$`% of Nati
onal Dairy`))
d.dairy$Region <- factor(trimws(d.dairy$Region))
d.dairy$Season <- factor(d.dairy$Season)
d.dairy <- subset(d.dairy,!is.na(Season))
```

Where the variance of the ME and CP were not known for a given season in a region, we estimated the corresponding value by using the pooled estimate from all regions. This makes the assumption that the pooled value does not depend on the region; we suspect this is not true but have little evidence to make a better estimate.

```
pooled.me.var <- mean(d.dairy$`ME var`,na.rm=TRUE)
pooled.cp.var <- mean(d.dairy$`CP var`,na.rm=TRUE)
d.dairy$`ME var` <- ifelse(is.na(d.dairy$`ME var`),pooled.me.var,d.dairy$`
ME var`)
d.dairy$`CP var` <- ifelse(is.na(d.dairy$`CP var`),pooled.cp.var,d.dairy$`
CP var`)
```

Deer, Sheep and Beef

The deer, sheep and beef data were loaded and processed in a similar manner as for dairy. The code will not be repeated here, for brevity, but it follows a similar pattern to the code above. The sheep and beef data were loaded in a slightly different manner as they come from different worksheets in the same spreadsheet.

Sampling Requirement Calculation

```r
sample.size <- function(mean.estimate,var.estimate,specified.mean.accuracy
,specified.accuracy.ci) {
  sd.estimate <- sqrt(var.estimate)
  alpha <- (1 - specified.accuracy.ci)/2
  z <- qnorm(1 - alpha)
  n <- ceiling((z*sd.estimate/(specified.mean.accuracy*mean.estimate))^2)
  n <- ifelse(n == 1,2,n)
  n1 <- n
  tval <- qt(1 - alpha,n - 1)
  n <- ceiling((tval*sd.estimate/(specified.mean.accuracy*mean.estimate))^
2)
  n2 <- n
  tval <- qt(1 - alpha,n - 1)
  n <- ceiling((tval*sd.estimate/(specified.mean.accuracy*mean.estimate))^
2)
  n3 <- n
  #cat(paste0('Alpha = ',alpha,' Z = ',z,' N1 = ',n1,' N2 = ',n,' N3 = ',n
3,'\n'))
  return(as.integer(n))
}
```

As an example, say we have a pilot survey that establishes an estimated mean of 15 and variance of 38.44, then in order to find the mean with an precision of plus-or-minus 10% at the 90% confidence level we estimate the sample size (which turns out to be 49) as follows.

```r
n.est <- sample.size(15,6.2^2,0.1,0.90)
n.est

## [1] 49
```