Estimation of errors associated with the calculation of carbon in Kyoto Forests

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Disclaimer

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EXECUTIVE SUMMARY

- Uncertainty associated with changes in carbon stock is from two additive variance components:
    - Prediction error, a measure of possible bias in the allometric equations used to predict above ground tree carbon.
    - Sampling error, a measure of variation recognizing that only a very small proportion of Kyoto forest is actually surveyed.

- The average prediction error is estimated to be around 1 %. This figure is likely to be an underestimate, especially when estimating changes in carbon stock over 2008 - 2013. More biomass data are required to verify this uncertainty. While we show the effects of varying prediction error on total uncertainty, the confidence intervals in this report are calculated only in terms of sampling error.

- The estimates of carbon stock from the 2004 Nelson and Marlborough pilot data are 64.4 ± 12.6 t/ ha (95% confidence interval). This estimate uses analytical methods to calculate the uncertainty. Carbon stock is estimated from 104 plots for six pools:
    - Above-ground live planted trees.
    - Above-ground live other species (includes unplanted trees and shrubs).
    - Below-ground live planted trees.
    - Below-ground live other species (includes unplanted trees only).
    - Coarse woody debris.
    - Fine litter.

- Estimates of change in carbon stock using C_Change to predict carbon for 2008 and 2013 are 55.0 ± 10.3 t/ ha. The estimate of change in carbon is for four pools:
    - Above-ground live planted trees.
    - Below-ground live planted trees.
    - Coarse woody debris.
    - Fine litter.

- Uncertainty is expected to be reduced in a nationwide survey, with 200 sites the confidence interval is estimated to be ± 4.9 t/ ha. This estimate assumes that the two surveys, 2008 and 2013 are correlated with ? = 0.90. There is some evidence that the correlation could be as high as 0.97 but may be less than this if there is extra variation from genetic, silviculture and climatic factors. A conservative approach should be adopted in choosing the final number of sites in the nationwide survey to allow for future extra variation.

- Estimates of uncertainty have been derived using analytical methods and it is not necessary to use Monte Carlo simulation.

- Extra error from area definition will inevitably increase uncertainty associated with total carbon stocks. The estimated errors apply to carbon density (t / ha).

1. INTRODUCTION

As a signatory to the Kyoto Protocol New Zealand has agreed to report, in a transparent and verifiable manner, greenhouse gas emissions by sources, and removals by sinks, associated with direct human-induced land-use change and forestry activities. These land-use change and forestry activities are limited to afforestation, reforestation and deforestation that have occurred since 1990. In order to provide the necessary data to allow carbon stocks, and changes in carbon stock, to be estimated in accordance with the recently-adopted Good Practice Guidance for Land-Use, Land-Use Change and Forestry (IPCC 2003), a national forest inventory specifically designed for carbon monitoring is being implemented. The initial focus of the inventory will be planted Kyoto-compliant forests. These are forests which were established after 1 January 1990 on land which did not previously contain forests. Part of the preliminary work associated with the development of this national inventory consisted of a pilot survey which was conducted in the Nelson and Marlborough regions. The purpose of the pilot study was to test the proposed field methodology and collect sufficient data to be able to produce initial estimates of carbon stocks and stock changes.

Any large-scale survey will include some errors (Merritt *et al*. 2005). Good practice in forest inventories means that uncertainty associated with the survey and estimation should be reduced as far as practicable. Good practice also recognizes that while there will be some uncertainty remaining it should be identified. Uncertainty analysis is concerned with this identification of credible limits to the accuracy of an estimate (Cullen and Frey 1999). Moreover, the good practice guide (IPCC 2003) for the preparation of greenhouse gas inventories stipulates that uncertainties associated with estimates of sources and removals must be quantified.

In this report we present estimates of the uncertainty associated with the carbon estimates from the pilot study to demonstrate procedures for future analysis when carbon is assessed at a nationwide scale.

2. METHODS

2.1. General approach

The purpose of this report is to use currently available data to provide an initial estimate of the change in national planted forests carbon stocks during Commitment Period 1 of the Kyoto Protocol (that is, 1 January 2008 through to 31 December 2012). The estimate of carbon stocks will be derived from the product of the estimated carbon density (t/ ha) and the estimated total area (ha) of Kyoto-compliant forest (this area of compliant forest is referred to in this report as Kyoto Forest). It is unclear at this stage how the area of Kyoto Forest will be determined. Therefore, in this analysis we have not included uncertainty associated with the estimate of Kyoto Forest area. Instead, we have focused on the uncertainty associated with the change in carbon density, that is, on a per hectare basis.

We considered two different types of error:

1. Prediction error, the error associated with allometric functions used to estimate carbon from measurements of tree diameter and height. We assumed the measurement of diameter and height was achieved without any systematic bias.
2. Sampling error, the error associated with the sampling process in which only a small proportion of the area of total Kyoto Forests is actually measured.

We considered the following carbon pools:

1. Above-ground live planted trees.
2. Above-ground live other species (includes unplanted trees and shrubs).
3. Below-ground live planted trees.
4. Below-ground live other species (includes unplanted trees only).
5. Coarse woody debris.
6. Fine litter.

We did not consider soil carbon because:

1. One hypothesis is that soil carbon stocks are approximately constant over the course of a rotation, and hence the change in soil carbon stocks is close to zero.
2. There is relatively little data currently available and/or some reported results are contradictory. (Davis and Condron 2002; Paul *et al*. 2002)

The primary source of data for the sampling error analysis was the Nelson/Marlborough pilot study conducted in 2004 (Moore *et al*. 2005). There were 128 plots established in the pilot survey. A summary is given below, and full details are given in Moore *et al*. (2005). Of these 128 plots, 24 were rejected as being unsuitable for various reasons (Peter Beets, ENSIS – pers. comm.). We used the remaining 104 plots in analysis, although it should be noted that twenty four of these plots were located in forests that were not strictly Kyoto compliant (e.g., some plots were located in forests that were planted prior to 1990, or in second rotation forests, or both). Further subsets of the pilot survey data can be created using these criteria.

Analysis of uncertainty used allometric equations and the C_Change model (Beets *et al.* 1999) to estimate carbon stocks and stock changes. The four stages in the analysis were:

1. Stage 1, allometrics 2004, all pools.
   Allometric relationships were used to estimate carbon stocks in the above-ground live and below-ground live pools for both planted and unplanted trees, using data from 104 plots in the pilot survey. Estimates of the carbon stored in shrubs and coarse woody debris were taken directly from the pilot survey report (Moore *et al.* 2005) and were not recalculated here. Because it was not possible to estimate the carbon stocks in the fine litter pool using allometric equations, we used the C_Change model estimates of the amount of carbon stored in this pool.

2. Stage 2, allometrics 2004, planted species only.
   This analysis used the same methods and data as in stage 1 but carbon stocks in the above and below-ground live pools are only calculated for planted species. Unplanted trees and shrubs are excluded.

3. Stage 3, C_Change 2004, planted species only.
   Using the same plots and pools as in stage 2, estimates of carbon stocks were derived from the C_Change model.

4. Stage 4, C_change 2008 to 2013, planted species only.
   The C_Change model, coupled with the 300 Index growth model (Kimberley *et al.* 2005), was used to project measurements from the pilot survey plots forward to allow estimation of changes in carbon stocks during Commitment Period 1.

The pools of carbon estimated in each stage are summarized in Table 1.

Table 1. *Carbon pools used in each of the four stages of analysis*

Pool	Stage 1	Stage 2	Stage 3	Stage 4
Above-ground live planted trees (*agpt*)	v	v	v	v
Above-ground live other species and unplanted trees (*agupt*)	v			
Live shrubs	v			
Below-ground live planted trees	v	v	v	v
Below ground live unplanted trees	v			
Course woody debris	v	v	v	v
Fine litter	v	v	v	v

This sequential approach was taken because although the allometric approach is the most likely method to be used to estimate carbon stocks, we needed to consider uncertainty associated with the estimate of the change in carbon stocks. Change in carbon stocks was estimated using the C_Change model to simulate future remeasurement of plots. The analysis was complicated by the partial mismatch between pools of carbon estimated by allometrics and by C_Change. C_Change can

not be used to estimate carbon contained in non-planted species (i.e., unplanted trees and shrubs) so the second stage in the analysis estimated uncertainty in the 2004 pilot data for the reduced number of carbon pools. Stage 3 analyses allowed direct comparison between the allometric estimates and C_Change estimates for the reduced number of carbon pools. Finally, stage 4 allowed analysis of the estimated change in carbon (for the reduced number of carbon pools) during the first Kyoto commitment period (using the change between mid-2008 and mid-2013 to approximate the change between 1 January 2008 and 31 December 2012).

2.2. Pilot survey

The pilot trial was undertaken in the Marlborough, Nelson and Tasman districts in 2004 (Moore *et al.* 2005). An overlapping (3-phase) sampling design was used, where sample plots were laid out on a 2 by 2 km grid, a 4 by 4 km grid and an 8 by 8 km grid with the same overall intersections. The three levels of sample intensity were used to estimate carbon from regional forest-growth yield tables (2 by 2 km grid), to estimate carbon from individual trees within the plot (4 by 4 km grid), and, at the coarsest grid, to estimate carbon from individual trees and from soil samples. Data from the 4 by 4 km grid were used to estimate the uncertainty associated with carbon stocks and stock changes.

Plot data were available from 32 sites that were located at the grid intersections of the 4 by 4 km grid. The sample plan used a hybrid two-stage sampling design. The plot layout was similar to that used by the United States Forest Inventory and Analysis programme and employs a cluster of four circular plots at each site. At the grid intersection, a 0.04 ha circular plot was established, with three further 0.04 ha circular plots established at a distance of 35 m from the center plot, on bearings of 0, 120 and 240^{o} (see Moore *et al.* (2005) for complete details of the design). The original aim of the pilot survey was to establish plots at 45 sites, but this number was reduced due to time and budget restrictions (Moore *et al.* 2005). In some instances there was prior information to indicate that the site did not contain Kyoto-compliant forest, and resources were directed towards sampling the Kyoto-compliant forests in the study area. Further reduction in sample intensity occurred because in several instances all four plots within a cluster were not always established at each site. Again, full details of the reasons are given in Moore *et al.* (2005), the most common being that the satellite plot was not in Kyoto-compliant forest although the hub and/or the other satellite plots were.

Within each plot, diameter at breast height was measured on all standing trees. Total height, pruned height and height to crown base were measured on a sub-sample of up to 30 trees per species that were selected to be representative of the range of tree diameters within the plot. A range of additional measurements were made including: forest health, sapling and seedling counts, shrub cover, coarse woody and fine woody debris, and plant biodiversity (Moore *et al.* 2005). Soil samples were collected from plots located on the 8 km by 8 km grid.

2.3. Allometric models

The total height of those trees not assessed for height was predicted using the following nonlinear function (Woollons 2003):

$$H = \exp(a + b/\sqrt{D}) \quad (1)$$

where H is the predicted stem height (m) and D is diameter at breast height (cm). Estimates of the a and b parameters were obtained by non-linear least squares by fitting Equation 1 to the height: diameter data, for each site, pooling all data within each site. For *Pinus radiata*, (by far the dominant species), this meant each regression had between 60-80 data.

A provisional allometric model to predict carbon from above-ground live planted trees (C_{agpt}) was developed using data from 408 *Pinus radiata* trees (ENSIS, unpublished data) collected from various regions and experiments throughout the North Island of New Zealand. A conversion factor of 0.5 was used to convert above-ground biomass to tonnes of carbon. We chose to restrict the data for the allometric model to the set of 408 trees that were aged 20 years or younger because they are more representative of the range of tree ages that will be encountered in Kyoto Forests. The following nonlinear model was developed to predict the amount (tonnes) of above-ground carbon in *Pinus radiata* trees:

$$C_{agpt} = b_1 D^2 H^{b_2} \quad (2)$$

The model did not include an intercept term to ensure stems of zero height had zero predicted carbon. We were confident to remove the intercept from (2) in that we had copious data very near the intercept. Equation 2 was used to predict carbon for all live planted trees in the pilot survey, regardless of species. This assumption was not unreasonable as more than 97% of trees in the pilot survey were *Pinus radiata*, with the remainder being *Pinus muricata*, *Pinus sylvestris* and *Pseudotsuga menziesii*.

The amount of above-ground live biomass in unplanted trees (B_{agupt}) was estimated using the following allometric equation developed by Coomes *et al*. (2002):

$$B_{agupt} = 0.0000598t\,(D^2 H)^{0.946}\,(1 - 0.0019D) + 0.03D^{2.23} + 0.0406D^{1.53} \quad (3)$$

where B_{agupt} is in kg, and t is wood density (kg/ m^3) varying by species class (see Moore *et al*. (2005) for details). Biomass was converted to carbon using the IPCC default conversion factor of 0.5. The estimate of carbon was then converted from kg to tonnes by dividing by 1000.

The amount of carbon contained in the below-ground live pool for planted and unplanted trees was assumed to be 25% of the respective above-ground live pool.

Estimates of shrub biomass were available directly for each plot. Moore *et al*. (2005) give the relevant methods and prediction equations in their Table 5 (on page 19). Estimates of coarse woody debris biomass were also obtained directly from plot data (refer to p. 18 of Moore *et al*. 2005).

2.4. Prediction error

The allometric prediction models (i.e. Equations 2 and 3) estimate carbon or, for unplanted trees, biomass which is then used to estimate carbon. Biomass was not measured directly in the pilot study. In this situation it is necessary to consider the idea of 'prediction error' and its contribution to uncertainty in the calculation of changes in carbon stocks in Kyoto Forests.

The parameters in Equations 2 and 3 were estimated from samples (using non-linear least-squares estimation techniques) and consequently any predictions can be expected to have some error. For example, the true relationship between *Pinus radiata* biomass and carbon and tree diameter and height will not be exactly as described in Equation 2. Either one, or both, of the slope and power parameter estimates could be inaccurate. Although Equation 2 gives estimates of carbon for individual trees and the key statistic for estimating uncertainty in carbon stock is estimates of total carbon among all trees in a sample plot, this prediction error does not necessarily 'cancel out'. There will still be prediction error associated with estimating plot-totals.

For a straight-line linear function with an intercept exact analytic expressions can be used to quantify prediction errors. Given the presence of independence, normality and homogeneity of errors, the variance of a single predicted value for a given value of X, X_i, is:

$$V(C_{agpt}) = s^2\left(1+\frac{1}{n}+\frac{(X_i-\bar{X})^2}{\sum x^2}\right) \qquad (4)$$

where n is the number of data used in building the linear function, ? x^2 is the corrected sum of squares of the X_i variable, $\bar{X}$ is the average X_i value, and s^2 is the model error mean square (Draper and Smith 1998). Similarly, the variance associated with estimating the average prediction for a given X_i is:

$$V(C_{agpt}) = s^2\left(\frac{1}{n}+\frac{(X_i-\bar{X})^2}{\sum x^2}\right). \qquad (5)$$

Estimating prediction error associated with the allometric models is more complex than this because the models (Equations 2 and 3) are nonlinear and there are no simple analytical solutions. While the assumptions of normality and independence are more than tenable, formulae for the variance of predicted values from nonlinear models are unfortunately approximate and involve partial differentiation of each parameter (Box 1971). Rather than introduce this complexity to estimate the standard errors of the allometric models we used the statistical software SAS to produce numerical approximations.

Regardless of how variance (or standard error) estimates were derived it is likely the prediction error will be underestimated. An unbiased estimate of prediction error depends strongly on the data used to build the allometric models. The assumption is that the trees used in the modelling are a representative random sample from the population of Kyoto forest trees. This is unlikely to be true for two reasons. The

currently available trees were predominately young and small, and secondly, were largely sourced from only two regions within NZ, one of which (Woodhill) is known to have high density (Cown *et al.* 1991). In these circumstances any derived prediction error is likely to be incorrect, and most probably underestimated.

2.5. Variance and sampling error estimation

Estimates of the among- and within-site variance in carbon stocks per hectare were calculated using analysis of variance methodology. In the pilot survey design, the starting point for the sampling grid was randomly selected. Given this randomization, we assumed sites could be treated as levels of a factor in an analysis of variance (ANOVA) model, with plots randomly nested within sites. For practical purposes the sampling design can be viewed as two-stage sampling, and therefore the sampling variance of the mean is given by Cochran, 1963:

$$V(\bar{y}) = \left(\frac{N-n}{N}\right)\frac{S_a^2}{n} + \left(\frac{M-m}{M}\right)\frac{S_w^2}{mn}, \qquad (6)$$

where N is the number of sites in the total population of which n are surveyed, M is the number of (potential) plots within each site of which m are surveyed, and $S^2{}_a$ and $S^2{}_w$ are the among- and within-site variances.

When N and M are unknown or very large this equation simplifies to:

$$V(\bar{y}) = \frac{S_a^2}{n} + \frac{S_w^2}{nm}. \qquad (7)$$

2.6. Uncertainty in future changes in total carbon

A major objective of New Zealand's Carbon Accounting System is to be able to estimate the change in carbon stocks over the first Kyoto Protocol commitment period (i.e., 2008-2012). By definition, such estimates are currently limited to projecting measurements made on existing plots forward in time and predicting the corresponding carbon stocks using appropriate models.

Predictions from the C_Change model (Beets *et al.* 1999) were used as surrogates for future carbon stocks. Carbon stock estimates for years 2008 and 2013 for the pilot study plots were provided by Peter Beets (ENSIS). These future predictions can be used to estimate the change in carbon stocks and to assess the uncertainty associated with this estimate of change. Estimating change in a variable usually has less uncertainty associated with it than estimating total levels of the variable when estimates are made from repeat (in part) sampling of the same plots because of the likely high correlation between present and future plot means (Skalski 1990). We anticipate that the plot data for 2008 and 2013 will contain a mixture of paired and unpaired plots - not all the plots in 2008 will be remeasured in 2013, and in 2013 there may be new plots measured. Therefore we did not use ratio estimation (i.e., 2013 estimate/2008 estimate) to calculate the variance of the change in carbon stocks. Nevertheless, it may be possible in the future to consider partial replacement sampling

variance formula to accommodate a combination of matched and unmatched plots (Ware and Cunia 1962).

To estimate uncertainty in the change in carbon stocks, variance components for sites, and plots within sites, were calculated for the difference in C_Change carbon stock estimates for 2008 and 2013. The variance of a difference between two correlated random variables, C_i and C_j is:

$$V(C_i - C_j) = s_i^2 + s_j^2 - 2r s_i s_j, \qquad (8)$$

where r is the correlation between C_i and C_j and s_i^2 is the variance of C_i (Meyer 1965).

2.7. Monte Carlo estimates of uncertainty

As an alternative to analytical methods to estimate the variance of the 2004 carbon stocks, we considered conducting a Monte Carlo simulation using a subset of the data produced by the C_Change model. This approach to estimating uncertainty in carbon stocks is briefly described in Brown, *et al*. (2005). More general discussions are given by Frey (1992) and Hammonds *et al.* (1994).

The basic plot data were collected through a two-stage sampling design and any distribution modelling of the data should recognise this structure. We attempted to model each carbon pool by two component distributions:

1. Among sites through the various site means.
2. Within sites through modelling the site standard deviations.

The data for all four pools contained several zero values as well as being appreciably right-skewed. We modelled the among-site distributions through standard Weibull distributions but allowed the location parameters to assume negative values to obtain adequate prediction of positive values for zero and near-zero amounts of carbon. Despite this, the results were not good. The goodness-of-fit statistics (Stephens 1974) for the distributions were poor, with the within-sites distributions sometimes being close to bi-modal.

This Monte Carlo approach only addressed sampling error. To account for prediction error inherent in the distributions, a new set of coefficients (from the allometric equation) would be needed to be generated for each iteration of the simulation process.

Given this extra complexity to simulate prediction error and the difficulty in fitting distributions and the limitations of the biomass data, the Monte Carlo approach was not explored further. Monte Carlo methods are surrogate techniques for estimating distributions when parametric methods are not possible and they are not designed primarily as equal alternatives (Manly 1997). In this application to estimate carbon stock we derived estimates of uncertainty using standard analytical methods and it was not necessary to rely on computational methods.

3. RESULTS

3.1. Building the *Pinus radiata* allometric model.

The provisional allometric model to predict total above-ground carbon from *Pinus radiata* was:

$$C_{agpt} = 0.000029 D^2 H^{0.5641} . \quad (9)$$

The model residual variance, s^2, was 0.000117. This is considerably smaller compared to a simpler model using D^2H as the predictor variable which had s^2 = 0.000167. The model had a near-linear relationship between predicted carbon and D^2H (Figure 1), although there is some evidence of mild heteroscedasticity and a slight degree of curvature. The heteroscedasticity was not sufficient to warrant the use of a weighted model and introduction of the extra complication of interpreting the model error. A histogram plot of residuals (not shown) confirmed the presence of normality of errors. A model including an intercept had a very small but non-significant positive value.

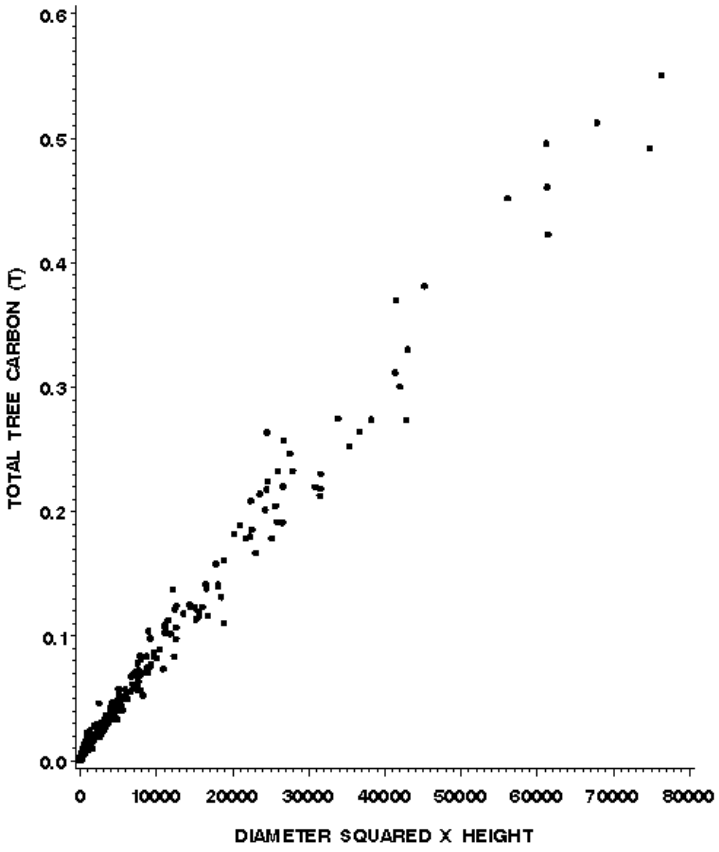

Figure 1. *Predicted above-ground carbon for Pinus radiata and D^2H, n = 408.*

3.2 Prediction error of the allometric model

The numerical approximate standard errors associated with the data used to construct the *Pinus radiata* allometric model (Equation 2) were not normally distributed (Figure

2). This is probably a consequence of the data used to derive the allometric model being dominated by smaller trees (see Figure 1).

A second (apparent) oddity is the graph of the standard errors plotted against tree size (Figure 3). Usually, prediction variation is minimal around the average predictor value and gradually increases evenly above and below this, while here, the minimum values are near zero. This is because in Equation 2 the intercept is not estimated and the model forces the prediction through the origin. Thus it is logical for minimum prediction errors to occur near zero but increase with larger tree size moving away from the origin.

Despite the lack of normality in the data the best estimate of average prediction error is the average standard error of the 404 predictions, which is ±0.00053 t/ ha. The average tree biomass is 0.0539 tonnes, and thus the prediction error is estimated to be around 1 %. This prediction error will increase for predicting trees larger than are in the current dataset.

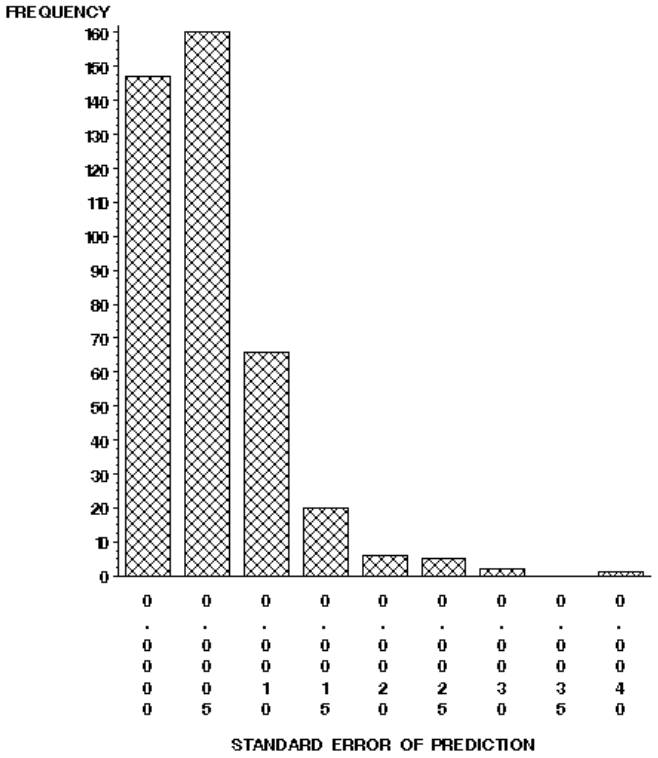

Figure 2: *Approximate prediction standard errors of the allometric model for* ***Pinus radiata****, Equation 2.*

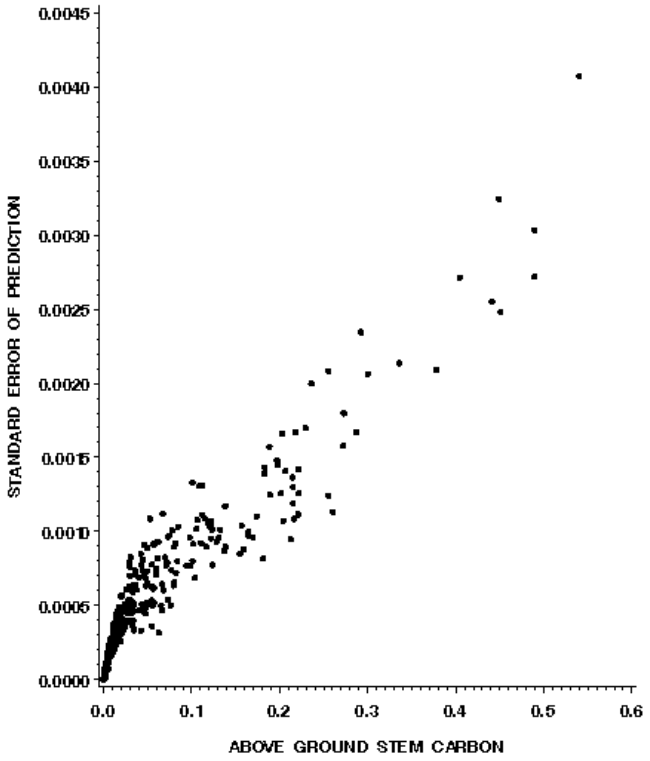

Figure 3: *Prediction standard errors and tree size*.

3.3 Uncertainty in 2004 carbon stocks estimated using allometric and C_Change models.

Estimates of carbon stocks in all pools (i.e., Stage 1 analysis) were made for each of the 104 plots used in the analysis using allometric models. Carbon from fine litter was estimated from the C_Change model. Above-ground carbon stocks in planted trees were estimated with Equation 9 using the (measured) tree diameters and either, measured tree heights, or heights predicted using Equation 1. The approach for estimating carbon stocks for the other pools (i.e., above-ground live unplanted trees, above-ground live shrubs, below-ground planted trees, below-ground unplanted trees, coarse woody debris, and fine litter) is described in the methods section. This method gave an overall estimate of average carbon stocks across all pools of 64.4 (t/ ha).

Analysis of variance was used to identify variance components (Table 2). In the analysis, 64% of the variation in estimated carbon stocks was attributable to variation among sites, the other 36% from variation within each site.

Table 2. *Analysis of variance for carbon estimates from all pools (Stage 1 analysis) using allometric models. There were 104 plots in the analysis.*

Source of Variation	df	MS	Expected mean Square	Variance component
Among Sites	26	4134.96	$3.85S^2_a + S^2_w$	936.16
Within Sites	77	530.87	S^2_w	530.87

The uncertainty associated with the estimate of carbon stocks was calculated using Equation 7. The survey design was slightly unbalanced because three of the 27 sites had fewer than four plots installed. Rather than use $m = 4$, we substituted the average number of plots per site and used $m = 3.85$:

$$\begin{aligned} V(\bar{y}) &= \frac{S_a^2}{n} + \frac{S_w^2}{nm} \\ &= \frac{936.16}{27} + \frac{530.87}{27 \cdot 3.85} \\ &= 39.77, \end{aligned}$$

giving a standard error of 6.31 and an approximate 95% confidence interval for total carbon stocks of 64.4 ± 12.6 t/ ha. The relative width of the confidence interval is 20%.

The estimated mean carbon stock in the above- and below-ground planted tree, coarse woody debris and fine litter pools (i.e., Stage 2 analysis) was 50.8. In the analysis of variance, 83% of the variation in estimated carbon stocks was attributable to variation among-sites, the other 17% from variation within each site (Table 3).

Table 3. *Analysis of variance for carbon stock estimates from planted tree, coarse woody debris and fine litter pools (Stage 2 analysis) using allometric models.*

Source of Variation	df	MS	Expected mean Square	Variance component
Among Sites	26	5455.98	$3.85S^2_a + S^2_w$	1346.31
Within Sites	77	272.62	S^2_w	272.62

Using the same method as in Stage 1 analysis, the estimated variance of the mean was 52.48 t/ ha, giving a standard error of 7.24 t/ ha and an approximate 95% confidence interval for total carbon of 50.8 ± 14.5 t/ ha and relative interval width of 29%.

Conducting the same analysis, but using data on carbon stocks from C_Change (Stage 3 analysis), yielded an average carbon stock of 50.4 t/ ha. In the analysis of variance 82% of the variation in estimated carbon stocks was attributable to variation among sites, the other 18% from variation within each site (Table 4). The estimated variance of the mean was 49.66, with a standard error of 7.05 t/ ha and an approximate 95% confidence interval for total carbon of 50.4± 14.1 t/ ha. The relative interval width was 29%. These estimates of carbon stocks and their associated uncertainty are very similar to those from the allometric models (Stage 2 analysis).

Table 4. *Analysis of variance for carbon estimates from planted tree, coarse woody debris and fine litter pools (Stage 3 analysis) using C_Change model.*

Source of Variation	df	MS	Expected mean Square	Variance component
Among Sites	26	1549.82	$3.85S^2_a + S^2_w$	1267.77
Plots within Sites	77	282.05	S^2_w	282.05

3.4 Uncertainty in the estimates of the change in carbon stocks between 2008 and 2013

The analysis of variance for 2008 and 2013 carbon estimated by C_Change (Stage 4 analysis) had similar variance components (in absolute terms) to the estimates from 2004 (Table 5).

Table 5. *Analyses of variance for carbon estimates projected to 2008 and 2013 using C_Change.*

	Source of Error	df	MS	Expected MS
2008	Among Sites	26	9537.55	$3.85S^2_a + S^2_w$
	Plots within Sites	77	799.42	S^2_w
2013	Among Sites	26	19846.00	$3.85S^2_a + S^2_w$
	Plots within Sites	77	1402.59	S^2_w

For the 2008 projected plot-data, variance among site was 2269 (74%) and variance within sites was 799 (26%). For 2013, variance among sites was 4791 (77%) and within site, 1402 (23%). From these analyses, estimates of carbon stocks for 2008 and 2013 were 92.2 19.1 t/ ha and 146.7 27.6 t/ha (95% confidence intervals), respectively.

There was a very strong relationship between carbon stocks estimated by C_Change for 2008 and 2013, with a correlation coefficient r = 0.97. This may seem an inordinately high value and likely to be biased because the same model was used for both 2008 and 2013 predictions. However, the correlation value of 0.97 may not be as unrealistic as it appears. Previous studies between sets of paired plots of even-aged stands have produced similar values. Figure 4 shows a plot of volume per ha at ages 11 and 16 years for two sets of plots taken from two *Pinus radiata* thinning trials in Kaingaroa and Northland (Woollons and Whyte 1990; Woollons *et al.* 1994). Ignoring the slight curvature, the linear correlations between volume at ages 11 and 16 years for the two experiments were 0.96 and 0.97. If the data are pooled the correlation is still 0.97, a consequence of increased data.

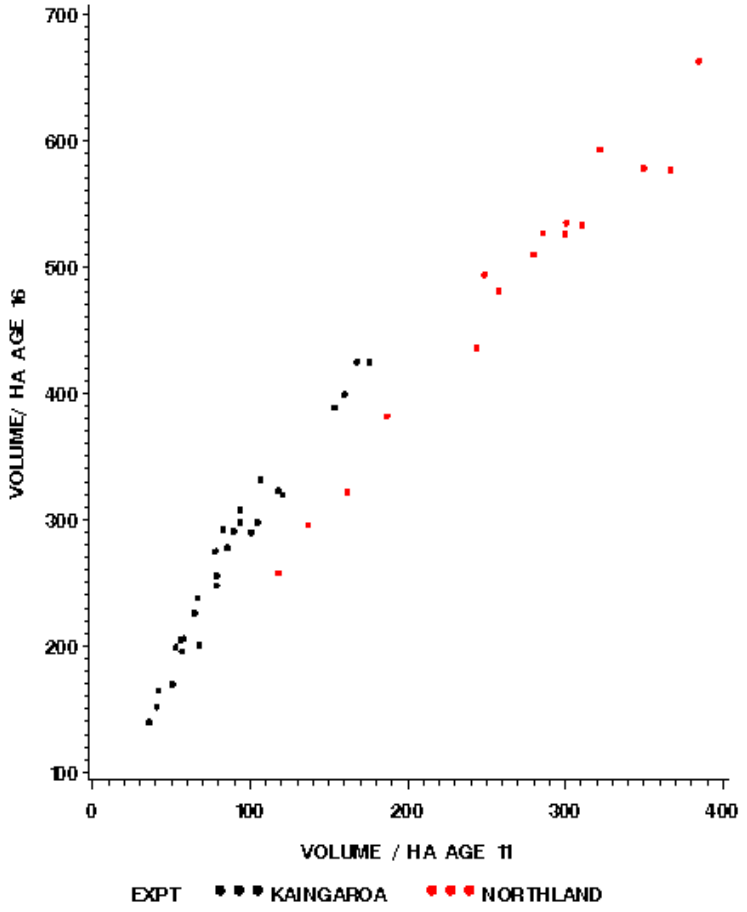

Figure 4. *Volume/ ha at ages 11 and 16 from two* ***Pinus radiata*** *experiments.*

Using the correlation of r = 0.97 and Equation 8, the change in carbon stocks over 2008-2013 was estimated to be 55.0 ± 10.3 t/ ha or 19 % (95% confidence interval).

3.5. Effect of correlation and sample size on confidence intervals based on sampling error.

Two factors that will affect the precision of the estimated change in carbon are the correlation among the estimates from the two surveys, and the sample sizes of the surveys. When there is high correlation among repeat surveys precision can be high and confidence intervals appreciably narrow. Large sample numbers (largely irrespective of the population size) also contribute strongly to high precision and hence, narrow confidence intervals (Stuart 1960).

The 95% confidence interval estimated for the change in carbon stocks over 2008 to 2013 was ±10.3 t/ ha or 19 %. The observed correlation of r = 0.97 is very high. As already discussed, the same model was used to predict the 2008 and 2013 plot measurements and this may have inflated the observed correlation. On the other hand, previous studies suggest r = 0.97 is not an unreasonable value for the correlation between two repeat measurements taken from the same plots. Nevertheless, the correlation may still be considered unrealistically high for three other reasons. The

estimates of carbon stocks for 2008 and 2013 were obtained from C_Change and did not include all pools of carbon (see Table 1). No allowance has been made for carbon from unplanted trees and shrubs. If these pools were included then the value of the correlation coefficient may be less 0.97. The second reason is that growth estimates are not adjusted for changes as a result of pruning, thinning or significant mortality that may occur in a proportion of the plots. Lastly, we (necessarily) assume that 'average' climatic conditions will occur over 2008-2013; this may not be the case.

Rather than speculate on a likely correlation value, we systematically re-estimated the interval for different values of the correlation coefficient but including a value of 0.97. (Table 6). This analysis used the among- and within-site variances from the pilot study and we assume these will be consistent with the variance components obtained in the nationwide surveys. We have also assumed that 4 plots will be installed at each site.

The effect of increasing sample size on the confidence interval is also shown in Table 6. When the New Zealand-wide surveys are conducted, the sample sizes will be considerably larger than in the pilot survey and precision should improve over what we have estimated here. Given the form of the equation to estimate variance of the sample mean (Equation 7), and that variation among sites is the dominant variance component, it is clear that the number of sites (n) will have a large effect on uncertainty and the size of confidence intervals. If there are 200 sites (800 plots) established nationwide, and a correlation of 0.9 between surveys, the interval will reduce to around ± 9 %, less than half the current estimate. If a correlation of 0.97 is achievable this reduces to ± 5 %.

Table 6. *Likely size (half-width percentages) of 95 % confidence intervals for estimates of change in carbon between 2008 and 2013, with various sample sizes (number of sites) and correlations (r) among the two years. Units are ± % .*

Number of Sites	r = 0.7	r = 0.8	r = 0.9	?= 0.97
27	36	31	24	19
100	19	16	13	10
200	13	11	9	7
300	11	9	7	6
400	9	8	6	5

3.6 Estimates of total error: combining sampling and prediction error.

In the sections 3.3 through 3.5 above we have summarised and discussed various confidence intervals that have a common element – the variation is confined to sampling error. In sections 2.4 and 3.2, we introduced and estimated the average prediction error associated with the *Pinus radiata* allometric equation. Here we consider total error and the effects on the width of confidence intervals.

We assume that the two sources of variation are approximately additive. Denoting the respective standard errors as s_p, s_s *and* s_t (prediction, sampling and total) then the total error is:

$$s_t = \sqrt{(s_p^2 + s_s^2)} \qquad (10)$$

Table 7 shows the 95 % confidence intervals for changes in carbon stock over 2008-2013 for various sample sizes and correlations but where the standard error term is now based on total error given by Equation 10 with the prediction error is estimated as 1, 2, and 4 %.

Table 7: *Likely size (half-width percentages) of 95 % confidence intervals for estimates of change in carbon between 2008 and 2013, with various sample sizes (number of sites), correlations (r) among the two years and prediction errors. Units are ± % .*

	Sites	r =0.7	r =0.8	r = 0.9	r =0.97
1 % prediction error	27	36.0	31.1	24.1	19.1
	200	13.2	11.2	9.2	7.3
	400	9.2	8.2	6.3	5.4
2 % prediction error	27	36.2	31.3	24.3	19.4
	200	13.6	11.7	9.8	8.1
	400	9.8	8.9	7.2	6.4
4 % prediction error	27	36.9	32.0	25.3	20.6
	200	15.3	13.6	12.0	10.6
	400	12.0	11.3	10.0	9.4

4. DISCUSSION

4.1. The likely influence of prediction error

In this report we have considered uncertainty in estimating carbon from two sources: prediction error and sampling error. Prediction error introduces uncertainty when the measurements and models used for prediction produce inaccurate results. For the data used to build the allometric model (Equation 2) the average prediction error is estimated to be 1 %. However this estimate is likely to be too low. The data are essentially limited to two sites in the North Island and the average age of the trees is young (only 7 years). If this allometric model is used in the NZ-wide survey of carbon stock over 2008-2013 larger trees and more variation in density will be encountered and we expect larger prediction errors. At this stage the size of these prediction errors are unknown.

The effects of the prediction component on total error and, therefore, on the size of confidence intervals, are given in the results section 3.6. If the prediction error is assumed to be no more than 2% then its effect on total error is minimal. At 4 % however, the underestimate may be large.

We recommend that an additional set of *Pinus radiata* trees be sampled for biomass and the allometric models re-estimated. Extra sampling should be directed to Kyoto forest trees with low density (for example, the South Island – especially in Otago and Southland) and at older ages. As of April, 2005 the estimated area weighted average age of Kyoto forests is around 9 years (Paul Lane, *pers. comm*.). Through 2008-2013 a significant amount of Kyoto growing stock will thus be 13-18 years in age. Biomass assessment of larger (older) trees is logistically tedious but it is important that these trees be included to allow more reliable estimation of prediction error.

4.2. Uncertainty in carbon estimates

Estimates of uncertainty based on sampling error only, were derived for the four stages of analysis of carbon stock (introduced in 2.1). Prediction error is not included in this discussion.

The estimated total carbon stock for all pools in 2004 (Stage 1 analysis) was 64.4 ± 12.6 t/ ha (95% confidence interval). Estimates of carbon from the four pools used in C_Change were 50.8 ± 14.5 t/ ha from allometric models (Stage 2 analysis) and 50.4 ± 14.1 t/ ha from the C_Change model itself (Stage 3 analysis). The smaller estimate of carbon from the Stage 2 and 3 analyses was due to the fact that not all carbon pools were included. The purpose of these last two estimates (Stage 2 and 3) were to allow comparison between the allometric and C_Change models because the C_Change model is used in the assessment of changes in carbon stocks over time.

In all three analyses the predominant source of variation was among sites (64%, 83% and 82% for Stage 1, 2, and 3 analyses, respectively). Therefore the most effective way to allocate extra survey effort to improve precision is to survey more sites rather than more plots within sites.

4.3. Uncertainty in change in carbon estimates

The estimate of uncertainty in the change in carbon stocks between 2008 and 2013 was derived from the C_Change output. The 95% confidence interval (sampling error only) for the change in carbon stocks was estimated as 55 ± 10.3 t/ ha. The precision of the estimated change in carbon stocks will improve when more sites are surveyed. Confidence intervals are likely to be half this width (i.e. ± 4.9 t/ ha) if there are data from 200 sites rather than the 27 that were used in this analysis. This assumes that among and within-site variances estimated from the pilot survey are reasonable estimates for those likely to be encountered in the nationwide survey.

The final estimate of stock change between 2008 and 2013 may not be as precise as ± 4.9 t/ ha if the correlation between stocks at the beginning and end of this period is less than the $r = 0.9$ used here. Although there is evidence that correlations of repeated measurements in time between paired plots can be very high, these may not eventuate. Reasons for having a lower correlation between the two measurement dates are discussed in the results section and include the fact that not all pools of carbon have been included in the estimate in this analysis, and that the future estimates of carbon stocks do not include possible extra variation from genetic, silviculture and climatic factors. Over time the effects of thinning, pruning, alternative species mixes, fertilizers, successions of droughts or improved genetic stock can introduce larger or smaller changes in tree growth than could be expected from deterministic growth models. Failure to include these possible sources is not a shortcoming of the models (such as C_Change) because it is not possible to model such factors, and is more an issue about cautious use of future predictions. A conservative approach should be adopted in choosing the final number of sites in the nationwide survey to allow for future extra variation.

4.4 Monte Carlo simulation

We encountered a number of difficulties in Monte Carlo simulation and recommend that analytical methods be the basis for future estimates of uncertainty. Monte Carlo methods are surrogate techniques for estimating distributions when parametric methods are not possible and they are not designed as equal alternatives (Manly, 1977). In this application to estimate changes in carbon stocks we have derived estimates of uncertainty using standard analytical methods and it is not necessary to rely on computational methods.

4.5. Area definition

Because it is unclear how the total area of Kyoto Forests will be determined, we have not included the uncertainty associated with the estimate of Kyoto Forest area in this report. Nevertheless, the different subsets of plots measured in the Nelson/ Marlborough pilot study can give some insight into the impact of population definition on uncertainty. The total standard deviation of carbon stocks, estimated using the allometric approach but excluding fine litter, for the 104 plots is 32.3 t/ ha. However the original data set from the pilot survey has information from 128 plots and the standard deviation of these is 35.3 t/ ha. The increase in variation is because the full set of 128 plots includes some plots that were in pasture and others in unplanted forest. The standard deviation can be increased further to 36.7 t/ ha if zero

carbon estimates are used as surrogates for measurements from plots that were not established to make up the full compliment of 4 plots at 45 sites.

These estimates of standard deviation are synthetic if not simplistic but they do illustrate the effect of errors in defining the target population. The target population is the land area in New Zealand that contains Kyoto-compliant forests. Errors in the spatial definition of the target population will mean that less than the full complement of plots will be established because some plots will fall outside Kyoto Forest. Secondly, if there are areas of Kyoto Forest not included in the spatial definition, these forests can not be included in the survey. Thirdly, any errors in the spatial definition of Kyoto Forest will mean that the estimate of the total area (ha) of these forests will have error associated with it. Any error in the area estimate will flow through to the estimate of total carbon stocks when the carbon stock density (t/ ha) is multiplied by the land area (ha).

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