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The Robustness of New Zealand Forestry Planning to Uncertainty in Yield Data

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EXECUTIVE SUMMARY

The objective of this research project was to determine the sensitivity of a representative New Zealand linear programming planning model to the level of precision of the inventory used to create the yield tables used in the model. The robustness of a planning model has a large bearing on the amount of uncertainty in the input data that is acceptable. Before attempting to study the robustness of New Zealand planning model, a suitable measure of robustness needed to be found. A review of the international literature did not reveal a suitable measure, so a large part of this project was devoted to developing a methodology for measuring the robustness of a forest planning model.

The developed measure is based on the distribution of breakpoints. The breakpoint is the volume per year of a particular log grade where the linear programming model goes from feasible to infeasible when one additional cubic metre of the log grade is added to the right-hand side of the constraint for that log grade. The distribution of breakpoints is created by repetitively randomly sub sampling plots for a number of different proportions of the original number of plots that were collected. The robustness of the model was determined by studying how the relative standard deviation changes as the proportion of the total plots used in the yield table generation changes.

The robustness of three different models was calculated, the different models being created by placing constraints on three different log grades. The results show the robustness of a simple linear programming model is sensitive to the relative abundance of the log grade within the estate being modelled. For scarce log grades, the linear programming model lacks robustness with respect to the number of plots used to generate yield. As the available volume in the estate for a grade increases, the model robustness increases, particularly as the number of plots increases. The model is very robust to changes in number of plots for the most abundant log grade. This result would suggest that when planning a cost-effective forest inventory the constraints placed on the planning model and potential financial gain or loss of not achieving those constraints should be taken into consideration.

INTRODUCTION

In forest planning, a range of mathematical modelling techniques can be, and are, used to help practitioners make important management decisions. In New Zealand, deterministic linear programming (LP) models are commonly used. The most common forest planning software products used locally historically are FOLPI [5] and more recently Woodstock, both of which use LP to obtain optimal forest plans.

Key inputs in forest planning are yield tables which describe the growth of forest stands. These are created using data obtained from forest inventory in combination with growth models that predict future yield. In New Zealand, almost without exception the growth models used are developed by fitting statistical mathematical models to tree growth data collected from permanent sample plots. Yield tables typically contain only information about the mean volume per hectare at a particular age for each product type. Generally no information about the precision of these volume estimates is included in a yield table.

Imprecise yield estimates are one of several sources of uncertainty that affect the decisions made by forest managers using planning models. Yield predictions are not only subject to sampling error, but also measurement and regression error, and these cannot be reduced through increasing the number of plots. Uncertainty in other inputs such as stumpage prices and cost are generally beyond the control of forest management planners. Even the mathematical growth method utilised to project yield forward in time can introduce additional error. These are normally developed independently of forest planning and management organisations, so forest managers may have little knowledge of the sources of error associated with a specific growth method. The sampling design, including the number of plots measured, is one of the important ways resource and planning foresters can manage the amount of uncertainty within the input data of their planning models.

If a forest inventory has been carried out in accordance with standard statistically valid sampling techniques, reliable estimates of inventory precision can be determined [14]. New Zealand forest inventory commonly utilises ground plots laid out using a systematic sampling design. The resource management unit is mapped out accurately, and plots are then located using a regularly spaced grid [7]. The number of plots allocated to an individual resource management unit can be calculated using some previous measurements of variance and a target of a desired level of precision. If no measure of variance is known, then experience and general percentage of area rules are applied. Many pre harvest inventories are planned to obtain a standard 10% Probable Limit of Error (PLE) on total recoverable volume. PLE on specific grades will always be greater than the target PLE [7]. PLE is a measure of precision of a forest inventory used in the New Zealand industry. It is defined as "the confidence limits expressed as a percentage of the estimated mean".

There is always a trade-off between the cost of carrying out inventory and the value of the information obtained [6]. Increasing the number plots is likely to reduce sampling error, which will result in a higher level of precision. In statistical terms this means the confidence interval around the projected volume per hectare will be tighter, which should allow users to have more confidence in the yield projected from the measurement data. Higher level of confidence comes at a cost as each additional plot costs additional time and money. Numerous research papers have been published [1, 4, 8, 9] that attempt to calculate the costs and benefits for different inventory scenarios, many using the cost-plus-loss methodology. In New Zealand, inventory costs can be seen as a discretionary cost that can be avoided altogether. However, the value of the information typically exceeds the cost of gathering and processing it, making regular forest inventory financially viable.

In forestry, like many other industries, most often the production and evaluation of solutions is driven by discounted-cash-flow (DCF) analysis. To facilitate this process, uncertainty in the input [redacted] future is uncertain, DCF is at best marginally helpful and at worst downright dangerous. Underestimating uncertainty can lead to strategies that neither defend a company against the threats nor take advantage of the opportunities that higher levels of uncertainty provide”. The problems caused by these uncertainties are exacerbated due to forestry’s relatively long term production cycle. The deterministic techniques used in FOLPI and Woodstock have little ability to either include estimates of data uncertainty in the solution evaluation process, or communicate the impact of the uncertainty on the solution selection to the decision maker.

Before trying to determine the extent to which robust optimisation techniques such as stochastic linear programming, dynamic programming and chance-constrained methods [13] could be utilised in New Zealand forest planning, it is important to determine how robust the existing planning models already deployed are to uncertainty in the underlying yield data. Boyland [2] carried out a study with the objective of developing a robustness test that measures the level of deviation between the projected plan and the implementation plan while still meeting project target levels. The paper shows that when using a maximum sustainable volume objective, both the simulation and optimisation models have very little robustness.

Little is known about the general robustness of forest planning models in New Zealand. The general impression in the industry is that current planning models are reasonably robust to uncertainty in yield data. The objective of this research is to determine just how robust a typical LP-based forest planning model is to uncertainty in yield predictions.

A simple ten-year tactical model has been used in this paper to try to measure how robust the results of the model are to different yield tables generated from the same population, but using different numbers of pre-harvest plots per planning unit.

METHODOLOGY

Plot Data

The plot data used in this project were obtained from a New Zealand forestry company and included only resource assessment units for which pre harvest inventory had been carried out within a five-year period. In reality, resource assessment units would not always align with the tactical planning model or harvest units. The resource assessment units included in the study were selected from the company's resource assessment database with an area that would most closely mimic tactical planning units. The resulting planning unit areas ranged between 4.5 and 49 hectares. This means that the total area included in the planning model is approximately 3740 hectares. In total 130 resource assessment areas were used in the research. These resource areas have been assumed to represent harvest planning units for the purpose of this research. Figure 1 gives the age class distribution (at the start of the planning period) for the planning units included in this study.

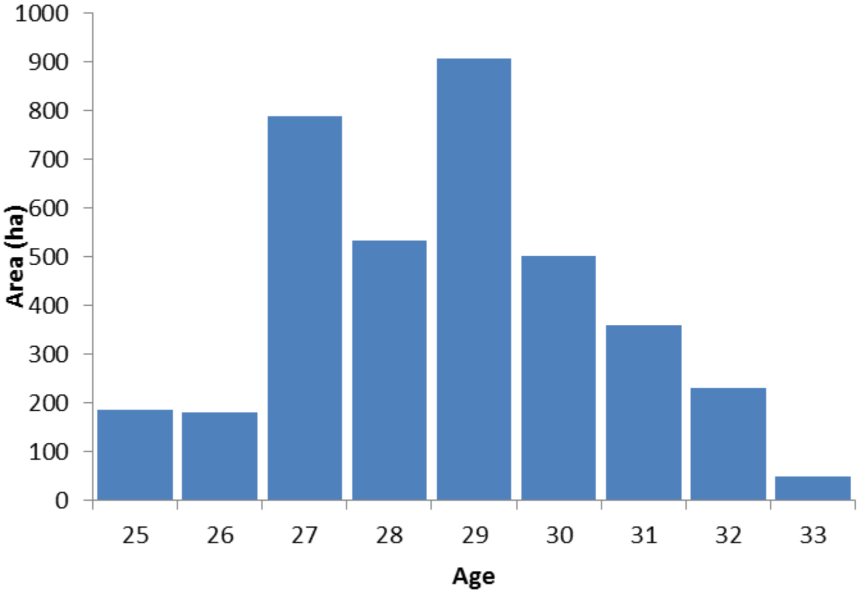


Figure 1. Area/Age Class Distribution (at the start of the planning period) for all 130 stands included the planning model.

The company determined the number of plots per resource assessment unit based on trying to achieve a minimum acceptable level of precision; however this rule is overwritten by minimum number of plots for smaller resource assessment units. All the plots were laid out using a systematic-based sampling scheme. Figure 2 shows the distribution of number plots per resource assessment area.

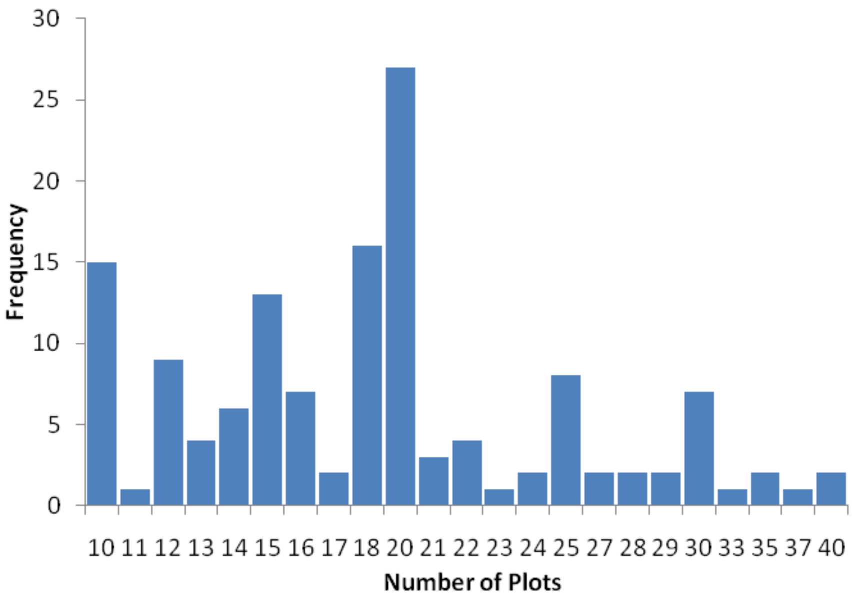


Figure 2. The Plot Number per stand distribution for all 130 stands included in the planning model

For reasons of confidentiality, stand names and geographical locations of these resource units have not been included in this paper.

Yield Table Generation

The plot data were processed using the yield table generation software YTGEN[1]. Each stand was simulated to grow from 2010 to 2020 using the PPM88 growth model. Table 1 summarises the models used to predict tree form, volume and growth from the inventory data. YTGEN is the most common forest yield analysis software used throughout New Zealand and Australia

Table 1. Models using in YTGEN

Model	Value
Volume	182
Taper	182
Breakage	1
Growth	PPM88

The trees are then virtually bucked using an optimal bucking algorithm embedded in the YTGEN software product with reference to the log product description given in
Table 2. The stand yield estimates was then determined by averaging the plot volume over the stand; where a stratified inventory approach was used and area weighted stratum averages were used to calculate stand yield.

[redacted]

Table 2. Overview of the Cutting Strategy used.

Grade	Value ($)	Min sed (cm)	Max sed (cm)	Max led (cm)	Lengths (m)	Branches (cm)
P1	129.5	40	80	80	4.9,5.25,5.5,6.1	<=1
P2	102	30	80	80	4.9,5.25,5.5,6.1	<=1
S1	88	40	80	80	4.9,5.5,6.1	<=7
S2	82.50	30	80	80	4.9,5.5,6.1	<=7
S3	69.50	20	60	60	4.9,5.5,6.1	<=7
Pulp	44.5	10	80	80	3-6.1@0.1	
A_12m	143	20	34	80	12	<=15
A	105	20	34	80	4,8	<=15
J	91	20	26	999	4,8,12	<=15
K	91	20	26	999	3.6,5.4,7.3,11	<=15

The amount of uncertainty or precision in the inventory dataset was varied. The easiest way to manipulate the precision of any inventory is to change the number of plots installed. As this project utilises historical inventory data, the inventory precision can be affected by reducing the number of plots included in the yield analysis. In total nine yield table scenarios were created using inventories with a different number of plots. The different plot selections were based on the selection criteria outlined in Table 3. The selection method ordered the plots in numeric order; the plot number modulus x was taken where x equalled 2, 3 or 4. Depending on the selection criteria the plot is selected if the answer either equal or does not equal zero.

Table 3. Plot Selection Criteria for Yield Table Scenarios.

Selection Criteria / Yield Table Scenarios	Plot Selection	Plot Selected
All Plots	All the original plots	
HalfNoPlots	Includes only every second plot	n % 2 = 0
ThirdNoPlots	Includes only every third plot	n % 3 = 0
TwoThirdNoPlots	Missing every third plot	n % 3 <> 0
QuarterNoPlots	Includes only every fourth plot	n % 4 = 0
ThreeQuarterNoPlots	Missing every fourth plot	n % 4 <> 0

n = plot number

Planning Model

The planning model developed for this project was a linear programming (LP) Type II formulation based on work carried out by Garcia [5]. The formulation mimics the formulation used in FOLPI (Forest Oriented Linear Programming Interpreter), a popular estate planning software product used widely in New Zealand and Australia in the 1980s and '90s. The planning model was developed using the PuLP mathematical programming language which allowed an increased degree of flexibility to change the modelling process over other commercially available products.

The linear programming formulation is relatively simple, with three structural constraints ensuring that the model can harvest only the area that exists at the start of the planning period, and all stands are replanted. The model was developed to mimic a simple 10-year tactical model, and hence is designed to assist decision makers with budgeting around infrastructure investment and wood flows. The linear programming formulation contains a "maximise net present value (NPV)" objective function which maximises the discounted revenues (log price * volume) minus the discounted costs. In this project a discount rate of 7% was used.

The same log prices as given in
Table 2 were used in the model. It was assumed that every planning unit required cable harvesting and hence a harvesting and road cost of $30 and $1 per cubic metre respectively was allocated to [redacted]

would be included as well as applying block-specific harvesting and roading costs. In this paper the constraints were placed on annual volume production, but in normal operational planning constraints can be placed on harvest area, costs and cash flow. Two different model formulations were tested to investigate how differing constraints will affect the robustness of the underlying model (Table 4). Minimum and maximum clearfell age constraints of 21 and 36 years were also placed on the model.

Table 4. Planning models used to test robustness

Model Name	Description
A_12>YYYYY	Total Volume per year <= 30,000 Total Volume per year >= 25,000 A_12 Grade per year >= YYYYY
P1>XXXX	Total Volume per year <= 30,000 Total Volume per year >= 25,000 P1 Grade per year >= XXXX
S1>XXXX	Total Volume per year <= 30,000 Total Volume per year >= 25,000 S1 Grade per year >= ZZZZZZ

To measure the robustness of each of the models, the LP model was iteratively run in a binary search. In the case of the A_12_>YYYYY model, the constrained volume (YYYYY) of the 12-metre "A" export grade was varied to find the breakpoint volume between the model being feasible and infeasible. It is the volume point where the estate cannot, in any one period, produce one more cubic metre of any grade. This search to find the breakpoint volume was carried out 75 times for each of the yield table scenarios to produce a distribution of feasible/infeasible points. The same procedure was repeated for P1>XXXX model and S1>ZZZZZZ model; for these scenarios the XXXX and ZZZZZ was altered to find the volume break point the large pruned grade and large sawlogs respectively.

Robustness Measures

A robust model is one that can achieve the required goals and objectives independent of the imprecision in the underlying data, which in this case are the yield data.

In order to investigate the robustness of the three models in relation to uncertainty in the yield predictions, the relative distributions of volume breakpoints were assessed for each yield table scenario. The volume breakpoint distributions consist of the results from the 75 replicates for each yield table scenario. If the volume breakpoint distributions were similar for the different yield table scenarios then the conclusion could be made that the model is robust to the number of plots used to generate the yield tables. However if the shape of the volume breakpoint distributions changes due to the number of plots used, this signifies that the model may not be robust to uncertainty in the yield predictions. The rate at which the volume breakpoint distribution shape changes in relation to the number of plots used can be used to assess the robustness of a model.

The distributions for volume breakpoints were assumed to be normal and hence the shape of the distribution is described using the mean and standard deviation. Figure 3 shows how some theoretical response curves in the shape of the distribution to number of plots can be interpreted to assess model robustness. To be able to compare the relative robustness of different models, the relative standard deviation (standard deviation/mean) will be reported.

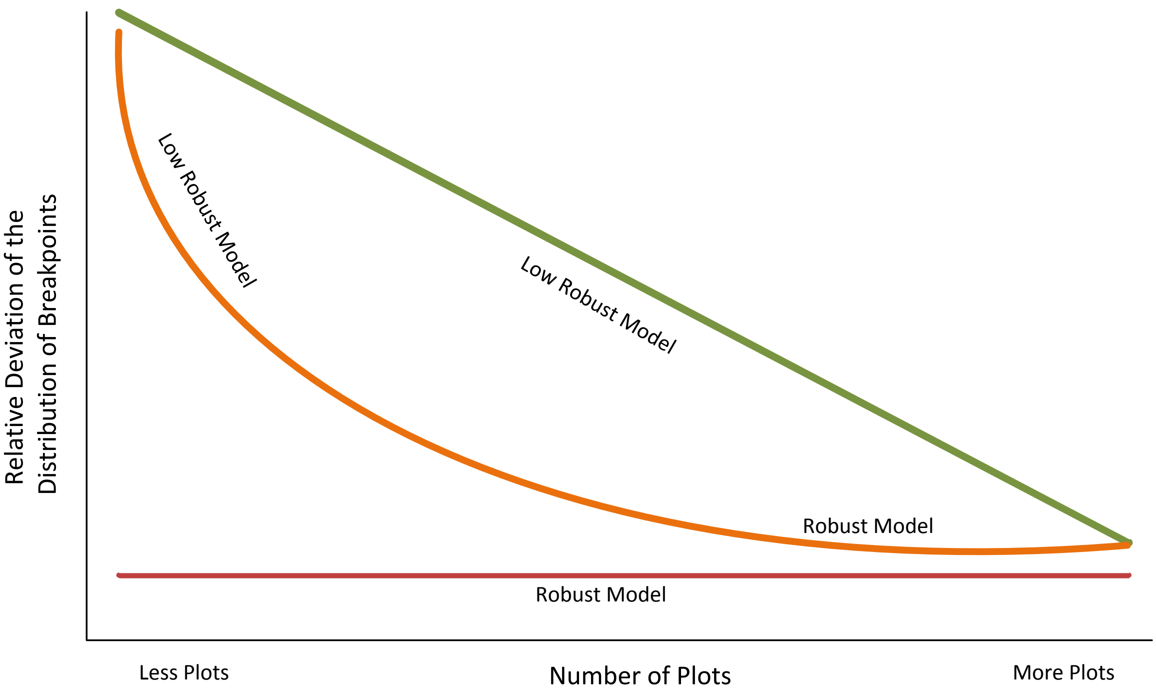


Figure 3. Theoretical deviation response curves as a measure of a model's robustness

A flatter curve is indicative of a model which is more robust to changes in the number of plots used to generate the yield tables used in the model. In Figure 3, the red line represents the most robust model. It is not the level of the line that is important but the rate of change – the red line does not change over the entire range of plot numbers, indicating robustness to precision fluctuation in yield estimates. The green line illustrates a model that lacks robustness and the orange curve represents a model that lacks robustness with a low number of plots but becomes more robust as the number of plots increases.

RESULTS

The results section has been divided into two; the first section summarises how the precision of the inventory varies as the number plots used decreases from the operational reality, and the second section summaries the results of the robustness measures for the three models outlined in Table 4.

Precision Level of Inventory

Table 5 shows the total number of plots for each of the yield table scenarios for the 130 planning units. Due to the original plot numbers and the selection criteria, the percentage number of plots selected does not exactly match the target percentages. The average plot intensity is simply calculated by dividing the total number of plots by the total area.

Table 5. Number of plots selected under the different selection criteria

Selection Criteria / Yield Table Scenario	Average Number of Plots	Average Percentage of All Plots	Average Plots Intensity (Plots/ha)
1/8 No of Plots	389	15.0 %	0.10
1/5 No of Plots	550	21.2%	0.15
1/4 No of Plots	693	26.7 %	0.19
1/3 No of Plots	907	68.2 %	0.24
1/2 No of Plots	1317	50.8%	0.35
2/3 No of Plots	1687	23.2 %	0.45
3/4 No of Plots	1901	73.3 %	0.51
4/5 No of Plots	2044	78.8 %	0.55
7/8 No of Plots	2205	85.0%	0.60
AllPlots	2594		0.70

A data collection cost is assumed on average to be approximately $100 per plot (David Herries pers comm.). Clearly a reduction in plot numbers will reduce the total cost of carrying out a forest inventor, but that reduction in cost comes at the cost of precision.

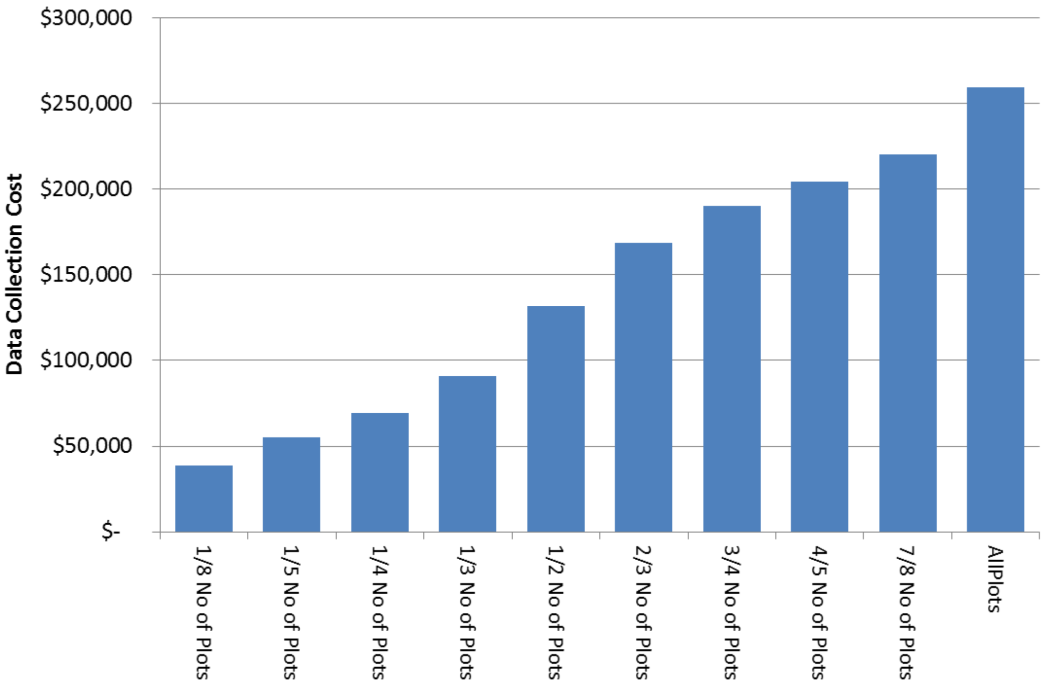


Figure 4. Relationship between number of plots and data collection cost.

Measures of Robustness

Significant cost saving can be made by reducing the number of plots collected as part of a pre-harvest inventory (Figure 4). This reduction in plot numbers can come with a potential cost in terms of certainty for decision makers using the information derived from the plots. This section shows how the robustness of the model varies both with changes in the number of plots and the constraints included in the model.

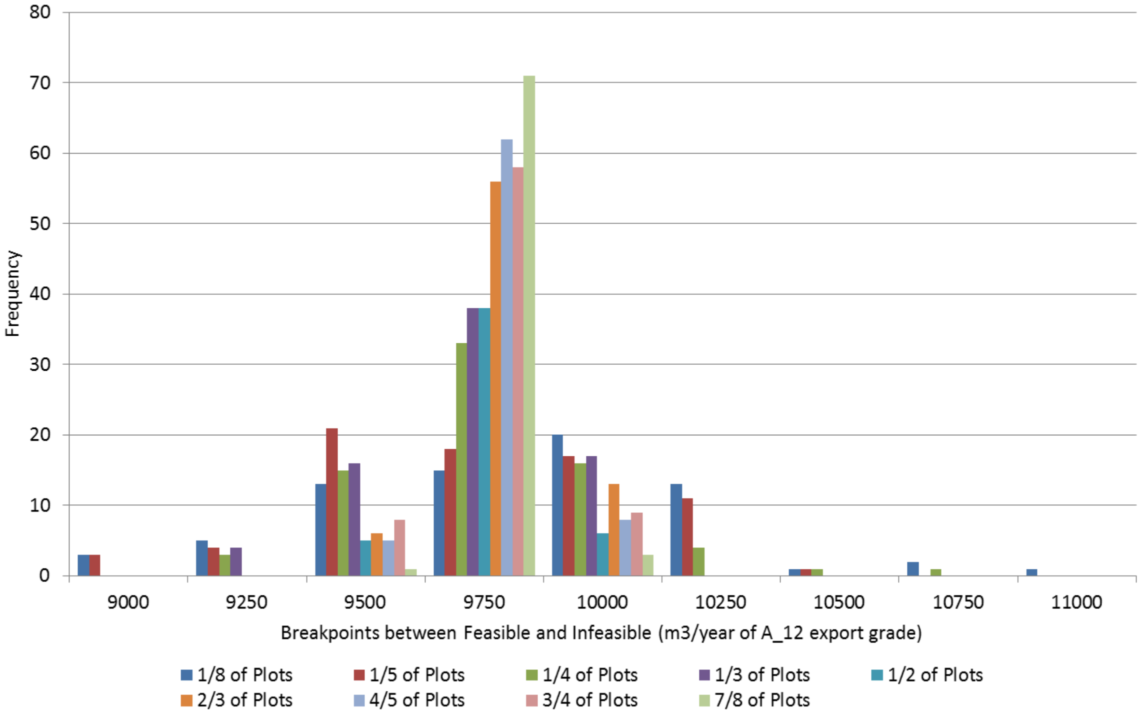


Figure 5. Distribution of Volume Breakpoints between Feasible and Infeasible for the 12-metre A Export Grade

The distribution (
Figure 5) of breakpoints when the model is being constrained by 12-metre A export log grade shows that as the number of plots increases, the spread of the predicted breakpoints decreases. The breakpoint volume for 12-metre "A" export grade when all the plots in the database were used was 9740 m^3 per year. The wider the distribution the greater the chance the model will suggest that the wrong maximum volume of 12-metre "A" export grade can be produced from the estate. For example the distribution in
Figure 5 shows that when using only one eighth of the original number of plots, there was one model run out of the 75 that would suggest that approximately 11000 m^3 of 12-metre "A" export grade could be produced. That works out to be over 3000 m^3 more than suggested when the yield tables were generated using all of the possible plots. Based on that result the forest company may have over-sold the product by 3000 m^3 which could be an expensive mistake as that 3000 m^3 may have to be obtained from another source to meet contractual obligations. Figure 6 shows the relative standard deviation response curve for the distributions in
Figure 5.

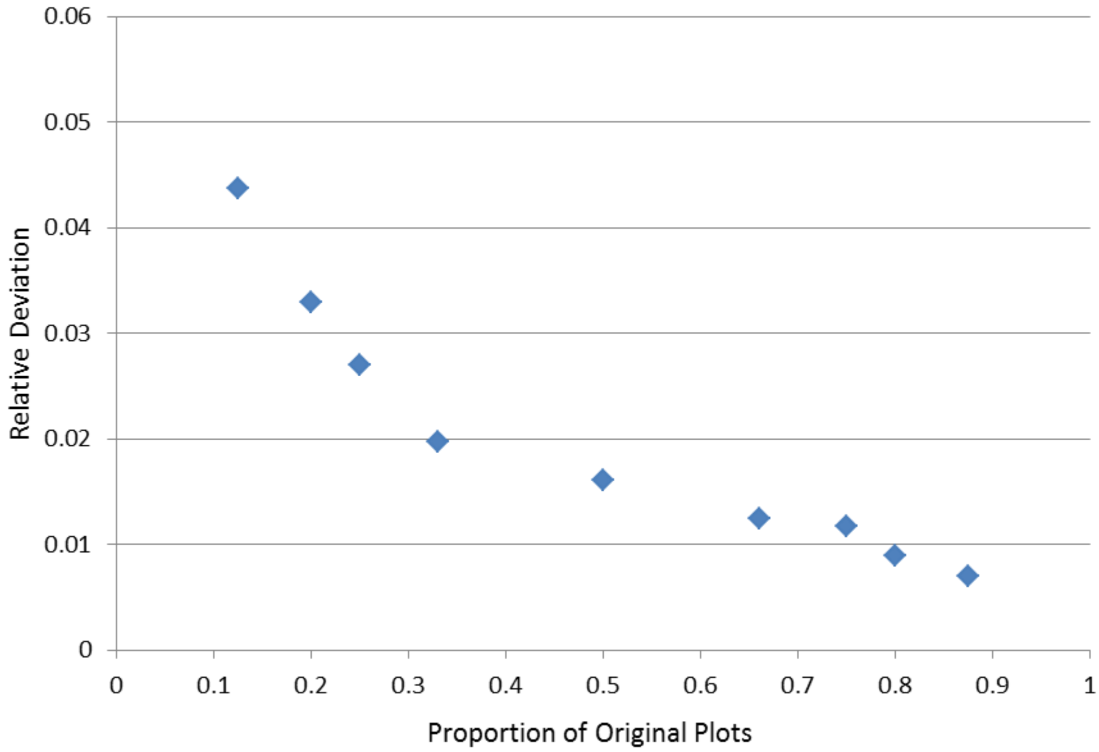


Figure 6. Relative standard deviation response curve for the A_12

The important aspect of the response curve is the rate of change – the steeper the slope the less robust the model is to change in the number plots used in the yield generation. The rate of change is high as the number of plots used increases from ⅛ to ½ of the original plots, illustrating that over that range the model is not robust to changes in the number of plots used. In the middle section of the curve, between ½ to ¾ of the number of plots, the curve flattens out and the rate of change decreases; indicating that the model is relatively robust over this range.

Figure 7 shows the breakeven volume distribution for large pruned grade. The breakpoint volume for large pruned grade when all the plots in the database were used was 2872 m^3 per year. All the distributions for the different numbers of plots are centred on that volume.

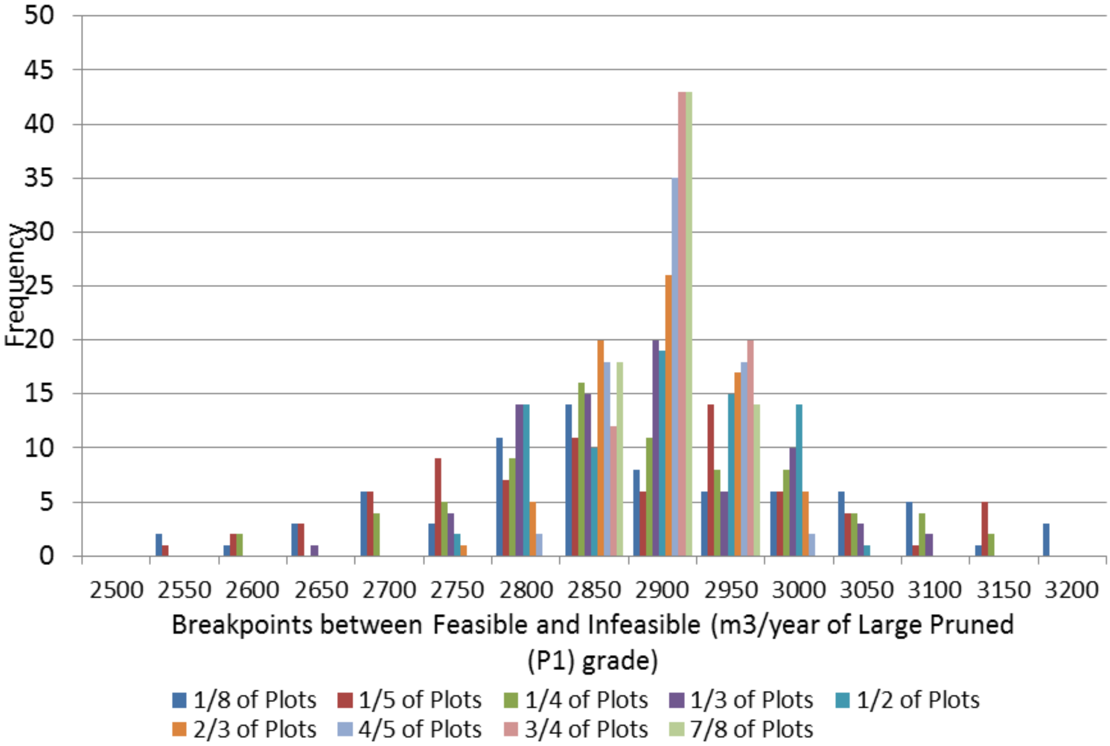


Figure 7. Distribution of Volume Breakpoints between Feasible and Infeasible for the Large Pruned Grade when different proportions (from 1/8 to 7/8) of forest inventory plots were measured

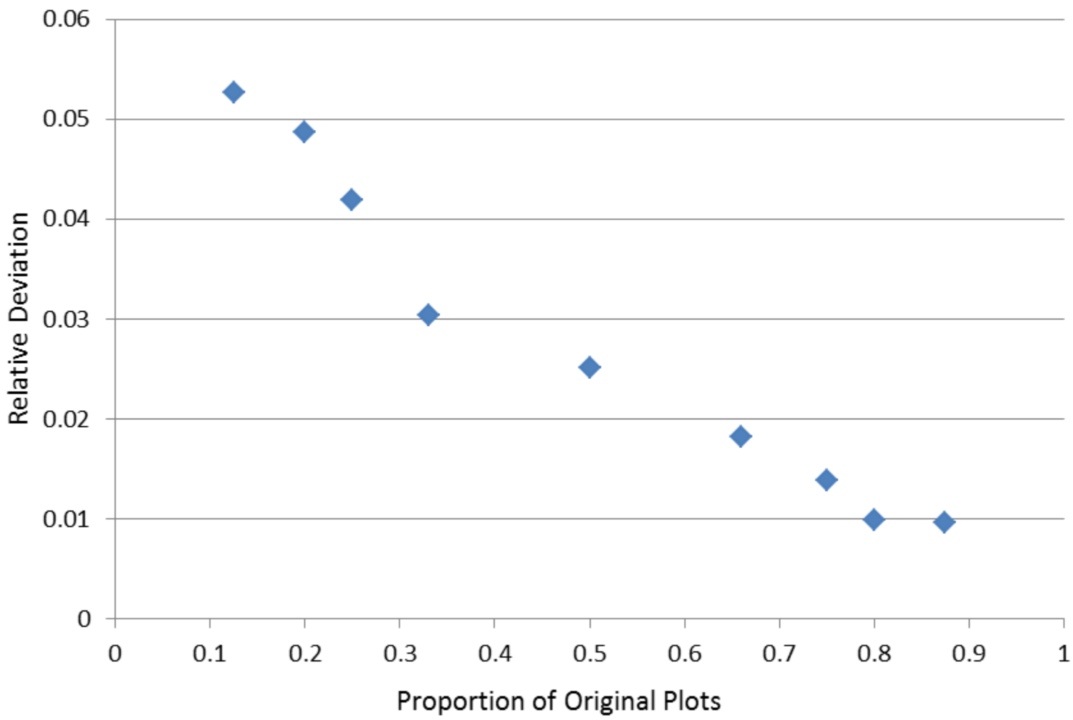


Figure 8. Relative Deviation of the Pruned (P1) Grade

The response curve (Figure 8) for the relative deviation is more linear in shape than Figure 6, with a relatively steep slope. This indicates that when trying to constrain the large pruned grade volume, the model lacks robustness in relation to the number of plots used in the yield generation for this model. The large pruned grade is substantially more scarce than the 12-metre A export log grade. Also the ability for the planning model to rearrange the harvest period of planning unit to ensure that the volume constraint is achieved is restricted, as not all the planning units can produce pruned log volume. The combination of these reasons leads to the lack of robustness in the model when constrained by the minimum pruned production in comparison to the 12-metre A export log grade.

The last test model placed a constraint on the model for the large sawlog grade which is the most abundant grade in the estate. The absolute maximum sustainable volume for large sawlog (S1) grade was projected to be 149,787 m^3 per year when all the plots in the database were used.

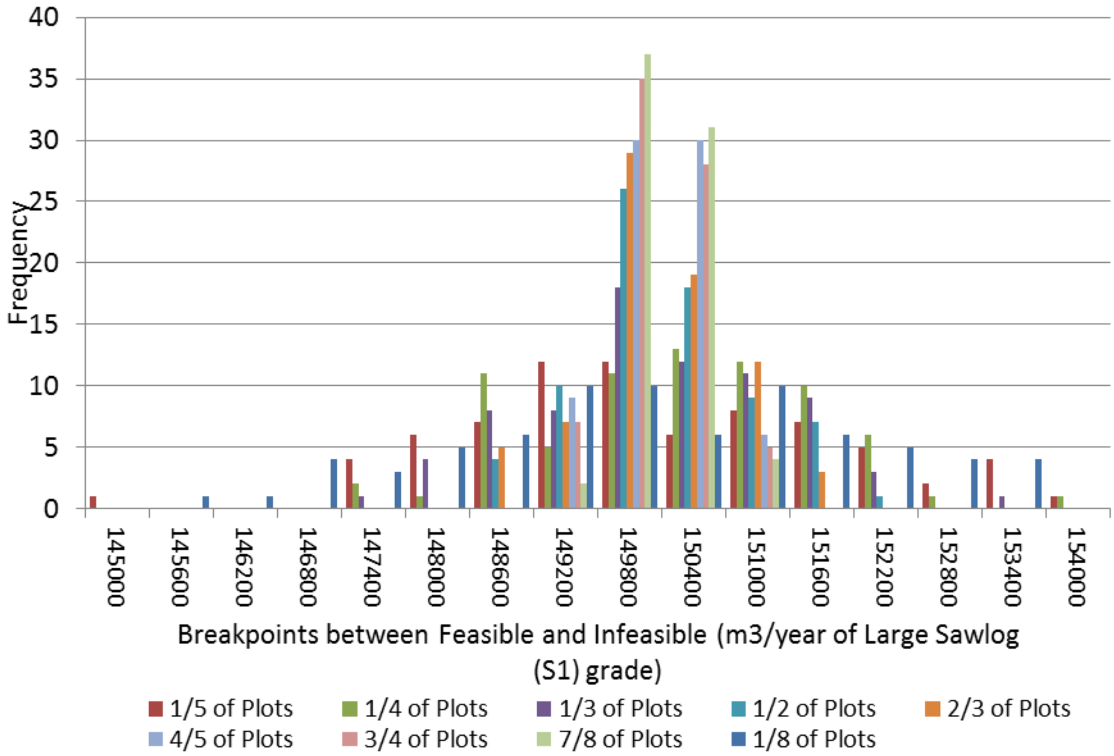


Figure 9. Distribution of Volume Breakpoints between Feasible and Infeasible for the Large Sawlog Grade

In Figure 10, the relative deviation response curve for the Large Sawlogs shows a relatively shallow slope that would indicate that when the model is constrained by a common log grade such as the Large Sawlog, the model is reasonably robust to changes in the number plots used to create the yield tables for the model.

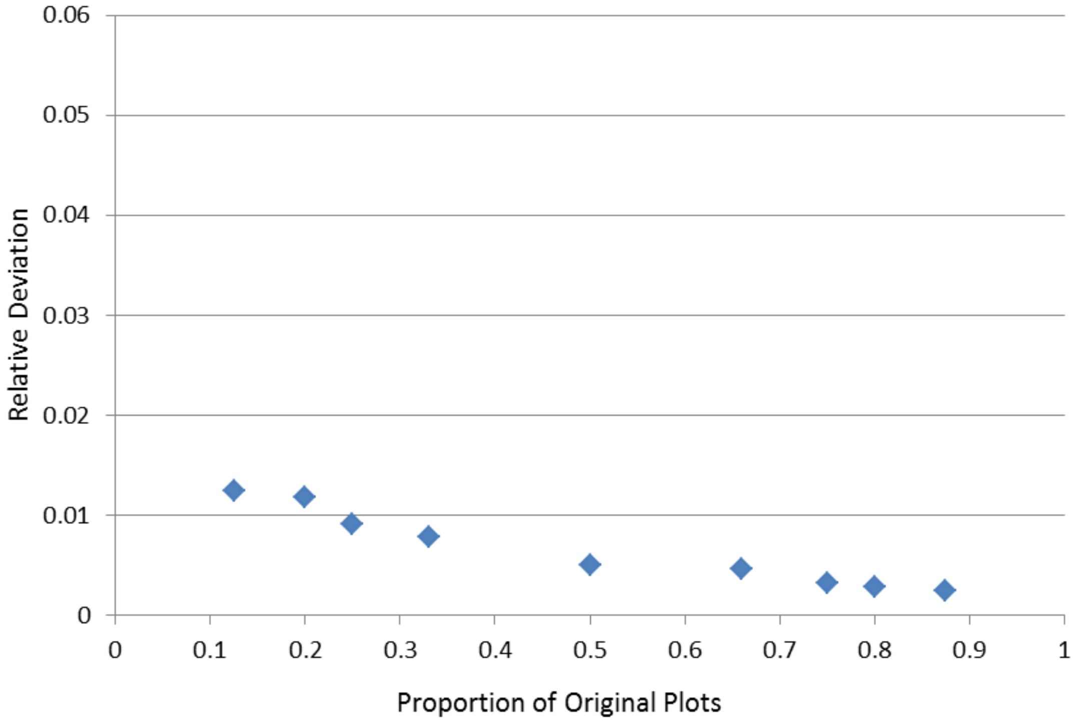
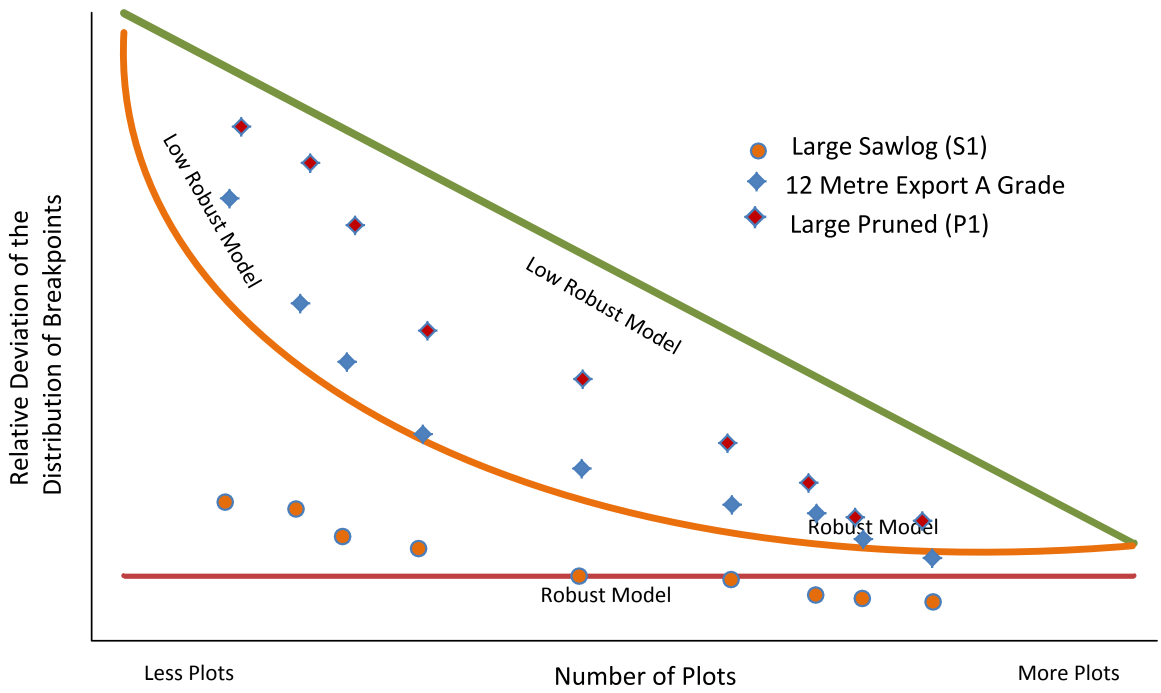


Figure 10. Relative Deviation of the Sawlog (S1) Grade

If the relative deviation curves from the three models are overlaid on to theoretical curves in Figure 3, it can be seen that they align with the three theoretical curves for model robustness.



DISCUSSION AND CONCLUSION

Most medium to large forest management companies in New Zealand use linear programming to solve their medium and long term planning problems. The yield tables used in these models are derived in a number of different ways. One of the common methods is to grow inventory data forward using growth models. The data certainty surrounding those yield tables is driven in part by the plot numbers measured in each sampling unit. At a cost of approximately $(NZ) 100 per plot for a standard pre-harvest inventory, reducing the number plots established is always seen as an easy way to save money. Although the cost of the inventory is easily determined, the dollar value benefit from the information obtained from forest inventory is not [1].

Discounted cash flow-driven linear programming planning models are not well suited to deal with uncertainty in input data [3]. Often uncertainty can be reduced in model inputs by investing more money on data collection. This is certainly the case with yield information for forest planning, where extra ground plots or auxiliary data such as remote sensing imagery can be obtained to increase the precision of the yield estimates. However if the forest planning decision making process is robust to uncertainty in the yield estimates, then any extra money would be wasted, as this extra information may not result in improved decisions. The small amount of literature on the robustness of forest planning that exists suggests the forest planning models are not particularly robust [2, 11].

Before studying the robustness of New Zealand forest planning models, a method for measuring robustness must be developed. A literature review of the international research did not reveal a suitable measurement of robustness that could be applied to linear programming in forest planning. The main objective of this research was to develop a measure for assessing the robustness of a typical linear programming-based forest model to changes in the number of plots used to generate the yield estimates. The developed measure is based on the distribution of breakpoints. The breakpoint is the volume per year of a particular log grade where the linear programming model goes from feasible to infeasible when one additional cubic metre of the log grade is added to the right hand side of the constraint for that log grade. A distribution of breakpoints can be created by repetitively randomly sub-sampling plots for a number of different proportions of the original plots that were collected. The robustness of the model was determined by studying how the relative standard deviation of the breakpoint distribution changes as the proportion of the total plots used in the yield table generation changes.

The results from this research using the newly developed measure seem to show that the robustness of the model is linked to the relative abundance of the subject log grade in the estate. For the most abundant log grade (large sawlog) any change in the number of plots used has little impact on the solution created by the forest planning model. This model possesses robustness, and the feasibility and optimality of a plan produced using this model will be unaffected by uncertainty in the underlying yield data. If the focus of the model was to determine whether there are enough large sawlogs to satisfy a long term supply contract, then putting in extra plots could not be justified financially to meet this planning objective.

In the case of the pruned log grade which in this estate is substantially less abundant than the large sawlogs, the response curve for pruned logs has quite a steep slope. This means that the model lacks robustness to changes in the number of plots used to generate yield estimates. As more plots are used, this increases the decision maker's chance of not over or under predicting the maximum amount of pruned sawlog that can be produced from the estate. Further investigations of the breakpoint distributions for the pruned grade, plus an in-depth knowledge of the pruned grade market, suggest it would be possible to determine the financial benefit of installing additional new plots.

Operationally, the number of plots collected for this estate was determined using a target level of precision of approximately 10% PLE. The response curve for 12-metre export "A" grade showed that only half the number of was required. The slope of the curve is steep when only small proportion of plots is used, but as the proportion of the plots increases the slope of the curve flattens out.

The results presented in this paper are based on extremely simple models compared to those used in the forest industry, with only one constraint being placed on a log grade at a time. Clearly the type of constraint placed on the model has an impact on the robustness of the model. The next step in this research is to determine how this robustness measure can be utilised in more complex models. Despite the simplicity of the models, the results show that when developing a cost effective inventory it is important to understand the relative importance of the constraints that will be placed on the planning model.

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