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Investigating the potential relationship between the FCM measures and LiDAR

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1 EXECUTIVE SUMMARY

Objective

The objectives of this study were to summarise the crown condition assessment data collected during the 2010 FCM survey and to process and extract metrics from the LiDAR dataset which was obtained for FCM plots. Once this data was collated the aim of this project was to investigate relationships between crown condition and LiDAR metrics and attempt to build predictive models for crown condition base on LiDAR data.

Key Findings

LiDAR point clouds for the study plots were successfully isolated and used to generate metrics for use in the modelling work in this study. Good relationships were found between crown condition indicators and LiDAR metrics and predictive models were produced. The transparency of the entire crown indicator was notably successful with a model produced which accounted for more 77% of the variation in the crown condition indicator. The relationships with the transparency of the upper crown and needle retention indicators were weaker but still very promising, but no strong relationship was found between LiDAR metrics and defoliation. A pilot study for the segregation of the LiDAR point cloud associated with individual trees based on tree locations has been produced and is promise but requires validation.

Application

The predictive models for crown condition mean that crown condition indicators can be predicted using LiDAR metrics for radiata pine forests in New Zealand established before 1990. This means that it is likely that the number of plots measurements required to monitor forest condition can be reduced. With further validation it is also possible that the model can be used for the prediction of crown condition at a regional or estate level.

Further work

Interpine recommends that the following projects will provide significant benefits in relation to this topic:

- Further validation of the predictive models and investigation of alternative model types.
- Investigation of the effect of incorporating remote sensing upon the sampling design required to monitor forest condition nationally.
- Development of a methodology to validate the predictive models for use at a regional or estate level.
- Further study into the pilot study approach to isolation of the point cloud associated with individual trees presented in this paper.
- Investigation of the capability of alternate remote sensing technologies for predicting crown condition.

2 CONTENTS

Contents

3 INTRODUCTION

Visual crown condition assessments over time provide a basis for assessing changes in tree and forest condition. On a global scale forests are declining under the influence of anthropogenic pressure from population growth, air pollution and climate change (Anon 2001). Stimulated by global concerns about forest decline the New Zealand Forest Owners Association (NZOFA) commissioned Interpine Forestry Limited (Interpine) to design and implemented a Forest Condition Monitoring (FCM) programme for New Zealand's plantation forest estate[1]. The visual assessment of crown condition indicators, such as defoliation and crown transparency, provides a scientifically valid and internationally accepted means of assessing forest condition and underpins the New Zealand FCM programme.

As part of their commitment to report under the United Nations Framework on Climate Change (UNFCC) and the Kyoto protocol the change in carbon stocks in New Zealand's forests must be estimated, and reported on, by the New Zealand government. To achieve this objective the Ministry for the Environment (MfE) have implemented a nationwide inventory programme consisting of a 4 km ground plot network and concurrent airborne Light Detection and Ranging (LiDAR) scanning. In 2010 the FCM assessments procedures developed by Interpine were used to assess trees in each ground plot in the 2010 measurement programme. High grade Global Positioning System (GPS) units were used to fix the position of the ground measurement plot centre and the distance and bearing to each tree from the plot centre were recorded. This means it is possible to geographically match up the data from both LiDAR and ground measurements and investigates relationships between them.

Once the ground returns are filtered out the pattern of returns from airborne LiDAR provides useful information about the structure of the forest vegetation. Combined with data from ground plots and used in a statistical modelling approach LiDAR has the potential to provide detailed information statistics about the nature of the forest which are particularly beneficial to foresters. The use of modelling approaches to forest inventory including a LiDAR component is increasing rapidly (Romboutts et al. 2010, Mannes et al 2009, Stephens et al. 2009) to derive traditional forestry statistics (Volume, height etc.) and carbon stocks and could be argued to represent a new paradigm in Australasian forest inventory. With an appropriate data set it is possible that this approach can be extended to a survey of crown condition and if so could have significant benefits in reducing the number of field plots required for future monitoring of forest condition and increasing the size of the dataset which is available for analysis.

In New Zealand there have been a limited number of studies that have attempted to incorporate crown condition assessments into models including LiDAR metrics with a limited degree of success. Beets et al. (2008) investigated relationships between crown condition indicators, including transparency, and leaf area index (LAI), in a 9 year old stand and described the relationship. Beets et al. (2008) also found that crown transparency was negatively related to the LiDAR metric P50fp and positively related to the LiDAR metric %Veg[2] and reported a coefficient of variation (R^2)of 55%. However, these results were specific to the 9 year old Puruki site and Beets et al (2008) report that

[1] FCM Sampling Strategy Report Prepared by Interpine Forestry on behalf of the NZFOA
[2] P50fp is a LiDAR height metric relating to the height above ground corresponding with the 50th percentile of the point cloud above the base height and %veg refers to the percentage of first LiDAR returns above 0.5m.

when they extended their approach to 74 plots in the Nelson/Marlborough region they could not find any relationship between crown transparency and LiDAR metrics.

Beets et al. (2009) extended their work to study the relationship between crown condition assessments, LiDAR and volume increment as predicted by the 300 index model. The authors did not report the development of any crown condition predictor models in their research but were able to show a moderately strong relationship between volume increment as predicted by the 300 index model and LiDAR metrics.

In Scandinavia, where airborne LiDAR has formed a large part of forest resource assessment for some time, a significant effort has been placed on investigating the relationships between LiDAR metrics and defoliation and the potential for using LiDAR data to map defoliation events spatially and through time. In the majority of cases, research efforts focus on changes in LAI which can be mapped using LiDAR (Solberg et al. 2005) and over time repeated scans have been used for mapping extreme defoliation events caused by an insect infestation (Solberg et. Al 2006). A further study has also indicated that defoliation events can be detected using a single LiDAR scan by applying two independent algorithms to the data set which produce both expected and actual LAI for a given portion of forest (Solberg and Naesset 2007).

Airborne LiDAR has been investigated as a means to developing a new methodology for assessing a nationwide forest health system in Norway in a study which concluded that LiDAR when combined with multi-spectral imagery and extensive ground truthing provides a promising tool for forest condition monitoring (Solberg et al. 2004).

The current study will for the first time investigate the relationship between LiDAR metrics and crown condition indicators using a national level data set for New Zealand's radiate pine estate. If promising relationship are found specific models will be produced which can be used to predict crown condition variables using LiDAR data.

3.1 Objectives

The objectives of this report are to:

- Investigate any relationships which may exist between crown condition indicators and LiDAR in the 2010 national FCM plot network;
- Where relationships exist derive coefficients which will allow the prediction of crown condition indicators by LiDAR metrics where available.

4 METHODOLOGY

4.1 DATA AND DATA PROCESSING

The following sections outline the sources of the data available for use in the current project. The crown condition data for this project was collected as part of the 2010 forest condition monitoring programme and was collected from plots measured as part of MfE's LUCAS measurement. As a result a data set comprising crown condition, LiDAR data and high grade GPS information is available for each plot.

4.1.1 Crown condition data

Key crown condition indicators used in this study are Defoliation, transparency of the entire tree crown, transparency of the top half of the crown and needle retention. Data were accessed via an SQL query from the LUCAS Gateway database maintained by Interpine. Only plots containing live radiata pine trees with a crown condition assessment for each of the four key variables listed above were included in the dataset for analysis. This resulted in a dataset comprising 4043 individual tree measurements across 146 plots located throughout the country.

4.1.2 Crown Transparency

Following the methodology set out in the FCM manual (Interpine 2009) the crown transparency index used in this project refers to the transparency of individual tree crowns obtained by viewing the crown from an oblique angle and through allocating a score based on a detailed set of reference photographs. Crown transparency was scored for the entire tree crown and for the top 50% of the tree crown as per the methodology set out by Bulman (2008).

4.1.3 Defoliation

Defoliation refers to the percentage of needles missing from a subject tree when compared with a photograph of a maximally foliated tree. Individual trees are assessed from an oblique angle and assigned a defoliation percentage score based on 5% increments with reference to a large set of reference photographs as set out by Interpine (2009).

4.1.4 Needle Retention

Needle retention is a count of the number of needle age classes present in the lower third of the unsuppressed tree crown. In a normal healthy radiata pine tree needles are typically retained for three years. Radiata pine trees with needle retention of less than three years may be affected by foliar diseases such as Cyclaneusma or Dothistroma (Bulman 2009).

4.2 LIDAR DATA

The raw LiDAR data for the pre-1990 LUCAS plots with Forest Condition Monitoring metrics collected was obtained from the Ministry of Environment (MfE). The data was collected between 30 January and 4 June 2010. An Opech ALTM 3100EA LiDAR scanner was used for this project. The LIDAR points provided by MfE had been classified by New Zealand Aerial Mapping (NZAM) into ground, first and intermediate returns. The LiDAR data file for each plot contains information for a substantially larger area then the plots measured. Using the differentially corrected GPS location and plot diameter the LiDAR return from within the measurement plots were isolated. To eliminate the effects of topography on the elevation of the LiDAR hits it is necessary to subtract from each LiDAR return the height of the underlying terrain. To enable this a Digital Terrain Model (DTM) with a spatial resolution of 1 m was generated by extracting the LiDAR returns that were classified as having reached the ground. The Grid Surface Create tool of the FUSION LiDAR analysis software was used to create the DTM (McGaughey 2010).

The LiDAR metrics for each plot were obtained using the Cloud Metric functionality of the FUSION LiDAR analysis software. Work carried out by Beets et al (2008) and Kimberley et. al (2009) has shown that the important metrics in these modelling application are height percentiles (P5ht – P95ht) along with mean, minimum and maximum height, several statistics describing the height distribution (coefficient of skewness, coefficient of variation (CV), standard deviation (SD), and coefficient of kurtosis), the percentage of returns reaching within 0.5 m of the ground (%Zero), the percentage of 1st returns above 0.5 m (%Cover), a composite variable based on mean height and %zero for volume and carbon predictions. Dalponte et. al (2009) suggested that crown depth (one of the FCM measurement) could be related to percentage of 1st, 2nd, 3rd,4th returns.

4.3 STATISTICAL ANALYSIS

Relationships between the various crown condition indicators and LiDAR metrics were investigated using linear models in the R statistical computing environment (R Development Core Team 2010) version 2.12.2 for Windows.

5 Results

The following sections summarise the key results of the research undertaken.

5.1 Crown condition indicators

The dataset used for this project consisted of 4043 assessments FCM indicators across 146 plots. The plot level statistics obtained for use in the analysis are given in Table 1

Table 1. Summaries for the plot data used in the current study

	Mean	Minimum	Maximum
Age (Yrs)	17.5	3	41
Stocking (sph)	460.39	16.67	2283.33
Defoliation Percentage	12.01	1	39
Transp. % Entire crown	52.03	1	87
Transp. % Top Half	36.68	5	78
Needle Retention	1.283	1	3

The relationship between the crown condition variables were examined and compared to previously published results. The transparency of the upper crown was positively correlated with and found to account for 77% of the variation in the entire crown. The relationship between transparency in the top half of the crown and the entire crown can be described by the following function:

Transp. (Top half) = 0.1608 + 06972 * Transp. (Total crown)

This result is similar to that produced by Beets et al. (2009) for eleven plots measured by an experienced field assessor (L. Bulman) which suggests that the methodology for the assessment of transparency in both crown portions is well defined and consistent over time and between assessors.

Needle retention was found to be negatively related to both crown transparency measures and to defoliation. This is as would be expected as it indicates that trees that retain their needles longer are less transparent and less defoliated. The coefficient of variation and the P-value acquired for the relationship between needle retention and the other crown condition indicators is show in Table 2. These statistics suggest that there is no relationship between needle retention and defoliation and that there is a significant but weak relationship between needle retention and the two transparency measures.

Table 2. The coefficient of variation (R^2) and p-value obtained when comparing the relationship between needle retention and the other crown condition indicators

	R^2	P - Value
Defoliation	0.017	0.1185
Transp. Entire Crown	0.2865	<0.001
Transp. Top half crown	0.1006	0.0002583

The relationship between defoliation and the two measures of transparency was found to be significant ($p>0.05$) but weak with transparency of the entire crown accounting for 20% and transparency of the upper crown accounting for 21% of the variability in the defoliation indicator. The relationship between defoliation and the two transparency indicators was found to have the following form:

Defoliation = -2.61824 + 0.13198 * Transp. (Total crown) + 0.16447 * Transp. (Top half)

5.2 RELATIONSHIPS BETWEEN CROWN CONDITION AND LIDAR

5.2.1 LiDAR metrics collinearity

The methodology followed by Kimberly et al. (2009) provides a suitable template for deriving relationships between LiDAR metrics and forest characteristics and is used as a framework in this study. Many LiDAR metrics are highly correlated and it is undesirable to include highly correlated independent variables in a multiple regression model as this can lead to instability in prediction. Kimberley et al. (2009) undertook a principal component analysis which indicated that 92% of the variability in the LUCAS LiDAR dataset could be accounted for by 5 factors. Kimberly et al. (2009) produced a correlation matrix which indicated that the LiDAR metrics can be classified into five collinearity groupings and that when fitting multiple regressions only one variable from each class should be included within any model used. The collinearity groups are shown in Table 3.

Table 3. The LiDAR metrics associated with each of the collinearity groups defined by Kimberly et al. (2009)

Collinearity Group	LiDAR metrics
1	Height variables
2	Intensity variables
3	Cover variables
4	Kurtosis
5	MinHeight

5.2.2 Regression models for crown condition

The performance of regression models for predicting the four main crown condition indicators were assessed and are summarised in Table 4; only the best fitting models for one two and three variables are shown.

Table 4. The Percentage variation (R2) by numerous crown condition indicator versus LiDAR metric multiple regression models

No of Variables	Variable	Defoliation	Transp. (Full Crown)	Transp. (Top Half)	Needle Retention
1	Mean return height	0.05485	0.6598	0.3538	0.263
1	P70	0.06204	0.6815	0.3859	0.264
1	P99	0.0797	0.6877	0.3927	0.2687
1	%Cover	0.0215	0.38	0.1755	0.2414
1	Int P50	0.04572	0.4962	0.2545	0.3049
1	Int Mean	0.06593	0.5343	0.2841	0.294
2	ElevP99 + Int Mean	0.0794	0.724	0.4046	0.3268
2	ElevP99+Int P50	0.07225	0.7125	0.3969	0.3365
2	ElevP99+%Cover	0.0721	0.7001	0.3925	0.2994
3	ElevP99+IntMean+Age	0.1338	0.7346	0.4053	0.3262
3	ElevP99+Int P50+Age	0.123	0.7225	0.3969	0.3377

The height metric ElevP99 was the best single variable for defoliation and both crown transparency measures describing 7.9% of the variation for defoliation 68% of the variation for transparency of the entire crown and 39 % of the variation for the transparency of the top half of the crown. IntP50 was the best performing metric for needle retention explaining 30% of the variation.

When bivariate models were investigated ElevP99 + IntMean was the best two variable combination for the defoliation and needle retention measures increasing the R^2 in all three cases. The situation for needle retention was slightly different again with Elev99 + IntP50 the best performing bivariate model. When a third independent variable was added it was found that if the age of the stand is included then the model performance was improved further. Since radiata pine stands in New Zealand are generally even aged with a known planting year it was deemed acceptable to include age in a predictive model. Adding additional variables was found to make no significant improvements to the model.

Through this process two predictive models for crown condition indicators using LiDAR metrics have been developed; one for defoliation and crown transparency and the other for needle retention. The difference being the exchange of IntMean for IntP50 in the needle retention model. The coefficient estimates and model statistics are displayed in Table 5 -8. In both cases the final models contain two LiDAR metrics one relating to a LiDAR height measurement and the other relating to LiDAR intensity.

Table 5. Regression model for predicting transparency of entire crown in pre 1990 Radiata forest using LiDAR metrics

Coefficient	Estimate	Standard Error
Intercept	47.0493	5.65
Elev P99	0.5947	0.19
Int Mean	-0.8246	0.16
Age	0.5981	0.23
R^2	73.46	

Table 6. Regression model for predicting transparency of the top half of the crown in pre 1990 Radiata pine forest using LiDAR metrics

Coefficient	Estimate	Standard Error
Intercept	31.3308	6.61
Elev P99	0.4317	0.22
Int Mean	-0.4179	0.20
Age	0.2912	0.27
R^2	41.53	

Table 7. Regression model for predicting defoliation in pre 1990 Radiata pine forest using LiDAR metrics

Coefficient	Estimate	Standard Error
Intercept	11.8194	5.6203
Elev P99	-0.2081	0.1636
Int Mean	-0.2445	0.1707
Age	0.5329	0.1918
R^2	13.38	

Table 8. Regression model for predicting needle retention in pre 1990 Radiata pine forest using LiDAR metrics

Coefficient	Estimate	Standard Error
Intercept	0.914783	0.241328
Elev P99	-0.002796	0.009375
Int Mean	0.026795	0.007108
Age	-0.012423	0.011307
R^2	33.77	

5.2.3 *Residual Analysis*

A full analysis of the quality of the models produced is beyond the scope of this project but some residual analysis has been undertaken to look for bias in the models. The mean residual (actual-predicted) was calculated for the crown condition indicators and is presented in Table 9. An unbiased model should produce a mean residual which is approaching zero. Negative residuals suggest over prediction and positive residuals indicate under prediction. The mean residuals in Table 9 suggest that all models over predict slightly with the exception of the transparency of the entire crown model which shows no bias based on the mean residual.

Table 9. The mean residual for the 4 models produced

Indicator	Mean Residual
Transp. Entire Crown	0.00
Transp. Top half	-0.11
Defoliation	-1.94
Needle Retention	-0.17

A graphical analysis of the residuals provides some insight into model behaviour. A graphical analysis for the transparency of the entire crown model is plotted in Figure 1 and 2. Distribution of the residuals in Figure 2 indicates that the model is unbiased but that model performance is poor for younger trees. This is probably because of the relatively small number of younger plots used to fit the model and may also suggest that the relationship is non-linear.

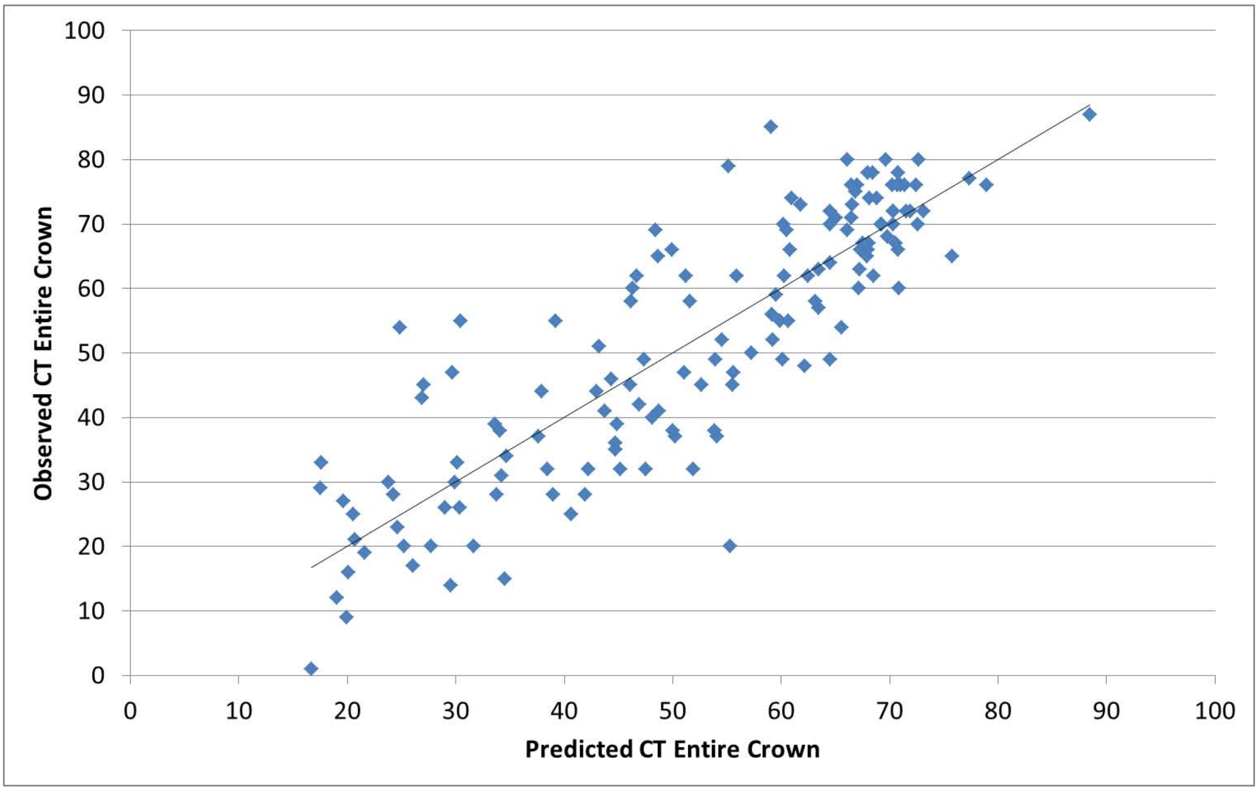

Figure 1. The observed and predicted CT for the entire crown model

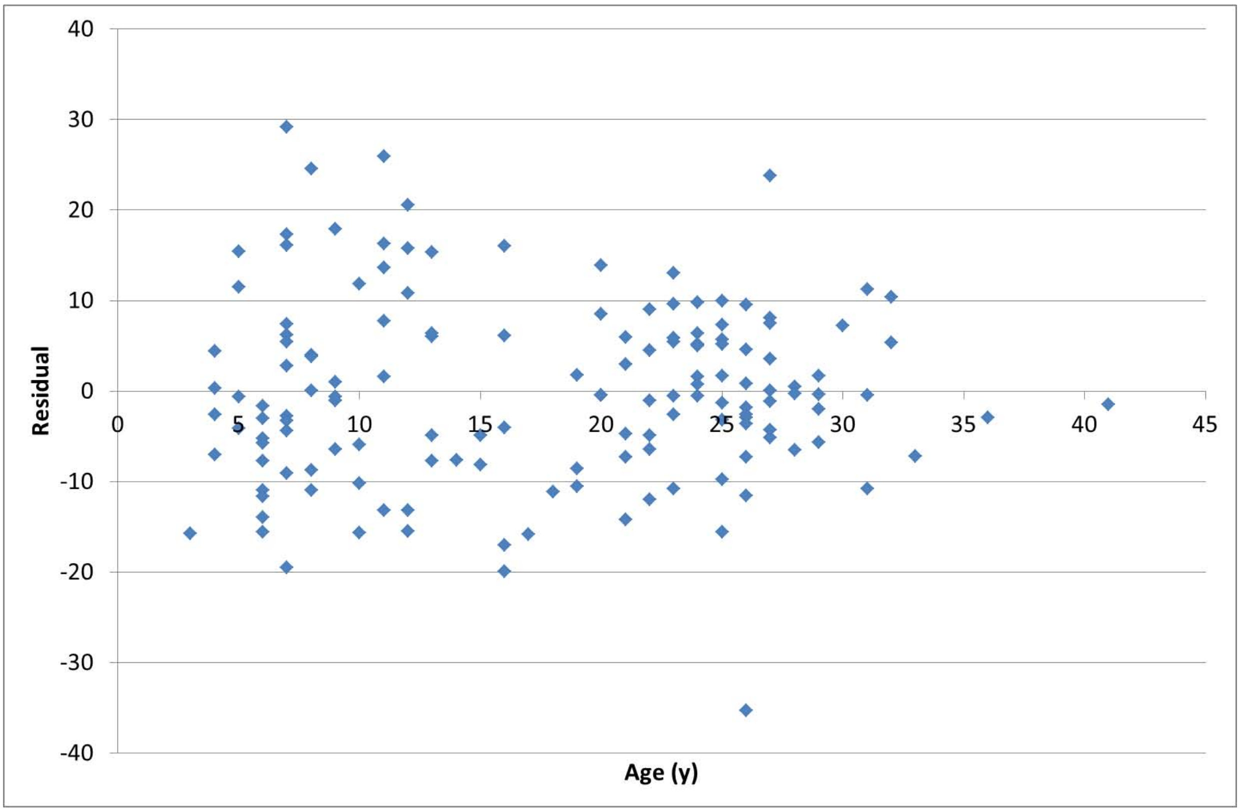

Figure 2. The mean residual and age of each plot for the transparency of the entire crown model

Figures 3 and 4 provide a graphical analysis of the residuals for transparency of the top half of the crown model. The spread of the observed and predicted results in Figure 3 show that the model performs slightly worse than the entire crown transparency model and similarly performs less well for younger plots.

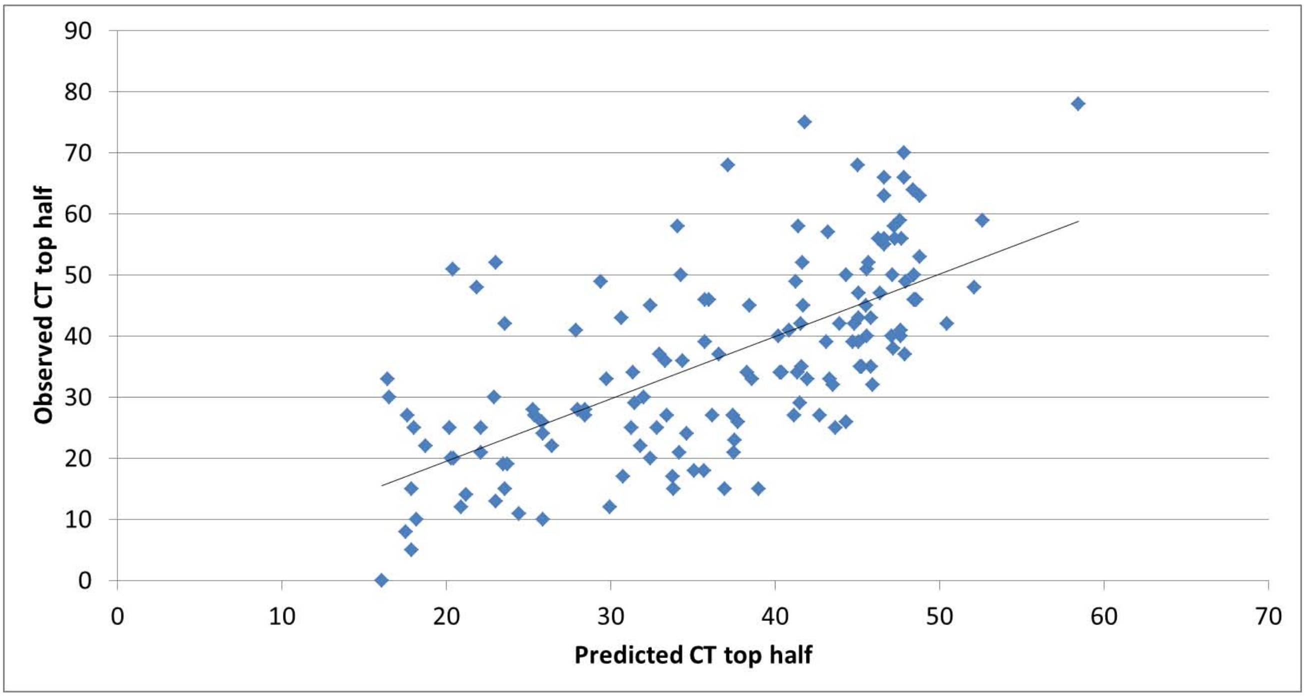

Figure 3. The observed and predicted CT for the top half crown model

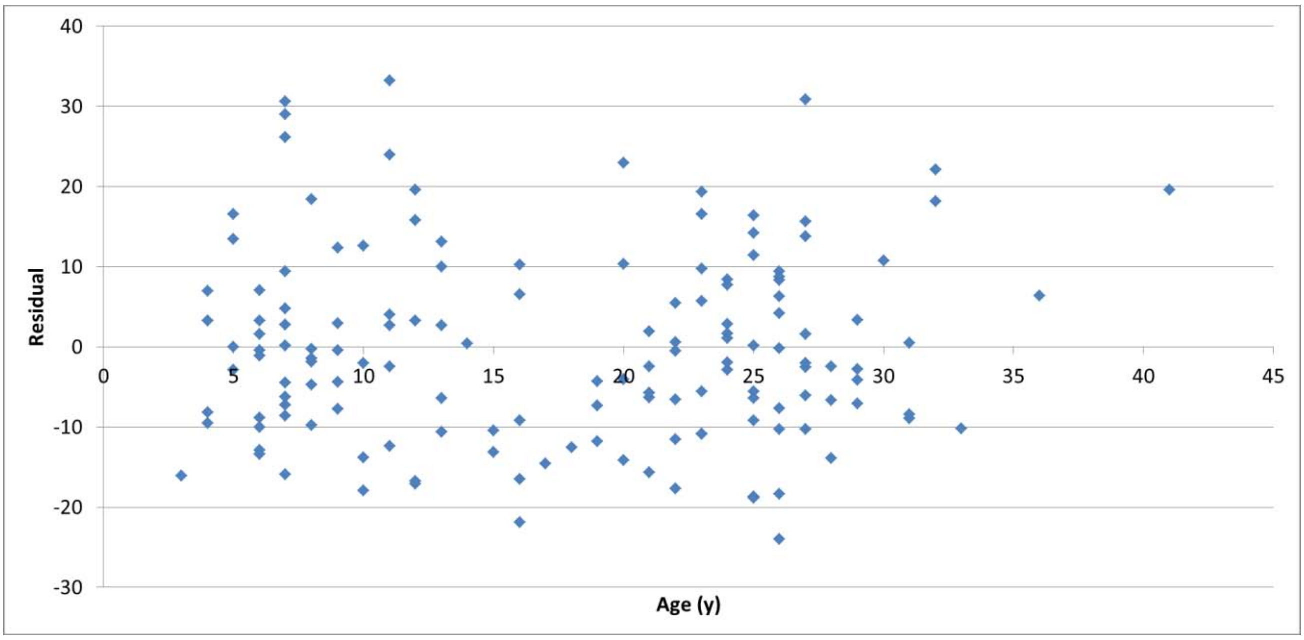

Figure 4. The mean residual and age of each plot for the transparency of the top half crown model

Figures 5 and 6 refer to the defoliation which performs considerably worse than the two defoliation models; the performance of the model is not strongly affected by age.

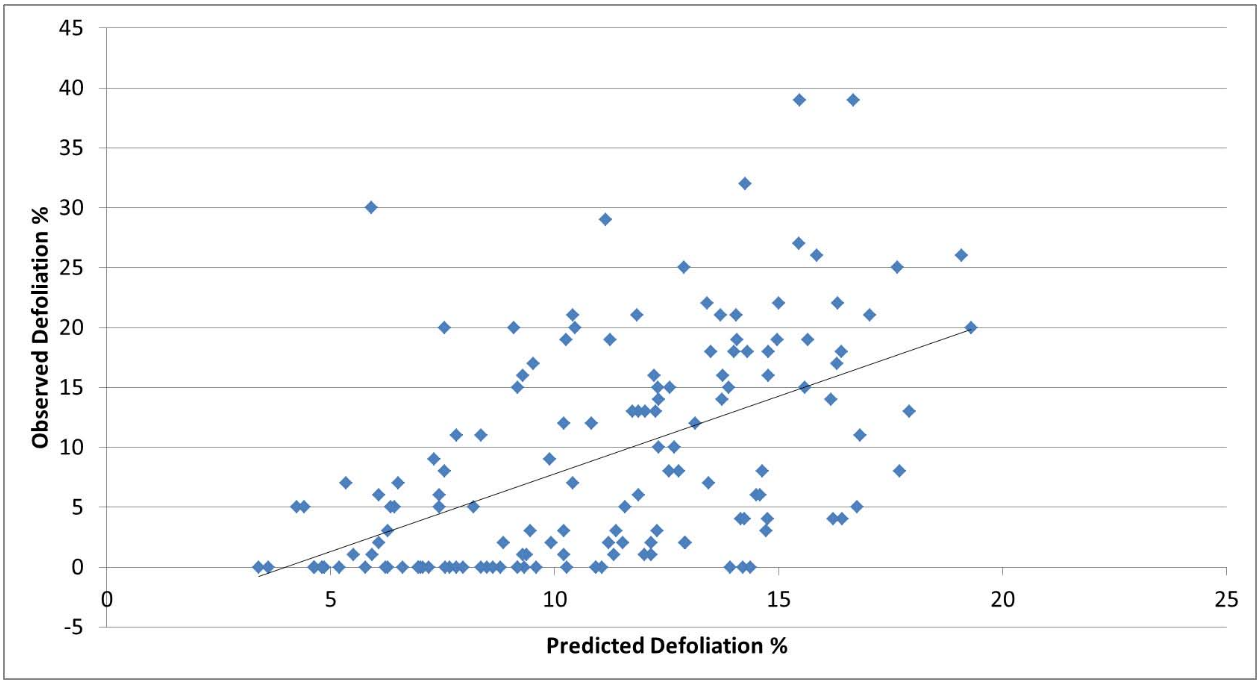

Figure 5. The observed and predicted Defoliation

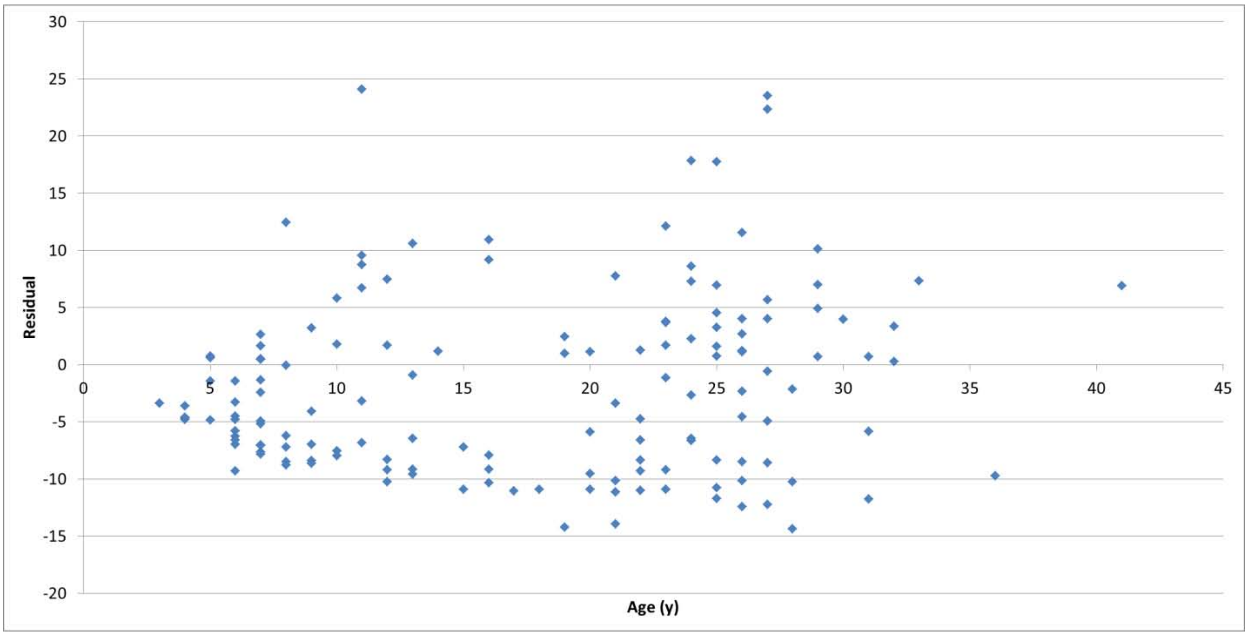

Figure 6. The mean residual and age of each plot for the defoliation model

5.3 Regression analysis for individual trees

The detection and segmentation of individual tree data from the point clouds derived from airborne LiDAR scanning is the subject of significant research (Koch et al. 2006, Koukoulas and Blackburn 2005) and there are numerous software products available which carry out segmentation with varying degrees of success. Under the methodology followed to collect the data used in the current study a high grade GPS was used to fix the location of each plot centre to sub-metre accuracy and the distance and bearing from the plot centre was recorded for each tree in the plot. This means that the location of each tree in the survey was known and this provided an opportunity for us to isolate the LiDAR point cloud associated with individual trees without relying on experimental algorithms to partition the data. With this in mind we carried out a pilot study to investigate the relationship between the crown condition of individual trees and LiDAR metrics. Once the location of each tree was established a relationship between tree diameter and crown width was used to isolate the LiDAR points associated with an individual tree. It should be noted that no validation of the co-location was carried and that this should be the subject of future research.

To investigate the relationship between LiDAR metrics and individual trees a dataset comprising 439 trees was extracted from the database and the corresponding LiDAR point cloud for each tree was also obtained. The tree level data is summarised in Table 10, trees that could be easily extracted matched to LiDAR data were used and all multi-leader trees were excluded from the analysis. This is acceptable as the objective of this is a scoping exercise to test the methodology employed but would have to be addressed for the development of a predictive tree level model for crown condition based on LiDAR data. The authors note that the methodology of tree selection for individual trees is not statistically valid and that a randomisation process should be followed for the development of a tree level predictive model.

Table 10. Summary of the tree level data used for individual tree regressions

	Mean	Max	Min
Age	17.94	33	6
Defoliation	5.78	65	0
Transp. Entire crown	50.15	95	0
Transp. Top half	33.94	90	0
Needle retention	1.301	1	3

It was hypothesised that the plot level relationships developed in section 5.2 from the national dataset would remain valid for the subsample of individual trees investigated. The models developed in 5.2 were fitted using the individual tree dataset and the coefficient of variation is presented in Table 11 and provides a measure of the strength of the model. The coefficients in Table 10 are lower than those reported for the respective models when the plot averages were used although the R^2 calculated in each case are sufficiently similar to suggest that the relationships developed for plot averages are valid for individual trees. The consistency of relationships built at the plot level with those at built the tree level suggest that the co-location methodology is probably broadly valid. However, the reduced model strength may be due to some errors in co-location.

Table 11. The coefficient of variation for the four models investigated.

Crown Condition Variable	R^2
Transp. Entire crown	58
Transp. Top half crown	34
Defoliation	7
Needle Retention	33

6 DISCUSSION AND CONCLUSIONS

The data collected during the 2010 forest condition monitoring survey was summarised and queried to make the data available in an appropriate format for analysis. When plot averages were considered in the national data set transparency of the entire crown and transparency of the upper crown were strongly positively correlated. A linear regression model was built which describes the relationship between the two transparency measures and it was found that changes in crown transparency of the upper crown accounted for 77% of the variation in the transparency of the entire crown. This relationship is similar to one reported by Beets et al (2009) when a highly experienced assessor was used to measure crown transparency. This result indicates that the teams used to measure transparency in the 2010 FCM survey have a good understanding of the assessment of these indicators and that the indicator is relatively stable over time and across assessors. The relationships between the transparency indicators and defoliation and needle retention were weaker but still significant. These relationships suggest can be interpreted either as meaning that the measurement variability for defoliation and needle retention is either too great to establish a valid relationship or that one or other of the indicators is not well correlated with tree health. However, as there is no relationship between defoliation and needle retention in the national dataset it seems likely that transparency provides the best option for visual assessment of crown condition given the current level of training of the assessors.

LiDAR data provided by the Ministry for the Environment was successfully trimmed to the plot locations of the FCM plots based on differentially corrected GPS coordinates for the plot centre. The point cloud for each plot was then used to derive LiDAR metrics which were used in the development of predictive models for forest condition indicators.

An iterative regression modelling procedure was followed which resulted in the identification of key LiDAR metrics for modelling crown condition. In the final models produced the height metric P99 (relating to the 99^{th} percentile of LiDAR returns) and IntMean (relating to the average intensity of LiDAR returns) were found to have the strongest relationship with the crown condition indicators. The addition of age was found to improve the strength of the model for all indicators and was deemed acceptable for inclusion in a predictive model as New Zealand stands are generally even aged and in the majority of cases planting year will be available. Significant steps towards the production of national predictive models for crown condition variables in 2010 have been taken but it should be noted that significant effort is still required for model validation and for fine tuning of model form. It should also be noted that without time series measurements no predictions about future changes in condition can be made.

By far the strongest model produced (R^2 = 73.4) related to the relationship between transparency of the entire crown, LiDAR and age. A R^2 of this magnitude indicates that the independent predictor variables account for 73.4% of the variation in the response variable. Using the coefficients and the model form reported in this document it is possible to predict the transparency of the entire crown for any plot in the sampling frame for the 2010 measurements. As the sampling frame for 2010 only included the Radiata estate established before 1990 the continuation of field measurement to 2011 will provide a dataset to fit this model to the remaining estate. Residual analysis undertaken on the model suggested that the model is unbiased but that it predicts less well for younger plots. This could be because there were insufficient young plots to fit the model accurately, or it may suggest that the relationship is non-linear. Answering this question is beyond the scope of this project but this could provide valuable insight from future research.

Moderately strong relationships between transparency of the upper crown (R^2 = 41.5) and needle retention (R^2 = 33.8) were produced. The predictive model for needle retention was found to perform better when the LiDAR metric Int P50 was substituted for Int Mean. Only a weak relationship (R^2=13.4) was developed for defoliation. This is of significant concern and suggests that the variability is too large for this indicator and that it does not relate well to tree condition in the 2010 dataset. As this is the primary indicator used for the visual assessment of crown condition internationally significant training and quality assurance effort is required to improve the quality of this measure in the future.

A pilot study has been undertaken aimed at developing a methodology for investigating the relationships between the crown condition of individual trees in the 2010 dataset and LiDAR. A methodology for isolating LiDAR point clouds for individual trees has been developed. The plot level models developed were re-fitted using a subsample of individual tree data. This analysis resulted in decreased model strength, as expected because only a subsample of trees were used, but the pattern of model statistics produced for each model was similar. This suggests that the relationships developed at the plot level can be used as a basis for developing tree level relationships between crown condition indicators and LiDAR. Further work is required to validate the methodology used to isolate the LiDAR point cloud associated with individual trees.

6.1 Further Work

Interpine recommends the following areas of future research will provide significant benefit in relation to the topics covered in this paper:

- Extension of the collection of crown condition indicators to the 2011 measurement of planted forest plots. This will provide an opportunity to validate the predictive models produced in this study and provide an additional dataset to improve model fit.
- A methodology needs to be produced for the validation of the modelling approach for prediction at a regional or forest level as well as at the national level.
- Additional research to investigate non-linear approaches to model fitting and a full residual analysis may improve the quality of the models produced further.
- The single tree approach piloted in this paper provides an interesting avenue for further research and requires validation.
- There is a potential that an approach similar to the one developed here could be extended to other types of remote sensing which may prove more economic than aerial LiDAR.

6.2 Conclusion

National level predictive models for crown condition indicators based on LiDAR data have been produced for the first time and can predict crown condition across New Zealand's Radiata estate established before 1990 as at the 2010 measurement season. The strongest model has been built with the transparency of the entire crown indicator. There is significant concern about the quality of the defoliation measurements; only weak models could be fitted to this dataset. The implications of this work may mean that less plots need to be measured in future years to carry out monitoring of forest condition. The predictive models produced, following extensive validation, can be applied to a regional or estate level to provide condition monitoring at a finer scale.

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