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Development of Total Stem Volume and Velocity Maps from LiDAR Metrics

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TABLE OF CONTENTS

EXECUTIVE SUMMARY

A number of New Zealand-based forestry managers have been trialling LiDAR technologies to estimate the volume of wood in a stand. This research was conducted specifically to test (as a proof of concept) whether LiDAR can estimate total stem volume (*TSV*) and outerwood velocity (*V*) in a plantation forest. Can LiDAR give increased precision of harvestable volume or provide the same level of precision with fewer measurements (thereby reducing recording time and costs) than conventional measurement techniques?

The utility of LiDAR metrics for predicting total stem volume (*TSV*) and outerwood velocity (*V*) was examined within an even-aged mature forest of moderate size that included stands covering a wide range of stocking and *TSV*. Measurements were made on 172 plots representing 217.8 ha. Measurements of outerwood acoustic velocity were made on 35 of these plots. Statistical models to predict total stem volume that incorporated both LiDAR and non LiDAR measurements were developed. Spatial maps of TSV were developed for this forest. Essentially, the same methodology as for *TSV* was used to predict outerwood velocity

The best statistical models that included only LiDAR data explained 60% and 37% of the variation in TSV and V respectively. Inclusion of stocking data significantly improved prediction, so that 76% of variation in total stem volume was predicted. Combining LiDAR data with stocking rate and mean shortwave solar radiation resulted in a model that could predict 77% of variation in outerwood velocity.

These results provide a proof of concept. LiDAR technology can be used to estimate wood volume in plantation forestry in New Zealand. Forest managers can use spatial maps of total stem volume to help plan logistics and resource allocation for harvesting operations.

INTRODUCTION

Light Detection and Ranging (LiDAR) provides a highly accurate measure of distance. Usually mounted on an airborne system, the application of LiDAR for aerial laser scanning has been studied for its application in forestry since about 1978. However, it is only in recent years that the combination of precise airborne navigation, high quality instruments and effective post-processing software have allowed the technology to progress to operational use (Næsset, 2002; Nilsson, 1996). Innovation in laser scanning technology is advancing rapidly and it is impossible for the peer-review academic literature to keep pace. Nevertheless, there are several benchmark papers that describe the technology and review sensor characteristics (e.g. Wehr and Lohr, 1999; Baltsavias, 1999; McGlone *et al*., 2004).

Internationally, LiDAR data have been used to provide estimates of forest basal area (Means *et al*. 1999), diameter, volume (Næsset 1997b; Holmgren 2003) and canopy properties (Næsset & Økland 2002). In establishing tree height and volume, the accuracy of LiDAR-derived estimates is reported to be similar to or better than manual field measurement methods (Holmgren 2003; Næsset 2002; Watt 2005). LiDAR data are used operationally in Norway and Sweden (marketed on the premise that better data results in better decisions) to provide forest estimates at the compartment level (Eid *et al*. 2004).

In New Zealand, studies that have used LiDAR to describe stand metrics have produced similar results to those observed internationally (Watt & Haywood 2006; Watt & Haywood 2007). For radiata pine (*Pinus radiata*), LiDAR has been most accurately used to describe mean top height. At the national level, LiDAR has been used to describe accurately stand level *P. radiata* carbon and stem volume. Previous research has shown LiDAR metrics to have high correlations with mean top height, moderate with stand basal area, and weakly correlated with stocking.

Although LiDAR has been used previously to describe volume from national datasets, little research has used LiDAR to describe volume at the forest level. We are unaware of any research that has used LiDAR to predict key metrics describing wood quality such as outerwood velocity. Development of such models would allow spatial representation of volume and wood quality at a scale that would be of use for sales and harvest planning. Further research will report on the cost efficacy of such models.

Objectives

Using spatially coincident LiDAR imagery and inventory data obtained from a North Island *P. radiata* forest, the objectives of this study were to examine the possibility of developing models of total stem volume (*TSV*) and outerwood velocity (*V*) from LiDAR metrics, stand stocking and environmental datasets. Spatial surfaces of *TSV* and *V* were then developed from the best models.

METHODS

Data Collection

Stand Information

The data for this study were obtained from a forest located in Eastern Bay of Plenty on steep country with an elevation range of approximately 150 to 300 metres above sea level. The forest is first rotation planted onto cleared native forest.

A standard pre-harvest inventory was installed using the stand/harvesting boundaries as inventory population. In total 172 plots were installed in the stands where the trees were still standing at the time of inventory. These plots represented a sample area of 217.8 hectares. The circular plots were laid out within each population on a systematic grid as is normal practice in New Zealand. The plot size varied from population to population so that a target of approximately of 20 trees per plot could be obtained. The exact locations of the plots were measured using a high grade GPS capable of post differential correction. Within each plot all trees were measured for diameter, with a subset of heights being measured. The trees were cruised for stem quality using the method described in PlotSafe Overlapping Feature Cruising Forest Inventory Procedures (YTGEN User Group 2007). The field data were collected in the early part of 2011.

Total stem volume, *TSV*, was determined from stand basal area, BA, and mean top height, *MTH,* using the following nationally applicable equation (Kimberley and Beets, 2007),

$$TSV = H_t \, \mathrm{BA}(0.942(MTH - 1.4)^{-1.161} + 0.317) \qquad (1)$$

For Equation 1, *MTH* was determined directly from the LiDAR metrics rather than plot measurements, as height was determined on only a small subsample of trees (2) within each plot. *MTH* was estimated from the LiDAR metrics using the following equation (P. Beets unpub. data),

$$MTH = 1.372 + 1.087H_{95} \qquad (2)$$

where H_{95} is the 95^{th} percentile of the LiDAR height distribution.

Outerwood Velocity

Outerwood acoustic velocity (*V*) was measured in 35 of the inventory plots. Plots were selected to cover the range in stem slenderness and stocking present throughout the forest. Where possible, measurements were taken from at least 20 trees within the plot.

Velocity measurements were taken using the ST300 tool. Due the steepness of the site, these were taken from the upside of the tree and centred where possible around breast height (1.4m). Using paths that avoided any large branch stubs or obvious malformations, two measurements were taken on each stem at a distance of approximately 1 m apart. Measurements of velocity were taken on opposite sides of each tree as close to 180 degrees apart as possible.

Predictive Variables Included in the Modelling

LiDAR Dataset and Stocking

The study site was flown for LiDAR data and aerial imagery by New Zealand Aerial Mapping between 24 May and 1 June 2011, using NZ Aerial Mapping's Optech ALTM 3100EA LiDAR system (05SEN178) and Trimble AIC medium format digital camera. The LiDAR data were collected at a minimum of 2 points per m^2 on open ground. The raw LiDAR data was processed by the supplier into LAS format, georeferenced into the New Zealand Transverse Mercator (NZTM) coordinate system. Plot locations – found using high grade differentially corrected GPS – were used to 'cut out' the sections of LiDAR data relating to each plot, assuming a circular plot centred on the GPS location. The software package FUSION was used for this task, as well as generating the LiDAR height metrics used in the regression. The height metrics were generated using a manually corrected Digital Terrain Model (DTM) supplied by the data provider. All returns within 0.5 m of the ground were eliminated to remove the effects of understorey.

In order to extrapolate this relationship from the sampled plot locations to the whole forest, FUSION was again used to generate LiDAR height metrics for the forest on a 20 m x 20 m grid. This grid was converted to ASCII text, clipped to harvest area shape files, and predictive equations for *TSV* and *V* were applied in the Matlab numerical programming environment.

Stocking was determined from the plot data.

Environmental Dataset

From the co-ordinates of each of these permanent sample plots, data were extracted from biophysical GIS surfaces that described climatological data and topographical exposure (described below). Meteorological data were obtained from thin-plate spline surfaces (Hutchinson and Gessler, 1994) fitted to meteorological station data (Leathwick and Stephens, 1998), at a spatial resolution of 100 m^2. Average monthly and annual values were extracted from these climate raster surfaces for windspeed, solar radiation, total rainfall, mean, minimum, maximum air temperature and vapour pressure deficit.

Physiographic data included measurements of topographical exposure (topex), elevation and aspect. Topex was determined using GIS from digital terrain maps as the sum of measured angles from the point of reference (plot centre) to a distance of 1 km over the eight major compass bearings (Hannah *et al.*, 1995). Topex has been found previously to be an accurate predictor of windspeed (Hannah *et al*., 1995) as declinations (negative values), values of 0 and inclinations (positive values) respectively distinguish exposed hilltops, flat areas and sheltered gullies.

Analysis

Models used to predict total stem volume and outerwood velocity were generated using SAS (SAS-Institute-Inc 2000), by a general linear model (for *TSV*) and PROC NLIN (for *V*). The latter model was used for velocity as there was non-linearity in this model and PROC NLIN is able to accommodate a range of linear and non-linear functional forms. Variables were introduced sequentially into each model starting with the variable that exhibited the strongest correlation, until further additions either
(i) were not significant, or
(ii) were not physiologically reasonable, or
(iii) did not markedly improve model precision.

Variable selection was undertaken manually, one variable at a time, and plots of residuals were examined prior to variable addition to ensure that the variable was included in the model using the least biased functional form.

RESULTS

Total Stem Volume

Development of Models Describing Total Stem Volume

The best predictive model of *TSV* with only LiDAR variables included the 30th LiDAR height percentile (H_{30}). The relationship between H_{30} and *TSV* was positive, and linear and H_{30} accounted for 60% of the variation in *TSV* (Fig. 1), with RMSE of 87.0 m^3/ha. The relationship between H_{30} and *TSV* was highly significant (P<0.0001) and described by the following linear equation :

$$TSV = 155.54 + 27.96H_{30} \quad (3)$$

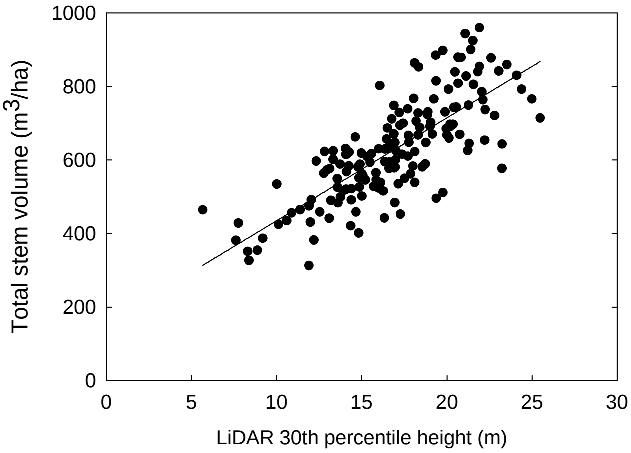

Figure 1. Relationship between the 30th percentile LiDAR height and total stem volume.

The best model of *TSV*, using all available variables, included H_{30} and stand stocking (S), in the following equation:

$$TSV = 4.84 + 22.08H_{30} + 1.01S \quad (4)$$

The overall model was highly significant (P<0.0001), as were the two variables included in the model (P<0.0001). The model accounted for 76% of the variation in *TSV* and had a RMSE of 67.7 m^3/ha. A plot of predicted against actual *TSV* showed the model to be relatively unbiased (Fig. 2). Partial response functions showing the change in *TSV* with changes in both variables, show the model to be more sensitive to H_{30} than S (Fig. 3). Residuals of *TSV* were normally distributed (Shapiro-Wilk P > 0.05) and exhibited little correlation with any of the environmental variables, including slope, aspect and topex.

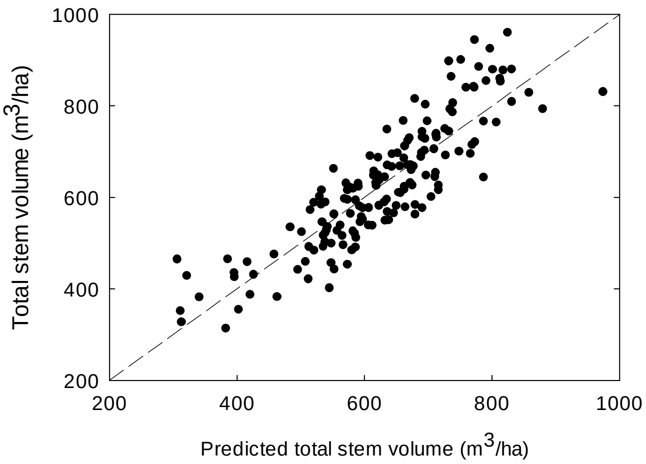

Figure 2. Relationship between predicted and actual total stem volume. For reference the 1:1 line is shown as a dashed line.

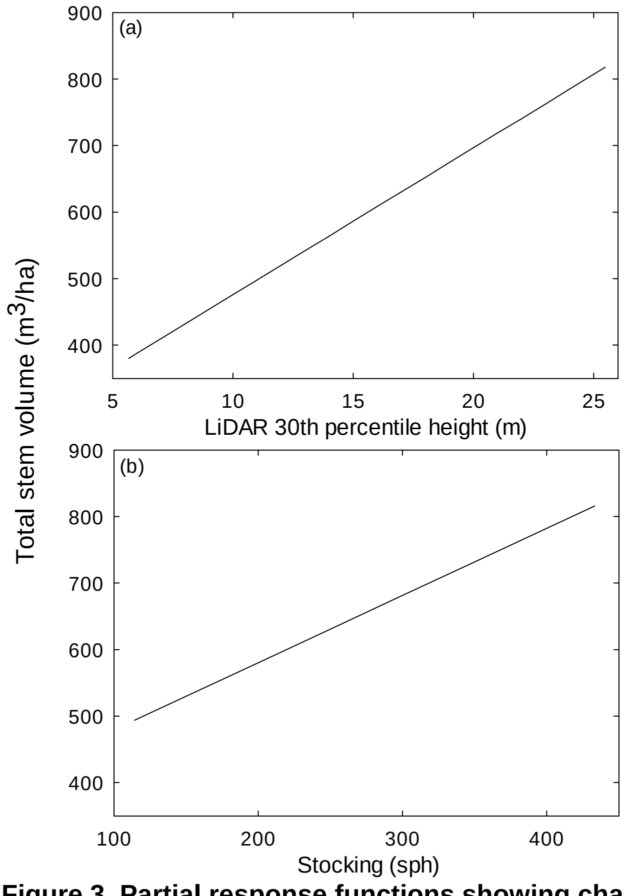

Figure 3. Partial response functions showing changes in total stem volume with variation across the range in (a) LiDAR 30th percentile height and (b) stand stocking.

Spatial Description of Total Stem Volume

Spatial variation in *TSV* using Equation 3 is shown in Figure 4. This shows widespread variation in *TSV* with low *TSV* occurring in the northwest of the forest and higher *TSV* in southern and south-eastern regions.

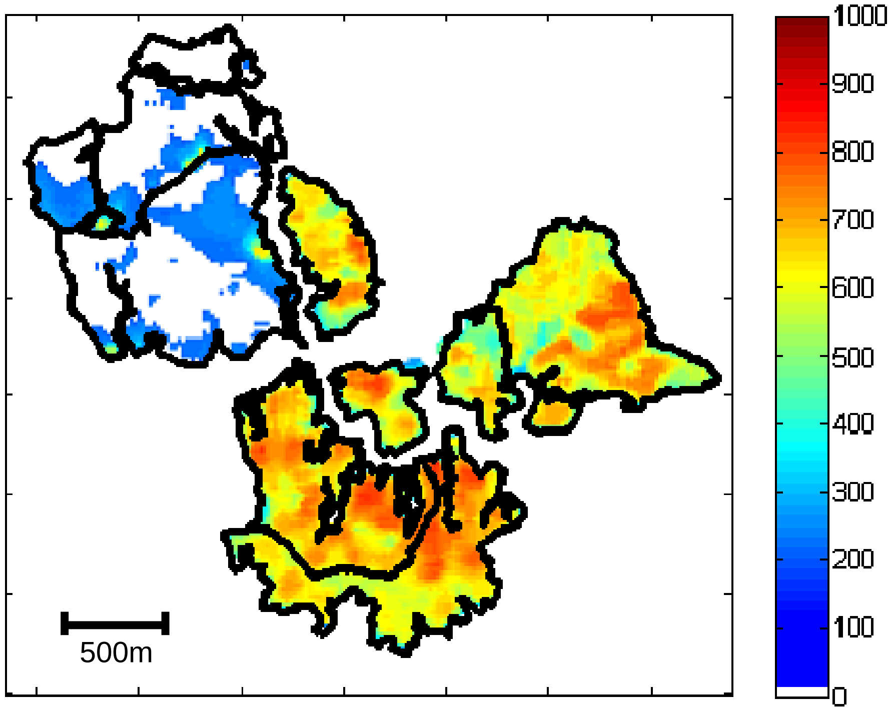

Figure 4. Spatial distribution of total stem volume (m^3/ha) predicted using the model with only LiDAR metrics (Equation 3).

Outerwood Velocity

Development of Models Describing Outerwood Velocity

The best predictive model of *V* with only LiDAR variables included the standard deviation in LiDAR heights relative to ground level, (H_{sd}) and the percentage of first returns above the cutoff of 0.5m (PC_{veg}). The model had an R^2 of 0.37, RMSE of 0.12 km s^{-1}, and was described as:

$$V = 5.41 + 0.0732H_{sd} - 0.0187PC_{veg} \quad (5)$$

The overall model was significant (P=0.0013) as was H_{sd} (P<0.0001). Although PC_{veg} was marginally insignificant (P=0.11), this variable was retained as it was a useful predictor in the more complex model outlined below. A plot of model predictions against actual velocity showed little apparent bias (Fig. 5).

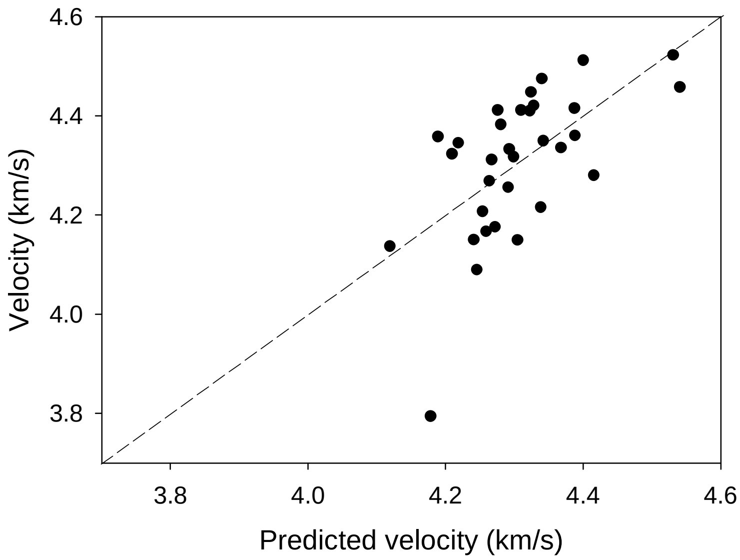

Figure 5. Relationship between predicted and actual velocity developed from the model with LiDAR only metrics. For reference the 1:1 line is shown as a dashed line.

Using all available variables, the best predictive model included H_{sd}, PC_{veg}, stocking (S) and mean shortwave radiation, (R), in the following formulation,

$$V = 8.30 + 0.0621\ H_{sd} - 0.494\ PC_{veg} + 0.851(1\text{-}\exp(-0.00566\ S)) - 0.00021R \qquad (6)$$

The overall model was significant, as were all variables (P<0.05). Stocking was included as an exponential increase to a maximum, rather than a polynomial form, as the former made more sense biologically. The model accounted for 77% of the variance in V, with RMSE of 0.0730 km s^{-1}. A plot of predictions against actual velocity was relatively unbiased (Fig. 6), although there was one outlier with a low velocity (Fig. 6). Residuals from the final model were normally distributed (Shapiro-Wilk P > 0.05) and there was little correlation between residuals from the second model and any of the environmental variables not included within the model.

Partial response functions show linear relationships between velocity and all variables apart from stand stocking. For stand stocking there was an exponential increase in velocity with increases in stocking which started to threshold at stockings exceeding 400 stems/ha (Fig. 7).

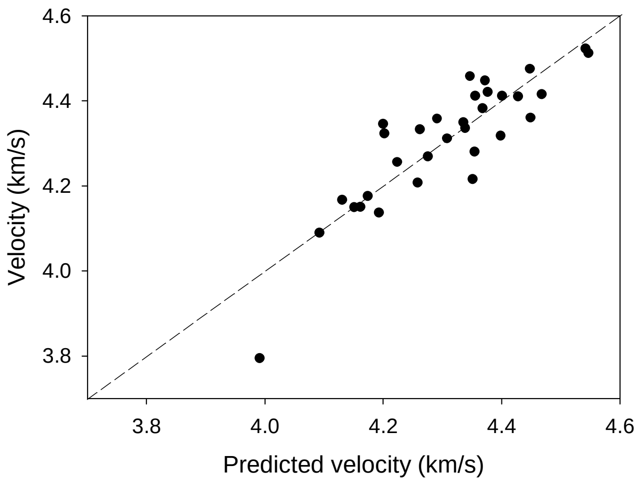

Figure 6. Relationship between predicted and actual velocity developed using all available variables. For reference the 1:1 line is shown as a dashed line.

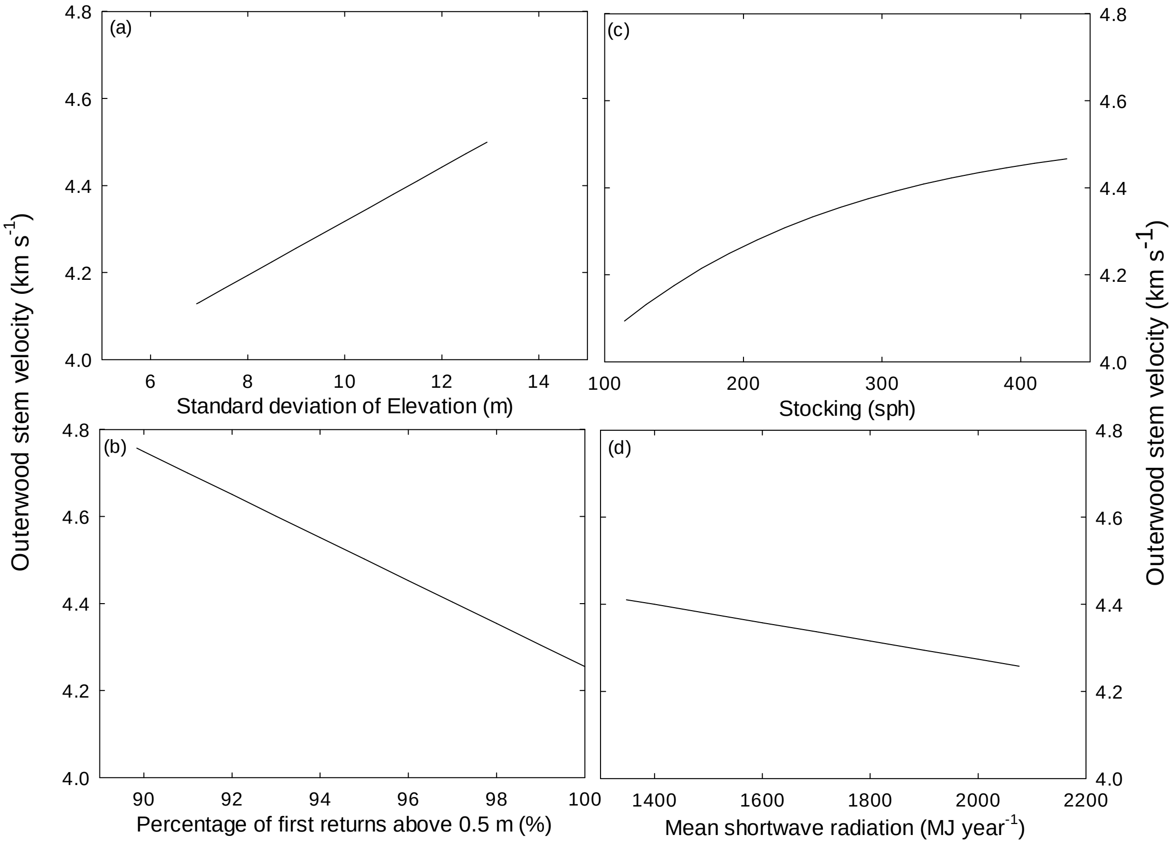

Figure 7. Partial response functions showing changes in velocity with variation across the range in (a) standard deviation of elevation (b) percentage of first returns above 0.5 m, (c) stocking and (d) mean shortwave radiation.

Spatial Description of Velocity

Spatial variation in *V* using the model described by Equation 5, is shown in Fig. 8. Velocity was quite variable and lowest in southern regions, and in particular the ridgeline of the most southern compartments (evident in a Digital Elevation Model overlay not shown here). Velocity reached high values in northeastern regions of the forest (Fig. 8).

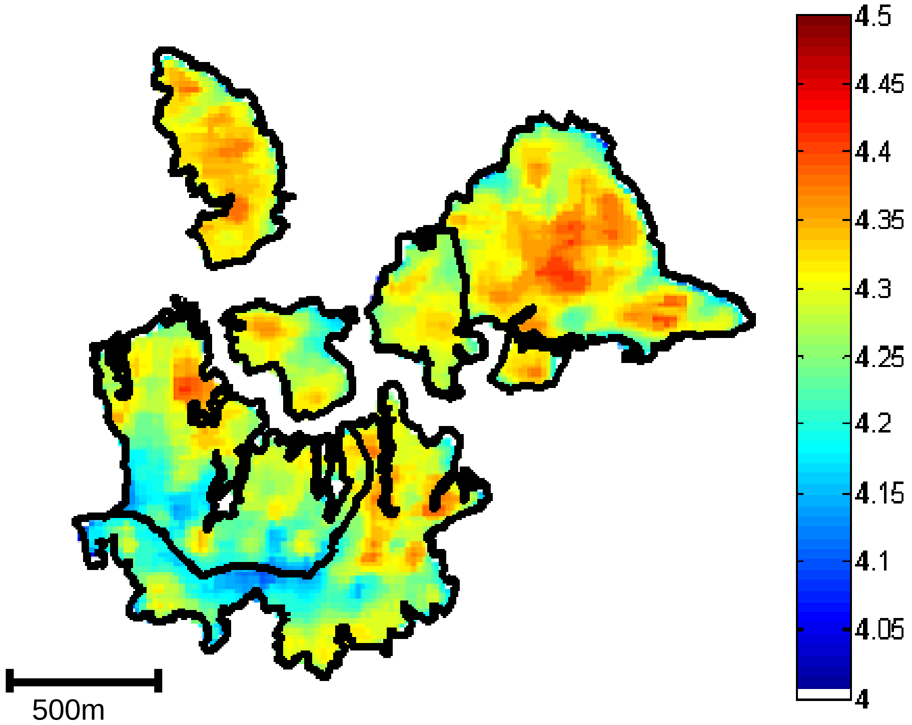

Figure 8. Spatial distribution of velocity predicted using the model with only LiDAR metrics (Eqn. 5).

DISCUSSION

LiDAR-total Stem Volume Relationships

This study demonstrates that LiDAR can be used to develop robust models of *TSV* at a regional level. Predictive power of the best *TSV* model shown here was within the range cited by previous localised studies where coefficient of determinations varied from 0.46 (Naesset 1997) to 0.97 (Means *et al.* 2000). The relatively high coefficient of determination found here partially reflects a wide range in the dependant variable (*TSV*), which tends to inflate the percentage of variance explained. As RMSE is not subject to the same limitation, this statistic provides a more conservative estimate of precision. When compared to previous research, the RMSE for the best model of 67.7 m^3 ha^{-1} found here is within the mid-range of previous values that include 28 m^3 ha^{-1} (Naesset 1997, 2002; van Aart *et al*. 2006), 18.3 – 31.9 m^3 ha^{-1} (Holmgren and Jonsson 2004), 38.03 – 56.73 m^3 ha^{-1} (Naesset 2002), 26.1 – 82.8 m^3 ha^{-1} (van Aart *et al*. 2006) and 73 m^3 ha^{-1} (Means *et al.* 2000).

The developed model of *TSV* appeared to be generalisable across the environmental range found throughout the forest. Although previous LiDAR models developed over broad scales have often demonstrated a lack of generality, it is worth noting that these studies typically combine changing environment with variation in species composition (Drake *et al*. 2003; Naesset and Gobakken 2008). The insignificant effect of environment on LiDAR-volume relations is consistent with previous research in the Pacific Northwest showing generality of LiDAR across environment for other stand metrics, such as tree height, above-ground biomass and leaf area index (Lefsky *et al*. 2002; Lefsky *et al*. 2005). This generality is also consistent with a national LiDAR-*TSV* model that has been recently developed for New Zealand (Watt *et al*., in prep).

The variables included in the final models were consistent with previous research and have sound mechanistic basis. Logically, LiDAR models describing *TSV* should combine stem height with variables that provide a measure of stocking and stem diameter. The stem height variable used, H_{30}, was appropriate as is affected by the point cloud of almost all trees of significant size, as opposed to top-end height percentiles (e.g. H_{95}) which are altered only by the point clouds of the highest trees. Inclusion of stocking directly was found to be superior to use of LiDAR metrics that approximate stocking.

Stocking could be included as a driving variable at a range of resolutions. At a coarse level, stocking for the compartment could be used as input to the model. Alternatively tree counting software such as TiMBRs could be used to identify tree locations. Once these locations are ascertained it would be relatively simple to generate a map of stocking by overlaying a grid and allocating tree locations to a grid cell.

LiDAR-velocity Relationships

The model of *V* developed here demonstrates that LiDAR can be used to predict variation in wood quality. Inclusion of stand stocking greatly improves the predictive power of the final model. After shortwave radiation was included, the final model was unbiased against other environmental variables.

Stem slenderness has previously been identified as one of the key drivers of *V* and modulus of elasticity (Watt *et al*., 2009, 2010). It is very likely that the standard deviation of height and stocking are acting as surrogates for slenderness in the final model, as both exhibit highly significant (P<0.0001) positive relationships with stem slenderness in this dataset. Similarly, there was a weak, albeit marginally insignificant (P=0.05) negative relationship between shortwave radiation and slenderness. This relationship may account for inclusion of this variable in the model, as low values of shortwave radiation are associated with higher slenderness and higher values of *V*.

Industry Application

The relationships developed here could be used in a number of ways to improve precision around estimates of *TSV* and/or reduce the plotting frequency. Current methods for estimating mean top height (*MTH*) include sampling a small number of trees and using these within a regression model, with often poor predictive power, to predict *MTH* from diameter at breast height of plot trees. In contrast, LiDAR metrics can be used more to evaluate height of all trees in the plot, which can then be averaged to a mean. As measured *MTH* generally exhibits a very strong correlation with the upper LiDAR height percentiles, the use of LiDAR for this purpose is likely to yield more precise estimates of *MTH,* and by association, *TSV*.

Equations for *TSV* developed here could be used to stratify the resource at a compartment level. Such stratification would allow plots to be averaged across areas of similar *TSV* increasing the precision around TSV estimates. An initial analysis using data described here shows that 27% more plots are required in an unstratified resource to obtain the same probable limit of error (PLE) as is obtained when the resource is stratified using estimates of *TSV* described by Equation 3. A simplification of this method would involve the LiDAR provider splitting a generically useful LiDAR metric such as H_{30} or H_{95}-H_{30} into four groups that could be used for the stratification. Such a method would also allow pre-inventory plots to be more efficiently allocated. LiDAR estimates of *TSV* could be used more directly to estimate mean *TSV* of compartments using a double sampling approach.

CONCLUSION

LiDAR metrics can be of considerable use for predicting velocity and total stem volume at the forest level. The most precise models of *V* and *TSV* included stand stocking as a predictive variable. There are a number of ways in which LiDAR could be used to improve the precision on predictions of *TSV*. These include:

- estimating *MTH*;
- stratifying the resource, or
- directly estimating *TSV* in conjunction with inventory plots in a double sampling capacity;
- using the LiDAR relationships to directly estimate volume across the resource (as undertaken here)

A further report will undertake a cost-benefit analysis to understand the economic feasibility of these approaches.

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