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Predicting living and dead wood volumes in a mature managed Swedish forest with airborne laser scanning

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Abstract

Detecting dead wood with airborne laser scanning (ALS) would have many benefits. It would make it easier to find areas with high mortality rates, help make better decisions on which areas to preserve, and increase the accuracy of volume- and value-estimations. In this study, we tried to assess the accuracy of volume predictions of living wood, standing dead wood, and lying dead wood, as well as pinpoint the most descriptive ALS variables. The focus was on homogenous mature managed forests on good site indexes.

A plane equipped with LiDAR was flown over a 7500 ha forest area in Dalarna, Sweden. Laser variables were made to describe the point cloud from the LiDAR. 102 field plots were generated in mature managed stands and all trees (including bigger lying wood) were measured for diameter and height. The volume of living wood, standing dead wood, and lying wood was found for each field plot. The field plots were then run in a simulation with 500 iterations. For each iteration, 81 random field plots were used as calibration plots and the remaining 21 field plots were used as prediction plots. For each iteration, multiple variable linear regression and a “k nearest neighbour”-algorithm (kNN) with one, two, and three neighbours were calibrated on the calibration plots and then used to predict the volumes on the prediction plots. The mean difference between predicted and real volume were found for each method (regression and kNN with one, two, and three neighbours) and tree class (living, standing dead, and lying dead).

When predicting living volume, regression got a good fit with an adjusted R^2 value of 0,73. Standing dead volume got a medium fit with an adjusted R^2 value of 0,46. Lying dead volume got a very low fit with an adjusted R^2 value of just 0,12. Overall, the kNN algorithm did better with one neighbour, compared to two or three. Regression achieved very low systematic errors across the board, while the kNN algorithm got higher systematic errors but slightly lower standard errors of the mean compared to regression.

The most descriptive laser variables for living volume were related to branches in the upper and middle parts of the stems. The most descriptive laser variables for describing standing dead wood volume were related to tree heights and branches in the middle and lower parts of the stem. Lying dead wood had too low a correlation with the laser variables to find a clear pattern. When predicting wood volumes with kNN, a higher k did not improve the results.

Sammendrag

Å finne døde trær i skog med flybåren laserskanning (ALS) hadde hatt mange fordeler. Det hadde gjort det lettere å oppdage områder med høy mortalitet, hjulpet til med å ta bedre beslutninger om vern, og det kunne forbedret volum- og verdi-estimeringer i skog. I denne studien har vi sett på nøyaktigheten av volumprediksjoner av levende volum, stående dødt volum, og liggende dødt volum, i tillegg til å se på hvilke laservariabler som var mest beskrivende. Studien er gjort i eldre homogene skjøtte bestand på gode boniteter.

Et fly utstyrt med en LiDAR-sensor ble fløyet over et 7500 ha stort skogsområde i Dalarna i Sverige. Det ble laget laservariabler som beskrev punktskyen fra LiDAR-sensoren. Så ble det generert 102 prøveflater i samme område. Alle trær på prøveflatene ble målt for høyde og diameter i brysthøyde (inkludert større liggende stammer/stokker). Levende volum, stående dødt volum, og liggende dødt volum ble beregnet for hver prøveflate. Prøveflatene ble kjørt i en simulering med 500 iterasjoner. For hver iterasjon ble 81 tilfeldige prøveflater brukt som kalibreringsflater, mens de resterende 21 prøveflatene ble brukt som predikeringsflater. For hver iterasjon ble kalibreringsflatene brukt til å finne den beste modellen for multippel lineær regresjon, i tillegg til å brukes som kalibreringsflater for en «k nearest neighbour»-algoritme (kNN) med en, to, og tre «naboer». Regresjonsmodellen og kNN-algoritmene ble så brukt til å predikere volumet på prediksjonsflatene. Gjennomsnittlig differanse mellom predikert volum og virkelig volum ble funnet for hver metode (regresjon og kNN med en, to, og tre «naboer») og hver tre-klasse (levende, stående dødt, og liggende dødt).

Regresjon fungerte godt til å predikere levende volum, med en gjennomsnittlig justert R^2-verdi på 0,73. Stående dødt volum fikk en gjennomsnittlig justert R^2-verdi på 0,46 mens liggende dødt volum fikk veldig lave 0,12. kNN-algoritmen gjorde det generelt bedre med en «nabo», i forhold til to og tre. Regresjon ga veldig lave systematiske feil, klart lavere enn kNN. Standardfeilen til gjennomsnittet var derimot alltid noe lavere med kNN i forhold til regresjon.

De mest beskrivende laservariablene for levende volum var relatert til mengden greiner fra toppen til midten av stammene. De mest beskrivende laservariablene for stående dødt volum var relatert til tre-høyder og mengden greiner fra midten av stammene og ned. Liggende død ved hadde for lav korrelasjon til å finne en klar sammenheng med laservariablene. Predikeringer med kNN ble ikke bedre med flere «naboer».

Table of contents

1 Introduction

Forests are an extremely important resource. About 31% of the global land area is covered by forests (UN, 2020), and in the Nordic countries, Finland has the biggest part of their landmass covered by forests with 76% (MAFF, 2020). Forests have different values for different people. A forest owner is usually interested in the economic value, while a hiker is probably most interested in the look and feel, and its recreational value. A politician might be more concerned about the forest as a resource on a local and national scale. With a resource that requires such big areas, it is only logical that there will be a lot of interested parties and differing opinions, which in turn can make the management of such a resource very difficult. One step in the direction of making the management easier and more knowledge-based is to have a more detailed overview of what the forests contain in terms of resources, and how it differs throughout the areas. This way, it will be easier to manage the forest in a way that is favourable to both different people and biodiversity.

Knowledge-based planning requires a good overview of the resources available and their development. In Norway, the National Forest Inventory (NFI) has had the responsibility of mapping the forests since 1919 (Granhus, 2022). They have permanent inventory plots that get measured about every ten years. That way they can keep track of the Norwegian forests and their development, both regionally and nationally. Sweden, Denmark, and Finland also have similar systems (Fridman, 2016) (Nord-Larsen, 2016) (Tomppo, 2009).

Mapping of the total forest resources in a country is important for the national government to make sure they can make their goals and keep their promises to agreements like the Paris agreement and The LULUCF Regulation (UNFCCC, 2020) (EC, 2021). These agreements require its members to have control over their forest areas' development. It's also important to make more detailed mappings over smaller areas, like a forest property. This is important for the decisions on a smaller scale, like the timing of management measures or felling. The goal when performing these mappings is to reach a good trade-off between accuracy and price. Historically, the most expensive part of forest resource mapping is the data collection in the field. Because of this, efforts have been made to decrease the amount of necessary fieldwork. This usually involves using new technology to reach the required precision in the mapping.

Towards the end of the 1970s, the forest sector started using photogrammetry in the mapping process (Næsset, 2014). This method required less fieldwork and was therefore cheaper. Soon after, airborne laser scanning (ALS) started being used for topographic mappings. The potential for ALS being used for forest mapping was low at the time, mostly because of the low point density on the ground. As technology advanced, so did the point density, and the potential for use in forest mapping became apparent. The first tests in the Nordics were carried out in 1991 (Naesset et al., 2004). In 1995 ALS was first tested for estimating average height and volume in forest stands (Naesset, 1997). The potential was clear, and many studies followed both in the Nordic countries and in other parts of the world. Experiences from Norway, Sweden, and Finland showed that ALS was at least as good as photogrammetry for estimating average height and volume in forest stands (Naesset et al., 2004). The precision of the estimates varied between parameters, but in the Nordics at the beginning of the 2000s, the total standing volume could be estimated with a consistent precision of between ten and fifteen percent (Næsset, 2014).

Laser scanners have advanced quite drastically since the beginning. In the first test in the 90s, the laser scanners had a repetition frequency of two kHz. This translated into about 0,1 ground hits per square meter (Næsset, 2014). In the following fifteen years, the repetition frequency got about 100 times faster (Næsset, 2014). More ground hits per area translate into more detailed point clouds, which makes it possible to extract more (and more detailed) data. Higher repetition frequency also made it possible to fly at higher altitudes during measuring, and thereby collect data more efficiently (Næsset, 2014).

In the beginning, one of the biggest problems was finding the exact location of the laser points on the ground (Naesset et al., 2004). This problem was pretty much solved already in the 90s when they started using both GPS and the plane's integrated navigation system to pinpoint the movement of the plane and scanner (Naesset et al., 2004). After this, it didn’t take long before they managed to calculate the position of the laser points on the ground with a precision of about 0,5 meters (Naesset et al., 2004).

A laser scanner can detect several returns from the same pulse. At first, they didn’t see the use for this in forest mapping, and they only recorded the last return from each pulse (Næsset, 2014). But eventually, it became clear that recording several returns from each pulse could provide information about the canopies and branches. This meant that ALS could be used to collect data for a much wider spectre of parameters than before.

After collecting ALS data, you end up with a point cloud made of laser echoes. This point cloud is then analysed and turned into variables that describe the distribution of the echoes. These variables are not very descriptive by themselves, so they need to be interpreted by matching them to real ground values. Some fieldwork is required to collect data from calibration plots. When we have both real values from calibration plots and the laser variables that describe the point clouds from the calibration plots, this can be used to estimate values for new areas.

Laser data can be interpreted in different ways, but the most common is to use regression for modelling. This method is used to fit models that best explain the ground values, using laser variables. It is also possible to use non-parameter methods. An example of this is to use a “k nearest neighbour” (kNN) algorithm, which is widely used in both Sweden and Finland (Maltamo and Packalen, 2014). kNN compares laser data from new areas with laser data from ground plots and gives the new area the same values as the most similar ground plot(s). This can have several advantages over regression. Among the most obvious, kNN can better describe an area where the correlation between ground values and laser variables is different from the correlation described by regression. For example, linear regression is used in this study, but if the correlation is not linear, kNN might be a better choice for predicting values in new areas. Another positive is that the kNN method never extrapolates, every area is given values within the range of the calibration plots. This also leads to one of the biggest pitfalls with kNN: it requires that the calibration plots cover the whole spectre of the forest. If a new area is outside of the range that the calibration plots cover, it will be assigned false values (Maltamo and Packalen, 2014).

1.1 Estimating dead wood

Having an overview of the amount of dead wood has many advantages. Estimating dead wood volumes with ALS can help make more accurate value estimations of the standing volume or help locate areas with high mortality. And with today's big focus on sustainability and biodiversity, it can be used to make better decisions on which areas to preserve and which areas to cut. Preserving areas with high amounts of dead wood can increase the total amount of dead wood in the forests over time. That would be good news for the more than 7500 different species tied to dead wood in the Nordics (Stokland, 2012).

The more advanced the ALS systems become, the more we can do with them. There has been some research on predicting dead wood volume and the number of dead trees in the past (Pesonen et al., 2008) (Pesonen et al., 2009). They have shown that it’s easier to do predictions on dead wood in natural forests compared to managed forests. This is mostly because thinning changes the spatial forest structure. This makes it harder to find dead wood based on openings in the canopy layer.

As the technology advances further, eventually, we should be able to do estimations on dead wood with reasonable accuracy. Since the previous studies on the matter are getting old, it is about time to have a look at it again. And that is the purpose of this study. The goal of this thesis is to assess the accuracy of volume predictions of dead wood in a mature managed forest, as well as pinpointing the most descriptive ALS variables.

2 Materials and methods

2.1 Study area

The data collection was conducted on a forest property owned by Kopparfors Skogar AB in June 2021 just outside Hedemora, Sweden (542942,6666299). The forest area was around 7500 ha in total and mostly covered by homogenous stands of Scots pine (*Pinus sylvestris*) or Norway spruce (*Picea abies*). There were some stands with only deciduous trees, and most stands had a few deciduous trees spread out in the stand. In this study we only included stands with mainly coniferous trees. In general, the area was managed for commercial use.

102 field plots were generated at random in mature forest stands, with a 10-meter buffer sone to eliminate edge effects. All plots were in stands with primarily Scots pine (*Pinus sylvestris*) or Norway spruce (*Picea abies*) in felling classes 4 and 5. Most stands seemed to have been thinned at least once. The volume distribution of the field plots is shown in Figure 1 and Figure 2.

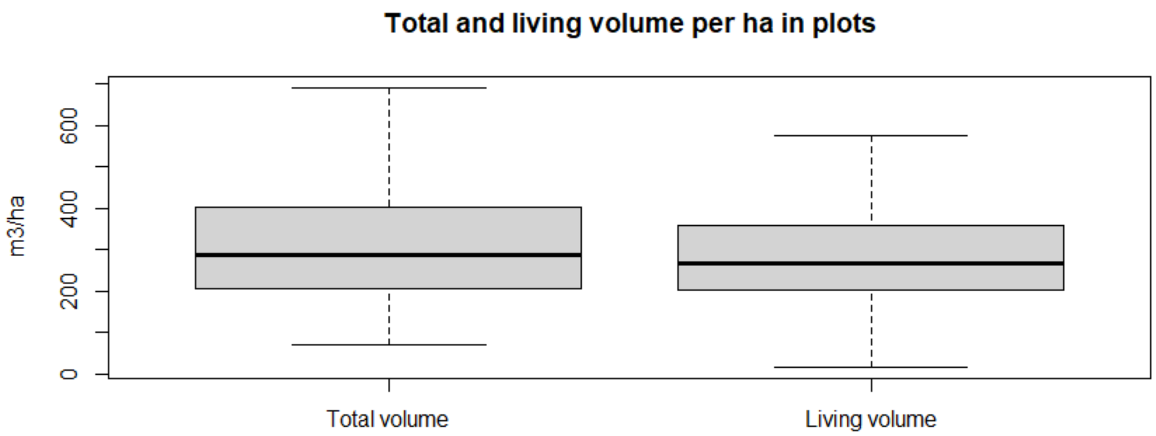

Figure 1: Distribution of total and living volume in the field plots. Volumes are given in m^3 per hectare.

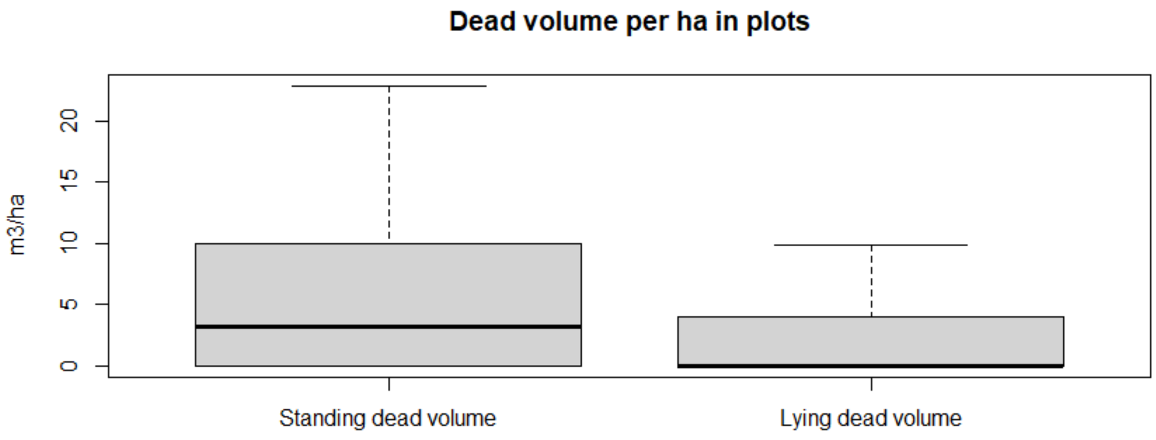

Figure 2: Distribution of standing dead and lying dead volume in the field plots. Volumes are given in m^3 per hectare.

2.2 Field inventory

One field plot was generated in every mature stand in felling classes 4 and 5. 102 field plots were generated in total, with a couple of stands having two field plots in them. The field plots were circular with a radius of ten meters, but this was changed after the data collection. After the collection, the trees further than nine meters from the plot centre were removed, due to the laser variables being made for a 9-meter radius. The number of field plots with living, standing dead and lying dead trees, as well as volumes in the field plots (with a 9-meter radius) is presented in Table 1. The middle point of each field plot was found with a mobile phone running google maps. When the distance to the point was zero meters on the phone, it was counted as the middle point of the plot. We used a Haglöf postex system with ultrasound to get the coordinates for every tree within the plot. The Haglöf system was set up in the middle of the plot together with an external GPS antenna connected to a field computer. The field computer registered the location from the GPS every second for at least 1300 seconds on every plot. The Haglöf system uses three ultrasound transponders on a tripod to triangulate the position of every tree, and we used a compass to line up the transponders in the right direction. We registered the coordinates of every tree within the plot with a diameter of above five cm in breast height (DBH), as well as registering DBH and species (pine, spruce or other). We also registered the coordinates and diameter of every lying tree with a diameter at the thickest point within the plot of at least fifteen cm and a length (within the plot) of at least one meter. The coordinates were registered at the thickest point. Every registered tree was also classified as alive, dead, or lying dead. Standing trees that showed clear signs of dying (for example losing needles or loose bark) were classified as dead. The height was measured for every dead tree within the plot, and most living trees. On plots with many trees, the smallest living trees often didn't get measured for height (to save time). Trees that were overly bent or were standing at an angle had their height measured from the ground directly under the top, to the top of the tree. The length of lying wood was measured as the length lying within the plot. A height model (height-to-DBH) was found using a mixed-effect model by tree species, using the R function "nlme" (Pinheiro, 2022) with plot ID for a random effect. The function used for this was "Korf", shown in Equation 1. That model was then used to get height values for trees without height measurements. Tree volumes were calculated with Swedish volume functions from Brandel (1994). Total volumes for each tree class (alive, dead, and lying dead) were calculated for each field plot.

Equation 1: «Korf» equation. a and b are parameters to be estimated. d is DBH.

$$a*\exp(-b*d^{-1})$$

Table 1: Number of field plots with > 0 volume, and mean volume and standard deviation for volume (for each tree class).

	Living	**Standing dead**	**Lying dead**
Number of plots with > 0 volume	102	73	31
Mean volume (m^3/ha)	280,8	18,3	3,1
Standard deviation (m^3/ha)	132,9	52,4	6,5

2.3 Laser scanner data

Laser data was collected by plane equipped with a dual-channel "Riegl VQ-1560i-DW" LiDAR sensor with a repetition frequency of 1000 kHz (for both channels), flying at an altitude of 610 to 650 meters at 120 knots (ground speed). The sensor had one green 532 nm channel and one infrared 1064 nm channel. Max opening angle was 28 degrees. Point density was around fifty points per m^2 after cutting flightline overlap. The LiDAR data was collected and processed by MW Forest Sense AB and interpreted by Arbonaut Oy Ltd. Laser echoes were found for each plot and converted into a set of height and density variables describing the point cloud. The laser variables are presented and described in Table 2. To get the density variables, the distance between two meters above ground and the 95th height percentile was derived into ten equal fractions. The 95th height percentile is the height at which 95% of the laser points are below. Each density variable gives the share of echoes above the lower height limit of the given fraction. This way, the density variables can describe at which heights the laser points got reflected the most. Up to two return pulses were recorded for every laser pulse. This means that we had two of every laser variable; one for first return pulses and one for last return pulses.

Table 2: Laser variables used for predictions. Height variables start with "H", and density variables start with "D". Every variable has two versions: one for 1st echo and one for 2nd echo.

Variable	Description
Hmax	Highest laser echo height (m)
Hmean	Average laser echo height (m)
Hsd	Standard deviation for laser echo heights (m)
Hcv	Coefficient of variation for laser echo heights (m)
Hkurt	Kurtosis (m)
Hskewness	Skewness (m)
Hqav	Average square height (m)
H10	10th percentile height (m)
H20	20th percentile height (m)
H30	30th percentile height (m)
H40	40th percentile height (m)
H50	50th percentile height (m)
H60	60th percentile height (m)
H70	70th percentile height (m)
H80	80th percentile height (m)
H90	90th percentile height (m)
D0	Share of laser echoes above 2 meters
D1	Share of laser echoes above first height limit
D2	Share of laser echoes above second height limit
D3	Share of laser echoes above third height limit
D4	Share of laser echoes above fourth height limit
D5	Share of laser echoes above fifth height limit
D6	Share of laser echoes above sixth height limit
D7	Share of laser echoes above seventh height limit
D8	Share of laser echoes above eighth height limit
D9	Share of laser echoes above ninth height limit

2.4 Data analysis

The field plots were divided into 81 calibration plots and 21 validation plots. The calibration plots were used to fit multiple linear regression models with the laser variables to find the volumes on the plots. The models were limited to a maximum of four variables. One model was chosen for each tree class. The best models were chosen with the Bayesian information criterion (BIC) (Schwarz, 1978). The models were then used to predict the volumes on the validation plots. This was done 500 times in a loop, with calibration plots and validation plots chosen at random for each iteration of the loop. This was done to get many different compositions of calibration plots and validation plots and make predictions under many different circumstances.

A kNN algorithm (Zhang, 2016) was also used to predict the volumes on the validation plots. This was also done 500 times in a loop, with the same compositions of calibration plots and validation plots as with regression. For each validation plot, the kNN algorithm found which calibration plot(s) had the most similar laser variables. The validation plot was given the average volume of the k most similar calibration plots. The algorithm was run with one, two, and three neighbours (k).

Every time a plot was predicted, the difference between the predicted volume and the real volume was recorded for every tree class. That meant that for each of the 500 different compositions of calibration and validation plots, we got 81 differences for regression and 81 differences for each version of kNN (k set to one, two, and three), for every tree class. This was used to make one mean value for each iteration and tree class, for regression and every version of kNN. That meant we had 500 mean differences for every tree class for both regression and every version of kNN.

Mean difference (MD) was calculated as the mean value of the 500 mean differences. The standard error of the mean (SE) was calculated as the mean standard deviation of the 500 mean difference values. Relative MD and SE values were calculated as MD or SE divided by the average volume in the 500 different compositions (the average volume of the given tree class). The p-values were calculated as the average p-value for the 500 MD values.

To analyse which laser variables were the most descriptive of each tree class, I counted how many times each laser variable was included in the best regression model for the given tree class. The fifteen most common laser variables for each tree class are presented in Table 5, Table 6, and Table 7. Since we have both first and last echo variables, the first echo variables end with ".1", while the last echo variables end with ".2". I also recorded the most common relationship (positive or negative) as the main relationship for the variables in the models. Because some variables have a positive relationship in some models and negative in others, I also included how often the main relationship occurred.

3 Results

3.1 Living volume

Both regression and kNN had an average difference from the real volume of close to zero, which means a small systematic error. Regression had a slightly smaller systematic error compared to every iteration of kNN, while kNN overall got a slightly smaller range of difference and standard error of the mean. No substantial difference between the different kNN iterations. The range of the mean differences is visualised in Figure 3, and statistics are shown in Table 3 and Table 4.

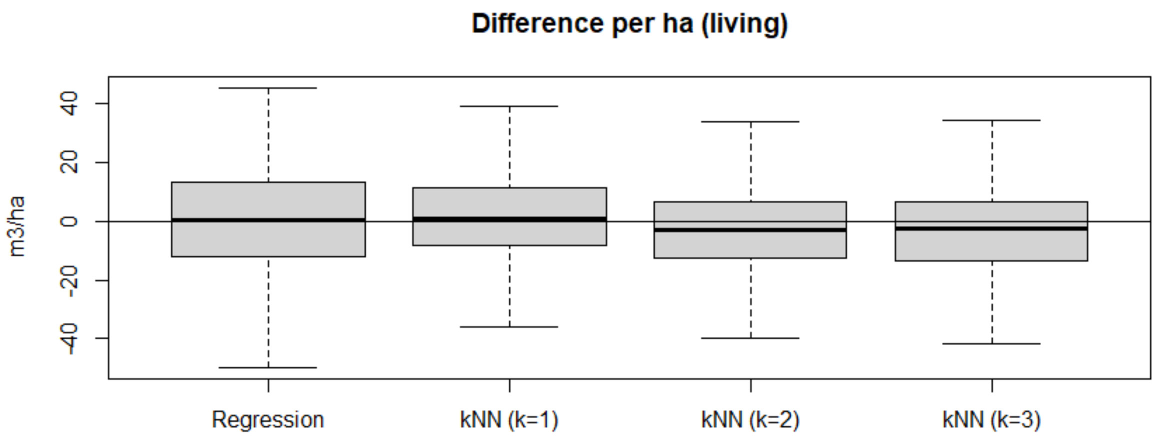

Figure 3: Difference between predicted and real volume in field plots for the living tree class. Result of simulation with 500 iterations, and 21 field plots predicted for each iteration.

3.2 Standing dead volume

Regression got a significantly lower systematic error of the MD compared to every version of kNN. The standard error of the mean was very high for both kNN and regression. kNN got a lower systematic error of the MD with one or two neighbours compared to three, as well as a higher p-value (higher is better). The range of the mean differences is visualised in Figure 4, and statistics are shown in Table 3 and Table 4.

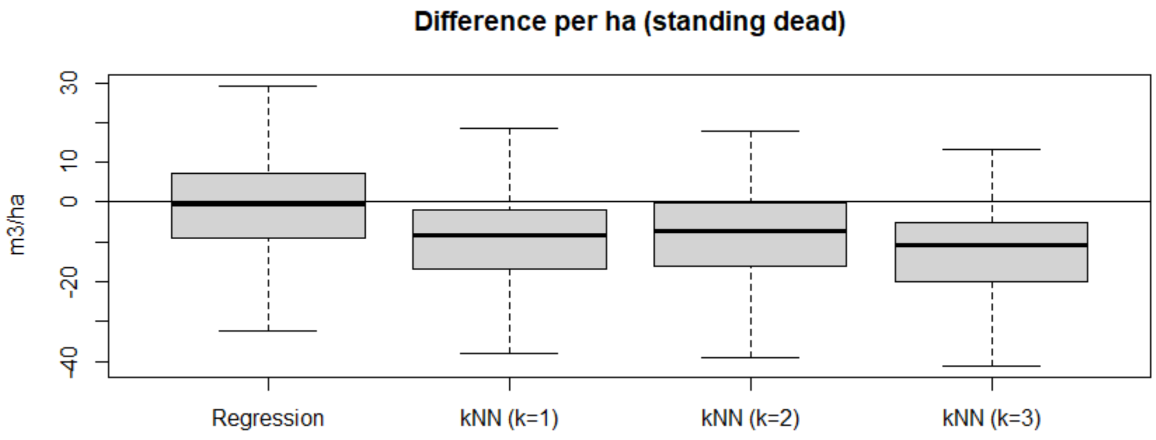

Figure 4: Difference between predicted and real volume in field plots for the standing dead tree class. Result of simulation with 500 iterations, and 21 field plots predicted for each iteration

3.3 Lying volume

Regression got a much lower systematic error of the MD compared to kNN. The standard error was high among every method. kNN got significantly higher p-values with one and two neighbours compared to three (higher is better). The range of the mean differences is visualised in Figure 5, and statistics are shown in Table 3 and Table 4.

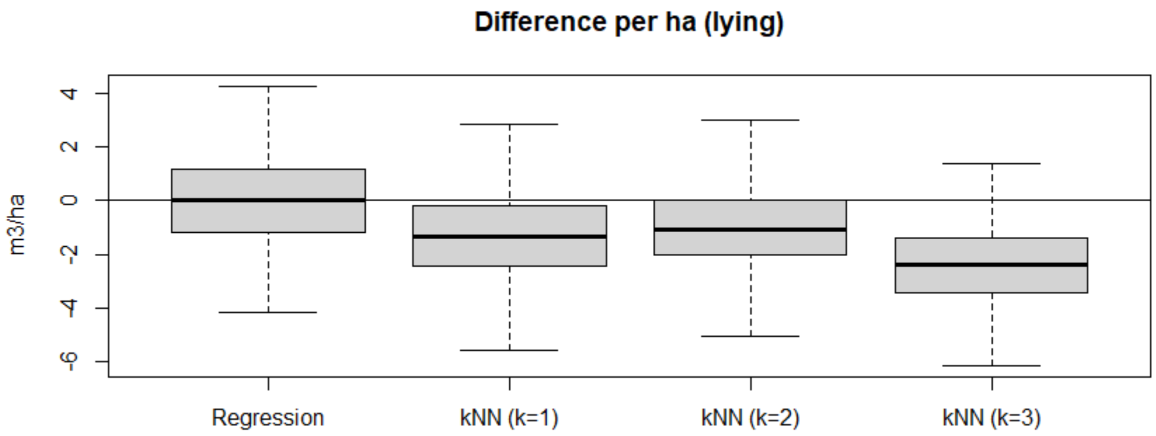

Figure 5: Difference between predicted and real volume in field plots for the lying dead tree class. Result of simulation with 500 iterations, and 21 field plots predicted for each iteration.

3.4 Statistics

None of the mean differences (MD) is significantly different from zero (with a 95% confidence level). With regression, the systematic error was consistently lower compared to that obtained using kNN, while also consistently getting the highest standard error of the mean (SE). For dead volumes, kNN did better with k set to one or two. Overall, the standing dead volume got the highest systematic errors and the highest standard errors of the mean.

Table 3: MD: mean difference (in m^3/ha) between predicted and real volume. MD (%): Mean difference between predicted and deal volume in % of mean volume of tree class in predicted plots. SE: standard error of the MD values (in m^3/ha). SE (%): standard error in % of mean volume of tree class in predicted plots. P-value: p-value for MD values. R^2_{adj}: mean adjusted R^2 value for the best models.

Regression	MD (m^3/ha)	MD (%)	SE (m^3/ha)	SE (%)	p-value	$R^2_{adj.}$
Living	0,6	0,2%	19,8	7%	0,46	0,73
Standing dead	-1,3	-7,1%	11,8	67%	0,44	0,46
Lying	-0,1	-2,4%	1,7	52%	0,46	0,12

Table 4: k represents the number of neighbours used in the kNN algorithm. MD: mean difference (in m^3/ha) between predicted and real volume. MD (%): Mean difference between predicted and deal volume in % of mean volume of tree class in predicted plots. SE: standard error of the MD values (in m^3/ha). SE (%): standard error in % of mean volume of tree class in predicted plots. P-value: p-value for MD values.

kNN (k=1)	MD (m^3/ha)	MD (%)	SE (m^3/ha)	SE (%)	p-value
Living	1,5	0,5%	15,8	6%	0,53
Standing dead	-9,9	-56,0%	10,9	62%	0,38
Lying	-1,3	-40,1%	1,6	50%	0,42
kNN (k=2)	**MD (m^3/ha)**	**MD (%)**	**SE (m^3/ha)**	**SE (%)**	**p-value**
Living	-2,8	-1,0%	14,3	5%	0,50
Standing dead	-8,9	-50,3%	10,7	60%	0,38
Lying	-1,1	-34,0%	1,6	48%	0,45
kNN (k=3)	**MD (m^3/ha)**	**MD (%)**	**SE (m^3/ha)**	**SE (%)**	**p-value**
Living	-3,4	-1,2%	15,1	5%	0,48
Standing dead	-12,7	-71,8%	10,4	59%	0,24
Lying	-2,4	-75,2%	1,5	45%	0,22

3.5 Variables used in regression models

3.5.1 Living volume

Density variables within the middle and lower fraction were the most common, and the two most common variables used in the models were both density variables within the middle fraction. The height variables mostly describe average laser echo height values. The last echo variables were most common. The fifteen most common laser variables in the best models are shown in Table 5.

Table 5: The 15 most common variables used in the best regression models when predicting living volume. The first echo variables are marked with ".1" and the last echo variables are marked with ".2". Count: how many times the variable was used in the best model of an iteration in the simulation (500 iterations in total). Relationship: the most common relationship for the variable in the best models. % main relationship: how often the main relationship for the variable occurred in the best models.

Variable	Count	Relationship	% main relationship
D5.1	332	Negative	100%
D3.2	271	Positive	100%
Hmean.2	261	Positive	100%
Hqav.2	126	Positive	100%
Hskewness.1	79	Positive	100%
H90.1	72	Positive	100%
D4.1	69	Negative	100%
D2.2	69	Positive	100%
D0.2	48	Positive	100%
H90.2	46	Negative	72%
D4.2	37	Positive	100%
Hsd.2	34	Negative	100%
Hmax.1	16	Positive	100%
Hmax.2	16	Negative	100%
D6.1	15	Negative	100%

3.5.2 Standing dead volume

The two most used variables were height variables in the highest fraction of the stem. Apart from those, almost all the other variables were density variables. No preference for first or last echo variables. The fifteen most common laser variables in the best models are shown in Table 6.

Table 6: The 15 most common variables used in the best regression models when predicting standing dead volume. The first echo variables are marked with ".1" and the last echo variables are marked with ".2". Count: how many times the variable was used in the best model of an iteration in the simulation (500 iterations in total). Relationship: the most common relationship for the variable in the best models. % main relationship: how often the main relationship for the variable occurred in the best models.

Variable	Count	Relationship	% main relationship
H90.1	474	Positive	100%
H90.2	416	Negative	100%
D3.1	254	Positive	100%
D5.2	191	Negative	100%
D4.2	172	Negative	100%
D4.1	139	Positive	100%
D0.1	67	Positive	100%
D2.2	50	Negative	100%
H80.2	45	Negative	100%
D1.2	43	Negative	100%
D6.2	25	Negative	100%
D2.1	20	Positive	100%
D1.1	15	Positive	93%
D3.2	12	Negative	100%
H70.2	12	Negative	100%

3.5.3 Lying volume

No variables were hugely dominating the models when predicting lying wood. The variables were distributed between density variables in the upper fraction and various height variables. First echo variables were most common. The fifteen most common laser variables in the best models are shown in Table 7.

Table 7: The 15 most common variables used in the best regression models when predicting lying volume. The first echo variables are marked with ".1" and the last echo variables are marked with ".2". Count: how many times the variable was used in the best model of an iteration in the simulation (500 iterations in total). Relationship: the most common relationship for the variable in the best models. % main relationship: how often the main relationship for the variable occurred in the best models.

Variable	Count	Relationship	% main relationship
D9.1	126	Positive	100%
D8.2	95	Negative	100%
H60.1	93	Negative	100%
Hmax.2	92	Negative	100%
Hsd.1	91	Positive	100%
Hmax.1	91	Positive	100%
H70.1	74	Positive	99%
D9.2	69	Positive	99%
D8.1	51	Negative	96%
H80.1	45	Positive	100%
D5.1	38	Negative	100%
D7.2	27	Positive	96%
D7.1	27	Positive	100%
Hqav.1	21	Positive	100%
H30.1	21	Negative	100%

4 Discussion

4.1 Differences between tree classes

The standard error of the mean was always lower with kNN, which usually gets a suppressed variation range. This is due to larger values getting underestimated, while smaller values usually get overestimated (Tomppo et al., 2008). Because of its smaller variation range, the kNN method got a higher p-value compared to regression when predicting living volume. On the downside, this in turn lead to a higher systematic error.

There was a clear difference in the systematic error when predicting volumes for different tree classes. This is especially true for kNN which systematically underestimated the dead volumes significantly compared to regression. This might be driven by the fact that most plots did not contain any dead wood (or very little), which could lead to an underestimation more often than an overestimation. This is especially true when using two or three neighbours (k set to two or three). Since most plots had either very little dead wood or none, when predicting a plot that contained dead wood most of the calibration plots to choose from contained less dead wood than the plot that was being predicted. This might be one of several contributors to the consistent underprediction of dead wood with kNN. This should not be a problem when predicting living volume since that volume was more consistent across all plots.

Previous research has shown that it's harder to predict dead wood in managed forests compared to unmanaged forests (Maltamo et al., 2014). This is especially true for lying dead wood. In a natural forest, openings in the canopy layers are often a result of a fallen tree. In a managed forest, an opening in the canopy layer is usually a result of thinning. This makes it harder to use the spatial forest structure to find lying wood. By comparing our R^2 values from the regression approach with the R^2 values from Pesonen et al. (2008), it is clear to see that the correlation between laser metrics and lying dead wood is far better in a natural forest. It could help to include more types of data to get a better correlation in a managed forest. One idea could be to include optical data, like hyperspectral imaging.

Another thing to note from Pesonen et al. (2008) is that they got the best results when predicting lying dead wood (compared to standing dead), while our results are less clear. When looking at the results from the regression in Table 3 we can see that the R^2 value were much higher when predicting standing dead wood compared to lying dead, while both the relative MD and the relative SE were lower. This could be an indication that the correlation for lying dead volume is not linear. By briefly looking at some residual plots of some of the regression models, it seemed like lying dead volume were slightly leaning towards a quadratic correlation.

4.2 Varying the number of neighbours in kNN

Judging by the p-values, kNN got the best results with one or two neighbours. This also holds when comparing the MD values, especially for standing dead volume and lying volume. This is again a result of most of the plots containing no dead wood or very little dead wood. The standard error of the mean is slightly smaller with more neighbours because of the suppressed variation range (Tomppo et al., 2008).

The differences between kNN with one and two neighbours are quite small, and it does not seem to matter which one you use. When predicting living volume, one neighbour got the smallest MD, but only beat kNN with two neighbours by 0,5% (and beat three neighbours with 0,7%). When predicting dead wood (both standing and lying), two neighbours seemed to be doing slightly better, but both got very similar results.

4.3 Variables used in regression models

The main logic behind estimating dead wood with LiDAR is that there should be a correlation between the spatial forest structure and the amount of dead wood. Previous research in natural forests has shown that there is a clear correlation between spatial forest structure and dead wood, and even other phenomena, like natural regeneration on the forest floor (Pesonen et al., 2008) (Bollandsas et al., 2008). As mentioned above, it is to be expected that managed forests have a weaker correlation between spatial structure and what is happening on the forest floor. But since the laser pulses within two meters from the ground are aggregated into one height variable and one density variable, you must look at the spatial forest structure above two meters to analyse the forest floor with ALS. When using two echoes from the same laser pulse, the first pulse will describe the canopy surface, while the last echo will penetrate the surface and account for vertical canopy variation (Bollandsas et al., 2008).

4.3.1 Living volume

When living volume was predicted with regression, the last echo variables were most common. The first echoes probably had a larger variation, due to branches and needles in the canopy. That could make them less consistent, and less useful when predicting the volume of living wood. The most common variables were density variables in the middle and lower parts of the stem. This indicates that the amount of branches in the middle and lower parts of the stem has a high correlation with the living volume, and that was the easiest correlation for the

ALS to pick up on. The most common height variable is the mean height of the laser echoes, with a positive relationship. This indicates that more branches in the canopy layer means higher volume.

4.3.2 Standing dead volume

The standing dead tree class is a bit broader than the other two classes. In the field, the standing dead wood category included every standing tree that was dead or dying (and not lying). That means some trees might look almost normal, while still being classified as dead. This is especially true for trees that just recently got injured so that they have not yet lost vast amounts of needles and branches. That means that it can be extremely hard to use ALS data to recognise standing dead trees, as a lot of the time they will look almost exactly like living trees.

From Table 6 we can see that the first and last echo height variables in the highest fraction were by far the most used variables when predicting standing dead wood. When a plot contains many dead trees there might be a bigger difference between the first and last echo height variables. This is probably because it is fewer branches in the canopy layer. That in turn should lead to a bigger height difference between the first and last echoes. The other main variables were density variables in the middle fraction. This indicates that the amount of branches at medium height is correlated with standing dead volume. This makes sense as many of the dead trees have just a few branches at the top of the stem, or no branches at all.

4.3.3 Lying dead volume

The lying dead volume were mostly predicted based on the first echo variables. This supports the theory that openings in the canopy layer are the best indication of lying wood. At the same time, the most used variable was a density variable in the top fraction with a positive correlation. This indicates that a more closed canopy layer means more lying wood. Overall, this makes very little sense and shows that regression had a hard time finding anything that strongly correlated with lying wood in a managed forest like this. This is also supported by the low R^2 value.

4.4 General comments

There were some uncertainties regarding exact tree locations that might have influenced the results. There seems to be an inherent error in the Haglöf system. We used a 10-meter radius in the field plots, which means that no tree can be more than twenty meters from any other tree in the plot. But by going through just a few of the plots we found some trees being as much as 22,3 meters from each other. This could influence the volume values of the plots. This is because we had to adjust which trees to include in the plot values, because of the difference in radius used in the field and the radius used to make ALS variables. We used GIS to remove all trees further than nine meters from the plot centre. Because of the error in the Haglöf system, we cannot be sure that we included all the right trees. If the error is systematic there is a chance this could have influenced the results, though unlikely very much.

The field plots were overall very similar in terms of spatial structure. Some field plots were placed in dense forest, but most of the plots did not differ much. Because of this, the average values of the calibration plots and the validation plots should not differ much no matter how the plots are distributed. This could mean that the low systematic errors are a result of similar mean values in all iterations of the simulation. That would explain how the systematic errors can be so low while the R^2 values are also low (especially for lying wood). When the R^2 value is so low for lying wood, it is better just to use average values from field plots for estimation of the volume in a bigger area.

To improve the study, we could have added more data variables. An obvious next step is to include hyperspectral imaging data. That might help to see some of the things that are not picked up by the point cloud. We could also have looked for different correlations, not just linear.

5 Conclusion

In a mature managed forest like this one, ALS variables have a moderate correlation with standing dead wood. The most descriptive laser variables for living volume were related to branches in the upper and middle parts of the stems. The most descriptive variables for standing dead wood volume were related to tree height and branches in the middle parts of the stems. Variables from ALS were not descriptive for lying dead wood volume. When predicting wood volume with kNN, a higher k did not improve the results.

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