LiDAR as a tool for remote sensing of moose (Alces alces) forage biomass

LiDAR som verktøy for fjernregistrering av biomasse elg(Alces alces)beite

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Preface

This thesis represents the completion of five years of education within forest- and nature management, the two last within the Norwegian University of Life Sciences, department of Ecology and Natural Resource Management. The thesis-process has been educational and rewarding. Finishing this thesis had not been a reality without my supervisors. I owe them great thanks! Leif Egil Loe as the main supervisor was especially helpful on model development and interpreting the results. He has also given well advices during the writing process. Karen Lone for almost daily contact during the data analyzes process and she has rescued me many times when I was stuck in R. Terje Gobakken for LiDAR data delivery and processing. I will also like to thank Jos Milner and Floris van Beest in the moose foraging project to let me inheriting some of their data and being helpful with answering questions about methods.

Most of all I want to thank my family, especially Ida, for having the faith in me and being patient during all the working hours and the late nights of writing.

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Abstract

Moose (*Alces alces*) play an ecological keystone role in the boreal forest ecosystem and increasingly so during the last decades due to the large population increase. The growing moose population has a large impact on forage plant species, including commercially important tree species. Conversely, the quantity and quality of forage feedback on the body weight and condition of the moose, which is a key trait for moose managers. To improve moose management it is central to estimate and monitor "carrying capacity" over time and on realistic management scales. In forest inventory remote sensing is extensively used with different tools, such as LiDAR (Light Detection and Ranging).

This study examined the potential of LiDAR as a tool for remote sensing of moose forage biomass. The study was conducted on a 735 km^2 area, within the counties of Telemark and Vestfold (N 59^{o}20.285 E 9^{o}39.664) in the south-eastern part of Norway. The field data used in this study were collected during a moose forage study carried out in August 2007. The field data included biomass data for 640 circular (2500 m^2) plots. The LiDAR data used in this study were collected in the years 2008-2010 for multipurpose. Three modeling approaches were used: One model with only field inventory variables origin from forest inventories (Forest model), one model with only LiDAR derived variables (LiDAR model) and one model combining both forest and LiDAR variables. The aim was to asses if including LiDAR derived information resulted in better models for moose forage biomass. All models were mixed effects regression models.

For all combination of tree species and seasons, one or more LiDAR variables were included in the best model. In the model validation the LiDAR + Forest models (r ranging from 0.38 to 0.51) generally performed better than the pure Forest models (r ranging from 0.35 to 0.49) which again always performed better than the pure LiDAR models (r ranging from 0.21 to 0.37). Important LiDAR variables like Understory LiDAR Cover Density (ULCD) and Spacing Index (Spi) replaced forest variables such as cutting class in some of the model groups. This study concludes that LiDAR can improve the ability to predict moose forage biomass if variables from traditional forest inventory, such as site index, dominant tree species, and cutting class, are added. Still, the validation revealed that models had low generality. This study is based on field data with a relatively low spatial precision and with a temporal mismatch between LiDAR and field data sampling. Future studies should sample data simultaneously and with higher precision to investigate if large scale monitoring of moose forage with LiDAR may become an operative tool in management.

Sammendrag

Elg (*Alces alces*) spiller en rolle som økologisk nøkkelart i det boreale skogøkosystemet med sin økende populasjonsstørrelse de siste tiår. Den økende elgbestanden har stor påvirkning på beiteplantene inkludert kommersielle treslag. Og motsatt, den kvantitative og kvalitative effekten av beitet på kroppsvekt og kondisjon hos elg er sentralt i elgforvaltningen. For å forbedre elgforvaltningen står estimering og overvåking av bæreevnen over tid, på realistiske forvaltningsenheter, sentralt. I skogtakseringer er fjernregistrering mye bruk med ulike verktøy, slik som LiDAR (Light Detection and Ranging).

Denne studien undersøkte potensiale av LiDAR som verktøy for fjernregistrering av biomasse elgbeite. Studien ble utført på et 735 km^2 stort studieområde i fylkene Telemark og Vestfold (N $59^o20.285$ E $9^o39.664$) i det sør-østlige Norge. Feltdataene benyttet i denne studien ble samlet inn gjennom et elgforingsprosjekt i august 2007. Felt dataene inkluderte data fra 640 sirkulære (2500 m^2) plot. LiDAR dataene ble innhentet 2008-2010 til forskjellige formål. Tre modelltilnærminger ble benyttet: En med kun feltvariabler (fra tradisjonell skogtaksering) kalt Forest modell. En med kun LiDAR variabler (LiDAR model) og en som kombinerte både felt- og LiDAR variabler. Formålet var å vurdere hvor vidt inkludering av LiDAR utledet informasjon forbedret modellenes evne til å predikere biomasse elgmat. Alle modeller var blanda effekt regresjonsmodeller.

For alle kombinasjoner av treslag og årstider, ble en eller flere LiDAR variabler inkludert i sluttmodellene. I modellvalideringen presterte LiDAR + Forest modellene (r fra 0,38 - 0,51) generelt bedre enn Forest modellene (r fra 0,35 - 0,49) som igjen alltid presterte bedre enn de rene LiDAR modellene (r fra 0,21 - 0,37). Viktige LiDAR variabler som Understory LiDAR Cover Density (ULCD) og Spacing Index (Spi) erstattet variabler som hogstklasse i noen modeller.

Denne studien konkluderer med at LiDAR kan forbedre evnen til å predikere biomasse elgbeite hvis variabler fra tradisjonell skogtaksering, slik som bonitet, dominerende treslag og hogstklasse blir lagt til. Allikevel, valideringen avdekket at modellene hadde lav grad av generalitet. Denne studien baserte seg på feltdata med relativt lav romlig presisjon og med tidsforskyvning mellom LiDAR- og feltdata innhenting. Framtidige studier bør innhente data parallelt og med høyere presisjon hvis storskala kartlegging av elgbeite med LiDAR skal bli et operativt forvaltningsverktøy.

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Introduction

Background

Moose (*Alces alces*) play an ecological keystone role in the boreal forest ecosystem and may affect the abundance and competitive interactinos between tree species (Edenius et al. 2002; Mathisen & Skarpe 2011). In recent years, there has been a popular debate in Scandinavia about the relationship between the growing moose population and its browsing plants (Solbraa 2005; Solbraa 2008; Aanesland 2009), and how large the carrying capacity is. At the same time, the focus in moose management has mostly been on the number of moose individuals (Solberg & Saether 1999; Ronnegard et al. 2008; Månsson et al. 2011) and forest damages as a result of browsing (Andrèn & Angelstam 1993; Ericsson et al. 2001; Ball & Dahlgren 2002; Siipilehto & Heikkilä 2005; De Jager & Pastor 2010;). When it comes to the spatial distribution and quantity of the preferred forage species, good tools for mapping large areas is missing

Moose and moose forage

The Norwegian moose population has increased exponentially in the last century with the number of moose harvested ranging from less than 100 in the first part of the 20th century to almost 40 000 individuals at the top in 1999. The number was in 2012 reduced to 35 000 moose harvested annual. At the same time, average annual increment from pine was in 2007-2011 almost 6 million m^3 in Norway. The productive forest represents 22 % of the total Norwegian land area and pine(*Pinus sylvestris*) dominated forests represent 21 % of the productive forest (Statistisk-Sentralbyrå 2013). Combining moose and timber production, especially pine, a preferred winter food, can be challenging. An economic study reports that 90 % of the value from moose-timber management comes from the timber part of the production (Wam et al. 2005). Wam et al. (2005) also suggest that moose population should be kept at a 70 % lower level in management regimes that combine timber and moose production compared with a regime that only focus on timber production. Browsing damages clearly have a big economic impact on forest owners in areas with dense moose populations. In a wildlife management perspective, knowledge about the forage recourses is of considerable interest. Studies investigating changes in forage input with the response in biomass production in the moose population has revealed that forage ability is positively correlated whit increasing body mass in the population (Milner et al. 2012). In second order, the increasing body mass on moose cows is positively correlated with the number of calves in the population (Sæther & Haagenrud 1985).

The spatial distribution of moose in the landscape is correlated with the distribution of forage and cover. Moose habitat selection is often described with a multi-scale approach (Herfindal et al. 2009). In a landscape scale moose select species and habitats with large volume of biomass, within home-range scale moose select quality over quantity (van Beest et al. 2010). Species- and habitat selection also vary between seasons. (Nikula et al. 2004). Most Norwegian moose migrate between summer and winter browsing habitats. Summer habitats are in general evenly spread out in the landscape, but winter habitats are more clustered. A typical winter habitat is at low altitude, often along riversides on the valley (Andersen 1991; Histol & Hjeljord 1993; Ball et al. 2001; Ball & Dahlgren 2002). Knowledge about the spatial and temporal distribution of moose in the landscape together with the number of individuals is two key factors in moose management. Information about the quantity and the spatial distribution of the forage species in the landscape is the third factor necessary to effectively manage the moose population. A lack of methods for quantifying forage biomass on a landscape scale complicates this.

Remote sensing of resources

Using remote sensing to quantify and map resources is becoming increasingly common, both for research and applied purposes (Koch 2010). Airborne LiDAR (Light Detection and Ranging) is one remote sensing technique that has been used for forest inventory purposes since 1991 (Næsset et al. 2004; Næsset 2004). The research has mostly been on forestry and quantifying forest resources suitable for timber production (Næsset 2004; Gobakken & Næsset 2004; Næsset & Bjerknes 2001; Yamamoto et al. 2011). More recent LiDAR research has also been conducted on biodiversity topics (Bater et al. 2009; Muller & Brandl 2009; Bassler et al. 2011; Tattoni et al. 2012) and biomass prediction in forest ecosystems for bioenergy purpose (Andersen et al. 2011; Hauglin et al. 2012). Airborne LiDAR technology relies on laser pulses which are transmitted from an airborne laser scanner. The scanning system can transmit up to 100 000 pulses per second to the surface of the landscape. The pulses reflect on vegetation, buildings and ground surface. The echoes (the reflected pulse) are received in a sensor placed on the scanner. The sensor measures the time of travel for each pulse and calculates the distance from the aircraft to the point of reflection with the accurate knowledge of aircraft position and movement, the distance measurements are converted to a dataset of points in space. The typical point density in forest inventory scanning ranges from 0.1 -10.0 pulses m^{-2} (Wehr & Lohr 1999; Næsset 2004; Næsset et al. 2004) Predictive models can be developed using regression techniques based on field variables and LiDAR variables (Næsset et al. 2005).

In management of other species, such as reindeer (*Rangifer tarandus tarandus*), knowledge about the pasture resources and the number of animals is a central part of the management (Colpaert et al. 2003). Remote sensing of reindeer pasture in alpine environment using satellite data is a common practice in Scandinavia as a tool for managing reindeer both wild and tame (Edenius et al. 2003; Gilichinsky et al. 2011). The same type of information could be useful in moose management as well, for a more accurate approach to quantification of carrying capacity on realistic management scales (such as management area scale). A Norwegian study that investigated the spatial and quantitative distribution of forage species and related this to moose habitat selection, resulted in predictive models for forage biomass based on variables origin from forest planning tools (van Beest et al. 2010).

The aim of the present study is to explore the potential role of LiDAR in predicting moose forage biomass. The study uses a subset of the data used in van Beest et al. (2010), and the concrete question is whether adding LiDAR variables can improve on the predictive models used therein, and how pure LiDAR models compare to these.

Material and methods

The study area

This study was conducted on a 735 km^2 area, within the counties of Telemark and Vestfold (N 59^o20.285 E 9^o39.664) in the south-eastern part of Norway (figure 1). The area belongs to the boreonemoral vegetation zone (Moen et al. 1998) and it is mostly covered by commercial managed forests. The composition of tree species is 26 % pine 72 % spruce (*Picea abies*) and 3 % deciduous species. The group deciduous species consist of downy birch (*Betula pubensence*), silver birch (*Betula pendula*), rowan (*Sorbus aucuparia*), willow (*Salix spp.)* and aspen (*Populus tremula*). The field layer is dominated by species from the heather family (*Ericaceae*) particularly *Vaccinium spp*. In areas with disturbed vegetation, such as clear-cuts, the pioneers fireweed (*Epilobium angustifolium*) and raspberry (*Rubus idaeus*) occur clustered.

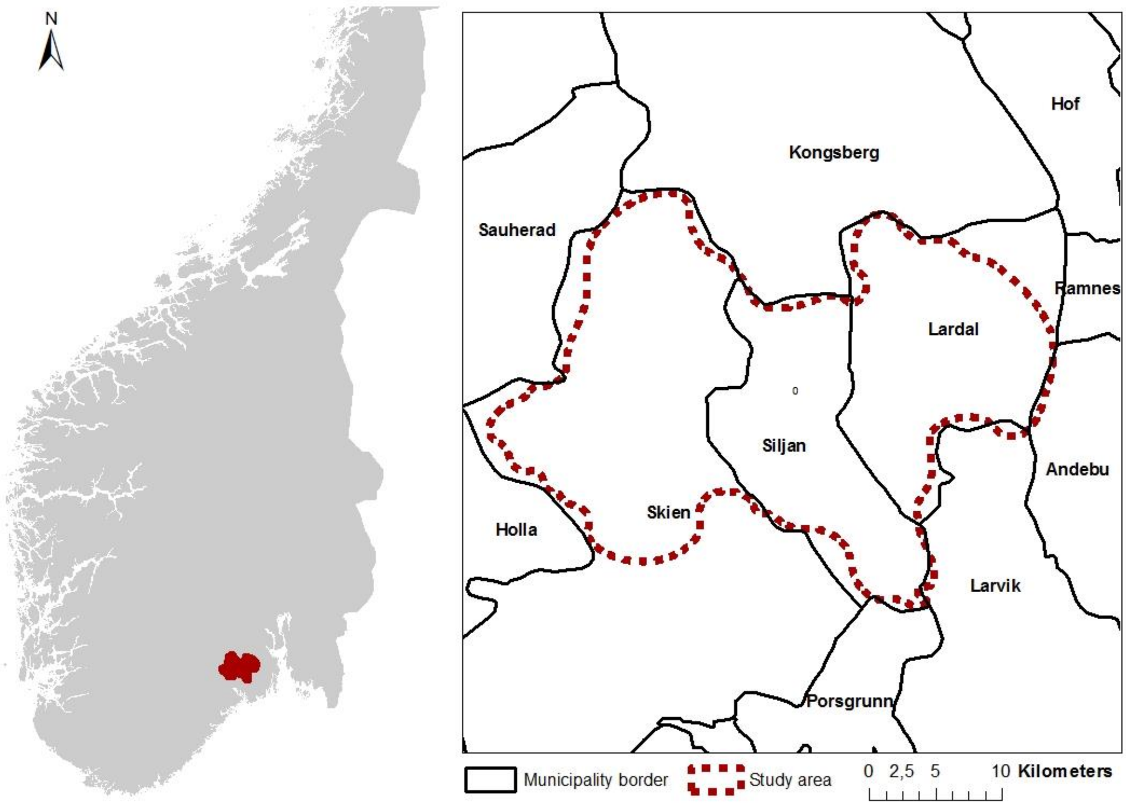

Figure 1: The location of the study area in south-eastern Norway.

The climate is normal for this south-eastern part of Norway with 1008 mm annual precipitation and average summer temperature (Jun-Aug) 15.3^{o}C and winter temperature (Dec-Feb) -4.3^{o}C. All climate values are average values from three weather stations within the study area (Siljan, Skien-Geiteryggen and Lardal) (Met.no). Moose density in the study area is approximately 1.3 moose/km^2 (Milner et al. 2012). The average annual harvest was 198 individuals during the years 1986-2012 (Siljan, Lardal and Skien municipalities) (Statistisk-Sentralbyrå 2013). Large predators capable of killing moose are virtually absent in this part of Norway (Wabakken et al. 2010; Wabakken et al. 2008; Wabakken et al. 2009).

Forage biomass-study design and field data

The field data used in this study were collected during a moose forage study carried out in 2007-2008 (van Beest et al. 2010) as a part of a large moose project in the southern part of Norway (Milner et al. 2012). In August 2007, biomass data were collected by sampling 50 individual trees from six target tree species. From this, biomass models were developed and made it possible to predict canopy biomass from easily measured tree characteristics, such as shape and size (van Beest et al. 2010). The target tree species were rowan, aspen, willows, silver birch, downy birch and pine. Rowan, aspen and willow were referred to as a group: RAW. RAW are known as high quality species and are highly preferred by moose (Solbraa 2002; Månsson et al. 2007; Wam & Hjeljord 2010) .

The second phase in the study by van Beest et al. (2010) was to sample target tree characteristics from a number of plots stratified on forest characteristics to predicting biomass over the entire study area. This was conducted as a field inventory during June and July 2008. From this data 640 plots in 128 different forest stands were within the area covered by LiDAR data (see LiDAR data below) and could be used in my study. In each stand, one main plot consisted of five subplots (figure 2). The five subplots were 50 m^2 circular plots. One placed in the center of the main plot and the four remaining was placed 25 m from the center in each cardinal direction. In each subplot, biomass was predicted as summer biomass (leaf) or winter biomass (twigs).

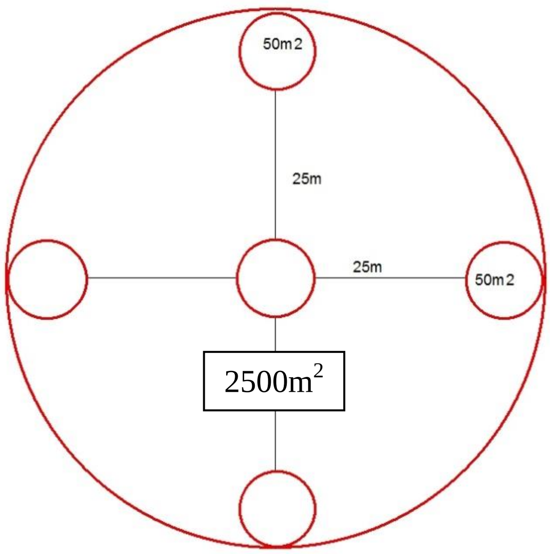

Figure 2: The study design used to quantify moose forage biomass-one main plot consist of 5 subplots.

In the last phase van Beest et al. (2010) modeled biomass as a function of standard forest parameters originating from an earlier forest inventory. These parameters were cutting class (1-5), dominant tree species (deciduous, pine and spruce stands), stand productivity (high or low), altitude (m), slope (^{o}), aspect (N, W, S, E), hill shade (index of solar incidence) and sky view (percentage of sky not obstructed by terrain features). For more details se van Beest et al. (2010).

Target species selected for the present study was RAW, pine and the total amount of biomass. The total biomass included biomass values calculated from all target species and species from the field layer such as fireweed, raspberry and bilberry (*Vaccinium myrtillus*). The *Betula spp*. was excluded because of the small sample size after selecting plots that only corresponded with LiDAR data. For forest characteristics see appendix 1.

LiDAR data

The LiDAR data used in this study was collected in the years 2008-2010 for multipurpose. The data covers the municipalities of Skien, Siljan and Porsgrunn in Telemark county and Lardal in the county of Vestfold. The Norwegian Mapping Authority was principal in this project and BLOM Geomatics AS was responsible for the scanning performance. Table 1 shows the sub-projects in detail. All scanning flights were conducted during early summer. The flying altitude ranged from 690 m to 1700 m and average point density from 0.7 m^2 to 10.0 m^2. The point clouds had been processed and digital terrain model subtracted, so that each point were specified by x/y coordinates, and dz (the height above the ground).

Table 1: Detail summary of the different LiDAR projects used in this study

Project name	Skien/Siljan 2010	Lardal 2009	Skien	Porsgrunn
Project code	BNO10019	BNO097010	BNO08752	BNO08765
Date of flight	02.06.2010	21-25.05.2009	05.05.2008	05.05.2008
Scanningsystem	Optech ALTM Gemini	Optech ALTM05SEN180 and ALTM04SEN161	-	-
Flying altitude	1600m	690 m	1700m	1400m
Puls repetition freq.	70 000 Hz	125 000 Hz	70000Hz	70000Hz
Scan freq.	-	70 Hz	31 Hz	34 Hz
Average point density	0.7/m^2	10.0 /m^2	0.7/m^2	0.7/m^2

LiDAR data was obtained for the 128 main field plots used by van Beest et al. (2010). Because the central coordinate of the field plots were recorded by handheld GPS (van Beest pers. comm.), accurately extracting LiDAR data corresponding to the sub-plots was not possible. Instead of risking misrepresentation at the scale of the small sub-plots, LiDAR data was extracted from a 2500 m2 circle corresponding to an area roughly covering all the field plots (figure 2 & 3) and associated with all five subplots. All echoes lower than 0.5 m were classified as ground echoes. Also, dz ≤ 0 was assumed to be ground hits. The remaining first and last echoes were considered to be canopy hits. Therefore, echoes above 0.5 dz was classified as vegetation hits. A various number of variables were derived from the echoes between ground (dground) and the highest dz value (hmax), such as density variables, height percentiles and measures of the height variation (table 2). Understory LiDAR Cover Density (ULCD) is a variable that describes the cover of the understory vegetation. The variable is modified from (Wing et al. 2012) and (Martinuzzi et al. 2009). In my study, ULCD is calculated as the ratio of understory (dus) (>0.5 to 2.0dz) echoes to the total number of understory and ground echoes (dground) (Eq. 1).

$$ULCD = \frac{dus}{dus + dground} \qquad (1)$$

A variable specially made for this study is the spacing index (spi) variable. The spi is an attempt to describe gaps in the canopy. Gaps in the canopy make more light available at the ground level and these places are therefore more amenable sites for understory vegetation (Long et al. 2004; Smith et al. 1997), such as vegetation important for moose forage. In the spi variable the gaps are weighted with the height of the canopy. Gaps have to be bigger (in cross section) in tall stands to let through the same amount of light to the forest floor as in lower stands. To make the spi variable it was first necessary to make a canopy density variable (cpd). Cpd is the proportion of echoes >2.0 m (CP) out of the total number of echoes (NT) (Eq. 2). Dz = 2.0 are assumed to represent the border between the understory and the canopy (Nilsson 1996). To get the spi variable cpd is then multiplied with h90 (the 90th percentile of the canopy height) (Eq. 3). For more details of the LiDAR data see appendix 2.

$$Cpd = \frac{CP}{NT} \tag{2}$$

$$Spi = Cpd * h90 \tag{3}$$

Table 2: Description of the variables extracted from LiDAR data

Variables	**Description**
dground	Proportion of all echoes < 0.5 dz
d0.5	Proportion of all echoes between 0.5 and 2.5 dz
d2.5	Proportion of all echoes between 2.5 and 4.5 dz
d4.5	Proportion of all echoes > 4.5 dz
h0	
h10	
h20	
h30	
h40	Heights of the 0-90th percentile of the echo height distirbution
h50	
h60	
h70	
h80	
h90	
hmax	Maximum echo height
hcv	Coefficient of variation for echo heights
hsd	Standar deviation for echo heights
cpd	Canopy density
	(The porportion of echoes >2.0 m out of the total number of echoes)
ulcd	Understory lidar cover densityratio of understory
	Ratio of understory (>0.5 to 2.0dz) echoes to the total number of understory and ground echoes
spi	Spacing index (cpd *h90)

Plot	**114**
hmean	9.8
hmax	23.4
cpd	0.7
ulcd	0.1
spi	10.9

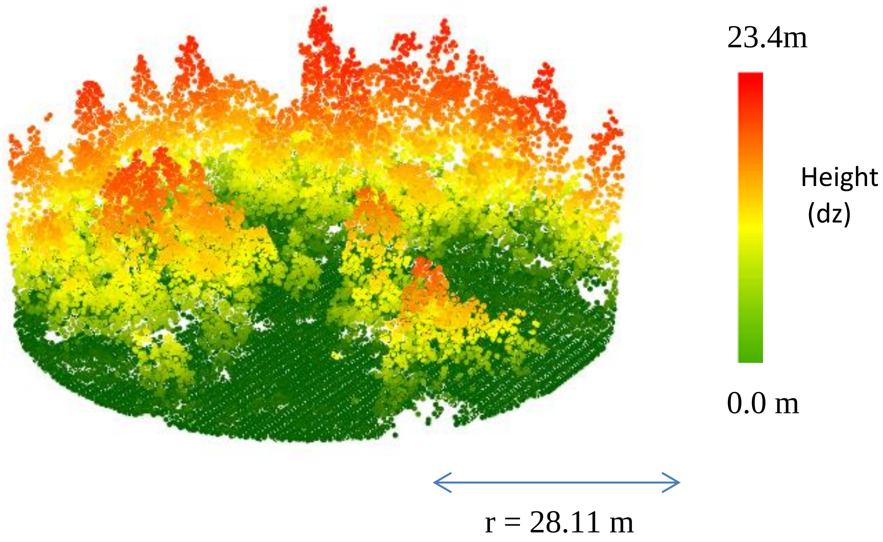

Figure 3: A 3D visualization of the LiDAR-data from plot nr. 114 made in ArcScene 10.1. For variable codes see table 2.

Statistical analyses

The two datasets (Field- and LiDAR data) were joined together and 20 % of the data were randomly sampled and withheld for model validation. The remaining 80 % of the data were used to parameterize the models. All the covariates were tested for collinearity. If exceeding the threshold value r>0.6 one of the variables in the correlated pair was censored from further analyses (retaining the one with the lowest AIC (Akaike`s Information Criterion)) in univariate tests. Following the approach of van Beest et al. (2010), I used mixed effects models with log link function where forage biomass was the response variable, stand number was included as a random effect (Bolker et al. 2009) and a combination of field and LiDAR derived variables served as predictor variables. I fitted 15 candidate models, three within each target species (RAW, pine and the total amount of forage biomass) and seasons (winter or summer forage). Pine models for summer were not investigated because moose only browse pine in the winter (Fremming 1999; Solbraa 2002). Within each tree species/season group I fitted three suites of models: Forest model, LiDAR model and LiDAR + Forest model. The forest model included only variables describing forest characteristics, available from traditional forest inventories. The LiDAR models included only LiDAR derived variables. LiDAR + Forest models combine variables from both LiDAR model and forest model.

Stepwise backwards model selection was used to select the best models. In every selection step the least significant variable was removed, repeating until the model consisted only of significant variables ($p<0.05$). After this, the three best models within each suite (RAW, pine, total biomass, etc.) were compared using likelihood ratio tests. The mixed effects regression analysis was performed using the lme4 packages (Bates 2012) implemented in R (R-Core-Team 2012).

To test the predictive ability of the final models Pearson´s product-moment correlation, r (Pearson), was calculated for the relationship between predicted and observed biomass values for the 20 % of the data retained for validation. Finally, the models were ranked after highest correlation, in total and within groups. All statistical analyses were performed in R (R-Core-Team 2012) and map example (Appendix 3) was created in ArcMap (Esri 2012) .

Results

Modeling available forage

Adding LiDAR variables improved the models based on only forest properties from a field based forest inventory. Testing for the improvement of the LiDAR + Forest model over the Forest model showed a significant improvement for the models predicting RAW-summer biomass ($p=0.002$), pine biomass in winter ($p<0.001$) and the models predicting the total amount of biomass summer ($p=0.007$) and winter ($p<0.001$). The likelihood ratio test did not support inclusion of LiDAR variables for the models of RAW biomass in winter ($p=1$) (table 3). Table 4-8 shows the estimates of the best models predicting available biomass of RAW species during summer (table 4), RAW in winter (table 5), pine winter (table 6) and the total amount of biomass summer (table 7) and winter (table 8). For each table the three model groups are compared (Forest, LiDAR and LiDAR +Forest) and AIC values are compared

Table 3: Comparing AIC values and p-value for log-likelihood test within target species using Forest model as the baseline model.

	Target species				
Model group	**RAW summer**	**RAW winter**	**Pine winter**	**Total biomass summer**	**Total biomass winter**
Forest model	4917.9	3163.0	2462.0	4704.0	5346.4
LiDAR + Forest Model	4910.7	3171.0	2456.9	4698.9	5335.1
p-values	0.0020	1.0000	0.0000	0.0076	0.0003

The LiDAR-variables that improved the pure forest model were the height percentile-variables (h20-h70). The ULCD variable was retained in 6 out of 10 models with LiDAR variables. ULCD was not present in LiDAR and LiDAR + Forest models predicting Pine biomass in winter (table 6). ULCD was also missing in the LiDAR + Forest models predicting total biomass summer and winter (table 7 and 8). The Spi variable was present in 9 out of 10 LiDAR based models. Spi was not retained in the total biomass summer model (table 7). When predicting RAW biomass, summer and winter, cutting class was excluded from the best model when LiDAR variables were added to the Forest model (table 4 and 5).

Table 4: Summer available RAW biomass**.** Comparison of three different mixed effects regression models predicting available RAW species forage during the summer including a model with variables from forest inventory, a model with LiDAR variables and a combined model which includes both categories of variables. The likelihood ratio test compares and ranks the tree models with p-values. *Reference= cutting class 1. ** Reference = deciduous. *** Reference =high site index.

	RAW-summer	**Forest model**		**LiDAR model**		**LiDAR + Forest model**	
	Fixed effects						
		β	SE	β	SE	β	SE
	Intercept	2.414	0.544	-0.548	0.833	0.140	0.964
Forest inventory variables	**Cuttingclass***						
	2	-0.423	0.516	-	-	-	-
	3	-1.230	0.497	-	-	-	-
	4	-0.054	0.521	-	-	-	-
	5	-0.937	0.554	-	-	-	-
	Treespecies**						
	pine	-1.956	0.443	-	-	-1.963	0.496
	spruce	-0.842	0.424	-	-	-0.863	0.443
	Siteindex***						
	Low	1.101	0.421	-	-	0.889	0.424
LiDAR variables	**h20**	-	-	1.215	0.536	1.245	0.506
	h40	-	-	-2.515	1.185	-2.569	1.111
	h50	-	-	1.865	0.846	1.961	0.796
	ulcd	-	-	17.011	4.377	12.281	4.301
	spi	-	-	-0.327	0.101	-0.389	0.097
	Random effects	SD		SD		SD	
	Stand number	1.724		1.797		1.678	

Likelihood ratio test	**Df**	**AIC**	**BIC**	**logLik**	**χ^2**	**χ^2 df**	**Pr(>χ^2)**
LiDAR model	7	4920.2	4950	-2453.1			
Forest model	9	4917.9	4956	-2450.0	6.2873	2	0.0431
Forest + LiDAR model	10	4910.7	4953	-2445.3	9.2292	1	0.0024

Table 5: Winter available RAW biomass**.** Comparison of three different mixed effects regression models predicting available RAW species forage during the winter including a model with variables from forest inventory, a model with LiDAR variables and a combined model which includes both categories of variables. The likelihood ratio test compares and ranks the tree models with p-values. *Reference= cutting class 1. ** Reference = deciduous. *** Reference =high site index.

RAW-winter

		Forest model		LiDAR model		LiDAR + Forest model	
	Fixed effects						
		β	SE	β	SE	β	SE
	Intercept	2.211	0.621	-1.765	0.856	0.189	0.954
Forest inventory variables	**Cuttingclass***						
	2	-0.637	0.592	-	-	-	-
	3	-1.402	0.574	-	-	-	-
	4	-0.361	0.599	-	-	-	-
	5	-1.129	0.637	-	-	-	-
	Treespecies**						
	pine	-2.460	0.506	-	-	-1.904	0.523
	spruce	-1.652	0.485	-	-	-1.519	0.510
	Siteindex***						
	Low	0.942	0.482	-	-	-	-
LiDAR variables	**h20**	-	-	-	-	-	-
	h40	-	-	-	-	-	-
	h50	-	-	0.393	0.147	0.395	0.139
	h70	-	-	-	-	-	-
	ulcd	-	-	19.550	4.452	13.130	4.518
	spi	-	-	-0.323	0.106	-0.348	0.100
	Random effects	SD		SD		SD	
	Stand number	1.942		2.034		1.913	

Likelihood ratio test	Df	AIC	BIC	logLik	χ^2	χ^2 df	Pr(>χ^2)
LiDAR model	5	3172.1	3193.3	-1581.0			
Forest model	9	3171.4	3209.6	-1576.7	0.00	2	1.0000
Forest+ LiDAR model	7	3163.0	3192.7	-1574.5	13.07	2	0.0015

Table 6: Available pine winter forage**.** Comparison of three different mixed effects regression models predicting available pine forage during the winter including a model with variables from forest inventory, a model with LiDAR variables and a combined model which includes both categories of variables. The likelihood ratio test compares and ranks the tree models with p-values. *Reference= cutting class 1. ** Reference = deciduous. *** Reference =high site index.

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Pine-winter

		Forest model		LiDAR model		LiDAR + Forest model	
	Fixed effects						
		β	SE	β	SE	β	SE
	Intercept	-4.434	1.053	0.862	1.300	-2.043	1.017
Forest inventory variables	**Cuttingclass***						
	2	2.318	0.828	-	-	2.287	0.800
	3	0.040	0.836	-	-	0.764	0.822
	4	-0.339	0.892	-	-	0.505	0.927
	5	-0.369	0.914	-	-	0.302	0.902
	Treespecies**						
	pine	3.765	0.744	-	-	3.533	0.706
	spruce	-0.604	0.830	-	-	-0.985	0.831
	Siteindex***						
	Low	1.332	0.845	-	-	-	-
LiDAR variables	**h20**	-	-	1.826	0.780	-	-
	h40	-	-	-	-	-	-
	h50	-	-	-2.614	1.037	-	-
	h70	-	-	1.223	0.594	-	-
	ulcd	-	-	-	-	-	-
	spi	-	-	-0.423	0.176	-0.229	0.089
	Random effects	SD		SD		SD	
	Stand number	2.271		3.158		2.188	

Likelihood ratio test	Df	AIC	BIC	logLik	χ^2	χ^2 df	Pr(>χ^2)
LiDAR model	6	2505.4	2530.8	-1246.7			
Forest model	9	2462.0	2500.1	-1222.0	49.41	3	1.065E-10
Forest + LiDAR model	9	2456.9	2495.1	-1219.5	5.06	0	2.2E-16

Table 7: Total available summer forage**.** Comparison of three different mixed effects regression models predicting total available forage during the summer including a model with variables from forest inventory, a model with LiDAR variables and a combined model which includes both categories of variables. The likelihood ratio test compares and ranks the tree models with p-values. *Reference= cutting class 1.
** Reference = deciduous. *** Reference =high site index.

Total biomass-summer

		Forest model		LiDAR model		LiDAR + Forest model	
	Fixed effects						
		β	SE	β	SE	β	SE
	Intercept	3.1744	0.3032	3.249	0.208	4.134	0.460
Forest inventory variables	**Cuttingclass***						
	2	0.1048	0.2857	-	-	-0.036	0.282
	3	-0.8838	0.275	-	-	-0.880	0.267
	4	-0.3637	0.2908	-	-	-0.170	0.291
	5	-1.0424	0.3082	-	-	-0.943	0.301
	Treespecies**						
	pine	-0.6435	0.2458	-	-	-0.712	0.240
	spruce	-0.4725	0.2377	-	-	-0.481	0.231
	Siteindex***						
	Low	0.805	0.235	-	-	0.671	0.234
LiDAR variables	**h20**	-	-	-	-	-	-
	h40	-	-	-	-	-	-
	h70	-	-	-	-	-0.081	0.030
	h50	-	-	-	-	-	-
	ulcd	-	-	4.293	1.740	-	-
	spi	-	-	-0.092	0.024	-	-
	Random effects	SD		SD		SD	
	Stand number	0.971		1.047		0.942	

Likelihood ratio test	**Df**	**AIC**	**BIC**	**logLik**	**χ^2**	**χ^2 df**	**Pr(>χ^2)**
LiDAR model	4	4710.9	4727.8	-2351.4			
Forest model	9	4704.0	4742.1	-2343.0	16.87	5	0.0047
Forest + LiDAR model	10	4698.9	4741.2	-2339.4	7.13	1	0.0076

Table 8: Total available winter forage**.** Comparison of three different mixed effects regression models predicting total available forage during the winter including a model with variables from forest inventory, a model with LiDAR variables and a combined model which includes both categories of variables. The likelihood ratio test compares and ranks the tree models with p-values. *Reference= cutting class 1. ** Reference = deciduous. *** Reference =high site index.

Total biomass-winter

		Forest model		LiDAR model		LiDAR + Forest model	
	Fixed effects						
		β	SE	β	SE	β	SE
	Intercept	2.046	0.445	2.868	0.317	3.021	0.495
Forest inventory variables	**Cuttingclass***						
	2	0.794	0.416	-	-	0.776	0.396
	3	-0.794	0.404	-	-	-0.474	0.394
	4	-0.515	0.428	-	-	0.069	0.437
	5	-1.019	0.449	-	-	-0.634	0.440
	Treespecies**						
	pine	-0.413	0.356	-	-	-0.818	0.355
	spruce	-1.337	0.348	-	-	-1.524	0.336
	Siteindex***				-		
	Low	1.287	0.347	-	-	1.220	0.331
LiDAR variables	**h20**	-	-	-	-	-	-
	h40	-	-	-	-	-	-
	h50	-	-	-	-	-	-
	h70	-	-	-	-	-	-
	ulcd	-	-	7.914	2.659	-	-
	spi	-	-	-0.193	0.037	-0.134	0.036
	Random effects	SD		SD		SD	
	Stand number	1.400		1.578		1.329	

Likelihood ratio test	**Df**	**AIC**	**BIC**	**logLik**	**χ^2**	**χ^2 df**	**Pr(>χ^2)**
LiDAR model	4	5362.3	5379.2	-2677.1			
Forest model	9	5346.4	5384.6	-2664.2	25.83	5	9.61E-05
Forest + LiDAR model	10	5335.1	5377.4	-2657.5	13.36	1	0.00026

Model evaluation summarized

The fit of the models and the models ability to predict available biomass moose forage are expressed as the Pearson's product-moment correlation of the model fit and for the correlation between observed and predicted values within the validation data (20%) (Table 9). In general, we can say that the r (Pearson) for predicted and observed values was low for all models, ranging from 0.21 to 0.51. Nevertheless, adding LiDAR variables to the forest model (LiDAR + Forest) improved the prediction ability to some extent. The prediction ability (r for observed and predicted biomass) is basis for the ranking. The LiDAR + Forest model was in general highest raked within all groups of species and seasons (sub ranking).

The best models invariably fitted the data well (r ranging from 0.86 to 0.89). However, the correlation between predicted and observed values in retained 20 % of the data (validation) was much lower. In this model validation the LiDAR + Forest models (r ranging from 0.38 to 0.51) always performed better than the pure Forest model (r ranging from 0.35 to 0.49) which again always performed better than the pure LiDAR models (r ranging from 0.21 to 0.37) (table 9, figure 4 and 5). The prediction ability (r for observed and predicted biomass) is basis for the ranking. The LiDAR + Forest model was in general highest ranked within all groups of species and seasons (sub ranking in Table 9).

Table 9: Model evaluation**.** Comparison of three different mixed effects regression models predicting available forage including models with variables from forest inventory, model with LiDAR variables and a combined model including both categories of variables. The rankings are based on r (Pearson) observed /predicted from validation dataset, 20 %).

Forage	Model	r (pearson) obs/pred	Sub ranking	Ranking
RAW-summer	LiDAR + Forest model	0.38	1	8
	Forest model	0.35	2	11
	LiDAR model	0.21	3	15
RAW-winter	LiDAR + Forest model	0.46	1	3
	Forest model	0.38	2	9
	LiDAR model	0.37	3	10
Pine-winter	LiDAR + Forest model	0.51	1	1
	Forest model	0.49	2	2
	LiDAR model	0.29	3	12
Total biomass-summer	LiDAR + Forest model	0.42	1	4
	Forest model	0.41	2	5
	LiDAR model	0.27	3	13
Total biomass-winter	LiDAR + Forest model	0.41	1	6
	Forest model	0.40	2	7
	LiDAR model	0.26	3	14

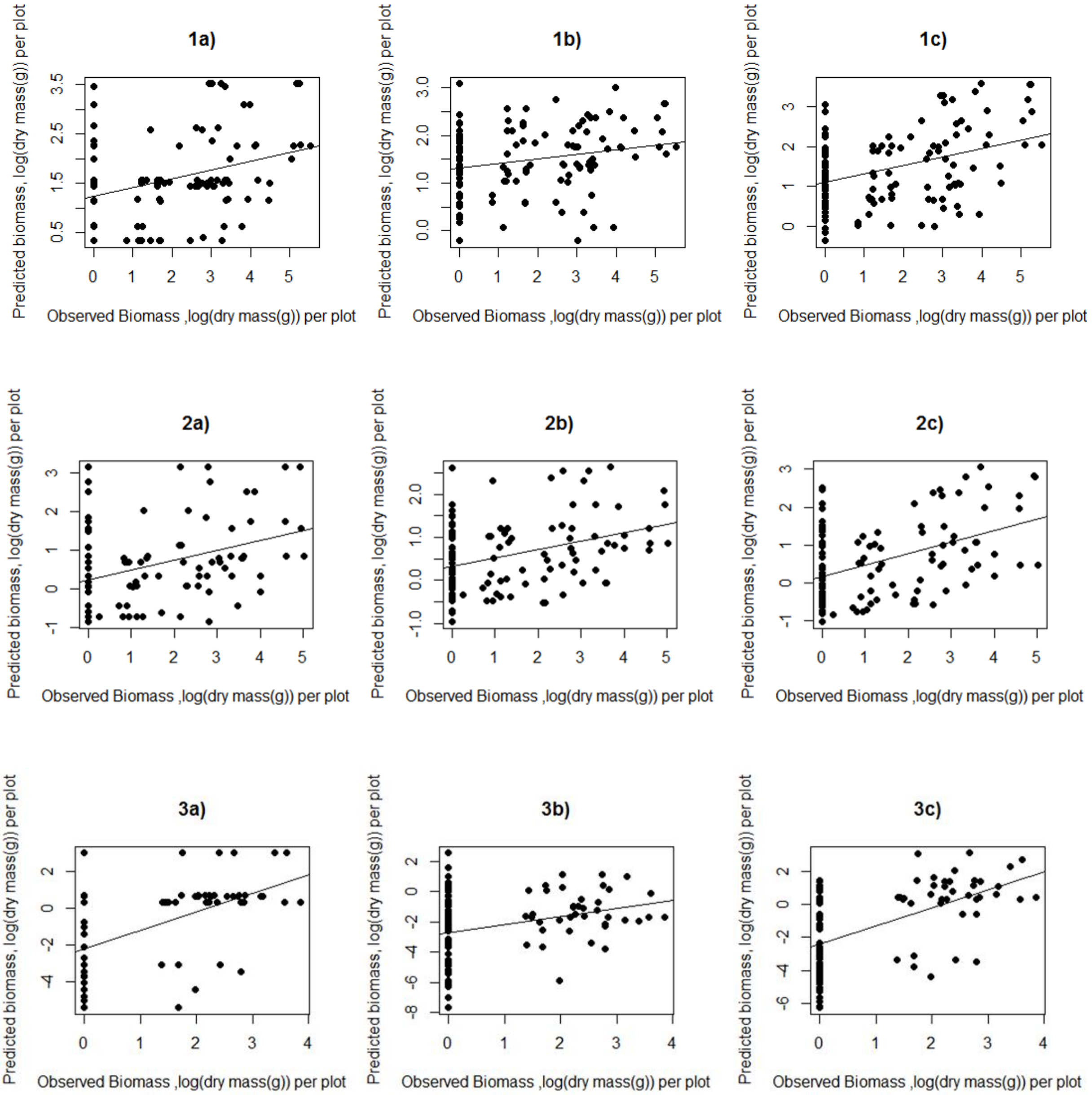

Figure 4: Plotted values for predicted and observed biomass (validation dataset, 20 %) within different target species and seasons. (1) RAW species→summer, (2) RAW species → winter and (3) Pine →winter. Forest models (a), LiDAR models (b) and Forest + LiDAR models (c).

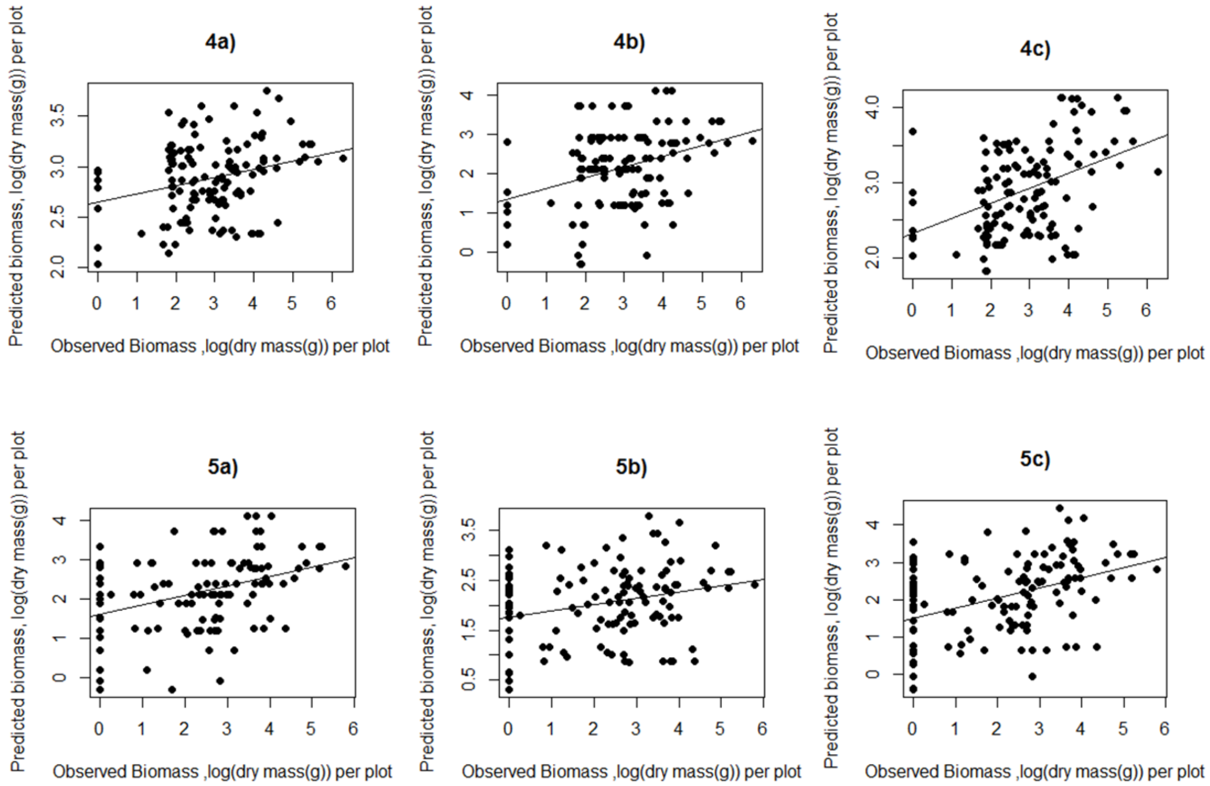

Figure 5: Plotted values for predicted and observed biomass (Validation dataset, 20%) within different target species and seasons. (4) Total biomass→summer and (5) Total biomass→ winter. Forest models (a), LiDAR models (b) and combined models (c).

Discussion

Quantifying forage availability

This study found that LiDAR could improve previous models describing forage biomass at a regional scale. LiDAR variables significantly contributed to explain variation in moose forage biomass for all tree species and seasons, and always increased the prediction ability on independent data although in some cases only marginally. My study is, to date, the only study that has investigated this possibility of using LiDAR to remotely sense forage biomass in a boreal forest landscape. Although the LiDAR variables improved the explanatory power of models of van Beest (2010), they did not produce adequate models when used on their own. The models using only LiDAR variables had the poorest fit to the dataset and made the least usable model out of the three model types. The forest inventory data most difficult to replace may be the species type. LiDAR have trouble to detect and distinguish between tree species which requiring high point densities (Li et al. 2013).

In some ecosystems, remote sensing of resources is an established and frequently used method. In reindeer management remote sensing of pastures is a common practice in order to maintaining an appropriate population size relative to the carrying capacity of the pasture species (Colpaert et al. 2003; Johansen & Karlsen 2005). These techniques use satellite based infrared (IR) images to recognize vegetation and lichen cover based on calibration from field data (Gilichinsky et al. 2011). The method also performs well in predicting lichen biomass using vegetation indices (Nordberg & Isrse 1998). A major challenge associated with remote sensing of selected resources on the ground is to measure the relevant components and ignore the irrelevant components. Nordberg & Isrse (1998) reported that the lichens had to represent more than 50 % of the total vegetation cover to give a reliable result.

The challenging part of remote sensing of moose forage is due to the fact that a major part of the moose forage is in a forest landscape with more or less closed canopy (Edenius et al. 2002). The moose forage is a part of the forest canopy or the understory and the task is therefore to use LiDAR to separate forage biomass information from the rest of the forest biomass. In a Swedish study by Kalén & Bergquist (2004) biomass available for browsing were predicted using tree morphological variables. The study found a relationship between increasing tree height and browse available biomass up to 4 m height for pine. The approach to predict biomass using tree characteristics is more or less similar to the method which was basis for the biomass prediction in van Beest (2010) and basis for my field data. Models using tree height could be used combined with LiDAR for prediction of forage biomass, this because of the ability of LiDAR to predict tree heights (Nilsson 1996; Næsset & Bjerknes 2001; Yamamoto et al. 2011). There is, however, not a simple straight forward way to distinguish individual trees using LiDAR. The use of individual tree crown (ITC) techniques may detect individual trees but the method is weak when it comes to predicting small trees such as forage trees for moose (Breidenbach et al. 2010; van Leeuwen & Nieuwenhuis 2010; Larsen et al. 2011)

LiDAR contribution to improvement

The species selected as target species were selected with the knowledge of moose preferred browsing species from previous studies (Fremming 1999; Edenius et al. 2002; Månsson et al. 2007; Wam & Hjeljord 2010). After joining the LiDAR and field data together the number of plots (a number of field plots was without LiDAR cover) with birch species was so low that it was decided to exclude birch from further analyses. Birch is a highly preferred forage species during the summer period, especially if they occur in large quanta in the landscape (Hörnberg 2001; van Beest et al. 2010; Wam & Hjeljord 2010). It would be important to predict also birch biomass in LiDAR models of forage and with the inclusion of more field plots with birch, the same modeling exercise could be done also for birch.

The LiDAR variables included in the best models capture relevant physical and ecological aspects of the habitat. The moose differs from other grazing herbivore being a browsing herbivore utilize the higher parts of the understory vegetation typically in the area 0,5 -2,5 above ground (Kalén & Bergquist 2004) and being selective among tree species and individual trees (Shipley et al. 1998). The main part of the tree species preferred by moose is light-demanding pioneer species (den Herder et al. 2009) most frequently found on disturbed areas, such as clear-cuts, or under a less dense canopy (Gromtsev 2002). There is therefore obvious that the understory vegetation plays an important role as moose forage. Previous research has focused on the cover of the understory vegetation, but less on the volume aspect of the understory. Kerns & Ohmann (2004) used climatic and topological information as explanatory variables to develop regression models for predicting the cover of deciduous shrub cover in Oregon coastal province. Wing et al. (2012) had the same approach but used LiDAR metrics as explanatory variable. The method was applicable to predict the cover of understory Ponderosa pine (*Pinus ponderosa*) using an understory LiDAR cover density variable. A modified version of the same variable was also used in my study and was present in 6 out of 10 LiDAR based models. Martinuzzi et al. (2009) also used LiDAR for mapping the understory shrubs and also snags. The approach was also here the presence or absence of understory vegetation.

A quantification of gaps from the LiDAR data also provided valuable model input. To approach the canopy 3D aspect Suchar & Crookston (2010) investigated the hypothesis of the relationship between canopy density and the presence of the understory. They found no relationship between the canopy cover and the understory cover. Nevertheless, Smith et al. (1997) discuss the effects of canopy gaps and the effects of the size and spatial placement of the gap on understory vegetation. It seems that the size of the gap and the height of the surrounding canopy play an important role in the understanding of the effects of canopy gaps and the presence of understory vegetation. This is reflected in the LiDAR derived variable spacing index (Spi) used in my study. Here, the size of the gap is weighted by the height of the canopy, the rationale being that a gap surrounded by a tall canopy is less important for the occurrence of understory vegetation than the same size gap surrounded by a lower canopy. The variable present completely different information from that available in the forest inventory variables and turned out to be important in 9 out of 10 LiDAR models in the present study. Bater et al. (2009) reported that LiDAR metrics such as height percentiles was a promising variable for predicting dead trees in a forest landscape. The advantages of height percentiles and also coefficient of variation (hcv) of height echoes made it possible to detect and distinguish trees without foliage from the rest of the stand. Height percentiles variables were also present in my models predicting RAW biomass in winter, which is a season without foliage for the RAW species.

Models prediction ability

The lack of predictability is most likely due to the differences in spatial resolution between the LiDAR data and the field data. The field data was sampled for a different purpose not requiring the same accuracy. Using field plot locations obtained with differential GPS (accuracy < 1 dm) would be more appropriate for accurate spatial matching with LiDAR data. LiDAR data was obtained 2 years after the field sampling. This may have affected the results to some extent. The effect is probably minor, but the target species in this study are early successional species with rapid juvenile growth (Smith et al. 1997) so there could be some changes from one year to the next. Johnson & Gillingham (2008) reported that prediction success was strongly influenced by sampling bias and positional errors. This is consistent with the relatively low prediction ability of my models. Future projects should strive for accurate spatial positioning. A suitable approach to field data sampling in future research within this topic would be to use the biomass approach like the one used in van Beest et al. (2010) and Kalén & Bergquist (2004) in combination with national forest inventory data as the field training- and validation data. The national forest inventory data is data captured with high accuracy (Skogoglandskap 2008) and will therefore solve the problem with differences in spatial accuracy between field data and LiDAR data. The second consideration is to also capture data parallel in time.

The use of remote sensing is a trade-off between quality requirements and data capture cost. LiDAR data with high point density are expensive but could improve the ability to classify tree species significantly (Li et al. 2013). If we disregard the cost-level, LiDAR has several possibilities. The combination with optical data is promising and is already in use for different purposes such as in combination with color infrared (CIR) orthophoto to predict stem volume (Straub et al. 2009) or tree species identification (Holmgren et al. 2008). This type of data is referred to as multi-sensorial data and will in the future also include hyper spectral data such as the promising EnMap (Environmental Mapping and Analysis Program) (Koch 2010). This is a satellite based system that delivers high resolution data and are expected to improve species identification significantly (Schwind et al. 2012; Koch 2010). More accurate species identification could replace forest inventory variables such as dominant tree species used in the Forest models in my study.

Conclusion and management implications

I suggest that the main reason for a low performance in the field validation is lack of spatial precision of the field data. The lack of predictability inhibits the use of existing multipurpose LiDAR data and existing field validation data sampled with handheld GPS. To know if we can achieve models with much better predictability, which is needed for managers, new data with improved spatial resolution needs to be sampled. My thesis is a promising first attempt, also internationally, to use LiDAR to model the food abundance and distribution of a forest dwelling large herbivore. For national wildlife management, it is a starting point in implementing LiDAR as a tool to quantify regional carrying capacity of moose. Taking into account that the LiDAR data is expensive it is necessary to capture data for more than one purpose. Data necessary for predicting forage biomass is a by-product from already systematized scans in connection with forest inventories. The models could therefore be implemented in ordinary forest inventory and make forage biomass data available in forest plans alongside traditional forest resources. This study concludes that LiDAR can improve the ability to predict moose forage biomass if variables from traditional forest inventory, such as site index, dominant tree species and cutting class, are added. More research is needed to reveal the full potential of LiDAR as a tool for remote sensing of moose forage biomass.

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Appendix 1

Table 10: Field data attributes.

Characteristics	Range	Mean	n
Training data (80 %)			
Bonitet	8-23	13,4	
high (8-14)			131
low (17-23)			381
Dominant treespecies			
Decidious			12
Pine			205
Spruce			181
Cuttingclass			
1			80
2			118
3			130
4			97
5			87
Altitude (m)	20-660	308,6	
Hillshade[a]	41-246	173	
Slope (^{o})	0-35	12,7	
Skyview[b]	72-94	84,3	
Validation data (20 %)			
Bonitet	8-23	12,8	
high (8-14)			29
low (17-23)			99
Dominant treespecies			
Decidious			29
Pine			60
Spruce			39
Cuttingclass			
1			30
2			22
3			40
4			23
5			13
Altitude (m)	20-583	313,9	
Hillshade[a]	41-246	174	
Slope (^{o})	0-35	11,7	
Skyview[b]	74-98	83,9	

[a]index of solar incidence

[b]percentage of sky not obstructed by terrain features

Appendix 2

Table 11: The LiDAR data attributes

	Training data (80 %)		Validation data (20 %)	
LiDAR variables	**Range**	**Mean**	**Range**	**Mean**
dground	0.089 - 0.983	0.482	0.089 - 0.977	0.467
d0.5	0.002 - 0.209	0.042	0.002 - 0.146	0.040
d2.5	0.001 - 0.214	0.065	0.002 - 0.137	0.063
d4.5	0.004 - 0.828	0.411	0.005 - 0.828	0.431
h0	0.500 - 0.710	0.510	0.500 - 0.710	0.511
h10	0.536 - 9.084	3.137	0.540 - 5.970	3.208
h20	0.602 - 11.542	4.645	0.630 - 8.665	4.767
h30	0.670 - 13.315	5.869	0.670 - 10.670	6.080
h40	0.950 - 14.800	6.971	1.060 - 12.580	7.250
h50	1.060 - 16.890	8.083	1.360 - 13.955	8.387
h60	1.200 - 18.840	9.193	1.750 - 15.190	9.494
h70	1.370 - 20.580	10.416	3.020 - 16.420	10.705
h80	1.580 - 22.470	11.802	3.400 - 18.020	12.032
h90	1.198 - 24.840	13.600	4.000 - 20.610	13.780
hmax	9.201 - 32.180	19.820	7.090 - 29.520	19.820
hcv	32.540 - 123.070	50.420	34.270 - 101.400	48.440
hmean	1.340 - 16.154	8.261	2.229 - 13.179	8.465
hqmean	2.124 - 17.573	9.194	2.596 - 14.164	9.381
hsd	1.332 - 6.918	3.972	1.332 - 6.215	3.993
cpd	0.008 - 0.891	0.484	0.008 - 0.891	0.501
ulcd	0.004 - 0.262	0.072	0.004 - 0.262	0.070
spi	0.018 - 19.587	7.044	0.057 - 18.248	7.245

Appendix 3

Example of use: pine forage biomass mapped in ArcGIS after calculation in R (R-Core-Team 2012) using raster calculator in the “raster” package (Hijmans & van Etten 2013). The raster is classified using quantil classification.