A comparison of forest height prediction from FIA field measurement and LiDAR data via spatial models

Yuzhen Li[1]

ABSTRACT: *Previous studies have shown a high correspondence between tree height measurements acquired from airborne LiDAR and that those measured using conventional field techniques. Though these results are very promising, most of the studies were conducted over small experimental areas and tree height was measured carefully or using expensive instruments in the field, which is not feasible in a practical forest inventory context. In this study, 105 plots located west of the Kenai Mountains, Kenai Peninsula, Alaska were measured and LiDAR data over the same set of field plots were acquired. Plot tree height, stand height, LiDAR mean height and LiDAR 90th percentile height were computed. Using the Matern covariance model for constant mean Gaussian spatial process, ordinary kriging was implemented and contour maps of predicted plot-level height from field height measurements and from LiDAR data were produced over the entire region along with maps of estimated standard error. Results indicate that at 300m by 300m pixel resolution, the spatial trends of predicted plot-level height are similar between field measurements and LiDAR measurements. The distribution of predicted stand height is very similar to the distribution of predicted LiDAR mean height with mean difference of only 0.28m. The mean of predicted plot tree height is comparable to the mean of predicted LiDAR 90th percentile height, but the distribution of predicted LiDAR 90th percentile height has much heavier tails.*

KEYWORDS: LiDAR, plot-level height, Gaussian process**,** Ordinary kriging

Introduction

Forest height is a crucial inventory attribute for calculating timber volume, forest biomass, site potential, and silvicultural treatment scheduling. Measuring height by current photogrammetric or field survey techniques is time consuming and expensive. As a new emerging remote sensing tool, airborne laser scanning system - Light Detection and Ranging (LiDAR) data have been studied to derive height information. Two different approaches have been used to obtain height measurements from LiDAR data. The first approach is to identify individual trees using a canopy height model and extract their height. The second approach is to regress plot-level or stand-level height on derived LiDAR metrics which describe vertical and horizontal distribution of forest canopy (Anderson et al 2006, Hyyppä et al 2000, Maltamo et al 2004, Næsset 2002, Persson et al 2002). Many studies have reported that accuracy of height estimate from LiDAR data is comparable

[1] College of Forest Resources, University of Washington, Seattle, WA, PO box 352100, USA; email: yzhli@u.washington.edu

In: McWilliams, Will; Moisen, Gretchen; Czaplewski, Ray, comps. 2009. 2008 Forest Inventory and Analysis (FIA) Symposium; October 21-23, 2008: Park City, UT. Proc. RMRS-P-56CD. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 1 CD.

with field height measurement, while others found LiDAR tends to underestimate individual tree height because of the low probability of a small-footprint laser pulse intercepting the apex of tree top (Anderson et al 2006, Gaveau and Hill 2003, Hyyppä et al 2000, Yu et al 2004). Though these results are promising, most of reported studies were conducted over small areas and field heights were measured carefully or using more expensive and accurate instruments than the hand-held rangefinder that is commonly used in forest inventory practice such as the Forest Inventory and Analysis (FIA) program in the USDA Forest Service. The accuracy of LiDAR-derived height when compared to field height measurement is not clearly understood in an operational forest inventory setting.

Another issue with large-area operational forest inventory is the accuracy of plot locations. Often less accurate, easy-to-carry GPS receivers are used to get a location for field plots. Thus may introduce inaccurate geographical co-registration of field plots with LiDAR data. For example, Rockwell Precision Lightweight GPS Receiver is used in the FIA program and its accuracy is 7 meters under forest canopy (Hoppus and Lister 2006). If field plots are poorly georeferenced, it is likely that the empirical regression relationship between field height and LiDAR metrics will be affected.

Forests are spatially structured and spatially close forests tend to be more similar due to the fact that they may experience similar living conditions, such as nutrient supply. Spatial models describing spatial correlations have been frequently used to determine forest biophysical parameters and characterize forest ecosystem structure (Biging and Dobbertin 1995, Lappi, J. 2001, Stoyan and Penttinen 2000, Stoyan and Stoyan 1998, Zawadzki et al 2005). In this study, instead of linking field plots with LiDAR data directly, a stationary spatial process was assumed for plot-level height, and then spatial models were applied to predict plot-level height at unobserved locations both from field inventory and LiDAR data respectively. The particular objective is to produce maps of predicted plot-level height over a large region, and then compare the distributions of heights predicted from operational field inventory and from LiDAR measurements.

Study area and data description

The study area is located in the west of the Kenai Mountains, Kenai Peninsula, Alaska (151.804W to 149.498W, 59.580N to 61.456N, Figure 1). The area covers approximately 5,000 square miles. A total of 105 forest inventory field plots are located in this study area. Each field plot consists of a cluster of four circular subplots approximately 1/24 acre in size with a radius of 24.0 ft, and each subplot contains a 6.8-foot fixed-radius microplot (Bechtold and Patterson 2005). Within each subplot, the height of trees with diameter at breast height of 5.0 inches or greater were measured; within each microplot, the height of saplings (1.0-4.9 inches DBH) and seedlings were measured. At each subplot center, a polygon type, which is a unique combination of land cover type, forest density, forest stand size and forest stand origin, was determined and the size of the polygons was collected (field procedures for coastal Alaska inventory 2003). Two aggregated plot-level heights, plot tree height and stand height, were defined and calculated for the purpose of this study. Plot tree height is defined as the average height of individual trees with DBH equal or greater than 5 inches weighted by polygon area. Stand height is defined as the average height of trees with DBH equal or greater than 5 inches, seedlings, and sapling weighted by polygon area.

LiDAR data were collected over each field plot and its surrounding area. A total of 105 LiDAR virtual patches were produced with each covering an area of approximately 9 hectares (300m by 300m, Figure 1). Multiple flights were made for some plots, because the initial flight didn't cover the entire field plot. For each 300m by 300m LiDAR coverage, a digital terrain model (DTM) was generated using returns classified by the data provider as bare-earth points, then all LiDAR returns were spatially registered to the DTM using their coordinates. The relative height of each return was computed as the difference between its vertical Z coordinate and the terrain surface height. Returns with a relative height value less than 2 m were excluded to eliminate ground returns, rocks, stumps and low vegetation. The remaining points were considered to be laser canopy hits. Finally, the laser canopy hits within the boundary of a 144-foot fixed radius plot containing the four subplot plots were extracted, and LiDAR plot mean height and 90th percentile height were calculated. The large plot was used instead of four individual subplots to decrease the effect of inaccurate field plot locations that results from poor GPS positions or azimuth and distance errors when locating the individual subplots.

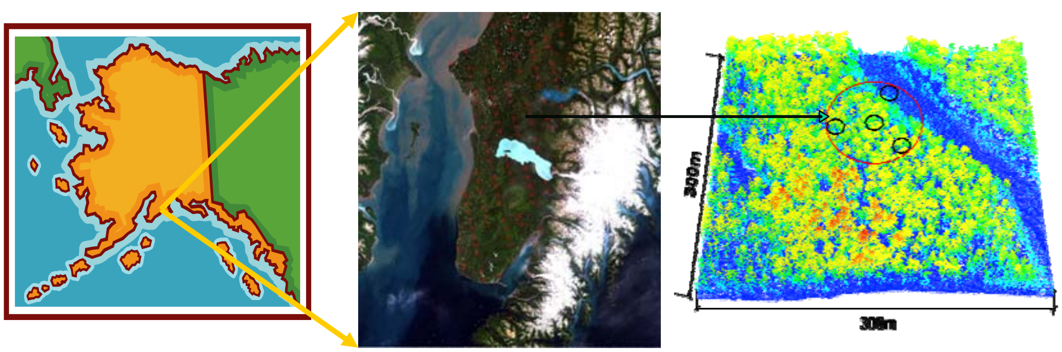

Figure 1: Map of study area. Picture in the middle is LANDSAT ETM+ image for the study area and red circles indicate field plot locations. Picture in the right is the LiDAR coverage over one example field plot and colored by height.

Method

Four aggregated plot-level heights (plot tree height and stand height from field measurements, LiDAR plot mean and LiDAR 90th percentile height) from 105 plots were assumed to be a partial realization of a stationary Gaussian process. That is $\{Z(s) : s \in D \subset \Re^2\}$, $Z = (Z(s_1), , \ldots Z(s_n))^T$ has a multivariate normal distribution, where Z(s) represents aggregated plot-level height at location s, D is a fixed subset of 2-dimensional Euclidean space; $D \subset \Re^2$ contains spatial coordinates s={s_1,…,s_n} and s_i is the longitude and latitude coordinates at location i. n is the number of locations, 105 in our case. Stationary means that for any set of n sites {s_1,…,s_n} and any $h \in \Re^2$, the distribution of ($Z(s_1)$,…, $Z(s_n)$) is the same as that of ($Z(s_1+h)$,…, $Z(s_n+h)$), which implies that the joint distribution doesn't change when shifted in space. Further, an isotropic process was assumed, which means that the semivariogram function depends upon the separation vector h only through its length ||h||. For the sake of simplicity, the Gaussian process was assumed to have a constant mean, that is $Z(s) = \mu + \omega(s) + \varepsilon(s)$, where μ is the mean component of the model, and ω(s) is a zero-centered stationary Gaussian spatial process, which captures the residual spatial association, and the ε(s) is an uncorrelated pure error term. The ω(s) introduces the partial sill and range parameter and ε(s) adds the nugget effect (Banerjee et al 2004).

Empirical semivariograms of plot-level heights were first fitted by four theoretical parametric models: Gaussian, exponential, Matern and Spherical class. Model parameters were estimated by restricted maximum likelihood methods. For detailed differences between theoretical semivariogram models, please refer to Banerjee et al (2004). The theoretical models allow us to calculate semivariance values for any h that are necessary for other geostatistical calculations and analyses such as kriging. Finally ordinary kriging was applied and maps of predicted height were produced over the entire region along with its standard error. All computations were conducted in the geoR package in R (Ribeiro Jr. and Diggle 2001).

Results

Empirical semivariogram model fitting

Figure 2 shows empirical semivariogram and its fitting by four theoretical models for both field-measurement-based and LiDAR-based plot-level heights. The semivariogram is the function describing the degree of spatial dependence of aggregated plot-level heights and the empirical semivariogram is a nonparametric estimate of the semivariogram. The empirical semivariance for a vector of separation h is derived by calculating one-half the average squared difference in plot-level height for every pair of plots locations separated by h. These values are then plotted again the distances between data pairs. Field plots in our sample were spread over the western Kenai region with the maximum distance of about 163,500 m. It is common to not compute the empirical semivariogram up to the largest possible distance due to the fact that shrinking number of available pairs for larger distances increases the variability of the empirical semivarogram. A general recommendation is to compute the empirical semivariogram up to about one half of the maximum separation distance in the data (Schabenberger and Gotway 2005). In addition, since field plots don't fall on a regular grid, the distances between pairs are all different. The distance considered need to be divided into regular bins and the distance value represented by the bin midpoint.

At least 30 pairs per bin were used to calculate empirical semivariogram (Banerjee et al 2004).

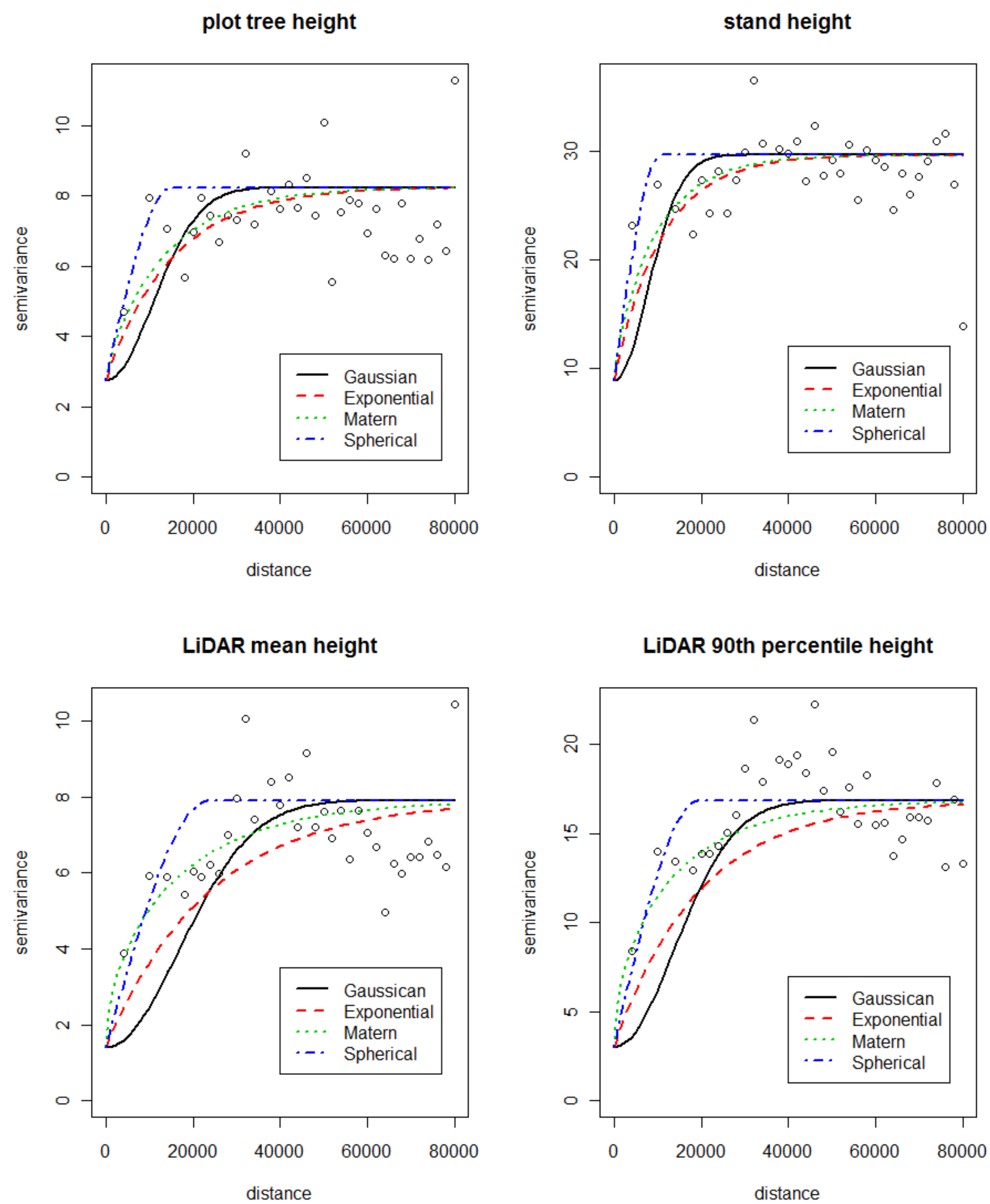

Figure 2: Empirical semivariogram fitting of four aggregated plot-level height

Figure 2 clearly shows that semivariance of aggregated plot-level heights has a similar pattern along distance. All semivariograms rise to a distance around 40,000 m then level off or decrease, which implies that aggregated plot-level heights from two plots may not be correlated when their distance is beyond 40,000 m. No semivarigrams pass through the origin, which suggests that the nugget effect is not zero for all cases. However, estimated sills are not the same. The estimated sill values are about 8, 30, 8, 17 for plot tree height, stand height, LiDAR mean height and LiDAR 90th percentile height respectively. The estimated sill is the sum of total variation explained by the spatial structure and nugget effect. It seems stand height has more variation across the area than plot tree height in which only trees are considered. LiDAR 90th percentile height appears to have more variation than LiDAR mean height.

Four different semivariogram models - Gaussian, exponential, Matern and spherical model were fit to empirical semivariograms. The main differences among these theoretical models lie on curve smoothness and whether sill can be reached or not. The smooth parameter is infinity for Gaussian model, 1 for Matern model and 0.5 for exponential model. These models were fit interactively "by eye" and curves based on the best fitting model parameters were drawn in Figure 2. Within small distances, the spherical curve rises quickly and reaches the plateau in short distance. The curvature of Gaussian curve changes sign within a short distance. There is not much difference between exponential (red dash line) and Matern (green dot line) models. From visual examination, no models fit well. The better fitting - Matern model was finally chosen to be the covariance function.

Spatial prediction

Using the Matern covariance model, ordinary kriging was applied and height prediction and standard error over the region were computed at 300m by 300m pixel resolution. Contour maps of predicted height and standard error are displayed in Figure 3 and summary statistics are shown in Table 2. Empirical cumulative distribution functions and probability density functions of predicted plot-level height are plotted in Figure 4. As expected, predicted plot tree height is higher than predicted stand height and predicted LiDAR 90th percentile height is higher than predicted LiDAR mean height. The mean of predicted plot tree height is very similar to the mean of predicted LiDAR 90th percentile height, but predicted plot height has much less range than predicted LiDAR 90th percentile height. This is confirmed by distribution curves in Figure 4 in which the predicted LiDAR 90th percentile height represented by blue line spreads more widely than the predicted plot tree height represented by black line. Predicted stand height has similar mean and range as predicted LiDAR mean height. In fact their empirical distributions (green and red lines in Figure 4) seem very close. But predicted stand height has much larger kriging standard error (5.05-5.37 m) than predicted LiDAR mean height (1.94 to 2.78 m).

Table 1: Summary of predicted plot-level height

	Mean (m)	Median (m)	Minimum (m)	Maximum (m)
Plot tree height	12.34	12.41	10.12	14.62
Stand height	7.66	7.72	4.62	10.96
LiDAR mean height	7.37	7.49	4.12	11.25
LiDAR 90th percentile height	12.00	12.22	6.05	17.18

Contour maps shown in Figure 3 reveal similar spatial patterns for height predicted from field measurements and LiDAR data. A circular area of low height is shown in the north-east of the Kenai Peninsula. Maps of kriging standard error also show the same pattern among different types of plot-level heights except that standard error of predicted stand height is a slightly larger. As expected, all standard error maps indicate that standard error is small near the location of the observed points.

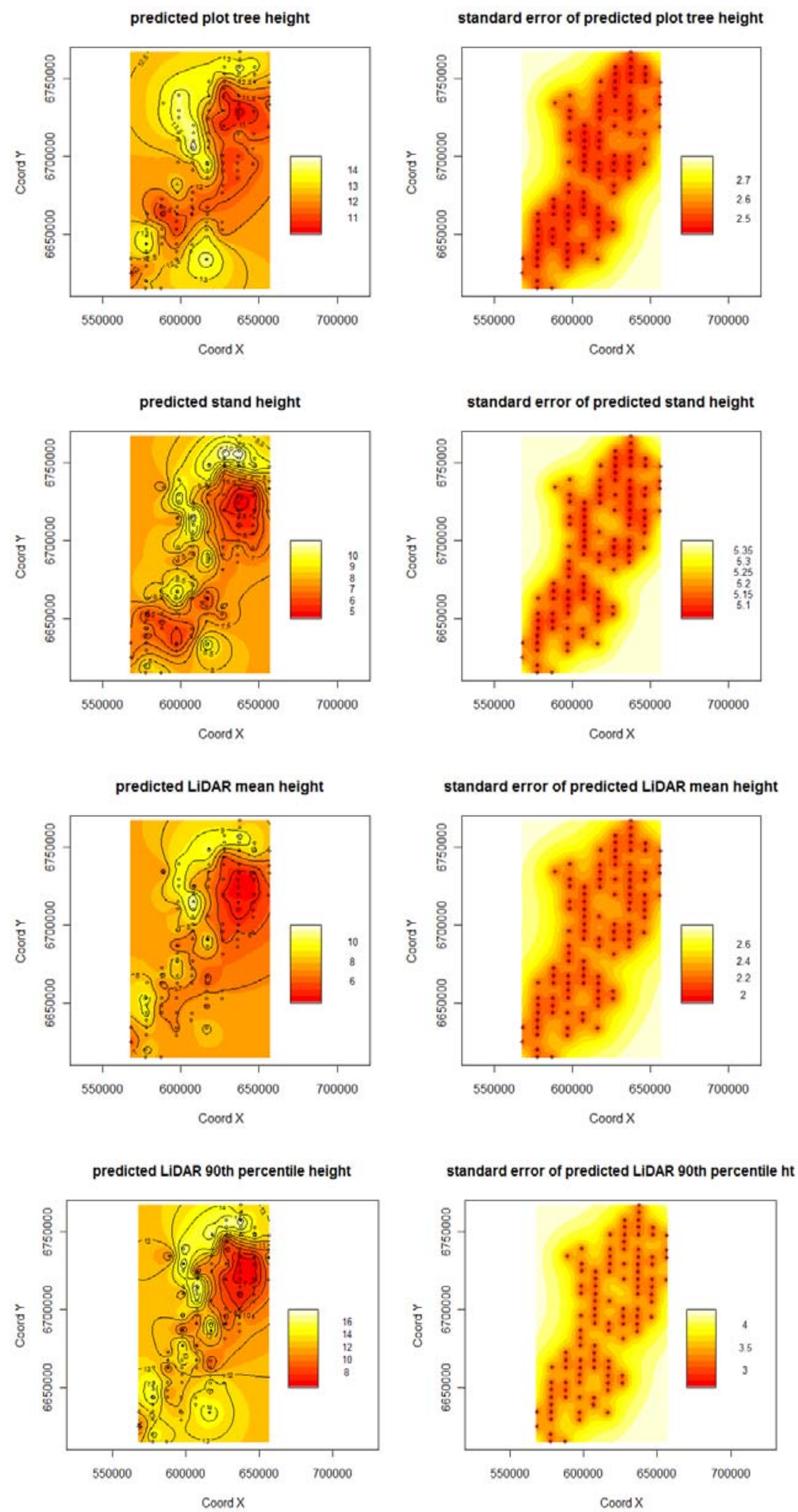

Figure 3: Maps of predicted plot-level heights along with their standard error estimates

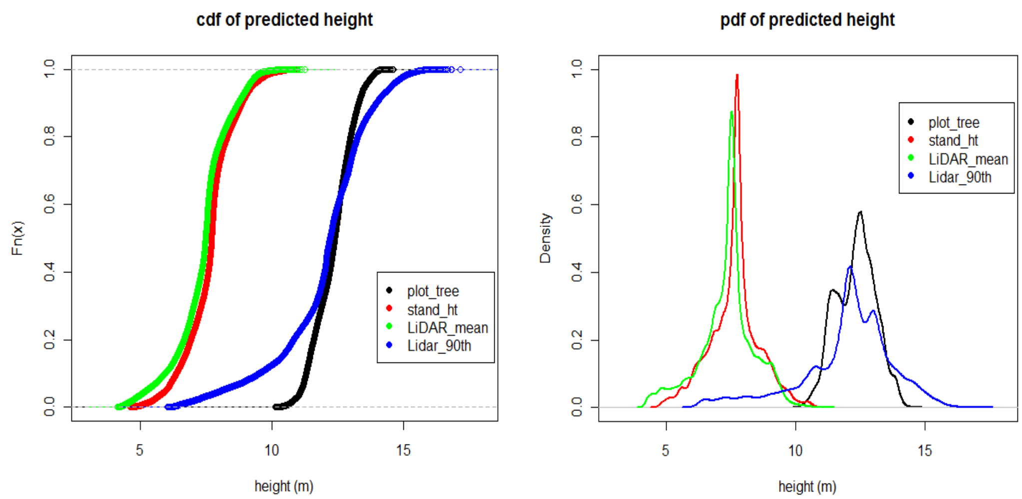

Figure 4: Empirical cumulative distribution function and kernel density function of predicted plot-level heights

Difference of predicted plot-level heights between field-based measurements and LiDAR-based measurements

Predicted plot tree height and predicted LiDAR mean height, predicted plot tree height and predicted LiDAR 90th percentile height, and predicted stand height and predicted LiDAR mean height were compared. Maps of the differences are shown in Figure 5. On average, predicted plot tree height is much higher than predicted LiDAR mean height with a mean difference 4.97m. The differences between predicted plot tree height and predicted LiDAR 90th percentile height, and between predicted stand height and predicted LiDAR mean height, are very small. For the majority of grids, these differences are within 1m as shown in Figure 6. On average, predicted plot tree height is higher than predicted LiDAR 90th percentile height by 0.34m and predicted stand height is higher than predicted LiDAR mean height by 0.28m.

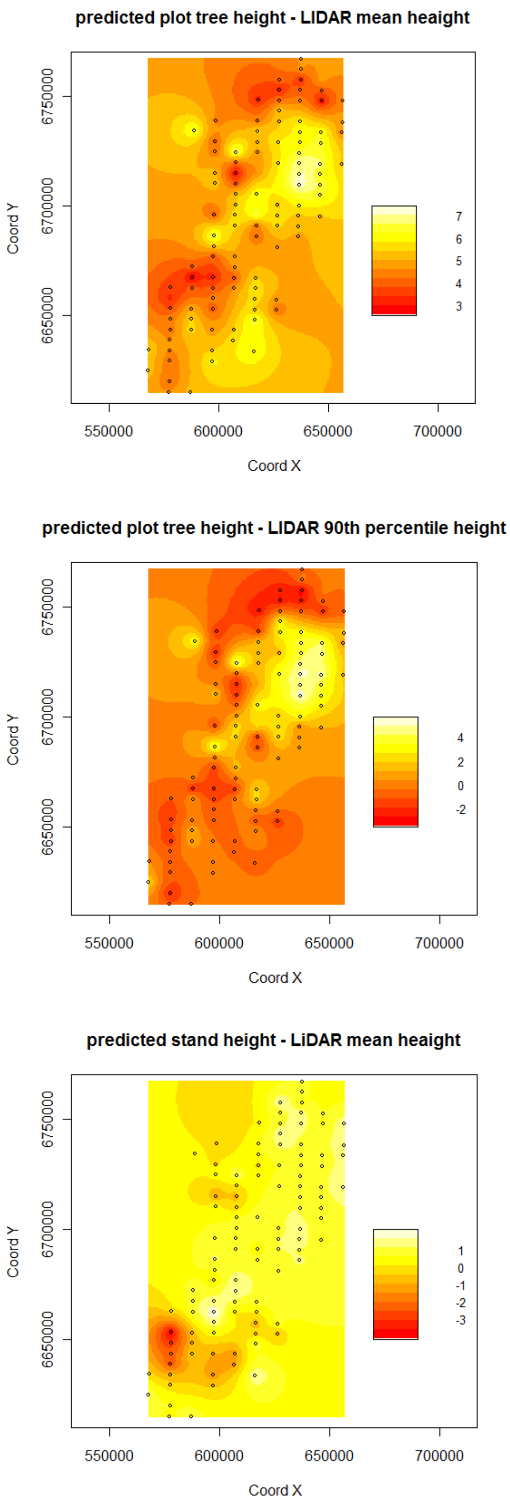

Figure 5: Differences of predicted plot-level heights between field-based measurements and LiDAR-based measurements

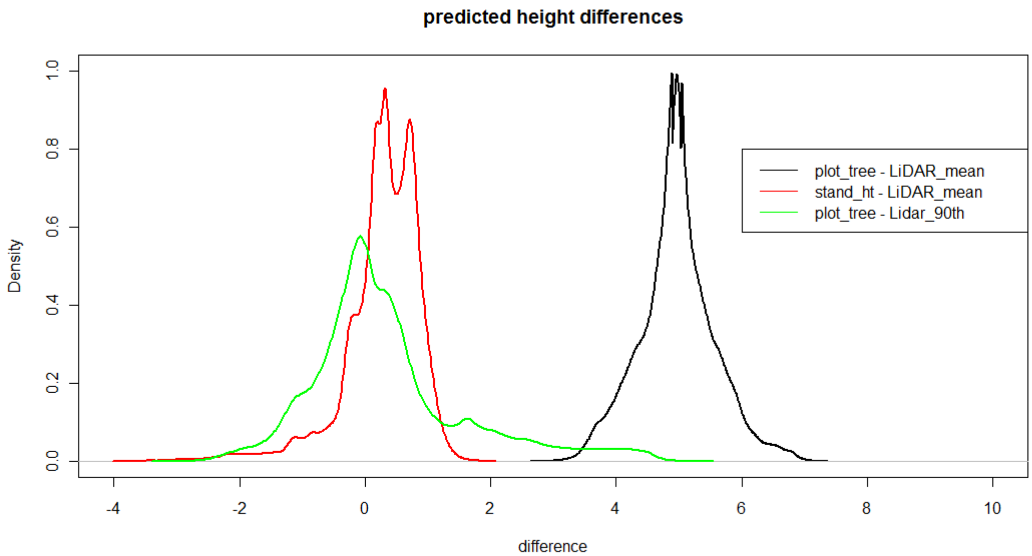

Figure 6: Empirical probability density function of the differences of predicted plot-level heights

Discussion

Semivariogram results indicate that aggregated plot-level heights in this dataset seem to spatially correlate until the distance between locations exceeds about 40,000m. However, since few pairs are located within short distances due to the fact that FIA plots are established based on an array of approximately 6,000-acre hexagons with each hexagon containing one plot (Bechtold and Patterson 2005), results may be different if field plots have a different distribution pattern.

Spatial prediction results show that at 300m by 300m pixel resolution, the distribution of predicted stand height is comparable to the distribution of predicted LiDAR mean height with a mean difference of only 0.28m, but predicted plot tree height is much higher than predicted LiDAR mean height with a mean difference of 4.97m. As described earlier, stand height is calculated from trees, saplings and seedlings, while plot tree height is calculated from trees only. In the literature, mean tree height measured on the ground is often reported to be higher than laser canopy height averaged over the sample plots due to the fact that the majority of laser returns would miss tree tops and would be reflected from the side of the crowns of dominant and co-dominant trees. The magnitude of difference depends on forest conditions and the LiDAR acquisition specifications used and it may vary from study to study, but is usually within 3m (Næsset et al 2004). The big difference between predicted plot tree height and predicted LiDAR mean height in our results is probably because forests in the western Kenai region have very low stand density (the mean is 66 trees per acre), low height and relatively open canopies, the laser can easily pass through the upper canopy so some lasers returns are indeed reflected from saplings and seedlings. This also explains why average height from trees, saplings and seedlings is very similar to the predicted LiDAR mean height. In addition, field plot height is the weighted average of tree height from four surveyed subplots while LIDAR mean height is the average of the canopy return heights within the big plot containing all four subplots.

The mean of predicted plot tree height is comparable to the mean of predicted LiDAR 90th percentile height, but predicted plot tree height tends to have smaller standard error and range than predicted LiDAR 90th percentile height. Both field-based plot-level height and LiDAR-based height display similar spatial patterns across the whole region.

The choice of the covariance function impacts the kriging prediction. Since our primary interest is spatial prediction, the correctness of covariance model is important. Unfortunately the selected parametric Matern model doesn't fit the empirical semivariogram very well even though cross validation results indicate it is acceptable, it should be noted that spatial prediction may not be very accurate. Nevertheless, kriging surface maps produced in this study provide a visual display describing the spatial distribution of height, which is very useful information for forest inventory and monitoring. For the sake of simplicity, a constant mean model of Gaussian process was assumed. Considered the large area coverage, adding some covariant variables, such as weather parameters and site conditions, may improve prediction precision.

Conclusions

Assuming constant mean Gaussian process, spatial explicit maps of predicted plot-level heights are produced from field inventory and LiDAR data for western Kenai peninsula, Alaska. General spatial trends of predicted plot-level height are similar between field measurements and LiDAR measurements. The distribution of predicted stand height is very similar to the distribution of predicted LiDAR mean height, and the mean of predicted plot tree height is comparable to the mean of predicted LiDAR 90th percentile height, but the distribution of predicted LiDAR 90th percentile height has much heavier tails.

Reliable tree height mapping is useful to support forest inventory and monitoring. Most vegetation mapping today is conducted by manual photo-interpretation or satellite imagery combined with field surveys. The manual photo interpretation technique is costly and the results are dependent on the interpreter. Mapping based on optical satellite imagery requires that the area of interest is cloud-free. Nearly persistent cloud cover precludes acquisition of useful optical satellite images for a particular time period in Alaska. A remote measurement of forest structure that is rapid, reproducible and that provides reasonable spatial resolution is needed. As a rapidly-growing remote sensing technology, LiDAR offers great potential to capture canopy structure. However, due to high costs, LiDAR data are primarily acquired over specific project areas that are typically much smaller than the spatial extent at which most satellite image datasets are routinely acquired. In addition, it is unusual to have accurately georeferenced field plots available over large regions. These factors may limit the operational use of LiDAR. In this study, instead of developing regression models assuming accurate field plot location, we develop a new approach that uses discontinuous LiDAR coverage and spatial models. We produced estimates of plot-level height over a large region using discontinuous LiDAR data that are comparable to those obtained using field inventory. The results are particularly useful for remote areas like Alaska where field work is expensive and optical satellite imagery is not easy to obtain. This approach could save time when greater accuracy is not needed, but quick assessment is necessary.

Acknowledgements:
The author would like to thank Robert McGaughey and Hans-Erik Andersen for their advice and helpful review on the manuscript.

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