USING LIDAR DATA TO QUANTIFY FOREST STRUCTURAL HABITAT VARIABLES IMPORTANT TO FISHERS AND MARTENS

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SUMMARY OF FINDINGS

Fishers (*Pekania pennanti*), martens (*Martes americana*), and many other wildlife species rely on three-dimensional structural habitat characteristics to provide essential resources. Spatially-continuous data on fine-scale structural habitat features are generally not available across large landscapes because passive remote sensing systems are not capable of measuring three-dimensional characteristics and because it is financially and logistically challenging to collect field-data continuously across the landscape. Light detection and ranging (LiDAR) is an active remote sensing technology capable of providing accurate, high-resolution data on three-dimensional vegetation structure across large spatial extents. Many past studies have demonstrated that LiDAR data can be used to map coarse- and fine-scale habitat characteristics at the scale of individual trees, field plots, or forest stands. However, most research has focused on forestry applications, and relatively few studies have focused on modeling structural variables that serve as basic wildlife habitat indicators.

We were interested in using LiDAR to supplement field data collected as part of a long-term project on fisher and marten ecology in Minnesota. Our objectives were to evaluate the potential of LiDAR technology to quantify both coarse- and fine-scale forest habitat metrics and to evaluate the effect of pulse density on prediction accuracy. We acquired high-density LiDAR data (8 pulses/m^2) for a portion of our marten study area and selected 200 random locations within that portion to collect detailed vegetation measurements. Random sites were selected using a LiDAR-informed stratified random sampling design. We measured vegetation on 189 of the 200 plots during summer 2015 and 2016; the remaining plots could not be sampled due to wind disturbances that altered forest structure after LIDAR data collection. Statistical analyses are ongoing, and we defer reporting results until final analyses are completed.

INTRODUCTION

To create and implement effective habitat management plans, wildlife managers depend on reliable knowledge of species-specific habitat requirements, accurate information on the current abundance and distribution of suitable habitat features, and an understanding of how management actions influence habitat suitability over a range of spatio-temporal scales. In many situations, having accurate information on abundance and distribution of habitat characteristics is necessary for understanding species-specific habitat requirements and evaluating how management actions influence habitat use. Forest wildlife species vary in their dependence on specific habitat characteristics. For some species, habitat requirements may be adequately

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described using coarse-resolution data such as forest cover type, stand age or successional stage, or proximity to permanent water or other specific landscape features. For these species, broad-scale forest inventory data and GIS layers derived from passive remote sensing technologies (e.g., satellite imagery, aerial photographs) are often adequate to map and monitor changes in habitat quality. However, other wildlife species, including fishers, martens, and many forest songbirds, respond to three-dimensional, structural habitat features at fine spatial scales. Spatially-continuous data on fine-scale structural features generally are not available because passive remote-sensing systems are not capable of measuring three-dimensional characteristics and because it is financially and logistically challenging to collect fine-scale, field-based measurements continuously across large areas. Instead, habitat models for these species typically incorporate information gathered from detailed field-sampling at sites used by the species of interest, often for specific purposes (e.g., foraging, nesting, or denning sites). While site-level habitat models created from field data provide informative and mechanistic insights into a species' habitat requirements, they are often difficult to apply to larger scales at which forest management decisions are generally made. Regardless of whether a species relies on coarse- or fine-scale characteristics, having data on forest characteristics at continuous spatial scales is critical for sound habitat management and assessment.

Light detection and ranging (LiDAR) is an active remote sensing technology capable of providing accurate, high-resolution (<1 to >20 laser pulses/m^2) data on three-dimensional physiographic and vegetative structure over large spatial extents (e.g., entire study areas or wildlife management units up to statewide coverage; Merrick et al. 2013, Vierling et al. 2008). LiDAR data are collected from a scanner that emits frequent, short-duration laser pulses and records the reflected signal returning to the sensor. As the emitted laser pulse is intercepted by an object or surface (e.g., vegetation, building, terrain), a portion of the laser energy is reflected and returned to the sensor. Discrete-return LiDAR systems record the spatial coordinates where the laser pulse intercepted an object or surface, resulting in a three-dimensional "cloud" of interception points or "returns". Modern discrete-return LiDAR systems are capable of recording ≥4 returns per laser pulse (Vierling et al. 2008).

High pulse density, multiple-return LiDAR data provide the detail necessary to accurately map a variety of forest structural attributes including both fine-scale attributes (e.g., canopy height [Means et al. 2000], canopy cover [Lefsky et al. 2002], shrub-density [Martinuzzi et al. 2009]) and coarse-scale attributes (e.g., forest successional stage [Falkowski et al. 2009]) continuously and with high precision across the landscape. Because of these capabilities, LiDAR is increasingly used to analyze forest structure and is becoming an integral part of operational forest management (White et al. 2013). LiDAR can be used to measure biophysical variables at the level of individual trees, forest inventory plots, and forest stands (Falkowski et al. 2006, White et al. 2013). Forest inventory metrics that have been successfully predicted at the plot and stand level using LiDAR include canopy height (Hawbaker et al. 2009, Thomas et al. 2006), canopy density or volume (Lefsky et al. 2002, Martinuzzi et al. 2009), basal area (Means et al. 2000, Woods et al. 2011), average diameter at breast height (Hawbaker et al. 2009, Jakubowski et al. 2013), tree density (Treitz et al. 2012), and forest biomass (Thomas et al. 2006, Treitz et al. 2012, Woods et al. 2011). LiDAR data can be used to make direct estimates for some attributes such as canopy cover, canopy height, and canopy volume (Graf et al. 2009, Lefsky et al. 2002, Merrick et al. 2013). However, many structural metrics require accurate field-plot data that can be used to build predictive models from LiDAR-derived explanatory variables. Overall, studies have focused on forestry-specific metrics and there has been less work focused on predicting structural attributes important to wildlife (but see Goetz et al. 2010, Graf et al. 2009, Hagar et al. 2014, Martinuzzi et al. 2009).

The potential for LiDAR to improve wildlife research and management has been recognized for some time. LiDAR data can be used to improve wildlife-habitat modeling in 2 different ways (Merrick et al. 2013, Vierling et al. 2008). First, it provides a tool that can be used with telemetry data or known species distributions to better understand resource selection. Forest attributes can be measured at fine spatial scales with LiDAR, allowing researchers to assess resource use at scales near those at which animals respond to structural attributes (Vierling et al. 2008). By providing spatially-continuous data, LiDAR data allows researchers to directly address how both landscape composition and configuration influence habitat selection. Furthermore, LiDAR can be used to investigate resource selection across a wide range of spatial scales including sites used for specific behaviors, individual home ranges, and entire wildlife management units or other regional units. Second, LiDAR can be used to predict habitat suitability or species distributions based on prior knowledge of habitat requirements or life-history characteristics. The ability to translate habitat models into spatially-explicit maps is particularly useful for wildlife management, for example, by providing accurate predictions of the distribution and abundance of suitable habitat or by allowing managers to monitor changes in habitat suitability through time with repeated LiDAR acquisitions.

Fishers and martens are two species that could benefit from LiDAR-based habitat modeling because they respond to both coarse- and fine-scale forest attributes (Joyce 2013, Raley et al. 2012, Thompson et al. 2012), habitat loss from human land use is thought to be a major threat to population persistence for both species (Proulx et al. 2004), and continuous data on fine-scale attributes required by fishers and martens are not currently available. At coarse scales, fishers and martens show strong selection for mature and old-growth forest conditions (Buskirk and Powell 1994), although both species have been documented using a variety of seral stages (Joyce 2013, Raley et al. 2012, Thompson et al. 2012). Fine-scale attributes, however, appear to drive fisher and marten habitat selection at multiple spatial scales. Both species depend on large-diameter cavity trees and other specific forest structures that serve as rest sites and reproductive dens (Joyce 2013, Raley et al. 2012, Thompson et al. 2012). Sites used for resting and denning typically have dense overhead cover, abundant coarse woody debris (CWD), and large-diameter trees (Aubry et al. 2013, Joyce 2013, Thompson et al. 2012). CWD provides subnivean access (Corn and Raphael 1992) and is a critical component of marten winter foraging behavior in the boreal forest (Andruskiw et al. 2008). At landscape scales, shrub cover (Slauson et al. 2007) and canopy cover (Cushman et al. 2011, Shirk et al. 2014) are associated with home ranges selected by martens. Furthermore, canopy cover is one of the strongest and most consistent predictors of fisher habitat use across spatial scales (Raley et al. 2012).

Despite the amount of research focused on understanding fisher and marten habitat requirements, there are critical aspects of habitat ecology that are not well understood. For example, several studies have suggested that availability of suitable denning habitat could limit fisher and marten populations (e.g., Ruggiero et al. 1998), but few studies have investigated distribution of suitable denning habitat, in part because continuous fine-scale data are needed to apply den-site habitat models across the landscape but are generally not available. Furthermore, most studies have focused on landscape composition, but landscape configuration likely also drives habitat use (Sauder and Rachlow 2014), and landscape configuration is strongly influenced by ownership and management history (Cohen et al. 2002, Kennedy et al. 2012, Spies et al. 1994). Because of their dependence on structural features that have been accurately predicted using LiDAR, LiDAR data has the potential to provide novel insights into fisher and marten habitat ecology and improve habitat management for these species.

Many of the resources exist for LiDAR data to be incorporated into natural resource management in Minnesota. Minnesota is one of a growing number of states for which statewide LiDAR data have already been acquired. One important question that still needs to be addressed to use the statewide data or direct future LiDAR acquisitions is what pulse density is required to accurately quantify forest structural attributes at plot and stand levels. LiDAR acquisition costs increase with increasing pulse density (Jakubowski et al. 2013). Therefore, acquiring LiDAR data at the minimum pulse density necessary for accurate predictions will enable researchers and managers to maximize gain from finite resources. Previous research has shown that many forest metrics can be accurately predicted at fairly low pulse densities and that higher pulse density does not necessarily improve model accuracy, but the effect of pulse density on model accuracy depends on the variable of interest (Thomas et al. 2006, Treitz et al. 2012, Jakubowski et al. 2013). In general, the structural variables measured in these studies are strongly biased toward forestry applications. Although some of the biophysical variables evaluated are important indicators of wildlife habitat, a better assessment of how pulse density affects wildlife-specific forest attributes (e.g., canopy structure, CWD, shrub cover) is necessary before LiDAR can be used in the same operational capacity for wildlife management as it is currently being used for forestry.

Our objective was to evaluate the potential of LiDAR technology to quantify both coarse- and fine-scale forest habitat variables and to create applied GIS tools that can be used in day-to-day decision-making by forest and wildlife managers. Additionally, we will evaluate the effect of pulse density on prediction accuracy. This project will provide new information and tools for applied habitat management for fishers and martens, and will also increase the value of data already collected in ongoing research on fisher and marten ecology. Combining LiDAR-derived estimates of forest structural attributes with location data from radiocollared fishers and martens will enable us to address important research questions aimed at improving management of these species in Minnesota.

STUDY AREA

Marten research has taken place in portions of east-central St. Louis and west-central Lake counties in northeastern Minnesota (Figure 1). The marten study area (~1250 km^2) is composed of a variety of forest types including upland mixed coniferous-deciduous forest, lowland conifer or bog, upland coniferous forest, and regenerating forest, as well as marshes, fens, shrublands, and anthropogenic cover types. We acquired high-density LiDAR data for a 65 km^2 portion within the larger marten study area during spring 2014 (Figure 1). The location of the high-density LiDAR acquisition was chosen because it included a large number of locations from radiocollared fishers and martens (i.e., rest sites, dens, and aerial telemetry locations), it encompassed ~100 ground-based vegetation survey sites measured previously as part of the larger fisher/marten research project, and it contained almost all of the forest types and successional stages available throughout the larger marten study area. Both the marten and embedded LiDAR study areas are predominantly public ownership including portions of the Superior National Forest, state, and county lands.

METHODS

There are two LiDAR datasets available that provide variable coverage of our study area (Table 1). Both datasets are discrete, multiple-return LiDAR data acquired from fixed wing aircraft during leaf-off conditions. The first dataset (hereafter, statewide data) was collected during spring 2011 as part of the Minnesota elevation mapping project (http://www.mngeo.state.mn.us/chouse/elevation/lidar.html) and provides complete coverage for Carlton, Cook, Lake, and St. Louis counties. The second dataset (hereafter, high-density data) was acquired in spring 2014 over a 25 square-mile portion of the marten study area. In general, specifications from both datasets (Table 1) match recommendations for forest inventory analysis (White et al. 2013). Those that do not (e.g., scan angle) are consistent with published studies that have successfully modeled forest structure using LiDAR (e.g., Treitz et al. 2012 used a scan angle of ±20˚).

Several pre-processing steps are necessary prior to vegetative analysis. Raw LiDAR return points must be classified as ground or non-ground (e.g., vegetation, water, buildings) returns and manual quality assurance/quality control (QA/QC) steps must be taken to verify data conform to desired specifications. Digital elevation models (DEMs) are then created from ground returns and converted to digital terrain models (DTMs). Pre-processing steps have been completed for statewide data. For the high-density LiDAR data, we are using LP360 (QCoherent Software, LLC) for LiDAR point classification and DEM construction.

We are using the area-based approach to create predictive models of forest structural attributes that relate to habitat quality for marten. The area-based approach combines field-plot and LiDAR data to create predictive statistical models that can be projected across an entire landscape (White et al. 2013). The area-based approach has 4 main steps: 1) collect and summarize field-plot data; 2) extract and summarize LiDAR data corresponding to field sampling locations; 3) create and evaluate predictive models; and 4) apply models across the area of interest. Additionally, we are evaluating whether LiDAR can be used to directly detect individual pieces of CWD.

We measured forest inventory plots at random sites distributed throughout the high-density LiDAR acquisition area. We used a stratified random sampling design to ensure field sampling covers a large range of the forest conditions present on our study area (Hawbaker et al. 2009, White et al. 2013). We calculated mean LiDAR return height (m above ground) and standard deviation of return height for each 20- x 20-m cell in the study area to represent the range of structural conditions present throughout the landscape (Figure 2). Each cell in forest condition represented a potential sample location. Sample locations were further stratified into upland and lowland soil types using ecological landtype classifications from the Superior National Forest's terrestrial ecological unit data to ensure sampling covered a variety of soil types. For each broad soil type category, the available sampling space defined by the two LiDAR metrics was divided into 8 quantiles for mean return height and 2-3 quantiles for the standard deviation of return height to form 23 sample strata per soil type (Hawbaker et al. 2009). We selected a total of 200 random locations to sample. The number of locations selected per stratum was proportional to the total number of available cells in each stratum throughout the entire study area.

At each randomly-selected location, we measured structural variables within a 400-m^2 (11.3-m radius) circular plot. Plot size was selected to match recommendations for LiDAR-based forest inventory modeling (Laes et al. 2011, White et al. 2013) and corresponds to a 20-m pixel for landscape-level application of predictive models. Structural attributes were selected based on their importance to marten habitat from published literature (e.g., Andruskiw et al. 2008, Allen 1982, Raphael and Jones 1997, Slauson et al. 2007) and previous research in Minnesota (Joyce 2013; Table 2). Sampling protocols were largely based on United States Department of Agriculture (USDA) Forest Inventory and Analysis program protocols to maintain consistency with previous data collected at rest sites and reproductive dens used by radiocollared marten in Minnesota (Joyce 2013). All field measurements were taken in full leaf-on condition, although canopy cover and understory density also were sampled during leaf-off condition for a subset of field plots. During field sampling, locations of field plots were recorded using both consumer-grade (Garmin eTrex 30) and mapping-grade GPS receivers (Geneq SXBlueII+GNSS). The mapping-grade receiver communicated with both GPS and GLONASS satellites and utilized a combination of space-based augmentation system (SBAS) and real-time differential correction to obtain precise locations without post-processing. When using the mapping-grade GPS, we collected points for ≥30 minutes at a rate of ~20 points/min. Preliminary data at geo-referenced survey markers suggested mapping-grade GPS locations collected this way provided sub-meter accuracy under full forest canopy (Joyce, unpublished). For the consumer-grade GPS, we used location averaging for ≥30 minutes.

LiDAR can be used to directly measure a subset of the forest attributes being measured at field plots (e.g., canopy height, canopy cover/closure, canopy structure metrics; Merrick et al. 2013, White et al. 2013), and we are currently evaluating whether LiDAR data can be used to detect individual pieces of CWD. For remaining attributes, we will create predictive statistical models using LiDAR metrics as explanatory variables and attributes summarized from field plot data as response variables. We will use FUSION software (McGaughey 2013) to extract LiDAR point clouds corresponding to field plots and summarize statistical properties of individual point clouds based on return height, return intensity, or point density for use as explanatory variables in statistical modeling.

The type of statistical model we used depended on the structural characteristic. We used multiple linear regression for continuous variables (e.g., average diameter at breast height). We used Poisson or negative binomial GLM count models for count variables (e.g., tree density). Snags were not present at a large number of plots. Consequently, Poisson GLM count models and multiple linear regression could not account for inflated zeros, and use of these types of statistical models could produce biased estimates of snag characteristics (Russell 2015, Zuur and Ieno 2016). We used zero-altered (hurdle) models for snag density (zero-altered Poisson), snag volume (zero-altered gamma), and average snag diameter (zero-altered gamma). Zero-altered models have 2 components (Zuur and Ieno 2016). The first component accounts for presence/absence of snags, while the second component accounts for snag density, volume, or diameter if snags were present.

Despite differences in model type, we used the same statistical framework for all forest structural variables. There are 3 steps in the statistical framework: 1) model-fitting and model selection, 2) model evaluation using cross-validation, and 3) model re-calibration. First, for each response variable, we created a set of candidate models using individual predictor variables or combinations of non-collinear predictor variables. The number of predictor variables included in multi-variate models did not exceed sample-size-based recommendations to avoid over-fitting data (Babyak 2004, Guidice et al. 2012). Models were fit in Program R (R Development Core Team, 2013) using techniques and packages best-suited to the type of model being fit. Candidate models were compared using an information-theoretic approach to select the best-supported model(s) from the candidate set (Burnham and Anderson 2002). Candidate models were chosen based on expected relationships between response variable and individual predictor variables. Second, we evaluated how well best-supported models predicted new data using a five-fold cross-validation procedure. We evaluated each cross-validation set using root mean squared error (RMSE), R^2, and bias. Finally, we used a bootstrapping procedure to re-calibrate model coefficients in an effort to reduce the effect of over-fitting and therefore improve prediction accuracy (Harrell 2001, Giudice et al. 2012, Fieberg and Johnson 2015).

To evaluate the effect of LiDAR pulse density on accuracy of predictive models we will subsample LiDAR data to obtain 7 different pulse densities (8, 6, 4, 2, 1, 0.5, and 0.25 pulses/m^2) using FUSION software. Subsampling will be performed in a way that accurately simulates data acquired at specific pulse densities (i.e., we wish to thin the density of laser pulses rather than the number of returns per pulse). Predictive models will be created at each pulse density, and prediction accuracy will be plotted as a function of pulse density (Jakubowski et al. 2013). Prediction accuracy will be assessed using R^2, RMSE, and bias. From these plots we will determine the minimum pulse density necessary to create accurate predictive models (turning point, *sensu* Jakubowski et al. 2013) as well as the pulse density corresponding to the most accurate predictive model (best accuracy *sensu* Jakubowski et al. 2013). Results from this analysis will determine which forest attributes can be predicted throughout the entire marten study area using statewide LiDAR data (0.45 pulses/m^2).

RESULTS AND DISCUSSION

Pre-processing steps (QA/QC, point classification, DEM creation and conversion) have been completed for the statewide LiDAR data. High-density LiDAR data were collected during spring 2014 and delivered from the vendor during fall 2014. We have completed QA/QC on the high-density data and classified returns for large portions of the dataset. We are still refining point classification protocols, and final point classification should be complete during summer 2018. DEMs will be created and converted to DTMs once we complete point classification. Additional information about point classification and DEM construction is not provided here because methodology is still being refined.

Our 200 randomly-selected field plots included 115 plots in upland soil types and 85 plots in lowland soil types. During summer 2015, we measured 100 forest inventory plots. Data from these plots have been entered and checked for errors. We measured 89 additional plots during summer 2016, and completed data entry for all plots. We were not able to measure all 100 remaining plots in 2016 because wind storms altered some of the pre-selected plots before we could measure them. The final set of 189 field plots includes 110 plots in upland soil types and 79 plots in lowland soil types. We have started preliminary statistical analyses, but we defer results until all statistical analyses are completed.

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Table 1. Specifications for statewide (2011-12) and high-density (2014; portion of St. Louis County) LiDAR datasets collected in Minnesota.

Specifications	Statewide	High-resolution
Acquisition Date(s)	Spring 2011 & Spring 2012	Spring 2014
Vendor	Wolpert, Inc.	AeroMetric, Inc.
Laser System(s)	ALS60, ALS70, and Optech GEMINI	ALS70
Altitude	2000-2300 m	1050 m
Flight Speed	240 - 278 km/h	278 km/h
Scan Angle	± 20˚	± 20˚
Side Overlap	25%	50%
Nominal Point Spacing	≤ 1.5 m	≤ 0.35 m
Pulse Density	0.45 pulses/m^2	8.0 pulses/m^2
Vertical Accuracy	5.0 cm (RMSE)	6.7 cm (RMSE)
Horizontal Accuracy	1.16 m (95% confidence)	100 cm

Table 2. Partial list of forest attributes that will be estimated using LiDAR data collected in Minnesota from 2011-14. Attributes were selected because of their biological significance to martens.

Forest attribute	Biological significance	Citation(s)[a]
Coarse woody debris density/volume	Prey habitat, facilitates prey capture, subnivean access, rest and den site characteristic	Andruskiw et al. (2008), Corn & Raphael (1992), Joyce (2013)
Tree diameter at breast height (dbh)	Indicator of stand age, related to arboreal denning and resting structures	Raphael & Jones (1997), Slauson & Zielinski (2009)
Basal area	Indicator of stand age, related to arboreal denning and resting structures	Payer & Harrison (2003,2004)
Canopy closure	Open canopy forests and non-forested habitat associated with predation risk and low prey availability	Slauson et al. (2007), Moriarty et al. (2015)
Canopy structure/heterogeneity	Associated with structural diversity of stands	Zielinski et al. (2006), Weir et al. (2012)
Stand height	Indicator of developmental stage	Bowman & Robitaille (1997)
Sapling density	Provides habitat for prey species (snowshoe hare) and may serve as escape cover	Carreker (1985), Slauson et al. (2007), Joyce (2013)
Shrub density	Provides habitat for prey species (snowshoe hare) and may serve as escape cover	Carreker (1985), Slauson et al. (2007)
Snag density/volume	Indicator of stand age and vertical complexity	Gilbert et al. (1997); Slauson & Zielinski (2009)
Horizontal cover	Related to sapling and shrub density; may serve as escape cover or provide habitat for prey species (snowshoe hares)	Carreker (1985), Slauson et al. (2007)

[a]Citation for biological significance of attribute to martens.

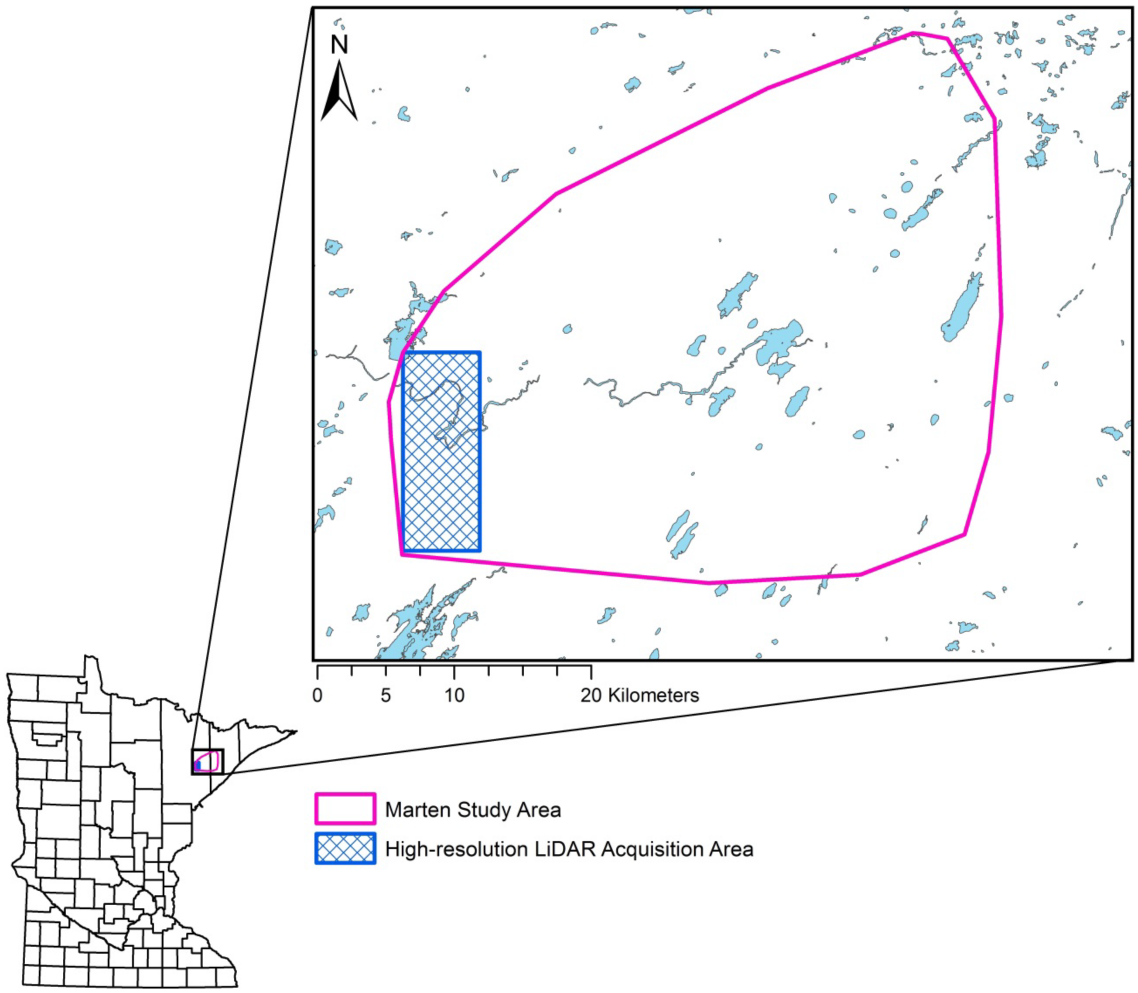

Figure 1. Map of primary marten study area in northeastern Minnesota with the location where high-density LiDAR data were acquired in 2014.

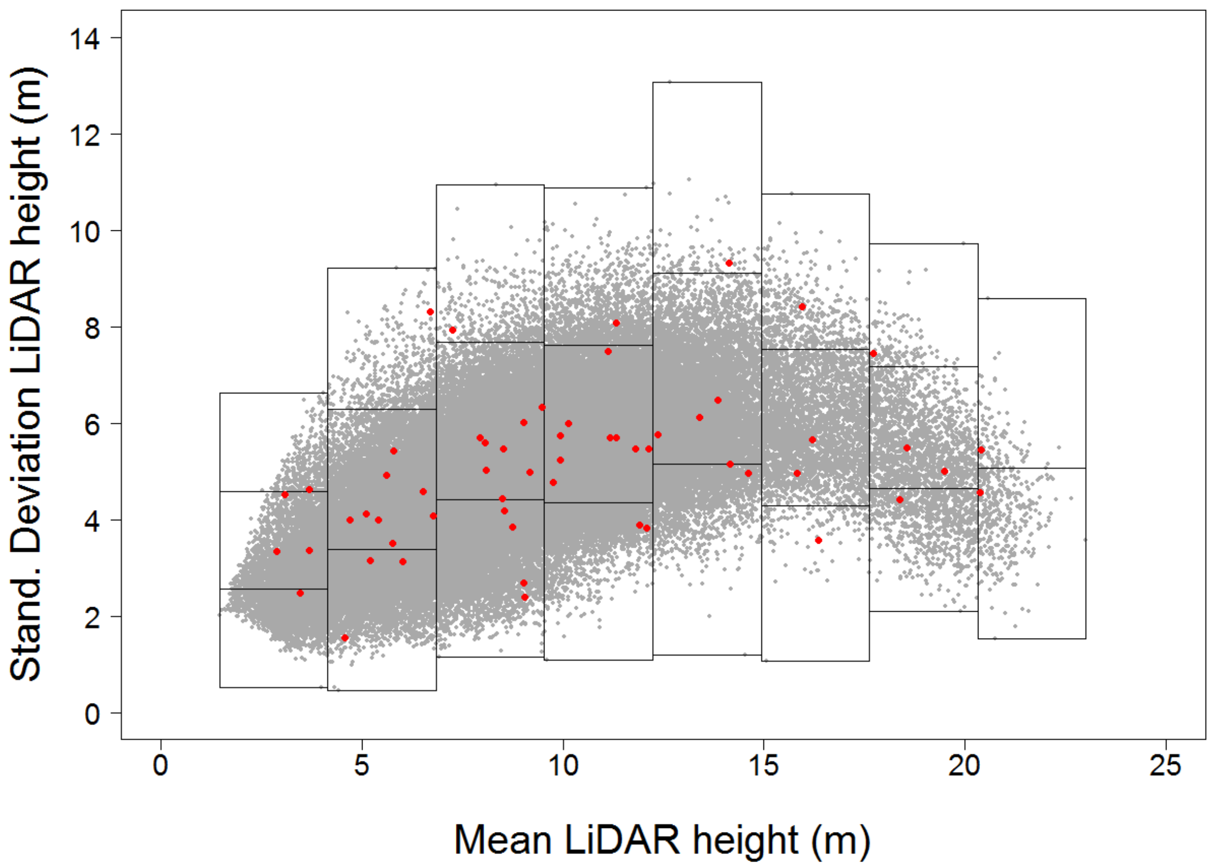

Figure 2. Sampling space for LiDAR-informed stratified random sampling design in a 25 mile^2 portion of St. Louis County, Minnesota. Structural variability within the study area is represented by mean and standard deviation in LiDAR return height for each 20 m pixel in the study area (gray circles). Black squares represent strata from which a random sample of plots was selected (red circles) and surveyed from 2014-16. Stratification was performed separately for areas with upland and lowland soil types.