Into the Third Dimension: Benefits of Incorporating LiDAR Data in Wildlife Habitat Models

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Abstract—LiDAR (Light detection and ranging) is a tool with potential for characterizing wildlife habitat by providing detailed, three-dimensional landscape information not available from other remote sensing applications. The ability to accurately map structural components such as canopy height, canopy cover, woody debris, tree density, and ground surface has potential to improve wildlife habitat models because animals interact and respond to three-dimensional habitat features. Prior to LiDAR, accurate measurements of structural features were difficult to obtain over large areas as other remote sensing data are based on two-dimensional spectral responses. The Southwest harbors a large diversity of unique vegetation communities, each with an associated wildlife assemblage with various management needs. Managers can use LiDAR to accurately characterize vegetation and landscape structural characteristics for entire districts or management units. Data surfaces derived from the LiDAR point cloud can be readily incorporated into species-specific or multispecies habitat models. Although LiDAR has received much attention in characterizing forest structure, fewer studies (n = 29) have suggested or incorporated this technology to improve wildlife habitat models specifically. Herein we provide a review of current LiDAR applications in wildlife habitat models, provide future directions, and detail how LiDAR can increase our ability to represent the world that animals experience.

Introduction

Managing landscapes for diversity and persistence of wildlife is dependent on our understanding of vegetative, structural, physiographic, and bioclimatic needs of species and how these factors contribute to vital parameters such as growth, survival, and coexistence (Morrison and others 2006). Increasingly, managers are faced with the need to monitor, conserve, and predict a diversity of plant and animal species and their specific habitat requirements over broad spatial scales; scales at which ground-based sampling is cost prohibitive, or infeasible due to remoteness. The vegetative communities and associated faunas in the Madrean Archipelago are extremely diverse, and harbor many endemic and endangered species (Lasky and others 2011; Poulos and others 2007), requiring substantial monitoring efforts over large areal extents. To conserve and manage the unique biotic assemblages on state and federal lands within the Madrean Archipelago, improvement in inventory of species diversity, identification of habitat requirements for a variety of taxa-from arthropods to large mammals-identification of areas of particular conservation importance, and continued monitoring of these areas to ensure species viability and probability of persistence would be beneficial.

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An important management tool is the ability to correlate the presence of a species with particular physiographic and vegetative features thought to be important components of the species' habitat. Many of these species-specific physiographic and vegetative features can be characterized with remote sensing data and, therefore, mapped over large areas to produce a habitat model (Lurz and others 2008). Habitat variables in such models are typically represented with remote sensing data obtained from passive sensors intercepting wavelengths of reflected light or heat from the earth's surface. These remote sensing products are only capable of representing the complexity of the landscape in two dimensions and do not directly measure structure (Vierling and others 2008; Lefsky and others 2002), which limits our ability to accurately describe and predict wildlife-habitat relationships. Active sensor technologies, such as light detection and ranging (LiDAR), can improve wildlife habitat models by more accurately describing fine-scale, spatially explicit, three-dimensional structural features related to animal use, occurrence, and reproductive success (Vierling and others 2008) and measure these features across entire management units, mountain ranges, or districts (Reutebuch and others 2005).

LiDAR data is generally collected from a laser-emitter scanner linked to an accurate global positioning system and inertial measurement unit (Reutebuch and others 2005); the resolution and quality of the data depends on both the scanner and the pulse density (Evans and others 2009; Reutebuch and others 2005). LiDAR data can be broadly categorized into two classes depending on the type of sensor: largefootprint wave-form data in which the pulse-return intensity over time is digitized, and small-footprint discrete return data (fig. 1) in which the spatial coordinates at which each laser pulse intersects an object are recorded (see Anderson and others 2005; Evans and others 2009;

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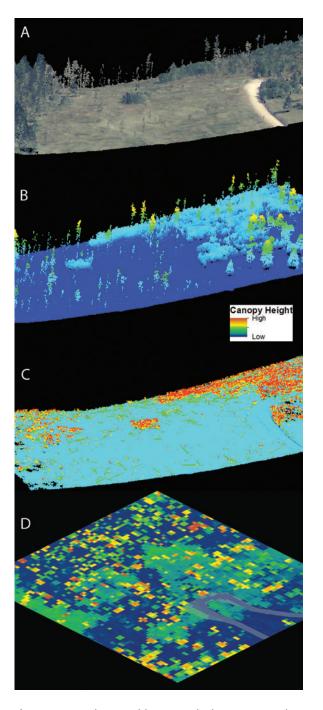


Figure 1—A visualization of discrete, multiple return LiDAR data: (A) LiDAR point cloud draped with georeferenced aerial imagery, (B) Height of LiDAR pulse returns above the ground showing all vegetation structure and density, (C) Height of LiDAR pulse returns ≤2 meters above the ground showing shrub/sapling vegetation structure and density, (D) raster layer created from mean canopy height surface, 3 m pixel resolution.

Lefsky and others 2002; Reutebuch and others 2005; and Vierling and others 2008 for excellent reviews). There are positives and negatives to each method (Evans and others 2009) and both provide unique structural information not available from spectral or thermal sensor technology and can greatly improve our ability to classify landscape

features and describe how animals relate to them. Herein we provide a review of current LiDAR applications in wildlife habitat models.

Methods

Literature Review and Synthesis

We conducted a search of published literature referenced in the Science Citation Index via Thompson Reuters Web of Science, accessing all years through 30 March 2012. We used five search routines: (1) wildlife habitat AND LiDAR in "Title," (2) habitat AND LiDAR in "Title," (3) wildlife habitat in "Topic," LiDAR in "Title," (4) habitat in "Topic," LiDAR in "Title," and (5) habitat AND LiDAR in "Topic." We tabulated the number of references returned in each search iteration. We selected references relevant to studies of wildlife-habitat relationships for further review. For each selected reference, we summarized main objectives, methodology, main conclusions, and management implications either stated or implied. We also examined whether the study was taxa specific, whether LiDAR-derived variables were correlated with landscape features of interest and whether or not incorporation of LiDAR-derived variables enhanced or significantly improved predictions and classification. We compiled these data to identify current uses of LiDAR in habitat models, commonly utilized LiDAR-derived variables, and new ideas or emerging techniques.

Results

Many studies refer to LiDAR as a tool potentially applicable to wildlife habitat assessment, monitoring, classification, and prediction, as indicated by the substantial number of references returned via our most general search criteria (fig. 2; habitat AND LiDAR in "Topic," n = 154), indicating the growing interest in and awareness of LiDAR technology. Relatively few references explicitly mention use of LiDAR in wildlife habitat applications (fig. 2; n = 18). However, a considerable subset of total references specifically address the applicability of LiDAR data to predict species presence, diversity, reproductive performance, or for creating variables that represent important structural features useful in wildlife habitat models. We reviewed 59 studies relating the use of LiDAR data to wildlife habitat characteristics and summarized some common research aims (table 1). The stated aims included assessment of LiDAR's ability to identify or quantify organisms, predict species presence, diversity, or performance, and predict physical and vegetative characteristics associated with species presence.

Of the 59 publications that we reviewed, the majority (45 or 76%) assessed the predictive capability of LiDAR-derived variables relative to field-based measurements; of these, all but two reported significant relationships between LiDAR-derived and field-based measurements (table 1). Just over half (31 or 53%) of the publications focused on a particular species or group of organisms (e.g. breeding forest birds, tree species, forest spiders, fish communities). Of these, all but two publications focused on using LiDAR to describe important habitat characteristics, animal relationships to structural features, and predicting occurrence based on these structural affinities. Avian habitat relationships were the most common area of taxon-specific focus (table 1; 13 or 42%). We detected no use of the term "LiDAR" within publications from wildlife-specific journals such as *The Journal of Wildlife Management* or *Wildlife Research*.

Many LiDAR-derived variables are strongly correlated with standard, field-based habitat measures, allowing for accurate predictions at multiple spatial scales (table 2; Hyde and others 2005; Lefsky

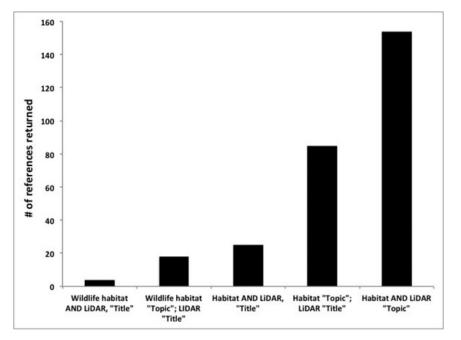


Figure 2—Number of published journal articles referencing LiDAR, habitat, and wildlife habitat returned from Web of Science search criteria including all years through 30 March 2012.

Table 1—Summary of common research aims from 59 studies relating the use of LiDAR data to wildlife habiat characteristics

Stated aims	# results	% of stated aims	Additional characteristics	# studies
- Assess potential to identify or quantify organi	sms		Predictive?	45
based on structural association	3	3.3		
 Assess potential to predict species performan based on structural associations 	ce 3	3.3	Significant relationship between LiDAR data and variable of interest?	43
 Assess potential to predict physical character 	istics 8	8.7	Incorporate spectral data?	12
 Review or comment 	9	9.8	Improvement over spectral data alone?	9
 Discuss applications 	11	12.0	Multiscale?	10
– Assess potential to predict vegetation				
characteristic	17	18.5	Taxa specific?	31
 Classification and mapping 	17	18.5	Taxa considered:	
- Assess potential to predict species presence o	r			
diversity based on structural associations	24	26.1	amphibians	1
· · · · · · · · · · · · · · · · · · ·			reptiles	1
Total aims	92		mammals	2
			arthropod	4
			fish	4
			plants	6
			birds	13

and others 2002; Vierling and others 2008). Some variables, such as canopy cover, tree or vegetation height, and canopy volume within various height categories, were obtained directly from the point cloud or waveform intensity, whereas other LiDAR-derived variables are secondarily estimated based on the relationship between primary LiDAR metrics and plot-based measurements such as basal area, biomass, and leaf area index (table 2; Dubayah and others 2000; Lefsky and others 2002; Ruetebuch and others 2005; Vierling and others 2008). Still other LiDAR-derived variables provide novel information that is difficult to obtain from field-based measurements such as highly accurate terrain models and secondarily derived metrics of slope, aspect, and rugosity (a measure of surface height variability).

Information unique to LiDAR data includes measures of pulse-return intensity, which can be used to distinguish among live and dead trees (Bater and others 2009; Kim and others 2009) and identify ephemeral wetlands beneath forest canopy cover (Julian and others 2009), as well as vertical structural complexity and volume. Vertical structural complexity and volume can then be used to model fine-scale differences in canopy use within bird communities (Clawges and others 2008), or specific nesting requirements of a single species (Goetz and others 2010). Additionally, new variables may be developed for describing vegetative composition, complexity, and physiographicvegetative associations based on ratios, linear relationships, or other novel combinations, which may further refine our ability to describe

 Table 2—Examples of LiDAR-derived metrics and applications for incorporating LiDAR variables in wildlife habitat models. Primary

 LiDAR metrics can be obtained directly from the LiDAR point cloud.
 Secondary LiDAR derivatives must be modeled based on the

 relationship between primary metrics and ground-based training data.
 Referen ces include studies incorporating metrics and/or

 applications.

LiDAR-derived metric	Primary or secondary?	Applications	LiDAR method	References
Canopy surface model	Primary	Height of trees or other features without terrain subtracted. Depict elevation of canopy surface above sea level.	Discrete return, waveform	Andersen and others 2005; Graf and others 2009
Canopy cover/closure	Primary	Produced from canopy surface model, important in habitat models for many bird and forest obligate species, but also those that prefer open areas	Discrete return, waveform	Dubayah and Drake 2000; Lefsky and others 2002; Hyde and others 2005; Martinuzi and others 2009
Canopy/vegetation height model	Primary	Height of trees or other features with terrain subtracted. Identify forest seral stages, habitat preferences for species with varying affinities for canopy, portions of the canopy, or stand age	Discrete return, waveform	Dubayah and Drake 2000; Lefsky and others 2002; Hyde and others 2005; Graf and others 2009
Canopy/vegetation profiles	Primary	ű	Waveform	Dubayah and Drake 2000; Lefsky and others 2002; Goetz and others 2010
Canopy base height	Primary	Identify inhabitable canopy area when subtracted from canopy height	Discrete return, waveform	Andersen and others 2005
Canopy volume	Primary	Identify differences in canopy structure among forest age classes, distinguish among canopy structural affinities of various species	Waveform	Lefsky and others 2002
Coefficient of variation vegetation height	Primary	Identify forest seral stages and be used with field data to predict occurrence of snags and woody debris	Discrete return	Bater and others 2009
Digital terrain model (DTM)	Primary	Delineate streambeds, create very accurate DEM, slope, aspect, ruggedness layers	Discrete return, waveform	Reutebuch and others 2003; Graf and others 2009
Digital Elevation Model	Primary	Elevation and other interpolated surfaces: slope, aspect, rugosity commonly used in habitat models	Discrete return, waveform	Goetz and others 2010; Martinuzi and others 2009
Foliage height diversity	Primary	Parse LiDAR vegetation returns within height intervals to estimate shrub or foliage density, important for ground nesting birds or other species that respond to foliage density at varying heights	Discrete return, waveform	Clawges and others 2008; Martinuzi and others 2009
Return intensity	Primary	Distinguish between live and dead biomass as dead trees,vegetation, and water have low return intensity compared to live trees and vegetation	Discrete return	Kim and others 2010
Standard deviation of vegetation height/ mean absolute deviation height	Primary	Index of stand structural complexity, age, seral stage, used to identify snags	Discrete return, waveform	Graf and others 2009; Martinuzi and others 2009
Vertical distribution of canopy structure	Primary	Estimate above-ground biomass, identify forest seral stage	Waveform	Dubayah and Drake 2000; Goetz and others 2010

Above-ground biomass	Secondary	Provides an estimate of forage availability and, when combined with multispectral band information, forage quality	Discrete return, waveform	Dubayah and Drake 2000; Lefsky and others 2002; Hyde and others 2005
Basal area	Secondary	Provides information on forest structure and density, an important variable in habitat models of forest-dwelling species	Discrete return, waveform	Dubayah and Drake 2000; Lefsky and others 2002
Canopy complexity/ diversity	Secondary	Describes the vertical complexity of vegetation structure, important for arboreal species	Waveform	Lefsky and others 2002; Goetz and others 2010
Diameter Breast Height (DBH)	Secondary	Provides information on stand age, tree maturity could serve as a proxy for food or nest site availability	Discrete return, waveform	Dubayah and Drake 2000; Lefsky and others 2002
Leaf area index (LAI)	Secondary	Provides an estimate of forage availability and, when combined with multispectral band information, forage quality	Discrete return, waveform	Dubayah and Drake 2000; Lefsky and others 2002
Timber/vegetation volume	Secondary	Identify habitable areas within tree or shrub cover	Discrete return, waveform	Dubayah and Drake 2000; Clawges and others 2008
Vertical distribution ratio	Secondary	Differenctiate among areas with high and low understory canopy structure, important for species sensitive to understory vegetative cover	Waveform	Goetz and others 2010

Table 2—Continued

important habitat features and predict presence of organisms on the landscape (Vierling and others 2008). Below, we briefly examine four application domains common to wildlife studies that have benefitted from incorporation of LiDAR-derived variables; we also provide a summary of LiDAR-derived variables applicable to studies of wildlife-habitat relationships (table 2).

Habitat Mapping

LiDAR's ability to accurately characterize physical terrain and vegetative structure can contribute to landscape classification efforts (Lefsky and others 2002). Classification techniques often include classification and regression trees, machine learning algorithms such as Random Forest (Martinuzzi and others 2009), and image segmentation via object based image analysis routines (Arroyo and others 2010). Adding three-dimensional structure increases a classification routine's ability to resolve among similar vegetative types and fine-scale physiographic features. When structural information such as canopy height, return intensity, and rugosity are combined with multispectral data from satellites like Landsat ETM, QuickBird, IKONOS (Arroyo and others 2010; Bradbury and others 2005; Clawges and others 2008) or hyperspectral data, classification accuracy is improved. With sufficient training data, LiDAR can be used to accurately classify, map, and model important structural habitat variables over broad spatial scales (Bradbury and others 2005; Lefsky and others 2002). Resulting classifications or maps can then be incorporated into predictive models of species presence or use of an area (Graf and others 2009; Martinuzzi and others 2009).

Predicting Pre sence or Use

The ability to predict an organism's presence and monitor for its continued persistence is a central goal among land managers and wildlife biologists alike (Hyde and others 2005). Because LiDAR data directly measures structural features that animals respond to (i.e. select for) at hierarchical spatial scales, LiDAR-based parameters have potential to improve the predictive capability of species distribution and probability of use models (Bradbury and others 2005; Seavy and others 2009). LiDAR-derived variables can be used to correlate finescale structural associations measured in the field and map these over large spatial extents, indicating areas where a species or community is likely to be found. For example, many species require dead trees (snags) for nesting (bluebirds, woodpeckers, and many tree squirrels), and may only use an area if such features are available. LiDAR can be useful in identifying or predicting the presence of snags, either based on the tendency for older forest structural stages to harbor more woody debris (Bater and others 2009; Martinuzzi and others 2009), or by the change in the intensity of LiDAR pulse returns based on the amount of dead wood in a plot (Kim and others 2009). Once maps of snag-class presence or absence were created for a single mountain, Martinuzzi and others (2009) used this information to predict the mountain-wide probability of use for several bird species based on their affinities for snags of particular sizes.

Availability of preferred microclimates can allow species to persist in otherwise extreme environments (Suggitt and others 2011). LiDAR's ability to accurately map fine-scale topographic features has potential for creating variables based on species' microclimate needs, and thermally important areas such as suitable sites for rearing neonates and likely locations for ectotherm burrows could be mapped at broad scales.

Correlates of Habitat Quality

Defining and improving habitat quality are topics of considerable interest in the wildlife literature and major goals for efforts such as land management, conservation, restoration, and endangered species recovery. In reality, however, habitat quality is difficult to assess, especially with metrics meaningful to the organism of interest (Hinsely and others 2006). Because of the difficulty in measuring structurally complex landscapes, habitat quality is often inferred from measures of reproductive success within a defined area. If reproductive success is strongly correlated with specific physiographic or vegetation structural features, then LiDAR can be used to define areas of predicted high reproductive success and habitat quality. LiDAR-derived metrics of canopy height were strongly correlated with mean chick body mass in Parus major over a 7-year study, and the direction of this relationship changed depending on springtime temperatures (Hinsley and others 2006). With this complicated interaction between climate, position in canopy, and nestling success established, it is conceivable that mean nestling mass and inferred habitat quality could be predicted annually over an entire forest based on LiDAR data and climate predictions.

Correlates of Biodiversity

With the threat of climate change and associated disturbance events, there is an increased need for rapid biological assessments of state and federal lands to both inventory and monitor species diversity and focus conservation efforts on areas associated with high biodiversity (Bergen and others 2009; Lesak and others 2011). Structural complexity and heterogeneity in both vegetation and physiography are associated with higher levels of plant and animal diversity relative to less complex sites (Bergen and others 2009). Therefore, LiDAR-derived variables should aid in identifying areas of high biodiversity and in predicting biodiversity of certain species assemblages based on their structural affinities (Bergen and others 2009). Forest dwelling beetle diversity and richness were correlated with LiDAR-derived measurements of elevation and tree height (Müller and Brandl 2009). Songbird species richness in deciduous forests was related to LiDAR-derived measures of forest structure such as canopy and midstory height and midstory density, with intra-guild species diversity (e.g. ground vs. aerial foragers, edge vs. interior specialists) described by different forest structural metrics (Lesak and others 2011).

Discussion

Proven Tool

LiDAR technology has become increasingly accessible and affordable over the last 10-15 years and continues to improve, providing valuable datasets that can be used by resource managers toward a variety of applications, from forestry and watershed science, to wildlife conservation and management over large spatial extents (Lefsky and others 2002; Ruetebuch and others 2005; Vierling and others 2008). While not all LiDAR data is equal (Evans and others 2009), it is evident that LiDAR technology and its various applications are no longer just theoretical. LiDAR technology has proven a useful tool when applied to many wildlife-habitat studies, and will continue to be refined. Every article we reviewed touted LiDAR's ability to quantify (often accurately) landscape and aquatic structural features that organisms identify as habitat, to map fine scale habitat associations over large areas, and to improve predictive models of species presence, use, reproductive success, and overall biodiversity. Combining LiDAR and multispectral datasets allows for maximal exploration of species' biotic and structural associations to more adequately represent the real world that animals inhabit and to which they respond.

Promising Future

In the Madrean Archipelago, LiDAR data collection has begun for the Coronado National Forest, and LiDAR-derived metrics promise to improve forest inventory and monitoring efforts, including habitat assessment and modeling for a variety of wildlife species. The sheer size and topographic and biotic diversity of national forests like the Coronado are representative of the challenges this vast and complex region poses in terms of conservation and management, and also represent an opportunity to demonstrate the benefits of incorporating LiDAR data to accurately describe, quantify, monitor, and conserve its great biological diversity and natural resources.

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The content of this paper reflects the views of the authors, who are responsible for the facts and accuracy of the information presented herein.