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Review

LiDAR Utility for Natural Resource Managers

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Abstract: Applications of LiDAR remote sensing are exploding, while moving from the research to the operational realm. Increasingly, natural resource managers are recognizing the tremendous utility of LiDAR-derived information to make improved decisions. This review provides a cross-section of studies, many recent, that demonstrate the relevance of LiDAR across a suite of terrestrial natural resource disciplines including forestry, fire and fuels, ecology, wildlife, geology, geomorphology, and surface hydrology. We anticipate that interest in and reliance upon LiDAR for natural resource management, both alone and in concert with other remote sensing data, will continue to rapidly expand for the foreseeable future.

Keywords: LiDAR applications; management; natural resources; remote sensing; review

1. Introduction

Light Detection and Ranging (LiDAR) increasingly is drawing the attention of natural resource managers. LiDAR data provide the needed resolution and detail of forests, rangelands, watersheds, roads, and other valued resources to inform and improve management decisions. LiDAR characterizations of ground and vegetation attributes of interest are consistently accurate, highlighting its potential for broad-scale applications. Multiple research studies in the past twenty years, many of which will be cited in this review, have contributed to a groundswell of interest that now extends well beyond the research community. Our objective in this review is to give forest managers and forest science researchers a better sense of how they might benefit by employing LiDAR, and why LiDAR might provide substantial improvement over other remote sensing data that they may (or may not) have tried to use in the past, perhaps with less satisfying results.

Unlike two-dimensional imagery, the vertical component of three-dimensional LiDAR data allows the analyst/user to separate ground vs. vegetation information, which is a prerequisite to most LiDAR applications, many of which focus exclusively on one or the other component. The most obvious and common example is the digital elevation model (DEM), the primary product of a LiDAR survey, used for hydrological, geomorphological, and other applications. The DEM of predicted ground elevation is an interpolated surface that accounts for topographic variation in the three-dimensional point cloud. Subtracting the DEM from the point cloud essentially "flattens" the earth, with the residual variation representing objects above the ground surface. Objects may be buildings in developed areas but otherwise represent predominantly trees and other vegetation.

Many LiDAR data users look no farther than the DEM, ignoring this residual variation. However, the residuals deserve the consideration of all users, because LiDAR ground vs. vegetation returns are not independent. This is evident when comparing DEMs generated from vegetated vs. non-vegetated environments. A DEM generated where vegetation is lacking is much "smoother", and more accurately predicts ground elevation; a DEM from a vegetated environment is "rougher" because a lower proportion of returns penetrate the canopy to reflect the ground surface. Thus, the decreased continuity of ground returns in a vegetated environment leads to increased discontinuities in the DEM, with associated uncertainties.

The residual variation in the LiDAR point cloud due to vegetation might be considered "noise" to users interested only in the DEM but is considered a "gold mine" of information by vegetation and wildlife ecologists, in addition to managers. Most obvious is the canopy height information, while another measure having a direct physical basis is percent canopy cover, calculated as the percentage of LiDAR returns intercepted by the vegetation canopy, within a bin size (cell resolution) specified by the user. Calculated height, cover, or other vegetation metrics within these bins can be output as two-dimensional raster layers. These raster outputs are analogous to the bands in a multispectral image, but with the LiDAR outputs indicative of structural features rather than spectral. The distribution of canopy height values within a defined bin is effectively a "structural signature" analogous to the "spectral signature" of a hyperspectral image pixel, but they characterize very different vegetation properties. A structural signature would be a better basis by which to classify, say, potential old-growth, while a spectral signature should be more sensitive to, say, vegetation health. There is tremendous potential for complementarity between structural signatures and spectral signatures in future data integration research.

There is additional useful information associated with LiDAR points, including intensity values and return levels. Intensity values can differ between the ground and vegetation, or between coniferous and deciduous trees. Return level can provide additional information on whether a point more likely reflects the ground (i.e., "last" return) or the top of the vegetation canopy (i.e., "first" return). Excluding the first and last returns, the probability of intermediate (2nd, 3rd, 4th, etc.) returns occurring at a given location should be in proportion to the canopy complexity. A fundamental characteristic of LiDAR that often is overlooked is that it is a sampling (not an imaging) tool. Even in the case of "scanning" or "imaging" discrete-return LiDAR systems, the fundamental sampling unit, or laser pulse "footprint", rarely is distributed so densely as to provide continuous spatial coverage, like image pixels. Moreover, they are vertically distributed discontinuously in the third dimension, which is the main reason why LiDAR point densities vary in proportion to surface complexity across the landscape, while image pixel densities are spatially continuous.

Over the past decade, many LiDAR papers have been published including LiDAR reviews [1–5]. As LiDAR projects migrate into the operational realm, an increasing proportion of these recent papers exemplify the utility of LiDAR for natural resource managers. In a companion paper, Evans et al. (this issue) present LiDAR acquisition, processing, and product standards intended to be used as a guide for terrestrial natural resource managers interested in employing LiDAR but perhaps discouraged from doing so due to lack of technical expertise. Our intention for this review is to improve understanding and appreciation for the nature and utility of LiDAR data across a broad suite of natural resource applications. This cross-section of the current literature in terrestrial natural resource applications of LiDAR will be broken down into the following three topics: (1) characterization of forest structure which includes canopy surface, canopy interior, and individual trees; (2) natural resource applications which encompass forest inventory, fire and fuels, ecology and wildlife, geology, geomorphology, and surface hydrology; and (3) sensor integration. This paper will conclude with suggestions for further natural resource applications for managers and researchers.

2. Characterization of Forest Structure

Measures related to vegetation canopy height are the most commonly used attributes used to describe forest structure [6]. Prior studies have established relationships between tree height and diameter at breast height [7], providing a framework for quantifying other structural attributes using height as a proxy. Several physically based variables that can be modeled readily with LiDAR-derived height measures and are key for modeling forest structure include: number of canopy strata, tree crown diameter, tree height, stem density, biomass, basal area, volume, and understory vegetation components (height and cover). Canopy cover, calculated as the percentage of the LiDAR returns intercepted by vegetation, can be used to describe a variety of structural and ecological components. Canopy measures such as gap size and distribution have been used to identify late successional forest structures [8,9], describe habitat quality, and greatly influence radiation budgets in forest [10]. Multitemporal LiDAR provides the means to characterize gap dynamics [11]. Tree crown diameter estimates also have been useful in providing measures of successional stage, habitat diversity, stand development, and ecosystem function [8,12]. Natural and anthropogenic influences cause dramatic fluxes in carbon, making remote sensing of carbon stocks elusive. Because LiDAR has the ability to represent the variability in vertical canopy structure and provide accurate biomass estimates, ecosystem dynamics models can use LiDAR-derived inputs to quantify and monitor net carbon stocks and carbon flux in ecosystems [13,14].

Quantifying forest structure using LiDAR has been approached in three ways: (1) binning the data in the three-dimensional point cloud to reduce the data volume to a single measurement (e.g., height) representing the canopy surface; (2) calculating distributional moments (i.e., mean, variance, skewness, kurtosis) and other statistics (e.g., minimum, median, maximum, percentiles, etc.) on the height or density measures, also within a bin; and (3) identifying individual trees.

2.1. Canopy Surface

Measuring canopy surface height was the primary goal in early, single return, profiling systems [15–18], enabling estimation of biomass and vegetation structure characteristics. Attributes such as aboveground biomass could be predicted due to strong relationships with height [7]. Information regarding light gaps could be explored using canopy height distributions [19]. In a study to explore the aerodynamic properties of canopies, height profiles were used to quantify the aerodynamic roughness length, identifying the canopy height where the wind speed becomes zero [20]. Experiments such as this could eventually provide a risk index for potential wind blow-down events in forested systems. Using an inexpensive profiling system that was deployed using a low-flying helicopter, canopy height and canopy surface rugosity were used to classify trends in internal canopy structure such as percent cover and maximum and mean height [21]. This study empirically demonstrated that measures of the canopy surface can be used to identify certain internal structural characteristics.

2.2. Canopy Interior

Prior to the advent of LiDAR, measures of internal canopy structure historically have been highly impractical and thus virtually unattainable at landscape levels. LiDAR data provide densely spaced canopy height measures that can be empirically related to field measures of stand height [22,23], as well as other measures of stand structure [24]. To provide measures of vertical structure, the foliage-height profile [25,26] was adapted to LiDAR as the canopy-height profile [27] to infer the vertical distributions of all material within the canopy [28]. This method provides a means of quantifying complex structures that influence functional processes such as light interception and crown competition. Although the focus of this review is on discrete-return LiDAR systems, a notable advantage of waveform (i.e., "continuous return") LiDAR systems is their more detailed characterization of vertical canopy structural profiles. Specifically, the canopy volume method classifies height ranges as a set of volumetric pixels (i.e., voxels), using LiDAR collected from waveform systems such as the Scanning LiDAR Imager of Canopies by Echo Recovery (SLICER) sensor [29]. Each voxel's location in the canopy is classified along with the amount of light intercepted, describing biophysical differences across forest and successional types and greatly improving understanding of canopy structure. SLICER and other waveform sensor data are also related to canopy light penetration, leading to significant correlations between LiDAR-derived and field-based measurements of photosynthetically active radiation [30]. Similarly robust relationships have been established between field measures of incident photosynthetically active radiation and estimates derived from more commonly available discrete-return LiDAR [31]. The number of canopy returns above some height threshold (e.g., 1.37 m or breast height), divided by the number of total returns, is a highly useful measure of fractional cover. Fractional cover models that also use the intensity and return level information, and not just the proportion of canopy returns, have been found to be more accurate across different forest ecozones [32].

Stand structure attributes and aboveground biomass have been successfully estimated across different forest biomes using a variety of techniques including height quantile relationships and simple regression [29,33–36]. A suite of structural attributes were predicted in northern hardwood forests [37] and in Scandinavia [38], using moderate density LiDAR data and stepwise multiple regression models to predict: mean tree height, mean diameter, stem density, basal area, and timber volume. These same standard forestry inventory measures have been accurately predicted in coniferous and deciduous forests using best subsets regression and discrete-return LiDAR with relatively sparse pulse densities of 2–3 m [39,40]. Studies such as these make a strong case for LiDAR-based, landscape-level forest inventories in a management context. LiDAR's ability to accurately represent canopy height and cover at variable sampling densities makes prediction and comparisons of vegetation structures feasible [41]. Indeed, scale-invariant approaches to predicting forest structural attributes hold much promise for predicting forest biomass [42] and other fundamental structure attributes of interest to forest managers. LiDAR-derived canopy height and density metrics (or structural indices) can also provide a means of assessing biodiversity [43] and exploring complex landscape patterns across a variety of scales. The advantages of higher sampling densities may be overblown, as increased LiDAR sample point densities only affect canopy height and density metrics from the very top or base of the canopy, and thus may add little value to stand-level management [44]. Single-story and multistory stands can be distinguished with 97% accuracy [45] with less than current technological capabilities.

Canopy complexity and complex terrain interact, potentially making LiDAR forestry applications more difficult. However, LiDAR enabled accurate prediction of canopy and subcanopy height under a wide range of canopy conditions in tropical systems, although accuracy was reduced under configurations of obscured ground and high slopes [46]. In a temperate mixed-conifer forest where individual conifer species distributions vary largely in response to topography, a variety of vegetation and topographic metrics generated from LiDAR data were used to predict plot-level basal area and tree density of [47,48]; the nonparametric Random Forests [49] algorithm yielded the most accurate and robust models. Studies characterizing the interior of closed canopies with plot-level variables are currently more applicable to operational stand-level management than studies focused on individual tree-level variables.

2.3. Individual Trees

Discrete-return sensors can collect data at point densities sufficient to accurately identify individual tree crowns in open canopies, such as in savanna woodlands [50]. The primary hurdle in large scale applications is the separation of tree crowns in dense forest [51,52]. In dense closed canopies tree crowns overlap, causing a model to perceive several trees as one, producing high rates of commission and omission errors in estimated single tree attributes from canopy height models. One successful approach combined canopy height model information with a quantitative measure of the relative penetration of small footprint discrete-return LiDAR pulses through the canopy, to reliably extract stem height and crown cover estimates that were sufficiently accurate for the inventory of multistory Australian woodlands with <700 stems ha^{-1} [53].

Several other novel approaches have been used in identification of individual trees for various applications. One study used multiscale smoothing on a canopy height model and then fit a parabolic surface at each scale to determine the best scale for identifying individual tree crowns; using the segmented crowns, crown shape information was derived to effectively separate pine and spruce [54]. A related study used a similar approach to identify tree crowns and then regression equations were fit to estimate stem diameter and tree height [55]. A wrapped surface approach was developed and applied to urban trees to estimate tree height, crown width, live crown base, height of the lowest branch, and crown volume [56]. Pre- and post-harvest LiDAR data have been used to identify specific trees removed from a segmented watershed [57]. Change detection at this scale has broad implications for forest ecology and management (e.g., harvest contract inspection).

In a study conducted in Finland on a mixed Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*) forest, the accuracy of LiDAR in predicting individual tree height was assessed [58]. Accuracies were high on detecting dominant trees (83%) but were reduced considerably in mixed heterogeneous stands (40%). A variable moving window approach was developed to account for heterogeneous structures in the Piedmont physiographic province, Virginia, USA; validation gave support to the variable window approach, which explained 85% of the variation in tree height [59]. Further application of the variable window algorithm estimated volume and biomass based on identified tree heights and crown diameters [60,61]. Validation of these results using Forest Inventory and Analysis (FIA) data across a range of vegetation and structural types explained 62% of the variation in crown diameter of dominant trees and 78% of the variation in biomass.

Several other individual tree identification methods have been considered and include local height maxima, minima or valley-following methods [62], and multiscale object-oriented approaches [52]. A multiscale two-dimensional discrete approximation to the continuous wavelet transformation showed some improvement over the variable window approach in a western mixed conifer forest [63,64]. These results demonstrate promise in the upscaling of individual trees for developing stand-based inventory distributions and structural projections.

3. Applications for Natural Resource Management

3.1. Forest Inventory

Many of the above studies support the development of large-scale inventory efforts, potentially being extended to regional level estimates utilizing data such as U.S. Forest Service Forest Inventory and Analysis (FIA) plots. A few promising inventory approaches have been proposed treating LiDAR as a subsample to provide large-scale inventory data [4]. A classic double sampling methodology for inventory estimates using LiDAR shows great promise [65,66]. Operational large-scale inventory efforts produced accuracies commensurate with field-based inventories in Norway [38] and Austria [67,68]. LiDAR has tremendous potential as a broad-scale sampling tool, such as in remote areas of Alaska, to inventory forest condition class and discriminate between deciduous and coniferous forest types, based on the intensity values collected during leaf-off conditions [69]. In closed canopies where tree crowns overlap, the ability to discriminate deciduous and coniferous species based on return intensity values, is more problematic and varies with LiDAR sensor settings [70]. In Norway, spruce vs. birch classification accuracies of 77% and 73% were obtained using structural and intensity features, respectively; combining these features increased the classification accuracy to 88% [71].

The tree attribute most readily measured in the field is diameter at breast height, and traditional forest inventories result in a distribution of diameters, typically measured in variable radius plots within stand sampling units. The density of LiDAR canopy height measures allows for much higher resolution maps, calibrated and validated with tree diameter distributions measured within independently geolocated, fixed-radius plots. Tree growth can be projected by coupling tree lists to a growth engine such as the Forest Vegetation Simulator (FVS; [72]). In mixed conifer forests of northern Idaho, LiDAR-based basal area predictions mapped at a 30 m × 30 m resolution were aggregated to the stand level and found to be statistically equivalent to predictions projected with FVS from industry stand exams [73]. A single LiDAR collection provides only a snapshot in time, yet the canopy height distribution is sufficiently informative to predict successional stage [74]. Diameter distributions of trees >12.5 cm can be reliably predicted from LiDAR canopy height data, as trees grow taller and stands less dense [75]. Predictive ability may be enhanced by using mixture models to help account for irregularities in structure at the plot level [76]. Direct detection of seedlings with airborne LiDAR is probably unrealistic, but because seedling densities relate to overstory canopy structure, this relationship could be exploited to improve predictions of regeneration success [77]. Not surprisingly, forest height growth can be directly measured with multitemporal LiDAR with more certainty at the plot level than at the tree level [78].

3.2. Fire and Fuels

The role that fire plays in the ecosystem as both a mechanism of disturbance and a threat to people, property, and natural resources makes fuel and fire behavior modeling essential for both researchers and managers. Fire models based on stand inventories have been used extensively for providing information on fuel attributes, with remote sensing playing an underutilized role [79]. The small role that remote sensing has played in fuel modeling is mostly due to the inability of spectral data to capture the structural complexity of closed canopies. Variables such as crown bulk density, crown fuel weight, and crown base height are by nature vertically organized through the canopy, making LiDAR uniquely suited to characterize these fuel attributes. There has been increased interest in using LiDAR to provide landscape-level input into fire behavior and fuel loading models [80–85], for which vertical structural information is critically needed.

To model specific variables for input into the FARSITE model [86], LiDAR was used to successfully predict crown bulk density, foliage biomass, and crown volume [81]. In another study, LiDAR-derived canopy density and modeled crown base height were input into FARSITE and found to describe much of the spatial variability associated with different fuel treatments [85]. Because FARSITE is a spatially explicit simulation model and these variables provide an accurate representation of the vertical canopy structure, it is now possible to derive a very accurate picture of spatially distributed fire behavior. Fuel model types [87] have been successfully identified using a LiDAR-derived measure of surface texture at the ground, thus characterizing fuel beds at the plot level [82]. A regression approach was used to predict crown bulk density, canopy base height, and crown fuel weight, demonstrating the effectiveness of LiDAR for characterizing landscape-level fuel-related variables [84]. Ground-based terrestrial laser scanner (TLS) LiDAR systems have been used to more precisely quantify fuel volume and other fine-scale fuelbed characteristics [88,89].

3.3. Ecology and Wildlife

Influences of habitat condition and forest structure on faunal assemblages have been well explored in wildlife studies. The seminal MacArthur and MacArthur study [90] established strong relationships between height diversity and bird species richness. Spectral remote sensing has provided landscape-level ecological data for describing the distribution and habitat utilization of key indicator species such as neotropical migrant birds [91]. However, most studies integrating remotely sensed data utilize only two-dimensional variables (e.g., land cover). Using LiDAR, three-dimensional relationships can be much more thoroughly explored [92], furthering our understanding of habitat use within the internal canopy. Because LiDAR can provide detailed structure information at various scales across the entire landscape, spatially-explicit hypotheses can now be tested allowing for quantification of the significance and sensitivity of relationships as well as spatial predictions. For instance, maps of the key wildlife habitats of understory shrubs and snags were predicted from LiDAR canopy density and height metrics in north-central Idaho [93]. Further use of LiDAR in building landscape structural relationships with faunal species is relatively unexplored and is a field ripe for further research [94].

3.4. Geology, Geomorphology, and Surface Hydrology

The DEMs derived from LiDAR provide fine-scale topographic features in unprecedented detail and improved accuracy over traditional DEMs, particularly in areas of low relief (e.g., wetlands) where precision limitations of traditional DEMs cause considerable mapping error [95]. LiDAR applications in the earth sciences—much like those in forestry—have progressed given the additional structural properties captured by LiDAR beyond what spectral imaging can provide. Geologists have used LiDAR extensively to identify fault lines, sediment transport, and bedrock types [96–98]. A variety of surface roughness metrics derived from LiDAR were used to quantify surface morphology and identify potential deep-seated landslides near Christchurch, New Zealand [99]. Another study quantified material type and topography influencing two canyon-rim landslides in southern Idaho [100]. Surface downwasting in a glacial environment was quantified by subtracting LiDAR-derived DEMs collected two years apart [101]. Similarly, a bare-earth DEM was subtracted from a peak snowpack DEM to accurately map snow depth [102]. LiDAR-based topography has been used to map side channel shallow water refuge habitats for targeted salmon stream restoration [103]. Subsequently, an airborne, blue-green waveform LiDAR (EAARL) was used to quantify the topographic amplitude of stream channel morphology and predict salmon nesting habitats [104].

4. Sensor Integration

Whereas LiDAR provides detailed forest structure information, spectral remote sensing is more sensitive to vegetation composition and phenology. Integration of LiDAR and spectral data thus provides a much more comprehensive view for understanding ecosystems. Besides providing a comprehensive classification of vegetation, the fusion of image and LiDAR data can be used to build empirical relationships that can be extrapolated to areas where spectral data are available but LiDAR data are not, offsetting the high cost of LiDAR [105,106]. A study integrating spatially discontinuous

LiDAR with spatially continuous Landsat ETM+ data using both aspatial regression and spatial statistical models produced more accurate canopy height maps than using either modeling method alone [105]. Similarly improved height predictions were achieved in boreal forests by relating LiDAR to vegetation units derived from segmented Landsat ETM+7 imagery [106]. In a related study to measure wildfire effects on boreal forest structure, spatial patches analogous to forest stands were segmented from multitemporal Landsat imagery, then related to pre- and post-fire profiling LiDAR transects, to capture fire-induced structural change [107].

A number of other sensor integration studies cut across the fields of natural resource applications exemplified in the preceding sections. In a forestry application, LiDAR and four channel multispectral data were used to identify individual tree species and height [108]; by combining LiDAR and spectral information they improve their classification accuracy by up to 30% over a single data source. An accuracy of 96% was achieved in identifying individual tree species when combining LiDAR and multispectral image data [109]. Leaf Area Index (LAI), a critical structural property of vegetation canopies used to predict mass and energy fluxes, was reliably predicted from LiDAR in coniferous forest; however, the inclusion of SPOT image-derived spectral vegetation indices in an integrated model provided only negligible improvement [110]. A method was formulated for using LiDAR and effective LAI to validate vegetation cover estimated from multispectral IKONOS and Landsat ETM+ imagery [111] in ponderosa pine forest. In the Black Hills of South Dakota, USA, vegetation height layers identified from LiDAR were combined with IKONOS multispectral satellite imagery to assess avian species occurrence, density, and diversity [112].

Forest biomass estimates have been improved by integrating LiDAR and hyperspectral image data [113]. LiDAR and hyperspectral image data have been combined in Hawaiian rain forests to detect invasive species [114], particularly alien grasses that have altered the fire regime in Hawaii [115]. Fusion of LiDAR, multispectral, and Interferometric Synthetic Aperture Radar (InSAR) data was tested to optimize prediction of variables relating to wildlife habitat and carbon stores [116]; results showed that the best combination of variables were from LiDAR and ETM+7, whereas InSAR and Quickbird did little to improve models. A similar study explored LiDAR-radar synergy for predicting aboveground biomass, and found only negligible improvement by including radar [117]. LiDAR has also been found to be superior to radar for accurately detecting the height of individual trees and forest plots [118]. However, others argue that because LiDAR and radar sensitivities differ so markedly at fine scales, LiDAR-radar comparisons are only useful at broad scales [119]. For instance, aboveground biomass was accurately estimated across the entire forested region of southern Quebec province in Canada by integrating DEM information from the Shuttle Radar Topography Mission (SRTM), spaceborne waveform LiDAR from the ICESat Geoscience Laser Altimeter System (GLAS), airborne profiling LiDAR collected over ground plots, and ground inventory plot data [120].

Much less is known regarding the utility of LiDAR assessments in nonforested ecosystems than in forests. One challenge arises from an inherent electronic limitation of discrete-return LiDAR systems. Discrete-return systems can only record returns separated by nanosecond time intervals that translate into a vertical distance of several cm. Dense, low vegetation can generate a return but may lie too close to the ground for the sensor to reset in readiness for a subsequent ground return from a given laser pulse. LiDAR returns in dense shrublands have been found to reflect the larger woody structures within the shrub layer, rather than the shrub canopy surface [121]. This systematic height underestimation bias has been widely observed in forest canopies but may be more problematic in shrublands given their much lower height relative to the ground. Thus, theoretically, a lower proportion of ground returns would be collected from a shrubland having the same canopy cover as a forest, but rigorous testing of this theory is required. In practice, the high pulse density capability of current discrete-return systems should ensure adequate ground returns for most applications. Small footprint full-waveform LiDAR systems can provide more detailed information than discrete-return LiDAR systems in low vegetation and forest understories [122]. Data integration may provide another practical solution. One recent study observed that the application of either high pulse density LiDAR or corresponding very high spatial resolution (0.25 m) spectral imagery enabled individual shrub metrics to be determined at accuracies similar to other studies focused on individual trees [123]. At the very least, the canopy structure detail provided by LiDAR can be integrated with multispectral imagery to enhance the accuracy of rangeland vegetation classification [124].

5. Conclusions

The body of knowledge and literature on useful LiDAR applications has rapidly expanded in recent years. This points to the improved ability of LiDAR, compared to passive optical imagery, in capturing the three-dimensional form of the earth's surface. LiDAR is especially informative and advantageous wherever the surface structure is complex. Greater awareness regarding LiDAR utility and limitations is becoming increasingly relevant for a broader audience as LiDAR projects migrate from the research to operational realms. As highlighted in this review, most LiDAR research applications have focused on "what can we do" questions, such as can we measure individual tree heights and crown dimensions, canopy fuel loads and biomass, etc. This methodological focus is exemplified by the considerable body of papers that focus on ever improved methods to derive accurate DEMs, characterize individual trees, assess differing sensor characteristics, evaluate between conifers and deciduous species, among other topics. Moreover, most studies to date are case studies that focus on a static condition (e.g., vegetation structure) at a single point in time. As more natural resource managers begin to employ LiDAR datasets, research will be needed to link both the structural and spectral signatures in novel ways that actually help elucidate ecological processes at larger spatial and temporal scales. Aspects of such research may include the direct input of LiDAR-derived metrics into empirical growth and ecophysiological process models such as FVS and Biome BGC, respectively. New LiDAR research directions will likely include multitemporal assessments to measure and monitor processes such as forest growth, fuel accumulation, and carbon sequestration.

We expect that the quantity and quality of natural resource applications of LiDAR remote sensing will continue to expand, with new research developments continuing to meet operational demands, and operational needs in turn driving research questions. This is exactly what drives productive research and technology transfer in the broader LiDAR user community. For these reasons, we anticipate that LiDAR remote sensing will continue to be a dynamic and exciting field for the foreseeable future.

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