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Authors

Guo, Q
Su, Y
Hu, T
et al.

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Lidar Boosts 3D Ecological Observations and Modeling

A review and perspective

**QINGHUA GUO, YANJUN SU, TIANYU HU, HONGCAN GUAN, SHICHAO JIN,
JING ZHANG, XIAOXIA ZHAO, KEXIN XU, DENGJIE WEI, MAGGI KELLY,
AND NICHOLAS C. COOPS**

The advent of lidar has revolutionized the way we observe and measure vegetation structure from the ground and from above and represents a major advance toward the quantification of 3D ecological observations. Developments in lidar hardware systems and data processing algorithms have greatly improved the accessibility and ease of use of lidar observations in ecological studies. A wide range of studies has been devoted to accurately measuring and modeling vegetation structural and functional attributes from lidar data across a range of spatial scales (from individual organs to global scales) and ecosystem types (e.g., forest, agricultural, grassland, and urban ecosystems).

As lidar technologies and applications advance, there is an increasing recognition of the importance of studying 3D ecosystem structures. Research has demonstrated that lidar observations can be effectively used to calibrate and improve ecological models and produce more detailed and accurate results, bringing new ecological insights that challenge our existing knowledge. Nevertheless, we argue that the incorporation of 3D lidar observations into ecological models remains in its infancy, and the potential of fusing 3D lidar observations with multisource remote sensing data for contributing to a new understanding of ecological processes has not yet been fully explored. The acquisition of 3D ecological observations should continue embracing the era of multidimensional big remote sensing data, bringing both new challenges and opportunities. Exploring the potential of multitemporal and multiplatform remote sensing

data through data fusion will benefit the next generation of ecological models.

OVERVIEW

Remote sensing has been recognized as an effective technique for describing and analyzing the status of ecosystems from individual plots to the entire biosphere [1], [2]. Data sets acquired by near-surface, airborne, and spaceborne platforms are widely used by ecologists to characterize and model ecosystem processes and to understand the fundamental theories that shape our ecosystems [3], [4]. The accumulation of time-series remotely sensed imagery from the Landsat set of sensors, the Sentinel set of sensors, and Moderate-Resolution Imaging Spectrometer (MODIS) further advances our capability to monitor ecosystem changes and predict their responses to the changing climate [5]–[8]. Using this type of optical, passive remotely sensed data, our ecological interpretation depends upon the observed land surface reflectance, which is a function of the sun and sensor viewing geometry and of the optical attributes of the land surface objects (Figure 1) [9], [10]. When these interpretations are linked to vegetation, they are mostly limited to the canopy surface since the observed within-canopy and ground reflectance is a function of vertical plant area densities [11]. However, the vertical information and internal structure of vegetation are often neglected or represented by simple geometric models in these types of ecological studies [12], [13]. Although a wide body of work is devoted to deriving vegetation structure information from these passive optical images [14], the accuracy of the derived vegetation structural attributes has generally been

low [15], [16] and progressed slowly until the emergence of lidar technology.

Unlike optical remote sensing, which measures land surface reflectance, lidar is an active remote sensing technique that measures the distance from the sensor to targeted objects by recording the time of flight of emitted laser pulses (Figure 1). The distance measurements are then converted to accurate 3D coordinates through the aid of positioning techniques (i.e., integrated navigation algorithms and simultaneous localization and mapping algorithms) [17]–[19]. Because short-wavelength laser pulses can penetrate vegetation canopies through gaps in leaves and branches, lidar can accurately depict the internal structure of vegetation canopies and shows early potential in overcoming the aforementioned obstacles of optical remote sensing [20]–[23]. Over the last three decades, lidar has been successfully used to estimate 3D vegetation attributes [e.g., vegetation height, leaf area density (LAD), and branching architecture] from plot to global scales and from individual to group levels [24], [25], enabling progress toward tackling 3D ecological problems [26]–[28].

In this review, we highlight how the increasing use of lidar has allowed a transition of ecological observations and modeling from 2D to 3D, how lidar sheds light on understanding important ecological processes, and how lidar applications should be further developed under the new paradigm of big data.

LIDAR DEVELOPMENT FOR ECOLOGICAL OBSERVATIONS

The increasing use and accessibility of lidar-based ecological observations can first be attributed to the development of hardware systems and data processing algorithms. On the hardware side, lidar sensors have evolved from being capable of recording only single returns per emitted pulse along a single transect [29] to recording the entire returned waveform [30]; meanwhile, the size and cost of lidar sensors has decreased significantly, greatly expanding the availability of lidar data for ecological observations. On the algorithm side, the requirement for new algorithms to deal with the complex and large-volume 3D data has introduced unprecedented challenges for the remote sensing community. Currently, we are still in the stage of developing algorithms that are robust under different topographic and vegetation conditions.

HARDWARE DEVELOPMENT

Lidar was initially designed for altimetric tasks (i.e., sea ice surface mapping and topographic mapping) using laser profiling systems [31]–[33] that recorded up to one return per emitted laser pulse [34]. Vegetation returns were usually treated as noise during this stage [33], [35]. Later, engineers equipped laser scanners with the ability to record multiple returns per emitted laser pulse and used highly precise positional information from satellite-based positioning systems, allowing the development of the basic data format of

FIGURE 1. The principles of passive optical remote sensing and active laser scanning.

lidar, i.e., the point cloud [33], [36]. Since returns within the vegetation canopy can better describe vegetation structure, multireturn lidar represented a big leap in lidar ecological applications [37]. Further enhancing the capability of lidar in capturing vegetation structure, waveform lidar capable of recording the total amount of returned energy with a short time interval (1–5 ns, typically) emerged [30].

Laser scanners can be mounted on various types of platforms [e.g., tripods, backpacks, automobiles, unmanned aerial vehicles (UAVs), manned aircraft, and satellites], with capabilities ranging from the plot level to the global scale (Figure 2). Terrestrial laser scanners usually have a ranging limit of 100–500 m and are a desirable tool for plot-level ecological observations [38]. Although certain terrestrial laser scanners can reach a maximum range of >1 km (e.g., REIGL VZ-2000i), their use is often constrained for ecological applications due to issues of increasing sensitivity to noise in vegetated areas [39]. Traditionally, terrestrial laser scanners are mounted on fixed tripods and use a stop-and-go mode to acquire data, a method that requires a huge effort to register multiscan lidar data [40]–[42]. Recent advances in integrated navigation techniques and simultaneous localization and mapping algorithms create new possibilities to mount terrestrial laser scanners on mobile platforms, such as backpacks and ground vehicles [43], [44], greatly improving data acquisition efficiency.

Airborne lidar systems, also known as airborne laser scanning, involve the integration of positioning and

FIGURE 2. The resolution and spatial extent of various lidar platforms: terrestrial lidar, backpack and mobile lidar, unmanned aerial vehicle (UAV) and airborne lidar, and spaceborne lidar.

inertial measurement technologies and have greatly increased ranging capacity. They are often mounted on an aircraft, such as a helicopter, to cover areas ranging from hundreds to thousands of square kilometers. With the development of manufacturing technology, commercial laser scanners are becoming lighter, smaller, and cheaper. For example, solid-state lidar sensors can be lower than 1 kg in weight and less than US\$1,000 in price. These sensors have greatly promoted the development of UAV lidar systems, which significantly increase the flexibility and reduce the cost of collecting landscape-scale lidar observations [45].

Spaceborne lidar systems have the longest ranging capability and are configured with a profiling design including multiple lasers. They can produce tracks or transects of laser pulses that are driven by the orbits of the platforms. For example, the footprint of the Geoscience Laser Altimeter System (GLAS) onboard the *Ice, Cloud, and Land Elevation Satellite (ICESat)* has a nominal diameter of ~65 m and is separated by 170 m along track and by tens of kilometers across tracks with global coverage [46]; the footprint of the Global Ecosystem Dynamics Investigation (GEDI), launched on the International Space Station on 5 December 2018, has a nominal diameter of ~25 m and is separated by 60 m along track and by ~600 m across tracks and constrained between 50° S and 50° N [47]. The recent development of single-photon counting technology allows for a new mode for long-range laser scanning [48]. It uses plane array detectors to receive laser pulses with low energy and, therefore, can generate lidar data with high point density at high altitude [49]. *ICESat-2*, launched in 2018, adopted this technology to replace the waveform lidar approach of the original *ICESat* GLAS [50].

Besides the aforementioned hardware progress, recent hardware development has equipped lidar with the ability of emitting laser pulses in multiple bands (e.g., multispectral or hyperspectral lidar) [51]–[54]. This can overcome the weakness of the lack of spectral information of current lidar

sensors and is beneficial for differentiating vegetation species and organs and retrieving physiological traits [55]–[57]. However, multispectral and hyperspectral sensors are still in their early developmental stages, and multispectral and hyperspectral lidar data are still very rare and expensive.

ALGORITHM DEVELOPMENT

With the continuous improvement of lidar hardware systems and the increasing availability of ground-based and aerial lidar observations, the demand for ecologically meaningful vegetation attributes from lidar observations has grown significantly. However, lidar data have required radically different data processing principles and pipelines than those provided by existing remote sensing algorithms and software.

Lidar data can be categorized into discrete lidar data and full-waveform lidar data on the basis of the data acquisition method. Discrete lidar data are most commonly distributed in the LAS format, a format specifically dedicated to storing 3D data that is standardized, documented, and maintained by the American Society for Photogrammetry and Remote Sensing. This point data format enables point cloud data to be stored optimally and contains a variety of metadata and point attributes unique to each data campaign. Accessing and processing the data from the LAS data format, however, still require a large amount of memory, necessitating the development of lidar-specific algorithms and packages to optimize processing speed and memory requirements. A range of open source and commercial applications and packages have emerged in recent years and include LiDAR360, Terrasolid Fusion, and the lidR R programming package [58], making discrete lidar data processing with user-friendly interfaces more accessible.

Compared with discrete lidar, full-waveform lidar data have the potential of detecting weak pulses [59] and providing extra waveform parameters (e.g., echo amplitude and width) [60], which have shown advantages in vegetation structure mapping and species recognition [61], [62]. However, full-waveform lidar data can be relatively difficult to interpret visually and are usually decomposed into discrete lidar data before use [63]. Decomposition processes assume that lidar waveform is a sum of Gaussian components that can be described by Gaussian functions [30]. The essential step is to discriminate the number of land surface responses from lidar waveforms and to estimate the initial parameters for waveform decomposition [64].

Several approaches have been developed to fulfill this goal, including the traditional pulse detection approach [63], the nonlinear least-squares approach using the Levenberg–Marquardt optimization algorithm [61], [65], [66], the maximum likelihood approach using an expectation–maximization algorithm [67], and the stochastic approach using the reversible jump Monte Carlo Markov chain method [68]. With the estimated initial parameters, waveform decomposition can be implemented by iteratively fitting each detected echo with a Gaussian model, and different Gaussian models

(i.e., Gaussian, lognormal, and generalized Gaussian) should be selected based on the land surface type [62]. Once decomposed, waveform lidar data can be further processed using the same pipeline as discrete lidar data for ecological applications. It should be noted that, although a spatiotemporal analysis approach has been developed to extract features directly from lidar waveforms, it has been mostly used in areas with regular-shaped objects and rarely used in vegetation-related applications [30]. Therefore, this review focuses mainly on discrete or decomposed lidar point clouds hereafter.

Currently, standardized protocols for processing lidar point clouds in ecological studies include four steps: outlier removal, ground point filtering, normalization, and vegetation attribute extraction (Figure 3). Outlier removal aims to remove noisy points caused by high-flying objects or low-level errors, and commonly used algorithms include *k*-means cluster filtering, bilateral filtering, Laplacian operator-based filtering, and mean shift filtering, for example [69], [70]. Ground point filtering aims to identify ground points from lidar data and thereby generate high-precision and high-resolution digital elevation models (DEMs) using interpolation algorithms (e.g., kriging, inverse distance weighting, and triangulated irregular network algorithms) [71], [72]. Many algorithms have been developed to fulfill this task of ground-point filtering by treating terrain as a continuous surface, including slope-based filters, interpolation-based filters, morphology filters, and segmentation-based filters [73], [74]; however, the performance varies significantly under different terrain and vegetation conditions [75], [76]. Special attention needs to be paid to the selection of filtering algorithms based on the characteristics of the study area. Normalization is designed to remove the influence of terrain elevation on lidar height measurements [77]. A normalized point cloud can be calculated by subtracting the terrain elevation from lidar points.

With normalized lidar point clouds, vegetation attributes can be extracted using a variety of approaches. Two well-established types of approach for deriving vegetation attributes are regression-based approaches (also known as area-based approaches) and individual plant segmentation-based approaches [78]. Regression-based approaches estimate vegetation attributes for preestablished grid cells (typically 20–30 m across) by building regression models between field measurements and lidar metrics that summarize the distribution of lidar points within each cell [79], [80]. Among the various regression methods, linear regression has been recognized as one of the most effective because of its ease of interpretation and relatively high accuracy [81]. In addition to linear regression, the random forest method also shows a remarkable performance in deriving vegetation attributes because it can overcome the overfitting problem seen with decision tree algorithms and does not require an assumption of normality of the data [81].

To date, vegetation attributes that have been successfully modeled using regression-based approaches include height, canopy cover, basal area, biomass, and volume at

the community level [37], [82]–[84]. Since regression-based approaches can use a sampling strategy to derive wall-to-wall maps of vegetation attributes [85], they can potentially reduce the need for highly intensive field-based programs and, as a result, offer more spatial details [86].

As the quality of lidar data improves (e.g., point density and accuracy), the demand for deriving vegetation structural attributes at the individual plant level also increases [87]. Individual plant segmentation, i.e., delineating individual plants from the lidar point cloud, has therefore become the prerequisite first step, and the procedures can be generally divided into two categories: canopy height model (CHM)-based methods and point cloud-based methods. CHM-based methods rely on gaps among plants in lidar-derived CHMs and use image segmentation techniques (e.g., watershed segmentation) to delineate the boundary of individual trees [88]–[91]. Point cloud-based methods segment points of each individual plant directly from lidar point clouds [92]–[95]. Vegetation structural attributes at the individual plant level [e.g., tree height, diameter at breast height (DBH), leaf area index (LAI), crown base height, and crown diameter] can then be extracted from individual plant points using geometry-based methods [96]. However, the performance of these algorithms varies significantly across different topographic and vegetation conditions [90], [97]. Depending on the accuracy of tree identification, these methods can be prone to errors in both individual object detection and in tree crown delineation [97], [98] and become less reliable in vegetation stands or communities that are highly vertically complex and have many suppressed and lower-level structures [90].

Recently, deep learning techniques have been successfully used to identify and extract features from 3D lidar point clouds and have segmented individual plants with very high accuracy [99], [100]. This includes separating individual organs (e.g., stem, branches, and leaves) of an individual plant [101], [102] and, therefore, makes quantifying the structural attributes of individual plant organs (e.g., branch length, branching angle, and leaf length) possible [103], [104]. Although deep learning techniques in lidar data processing are still under development, they are expected to play an increasingly important role in the future [105].

THE TRANSITION FROM 2D TO 3D ECOLOGICAL OBSERVATIONS

The highly accurate and informative 3D information provided by lidar sensors is changing the way we study and understand terrestrial ecosystems and is leading the transition from 2D to 3D ecological observations. In this section, we illustrate recent progress in 3D ecological observations and present examples from four terrestrial ecosystems: forest, agricultural, grassland, and urban ecosystems.

FOREST ECOSYSTEMS

Lidar has been widely used to measure forests in 3D at different scales [106]. Among the various lidar platforms,

terrestrial laser scanning (TLS) can capture the most accurate and detailed tree structure information and has been largely used to improve the efficiency of forest inventory practices, especially with the help of terrestrial mobile lidar systems (e.g., backpack lidar and mobile lidar) (Figure 4) [19], [43], [107], [108]. Forest structural attributes that can be measured from TLS data include, but are not limited to, DBH, tree height, LAI, clumping index, LAD, leaf inclination angles, crown diameter, crown base height, and crown volume [109]–[114]. Many of the structural attributes derived from lidar data avoid the saturation effect that is typical for passive optical sensors and may even challenge the accuracy of traditional field measurements [115]–[117]. For example, the accuracy of TLS DBH measurements was reported to range from 0.74 to 3.51 cm and tree height measurements from 1.36 to 6.53 m [38], [118], [119]. The accuracy of TLS measurements is primarily influenced by the density and accuracy of point clouds, tree density, and forest type [120], [121]. Moreover, structural features extracted from TLS data also showed the potential to identify tree species by using deep learning techniques [122]–[124]. The combination of TLS volume estimations and tree species information can be used to model aboveground biomass with an accuracy equivalent to that obtained from allometric equations [125], [126]. With the development of stem-leaf separation algorithms, the extraction of tree structure measurements has moved toward quantifying branching architecture, including branching angle, branch diameter, and branch length [25], [127]. Detailed tree structure models from TLS data also provide the opportunity to parameterize 3D radiative transfer models to simulate light distribution and gas exchanges of the canopy [128], [129].

Moving toward the landscape scale, airborne and UAV-borne lidar data are the two main platforms used for measuring wall-to-wall forest attributes [45], [130], [131]. Besides high-resolution topographic products (e.g., digital elevation model and slope) [71], [132], wall-to-wall forest attributes—such as tree height, LAI, LAD, canopy cover, basal area, and aboveground biomass—can also be estimated from lidar data using either object- or area-based approaches (Figure 4) [82], [130], [133]–[138]. Past research has demonstrated strong correlations between field and lidar measurements of height, volume, and biomass, among others ($R^2 = 0.43$ – 0.94) [139], with accuracies driven by topographic conditions, lidar point density, scan angle, and forest type [140]. For example, canopy cover calculated from lidar data with large scan angles ($>20^\circ$) tends to be overestimated [141]. By combining the structure information provided by lidar with optical imagery acquired from satellite or aircraft, vegetation communities in homogeneous forests can be identified more accurately [142], and shrubs can be distinguished from trees more easily than when using optical imagery alone [143].

Airborne and UAV-borne lidar data can also be used to estimate individual tree structural attributes through the

FIGURE 4. Examples of cross-scale forest attribute estimations from lidar observations. At a local scale, detailed and accurate individual tree-level attributes can be obtained from near-surface lidar systems. At landscape to regional scales, forest attributes can be derived either at the individual tree scale or at the group scale. At the global scale, forest attributes are commonly estimated through the fusion of field estimations, near-surface lidar data, spaceborne lidar data (e.g., GLAS full-waveform lidar data), and optical imagery. LAI: leaf area index; LAD: leaf area density; DBH: diameter at breast height.

aid of individual tree segmentation algorithms [92], [93], [144]–[146]. However, the accuracy of individual tree segmentation from airborne and UAV-borne lidar data is not as high as using TLS data [94], [147]–[150]. Attributes that can be extracted are limited to the upper canopy—e.g., tree height, crown base diameter, and crown base height—due to the relatively low point density [140], [151], [152]. UAV-borne lidar data are more preferred for extracting individual tree-level parameters than are airborne lidar data since they have higher point density (>100 points/m²) [45], [153]. Airborne and UAV-borne acquired lidar data provide unique data sets that can be used to reconstruct and visualize forest landscapes and are increasingly used by forest managers [154], [255].

At regional to global scales, none of the existing lidar platforms can provide complete coverage alone, and the integration of multiplatform lidar data with multisource remote sensing data (e.g., optical imagery or radar data) is the most commonly used method for generating spatially continuous forest products (Figure 4). Field measurements (or TLS measurements) can be first linked with airborne or UAV-borne lidar data to generate landscape-scale

estimations, which are then linked with spaceborne lidar data, optical imagery, and radar data to generate regional- and global-scale forest attributes using regression methods [155]–[158]. For example, Su et al. [159], Lefsky [160], and Simard et al. [161] used this strategy to generate tree height maps of the Sierra Nevada of California and of the whole terrestrial biosphere. Hu et al. [162], Nelson et al. [156], and Su et al. [163] also successfully used this strategy to estimate the large-scale distribution of aboveground biomass.

Spaceborne lidar data have played an important role in this strategy since they can alleviate the saturation effect in the upscaling process [162], [163]. GLAS data onboard *ICESat* provided one of the few available spaceborne lidar data sets. Despite the relatively sparse footprints, these data have been used in a number of freely available global forest height and biomass products undertaken with reasonable accuracy (R^2). The newly launched *GEDI* and *ICESat-2* are providing spaceborne data with smaller and denser footprints, which may help improve the accuracy of regional and global forest attributes. However, a combination of both field observations and likely midscale airborne or UAV-borne point clouds is needed to ensure this at continental to global

scales. Regression models built for one specific vegetation type cannot be transferred reliably and accurately to other study sites with different vegetation types [164], [165], and, therefore, collecting airborne or UAV-borne lidar data covering different vegetation types is important for regional to national forest attribute estimation.

Across temporal scales, repeated lidar observations could be used to monitor forest structure dynamics and evaluate large-scale tree competition mechanisms. For example, repeated TLS observations can monitor seasonal forest structure dynamics using the variations in lidar vertical profiles [166], [167]; bitemporal airborne lidar data can be used to detect forest structure changes caused by forest thinning, wildfires, and so on [127], [168]–[171]; and multi-temporal lidar data can evaluate tree growth and mortality and investigate tree competition mechanisms [172].

While the application of lidar in the forest ecosystem is more mature compared to its application in other ecosystems, research needs remain. The robustness of forest structural attribute extraction algorithms, for example, still needs improvement. Many algorithms have been derived and applied to specific forest types, topographies, or regions, with less research done on transferability. Although deep learning techniques show great potential in addressing this obstacle, more studies are needed to develop networks with high efficiency and accuracy. Moreover, lidar has been less frequently used in forest ecosystem monitoring due to the lack of temporal lidar data sets, despite the unprecedented 3D observations for forest ecosystems provided. More data collection campaigns to acquire lidar data with a constant time interval (e.g., the National Ecological Observatory Network) are needed.

AGRICULTURAL ECOSYSTEMS

Lidar applications in agricultural systems are still in their early developmental stages. Of areas where lidar data are being applied, the monitoring and modeling of crop growth in agricultural ecosystems show the potential to revolutionize the field of crop phenotyping and function modeling [173], [174].

Current progress in lidar-based crop phenotyping and structure modeling centers mainly on target detection and phenotype extraction [Figure 5(a)]. Target detection aims to detect the location of individual plants or organs. Until recently, most target detection studies have been based on detecting panicles [175], blooms [176], and roots [177], [178] from images. Lidar-based target detection has been recognized as a difficult task due to the challenges in processing the massive, irregular, and unordered lidar data. Jin et al. [99] built a Faster R-CNN deep learning network to detect individual maize plants from terrestrial lidar data, laying the foundation for analyzing crop density and structure variations at the individual plant level [104], [179], [180]. Jin et al. [103] further demonstrated a deep learning-based method for the separation of stem and leaves of an individual maize plant from terrestrial lidar data. Similarly,

Malambo et al. [104] detected individual sorghum panicles using a density-based clustering method from terrestrial lidar data. The classification and separation of individual crop organs offer the possibilities to measure crop phenotypes more precisely.

Extracting crop phenotypes from segmented lidar point clouds relies mainly on geometric methods. Compared to traditional manual and image-based methods, lidar-based methods have the advantages of being nondestructive, accurate, and robust [181]–[183]. Currently, TLS and mobile lidar platforms are most commonly used in the extraction of fine phenotypes at the individual plant level [184]–[187], while drone and airborne lidar systems are generally applied to derive large-scale community-level phenotypes [188], [189]. For example, Madec et al. [186], Walter et al. [187], and Jimenez-Berni et al. [190] estimated canopy height and canopy cover of wheat from a mobile lidar system and found them consistent with manual measurements, outperforming imagery-based methods; Jin et al. [103], [165] extracted individual maize height from TLS data with a high agreement with manual measurements ($R^2 > 0.91$) and systematically evaluated the accuracy of phenotypes at stem and leaf levels, including leaf inclination, leaf length, and stem diameter. The high accuracy of phenotype extractions proves that lidar is a promising and valuable tool for the structural modeling of crops and also promotes the development of function modeling in agriculture.

Biomass and yield estimation are indispensable function indicators for crop breeding and agricultural management and are closely linked to crop structure [187], [190]. For example, Walter et al. [187] estimated wheat biomass from lidar projected volume ($r = 0.86$); Jimenez-Berni et al. [190] estimated wheat biomass from a lidar-derived 3D voxel index and a 3D profile index, with an R^2 of 0.93 and 0.92, respectively. Biomass estimation from lidar-derived vegetation indices has been evaluated for various crop types [189]. On the basis of biomass estimation, crop yield can be modeled through a conversion of the harvest index [191]. Moreover, lidar, especially the field lidar phenotyping system, is increasingly used to monitor temporal (e.g., diurnal and seasonal) changes of crop phenotypes (e.g., height, leaf area, and biomass) under environmental stresses, allowing timely observations of phenotype dynamics [Figure 5(b)] [166], [192].

The high price of field phenotyping systems has been one of the major obstacles preventing it from being used at scale. The recent development of near-surface lidar systems (e.g., backpack and unmanned ground vehicle systems) has both reduced the costs and improved the efficiency for collecting lidar data, which may further boost the application of lidar in agricultural systems [193]. However, conventional lidar data lack spectral information, and integrating lidar with other remote sensing sensors (e.g., hyperspectral, thermal, and fluorescence sensors) is indispensable in exploring more diverse structural and function phenotypes [194]–[196].

GRASSLAND ECOSYSTEMS

Grasslands are characterized by very dense but relatively low vegetation. Traditional grassland resource inventories rely heavily on field sampling, which might be inaccurate and time inefficient [197]–[199]. Beyond the spectral information provided by optical remote sensing [200]–[202], we are seeing increasing applications of lidar in grassland ecosystems to extract a range of structural attributes.

Structural attributes are important indicators for characterizing grassland ecosystems [203] and are closely correlated to functional attributes [204]–[206]. However, evaluating structural attributes of grasslands at the individual plant level is difficult even with lidar due to the low height and high density of grass [Figure 6(a)] [199]. At present, structural attributes (e.g., canopy height, canopy volume, and canopy cover) at the community level are the most widely used. Canopy height can be extracted using point- [203], [207], CHM- [199], [208], [209], and voxel-based methods [197], [203], [210]. Point-based methods have been reported to often underestimate grass height for lidar data with relatively low point density [207]. CHM- and voxel-based methods can be highly influenced by the choice of pixel (or voxel) size [197]. Canopy volume can be calculated from lidar data using volume surface differencing approaches [198], voxel counting approaches [204], [210], and convex-hull approaches [210]. Greaves et al. [204] showed that a volume surface differencing approach can generate canopy volume estimations with accuracies similar to those of other approaches but with higher efficiency. Canopy cover is commonly calculated as the ratio of the number of vegetation lidar echoes to the total number of lidar echoes [199].

Using lidar-derived structural attributes as predictors, grassland functional attributes can also be estimated by means of regression-based methods [Figure 6(b)]. Aboveground biomass, a functional indicator of grassland productivity, has been extensively studied by relating destructive field biomass measurements to lidar parameters (e.g., canopy height, canopy volume, and canopy cover) to generate wall-to-wall biomass products [198], [204], [205], [211]. Both Schulze-Brünninghoff et al. [210] and Xu et al. [199] have suggested that lidar-derived canopy height and canopy cover are strongly correlated with aboveground biomass; random forest and stepwise linear regression have been found to produce more robust regression models for

FIGURE 5. Lidar technology enables accurate crop phenotyping and growth monitoring. (a) Individual organ-level crop structural phenotype extraction using a field phenotyping system built by the authors' team ([185]). (b) Crop growth monitoring during the whole growth cycle and environmental stresses.

aboveground biomass estimation [199]. Moreover, it has been reported that the integration of lidar with spaceborne optical imagery can be used to extrapolate aboveground biomass with a higher accuracy than using only optical imagery [Figure 6(c)] [208].

The applications of lidar in grassland research is still in its infancy as there are still a number of technical questions that need to be addressed. For example, filtering lidar ground points in grasslands, which is the prerequisite step for extracting structural attributes, is a difficult task due to the dense canopy coverage. Structural attributes derived from lidar have been very limited in grassland ecosystems, and more studies are needed to develop ecologically meaningful grassland attributes. Moreover, combining spectral data with structure and functional attributes extracted from lidar data and exploring the relationship between them are another key direction that will need attention in the future [212].

URBAN ECOSYSTEMS

In urban ecosystems, lidar not only allows the quantification of 3D vegetation structures but also can be used to extract and assess buildings. One of the first data sets to be applied in lidar urban applications was airborne lidar data [213], [214]. Recently, terrestrial mobile lidar systems, such as backpack lidar and mobile lidar, have become dominant

FIGURE 6. Grassland structure and functional attribute estimations using lidar observations. (a) Community-level structural attribute estimation through the voxel-based method; (b) functional attribute (biomass as an example) estimation using the regression-based method; and (c) structure and functional attribute upscaling through the integration of multiplatform and multisensor remote sensing data.

in urban applications due to their unique advantage of allowing data to be collected along roads (Figure 7) [215]. UAV lidar systems have been used less frequently due to the strict flying regulations in urban areas [216].

Unlike in other ecosystems, lidar applications in urban ecosystems have the unique prerequisite of classifying vegetation (e.g., trees and grass cover) and artificial objects (e.g., buildings, power lines, bridges, vehicles, and railways) from lidar point clouds (Figure 7). Various classification algorithms have been introduced that can be generally divided into four categories: pixel-wise classification based on lidar-derived surfaces, object-based segmentation based on lidar-derived surfaces, hierarchical semantic segmentation based on lidar point clouds, and deep learning-based methods.

Pixel-wise classification methods apply traditional machine learning methods (e.g., artificial neural network, maximum likelihood, support vector machine, random forest, Gaussian mixture modeling, rule-based classification, conditional random fields, and Markov random fields) on lidar-derived surfaces (e.g., digital surface models and intensity maps) to classify urban objects [217]–[223]. Object-based segmentation methods, which employ a user-defined procedure to classify segmented objects from lidar-derived surfaces [224]–[226], are designed to avoid the salt-and-pepper effect resulting from pixel-wise classification [227],

[228]. Numerous studies have reported that object-based methods can achieve an overall accuracy of >80%, which is higher than what can be derived with pixel-wise methods [229]–[234].

To date, much of the focus in an urban context has been on the identification of large urban objects, while small objects (e.g., trees, street lamps, and power lines) are often neglected. Instead of classifying urban objects from lidar-derived surfaces, hierarchical semantic segmentation methods rely on the entity and contextual information (e.g., points, voxels, planar segments, and objects) within lidar point clouds, which can be used to classify specific urban objects (e.g., roofs, walls, pavements, grass fields, trees, and street lamps) with an accuracy of greater than 90% [235]–[237]. Deep learning-based methods apply convolution neural networks directly to lidar point clouds or lidar-derived surfaces to classify urban objects, and studies have shown that they are highly robust and can achieve an overall accuracy of greater than 96% [238]. Moreover, recent studies have suggested that combining lidar data with color information, such as from aerial or street view photos, can further improve the classification accuracy [218], [224].

Vegetation structure and functional attributes—such as tree height, DBH, crown diameter, crown base height, LAI, tree species, vegetation volume, vegetation coverage, and aboveground biomass—can be extracted from the

classified lidar point clouds in urban environments (Figure 7) [162], [214], [239]–[242]. The accuracy of these extracted attributes is usually higher than in forested areas due to the relatively simple tree species composition and regular tree arrangement in urban ecosystems [239], [243]. One parameter that has drawn the attention of researchers is the urban green space—the public and private urban spaces primarily covered by vegetation [244], [245]. Lidar offers a new way to quantify urban green space from 2D horizontal arrangements to 3D horizontal and vertical arrangements, greatly benefiting studies of urban function connectivity, urban planning and management, and biodiversity [242], [246], [247]. Besides vegetation indices, attributes related to buildings can be also developed from the lidar points, including building height, building mass, building volume, building 3D model type, urban envelope index, and sky openness (Figure 7) [238], [242], [248]–[252]. These 3D building indices can be used together with urban vegetation attributes to study microclimates and urban flora and fauna, as well as urban planning and management.

Overall, lidar applications in urban ecosystems share common characteristics with other ecosystems in terms of extracting vegetation information, but they involve more efforts in recognizing and processing artificial urban components. The current major obstacles lie in how to handle the huge amount of lidar data at a city scale, especially for data collected by mobile lidar systems. Moreover, how to incorporate lidar-derived 3D parameters into urban ecological studies and modeling still needs to be further explored.

LIDAR OBSERVATIONS TO INFORM 3D ECOLOGICAL MODELING

The observation and quantification of ecological attributes from lidar data are providing key insights into ecological modeling studies. In forest ecosystems, accurate forest structure observations from lidar allow the integration of vegetation structure information into solar radiation modeling, vegetation dynamic modeling, and biodiversity modeling across scales, which ultimately can lead to a better understanding of forest ecosystems. Approaches

FIGURE 7. 3D lidar observations in urban ecosystems and ecological index examples that can be derived from classified lidar point clouds. Backpack and mobile lidar data can be used to cover areas along and off the road, respectively, while UAV and airborne lidar data can cover a large urban area. The fusion of multiplatform lidar data can provide more complete 3D urban observations. The numbers in brackets represent corresponding references. GML: geography markup language.

like voxel-based transfer models and discrete anisotropic radiative transfer models can be used to simulate accurate 3D radiation distribution [128], [253], [254] and thereby investigate the influence of canopy structure on the canopy light regime and photosynthetic partitioning [129]. Accurate 3D tree structural attributes also provide the opportunity to validate hypotheses in current vegetation dynamic models. For example, Su et al. [256] used TLS data to prove that canopy architecture displays a strong spatial variability along climate gradients and to reject the current hypothesis in vegetation dynamic models of a constant ratio between canopy height and canopy size. Tao et al. [257] found that canopy height exhibits a hump-shaped correlation with water availability, rejecting the prevailing assumption that canopy height follows a linear correlation with water availability. Xue et al. [258] further proved that tuning vegetation dynamic models with lidar-derived attributes can lead

to significantly different carbon modeling results. These studies suggest that interpreting the spatial and temporal dynamics of forest structure and incorporating them into the current dynamic vegetation models are necessary and important research directions [256].

Moreover, the vertical dimension provided by lidar data enables much more comprehensive and accurate descriptions of animal habitats [259]. Forest canopy structure is a very important factor influencing animal behavior (e.g., nesting, hunting, and breeding) that is often neglected in current niche modeling studies [26], [260]. Feeding niche models with lidar-derived vegetation structural attributes has the potential to overcome this obstacle. For example, Zhao et al. [261] showed that lidar-derived structural attributes could better characterize fisher (a rare mammal) dens; García-Feced et al. [262] and North et al. [263] found that using lidar-derived snag trees and the cover of tall trees could predict California spotted owl nesting habitats; Loarie et al. [264] used lidar-derived vegetation structure to explain the hunting behavior of male lions; and Blakey et al. [265] and Eichhorn et al. [266] used lidar-derived structure information to understand how deer, birds, and bats choose their habitats. Coops et al. [267] proposed a 3D index using lidar data capturing the three main components of vertical and horizontal vegetation structure (i.e., height, cover, and complexity) and proved that this index can be used to predict avian species richness more accurately than using climate or land cover data alone. However, animals of different taxonomic groups interact with forest canopy differently. Thus, investigating the influence of 3D forest canopy structure on a wider range of animals can benefit our understanding of the correlation between canopy structure and biodiversity.

In agricultural ecosystems, lidar has improved the accuracy of crop growth modeling. Crop growth models aim to simulate the crop growth cycle with the input of environmental variables (e.g., temperature, precipitation, soil moisture, and fertilizer) [268], [269]. Lidar can provide detailed and accurate structural traits at an individual organ level, which could be a robust information source for validating and calibrating crop growth models. Additionally, the 3D light regime of agricultural ecosystems can be more accurately modeled with the aid of 3D radiative transfer models [270], which can refine the environmental input of crop growth models. The combination of improved crop growth models and accurate lidar observations could ultimately lead to more efficient crop management. However, the incorporation of lidar data into crop growth models is still in its very early stages. A recent study by Liu et al. [271] used a function–structure–plant model to provide *in silico* experiments for exploring the feasibility of lidar-based phenotype estimation (e.g., a green area index) with machine learning methods. More studies are still urgently needed to investigate the potential of lidar in the crop growth modeling process.

In grassland ecosystems, airborne and UAV lidar data have been used to model spatial heterogeneity and

biodiversity [211], [272]. For example, Jansen et al. [273] used lidar-derived structural attributes to model the influence of grazing on the spatial heterogeneity of a bunchgrass prairie ecosystem; Moeslund et al. [274] successfully used airborne lidar data to assess the local biodiversity of grasslands and meadows in bushes; and Marcinkowska-Ochtyra et al. [275] and Fisher et al. [276] modeled the distribution of grassland invasive species. These results, combined with biomass modeling results from lidar [199], can ultimately provide much more accurate information for managing and protecting grassland ecosystems. However, currently, studies in this direction are still few in number. More studies are urgently needed to link lidar-derived structural attributes with functional attributes to better simulate grassland ecosystem processes.

In urban ecosystems, detailed 3D information of built and vegetation structures can be assimilated into models to understand urban microclimates, investigate urban biodiversity, and ensure the health of urban ecosystems. The 3D arrangements of buildings and vegetation can alter the spatial and temporal variability of solar radiation [277]–[281], and assimilating the 3D information of buildings and vegetation into climate models can improve the accuracy of microclimate simulations [282]–[285]. Moreover, urban ecosystems have become an important habitat for both flora and fauna, and anthropogenic activities are important factors influencing the biodiversity of urban ecosystems. The integration of lidar-derived information into biodiversity studies can help better describe the spatial distribution of vegetation and animal species in an urban environment [286], [287]. Modeled vegetation and animal distribution can be further used to analyze and predict human health risks (e.g., exposure to pollen and mosquito abundance) [288]–[290]. In addition, lidar data can be used to model risks related to power lines, flooding, and so on, and thus help in devising management plans that ensure the health of urban ecosystems [196], [291]–[295].

To conclude, lidar-derived 3D information is an important input for ecological models. The integration of lidar observations into ecological models can improve our understanding and may even challenge our existing theories on ecological processes. Despite the consensus on the importance of integrating lidar observations into ecological models, this process is still in the early stages across ecosystems. Incorporating 3D lidar observations across scales and ecosystems need to be extensively explored in future studies.

FROM 3D TO THE MULTIDIMENSIONAL BIG DATA ERA

In conjunction with optical remote sensing and field surveys, lidar has played a crucial role in the development of 3D ecological observations and modeling. Lidar data have allowed researchers to gain new insights and gather finer details about ecological processes [256], [257]. Nevertheless, increasing demands have emerged to expand our ecological observations from 3D (i.e., X, Y, and Z) to multiple

dimensions (i.e., X, Y, Z and the spectral and temporal dimensions) to compensate for the weaknesses of single-type or single-date remote sensing data.

MOVING TOWARD THE FUSION OF STRUCTURAL AND SPECTRAL INFORMATION

Lidar has the known limitation of lacking spectral information. The intensity recorded by lidar sensors is highly influenced by signal attenuation and multipath effects [142], [296]. Although there have been significant efforts in developing algorithms to calibrate lidar intensity [52], [297]–[301], it is still difficult to generate physically meaningful spectral reflectance values or cross-platform comparable intensity values [296]. Moreover, most current lidar systems have only one band in the near-infrared wavelength range. Recent developments in dual-band and multiband lidar sensors show the potential to address the limitations of single-band lidar systems [57], [302]–[304], yet the costs of dual-band and multiband lidar sensors are high and their capability to derive cross-platform comparable reflectance values is still questionable [305]. Another solution for addressing this problem is to fuse lidar data with multispectral and hyperspectral data to compensate for the weakness of each type of data (i.e., lidar data lack spectral information and multispectral and hyperspectral data lack structural information). Studies have proven that by fusing lidar data with multispectral or hyperspectral data, the resulting data can outperform the single type of data in terms of species classification, vegetation mapping, biomass estimation, and so on [163], [224], [305]–[308]. Therefore, the simultaneous collection of multisource remote sensing data remains the trend for future ecological observations.

MOVING TOWARD REGULAR TIME-SERIES ECOLOGICAL OBSERVATIONS

Current available lidar data sets have been used to create valuable benchmarks of ecosystem attributes (e.g., vegetation attributes, snow depth, and tree line information) [163], [309]–[311], which can then be used as important baselines to evaluate ecosystem dynamics under the background of global climate change. However, we need to monitor vegetation dynamics using multitemporal data so that we can further understand ecological processes and predict possible ecosystems changes in future climate scenarios. Thus far, such studies have been dominated by the use of time-series optical images and radar data across the globe (e.g., *Land-sat TM*, *MODIS*, *Sentinel-1*, and *Sentinel-2*) [5], [312]–[314]. Although there are studies using multitemporal lidar data to investigate ecosystem dynamics [169], [170], [172], [192], [315], collecting time-series lidar data with a constant time interval has been sporadic due to the paucity of spaceborne lidar sensors and the high cost of collecting airborne and terrestrial lidar data. Recent developments in near-surface lidar platforms (e.g., backpack lidar and UAV lidar) have greatly reduced the cost and increased the flexibility of lidar data collection. Moreover, newly launched spaceborne lidar

sensors (e.g., *GEDi* and *ICESat-2*) can provide global-scale time-series lidar observations. This progress in lidar sensors has made the collection of time-series lidar data possible.

MOVING TOWARD THE ERA OF BIG DATA

It has been estimated that the data streaming from the National Aeronautics and Space Administration active space missions alone represent more than 1.7 gigabytes [316]. With the accumulation of multisource, multitemporal, and multiscale remote sensing data, the amount of ecological observations will grow explosively [317]. Remote sensing-based ecological observations are stepping into the big data era.

Upon the transition of ecological observations from 3D to the multidimensional big data era, three common challenges are being faced across ecosystems. First, how should lidar data be fused with multispectral and hyperspectral data? The majority of existing studies have simply compressed the 3D lidar data into 2D vegetation attributes and then fused the derived vegetation attributes with those from multispectral and hyperspectral data directly based on spatial information [307], [318]. Further studies are needed to explore the possibility of fusing lidar data with multispectral and hyperspectral data in 3D so that the potential of multisource data can be fully explored. The use of 3D radiative transfer models in the data fusion process might be a potential solution to this question.

Second, how should changes from multitemporal lidar data sets be detected? Due to the changes in lidar sensors, viewing angles, vegetation conditions, and so on, lidar data collected at different times and from different platforms can hardly be directly compared [319]. The registration error of multitemporal lidar data may further increase the difficulty of detecting ecosystem changes [41]. Finding a method that can be used to compare lidar data across platforms and time is urgently needed.

Third, how should the accumulation of big remote sensing data be handled? With the increasing amount of data acquisition, the computation pressure of data processing is becoming a new challenge. New opportunities for data exploration may exist by using deep learning techniques with computation acceleration techniques (e.g., parallel processing and graphic processing unit acceleration). In addition, new data sharing policies and platforms are also urgently needed to promote widespread data availability.

CONCLUSIONS

Lidar has become an indispensable tool for ecological observations and modeling and will play an increasingly important role in the future. The development of lidar sensors, especially emerging near-surface lidar systems, significantly improves the flexibility and reduces the cost of lidar data acquisition. Robust and efficient lidar data processing algorithms are evolving, fostering the development of 3D ecological observations. Many studies have been conducted to extract accurate 3D ecosystem attributes from lidar data

across scales (from individual organs to global scales) and ecosystems (from forest to agricultural to grassland to urban ecosystems). These 3D attributes offer new sources of data for modeling ecosystem processes.

Although new insights and refined details have been achieved through the integration of lidar observations into ecological models, new efforts for developing and improving current ecological models should still be a high research priority. With the accumulation of a wide range of remote sensing data, ecological observations are moving from 3D to an era of multidimensional big data. How to handle and fully explore the potential of time-series multiplatform data through data fusion is becoming a new challenge for the research community, but it also opens new opportunities for understanding ecological processes.

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AUTHOR INFORMATION

Qinghua Guo (guo.qinghua@gmail.com) is with the Institute of Ecology, College of Urban and Environmental Science, Peking University, Beijing, China. Yanjun Su and Qinghua Guo contributed equally to this work.

Yanjun Su (ysu@ibcas.ac.cn) is with the State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing, China, and also with the University of Chinese Academy of Sciences. Yanjun Su and Qinghua Guo contributed equally to this work.

Tianyu Hu (tianyuhu@ibcas.ac.cn) is with the State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing, China, and also with the University of Chinese Academy of Sciences.

Hongcan Guan (guanhongcan@gmail.com) is with the State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing, China, and also with the University of Chinese Academy of Sciences.

Shichao Jin (jinshichao1993@gmail.com) is with the State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing, China, and also with the University of Chinese Academy of Sciences.

Jing Zhang (eve.zhangj@gmail.com) is with the State Key Laboratory of Vegetation and Environmental Change,

Institute of Botany, Chinese Academy of Sciences, Beijing, China, and also with the University of Chinese Academy of Sciences.

Xiaoxia Zhao (xxia_zhao@163.com) is with the State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing, China, and also with the University of Chinese Academy of Sciences.

Kexin Xu (kexin_xu4ever@163.com) is with the State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing, China, and also with the University of Chinese Academy of Sciences.

Dengjie Wei (weidengjie@ibcas.ac.cn) is with the State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing, China, and also with the University of Chinese Academy of Sciences.

Maggi Kelly (maggi@berkeley.edu) is with the Department of Environmental Science, Policy, and Management, University of California Berkeley, Berkeley, California, USA, and also with the Division of Agriculture and Natural Resources, University of California Davis.

Nicholas C. Coops (nicholas.coops@ubc.ca) is with the Department of Forest Resource Management, University of British Columbia, Vancouver, British Columbia, Canada.

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