Beyond 3-D: the new spectrum of lidar applications for Earth and Ecological sciences

Jan U.H. Eitel^{a,b*}, Bernhard Höfle^c, Lee A. Vierling^{a,b}, Antonio Abéllan^d, Gregory Asner^e, Jeff S. Deems^f,
Craig Glennie^g, Philip C. Joerg^h, Adam LeWinterⁱ, Troy S. Magney^j, Gottfried Mandlbürger^k, Douglas
Morton^l, Jörg Müller^m, Kerri Vierlingⁿ

^a Geospatial Laboratory for Environmental Dynamics, University of Idaho, Moscow, ID 83844, USA

^b McCall Outdoor Science School, University of Idaho, McCall, ID 83638, USA

^c Institute of Geography, University of Heidelberg, 69120 Heidelberg, Germany

^d University of Lausanne, Risk Analysis Group, 1015 Lausanne, Switzerland

^e Department of Global Ecology, Carnegie Institution for Science, Standford, CA 94305, USA

^f National Snow and Ice Data Center, University of Colorado, Boulder, CO 80309, USA

^g Department of Civil & Environmental Engineering, University of Houston, TX, USA

^h Department of Geography, University of Zürich, 8057 Zürich, Switzerland

ⁱ Cold Regions Research and Engineering Laboratory, Hanover, NH 03755-1290, USA

^j NASA Jet Propulsion Laboratory, Carbon Cycle and Ecosystems, Pasadena, CA 91109, USA

^k Department of Geodesy and Geoinformation, TU Wien, 1040 Wien, Austria

^l Department of Geographical Sciences, University of Maryland, College Park, MD 20742, USA

^m Bavarian Forest National Park, 94481 Grafenau, Germany

ⁿ Department of Fish and Wildlife, University of Idaho, McCall, ID 83638, USA

*Corresponding author (Tel.: 208 596 9277, E-mail address: jeitel@uidaho.edu)

Abstract

Capturing and quantifying the world in three dimensions (x,y,z) using light detection and ranging (lidar) technology drives fundamental advances in the Earth and Ecological Sciences (EES). However, additional lidar dimensions offer the possibility to transcend basic 3-D mapping capabilities, including i) the physical time (t) dimension from repeat lidar acquisition and ii) laser return intensity (LRI_λ) data

dimension based on the brightness of single- or multi-wavelength (λ) laser returns. The additional dimensions thus add to the x, y , and z dimensions to constitute the five dimensions of lidar ($x, y, z, t, LRI_{\lambda_1 \dots \lambda_n}$). This broader spectrum of lidar dimensionality has already revealed new insights across multiple EES topics, and will enable a wide range of new research and applications. Here, we review recent advances based on repeat lidar collections and analysis of LRI data to highlight novel applications of lidar remote sensing beyond 3-D. Our review outlines the potential and current challenges of time and LRI information from lidar sensors to expand the scope of research applications and insights across the full range of EES applications.

Keywords: multitemporal lidar, hypertemporal lidar, multispectral lidar, hyperspectral lidar, laser return intensity, data dimensions

1. Introduction

The advent of light detection and ranging (lidar) technology has spurred myriad advances in Earth and Ecological Sciences (EES) by enabling high fidelity mapping and quantification of three-dimensional (3-D) Earth surface properties and processes (Liang et al., 2016; Davies and Asner, 2014; Deems et al., 2013; Hodgetts, 2013; Zolkos et al., 2013; Jaboyedoff et al., 2012; Wulder et al., 2012). As a result, the number of studies published each year with the Boolean search keywords ‘lidar’ AND ‘(earth OR ecol*)’ included in the ISI Web of Science Core Collection has doubled since 2007, while the number of papers cited containing these keywords has increased six-fold. The EES community is therefore well aware of the utility of lidar for quantifying 3-D surface properties for many research areas (e.g., Table 1A), many of which have been reviewed elsewhere (e.g., Liang et al., 2016; Davies and Asner, 2014; Zolkos et al., 2013; Deems et al., 2013; Hodgetts, 2013; Jaboyedoff et al., 2012; Wulder et al., 2012).

In contrast, the physical time dimension (t) offered by repeat lidar for change detection and additional data dimensions offered by single- or multi-wavelength laser return intensity (LRI) (i.e., backscatter) information recorded by lidar systems represent growth areas in lidar research (Figure 1). LRI contains

information relating to the reflectance of an object in the actively emitted lidar wavelength(s) and thus is potentially useful for obtaining spectral information about biophysical and chemical surface properties. Although not the focus of this review, there has also been significant activity in the analysis of echo backscatter from full-waveform lidar systems (e.g., Mallet and Bretar, 2009) for object characterization and classification, especially in the forestry community (e.g., Pirotti, 2011). The physical x, y, z and t dimensions, combined with the LRI_{λ} data dimension at one or more wavelengths (λ), thus constitute what we refer to as the “five dimensions” of lidar data ($x, y, z, t, LRI_{\lambda_1 \dots \lambda_n}$) (Figure 2). Together, these additional dimensions of lidar provide new sources of information about the Earth’s structural, biophysical, chemical, and ecological properties that transcend basic lidar 3-D mapping capabilities.

The goal of this review is not to add to the existing body on literature on 3-D lidar that has been recently and extensively reviewed elsewhere (e.g. Liang et al., 2016; Davies and Asner, 2014; Zolkos et al., 2013; Deems et al., 2013; Hodgetts, 2013; Jaboyedoff et al., 2012; Wulder et al., 2012). Rather, the goal of this work is to review recent lidar research that specifically leverages the additional time- and LRI information, and to highlight their potential for advancing EES applications. We first review the fundamentals of lidar data acquisition and briefly summarize the breadth of studies utilizing traditional 3-D lidar. We then highlight recent work that demonstrates the promise of the physical time (t) and the LRI data dimensions of lidar. Finally, we present and discuss examples from the new spectrum of research that these additional lidar dimensions may enable for EES.

Table 1. Selected studies in the Earth and Ecological sciences (EES) to illustrate the breadth of studies that relied on the following lidar dimensions: A) x, y, z ; B) x, y, z + time (multitemporal with > 1 month return interval); C) x, y, z + time (hypertemporal with < 1 month return interval); D) x, y, z + LRI_{λ} (monospectral); E) x, y, z + LRI_{λ} (hyperspectral); F) x, y, z + time + LRI_{λ} .

Lidar Dimensions	Topic	Subtopic	Keywords and Citations
(A) x, y, z	Earth Sciences	Geology*	<ul style="list-style-type: none">• <i>Mass wasting</i> Jaboyedoff et al., 2012; Abellan et al., 2014• <i>Geomorphology</i> Brasington et al., 2012; Charlton et al., 2003• <i>Active tectonics</i> Hudnut et al., 2002; Zielke et al., 2010• <i>Outcrop mapping</i> Buckley et al., 2008; Hodgetts, 2013
		Glaciology*	<ul style="list-style-type: none">• <i>Glacier morphology</i> Hopkinson et al., 2001; Kennett and Eiken, 1997
		Hydrology*	<ul style="list-style-type: none">• <i>Flood modeling</i> Hohenthal et al., 2011• <i>Snow depth</i> Prokop, 2008; Tinkham et al. 2013; Deems et al., 2013• <i>Instream habitat modelling</i> Hauer et al., 2009
	Ecology	Biogeochemistry*	<ul style="list-style-type: none">• <i>Biomass and carbon distribution and storage</i> Mascaro et al., 2014; Hudak et al., 2012; Asner et al., 2005• <i>Vegetation structure</i> Greaves et al., 2015; Hämmerle and Höfle 2014; Clawges et al., 2007; Jensen et al., 2008; Zolkos et al., 2013
		Terrestrial Ecology*	<ul style="list-style-type: none">• <i>Habitat monitoring</i> Vierling et al., 2008; Vierling et al., 2014 ; Davies and Asner, 2014; Hill et al., 2014; Lindberg et al., 2015
(B) x, y, z + time (multitemporal)	Earth Sciences	Geology	<ul style="list-style-type: none">• <i>Landslide evolution and tracking</i> Ventura et al., 2011; Daehne and Cosini, 2014; Teza et al., 2008; Travelletti et al., 2008• <i>Rockfall phenomena</i> Rosser et al., 2005; Abellán et al., 2010; Royan et al., 2015• <i>Fault monitoring and earthquake analysis</i> Oskin et al., 2012, Glennie et al., 2014 and Zhang et al., 2015; Mukoyama, 2008; Nissen et al., 2014• <i>Active volcanism</i> LeWinter, 2014; Favalli et al., 2010, Neri et al., 2008
		Glaciology	<ul style="list-style-type: none">• <i>Glacier and ice cap monitoring</i> Bollmann et al., 2011; Geist, 2005; Hopkinson and Demuth, 2006; Zwally et al., 2002; Kääb, 2008; Kääb et al., 2012
		Hydrology	<ul style="list-style-type: none">• <i>Snow depth, ablation, and distribution</i> Tinkham et al., 2014; Schober et al., 2014; Painter et al., 2015• <i>Fluvial geomorphology</i> Heritage and Heatherington, 2007; Legleiter, 2012; Moretto et al., 2014• <i>Instream habitat modeling</i> Mandelburger et al., 2015
	Ecology	Biogeochemistry	<ul style="list-style-type: none">• <i>Carbon pools and fluxes</i> Dubayah et al., 2010; Hudak et al., 2012; Anderson et al., 2013; Srinivasan et al. 2014; Liang et al., 2012; Meyer et a.;, 2013; Tilly et al., 2014; Hoffmeister et al., 2015; Cao et al., 2016; Réjou-Méchain et al., 2016
		Terrestrial Ecology	<ul style="list-style-type: none">• <i>Wildlife distributions</i> Vierling et al. 2014• <i>Plant phenology</i> Clawges et al., 2007
	(C) x, y, z + time (hypertemporal)	Earth Sciences	Geology
Glaciology			<ul style="list-style-type: none">• <i>Glacier monitoring</i> LeWinter et al., 2014
Hydrology			<ul style="list-style-type: none">• <i>Hydrological modeling</i> Egli et al., 2012• <i>Riverbed morphology</i> Milan et al., 2007• <i>Snowpack dynamics</i> Adams et al., 2013
Ecology		Biogeochemistry	<ul style="list-style-type: none">• <i>Vegetation structure</i> Eitel et al., 2013; Portillo-Quintero et al., 2014
		Terrestrial Ecology	<ul style="list-style-type: none">• <i>Circadian rhythm</i> Puttonen et al., 2016• <i>Plant phenology</i> Calders et al., 2015; Sankey et al., 2014• <i>Wildlife distributions</i> Hill and Hinsley, 2015; Vierling et al., 2014
(D) x, y, z + LRI _λ (single wavelength)		Earth Sciences	Geology
	Glaciology		<ul style="list-style-type: none">• <i>Broadband albedo</i> Joerg et al., 2015• <i>Glacier facies types</i> Lutz et al., 2003
	Hydrology		<ul style="list-style-type: none">• <i>Surface moisture</i> Nield et al., 2014• <i>Snow chemistry</i> Kaasalainen et al., 2009• <i>Seabed reflectance</i> Tulldahl et al., 2007; Collin et al., 2008
	Ecology	Biogeochemistry	<ul style="list-style-type: none">• <i>Photosynthesis</i> Magney et al., 2014• <i>Foliar nitrogen</i> Eitel et al., 2011, Eitel et al., 2014a• <i>Foliar chlorophyll</i> Eitel et al., 2010
		Terrestrial Ecology	<ul style="list-style-type: none">• <i>Leaf area distribution</i> Béland et al., 2014
	(E) x, y, z + LRI _λ (multi- and hyperspectral)	Earth Sciences	Geology
Glaciology			<ul style="list-style-type: none">• NA
Hydrology			<ul style="list-style-type: none">• NA
Ecology		Biogeochemistry	<ul style="list-style-type: none">• <i>Foliar water</i> Gaulton et al., 2013• <i>Foliar pigments</i> Nevalainen et al., 2014; Li et al., 2014• <i>Drought stress</i> Juntilla et al., 2015
		Terrestrial Ecology	<ul style="list-style-type: none">• <i>Plant phenology</i> Rall and Knox, 2004
(F) x, y, z + time ^{**} + LRI _λ ^{***}	Earth Sciences	Geology	<ul style="list-style-type: none">• NA
		Glaciology	<ul style="list-style-type: none">• NA
		Hydrology	<ul style="list-style-type: none">• NA
	Ecology	Biogeochemistry	<ul style="list-style-type: none">• <i>Photosynthesis</i> Magney et al., 2014• <i>Plant nutrition</i> Eitel et al., 2014b• <i>Foliar pigments</i> Hakala et al., 2015
Terrestrial Ecology		<ul style="list-style-type: none">• NA	

** Multi- or hypertemporal

*** Single wavelength, multispectral, or hyperspectral

Figure 1. Number of publications with the following keywords searchers using the Web of ScienceTM

database: “lidar”, “lidar and multitemporal”, “lidar and hypertemporal”, “lidar and Intensity”, and “lidar and multi-wavelength” (results as of January 2016).

Figure 2. The “five dimensions” of lidar: The physical x,y,z dimension, the physical time (t) dimension, and the laser return intensity (LRI) data dimension at one or more wavelengths (λ).

1.1 The Growth of Lidar Dimensionality

Lidar data containing x,y,z information (hereinafter referred to as a “point clouds” or “waveforms”) span a wide array of spatial scales. Datasets range from global sampling acquired via satellite (such as the waveform-recording Geoscience Laser Altimeter System (GLAS) instrument onboard ICESat – Zwally et al., 2002), to landscape/regional data acquired by airborne platforms (hereafter referred to as Airborne Laser Scanning or ALS), to mm-cm level data using both static and mobile terrestrial platforms (hereafter referred to as Terrestrial Laser Scanning or TLS). As opposed to passive remote sensing systems that rely on reflected solar radiation, lidar instruments utilize their own active light source to survey the x,y,z location of object surfaces relative to the sensor location at a rate of up to one million survey points per second. To determine the x,y,z location, lidar instruments measure the line-of-sight distance as well as the angle to each survey point (Van Genechten et al., 2008; Eitel et al., 2013). The distance is measured by a laser that works on either the phase shift or time-of-flight principle. To determine the distance, phase based lasers use the phase shift between the sinusoidally modulated laser light that is transmitted and received by the sensor (Van Genechten et al., 2008). Time-of-flight lasers determine the distance based on the time of flight of a laser pulse between the sensor and the survey point (distance = $ct/2$, where c is the speed of light and t is round-trip elapsed time of light propagation). Two types of time-of-flight recording systems exist: full-waveform and discrete return (Evans et al., 2009; Fernandez-Diaz et al., 2014). Full-waveform systems record the entire backscattered energy or waveform. In contrast, discrete return systems record only one or more discrete points (i.e., distances and intensities exceeding a nominal energy threshold) per returned laser shot. Full-waveforms are most commonly transferred to discrete return data after applying echo detection procedures in a post-processing step. Phase-based lasers are commonly only found in TLS systems due to their limited range capabilities (< few hundred meters) compared to time-of-flight lasers that are used by terrestrial, aerial, and satellite platforms (i.e., a few kilometers for airborne sensing to about 600 km for satellite lidar systems). Based

on the distance and measured angles, the x, y , and z location can be calculated for each point using trigonometric principles (e.g., Eitel et al., 2013).

The assemblage of points and their arrangement in space can be visualized as a three-dimensional (3-D) point cloud of the surveyed object(s) (Figure 3). Spatially explicit height (x, y) or elevation (z) information provided by lidar data is commonly used to create high-resolution digital elevation models (DEMs) with the digital surface model (DSM) representing the Earth surface including objects (e.g., buildings and trees) and the digital terrain model (DTM) as bare ground surface without objects. Further DEM-based models include a range of structural derivatives of interest to EES such as snow depth and vegetation structure (Table 1A). To date, however, most lidar based research in the EES makes use only of the static geometric information obtained from a single lidar acquisition, without taking advantage of additional time and LRI information.

A small but growing body of literature shows that studies focused on lidar (x, y, z) structural data can be further enhanced by making use of (1) lidar time-series to monitor structural dynamics and Earth surface processes, and (2) laser return intensity of single or multiple lidar wavelengths for mapping Earth surface features and their biophysical and -chemical properties. Here, we briefly review pioneering work and highlight its potential for advancing research in EES.

Figure 3. Terrestrial lidar point cloud colored by recorded signal amplitude showing both vegetation and rock outcrop. Vegetation is characterized by a lower laser return intensity signal in the near-infrared wavelength of the scanner (Riegl VZ-6000 with wavelength of 1064 nm) compared to the bare rock surfaces.

2. Lidar in 4-D: The temporal dimension (t)

Three-dimensional processes such as plant growth and disturbance, snow/ice accumulation and melt, fluvial and soil erosional processes and other aspects of landscape evolution are inherently dynamic. Multitemporal (> 1 month return interval) and hypertemporal (≤ 1 month return interval) lidar stands to increase our understanding of these dynamic (x,y,z) processes, and will complement the time stacks of (x,y) information from passive remote sensing used for decades to study and monitor change (e.g., Wulder and Coops, 2014).

2.1 Multitemporal lidar

A growing number of studies make use of repeat lidar to better understand and monitor spatiotemporal dynamics (Table 1B). Maps derived from repeat lidar studies are of great value for calibrating, validating, and constraining a variety of models at the plot and landscape scale, including hydrological, geomorphological, vegetation, and habitat models. For example, erosion and deposition mapped and quantified by multitemporal lidar has provided unprecedented details into the fundamental processes that underlie Earth flow kinematics (Daehne and Corsini, 2014), riverbank and postfire erosion (Grove et al., 2013; Rengers et al., 2016), rockfall activity (Lim et al., 2005; Heckmann et al., 2012), precursors to rock slope failures (Rosser et al., 2007; Royán et al., 2015), carbon pools and fluxes (Dubayah et al., 2010; Goetz et al., 2011; Hudak et al., 2012; Liang et al., 2012; Anderson et al., 2013; Meyer et al., 2013; Srinivasan et al., 2014; Hoffmeister et al., 2015; Cao et al., 2016; Réjou-Méchain et al., 2016), vegetation disturbance (Anderson et al., 2011; Dolan et al., 2011; Huang et al., 2013) and snow accumulation patterns (Veitinger et al., 2014).

The full potential of multi-temporal lidar for science and environmental monitoring information has yet to be realized, however (Figure 1). Incompatibility of lidar collections is one reason; acquisition parameters (footprint size, wavelength, scan pattern, beam divergence) are often different between acquisitions (e.g., Hudak et al., 2012), complicating the processing and analysis of multitemporal lidar datasets without further studies to understand how time lags between lidar and field-based data should be treated (e.g., Vierling et al. 2014; Hill and Hinsley, 2015). Data availability also helps to explain why relatively few lidar studies incorporate the time dimension; the high costs associated with frequent lidar acquisitions and data processing efforts, particularly over larger areas, is often prohibitive (Skowronski et al., 2014; Orem and Pelletier, 2015). However, costs associated with data acquisition are declining as airborne, mobile, and terrestrial lidar instrument technology becomes more mainstream. In addition, advances in change detection algorithms and approaches (e.g., Monserrat and Crosetto, 2008; Brodu and Lague, 2012; Kromer et al., 2015), data storage, management, and processing infrastructure have enabled

an ever increasing number of studies to take advantage of change detection information provided by multitemporal lidar (e.g., Rieg et al., 2014). Complementing the increased number of datasets is the evolution of data sharing platforms, where users can freely share their lidar datasets via geospatial data clearinghouses such as OpenTopography (<http://www.opentopography.org>), the Rockbench repository (Lato et al., 2013), GRiD (<https://rsgis.crrel.usace.army.mil/usc>), and Laserdata (<http://laserdata.at>).

2.2 Hypertemporal lidar

The study of structural processes that change at rapid timescales (i.e., daily to weekly), such as snowpack and vegetation dynamics, may require (what we refer to as) hypertemporal lidar. Several pioneering applications of hypertemporal lidar data include studies of riverbed morphology (Milan et al., 2007) and phenological variation at fine structural and temporal resolutions across the vertical profile of a vegetation canopy (Calders et al., 2015) (Table 1C). Hypertemporal lidar has also shed light onto rockfall phenomena, such as the importance of the precursory indicators, the superimposition of rockfall events and the acceleration of deformation patterns before failure (Rosser et al., 2007; Crown et al., 2013; Royan et al., 2015; Kromer et al., 2015). Further, Crown et al. (2013) demonstrated the capability of hypertemporal lidar to observe and measure dimensional, volumetric, and surface morphology of an evolving lava flow, including the calculation of the local lava supply flow rate and flow inflation (Figure 4). Hypertemporal lidar can also provide valuable data for initializing and validating the snowpack dynamics component of hydrological models (Egli et al., 2012) and to support operational water management efforts (e.g., via the NASA JPL Airborne Snow Observatory program: <http://aso.jpl.nasa.gov/>; Painter et al., 2015).

Figure 4. Hypertemporal lidar of an active pahoehoe lava flow on the flanks of the Kilauea Volcano: Comparisons of four terrestrial lidar scans to an initial baseline scan reveal height change, or accumulation of lava, over time.

Despite the great promise of hypertemporal lidar for novel applications in EES, only a few studies have yet incorporated such data. The primary impediment to greater deployment of hypertemporal lidar is cost (Wallace et al., 2012). However, recent technological advancements now allow operational acquisition of hypertemporal lidar for lower capital and time investment. For acquiring hypertemporal lidar datasets at the plot scale, autonomously operating terrestrial laser scanners (ATLSs) have recently become available (Adams et al., 2013; Eitel et al., 2013; Portillo-Quintero et al., 2014; LeWinter et al., 2014; Culvenor et al., 2014; Griebel et al., 2015). For example, Eitel et al. (2013) described and tested a low-cost (< \$12,000) ATLS and showed its suitability for capturing daily changes in plant structure throughout a period of 17 days during fall leaf drop in a mixed conifer-quaking aspen (*Populus*

tremuloides) stand. This study also captured how a snow event (and subsequent melt) affected the overall canopy physical structure of both aspen and conifer species. Similarly, Portillo-Quintero et al. (2014) used an ATLS to map daily changes in Plant Area Index (PAI) for a period of 22 days during leaf drop in a Boreal-Mixed forest. To study dynamic changes in soil microtopography under changing weather conditions, Bechet et al. (2015) tracked rainfall simulation induced microtopographic changes with hypertemporal lidar. For monitoring snowpack dynamics and snow avalanches, Adams et al. (2013) acquired lidar data with an ATLS of a mountainside in the Austrian Alps twice per day for a period of five months (February 5th 2013 to June 6th 2013).

The potential of ATLS to provide novel insights into dynamic structural processes is illustrated in Figure 5. In this work, ATLS point clouds were acquired once per day across an approximately 5000 m² area throughout the 2014-2015 winter season with the goal of quantifying snowpack dynamics within a mixed-conifer forest stand near McCall, Idaho, USA. The hypertemporal ATLS point cloud data enabled structural changes to be quantified for each of the more than 300,000 survey points shown within the scan image. Among other quantities, this dataset allows the study of discrete spatial differences in snowpack evolution for survey points located beneath tree crowns versus survey points located in the open canopy (Figure 5-II), thereby greatly extending the applications possible using current hypertemporal snow monitoring protocols that focus on a single point (e.g., the SNOWpack TELemetry observational network) (Serreze et al., 1999).

At the landscape scale, longer range, lighter weight, and/or more portable lidar instrumentation are becoming more widely utilized. For example, the ATLS Atlas system, using the Riegl VZ-6000 long range TLS scanner, was recently deployed to monitor the 6 km wide terminus of Helheim Glacier in southeast Greenland (LeWinter et al., 2014). The Goddard Lidar, Hyperspectral, and Thermal Imager (G-LiHT; Cook et al., 2013) was designed to be flexibly mounted on the wing-strut of small aircraft, allowing it to be transported easily and reducing expensive ferrying charges that can deter repeat lidar flights over an area. Even smaller instruments (e.g., see Riegl VUX-1; Velodyne HDL-32E scanner; YellowScan) designed to be carried by small Unmanned Aerial Vehicles (UAVs) could allow repeat

acquisition of lidar data from an area of interest over prolonged periods of time at moderate deployment costs (Wallace et al., 2012; Anderson and Gaston, 2013; Vanderjagt et al., 2013; Wallace et al., 2014; Esposito et al., 2014; Mandlbürger et al., 2015). For example, Wallace et al. (2012) assessed the suitability of a UAV-borne lidar for forest surveying and found that the system accuracy was suitable for this purpose. The study also highlights the potential of UAV-borne lidar for hypertemporal forest surveys. Further, other 3-D sensors and workflows (e.g., 3-D gaming devices such as Microsoft Kinect, structure-from-motion and dense matching, etc.) will undoubtedly provide new insights into different natural phenomena in forthcoming years (e.g., Azzari et al., 2013; Hämmerle et al., 2014; Vander Jagt et al., 2015).

Figure 5. Illustration of the potential of hypertemporal lidar data from an autonomously operating terrestrial laser scanner (ATLS) for studying dynamic structural processes at very high spatial and temporal resolution. Figure 5-I shows an example of an ATLS point cloud, Figure 5-II shows the snowpack evolution derived from hypertemporal lidar at an open (1) and closed (2) canopy site, and

Figure 5-III shows a cross section of the snowpack in the open canopy stand acquired during Julian day 20 (A), Julian day 34 (B), and Julian day 51 (C).

3. Lidar in 5-D: The laser return intensity (LRI) data dimension

Using lidar to differentiate the physiochemical properties of objects can be difficult. To address this problem, an increasing number of applications use lidar data in conjunction with imagery from multi- and hyperspectral remote sensing systems (Erdody and Moskal, 2010; Hudak et al., 2002; Asner et al., 2007; Cook et al., 2009; Cook et al., 2013; Wang and Glennie, 2015; Painter et al., 2015). Spectral information from passive remote sensing systems has been used for decades for classifying Earth surface features (e.g., Goetz et al., 1985), plant monitoring (e.g., Tucker 1979), and for obtaining information about biological, physical, and chemical surface properties such as foliar water content and biochemistry (e.g., Knipling, 1970; Gausman, 1985; Gamon et al., 1992; Gao, 1996) and rock minerals (e.g., Hunt, 1977). For these applications, the remote sensing commonly relies on spectral indices that are ratios or linear combinations of reflectance values designed to quantify spectral features associated with the variable of interest (e.g., Jackson and Huete, 1991).

Given the potential of combining the structural information from lidar with information obtained from passive remote sensing, more remote sensing platforms are becoming available that simultaneously acquire lidar and multi- or hyperspectral imagery (e.g., the U.S. National Ecological Observing Network (NEON) Airborne Observing Platform, the Carnegie Airborne Observatory, NASA's G-LiHT, Carbon-3D, and NASA's Airborne Snow Observatory). To make use of the information measured by these platforms, there is heightened interest in combining lidar with optical and thermal remote sensing data (Lyzena, 1985; Hudak et al., 2002; Hyde et al., 2006; Anderson et al., 2008; Dalponte, 2008; Koetz et al., 2007; Swatantran et al., 2011). For example, fusing lidar with passive remote sensing data has shown to improve tree species classification (Dalponte, 2008; Puttonen et al., 2010) and geologic outcrop mapping (Buckley et al., 2013). Many of the listed studies simply combine lidar metrics with optical

remote sensing data using conventional statistical models that may not necessitate that the lidar ground instantaneous field of view (GIFOV) perfectly aligns with the GIFOV of the passive remote sensing system. However, to gain a more holistic view of the combined structural, biophysical, and chemical properties of Earth surface features and how they might affect processes such as biogeochemical cycling, it is important to accurately integrate lidar with passive remote sensing data. Though sophisticated integration approaches exist that involve co-locating the instruments on the same mounting plate onboard the aircraft, careful time-registration of each measurement, and data integration using ray tracing or camera models for each instrument (Asner et al., 2007; Asner et al., 2012), it remains challenging to accurately co-register a given lidar return with associated reflectance readings from passive remote sensing systems due to sensor GIFOV differences (Lyzenga, 1985, Mundt et al., 2006; Suomalainen et al., 2011; Nevalainen et al., 2014). For example, Suomalainen et al. (2011) showed that 400 TLS laser points occurred within the GIFOV of a hyperspectral sensor.

Further, the radiance measured using passive remote sensing is a function of the total vertical canopy + soil column whereas the laser return allows different types of surfaces to be resolved in the vertical (z) dimension. Hence, the passively measured reflectance signal might not be representative of a given object (e.g., leaf or branch) surveyed by the lidar (Hartzell et al., 2014a). The challenge of passively collecting remote sensing data adds an additional constraint to data fusion efforts – lidar can be flown at night or under other conditions that are suboptimal for optical sensors, and flight line orientation is dictated by solar geometry when optical sensors are part of the payload, while a lidar-only flight plan might be more efficient for achieving required ground point densities.

The use of laser return intensity (LRI) information offers the potential to achieve many benefits of combined lidar/optical data to simultaneously obtain information on structural, biological, physical, and/or chemical surface properties and enabling a new wave of scientific investigation in the EES. Besides measuring the x,y,z structural information for each surveyed point, most lidar systems also record a sensor specific LRI signal that contains information on the object's reflectance in the lidar wavelength (Figure 3). The added value of LRI for surface characterization can be seen in the point cloud colored by

recorded signal amplitude shown in Figure 3, wherein vegetation clearly differs from bare rock surfaces because rock has stronger backscatter in the laser wavelength of 1064 nm.

Besides avoiding the registration issues, other key advantages exist when using LRI compared to fusing passive remote sensing data with structural information from lidar: (1) It eliminates time and processing intensive steps that are required when fusing lidar with passive remote sensing data (Mundt et al., 2006), (2) LRI is independent of illumination conditions such as shading since lidar instruments provide their own light source (Nevalainen et al., 2014; Hartzell et al., 2014b; Rottensteiner et al., 2005), (3) lidar allows vertical differentiation of the reflectance signal (x,y,z) (Rall and Knox, 2004; Wang et al., 2015), and (4) Spectral mixing within the measured LRI signal is minimized (e.g., of soil background reflectance and vegetation) due to the relatively small IFOV of the laser pulse (mm for TLS and dm for ALS) combined with the height information it provides (e.g., height above a threshold can assumed to be reflectance from vegetation canopies) (Rall and Knox, 2004; Eitel et al., 2011; Woodhouse et al., 2011). Finally, the inherently high spectral resolution (1 nm) of the recorded LRI might allow narrow absorption features to be detected that cannot be resolved with broadband (> 30 nm) passive optical sensors (Magney et al., 2014).

However, in contrast to the radiance and/or reflectance signal commonly measured by passive remote sensing platforms, the LRI is not yet a fully transparent, standardized and openly defined value by sensor manufacturers (Höfle and Pfeifer, 2007; Kaasalainen et al., 2009). For example, the open LASer (LAS) file format commonly used for storing lidar data defines LRI as an “integer representation of the pulse return magnitude” that is “system specific”. Others define the LRI as the “relative magnitude of the backscattered illumination” (e.g., Glennie et al., 2013) that is related to the peak power of the recorded echo (Wagner, 2010; Höfle and Pfeifer 2007). Here, we define LRI as a measure for the strength of the recorded backscatter at a given wavelength (λ).

3.1 Radiometric calibration and correction

Before retrieving spectral information about objects from LRI, the dimensionless and sensor specific LRI values must be radiometrically calibrated. LRI values have been calibrated against reflectance standards (e.g., Kaasalainen et al., 2009; Eitel et al., 2010; Hartzell et al., 2014a), following well established approaches for converting dimensionless digital number (DN) values from passive remote sensing platforms into physical radiance and reflectance values (e.g., Jackson et al., 1987). Reflectance standards used for radiometrically calibrating LRI include reference panels, reference tarps (e.g., Kaasalainen et al., 2008; Eitel et al., 2010; Hartzell et al., 2014a; Schofield et al., 2016) and natural calibration targets such as sand and gravel (Kaasalainen et al., 2009). Besides using reflectance standards, a calibration procedure based on in-situ measurements of reference surfaces has been proposed (Briese et al., 2008) utilizing a spectrometer or reflectometer operating in the respective lidar wavelength. The latter approach has also been applied to multi-spectral airborne lidar data (Briese et al., 2012; Briese et al., 2014). Beyond that, a new generation of lidar instruments are becoming available that automatically calibrate LRI. For example, the Riegl V-line scanners are delivered with a factory supplied empirical radiometric calibration that uses onboard look up tables to relate raw peak amplitudes to calibrated reflectance (Pfennigbauer and Ullrich, 2010). In addition some research prototype dual wavelength terrestrial laser scanners are also being calibrated using empirical approaches (Li. et al., 2016; Schofield et al., 2016).

One unfortunate side effect of the collinear observation geometry employed in most laser scanners (i.e., the lidar source and optical detector alignment are nearly coincident), is that in this viewing geometry there may be a retroreflective peak in the return energy from some materials (Hartzell et al., 2014b). This influence is commonly called the hotspot effect or opposition surge (Papetti et al., 2007; Kaasalainen et al., 2005). The backscatter surge at the direct backscatter location is normally quantified as the ratio of scattered energy intensity in the direct backscatter direction to that of an off-axis direction outside of the hotspot region (typically no more than a few degrees). Experimental results have shown

that ratios between 0 and 2 exist and are dependent on laser aperture diameter (Kaasalainen et al., 2005) and laser wavelength and polarization (Papetti et al., 2007). The presence of the hotspot effect limits both the accuracy with which lidar intensity values can be radiometrically calibrated, and the comparison of the resultant reflectance values with their passive counterparts (e.g., from spectroradiometer devices), whose collection geometry is generally not coincident. As a result, given the variable and unknown hotspot effect for different materials, including calibrated reflectance standards, the accuracy of reflectance observations from lidar can differ by 10% or more from passive reflectance observations (Hartzell et al., 2014a, Hartzell et al., 2014b).

Besides the radiometric calibration, LRI values also must be corrected for variations of the laser beam incidence angle on the targets and the decreasing light intensity with increasing range between the lidar instrument and the surveyed object (see Eq. 1) (e.g., Lichti, 2005; Coren and Sterzai, 2006; Briese et al., 2008; Kukko et al., 2008; Balduzzi et al., 2011; Shaker et al., 2011; Kaasalainen et al., 2011; Krooks et al., 2013). With some exceptions (e.g., see Pfeifer et al., 2008), the light attenuation with increasing distance can be described by the inverse distance square law of light (cf. Höfle and Pfeifer, 2007). Approaches that correct for the attenuation of light with increasing sensor-object range include data-driven approaches - empirically relating recorded LRI and range (e.g., Höfle and Pfeifer, 2007; Höfle et al., 2013; Höfle, 2014; Koenig et al., 2015) and model-driven approaches - based on the radar equation (Höfle and Pfeifer, 2007; Ding et al., 2013). Similarly, correcting for incidence angle effects on LRI is generally based on data-driven approaches (e.g., Kaasalainen et al., 2011; Krooks et al., 2013; Zhu et al., 2015). An example of using a range-amplitude correction function for adjusting the originally recorded amplitudes can be seen in Figure 6. The correction function was determined in the lab from Spectralon™ (Labsphere, Inc., North Sutton, NH) reflectance panel readings at various distances. The displayed outcrop was captured from two scan positions at different distances. After radiometric calibration the range effect has been successfully removed from the amplitude measurements. After this procedure, the calibrated backscatter can in some situations be used for surface classification, such as the detection of different rock layers and to map vegetation (e.g., Hartzell et al., 2014a; Douglas et al., 2015). Spectral

indices that can be calculated from multi- or hyperspectral LRI data have also been shown to account for range effects on LRI (e.g., Eitel et al., 2014b). Similarly, calculating LRI ratios based on the current LRI and previous LRI value for a given location from repeat lidar acquisitions has been successfully used to correct for range effects when using LRI for change detection (Nield et al., 2014; Burton et al., 2011).

Figure 6. lidar signal amplitude before (left) and after (right) the removal of the range-dependent effects. The red arrows indicate the border between the overlapping point clouds captured from two different distances (150m and 255m). It can be seen that the range correction removes the predominant range-dependent effects. The data were calibrated using a range-amplitude correction function determined in the lab for the Riegl VZ-6000 operating at 1064 nm.

LRI range- and angle correction approaches, as well as radiometric calibration approaches, are often based on assumptions including 1) surveyed objects are Lambertian reflectors at wavelength(s) employed by lidar, 2) the emitted laser pulse is temporally and thermally stable (i.e., no change of pulse shape and power with changes in temperature and over time), 3) the echo width is independent of the range between the lidar instrument and the surveyed object, 4) the area extent of the surveyed target is big enough to completely encompass the laser beam field of view (i.e., area extended targets), and 5) the

atmospheric conditions are constant. In practice, many of these assumptions are violated if considering the entire dataset. For example, many natural objects are non-Lambertian reflectors (e.g., Brakke et al., 1989; Schaepman-Strub et al., 2009), laser temperature is often not constant and affects LRI (Schofield et al., 2016), and beam divergence is a function of the distance between the laser and the surveyed object. Hence, further basic research is required for devising robust and practical calibration approaches (Briese et al., 2008; Kaasalainen et al., 2009; Wagner, 2010; Briese et al., 2012; Briese et al., 2014; Schofield et al., 2016; Li et al., 2016).

3.2 Single wavelength lidar

Calibrated LRI from single wavelength lidar has been successfully used for classifying surveyed objects and providing information about their biophysical and biochemical properties (Table 1D). For example, single wavelength LRI has been used for mapping rock types within geologic outcrops (Franceschi et al., 2009; Penasa et al., 2014; Humair et al., 2015; Matasci et al., 2015). Others used single wavelength LRI to classify woody and leafy canopy components (Béland et al., 2014), and land-cover, such as vegetation, ice, water, snow, rock and man-made features including roads and buildings (e.g., Song et al., 2002; Charaniya et al., 2004; Fritzmann et al., 2011).

In addition to the use of LRI for classification, recent work has shown that single wavelength LRI can be used to derive valuable information about biophysical and biochemical surface properties such as foliar biochemistry (Eitel et al., 2010; Eitel et al., 2011; Magney et al., 2014; Eitel et al., 2014a), surface moisture (Nield et al., 2014), snow chemistry (Kaasalainen et al., 2008), and lithology (Franceschi et al., 2009; Burton et al., 2011). Findings by Nield et al. (2014) showed a statistically significant relationship ($r^2 = 0.87$) between the average LRI_{532nm} and gravimetric moisture content for two different sediment types (sand and green glass beads). Burton et al. (2011) showed strong log-linear relationships ($r^2 = 0.77$) between the LRI_{1500nm} and weight percent clay and LRI_{1500nm} and weight percent combined quartz, potassium-feldspar, and plagioclase. Similarly, Franceschi et al. (2009) found a strong ($r = -0.85$) inverse

linear relationship between LRI_{1535nm} and the abundance of clay minerals in rock samples. In vegetation studies, Eitel et al. (2010 and 2011) showed strong agreements between the LRI_{532} and foliar nitrogen ($r^2 = 0.68$) in wheat (*Triticum aestivum* L.) (Figure 7) as well as chlorophyll concentration in sugar maple (*Acer saccharum*) and bur oak (*Quercus macrocarpa*) leaves ($r^2 = 0.77$). Green LRI_{532} has also shown promise for enabling 3-D mapping of photosynthesis in plant canopies (Magney et al., 2014). Magney and colleagues (2014) found strong agreements between LRI_{532nm} and measures of plant photosynthetic performance (xanthophyll cycle de-expoxidation and non-photochemical quenching).

Figure 7. Relationship between foliar nitrogen concentration of wheat (*Triticum spp.*) and calibrated green (532 nm) laser return intensity (figure adapted from Eitel et al., 2011).

The focus on single wavelength LRI shares some important heritage with full waveform recording and processing. Although not the focus of this review, it is deserving of attention to briefly mention recent progress on full waveform recording and processing. Full waveform lidar refers to the process of recording the entire backscattered signal from each outgoing laser pulse for subsequent post processing. This is a powerful approach because it transitions the analysis of backscattered energy away

from a fixed hardware implementation to a post-mission software analysis whereby customized processing solutions specific to user applications can be developed (Parrish et al., 2011; Mallet and Bretar, 2009). Early on, the analysis of full waveform returns focused on the extraction of additional echo locations below the energy thresholds set by discrete return systems (e.g. Blair et al., 1999; Wagner et al., 2006). However, a more detailed analysis of the return energy from the entire laser cone of diffraction has been exploited in many areas such as forestry (Harding et al., 2001, Pirotti, 2011), where the total area under the waveform return profile is a proxy for above ground biomass. Additional metrics derived from the return waveform shape are also being used for enhanced object classification and discrimination, for example (Pan et. al., 2016; Rogers et al., 2015). Therefore, there is additional potential for full waveform processing and analysis to provide additional metrics beyond the time and LRI domains described in this review.

3.3 Multi- and hyperspectral lidar

The potential for lidar LRI is not limited to single-wavelength laser systems. To date, few commercially available multi-wavelength laser systems exist, as additional laser wavelengths add cost, and the benefit of additional wavelengths is not widely recognized (personal communication, Lonnie Price), outside of bathymetric lidar systems. However, having only one available wavelength constrains the use of lidar systems to only a few chemical surface properties that happen to distinctively absorb the wavelength employed by the lidar system (Eitel et al., 2011; Nield et al., 2014). One sole wavelength also limits the ability to classify land cover (Fritzmman et al., 2011; Danson et al., 2014; Wang et al., 2013; Hartzell et al., 2014a) and separate ground from vegetation returns (Rall and Knox, 2004; Hancock et al., 2012; Eitel et al., 2014b). Furthermore, a single wavelength does not allow the calculation of spectral vegetation indices that, in addition to enabling corrections of range effects on LRI (e.g., Eitel et al., 2014b), have been shown to reduce noise caused by the viewing and illumination geometry (e.g., Shi et al., 2015).

In response to these potential limitations of single wavelength LRI, the research community has developed a range of multi-wavelength lidar systems (Irish et al., 1999; Rall and Knox, 2004; Tan and Narayanan, 2004; Woodhouse et al., 2011; Wei et al., 2012; Douglas et al., 2012; Gaulton et al., 2013, Danson et al., 2014, Eitel et al., 2014b; Niu et al., 2015; Douglas et al., 2015). A few of these systems are now commercially available (e.g., Optech Titan, Optech Incorporated, Vaughan, Canada; Leica Chiroptera II™, Leica Geosystems, Heerbrugg, Switzerland). Supercontinuum generation, where a single-wavelength laser pulse is spectrally broadened into a range of wavelengths, even supports hyperspectral (> 30 wavelengths) laser systems (Dudley et al., 2006; Chen et al., 2010; Kaasalainen et al., 2007; Hakala et al. 2012; Nevalainen et al., 2014; Li et al., 2014).

These multi- and hyperspectral lidar data have enabled a new class of spectral laser indices to be calculated as analogues to spectral indices derived from passive remote sensing data (Nevalainen et al., 2014; Eitel et al., 2014b; Li et al., 2014; Niu et al., 2015; Hakala et al., 2015; Juntilla et al., 2015). For example, based on laser return intensity values from a multi-wavelength laser system, Niu et al. (2015) calculated the Photochemical Reflectance Index (PRI; Gamon et al., 1992) and the Normalized Difference Vegetation Index (NDVI, Tucker 1979) for *Platanus spp.* and *Bauhinia spp.* leaves and showed intermediate to strong agreements between laser derived spectral indices and spectral index values derived from spectrometer data (r^2 for NDVI ≥ 0.98 ; r^2 for PRI = 0.49).

Fueled by the increasing availability of multi- and hyperspectral lidar systems, the types of biophysical and chemical surface properties that can be mapped with lidar systems is likely to expand considerably (Table 1E). For example, Nevalainen et al. (2014) used a prototype of a full-waveform hyperspectral terrestrial lidar to map chlorophyll concentration in Scots pine (*Pinus sylvestris*) and found strong correlation ($r^2 = 0.88$, RMSE = 0.10 mg/g) between hyperspectral lidar derived vegetation indices and chlorophyll concentration. Other work (Gaulton et al., 2013) found strong correlation ($R^2 = 0.8$, RMSE = 0.0069 g cm⁻²) between vegetation moisture content quantified by the Equivalent Water Thickness (EWT) and a normalized ratio water index (SALCA Normalized Ratio Index = (p1063 – p1545)/ (p1063 + p1545) calculated from the laser return intensity of a two-wavelength (1063 nm and

1545 nm) full waveform terrestrial laser system. Similarly, Junttila and colleagues (2015) showed the suitability of hyperspectral lidar for detecting drought stress in spruce and pine trees. The combined use of a red (660 nm) and NIR (780 nm) laser return intensity has also shown to be suitable for monitoring tree phenology (Rall and Knox, 2004).

The availability of multi- and hyperspectral laser systems might also improve the accuracy of lidar based land cover classifications, biomass estimates, automatic point cloud classification, and water depth estimates (Gong et al., 2015; Wang et al., 2015; Hancock et al., 2012; Suomalainen et al., 2011; Irish et al., 1999). The combined use of LRI from a near-infrared (1064 nm) and mid-infrared (1550 nm) lidar was shown to improve land cover classification accuracy from lidar when compared to using LRI from a single wavelength lidar (Wang et al., 2014). Similarly, Gong et al. (2015) found that the use of LRI from a multi-wavelength (556, 670, 700, and 780 nm) lidar enhanced object classification by up to 39.2% when compared to the LRI from a single wavelength lidar system.

Multi- and hyperspectral lidar may also improve our ability to separate ground from vegetation returns and leaves from woody materials, which ultimately will improve lidar based biomass estimates (Suomalainen 2011; Hancock et al., 2012; Eitel et al., 2014b; Howe et al., 2015; Douglas et al., 2015). For example, findings by Suomalainen (2011) showed that the spectral information obtained from hyperspectral terrestrial lidar allows an automatic classification of different canopy components including needles, branches, and background. Additional evidence suggests that spectral indices better account for variations in viewing and illumination geometry than LRI from single wavelength laser systems (Danson et al., 2014; Nevalainen et al., 2014). However, it has to be cautioned that calculating spectral indices might also aggravate the viewing and illumination effects if there are pronounced differences in the bidirectional reflectance distribution function (BRDF) between the employed wavelengths (Eitel et al., 2014b).

4 Beyond 3-D: Research Opportunities

4.1 General Earth and Ecological Sciences Research Community

Many disciplines within the EES make use of passive aerial or satellite remote sensing data to derive physically based parameters such as leaf area index or land cover characteristics. To derive these physical parameters from satellite or airborne remote sensing data, ground calibration and validation is generally required because the measured reflectance is a complex interaction of factors such as the mixture of reflectance signal from the object of interest and background and viewing geometry (Jacquemoud and Baret, 1990; Verhoef, 1984; Jackson and Huete, 1991). Instead of manual ground validation measurements that are labor intensive and costly, the highly spatially and temporally resolved structural information within an ATLS footprint could allow accurate determination of structural information within one or more pixels (Rall and Knox, 2004; Portillo-Quintero et al., 2014). In contrast to the spectral information from passive remote sensing instruments, the x,y,z data measured by lidar provide physically based structural estimates such as height, area, or volume. These physical estimates from a network of ATLS with remote downloading capabilities could allow satellite imagery to be calibrated and validated by fitting simple calibration equations (Rall and Knox, 2004; Portillo-Quintero et al., 2014), or be used to parameterize sophisticated, 3-D radiative transfer models to compare the expected and observed reflectance characteristics (e.g., North et al., 2010; Gastellu-Etchegorry et al., 2015). Below, we summarize research opportunities enabled via the 5 dimensions of lidar, using a hierarchy of scientific fields and sub-fields in keeping with that used by the United States (U.S.) National Academy of Sciences and the U.S. National Science Foundation when describing Ph.D. research fields.

4.2 Earth Sciences

4.2.1 Geology

Geological sciences increasingly leverage the 3-D structural information provided by lidar for geological mapping, structural characterization, tectonics, and monitoring active volcanism and mass wasting events (Buckley et al., 2008; Cavalli et al., 2008; Neri et al., 2008; Wechsler et al., 2009; Jaboyedoff et al., 2012; Abellán et al., 2014). As a result, the amount of research in the geological sciences making use of lidar technology has exponentially increased during the last decade (Hodgetts, 2013), and use of the 4th and 5th lidar dimensions will likely help fuel this positive trend in coming years. Multitemporal lidar has already been extensively used in the geological sciences for investigating dynamic behaviour or mass movements including the tracking of diverse landslide features (Teza et al., 2007; Travelletti et al., 2014), the adaptation of Particle Imaging Velocimetry (PIV) for estimating the landslide velocity field (Aryal et al., 2012), the computation of the Euler rotation angles for 3-D tracking of rocky boulders (Monserrat and Crosetto, 2008), tracking the evolution of active volcanic processes (Favalli et al., 2010; Crown et al., 2013; LeWinter, 2014), and the investigation of a progressive failure (Oppikofer et al., 2008; Royan et al., 2015). These investigations have been conducted in different settings such as mountainous areas, active volcanic regions, marine cliffs, and transportation corridors, and at different spatial scales ranging from fine scale diffuse erosion (Loye et al., 2012) and fragmental rockfalls (Rosser et al, 2005; Abellán et al., 2011; Heckmann et al., 2012; Stock et al. 2012) to several million cubic meters (Oppikofer et al., 2008; Rabatel et al., 2008).

The field of active tectonics was an early adopter of lidar technology (Hudnut et al., 2002). Geologists quickly latched onto the ability to discover and document previously unknown faults (e.g., Haugerud et al., 2003; Johnson et al., 2004) and better understand faulting mechanisms from the high resolution terrain models. However, limitations with single epoch datasets were many (Wesnousky,

2006), and multitemporal lidar provided high resolution pre- and post-event elevation models to directly relate surface deformation to energy release at depth (Oskin et al., 2012). This insight led to an effort in the scientific community to capture high resolution pre-event lidar observations on the major fault lines in California through the ‘B4’ (southern California) and Earthscope (northern California) projects in 2005 and 2008 (Bevis et al., 2005; Prentice et al., 2009). These observations will provide a baseline for forthcoming earthquake events.

The first case of differencing lidar datasets for pre- and post-earthquake analysis in documenting the M_w 7.2 Sierra El-Mayor-Cucapah Earthquake (Oskin et al., 2012, Glennie et al., 2014; Zhang et al., 2015). Pre- and post-event lidar differencing has also been performed on the M_w 6.9 Iwate-Miyagi (Mukoyama, 2011; Nissen et al., 2014), M_w 7.1 Fukushima-Hamadori (Nissen et al., 2014) and the M_w 6.0 24 August 2014 (Hudnut et al., 2014) earthquakes. To date, the majority of this change detection analysis has relied solely upon the spatial (x,y,z) content of the point clouds, and estimated deformation using the iterative closest point technique (ICP – Besl and McKay 1992). However, recently Zhang et al. (2015) proposed an extension to ICP which allowed for anisotropic weighting of the lidar points to account for differences in accuracy between pre- and post-event point clouds. This framework has potential to also be further extended to incorporate LRI weighting and matching into the registration of before and after point clouds. Deformation maps created by differencing of pre- and post-event lidar datasets are, for the first time, providing promising insight into near-field deformation (i.e. < 1 km from fault rupture) from earthquakes. Whereas techniques such as InSAR or optical pixel tracking (e.g. Massonnet et al., 1993; van Puymbroeck et al., 2000) are well established for measuring earthquake deformation in the far-field, they often lose coherence or tracking near the fault due to the steep phase gradients and intense ground shaking, and are only able to recover a portion of the 3D deformation field (Nissen et al., 2014). LiDAR differences have the potential to overcome these limitations, and provide near-field 3D deformation fields that constrain shallow-slip distribution and elucidate shallow fault physics (e.g., Frankel et al., 2007).

The expected rate of the geomorphologic changes should define how the site of investigation must be monitored; unfortunately, this strategy is not always used or possible, and the use of multitemporal lidar with an insufficient temporal resolution increases the likelihood of superimposition and coalescence of multiple failures, ultimately distorting the characteristic magnitude-frequency laws of captured failures (Lim et al., 2009). Hence, hypertemporal lidar may often be warranted to fully capture geomorphologic changes. While hypertemporal lidar studies in the geological sciences are rare, Crown et al. (2013) collected repeat lidar scans (30-second intervals) of an active Pahoehoe lobe over the course of 3-hours, demonstrating the capability of hypertemporal lidar for lava flow analyses. Similarly, LeWinter (2014) used hypertemporal lidar scans (5-second intervals, 2-hour survey length) to capture short-term variation in lava lake surface topography and activity. The increasing availability of ATLS (see section 2) together with the development of new techniques for hypertemporal data processing may soon help geologists to better study, understand and model the almost imperceptible changes preceding the occurrence of mass movement events.

Using the LRI data dimension of lidar has revolutionized the use of digital outcrop models in the petroleum industry and for investigations of inaccessible outcrops (Burton et al., 2011; Hodgetts, 2013). Further, LRI holds great promise in helping to map lithology, complementing or replacing time consuming field surveys (Franceschi et al. 2009; Burton and Wood, 2008; Hodgetts, 2013). Remarkably, correct calibration of the LRI has recently allowed different geological layers to be discriminated (Humair et al., 2015; Matasci et al. 2015), opening up new avenues for automatic geological mapping.

Furthermore, the observation of LRI from multiple frequencies simultaneously, i.e. multispectral lidar shows tremendous potential for being able to automatically delineate and detect different rock types, and overcome problems with passive electro-optical digital photography and hyperspectral imagery (Hartzell et al., 2014).

4.2.2 Glaciology

The temporal dimension of lidar plays an important role in monitoring glacier and ice cap volume in response to environmental change. Besides long term *in situ* monitoring, volume changes across larger extents can be quantified by integrating elevation changes over the entire glacier or ice cap surface from multitemporal DEMs (cf. Zemp et al., 2013). Traditionally, these DEMs have been derived from multi-angular passive optical imagery using photogrammetric methods (e.g. Haug et al., 2009; Koblet et al., 2010). More recently, multitemporal lidar has been used to monitor changes of glaciers and ice caps over time (Geist, 2005; Hopkinson and Demuth, 2006; Larson et al., 2015). When compared to traditional photogrammetric approaches, topographic data from lidar feature lower systematic and stochastic uncertainties due to the ability to accurately map in cast shadows and to better cope with low contrast surfaces such as fresh snow. Consequently, topographic data from lidar are preferred to data from photogrammetric approaches (Baltsavias et al., 2001; Geist, 2005; Knoll and Kerschner, 2009; Abermann et al., 2010; Joerg et al., 2012; Jóhannesson et al., 2013; Fischer et al., 2015).

Monitoring glaciers and ice caps across large spatial extents generally relies on repeat spaceborne lidar acquisition (Zwally et al., 2002; Kääb, 2008; Kääb et al., 2012; Schenk and Csathó, 2012; Bolch et al., 2013). In contrast, for monitoring small to medium size glaciers, repeat lidar acquisitions from terrestrial or airborne platforms are preferentially used because their point density is much higher and the sampling locations are typically better distributed on a glacier's surface area (e.g., Geist, 2005). Such measurements have been frequently used to investigate the changes in single glaciers as well as those occurring across entire mountain ranges, and have contributed to glacier inventories (Abermann et al., 2010; Geist, 2005; Joerg et al., 2012; Knoll and Kerschner, 2009; LeWinter et al., 2014; Larson et al., 2015).

Along with the lidar topographic data and its 4-D benefits mentioned above, the additional data dimension provided by LRI could be of great benefit for glaciology. Currently, most lidar systems used in glaciology utilize laser wavelengths within the near-infrared part of the electro-magnetic spectrum (e.g., at 1064 nm). The LRI from such lidar instruments can be converted to infrared reflectance images to distinguish different surface facies types of glaciers (i.e., snow, firn, and ice; e.g., Lutz et al., 2003; Höfle

et al., 2007). A more advanced product derivable from LRI could be the broadband albedo (ratio of reflected to incident radiation), which is a major driver of snow- and ice melt (Warren and Wiscombe, 1980; Warren and Warren, 1980; Schaepman-Strub et al., 2009). Knowledge of the distributed albedo derived from LRI data dimension coupled with structural information from lidar could be of great value for glacier mass balance modeling. Although surface broadband albedo could be derived from LRI of a single wavelength lidar system (Joerg et al., 2015), the increasing availability of multispectral lidar systems will likely enable a better representation of broadband albedo as a function of $(x,y,z,time)$, especially when wavelengths in the visible part of the spectrum are included. Cast shadows affect the derivation of a glacier's broadband albedo from photogrammetric data, particularly because shadows can be quite extensive at the high latitudes and complex terrain where glaciers are common. The lidar's active illumination, and accurate representation of the topography existing in these extensive cast shadow areas, could consequently provide a more homogeneous broadband albedo.

4.2.3 Hydrology

Coastal zones and regions with inland water are highly dynamic in their hydrology, geomorphology, and hydro-biology. Variation in discharge causes riparian areas to experience a range of hydrological conditions (from being entirely submerged to completely dry) and drive changes in sediment transport and bank erosion. The resulting morphological changes can have important effects on water quality, aquatic habitats, and flood risk. Though a single lidar acquisition is sufficient to describe the morphological state of the water body, the dynamic nature of water bodies necessitates repeat lidar to reliably assess the state of habitats, the quality of the fresh water resources, and the flood risk as required in many countries (e.g., European Union, 1992, 2000, 2007).

Given the inherent dynamic nature of water bodies, there is a great need for approaches that allow operational monitoring of alluvial areas. Both passive remote sensing and ground based terrestrial surveys have traditionally been used for such a purpose (Brasington et al., 2000; Marcus and Fonstad, 2008;

Wheaton et al., 2010a; Wheaton et al., 2010b). Besides these traditional approaches, ALS has been established as the state-of-the-art data acquisition method for monitoring alluvial systems. However, because conventional topographic ALS sensors generally employ near-infrared laser wavelengths (e.g., 1064 nm, 1550 nm) that cannot penetrate water, ALS acquisitions of floodplains and riparian areas are often combined with bathymetric data from either echo sounding, ground based terrestrial surveys, or spectral information of passive imagery (e.g., Moretto et al., 2014, Vetter et al., 2011). Though not as widely available as topographic lidar, bathymetric lidar sensors employ a green laser wavelength (532 nm) that penetrates shallow water (typically 2-20m depending on turbidity and bottom reflectivity). The provided data thus allow characterizing the morphology of the entire alluvial area (floodplain and bottom of shallow water bodies) at high and homogeneous point density (>10 points per m^2) and good height accuracy (<10 cm).

Repeat lidar surveys could help to improve our ability to link geomorphic changes to fresh water resource quality, flood risk, and habitat quality. One of the rare studies that illustrated the potential of such datasets has been conducted at the pre-alpine Pielach River (Mandlbauer et al., 2015). Based on repeat bathymetric surveys the impact of a one-year flood in 2013 and a 30-year flood in 2014 were analyzed. By applying hydrodynamic-numerical and mesohabitat modelling, the study demonstrated the potential of 4-D (x,y,z,time) bathymetric lidar for understanding linkages between geomorphic changes and in-stream meso- and microhabitats.

While the use of radiometric information from passive imagery is widespread, either for the derivation of bathymetry (e.g., Legleiter et al., 2012, Moretto et al., 2014) or for the classification of benthic habitats (Zhang, 2015), the use of LRI in studying inland water bodies remains rare (e.g., Wang and Philpot, 2007; Collin et al., 2008). This is in particular true for bathymetric lidar, since the interaction of the green laser signal with the different targets and media (air and water) adds additional complexity when interpreting the LRI information. Future research is therefore needed to devise procedures for calibrating LRI from bathymetric lidar. If successful, LRI may allow physiochemical properties of the water body and bottom (e.g., benthos) to be characterized. Combined with both the structural and

temporal dimension of lidar, the use of calibrated LRI may help in monitoring inland water bodies and improve our understanding of linkages between morphological and physiochemical dynamics in these waters.

Research and applications relating to the hydrological and dynamic properties of snow stand to benefit dramatically from both hypertemporal lidar and use of LRI information. For example, at the watershed scale, recent efforts have demonstrated that repeat mapping of snow depth distribution provides an important new avenue for scientific investigations into and operational management of snowmelt-dependent hydrologic systems (Painter et al., 2015). On the scale of individual slopes or terrain features, repeat, high resolution mapping of snow depth and snow depth change can provide important information for understanding and managing avalanche hazards (e.g., Prokop, 2008; Deems et al., 2015).

Mapping of snow depth via lidar is a relatively straightforward geodetic method involving subtraction of a snow-free DEM from a snow-covered DSM (or consecutive DSMs for snow depth change detection), and provides a reliable method for retrieving one of the most important drivers of snowmelt runoff variability and avalanche potential (Deems et al., 2013). While a single snow depth map can be extremely valuable, repeat mapping can quantify spatial patterns in accumulation or ablation that are very difficult to simulate or to monitor through other methods.

Over the past three years, the NASA Airborne Snow Observatory (ASO) has conducted repeat mapping of full watershed snow distributions over several river basins in the western US, including on a nominally weekly interval over the Tuolumne River Basin in California (Painter et al., 2015). Of note is the fusion of lidar and hyperspectral data in the ASO processing workflow wherein the spectral land cover classification is used to identify snow-free areas and subsequently ensure that the calculated snow depths in those areas are zero. In addition, the hyperspectral data help to determine snow albedo, a key determinant of melt rate. These procedures suggest the opportunity to apply radiometrically corrected LRI values to identify snow/not-snow ground returns for surface type discrimination and quality control, as well as for quantifying snow albedo. These potential LRI applications could be employed either for

ASO data collected under suboptimal imaging conditions, or for other snow-mapping projects that lack an integrated imaging spectrometer.

A great advantage of mapping snow distributions with lidar is the ability to detect snow and ground surfaces under forest canopies (e.g., Hopkinson et al., 2001). While numerous ecosystem studies benefit directly from lidar surveys – quantifying forest structure before and after a forest disturbance, for example – an additional promise is the capacity to quantify changes in snow accumulation and ablation following forest mortality events, such as from fire, insect infestation, or harvest. Reduction or loss of forest canopy cover can result in reduced snowfall interception and sublimation and thus increased accumulation, while in the ablation season increased solar input and at-surface wind speed can hasten snowmelt (e.g. Pugh and Gordon, 2012; Livneh et al., 2015) – each of these processes can be quantified or characterized by repeat lidar surveys.

TLS has seen steadily increasing use for mapping snow distributions in avalanche terrain (e.g., Prokop, 2008; Grünewald et al., 2010; Maggioni et al., 2013; Deems et al., 2015). Recent efforts in particular have explored repeat TLS surveys on operational time scales, with collections conducted before and after snow accumulation events with rapid generation of snow depth change maps for use in planning avalanche control efforts (Deems et al., 2015) (Figure 8). A third scan after avalanche control operations have concluded allows quantification of induced avalanche activity and an assessment of the effectiveness of control efforts. Operational integrations such as this example hold much promise for improving avalanche control efforts, and also suggest the potential for application of ATLS systems.

Figure 8. East Wall area at Arapahoe Basin Ski Area, Colorado, USA, on 1 February, 2014. Colors indicate change in snow depth relative to 23 January, prior to a snow accumulation event. Large avalanche was initiated by a single explosive charge detonated at point “X”. White coloration on the avalanche bed surface indicates that the sliding layer is the old, pre-storm snow surface (from Deems et al., 2015).

An ongoing ATLS project at Mammoth Mountain in California, USA has been used to demonstrate infrastructure, control, and data management systems for ATLS deployment in snow regions, and the snow accumulation and melt processes have been quantified from the resulting data set (e.g., LeWinter et al., 2012). Project-specific development such as this, or as for the ATLS Atlas system deployed in Greenland (see above and LeWinter et al., 2014), combined with manufacturer investments in housing and control engineering, will soon enable remote monitoring of avalanche prone slopes, and in conjunction with *in situ* active mitigation systems, will help maintain public and infrastructure safety.

4.3 Ecology

4.3.1 Biogeochemistry

Lidar remote sensing from TLS, ALS, and space-based lidar provides important information for biogeochemical research, including information on biomass, LAI, and foliage profiles (Lovell et al., 2003; Jupp et al. 2009; Yao et al., 2011; Zhao et al., 2011; Zhao et al., 2013; Montesano et al., 2014; Zolkos et al., 2013). Recent applications of lidar remote sensing for biogeochemical research have emphasized large area coverage from airborne (e.g., Asner et al., 2011; Asner et al., 2013) or space-based lidar systems (Saatchi et al., 2011; Baccini et al., 2012; Neigh et al., 2013; Morton et al., 2014), providing insight into drivers of regional variability in ecosystem structure and function.

Multitemporal and hypertemporal lidar data offer unprecedented detail regarding seasonal dynamics in ecosystem structure. Portable, low-cost TLS systems have been used to study vegetation phenology across a range of ecosystem types (e.g., Eitel et al., 2013; Portillo-Quintero et al., 2014; Calders et al., 2015; Sankey et al., 2014). Phenology strategies frequently differ vertically between understory and canopy trees, between trees of different functional types and even between canopy dominants and emergent trees (Calders et al., 2015). As opposed to using passive remote sensing data (e.g., NDVI or EVI time series) that provide a total canopy integrated LAI estimates, repeat lidar can generate vertically resolved changes in phenology throughout the growing season (Calders et al., 2015; Carlos Portillo-Quintero et al., 2014). Interactions between vegetation structure and radiation also change throughout the season, enabling improved modelling of temporally and spatially varying processes such as the interaction between light environment and canopy elements (Cote et al., 2009; van der Zande et al., 2011; Bittner et al., 2012; van Leeuwen et al., 2013; Bode et al., 2014; Cifuentes et al., 2014; Magney et al., 2016). For example, repeat LiDAR acquisitions could help to understand the dynamics of modelled radiative transfer as the 3D structure of the vegetation canopy changes seasonally (Gastellu-Etchegorry et

al., 2015), potentially opening new avenues of understanding floral and faunal phenology relating to the life cycles of fungi, plants, insects, birds, and other organisms that inhabit complex canopies. There is also evidence that highly spatially and temporally resolved lidar datasets provide a more accurate account of changes in vegetation productivity throughout a growing season than time series from passive remote sensing (Calders et al., 2015).

The ability to separate and quantify woody (non-photosynthetic) and photosynthetic elements, whether from multitemporal (e.g., Portillo-Quintero, 2014) or multi-wavelength data (e.g., Nevalainen et al., 2014; Douglas et al., 2015), is a critical advance in our understanding of ecosystem structure (Zheng et al., 2015). Information on branch architecture is a priority for carbon cycle studies (e.g., Hunter et al., 2013) and remote sensing science (e.g., Morton et al., 2014). For example, multitemporal TLS scans of tree volume offer a pathway to improve species-specific allometric models (Clawges et al., 2007, Calders et al., 2015). Multitemporal ALS data can also be used to track fine-scale changes in forest architecture, including sub-lethal canopy damages common in tropical forests (Figure 9). Branch falls substantially alter carbon stocks in tropical forests, since crown material accounts for 1/3 of total aboveground biomass (Higuchi et al., 1998).

Figure 9. High-density airborne lidar (ALS) data can be used to identify branch, tree, and multiple treefall events ($\geq 4 \text{ m}^2$, red outlines) in undisturbed Amazon forests areas over annual time scales (a, 2012; b, 2013; based on methods described in Morton et al., 2016).

Multitemporal lidar data also capture the timing and magnitude of forest disturbances. Many studies have examined rates of canopy turnover and gap dynamics using multitemporal lidar (e.g., Dubayah et al., 2010; Kellner et al., 2009; Vepakomma et al., 2010; Hunter et al., 2015). Related work has focused on pre and post-disturbance changes in forest structure and biomass (e.g., Skowronski et al., 2014), understory vegetation (Portillo-Quintero et al., 2014), and fuels (e.g., Skowronski et al., 2011). Hypertemporal lidar could provide novel insights into circadian rhythms of canopy structure and their underlying mechanisms (Puttonen et al., 2016).

The key advantage of the multi or hypertemporal lidar studies is the ability to characterize forest dynamics at finer time scales than typical forest inventories (1-10 years), especially for disturbance events with distinct structural fingerprints (e.g., fire in tropical forests, Figure 10). One important advance is the

ability to confront ecosystem models with estimates of vegetation structure and dynamics derived from multitemporal lidar.

Figure 10. Multitemporal lidar data capture delayed mortality (red) and canopy height gains (blue) between 2012-2014 in an Amazon forest exposed to four understory fires between 2004-2009 (for study site details, see Brando et al., 2014).

When combined with the four physical dimensions, the additional data dimension of LRI significantly expands the scope of lidar applications in biogeochemical research. Calibrated intensity data offer great promise for target classification (e.g., Douglas et al., 2015; Béland et al., 2014; Wing et al., 2010); 3-D assessments of environmental heterogeneity, including the use of LRI polarization to study surface roughness, ice, and liquid water (Harding et al., 2011); and co-registration of lidar with passive optical imagery for data fusion studies (e.g., Cook et al., 2013).

991 However, some of the most promising avenues for the use of LRI information in lidar studies
992 reflect the unprecedented ability to provide spatially-explicit, 3-D estimates of foliar biochemistry and
993 function throughout plant canopies. For example, Nevalainen et al. (2014) demonstrated that lidar data
994 can be used to derive spatially-explicit, 3-D characterization of foliar chemistry throughout tree canopies
995 using a hyperspectral TLS system. Similarly, Gaulton et al. (2013) provided evidence that lidar data could
996 be used to directly quantify canopy foliar water content in 3-D. Other recent work has highlighted the
997 potential of lidar to evaluate physiological changes, such as foliar photoprotection, in 3-D (Magney et al.,
998 2014).

999 Another significant advantage of using LRI from lidar when compared to passive remote sensing
1000 could be the ability to remotely monitor and compare changes in foliar biochemistry not only during the
1001 day, but also at night. Many important plant physiological changes such as the replenishment of foliar
1002 water or the relaxation of photoprotective mechanisms (e.g. xanthophyll cycle epoxidation) occur during
1003 the nighttime. However, passive remote sensing approaches traditionally ignore this physiologically
1004 important time period because they rely on solar radiation. The ability to monitor biochemical function at
1005 all times of the day is an exciting new research direction to pursue using lidar LRI. We anticipate that
1006 additional creative uses of LRI will emerge to elucidate a wide range of ecosystem applications.

1007 The growing diversity of lidar technology expands the potential scope of LRI research. These
1008 advances include calculation of 3-D estimates of narrow-band vegetation indices, pairing lidar systems
1009 with new single photon detectors, and advancing the study of laser-induced fluorescence. In the near
1010 term, novel applications of LRI data dimension are most likely to come from TLS systems. Terrestrial
1011 laser scanners offer small footprints, high pulse density, and autonomy in target selection and repeated
1012 data collection. Continued development of low-cost instruments and airborne platforms will also
1013 accelerate the use of lidar to characterize additional aspects of vegetation dynamics (fruiting, flowering)
1014 using multitemporal lidar LRI data.

4.3.2 Terrestrial ecology

The static structural information from a single lidar acquisition provides valuable information for describing physical habitat characteristics that influence the diversity of animal communities (e.g., Vierling et al., 2008; review by Bergen et al., 2009 Goetz et al., 2011; review by Davies et al., 2014), but there are multiple promising avenues of research that might be opened with the additional physical (i.e., time) and data (i.e., LRI) dimensions provided by lidar. For example, in forests, species diversity can be related to structural information provided by lidar (reviewed in Müller and Vierling 2014). Repeat lidar would lend itself to examinations of species turnover as responses to structural changes that occur either on a monthly, seasonal, or sub-annual cycle, and such data would strengthen our understanding concerning the mechanisms associated with animal community structure and turnover.

Additionally, repeat lidar data would assist in assessing single species responses to changing environmental conditions. Animals respond to a variety of different structural variables at different spatial scales (Weisberg et al. 2014), and the temporal nature of data necessary to answer specific questions will vary with taxa. Multitemporal lidar collected simultaneously with animal movement data would likely provide greater insight into the mechanisms associated with movement, reproduction, and survival, especially for species that are migratory or range widely over broad landscapes (Bischof et al., 2012; Melin et al. 2013). For instance, moose (*Alces alces*) movements may be related to interactions between forage quality, thermal cover, and/or predator protection (Melin et al. 2013, Lone et al. 2014). Similarly, multi-temporal lidar could help determine changing predator-prey relationship dynamics, for example, with lion kill sites in an African thicket (Davies et al., 2016), or the response of deteriorating habitat on sable antelope populations (Asner et al., 2015). Because vegetation structure might be critical for providing certain resources at certain times of year, repeat lidar (week to years return interval) would be critical for being able to assess how changing animal movements might be related to changing vegetation structure (Neumann et al. 2015). Further, the ability of repeat lidar to measure vertical phenology could

provide important information that currently cannot be gained from passive remote sensing instruments. For example, phenological differences in the herb and tree layer are of high importance in research on leaf feeding insects.

Multitemporal and hypertemporal lidar data might also assist with expanding avenues of research within forested environments. Within forests, the classification of tree species (deciduous vs. coniferous) can be important in wildlife resource selection studies, and being able to detect phenophases at fine temporal scales and vertical profiles including the understory, intermediate, and upper canopy (e.g., see Calders et al., 2015) may assist in understanding the drivers of animal resource selection. For instance, the period of breaking leaf buds adds structural complexity to an environment, and for bats, obstacles in 3-D caused by different phenophases can influence their foraging patterns (Müller et al., 2012). In addition, the interactions among species and their 3-D environment could help to explain the spatial distribution of plant species as a response to termites (Davies et al., 2016).

Moreover, the temporal development of plant leaves is strongly related to the quality of food for herbivores near the ground but also in canopies. Such information on food quality, which is often related to foliar nitrogen content, could be tracked based on LRI information (e.g., Eitel et al., 2010; Eitel et al., 2011; Nevalainen et al., 2014) and provide new opportunities to study food quality driven animal movements across time a space within and across years (e.g., Bischof et al., 2012). The LRI is also likely to augment plant species and habitat type identification beyond the application of lidar physiognomy data or aerial photos (Hudak et al., 2006; Bäessler et al., 2011). For example, based on both the structural (x,y,z) and LRI information from lidar, different canopy components (e.g., needles, branches, and bark surface) could be quantified and mapped across different strata at very high precision (Ma et al., 2015; Béland et al., 2014; Danson et al., 2014; Clawges et al., 2007). Such novel datasets could aid in testing fundamental hypotheses in ecology, such as the species energy hypothesis postulating that areas with greater resources support higher species richness due to larger populations (Turner et al., 1988) or the habitat heterogeneity hypothesis postulating that the number of habitats increases with area and, as long as species use different habitats, species richness should also increase with area (e.g. Simpson 1949;

MacArthur & MacArthur 1961; Tews et al. 2004). The use of LRI can also assist in habitat selection studies as they relate to climate change; for instance, LRI has been used to better understand patterns of nest site selection of two arctic breeding birds, where timing of snowmelt and standing water might be critical in the selection of nest sites (Boelman et al., under review).

Other wildlife related research might take full advantage of the 5-D mapping capabilities of lidar (Table 1F). For example, 5-D mapping capabilities of lidar may allow obtaining a more complete picture of disturbance driven succession such as initiated by bark beetles. These beetles initiate a cascade of habitat altering events from first shifts in leaf biochemistry and tree function detectable by LRI (e.g., Gaulton et al., 2013, Danson et al., 2014; Eitel et al., 2010; Magney et al, 2014; Junttila et al., 2015) to habitat structural changes over time quantifiable by repeat lidar.

5 Challenges

Expanding the use of lidar data to incorporate the physical time- and LRI data information has great potential to advance 5-D research and applications in EES. To realize this potential, several challenges have to be overcome: (1) *Limited availability of appropriate datasets*: Currently, only a few commercially available multi-wavelength lidar systems exist, and, to our knowledge, no commercially available hyperspectral lidar system exists. Similarly, only a few lidar systems are operational for autonomously acquiring hypertemporal lidar datasets over a prolonged period of time (> several days) under a range of weather and environmental conditions. Ongoing instrument development, spurred by recent advances in lidar research, can address this issue in the coming years, especially for lidar multi-wavelength and hypertemporal lidar applications; (2) *Lack of standardized processing and analysis approaches*: Due to the relatively small number of studies that use hypertemporal lidar and LRI, efforts to develop standardized processing and analysis approaches have been limited. For example, a wide variety of approaches have been used to correct LRI for range effects, but it is difficult to compare study results derived from different methods and evaluate their transferability. Standardized processing and analysis

approaches for multi-temporal and LRI data would help spur additional 5-D lidar research; (3) *Large dataset size*: lidar datasets are large, and data volumes will increase with the expansion of the spectral and temporal dimensions of lidar data. Hence, there is a need to continue development of point cloud management and analysis approaches for efficiently visualizing, managing, and analyzing large 5-D lidar datasets. Promising starting points for such approaches could be existing transient data management systems and point cloud based change detection algorithms, such as the M3C2 algorithm of Lague et al. (2013), the GPU-based change detection by Richter and Döllner (2014), and the 4-D filtering technique recently proposed by Kromer et al. (2015); (4) *Integration into EES modeling and decision making*: A wide variety of EES models and decision making could benefit from the 5-D information provided by lidar. However, there is a lack of methods for more seamless integration of 5-D lidar into EES models and decision making. Hence, methods and tools are needed that allow creating model-ready datasets that can be easily integrated into models and decision making even by non-lidar experts; (5) *Standardization of terminology*: Building on existing efforts (e.g., Schaepman-Strub et al., 2006), there is a need to further standardize terminology within this field of newly emerging lidar research to ensure effective and clear communication. Each of these challenges (data, instrumentation, processing, integration, and terminology) reflects the novelty of 5-D lidar applications. Continued growth of the lidar research community will undoubtedly surmount these challenges to meet the promise and potential of taking EES lidar applications beyond 3-D.

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2074

2075 **List of figure captions**

2076 **Figure 1.** Number of publications with the following keywords searchers using the Web of Science™
2077 database: “lidar”, “lidar and multitemporal”, “lidar and hypertemporal”, “lidar and Intensity”, and “lidar
2078 and multi-wavelength” (results as of January 2016).

2079

2080 **Figure 2.** The “five dimensions” of lidar: The physical x,y,z dimension, the physical time (t) dimension,
2081 and the laser return intensity (LRI) data dimension at one or more wavelengths (λ).

2082

2083 **Figure 3.** Terrestrial lidar point cloud colored by recorded signal amplitude showing both vegetation and
2084 rock outcrop. Vegetation is characterized by a lower laser return intensity signal in the near-infrared
2085 wavelength of the scanner (Riegl VZ-6000 with wavelength of 1064 nm) compared to the bare rock
2086 surfaces.

2087

2088 **Figure 4.** Hypertemporal lidar of an active pahoehoe lava flow on the flanks of the Kilauea Volcano:
2089 Comparisons of four terrestrial lidar scans to an initial baseline scan reveal height change, or
2090 accumulation of lava, over time.

2091

2092 **Figure 5.** Illustration of the potential of hypertemporal lidar data from an autonomously operating
2093 terrestrial laser scanner (ATLS) for studying dynamic structural processes at very high spatial and
2094 temporal resolution. Figure 5-I shows an example of an ATLS point cloud, Figure 5-II shows the
2095 snowpack evolution derived from hypertemporal lidar at an open (1) and closed (2) canopy site, and

Figure 5-III shows a cross section of the snowpack in the open canopy stand acquired during Julian day 20 (A), Julian day 34 (B), and Julian day 51 (C).

Figure 6. lidar signal amplitude before (left) and after (right) the removal of the range-dependent effects. The red arrows indicate the border between the overlapping point clouds captured from two different distances (150m and 255m). It can be seen that the range correction removes the predominant range-dependent effects. The data were calibrated using a range-amplitude correction function determined in the lab for the Riegl VZ-6000 operating at 1064 nm.

Figure 7. Relationship between foliar nitrogen concentration of wheat (*Triticum spp.*) and calibrated green (532 nm) laser return intensity (figure adapted from Eitel et al., 2011).

Figure 8. East Wall area at Arapahoe Basin Ski Area, Colorado, USA, on 1 February, 2014. Colors indicate change in snow depth relative to 23 January, prior to a snow accumulation event. Large avalanche was initiated by a single explosive charge detonated at point “X”. White coloration on the avalanche bed surface indicates that the sliding layer is the old, pre-storm snow surface (from Deems et al., 2015).

Figure 9. High-density airborne lidar (ALS) data can be used to identify branch, tree, and multiple treefall events ($\geq 4 \text{ m}^2$, red outlines) in undisturbed Amazon forests areas over annual time scales (a, 2012; b, 2013; based on methods described in Morton et al., 2016).

Figure 10. Multitemporal lidar data capture delayed mortality (red) and canopy height gains (blue) between 2012-2014 in an Amazon forest exposed to four understory fires between 2004-2009 (for study site details, see Brando et al., 2014).