Laser Vision: Lidar as a Transformative Tool to Advance Critical Zone Science

Adrian A. Harpold*, University of Nevada, Reno, aharpold@email.arizona.edu

Jill A. Marshall, University of Oregon, jillm@uoregon.edu

Steve W. Lyon, Stockholm University, steve.lyon@natgeo.su.se

Theodore B. Barnhart, University of Colorado, theodore.barnhart@colorado.edu

Beth Fisher, University of Minnesota, wene0018@umn.edu

Mitchell Donovan, University of Maryland – Baltimore County, mdonovan@umbc.edu

Kristen M. Brubaker, Hobart and William Smith Colleges, brubaker@hws.edu

Christopher J. Crosby, UNAVCO, Crosby@unavco.org

Nancy F. Glenn, Boise State University, nancyglenn@boisestate.edu

Craig L. Glennie, University of Houston, clglenni@central.uh.edu

Peter B. Kirchner, University of California, Los Angeles, peter.b.kirchner@jpl.nasa.gov

Norris Lam, Stockholm University, norris.lam@natgeo.su.se

Kenneth D. Mankoff, Woods Hole Oceanographic Institute, kmankoff@whoi.edu

James L. McCreight, National Center for Atmospheric Research, mccreigh@gmail.com

Noah P. Molotch, University of Colorado, Boulder, noah.molotch@colorado.edu

Keith N. Musselman, University of Saskatchewan, keith.musselman@usask.ca

Jon Pelletier, University of Arizona, jon@geo.arizona.edu

Tess Russo, Pennsylvania State University, russo@psu.edu

Harish Sangireddy, University of Texas, Austin, hsangireddy@utexas.edu

Ylva Sjöberg, Stockholm University, ylva.sjoberg@natgeo.su.se

Tyson Swetnam, University of Arizona, tswetnam@email.arizona.edu

Nicole West, Pennsylvania State University, nxw157@psu.edu

*Corresponding author: Adrian A. Harpold, aharpold@cabnr.unr.edu

Laser Vision: Lidar as a Transformative Tool to Advance Critical Zone Science

Observation and quantification of the Earth surface is undergoing a revolutionary change due to the increased spatial resolution and extent afforded by light detection and ranging (lidar) technology. As a consequence, lidar-derived information has led to fundamental discoveries within the individual disciplines of geomorphology, hydrology, and ecology. These disciplines form the cornerstones of Critical Zone (CZ) science, where researchers study how interactions among the geosphere, hydrosphere, and biosphere shape and maintain the 'zone of life', extending from top of unweathered bedrock to the top of the vegetation canopy. Fundamental to CZ science, is the development of transdisciplinary theories and tools that transcend individual disciplines and inform other’s work, capture new levels of complexity, and create new intellectual outcomes and spaces. Researchers are just beginning to utilize lidar datasets to answer synergistic, transdisciplinary questions in CZ science, such as how CZ processes co-evolve over long-time scales and interact over shorter time scales to create thresholds shifts in states and fluxes of water, energy, and carbon. The objective of this review is to elucidate the transformative potential of lidar for CZ science to simultaneously allow for quantification of topographic, vegetative, and hydrological processes. A review of 147 peer-reviewed studies utilizing lidar highlights a lag in utilizing lidar for CZ studies as 38% of the studies were focused in geomorphology, 18% in hydrology, 32% in ecology, and the remaining 12% had an interdisciplinary focus. A handful of exemplar transdisciplinary studies demonstrate that well-integrated lidar observations can lead to fundamental advances in CZ science, such as identification of feedbacks between hydrological and ecological processes over hillslope scales and the synergistic co-evolution of landscape-scale CZ structure due to interactions amongst carbon, energy, and water cycles. We propose that using lidar to its full potential will require numerous advances across CZ applications, including new and more powerful open-source processing tools, exploiting new lidar acquisition technologies, and improved integration with physically-based models and complementary *in situ* and remote-sensing observations. We provide a five-year vision that advocates for the expanded use of lidar datasets and highlights subsequent potential to advance the state of CZ science.

1. INTRODUCTION

Complex interactions among the geosphere, ecosphere, and hydrosphere give rise to present-day landforms, vegetation, and corresponding water and energy fluxes. Critical Zone (CZ) science studies these interactions in the zone extending from top of unweathered bedrock to the top of the vegetation canopy. Understanding CZ function is fundamental to characterizing regolith formation, carbon-energy-water cycles, meteorological controls on ecology, linked surface and subsurface processes, and numerous other Earth surface processes (NRC, 2012). Improved understanding of CZ functions is thus important for quantifying ecosystem services and predicting their sensitivity to environmental change. However, CZ processes are difficult to observe because they occur over time scales of seconds to eons and spatial scales of centimeters to kilometers, and thus require diverse measurement approaches (Chorover et al., 2011). Light detection and ranging (lidar) technologies can be helpful in this regard because they generate repeatable, precise three-dimensional information of the Earth's surface characteristics.

Lidar allows for simultaneous measurements of aboveground vegetation structure and human infrastructure, as well as the topography of the earth surface, including soils, exposed bedrock, stream channels, and snow/ice. Depending on the data collection system and platform, observations can be made at the landscape scale (>1000 km^2) and at spatial resolutions capable of capturing fine-scale processes (<10 cm). These unique measurement capabilities offered by lidar have the potential to lead to transdisciplinary research questions, which transcend a single discipline, capture greater complexity, and create new intellectual advances that are synergistic (across disciplines) in nature. Fundamental CZ science questions often require transdisciplinary approaches that surpass what is possible in multidisciplinary (i.e. collaborations across disciplines that pose their own questions) or interdisciplinary (i.e. collaborations where information is transferred amongst disciplines) research settings. Because lidar can characterize geomorphic, ecologic, and hydrologic processes simultaneously across a range of scales, it is uniquely suited to address questions posed by CZ research.

Lidar acquisition capabilities are increasing exponentially (Stennett, 2004; Glennie et al., 2013) and new ground-based (terrestrial laser scanning, TLS), mobile platforms (airborne laser scanning, ALS or other mobile platforms like a truck or boat), and space-based platforms (spaceborne laser scanning, SLS) are leading to increased availability of lidar datasets with CZ-relevant information content. Different lidar platforms each have their own advantages and limitations, but operate based on a similar principle by emitting and measuring the time of travel of an energy pulse (laser light) and thus, measuring and mapping distance to a target. Collection via TLS methods typically involves lidar scanners that are mounted on tripods or other fixed locations. Fixed targets are used to georeference the lidar datasets, with a high resolution GPS, to composite multiple TLS scans into a single point cloud. TLS scanners are becoming more affordable and available to individual researchers and groups. lidar collections via mobile platforms are typically performed by mounting the lidar unit on an aircraft, helicopter, or vehicle that is moved over the study area of interest. The aircraft must be equipped with a GPS unit and Internal Measurement Unit (IMU) to track the orientation and location of the scanner. Similar to TLS collection, ALS methods require ground targets with known GPS locations for georeferencing. Lidar collection via SLS are much less common, but have been successfully deployed on orbiting spacecraft, and will become more prevalent in 2017 with the planned launch of ICESat-2 (Abdalati et al., 2010). In addition to the laser system, the spacecraft must have a GPS unit and altitude determination system in order to georeference the data. Each of these lidar platforms offer specifications that can be selected and adjusted for a given science application. Throughout this review we present studies using the suite of lidar methods and highlight the advantages of each method for differing scientific purposes.

The objective of this paper is to present a five-year vision for applying lidar to advance transdisciplinary CZ research. To accomplish this we first present the state of the science on applying lidar to disciplinary-specific research in geomorphology, hydrology, and ecology in Sections 1.1, 1.2, and 1.3, respectively. This is followed in Section 2.1 by an exploration of transdisciplinary studies that utilized complementary lidar-derived datasets to propel CZ science beyond what is possible within disciplinary endeavors. We summarize these exemplar transdisciplinary studies with the intent to guide future research. In Section 2.2 we describe how lidar-derived information is uniquely suited to advance three CZ research topics beyond the current state of the science: 1) quantifying change detection, 2) parameterization and verification of physical models, and 3) improved understanding of CZ processes across multiple scales. These topics are limited by a set of common impediments that we outline in Section 2.3. Finally, in Section 2.4, we present a vision to advance CZ science with lidar using examples of transdisciplinary research questions and provide a set of recommendations for the CZ community to increase usage and advocate for greater lidar resources over the next five years.

1.1 Advances in Geomorphology Using Lidar

High-resolution topographic datasets derived from lidar have greatly contributed to quantifying geomorphic change, identifying geomorphic features, and understanding ecohydrologically-mediated processes at varying scales and extents. These advances have allowed testing of geomorphic models, pattern and process recognition, and the identification of unanticipated landforms and patterns (e.g. waveforms) that were not possible using previous survey techniques. Generally, lidar information complements rather than replaces field observations, with lidar observations leading to new hypothesis and process cognition (Roering et al., 2013). Broadly, lidar technology has been useful in studying geomorphic response to extreme events such as fire and storms (e.g., Pelletier and Orem, 2014; Sankey et al., 2013; Perignon et al., 2013; Staley et al., 2014), human activities (e.g. James et al., 2009), and past climatic and tectonic forcings (e.g., Roering, 2008; Belmont, 2011; West et al., 2014). Meter and sub-meter scale time-varying processes, often derived from TLS, have been quantified in the response of point bar and bank morphodynamics (Lotsari et al., 2014) and in the formation of microtopography due to feedbacks with biota (e.g., Roering et al., 2010; Pelletier et al., 2012; Harman et al., 2014). Examples of larger scale change detection applications, typically ALS-derived, include measuring changes in stream channel pathways resulting from Holocene climate change and anthropogenic activities (e.g., Day et al., 2013; Kessler, 2012; James 2012; Belmont et al., 2011), rates of change in migrating sand dunes (Pelletier, 2013), the influence of lithology and climate on hillslope form (e.g., Marshall and Roering, 2014; Hurst et al., 2013; Perron et al., 2008; West et al., 2014), and channel head formation (e.g., Pelletier et al., 2013; Pelletier and Perron, 2012; Perron and Hamon, 2012). Automated tools to identify geomorphic features (i.e., floodplains, terraces, landslides) and transitional zones (i.e., hillslope-to-valley, floodplain-to-channel) have been used in conjunction with high-resolution elevation datasets from lidar, including Geonet 2.0 (Passalacqua et al., 2010), ALMTools (Booth et al., 2009), and TerrEX (Stout and Belmont, 2014).

1.2 Advances in Hydrology Using Lidar

Research utilizing lidar has advanced fundamental process understanding in snow hydrology (Deems et al., 2013), surface water hydraulics (Lane et al., 2004; Nathanson et al., 2012; Lyon et al., 2015), and land-surface-atmosphere interactions (Mitchell et al., 2011). Lidar-derived snow depths (derived by differencing snow-on and snow-off elevations) over large (>1 km^2) spatial extents from both ALS and TLS (Deems et al., 2013), have yielded unprecedented contiguous maps of spatial snow distributions (e.g. Fassnacht and Deems, 2006; McCreight et al., 2014) and provided new insights into underlying processes determining spatial patterns in snow cover (Trujillo et al., 2009; Kirchner et al., 2014), accumulation and ablation rates (Grunewald et al., 2010; Varhola and Coops, 2013), snow water resources for planning (Hopkinson et al., 2012), and estimating the effects of forest cover and forest disturbance on snow processes (Harpold et al., 2014a). Change detection techniques have been effective for determining glacier mass balances (Hopkinson and Demuth, 2006), ice surface properties (Williams et al., 2013), and calving front movements (e.g., Arnold et al., 2006; Hopkinson et al., 2006). Prior to lidar, many of these cryospheric processes had to be investigated using single point observations or through statistical rather than deterministic analyses; the additional information derived from lidar has yielded important insights that advanced scientific understanding. High- resolution topographic information from lidar has proved important for stream channel delineation (Kinzel et al, 2013), rating curve estimation (Nathanson et al., 2012; Lyon et al., 2015), floodplain mapping and inundation (Marks and Bates, 2000; Kinzel et al., 2007), and topographic water accumulation indices (Sørensen and Seibert, 2007; Jensco et al., 2009). Lidar measurements of micro-topography measured using lidar shows potential for improving soil property and moisture information (e.g., Tenenbaum et al, 2006), surface and floodplain roughness (Mason et al., 2003, Forzieri et al., 2010; Brasington et al., 2012; Brubaker et al., 2013), hydraulic dynamics and sediment transport (Roering et al., 2012; McKean et al., 2014), surface ponding and storage volume calculations (Li et al., 2011; French, 2003), and wetland delineation (e.g. Lane and D'Amico, 2010). Certain hydrological modeling fields are well-poised to utilize high-resolution topography, such as movement of water in urban environments (Fewtrell et al., 2008), in-channel flow modeling (Mandlburger et al., 2009; Legleiter et al., 2011), and hyporheic exchange and ecohydraulics in small streams (e.g. Jensco et al., 2009). Finally, high-resolution, three-dimensional lidar measurements of canopy and vegetation structure (Vierling et al., 2008) have direct implications for modeling the surface energy balance (Musselman et al., 2013) and evapotranspiration processes (Mitchell et al., 2011) at scales critical to increasing fidelity in physically-based models (Broxton et al., 2014).

1.3 Advances in Ecology Using Lidar

Lidar-based remote sensing of vegetation communities has transformed the way ecologists measure vegetation across multiple spatial scales (e.g. Lefsky et al. 2002; Maltamo et al. 2014; Streutker and Glenn 2006). Substantial work has been undertaken using lidar to map vegetation structure and biomass distributions (see reviews by Seidel et al. 2011 and Wulder et al. 2012). These include the estimation of Leaf Area Index (LAI) (Riaño et al. 2004, Richardson et al. 2009; Hopkinson et al., 2013), vegetation roughness (Streuker and Glenn, 2006; Antonarakis et al., 2010), alpine tree lines (Coops et al., 2013), and total carbon storage and sequestration rates in forest, grassland, savannahs and/or shrubland communities (Asner et al. 2012a, Baccini et al. 2012, Mascaro et al. 2011, Simard et al. 2011; Antonarakis et al., 2014). ALS has been used to characterize wildlife habitat in tree and shrub canopies (Hyde et al. 2005, Bork and Su, 2007; Vierling et al. 2008, Martinuzzi et al. 2009; Zellweger et al., 2014) and in aquatic systems (McKean et al. 2008, Wedding et al. 2008, McKean et al., 2009). ALS has been a critical tool in modeling catchment scale water-availability for vegetation at fine (Harmon et al. 2014) and broad spatial scales (Chorover et al. 2011). Radiation transmission and ray-tracing models utilizing lidar provide ecologists with better tools to quantify in-canopy and below-canopy light environments (Lee et al., 2009; Bittner et al. 2014; Musselman et al. 2013; Bode et al., 2014; Moeser et al., 2014). Additionally, ecologists are beginning to quantify the impact of vegetation on micro-topography (Sankey et al. 2010; Pelletier et al., 2012; Harmon et al., 2014), as well as larger landform processes (Pelletier et al. 2013). Broad-scale lidar data allows for quantification of patches and mosaics amongst plant functional types across landscapes (Antonarakis et al., 2010, Dickinson et al., 2014) and global forest biomass estimates (Simard et al., 2011). Ecologists have fused data from hyperspectral imaging and lidar to enable species classification for close to a decade (e.g. Mundt et al., 2006). However, new opportunities exist to link species-level detail and plant functional response through emerging technologies, including co-deployment of hyperspectral and lidar sensors (Asner et al. 2012b), and hyperspectral (supercontinuum) laser technology (Kaasalainen et al. 2007, Hakala et al. 2012). By linking lidar with additional observations, researchers have begun to quantify species-level detail and plant health estimation (Cho et al. 2012, Féret and Asner 2012; Olsoy et al., 2014) and model forest carbon fluxes (Antonarakis et al., 2014).

2. Current Toolkits and Open Questions Using Lidar in CZ Science

Research based on lidar-derived information accounts for substantial advances within the cornerstone CZ disciplines. However, many open questions in CZ science require linked, transdisciplinary investigations across multiple disciplines that create new intellectual spaces for scientific advancements. For example: How do CZ processes co-evolve over long-time scales and interact over shorter time scales to develop thresholds and shifts in states and fluxes of water, energy, and carbon? What will be the response of the CZ structure to disturbance and land use change? These CZ science questions must elucidate feedbacks and interactions among the geosphere, ecosphere, and hydrosphere that cannot be accomplished within individual disciplines (multidisciplinary) or sharing information across disciplines (interdisciplinary), but instead require synergistic transdisciplinary science that spans multiple spatial and temporal scales.

A key advantage of lidar for understanding CZ feedbacks is the coupling of previously unprecedented coverage over both broad temporal and spatial scales (Figure 1). The utility of lidar for geo- eco- and hydro-sphere investigations is dependent on the platform (e.g. TLS, ALS, or SLS) with cross-platform observations capable of resolutions from 10^{-3} m to continental scales (Figure 1). In terms of temporal extent, TLS, ALS and SLS are capable of employing weekly to sub-hourly repeat scan rates (Figure 1). Technologies allowing for faster scan rates will typically limit the spatial extent (Figure 1). Advances in technology described in Section 2.3 will increase the spatial and temporal resolutions for all lidar platforms in the next five years (Figure 1). The intersecting process scales shown in Figure 1 demonstrate the viability of extracting transdisciplinary information from lidar given thoughtful experimental design and data collection.

2.1 Lidar as Transdisciplinary CZ Tool

To investigate the state of the science of lidar in CZ research we conducted a literature review of 147 peer-review papers that employed lidar datasets to improve process-based understanding in the CZ domain. Our review found that most lidar studies to date have had a single disciplinary objective and that the CZ community are less likely to utilize the overlapping information in space and time generated by lidar available for transdisciplinary CZ advancement (Figure 1). This is not surprising given the rampant progress made in filling important knowledge gaps in the individual cornerstone CZ disciplines using lidar datasets (Sections 1.1 to 1.3). We organized the literature reviewed for this paper into a scoring system of geomorphic, hydrologic, and ecologic process knowledge advanced through individual lidar-based studies. For each paper we assigned 10 points among the three disciplines to capture potential transdisciplinary lidar use. For example, a study leading purely to hydrologic process advances would rank as 10 in the hydrology category and zero in the ecology and geomorphology categories. A study balancing the process-based inferences among the three disciplines, with a more prominent ecological focus, would have been assigned scores of 3, 3, and 4 for geomorphology, hydrology, and ecology, respectively. Of course, this is a subjective scaling based on author opinions. To limit potential impacts of subjectivity, three different authors of the current paper assigned independent scores to each study and we used the average score to place each paper in the relative ranking triangle (Figure 2).

The motivation for developing the conceptualization in Figure 2 is to facilitate identification of studies employing transdisciplinary synergies (e.g., lie within the internal triangle) that rely on the multi-faceted nature of lidar datasets. The review showed 38% of 147 studies were focused (score of 6 or higher) in geomorphology, 18% in hydrology, 32% in ecology, and the remainder had a more interdisciplinary focus. The few studies in the center of the triangle (i.e., studies receiving a minimum of 20% in each discipline) could be considered as potential exemplars of CZ science using lidar as they balance well among each cornerstone discipline. Several studies were transdisciplinary in nature, but focused on lidar-derived topography and did not maximize information content on hydrological and ecological processes from lidar: Pelletier et al. (2012), Persson et al. (2012), Brubaker et al. (2013), Pelletier (2013), Coops et al. (2013), Rengers et al. (2014), and Pelletier and Orem (2014). We instead draw focus to transdisciplinary studies that demonstrate the potential for complimentary information to be extracted from lidar and integrated into field campaigns to allow multi-scale observations of interacting geomorphologic, hydrologic, and ecologic processes.

We highlight three studies that can serve as possible roadmaps to guide future transdisciplinary investigations using lidar datasets (Figure 2): Harman et al., 2014, Pelletier et al., 2013, and Perignon et al., 2013. These studies used complimentary information from lidar to develop fundamental transdisciplinary advances in the theories and understanding of CZ processes and structure. For example, Harman et al. (2014) applied TLS to investigate coevolution of lidar-derived microtopography and vegetation (biovolume) at two 100-m long semi-arid hillslopes. Integrating lidar and limited field measurements, Harman et al. (2014) found that both alluvial and colluvial processes were important in shaping vegetation and soil dynamics on hillslopes. The insights found by Harman et al. (2014) relied on the high resolution and precision of lidar information and would not have been possible using coarser traditional survey techniques for topography and vegetation structure. Pelletier et al. (2013) investigated landscape-scale (>10 km^2) variability in above-ground biomass, hydrologic routing, and topography derived from lidar at two mountain ranges in southern Arizona and applied a landscape evolution model to demonstrate the need to include ecological processes (e.g. vegetation density) to correctly model topography. Lidar-derived vegetation structure provided new information not attainable from other methods that allowed for Pelletier et al. (2013) to test a novel model of CZ development based on eco-pedo-geomorphic feedbacks. Perignon et al. (2013) investigated topographic change following a major flood along a 12 km stretch of the Rio Puerco in New Mexico. They found that sedimentation patterns reflected complex interactions of vegetation, flow, and sediment at the scale of individual plants. This example demonstrates the value of lidar for testing ecohydrological resilience to extreme events to develop new understanding of the fine-scale ecological feedbacks (i.e. individual plants) on reach scale geomorphic response.

These exemplar studies demonstrate the utility of lidar for transdisciplinary process investigations at scales ranging from hillslopes (e.g. Harman et al., 2014), to stream reaches (e.g. Perignon et al., 2013), to mountain ranges (e.g. Pelletier et al., 2013). We believe that these exemplar transdisciplinary studies should serve as motivation for increased use of lidar and integrated, multi-scale field observations for advancing CZ science. To this end, in Section 2.4

we provide additional examples to illustrate the overlapping processes observable with lidar that are motivated by CZ science questions.

2.2 Applying Lidar in CZ Science

Through our literature review and subsequent conceptualizations (e.g., Figure 1) we have identified three clear areas where lidar observations have the potential to advance the state of CZ science in the next five years: 1) quantifying change detection, 2) parameterization and verification of physical models, and 3) improved understanding of CZ processes across multiple scales. Applying these tools is not mutually exclusive and each area has different levels of previous research and development. For example, change detection utilizing lidar has received notable use in the CZ science community, particularly by geomorphologists analyzing topographic change over time. The use of lidar to quantify scaling relationships and thresholds remains relatively unexplored, despite robust scaling theories and analysis tools from other fields that are portable to lidar datasets. Similarly, integration of lidar datasets for either parameterization or verification has had limited development within CZ-relevant models.

2.2.1 *Change Detection*

Lidar-based change-detection analyses (CDA), i.e. mapping landscape adjustments through time in multi-temporal ALS and TLS datasets, have provided comprehensive measurements of snow depth (e.g. Harpold et al., 2014b; Tinkham et al., 2014) and ablation (Egli et al., 2012), co-seismic displacements after earthquakes (e.g. Oskin et al., 2012; Nissen et al., 2014), changes in aeolian dune form and migration rates (e.g. Pelletier, 2013), fluvial erosion (e.g. Anderson and Pitlick, 2014; Pelletier and Orem, 2014), earthflow displacements (e.g. DeLong et al., 2012), knickpoint migration in gully/channel systems (e.g. Rengers and Tucker, 2014), cliff retreat along coasts (Young et al., 2010), permafrost degradation (Levy et al., 2013; Barnhart and Crosby, 2013), forest growth (Yu et al., 2004; Næsset and Gobakken, 2005), and changes in biomass (e.g. Meyer et al. 2013; Olsoy et al., 2014). Traditionally, lidar point clouds have been rasterized prior to differencing using open-source processing toolkits (e.g. GCD; e.g. Wheaton et al., 2010). However, new methods such as Iterative Closest Point (Nissen et al., 2012), particle image velocimetry (Aryal et al., 2012), and Multiscale Model to Model Cloud Comparison (Lague et al., 2013) enable direct differencing of point clouds. Continued methodological advances, coupled with increasingly available repeat datasets will progress the capabilities and quality of CDA. Structure from Motion (SfM) estimates three-dimensional structures from two-dimensional images providing an easily portable and low-cost method for making high-frequency change detection measurements (Westoby et al., 2012; Fonstad et al., 2013). There is also potential to apply time-series multi/hyperspectral lidar datasets to quantify changes in forest health over time. Similarly, integration of bathymetric lidar with ALS opens the potential to monitor dynamic changes in river flow and sediment transport (Flener et al., 2013). Although researchers often implement CDA using historic datasets (Rhoades et al., 2009), challenges arise from sparse metadata and reduced accuracy, thereby limiting dataset utility (e.g. Glennie et al. 2014). Future CDA may be improved by further establishing, through repositories such as OpenTopography and UNAVCO, best practices for dataset sharing and archiving.

2.2.2 ***Scaling CZ Processes***

While researchers have harnessed existing scaling theories and tools utilizing lidar datasets, there is room for expansion using the range of scales afforded by lidar technologies (Figure 1). Two complementary techniques, characterizing fractal patterns (e.g. Deems et al. 2006; Glenn et al., 2006; Perron et al., 2008) and process changes expressed as fractal breaks (e.g. Drake and Weishampel, 2000), benefit from the extensive breadth of spatial scales offered by lidar data. Self-similar patterns across scales indicate consistent processes and thus provide a framework for sampling, modeling, and re-scaling processes. Variograms and semi-variograms are commonly employed to plot lidar-derived attributes of interest such as snow distribution (e.g. Deems et al. 2008; Harpold et al., 2014a) or forest spatial patterns (e.g. Boutet et al. 2003) against scale. Fractal and fractal deviations, as well as the length-scales of landscape structure (Perron et. al. 2008), convey important CZ information, e.g., the effect of tree-root spacing through time on soil production (Roering et al., 2010), patterns in tree gap-formation (Plotnick et al. 1996; Frazer et al., 2005), and underlying abiotic and biotic controls on forest fractal dimensions (Drake and Weishampel, 2000). Within the CZ framework, lidar allows consideration of topographic variation and biomass distribution (Chorover et al. 2011), and spatial thresholds for interactions among vegetation, hydrology, lithology, and surface processes ranging from the grain to landscape scale (e.g., Musselman et al. 2013, Pelletier et al. 2013; Harman et al., 2014). Zhao et al. (2009) developed a scale-invariant model of forest biomass, which illustrated the utility of scale-independent methods. However, we caution that one scientist's signal may be another's noise (Tarolli, 2014). Signal recognition may involve smoothing at one scale to quantify a relevant landscape metric, such as hillslope curvature (and derived erosion rates) (Hurst et al. 2013), which in turn limits valuable information at another scale, such as hydrologically-driven surface roughness or the spacing of tree-driven bedrock disruption (Roering et al. 2010, Hurst et al 2012). Overall, lidar datasets retain the promise of up- or down- scaling feedbacks among multiple processes that are just beginning to be fully utilized.

2.2.3 *Model Parameterization and Verification*

The wealth of recently collected lidar data has potential to inform the choice of physically-based model parameters and verify model output. Improved terrain representation has helped characterize hysteretic relationships between water storage and contributing area in large wetland complexes within parameterized runoff models (Shook et al., 2013), improve mapping in and along river channels to parameterize network level structure and flood inundation models (French, 2003; Kinzel et al., 2007; Snyder, 2009; Bates 2012), and expanded investigation of geomorphological change in floodplains (Thoma et al., 2005; Jones et al., 2007). Lidar provides vertical information that permits the direct retrieval of forest attributes such as tree height and canopy structure (Hyyppä et al., 2012; Vosselman and Maas, 2010) that can be used to model canopy volume (Palminteri et al., 2012), biomass (Zhao et al., 2009), and the transmittance of solar radiation (Essery et al., 2008; Musselman et al., 2013; Bode et al., 2014). Lidar has also proven to be instrumental in the verification of model states. For example, lidar datasets have been used to verify physically-based models, including landscape evolution models (Pelletier et al., 2014; Pelletier and Perron, 2012; Rengers and Tucker, 2014), aeolian models (Pelletier et al., 2012; Pelletier, 2013), physiological models (Coops et al., 2013), snowpack energy balance models (Essery et al. 2008, Broxton et al., 2015), and an ecosystem dynamics model (Antonarakis et al., 2014). Simpler, empirical models have also been developed using lidar-derived estimates of soil erosion (Pelletier and Orem, 2014) and snow accumulation and ablation (Varhola et al., 2014). Better recognition of the potential benefits of lidar for model calibration and verification within CZ modeling community could lead to increased utilization and targeted acquisitions in the future.

2.3 Adoption and Utilization of Lidar Datasets

New and improved lidar datasets are more likely to result in transformative CZ science if a number of key opportunities (and impediments) are recognized. The research topics discussed in Section 2.2 require attention to four key areas in order to maximize the applicability of lidar in CZ science: 1) Emerging data acquisition technology, 2) Availability of processing and analysis techniques, 3) Linkages to *in situ* observations, and 4) Linkages to other remote sensing observations. The first two areas recognize the importance of technological advances and information sharing to enhance lidar data quality and coverage. The second two areas demonstrate the potential to extend scientific inferences made from lidar with linkages to multiple, complementary observations.

2.3.1 *Data Acquisition Technology*

Future advances in data acquisition technologies will provide greater information and spatiotemporal coverage from lidar (and lidar-like) datasets. Several new lidar technologies are rapidly increasing data quality (accuracy, precision, resolution, etc.) and information content. Full waveform lidar data promises to provide better definition of ground surface and vegetation canopy (Wagner et al, 2008, Mallet and Bretar, 2009). Utilizing blue-green light spectrum, lidar systems are capable of bathymetric profiling (McKean et al., 2009; Fernandez-Diaz et al., 2014) and potentially determining turbidity and inherent optical properties of the water column. Lidar systems have demonstrated the benefits of combining point clouds with alternative data sources by, for example, including intensity and/or RGB cameras (Bork and Su, 2007) that collect data synchronously with the lidar and provide metadata for each point in the cloud. Less expensive and more adaptable lidar systems (Brooks et al, 2013) and alternative 3-D remote sensing techniques, such as SfM or low-cost 3D cameras (Mankoff and Russo, 2013; Javernick et al., 2014; Lam et al., 2015), promise high resolution monitoring at finer temporal resolutions and lower costs. Increasingly, lidar observations are combined with passive electro-optical multispectral and hyperspectral images (Kurz et al., 2011). Lidar technology already includes active multispectral laser systems, and hyperspectral laser observations of object reflectance are likely only three to five years away (Hakala et al, 2012; Hartzell et al., 2014). These systems promise to lessen the need for multiple sensors, thus reducing uncertainties due to data registration, lowering costs, and reducing processing time. The combination of these technologies holds promise as a means to cost-effectively monitor aspects of the CZ at time scales of days or less, with information content that includes not only 3D structure, but also spectral information that is potentially capable of determining vegetation composition and health, soil and exposed bedrock composition, and soil water content.

In addition to emerging lidar acquisition systems, new and existing collection platforms are substantially broadening data coverage. Collection of lidar from fixed-wing aircraft is expanding to national scales through programs such as the U.S. Geological Survey's 3-D Elevation Program (3DEP), Switzerland's national lidar dataset collected by the Federal Office of Topography, Sweden's Lantmateriet (http://www.lantmateriet.se), Netherlands' Public Map Service (http://www.pdok.nl/en/node), Denmark's Geodata Agency (http://gst.dk), Finland's National Land Survey (http://www.maanmittauslaitos.fi/en/maps-5), United Kingdom's Environment Agency (http://www.geomatics-group.co.uk/GeoCMS), and Australia's AusCover (http://www.auscover.org.au/). Additionally, acquisition of aircraft and lidar systems by institutional research programs have led to greater capabilities for ecological research by the National Ecological Observatory Network (Kampe et al., 2010) and snow water resources via NASA's Airborne Snow Observatory (http://aso.jpl.nasa.gov). Institutional systems and operational expertise are also available for short-term research projects across a range of Earth science applications (Glennie et al., 2013) by the National Center for Airborne Laser Mapping (NCALM) and UNAVCO. Of particular interest to the CZ community is the development of unmanned aerial systems (UASs) that are capable of mounting small lidar systems for rapid deployment (Lin et al., 2011; Wallace et al., 2012). Long-range UASs offer the potential for repeat lidar acquisitions at a fraction of the cost of current ALS platforms. Best practices for collecting, processing and analyzing lidar over increasing extents (i.e. continental scales) are generally lacking, which can limit the effectiveness of datasets collected over vastly different physiographic conditions.

2.3.2 *Data Access, Processing, and Analysis*

The crux in successfully leveraging a flood of new lidar (and other high-resolution topographic information) data for CZ science (e.g. Stennett, 2004) will be the ability to extract meaningful information from these rich and voluminous datasets. These new lidar datasets require data processing and analysis tools be optimized to handle increasingly large datasets with greater information content. Processing limitations are likely to reduce the usability and extent of very high information datasets, e.g. waveform or multispectral datasets pose processing challenges at the continental scale that may be more manageable at the watershed scale. Further, new software and workflows need to be developed that enable scientists to incorporate lidar data into detailed models of the CZ without expertise in remote sensing. The CZ science community must engage in a concerted effort to develop (and/or adopt from other domains) new open source tools that leverage high performance computing resources available through programs such as NSF's XSEDE (https://www.xsede.org/home). By increasing the scalability of CZ lidar-oriented processing and analysis tools, computationally intensive analysis and modeling at the highest resolution of the lidar datasets will be possible. In addition to increasing software scalability, new processing tools are necessary to take advantage of new data types, such as full waveform lidar (Wagner et al, 2008, Mallet and Bretar, 2009) and hyperspectral laser technology (Hakala et al, 2012). Cloud computing and the 'big data paradigm' that is increasingly common in both industry and academia (Mattman, 2013) present opportunities for the CZ lidar community. One such opportunity for big data sharing is EarthCube (www.earthcube.org), a relatively new program that has potential to integrate lidar information (among other geospatial information) into data sharing efforts in the geosciences. Due to efforts such as NSF's OpenTopography (Crosby et al., 2011), there is a large volume of CZ-oriented lidar online and feely available to the community. For example from the U.S., OpenTopography already offers on-demand processing services (Krishnan et al., 2011) that permit users to generate standard and commonly used derivatives from the hosted lidar point cloud. By coupling data processing with data access, users are not required to download large volumes of data locally or have the dedicated computing and software resources to process these data. Although many CZ-oriented lidar datasets are already available to the community through resources such as OpenTopography in the U.S., there are numerous other lidar datasets globally that are not accessible because they are not available online or access is restricted. Many of these 'legacy' datasets are likely to be important temporal baselines for comparison against future data focused on understanding CZ processes (Glennie et al., 2014; Harpold et al., 2014a).

2.3.3 *Linkages To In Situ Observations*

Many CZ studies have incorporated *in situ* observations to extend or confirm inferences made with lidar-derived datasets. *In situ* measurements are time consuming to collect, often expensive to analyze, and limited in terms of spatial coverage. As a result, researchers must be judicious with *in situ* data collection and maximize integration with lidar datasets. Physical and chemical properties of soil and rock, and vegetation structure are among the *in situ* observations commonly integrated with lidar datasets. For example, lidar-based studies have integrated distributed measurements of soil hydraulic properties (Harman et al., 2014) and soil thickness (Roering et al., 2010; Pelletier et al., 2014; West et al 2014), as well as radioactive isotopes in soils (West et al., 2014). Lidar datasets have also been used to extend *in situ* observations of snow depth (Harpold et al., 2014a; Varhola and Coops, 2013) and carbon fluxes (Hudak et al., 2012) in both space and time. *In situ* observations of vegetation structural characteristics are commonly made to develop relationships with lidar observations and extend these relationships for forest inventory (e.g. Wulder et al., 2002). In addition to scientific inferences, lidar can be used to improve sampling design to reduce time and analytical expenses. For example, lidar has improved insight into sampling snow measurements necessary for water management (McCreight et al., 2014). A number of challenges remain to link lidar-derived information to *in situ* measurements, including poor GPS information for historical datasets, constraining the observational footprint of different measurements, and comparing lidar-derived metrics to typical field measurements. Despite these challenges, opportunities exist to better integrate historical measurements into lidar-based studies and develop new *in situ* observations that use lidar datasets to up-scale CZ processes.

2.3.4 *Linkages to Satellite Remote Sensing*

Satellite observations of surface-altimetry, reflectance, permittivity, and atmospheric profiles provide observations of CZ processes at multiple spatiotemporal scales, frequently with global coverage. The high spatial resolution offered by lidar technology complements the regular temporal frequency of optical and radar satellite observations, which could be used to co-calibrate and co-validate these types of datasets. Satellites also provide another platform for lidar acquisition. There are numerous examples where lidar datasets have been used to calibrate and verify coarser estimates of vegetation, cryosphere (e.g. glaciers, permafrost, snowpacks, etc.), and geomorphic processes and states made via optical and radar satellites. For example, Mora et al. (2013) used detailed lidar measurements of vegetation structure to quantify the spatial and temporal scalability of above ground biomass of continental forests measured with the very high spatial resolution (VHSR) satellite. In data-limited regions of Uganda, lidar fused with Landsat datasets have improved modeled biomass predictions and understanding of phenologic processes (Avitable et al., 2012). Varhola and Coops (2013) and Ahmed et al. (2014) introduce methods for detecting changes in vegetation structure and function from disturbance by fusing Landsat and lidar measurements, and Bright et al. (2014) used similar fused datasets to investigate changes following forest mortality. Applications combining lidar and satellite measurements to change detection have also been applied to evaluate the effects of vegetation on snowpack dynamics (Varhola et al., 2014) and for comparison with model and satellite-derived estimates of snow-covered area (Kirchner et al., 2014; Hedrick et al., 2014). A multifaceted approach for the prediction and monitoring of landslides was proposed by Guzzeti (2012) using measurements from optical satellites and lidar. The Ice, Cloud, and land Elevation Satellite (ICESat) was a

NASA mission from 2003 to 2009 that mapped changes in glacier mass balance using SLS (Kohler et. al. 2013). Scientists have used ICESat's Geoscience Laser Altimeter System (GLAS) to identify areas of forest regeneration along the Mississippi (Li et al., 2011) and it has been applied in development of a global forest height map (Simard et al., 2011). A second mission (ICESat-2) is slated to launch in 2017 and while focused on ice sheet and sea ice change, it will provide complementary products to characterize terrestrial ecology. Furthermore, other current and future satellite missions will provide CZ observations that integrate with lidar, including soil moisture, groundwater storage, soil freeze/thaw, carbon flux, and primary productivity (Schimel et. al. 2013). Of particular interest might be the Surface Water and Ocean Topography (SWOT) mission that provides coarse water and land topography using radar that has potential to complement finer-scale measurements acquired with lidar. To fully realize the potential information available from fused lidar and satellite datasets, critical attention must be paid to 1) efficient processing of large datasets that span collection platforms and spatiotempral variability, and 2) maintaining expert knowledge in data interpretation (Matmann, 2013).

2.4 A Proposed Five-Year Vision

The fields of CZ science and lidar-based technology are both advancing rapidly. Here, we present a vision that recognizes advances in science and technology to best position CZ researchers at the forefront of the lidar revolution, particularly with regards to new hardware, processing capabilities, and linkages with complementary observations. These ideas are guided by the recognition that lidar is capable of simultaneously observing process signatures from multiple CZ disciplines (Figure 1). To elucidate this point, we discuss three examples of transdisciplinary CZ research questions and suggest how they could benefit from current and future lidar technologies. We also provide specific recommendations for CZ researchers working (or considering working) with lidar datasets. Our intent is to catalyze CZ interest in the transdisciplinary possibilities of lidar datasets, while increasing the influence of CZ scientists within the broader group of lidar end-users.

Technological advances can be conceptualized as increasing data coverage, quality, and information, including new acquisition platforms or higher acquisition rates (Figure 3). Other advances, such as full-waveform information or hyperspectral lasers, will increase the data quality and information content extractable from lidar datasets. Some examples of linked transdisciplinary research questions (Figure 3) that demonstrate the value of technological advances in lidar for CZ science are, 1) How does co-variation between vegetation and hydrological flowpaths control the likelihood and distribution of earth flows and landslides? 2) How is the rapidly changing cryosphere influencing hydrological connectivity, drainage network organization, nutrient and sediment fluxes, land-surface energy inputs, and vegetation structure? 3) How does above- and below-ground biomass control bedrock to soil production rates, sediment mixing and transport and associated carbon fluxes via bioturbation and hillslope transport? These example questions demonstrate the need for research that transcends information sharing across disciplines to develop synergistic new theories and advances in CZ science.

These research questions span a wide-range of spatial and temporal scales, from smaller and faster (10^{-2} m and 10^{1} s) in Question 3 to larger and more long-term (10^{5} m and 10^{6} s) in Question 2 (see Figure 1). Our ability to answer these questions benefits from several facets of improving lidar technologies, including higher acquisition rates and larger ranges, more rapid and robust deployment options, and improved processing resources for extracting information. Future lidar technologies could address Question 1 by identifying specific vegetation species via hyperspectral laser technologies, increasing accuracy of bare-earth estimation to improve hydrologic routing using full waveform analysis, and increasing coverage of landslide-prone areas from different physiographic regions (Figure 3). New technology will address Question 2 by providing estimates of riparian vegetation productivity, measuring channel bathymetry using blue-green lidar, and with new platforms that increase sampling frequency via UASs or other low cost systems. Lastly, new technology will address Question 3 by providing improved estimates of above-ground biomass and bare-earth extraction using full waveform analysis, and improved fine-scale change detection with greater processing resources. The goal of these example questions and their conceptualization (Figure 3) is to provide the reader with concrete examples of what well-integrated lidar datasets can provide to stimulate and improve future CZ research.

We propose five recommendations as an attempt to unite the CZ community around improved utilization and advocacy of lidar technology in important transdisciplinary scientific contexts that integrate the opportunities and impediments discussed previously:

· **Open lines of communication**: Develop communication within and among groups, including individual CZ disciplines, remote sensing scientists, computer scientists, private industry, and funding agencies. Workshops have the potential to increase communication between ‘data-users’ and ‘data-creators’. CZ scientists must find ways to communicate their data acquisition specifications to the scientists and engineers who create lidar hardware and processing software through venues such as meetings with private industry, the development of advisory committees, and commentary pieces in trade journals that present a vision for the future needs of CZ scientists. Open communication among diverse CZ scientists is fundamental to developing collaborations capable of transdisciplinary advances. Working groups within CZ communities, like the critical zone exploration network (www.czen.org), and townhall meetings at international Earth science conferences have initiated sustainable communication venues. Future efforts focused on early-career CZ scientists that demonstrate the benefits of transdisciplinary efforts, such as focused conferences and pilot research projects, should be pursued.

- **Increase information extraction**: Advocate for lidar repositories that are interoperable and broaden data access, as well as open-source and community-centric processing resources. Ultimately, enhanced and streamlined data processing and analysis will enable CZ researchers to concentrate on understanding fundamental science problems instead of struggling with data access, processing, and analysis. Specifically, recent efforts focused on cloud storage and computing resources, and open source software tools could greatly aid this effort. Efforts to improve the efficiency of processing will become more important as the acquisition of lidar expands to continental scales. Information extraction at larger extents will require judicious tradeoffs between acquisition parameters and costs that consider variability in local physiographic conditions (i.e. higher sampling densities in areas with dense vegetation cover and high topographic complexity). Programs to support open source software and their long-term sustainability are required to support CZ science. Increasing open access to lidar datasets facilitates greater information extraction and the potential for meta-analysis studies. The value of open-access datasets will increase as improved processing tools become available. CZ scientists should also consider working with private lidar acquisition companies and their customers (i.e. forestry, mining, and urban planning organizations) to release what has previously been proprietary data to the public.

- **Increase accessibility of lidar systems**: Advocate for new acquisition technologies that lower the cost of lidar collection and increase its availability, such as unmanned platforms and less expensive and longer-range lidar systems. Institutional acquisitions of lidar systems also significantly increase accessibility. Community-supported lidar systems available to researchers, through agencies, such as UNAVCO and NCALM, should also be encouraged. A powerful advancement would be a 'clearinghouse' where agencies and institutions could exchange information on lidar systems, seek expert advice on lidar acquisition, and potentially trade or rent hardware to better meet the needs of individual projects.
- **Focus on key technologies**: Support the development of new lidar technologies that are useful for linking disciplinary observations. For example, our review has stressed the potential benefits for linking CZ functions to processes offered by hyperspectral laser technologies (Figure 3). Other key technologies include new acquisition platforms (UASs) and improved open-source processing capabilities and open-source industry-standard data formats. The community should continue a dialogue about critical technologies within CZ science venues in parallel with interactions with technology developers (as mentioned previously). The more united the CZ community is about the benefits of a particular technology (i.e. hyperspectral lidar) the more it can advocate within public and private sectors for its advancement.
- **Link complementary observations**: Consider other remote sensing observations that may be complementary to lidar (e.g. thermal, infrared, optical, and microwave). While fusing remote sensing data is becoming more common, the value of lidar information to coarser remote

sensing products is vast and underutilized. Be mindful of the potential synergistic benefits of collecting lidar data over areas with *in situ* observations and vice versa, consider how to improve collection of *in situ* observations based on lidar information. In particular, *in situ* information collected during lidar data collection can be extremely valuable and difficult to substitute for at a later date. Maintain awareness of competing, less expensive technologies, such as SfM, that may be more appropriate in some conditions and geographical locations. The multi-scale nature of transdisciplinary research (Figure 1 and 3) demands that lidar be integrated into a broader observational framework that does not neglect the value of *in situ* and coarser remote sensing observations.

Acknowledgements:

The workshop forming the impetus for this paper was funded by the National Science Foundation (EAR 1406031). Additional funding for the workshop and planning was provided to S.W. Lyon by the Swedish Foundation for International Cooperation in Research and Higher Education (STINT Grant No. 2013-5261). A.A. Harpold was supported by an NSF fellowship (EAR 1144894). The use of specific commercial or open-source packages and tools in this paper does not imply a specific endorsement.

References:

Abdalati, W., H.J. Zwally, R. Bindschadler, B. Csatho, S.L. Farrell, H.A. Fricker, D. Harding, R. Kwok, M. Lefsky, T. Markus, A. Marshak, T. Neumann, S. Palm, B. Schutz, B. Smith, J. Spinhirne, and C. Webb (2010), The ICESat-2 laser altimetry mission. *Proceedings of the IEEE*, 98(5), 735-751, doi: 10.1109/JPROC.2009.2034765

Ahmed, O. S., S. E. Franklin, and M. A. Wulder (2014), Interpretation of forest disturbance using a time series of Landsat imagery and canopy structure from airborne LiDAR, *Canadian Journal of Remote Sensing*, *39*(6), 521–542, doi:10.5589/m14-004.

Anderson, S., and J. Pitlick (2014), Using repeat LiDAR to estimate sediment transport in a steep stream, *J. Geophys. Res. Earth Surf.*, *119*(3), 621–643, doi:10.1002/2013JF002933.

Antonarakis, A. S., J. W. Munger, and P. R. Moorcroft (2014), Imaging spectroscopy- and LiDAR-derived estimates of canopy composition and structure to improve predictions of forest carbon fluxes and ecosystem dynamics, *Geophysical Research Letters*, *41*(7), 2013GL058373, doi:10.1002/2013GL058373.

Antonarakis, A. S., K. S. Richards, J. Brasington, and E. Muller (2010), Determining leaf area index and leafy tree roughness using terrestrial laser scanning, *Water Resources Research*, *46*(6), W06510, doi:10.1029/2009WR008318.

Arnold, N. S., W. G. Rees, B. J. Devereux, and G. S. Amable (2006), Evaluating the potential of high-resolution airborne LiDAR data in glaciology, *International Journal of Remote Sensing*, *27*(6), 1233–1251, doi:10.1080/01431160500353817.

Aryal, A., B. A. Brooks, M. E. Reid, G. W. Bawden, and G. R. Pawlak (2012), Displacement fields from point cloud data: Application of particle imaging velocimetry to landslide geodesy, *Journal of Geophysical Research: Atmospheres (1984–2012)*, *117*(F1), F01029, doi:10.1029/2011JF002161.

Asner, G. P., D. E. Knapp, J. Boardman, R. O. Green, T. Kennedy-Bowdoin, M. Eastwood, R. E. Martin, C. Anderson, and C. B. Field (2012a), Carnegie Airborne Observatory-2: Increasing science data dimensionality via high-fidelity multi-sensor fusion, *Remote Sensing of Environment*, *124*(0), 454–465, doi:10.1016/j.rse.2012.06.012.

Asner, G., J. Mascaro, H. Muller-Landau, G. Vieilledent, R. Vaudry, M. Rasamoelina, J. Hall, and M. van Breugel (2012b), A universal airborne LiDAR approach for tropical forest carbon mapping, *Oecologia*, *168*(4), 1147–1160, doi:10.1007/s00442-011-2165-z.

Avitabile, V., A. Baccini, M. A. Friedl, and C. Schmullius (2012), Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda, *Remote Sensing of Environment*, *117*(0), 366–380, doi:10.1016/j.rse.2011.10.012.

Baccini, A. et al. (2012), Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps, *Nature Climate change*, *2*(3), 182–185, doi:10.1038/nclimate1354.

Barnhart, T. B., and B. T. Crosby (2013), Comparing Two Methods of Surface Change Detection on an Evolving Thermokarst Using High-Temporal-Frequency Terrestrial Laser Scanning, Selawik River, Alaska, *Remote Sensing*, *5*(6), 2813–2837, doi:10.3390/rs5062813.

Bates, P. D. (2012), Integrating remote sensing data with flood inundation models: how far have we got? *Hydrol. Process.*, *26*(16), 2515–2521, doi:10.1002/hyp.9374.

Belmont, P. et al. (2011), Large Shift in Source of Fine Sediment in the Upper Mississippi River, *Environ. Sci. Technol.*, *45*(20), 8804–8810, doi:10.1021/es2019109.

Bittner, S., S. Gayler, C. Biernath, J. B. Winkler, S. Seifert, H. Pretzsch, and E. Priesack (2014), Evaluation of a ray-tracing canopy light model based on terrestrial laser scans, *Canadian Journal of Remote Sensing*, *38*(5), 619–628, doi:10.5589/m12-050.

Bode, C. A., M. P. Limm, M. E. Power, and J. C. Finlay (2014), Subcanopy Solar Radiation model: Predicting solar radiation across a heavily vegetated landscape using LiDAR and GIS solar radiation models, *Remote Sensing of Environment*, (0 SP - EP - PY - T2 -), doi:10.1016/j.rse.2014.01.028.

Booth, A. M., J. J. Roering, and J. T. Perron (2009), Automated landslide mapping using spectral analysis and high-resolution topographic data: Puget Sound lowlands, Washington, and Portland Hills, Oregon, *Geomorphology*, *109*(3-4), 132–147, doi:10.1016/j.geomorph.2009.02.027.

Bork, E. W., and J. G. Su (2007), Integrating LIDAR data and multispectral imagery for enhanced classification of rangeland vegetation: A meta analysis, *Remote Sensing of Environment*, *111*(1), 11–24, doi:10.1016/j.rse.2007.03.011.

Boutet, J., Jr, and J. Weishampel (2003), Spatial pattern analysis of pre- and post-hurricane forest canopy structure in North Carolina, USA, *Landscape Ecology*, *18*(6), 553–559, doi:10.1023/A%3A1026058312853.

Brasington, J., D. Vericat, and I. Rychkov (2012), Modeling river bed morphology, roughness, and surface sedimentology using high resolution terrestrial laser scanning, *Water Resources Research*, *48*(11), W11519, doi:10.1029/2012WR012223.

Bright, B. C., A. T. Hudak, R. McGaughey, H.-E. Andersen, and J. Negrón (2014), Predicting live and dead tree basal area of bark beetle affected forests from discrete-return LiDAR, *Canadian Journal of Remote Sensing*, *39*(sup1), S99–S111, doi:10.5589/m13-027.

Brooks, B. A., C. Glennie, K. W. Hudnut, T. Ericksen, and D. Hauser (2013), Mobile Laser Scanning Applied to the Earth Sciences, *Eos, Transactions American Geophysical Union*, *94*(36), 313–315, doi:10.1002/2013EO360002.

Broxton, P. D., A. A. Harpold, P. D. Brooks, P. A. Troch, and N. P. Molotch (In Press), Quantifying the effects of vegetation structure on wintertime vapor losses from snow in mixed-conifer forests, *Ecohydrol.*

Brubaker, K. M., W. L. Myers, P. J. Drohan, D. A. Miller, and E. W. Boyer (2013), The Use of LiDAR Terrain Data in Characterizing Surface Roughness and Microtopography, *Applied and Environmental Soil Science*, *2013*, 13, doi:10.1155/2013/891534.

Cho, M. A. et al. (2012), Mapping tree species composition in South African savannas using an integrated airborne spectral and LiDAR system, *Remote Sensing of Environment*, *125*(0), 214–226, doi:10.1016/j.rse.2012.07.010.

Chorover, J. et al. (2011), How Water, Carbon, and Energy Drive Critical Zone Evolution: The Jemez–Santa Catalina Critical Zone Observatory, *Vadose Zone Journal*, *10*(3), 884–899.

Coops, N. C., F. Morsdorf, M. E. Schaepman, and N. E. Zimmermann (2013), Characterization of an alpine tree line using airborne LiDAR data and physiological modeling, *Global Change Biology*, *19*(12), 3808–3821, doi:10.1111/gcb.12319.

Crosby, C., R. Arrowsmith, V. Nandigam, and C. Baru (2011), Online access and processing of LiDAR topography data, edited by G. R. Keller and C. Baru, Cambridge University Press.

Day, S. S., K. B. Gran, P. Belmont, and T. Wawrzyniec (2013), Measuring bluff erosion part 1: terrestrial laser scanning methods for change detection, *Earth Surface Processes and Landforms*, *38*(10), 1055–1067, doi:10.1002/esp.3353.

Deems, J. S., S. R. Fassnacht, and K. J. Elder (2006), Fractal Distribution of Snow Depth from LiDAR Data, *J. Hydrometeor*, *7*(2), 285–297, doi:10.1175/JHM487.1.

Deems, J. S., S. R. Fassnacht, and K. J. Elder (2008), Interannual Consistency in Fractal Snow Depth Patterns at Two Colorado Mountain Sites, *J. Hydrometeor*, *9*(5), 977–988, doi:10.1175/2008JHM901.1.

Deems, J. S., T. H. Painter, and D.C. Finnegan (2013), LiDAR measurement of snow depth: a review, *Journal of Glaciology*, *59*(215), 467-479, doi.org/10.3189/2013JoG12J154

DeLong, S. B., C. S. Prentice, G. E. Hilley, and Y. Ebert (2012), Multitemporal ALSM change detection, sediment delivery, and process mapping at an active earthflow, *Earth Surface Processes and Landforms*, *37*(3), 262–272, doi:10.1002/esp.2234.

Dickinson, Y., E. K. Zenner, and D. Miller (2014), Examining the effect of diverse management strategies on landscape scale patterns of forest structure in Pennsylvania using novel remote sensing techniques, *Can. J. For. Res.*, *44*(4), 301–312, doi:10.1139/cjfr-2013-0315.

Drake, J. B., and J. F. Weishampel (2000), Multifractal analysis of canopy height measures in a longleaf pine savanna, *Forest Ecology and Management*, *128*(1–2), 121–127, doi:10.1016/S0378-1127(99)00279-0.

Egli, L., T. Jonas, T. Grünewald, M. Schirmer, and P. Burlando (2012), Dynamics of snow ablation in a small Alpine catchment observed by repeated terrestrial laser scans, *Hydrol. Process.*, *26*(10), 1574–1585, doi:10.1002/hyp.8244.

Essery, R., P. Bunting, A. Rowlands, N. Rutter, J. Hardy, R. Melloh, T. Link, D. Marks, and J. Pomeroy (2008), Radiative Transfer Modeling of a Coniferous Canopy Characterized by Airborne Remote Sensing, *J. Hydrometeor*, *9*(2), 228–241, doi:10.1175/2007JHM870.1.

Fassnacht, S. R., and J. S. Deems (2006), Measurement sampling and scaling for deep montane snow depth data, *Hydrol. Process.*, *20*(4), 829–838, doi:10.1002/hyp.6119.

Fernandez-Diaz, J. C., C. L. Glennie, W. E. Carter, R. L. Shrestha, M. P. Sartori, A. Singhania, C. J. Legleiter, and B. T. Overstreet (2014), Early Results of Simultaneous Terrain and Shallow Water Bathymetry Mapping Using a Single-Wavelength Airborne LiDAR Sensor, *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of*, *7*(2), 623–635, doi:10.1109/JSTARS.2013.2265255.

Fewtrell, T. J., P. D. Bates, M. Horritt, and N. M. Hunter (2008), Evaluating the effect of scale in flood inundation modelling in urban environments, *Hydrol. Process.*, *22*(26), 5107–5118, doi:10.1002/hyp.7148.

Féret, J.-B., and G. P. Asner (2012), Semi-Supervised Methods to Identify Individual Crowns of Lowland Tropical Canopy Species Using Imaging Spectroscopy and LiDAR, *Remote Sensing*, *4*(8), 2457–2476, doi:10.3390/rs4082457.

Flener, C., M. Vaaja, A. Jaakkola, A. Krooks, H. Kaartinen, A. Kukko, E. Kasvi, H. Hyyppä, J. Hyyppä, and P. Alho (2013), Seamless Mapping of River Channels at High Resolution Using Mobile LiDAR and UAV-Photography, *Remote Sensing*, *5*(12), 6382–6407, doi:10.3390/rs5126382.

Fonstad, M. A., J.T. Dietrich, B.C. Courville, J.L Jensen, and P.E. Carbonneau (2013). Topographic structure from motion: a new development in photogrammetric measurement, *Earth Surface Processes and Landforms*, *38*(4), 421-430, doi: 10.1002/esp.3366.

Forzieri, G., G. Moser, E. R. Vivoni, F. Castelli, and F. Canovaro (2010), Riparian Vegetation Mapping for Hydraulic Roughness Estimation Using Very High Resolution Remote Sensing Data Fusion, *Journal of Hydraulic Engineering*, *136*(11), 855–867, doi:10.1061/(ASCE)HY.1943-7900.0000254.

Frazer, G. W., M. A. Wulder, and K. O. Niemann (2005), Simulation and quantification of the fine-scale spatial pattern and heterogeneity of forest canopy structure: A lacunarity-based method designed for analysis of continuous canopy heights, *Forest Ecology and Management*, *214*(1–3), 65–90, doi:10.1016/j.foreco.2005.03.056.

French, J. R. (2003), Airborne LiDAR in support of geomorphological and hydraulic modelling, *Earth Surface Processes and Landforms*, *28*(3), 321–335, doi:10.1002/esp.484.

Glenn, N. F., D. R. Streutker, D. J. Chadwick, G. D. Thackray, and S. J. Dorsch (2006), Analysis of LiDAR-derived topographic information for characterizing and differentiating landslide morphology and activity, *Geomorphology*, *73*(1–2), 131–148, doi:10.1016/j.geomorph.2005.07.006.

Glennie, C. L., A. Hinojosa-Corona, E. Nissen, A. Kusari, M. E. Oskin, J. R. Arrowsmith, and A. Borsa (2014), Optimization of legacy LiDAR data sets for measuring near-field earthquake displacements, *Geophysical Research Letters*, *41*(10), 2014GL059919, doi:10.1002/2014GL059919.

Glennie, C. L., W. E. Carter, R. L. Shrestha, and W. E. Dietrich (2013), Geodetic imaging with airborne LiDAR: the Earth's surface revealed, *Rep. Prog. Phys.*, *76*(8), 086801.

Guzzetti, F., A. C. Mondini, M. Cardinali, F. Fiorucci, M. Santangelo, and K.-T. Chang (2012), Landslide inventory maps: New tools for an old problem, *Earth Science Reviews*, *112*(1–2), 42–66, doi:10.1016/j.earscirev.2012.02.001.

Grünewald, T., M. Schirmer, R. Mott, and M. Lehning (2010). Spatial and temporal variability of snow depth and SWE in a small mountain catchment, *The Cryosphere*, *4*, 215-230, doi:10.5194/tc-4-215-2010

Hakala, T., J. Suomalainen, S. Kaasalainen, and Y. Chen (2012), Full waveform hyperspectral LiDAR for terrestrial laser scanning, *Opt. Express*, *20*(7), 7119–7127, doi:10.1364/OE.20.007119.

Harman, C. J., K. A. Lohse, P. A. Troch, and M. Sivapalan (2014), Spatial patterns of vegetation, soils, and microtopography from terrestrial laser scanning on two semiarid hillslopes of contrasting lithology, *J. Geophys. Res. Biogeosci.*, *119*(2), 163–180, doi:10.1002/2013JG002507.

Harpold, A. A. et al. (2014a), LiDAR-derived snowpack data sets from mixed conifer forests across the Western United States, *Water Resources Research*, *50*(3), 2749–2755, doi:10.1002/2013WR013935.

Harpold, A. A., J. A. Biederman, K. Condon, M. Merino, Y. Korgaonkar, T. Nan, L. L. Sloat, M. Ross, and P. D. Brooks (2014b), Changes in snow accumulation and ablation following the Las Conchas Forest Fire, New Mexico, USA, *Ecohydrol.*, *7*(2), 440–452, doi:10.1002/eco.1363.

Hartzell, P., C. Glennie, K. Biber, and S. Khan (2014), Application of multispectral LiDAR to automated virtual outcrop geology, *ISPRS Journal of Photogrammetry and Remote Sensing*, *88*(0), 147–155, doi:10.1016/j.isprsjprs.2013.12.004.

Hedrick, A., H. P. Marshall, A. Winstral, K. Elder, S. Yueh, and D. CLINE (2014), Independent evaluation of the SNODAS snow depth product using regional scale LiDAR-derived measurements, *The Cryosphere Discussions*, *8*(3), 3141–3170, doi:10.5194/tcd-8-3141-2014.

Hopkinson, C., and M. N. Demuth (2006), Using airborne LiDAR to assess the influence of glacier downwasting on water resources in the Canadian Rocky Mountains, *Canadian Journal of Remote Sensing*, *32*(2), 212–222, doi:10.5589/m06-012.

Hopkinson, C., J. Lovell, L. Chasmer, D. Jupp, N. Kljun, and E. van Gorsel (2013), Integrating terrestrial and airborne LiDAR to calibrate a 3D canopy model of effective leaf area index, *Remote Sensing of Environment*, *136*(0), 301–314, doi:10.1016/j.rse.2013.05.012.

Hopkinson, C., T. Collins, A. Anderson, J. Pomeroy, and I. Spooner (2012), Spatial Snow Depth Assessment Using LiDAR Transect Samples and Public GIS Data Layers in the Elbow River

Watershed, Alberta, *Canadian Water Resources Journal*, *37*(2), 69–87, doi:10.4296/cwrj3702893.

Hudak, A. T., E. K. Strand, L. A. Vierling, J. C. Byrne, J. U. H. Eitel, S. Martinuzzi, and M. J. Falkowski (2012), Quantifying aboveground forest carbon pools and fluxes from repeat LiDAR surveys, *Remote Sensing of Environment*, *123*(0), 25–40, doi:10.1016/j.rse.2012.02.023.

Hurst, M. D., S. M. Mudd, K. Yoo, M. Attal, and R. Walcott (2013), Influence of lithology on hillslope morphology and response to tectonic forcing in the northern Sierra Nevada of California, *J. Geophys. Res. Earth Surf.*, *118*(2), 832–851, doi:10.1002/jgrf.20049.

Hurst, M. D., S. M. Mudd, R. Walcott, M. Attal, and K. Yoo (2012), Using hilltop curvature to derive the spatial distribution of erosion rates, *Journal of Geophysical Research: Atmospheres (1984–2012)*, *117*(F2), F02017, doi:10.1029/2011JF002057.

Hyde, P., R. Dubayah, B. Peterson, J. B. Blair, M. Hofton, C. Hunsaker, R. Knox, and W. Walker (2005), Mapping forest structure for wildlife habitat analysis using waveform LiDAR: Validation of montane ecosystems, *Remote Sensing of Environment*, *96*(3–4), 427–437, doi:10.1016/j.rse.2005.03.005.

Hyyppä, J., M. Holopainen, and H. Olsson (2012), Laser Scanning in Forests, *Remote Sensing*, *4*(10), 2919–2922, doi:10.3390/rs4102919.

James, L. A., M. B. Singer, S. Ghoshal, and M. Megison (2009), Historical channel changes in the lower Yuba and Feather Rivers, California: Long-term effects of contrasting river-management strategies, *Geological Society of America Special Papers*, *451*, 57–81, doi:10.1130/2009.2451(04).

James, L. A., M. E. Hodgson, S. Ghoshal, and M. M. Latiolais (2012), Geomorphic change detection using historic maps and DEM differencing: The temporal dimension of geospatial analysis, *Geomorphology*, *137*(1), 181–198, doi:10.1016/j.geomorph.2010.10.039.

Javernick, L., J. Brasington, and B. Caruso (2014), Modeling the topography of shallow braided rivers using Structure-from-Motion photogrammetry, *Geomorphology*, *213*(0), 166–182, doi:10.1016/j.geomorph.2014.01.006.

Jencso, K. G., B.L. McGlynn, M.N. Gooseff, S.M. Wondzell, K.E. Bencala, and L.A. Marshall (2009), Hydrologic connectivity between landscapes and streams: Transferring reach-and plot-scale understanding to the catchment scale, *Water Resources Research*, *45*(4), doi:

10.1029/2008WR007225

Jones, A. F., P. A. Brewer, E. Johnstone, and M. G. Macklin (2007), High-resolution interpretative geomorphological mapping of river valley environments using airborne LiDAR data, *Earth Surface Processes and Landforms*, *32*(10), 1574–1592, doi:10.1002/esp.1505.

Kaasalainen, S., T. Lindroos, and J. Hyyppa (2007), Toward Hyperspectral LiDAR: Measurement of Spectral Backscatter Intensity With a Supercontinuum Laser Source, *Geoscience and Remote Sensing Letters, IEEE*, *4*(2), 211–215, doi:10.1109/LGRS.2006.888848.

Kampe, T. U., B.R. Johnson, M. Kuester, and M. Keller (2010), NEON: the first continental-scale ecological observatory with airborne remote sensing of vegetation canopy biochemistry and structure. *Journal of Applied Remote Sensing*, *4*(1), 043510-043510, doi: 10.1117/1.3361375

Khamsin, I., M. Zulkarnain, K. A. Razak, and S. Rizal (2014), Detection of tropical landslides using airborne LiDAR data and multi imagery: A case study in Genting highland, Pahang, *IOP Conference Series: Earth and Environmental Science*, *18*(1), 012033.

Kessler, A. C., S. C. Gupta, H. A. S. Dolliver, and D. P. Thoma (2012), LiDAR Quantification of Bank Erosion in Blue Earth County, Minnesota, *Journal of Environmental Quality*, *41*(1), 197–207, doi:10.2134/jeq2011.0181.

Kinzel, P. J., C. J. Legleiter, and J. M. Nelson (2013), Mapping River Bathymetry With a Small Footprint Green LiDAR: Applications and Challenges1, *JAWRA Journal of the American Water Resources Association*, *49*(1), 183–204, doi:10.1111/jawr.12008.

Kinzel, P. J., C. W. Wright, J. M. Nelson, and A. R. Burman (2007), Evaluation of an Experimental LiDAR for Surveying a Shallow, Braided, Sand-Bedded River, *Journal of Hydraulic Engineering*, *133*(7), 838–842, doi:10.1061/(ASCE)0733-9429(2007)133:7(838).

Kirchner, P. B., R. C. Bales, N. P. Molotch, J. Flanagan, and Q. Guo (2014), LiDAR measurement of seasonal snow accumulation along an elevation gradient in the southern Sierra Nevada, California, *Hydrol. Earth Syst. Sci. Discuss.*, *11*(5), 5327–5365, doi:10.5194/hessd-11-5327-2014.

Kohler, J., T. A. Neumann, J. W. Robbins, S. Tronstad, and G. Melland (2013), ICESat Elevations in Antarctica Along the 2007-09 Norway-USA Traverse: Validation With

Ground-Based GPS, *Geoscience and Remote Sensing, IEEE Transactions on*, *51*(3), 1578–1587, doi:10.1109/TGRS.2012.2207963.

Krishnan, S., C. Crosby, V. Nandigam, M. Phan, C. Cowart, C. Baru, and R. Arrowsmith (2011), OpenTopography: A Services Oriented Architecture for Community Access to LIDAR Topography, pp. 7:1–7:8, ACM, New York, NY, USA.

Kurz, T. H., S. J. Buckley, J. A. Howell, and D. Schneider (2011), Integration of panoramic hyperspectral imaging with terrestrial LiDAR data, *The Photogrammetric Record*, *26*(134), 212–228, doi:10.1111/j.1477-9730.2011.00632.x.

Lague, D., N. Brodu, and J. Leroux (2013), Accurate 3D comparison of complex topography with terrestrial laser scanner: Application to the Rangitikei canyon (N-Z), *ISPRS Journal of Photogrammetry and Remote Sensing*, *82*(0), 10–26, doi:10.1016/j.isprsjprs.2013.04.009.

Lam, N., M. Nathanson, N. Lundgren, R. Rehnström, and S.W. Lyon (2015), A Cost-Effective Laser Scanning Method for Mapping Stream Channel Geometry and Roughness, *Journal of the American Water Resources Association*, 1-10. DOI: 10.1111/1752-1688.12299.

Lane, S. N., C.J. Brookes, M.J. Kirkby, and J. Holden (2004), A network-index-based version of TOPMODEL for use with high-resolution digital topographic data, *Hydrological processes*, *18*(1), 191-201, doi: 10.1002/hyp.5208.

Lane, C. R., and E. D'Amico (2010), Calculating the Ecosystem Service of Water Storage in Isolated Wetlands using LiDAR in North Central Florida, USA, *Wetlands*, *30*(5), 967–977, doi:10.1007/s13157-010-0085-z.

Lee, H., K. C. Slatton, B. E. Roth, and W. P. Cropper (2009), Prediction of forest canopy light interception using three-dimensional airborne LiDAR data, *International Journal of Remote Sensing*, *30*(1), 189–207, doi:10.1080/01431160802261171.

Lefsky, M. A., W. B. Cohen, G. G. Parker, and D. J. Harding (2002), Remote Sensing for Ecosystem Studies: LiDAR, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists, *BioScience*, *52*(1), 19–30, doi:10.1641/0006-3568(2002)052[0019:LRSFES]2.0.CO.

Legleiter, C. J., P. C. Kyriakidis, R. R. McDonald, and J. M. Nelson (2011), Effects of uncertain topographic input data on two-dimensional flow modeling in a gravel-bed river, *Water*

Resources Research, *47*(3), W03518, doi:10.1029/2010WR009618.

Levy, J. S., A. G. Fountain, J. L. Dickson, J. W. Head, M. Okal, D. R. Marchant, and J. Watters (2013), Accelerated thermokarst formation in the McMurdo Dry Valleys, Antarctica, *Sci. Rep.*, *3*, doi:10.1038/srep02269.

Li, S., R. A. MacMillan, D. A. Lobb, B. G. McConkey, A. Moulin, and W. R. Fraser (2011), LiDAR DEM error analyses and topographic depression identification in a hummocky landscape in the prairie region of Canada, *Geomorphology*, *129*(3–4), 263–275, doi:10.1016/j.geomorph.2011.02.020.

Lin, Y., J. Hyyppä, and A. Jaakkola (2011), Mini-UAV-Borne LIDAR for Fine-Scale Mapping, *Geoscience and Remote Sensing Letters, IEEE*, *8*(3), 426–430, doi:10.1109/LGRS.2010.2079913.

Liu, Z. et al. (2008), CALIPSO LiDAR observations of the optical properties of Saharan dust: A case study of long-range transport, *Journal of Geophysical Research: Atmospheres (1984–2012)*, *113*(D7), D07207, doi:10.1029/2007JD008878.

Lotsari, E., M. Vaaja, C. Flener, H. Kaartinen, A. Kukko, E. Kasvi, H. Hyyppä, J. Hyyppä, and P. Alho (2014), Annual bank and point bar morphodynamics of a meandering river determined by high-accuracy multitemporal laser scanning and flow data, Water Resources Research, 50, 5532–5559, doi:10.1002/2013WR014106.

Lyon, S.W., M. Nathanson, N. Lam, H.E. Dahlke, M. Rutzinger, J.W. Kean and H. Laudon (2015), Can Low-Resolution Airborne Laser Scanning Data Be Used to Model Stream Rating Curves?, *Water*, *7*(4), 1324-1339, doi:10.3390/w7041324.

Mallet, C. and F. Bretar (2009). Full-waveform topographic LiDAR: State-of-the-art, *ISPRS Journal of Photogrammetry and Remote Sensing*, *64*(1), 1-16, doi: 10.1016/j.isprsjprs.2008.09.007.

Maltamo, M., E. Næsset, and J. Vauhkonen (Eds.) (2014), *Forestry Applications of Airborne Laser Scanning*, Springer, Netherlands.

Mandlburger, G., C. Hauer, B. Höfle, H. Habersack, N. Pfeifer, others (2009), Optimisation of LiDAR derived terrain models for river flow modelling, *Hydrol. Earth Syst. Sci.*, *13*(8), 1453–1466, doi:10.5194/hess-13-1453-2009.

Mankoff, K. D., and T. A. Russo (2013), The Kinect: a low-cost, high-resolution, short-range 3D camera, *Earth Surface Processes and Landforms*, *38*(9), 926–936, doi:10.1002/esp.3332.

Marks, K., and P. Bates (2000), Integration of high-resolution topographic data with floodplain flow models, *Hydrol. Process.*, *14*(11-12), 2109–2122, doi:10.1002/1099-1085(20000815/30)14:11/12<2109::AID-HYP58>3.0.CO;2-1.

Marshall, J. A., and J. J. Roering (2014), Diagenetic variation in the Oregon Coast Range: Implications for rock strength, soil production, hillslope form, and landscape evolution, *J. Geophys. Res. Earth Surf.*, *119*(6), 2013JF003004, doi:10.1002/2013JF003004.

Martinuzzi, S., L. A. Vierling, W. A. Gould, M. J. Falkowski, J. S. Evans, A. T. Hudak, and K. T. Vierling (2009), Mapping snags and understory shrubs for a LiDAR-based assessment of wildlife habitat suitability, *Remote Sensing of Environment*, *113*(12), 2533–2546, doi:10.1016/j.rse.2009.07.002.

Mascaro, J., M. Detto, G. P. Asner, and H. C. Muller-Landau (2011), Evaluating uncertainty in mapping forest carbon with airborne LiDAR, *Remote Sensing of Environment*, *115*(12), 3770–3774, doi:10.1016/j.rse.2011.07.019.

Mason, D. C., D. M. Cobby, M. S. Horritt, and P. D. Bates (2003), Floodplain friction parameterization in two-dimensional river flood models using vegetation heights derived from airborne scanning laser altimetry, *Hydrol. Process.*, *17*(9), 1711–1732, doi:10.1002/hyp.1270.

Mattmann, C. A. (2013), Computing: A vision for data science, *Nature*, *493*(7433), 473-475, doi:10.1038/493473a

McCreight, J. L., A. G. Slater, H. P. Marshall, and B. Rajagopalan (2014), Inference and uncertainty of snow depth spatial distribution at the kilometre scale in the Colorado Rocky Mountains: the effects of sample size, random sampling, predictor quality, and validation procedures, *Hydrol. Process.*, *28*(3), 933–957, doi:10.1002/hyp.9618.

McKean, J. A., D. J. Isaak, and C. W. Wright (2008), Geomorphic controls on salmon nesting patterns described by a new, narrow-beam terrestrial–aquatic LiDAR, *Frontiers in Ecology and the Environment*, *6*(3), 125–130, doi:10.1890/070109.

McKean, J., D. Isaak, and W. Wright (2009), Improving stream studies with a small-footprint green LiDAR, *Eos, Transactions American Geophysical Union*, *90*(39), 341–342, doi:10.1029/2009EO390002.

McKean, J., D. Tonina, C. Bohn, and C. W. Wright (2014), Effects of bathymetric LiDAR errors on flow properties predicted with a multi-dimensional hydraulic model, *J. Geophys. Res.*

Earth Surf., *119*(3), 2013JF002897, doi:10.1002/2013JF002897.

Meyer, V., S. S. Saatchi, J. Chave, J. Dalling, S. Bohlman, G. A. Fricker, C. Robinson, and M. Neumann (2013), Detecting tropical forest biomass dynamics from repeated airborne LiDAR measurements, *Biogeosciences Discussions*, *10*(2), 1957–1992, doi:10.5194/bgd-10-1957-2013.

Mitchell, P. J., P. N. J. Lane, and R. G. Benyon (2011), Capturing within catchment variation in evapotranspiration from montane forests using LiDAR canopy profiles with measured and modelled fluxes of water, *Ecohydrol.*, *5*(6), 708–720, doi:10.1002/eco.255.

Moeser, D., J. Roubinek, P. Schleppi, F. Morsdorf, and T. Jonas (2014), Canopy closure, LAI and radiation transfer from airborne LiDAR synthetic images, *Agricultural and Forest Meteorology*, *197*(0), 158–168, doi:10.1016/j.agrformet.2014.06.008.

Mora, B., M. A. Wulder, G. W. Hobart, J. C. White, C. W. Bater, F. A. Gougeon, A. Varhola, and N. C. Coops (2013), Forest inventory stand height estimates from very high spatial resolution satellite imagery calibrated with LiDAR plots, *International Journal of Remote Sensing*, *34*(12), 4406–4424, doi:10.1080/01431161.2013.779041.

Mundt, J. T., D. R. Streutker, and N. F. Glenn (2006), Mapping Sagebrush Distribution Using Fusion of Hyperspectral and LiDAR Classifications, *Photogrammetric engineering and remote sensing*, *72*(1), 47–54, doi:10.14358/PERS.72.1.47.

Musselman, K. N., S. A. Margulis, and N. P. Molotch (2013), Estimation of solar direct beam transmittance of conifer canopies from airborne LiDAR, *Remote Sensing of Environment*, *136*(0), 402–415, doi:10.1016/j.rse.2013.05.021.

Næsset, E. and T. Gobakken (2005). Estimating forest growth using canopy metrics derived from airborne laser scanner data, *Remote sensing of environment*, *96*(3), 453-465, doi: 10.1016/j.rse.2005.04.001.

Nathanson, M., J. W. Kean, T. J. Grabs, J. Seibert, H. Laudon, and S. W. Lyon (2012), Modelling rating curves using remotely sensed LiDAR data, *Hydrol. Process.*, *26*(9), 1427–1434, doi:10.1002/hyp.9225.

National Research Council (2012), *New Research Opportunities in the Earth Sciences*, National Academy Press, Washington D.C.

Nissen, E., T. Maruyama, J.R. Arrowsmith, J.R. Elliott, A.K. Krishnan, M.E. Oskin, and S. Saripalli (2014), Coseismic fault zone deformation revealed with differential lidar: examples from Japanese Mw ~7 intraplate earthquakes, *Earth and Planetary Science Letters*, 405, 244-256, doi: doi:10.1016/j.epsl.2014.08.031.

Nissen, E., A. K. Krishnan, J. R. Arrowsmith, and S. Saripalli (2012), Three-dimensional surface displacements and rotations from differencing pre- and post-earthquake LiDAR point clouds, *Geophysical Research Letters*, *39*(16), L16301, doi:10.1029/2012GL052460.

Olsoy, P. J., N. F. Glenn, P. E. Clark, and D. R. Derryberry (2014), Aboveground total and green biomass of dryland shrub derived from terrestrial laser scanning, *ISPRS Journal of Photogrammetry and Remote Sensing*, *88*(0), 166–173, doi:10.1016/j.isprsjprs.2013.12.006.

Oskin, M. E. et al. (2012), Near-Field Deformation from the El Mayor–Cucapah Earthquake Revealed by Differential LIDAR, *Science*, *335*(6069), 702–705, doi:10.1126/science.1213778.

Palminteri, S., G. V. N. Powell, G. P. Asner, and C. A. Peres (2012), LiDAR measurements of canopy structure predict spatial distribution of a tropical mature forest primate, *Remote Sensing of Environment*, *127*(0), 98–105, doi:10.1016/j.rse.2012.08.014.

Passalacqua, P., P. Tarolli, and E. Foufoula-Georgiou (2010), Testing space-scale methodologies for automatic geomorphic feature extraction from LiDAR in a complex mountainous landscape, *Water Resources Research*, *46*(11), W11535, doi:10.1029/2009WR008812.

Pelletier, J. D. (2013), Deviations from self-similarity in barchan form and flux: The case of the Salton Sea dunes, California, *J. Geophys. Res. Earth Surf.*, *118*(4), 2013JF002867, doi:10.1002/2013JF002867.

Pelletier, J. D. et al. (2013), Coevolution of nonlinear trends in vegetation, soils, and topography with elevation and slope aspect: A case study in the sky islands of southern Arizona, *J. Geophys. Res. Earth Surf.*, *118*(2), 741–758, doi:10.1002/jgrf.20046.

Pelletier, J. D., and C. A. Orem (2014), How do sediment yields from post-wildfire debris-laden flows depend on terrain slope, soil burn severity class, and drainage basin area? Insights from airborne-LiDAR change detection, *Earth Surface Processes and Landforms*, n/a–n/a, doi:10.1002/esp.3570.

Pelletier, J. D., and J. T. Perron (2012), Analytic solution for the morphology of a soil-mantled valley undergoing steady headward growth: Validation using case studies in southeastern Arizona, *Journal of Geophysical Research: Earth Surface (2003--2012)*, *117*(F2), doi:10.1029/2011JF002281.

Pelletier, J. D., S. B. DeLong, C. A. Orem, P. Becerra, K. Compton, K. Gressett, J. Lyons-Baral, L. A. McGuire, J. L. Molaro, and J. C. Spinler (2012), How do vegetation bands form in dry lands? Insights from numerical modeling and field studies in southern Nevada, USA, *Journal of Geophysical Research: Atmospheres (1984–2012)*, *117*(F4), F04026, doi:10.1029/2012JF002465.

Perignon, M. C., G. E. Tucker, E. R. Griffin, and J. M. Friedman (2013), Effects of riparian vegetation on topographic change during a large flood event, Rio Puerco, New Mexico, USA, *J. Geophys. Res. Earth Surf.*, *118*(3), 1193–1209, doi:10.1002/jgrf.20073.

Perron, J. T., and J. L. Hamon (2012), Equilibrium form of horizontally retreating, soil-mantled hillslopes: Model development and application to a groundwater sapping landscape, *Journal of Geophysical Research: Atmospheres (1984–2012)*, *117*(F1), F01027, doi:10.1029/2011JF002139.

Perron, J. T., J. W. Kirchner, and W. E. Dietrich (2008), Spectral signatures of characteristic spatial scales and nonfractal structure in landscapes, *Journal of Geophysical Research: Atmospheres (1984–2012)*, *113*(F4), F04003, doi:10.1029/2007JF000866.

Persson, A., A. Hasan, J. Tang, and P. Pilesjö (2012), Modelling Flow Routing in Permafrost Landscapes with TWI: An Evaluation against Site-Specific Wetness Measurements, *Transactions in GIS*, *16*(5), 701–713, doi:10.1111/j.1467-9671.2012.01338.x.

Plotnick, R. E., R. H. Gardner, W. W. Hargrove, K. Prestegaard, and M. Perlmutter (1996), Lacunarity analysis: A general technique for the analysis of spatial patterns, *Phys. Rev. E*, *53*(5), 5461–5468, doi:10.1103/PhysRevE.53.5461.

Rengers, F. K., and G. E. Tucker (2014), Analysis and modeling of gully headcut dynamics, North American high plains, *J. Geophys. Res. Earth Surf.*, *119*(5), 983–1003, doi:10.1002/2013JF002962.

Rhoades, E. L., M. A. O'Neal, and J. E. Pizzuto (2009), Quantifying bank erosion on the South River from 1937 to 2005, and its importance in assessing Hg contamination, *Applied Geography*, *29*(1), 125–134, doi:10.1016/j.apgeog.2008.08.005.

Riaño, D., F. Valladares, S. Condés, and E. Chuvieco (2004), Estimation of leaf area index and covered ground from airborne laser scanner (LiDAR) in two contrasting forests, *Agricultural and Forest Meteorology*, *124*(3–4), 269–275, doi:10.1016/j.agrformet.2004.02.005.

Richardson, J. J., L. M. Moskal, and S.-H. Kim (2009), Modeling approaches to estimate effective leaf area index from aerial discrete-return LIDAR, *Agricultural and Forest Meteorology*, *149*(6–7), 1152–1160, doi:10.1016/j.agrformet.2009.02.007.

Roering, J. J. (2008), How well can hillslope evolution models “explain” topography? Simulating soil transport and production with high-resolution topographic data, *Geological Society of America Bulletin*, *120*(9-10), 1248–1262, doi:10.1130/B26283.1.

Roering, J. J., B. H. Mackey, J. A. Marshall, K. E. Sweeney, N. I. Deligne, A. M. Booth, A. L. Handwerger, and C. Cerovski-Darriau (2013), “You are HERE”: Connecting the dots with airborne LiDAR for geomorphic fieldwork, *Geomorphology*, *200*(0), 172–183, doi:10.1016/j.geomorph.2013.04.009.

Roering, J. J., J. Marshall, A. M. Booth, M. Mort, and Q. Jin (2010), Evidence for biotic controls on topography and soil production, *Earth and Planetary Science Letters*, *298*(1–2), 183–190, doi:10.1016/j.epsl.2010.07.040.

Roering, J. J., L. L. Stimely, B. H. Mackey, and D. A. Schmidt (2009), Using DInSAR, airborne LiDAR, and archival air photos to quantify landsliding and sediment transport, *Geophysical Research Letters*, *36*(19), L19402, doi:10.1029/2009GL040374.

Sankey, J. B., D. J. Law, D. D. Breshears, S. M. Munson, and R. H. Webb (2013), Employing LiDAR to detail vegetation canopy architecture for prediction of aeolian transport, *Geophysical Research Letters*, *40*(9), 1724–1728, doi:10.1002/grl.50356.

Sankey, J. B., N. F. Glenn, M. J. Germino, A. I. N. Gironella, and G. D. Thackray (2010), Relationships of aeolian erosion and deposition with LiDAR-derived landscape surface roughness following wildfire, *Geomorphology*, *119*(1–2), 135–145, doi:10.1016/j.geomorph.2010.03.013.

Schimel, D. S., G.P. Asner, and P. Moorcroft (2013), Observing changing ecological diversity in the Anthropocene, *Frontiers in Ecology and the Environment*, *11*(3), 129-137, doi: 10.1890/120111

Seidel, D., S. Fleck, C. Leuschner, and T. Hammett (2011), Review of ground-based methods to measure the distribution of biomass in forest canopies, *Annals of Forest Science*, *68*(2), 225–244, doi:10.1007/s13595-011-0040-z.

Shook, K., J. W. Pomeroy, C. Spence, and L. Boychuk (2013), Storage dynamics simulations in prairie wetland hydrology models: evaluation and parameterization, *Hydrol. Process.*, *27*(13), 1875–1889, doi:10.1002/hyp.9867.

Simard, M., N. Pinto, J. B. Fisher, and A. Baccini (2011), Mapping forest canopy height globally with spaceborne LiDAR, *Journal of Geophysical Research: Atmospheres (1984–2012)*, *116*(G4), G04021, doi:10.1029/2011JG001708.

Snyder, N. P. (2009), Studying Stream Morphology With Airborne Laser Elevation Data, *Eos, Transactions American Geophysical Union*, *90*(6), 45–46, doi:10.1029/2009EO060001.

Staley, D. M., T. A. Wasklewicz, and J. W. Kean (2014), Characterizing the primary material sources and dominant erosional processes for post-fire debris-flow initiation in a headwater basin using multi-temporal terrestrial laser scanning data, *Geomorphology*, *214*(0), 324–338, doi:10.1016/j.geomorph.2014.02.015.

Stennett, T. A. (2004), LiDAR: Strap in tight, and prepare to go vertical, *Photogrammetric engineering and remote sensing*, *70*(5), 545–548.

Stout, J. C., and P. Belmont (2014), TerEx Toolbox for semi-automated selection of fluvial terrace and floodplain features from LiDAR, *Earth Surface Processes and Landforms*, *39*(5), 569–580, doi:10.1002/esp.3464.

Streutker, D. R., and N. F. Glenn (2006), LiDAR measurement of sagebrush steppe vegetation heights, *Remote Sensing of Environment*, *102*(1–2), 135–145, doi:10.1016/j.rse.2006.02.011.

Sørensen, R., and J. Seibert (2007), Effects of DEM resolution on the calculation of topographical indices: TWI and its components, *Journal of Hydrology*, *347*(1–2), 79–89, doi:10.1016/j.jhydrol.2007.09.001.

Tarolli, P. (2014), High-resolution topography for understanding Earth surface processes: Opportunities and challenges, *Geomorphology*, *216*(0), 295–312, doi:10.1016/j.geomorph.2014.03.008.

Tenenbaum, D. E., L. E. Band, S. T. Kenworthy, and C. L. Tague (2006), Analysis of soil moisture patterns in forested and suburban catchments in Baltimore, Maryland, using high-resolution photogrammetric and LIDAR digital elevation datasets, *Hydrol. Process.*, *20*(2), 219–240, doi:10.1002/hyp.5895.

Thoma, D. P., S. C. Gupta, M. E. Bauer, and C. E. Kirchoff (2005), Airborne laser scanning for riverbank erosion assessment, *Remote Sensing of Environment*, *95*(4), 493–501, doi:10.1016/j.rse.2005.01.012.

Tinkham, W. T., A. M. S. Smith, H.-P. Marshall, T. E. Link, M. J. Falkowski, and A. H. Winstral (2014), Quantifying spatial distribution of snow depth errors from LiDAR using

Random Forest, *Remote Sensing of Environment*, *141*(0), 105–115, doi:10.1016/j.rse.2013.10.021.

Trujillo, E., J. A. Ramírez, and K. J. Elder (2009), Scaling properties and spatial organization of snow depth fields in sub-alpine forest and alpine tundra, *Hydrol. Process.*, *23*(11), 1575–1590, doi:10.1002/hyp.7270.

Varhola, A., and N. C. Coops (2013), Estimation of watershed-level distributed forest structure metrics relevant to hydrologic modeling using LiDAR and Landsat, *Journal of Hydrology*, *487*(0), 70–86, doi:10.1016/j.jhydrol.2013.02.032.

Varhola, A., N. C. Coops, Y. Alila, and M. Weiler (2014), Exploration of remotely sensed forest structure and ultrasonic range sensor metrics to improve empirical snow models, *Hydrol. Process.*, *28*(15), 4433–4448, doi:10.1002/hyp.9952.

Vierling, K. T., L. A. Vierling, W. A. Gould, S. Martinuzzi, and R. M. Clawges (2008), LiDAR: shedding new light on habitat characterization and modeling, *Frontiers in Ecology and the Environment*, *6*(2), 90–98, doi:10.1890/070001.

Vosselman, G., and H.-G. Maas (2010), *Airborne and terrestrial laser scanning*, CRC Press, London.

Wagner, W., M. Hollaus, C. Briese, and V. Ducic (2008), 3D vegetation mapping using small-footprint full-waveform airborne laser scanners, *International Journal of Remote Sensing*, *29*(5), 1433–1452, doi:10.1080/01431160701736398.

Wallace, L., A. Lucieer, C. Watson, and D. Turner (2012), Development of a UAV-LiDAR System with Application to Forest Inventory, *Remote Sensing*, *4*(6), 1519–1543, doi:10.3390/rs4061519.

Wedding, L. M., A. M. Friedlander, M. McGranaghan, R. S. Yost, and M. E. Monaco (2008), Using bathymetric LiDAR to define nearshore benthic habitat complexity: Implications for management of reef fish assemblages in Hawaii, *Remote Sensing of Environment*, *112*(11), 4159–4165, doi:10.1016/j.rse.2008.01.025.

West, N., E. Kirby, P. Bierman, and B. A. Clarke (2014), Aspect-dependent variations in regolith creep revealed by meteoric 10Be, *Geology*, *42*(6), 507–510, doi:10.1130/G35357.1.

Westoby, M. J., J. Brasington, N. F. Glasser, M. J. Hambrey, and J. M. Reynolds (2012), “Structure-from-Motion” photogrammetry: A low-cost, effective tool for geoscience applications, *Geomorphology*, *179*(0), 300–314, doi:10.1016/j.geomorph.2012.08.021.

Wheaton, J. M., J. Brasington, S. E. Darby, and D. A. Sear (2010), Accounting for uncertainty in DEMs from repeat topographic surveys: improved sediment budgets, *Earth Surface Processes and Landforms*, *35*(2), 136–156, doi:10.1002/esp.1886.

Williams, G. D. et al. (2013), Beyond Point Measurements: Sea Ice Floes Characterized in 3-D, *Eos, Transactions American Geophysical Union*, *94*(7), 69–70, doi:10.1002/2013EO070002.

Wulder, M. A., J. C. White, R. F. Nelson, E. Næsset, H. O. Ørka, N. C. Coops, T. Hilker, C. W. Bater, and T. Gobakken (2012), LiDAR sampling for large-area forest characterization: A review, *Remote Sensing of Environment*, *121*(0), 196–209, doi:10.1016/j.rse.2012.02.001.

Young, A. P., M. J. Olsen, N. Driscoll, R. E. Flick, R. Gutierrez, R. T. Guza, E. Johnstone, and F. Kuester (2010), Comparison of Airborne and Terrestrial LiDAR Estimates of Seacliff Erosion in Southern California, *Photogrammetric engineering and remote sensing*, *76*(4), 421–427, doi:10.14358/PERS.76.4.421.

Yu, X., J. Hyyppä, H. Kaartinen, and M. Maltamo (2004), Automatic detection of harvested trees and determination of forest growth using airborne laser scanning, *Remote Sensing of Environment*, *90*(4), 451–462, doi:10.1016/j.rse.2004.02.001.

Zellweger, F., F. Morsdorf, R. Purves, V. Braunisch, and K. Bollmann (2014), Improved methods for measuring forest landscape structure: LiDAR complements field-based habitat assessment, *Biodivers Conserv*, *23*(2), 289–307, doi:10.1007/s10531-013-0600-7.

Zhao, K., S. Popescu, and R. Nelson (2009), LiDAR remote sensing of forest biomass: A scale-invariant estimation approach using airborne lasers, *Remote Sensing of Environment*, *113*(1), 182–196, doi:10.1016/j.rse.2008.09.009.

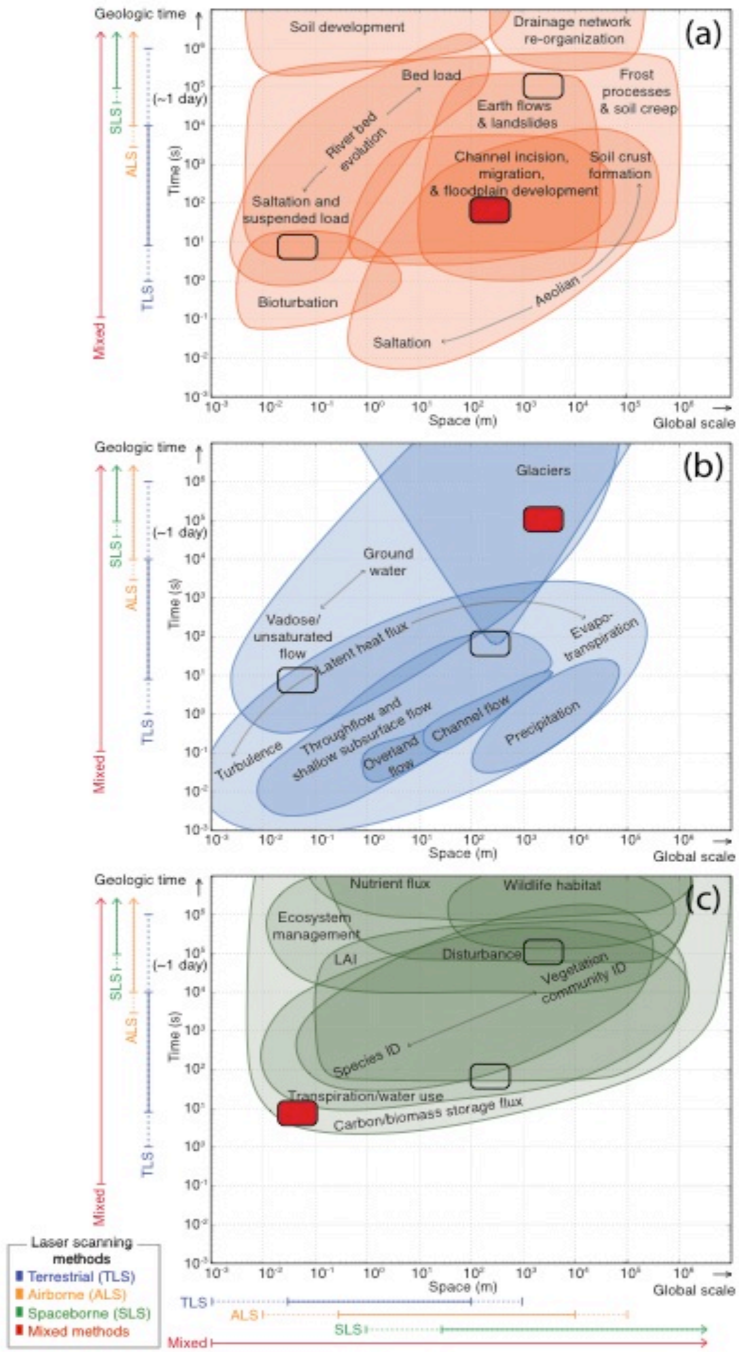

Figure 1. Important CZ processes graphed as a function of time versus space for geomorphology (a), hydrology (b), and ecology (c). The spatial and temporal scales that lidar is currently addressing are shown as colored bars, with dotted bars indicating increasing resolutions and larger extents available in the next five years. Overlapping spatiotemporal scales that encompass the example questions in the Figure 3 are also noted with red boxes.

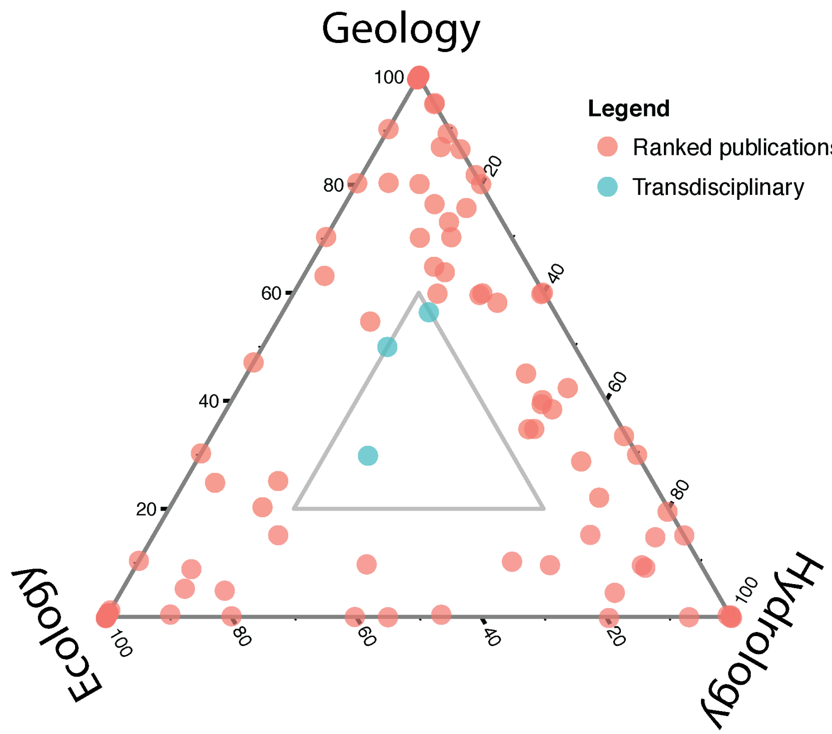

Figure 2. Depiction of the disciplinary focus of 147 journal articles using lidar. Articles were qualitatively ranked based on their applicability to geomorphological, hydrological, and/or ecological process understanding. Articles in the center are examples of transdisciplinary lidar applications, with those shown in blue used as exemplars in the text.

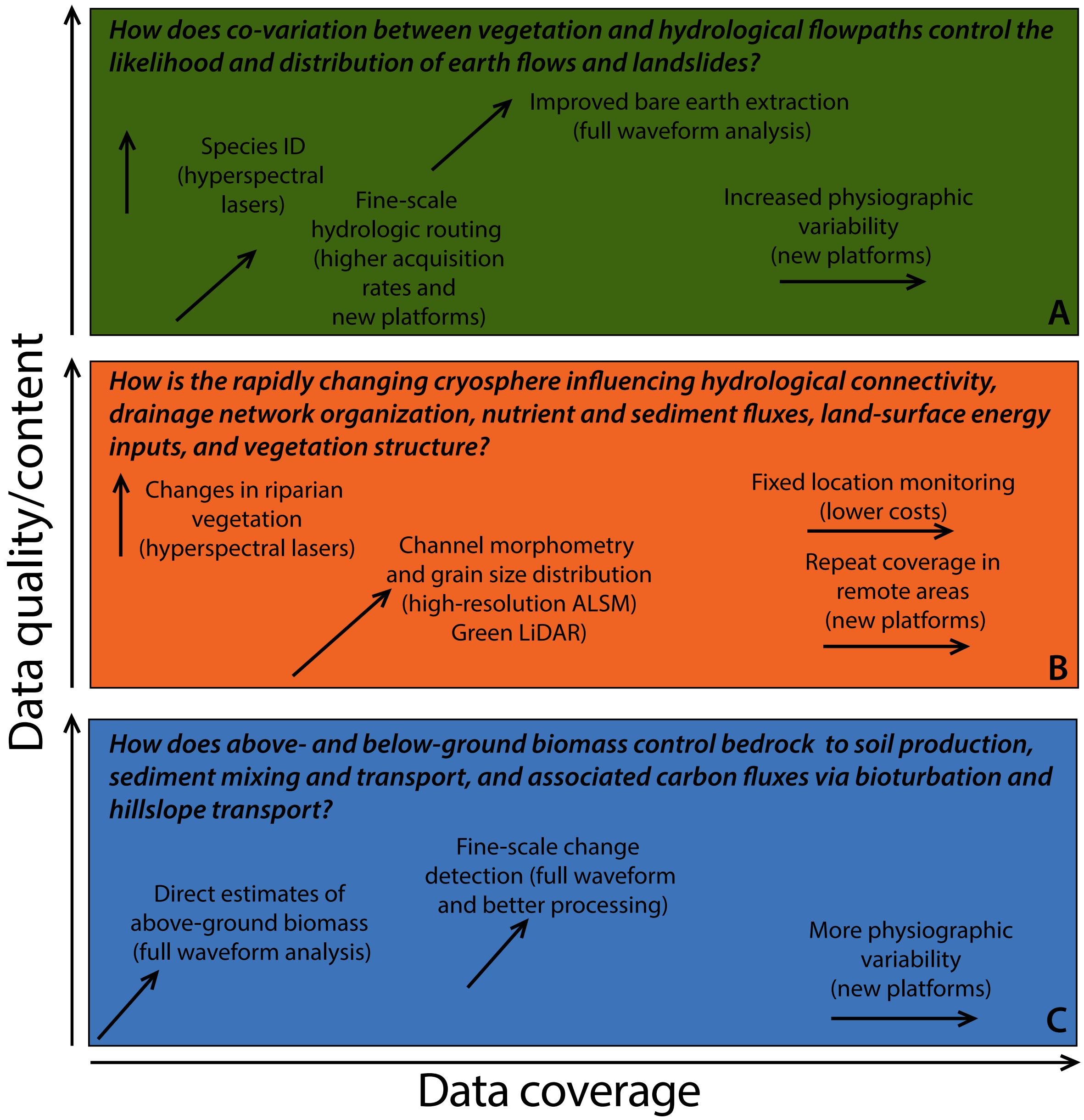

Figure 3. Example CZ research questions conceptualizing the transdisciplinary potential of lidar datasets when coupled with future technological advances. The questions encompass processes from geomorphology (a), hydrology (b), and ecology (c) that overlap spatial and temporal scales. These scales are noted in Figure 1. The text in the panel notes specific improvements offered and the technology needed in parentheses. The arrows qualitatively represent whether the technological advance expands data coverage and/or data quality/content.