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Constraining plant functional types in a semi-arid ecosystem with waveform lidar

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ABSTRACT

Accurate classification of plant functional types (PFTs) reduces the uncertainty in global biomass and carbon estimates. Airborne small-footprint waveform lidar data are increasingly used for vegetation classification and above-ground carbon estimates at a range of spatial scales in woody or homogeneous grass and savanna ecosystems. However, a gap remains in understanding how waveform features represent and ultimately can be used to constrain the PFTs in heterogeneous semi-arid ecosystems. This study evaluates lidar waveform features and classification performance of six major PFTs, including shrubs and trees, along with bare ground in the Reynolds Creek Experimental Watershed, Idaho, USA. Waveform lidar data were obtained with the NASA Airborne Snow Observatory (ASO). From these data we derived waveform features at two spatial scales (1 m and 10 m rasters) by applying a Gaussian decomposition and a frequency-domain deconvolution. An ensemble random forest algorithm was used to assess classification performance and to select the most important waveform features. Classification models developed with the 10 m waveform features outperformed those at 1 m (Kappa (κ) = 0.81–0.86 vs. 0.60–0.70, respectively). At 1 m resolution, lidar height features improved the PFT classification accuracy by 10% compared to the analysis without these features. However, at 10 m resolution, the inclusion of lidar derived heights with other waveform features decreased the PFT classification performance by 4%. Pulse width, rise time, percent energy, differential target cross section, and radiometrically calibrated backscatter coefficient were the most important waveform features at both spatial scales. A significant finding is that bare ground was clearly differentiated from shrubs using pulse width. Though the overall accuracy ranges between 0.72 and 0.89 across spatial scales, the two shrub PFTs showed 0.45–0.87 individual classification success at 1 m, while bare ground and tree PFTs showed high (0.72–1.0) classification accuracy at 10 m. We conclude that small-footprint waveform features can be used to characterize the heterogeneous vegetation in this and similar semi-arid ecosystems at high spatial resolution. Furthermore, waveform features such as pulse width can be used to constrain the uncertainty of terrain modeling in environments where vegetation and bare ground lidar returns are close in time and space. The dependency on spatial resolution plays a critical role in classification performance in tree-shrub co-dominant ecosystems.

1. Introduction

Climate and human driven disturbances in dryland ecosystems have adverse effects on biodiversity, ecosystem services, carbon storage, and desertification (Ahlstrom et al., 2015; Poulter et al., 2011). Furthermore, aridity in drylands is expected to increase in the future, causing expansion of land degradation and desertification (Huang et al., 2017). Ultimately, changes in the abundance and distribution of plant functional types (PFTs) in drylands can alter productivity and the capacity of these lands for carbon storage (Chen et al., 2017). Thus, PFTs are important indicators for monitoring the state of an ecosystem, as well as its resistance and resilience to climate and human driven disturbances

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(Lavorel et al., 1997; Poulter et al., 2015; Schimel et al., 2013). PFTs are frequently used as inputs for vegetation dynamics and earth system models (Krinner et al., 2005; Sitch et al., 2003; Wullschleger et al., 2014). However, uncertainty in PFTs, especially in dryland ecosystems between shrub, grass and forest classes reduces the accuracy of these models (Hartley et al., 2017). Hence, improved methods to capture the structure and function of PFTs in drylands are needed to accurately model carbon storage flux in these systems.

Due to its ability to capture three dimensional structure and some radiometric properties, light detection and ranging (lidar) is used to derive vegetation heights and digital terrain models, as well as to classify vegetation species, function and structure (Dalponte and Coomes, 2016). These products are further used for automated forest inventory estimates such as biomass and carbon stocks (Coomes et al., 2017; Dalponte and Coomes, 2016; Ene et al., 2017), as well as for ecosystem demography models (Thomas et al., 2008) to estimate carbon flux. Waveform lidar, which digitizes the total amount of lidar return energy at high vertical resolution (~1 ns = 15 cm), provides potential species-specific information about the illuminated target (Hancock et al., 2015; Hancock et al., 2011; Roncat et al., 2011; Wagner et al., 2006). The shape of the returning waveform results from a convolution of the temporal shape of the emitted pulse and system impulse (together called "system response/waveform") with the target cross-section. Thus the backscattered waveform contains target characteristics such as size, orientation, and spatial arrangement, as well as radiometric characteristics of individual vegetation species (Hovi and Korpela, 2014; Korpela et al., 2013; Wagner et al., 2006).

Each echo in a waveform signal corresponds to an individual reflection target or set of targets. Thus, an echo can be used to detect individual target properties, the position and the orientation in 3D space. Through optimal waveform processing techniques, such as the commonly used Gaussian decomposition (Wagner et al., 2006), linear fitting or other asymmetric fitting techniques (Jutzi and Stilla, 2006; Mallet et al., 2010; Roncat et al., 2011; Wu et al., 2011), numerous features can be derived from backscattered waveforms. Some of these additional waveform features and their biophysical relationships to the target are summarized in Table 1.

However, many of these waveform features (e.g. amplitude, pulse width, and backscatter cross section) are sensitive to system parameters such as incident angle, range and flying height (Abed et al., 2012; Hovi and Korpela, 2014; Lin, 2015; Wagner, 2010). Thus, it is necessary to correct the influence of these system parameters on waveform features prior to application (Bruggisser et al., 2017; Fieber et al., 2013; Wagner, 2010).

Waveform features and height information have been used to estimate vegetation structure as well as plant functional type and structural traits at both fine (< 2 m) and regional spatial scales (Alexander et al., 2015; Wagner et al., 2008). Classification of plant functional types and individual species in tree dominant ecosystems show great improvement of classification accuracy with inclusion of one or several of these waveform features (Hovi et al., 2016). The pulse width and location characterize the vegetation components along the waveform path and have been used to classify deciduous and coniferous species (Reitberger et al., 2008; Yao et al., 2012). Wagner et al. (2008) show that the scattering shape of backscattered signals can be used to separate vegetation from no vegetation with an accuracy up to 89%. Pulse widths can be used to classify vegetation in different patch conditions such as within varying soil roughness, understory and density (Hollaus et al., 2011). Vaughn et al. (2012) show that inclusion of frequency-domain full-waveform lidar features improves a five-species classification accuracy by 6% over discrete-return lidar alone, from 79 to 85%.

Numerous studies using combined features from discrete and waveform datasets have improved classification performance of tree and grass species (Heinzel and Koch, 2011; Neuenschwander et al., 2009; Vaughn et al., 2012). Backscatter cross-section alone can be used to distinguish ground, grass, and trees from each other (Fieber et al., 2013; Wagner et al., 2008). Further, lidar-derived height and energy related features have been used to delineate individual trees in object-based image analysis (OBIA) studies as the OBIA eliminates the discontinuity that is common in pixel-based classification (Zahidi et al., 2015).

In most of these studies, lidar-derived heights or height-based products such as canopy height models (CHM) and digital elevation models (DEM) play a critical role in delineation of individual tree crowns as well as in differentiating vegetation from bare ground (Hovi et al., 2016). Some vegetation studies use lidar returns above a certain height threshold (e.g. ~2 m above ground) for classification (Ene et al., 2017; Zahidi et al., 2015). However, in low-height vegetation, lidar does not return a separate energy peak unless the vegetation height is above the range resolution of the lidar system. Thus, bare ground lidar responses are typically mixed with low-height vegetation such as shrubs and grasses. This causes difficulties to measure the fractions of bare ground and vegetation, an important criterion for plant functional distribution mapping in dryland ecosystems (Hartley et al., 2017). Numerous studies in low-height ecosystems have documented that lidar heights underestimate vegetation heights (e.g. Streutker and Glenn, 2006). Similar underestimations and uncertainties appear in almost all studies which use lidar-based height features to model low-stature vegetated ecosystems across the world, which significantly affects regional ecosystem modeling and upscaling attempts (Hopkinson et al., 2005; Rango et al., 2000). Fortunately, waveform lidar is sensitive to the occurrence of low vegetation, where echoes often have a wider pulse than echoes from the bare ground. Although this limits the use of traditional lidar heights to separate ground from vegetation, the derivation of additional waveform features provides the opportunity to uncover hidden vegetation characteristics in the datasets.

In addition, vegetation distributions in many semi-arid ecosystems are topographically controlled and low-height vegetation often coexists with taller tree communities. The topographic and species complexity

Table 1
Summary of waveform features derived from individual waveforms and their biophysical relationships to the target.

Attribute	Biophysical relationship	Reference
Pulse width	Surface roughness and slope	Fieber et al., 2013
Amplitude	Optical response of the target to the emitted lidar wavelength	Fieber et al., 2013
Backscatter cross-section	Horizontal scattered cross-section of the target with respect to the deployed system wavelength, range, and incident angle	Wagner et al., 2006
Backscatter coefficient	The area-normalized backscatter cross-section corrected for incidence angle. A function of the target reflectance.	Wagner et al., 2008; Wagner, 2010
Differential target cross section	Laser system independent true target profile	Roncat et al., 2011
Rise time	Vertical structural distribution of target (e.g. in trees the vertical distribution of leaves and branches)	Ranson and Sun, 2000
Number of echoes	Vertical distribution and height of target	Heinzel and Koch, 2011
Height/height variability	Vertical distribution of target and its separation from ground	Fieber et al., 2013
Secondary explanatory features derived from any of the above parameters	N/A	Heinzel and Koch, 2011