EXTRACTING STRUCTURAL LAND COVER COMPONENTS USING SMALL-FOOTPRINT WAVEFORM LIDAR DATA

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1. INTRODUCTION

Remote sensing using light detection and ranging (LiDAR) technology has seen considerable advancement with the advent of full waveform digitizing sensors. LiDAR remote sensing systems operate by transmitting a monochromatic light pulse and measuring the reflection of this light pulse off of a scattering surface. The intensity of the laser pulse is recorded as a function of the time it takes for the energy to leave the emitter, interact with the surface, and return to the sensor. Waveform LiDAR sensors have the advantage of being able to record the backscattered energy at a very high sampling rate, typically on the order of nanoseconds. The combination of high temporal resolution detection and full backscatter digitization enable the extraction of structural information that is embedded within the waveform [1]. Various studies have shown that signal metrics, calculated from large footprint LiDAR waveforms (on the order of 10s of meters), can be used to assess vegetation structure in forested environments [e.g., 2, 3], while small-footprint LiDAR waveforms can be used to accurately classify various land cover types [4]. Measures such as tree height, crown volume, and biomass have been accurately predicted and modeled, resulting in good correlation between waveform-derived metrics and available field data [e.g., 5]. However, two specific challenges remain in terms of land cover assessment: (i) most previous work has dealt with large-footprint systems, which results in the measured field data typically being an order of magnitude smaller in actual ground area than the footprint size and (ii) a detailed breakdown of woody, herbaceous, and bare ground structural components, similar to the "end member" concept in an imaging spectroscopy context [6], is still lacking. This latter aspect has bearing on our ability to map land cover types in the structural (3D) domain, as opposed to the traditional spectral approaches.

The objectives of this study are to (1) establish a method by which to extract structural components, e.g., woody, herbaceous, and bare ground from small-footprint LiDAR waveforms, (2) assess how these components and their extraction vary within different footprint sizes, and (3) establish how these structural components can be mapped across the landscape. We will accomplish this by using plot-level waveforms, generated by compositing small-footprint waveform LiDAR (0.56 m footprint) returns, and extracting waveform-derived metrics to identify unique structural components and map woody and herbaceous biomass for a typical protected savanna land use area. This scalable approach will increase our understanding of the interaction between waveform footprint and land cover object sizes and aid in the development of improved relationships between structural waveform metrics and measured field data.

2. METHODS

The study area is located in and around the Kruger National Park (KNP) in South Africa. The area is bounded by (22°8’00” S; 30°34’52” E) and (25°32’48” S; 32°2’50” E). Field and remote sensing data have been collected for structural assessment of land degradation across a land use gradient that includes the KNP and an adjacent subsistence farming, communal area; this layout effectively juxta-positions a “protected” and “communal" area (Figure 1). An example of a protected savanna site from the study area is also shown in Figure 1. Plotted over the image are markers indicating the locations of plot-level field data on a 10 m grid spacing. The field data is based on 9 sites and 4-5 sites per land use type. Each site, in turn, consists of 36 plot-level measurements of herbaceous biomass, tree height and diameter, species, and a qualitative assessment of cover (crusting, bare soil, herbaceous, and woody cover). These field data will be modeled using metrics derived from composite plot-size waveforms composed of small-footprint waveform returns within each plot. Field data were collected during May 2008 in association with an airborne data collection campaign; waveform LiDAR data were collected by the Carnegie Airborne Observatory (CAO), using an Optech waveform digitizer, at 0.56 m footprint size and 1 ns temporal (vertical) resolution. Figure 2 shows an example of a composite waveform, constructed from 81 sample waveforms from a 9x9 pixel window around a plot-center. The resultant waveform footprint is approximately 5 meters in diameter.

We will test the assumption that plot-level composite waveforms are linear combinations of the structural components (structural end members) within each plot. This will be achieved by applying algorithms common in hyperspectral unmixing, such as linear mixture models (LMM), to determine the fractional abundance of structural components within a plot. It should be noted that linear and nonlinear mixture models have been applied to multi- and hyperspectral imagery as a way to unmix a pixel’s spectrum into abundances of target spectra, most commonly referred to as spectral end members, and provide a theoretical basis for our approach [7]. We will also test the assumption that these waveforms are nonlinear combinations of structural components as a comparative measure.

Waveform metrics such as canopy energy, ground energy, rise time of the leading edge of the waveform, fall time of the trailing edge of the waveform, height of median energy (HOME), and centroid height [4] will be extracted towards defining structural components (end members) within the waveform. Novel metrics, e.g., the time (ns) it takes to complete the 10-90% integration range of the entire integrated waveform area, will also be investigated. These metrics furthermore will be applied in different combinations in order to estimate the field-measured woody and herbaceous biomass for each plot. Combinations of waveform metrics, end member fractions, and biomass estimations will finally be compared across the protected and degraded sites to assess their usefulness for describing differences in land cover characteristics at the site level.

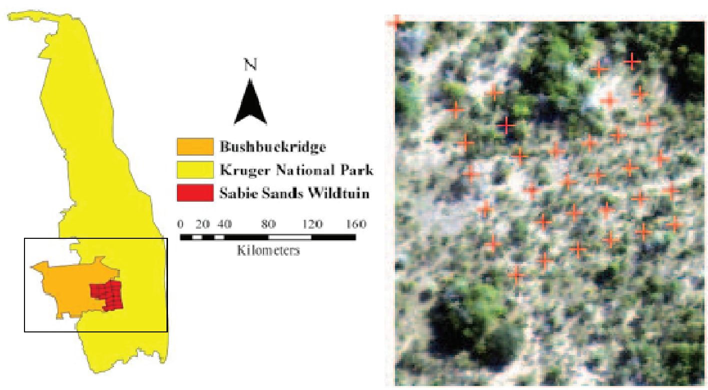

Figure 1. Left: Study area for this research. Our study focuses on the protected Kruger National Park and degraded Buschbuckridge (communal) areas. Right: An example of a protected savanna land use site in Kruger National Park, South Africa. Field-measured plots are shown as red crosshairs.

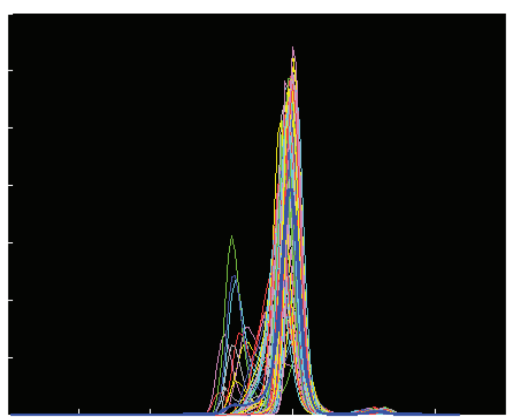

Figure 2. An example of a composite waveform, formed by averaging waveforms from a 9x9 pixel window (shown in dark blue), along with waveforms from each pixel in that window.

3. CONCLUSIONS

This research aims to contribute to improved modeling and estimation of plot level, land cover/use-specific structural parameters using metrics derived from small-footprint LiDAR waveforms. We expect that as the footprint size of these waveforms more closely resembles plot size, estimations of woody and herbaceous biomass, bare ground cover, woody cover, etc., will exhibit higher correlations with waveform metrics when compared to either significantly smaller- or larger-footprint sensors. We hypothesize that within-object waveform interaction (small-footprint waveforms) and the integration of multiple objects in a single waveform (large-footprint waveforms), will prove less amenable to extraction of structural land cover components than is the case with matched footprint-plot coverage. Results will be presented at the conference.

4. REFERENCES

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