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Semi-Arid Ecosystem Plant Functional Type and LAI from Small Footprint Waveform Lidar

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Abstract

Plant functional traits such as vegetation structure, density, and composition are indicators of ecosystem response to climate and human driven disturbances. We used small footprint waveform lidar with an ensemble random forest approach to differentiate the functional traits in a western US semi-arid ecosystem. We introduced a new gap fraction based leaf area index (LAI) estimator using lidar derived parameters. Results showed 60% - 89% accuracies discriminating plant functional types and estimating shrub LAI. These results imply the potential of waveform lidar to quantify plant functional traits in low-stature vegetation which is useful to assess climate impact in semi-arid ecosystems.

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INTRODUCTION

- In this study we use variables derived from full waveform lidar to demonstrate their capacity to differentiate key plant functional types (PFTs) including aspen (AS), Douglas fir (DF), juniper (JP), bitterbrush (BT), sagebrush (SG), bare ground (GD); and leaf area index (LAI) in a heterogeneous tree-shrub, co-dominant, semi-arid ecosystem.
- Our results provide a solution to difficulties in deriving shrub and LAI estimates from discrete return lidar in semi-arid ecosystems, in which returns are often too low to characterize the vegetation.
- By imputing our results, we can assess landscape-wide ecosystem structure, state, habitat suitability as well constrain uncertainties in vegetation dynamic models.

FULL WAVEFORM LIDAR

Full waveform lidar emits an amplified laser beam and digitizes the backscattered energy as a near continuous waveform with a high vertical resolution (~1 ns = 15 cm). The resultant 3D wave contains properties of both the emitted wave and the target (Fig. 1). These waveform properties can be used to infer biophysical properties of vegetation.

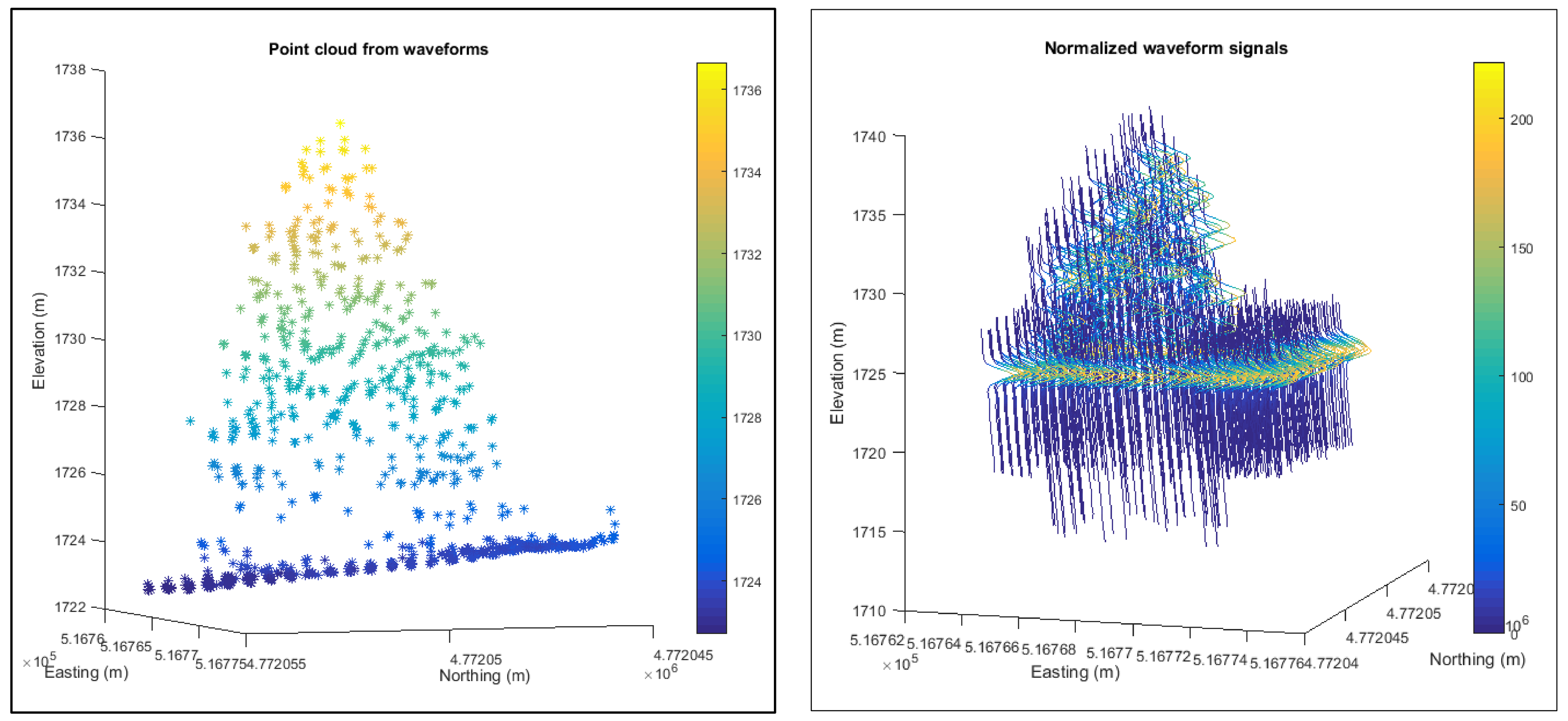


Figure 1. Discrete return lidar point cloud from a juniper tree (left). Full waveform lidar representation of the same juniper tree (right).

METHODS

Vegetation was classified into PFTs and the LAI was derived by first geolocating the waveforms and then approximating the backscattered full waveform signals. We implemented a sum of Gaussian approximation and frequency domain deconvolution techniques to extract the variables from waveform signals (Fig. 2). An ensemble random forest algorithm was applied to the derived variables at 1 m and 10 m spatial scales to differentiate the dominant PFTs in the study site (Fig. 3).

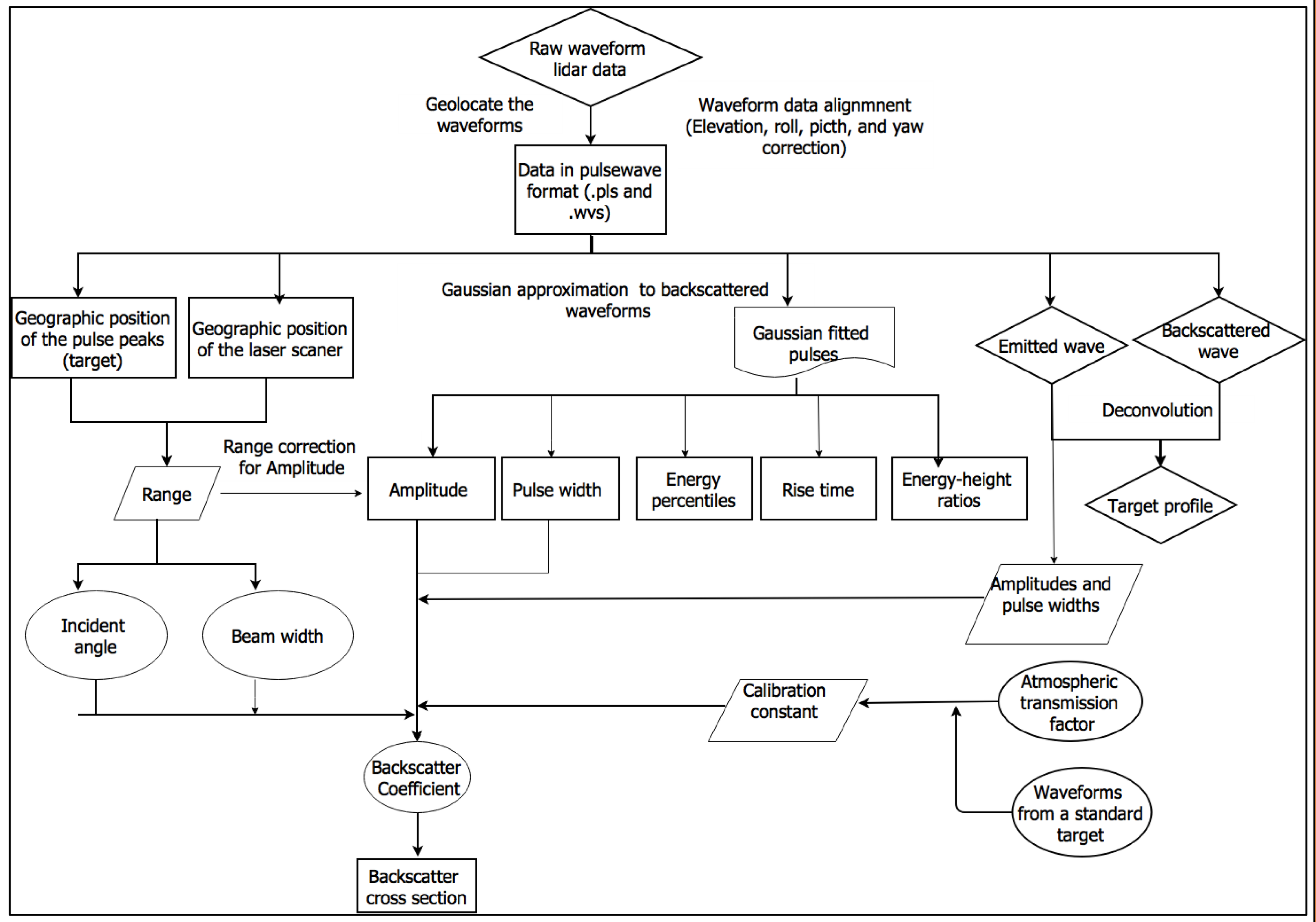


Figure 2. Variable derivation from the lidar waveforms.

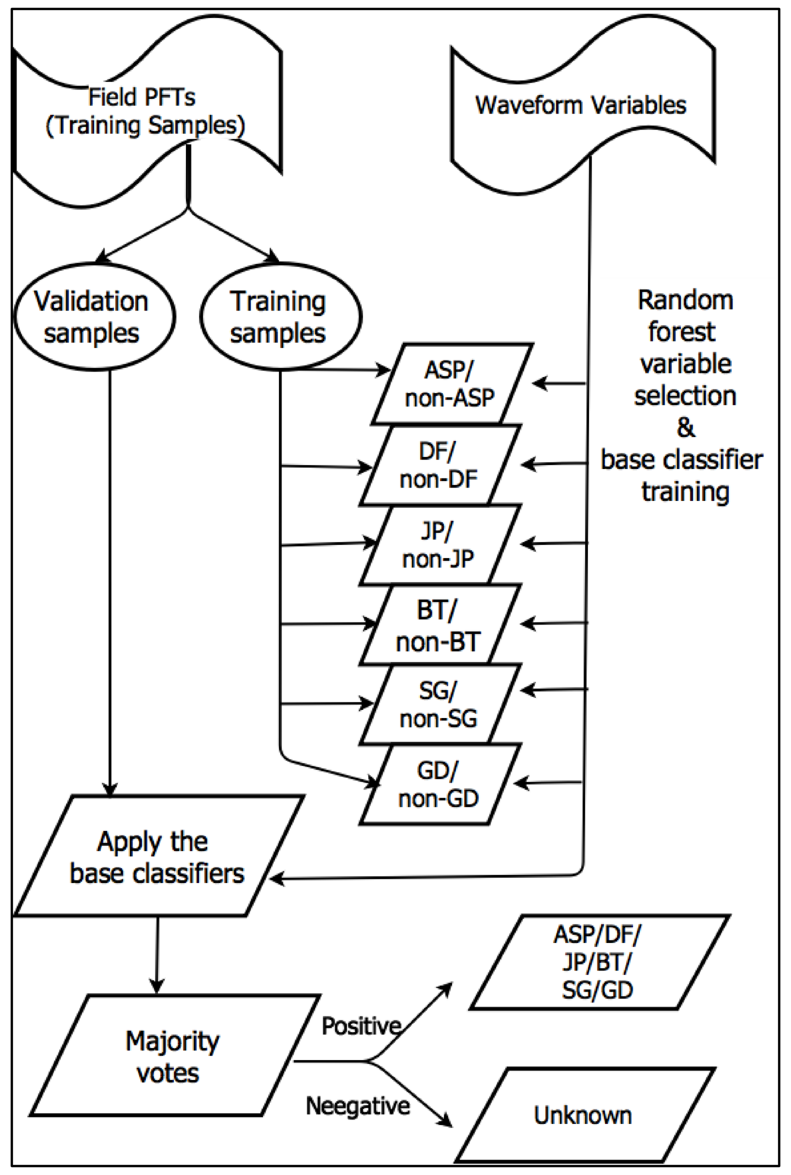


Figure 3. Ensemble random forest for PFT classification.

RESULTS

1. Associations of waveform derived percent energy, rise time, pulse width, backscatter cross section and deconvolved target profiles separate PFTs of trees and shrubs from each other and from bare ground (Fig. 4).

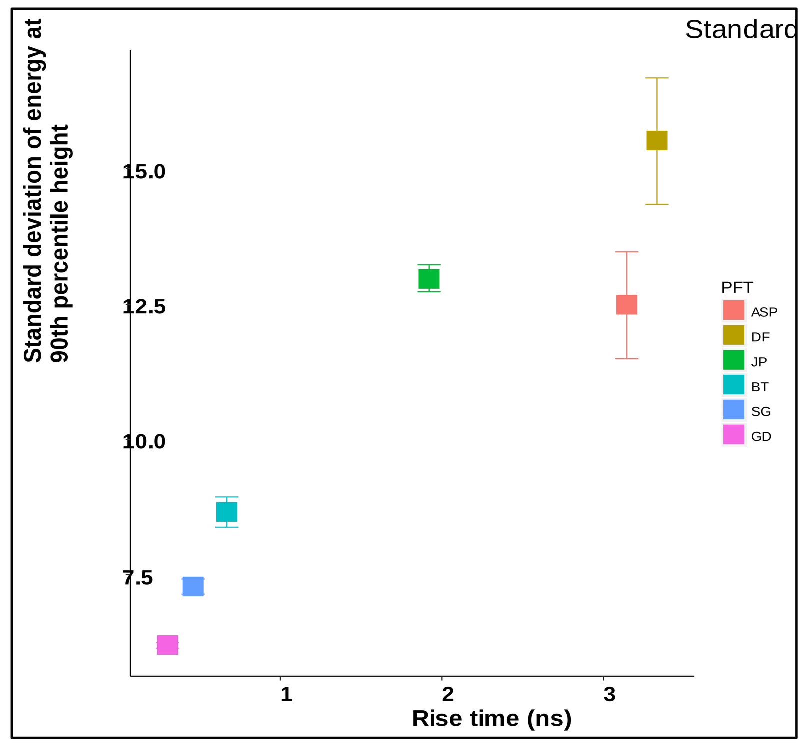


Figure 4. Distribution of rise time and standard deviation of cumulative lidar energy at 90[th] percentile of PFTs.

2. Lidar variables that relate to the target structure (pulse width, energy distribution, and rise time) dominate the variables that relate to radiometric properties (backscatter cross section) (Fig. 4, 5a, and 5b).

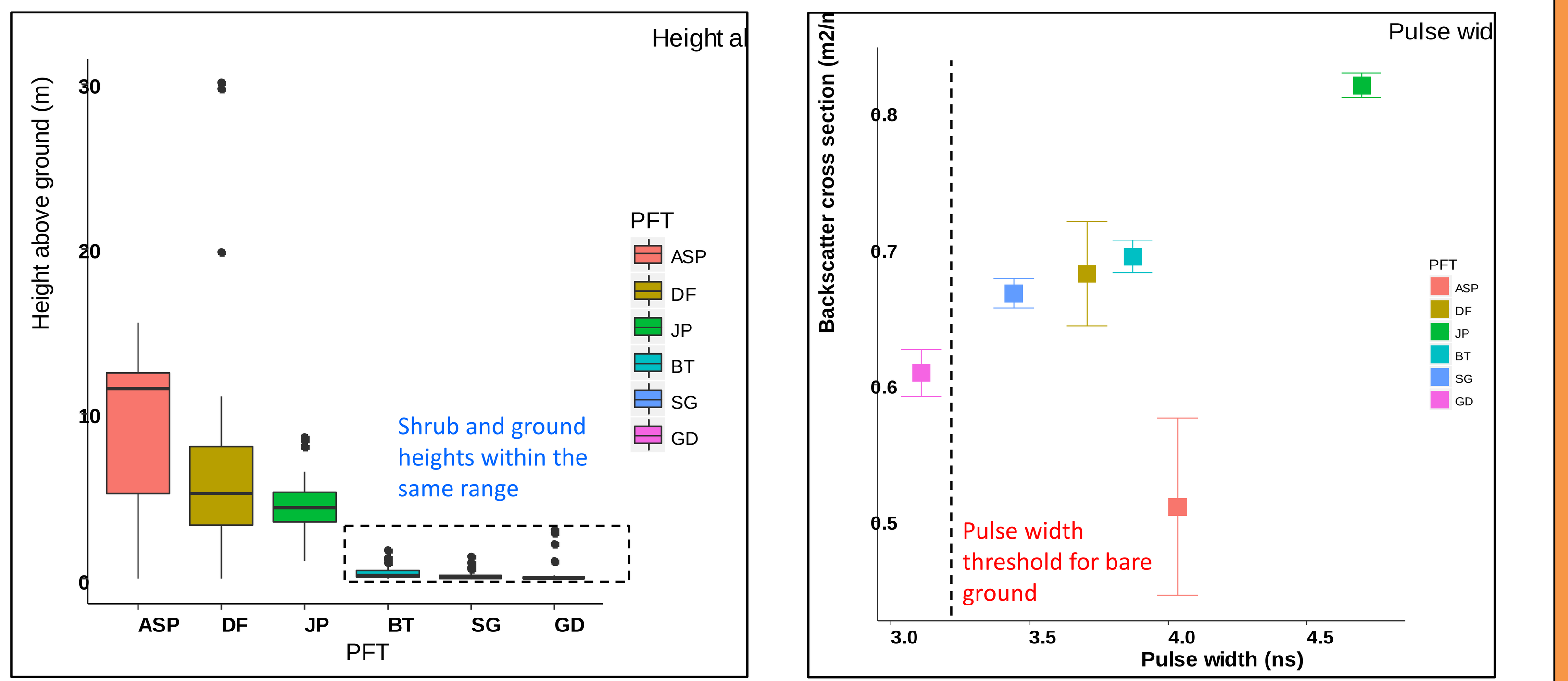
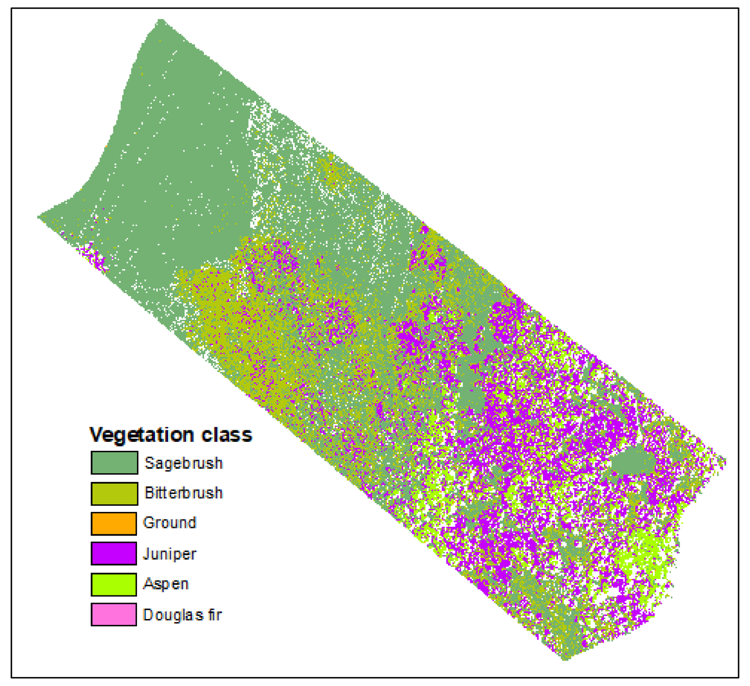


Figure 5. a) Distribution of height above ground of selected PFTs.
b) Distribution of pulse width and backscatter cross section of PFTs.

3. Inclusion of height above ground improves tree PFT separation, however shrub PFTs and ground were confused (Fig. 5a). Shrub-ground confusion can be eliminated using percent energy (Fig. 4), pulse with and backscatter cross section (Fig. 5 b)



4. Resulted in a high overall PFT accuracy (@1 m, 80%; @10m, 89% accuracy) (Fig. 6).

Figure 6. PFT classification map of a lidar flight line

5. Gap fraction derived from the waveform backscatter cross section shows a strong negative correlation with plot scale shrub LAI (Fig. 7).

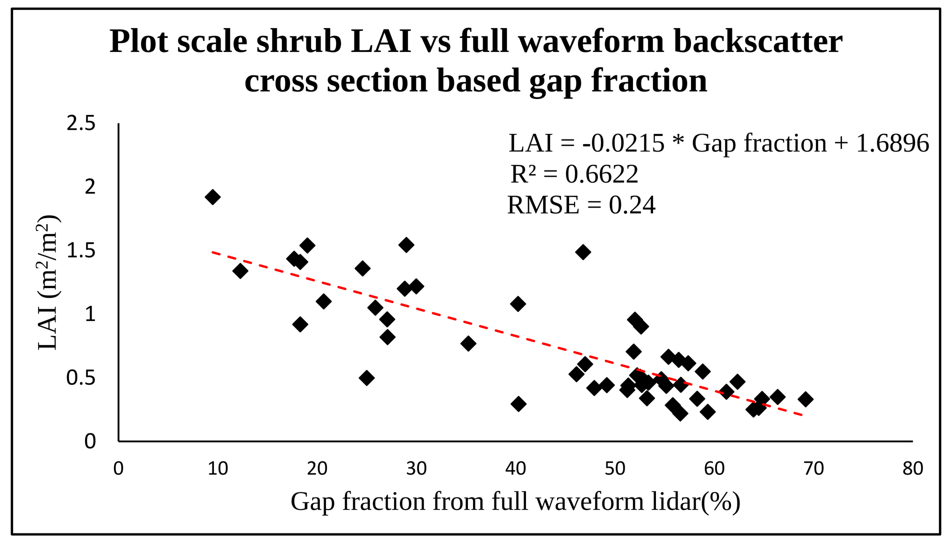


Figure 7. Correlation of waveform derived plot scale gap fraction and field observed LAI

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