MAPPING SEMIARID BIOCRUST COVER

Novel Remote Sensing Approach for Estimating Biocrust Fractional Cover In Semiarid Ecosystems

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1 INTRODUCTION

Drylands are particularly vulnerable to climate change and land degradation, which is a major issue given these represent Earth's largest biome and support the livelihoods of billions of people. Given their important role in terrestrial carbon and water cycles and their vulnerability to global change, it is imperative that we are able to monitor large-scale changes in dryland vegetation and soil cover types. However, most dryland classification algorithms have focused solely on detecting shrub cover (e.g., Brandt et al., 2020). Separating out the fractional cover (fCover) of other cover types in these sparse, heterogeneous ecosystems, including the biological soil crusts (biocrusts) that are characteristic of dryland ecosystems worldwide (Belnap et al., 2016) has been at the limit of what is possible given the spatial and spectral resolution of existing remote sensing (RS) data. However, with increasing availability of new and higher spectral and spatial resolution RS datasets, we are now entering an era in which the full spectrum of dryland cover types can be detected. Here we tested the use of unsupervised spectral unmixing methods and high resolution hyperspectral and LIDAR-derived canopy height data to separately detect the fractional cover of key plant and soil functional types at the semiarid Santa Rita Experimental Range savanna ecosystem in southern Arizona.

2 SANTA RITA EXPERIMENTAL RANGE

- Santa Rita Experimental Range (SRER) in southern Arizona (Fig. 1).
- Sparsely vegetated semi-arid mixed woody plant and C4 grass ecosystem.
- Biocrusts present areas not covered by vegetation.

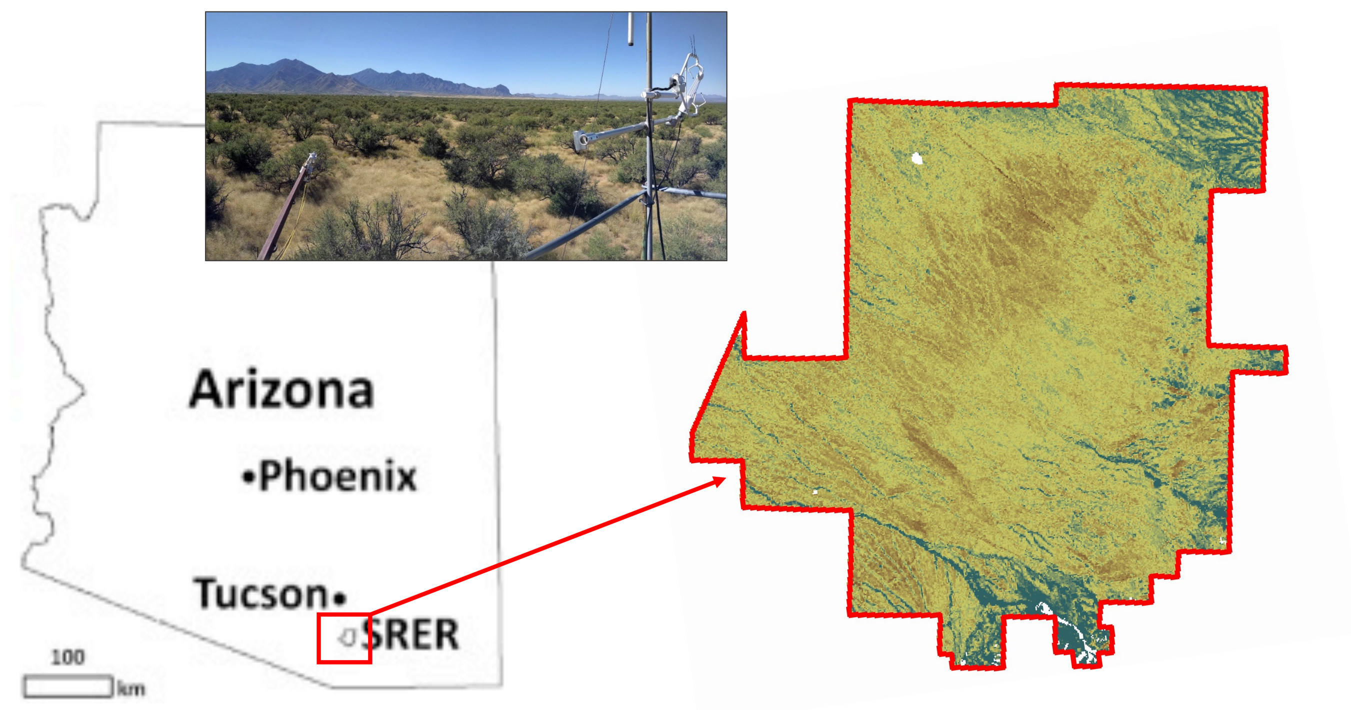

Figure 1: Location, outline with fractional shrub cover, and photo of the Santa Rita Experimental Range.

3 AIRBORNE REMOTE SENSING DATA

- National Ecological Observation Network (NEON) Airborne Observing Platform (AOP) data collected August 2018.
- Hyperspectral, LIDAR and camera imagery (see Table 1 for resolution).
- LIDAR data-derived canopy height model (CHM) used in classifications.

NEON Data	Resolution
Hyperspectral	1m
LIDAR	1m
Camera Imagery	0.1m

Table 1: NEON data products and resolution.

4 CLASSIFICATION METHODS

- Images pre-processing included: image mosaicking, data cleaning and bi-directional reflection distribution function (BRDF) correction to remove "seamlines" between
- Classification methods shown in Table 2. Aim to derive fractional cover of 3 main types: tall woody plants, low stature grasses, and bare soil.
- Fusion of both hyperspectral and CHM data tested.

Classification type	Class types	Method	Data (2018)
Unsupervised	Mixed pixel	Spectral Unmixing	Hyperspectral image only
		Fusion Unmixing	Hyperspectral+Lidar height

Table 2: Classification methods and data used.

- Different number of spectral endmembers tested in signature creation.
- Mean absolute difference and fuzzy error matrix used for accuracy assessment.
- Reference image from supervised classification of camera images based on 1000 manually classified ground control points.

5 SPECTRAL UNMIXING RESULTS FROM SRER

- Tall woody plants only separated from low stature grasses with 5 endmembers plus LIDAR-derived height data (Fig. 2f) (Pervin et al., *under review*).
- In addition to bare soil, vegetation, and shadow+noise classes, there is dominant presence of a unique spectral signature ("Other" red curve in Figs. 2c-f).
- "Other" spectral appears to be similar to hyperspectral signatures of "wet" lichen biocrust communities collected at another location in Utah (Smith et al., 2019; Fig. 2g)

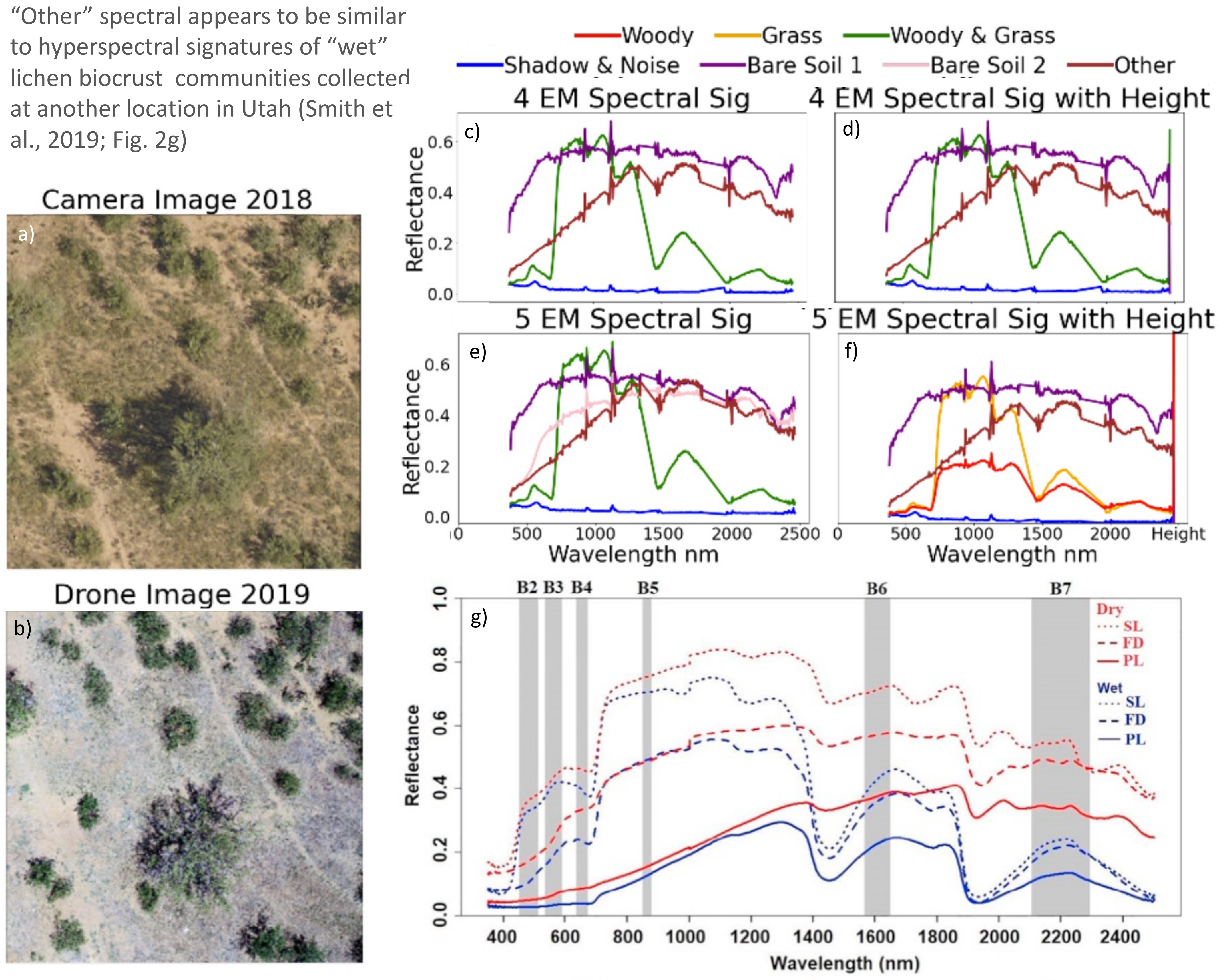

Figure 2: Example from one location in SRER of endmember spectra derived from unsupervised spectral unmixing signature creation: a) and b) imagery of the location; c) 4 endmembers (EM) with hyperspectral data only; d) 4 EM hyperspectral + height data; e) 5 EM hyperspectral only; and f) 5 EM hyperspectral + height data; g) from Fig. 10 Smith et al. (2019).

6 SUMMARY AND PERSPECTIVES FOR FUTURE WORK

- Unsupervised spectral unmixing appears to have detected an additional unique spectra of a dominant cover type that is not representative of bare soil or vegetation spectra.
- Comparison with existing biocrust spectra points towards this as an explanation for what this "Other" class may be.
- NEON field experimentalists working at SRER confirm presence of biocrusts. This work shows they may be widespread at SRER (Fig. 3).

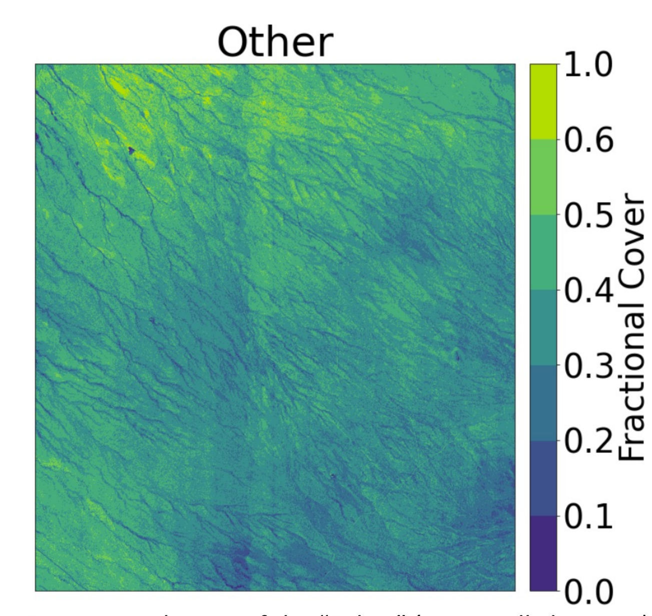

Figure 3: Fractional cover of the "Other" (potentially biocrust) class across the whole SRER study area.

- Potentially an exciting opportunity for mapping biocrusts using high spatial and spectral RS imagery at large scales → useful for understanding and modeling biocrust function.
- BUT need to do more field ground truthing of biocrust locations and spectra at SRER to confirm the result.

References: Brandt et al. (2020) (Nature); Belnap et al. (2016); Pervin et al. (under revision for IEEE JSTARS); Smith et al. (2019) (RSE).