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Remote Sensing of Drylands: Applications of Canopy Spectral Invariants

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Remote sensing of drylands: applications of canopy spectral invariants

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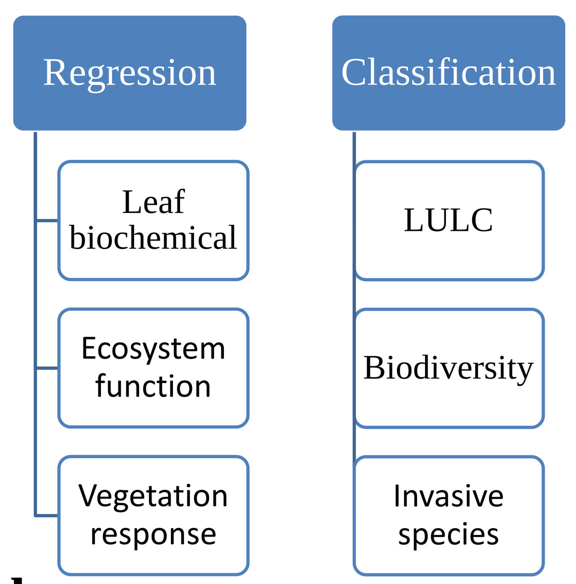
INTRODUCTION

Sparse distribution of vegetation, canopy cover, and the bright soil beneath the canopy make remote sensing of drylands a challenging task. Two common themes in hyperspectral remote sensing of vegetation are I) retrieving canopy biochemical variables (i.e. *regression problem*) and II) mapping vegetation cover (i.e. *classification problem*). Here we present the role of canopy spectral invariants (CSI) in both regression and classification approaches in drylands. Our work presents the potential limitations and applicatons of HyspIRI in drylands.

Retrieving foliar nitrogen using regression

Since nitrogen is not explicitly represented in radiative transfer models, statistical methods have been used as an alternative. Common statistical methods are partial least squares regression (PLS), random forest (RF), support vector machine (SVM) etc.



Classification of vegetation species in drylands

The environmental gradients in semi-arid ecosystems result in a range of challenges for classification. Soil and canopy structure in xeric areas have significant contributions to the total canopy radiation budget. On the converse, dense riparian areas along mesic areas represent complex interactions between different species and are characterized by high spectral variability.

THEORY OF CANOPY SPECTRAL INVARIANTS (CSI)

- The structure of the canopy can be represented by a spectrally independent parameter known as the recollision probability (p).
- Recollision probability can be interpreted as the probability of a photon scattered from part of the canopy to interact with the canopy again.
- In the generalized theory of CSI, the assumption of non-reflecting soil is relaxed.

$$BRF_\lambda = \frac{\rho(\Omega)\, i_0(\Omega_0)\, \omega_\lambda}{1-\omega_\lambda p}$$

p recollision probability
i_0 canopy interceptance
ρ escape probability
$\omega(\lambda)$ leaf albedo

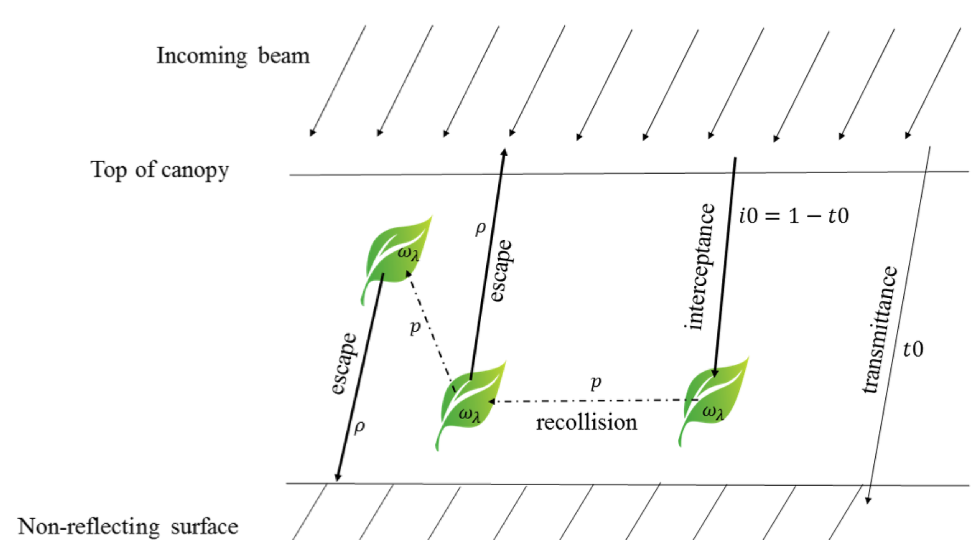


Figure 1. The concept of photon interceptance, recollision probability and escape factor

$$DASF = \rho(\Omega)\frac{i_0}{1-p}$$

Directional area scattering factor (DASF) is an estimate of the ratio between the total one-sided leaf area and the canopy boundary leaf area seen from a given direction

$$BRF_\lambda = DASF \cdot W_\lambda$$

where W_λ is the canopy scattering.

METHODS

Our study area is the Great Basin, western, USA. We collected airborne and field data.

Hyperspectral data
- AVIRIS-NG (1.6 m pixel size)
- FieldSpec Pro Spectroradiometer

Regression methods

PLS, SVM, RF and Bayesian

Classification methods

Spectral angle mapper (SAM)

Approach

- We used spectral invariants to correct BRF for canopy structure and soil and developed regressions
- Spectral invariants space was used to improve classification of dense canopies

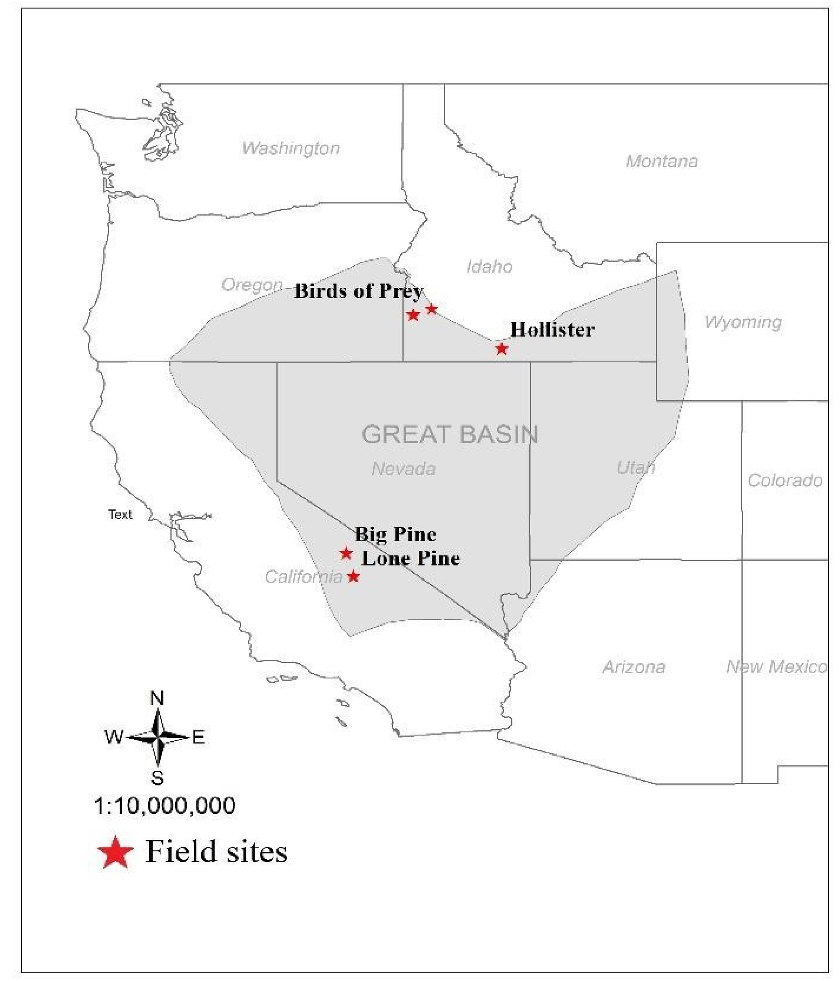


Figure 2. Field data were collected across five sites across the Great basin during 2014 and 2015

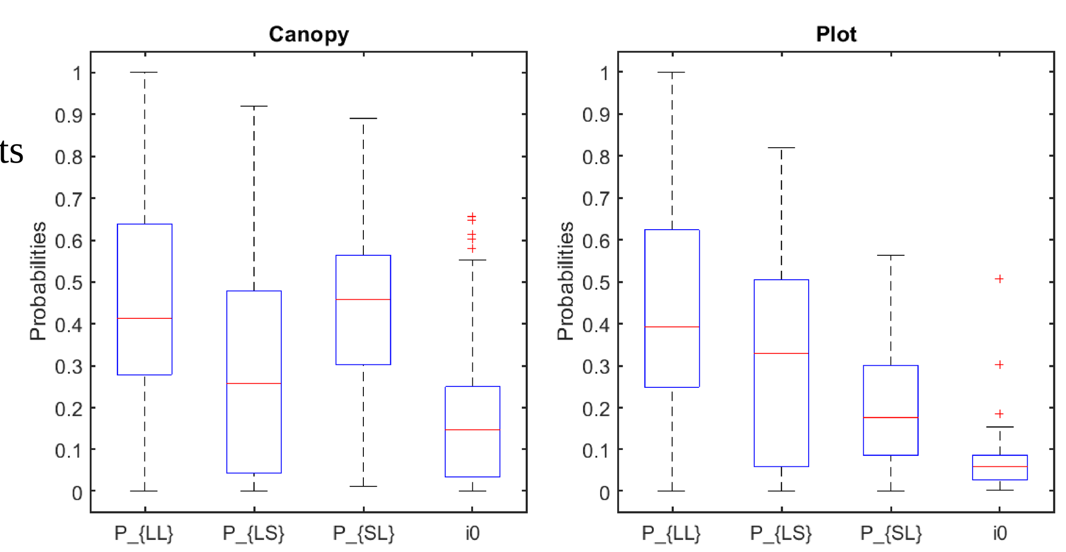
RESULTS

I) Regression

Canopy structure and soil dominate the total canopy reflectance

- At the canopy scale the mean of i_0 is 0.17, and at the plot scale, it is 0.05.
- If we assume no additional interaction between photons from vegetation and soil, the total canopy and plot reflectance is composed of 17% and 5% information, respectively.

Figure3. Boxplots of spectral invariants
P_{LL}: recollision probability between leaf-leaf
P_{LS}: recollision probability between leaf-soil
P_{SL} : recollision probability between soil-leaf



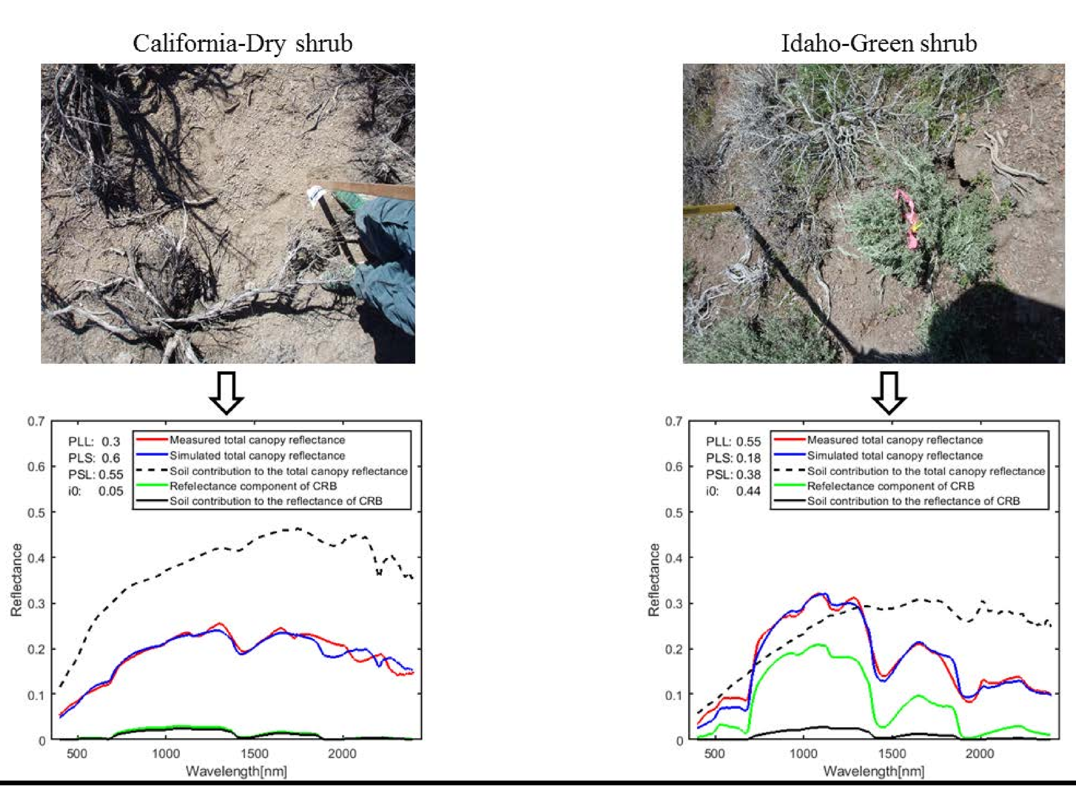


Figure 4. Simulation of canopy radiation budget for a green and dry shrub. The larger contribution of soil in dry shrub is observable.

Correction for canopy structure and soil leads to no N-BRF correlation

- Canopy scattering coefficients mimic leaf scattering and showed no correlation with N.
- Result is inconsistent with theory of counter factuals.
- Functional association between N and BRF do not always lead to correlation.
- One solution is using data assimilation. Our initial results with the ED2 vegetation model shows good agreement between measured and simulated N.

	Before correction for structure and soil					After correction for structure and soil				
	Ensemble			BR	PLS_ref	Ensemble			BR	PLS_ref
	PLS	SVM	RF			PLS	SVM	RF		
Smoothed										
R2	0.61	0.49	0.37	0.37	0.51	0.19	0.18	0.16	0.18	0.08
CV	16.87	21.90	22.6	18.3	19.1	26.54	26.7	30.3	23.7	27.38
Log transformation										
R2	0.60	0.62	0.37	0.47	0.52	0.18	0.19	0.16	0	0.08
CV	18.74	19.63	22.3	16.4	19.4	26.57	26.9	30.5	26.9	27.36
First derivative										
R2	0.57	0.54	0.61	0.35	0.42	0.17	0.16	0.15	0	0.07
CV	19.79	19.46	16.2	18.3	21.6	26.58	26.7	30.1	26.3	27.46
Log transformation of the first derivative										
R2	0.58	0.74	0.67	0.36	0.52	0.12	0.16	0.17	0	0.05
CV	18.27	14.21	15.4	16.1	19.2	26.52	26.5	30.3	27.0	27.41

Table 1. Regression methods may fail after correction for canopy structure and soil

II) Classification

Canopy structure can improve classification

- Whereas traditional classifications such as SAM fail to separate spectrally similar classes, the canopy spectral invariant space may offer improvements.
- In this example, the aspen and riparian classes are linearly separable in canopy spectral invariant space.
- Overall accuracy improved from 60% to 83%.

		Ground truth						
		Aspen	Riparian	Douglas fir	Juniper	Total	Producer accuracy	User accuracy
Classified	Aspen	2015	553	143	2	2713	0.44	0.74
	Riparian	2411	1806	316	64	4597	0.63	0.39
	Douglas fir	95	500	2083	105	2783	0.80	0.74
	Juniper	7	0	46	636	689	0.78	0.92
	Total	4528	2859	2588	807	10782	---	---

Table 2. Classification results using SAM: there is a great confusion between aspen and riparian

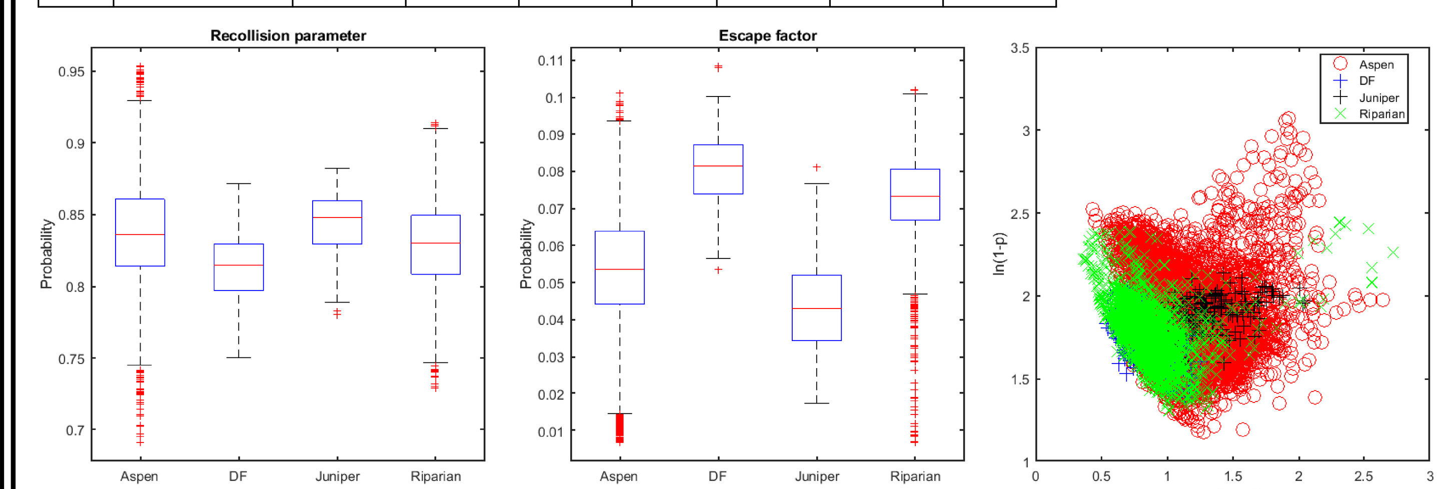


Figure 5: spectral invariants space can separate aspen and riparian

IMPLICATIONS

- Canopy structure and soil impact increases at coarser spatial resolution such as HyspIRI [60 m]
- Spaceborne lidar such as GEDI integrated with HyspIRI can help to elucidate the role of canopy structure and soil.
- CSI theory is an alternative to 3-RTMs in dynamic vegetation models such as ED 2.

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References:
[1]Y. Knyazikhin, et al, “Hyperspectral remote sensing of foliar nitrogen content.,” *Proc. Natl. Acad. Sci. U. S. A.*, vol. 110, no. 3, pp. E185-92, Jan. 2013.
[2] H. Dashti, et al, “Empirical Methods for Remote Sensing of Nitrogen in Drylands May Lead to Unreliable Interpretation of Ecosystem Function” In review
[3] H. Dashti, et al, “MESMA, spectral angle mapper, and spectral invariant theory to map dryland vegetation types with high resolution airborne hyperspectral imagery”, In review