Estimating Leaf Area Index in Shrublands With Imaging Spectroscopy: Statistical and Physical Models

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Dryland ecosystems

- Change in the structure and function of dryland vegetation communities and their positive/negative feedbacks on ecosystem state is complex and poorly understood.
  - Cross-scale interactions - non-linear & spatially heterogeneous

- SO 3336 - wildfire prevention, suppression, long term restoration (i.e. $56M for Soda Fire)

Soda fire 2015, ~ 280,000 acres

Non native cheatgrass competing with native sagebrush

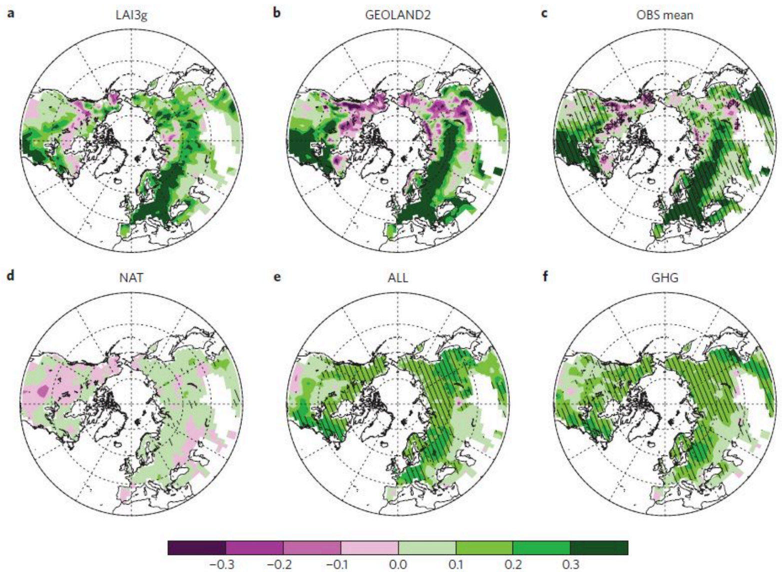
Greening

- Significant greening of the extratropical latitudes has been documented through satellite observations of LAI (1982-2011).
  - Spatial scale: 1km resampled to 1/12 degree, RMSE 0.66

- Is greening happening in semiarid ecosystems? What is the uncertainty?

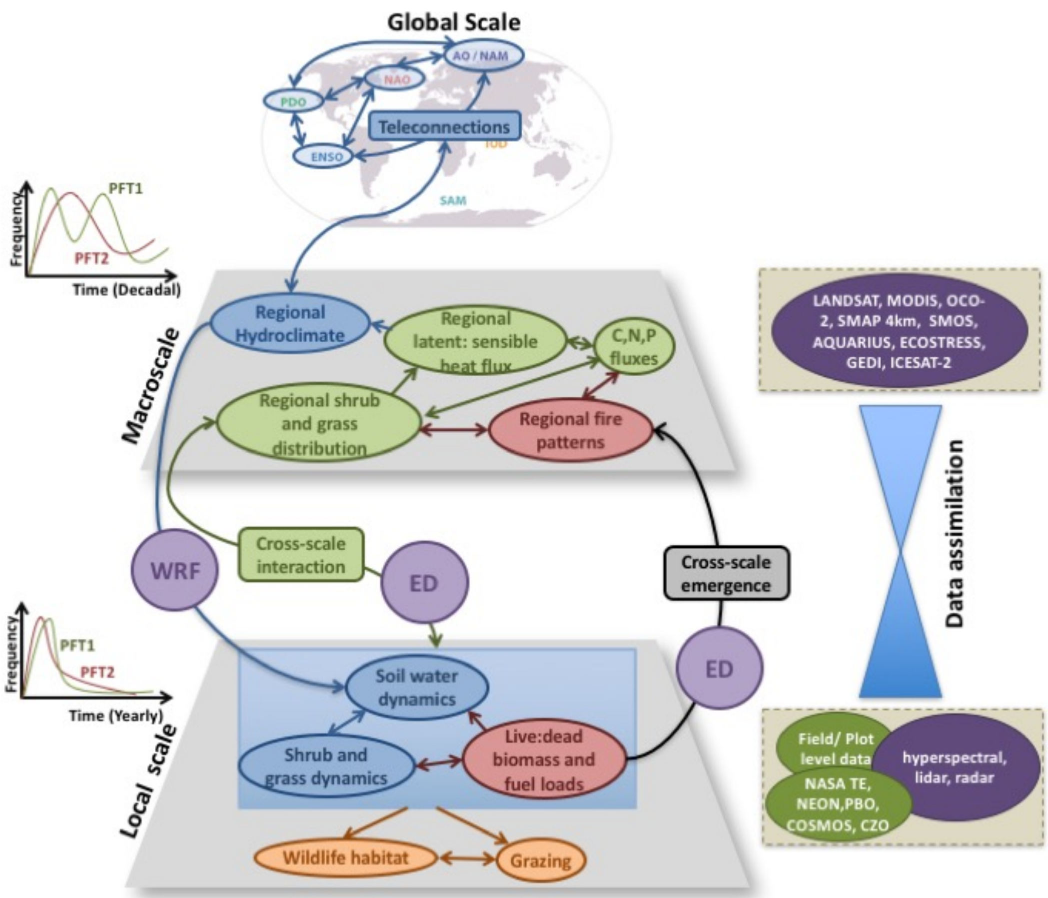
- If so does this reflect increased productivity of existing species (i.e. sagebrush) or has the composition of plant communities has changed?

- How will shifts in structural (and biochemical) changes that impact productivity levels be manifested across the landscape?



Credit: Jiafu Mao et al (2016); Nature. DOI: 10.1038/NCLIMATE3056

Cross-scale interactions

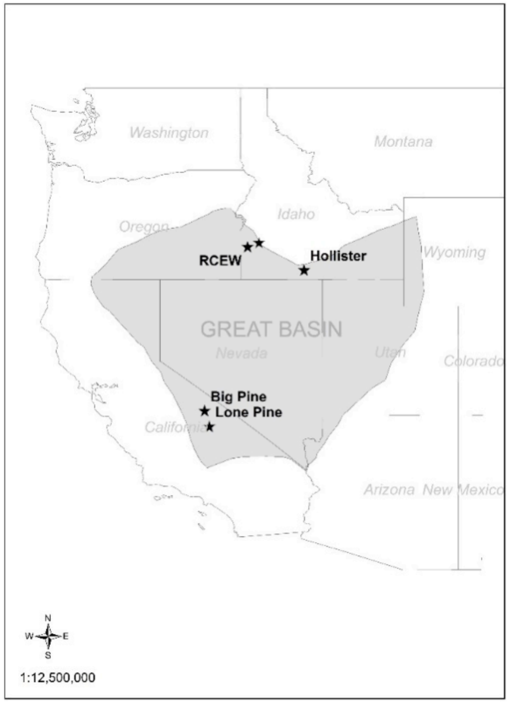


Adapted from Heffernan et al (2014) and Folke et al (2011).

Science questions

- What metrics capture vegetation productivity across scales?
- What are the uncertainties of parameters for improving predictions of vegetation dynamics across scales?
    - Structure - fractional cover, LAI, height, biomass
    - Biochemistry

Data collection

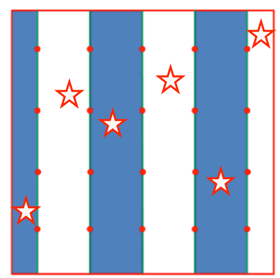


<u>Measurements (plot level)</u>

Density
Cover (line intercept method)
LAI

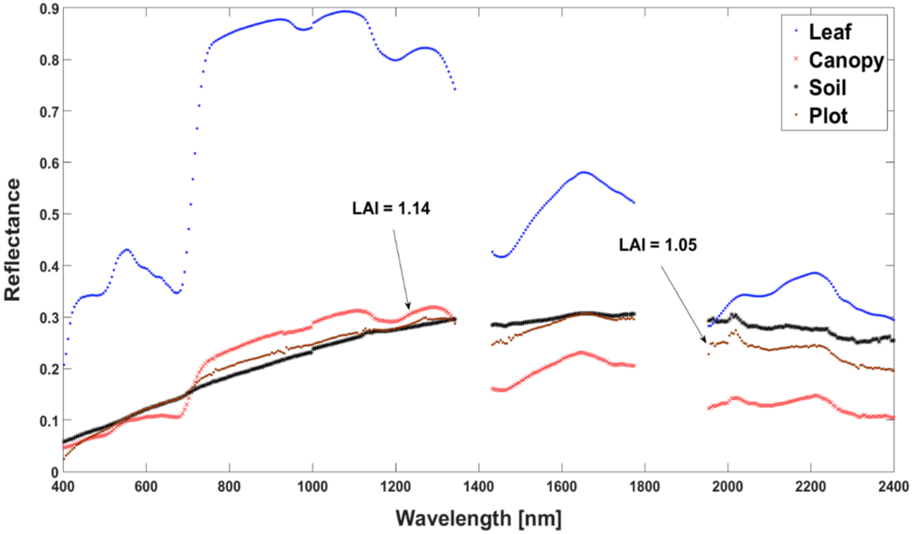
<u>Measurements (Individual)</u>

LAI
Allometry (widths and height)
Biomass
SLA
Leaf chemistry
Spectrometer
TLS



Year	2014				2015				
Sensors / Sites	ALS	AVIRIS	TLS	ASD	ALS	AVIRIS	TLS	ASD	Number of plots
RCEW	√	√	×	Some	×	√	√	√	53 (four revisit plots)
Hollister	×	√	×	×	×	√	×	×	17
Birds of Prey	×	√	×	×	×	√	×	×	26
Big Pine	√	√	×	√	×	√	×	√	30
Lone Pine	√	√	×	√	×	√	×	√	30 (all revisited)

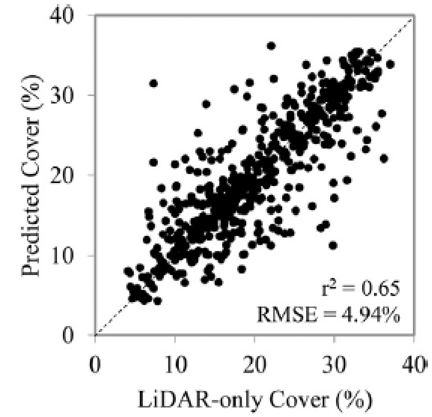
Challenges

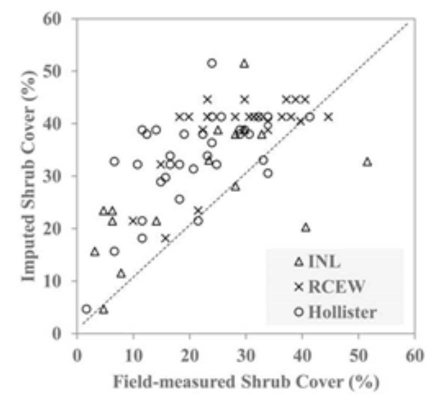


Mean (plots) LAI = 0.6, n=64
Bright soil and litter > the spectral contribution of plants
Lack of strong red edge
Canopy structural effects

Cover

- HyspIRI-simulated variables related to the red edge, water content and anthocyanins had high predictive power for shrub cover
- Scaling across sites resulted in small decrease in predictive power





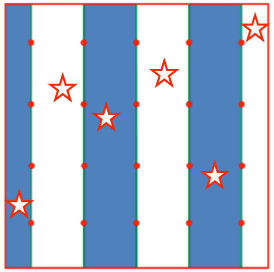
Mitchell, JJ; Shrestha, R; Spaete, LP; Glenn, NF, 2015, Combining airborne hyperspectral and LiDAR data across local sites for upscaling shrubland structural information: Lessons for HyspIRI, *Remote Sensing of Environment*.

Nitrogen

- PLSR using leaf mass per unit area & plot level imaging spectroscopy
  - $R^2 = 0.72$
  - $R^2 = 0.95$ (min bare ground)

Mitchell, JJ; Glenn, NF; Sankey, TT; Derryberry, DR; Germino, MJ, 2012, Remote sensing of sagebrush canopy nitrogen, *Remote Sensing of Environment*

- PLSR using LAI, density, & SLA with plot level imaging spectroscopy
  - $R^2 = 0.74\text{-}0.97$



Mitchell, JJ et al., in prep

LAI – optical methods

- Empirical methods (PLSR): based on relationships between vegetation indices and LAI.
    - Narrow band indices
    - Red edge inflection point
    - ….
- Physical methods: physics of radiation interaction with elements of a canopy.
    - Radiative transfer models (RTMs)
    - Geometric-optical models
    - Hybrid geometric-RTMs models
    - Computer simulation models
        - Monte Carlo ray tracing models
        - Radiosity methods
- Machine learning: mimic the underlying physical process
    - Artificial neural network (ANN)
    - Random forest
    - …..

LAI: all sites

Canopy scale

Dataset	RMSE	R^2	#comp	#features
Reflectance	0.51	0.33	5	1727
Reflectance_VIP	0.58	0.13	1	361
First Derivative	0.45	0.47	3	1727
First Derivative_VIP	0.33	0.70	4	607
Second Derivative	0.43	0.52	2	1712
Second Derivative_VIP	0.44	0.50	2	732

Plot Scale

Dataset all	RMSE	R^2	# comp	#features
Reflectance	0.31	0.38	6	354
Reflectance_VIP	0.27	0.52	8	140
First Derivative	0.20	0.73	9	354
First Derivative_VIP	0.21	0.72	10	110
Second Derivative	0.23	0.64	5	354
Second Derivative_VIP	0.25	0.59	4	121

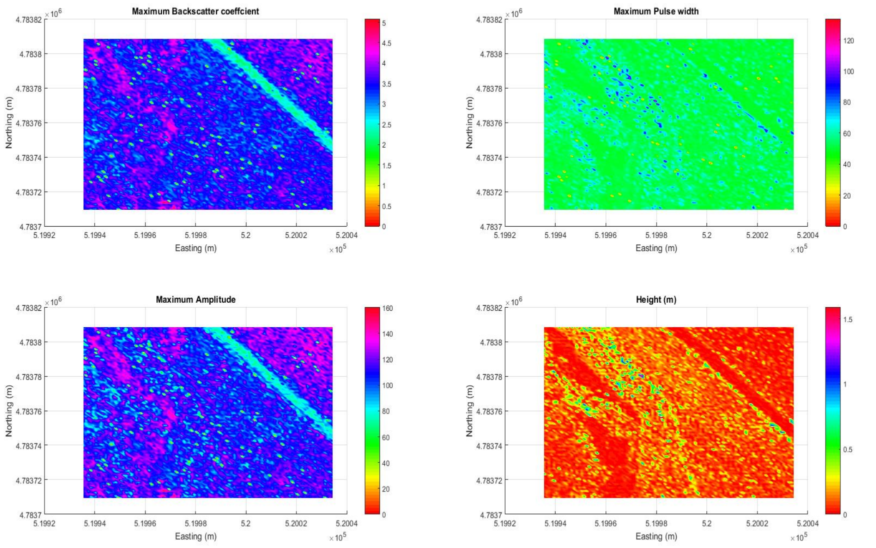
LAI: spatial & temporal stability

Dataset	RMSE	R^2	#comp	#features
SecondDerivative (~=RC14)	0.22	0.70	4	95
SecondDerivative (=RC14)	0.33	0	4	95
SecondDerivative (~=Holl14)	0.25	0.64	4	117
SecondDerivative (=Holl14)	0.50	0	4	117
SecondDerivative (~=RC15)	0.19	0.77	4	111
SecondDerivative (=RC15)	1.5	0	4	111
SecondDerivative (~=BoP15)	0.18	0.68	5	147
SecondDerivative (=BoP15)	0.47	0.02	5	147

Dataset	RMSE	R^2	#comp	#features
SecondDerivative_All (~=2014)	0.26	0.64	3	354
SecondDerivative_All (=2014)	1	0	3	354
SecondDerivative _All(~=2015)	0.22	0.31	1	354
SecondDerivative_All (=2015)	0.53	0	1	354
SecondDerivative _All(~=2014)	0.26	0.64	3	121
SecondDerivative _VIP (=2014)	1.08	0	3	121
SecondDerivative _VIP (~=2015)	0.22	0.34	1	133
SecondDerivative _VIP (=2015)	0.57	0	1	133

Full waveform lidar attributes

- Height based parameters
- Amplitude – relate to radiometric propertie of the target
- Pulse width- relate to surface roughness of the target
- Backscatter cross section/ backscatter coefficient – function of both area and reflectivity (calibrated parameter)
- Differential target cross section (through waveform deconvolution)
- Rise time - vertical structural distribution of the target (especially good when compare single pulse waveforms - ecosystems dominated by low stature vegetation)
- Total energy of the waveform – structural + radiometric response of the target



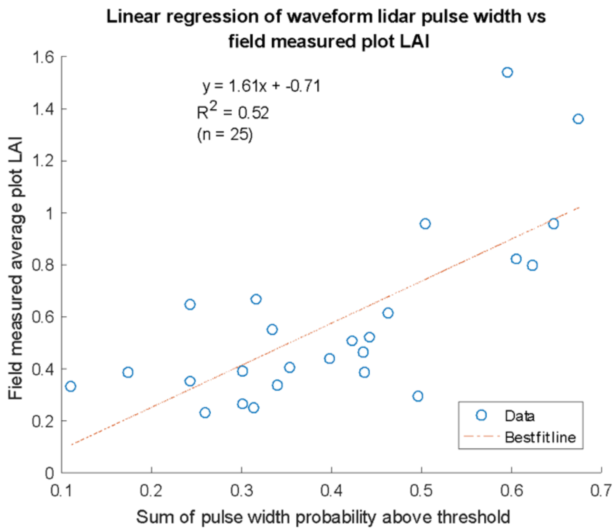
LAI: AVIRIS & ALS

Plots with both AVIRIS and ALS

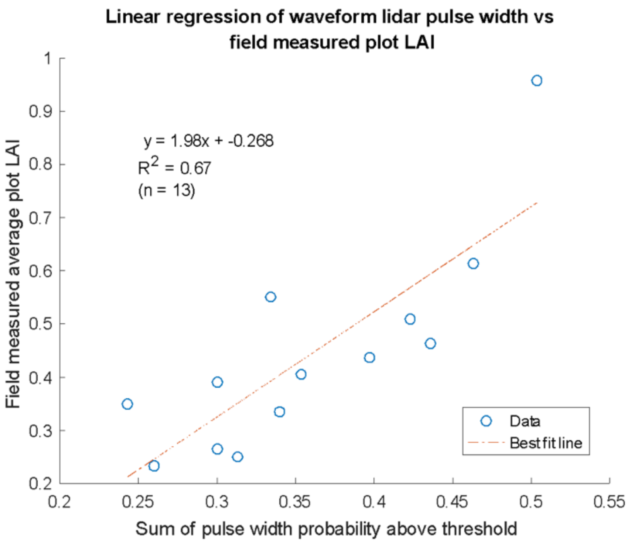
Dataset	RMSE	R^2	#comp	#features
Hyper-smoothed-lidar	0.25	0.30	1	362
Hyper-smoothed-lidar_VIP	0.24	0.35	1	210
First derv - lidar	0.13	0.80	3	362
First derv – lidar_VIP	0.13	0.78	2	122
Second derv – lidar	0.13	0.79	2	362
Second derv-lidar_VIP	0.15	0.72	1	133

Full waveform aerial lidar variables: mean and standard deviation of pulse width, rise time, backscatter coefficients and amplitude

Preliminary full waveform results: LAI



Cross –site, RCEW & Hollister

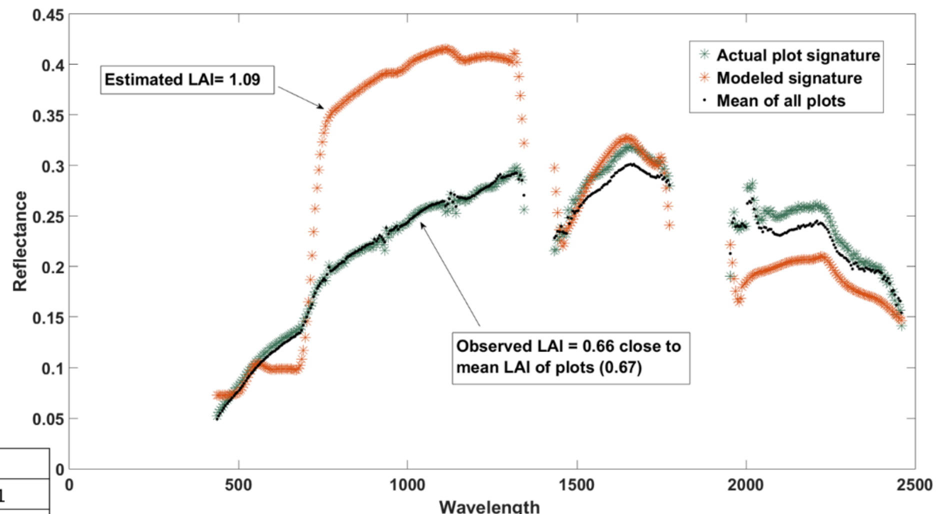


Single site, RCEW

RTM

1-D PROSAIL model

LUT inversion (sagebrush); the first 100 simulations with minimum RMSE with plot signature



	Parameters	Fixed	Min	Max	Mean	Sigma	Source
Leaf	Cab	-	20	90	45	30	Verger, 2011
	Car	-	3.4	38.3	10.3	4.21	LOPEX*
	Cbrown	0	-	-	-	-	Field experience
	Cw		0.0002	0.05	0.01	0.006	LOPEX*
	Cm	-	0.003	0.02	0.007	0.003	Verger, 2011
	N	-	1	2.5	1.5	1	Verger, 2011
Canopy	LAI	-	0	8	1	0.5	Verger, 2011 + Field data
	hspot	0.1	-	-	-	-	Verger, 2011
	rsoil	Dry	-	-	-	-	Field Experience
View and illumination	tts	47	-	-	-	-	NOAA*
	tto	0	-	-	-	-	Field experience
	psi	0					Filed experience

- Forward modeling had poor results
- LUT and ANN inversions didn't perform well
- 1-D can't capture the scene signature (i.e. canopy structure and background soil) using either forward or inverse approaches

Next: 3-D DART model

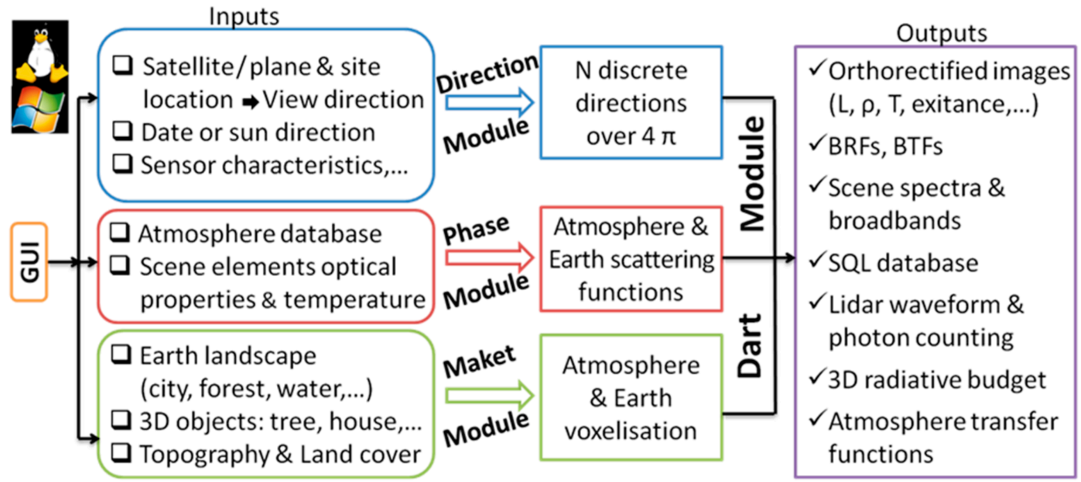
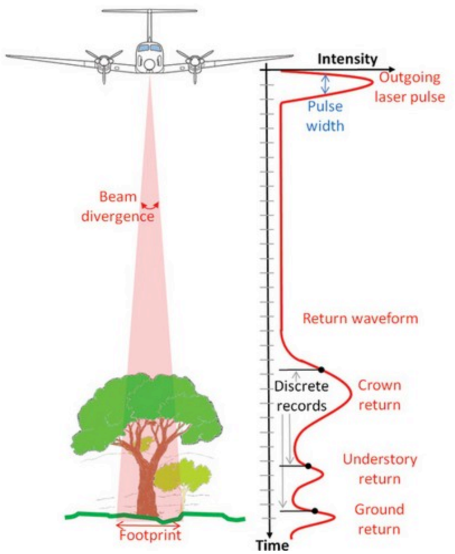


Image credit: Jean-Philippe Gastellu-Etchegorry et al (2015)



Lidar assimilation (ASO's Reigl LMS Q 1560, full waveform)

Structural correction

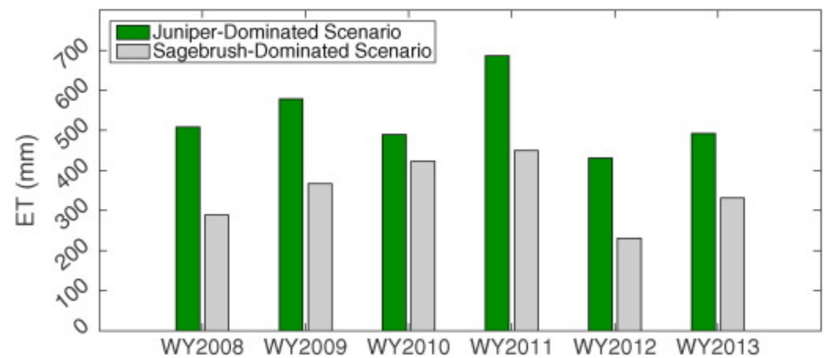
- Directional area scattering factor

Other Features

- Continuum removal
- Shape based indices ….

Conclusions

- Understanding shrubland dynamics:
  - leverage full range of imaging spectroscopy data
  - synergistically use lidar
  - explore productivity
  - consider type conversions / water use
- Cross-site and spatial heterogeneity need to be addressed:
  - patterns & distributions
  - seasonality



Kormos, et al 2016, *REAM*