

Early Estimation of Fire-Risk in the Eastern Mediterranean and Socioeconomic Informed Communications of Actionable Strategies

Nimrod Carmon, PhD

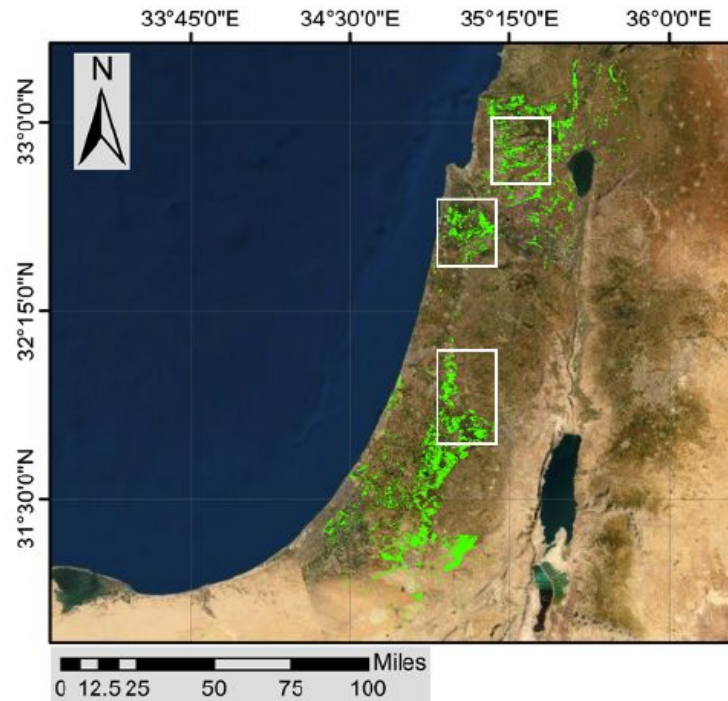


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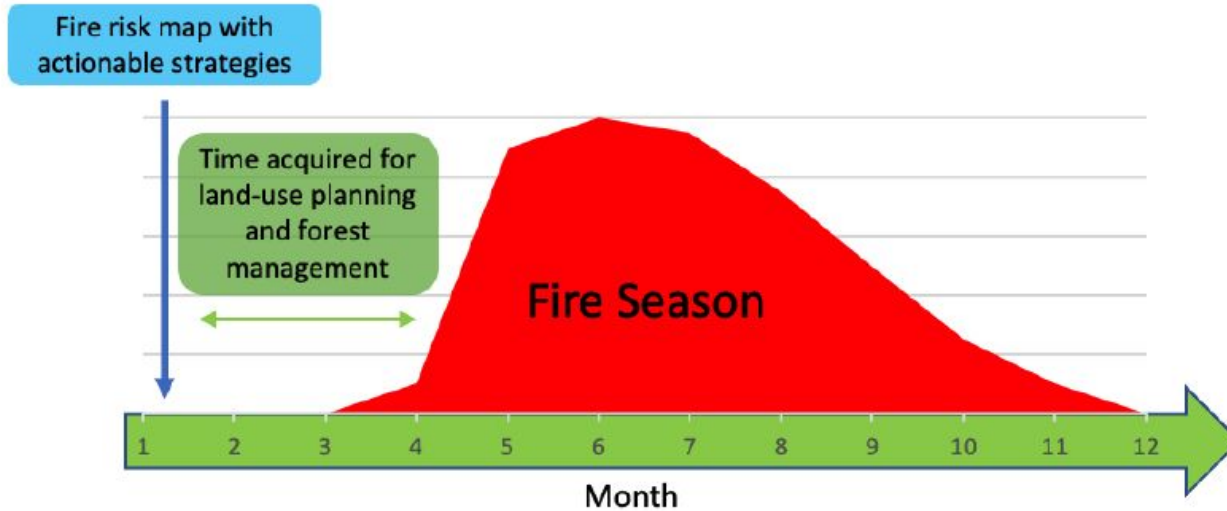
Wildfire in Israeli Forests

- Increased severity in the last 2 decades
- Wildfire risk factors
 - Forest conditions
 - Multi-year droughts
- Current products
 - Not high-resolution
 - No early predictions



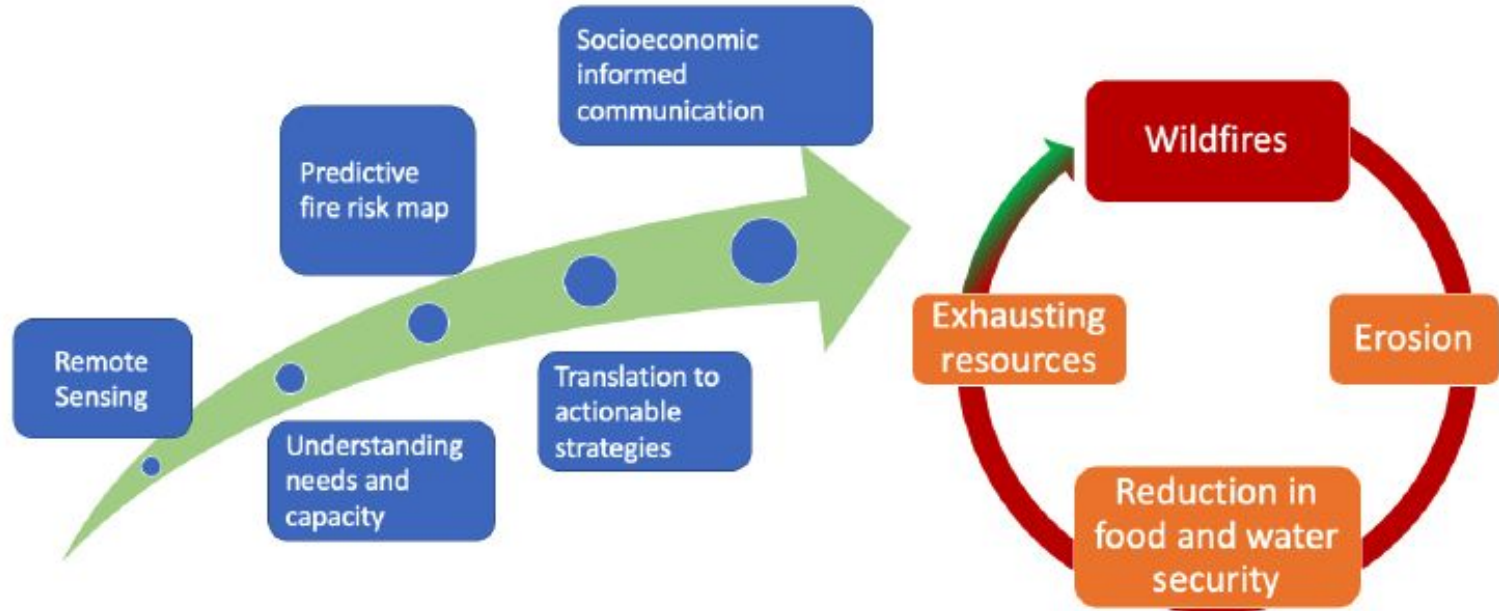
Early Prediction of Fire Risk

Allows for planning and applying mitigation strategies



Early intervention, tailored to the user

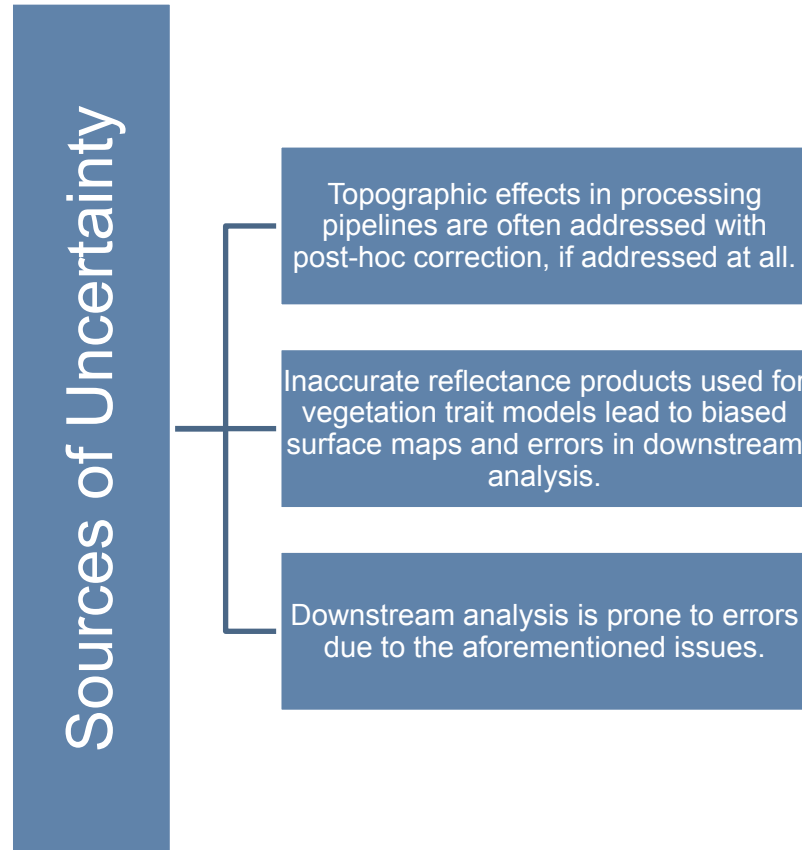
Breaking the cycle



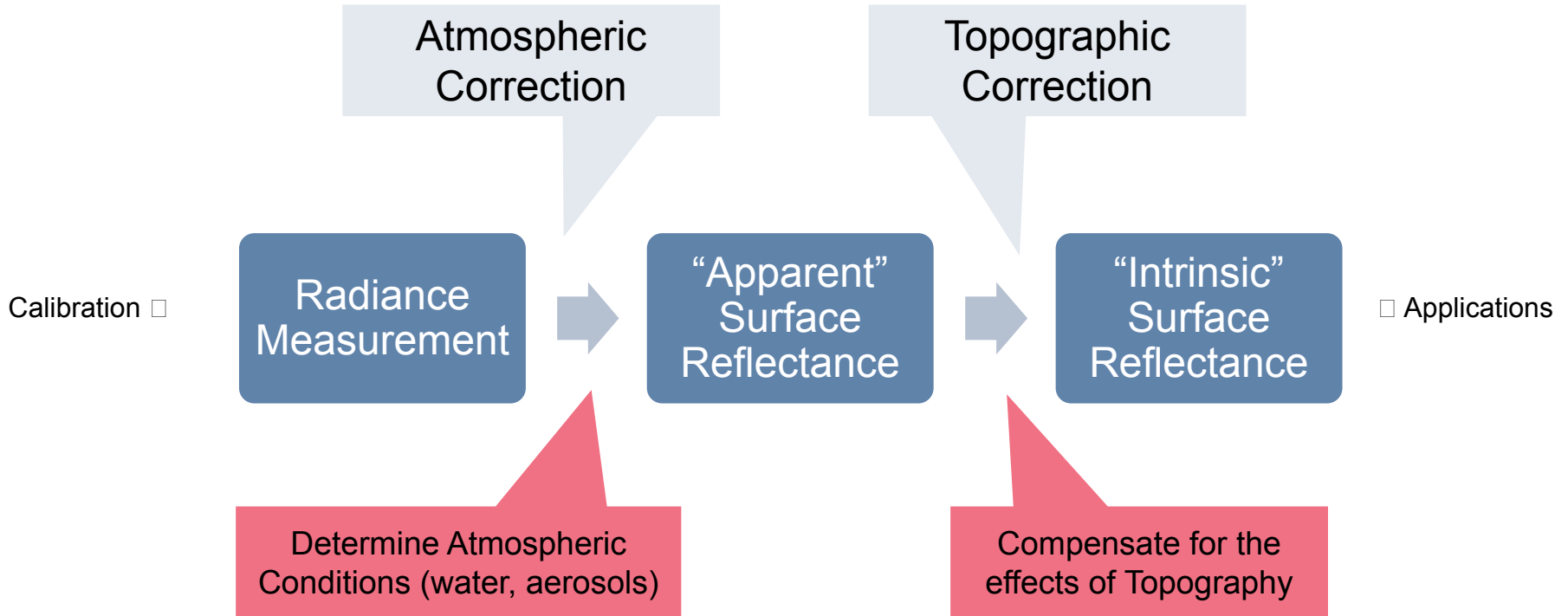
PLAN

Objective: To revolutionize vegetation mapping using orbital remote sensing by improving atmospheric correction retrievals and producing "intrinsic" surface reflectance signatures that are better suited for mapping vegetation traits with fine spectral signatures.

Problems

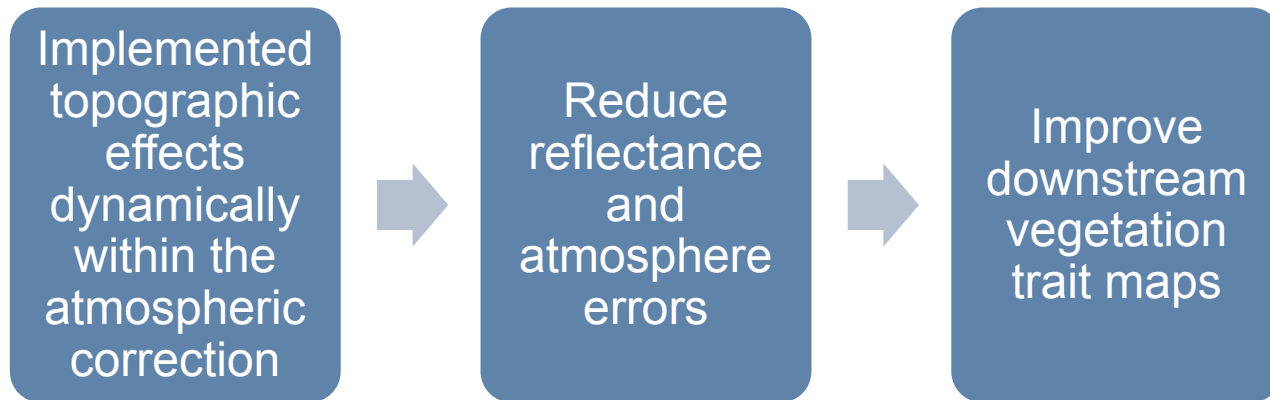


Post-hoc Topographic Correction



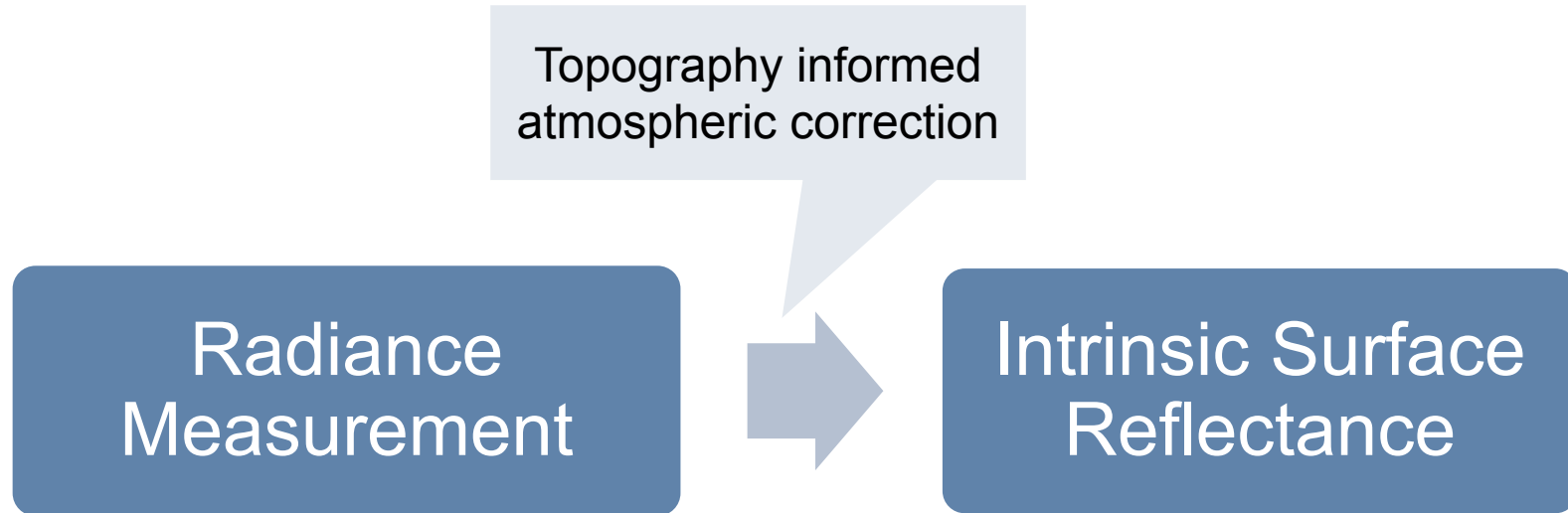
Solution

Unified Atmospheric-Topographic Correction



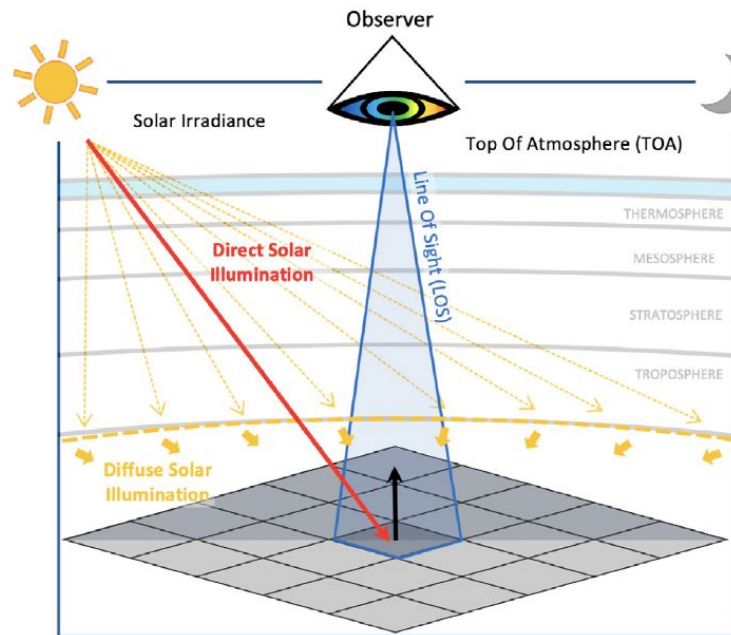
Unified Atmospheric-Topographic Correction

Incorporate topographic effects as a known parameter in the radiance-to-reflectance inversion

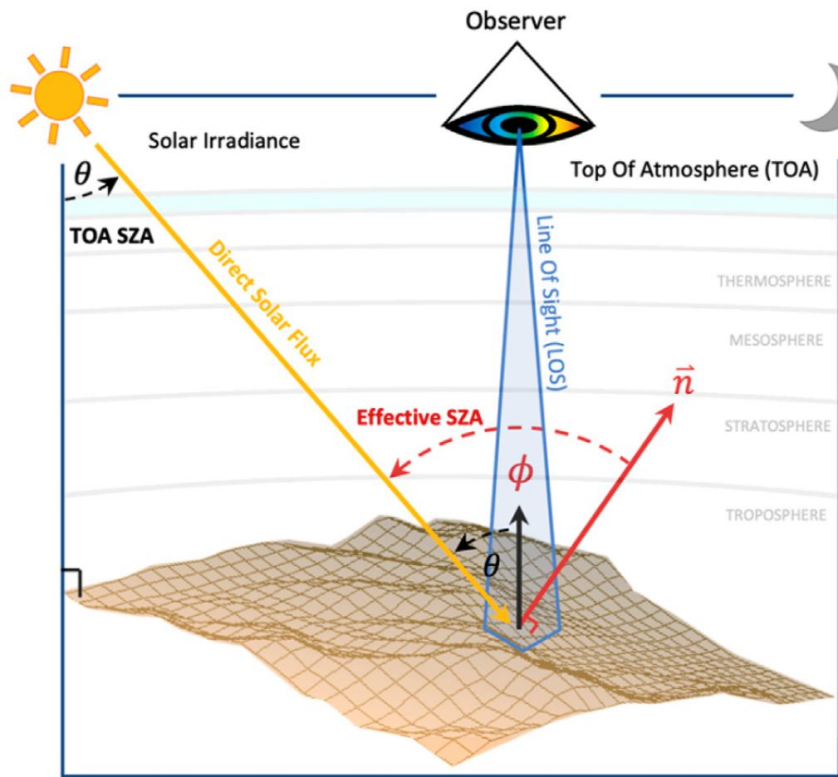


Atmospheric RTM Background

The global flux - sum of direct and diffuse solar illumination

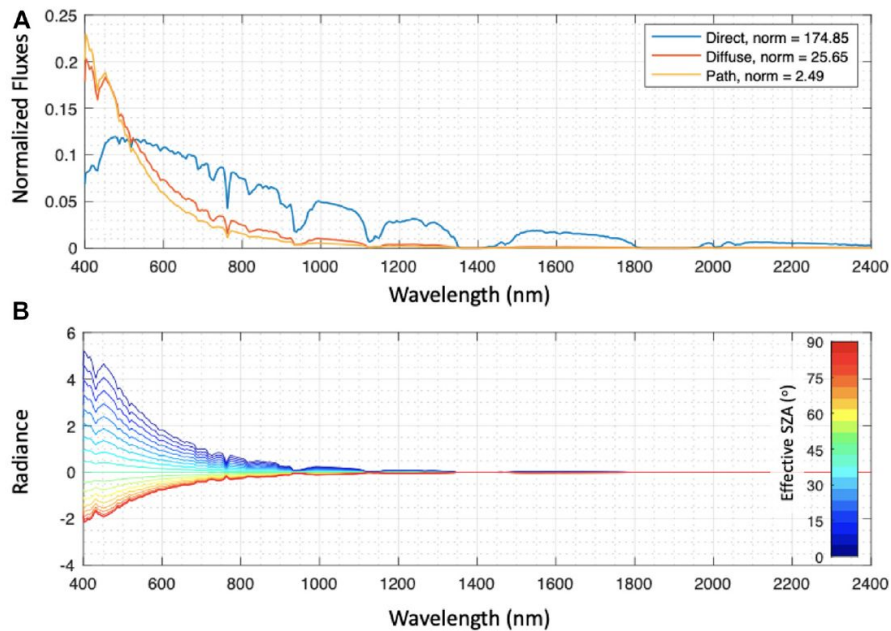


Topography – why it is important



Parameter	Description
	Top of atmosphere solar zenith angle
	Effective solar zenith angle
	The normal vector to the surface
LOS	Line of sight for a given pixel

Spectral effects of Topography



- The direct flux is directional and scaled by the cosine of ESZA
- The diffuse flux and the path radiance are not directional and are not affected by the ESZA

Topography Naïve vs. Topography Aware

Naïve

$$F_0: l_{obs} = l_p + \frac{e_g(0)}{1 - s\rho_s} t^\uparrow \rho_s, \text{ where}$$

$$e_g(0) = e_0 \mu_\theta \pi^{-1} (t_{dir}^\downarrow + t_{dif}^\downarrow).$$

Treats all pixels as flat

Aware

$$F_1: l_{obs} = l_p + \frac{e_o \pi^{-1} \mu_\phi t_{dir}^\downarrow + e_o \pi^{-1} \mu_\theta t_{dif}^\downarrow}{1 - s\rho_s} \rho_s t^\uparrow.$$

Dynamically incorporates
topography

Topography Naïve vs. Topography Aware

Naïve

$$F_0: l_{obs} = l_p + \frac{e_g(0)}{1 - s\rho_s} t^\uparrow \rho_s, \text{ where}$$

$$e_g(0) = e_0 \mu_\theta \pi^{-1} (t_{dir}^\downarrow + t_{dif}^\downarrow).$$

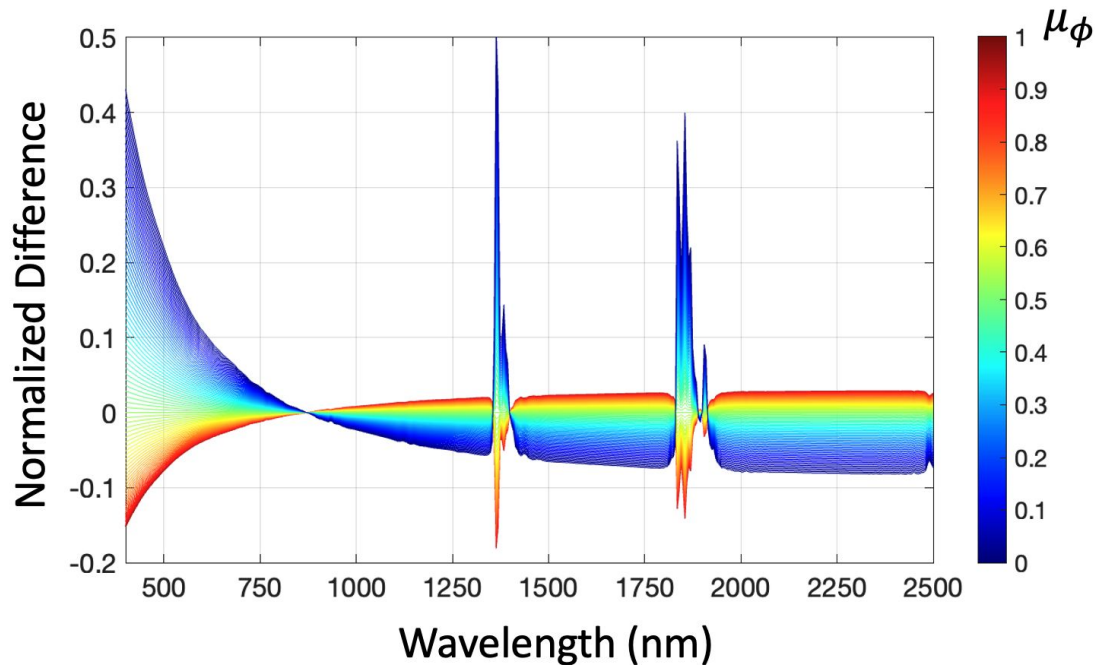


Aware

$$F_1: l_{obs} = l_p + \frac{e_0 \pi^{-1} \mu_\phi t_{dir}^\downarrow + e_0 \pi^{-1} \mu_\theta t_{dif}^\downarrow}{1 - s\rho_s} \rho_s t^\uparrow.$$

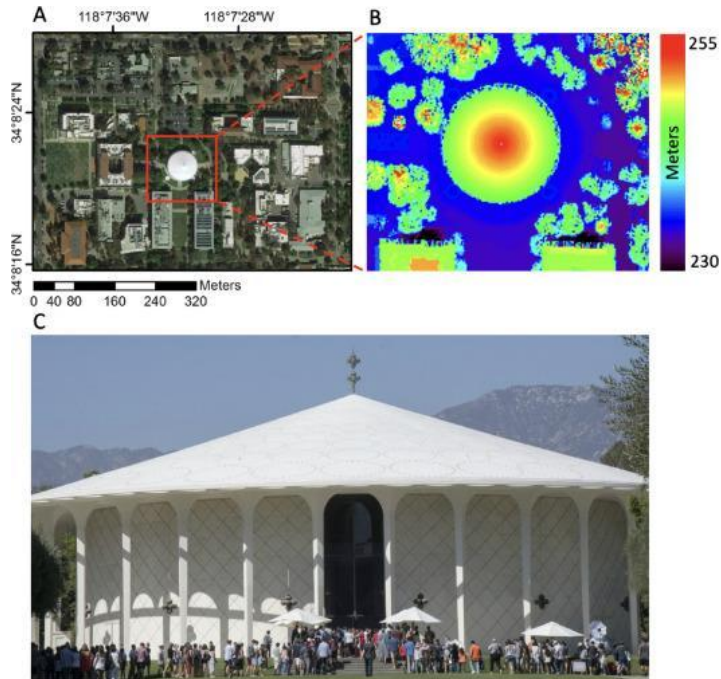


Relative Errors in Radiance



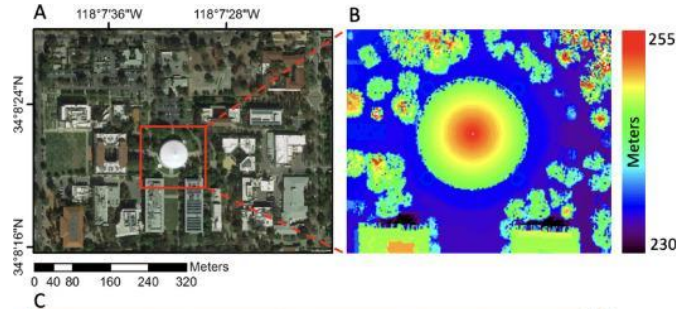
Homogeneous and Symmetric Target

Beckman Auditorium Roof



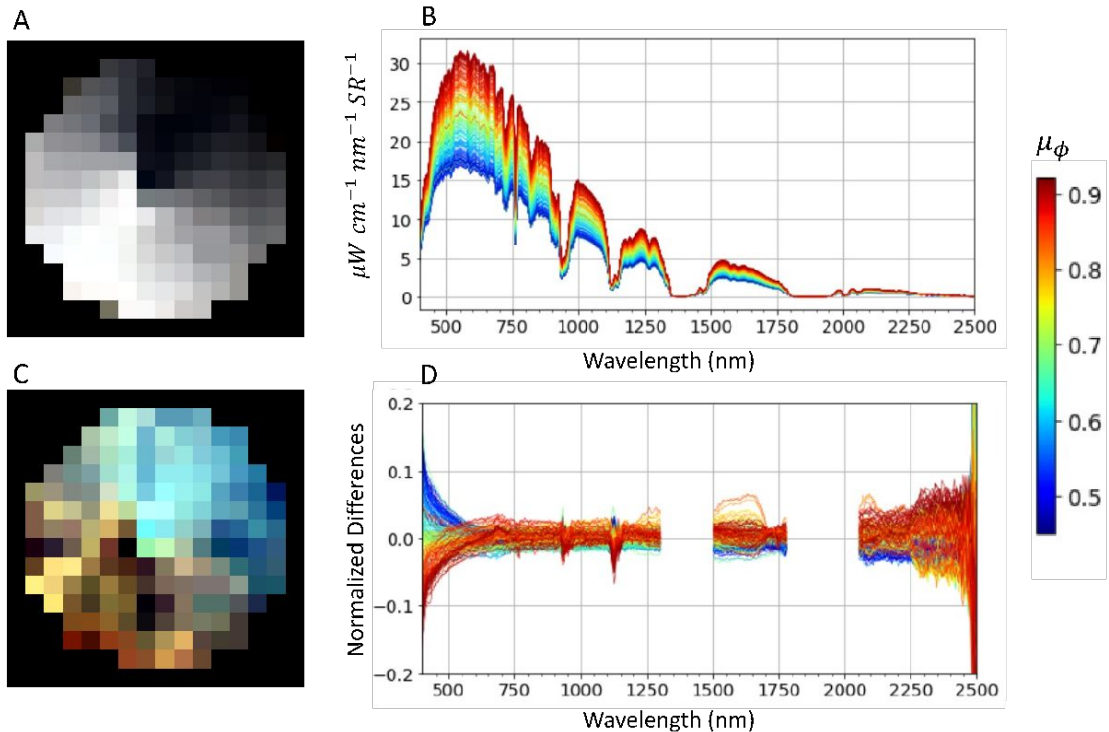
Homogeneous and Symmetric Target

Beckman Auditorium Roof

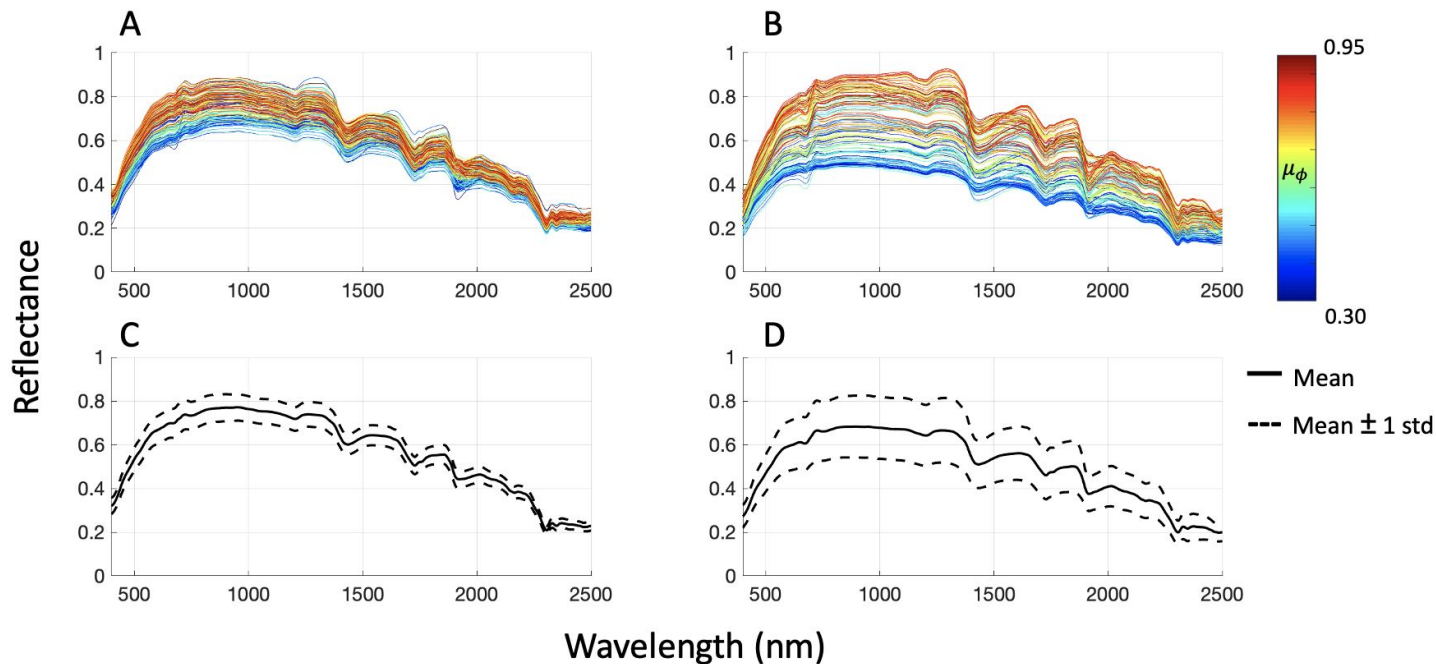


- Symmetric cone (Right-Cone) shape
- Relatively smooth surface
- Same surface material throughout
- Taller than its surrounding
- High resolution lidar available
- AVIRIS-NG radiances available

Empirical Evidence over Beckman Auditorium

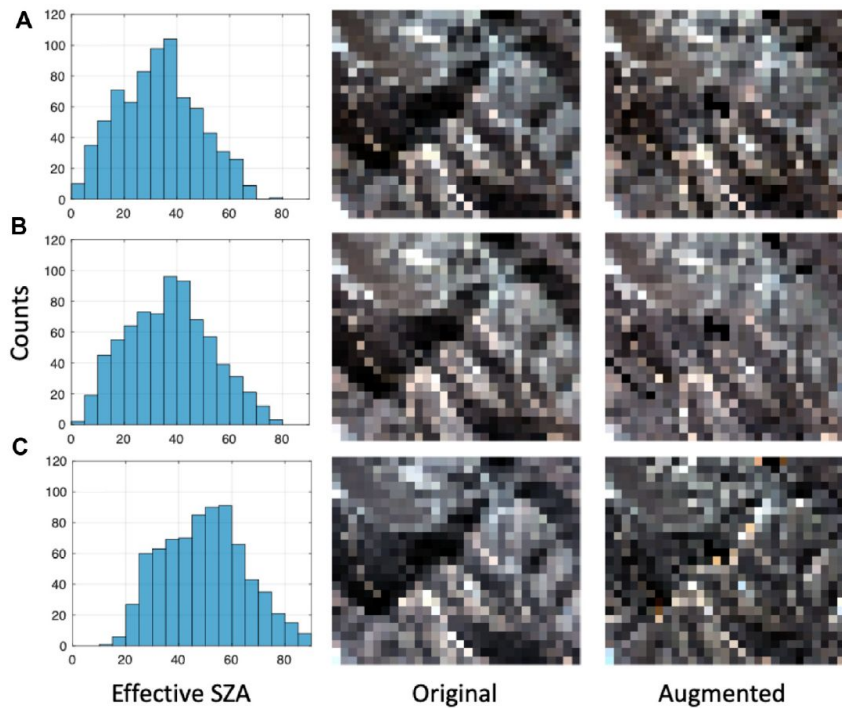
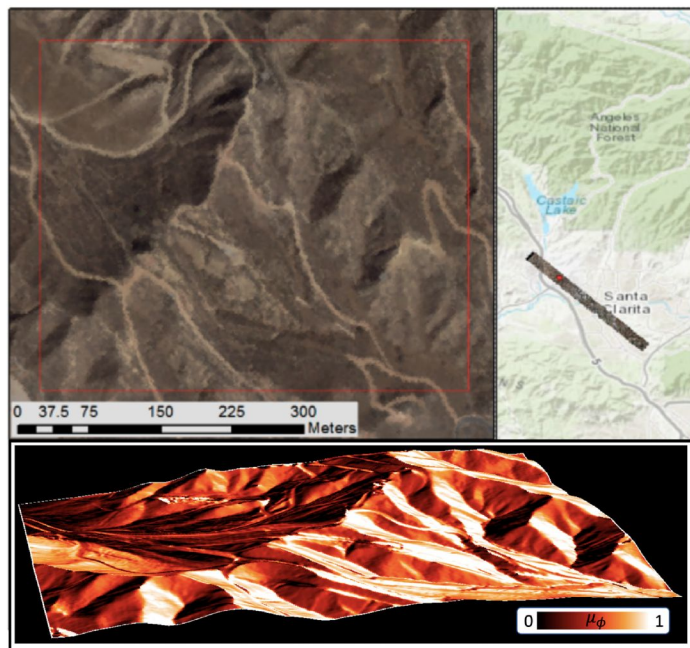


Error in Reflectance over Homogeneous Surface



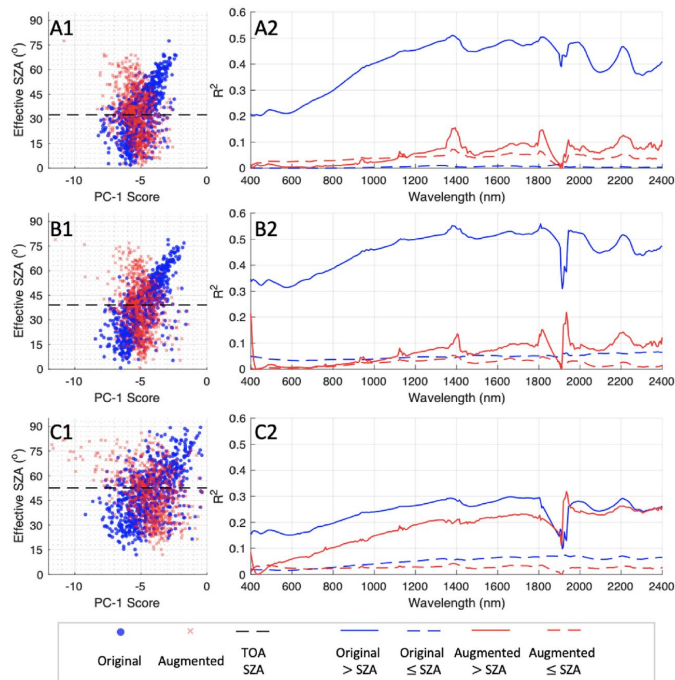
Experiment with Temporal Repeats

The Valencia Site

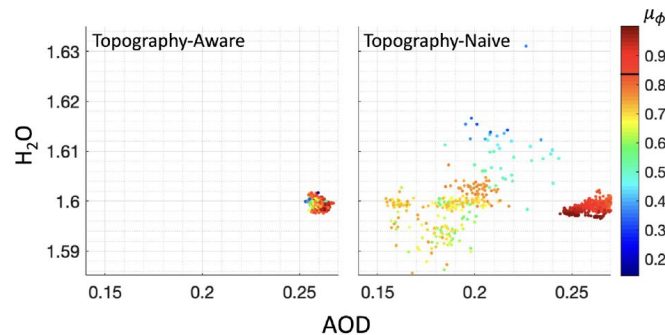


Results

Decorrelation of Reflectance from Topography

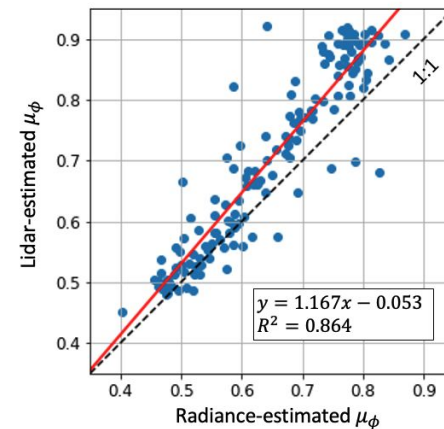
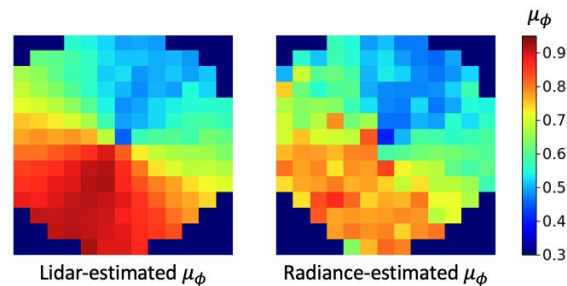
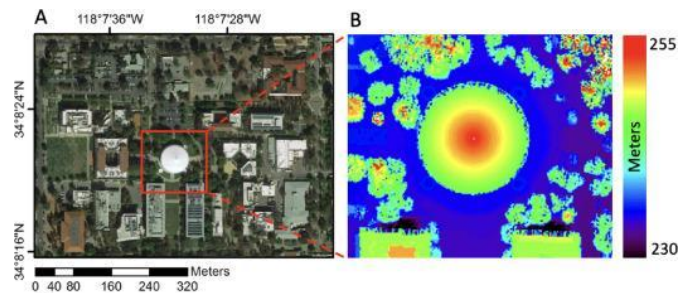


Smaller Errors in Atmosphere

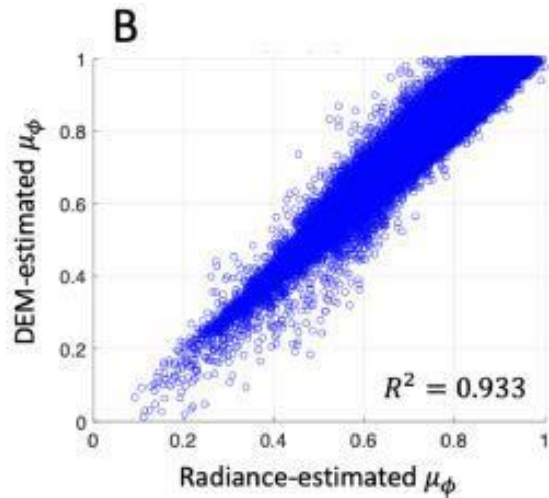


Carmon, Nimrod, et al. "Unified Topographic and Atmospheric Correction for Remote Imaging Spectroscopy." *Frontiers in Remote Sensing* 3 (2022): 916155.

Retrieval of $\cos(i)$ from radiance



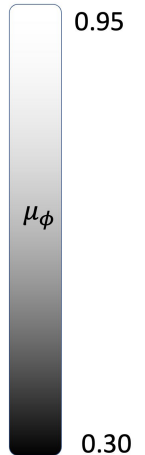
Estimating $\cos(i)$



Radiance-Based



Lidar-Based



Carmon, Nimrod, et al. "Shape from spectra." *Remote Sensing of Environment* 288 (2023): 113497.

Case Study – Israeli Forest

Example with EMIT measurements

Experimental Design (ongoing)

1. Process EMIT L1B Radiance to 'intrinsic' surface reflectance using developed algorithm
2. Apply vegetation trait models on both standard L2A product and on intrinsic reflectance
3. Evaluate and compare performance, capture results in manuscript and submit



Short Term Next Steps

1. Implement PROSAIL algorithm into pipeline
2. Tie PROSAIL trait maps to fire event record from JNF
3. Estimate precursor vegetation traits and train a predictive model

Questions and Discussion





Jet Propulsion Laboratory
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Mixed Pixels – a Problem

- Biogeophysical models simulate reflectance for a given endmember
- Remote-sensing pixels are usually a mixture of multiple endmembers
- Applying an endmember model on a mixture results in errors

The at-sensor signal for a given pixel arises from multiple type of surfaces: soil, green vegetation, dry vegetation

The different spectral signatures of the endmembers must be decomposed and retrieved individually to eliminate prediction errors

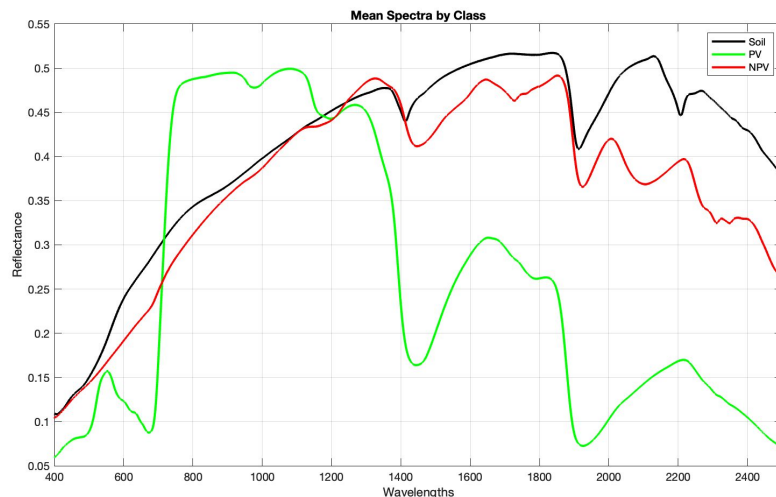
Traditional approaches first estimate the pixel-level reflectance, the “unmix” using linear methods



Our Solution

Dimension Reduction to Emphasize the Analysis of Mixtures (DREAMS)

- We implement a reflectance mixture model within the atmospheric correction routine
- We use dimension reduction (PCA) to formulate low-rank models of three endmembers (Soil, PV, NPV)
- We then optimize for their parameters within the atmospheric correction, simultaneously with endmember fractions and atmospheric variables
- This model can estimate both the endmember spectral signature and endmember fraction for each pixel in the image, directly from radiance



Capturing uncertainty due to DEM errors

