Well-Posed Retrieval of Vegetation Structure & Biochemistry using Red-Edge Directional Reflectance Spectra

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1. INTRODUCTION

Estimating both canopy structure (e.g. LAI) and biochemistry (e.g. Chlorophyll a+b content, Cab) from multispectral canopy reflectance (R) is generally ill posed. But, the problem is "better" posed given accurate prior constraints on structure or biochemistry (e.g. Fig. 1).

a. and b. uniform prior LAI and Cab distributions

c. uniform LAI distribution, fixed Cab 40μg/cm²

d. uniform Cab distribution, fixed LAI 3

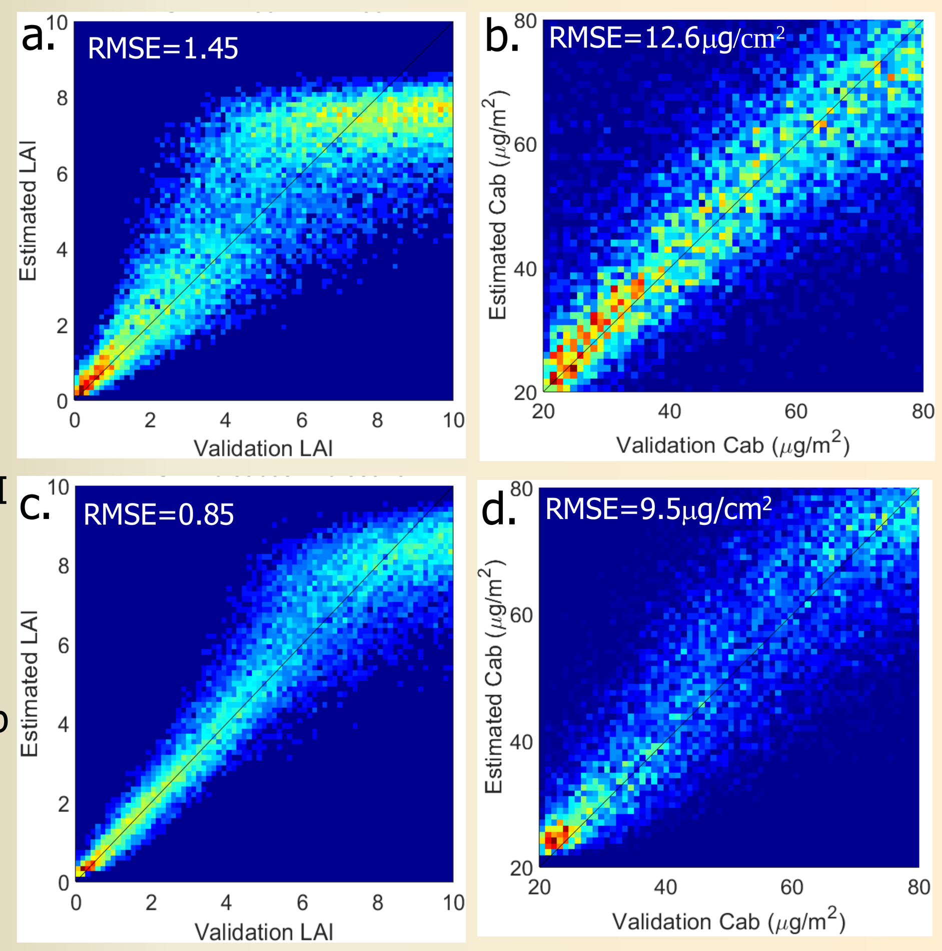


Fig. 1 Cross-validation of estimated LAI and Cab using neural network Inversion of PROSAILH database for Sentinel-2 (S2) Multispectral Imager (MSI) based on Simplified Level 2 Prototype.[1]

The **Directional Area Scattering Factor (D)**, defined as R if foliage single scattering albedo ω=1, can be estimated using red-edge spectra without prior knowledge of ω.[2]

HYPOTHESES

1. D can be estimated accurately (within +/-0.1) for arbitrary background conditions given S2 MSI VNIR measurements.
2. Constraining D will give similar uncertainty reduction of LAI and Cab estimates as when either are specified a priori.

2. How well can we estimate the Directional Area Scattering Factor, D?

D cannot be measured (easily). Three estimates (below) are compared to estimates from a discrete Radiative Transfer model (FLIGHT [3]) that can estimate D to within 4%. The empirical estimates are then derived from measurements and intercompared.

I. Polynomial regression, 10nm 710-790nm R, actual ω

Assuming R is a continuous function of ω, a convergent Taylor series polynomial exists. D extrapolated using 3rd order polynomial of R vs ω.

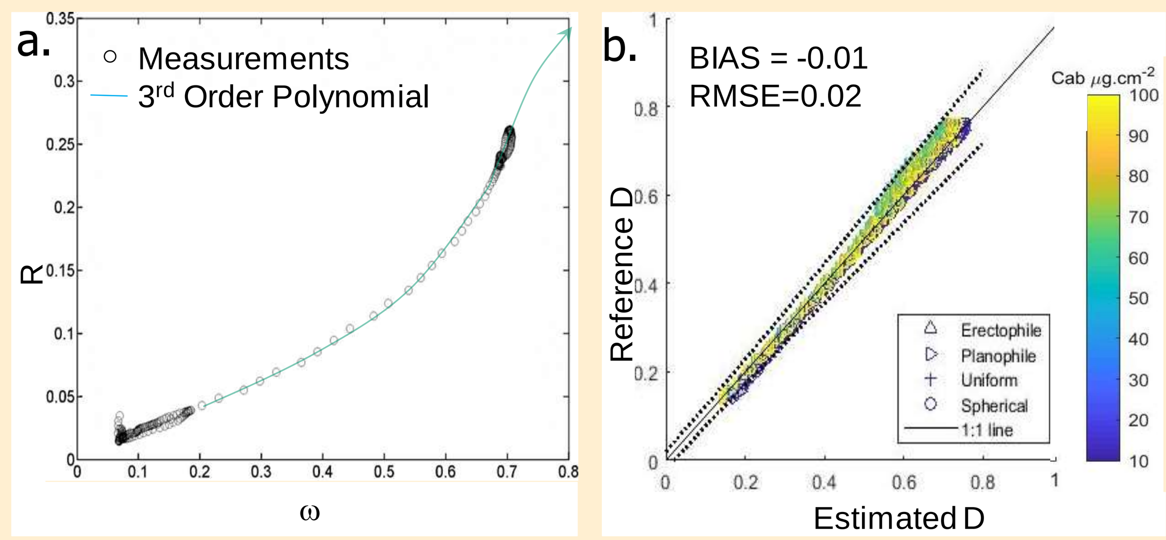


Fig. 2 a) Measured R and ω for typical conifer forest and interpolated polynomial b) Reference D from FLIGHT for a range of Cab, LAI and leaf angles versus estimate using 3rd order Taylor polynomial in ω.

II. Linear regression, 10nm 710-790nm R, reference ω_0.

Assuming R/ω is a continuous function of ω and ω is a constant ratio geometric series in ω_0 then D≈intercept/(1-slope) after [2].

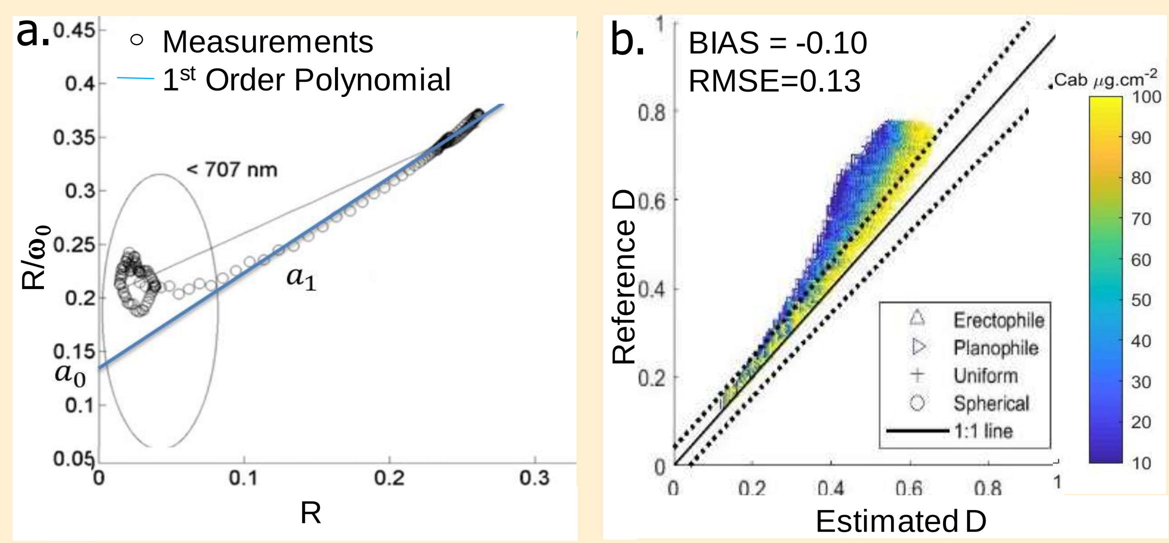


Fig. 3 a) Measured R divided by ω_0 versus R for typical conifer forest and linear regression fit b) Reference D from FLIGHT model simulations for a range of Cab and LAI versus D $\approx a_0/(1-a_1)$.

III.Non-linear regression, S2 MSI VNIR, PROSAILH database.

Single hidden layer backpropagation network for D trained with PROSAILH database similar to Sentinel Level 2 Prototype Processor[1] with uniform LAI, dry matter and Cab priors.

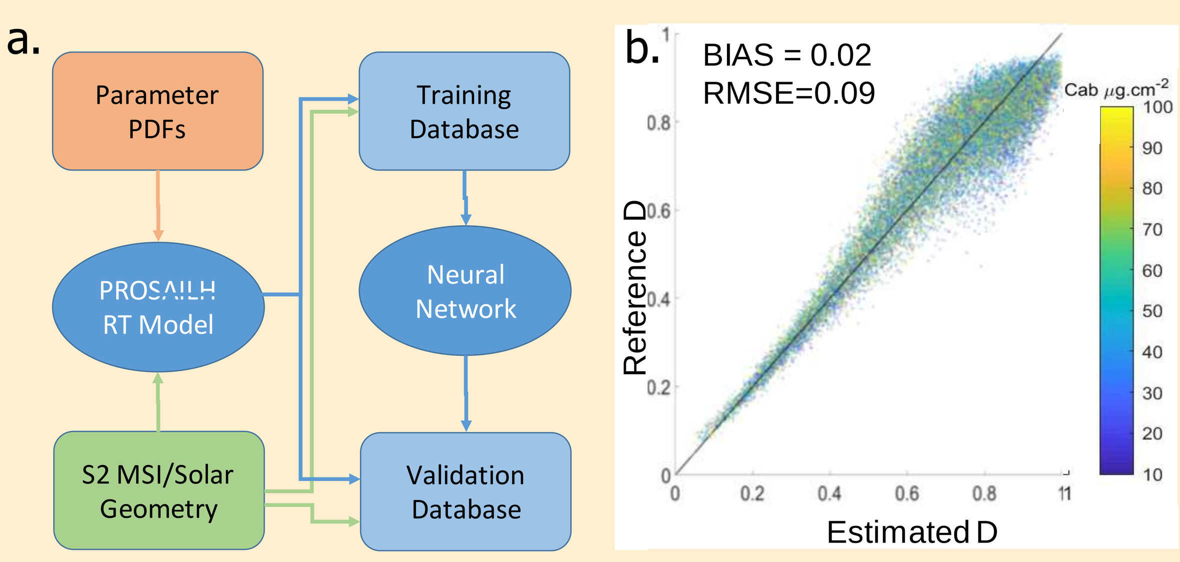


Fig. 4 a) Non-linear calibration and cross-validation approach b) D from PROSAILH[4] model simulations for a range of Cab and LAI versus neural network estimates with S2 MSI VNIR bands + geometry.

Intercomparison using Measurements

Six corn and soybean fields at CALMIT study area, Nebraska, USA.[5] In-situ measurements of 10nm nadir VNIR spectra, Cab, LAI, foliage reflectance ρ. Method I was used as reference D assuming $\omega = 2\rho$. Measurement intercomparisons agree with simulation cross-validation. D can be estimated to +/-0.1 from S2 MSI using Method III.

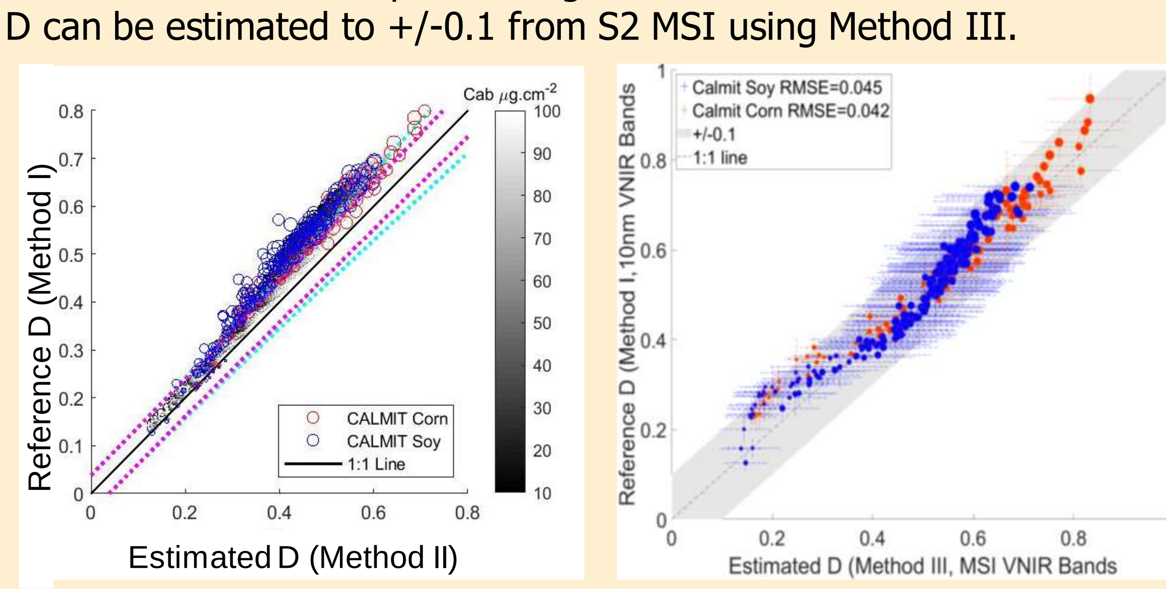
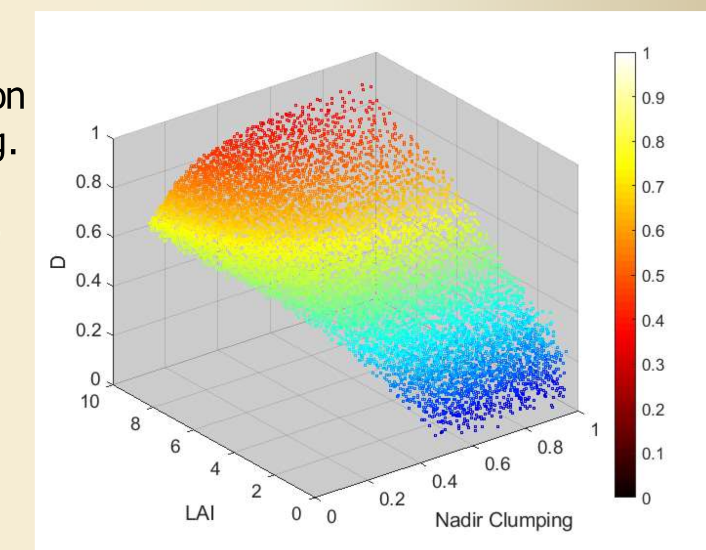


Fig. 5 Comparisons of Method I using measured R and w with a) Method II using $\boldsymbol{\omega_0}$ from PROSPECT5B with Cab=40ug/cm² superimposed on simulation results from Fig. 3 and b) Method III using S2 MSI bands and actual geometry together with 1 standard deviation confidence interval. Symbol size proportional to LAI.

3. Can we reduce uncertainty using the Directional Area Scattering Factor?

I. Expected relationship between D and canopy structure

Fig. 6 Simulated D at using FLIGHT as a function of LAI and nadir clumping. Nadir view, 45º solar zenith, uniform leaf angle distribution, sandy-loam soil reflectance.



II. Using D to constrain Sentinel 2 MSI LAI & Cab retrievals

Neural network trained to estimate D using MSI VNIR bands and to define 10 subsets of training database with similar D estimates. Ten networks trained using each subset for each parameter (Fig. 7). For application, global D network is applied and neural network corresponding to estimate D is used for each other parameter.

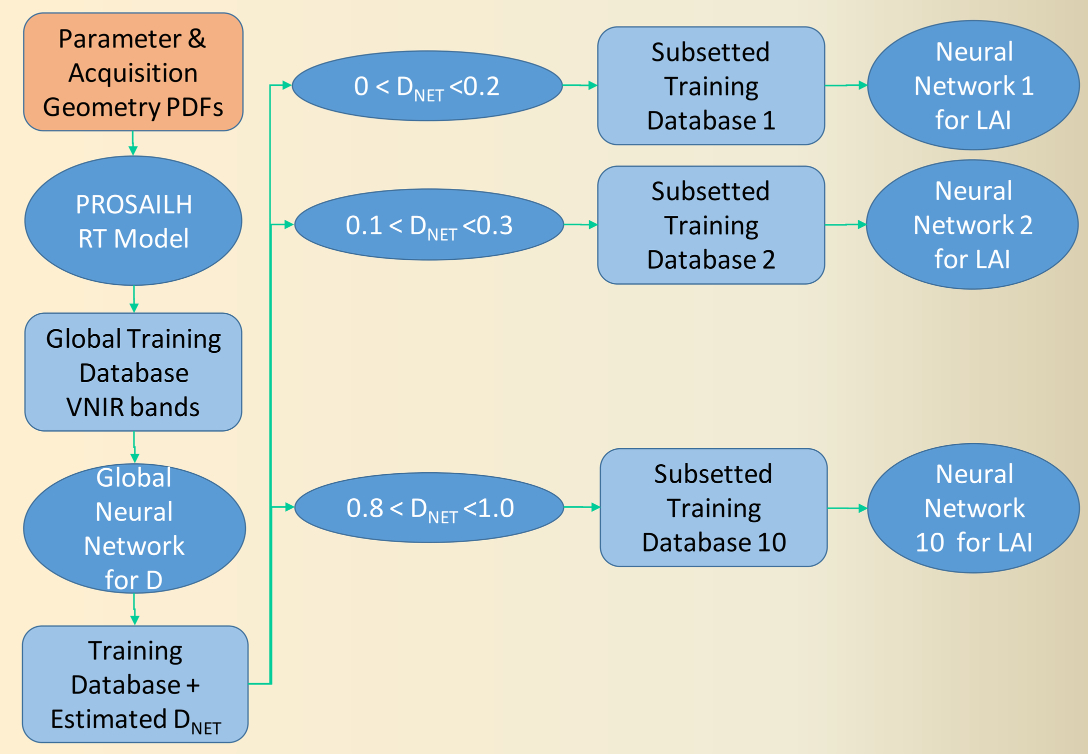


Fig. 7 Calibration of neural networks for LAI estimation using global neural network estimate of directional area scattering factor (D) to subset databases.

III.Hold out cross-validation using PROSAILH

Cross-validation using 1/3 hold-out of global training database consisting of ~1million simulations shown in Fig. 8. Results are (unrealistically?) optimistic for LAI and predict modest improvement for Cab in comparison to baseline cross-validation (Fig. 1).

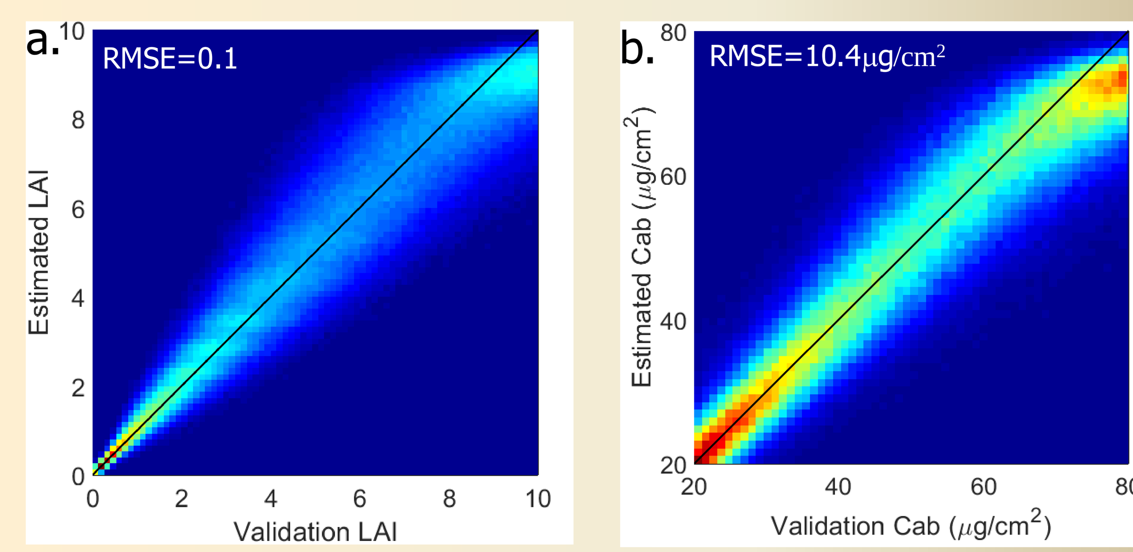


Fig. 8 Cross-validation estimates of (a) LAI and (b) Cab for global PROSAILH training database using Sentinel 2 MSI VNIR bands only.

Validation using Measurements

Constrained inversion method (Fig. 7) was applied to first retrieve D and subsequently LAI and Cab for 184 corn and 91 soybean spectra sampled to S2 MSI VNIR bands. Confidence intervals of estimates were derived using neural networks as in SL2P.1 LAI and Cab estimated within CEOS or SEN4SCI requirements (Fig. 9)

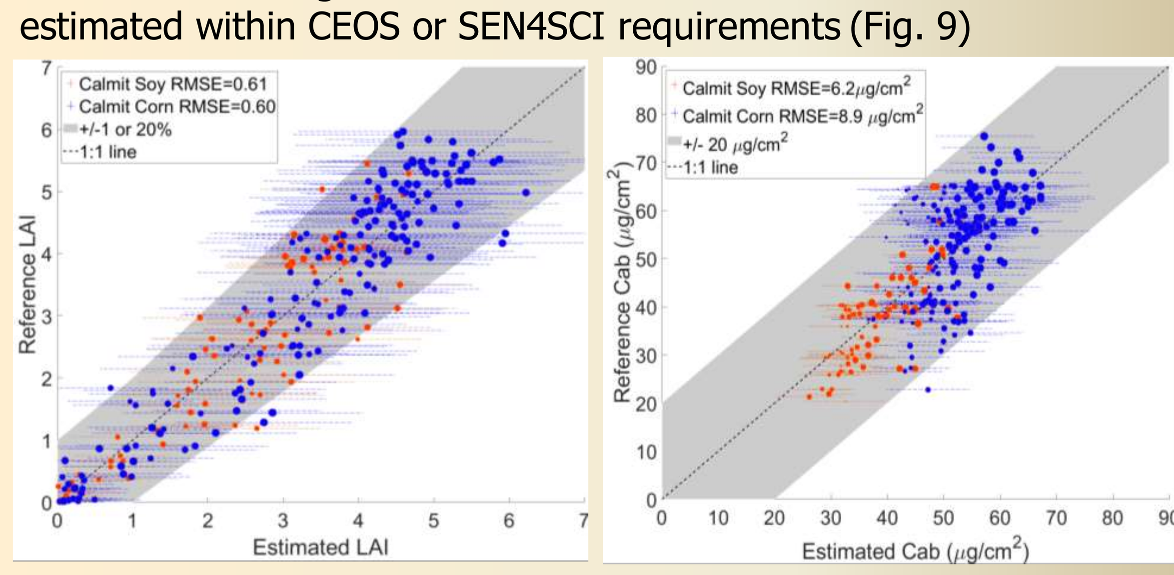


Fig. 9 Comparison of (a) LAI and (b) Cab estimated from constrained neural network applied to in-situ spectra using S2 MSI VNIR bands and local soil reflectance versus in-situ measurements at CALMIT sites. Bars indicate 1 standard deviation uncertainty for estimates. Symbols size proportional to (a) Cab or (b) LAI. Shaded region shows CEOS or SEN4SCI requirements.

4. CONCLUSIONS

The Directional Area Scattering Factor was estimated to within:

i) RMSE 0.02 or 4% using measured foliage albedo and 10nm red-edge directional reflectance spectra

ii) +/-0.1 using Sentinel 2 MSI VNIR bands without prior information regarding foliage albedo or Cab

The linear regression approach proposed for estimating the Directional Area Scattering Factor by Knyazikhin et al., 2013 had a RMSE of 0.13 and bias of 10-20%, inversely proportional to Cab.

Constrained radiative transfer model inversion using estimated D and local soil reflectance results in similar uncertainty reduction in LAI and Cab to theoretical reduction if either are specific a priori.

The constrained retrieval approach should be implemented and tested with hyperspectral and Sentinel 2 MSI data over a range of canopy conditions. We hypothesize that estimation errors will increase with greater variation in clumping and foliage properties.

5. REFERENCES

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6. ACKNOWLEDGEMENTS

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