Research Project:
Retrieval of plant biophysical and biochemical variables from remote sensing data using a hybrid machine learning method

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Abstract

This will be the abstract at the end [TO BE UPDATED]

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List of Abbreviations

3D . . . . Three-dimensional
INFORM . . . Invertable Forest Reflectance Model
RTM . . . . . . Radiative Transfer Model
SAIL . . . . . . Scattering by Arbitrary Inclined Leaves
PROSAIL . . The combination of PROSPECT and SAIL models
FLIM . . . . . Forest Light Interaction Model
LAI . . . . . . Leaf Area Index
MLRA . . . . Machine Learning Regression Algorithms
ML . . . . Machine Learning
DT . . . . Decision Trees
ANN . . . . . . Artificial Neural Networks
KBMLRM . . Kernel-Based Machine Learning Regression Methods
RF . . . . Random Forest
RFR . . . . . . Random Forest Regression
LUT . . . . . . Look-Up-Table
NN . . . . Neural Networks
SVR . . . . . . Support Vector Regression
SVM . . . . . . Support Vector Machines
GPR . . . . . . Gaussian Process Regression
GP . . . . Gaussian Process
VI . . . . Vegetation Index
DR . . . . Dimensionality Reduction
WT . . . . . . Wavelet Tranform
PCA . . . . . . Principal Component Analysis
AL . . . . Active Learning
NIR . . . . . . Near Infrared
SWIR . . . . . Short Wave Infrared

1 Methods

This section explains the methods used in this research.

1.1 Local sensitivity analysis

Local sensitivity analysis was performed to assess the effect of each of the main 6 plant biochemical and biophysical variables on the PRISMA image bands. In the local sensitivity analysis simulation is performed by keeping all the variables constant at their determined fixed or default values except the parameter of interest. This way the effect of a specific parameter on the simulated spectra can be assessed. In this research the plant parameters C_{ab}, C_w, C_m, LAI_s, CD and SD were varied each 15 times (Table (1.1)), while keeping the rest of the variables at their default values (Table (1.2)). The default and varied values were chosen based on the literature (e.g. Darvishzadeh et al. (2019); Laurent et al. (2011); Schlerf and Atzberger (2012)) where similar RTM method used to simulate reflectance for Spruce trees.

Table 1.1 shows the 6 parameters that were varied, their units, minimum and maximum values. Each parameter was varied 15 times, meaning 15 different spectra were simulated for each variable.

Table 1.1: INFORM Parameters varied in local sensitivity analysis (each parameter were varied 15 times)

Parameter	Abbrev.	Unit	Min	Max
Chlorophyll content	C_{ab}	$\frac{\mu g}{cm^2}$	20	60
Equivalent water thickness	C_w	$\frac{g}{cm^2}$	0.0035	0.035
Leaf dry matter content	C_m	$\frac{g}{cm^2}$	0.008	0.03
Leaf area index (single)	LAI_s	$\frac{m^2}{m^2}$	0	7
Stem density	SD	ha^{-1}	200	5000
Crown diameter	CD	m	1.5	8.5

Table 1.2 shows the determined default values for each INFORM parameter that were kept during the sensitivity simulation while one of the parameter was varied (Table 1.1).

Table 1.2: INFORM Parameters that were kept constant while one parameter was varied at a time

Parameter	Abbr	Unit	Value
Leaf structure parameter	N	$-$	3
Chlorophyll content	C_{ab}	$\frac{\mu g}{cm^2}$	40
Leaf cartenoid content	C_{ar}	$\frac{\mu g}{cm^2}$	8
Brown Pigment Content	C_{brown}	$-$	0.001
Equivalent water thickness	C_w	$\frac{g}{cm^2}$	0.0117
Leaf dry matter content	C_m	$\frac{g}{cm^2}$	0.03
Average leaf inclination angle	$ALIA$	$^\circ$	65
Leaf area index (single)	LAI_s	$\frac{m^2}{m^2}$	6
Leaf area index (understorey)	LAI_u	$\frac{m^2}{m^2}$	0.5
Hot spot parameter	Hot	$\frac{m}{m}$	0.02
Solar zenith angle	tts	$^\circ$	45.43
Observer zenith angle	tto	$^\circ$	0
Sun-sensor azimuth angle	psi	$^\circ$	181.41
Soil brightness	α_{soil}	$-$	0.5
Stem density	SD	ha^{-1}	700
Crown diameter	CD	m	5
Mean Height	H	m	20
Fraction of diffuse incoming	$skyl$	$-$	0.1
Soil reflectance spectrum	B_g	$-$	default

Solar zenith angle and *Sun-sensor azimuth angle* were calculated based on the PRISMA image acquisition parameters (date, lat/long etc.) using the website `https://www.esrl.noaa.gov/gmd/grad/solcalc/azel.html`.

RTM models PROSPECT5, 4SAIL and FLIM were coupled (INFORM) in order to simulate canopy reflectance. Simulations were carried out using the *ccrtm* package (Visser, 2021) in *R* (R Core Team, 2021). The default soil spectra provided by the the *ccrtm* package (Visser, 2021) was used for the simulations. Spectral resampling was performed in order to resample the INFORM output spectra (1nm resolution) into PRISMA image bands. For spectral resampling the *R* package *hsdar* (Lehnert et al., 2019) was utilized.

2 Results

2.1 Local sensitivity analysis

Figure 2.1 shows the result of sensitivity analysis. Chlorophyll content (C_{ab}) appears to almost exclusively impact the visible spectra. Some effect can also be noticed in the red-edge, but there is not a significant effect of varying C_{ab} on the simulated spectra within the near-infrared (NIR) and short wave infrared (SWIR) (Figure 2.1.a). Conversely, equivalent water thickness (C_w) (Figure 2.1.b) and leaf dry matter content (C_m) (Figure 2.1.c) both have large effects on simulated spectra within the NIR and SWIR but no significant effect within the visible spectra. Leaf Area Index (single) (LAI_s) (Figure 2.1.d), Crown diameter (CD) (Figure 2.1.e)) and Stem density (Figure 2.1.f) all have noticeable effect on the simulated canopy reflectance almost all over the spectra.

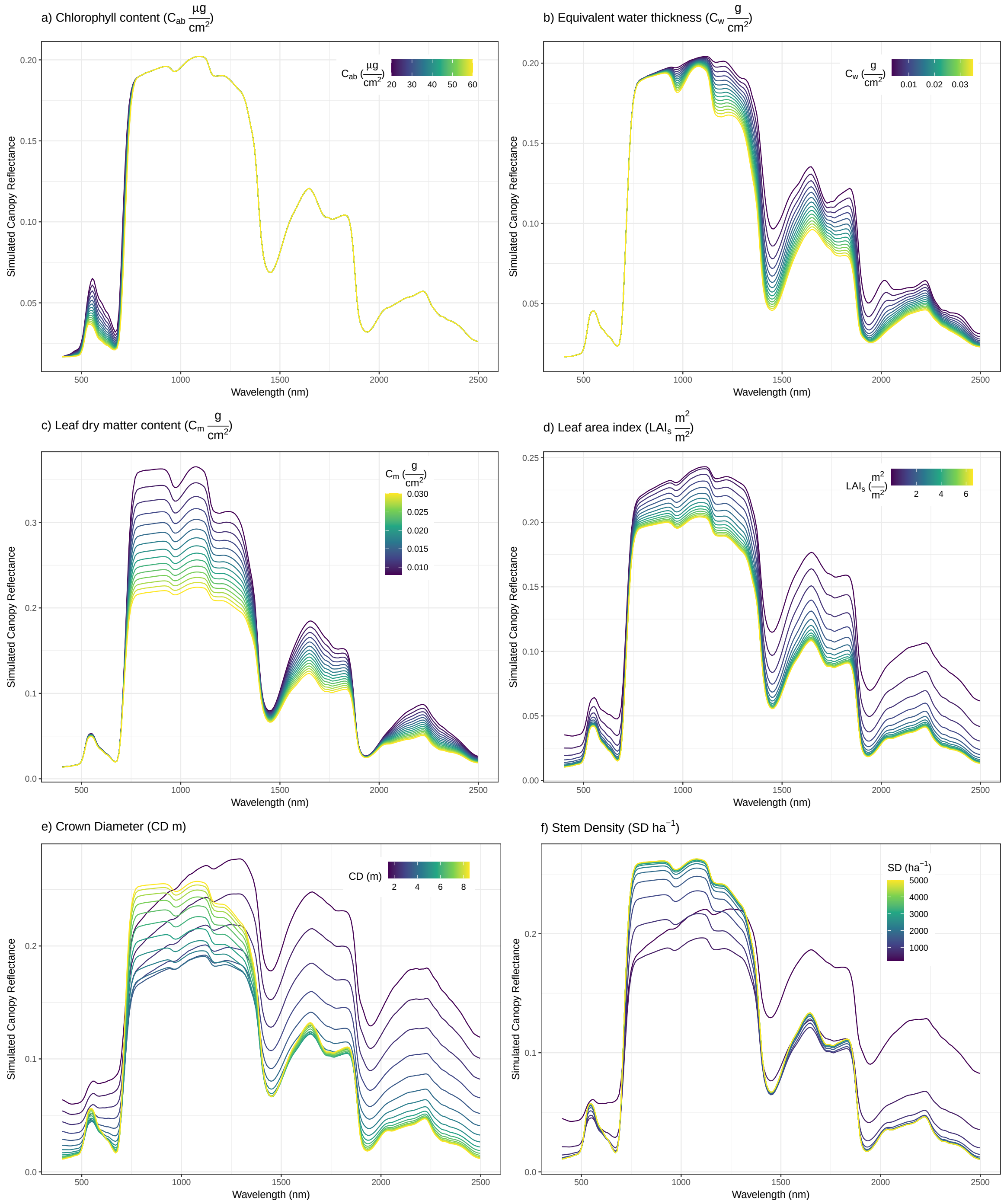

Figure 2.1: Effects of varying the chosen parameters on the simulated spectra

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