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INVERSION OF RADIATIVE TRANSFER MODEL THROUGH ONE-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK TO RETRIEVE FOLIAR TRAITS OF TEMPERATE FOREST CANOPIES WITH IMAGING SPECTROSCOPY

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ABSTRACT

Estimation of foliar traits through imaging spectroscopy is one of the current major challenge in remote sensing to monitor ecosystem functions. New spaceborne hyperspectral sensors are upcoming or already in activity. In this context, future estimation models are required to be robust to temporal variations (e.g. illumination and phenological conditions) and changes in vegetation geometry in order to cope with the wide variety of canopy observations.

Our work is threefold. First, we analyze the direct radiative transfer model to highlight potentials of one-dimensional CNN (1D-CNN) to retrieve foliar traits. Secondly, we build a 1D-CNN inverse model and search for an optimal architecture. Finally, we test the retrieval performance of our 1D-CNN on four oak species over four forest sites in California at different phenological stages during two years.

Index Terms— Foliar traits, One-dimensional CNN, PROSPECT, DART, temperate forests, AVIRIS

1. INTRODUCTION

Monitoring forest ecosystems at large scales has become a major challenge in ecology, which is needed to improve our understanding of forest resilience against the increased impact of global climate change. Forests provide ecosystem services and help regulating climate on both local and global scales. Past research in ecology defined foliar traits as indicators [1] of plant physiological processes (photosynthetic activity, biomass productivity and hydration status). Traits are related to the biochemical content of leaves in the canopy and they globally provide key information about tree and forest health status.

Foliar traits alter the light reflected by the canopy by absorbing incident light in specific wavelengths. In recent decades, several studies demonstrated that imaging spectroscopy, also known as hyperspectral imaging is a powerful tool to retrieve foliar traits [2].

Several hyperspectral spaceborne sensors are already in service or schedule for the next decade (e.g. PRISMA, EnMAP, CHIME, and SBG).

Previous studies lead to several strategies to map foliar traits from imaging spectroscopy at pixel scale using the sensed reflectance shaped as a vector. While radiative transfer models (RTMs) simulate the direct physical process of canopy/light interactions, estimation strategies rely on building the inverse model of this physical process. Most promising strategies; called hybrid methods; build the inverse model with a machine learning regression algorithm (MLRA) trained on a set of RTM simulations. Applying the trained MLRA model on imaging spectroscopy data enables estimating foliar traits. Most studies focused on classical MLRA including artificial neural networks (ANN) or multi-layer perceptron [3]. Simultaneously, convolutional neural networks (CNN) have emerged and have the ability to deal with complex supervised learning problems, such as image classification problems. However, to our knowledge, few studies have used it for vegetation analysis with spectroscopic data [4], [5].

Moreover, previous studies on hybrid methods lead to suitable estimation performances but present two drawback: foliar traits are estimated separately from specific spectral ranges and they were usually trained and evaluated on a single site at a specific date.

In this work, we seek to estimate four foliar traits: concentrations of chlorophylls a and b (C_{ab}), carotenoids (C_{xc}), equivalent water thickness (EWT), and Leaf Mass Area (LMA). The objective is to evaluate the performance of a new hybrid approach based on 1D-CNN and RTMs considering different forest sites, tree species and seasonal dates. We attempt to perform a joint estimation of the four foliar traits from the whole range 400 nm-2500 nm, which constitutes another original feature of our work.

Section 2 describes the synthetic and real dataset used to further build and evaluate our estimation model. Section 3 presents the method and Section 4 the results. Finally, we conclude our study in section 5.

2. MATERIALS

Our validation measurements is a dataset containing 114 leaf samples collected over four oak species (*Quercus Chrysolepis* (QUCH), *Quercus Douglasii* (QUDO), *Quercus Kelloggii* (QUKE), *Quercus Wislizeni* (QUWI)). Samples were collected on four study sites located on Sierra Nevada Mountains and its foothills, in California, with a latitude varying between 37° and 39°, an elevation gradient between 200 m and 1500 m above sea level and covering two ecosystem types (oak savanna, mixed conifer and broadleaf forests).

Leaf collection occurred in 2013 and 2014 at 3 seasons of the year (spring, summer and fall) to cover the phenological evolution of the target species and were followed by laboratory analysis to measure foliar traits that will be used as reference. Hyperspectral images at 14m ground sampling distance of the study sites were acquired with AVIRIS-Classic sensor close to all field sampling dates. Pixels related to field measurements and their spectra were extracted from AVIRIS images.

We build a synthetic dataset to train and test our 1D-CNN model. Radiative transfer simulations are performed with a combination of the leaf-based PROSPECT [6] and the 3D canopy-based DART [7] RTMs. They both proved to be reliable to simulate leaf and canopy optical properties and to retrieve foliar traits after inversion. PROSPECT include the four foliar traits as parameter and a leaf structure parameter (N). At the canopy level, we use a standard forest representation (SFR) in DART [8]. The SFR model admit illumination parameters (sun zenith angle SZA, sun azimuth angle SAA), parameters related to the canopy geometry (canopy cover CC, leaf area index LAI, average leaf angle ALA) and soil reflectance.

Table 1: Ranges of values used for latin hypercube generation

Variable	Min. value	Max. value
C_{ab} ($\mu\text{g}\cdot\text{cm}^{-2}$)	0	140
C_{xc} ($\mu\text{g}\cdot\text{cm}^{-2}$)	0	35
EWT (cm)	0.001	0.055
LMA ($\text{g}\cdot\text{cm}^{-2}$)	0.001	0.05
N	1.0	3.0
LAI ($\text{m}^2\cdot\text{m}^{-2}$)	0.05	7.0
ALA (°)	0	90
CC (%)	10	100

We simulated 29,000 reflectance spectra and saved 5000 simulations selected randomly as test data. Illumination angles were chosen according to those of the 29 AVIRIS images for the four study sites. Other simulation inputs were generated through a latin hypercube sampling. Other model inputs include foliar traits but also canopy geometry parameters (CC, LAI, ALA) and several types of soil reflectance. For each AVIRIS image, 1000 cases were generated using the ranges of variation defined in Table 1.

3. METHOD

This work is organized in three steps. First we perform sensitivity analysis to justify the use of 1D-CNN. Then we present the architecture of the 1D-CNN model and the calibration process of its parameters. Finally, we describe how we applied and evaluate the 1D-CNN performance to estimate foliar traits from AVIRIS spectra of the validation dataset.

3.1. JUSTIFICATION OF 1D-CNN FOR HYBRID APPROACH

Foliar traits rely on biochemical molecules that have wavelength specific absorption bands that influence the shape of the reflectance spectrum while all other parameters have wavelength independent influence on the entire optical domain. We made the hypothesis that specific features, sensitive to foliar traits, could be extracted from filters applied to reflectance spectra (such as wavelet filters).

To evaluate our assumption we assess the relative impact of foliar traits on several reflectance features. We performed a variance-based sensitivity analysis [9] on the DART-PROSPECT models combination. We compute with openturns python library [10] a Sobol indices experiment of size 1000 (leading to 13000 simulations).

We perform at first the sensitivity analysis on the reflectance for each spectral band, then on a continuous wavelet transform (CWT) of the reflectance, and compared the results.

3.2. 1D-CNN CALIBRATION

Our 1D-CNN is based on a classical CNN architecture and includes: several one dimensional convolution layers (each time followed by an activation layer and a maxpooling layer), a flatten layer, several fully-connected layers. Inputs of the network are reflectance at 160 wavelength (one wavelength every 10 nm between 400 nm and 2500 nm except for water absorption bands between 1270-1450 nm and 1800-1980 nm) and 4 outputs (the 4 foliar traits of interest).

This architecture involves at least five hyperparameters: number of convolutional layers, size of convolutional kernels, number of kernels, number of dense layer, and size of hidden layers. We explore different combination of hyperparameters with a TPE sampler [11] implemented in the Optuna library [12]. Additionally, the batch size and learning rate were parameters included in the TPE sampling. We trained our networks with a mean squared error loss during 50 epochs. Training our networks during 50 epochs was enough to reach convergence in the training process. TPE sampling is an adaptive sampling strategy and aims to reach the optimal hyperparameters that minimize the mean square error loss on test data.

3.3. EVALUATION OF 1D-CNN PERFORMANCES

Finally, with the validation dataset described in section 2, we estimate foliar traits from AVIRIS spectra with our 1D-CNN. We assess the performances of our method using a root mean square error (RMSE) metric.

4. RESULTS

4.1. JUSTIFICATION OF 1D-CNN FOR HYBRID APPROACH

The sensitivity analysis shows: LMA explains up to 20% of the total reflectance variation in the near-infrared range; EWT at most 10% of the variance, around 1650 nm; C_{ab} 15% around 650 nm and 720 nm; and C_{xc} less than 5% in the 500-550 nm range. In contrast, all the other parameters explain at least 70% of the reflectance variations in the optical domain.

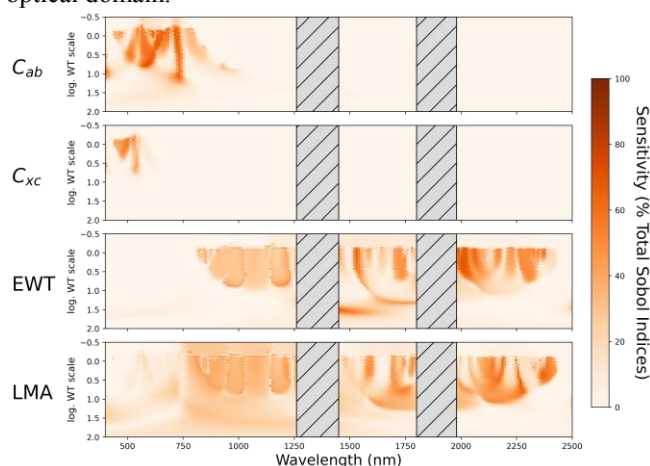


Figure 1: Results of the variance-based sensitivity analysis on canopy reflectance CWT for the four foliar traits (chlorophylls C_{ab} , carotenoids C_{xc} , Equivalent Water Thickness (EWT), Leaf Mass Area (LMA)). Hatched rectangles represent atmospheric absorption bands.

Foliar traits have significant influence on CWT outputs and even that a well-chosen filter can isolate the influence of a specific foliar trait. At a given wavelet scale, C_{ab} or C_{xc} explain more than 50% of the filtered output in the visible range. Similarly, EWT and LMA affect more than 60% of the output variance in the infrared (Figure 1). This experiment demonstrates that a proper MLRA for inversion should be able to construct a representation of the hyperspectral signal robust to variation of the canopy geometry and illumination condition. In this frame, 1D-CNNs are promising algorithms to create inverse models to assess canopy foliar biochemistry since the first layer of a CNN acts as a set of filters, and could indeed extract features from the shape of the spectra.

4.2. 1D-CNN CALIBRATION

We found that a learning rate between 5.10^{-4} and 7.10^{-4} leads to better results. Batch size was found optimal between 100 and 250, although the choice of batch size had less significant impact on the results. The best architecture is the following: a single convolution layer (16 kernels of size 115) and 3 dense layers (hidden layers of size 86 and 90).

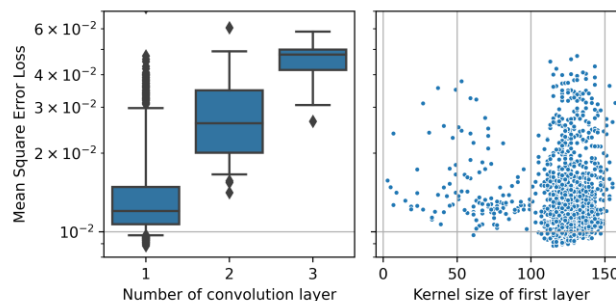


Figure 2: Distribution of mean square error validation loss compared for number of convolution layers (left) and kernel size of first layer (right)

More generally, our experiment highlights that one convolution layer is enough to extract features to retrieve foliar traits on simulated spectra (Figure 2: Distribution of mean square error validation loss compared for number of convolution layers (left) and kernel size of first layer (right)Figure 2). Moreover, better results were reached with architectures that include a single convolution layer with a kernel size greater than 100.

This architecture revealed able to estimate properly the foliar traits on the synthetic dataset. C_{ab} , EWT and LMA are correctly estimated (R^2 above 0.9, and RMSE respectively $10.5 \mu\text{g}\cdot\text{cm}^{-2}$; 0.0042 cm ; $0.0043 \text{ g}\cdot\text{cm}^{-2}$). C_{xc} is estimated with slightly less accuracy (R^2 : 0.85, RMSE: $3.74 \mu\text{g}\cdot\text{cm}^{-2}$).

4.3. EVALUATION OF 1D-CNN PERFORMANCES

The range of estimated C_{ab} is similar to the variation of measurements: between 10 to $60 \mu\text{g}\cdot\text{cm}^{-2}$. The estimated C_{ab} over all the sites and at every seasons leads to a Root Mean Square Error (RMSE) of $17.0 \mu\text{g}\cdot\text{cm}^{-2}$. Compared to the RMSE obtained by [13] over a Mediterranean forest at one date ($9 \mu\text{g}\cdot\text{cm}^{-2}$) and [14] over a sparse forest of conifers ($8.1 \mu\text{g}\cdot\text{cm}^{-2}$), the performance degrades by a factor 2. Performances do not significantly depend on the season and the site. The QUKE species has the worst RMSE mainly due to the presence of more senescent leaves at fall.

The range of estimated C_{xc} is 3 times wider than the range of measured values. This discrepancy is mainly due to two species from mixed broadleaf-conifer ecosystems (QUCH and QUKE). It is important to notice that C_{xc} and C_{ab} are considered independent in the retrieval process. Global RMSE for C_{xc} is poor ($12.20 \mu\text{g}\cdot\text{cm}^{-2}$) but suitable considering only QUWI and QUDO species ($3.8 \mu\text{g}\cdot\text{cm}^{-2}$).

For EWT, the variations ranges are similar for both estimated and measured values. But, EWT is overestimated with a mean bias of 0.01 cm and a RMSE of 0.011 cm. RMSE by species are similar. Performance remain poor compared to those obtained by [15] (0.0036 cm). For LMA, the variation ranges are similar, except for QUKE samples, which are overestimated (bias of 0.006 g.cm⁻²). The RMSE of 0.0056 is twice higher than the results obtained on one site by [16] (0.0020 g.cm⁻²) but equivalent to [13] (0.0053 g.cm⁻²).

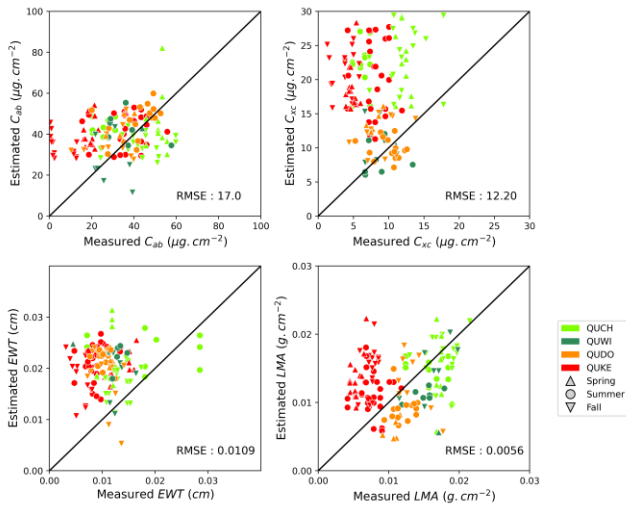


Figure 3: Estimated vs measured foliar traits values for validation data.

5. CONCLUSIONS

We proposed to use a 1D-CNN in a hybrid approach to estimate four foliar traits over four sites during three seasons. We demonstrate that a single convolution layer with a large kernel is the proper architecture. However, such architecture computes the cross-correlation only on few points, thus it is similar to classical neural network architecture with only fully connected layer. Suitable performances are obtained to estimate C_{ab} and LMA. On the contrary, EWT and C_{xc} are not well estimated but the performances highly depend on the species. Several potential source of errors can be identified: error on the field measurements, presence of multiple species in the 14m AVIRIS pixels, the simplified representation of forest mock-up, and the independence of C_{ab} and C_{xc} values in our retrieval process. Globally, the new proposed approach paves the way towards a global multi-ecosystem and multi-temporal strategy to estimate foliar traits for forests.

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