Hybrid Modelling of Canopy Biochemical Traits Using DESIS Imagery

A. B. Pascual-Venteo¹, J. Verrelst¹, A. Halabuk², T. Hank³, K. Gerhátová², M. Živčák⁴, E. Portales¹, K. Berger³

Ana.B.Pascual@uv.es

¹Image Processing Laboratory (IPL), Universitat de València, Spain
²Institute of Landscape Ecology, Slovak Academy of Sciences, Slovakia
³Department of Geography, LMU, Munich, Germany
⁴Department of Plant Physiology, Slovak University of Agriculture, Slovakia

September 2021
Recently launched satellite missions like the DLR Earth Sensing Imaging Spectrometer (DESIS) provides data streams of hyperspectral measurements.

This exceptionally high spectral data availability in the visible and near infrared (VNIR) domain (400-1000 nm) allows preparing efficient and accurate models for retrieval of biochemical traits, such as canopy chlorophyll (CCC) and canopy carotenoid contents (CCarC).

The objective of the current study was therefore to test hybrid retrieval methods on DESIS imagery for their suitability to provide reliable agricultural information products.
RTM PROSAIL-PRO Scheme of PROSAIL, coupling the leaf RTM PROSPECT-PRO and the bidirectional canopy reflectance model 4SAIL
Active Learning (AL) aims to achieve good results by reducing (and optimizing) the amount of labeled data used for model training.

Consider \( L = \{x_1, \ldots, x_{n_l}\} \) the labeled samples set and \( Y = \{y_1, \ldots, y_{n_l}\} \) their corresponding outputs. Active Learning seeks through a criterion which point from \( U = \{x_1, \ldots, x_{n_u}\} \) (unlabeled set) would increase the accuracy of the Learning model.
Active Learning

- AL strategy was Euclidean distance-based diversity
- Learning model was Gaussian Process Regression
- This has been done with ARTMO toolbox!

https://artmotoolbox.com/
Workflow

PROSAIL-PRO
*Spectral training data base with CCC and CCarC*

PCA (PC#20)

Active Learning (EBD) with GPR
\[ d_E = \| x_u - x_l \|_2^2, \]

DEESIS SCENE

Optimized training set & GPR model

CCC & CCarC estimated
Data set and Experiments

- DESIS image: North of Munich, Germany (30/03/2021)
- $U$ was generated with PROSAIL-PRO, $N = 1000$ samples
- After AL we obtained an optimal set of $n = 200$ samples
- Simulated reflectance (PROSAIL-PRO) resampled to match DESIS resolution
- In situ variables: Canopy Chlorophyll Content (CCC) & Canopy Carotenoid Content (CCarC) from a phenotyping field trial located at Pistany, Slovakia (200 samples).
Accuracy of the AL procedure

**Figure:** Normalized root mean squared error (NRMSE) of the AL procedure for the inferred variables

**Figure:** Coefficient of determination ($R^2$) of the AL procedure for the inferred variables
Figure: Scatter plot of CCarC measurements against their corresponding estimates through the GPR model.

Figure: Scatter plot of CCC measurements against their corresponding estimates through the GPR model.
Estimated maps

**Figure:** Estimated map of CCarC using GPR trained with optimized AL data set.

**Figure:** Estimated map of CCC using GPR trained with optimized AL data set.
Figure: Confidence map of CCarC using GPR trained with optimized AL data set.

Figure: Confidence map of CCC using GPR trained with optimized AL data set.
Conclusions & Future work

- General applicability of the retrieval models and processing of hyperspectral DESIS scene was achieved.
- The usage of GPR provides associated uncertainties together with the estimates, which supports confidence when transferring the developed models.
- In a future study, time series of DESIS imagery should be processed covering the whole growth cycle.
Conclusions & Future work

- General applicability of the retrieval models and processing of hyperspectral DESIS scene was achieved
- The usage of GPR provides associated uncertainties together with the estimates, which supports confidence when transferring the developed models
- In a future study, time series of DESIS imagery should be processed covering the whole growth cycle

Thank you for your attention!!