Canopy Nitrogen Content retrieval from hyperspectral satellite data through spectral band selection with Gaussian Processes

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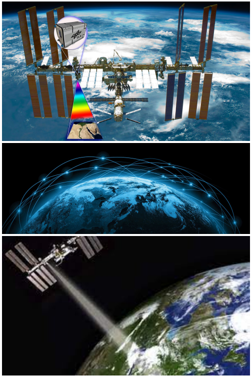
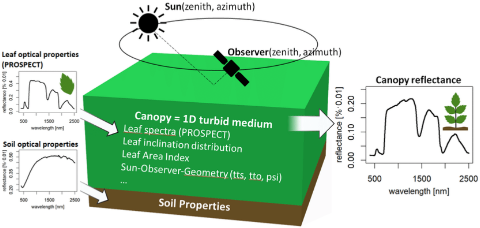
Introduction

- The CHIME sensor is built upon a push-broom concept providing contiguous spectra assembled by more than 200 narrow bands in the 400-2500 nm.
- These hyperspectral missions include, among others, the PRecursore IperSpettrale della Missione Applicativa (PRISMA) spectral rangeallows preparing efficient and accurate models for retrieval of biochemical traits, such as Canopy Nitrogen Contents (CNC)
- The objective of the current study was therefore to test hybrid retrieval methods on PRISMA imagery for their suitability to provide reliable agricultural information products

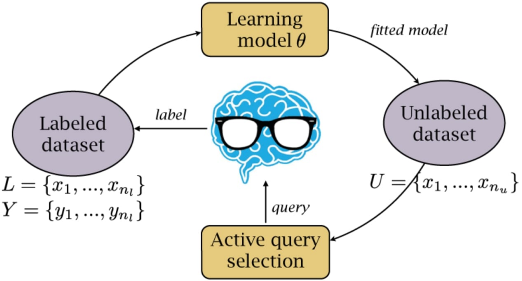


SCOPE RTM



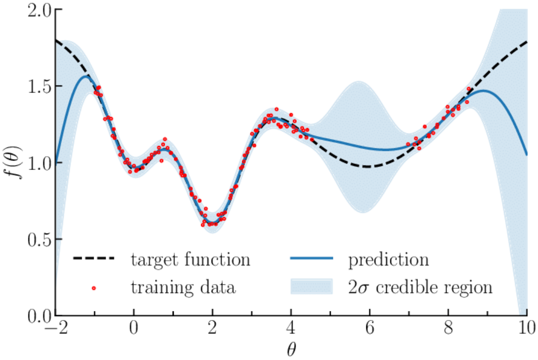
- We selected the Soil Canopy Observation, Photochemistry and Energy fluxes (SCOPE) model (version 1.7) [Van der Tol et al., 2014] for our purpose
- Within SCOPE, optical properties of the leaves are modeled by PROSPECT-5 [Feret et al., 2008] and Fluspect [Vilfan et al., 2016], whereas the canopy structural properties are described by SAIL.
- CHIME spectrometer is characterised by numerous contiguous spectral bands providing a vast amount of detailed information but also contain spectral redundancy and noise [Rasti et al., 2018]
- Consequently, ingesting all these bands directly into a MLRA would lead to long training times and suboptimal mapping performances [Rivera-Caicedo et al., 2017, Morales et al., 2021]

Active Learning



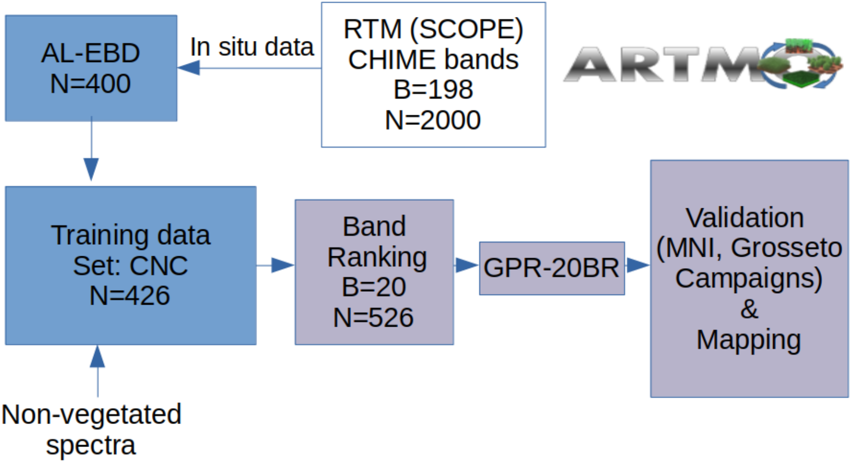
- Active Learning (AL) aims to achieve good results by reducing (and optimizing) the amount of labeled data used for model training
- Consider L the labeled samples set and Y their corresponding outputs
- Active Learning seeks through a criterion which point from U (unlabeled set) would increase the accuracy of the Learning model

Gaussian Processes

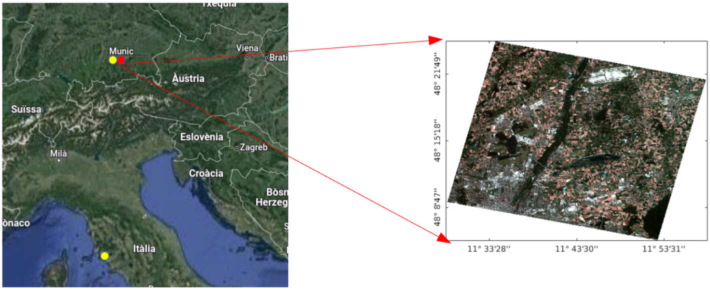


- AL strategy was Euclidean distance-based diversity
- Learning model was Gaussian Process Regression
- Both AL and GPs have been done through ARTMO toolbox! https://artmotoolbox.com/

Workflow


AL-EBD
N=400
In situ data
RTM (SCOPE)
CHIME bands
B=198
N=2000
Training data
Set: CNC
N=426
Band
Ranking
B=20
N=526
GPR-20BR
Validation
(MNI, Grosseto
Campaigns)
&
Mapping
Non-vegetated
spectra

Data set and Experiments



- PRISMA scene of North of Munich, Germany (30/03/2021). The Grosseto and MNI test are also indicated as yellow dots
- U was generated with SCOPE, $N = 2000$ samples
- After AL we obtained an optimal set of $n = 400$ samples
- Simulated reflectance (SCOPE) resampled to match CHIME resolution

Accuracy of the AL procedure

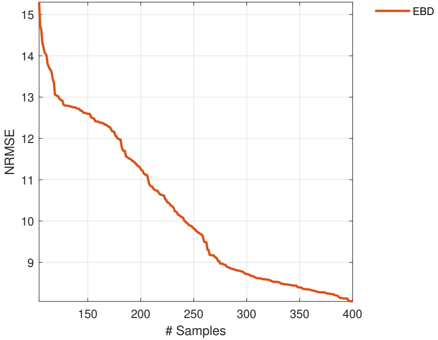


Figure: Normalized root mean squared error (NRMSE) of the AL procedure for the variable CNC

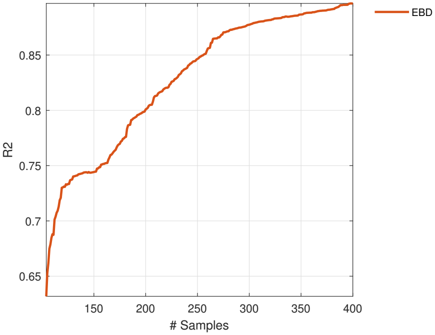


Figure: Coefficient of determination (R^2) of the AL procedure for the variable CNC when increasing the samples

Band Ranking

Band ranking procedure:

1. fit a GP with ARD kernel
2. remove the highest uncertain band according to the model
3. annotate the error, and repeat!

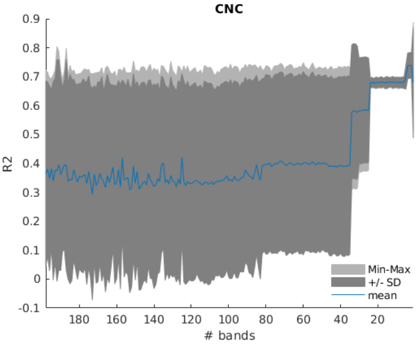


Figure: Results GPR_BR in R^2 terms

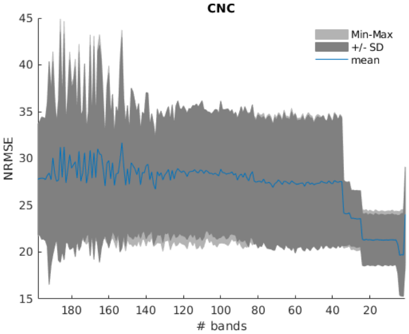


Figure: Results GPR_BR in NRMSE terms

Scatter plot error (Gaussian Process)

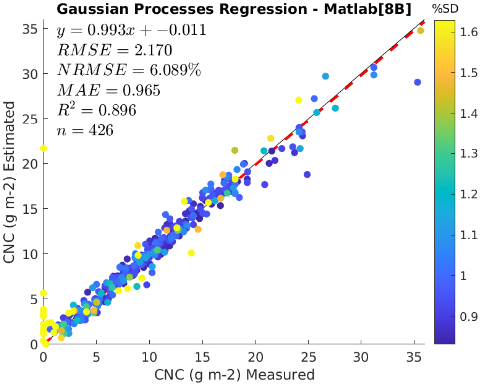


Figure: Scatter plot of CNC measurements against their corresponding estimates through the GPR model.

Estimated & Confidence maps

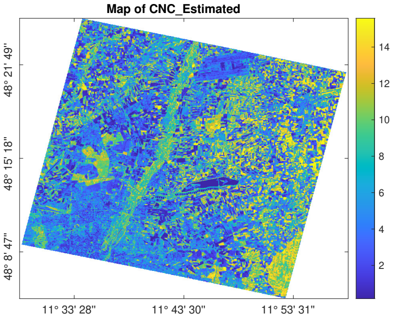


Figure: Estimated map of CNC using GPR Matlab with only 20 bands.

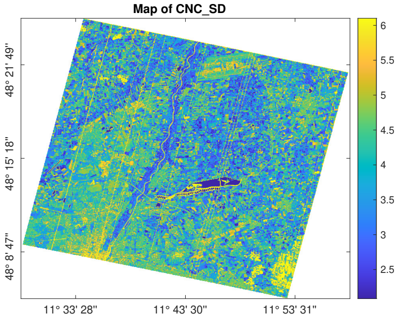


Figure: Confidence map of CNC using GPR Matlab with only 20 bands

Conclusions & Future work

- General applicability of the retrieval models and processing of hyperspectral PRISMA scene was achieved
- Results achieved in validation with in-situ data are promising
- Validity of the proposal to achieve good performance in the upcoming CHIME (mission)
- The usage of GPR provides associated uncertainties together with the estimates, which supports confidence when transferring the developed models
- In a future study, more variables can be included in the study along whit the use of time series of PRISMA imagery

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- Thank you for your attention!!

References I

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