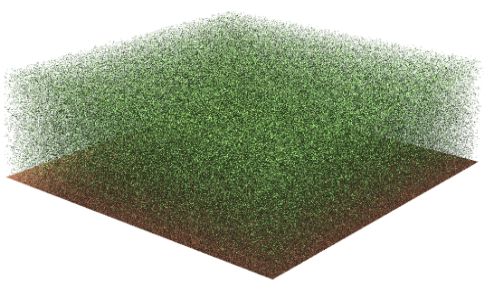
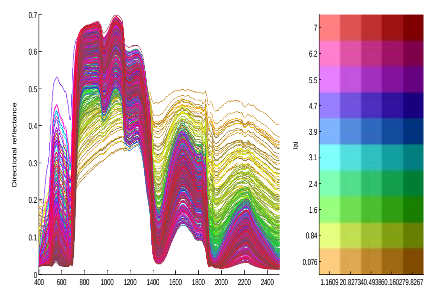
From model simulations towards vegetation properties mapping:

automating, optimizing & simplifying

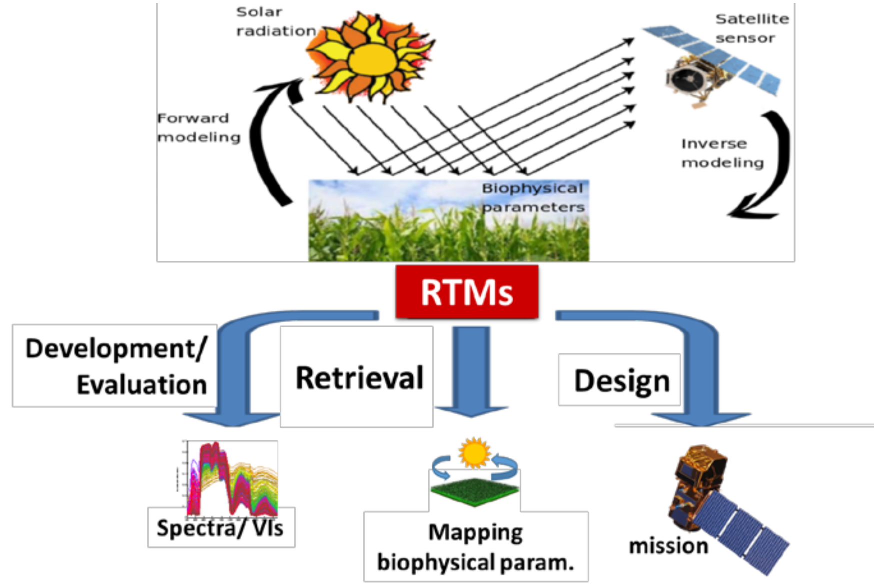




J. Verrelst, J.P. Rivera & J. Moreno

ISSI Workshop – 21-25 Nov2016

Background

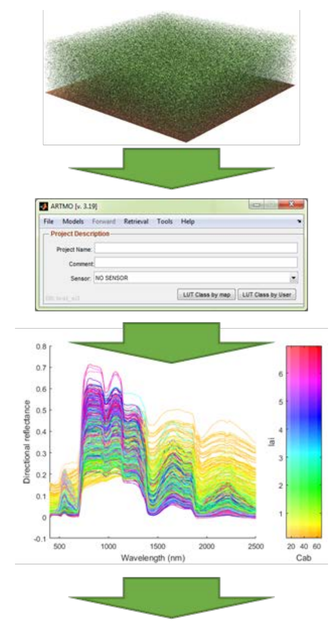


AUTOMATING RTMs

- RTMs
- ARTMO/forward
- Retrieval toolboxes

OPTIMIZING exploiting spectroscopy data

- Retrieval
- Band selection
- Dimensionality & sample reduction

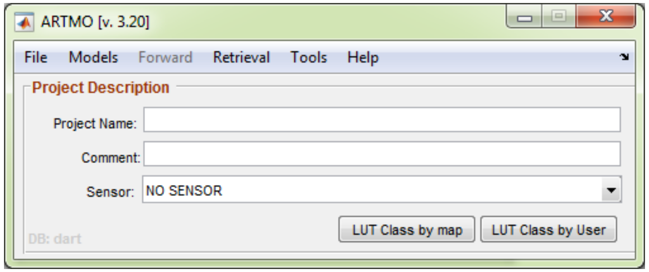


SIMPLIFYING RTMs

- Global sensitivity analysis
- Emulation
- Retrieval

AUTOMATING

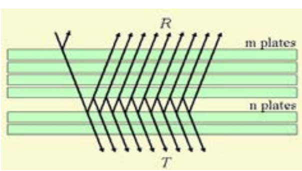
- RTMs
- ARTMO/forward
- Retrieval toolboxes



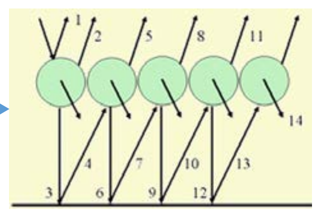
Radiative transfer models (RTMs)

Leaf RTMs

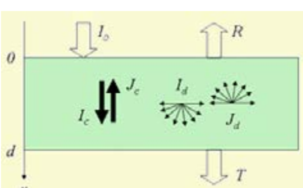
layers



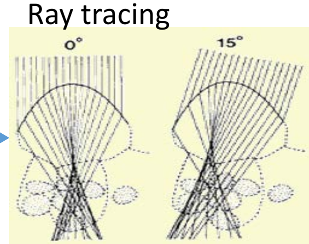
Compact spheres



N-fluxes

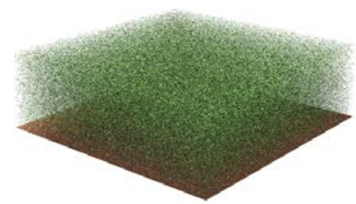


Ray tracing

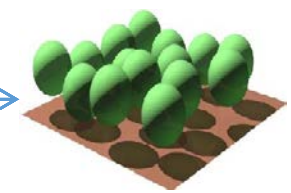


Canopy RTMs

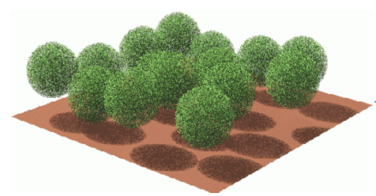
Turbid medium



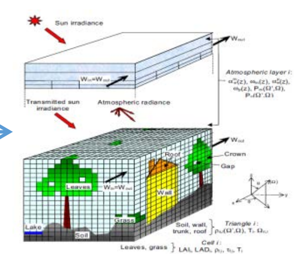
Geometric



Hybrid



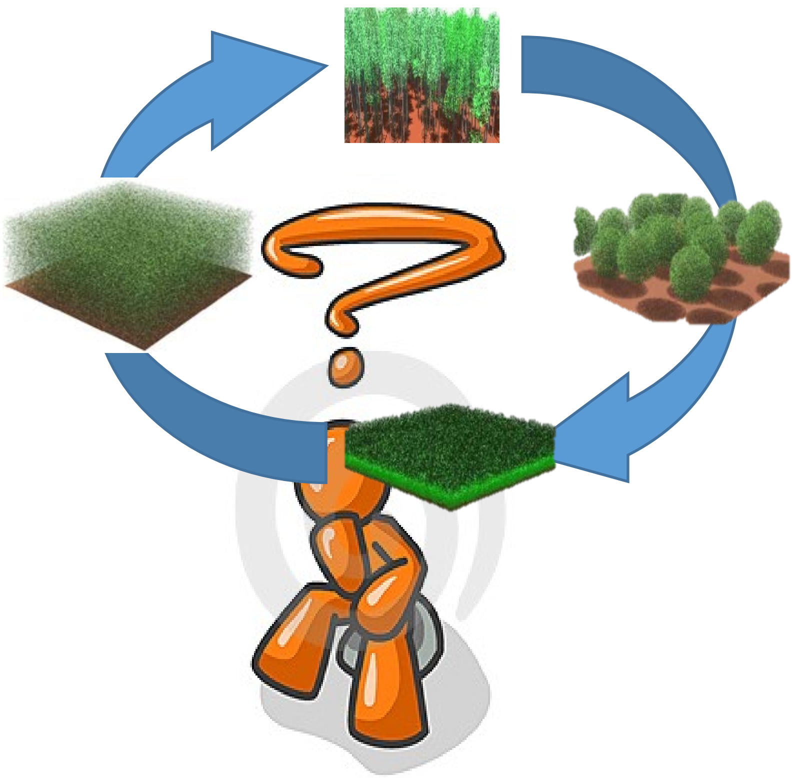
Volumetric



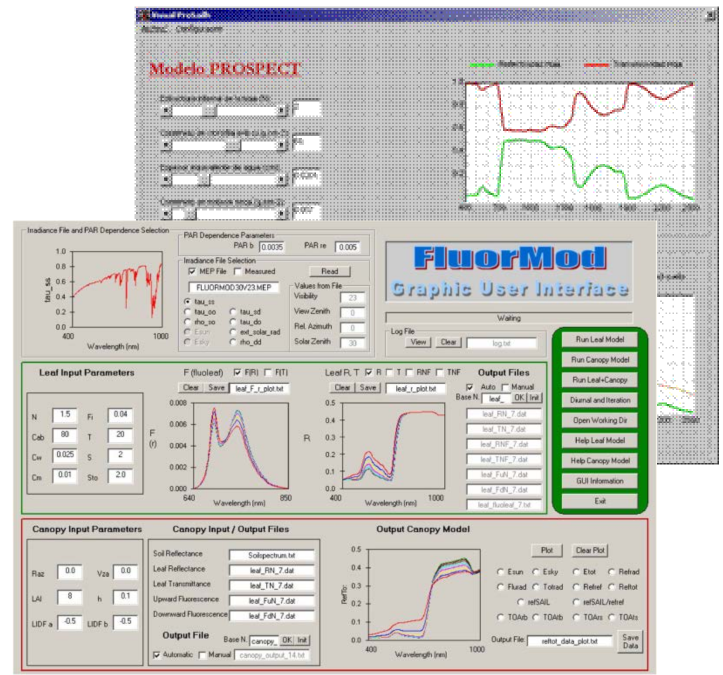
A diversity of RTMs exist with different complexity.

RTMs are important tools in EO research, but not always easy to use. Only very few of them offer user-friendly interfaces.

Which RTM to choose?



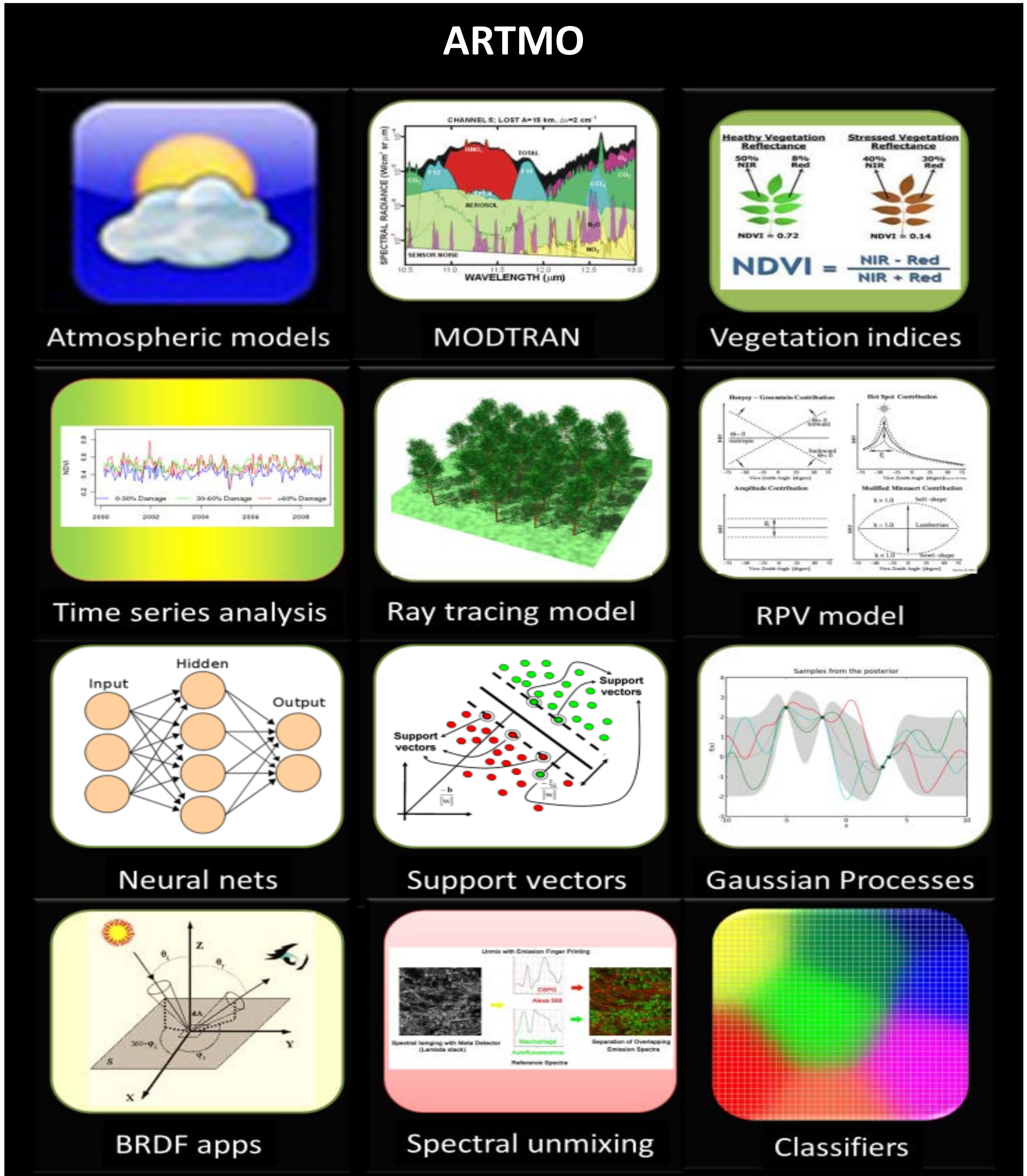
Only very few offer a GUI.



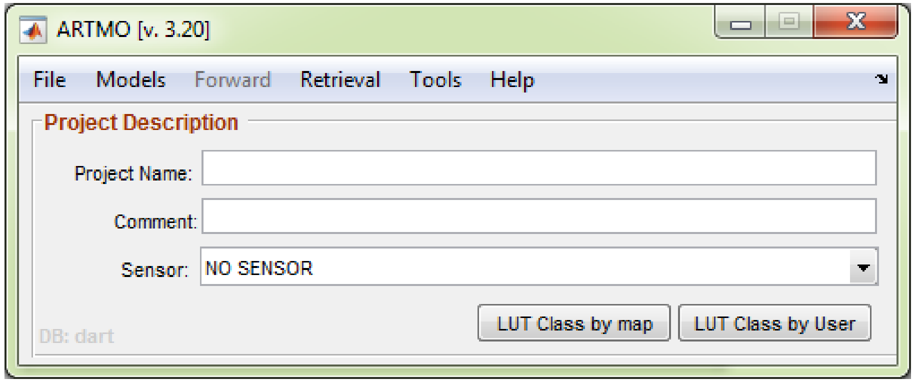
- **No interface exists that brings multiple RTMs together in one GUI.**
- **None of existing (publicly available) GUIs provide post-processing tools.**

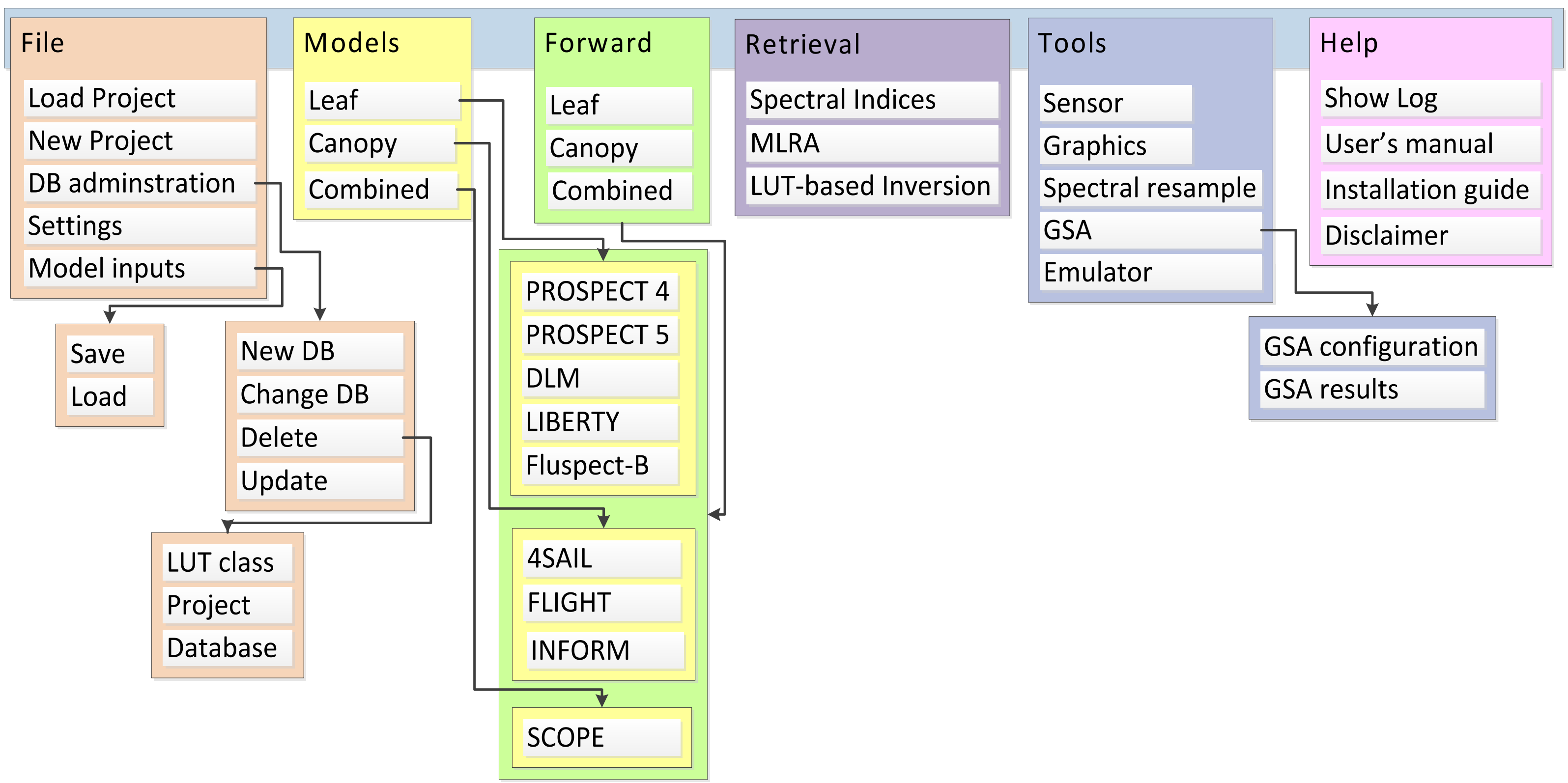
Toolbox for EO applications:

Automated
Radiative
Transfer
Models
Operator

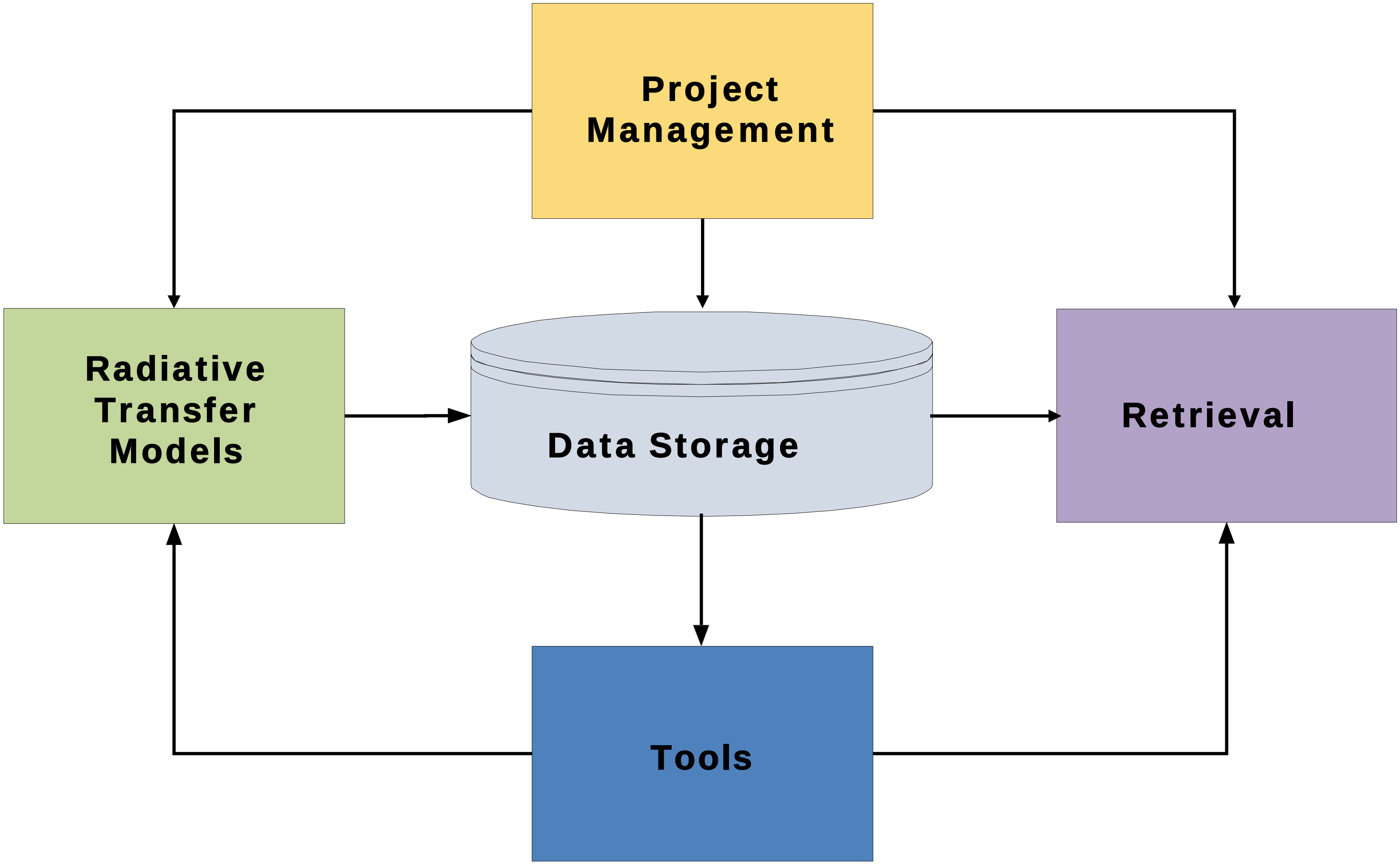

ARTMO
Atmospheric models
MODTRAN
WAVELENGTH (μm)
SPECTRAL RADIANCE
Heathy Vegetation Reflectance
Stressed Vegetation Reflectance
NDVI = 0.72
NDVI = 0.14
NDVI = NIR - Red / NIR + Red
Vegetation indices
Time series analysis
Ray tracing model
RPV model
Input
Hidden
Output
Neural nets
Support vectors
Support vectors
Support vectors
Samples from the posterior
Gaussian Processes
BRDF apps
Spectral unmixing
Classifiers

ARTMO v. 3: modular design

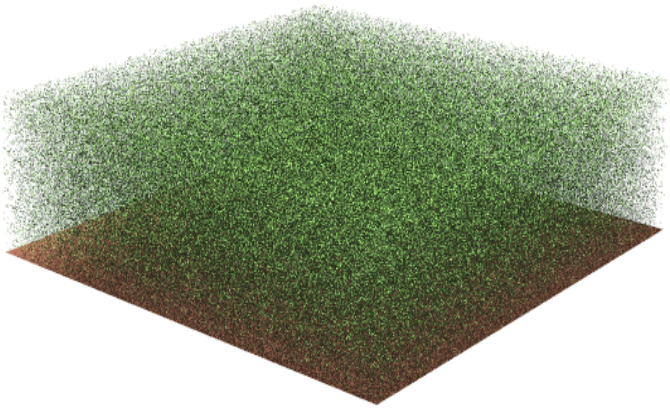


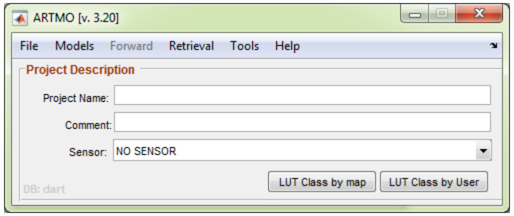


Conceptual architecture ARTMO



Forward




ARTMO [v. 3.20]
File
Models
Forward
Retrieval
Tools
Help
Project Description
Project Name:
Comment:
Sensor:
NO SENSOR
LUT Class by map
LUT Class by User
DB: dart

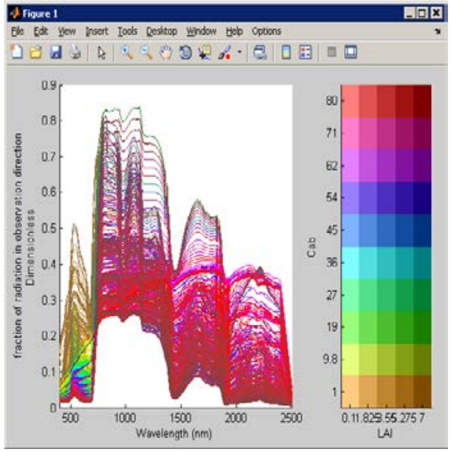
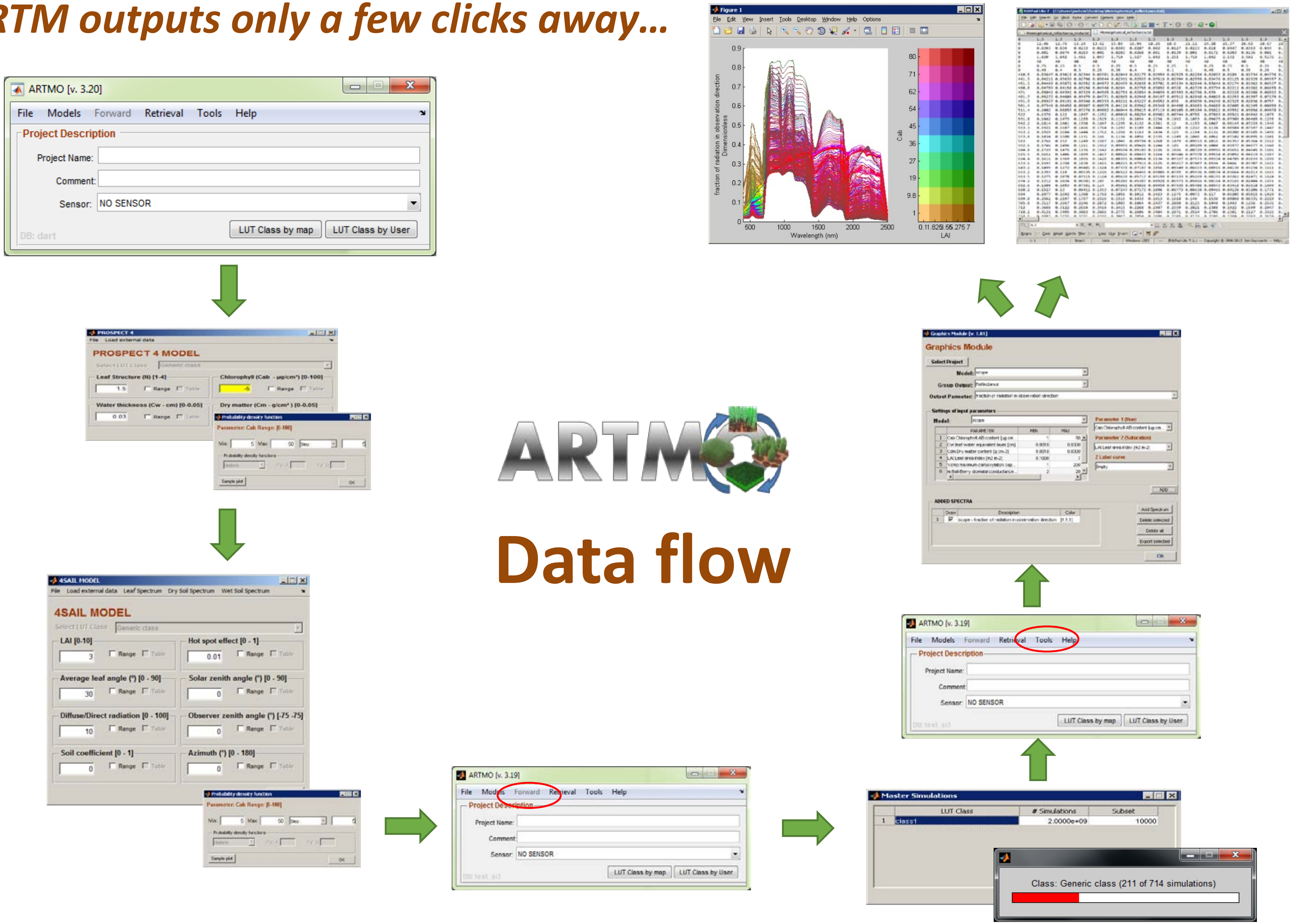


Figure 1
File Edit View Insert Tools Desktop Window Help Options
fraction of radiation in observation direction
Dimensionless
Wavelength (nm)
Cab
LAI

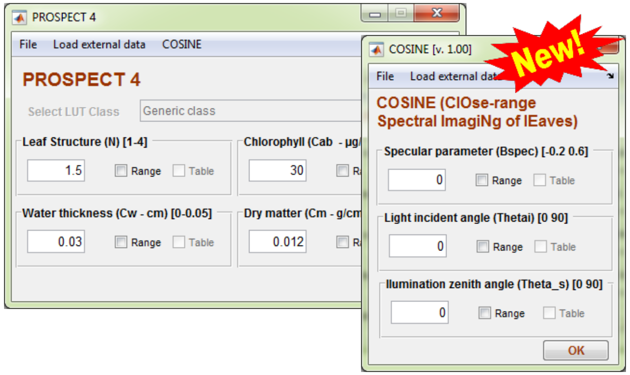
RTM outputs only a few clicks away…



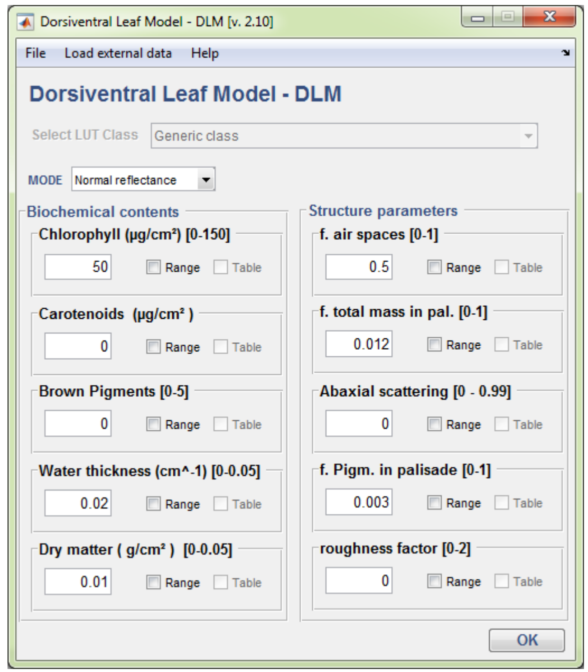
Radiative Transfer Models

ARTMO’s leaf models

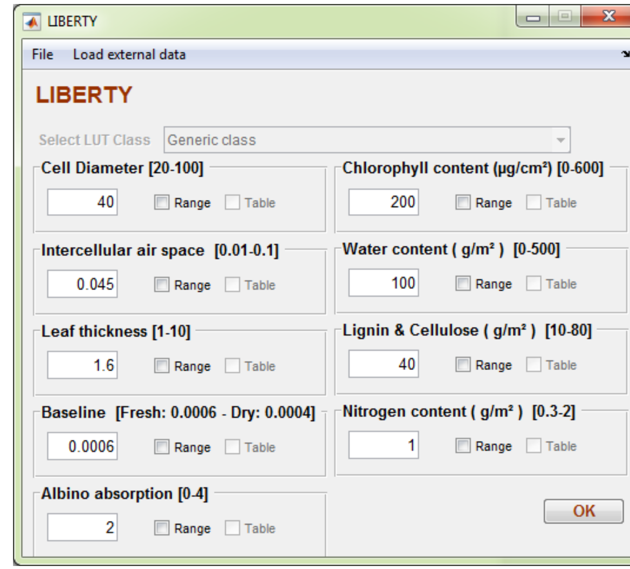
PROSPECT-4



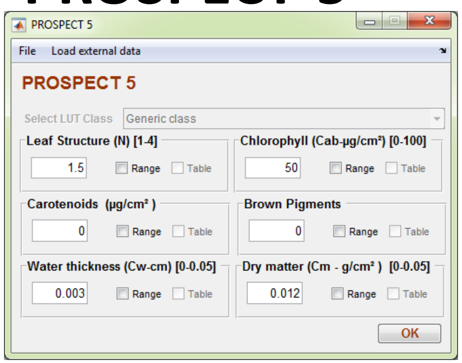
DLM



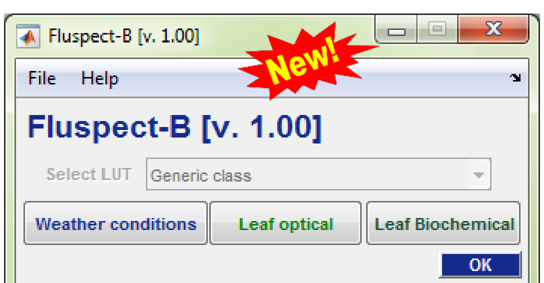
LIBERTY

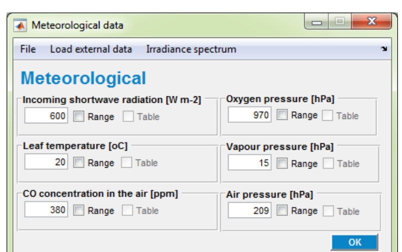


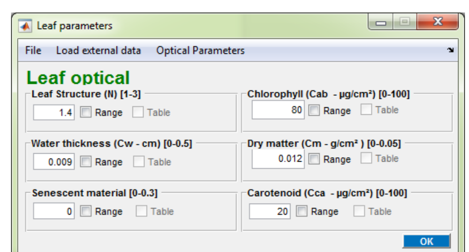
PROSPECT-5

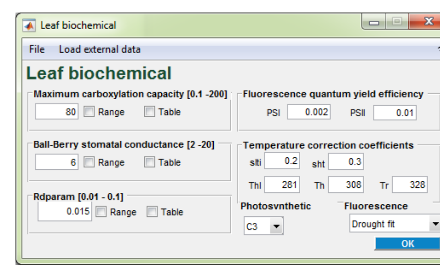


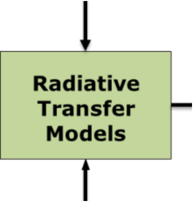
Fluspect-B





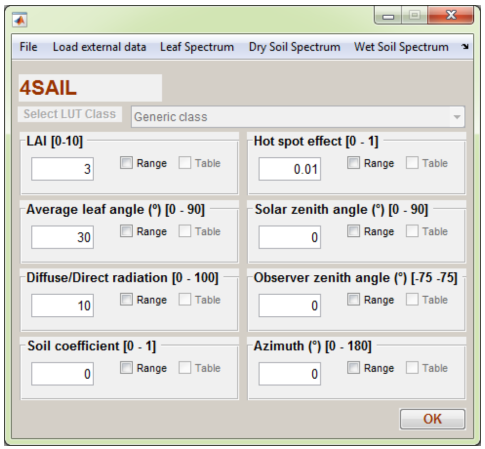




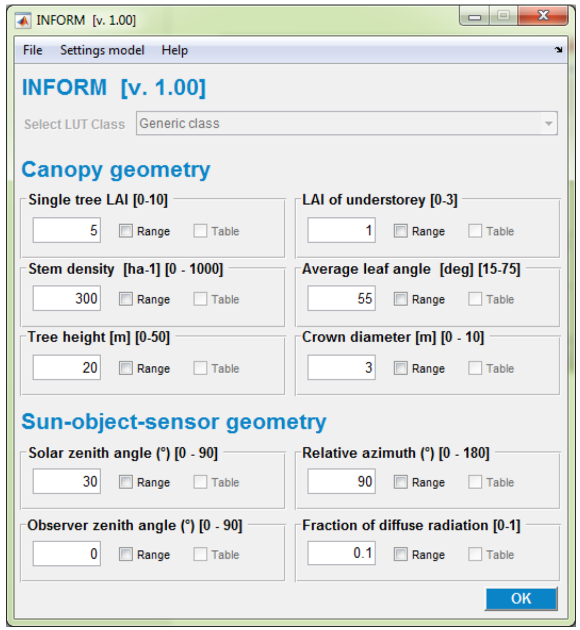


ARTMO's canopy models

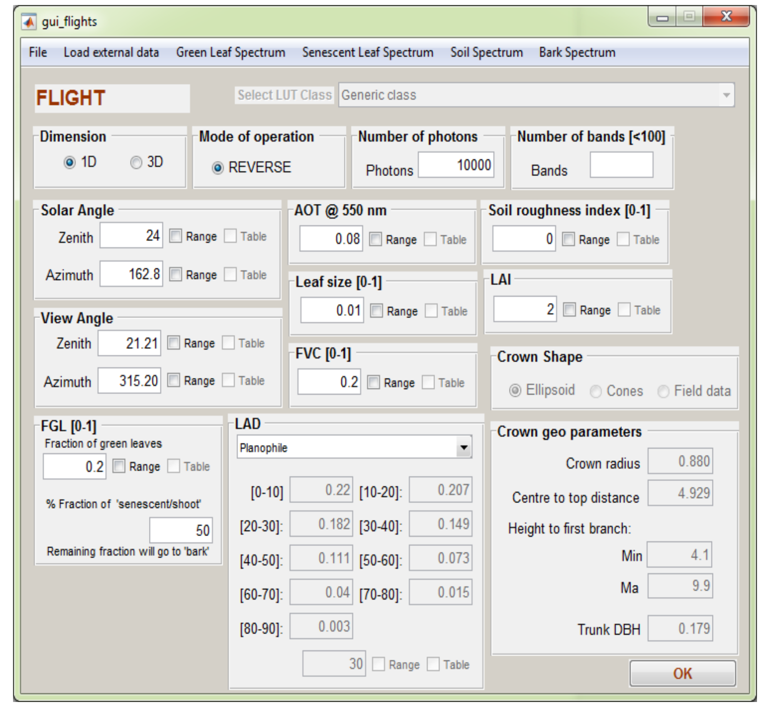
SAIL



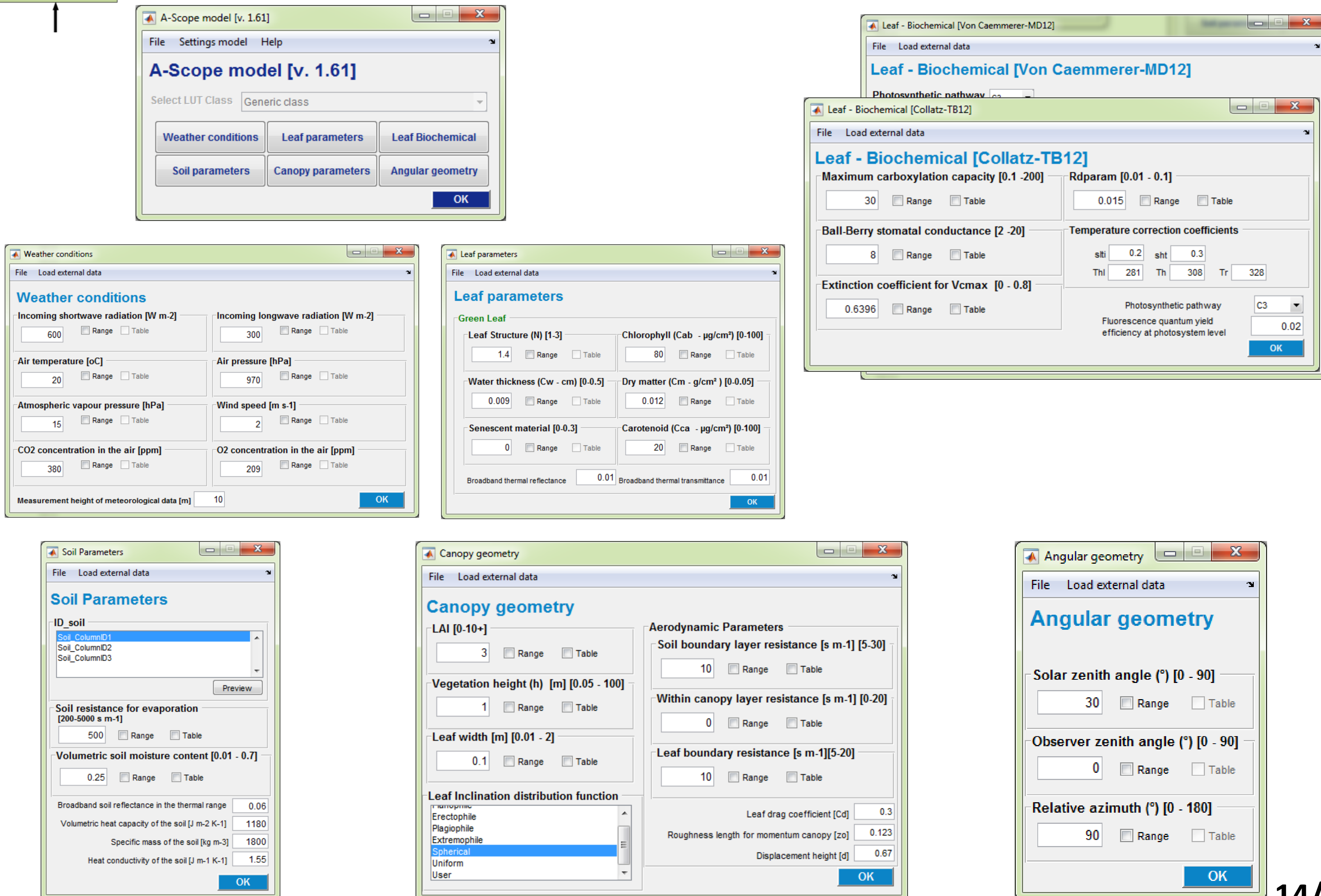
INFORM

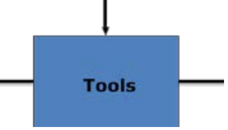


FLIGHT



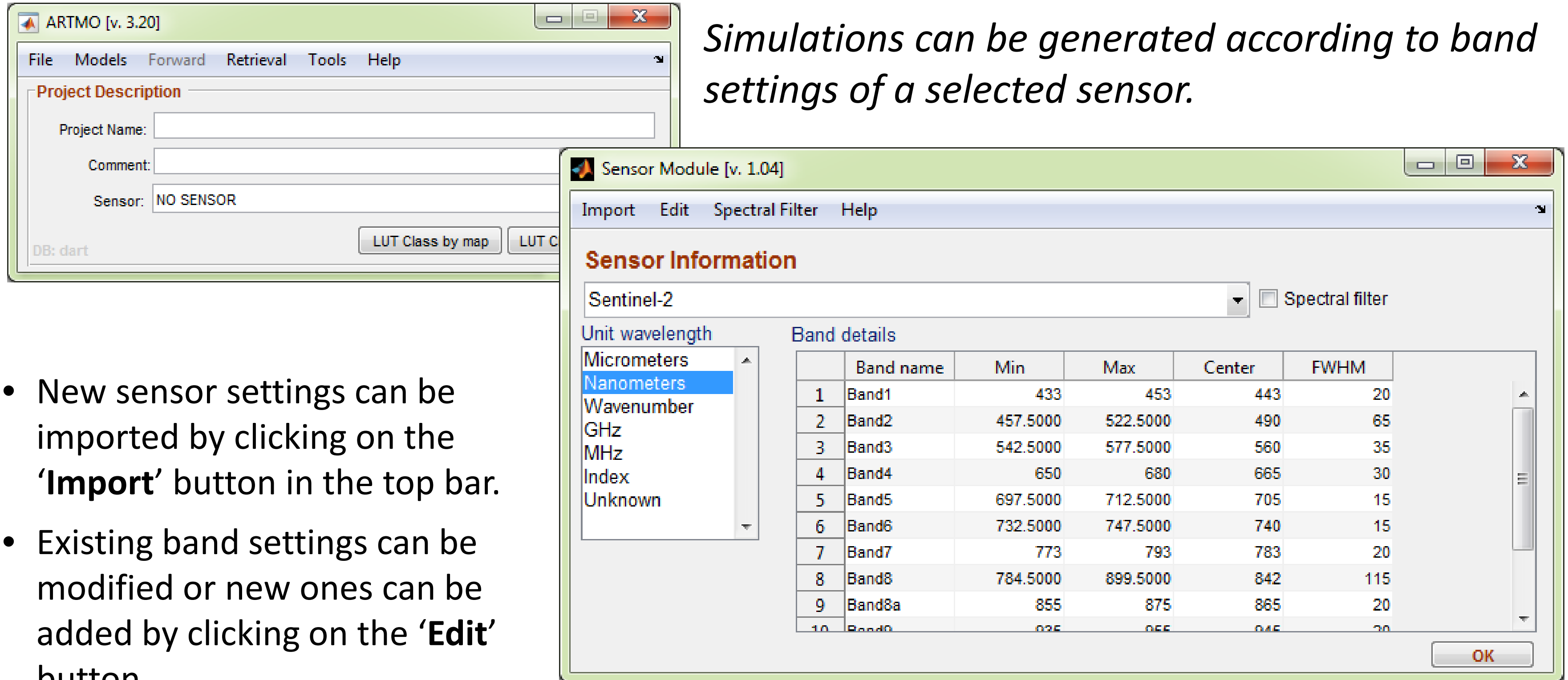
ARTMO's combined models: SCOPE





Sensor

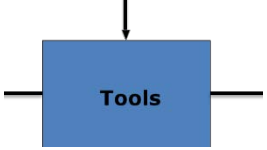
Simulations can be generated according to band settings of a selected sensor.



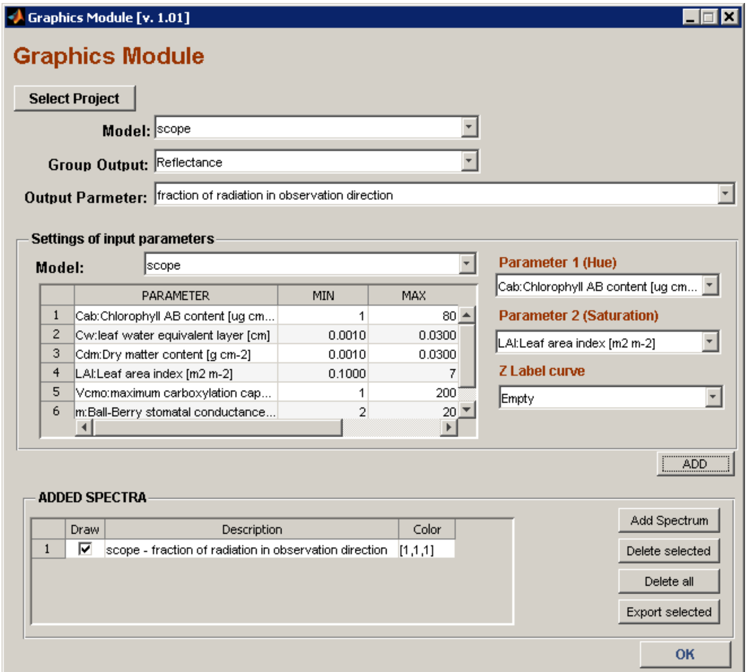
- New sensor settings can be imported by clicking on the '**Import**' button in the top bar.
- Existing band settings can be modified or new ones can be added by clicking on the '**Edit**' button.
- Also a spectral filter of a sensor can be imported or viewed by clicking on the '**Spectral Filter**' button.

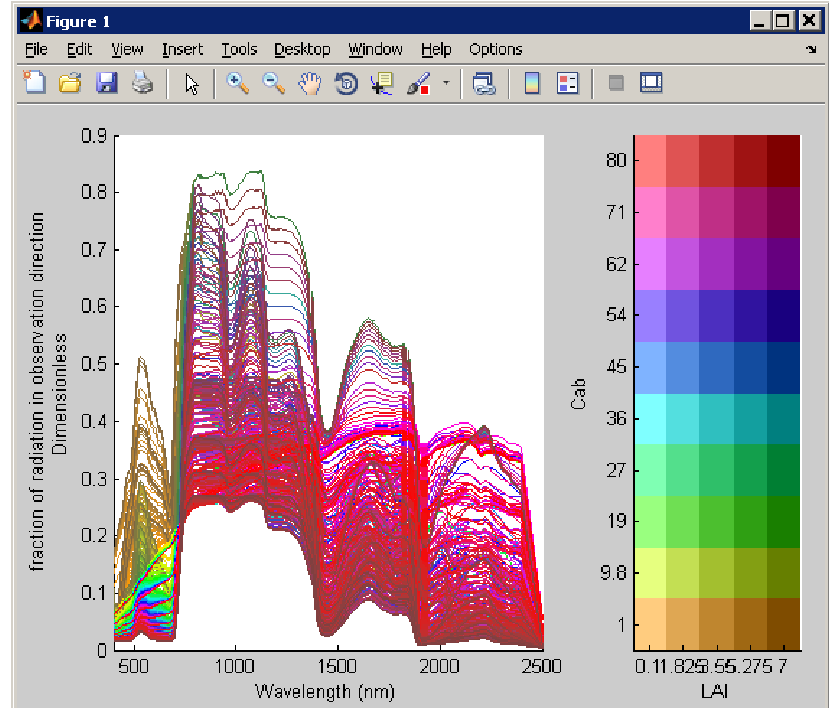
Default sensors:

- Landsat 7 TM
- Landsat 7 ETM+
- SPOT-4 VMI
- SPOT-4 HRVIR
- CHRIS Mode-3
- MODIS
- MERIS
- Sentinel-2
- Sentinel-3 OLCI
- Sentinel-3 SLSTR
- Landsat 8
- Pleiades-1A
- Quickbird

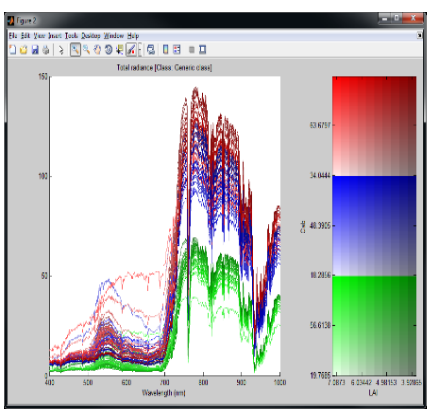


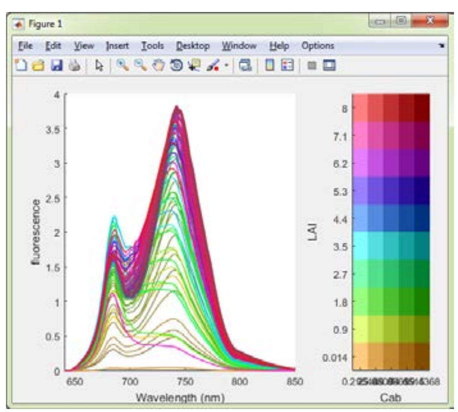
Graphics





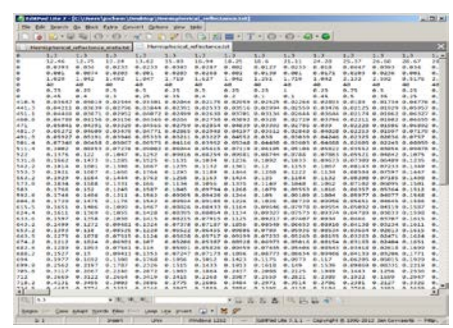
Visualization options:



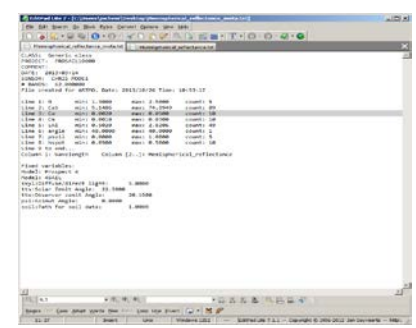


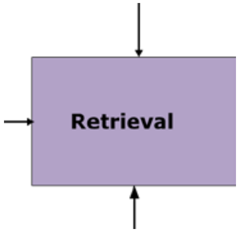
Export:

Spectral data

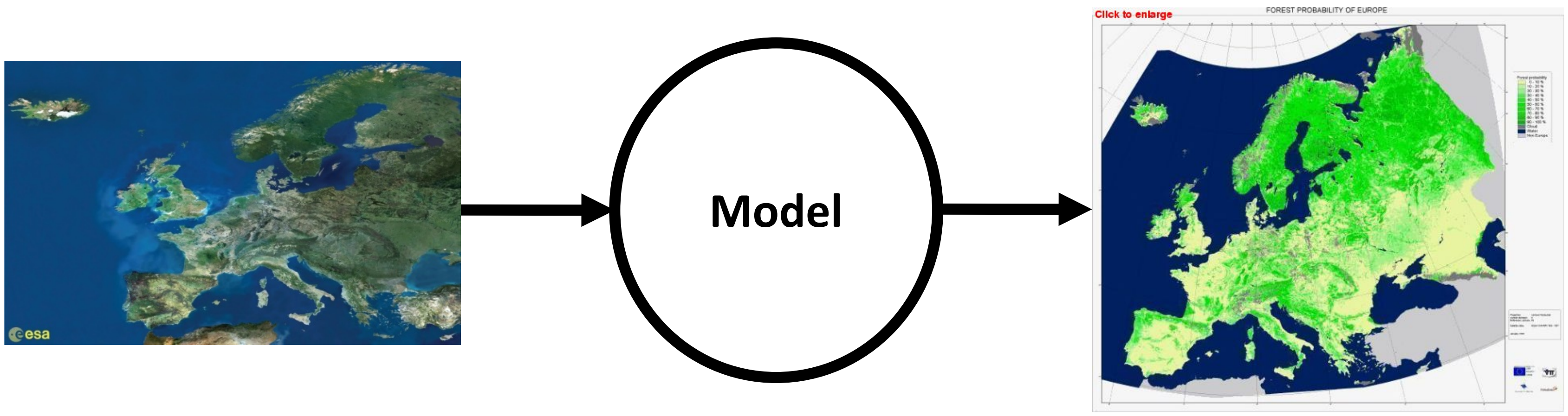


Associated metadata




Retrieval

Retrieval

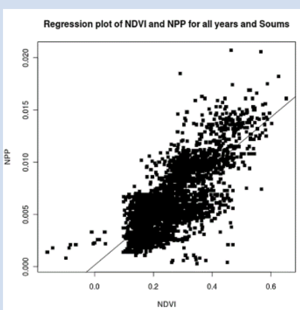

esa
Model
Click to enlarge
FOREST PROBABILITY OF EUROPE

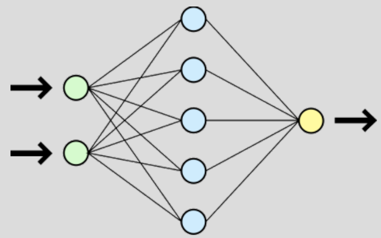
Retrieval families

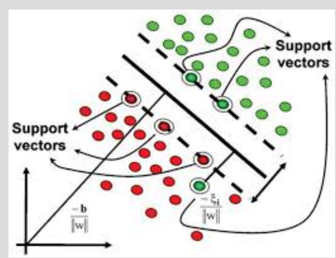
Parametric regression	Non-parametric regression	RTM inversion
Spectral relationships that are sensitive to specific vegetation properties	Advanced techniques that search for relationships between spectral data and biophysical variables	Models that simulate interactions between vegetation and radiation

$$NDVI = \frac{(\rho_{NIR} - \rho_{RED})}{(\rho_{NIR} + \rho_{RED})}$$

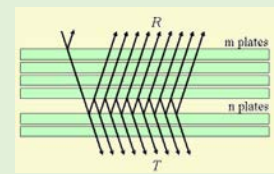
Normalized Difference Vegetation Index

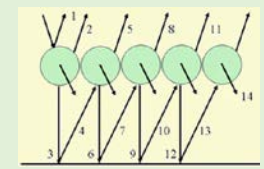




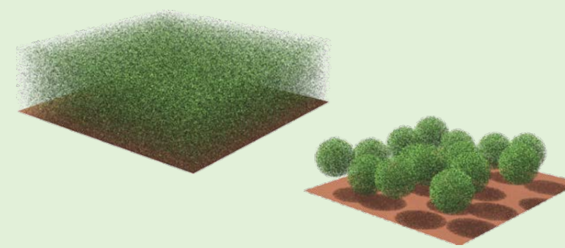


leaf

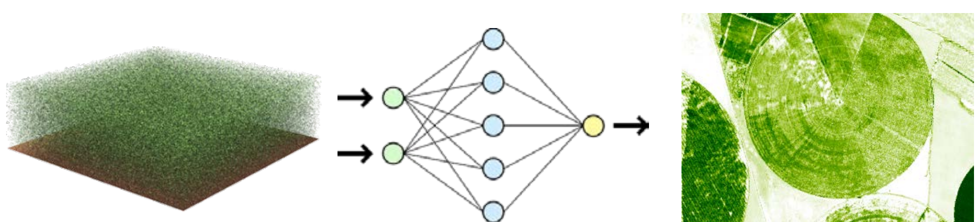




canopy

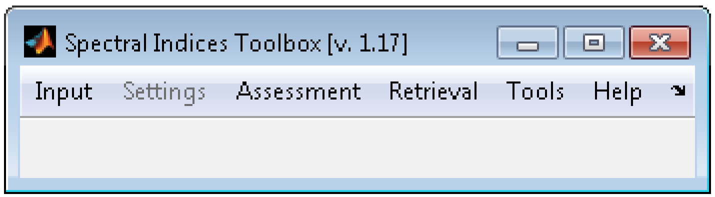


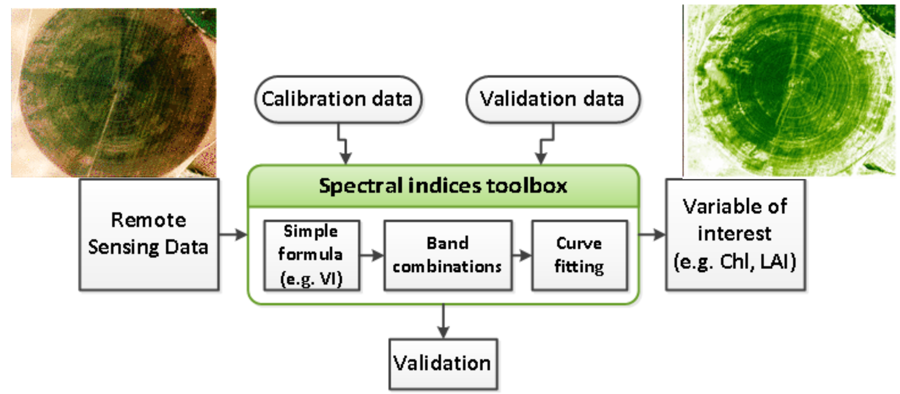
Methods of these different families can be combined: *hybrid methods*



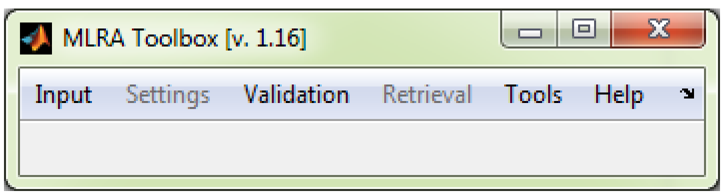
ARTMO's retrieval toolboxes:

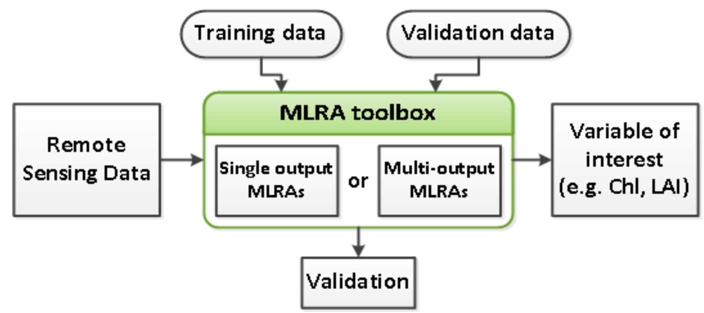
Spectral indices toolbox



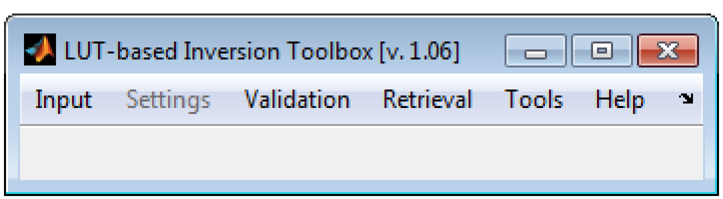


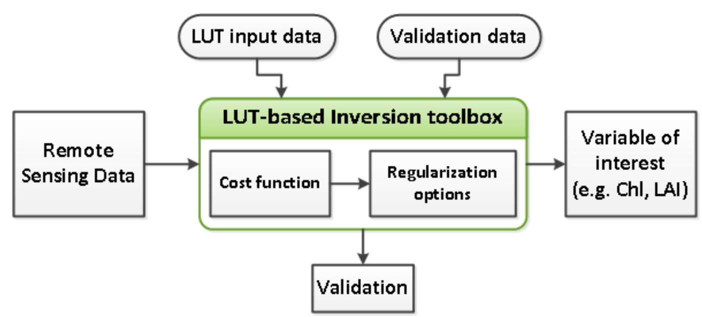
Machine learning regression algorithm toolbox





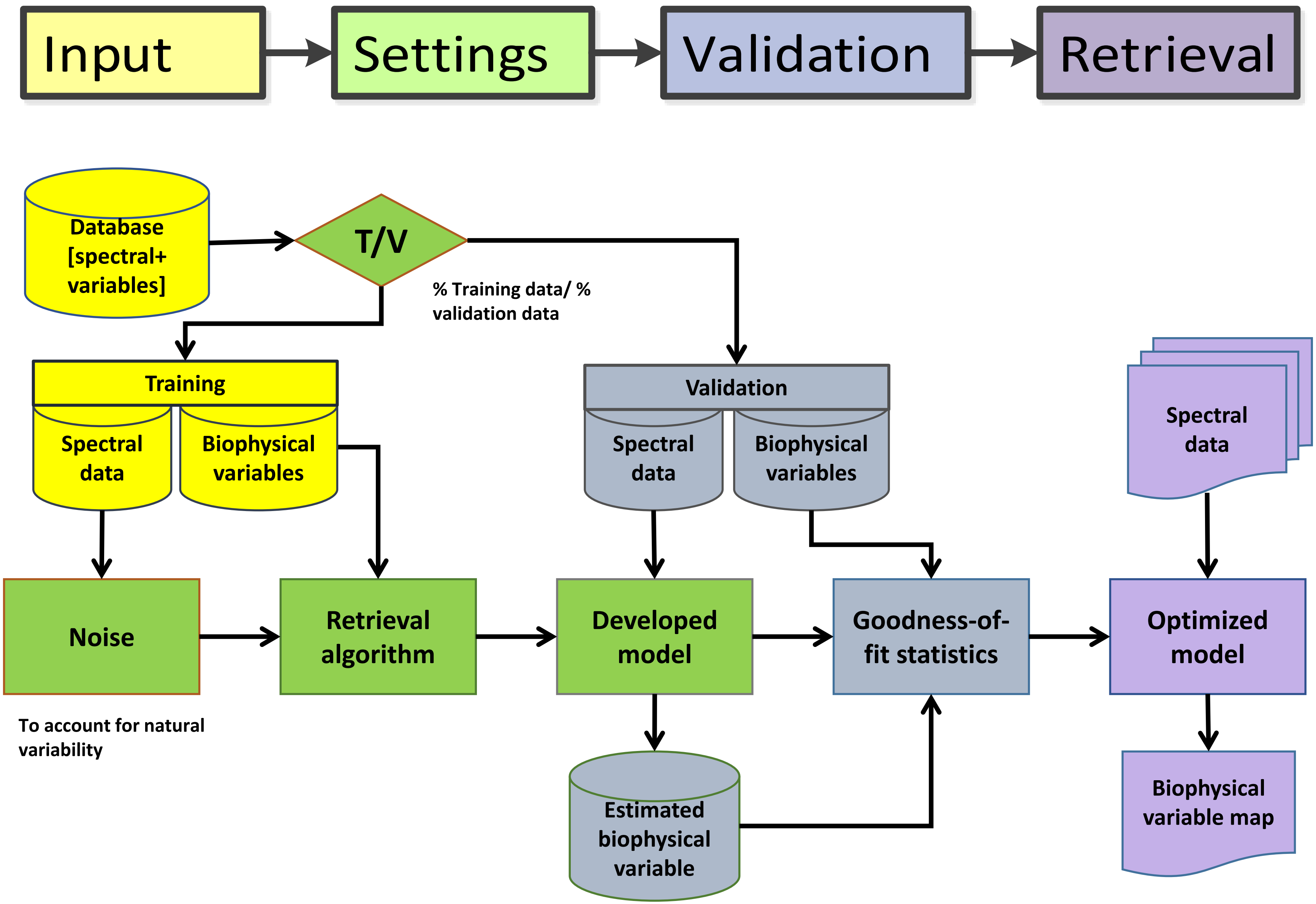
LUT-based inversion toolbox





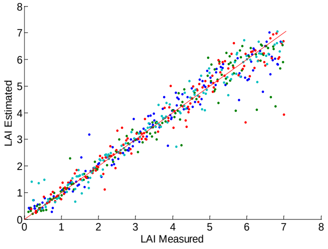
Optimizing and generating maps of vegetation properties only a few clicks away…

General structure:

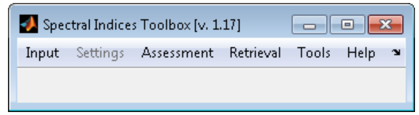


OPTIMIZING

- Retrieval: parametric/non-parametric/inversion
- Band selection
- Dimensionality & sample reduction

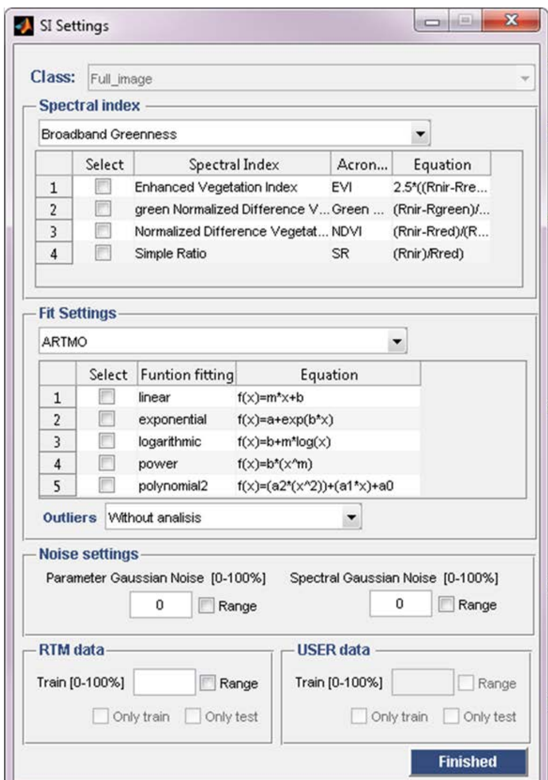


Spectral indices toolbox:



Properties:

- Calculates all possible band combinations.
- For index formulations with up to 10-band indices (#b[10], for a 10-band sensor that would be 10 billion combinations)
- Includes multiple fitting functions (linear, exponential, logarithmic, power, polynomial)
- Noise & Cross-validation options
- Results stored in MySQL
- Top-performing indices per formulation and fitting function are given.
- Can process both image or individual spectra.



If active, configure per land cover class.

Select an Index group

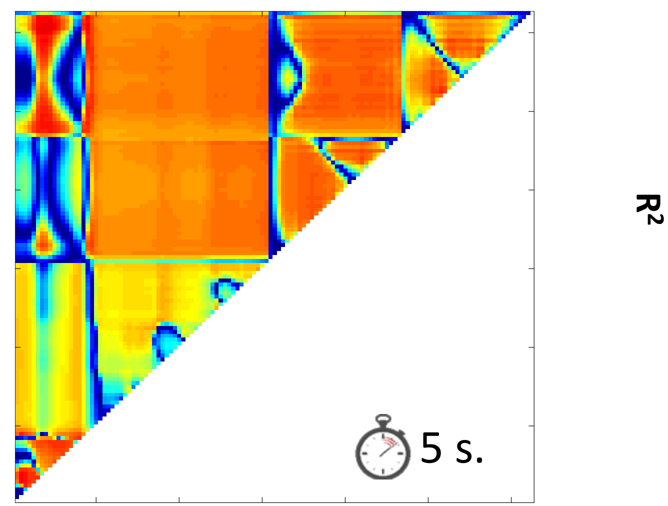
Select one or multiple indices

Select one or multiple curve fittings

Options to add noise

Option to mix RTM with field observations

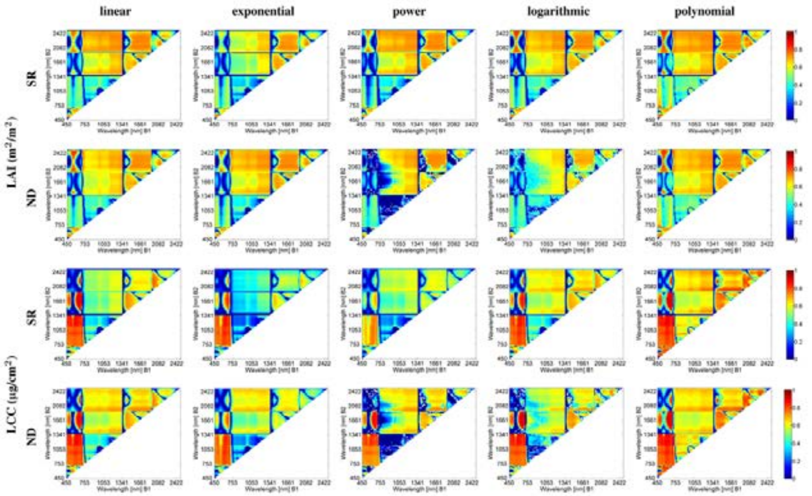
SPARC – HyMap - LAI

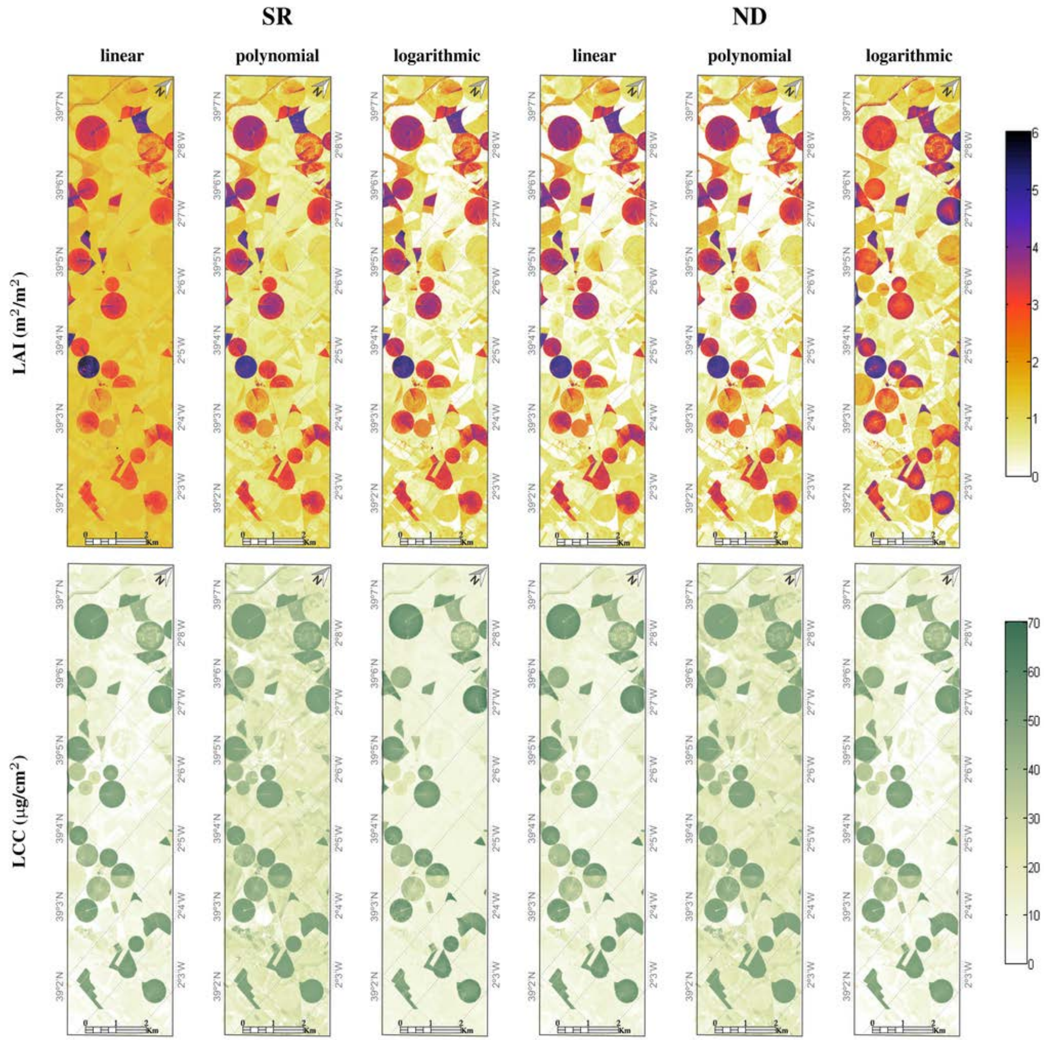


Best-performing index can be applied to an image.

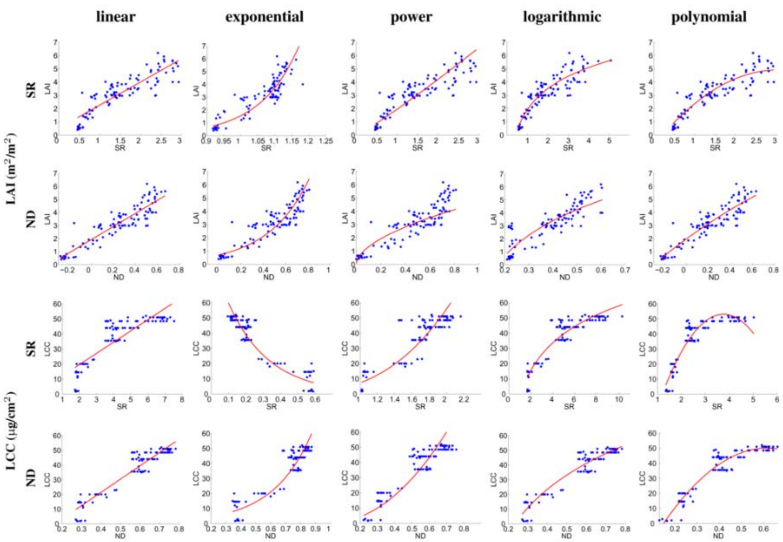
SPARC dataset (Barrax Spain); HyMap data

SR and ND for different fitting functions



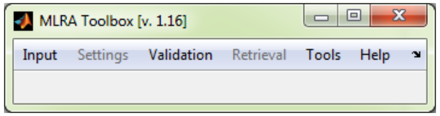


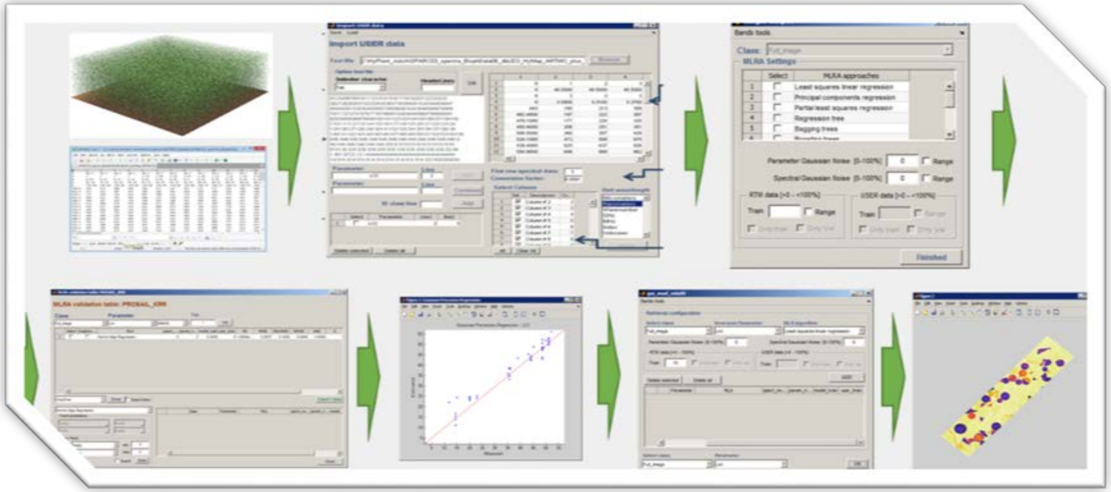
Best performing model.



- **Which VI method is most correct?**
- **Why restricting to a few bands only?**

Machine learning regression algorithm toolbox



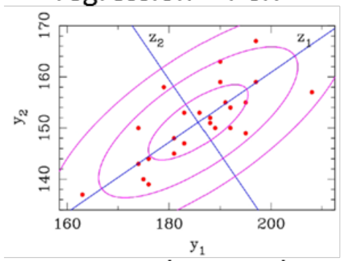


Simpler to execute than SI: no band selection needed.

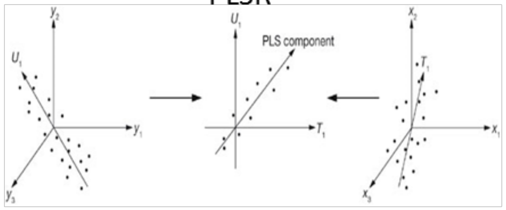
Properties:

- **About 15 MLRAs implemented**
- **Single-output & multi-output**
- **Noise & Cross-validation options**
- **Dimensionality reduction options**
- **Results stored in MySQL**
- **GPR properties: band relevance & uncertainties**
- **Can process both images or individual spectra.**
- **Active learning, GPR-BAT, dim. reduction**

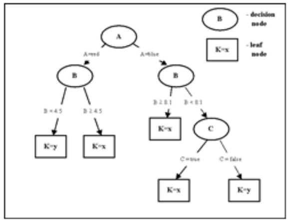
Principal component regression – PCR



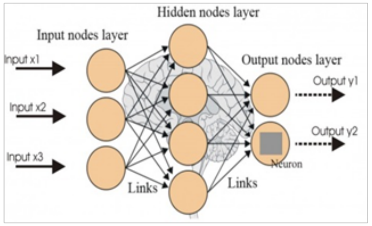
Partial least squares regression PLSR



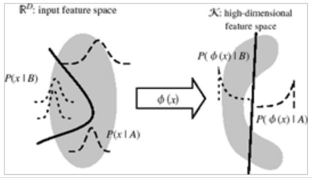
Decision Trees – DT



Neural networks NN

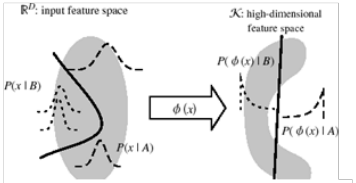


Kernel ridge regression KRR



$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2 / (2\sigma^2)).$$

Gaussian processes regression GPR



$$K(\mathbf{x}_i, \mathbf{x}_j) = \nu \exp\left(-\sum_{b=1}^{B} \frac{\left(\mathbf{x}_i^{(b)} - \mathbf{x}_j^{(b)}\right)^2}{2\sigma_b^2}\right)$$

Non-parametric models:

- **SimpleR** [Camps-Valls et al., 2013]
- http://www.uv.es/gcamps/code/simpleR.html

Also:

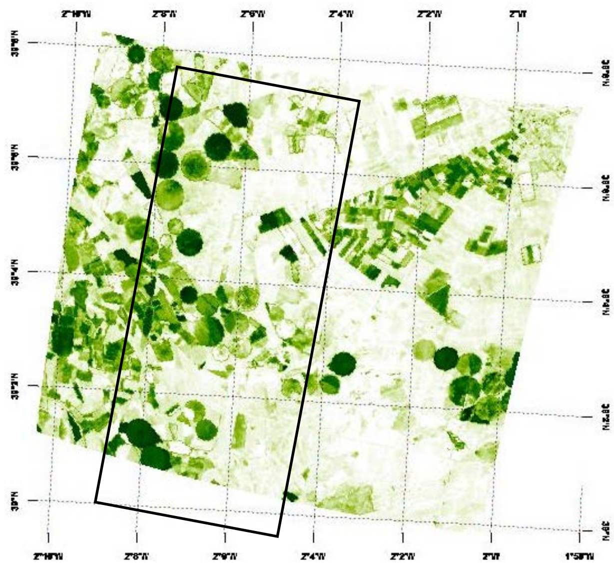
- **Bagging trees (BAGTREE)**
- **Boosting trees (BOOST)**
- **Neural networks (NN)**
- **Extreme Learning Machines (ELM)**
- **Support Vector Regression (SVR)**
- **Relevance Vector Machine (RVM)**
- **Variational Heteroscedastic Gaussian Process Regression (VHGPR)**

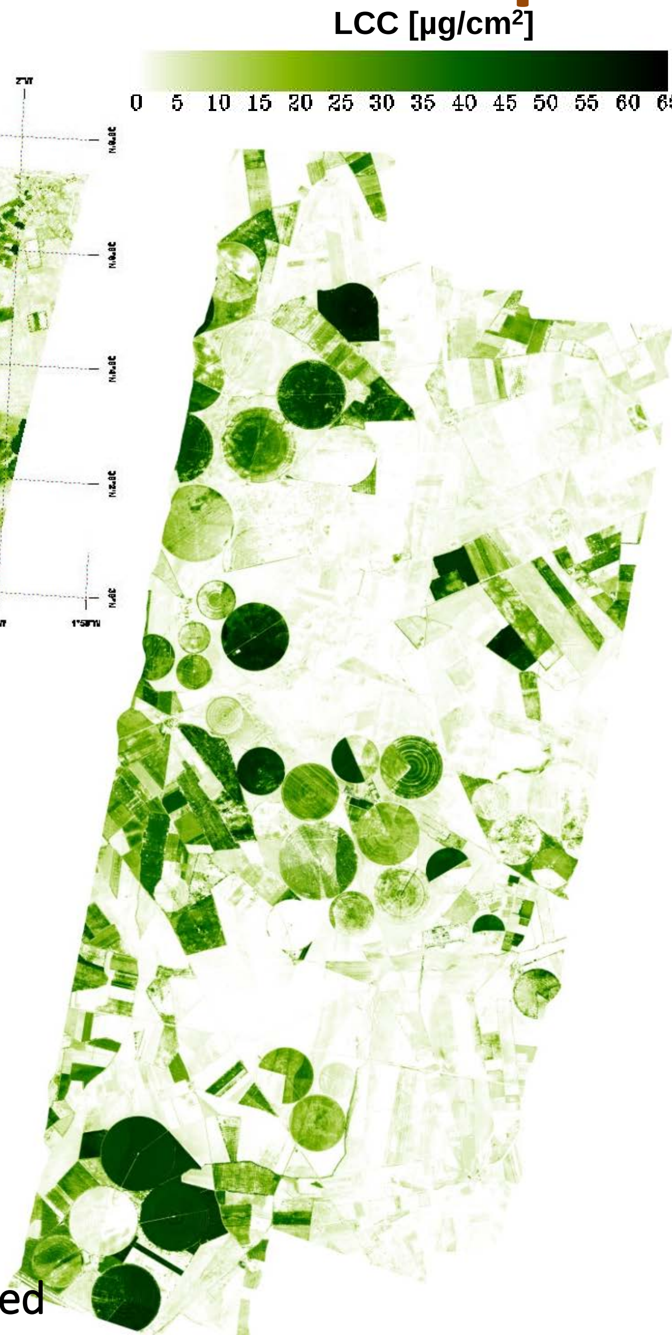
GPR in Bayesian framework also provides:

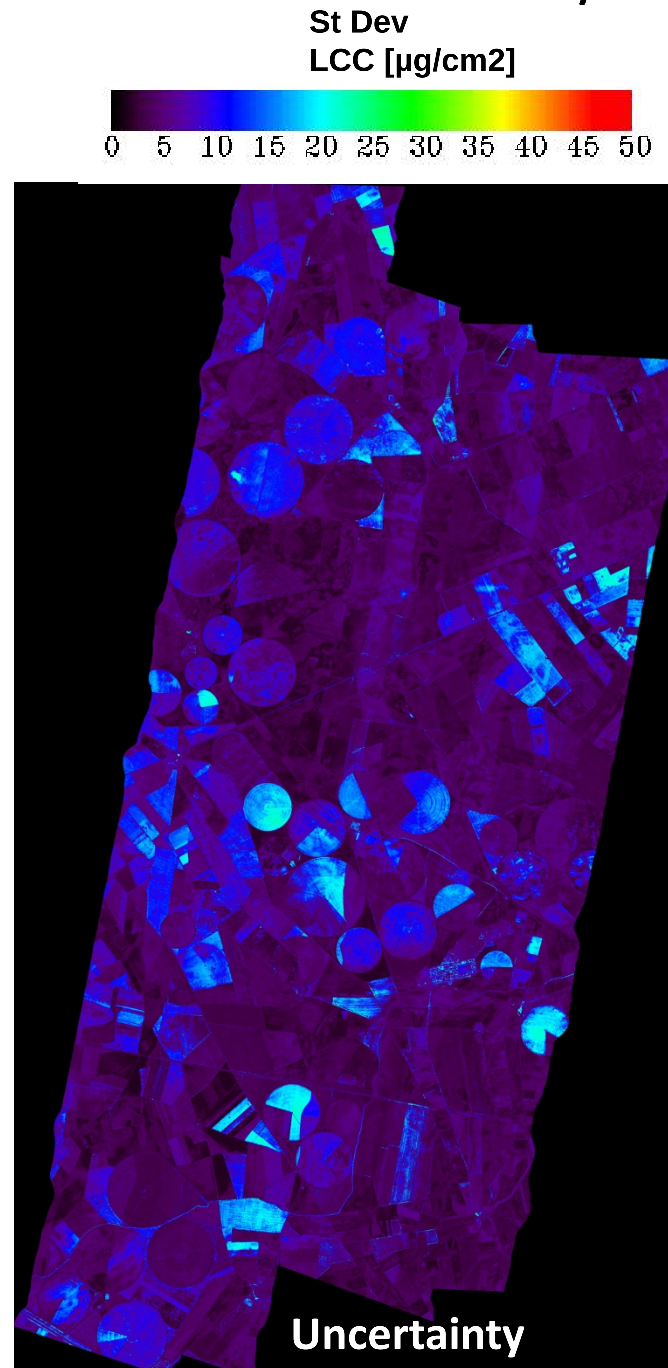
- **Band relevance**
- **Uncertainty estimates**

GPR maps

CHRIS



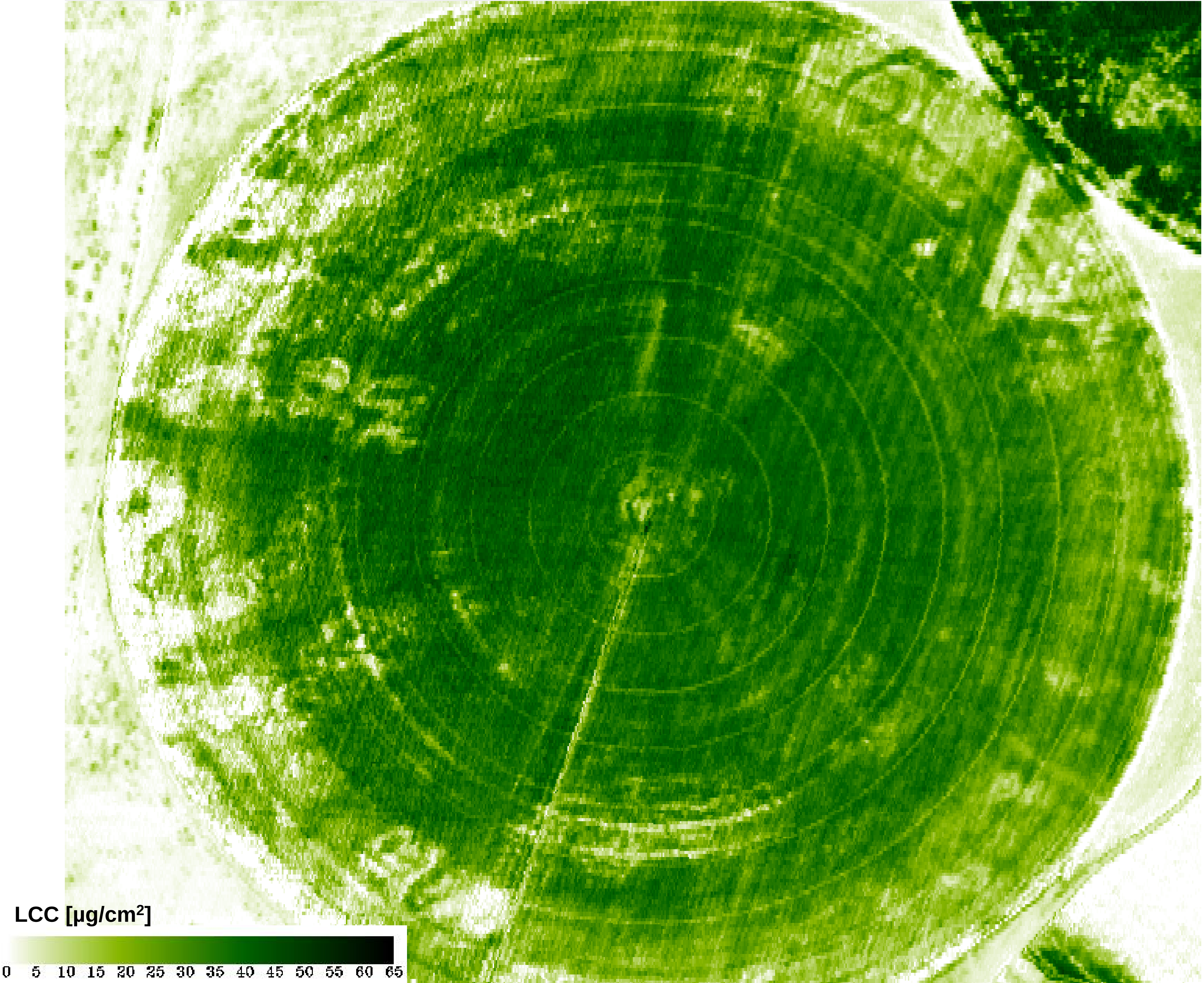


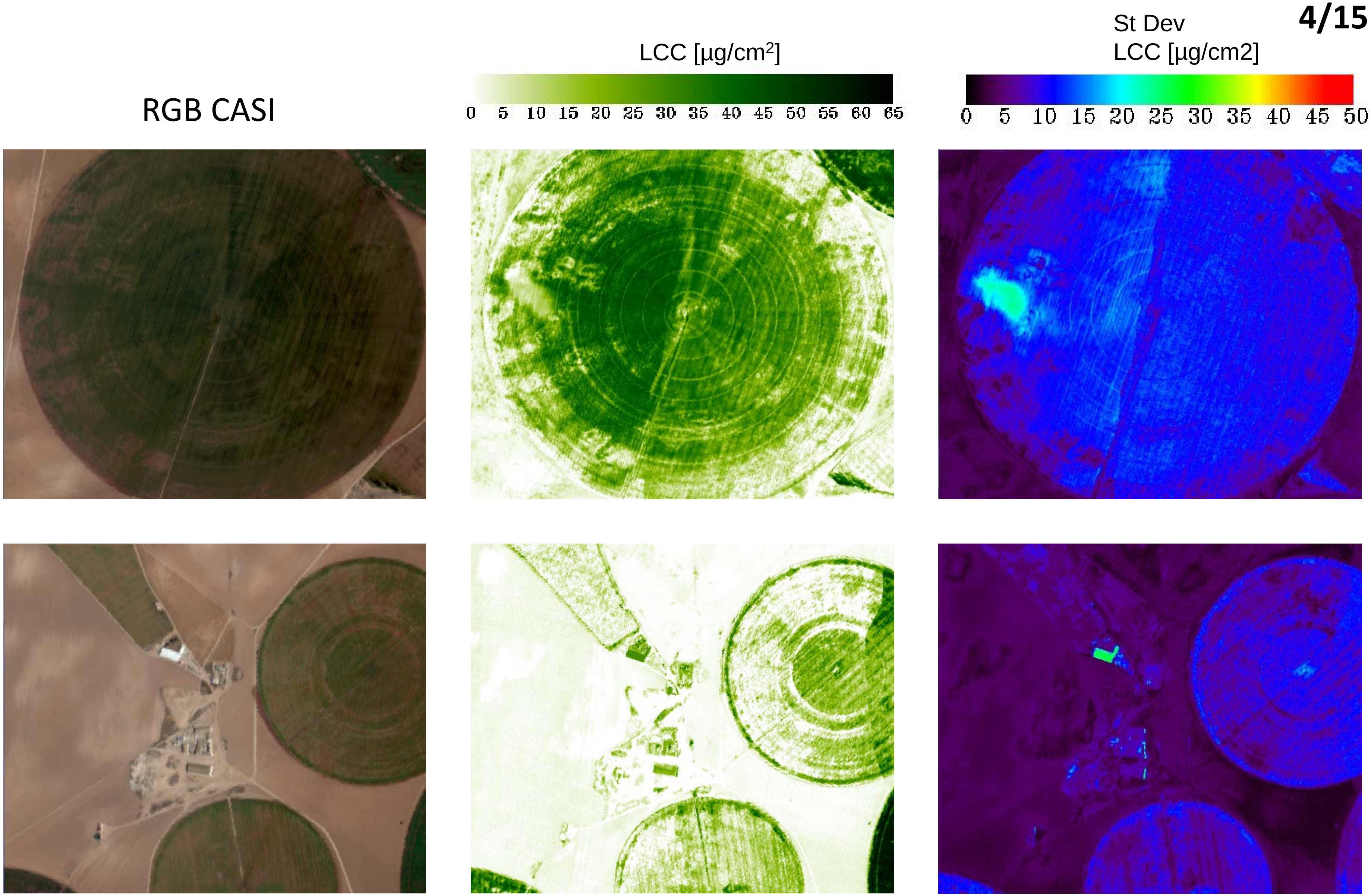


CASI1500
- pixel size: 1.4m
- 288 bands

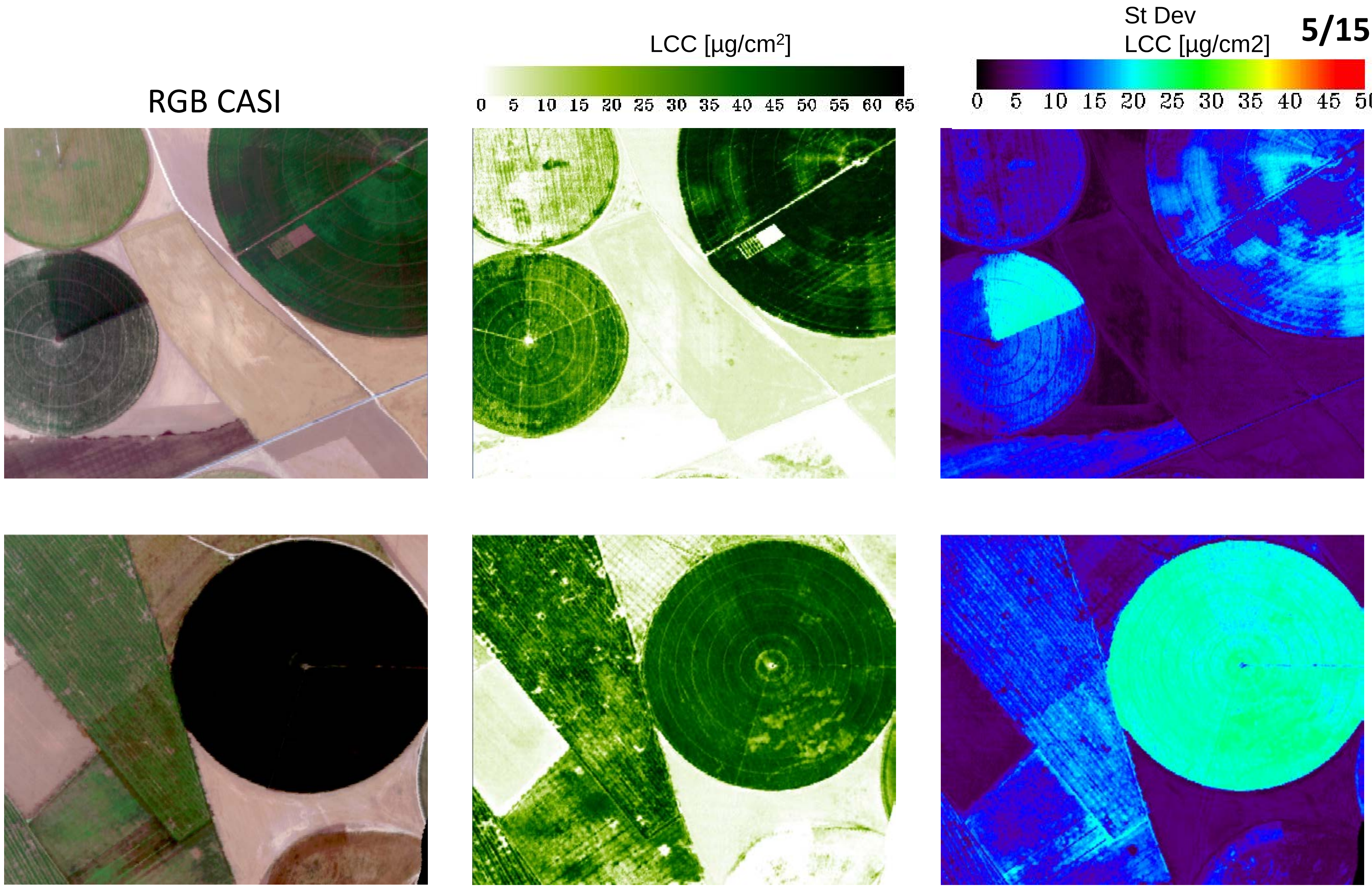
Same GP model was applied

3/15



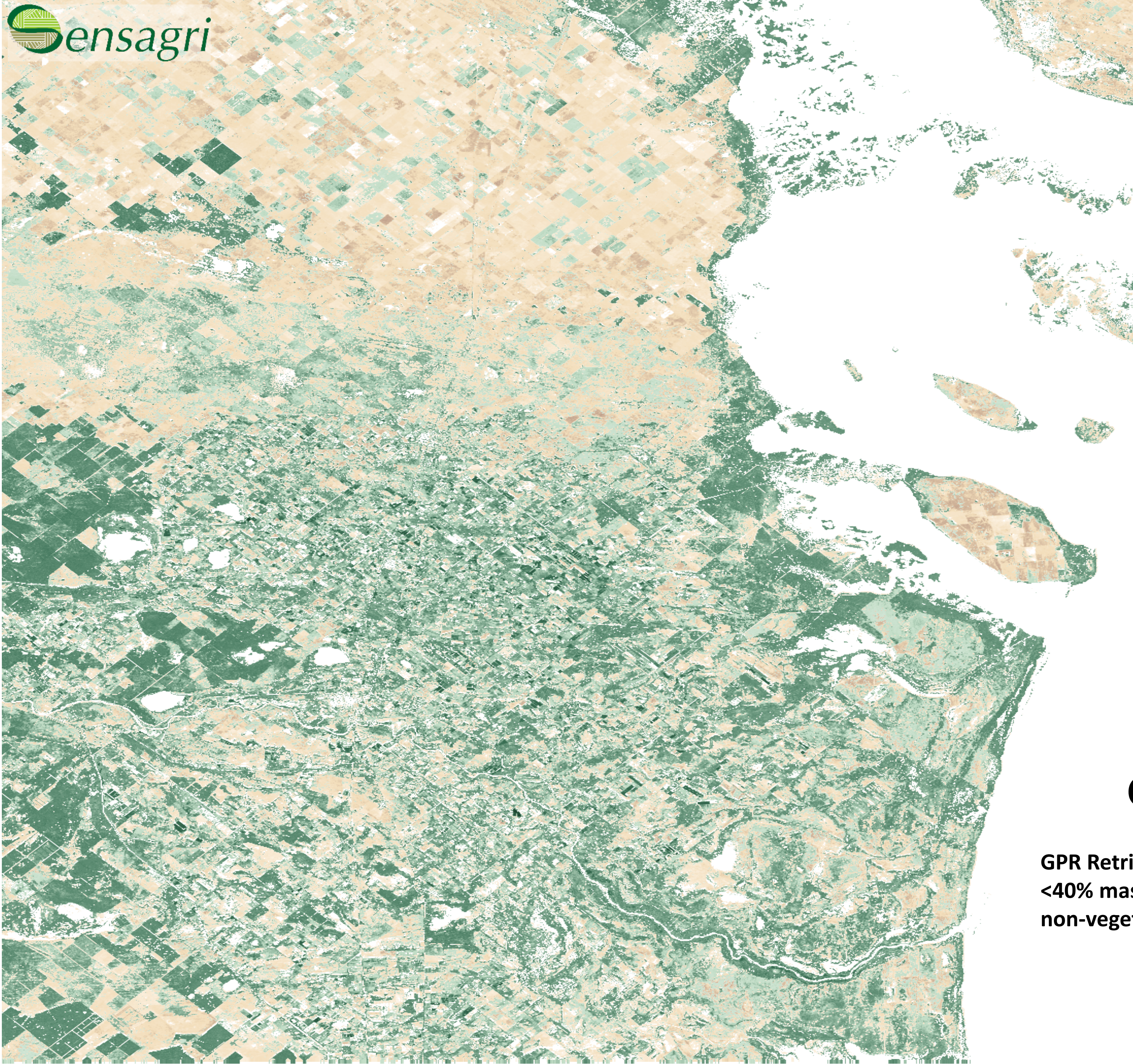


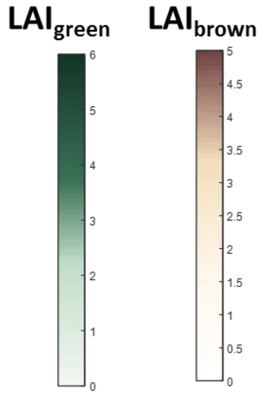
- **Uncertainty maps** provide **additional info** which may be hidden on the images.
- **Implausible estimations are detected.**



- In turn**, despite low uncertainties also good estimations**. No impact on recently irrigated areas (other methods have difficulties with wet soils).
- For operational applications, of interest to flag/mask regions with high uncertainties.

Sensagri





GPR to S2

GPR Retrievals with uncertainties <40% masked out (removes directly non-vegetated surfaces).

The challenge of machine learning applied to imaging spectroscopy

- ***Machine learning methods are adaptive and can be very powerful. However that goes a computational cost. This can be problematic when large datasets are involved, either in the sampling or in the spectral domain (e.g. for hybrid methods).***

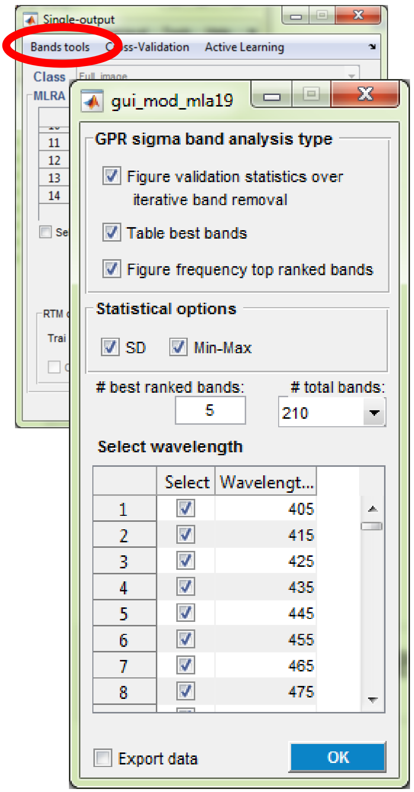
- ***Moreover, when many bands are involved: multicollinearity leads to statistical problems (suboptimal performance).***

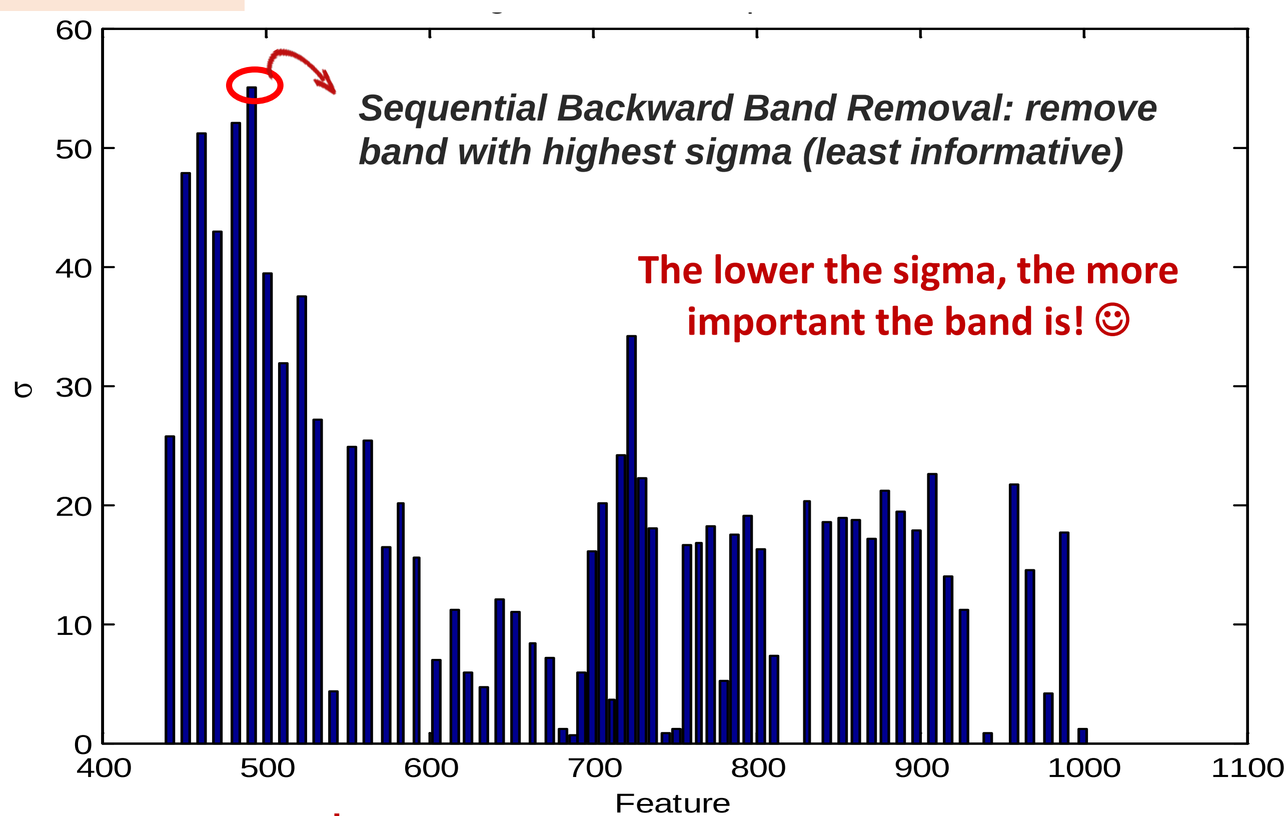
Solutions to deal with large datasets:

1. **Reducing spectral data:**
   I. **band selection (GPR-BAT),**
   II. **dimensionality reduction**
2. **Samples reducing : Active learning**

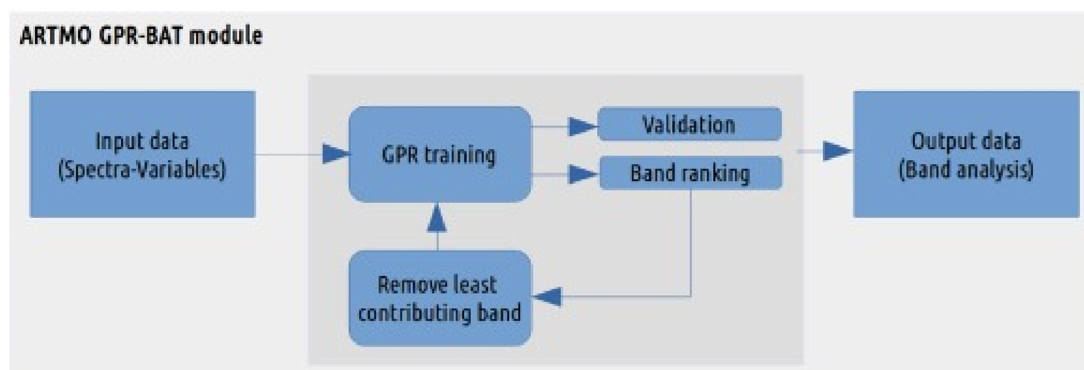
I) Band selection: GPR-BAT

Gaussian processes regression – Band analysis Tool (GPR-BAT).





automated

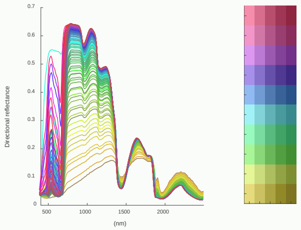


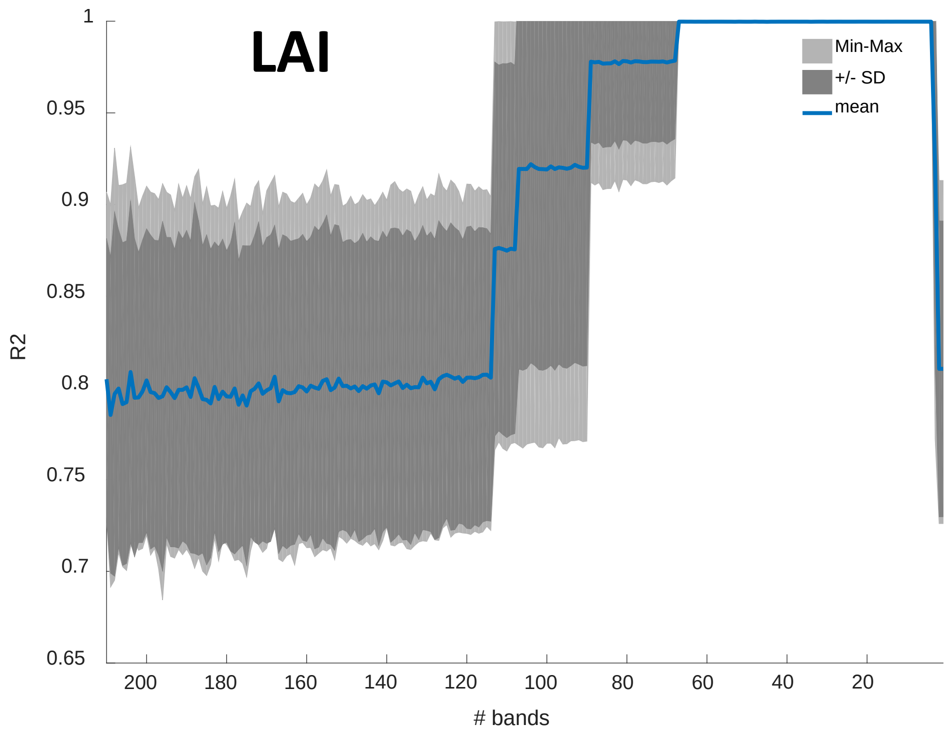
Best-performing method can be applied to an image.

GPR-BAT example with simulated data (PROSAIL)

Experimental setup:

- PROSAIL: LHS 100# @ 10 nm, 220b; Cab, LAI
- 4k cross-var sampling





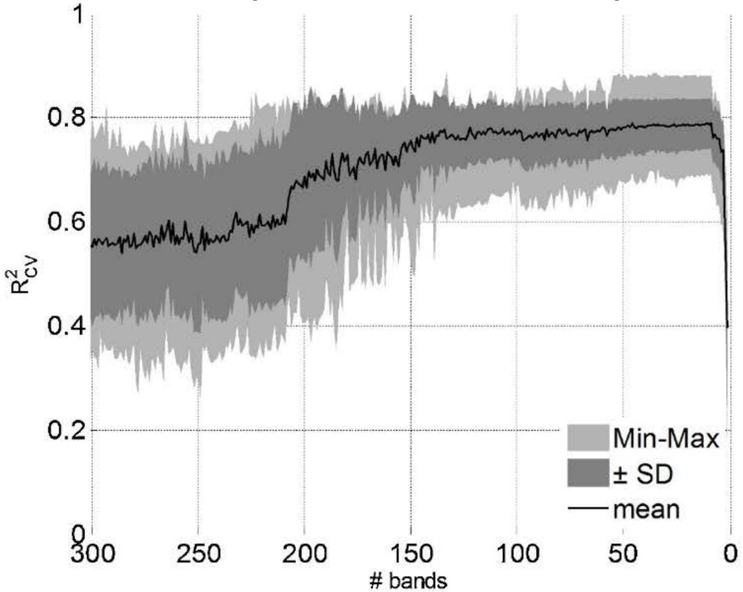
# band	R2	wavelengths
5	**0.9997**	815, 1145, 1205, 122, 1245
4	**0.9997**	815, 1145, 1205, 1245
3	0.9213	815, 1145, 1205
2	0.8104	815, 1145
1	0.8104	815

Best performances achieved between 70 and 4 bands

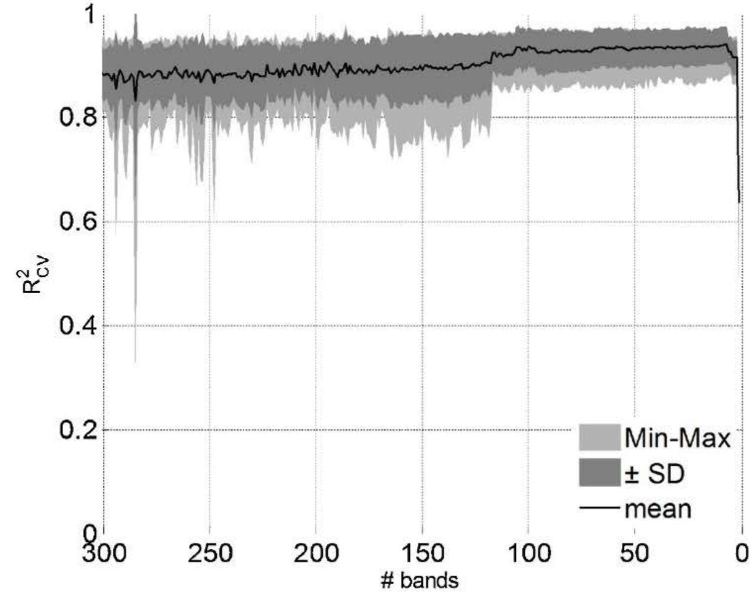
(using all bands or <3 bands not recommended)

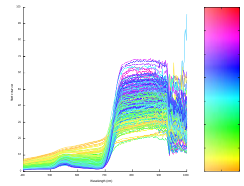
GPR-BAT example with A. Gitelson field data (maize/soybean, OO, 300#b)

LCC (best with 9 bands)



gLAI (best with 7 bands)

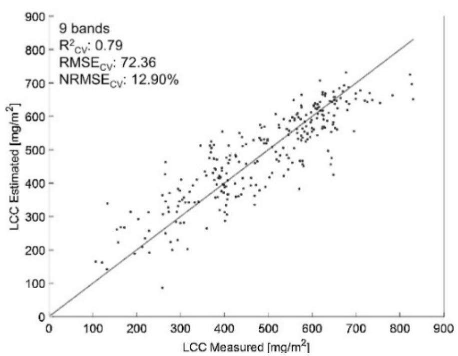




All bands

:

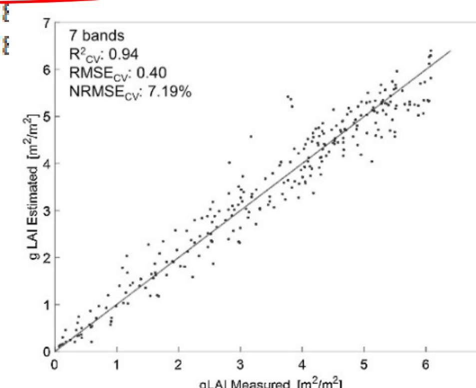
482, 500, 564, 566, 710, 712, 714, 878, 966, 980
482, 500, 564, 710, 712, 714, 878, 966, 980
482, 500, 564, 710, 712, 714, 878, 966
482, 500, 564, 710, 714, 878, 966
482, 500, 710, 714, 878, 966
500, 710, 714, 878, 966
500, 710, 714, 878
500, 710, 878
500, 710
710



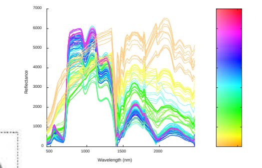
All bands

:

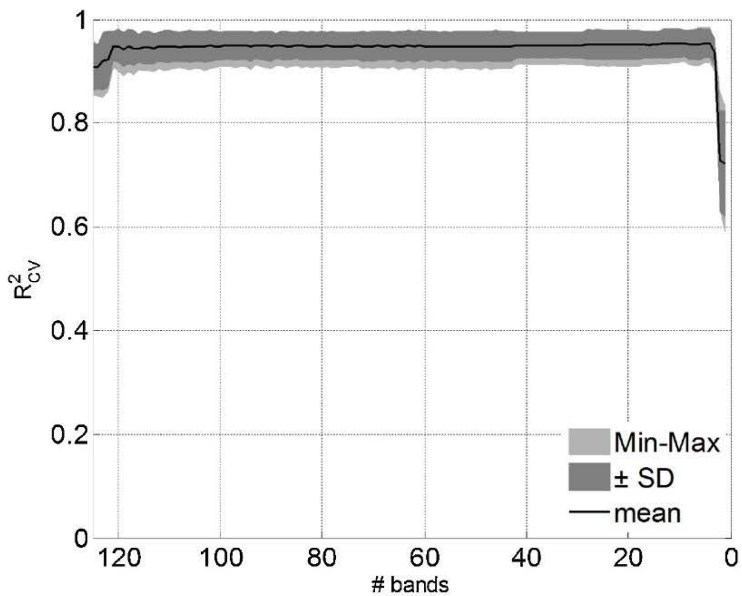
406, 746, 770, 790, 792, 794, 798, 808, 858, 878
406, 746, 790, 792, 794, 798, 808, 858, 878
406, 746, 790, 792, 794, 798, 858, 878
406, 746, 792, 794, 798, 858, 878
746, 792, 794, 798, 858
746, 792, 794, 798, 878
746, 792, 794, 798
746, 792, 794
746, 792
792



GPR-BAT example with field data (SPARC, Barrax, Spain; Hymap, 125#b)



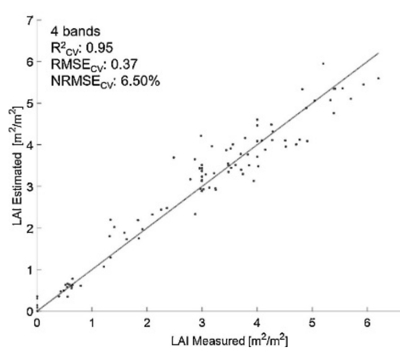
LAI (best with 4 bands)



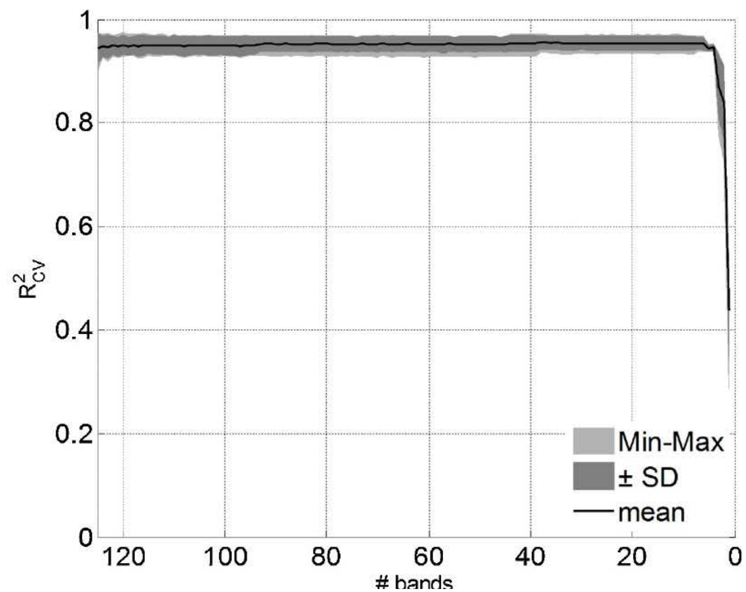
All bands

:
:

462, 478, 708, 723, 1215, 1243, 1272, 1327, 1635, 2483
462, 478, 708, 723, 1215, 1243, 1272, 1327, 2483
462, 478, 708, 723, 1215, 1243, 1272, 1327
462, 478, 708, 723, 1215, 1272, 1327
462, 478, 708, 723, 1215, 1327
462, 478, 708, 723, 1327
462, 708, 723, 1327
462, 708, 1327
462, 1327
462



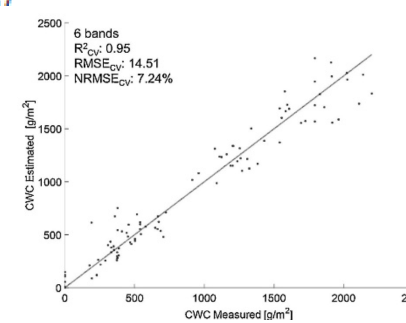
CWC (best with 6 bands)



All bands

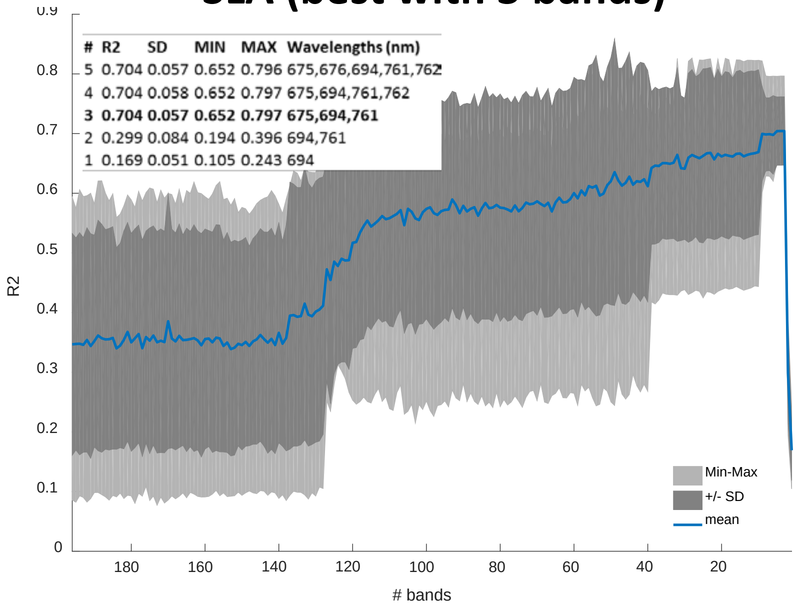
:
:

462, 723, 1128, 1157, 1272, 1286, 1299, 1327, 1419, 2483
723, 1128, 1157, 1272, 1286, 1299, 1327, 1419, 2483
723, 1128, 1157, 1272, 1286, 1327, 1419, 2483
723, 1128, 1157, 1272, 1286, 1327, 1419
723, 1157, 1272, 1286, 1327, 1419
723, 1157, 1272, 1286, 1327
723, 1157, 1272, 1286
1157, 1272, 1286
1157, 1286
1286

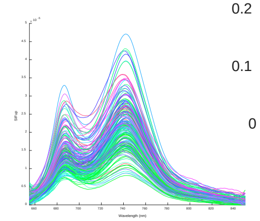


BIOHYPE & SCOPE: SIF (200#b)

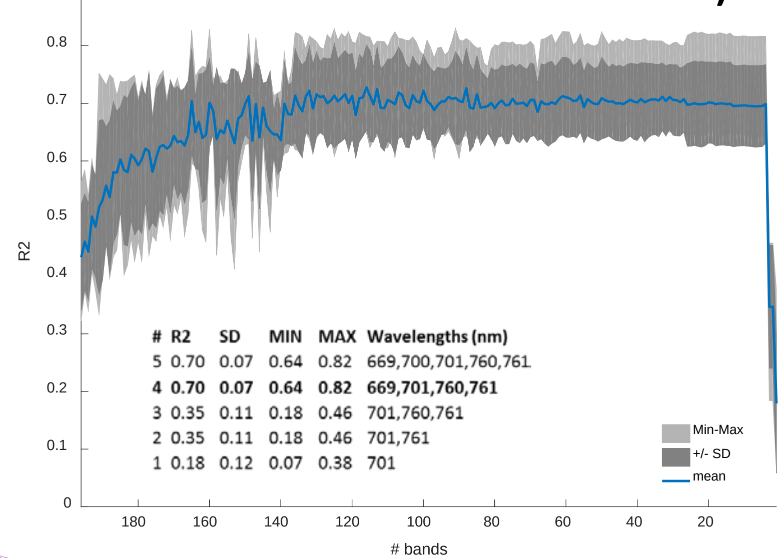
SLA (best with 3 bands)



#	R2	SD	MIN	MAX	Wavelengths (nm)
5	0.704	0.057	0.652	0.796	675,676,694,761,762
4	0.704	0.058	0.652	0.797	675,694,761,762
3	**0.704**	**0.057**	**0.652**	**0.797**	**675,694,761**
2	0.299	0.084	0.194	0.396	694,761
1	0.169	0.051	0.105	0.243	694

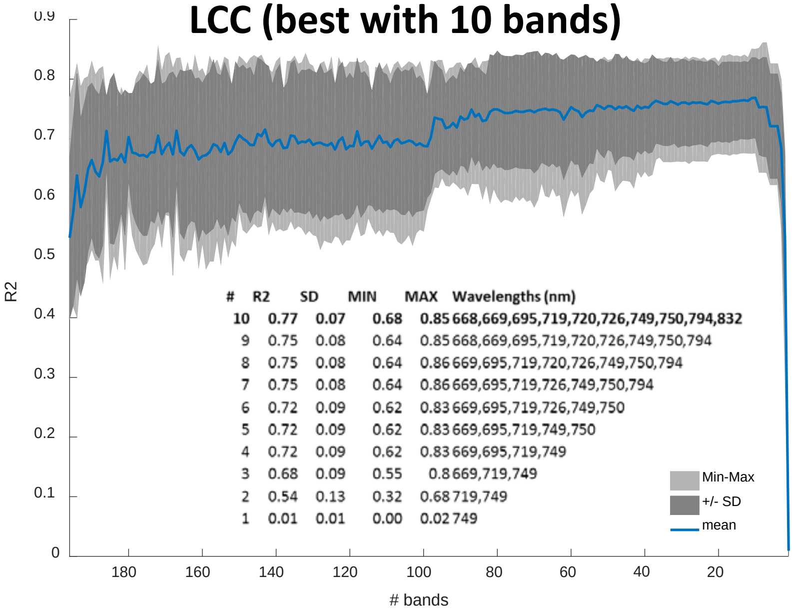


LWC (best with 116 bands, stable results from 4 bands onwards)



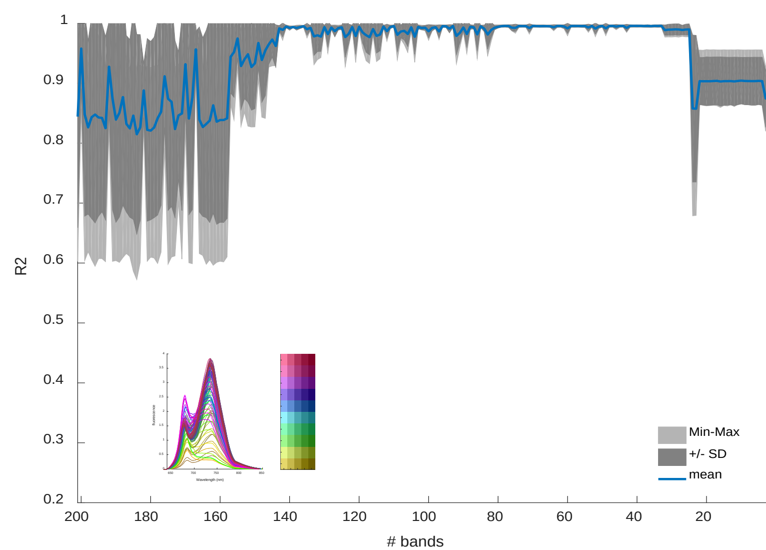
#	R2	SD	MIN	MAX	Wavelengths (nm)
5	0.70	0.07	0.64	0.82	669,700,701,760,761
4	**0.70**	**0.07**	**0.64**	**0.82**	**669,701,760,761**
3	0.35	0.11	0.18	0.46	701,760,761
2	0.35	0.11	0.18	0.46	701,761
1	0.18	0.12	0.07	0.38	701

LCC (best with 10 bands)

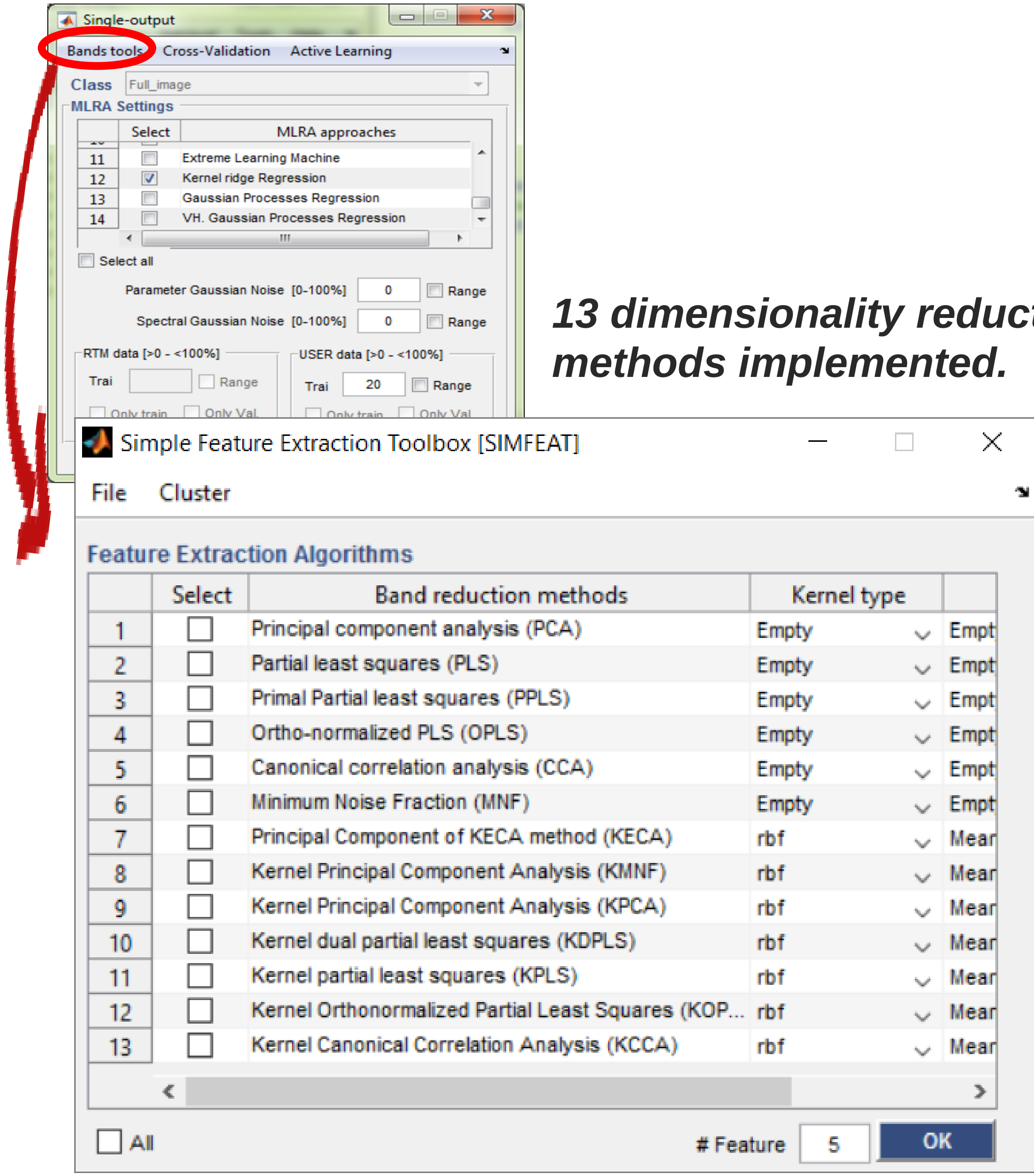


#	R2	SD	MIN	MAX	Wavelengths (nm)
10	**0.77**	**0.07**	**0.68**	**0.85**	**668,669,695,719,720,726,749,750,794,832**
9	0.75	0.08	0.64	0.85	668,669,695,719,720,726,749,750,794
8	0.75	0.08	0.64	0.86	669,695,719,720,726,749,750,794
7	0.75	0.08	0.64	0.86	669,695,719,726,749,750,794
6	0.72	0.09	0.62	0.83	669,695,719,726,749,750
5	0.72	0.09	0.62	0.83	669,695,719,749,750
4	0.72	0.09	0.62	0.83	669,695,719,749
3	0.68	0.09	0.55	0.8	669,719,749
2	0.54	0.13	0.32	0.68	719,749
1	0.01	0.01	0.00	0.02	749

SCOPE: LAI (best at 44 bands)



II) Dimensionality reduction: SIMFEAT



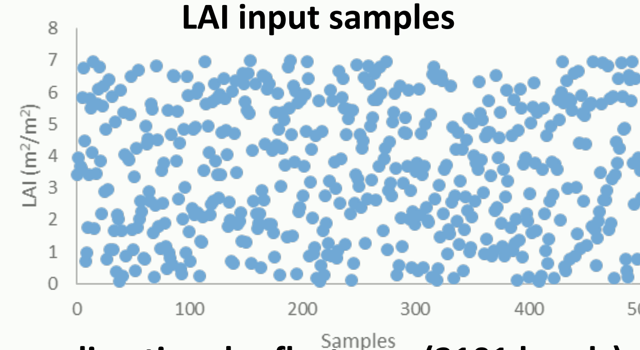
13 dimensionality reduction methods implemented.

Experimental setup:

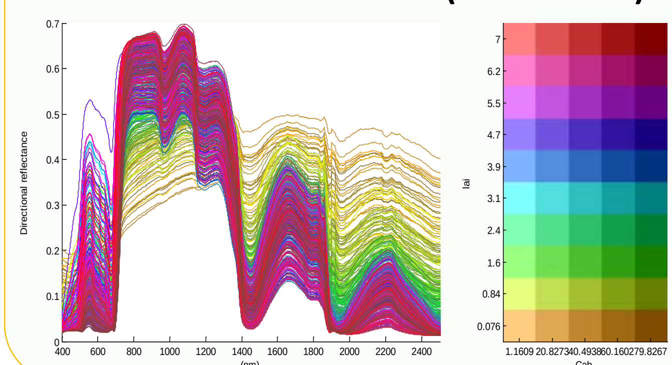
PROSAIL: 500 random samples

Variable	Min	Max
N	1.3	2.5
Cab	1	80
Cw	0.002	0.05
Cm	0.002	0.05
LAD	0	90
LAI	0.01	7

LAI input samples



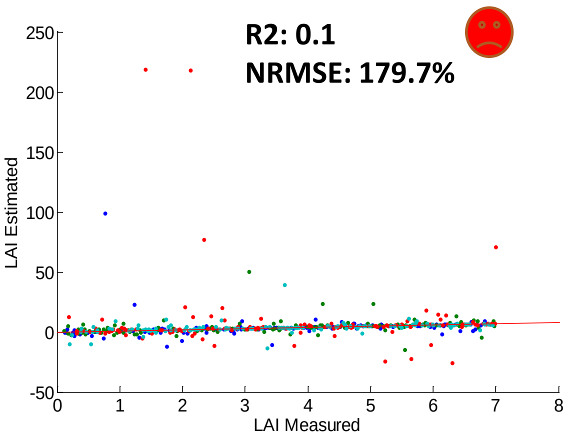
directional reflectance (2101 bands)

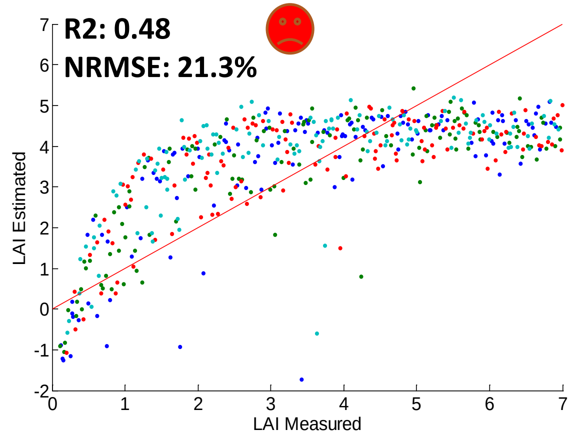


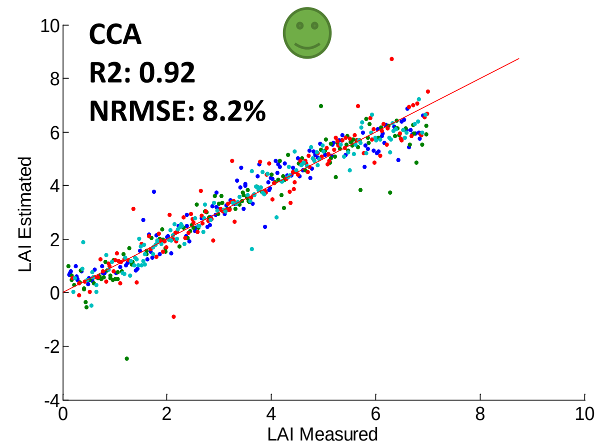
Impact of DR methods on PROSAIL data (2101#b) for LAI retrieval

No DR (2101#)	PCA (5#)	Best DR method (5#)

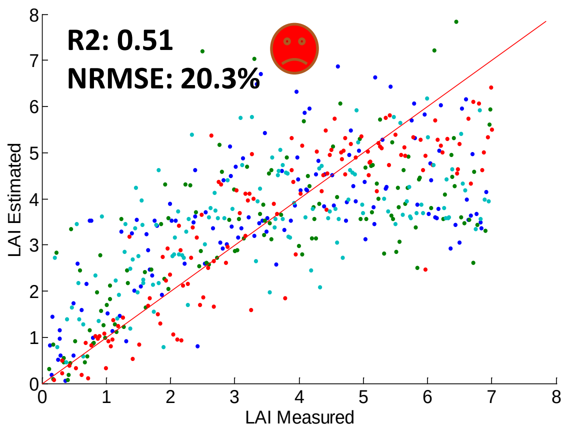
LR

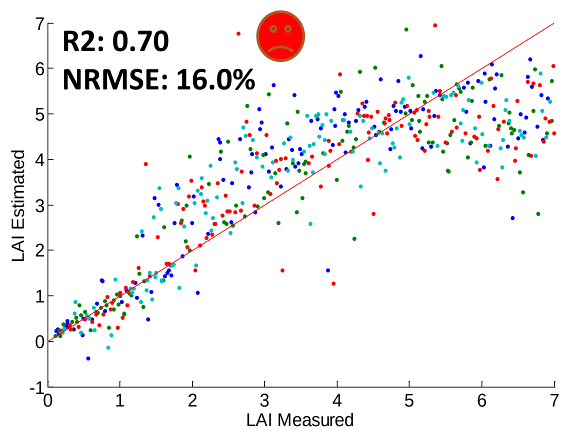


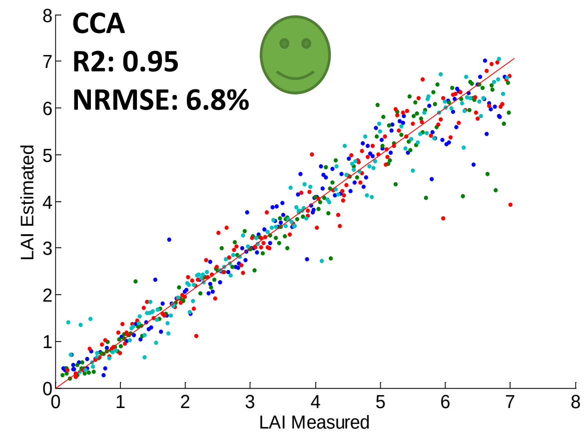




GPR

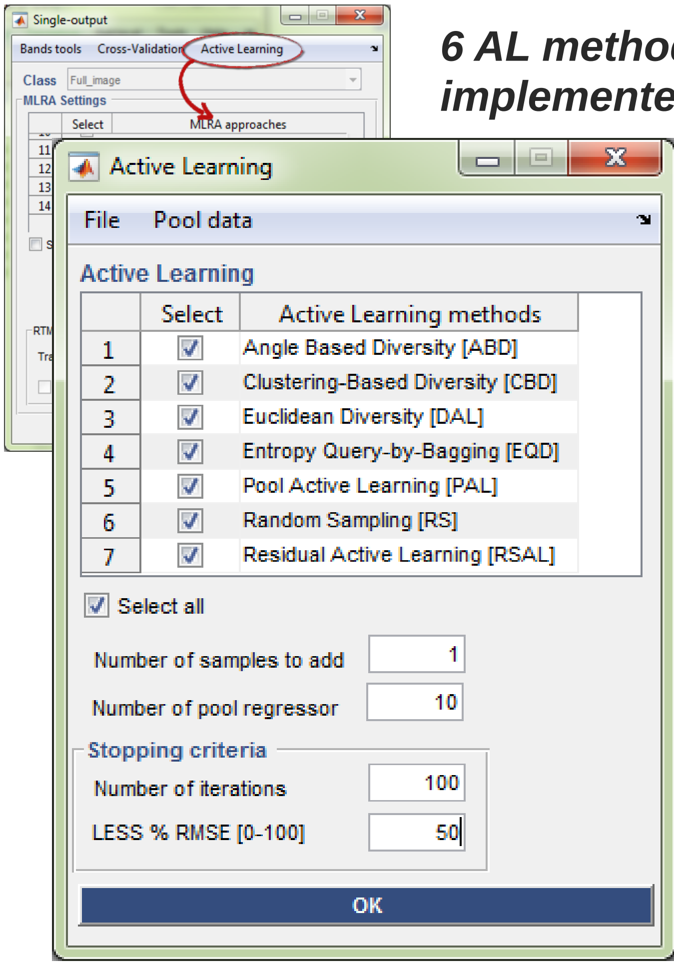






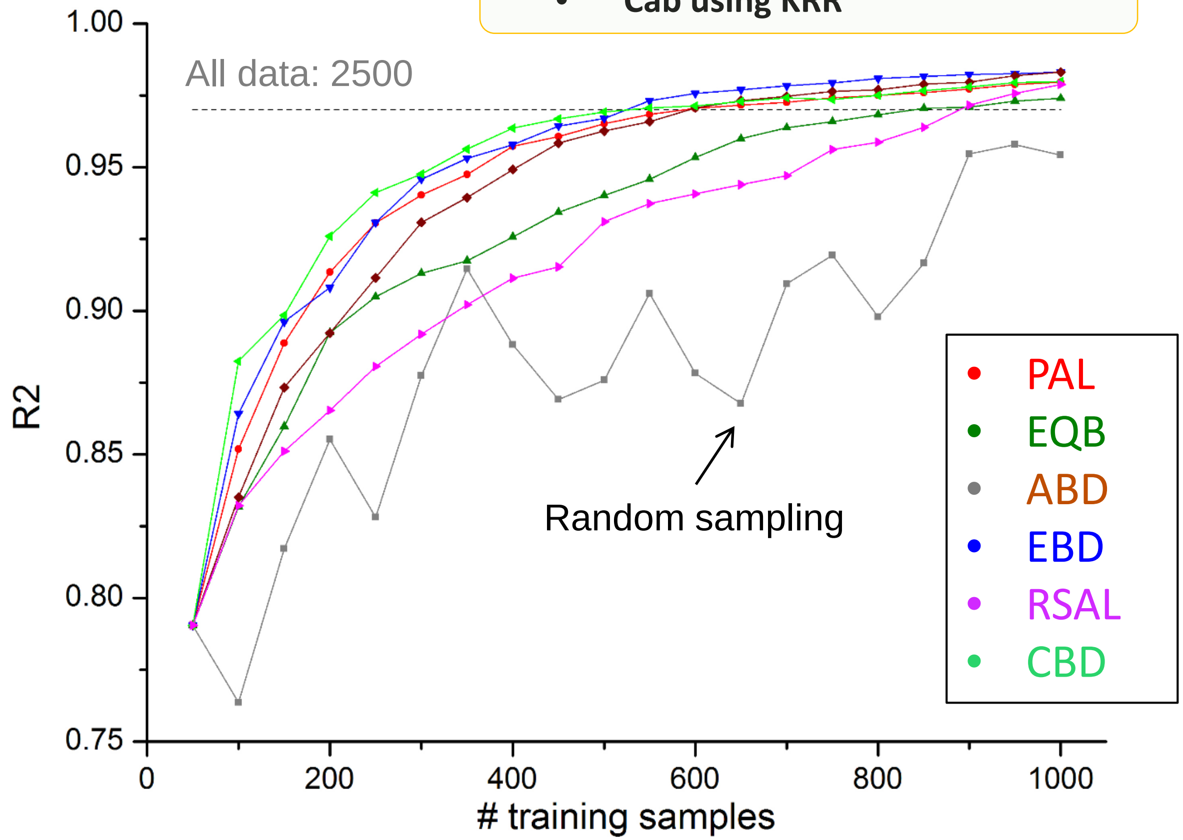
By combining advanced DR methods with (advanced) regression methods, hyperspectral data can exploited to the fullest. Or, full spectral dataset into regression require (advanced) DR methods.

2) Sample reduction: Active learning (AL)



6 AL methods implemented.

Experimental setup:
PROSAIL: 5000 samples
- **2500 training; 2500 validation**
- **Cab using KRR**

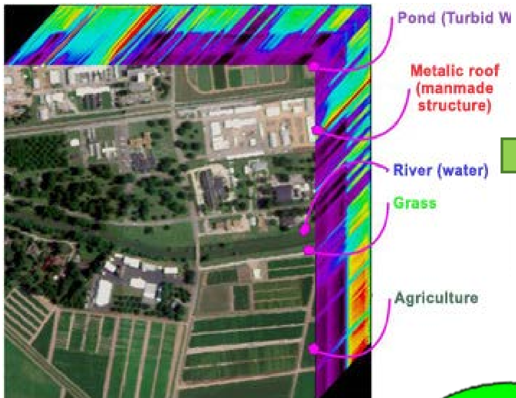


- Active learning (AL) searches for new samples from a data pool based on ***uncertainty*** (PAL, EQB, RSAL) and ***diversity*** (ABD, CBD, EBD).
- AL method search more efficiently for relevant samples than random sampling or when using all data.

Best-performing method can be applied to an image.

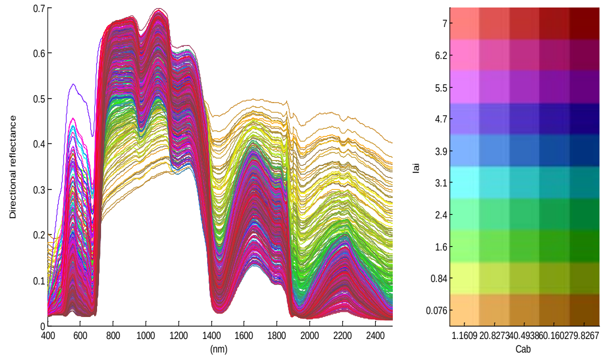
Background LUT-based inversion

RS imagery



Spectral block with 64 bands
from 415 nm to 900 nm

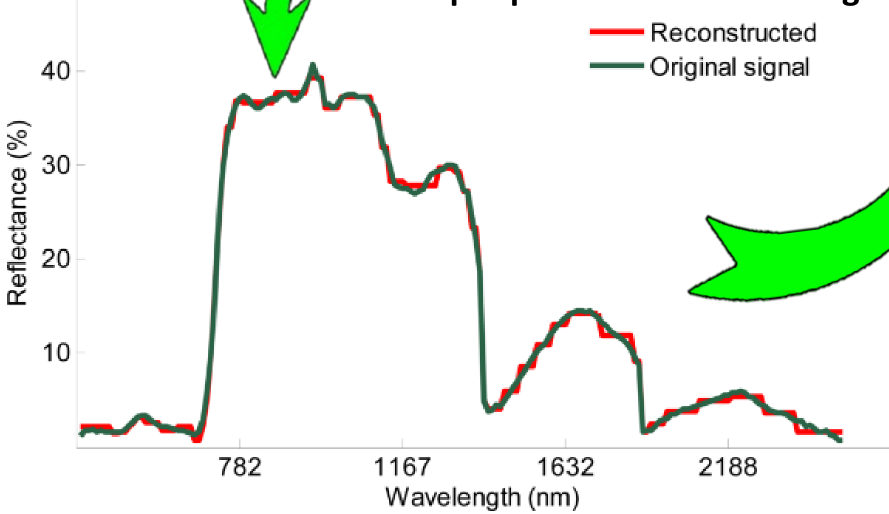
PROSAIL LUT



Best match is obtained through a 'Cost function', or 'Minimum distance function'.

CostFunction	Definition	Minimum	Maximum
C^{LS}	$\sum(Y-X)^2$	0	∞
C^{NC}	$\frac{\sum(X.Y)}{\sqrt{\sum X^2}\sqrt{\sum Y^2}}$	-1	1
C^{W}	$\sum_k \frac{n_k}{N}\frac{\sqrt{\mathrm{Var}(Y_k)}}{\mu(Y_k)}$	0	∞
C^{CR}	$\frac{1}{\mathrm{Var}(Y)}\sum_k \frac{n_k}{N}\mathrm{Var}(Y_k)$	0	1

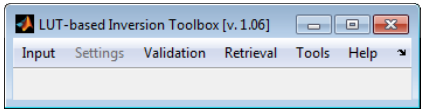
Search per pixel for best match against LUT

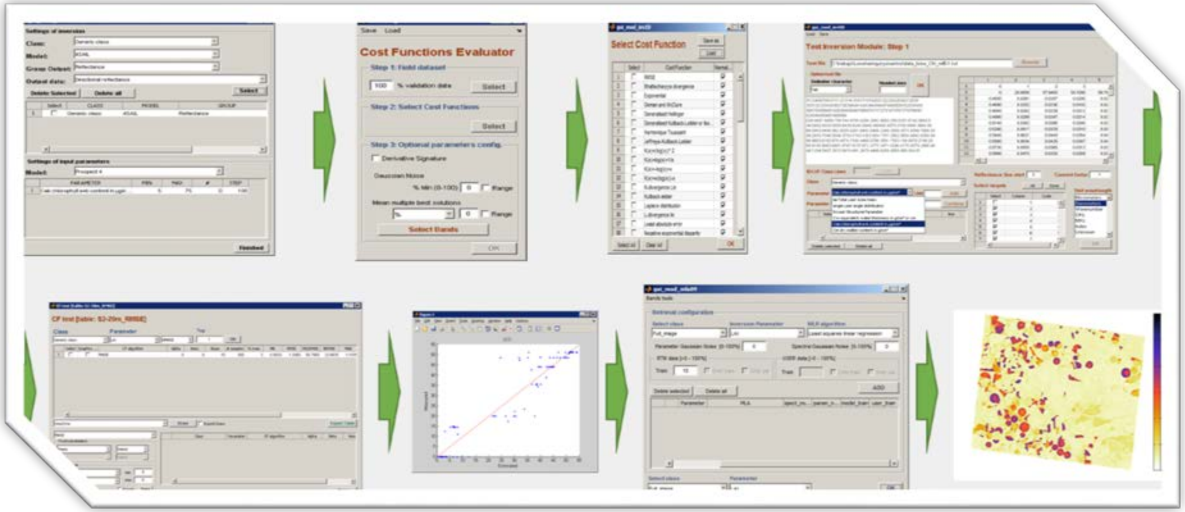


Other important factors:

- Adding **noise** (to account for natural variability)
- Selecting mean/median of **multiple solutions**

LUT-based inversion toolbox:

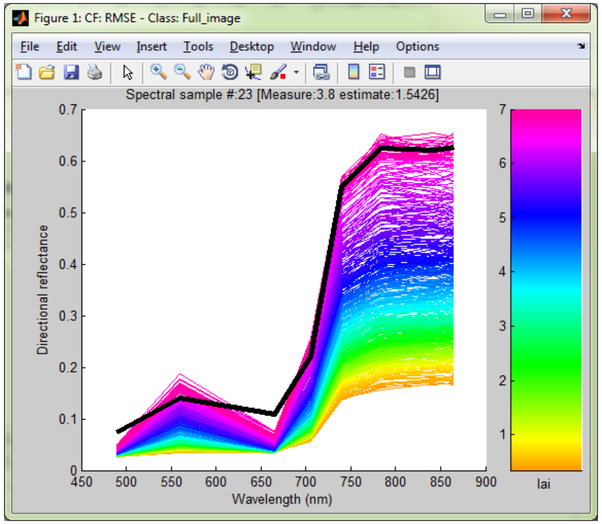


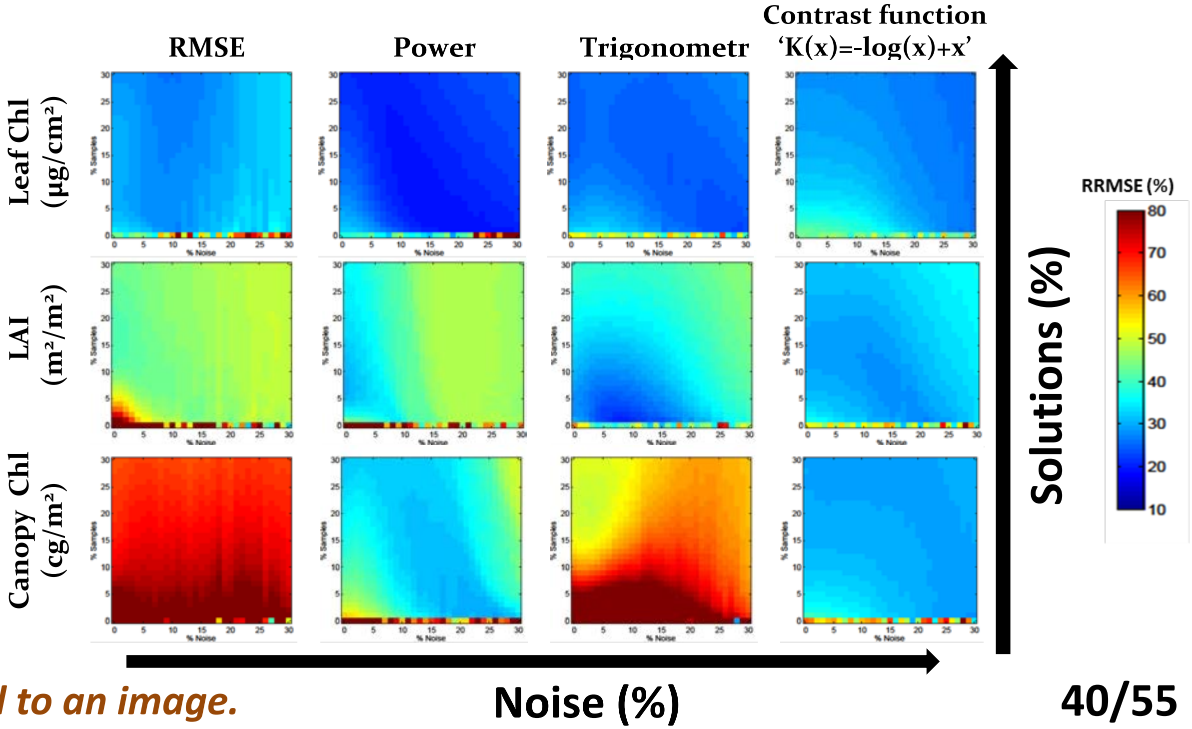


Properties:

- LUT ARTMO RTMs or external LUT
- Over 60 different cost functions
- Noise & multiple solutions
- Results stored in MySQL
- Top-performing inversion strategies are given.
- Can apply inversion to both image or individual spectra.

Matching a pixel against a part of the LUT.



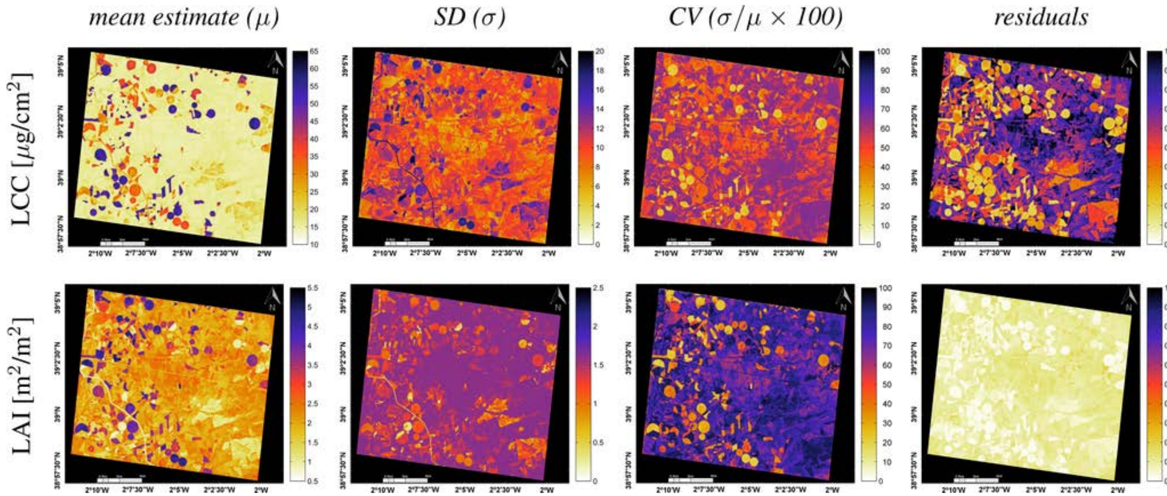


Best-performing method can be applied to an image.

SPARC dataset, CHRIS resampled to S2, S3

S2, 20m

Uncertainties



Optimized cost function for each variable.

One optimized cost function for simultaneous retrieval of multiple variables.

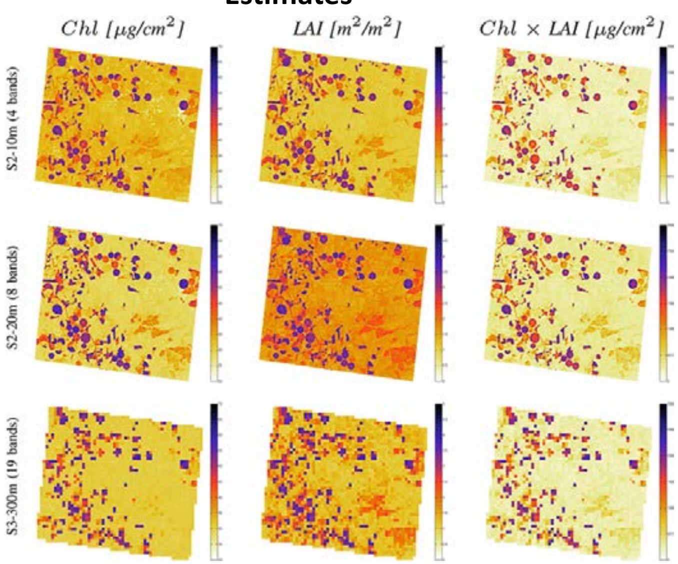
Sentinel	S2-10m	S2-20m	S3-300m
Spatial resolution [m]	10	20	300
# bands	4	8 (4 + 4 at < 20 m)	19
Band position	B2, B3, B4 and B8	B2 to B8a	O2 to O20
Wavelengths [nm]	490-665 and 842	490-865	413-940

Estimates

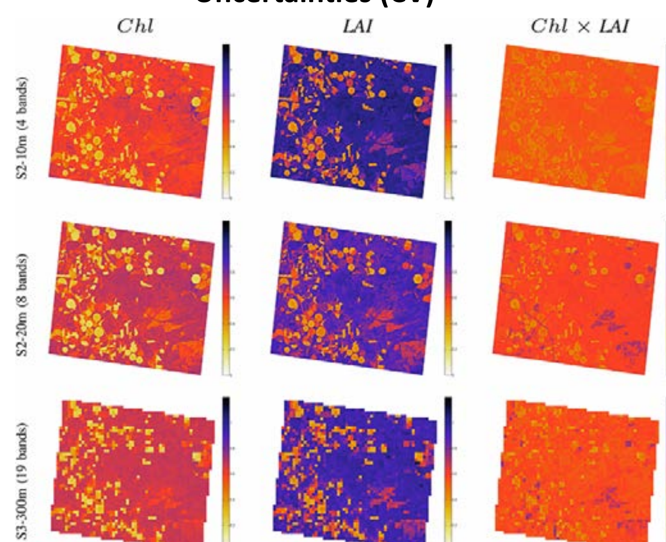
S2 – 10 m

S2 – 20m

S3



Uncertainties (CV)



SIMPLIFYING

- Global sensitivity analysis
- Emulation
- Retrieval

Global sensitivity analysis

<u>Global sensitivity analysis</u>: explores the full input parameter space, i.e. all input parameters are changed together.

Variance-based methods: the output variance is decomposed to the sum of **contributions of each individual input parameter and the interactions** (coupling terms) between different parameters.

Based on the work of **Sobol'**, **variance-based sensitivity measures** are represented as follows:

$$1 = \sum_i S_i + \sum_i \sum_{j>i} S_{ij} +, \cdots, + S_{12,\ldots,k},$$

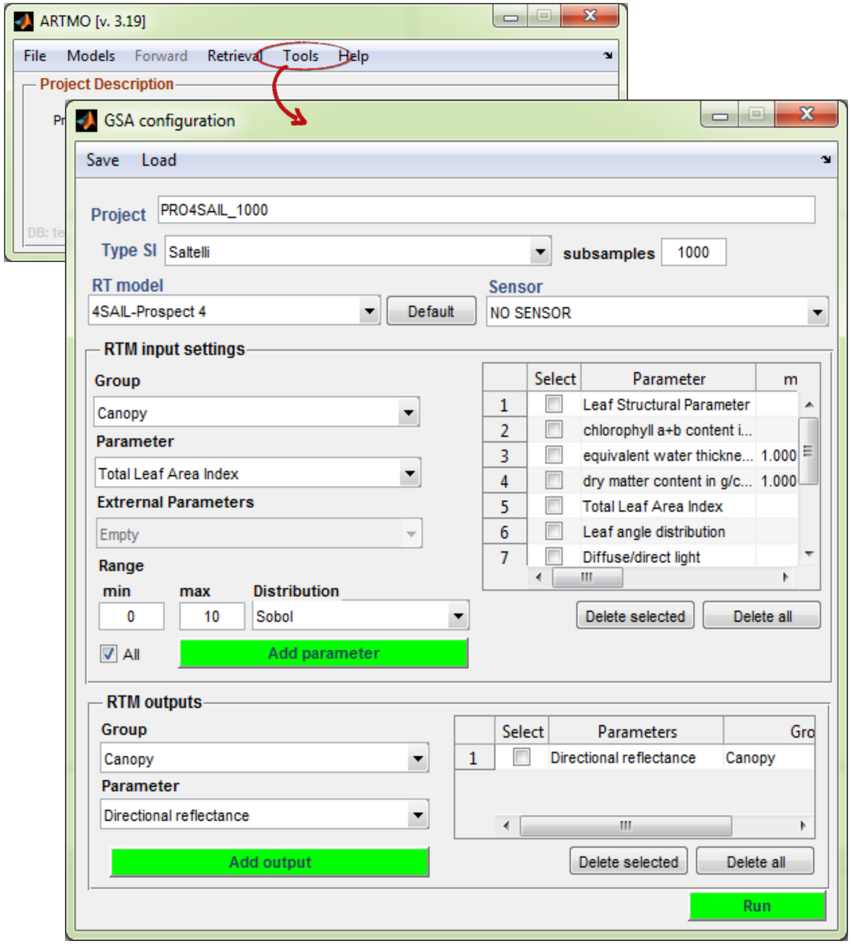
in this equation, S_i, S_{ij},…,$S_{12,\ldots,k}$ are ***Sobol's global sensitivity indices***.:

The ***<u>first order sensitivity index</u>*** S_i measures and quantifies the sensitivity of model **output Y to the input parameter X_i (without interaction term**s), whereas, S_{ij},…,$S_{12,\ldots,k}$ are the sensitivity measures for the higher order terms (interaction terms).

The ***<u>total effect</u>* <u>sensitivity index</u>** S_{Ti} measures **the whole effect of the variable X_i**, i.e. the first order effect as well **as its coupling terms with the other input variables**:

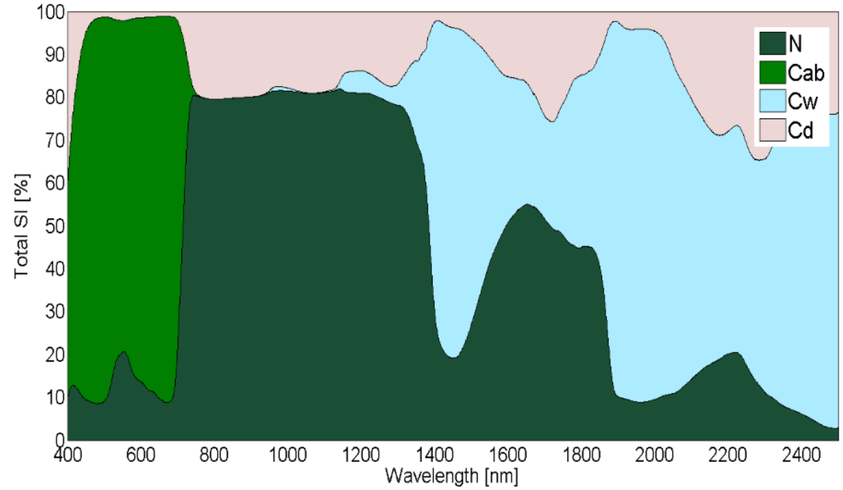
$$S_{T1} = S_1 + S_{12} + S_{13} + S_{123}$$

GSA toolbox



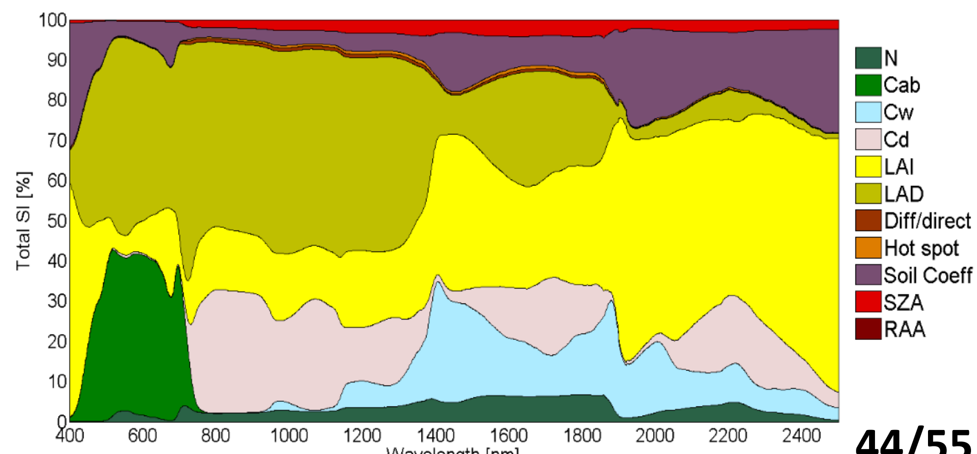
< 3 min

PROSPECT-4 Reflectance (#1000)



< 5 min

PROSAIL Directional Reflectance (#1000)

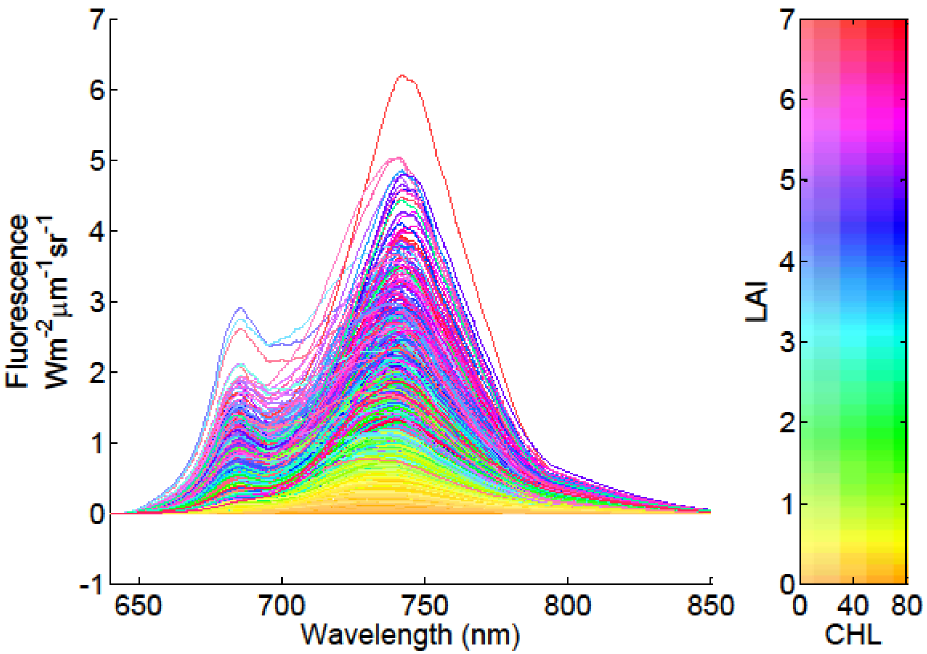


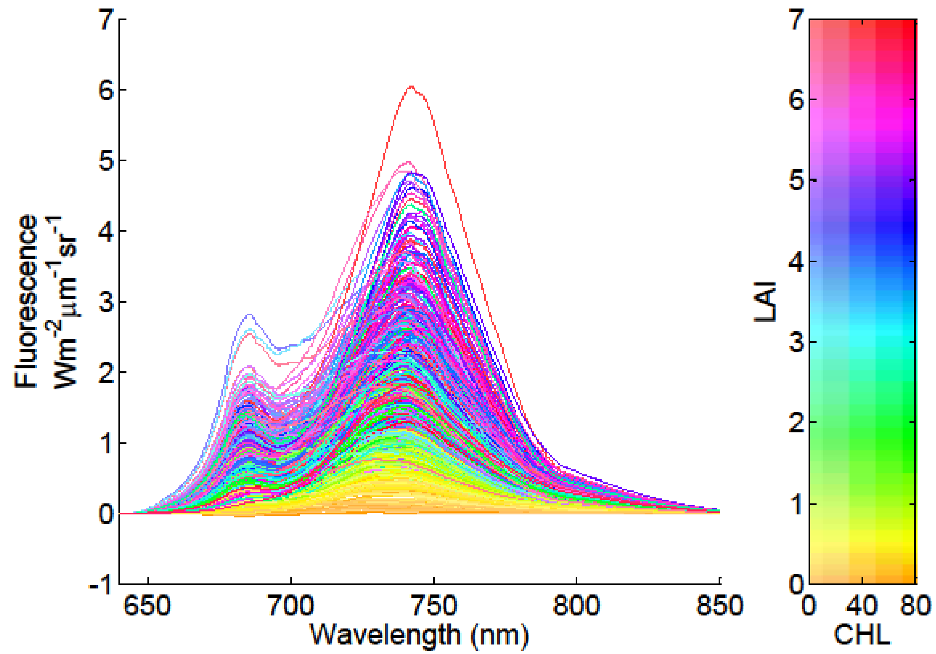
<u>Properties:</u>

- **ARTMO RTMs**
- ***Saltelli 2010* GSA method**
- **Various sample distributions**
- **Results stored in MySQL**
- **First order or total order Sobol Sensitivity indices**
- **Can process multiple RTM outputs.**

Any difference?

Which one would you choose?





12 min 54 s.

1 s.

SCOPE

Metamodel (emulator)

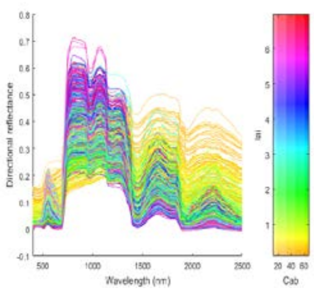
Emulation

Emulators are regression models that are able to approximate the processing of an RTM, at a fraction of the computational cost:

making a statistical model of a physical model

Emulators applied to RTMs:

- In principle any nonlinear, adaptive **machine learning regression algorithms (MLRAs)** can serve as emulators.

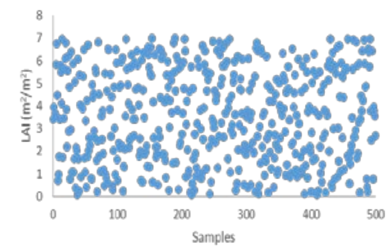


Spectra

MLRA →

← Emulator

Variables
(e.g. LAI, chlorophyll)



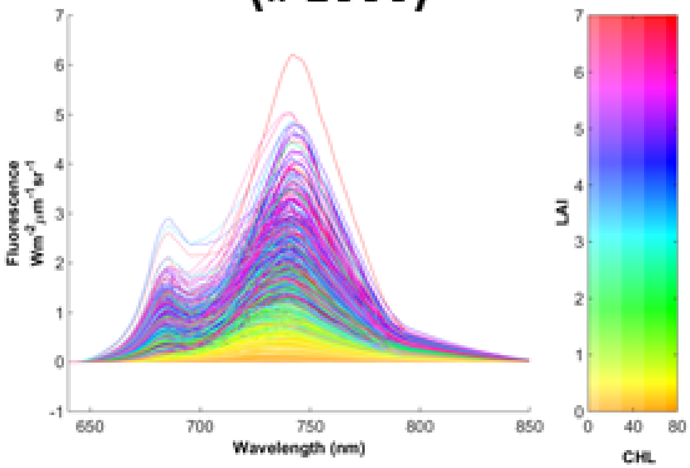
- To emulate RTMs, the emulator should have the capability to reconstruct multiple outputs, i.e. the complete spectrum: resolved with **dimensionality reduction** techniques (e.g. PCA).

Processing steps:

Input (variables + spectra) → Splitting into training/validation → PCA on spectra → MLRA training looping over components → Prediction of components → Reconstruction of full spectrum → Validation → Emulator

Emulating SCOPE fluorescence outputs

SCOPE RTM (# 1000)



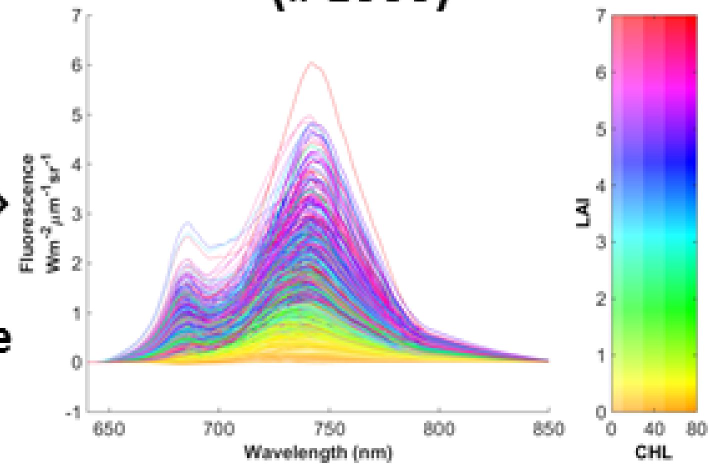
774 s.

Emulation

Training validating

Multi-output machine learning regression algorithm (e.g. KRR)

KRR emulator (# 1000)



1 s.

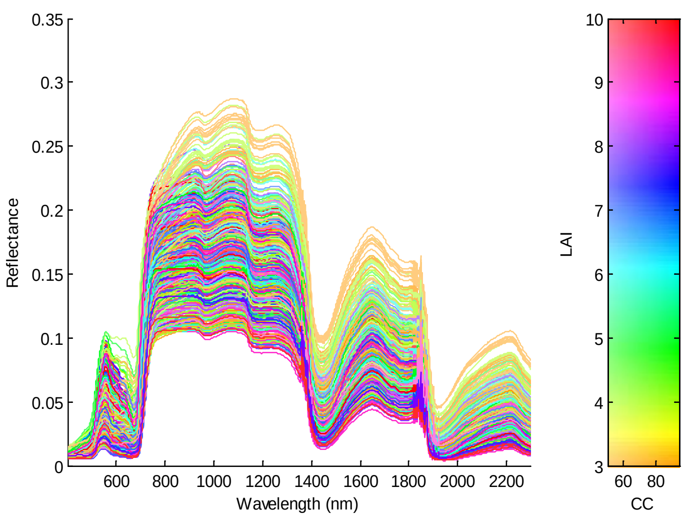
Because of the smooth profiles, SIF outputs are easy to emulate.

In Emulation, physical models go hand in hand with machine learning

Emulating a complex 3D RTM: DART

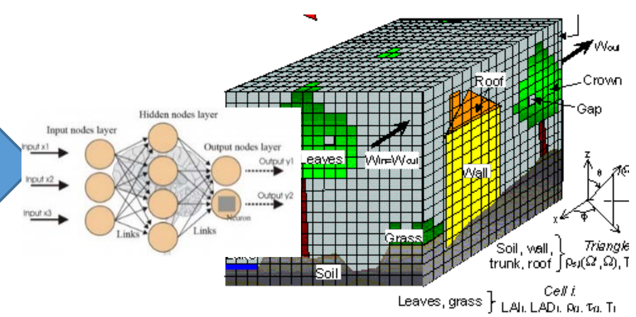
Experimental setup:
- DART: LUT1000# @ 1 nm; 7 variables
- 3 MLRAs tested: KRR, NN, GPR
- Various # PCA components tested (5, 10, 20, 30)

- N
- LWC
- DMC
- Carc
- LCC
- CC
- LAI
- TOPO



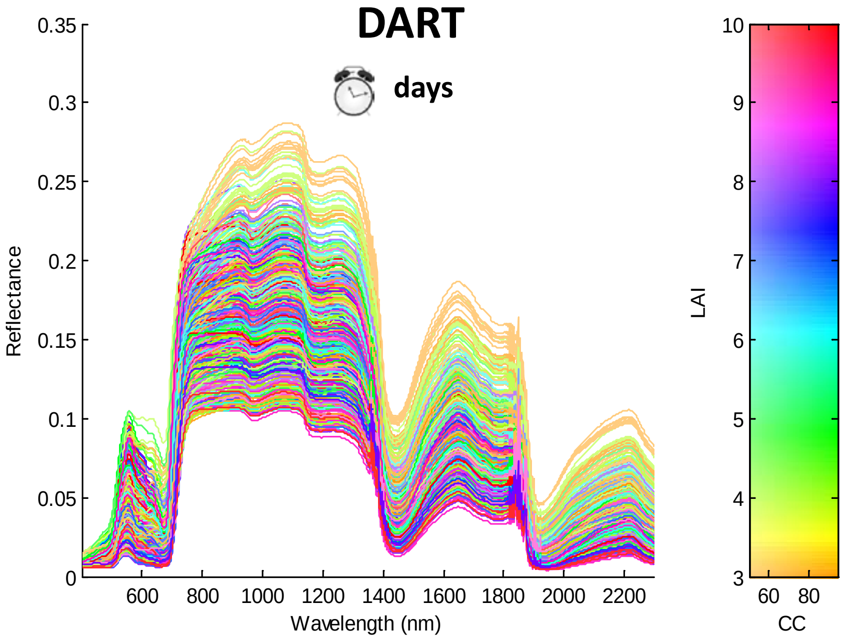
Emulator

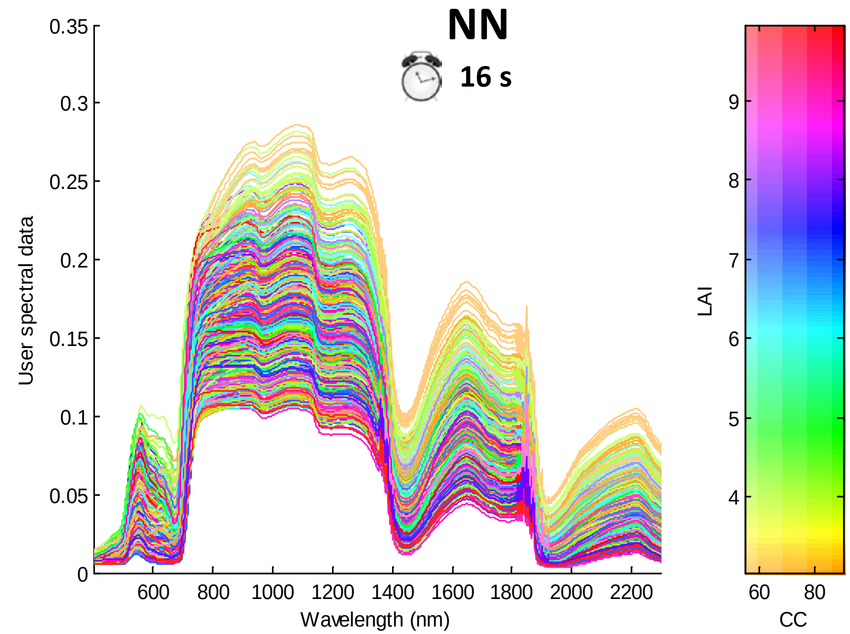
- KRR
- NN
- GPR

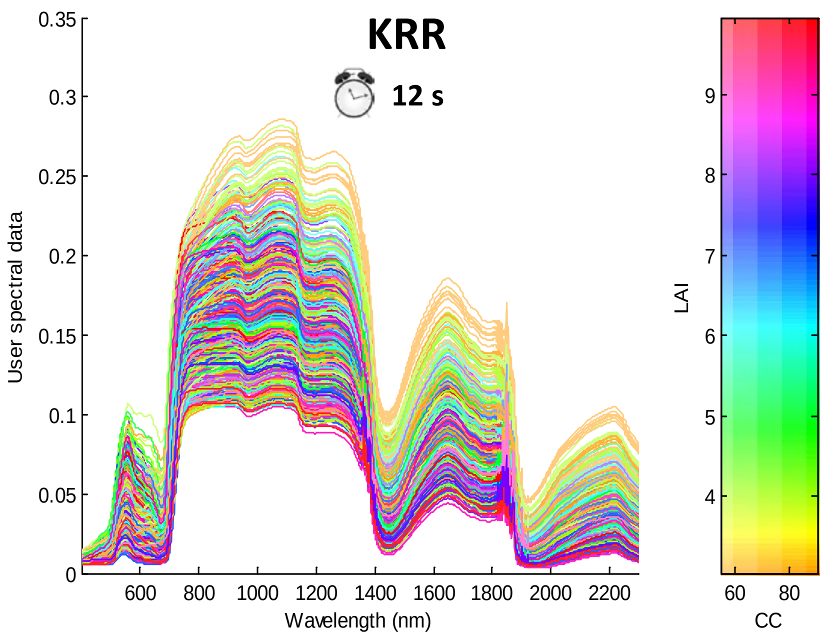


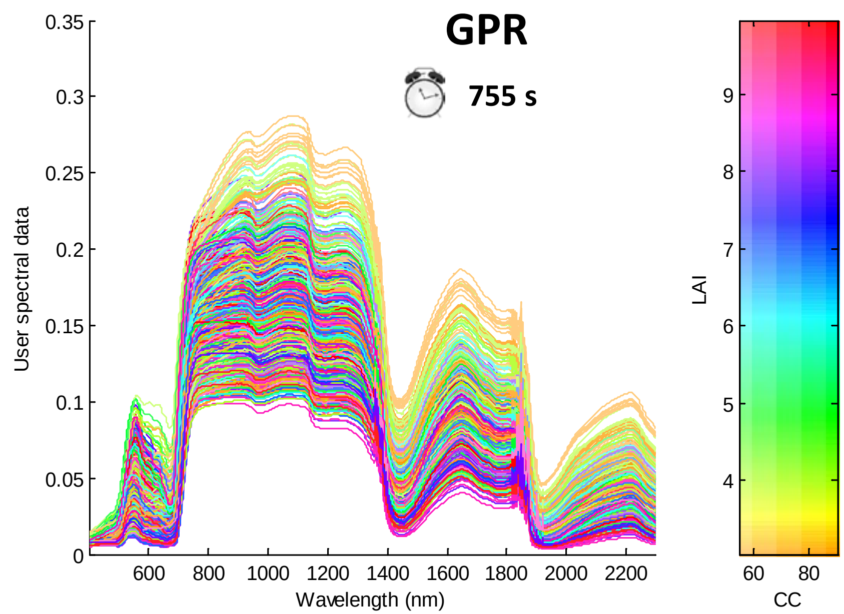
☺ *Thanks to Ruzena Janoutova, Lucie Homolova, Petr Lukes*

1000#

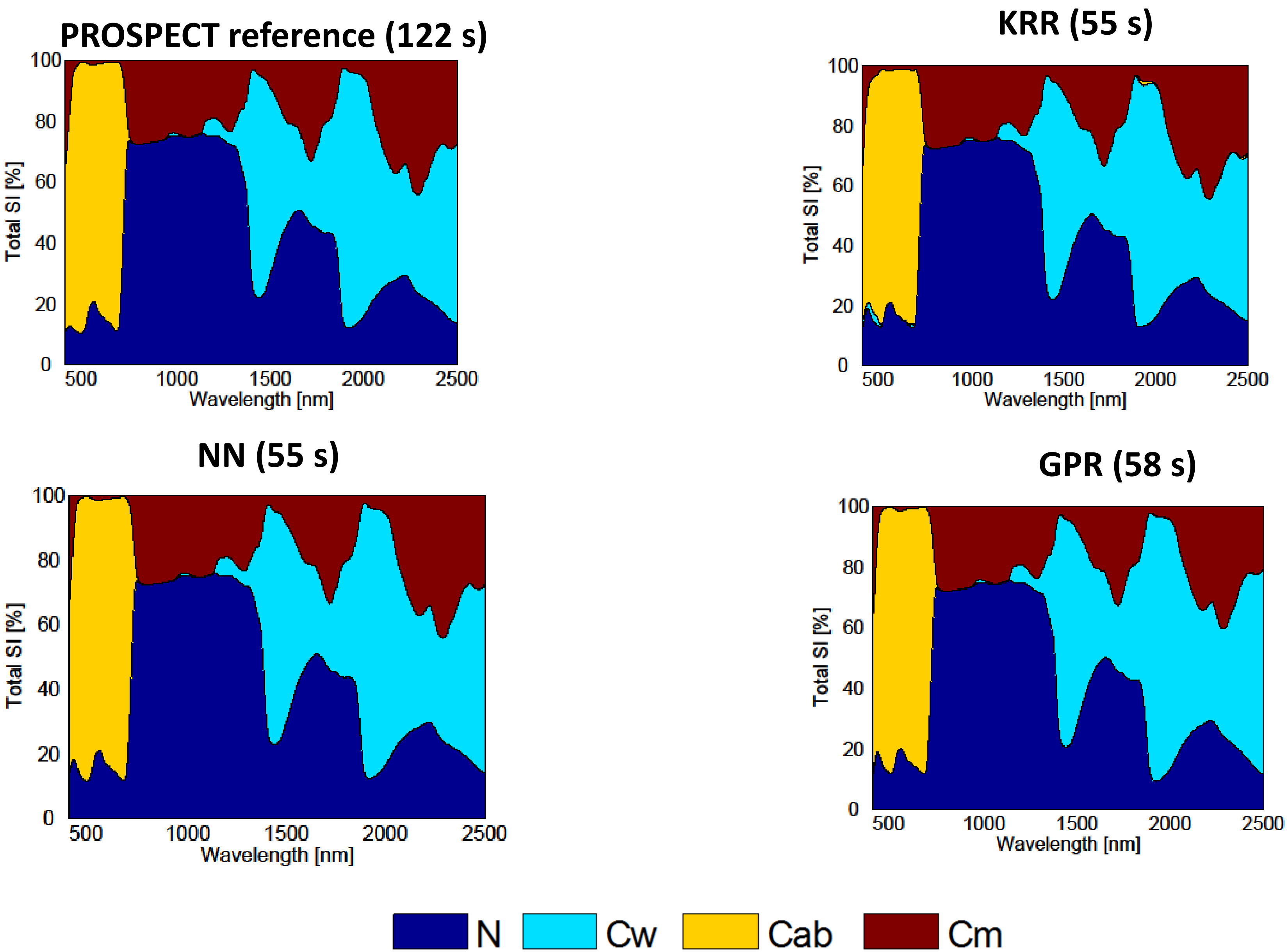

DART
days
Reflectance
Wavelength (nm)
LAI
CC


NN
16 s
User spectral data
Wavelength (nm)
LAI
CC


KRR
12 s
User spectral data
Wavelength (nm)
LAI
CC


GPR
755 s
User spectral data
Wavelength (nm)
LAI
CC

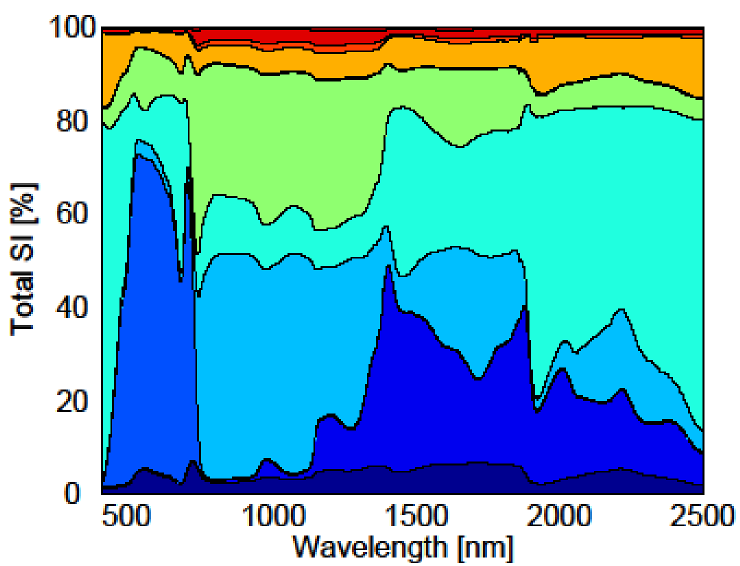
Emulators applied into GSA: PROSPECT-4



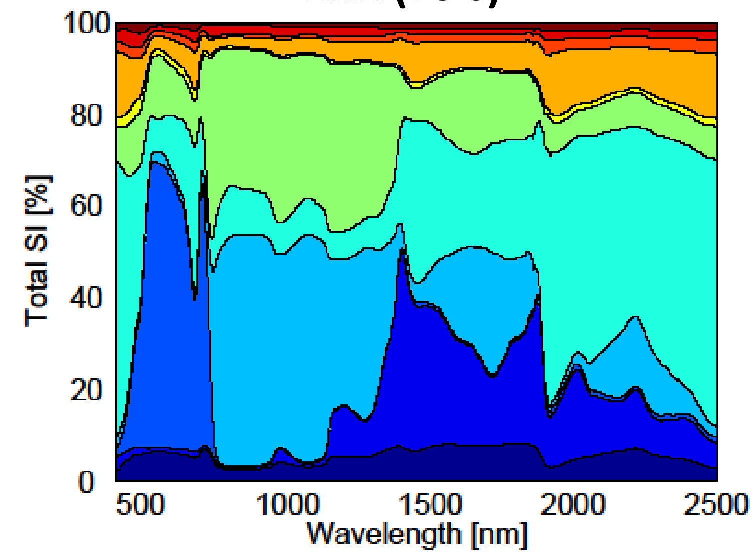
1000#/variable

PROSAIL emulators

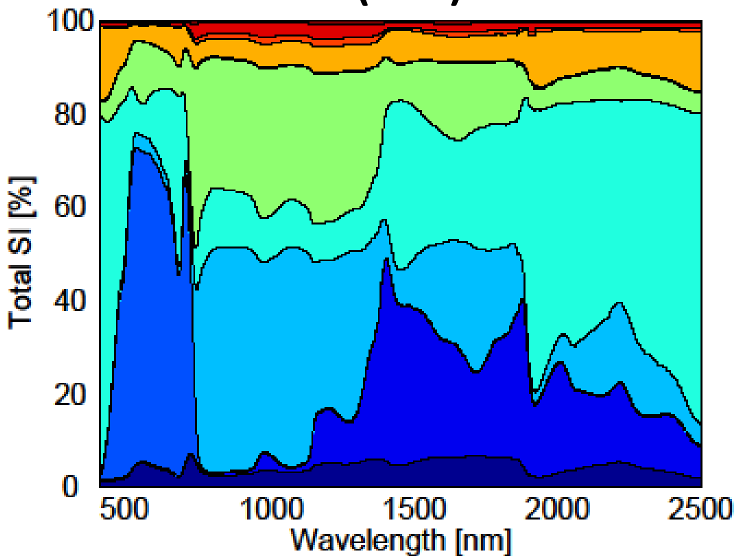
PROSAIL reference (279 s)



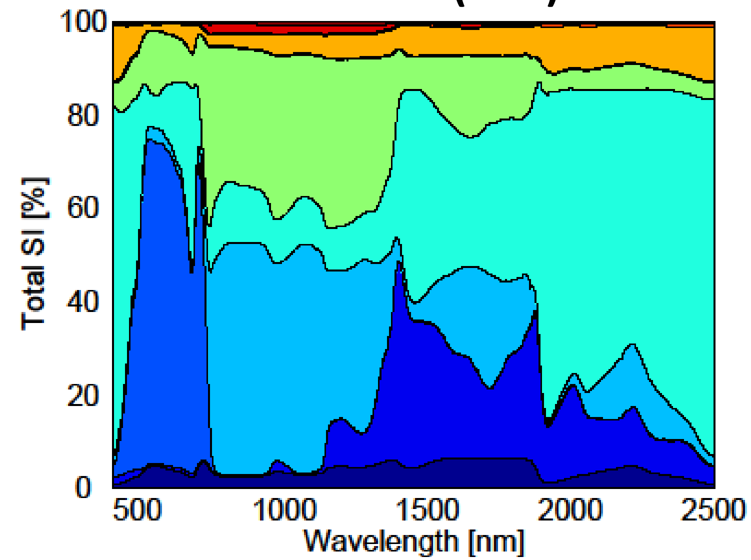
KRR (73 s)



NN (80 s)



GPR (79 s)

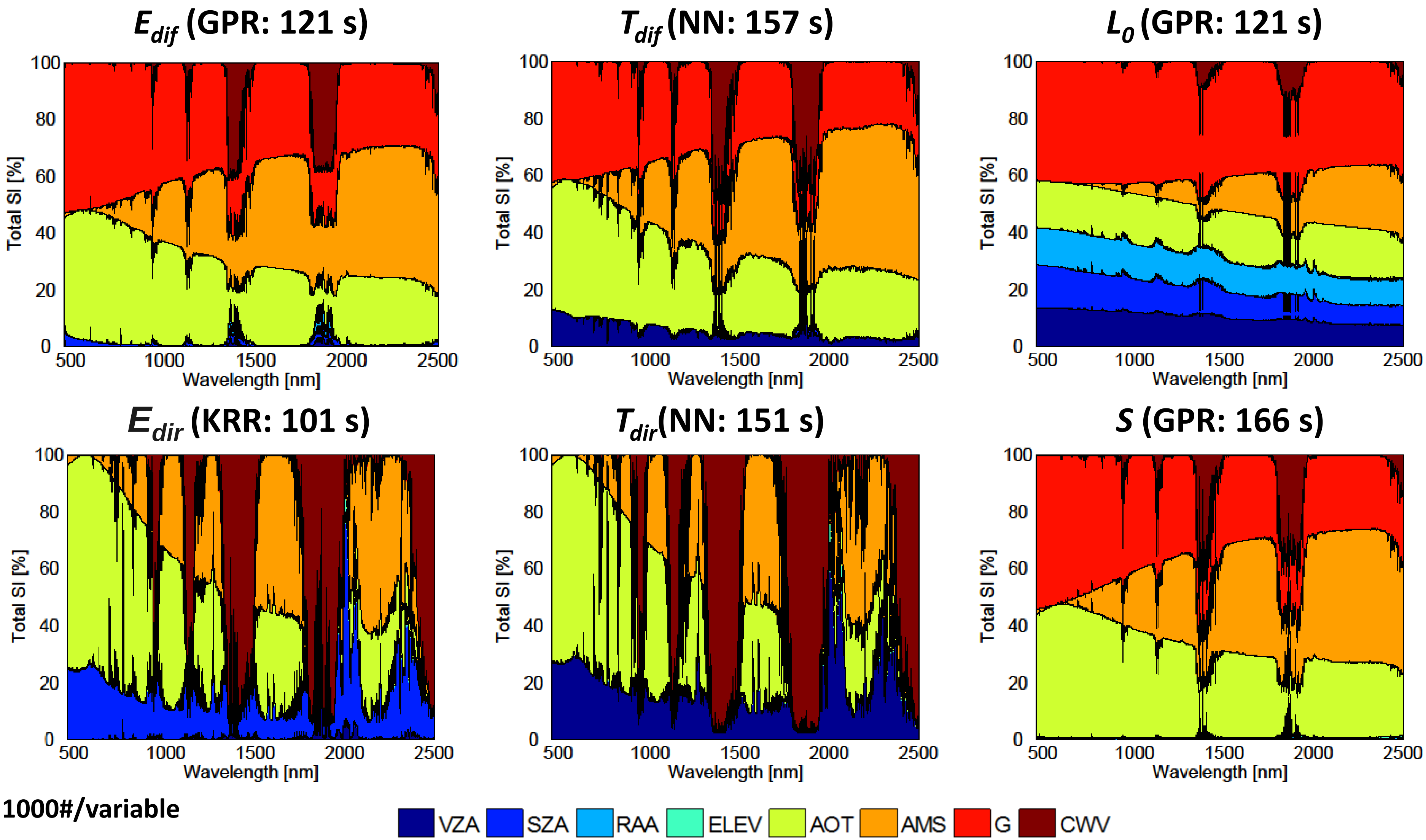


1000#/variable

N Cw Cab Cm LAI LAD skyl soil coeff SZA VZA RAA

MODTRAN atmospheric transfer functions:

$$L_{TOA} = L_0 + \frac{(E_{dir}\mu_s + E_{dif})(T_{dif} + T_{dir})\rho}{\pi(1 - S\rho)}$$

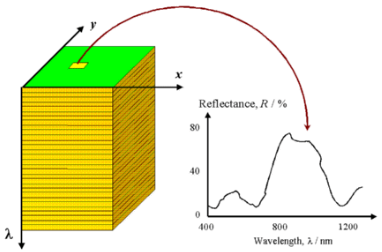


1000#/variable

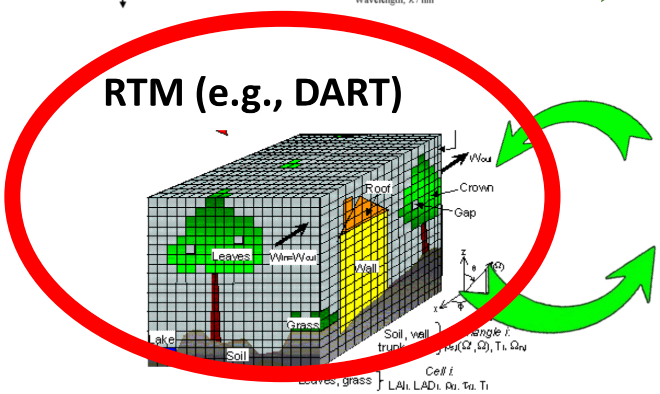
With emulators, processing speed is boosted in the orders of hundred thousand. Using the original MODTRAN simulations would take more than a month.

Emulators into numerical inversion

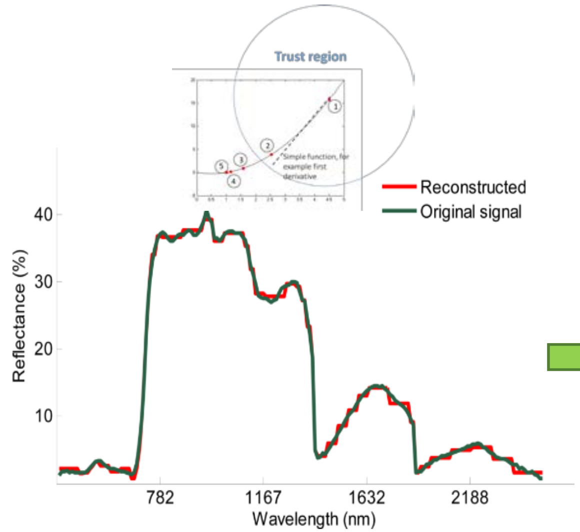
Image



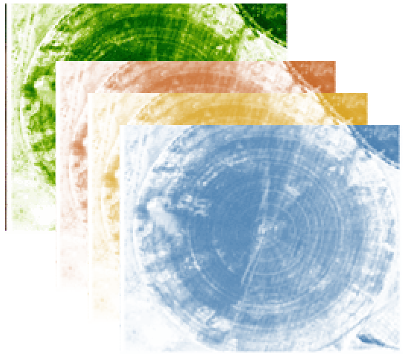
RTM (e.g., DART)



Minimization algorithm: lsqnonlin

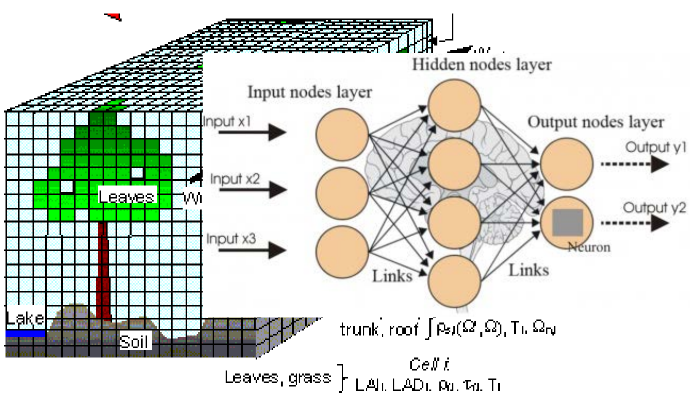


Output maps of RTM variables



Per-pixel RTM iterations: very slow method, inapplicable to computationally expensive RTMs.

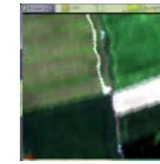
Emulation of an RTM



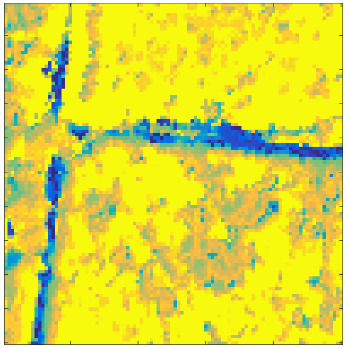
DART KRR emulator applied to HyPlant DUAL (450-2500 nm)

< 1 h

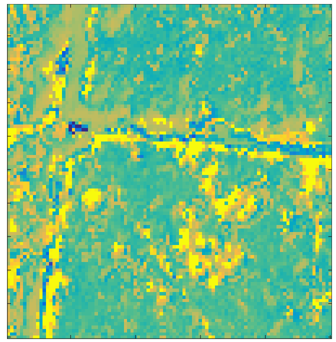
SCOPE KRR emulator applied HyPlant DUAL (bare soil spectra added)



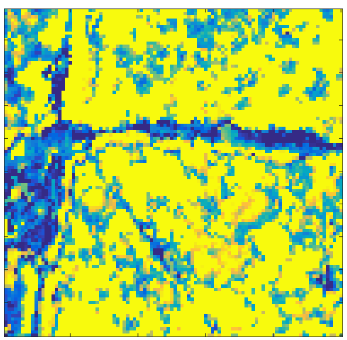
CC



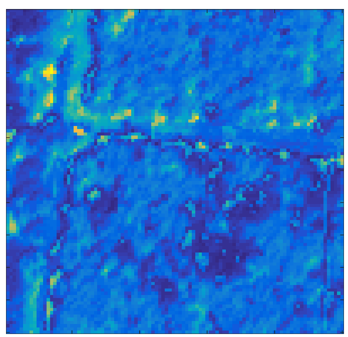
LCC



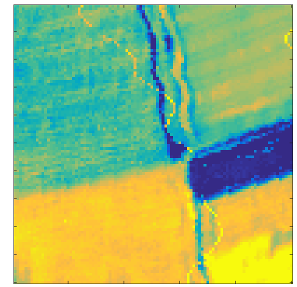
LAI



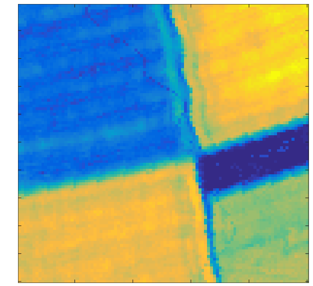
RMSE



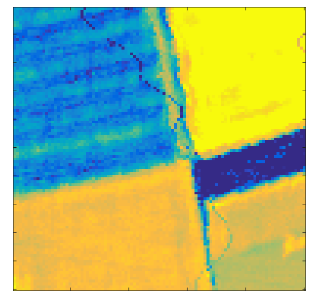
APAR



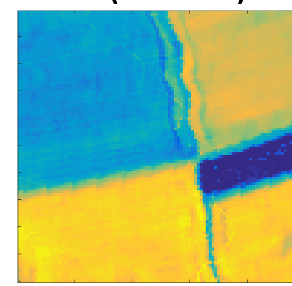
LAI



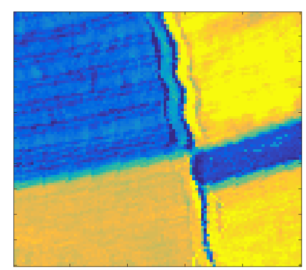
fAPAR



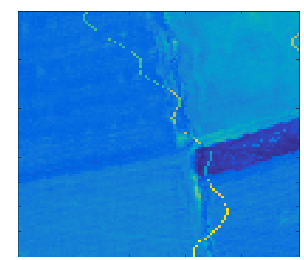
CCC (LCC x LAI)



CWC (Cw x LAI)

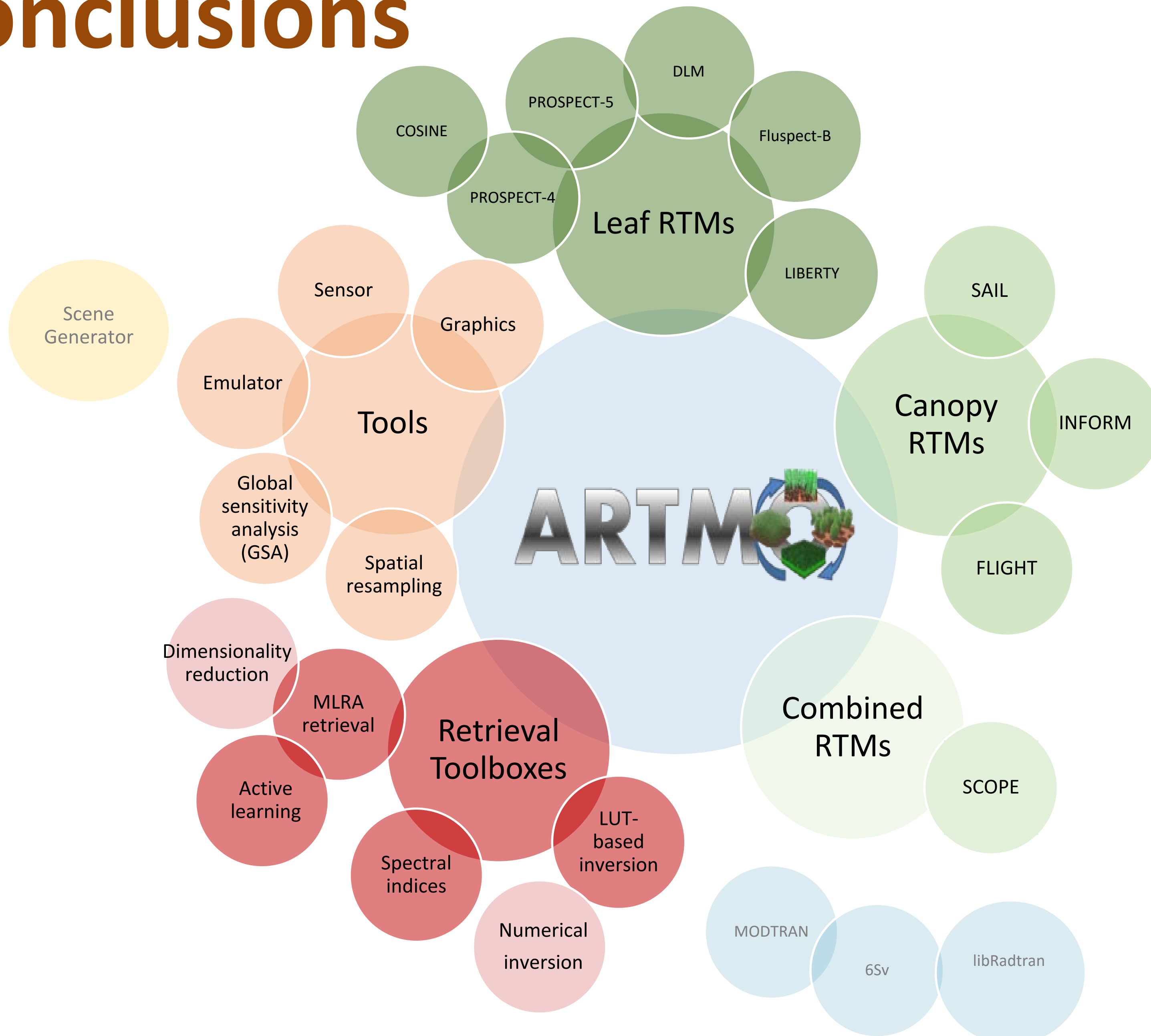


RMSE



Retrieval quality depends on : (1) emulator, (2) number and type of included variables.

Conclusions



Thanks

http://ipl.uv.es/artmo/