



Automated vegetation properties mapping:

Application of S2 vegetation loss quantification

ARTMO [v. 3.24]	Hap of AL Estimate
 File Models Forward Retrieval Tools Help Plugins	
Project Description	
Project Name:	100.
Comment:	
Sensor: NO SENSOR	
DB: flex_I2d_floris LUT Class by map LUT Class by User	

Jochem Verrelst

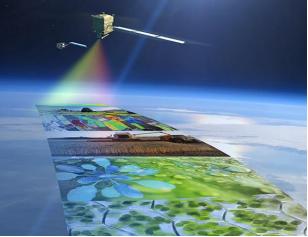
PECS, Bratislava, 20/09/2018



Wageningen (NI) (2005-2010)



Valencia (Es) (2010-now)



Hyperspectral vegetation properties mapping

FLEX: Sun-induced fluorescence mapping

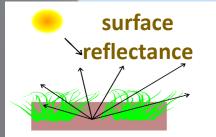
Quantification of vegetation properties from optical data

How to quantify vegetation productivity?



Operational

- Global coverage
- 🗆 300 m, 🕙



Greenness indicators Stress? Potential photosynthesis

8th Earth Explorer: FLEX

sentinel-3 🚷 flex

esa

Launch: 2022

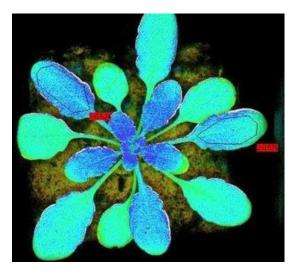
- Global coverage
- 🛛 300 m, 🕙

Vegetation emitted fluorescence

A signal coming directly from the plant Actual photosynthesis_{3/}

sentinel-3 flex

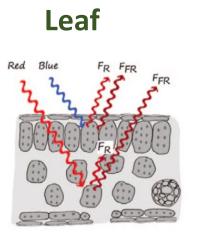
What is sun-induced chlorophyll fluorescence (SIF)?

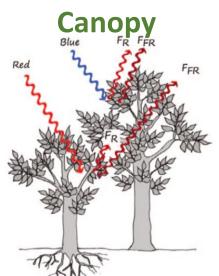


Reflectance 0.0010 0.20 SIF (0.5 - 2%) **PSII** total PSI-PSII decomposition 0.0008 total fluorescence 0.15 0.0006 0.10 0.0004 Absorption Photosynthesis (0-82% 0.05 0.0002 PSI 0.0000 0.00 650 700 750 800 wavelength (nm) Transmittance

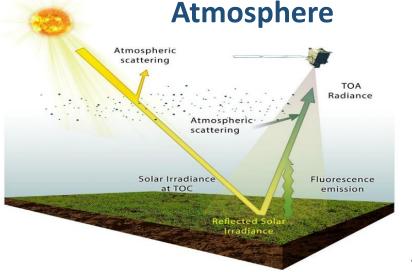
Heat (17.5 - 98%)

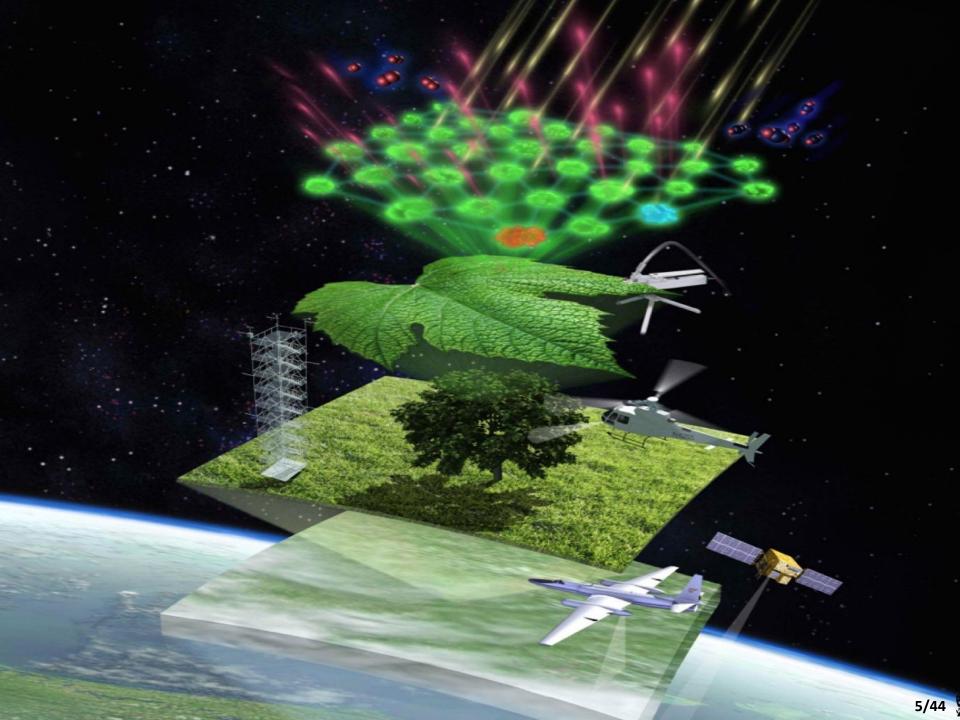
(re-)absorption and scattering mechanisms





Incident light





FLEX

Sentinel-3

ex

FLEX aims to quantify actual photosynthetic activity of terrestrial ecosystems from space, accounting for vegetation health status and stress conditions.

RASS CANDING BU

FLEX Sentinel-3 Space F OLCI nadir (1270 km) SLSTR 'nadir' (1400 km) SLSTR backward (740 km) State of the art HYPLANT Airborne **FLEX products** Canopy Leaf Cell

6/44

FLORIS (150 km)

d fluorescence (760

FLEX Sentinel-3 flex

Tandem mission concept driven by synergy:

- S3 OLCI & SLSTR used for FLEX atmospheric correction
- Synergy of S3 OLCI and FLEX-FLORIS for improved biophysical parameter retrieval.
- S3 & FLEX products used as inputs in photosynthesis model (CO2 assimilation)

FLORIS (150 km) OLCI nadir (1270 km) SLSTR 'nadir' (1400 km) SLSTR backward (740 km)

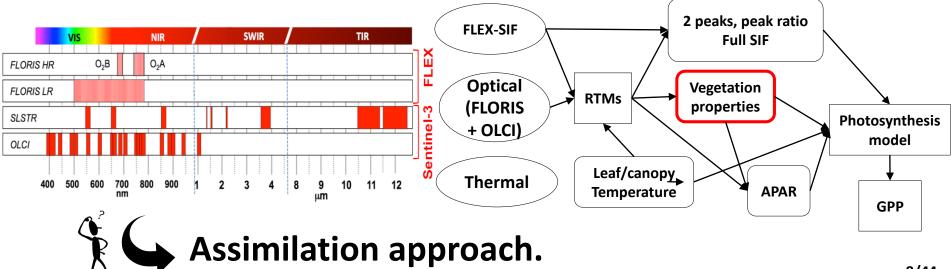
Mission characteristics:	
Tandem with Sentinel-3	
Sun-synchronous orbit	
Swath (km)	150
Spatial resolution (km)	0.3
Revisit time (days)	<27
Equatorial crossing	10:00

Synergistic approach to quantify photosynthesis

Chlorophyll SIF

Sentinel-3

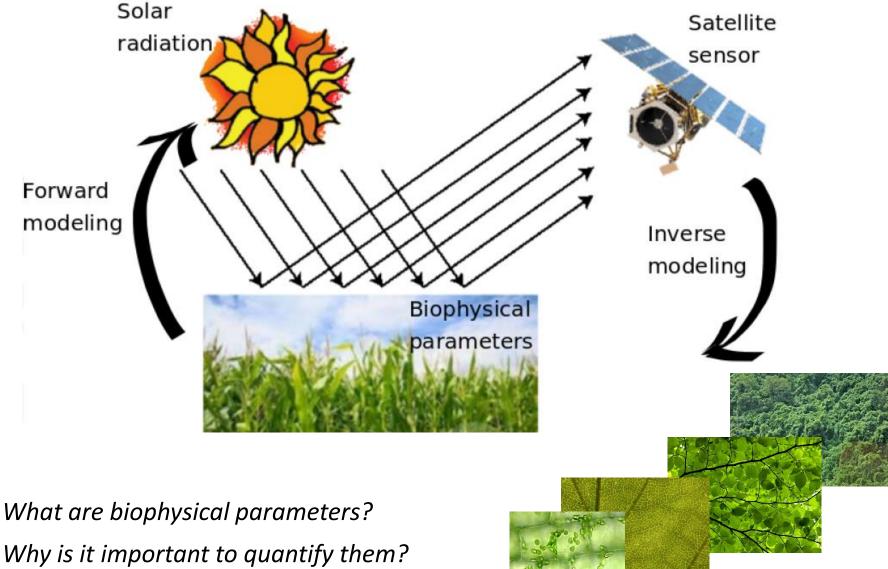
Vegetation productivity (GPP



How to quantify vegetation properties?



Today we will learn: Semi-automated mapping of vegetation properties from optical RS data



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The problem:

Biophysical parameter retrieval is an essential step in modeling the processes occurring on Earth and the interactions with the atmosphere.

The analysis can be done at **local** or **global** scales by looking at bio-geochemical cycles, atmospheric situations, ocean/river/ice states, and vegetation dynamics.

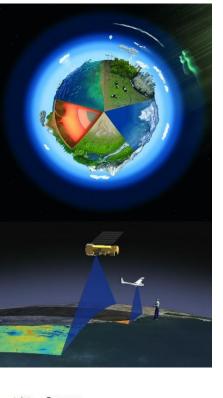
Main parameters: crop yield, biomass, leaf area coverage, chlorophyll content, fraction vegetation cover, GPP,....

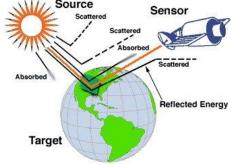
Land/vegetation parameters cannot be estimated directly from optical **RS data. A model is required!**

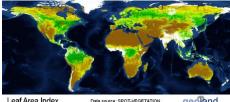
The objective: Transform measurements into biophysical parameter estimates.

The data:

- **Input data:** satellite/airborne spectra, in situ (field) radiometers, or • simulated spectra by RTMs
- **Output results:** estimation of a biophysical parameter







eaf Area Index

11/44

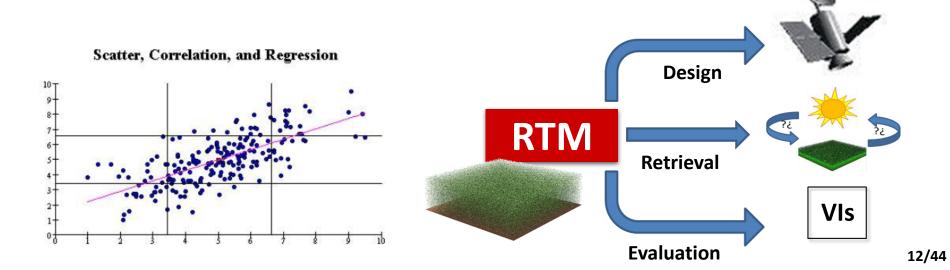
Introduction retrieval biophysical parameters



Statistical approaches

Retrieval of biophysical parameters from Remote Sensing (RS) data **always occurs through a model**, e.g. through statistical models or through inversion of physically-based **radiative transfer models (RTM)**.

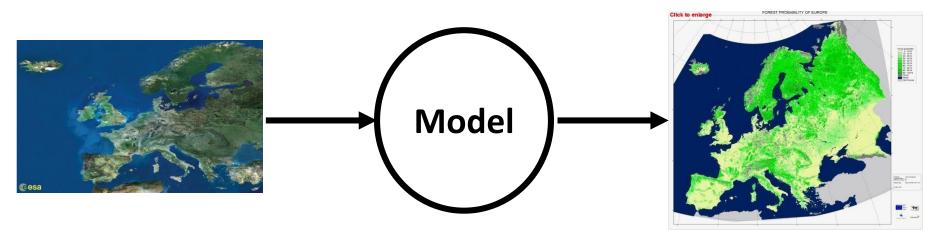
Physically based RTM approaches



Retrieval of (continuous) vegetation properties

Remote sensing image

Map of a vegetation property

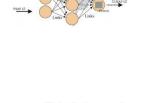


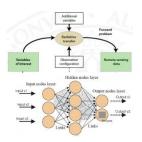
1. Statistical models

- 1. Parametric regression models
- 2. Nonparametric regression models
 - 1. Linear
 - 2. Nonlinear
- 2. Inversion of physically based radiative transfer models
 - 1. Numerical optimization
 - 2. Lookup-table (LUT)-based inversion

Taxonomy of retrieval methods, three main families:

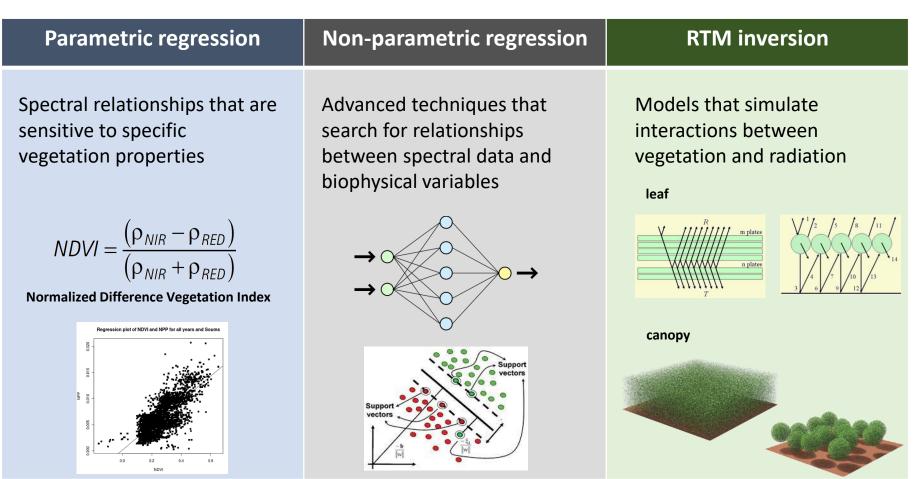
- *Statistical:* parametric and non-parametric: 1.
 - **Parametric** models rely on *some* physical knowledge of the problem and build explicit parametrized expressions that relate a few spectral bands with the biophysical parameter(s) of interest.
 - **Non-parametric** models are *data-driven* models. They are adjusted to predict a variable of interest using a training dataset of input-output data pairs.
- *Physical*: try to reverse RTMs. 2.
 - Physically based algorithms are applications of physical laws establishing photon interaction *cause–effect relationships*. Model variables are inferred based on specific knowledge, typically obtained with radiative transfer functions.
- Hybrid: 3.
 - A hybrid-method combines elements of nonparametric statistics and **physically based methods**. Hybrid models rely on the generic properties of physically based methods combined with the flexibility and computational efficiency of nonparametric nonlinear regression methods.



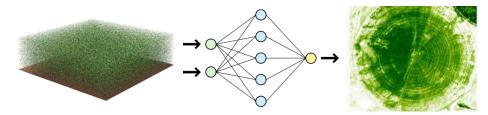




Retrieval families



Methods of these different families can be combined: hybrid methods



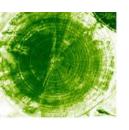
Statistical interpretation of RS

Remote Sensing Data

Statistical relationship

- Parametric regression
- Non-parametric regression

Variable of Interest

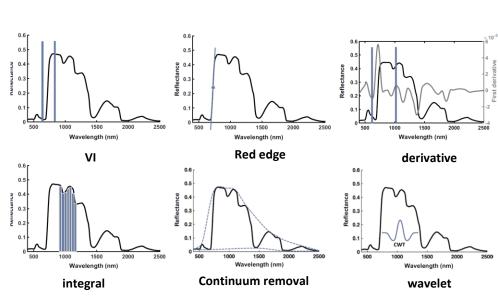


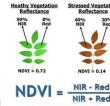
- Simple statistical relationships (VIs) constitute the **BULK of RS analysis**.
- These analyses allow to determine IF there is a relationship, not WHY there is a relationship.
- Linear methods such as VIs are **useful indicators** of biophysical (e.g. structure) or biochemical (e.g. chlorophyll) parameters, however in natural, complex environments indices are **confounded** by additional abiotic and biotic factors.
- VIs lack generality for estimating biophysical parameters.
- Apart from VIs a large number of powerful **alternative statistical retrieval** methods exists (e.g. non-parametric regression methods).

Parametric regression

Parametric regression assume an explicit model for retrieval

- Discrete band methods(VIs):
 - 2-band: SR, NDVI, PRI, OSAVI
 - 3-band: TVI, MCARI, SIPI
 - 4-band: TCARI/OSAVI
- Shape-based methods:
 - Red-edge position (REP)
 - Derivative/Integral indices
 - Continuum removal
 - wavelet





$$=\frac{(\rho 570 + \rho 531)}{(\rho 570 + \rho 531)}$$

$$TCARI / OSAVI = 3 \cdot \left[\left(\rho_{\mu 700} - \rho_{\mu 670} \right) - 0.2 \cdot \left(\rho_{\mu 700} - \rho_{\mu 550} \right) \cdot \right] \\ \left(\rho_{\mu 700} - \rho_{\mu 670} \right) \left(1 + 0.16 \right) \cdot \left(\rho_{\mu 800} - \rho_{\mu 670} \right) / \\ \left(\rho_{\mu 800} - \rho_{\mu 670} + 0.16 \right)$$
(2)

PRI

Parametric regression:



Strengths

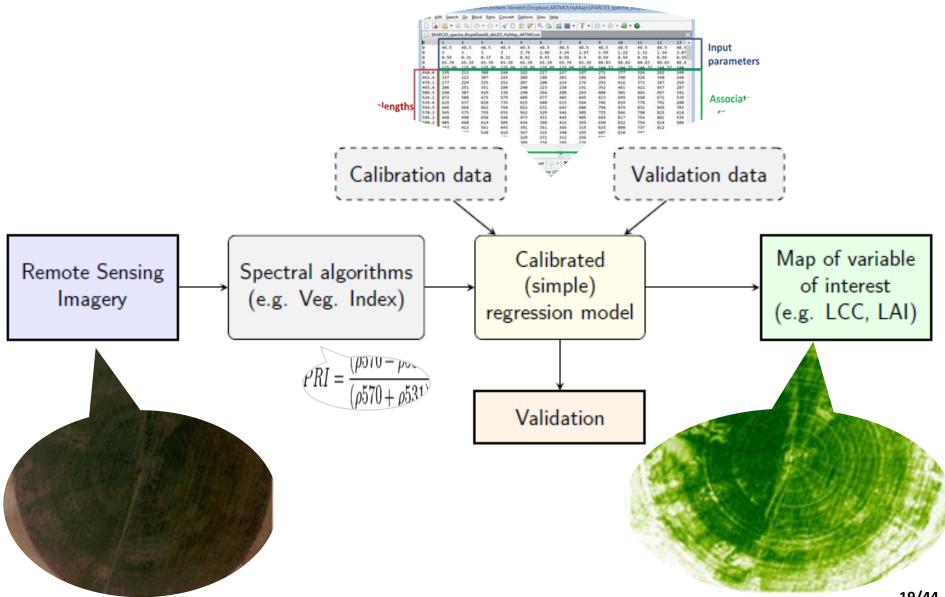
- Simple and comprehensive regression models; little knowledge of user required.
- Fast in processing
- Computationally inexpensive

Weaknesses

- Makes only poorly use of the available information within the spectral observation; at most a spectral subset is used. Therefore, they tend to be more noisesensitive as compared to full-spectrum methods
- Parametric regression puts boundary conditions at the level of chosen bands, formulations and regression function.
- Statistical function accounts for one variable at a time.
- A limited portability to different measurement conditions or sensor characteristics
- No uncertainty estimates are provided. Hence the quality of the output maps remains unknown.



Parametric regression

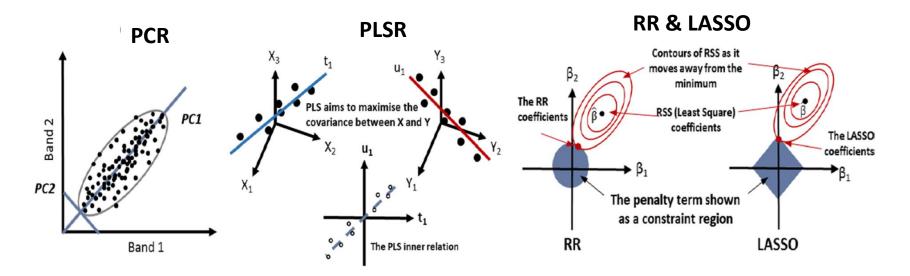


Non-parametric models (1/2):

Data-driven methods: Do not assume explicit feature relations

Linear nonparametric models:

- Stepwise multiple linear regression (SMLR)
- Principal component regression (PCR)
- Partial least squares regression (PLSR)
- Ridge regression (RR)
- Least Absolute Shrinkage and Selection Operator (LASSO)

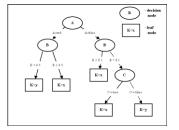


Non-parametric models (2/2):

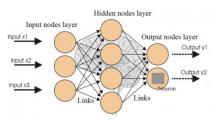
Data-driven methods: Do not assume explicit feature relations

Non-linear nonparametric models:

Decision Trees (DT)



Neural networks (NN)

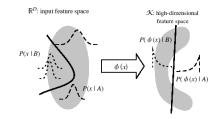


Also:

- Elastic Net (ELASTICNET)
- Bagging trees (BAGTREE)
- Boosting trees (BOOST)
- Neural networks (NN)

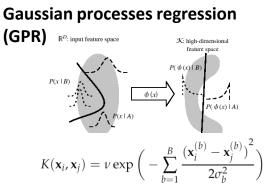
Support vector regression (SVR)

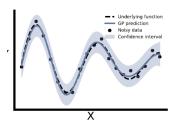
Kernel ridge regression (KRR)



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

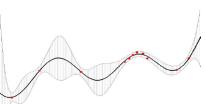
- Extreme Learning Machines (ELM)
- Relevance Vector Machine (RVM)
- Gaussian process Regression (GPR)
- Variational Heteroscedastic Gaussian Process Regression (VHGPR)



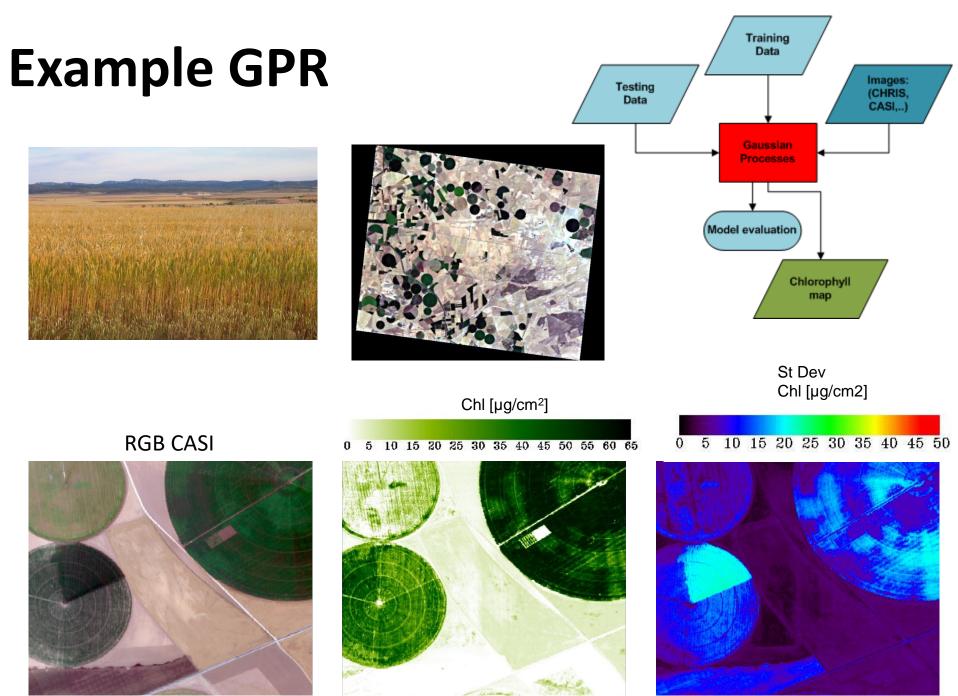


Gaussian Processes Regression (GPR)

- A **GPR** model is a **probabilistic** (**Bayesian**) model directly in function space, with no intermediate model or model parameters.
- GPR are equivalent to kernel ridge regression, least square suport vector machines (SVM), Kriging, large neural networks (NN) and very closely related to SVM regulazation networks.
- **GPR alleviates** some **shortcomings** of the previous methods, while maintaining very good numerical performance and stability:
 - GPR is far more simple than NN, and needs less sample points ⁽³⁾
 - Not only a mean prediction for each sample (pixel), but also a full distribution over the output values including an uncertainty of the prediction (confidence interval).
 - GPR provide a ranking of features (bands) and samples (spectra), thus partly overcoming the blackbox problem. ^(C)
 - <u>http://www.rainsoft.de/projects/gausspro.html</u>



A regression curve plot by the "Gaussian Process Regression Applet" using 11 data points. One can observe that uncertainty goes down when multiple data points are aggregated together.



Non-parametric regression:

Strengths

- Full-spectrum methods. They make use of the complete spectral information.
- Advanced, adaptive (non-linear) models are built.
- Methodologically, accurate and robust performance is enabled.
- Some MLRAs cope well with datasets showing redundancy and high noise levels.
- Once trained, imagery can be processed time efficient.
- Some of the non-parametric methods (e.g. ANNs, decision trees) can be trained with a high number of samples (typically >1,000,000).
- Some MLRAs provide insight in model development (e.g. GPR: relevant bands; decision trees: model structure).
- Some MLRAs can provide multiple-outputs (e.g. PLRS, ANN, SVR, GPR and KRR)

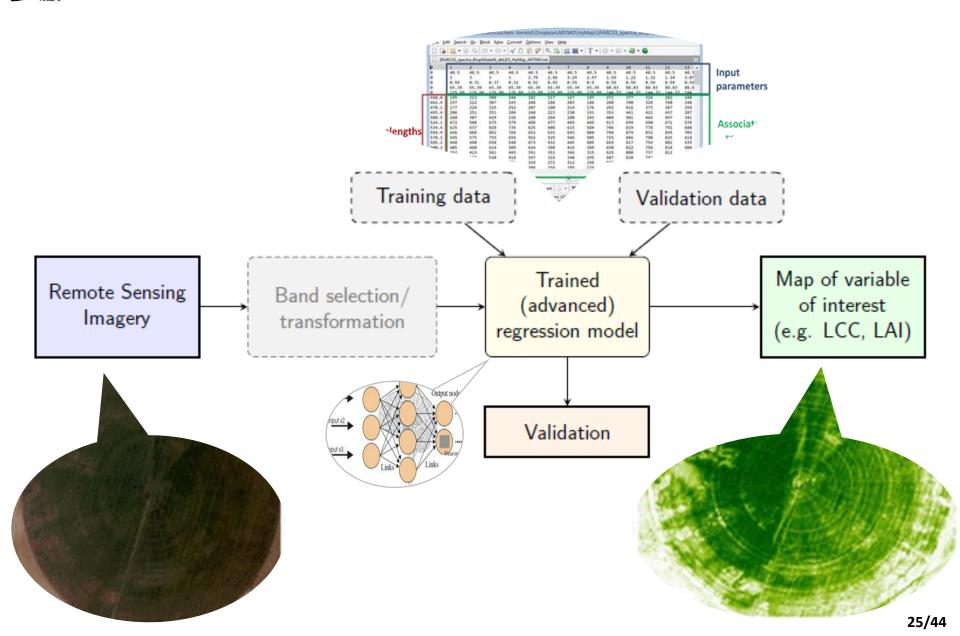
Weaknesses

- Training can be computational expensive.
- Hypercomplex models can be generated. Their generic potential is limited and hence they do not generalize well, based on the training data (problem of over-fitting).
- Some regression algorithms are difficult (or even impossible) to train with a high number of samples.
- Expert knowledge is required, e.g. for tuning. However, toolboxes exist automating some of the steps in this subprocess.
- Some of the methods can be considered as black boxes.
- Some regression algorithms elicit instability when applied with datasets statistically deviating from the datasets used for training.

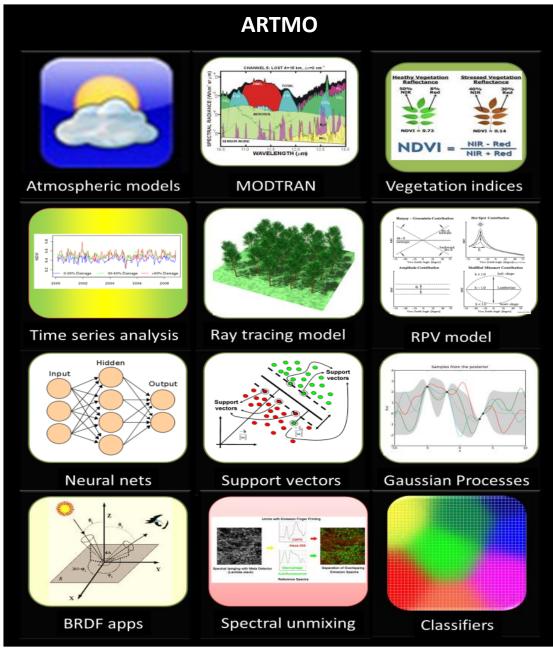
Some MLRAs provide uncertainty intervals (e.g. GPR).

Non-parametric regression

COOKBOOK

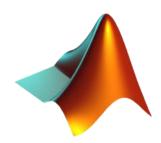




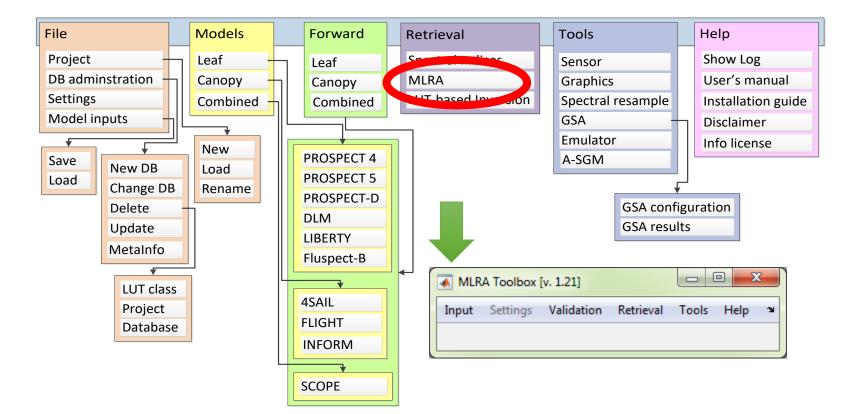


ARTMO v. 3.24

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



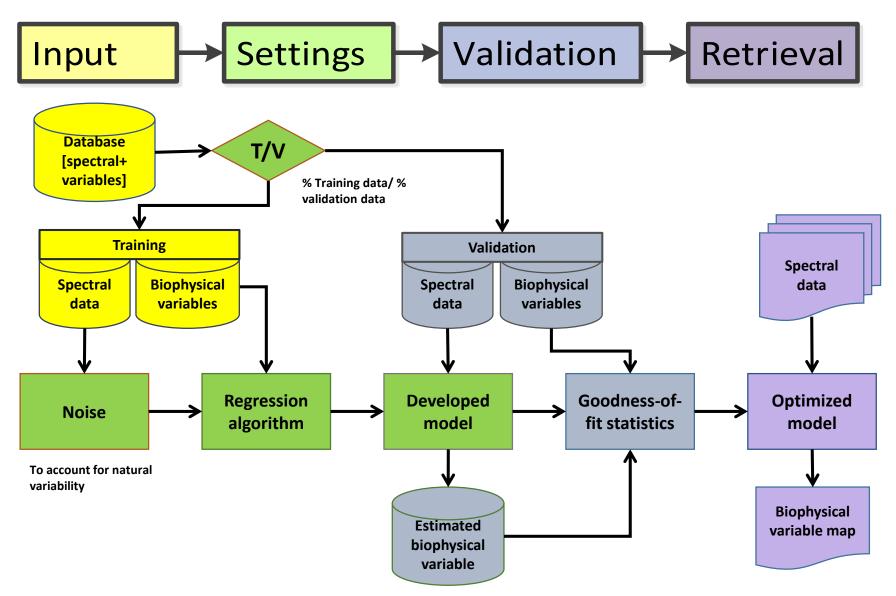
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Open Matlab and provide the ARTMO path In Matlab Command Window: artmo

MATLAB R2014b			
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	123456 OK Cancel	DB: MLRA_lecture	

Schematic overview for systematic evaluation of <u>nonparametric</u> regression models to estimate biophysical variables

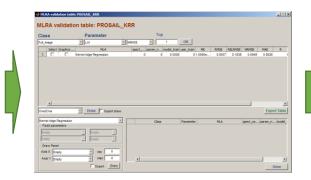


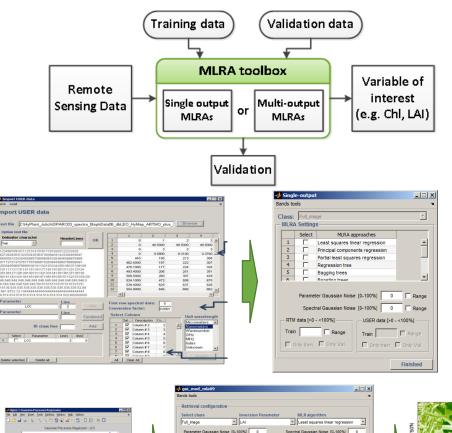
Outlook:

MLRA mapping based on User data

- User Input data
- MLRA setting •
- Validation •
- Mapping .

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9	48.5	48.5	48.5	48.5	48.5	48.5	48.5	48.5	48.5	48.5	48.5	48.5	48.5
3	3	3	3	3	2.79	2.96	3.24	2.97	1.59	1.22	1.32	1.34	3.07
3	0.59	0.31	0.37	0.32	0.92	0.93	0.59	0.9	0.59	0.59	0.59	0.59	0.59
3	65.39	65.39	65.39	65.39	65.39	65.39	65.39	65.39	88.83	88.83	88.83	88.83	88.8
3	125.99	125.99	125.99	125.99	125.99	125.99	125.99	125.99	144.37	144.37	144.37	144.37	144.
450.0	195	213	308	244	182	217	167	187	271	377	324	282	240
462.4	197	222	307	243	208	188	203	186	288	390	328	350	248
\$78.1	177	224	325	252	207	180	214	176	292	416	373	387	259
493.4	286	251	351	284	240	223	230	191	352	461	422	457	287
508.5	260	307	429	336	298	264	280	243	408	501	466	497	341
524.1	472	508	675	579	488	477	485	445	613	699	650	671	539
539.4	625	637	828	735	625	608	615	584	746	819	778	791	680
554.9	646	668	862	764	652	631	643	684	794	874	832	845	703
570.2	545	575	755	655	562	529	546	505	725	846	790	825	618
585.2	448	490	658	548	473	432	445	405	665	817	754	801	535
500.2	405	460	614	509	434	398	416	369	650	822	754	814	584
516.3	352	413	561	443	391	351	366	315	625	808	737	812	453
531.7	326	388	520	418	367	316	340	295	607	810	742	823	431
546.5	285	346	465	371	329	271	312	256	586	809	722	814	395
561.6	261	329	437	347	388	258	286	226	569	818	741	837	384 ¥
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Parame

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ADD

OK

spect_no... param_n... model_train user_train

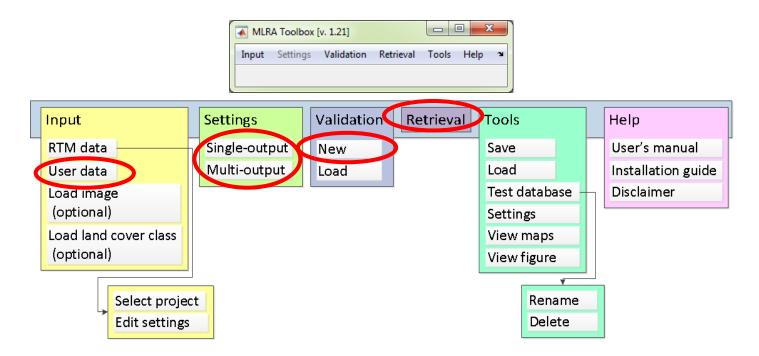
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MLRA mapping based on User data

To train and validate <u>single-output</u> and <u>multi-output</u> MLRA models and apply it to an image using a <u>field dataset</u>.

The procedure will be as follows:

- 1. User data: Insert field data for training and validation
- 2. Single-output: Choose single-output MLRA models and define training/testing partitioning
- 3. Validation: Validate the defined MLRA strategies
- 4. Retrieval: Apply the best one to a remote sensing image.

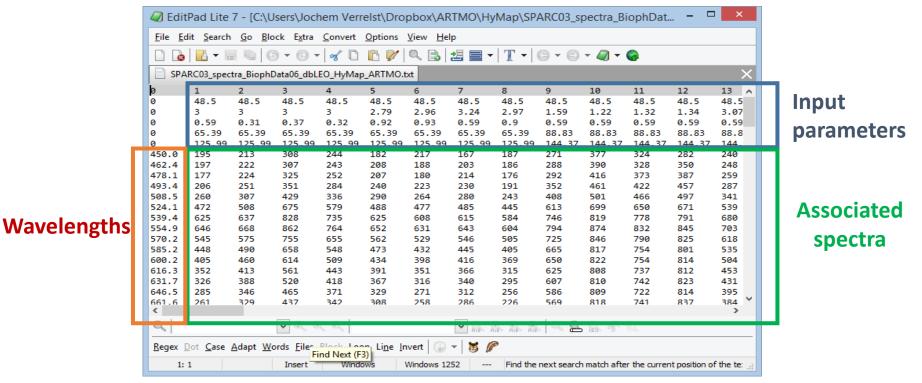


Input: User data (e.g. field data)

User data for training and validation requires one input file, including:

- 1. Biophysical parameters (e.g., LAI, chlorophyll content,...)
- 2. Associated spectra (e.g., obtained from a remote sensing image)

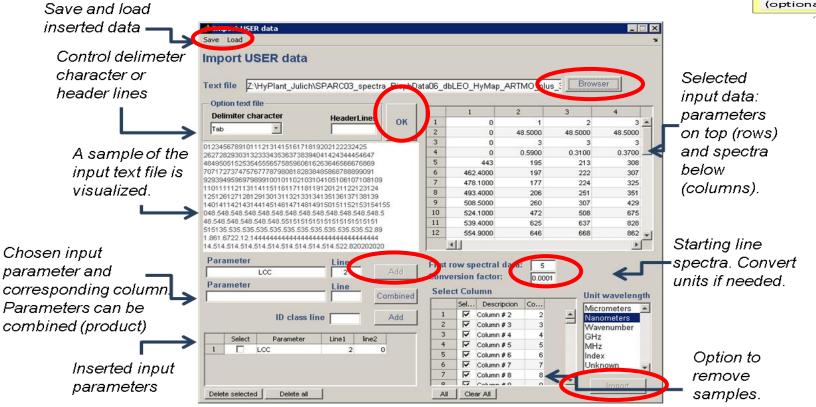
User data need to be organized in a matrix format in plain text file, according to example below:



- Make sure to fill up the whole Matrix! In case of empty cells, use **NaN** and remove those samples in the following step.
- Make sure that wavelengths are the same as the remote sensing image! They need to match. A band selection or band transformation can be later done in **Settings**.

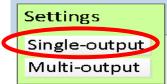
Import User data window

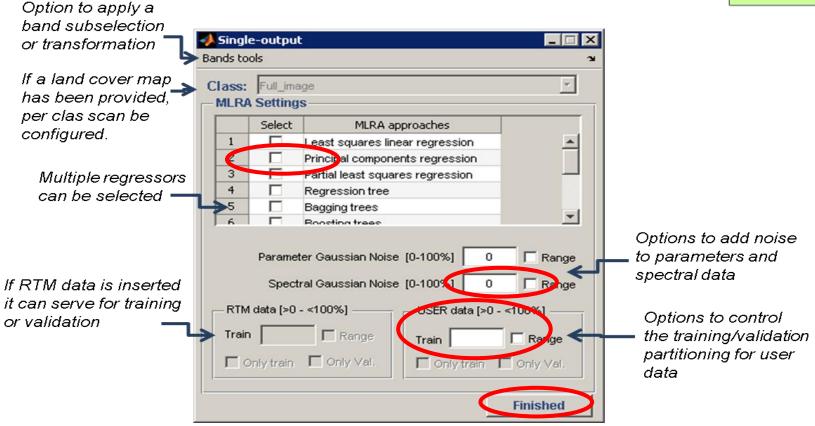




- **1. Browser**: Import User data file.
- 2. Inspect if right data in left panel. By clicking on **OK** data will appear in right panel.
- 3. Define a row with a parameter to its line. Click on **Add**. Multiple parameters can be define by repeating this step. Parameters can be combined.
- 4. Define the row where spectra starts.
- 5. If needed, **convert** spectral data.
- 6. Option to **remove** samples.
- 7. Configured input data can be **save**d and **load**ed as .m file.
- 8. Finally, click on **Import**.

Single-output Settings





- 1. Select the **MLRA** to be trained and validated.
- 2. The option to add Gaussian **noise** is provided. A range of noise scenarios can be applied.
- 3. Select the User data training/validation partitioning. This will randomly partition the input data in a training and validation dataset. Make sure to keep some data for validation (thus < 100% training). Also a range of training/validation partitioning scenarios can be applied. If no validation is required, go directly to Retrieval.</p>
- 4. Click on Finished.

Multi-output Settings

Settings Single-output Multi-output

Prepare models for multiple variables. When multiple input variables have been selected, the following regression algorithms provide multiple-outputs with the same single model:

- partial least square regression (PLSR)
- Multioutput support vector regression (MSVR)
- neural networks (NN)
- kernel ridge regression (KRR)
- Multi-output Gaussian process regression (MGPR)

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Bands t	ools C	ross-Validation	Advanced o	ptions		Ľ
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MLRA	Settings					
	Select	ML	RA approad	:hes		
1		Partial least square	s regression			
2		Multioutput support	vector regre	ssion		
3		Kernel ridge Regres	ssion			
4		Neural Network				
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∐ Se	lect all Paramete	er Gaussian Noise [0-100%]:	0	Range	
	Spectra	al Gaussian Noise [0-100%]:	0	Range	
RTM	data (>0 -	<100%]	USER data	a (>0 - <1	00%]	
Train	[%]:	🗌 Range	Train [%]	:	Ran	ge
	Only train	Only Val.	Only	train	Only Val.	
					Done	

The same options as Single-output are provided.

Cross-validation sub-sampling options

承 Single-output — 🗆 🗙	Figure 1: MLRA: Kernel ridge Regression CV methods: K-fold - </th
Bands tool Cross-Validation ctive Learning Advanced options 🏻	Save Load
Class Full_image MLRA Settings Select MLRA approaches 1 Least squares linear regression 2 Principal components regression 3 Partial least squares regression 4 Adaptive Regression Splines 5 Locally Weighted Polynomials 6 Random Forest (TreeBagger) 7 Random Forest (Fitensemble)	Method: K-fold Random 10 Done
	■ mod_cv_02 - □ ×
Parameter Gaussian Noise [0-100%]: 0 Range Spectral Gaussian Noise [0-100%]: 0 Range	MLRA: Kernel ridge Regression CV method: K-fold
RTM data [>0 - <100%]	Statistics MAE RMSE RRMSE R R2 R2adj NSE 1 Min 0.3180 0.4049 13.6622 7.3219 0.8978 0.8061 0.4910 0.7640
Train [%]: Range Range Range	2 Max 0.4679 0.6501 19.1126 12.3357 0.9726 0.9459 0.8454 0.9351 3 Mean 0.3766 0.4970 16.2467 9.7396 0.9445 0.8928 0.7129 0.8666
Only train Only Val. Only train Only Val.	4 Median 0.3648 0.4829 15.5446 9.0596 0.9531 0.9084 0.7596 0.9061 5 Std 0.0554 0.0923 2.4446 2.0410 0.0297 0.0554 0.1399 0.0725 6 Var 0.0031 0.0085 5.9759 4.1656 8.8009e 0.0031 0.0196 0.0053
Done	ОК

- K-fold: The partition divides the observations into k disjoint subsamples (or *folds*), chosen randomly but with roughly equal size.
- Leave-one-out: Leave-one-out is a special case of 'K-fold', in which the number of folds equals the number of observations.
- Hold-out: This partition divides the observations into a training set and a test (or *holdout*) set.

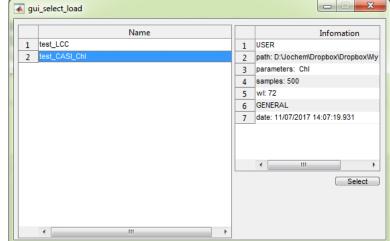


Validation

\checkmark	Start a	a New	validation:	provide	a name
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	Validation
	New
able name	Load
abie hame	
OK Cancel	

- ✓ All MLRA scenarios will be trained using training data and validated against validation data according to goodness-of-fit indicators:
 - R, R², RMSE, RRMSE, NRMSE, ME, MAE
- ✓ Results will be automatically stored in a MySQL table.
- ✓ When finished, an overview table will appear (see further). Such overview table can also be consulted when selecting: Load. A window with generated validation results and metadata will appear: (see next slide)



MLRA validation

Options to organize												
statistics per Class,			1000100		_					_	Imfad	1
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# of best results	MLRA vali	dation table:										
	Class	Parameter		Гор								
• • • • • • • • •	Full_image	LAI	RMSE 📩	1	ОК							
Overview of best	Select Gra	State and	spece param_	and a second second second	user_uain	ME		Contraction of the local division of the loc	NRMSE	MAE	R	
performing MLRAs. 📕		Kernel ridge Regression Partial least squares regression	20	0 0.1000	0	0.1017	1.2031	46.8297 50.2973	20.2876 21.7898	0.9536	0.7494 0.7346	
The check boxes	3	Gaussians Processes Regression	20	0 0.1000	0	-0.2049	1.4884	57.9376 65.9738	25.0998 28.5813	1.0609	0.5971	
allow to select a			20	0 0.5000	U	-0.2009	1.0343	03.9130	20.0010	1.2903	0.0002	
MLRA model for												
retrieval, the graphics												
for graphics outputs.	<u> </u>										>	
	One2One	Draw Export draw								Expor	t Table	
Graphic options: 🗾 🎓	Linear Regression		d	ass	Parameter		MLA		spect_no	param_n	model_	Option to export a
1:1-line, sigmas	Fixed paramete	rs	1 Full_image		LAI	Kernel ridg	e Regressio		20		~	table to a .txt file.
(GPR), and 2D	Empty											
correlation matrices.	Draw Panel											Selected MLRA
coneiation matrices.	Axis X spect_r	noise 💉 min 0										model. With Done it
	Axis Y model_t	rain 👻 max 50									•	
Options to control>	Reset setting	s Export Settings Draw								D	one 🗲	will be moved to
graphics properties.												Retrieval.

- 1. Choose how to **sort outputs,** according to parameter, statistic and number of top results per regression algorithm. Click on **OK**.
- 2. Select a MLRA scenario for retrieval (e.g. the top performing one). It will move to lower panel. When clicking on Done it will move to the Retrieval window (slide 11).
- 3. Select a MLRA scenario for **Graphics plottings: 1:1-line measured vs. predicted.** For GPR additional band relevance information will be provided. **Make sure to have User data loaded, because the selected model will be regenerated.**
- In case ranges were introduced (noise, training/validation partitioning), validation results can be plotted in a 2Dmatrix. Results are plotted according to selected parameter and statistic.
 38

Retrieval

Options to organize statistics per Class, Parameter, stat. and # of best results	mod_mla09 ols			
Select per land cover class, parameter and MLRA.	nage	oversion Param	Gaussian Proce	esses Regression
Options to add noise and select training %. Here, 100% training can	meter Gaussian Noise [0-100 data [0-100%] e selected Delete all	961 0 	Spectral Gaussian Nois USER data [0-100%] Train 100	ADD
	Class	Parameter	MLRA	spect_no param_n.
Selected MLRA	Full_image ∢		Saussian Processes Regressi	•
Mapping options		arameter CC	Bands Select option	е ок

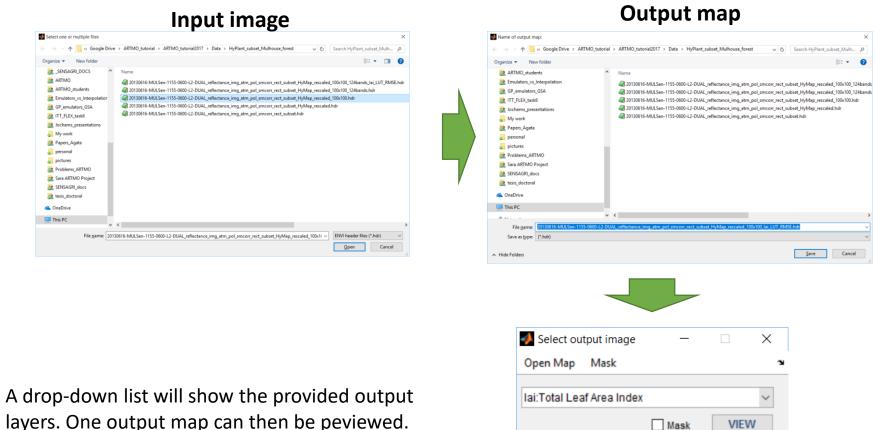
Instead of going through the validation procedure, **one can also choose to immediately train a regression model and apply it to a remote sensing image**. User data has for training to be first inserted.

- 1. Select the **parameter** and **the regression model**.
- 2. Optionally **noise** can be added.
- 3. Select the **training partitioning**. Here 100% training data can be applied. The configuration need to be **ADD**ed and chosen model will appear in the down panel. In case a model has been selected during the validation step, it will directly appear in that panel.
- 4. Band tools options are provided (e.g. spectral subset, PCA).
- 5. When clicking on **OK**, the mapping procedure will start (see next slide).

Retrieval

The mapping of selected biophysical parameter requires the following steps:

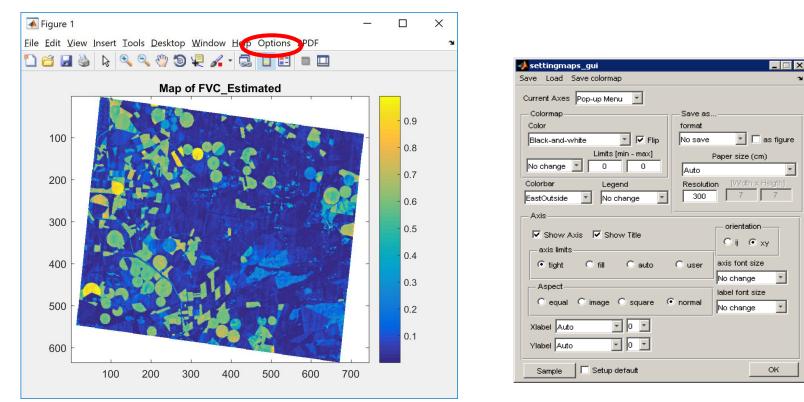
- 1. Select the directory with Input images
- Images according to **TIFF or ENVI file format** (including .hdr file) will be identified and listed. **Multiple images can be selected**. They will be processed one-after-another. 2.
- 3. Select the **Output directory**
- When the processing is done, the output maps can be viewed. Select one through **Open Map** and click 4. on **PRFVIEW**.



VIEW

Mask

Final maps



- Visualization of an output layer. In **Options**, map properties can be controlled (e.g. color scale, color table).
- Make sure to orient the map according to **ij** for **correct orientation**.
- The map can be **saved** according to various vector or bitmap formats. Redundant white space around the figure will be automatically removed.
- Settings can be set as **default** will be automatically applied to subsequent maps.
- Click on **Sample** to visualize the map. Click on **OK** to save it away.

Exercise



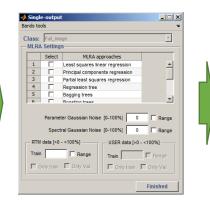
Evaluate the performance of MLRAs using a field dataset and S2 spectral data.

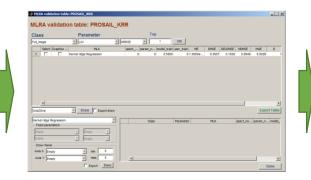
Apply the best performing regression algorithm to S2 images.

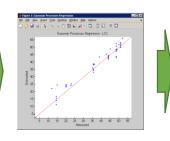


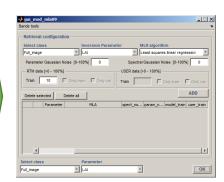
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8	0.59	0.31	0.37	0.32	0.92	0.93	0.59	0.9	0.59	0.59	0.59	0.59	0.59	
0	65.39	65.39	65.39	65.39	65.39	65.39	65.39	65.39	88.83	88.83	88.83	88.83	88.8	
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478.1	177	224	325	252	207	180	214	176	292	416	373	387	259	
493.4	206	251	351	284	240	223	230	191	352	461	422	457	287	
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524.1	472	508	675	579	488	477	485	445	613	699	650	671	539	
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554.9	646	668	862	764	652	631	643	684	794	874	832	845	703	
570.2	545	575	755	655	562	529	546	505	725	846	790	825	618	
585.2	448	490	658	548	473	432	445	405	665	817	754	801	535	
600.2	405	460	614	509	434	398	416	369	650	822	754	814	584	
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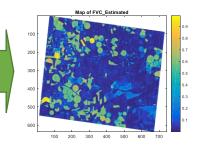
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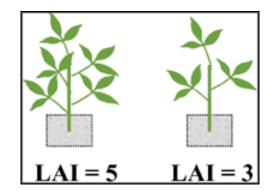








Subsets S2 before after Kineta fire



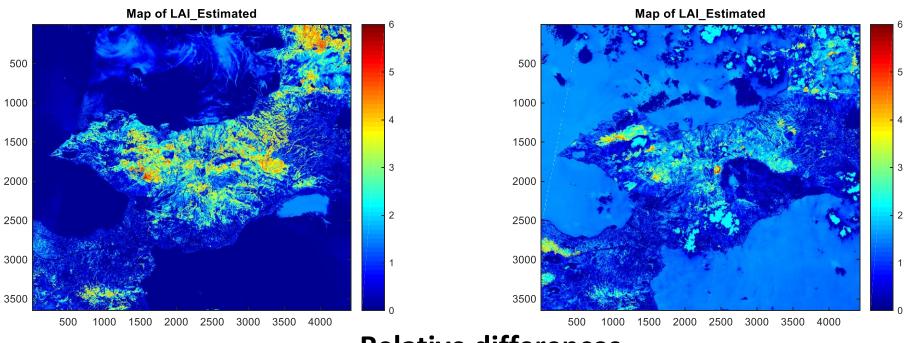
Map LAI before and after using a machine learning regression algorithm (MLRA)



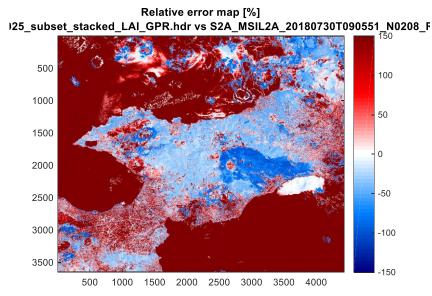




LAI after



Relative differences



44/44

