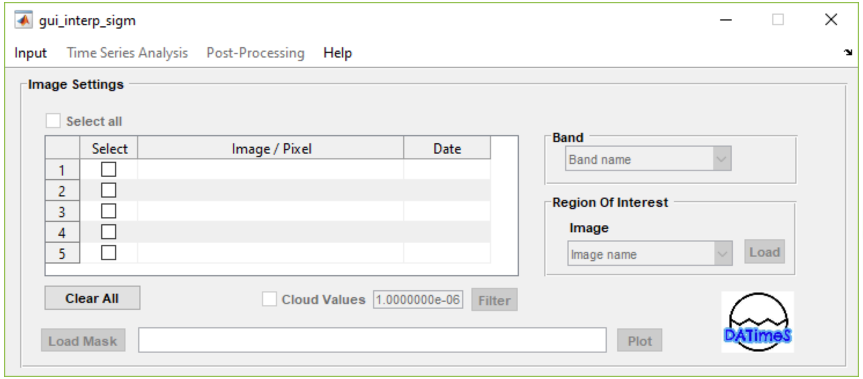
# DATimeS, a new toolbox for time series analysis: opportunities for Sentinels time series processing

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*Dr. Jochem Verrelst*
*Dr. Juan Pablo Rivera*
*Dr. Luca Pipia*
*Pablo Morcillo*

# About me

## Education and formation

- Engineer in Geomatics and Topography
- Engineer in **Geodesy and Cartography** (2nd cycle **degree**)
- Master's Degree in Remote Sensing
- PHD IN MATHEMATICAL METHODS AND MODELLING IN SCIENCES AND ENGINEERING

INSTITUTO DE DESARROLLO REGIONAL

UCLM
UNIVERSIDAD DE CASTILLA-LA MANCHA


**Department:**
**Remote sensing and GIS**

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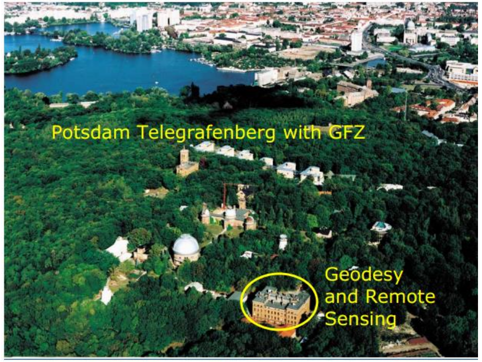
GEO

VIENNA UNIVERSITY OF TECHNOLOGY
DEPARTMENT FOR GEODESY AND GEOINFORMATION
RESEARCH GROUPS PHOTOGRAMMETRY & REMOTE SENSING

GFZ
Helmholtz Centre
POTSDAM




**Current position**

erc
European Research Council
Established by the European Commission

VNIVERSITAT DE VALÈNCIA

IPL
IMAGE PROCESSING LABORATORY

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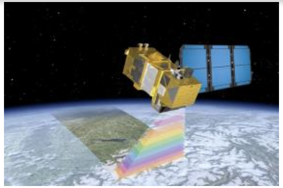
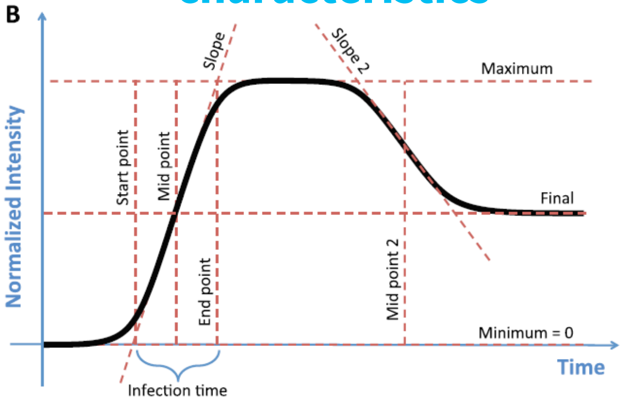


2. Vegetation phenological characteristics




3. Synergy of different satellite observations

+

https://www.esa.int/Our_Activities/Operations/Sentinel_mission_control_taking_shape

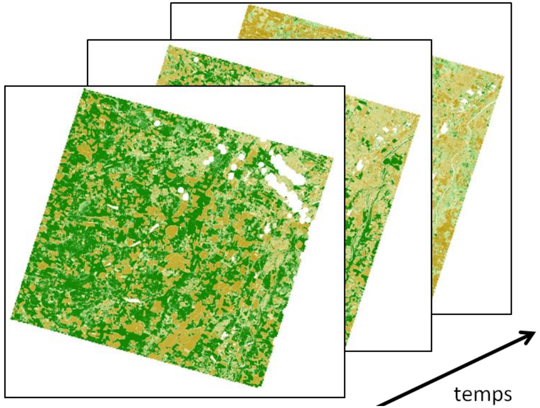
Sicegar: R package for sigmoidal and double-sigmoidal curve fitting M. Umut Caglar, Ashley I. Teufel and Claus O. Wilke

# 1. Gap Filling



## Goal:

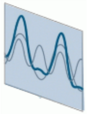
To reproduce spatially continuous fields from discontinuous data and cloud contamination




# Satellite Image Gap Filling Methods



## Harmonic methods



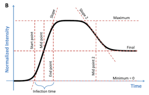
- Fourier analysis including offset, rate and quadratic terms

$$\mathrm{SLV}(t) = A_a \cos(\omega_a t - \phi_a) + A_{sa} \cos(\omega_{sa} t - \phi_{sa})$$
$$+ B + C(t - \bar{t}) + D(t - \bar{t})^2 + \varepsilon(t)$$

- Sliding window approach

## Double sigmoid functions

Nonlinear least squares regression



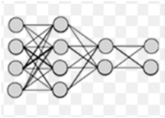
$$g(x) = a + \frac{b}{[1 + \exp(c - dx)] \times [1 + \exp(e - fx)]}.$$

## Matlab methods

| | |
|---|---|
| Polynomial fitting | Spline |
| Linear | Pchip |
| Nearest | Cubic |
| Next | Makima |
| Previous | |

## Machine learning algorithms

| | | | |
|---|---|---|---|
| Bagtree | **KRR** | RF1 | SKRRrbf |
| Ares | LWP | RF2 | TREE |
| ELM | LSLR | SKRRlin | WGPR |
| Boost | MSVR | RVM | VHGPR |
| KNRR | NNIPL | RLR | |
| **GPR** | RKS | SSGPR | |

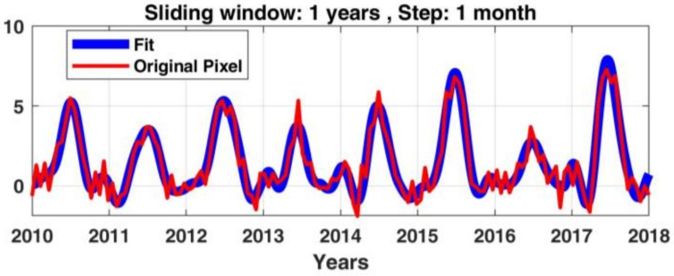


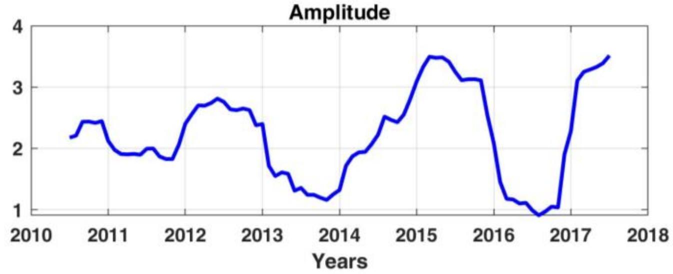
# Satellite Image Gap Filling Methods

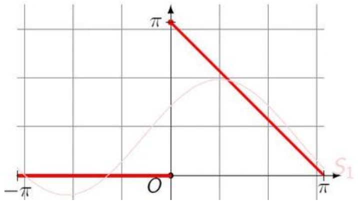


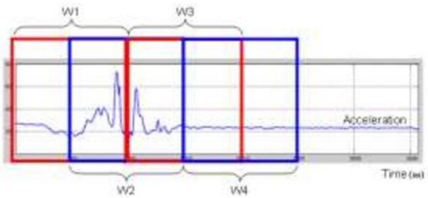
## Fourier Analysis: Sliding window MODEL

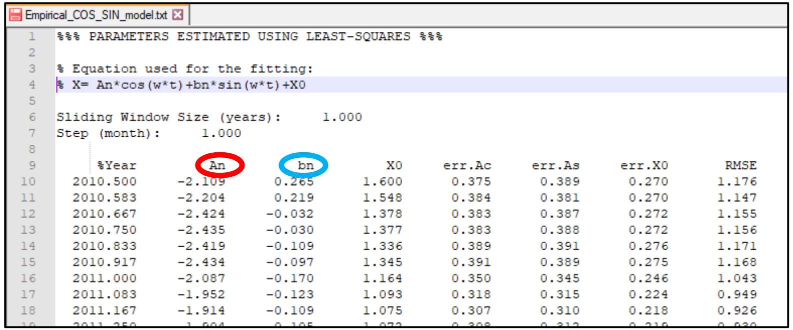
$$f(t) = \frac{a_0}{2} + \sum_{n=1}^{+\infty} \left[ a_n \cos\left(\frac{n\pi t}{L}\right) + b_n \operatorname{sen}\left(\frac{n\pi t}{L}\right) \right]$$





Empirical_COS_SIN_model.txt

```
%%% PARAMETERS ESTIMATED USING LEAST-SQUARES %%%

% Equation used for the fitting:
% X= An*cos(w*t)+bn*sin(w*t)+X0

Sliding Window Size (years):     1.000
Step (month):     1.000

   %Year        An        bn        X0    err.Ac    err.As    err.X0      RMSE
 2010.500    -2.109     0.265     1.600     0.375     0.389     0.270     1.176
 2010.583    -2.204     0.219     1.548     0.384     0.381     0.270     1.147
 2010.667    -2.424    -0.032     1.378     0.383     0.387     0.272     1.155
 2010.750    -2.435    -0.030     1.377     0.383     0.388     0.272     1.156
 2010.833    -2.419    -0.109     1.336     0.389     0.391     0.276     1.171
 2010.917    -2.434    -0.097     1.345     0.391     0.389     0.275     1.168
 2011.000    -2.087    -0.170     1.164     0.350     0.345     0.246     1.043
 2011.083    -1.952    -0.123     1.093     0.318     0.315     0.224     0.949
 2011.167    -1.914    -0.109     1.075     0.307     0.310     0.218     0.926
```

# 2. Vegetation phenological parameters



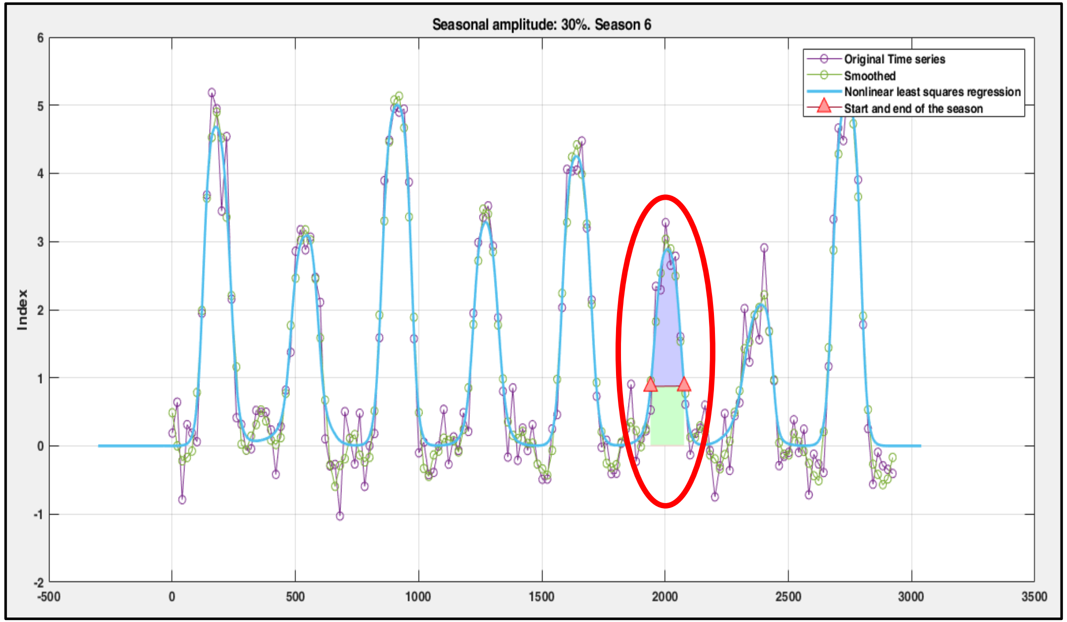
**Goal:**
To study of recurring patterns of vegetation growth and development, as well as their connection to climate.

In **agriculture** studies, they are used for yield determination, and to improve management and timing of field works.

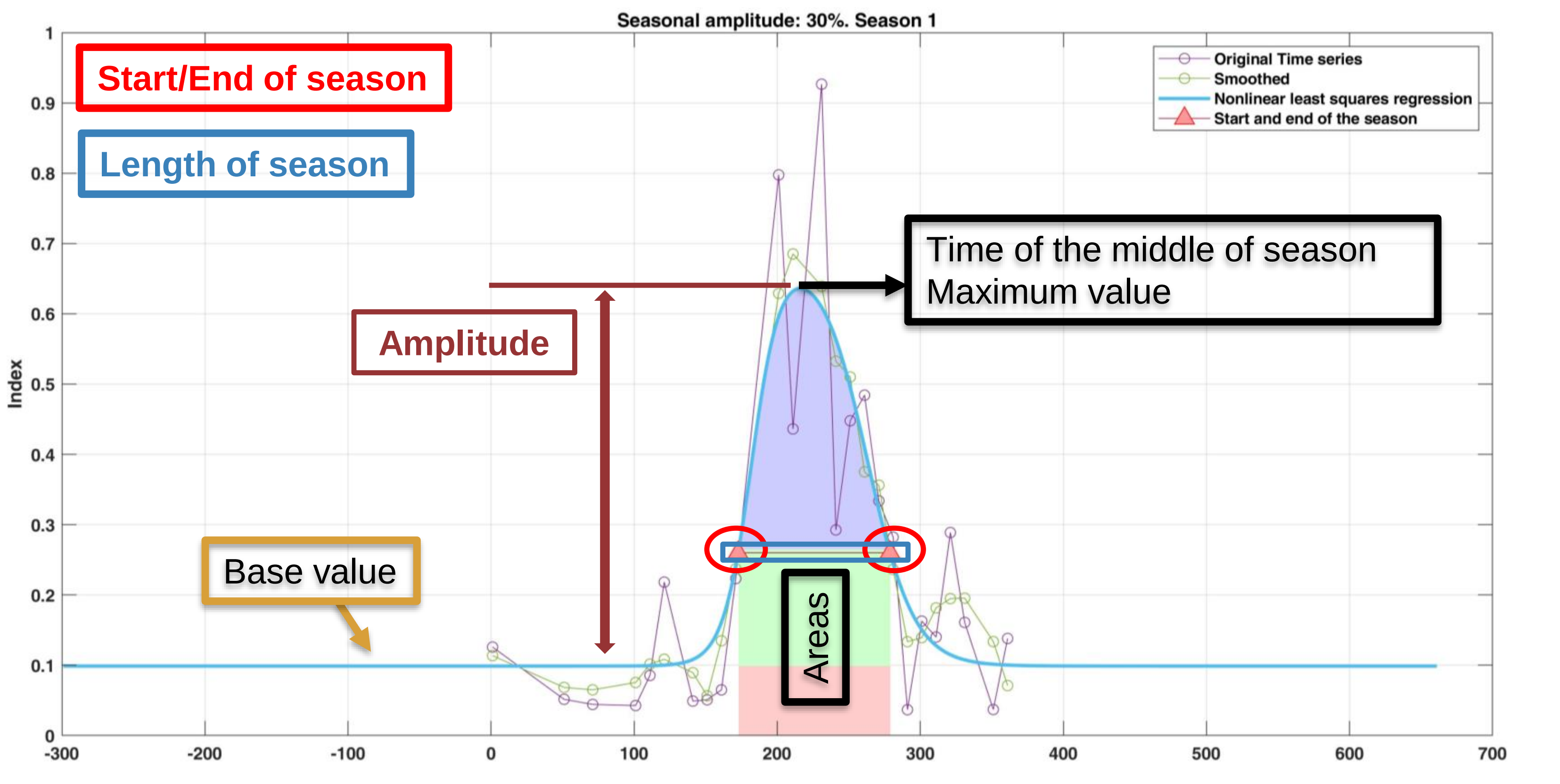
With long-term and frequent **satellite observations**, it is possible to monitor changes in key biophysical attributes.

# Vegetation phenological parameters



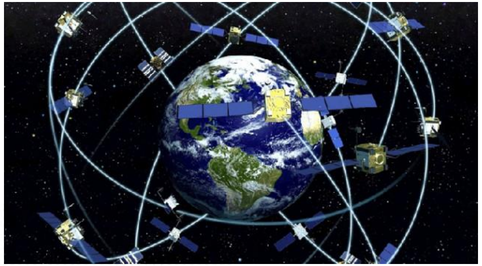


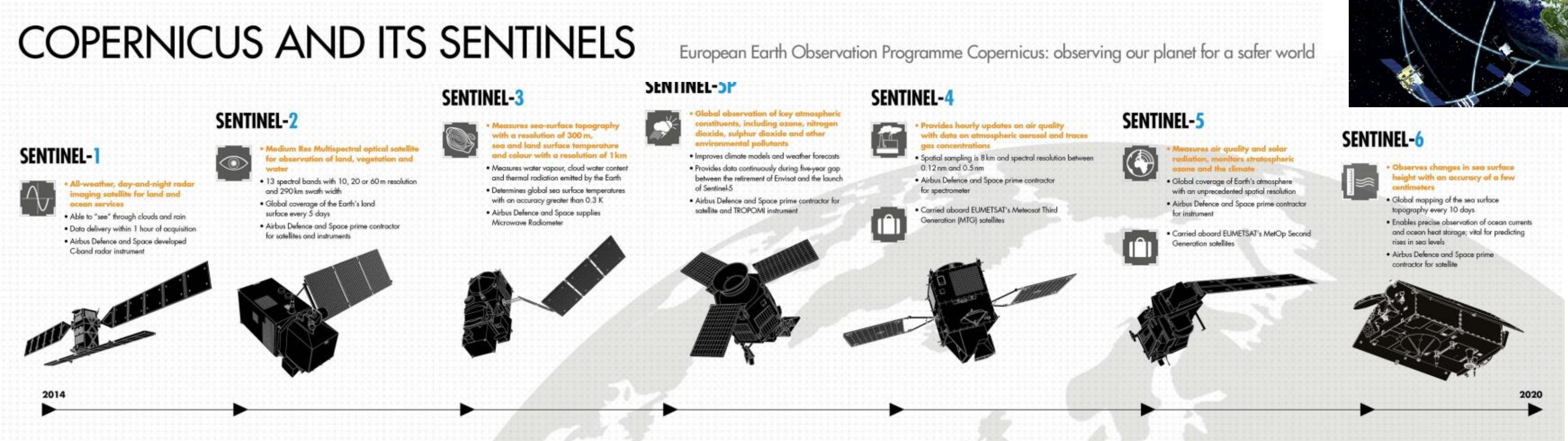
# Some of the seasonality parameters generated



# 3. Synergy of Satellite observation

- The presence of clouds reduces the availability of optical information of any land cover.
- The synergy of different satellite observations could help to obtain a more complete picture of phenological dynamics than could be gleaned from any single satellite on its own.
- Nowadays, a growing number of Earth Observation data comes from different satellites (e.g. Sentinels).
- The synergy of different satellite observations could help to obtain a more complete picture of phenological dynamics than could be gleaned from any single satellite on its own.

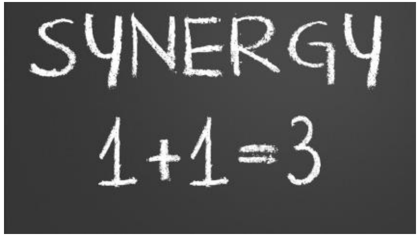




# Synergy: Research purpose

Using **Multi-Output Gaussian Process** (MOGP) regression to establish a **synergy** between vegetation descriptors from **active-passive imageries**, and tackle the problem of cloud-induced data gaps over vegetated areas.

Sentinel-1
Radar Vegetation Index (RVI)




Sentinel-3
Leaf Area Index (LAI)

# Why MOGP regression?

**Limitation of single Gaussian Process** (GPR): the obtained models are independent and do not take into account the relationships among outputs

It is based on the **linear model of coregionalization** (LMC), also known as co-kriging in the field of geostatistics.

For each multisensor time series, it creates a **specific model** providing a **prediction** of the vegetation descriptors at any date along with an estimation of its **uncertainty**.

MOGP is a **machine learning** technique that learns automatically the statistical relationships among multisensor time series (**capture the dependencies**).

MOGP can be trained at **any scale**, e.g., per-pixel or averaged per land cover.

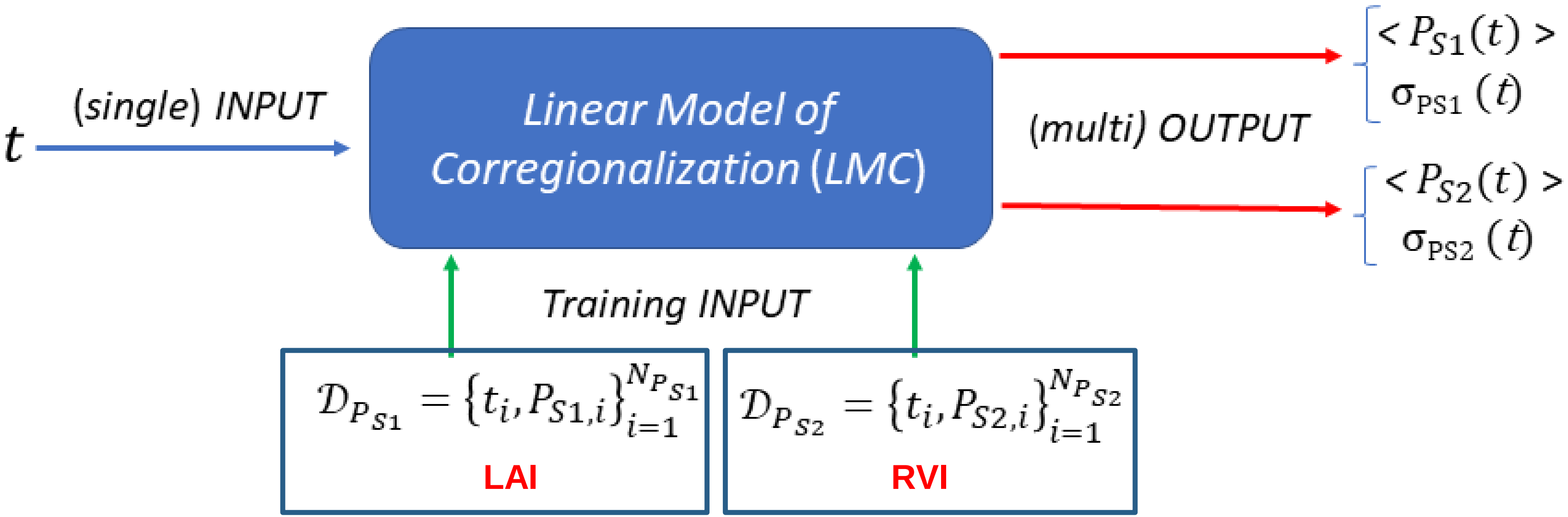
MOGP method provides **a quantifiable measure** on how well two distinct Earth Observation **products sources** are expected to **complement each other** in time series gap filling.

**See *Alvarez et al. (2012)* for details of the mathematical formulation**

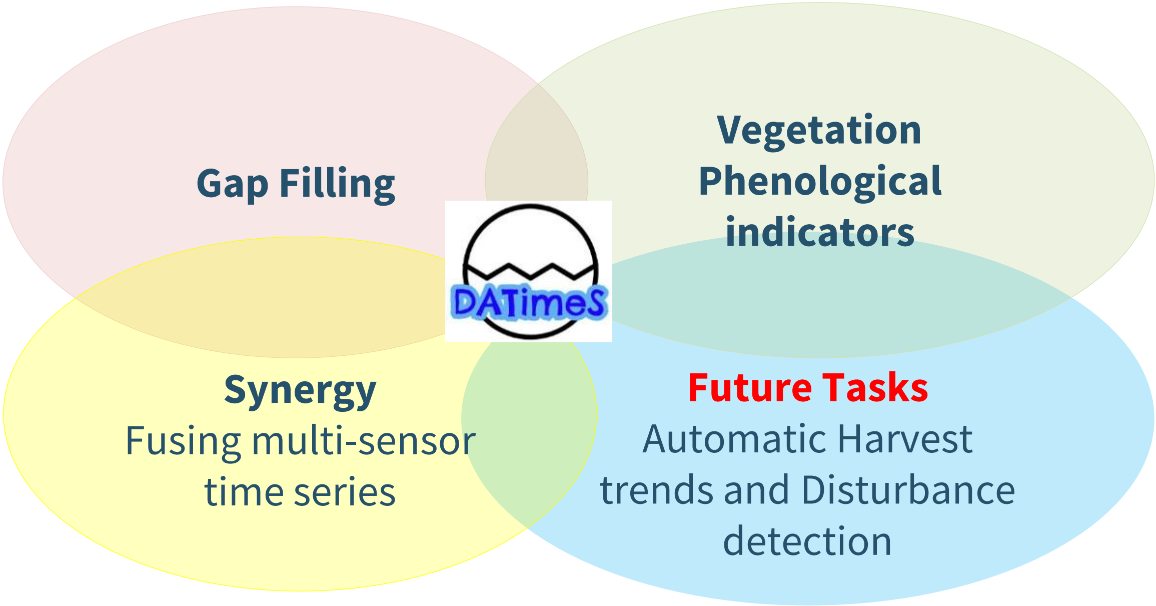
# Multioutput Gaussian Process Regression Modelling (MOGP)

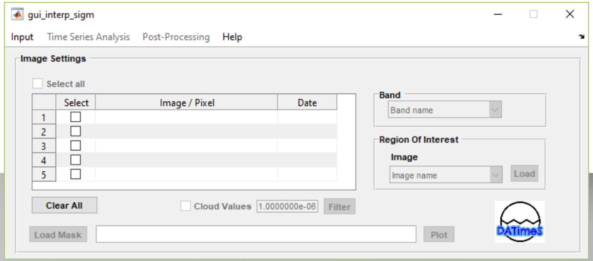
The time series of the two input parameters to be linked by MOGP, **$D_{PS1}$** and **$D_{PS2}$**, are used to train the model.

The trained MOGP model provides a prediction of **$P_{S1}$** and **$P_{S2}$** along with their uncertainty for each input time t.



# DATimeS Modules




**Acronym:**
**Descomposition and Analysis of Time Series (DATimeS)**

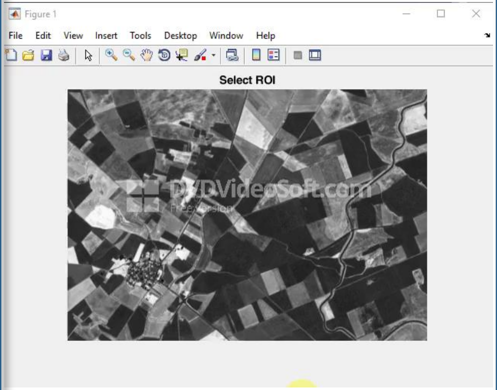
# Data Inputs



## Images can be processed in multiple formats



## Region of Interest



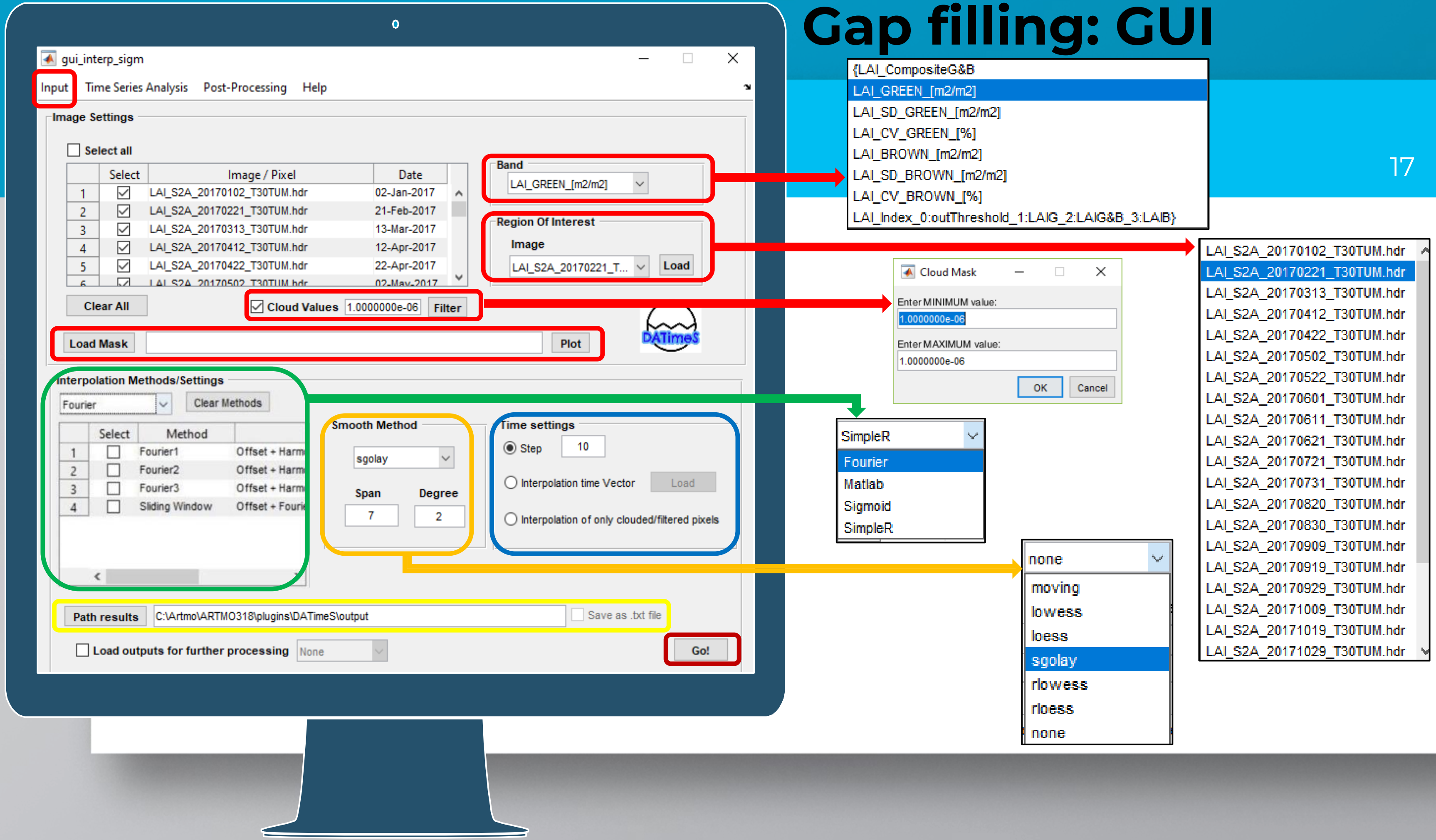

## Single pixel from .txt file

pixel_interpolation3.txt

| | | |
|---|---|---|
| 1 | 20151129 | 0.143270019531250 |
| 2 | 20151219 | NaN |
| 3 | 20151229 | NaN |
| 4 | 20160118 | NaN |
| 5 | 20160217 | 0.131915332031250 |
| 6 | 20160407 | 0.110396484375000 |
| 7 | 20160417 | NaN |
| 8 | 20160427 | NaN |
| 9 | 20160606 | 0.243423046875000 |
| 10 | 20160626 | 0.254109765625000 |
| 11 | 20160706 | 0.354363769531250 |
| 12 | 20160716 | 0.363953320312500 |
| 13 | 20160805 | 0.303975976562500 |
| 14 | 20160815 | 0.269918847656250 |
| 15 | 20160825 | 0.206165136718750 |
| 16 | 20160904 | NaN |
| 17 | 20160914 | NaN |
| 18 | 20160924 | 0.155874218750000 |
| 19 | 20161103 | 0.0944648437500000 |
| 20 | 20161203 | 0.0956170898437500 |
| 21 | 20161213 | NaN |
| 22 | 20161223 | NaN |
| 23 | 20170102 | NaN |
| 24 | 20170112 | NaN |
| 25 | 20170211 | NaN |
| 26 | 20170221 | 0.156574218750000 |
| 27 | 20170313 | 0.249560253906250 |
| 28 | 20170402 | 0.385856445312500 |
| 29 | 20170412 | 0.391757128906250 |

# Gap filling: GUI



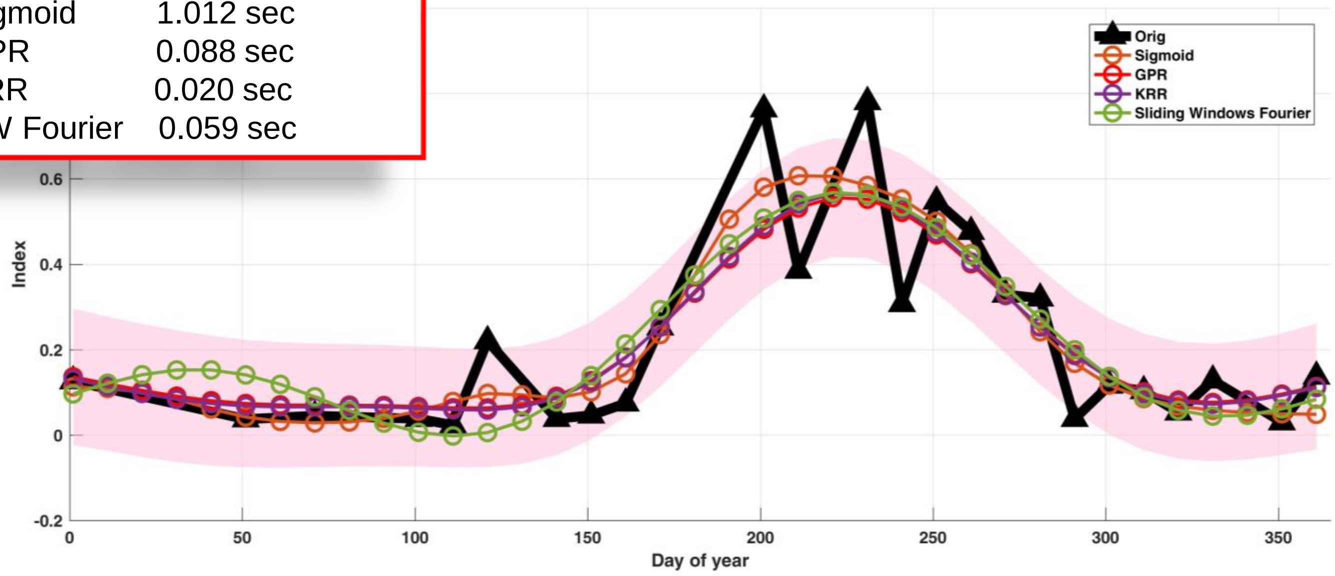


# Examples: Different seasonality patterns



**Average Computation time:**

| | |
|---|---|
| Sigmoid | 1.012 sec |
| GPR | 0.088 sec |
| KRR | 0.020 sec |
| SW Fourier | 0.059 sec |

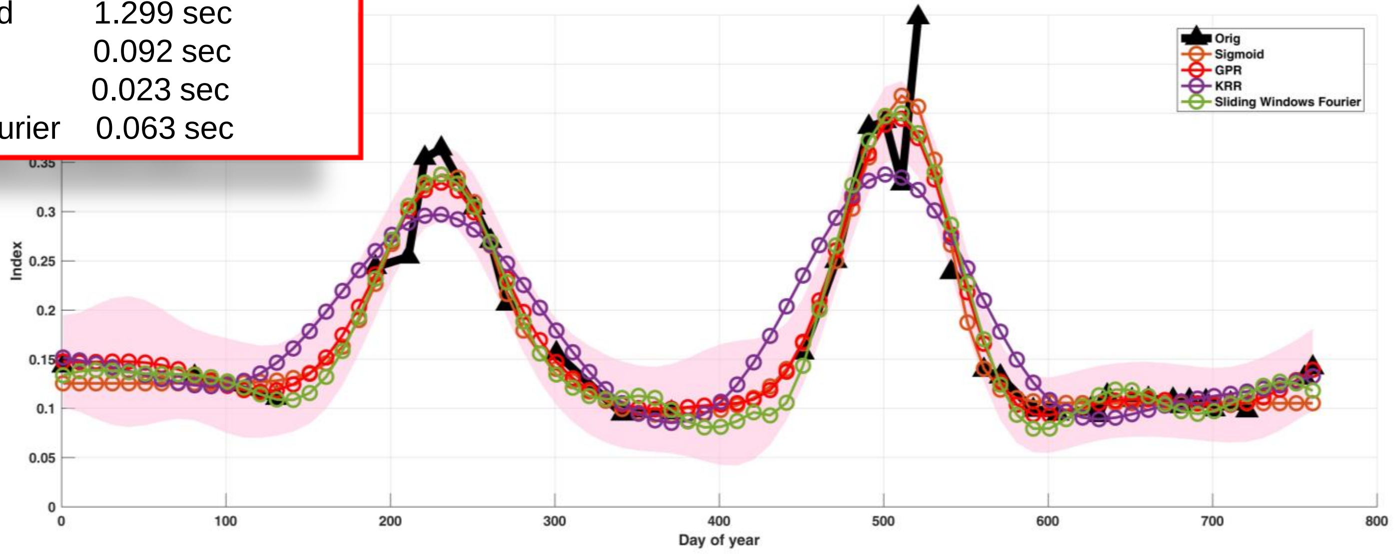


# Examples: Different seasonality patterns



**Average Computation time:**

| | |
|---|---|
| Sigmoid | 1.299 sec |
| GPR | 0.092 sec |
| KRR | 0.023 sec |
| SW Fourier | 0.063 sec |

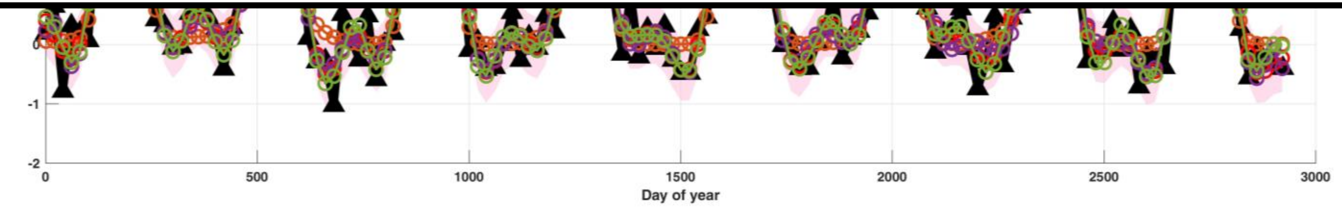


# Examples: Different seasonality patterns



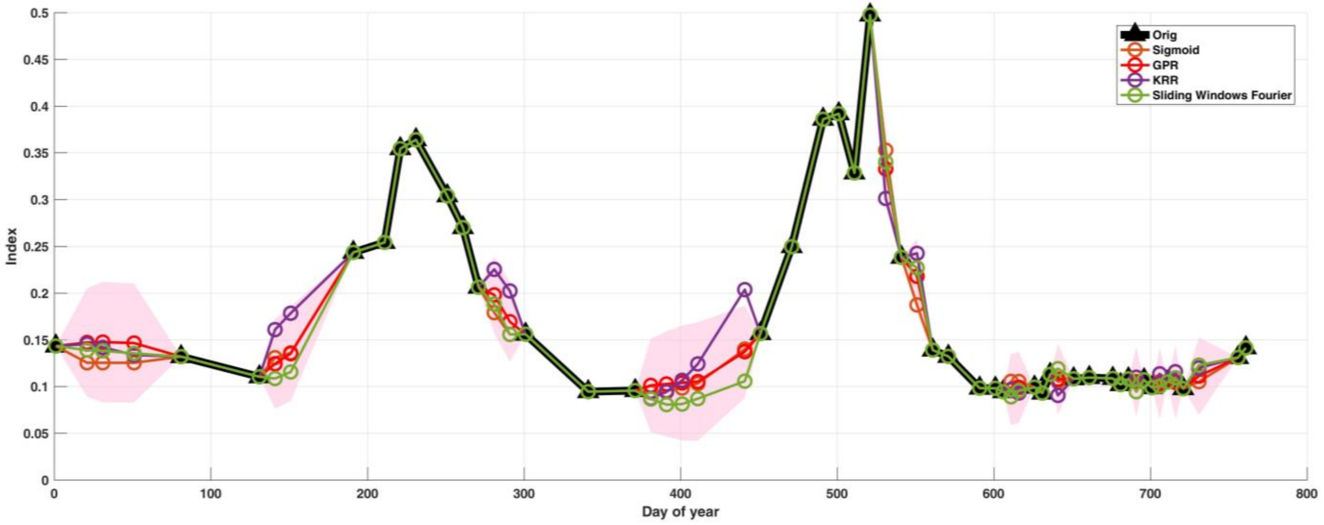
```
%%% Interpolation results %%%
% Column 1:                   Dates
% Column 2:      fourier_analysis3 ( Time: 0.011 sec )
% Column 3:                Sigmoid ( Time: 1.686 sec )
% Column 4:                 spline ( Time: 0.002 sec )
% Column 5:                   GPR_ ( Time: 0.138 sec )
% Column 6:Sliding Windows Fourier ( Time: 0.180 sec )
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

  20151129              0.1228                  0.1253                  0.1433                  0.1477                  0.1336
  20151209              0.1228                  0.1253                  0.1782                  0.1469                  0.1506
  20151219              0.1243                  0.1253                  0.1977                  0.1470                  0.1659
  20151229              0.1282                  0.1254                  0.2044                  0.1475                  0.1772
  20160108              0.1352                  0.1254                  0.2007                  0.1475                  0.1828
  20160118              0.1458                  0.1254                  0.1891                  0.1465                  0.1816
  20160128              0.1601                  0.1254                  0.1722                  0.1439                  0.1739
  20160207              0.1779                  0.1254                  0.1523                  0.1397                  0.1606
  20160217              0.1984                  0.1254                  0.1319                  0.1343                  0.1437
```



# Interpolation of only clouded/filtered pixels





# Inter



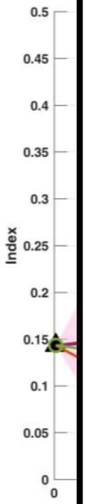
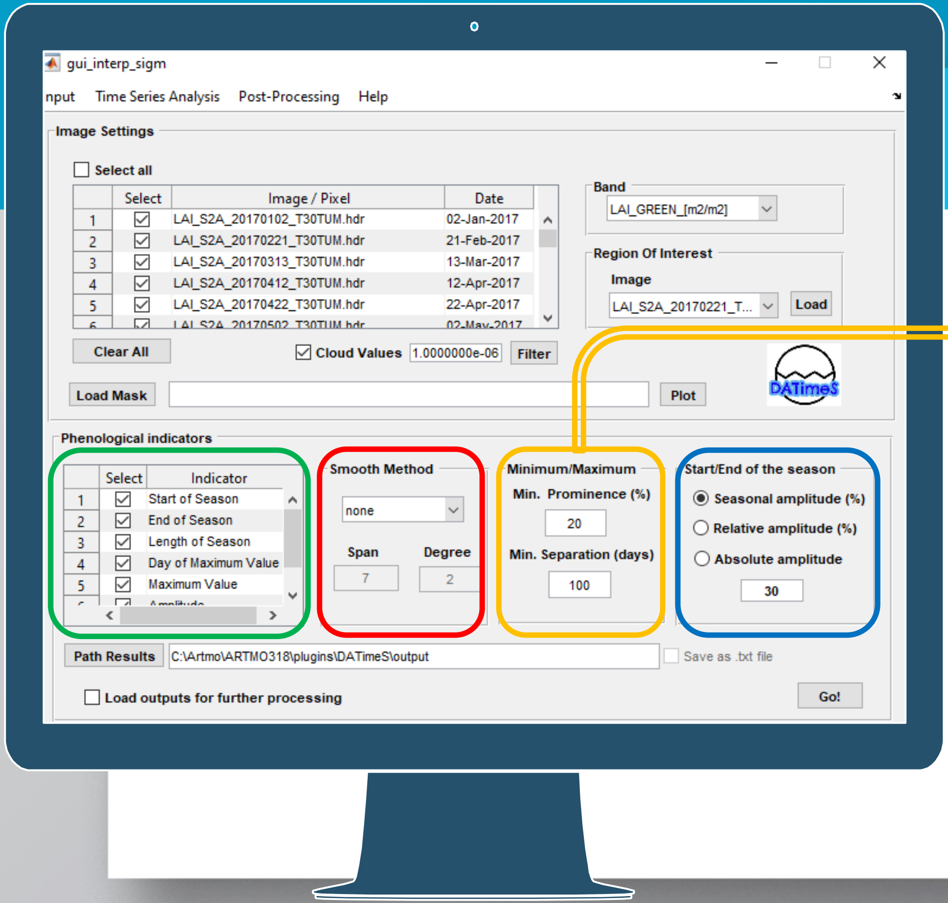


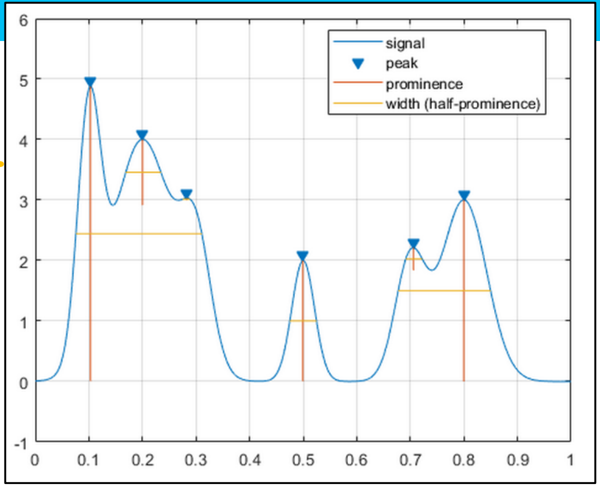

*Table 1. Goodness-of-fit statistical measures*

| | | |
|---|---|---|
| 1 | mean absolute error (MAE): | $\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \lvert V_{est}^{i} - V_{obs}^{i} \rvert$ |
| 2 | root mean squared error (RMSE): | $\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (V_{est}^{i} - V_{obs}^{i})^2}$ |
| 3 | relative RMSE (RELRMSE) : | $\text{RRMSE} = 100 \cdot \frac{\text{RMSE}}{\text{Mean(obs)}}$ |
| 4 | normalized RMSE (NRMSE): | $\text{NRMSE} = \frac{\text{RMSE}}{\text{Range(obs)}}$ |
| 5 | Correlation coefficient (R) | $r = \frac{\sum_{i=1}^{n} (V_{est}^{i} - \bar{V}_{est})(V_{obs}^{i} - \bar{V}_{obs})}{\sqrt{\sum_{i=1}^{n} (V_{est}^{i} - \bar{V}_{est})^2}\sqrt{\sum_{i=1}^{n} (V_{obs}^{i} - \bar{V}_{obs})^2}}$ |
| 6 | coefficient of determination ($R^2$) | $R^2 = 1 - \frac{\sum_{i=1}^{n} (V_{est}^{i} - \hat{V}_{est})^2}{\sum_{i=1}^{n} (V_{est}^{i} - \bar{V}_{est})^2}$ |
| 7 | Adjusted $R^2$ | $R^2 = 1 - \left[\frac{SSError}{SSTotal}\right]$ |
| 8 | Nash-Sutcliffe efficiency (NSE): | $\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (V_{obs}^{i} - V_{est}^{i})^2}{\sum_{i=1}^{n} (V_{obs}^{i} - \bar{V}_{obs})^2}$ |



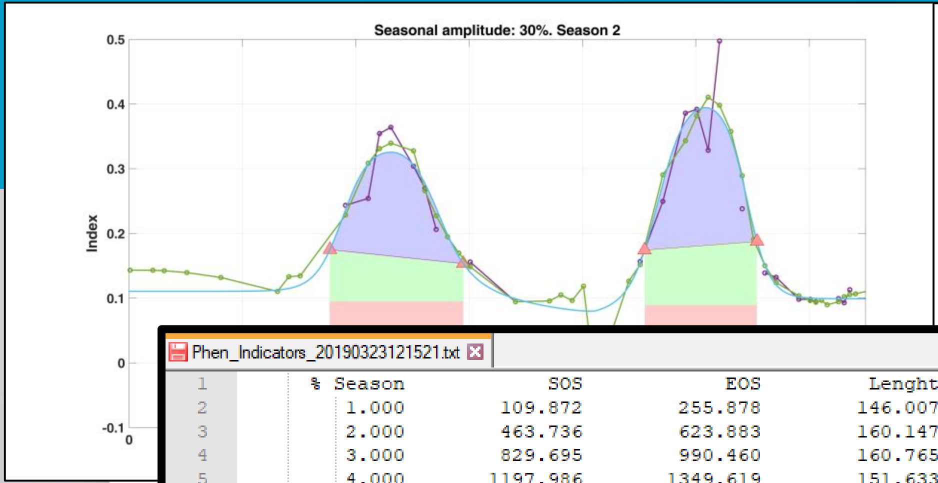

# Phenological Parameter: GUI

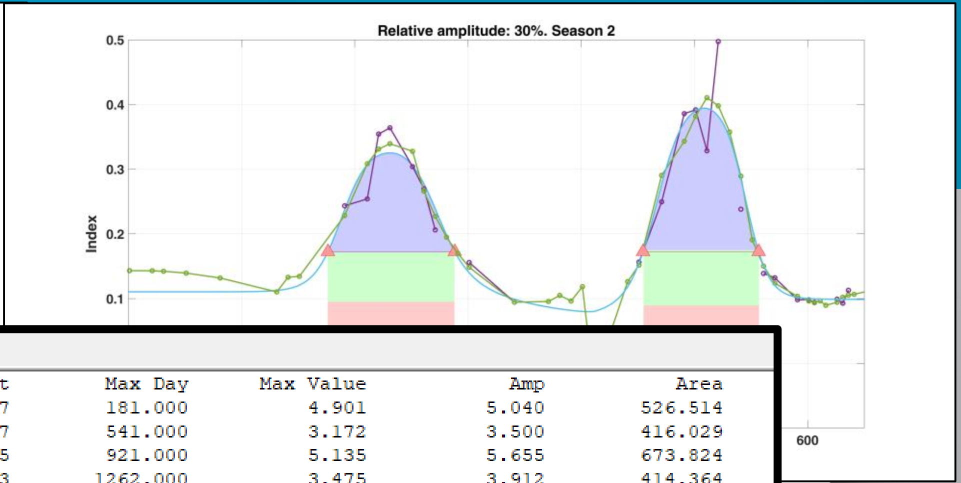





- Use ”Min Prominance” option to locate the peaks that have a prominence of at least ...
- Find Peaks with Minimum Separation

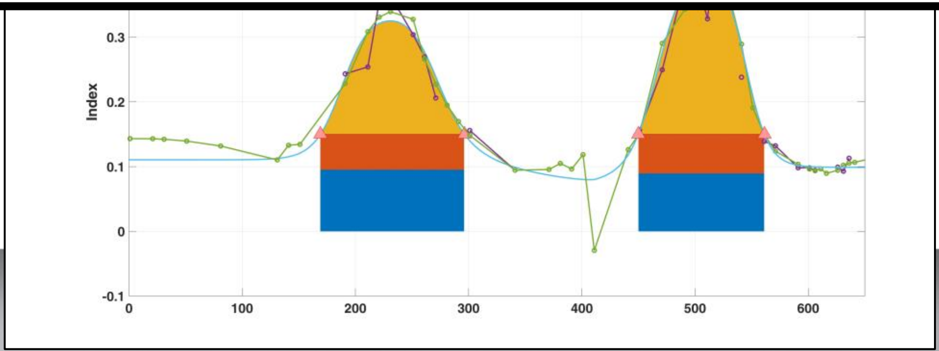
# Start and end of Season (SOS/EOS): different methods




Phen_Indicators_20190323121521.txt

| % Season | SOS | EOS | Lenght | Max Day | Max Value | Amp | Area |
|---|---|---|---|---|---|---|---|
| 1.000 | 109.872 | 255.878 | 146.007 | 181.000 | 4.901 | 5.040 | 526.514 |
| 2.000 | 463.736 | 623.883 | 160.147 | 541.000 | 3.172 | 3.500 | 416.029 |
| 3.000 | 829.695 | 990.460 | 160.765 | 921.000 | 5.135 | 5.655 | 673.824 |
| 4.000 | 1197.986 | 1349.619 | 151.633 | 1262.000 | 3.475 | 3.912 | 414.364 |
| 5.000 | 1562.796 | 1718.988 | 156.192 | 1642.000 | 4.421 | 4.792 | 543.533 |
| 6.000 | 1934.341 | 2084.996 | 150.655 | 2002.000 | 3.034 | 3.361 | 361.356 |
| 7.000 | 2279.022 | 2456.356 | 177.335 | 2402.000 | 2.217 | 2.641 | 332.554 |
| 8.000 | 2659.240 | 2813.740 | 154.500 | 2743.000 | 5.224 | 5.764 | 654.927 |

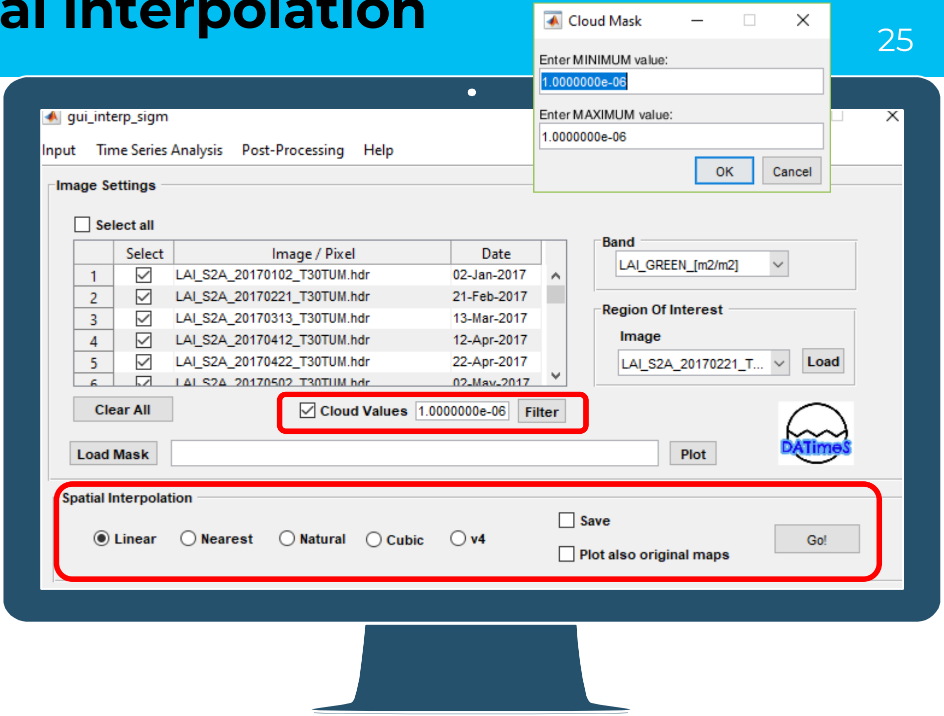


# Post – Processing: Spatial interpolation



This module only spatially interpolates NaN/clouded/filtered pixels.

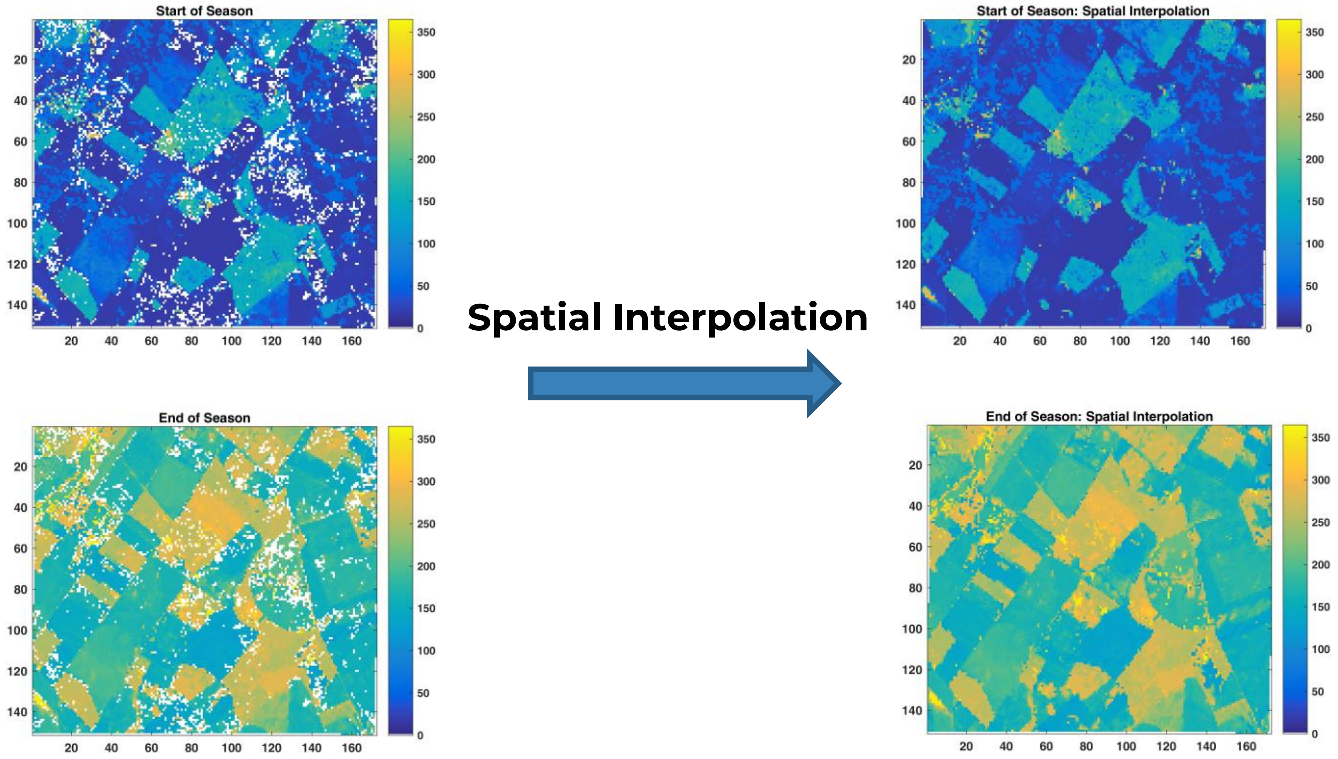
User can choose any image or the outputs previously estimated by using DATimeS.




As an example, the phenological indicators were spatial interpolated:

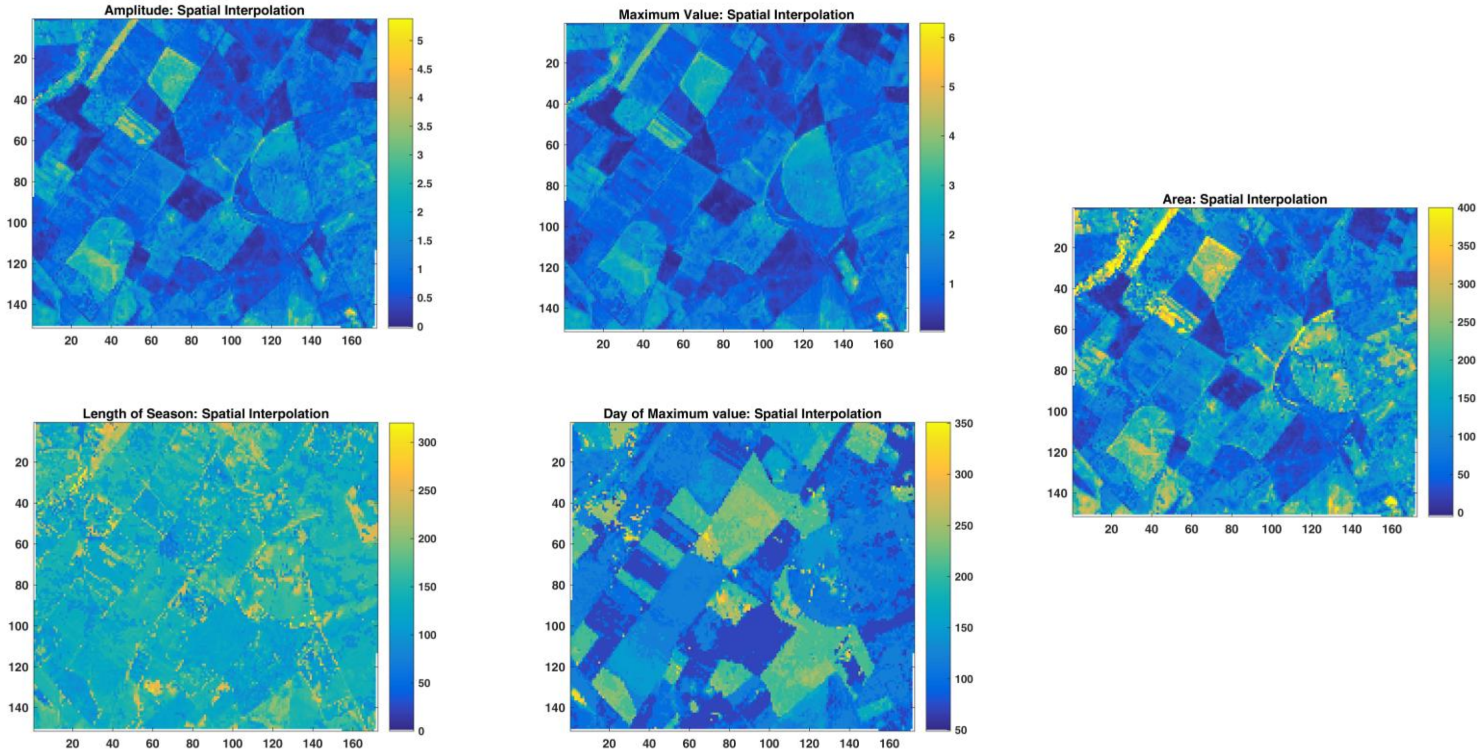
- Amplitude
- Maximum value
- Day of maximum value
- Area
- Length of season
- Start/End of season

# Post –Processing: SOS / EOS

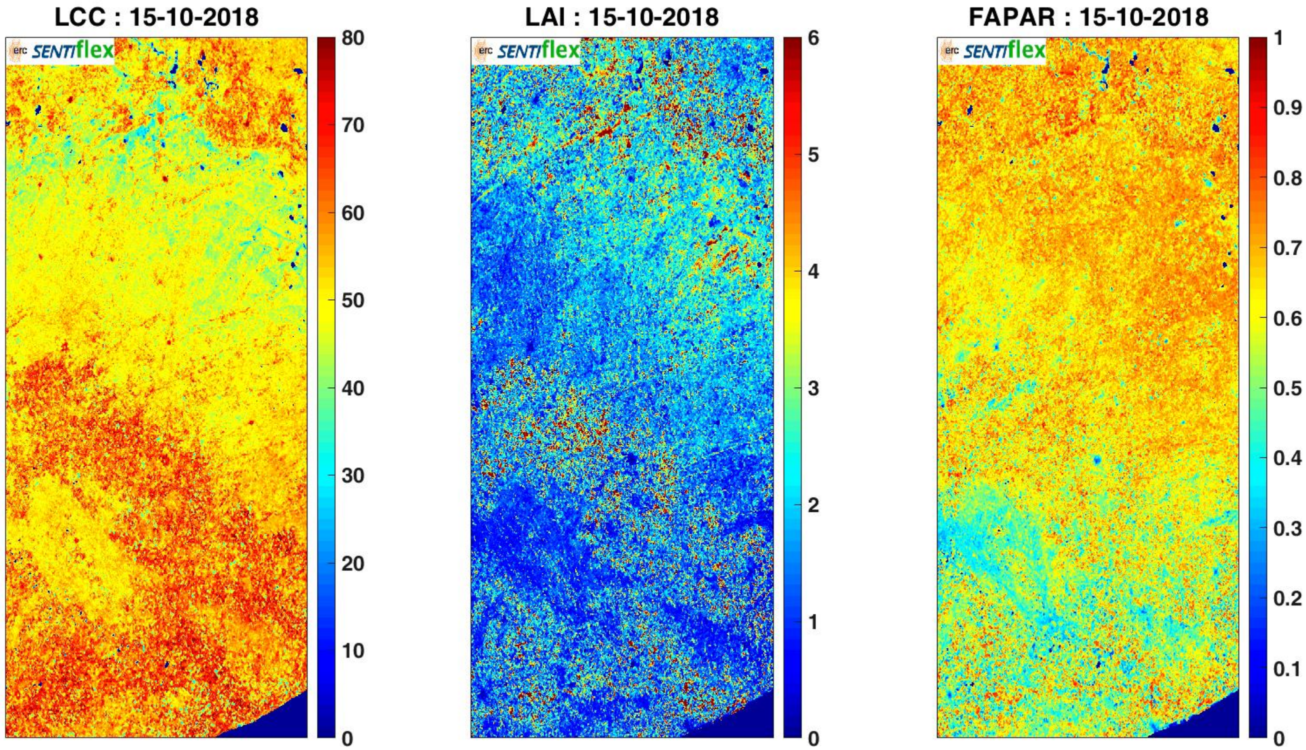


# Post –Processing: More available products

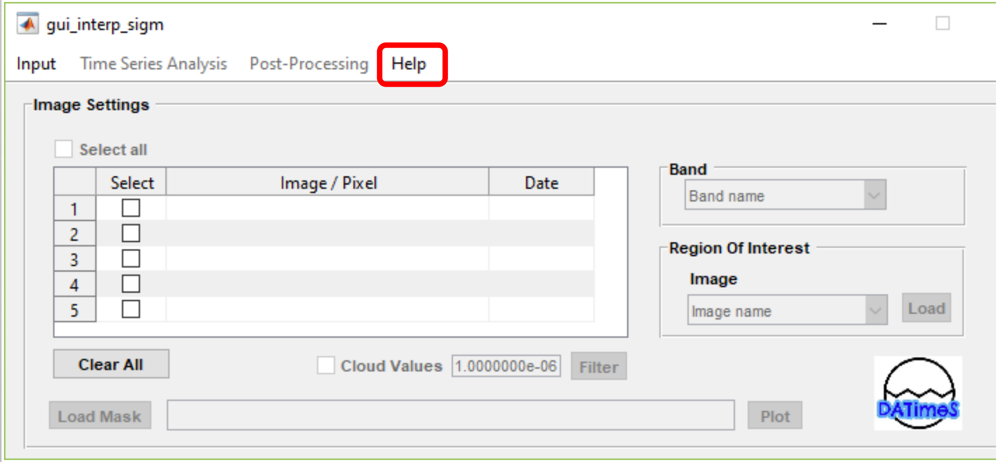




# Animations after temporal or spatial interpolation



# User's Manual



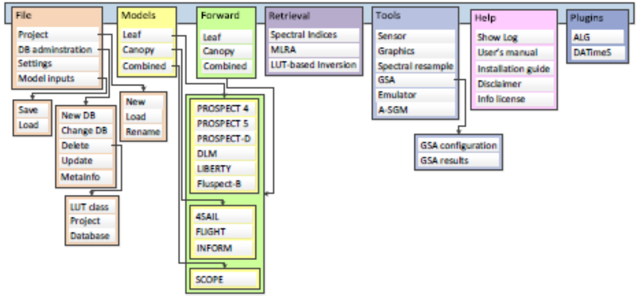
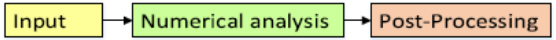



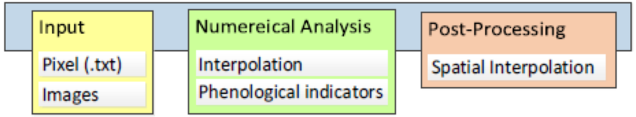

*Figure 2-2. ARTMO's hierarchical design as of July 2019.*

## 2.3 DATimeS sequential architecture

The DATimeS toolbox is organized according to sequential processing steps. First time series data need to be entered. That can be either a text file for a single pixel or images. Next, interpolation can be applied for generating composite images. Following, indicators of the seasonal status can be analyzed. In case time series appear to be too noisy, these phenology maps may not be resolved for each pixel. Hence, a final option is providing to apply a spatial smoothing. All these steps are provided within the same toolbox; the GUI will provide different windows depending on the selected step. The logical processing flow is visualized below:




To facilitate the user following the logical steps, some of the modules will be activated only when first the necessary input is provided, e.g. Setting will only be activated when Input data is provided.



# Demonstration Case 1

## Interpolation methods and phenological indicators



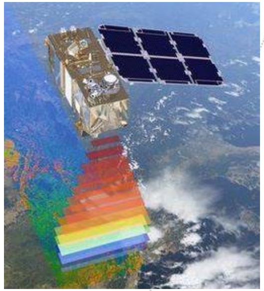
Heterogeneous crop area of approximately 140 km2 within the Castile and León region, North western Iberian peninsula

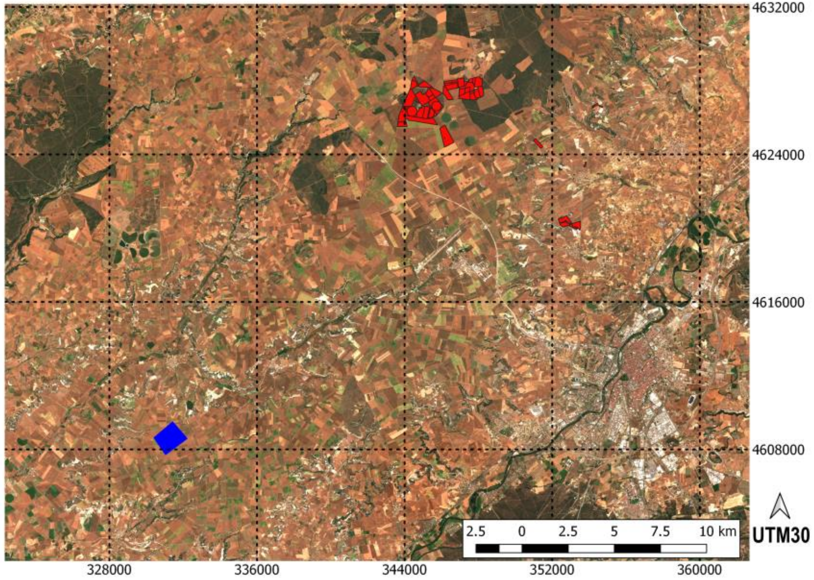
The Area of interest (AOI) belongs to a wider validation region of the H2020 Sensagri Project

Mainly dryland farming in winter (cereals, wheat, barley, or forage); irrigated farming in summer (maize, barley, wheat, sugar beet, alfalfa and potato).

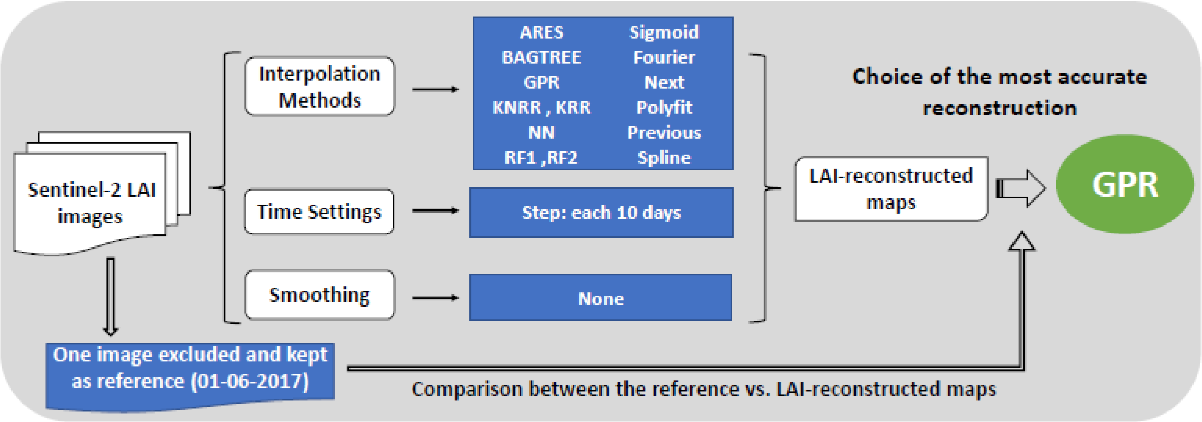
A land cover map is generated yearly since 2013 using a random forest classifier

**Sentinel-2 / Leaf Area Index (LAI): From 2015 to 2019**

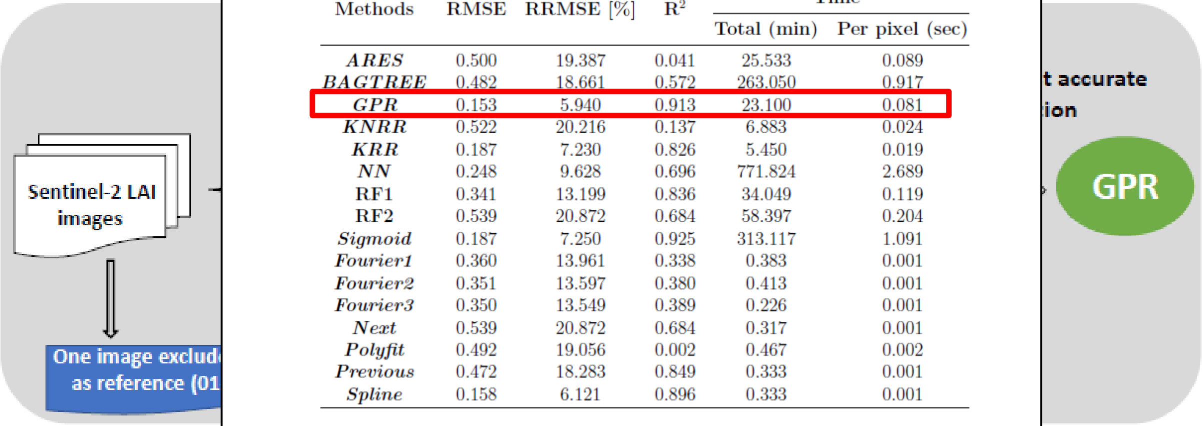




# Testing interpolation fitting methods



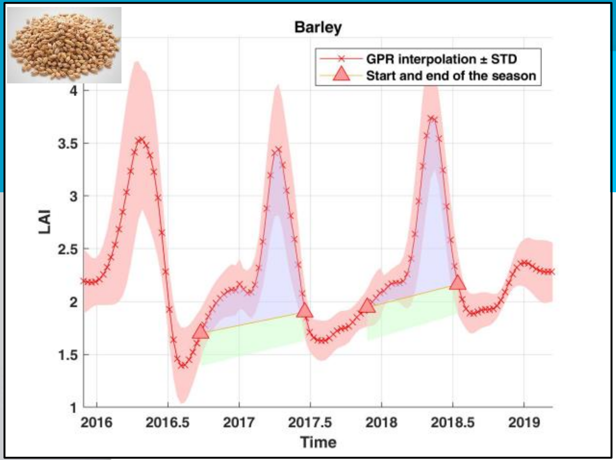
# Testing interpolation fitting methods

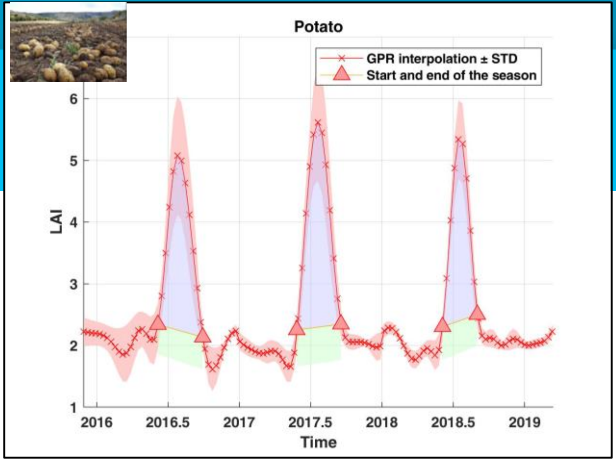


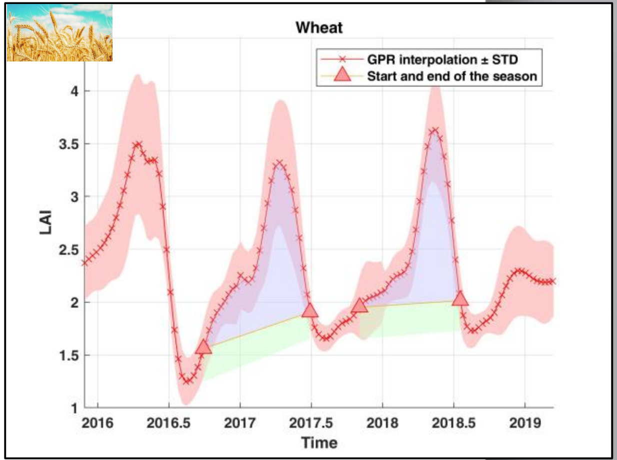

| Methods | RMSE | RRMSE [%] | $R^2$ | Time | |
|---|---|---|---|---|---|
| | | | | Total (min) | Per pixel (sec) |
| *ARES* | 0.500 | 19.387 | 0.041 | 25.533 | 0.089 |
| *BAGTREE* | 0.482 | 18.661 | 0.572 | 263.050 | 0.917 |
| *GPR* | 0.153 | 5.940 | 0.913 | 23.100 | 0.081 |
| *KNRR* | 0.522 | 20.216 | 0.137 | 6.883 | 0.024 |
| *KRR* | 0.187 | 7.230 | 0.826 | 5.450 | 0.019 |
| *NN* | 0.248 | 9.628 | 0.696 | 771.824 | 2.689 |
| RF1 | 0.341 | 13.199 | 0.836 | 34.049 | 0.119 |
| RF2 | 0.539 | 20.872 | 0.684 | 58.397 | 0.204 |
| *Sigmoid* | 0.187 | 7.250 | 0.925 | 313.117 | 1.091 |
| *Fourier1* | 0.360 | 13.961 | 0.338 | 0.383 | 0.001 |
| *Fourier2* | 0.351 | 13.597 | 0.380 | 0.413 | 0.001 |
| *Fourier3* | 0.350 | 13.549 | 0.389 | 0.226 | 0.001 |
| *Next* | 0.539 | 20.872 | 0.684 | 0.317 | 0.001 |
| *Polyfit* | 0.492 | 19.056 | 0.002 | 0.467 | 0.002 |
| *Previous* | 0.472 | 18.283 | 0.849 | 0.333 | 0.001 |
| *Spline* | 0.158 | 6.121 | 0.896 | 0.333 | 0.001 |

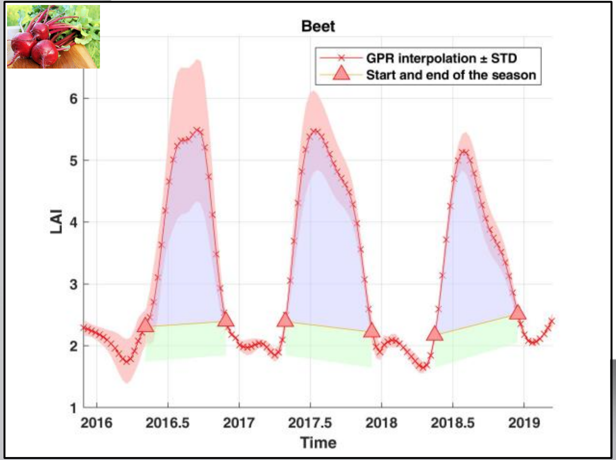
Table 3: Goodness-of-fit statistics and processing time for the reference vs. LAI-reconstructed map as produced by the gap-filling methods for 17218 pixels.

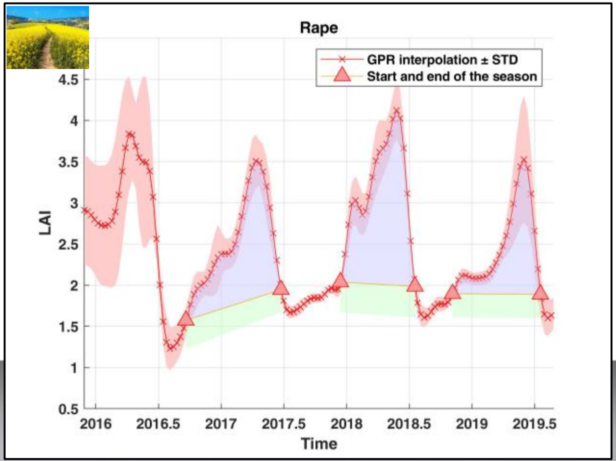
# Phenological metrics between different crops and seasons


Barley
GPR interpolation ± STD
Start and end of the season
LAI
Time


Potato
GPR interpolation ± STD
Start and end of the season
LAI
Time


Wheat
GPR interpolation ± STD
Start and end of the season
LAI
Time

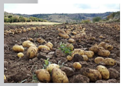

Beet
GPR interpolation ± STD
Start and end of the season
LAI
Time


Rape
GPR interpolation ± STD
Start and end of the season
LAI
Time

# The phenological metrics derived from the mean LAI of different crop types







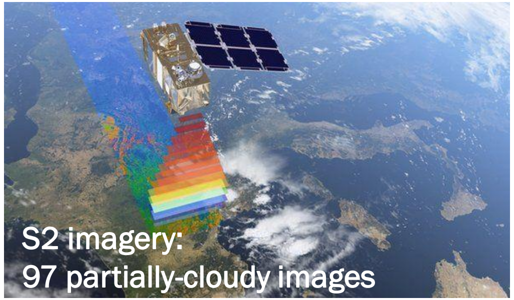
| Crop type | Season | SOS | EOS | LOS | DOM | Max Value | Amp | Area |
|---|---|---|---|---|---|---|---|---|
| Wheat | 1 | 273 (29-09-2016) | 180 (29-06-2017) | 273 | 102 (12-04-2017) | 3.320 | 1.869 | 268.065 |
| | 2 | 307 (03-11-2017) | 200 (19-07-2018) | 258 | 137 (17-05-2018) | 3.627 | 1.936 | 231.180 |
| Barley | 1 | 268 (24-09-2016) | 169 (18-06-2017) | 267 | 102 (12-04-2017) | 3.439 | 1.928 | 234.089 |
| | 2 | 329 (25-11-2017) | 196 (15-07-2018) | 232 | 127 (07-05-2018) | 3.733 | 1.975 | 198.765 |
| Rape | 1 | 264 (20-09-2016) | 175 (24-06-2017) | 276 | 102 (12-04-2017) | 3.502 | 2.053 | 299.794 |
| | 2 | 348 (14-12-2017) | 200 (19-07-2018) | 217 | 147 (27-05-2018) | 4.121 | 2.483 | 339.334 |
| | 3 | 309 (05-11-2018) | 200 (19-07-2019) | 256 | 152 (01-06-2019) | 3.524 | 1.920 | 221.604 |
| Beet | 1 | 126 (05-05-2016) | 333 (28-11-2016) | 207 | 258 (14-09-2016) | 5.487 | 3.691 | 507.208 |
| | 2 | 119 (29-04-2017) | 341 (07-12-2017) | 222 | 192 (11-07-2017) | 5.464 | 3.717 | 581.870 |
| | 3 | 137 (17-05-2018) | 350 (16-12-2018) | 213 | 207 (26-07-2018) | 5.126 | 3.278 | 441.477 |
| Potato | 1 | 158 (06-06-2016) | 273 (29-09-2016) | 115 | 208 (26-07-2016) | 5.078 | 3.343 | 241.555 |
| | 2 | 148 (28-05-2017) | 261 (18-09-2017) | 113 | 202 (21-07-2017) | 5.614 | 3.900 | 277.928 |
| | 3 | 156 (05-06-2018) | 245 (02-09-2018) | 90 | 197 (16-07-2018) | 5.340 | 3.456 | 195.900 |

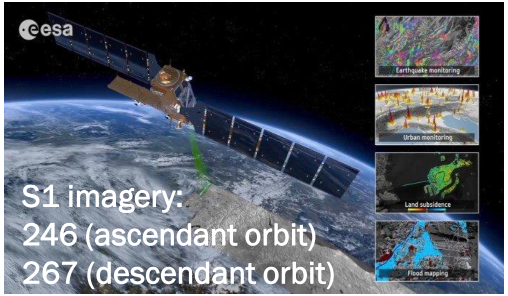
Is there any relationship with the Crop Yield and Weather?

# Demonstration Case 2: Synergy

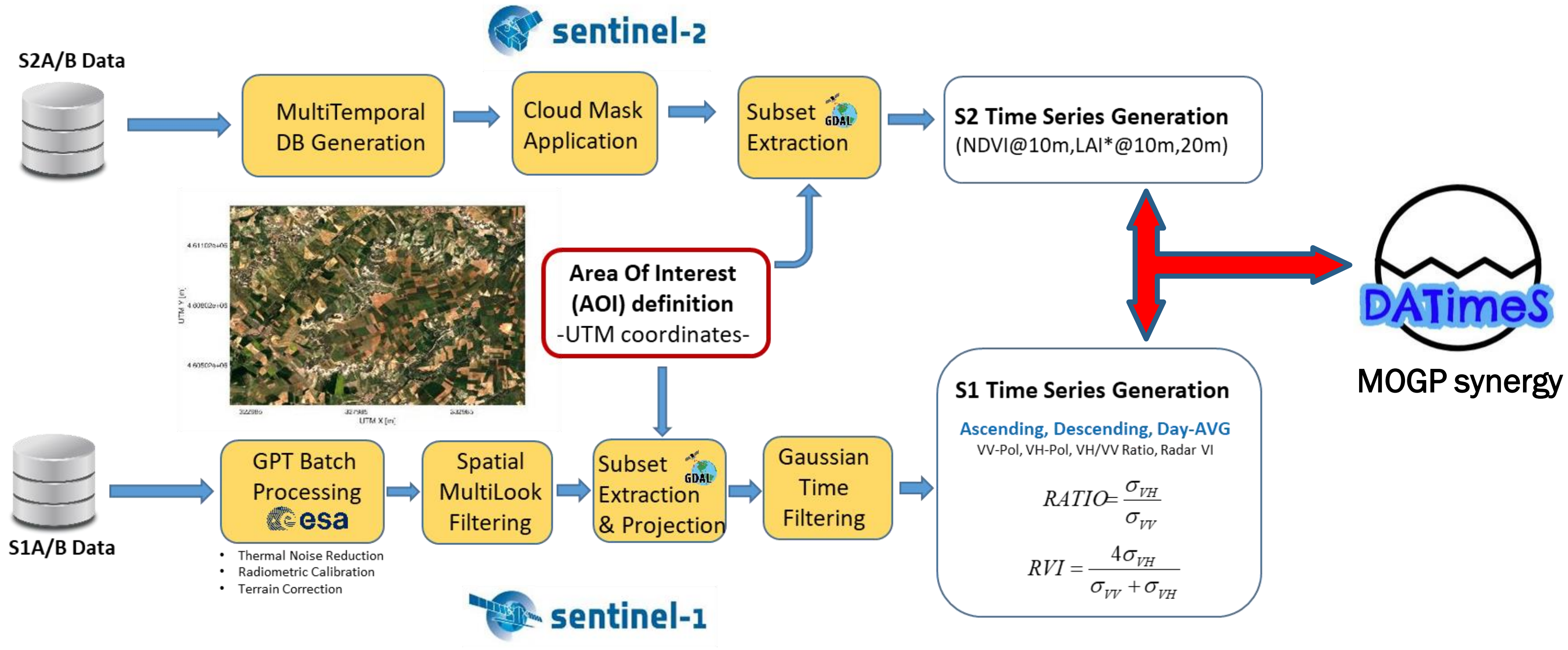
The research leading to these results has received funding from the European Union's Horizon 2020 Rese

From January 2015 to October 2018



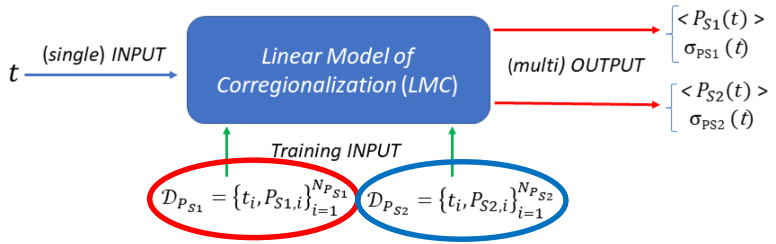
# Sentinel 1/2 preprocessing Chain



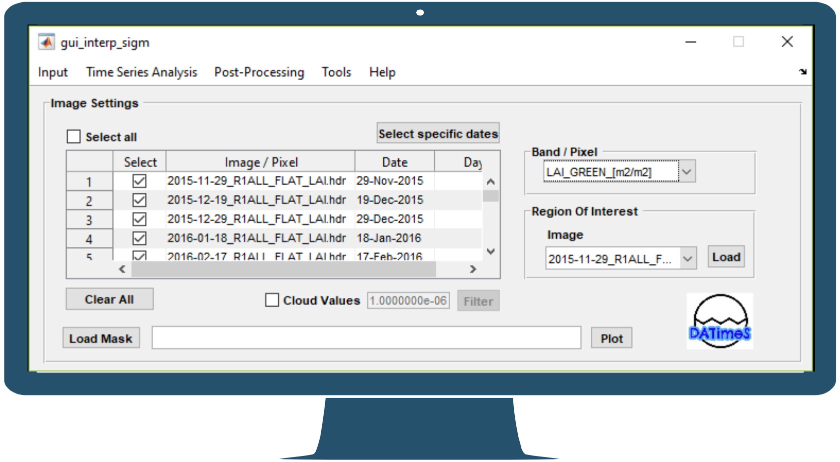

***LAI via GP Regression (SENSAGRI) adapted to MAJA distribution**

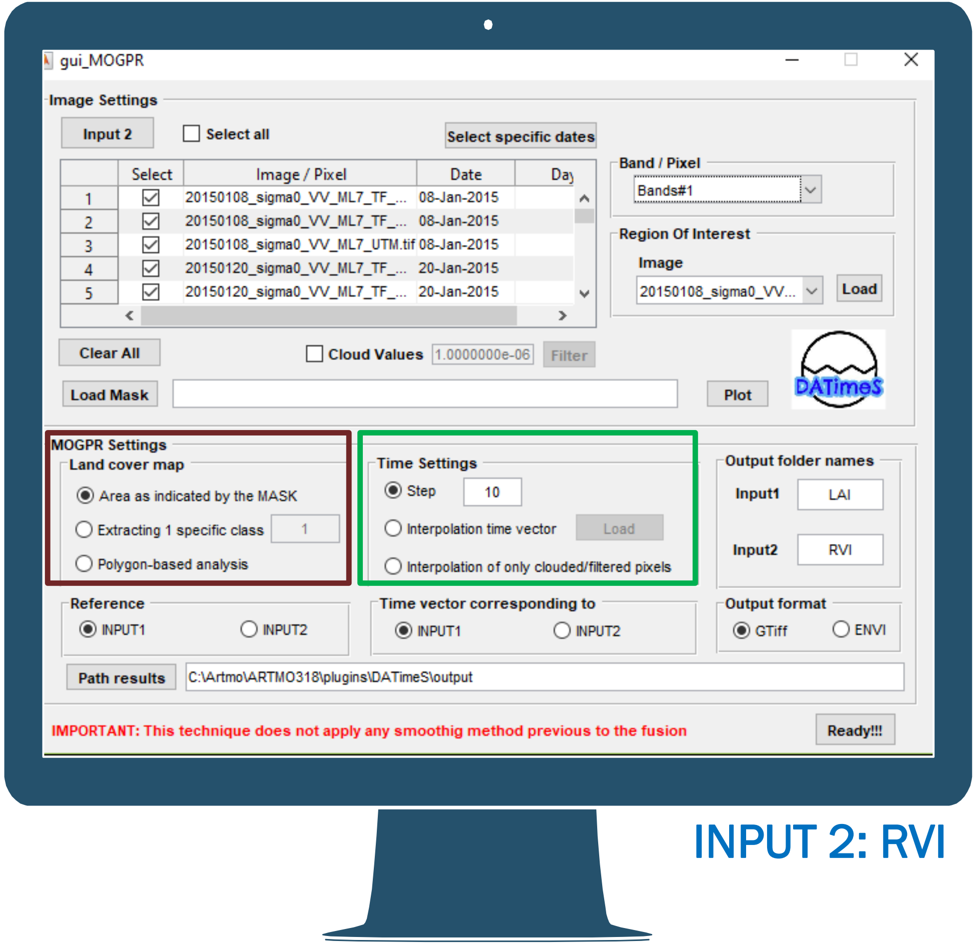
Amin, E., Verrelst, J., Rivera-Caceido, J.P., Pasqualotto, N., Delegido, J., Ruíz-Verdú, A., Moreno, J., The Sensagri Sentibel2 LAI Green and Brown Product: Form Algorithm Development Towards Operation Mapping, IEEE Igarss 2018

# DATimeS Toolbox: MOGP Synergy module




INPUT 1: LAI




INPUT 2: RVI

# Prediction analysis of temporal profile

*MOGP time gap-filling on crop polygon: **TRAINING***

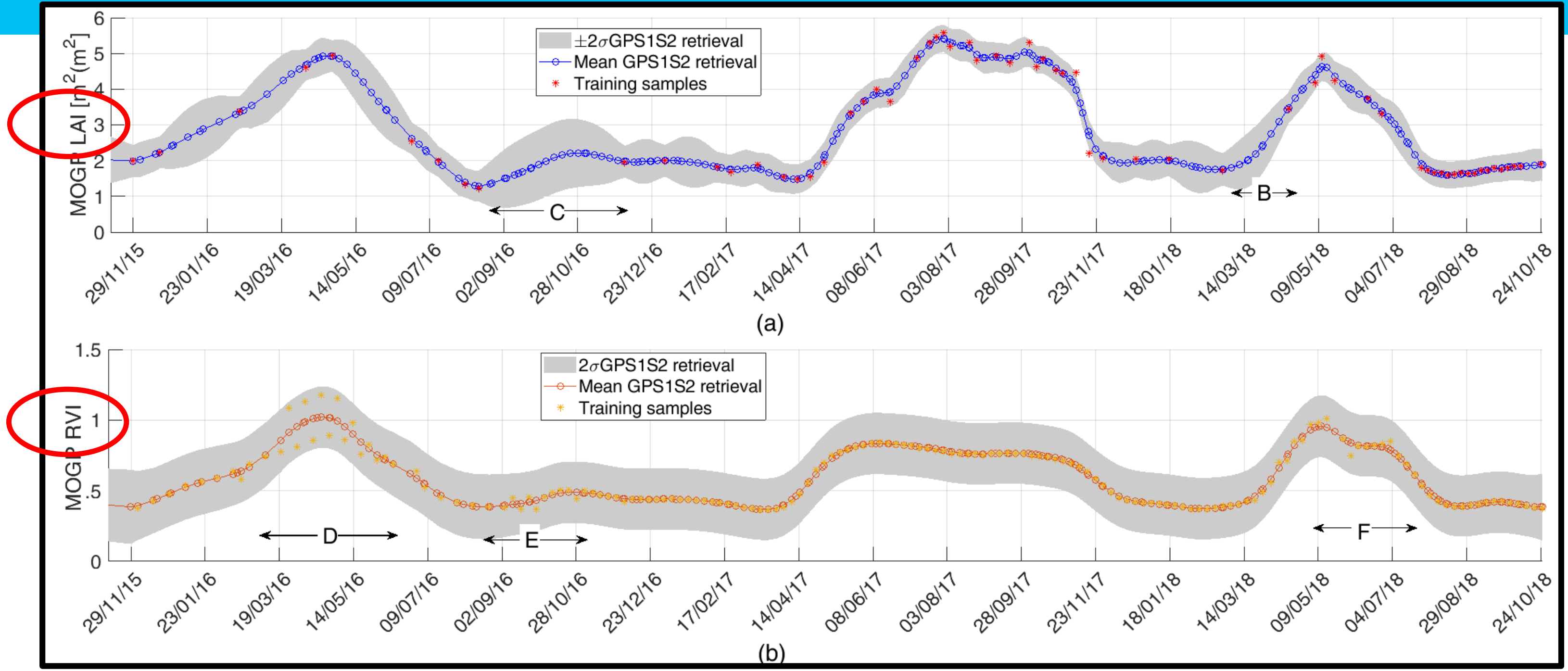



**Figure.** MOGP predictions (circles) of LAI and RVI on the union of S1 and S2 acquisition dates provided by the MOGP model trained on input time series (asterisks).

# Prediction analysis of temporal profile

## *MOGP vs standard GRP time gap-filling: ASSESSMENT*

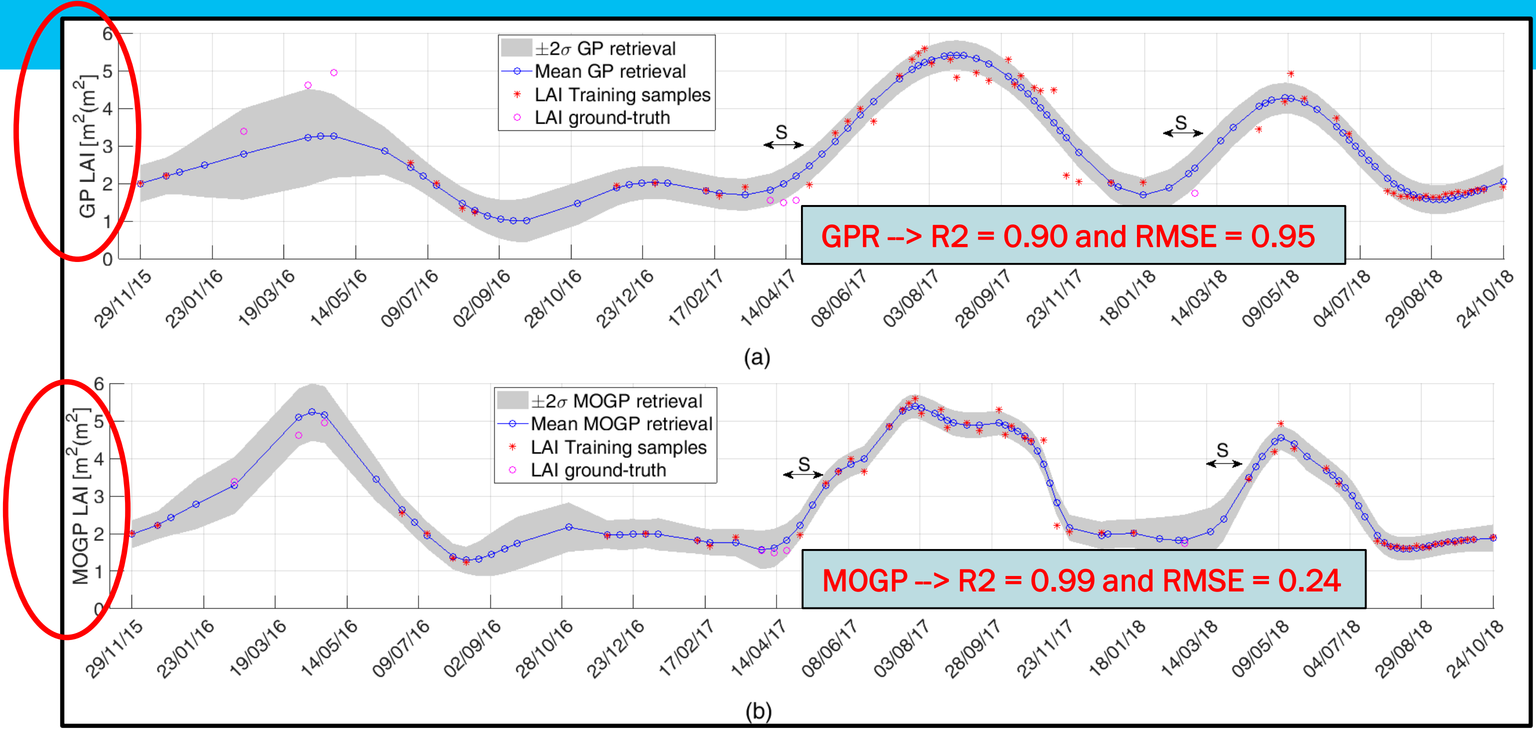
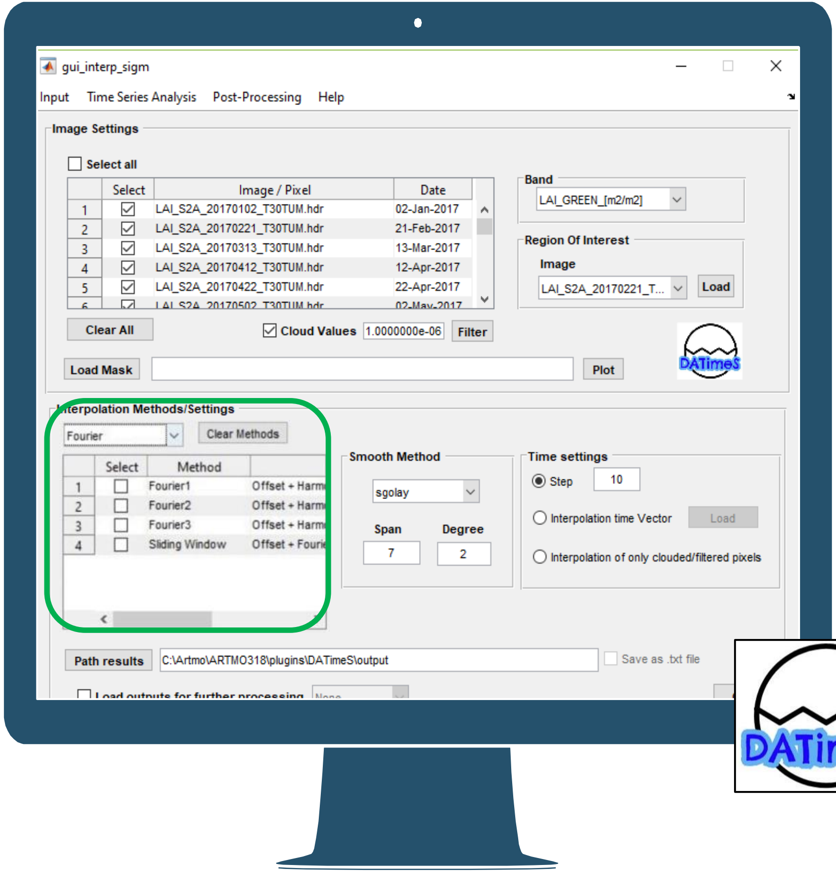



**Figure.** Assessment of standard GPR (a) and MOGP (b) predictions (blue circles) for data gap-filling on S2 cloud-free captures (magenta) eliminated from training information (red asterisks) and here used as reference.

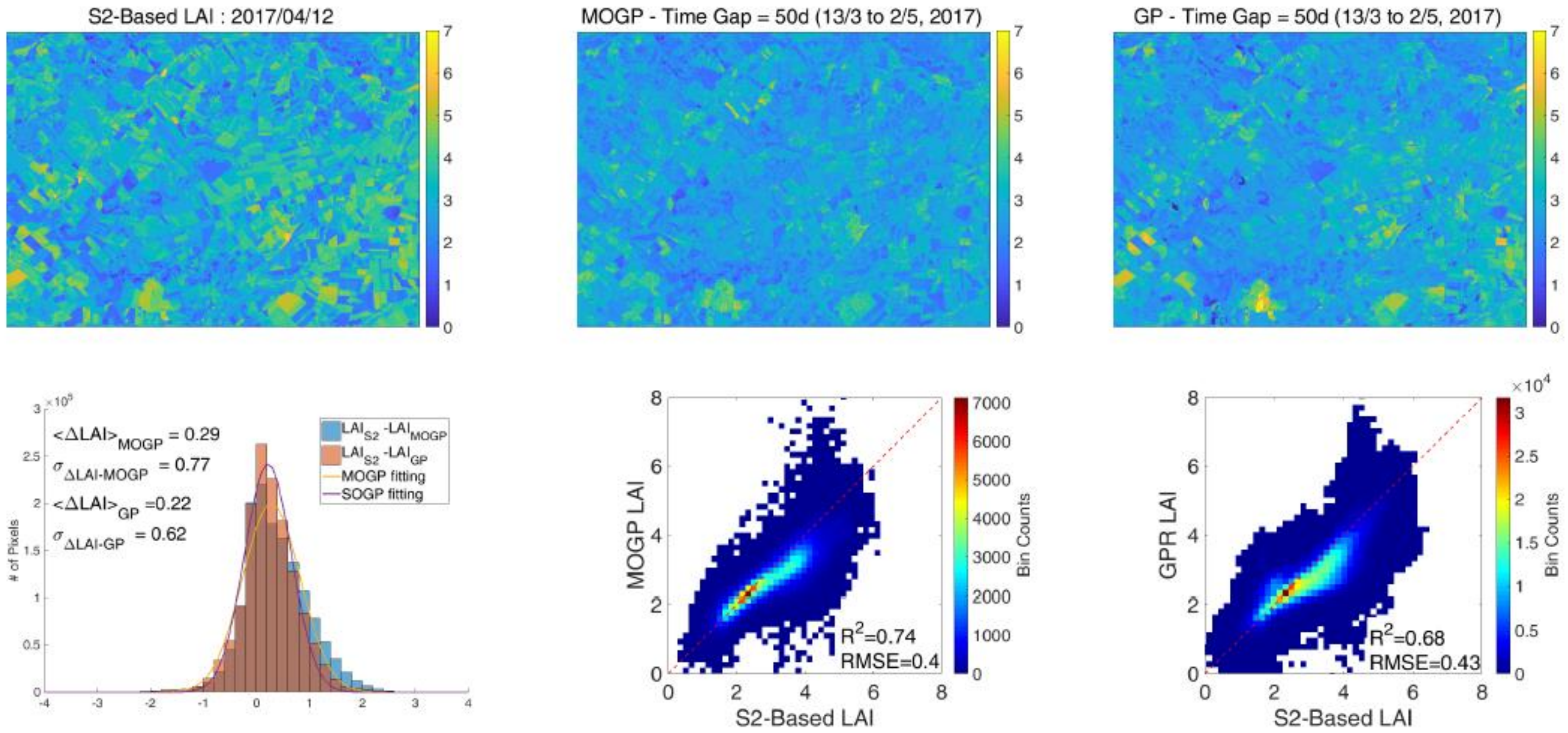
# Prediction analysis of temporal profile




| Interpolation Method | $R^2$ | $\Sigma$Res | RMSE |
|---|---|---|---|
| Fourier analysis: Offset + Harmonic analysis | 0.5307 | 5.3803 | 0.9896 |
| Polynomial curve fitting | 0.8329 | 16.0240 | 2.3874 |
| Double logistic curve | 0.3127 | 8.8674 | 1.6912 |
| Linear interpolation | 0.3006 | 7.9026 | 1.3926 |
| Nearest neighbor interpolation | 0.9734 | 7.1444 | 1.3061 |
| Next neighbor interpolation | 0.0645 | 8.2933 | 1.4231 |
| Previous neighbor interpolation | 0.8433 | 7.6838 | 1.4651 |
| Spline interpolation using not-a-knot end conditions | 0.6620 | 5.0872 | 0.9798 |
| Shape-preserving piecewise cubic interpolation | 0.6963 | 7.3767 | 1.3220 |
| Bagging trees | 0.2120 | 10.1841 | 1.7216 |
| Adaptive Regression Splines | 0.7446 | 12.2503 | 1.9048 |
| Boosting random trees | 0.0014 | 8.9694 | 1.5074 |
| Boosting trees | 0.2859 | 8.2312 | 1.5876 |
| k-nearest neighbours regression | 0.1452 | 8.2350 | 1.5764 |
| Gaussian Process Regression | **0.9081** | **5.7816** | **0.9527** |
| Neural networks | 0.7481 | 7.5766 | 1.3005 |
| Random forests | 0.9734 | 7.1444 | 1.3061 |
| Multi-Output Gaussian Process | **0.9900** | **1.3035** | **0.2377** |

# Spatial prediction analysis: long temporal gap

## MOGP LAI mapping and assessment (vs standard GPR)

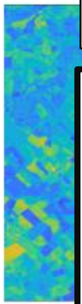


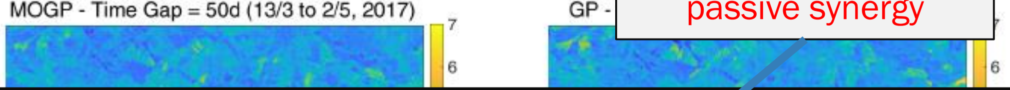
# Spatial prediction analysis: long temporal gap

## MOGP LAI mapping and assessment (vs stand

PIXELS fulfilling model-based conditions for profitable active-passive synergy

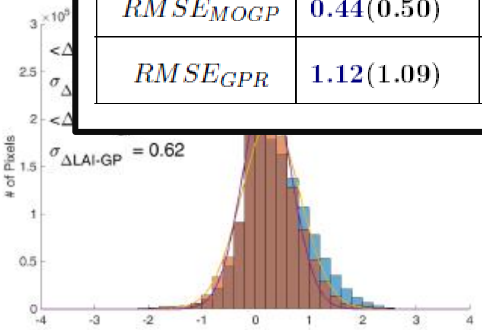
ALL VEG IMAGE PIXELS

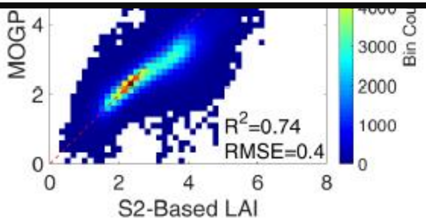


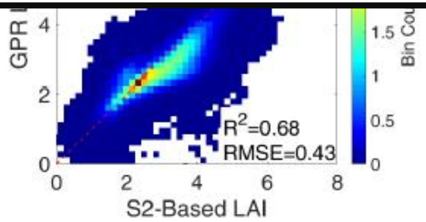



Prediction vs S2-based LAI

| | 2016/02/17 | 2016/04/07 | 2016/04/27 | 2017/04/02 | 2017/04/12 | 2017/04/22 | 2018/02/26 |
|---|---|---|---|---|---|---|---|
| $R^2_{MOGP}$ | 0.29(0.33) | 0.20(0.19) | 0.29(0.26) | 0.56(0.70) | 0.58(0.74) | 0.49(0.71) | 0.25(0.35) |
| $R^2_{GPR}$ | 0.12(0.12) | 0.06(0.08) | 0.08(0.08) | 0.67(0.67) | 0.68(0.68) | 0.70(0.70) | 0.40(0.40) |
| $RMSE_{MOGP}$ | 0.44(0.50) | 0.80(0.90) | 0.85(0.94) | 0.42(0.41) | 0.44(0.40) | 0.55(0.42) | 0.36(0.44) |
| $RMSE_{GPR}$ | 1.12(1.09) | 1.75(1.70) | 1.62(1.56) | 0.44(0.43) | 0.46(0.43) | 0.45(0.41) | 0.50(0.50) |

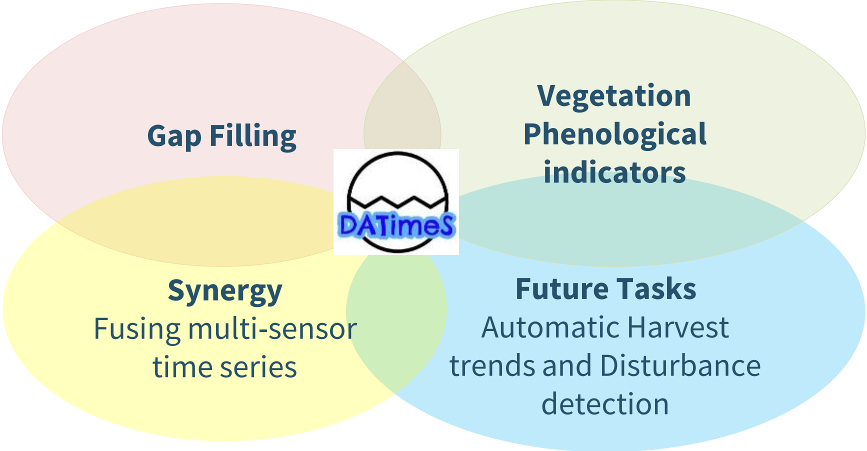


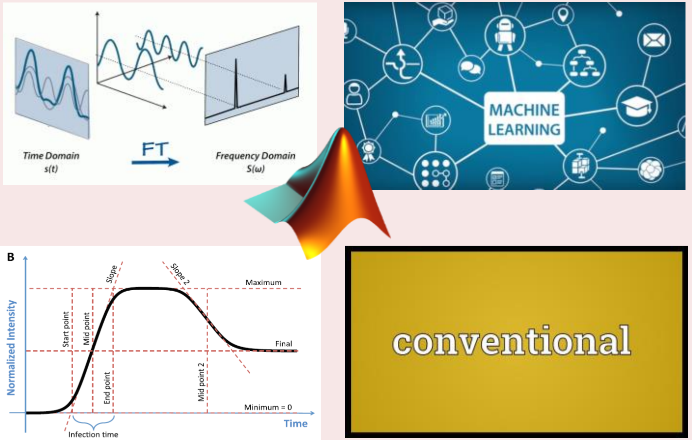



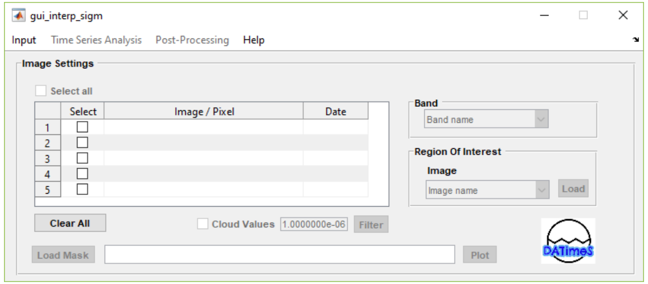
# Let's review DATimeS

DATimeS GOAL: improve the **knowledge of crop dynamics**, essential for agricultural applications (e.g. productivity, management and timing of field works).

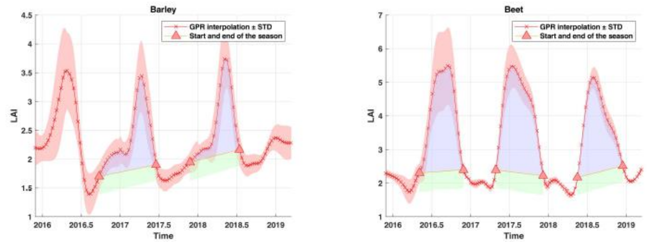



GAP filling: More than 30 methods




**Descomposition and Analysis of Time Series (DATimeS)**




**Phenological studies with different crop types**

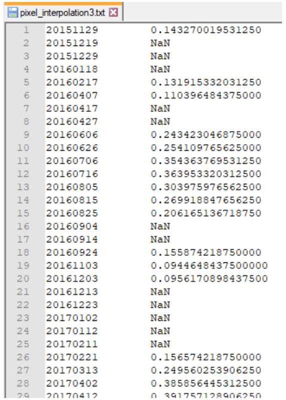
# Let’s review DATimeS

**Data Inputs**

**Images can be processed in multiple formats**

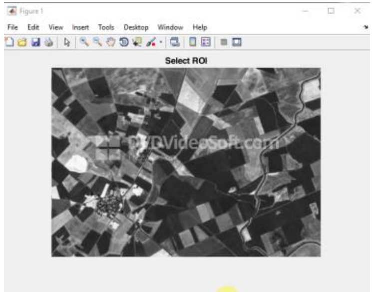


**Single pixel from .txt file**

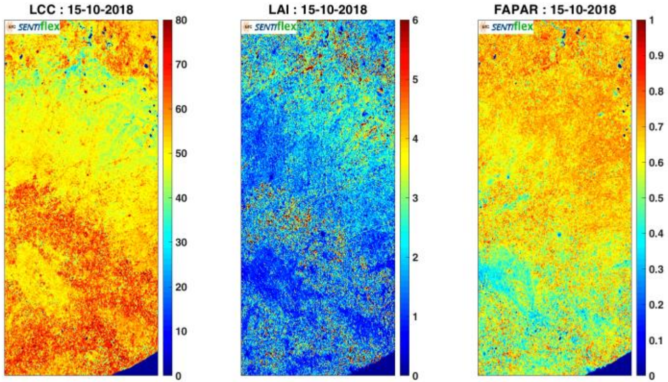

pixel_interpolation3.txt

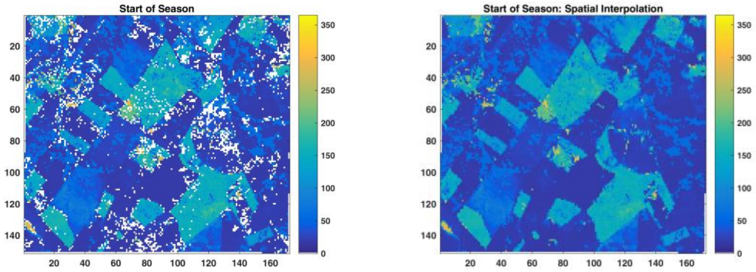
| | |
|---|---|
| 20151129 | 0.143270019531250 |
| 20151219 | NaN |
| 20151229 | NaN |
| 20160118 | NaN |
| 20160217 | 0.131915332031250 |
| 20160407 | 0.110396484375000 |
| 20160417 | NaN |
| 20160427 | NaN |
| 20160606 | 0.243423046875000 |
| 20160626 | 0.254109765625000 |
| 20160706 | 0.354363769531250 |
| 20160716 | 0.363953320312500 |
| 20160805 | 0.303975976562500 |
| 20160815 | 0.269918847656250 |
| 20160825 | 0.206165136718750 |
| 20160904 | NaN |
| 20160914 | NaN |
| 20160924 | 0.155874218750000 |
| 20161103 | 0.0944648437500000 |
| 20161203 | 0.0956170898437500 |
| 20161213 | NaN |
| 20161223 | NaN |
| 20170102 | NaN |
| 20170112 | NaN |
| 20170211 | NaN |
| 20170221 | 0.156574218750000 |
| 20170313 | 0.249560253906250 |
| 20170402 | 0.385856445312500 |
| 20170412 | 0.391757128906250 |

**Region of Interest**




**Animations (videos)**




**Spatial Interpolation**

# Let's review DATimeS:

User friendly

Compiled Version available

Different images formats

DOC DOCx RTF ODT

Advanced Harmonic analysis , machine learning algorithms and double sigmoidal functions have been implemented

Make smart and timely decisions to improve yield and profit based on the right and accurate data

Sustainable crop Production (global warming )

Future: Automatic Harvest and Disturbance detection (Pest and disease alarms).

# Any questions?

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» Santiago.belda@uv.es
» Jochem.verrelst@uv.es