Juhan Ross Legacy Symposium

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20 years of algorithms for the derivation of global vegetation products from European medium resolution sensors

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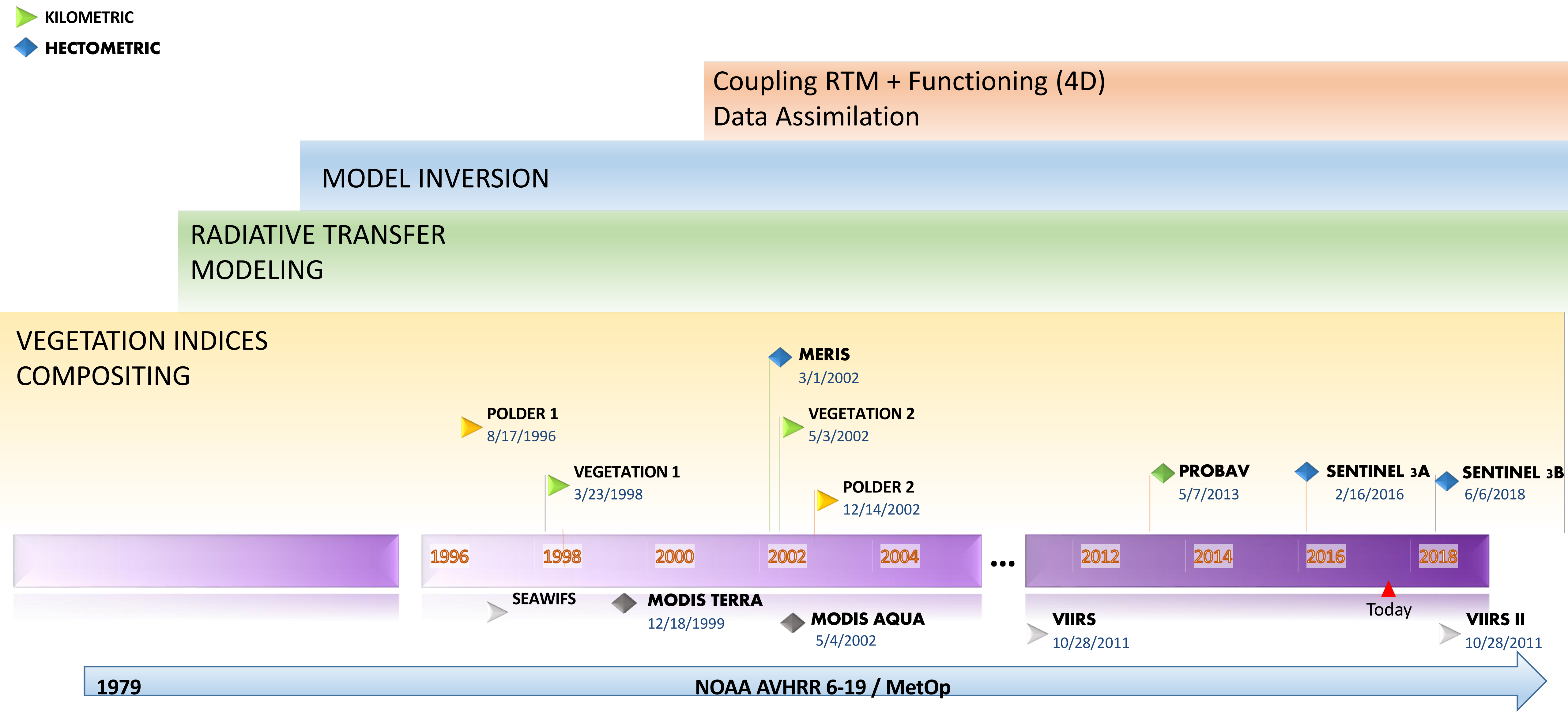
MEDIUM RESOLUTION: GLOBAL COVERAGE – HIGH TEMPORAL FREQUENCY



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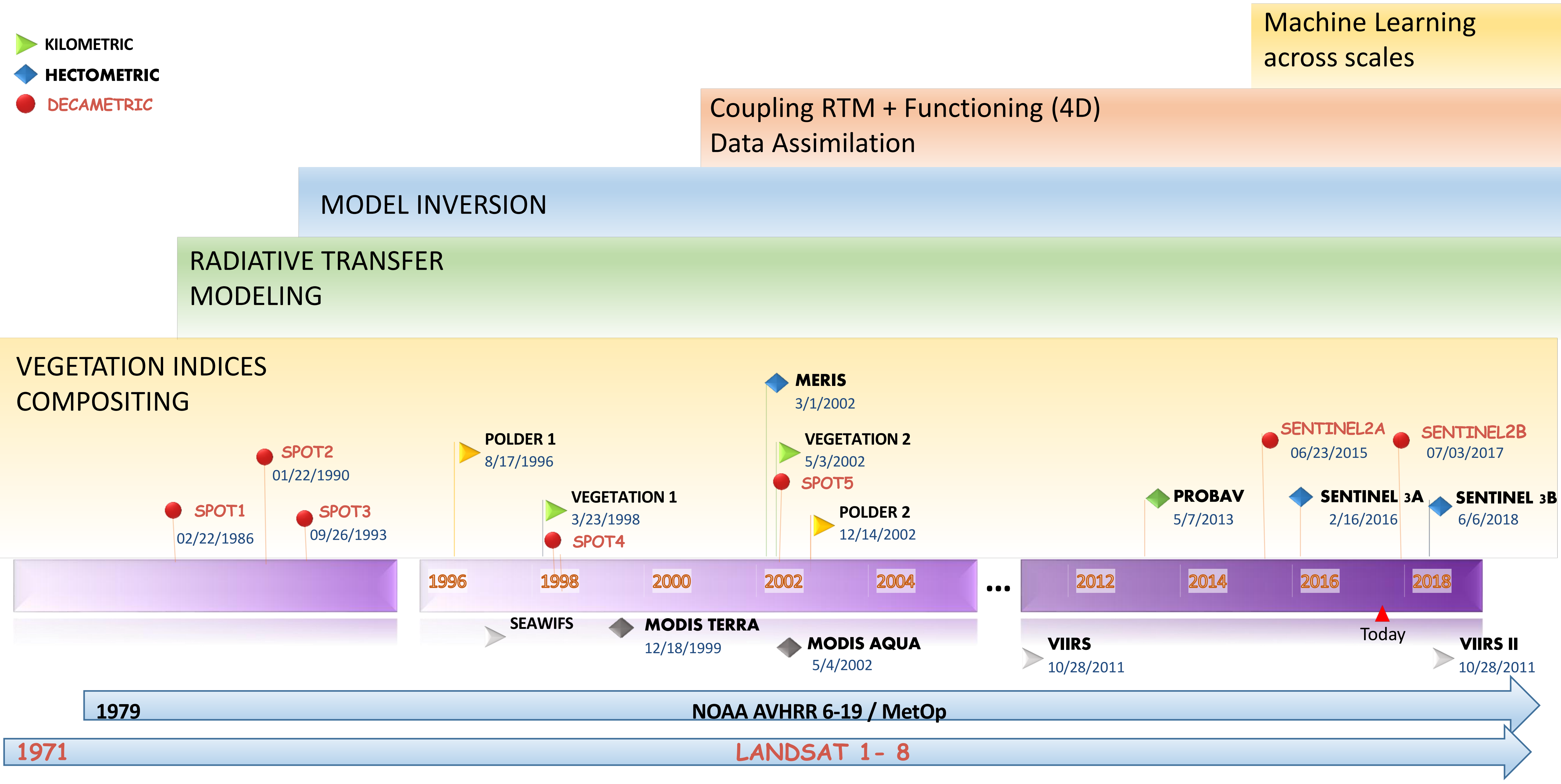


REQUIREMENTS FOR GLOBAL MEDIUM RESOLUTION PRODUCTS

⇨ GMES/Copernicus context:

- global monitoring for environment and security

⇨ Meet the user needs

- Accuracy : Quality Flags / Confidence Intervals / Validation
- Consistency : through time & between sensors
- No Gap

USER ALWAYS ASSOCIATED TO THE PRODUCT DEVELOPMENT

⇨ Meet technical requirements

- Operational context + Near Real Time
- Easy access to the community (ESA does not deliver Level2 & 3 data)

TECHNICAL CENTERS (VITO/CNES) INVOLVED IN PROJECTS

Biophysical Algorithms: Machine Learning

⇨ Principle:

- calibrate non linear relationships between inputs (reflectance) and outputs (biophysical variable)

⇨ Machine learning:

- currently neural networks
- Generic algorithm

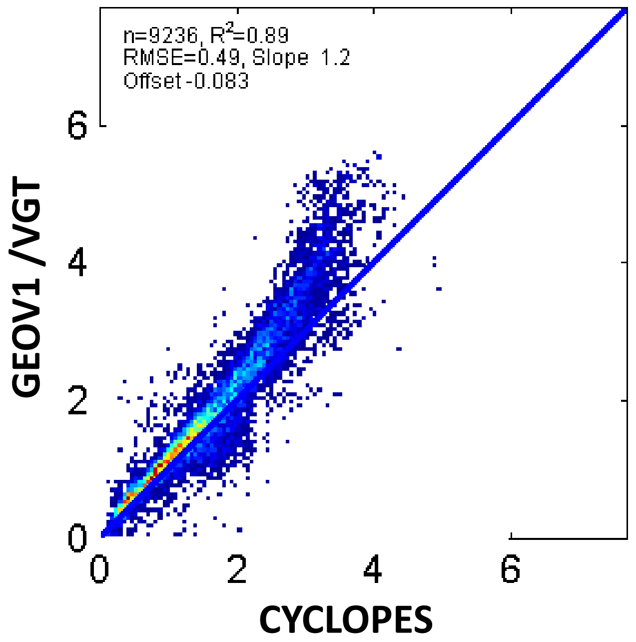
⇨ Setting up of the learning dataset is crucial: representativeness

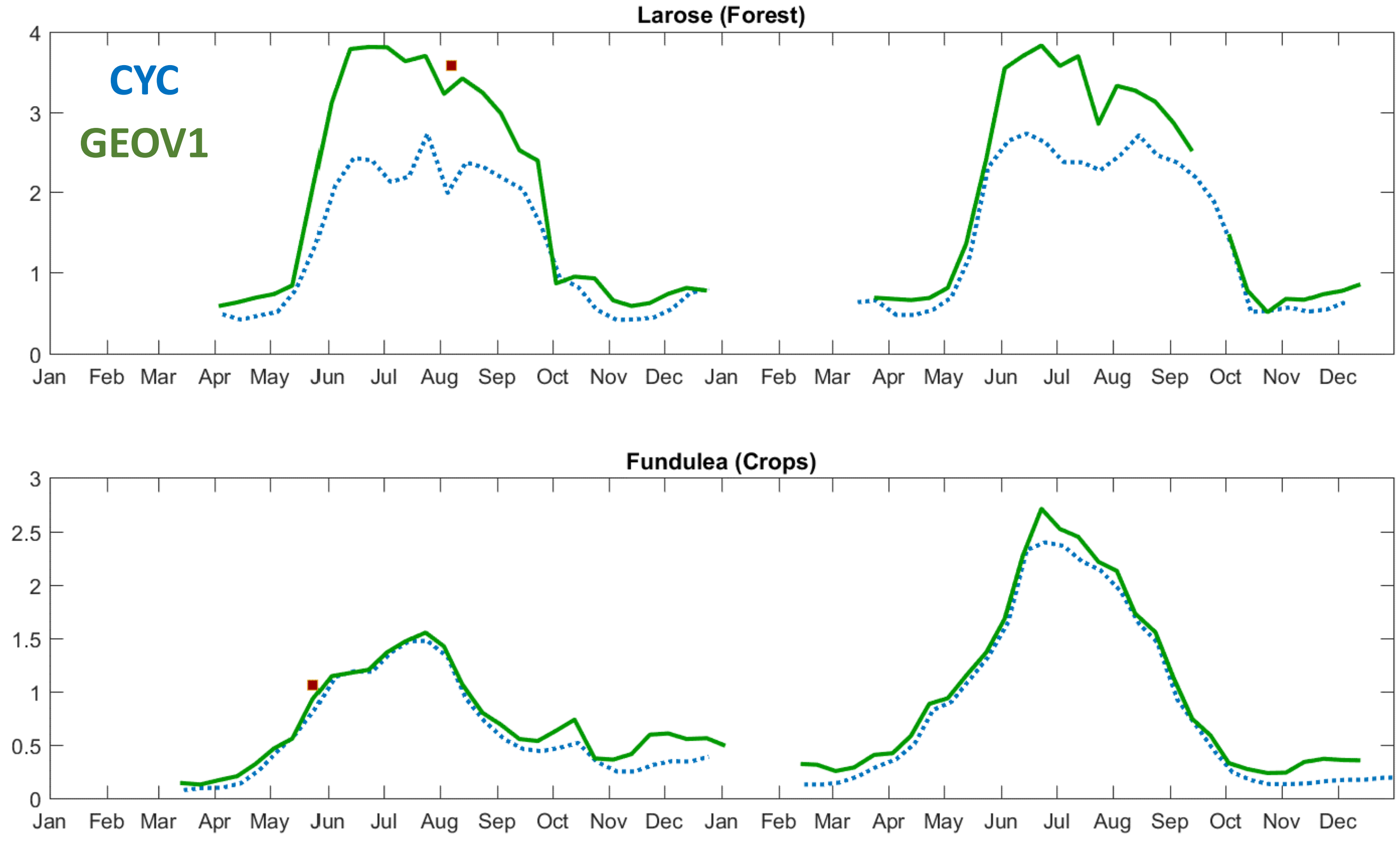
- Vegetation types, development stages & conditions
- Radiometric Noise
- Observational configuration

COPERNICUS PRODUCTS

	Name	Sensors	Resol.	Learning	Input	Temporal compositing			Improvement
						Smoothing	Gap Fil.	NRT	
	CYCLOPES	VGT1	1km	Sim. Generic	TOC Red/NIR/ SWIR	Reflectance Weighted 30 days	✗	✗	
	GEOV1	VGT1/VGT2 /PROBAV	1km	**Meas.** Generic	TOC Red/NIR/ SWIR	Reflectance Weighted 30 days	✗	✗	**Accuracy (High LAI)**
	GEOV2	VGT1/VGT2	1km	Meas. Generic	**TOA** Red/NIR/ SWIR	**Product** 30 days	✗	✗ **1-2 day lag**	**Temporal consistency**
	GEOV3 1km	VGT1/VGT2 /PROBAV	1km	Meas. **EBF/Non EBF**	TOC RED/NIR Red/NIR/ SWIR	Product **Variable temp window**	**Climato**	✓	**NRT, temporal consistency, completeness**
	GEOV3 300m	PROBAV	**300m**	Meas. EBF/Non EBF	TOC **Red/NIR**	Product Variable temp window	**Data**	✓	**NRT, spatial resolution**

RESULTS : PRODUCT COMPARISON CYCLOPES vs GEOV1

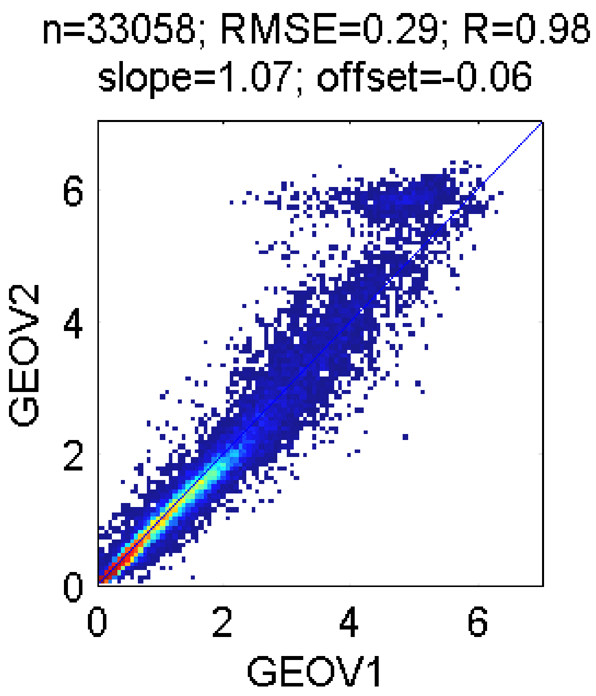


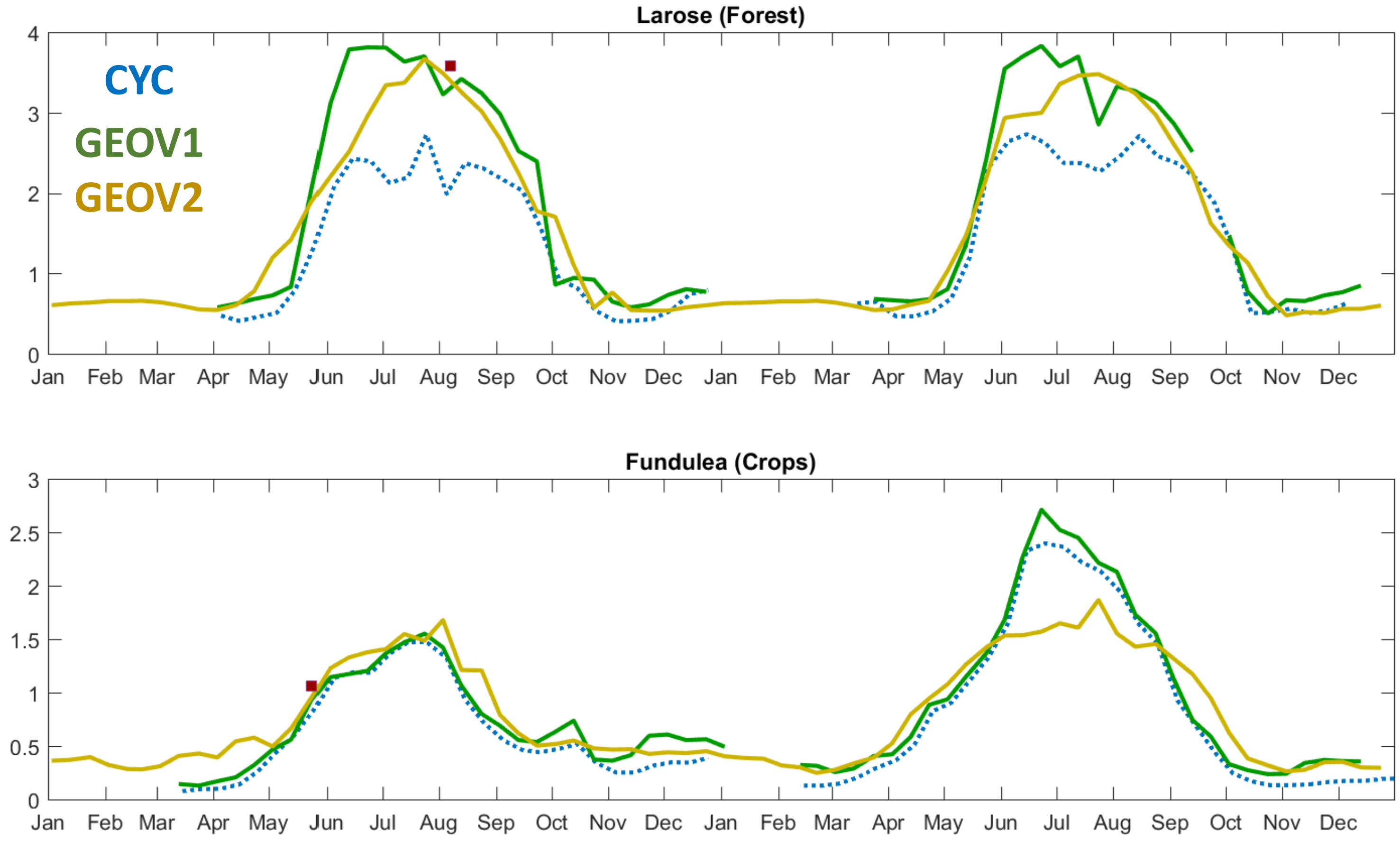


CYCLOPES/GEOV1:

1D simulations vs actual refl + fused MOD+CYC

RESULTS : PRODUCT COMPARISON GEOV2 vs GEOV1

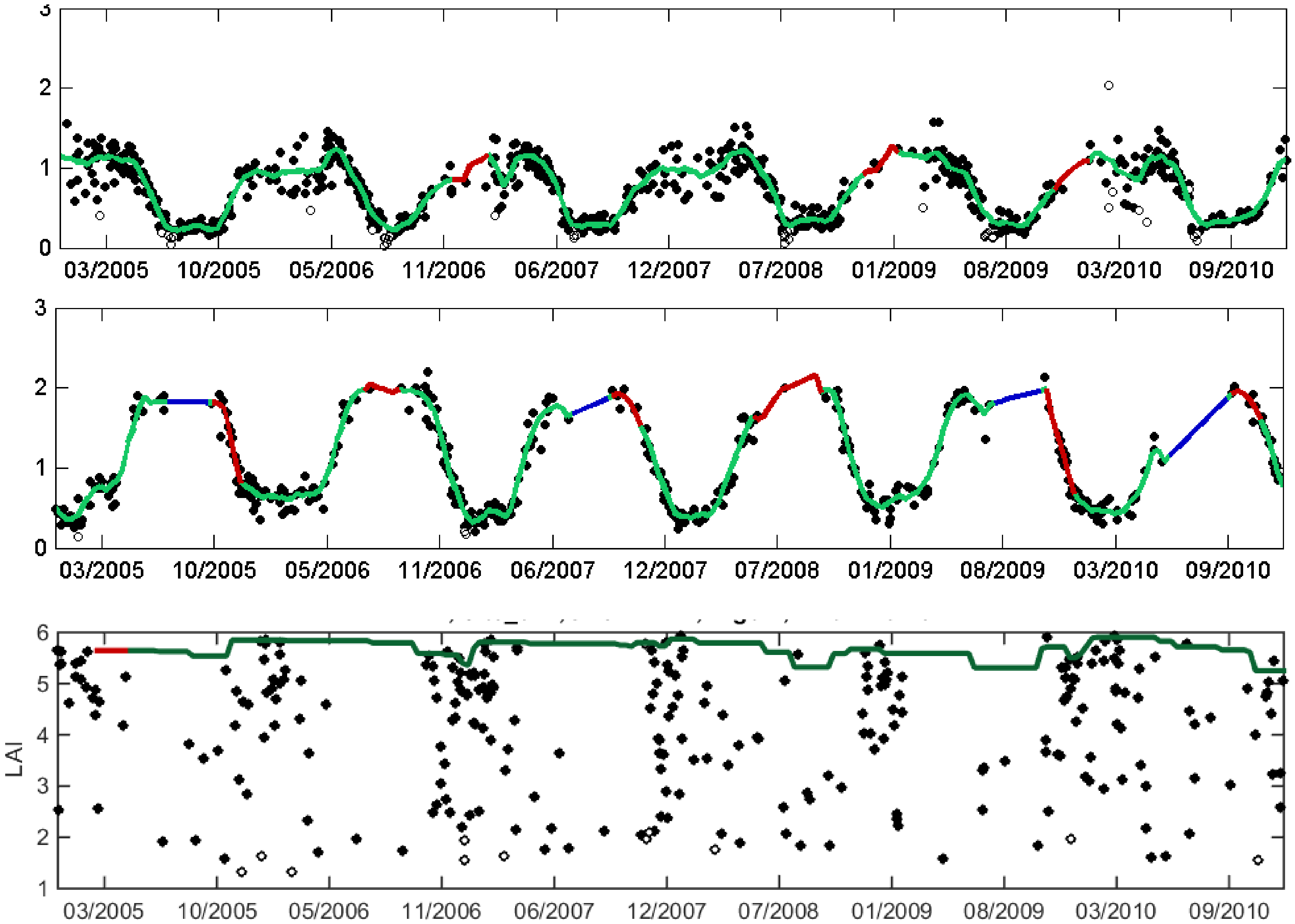




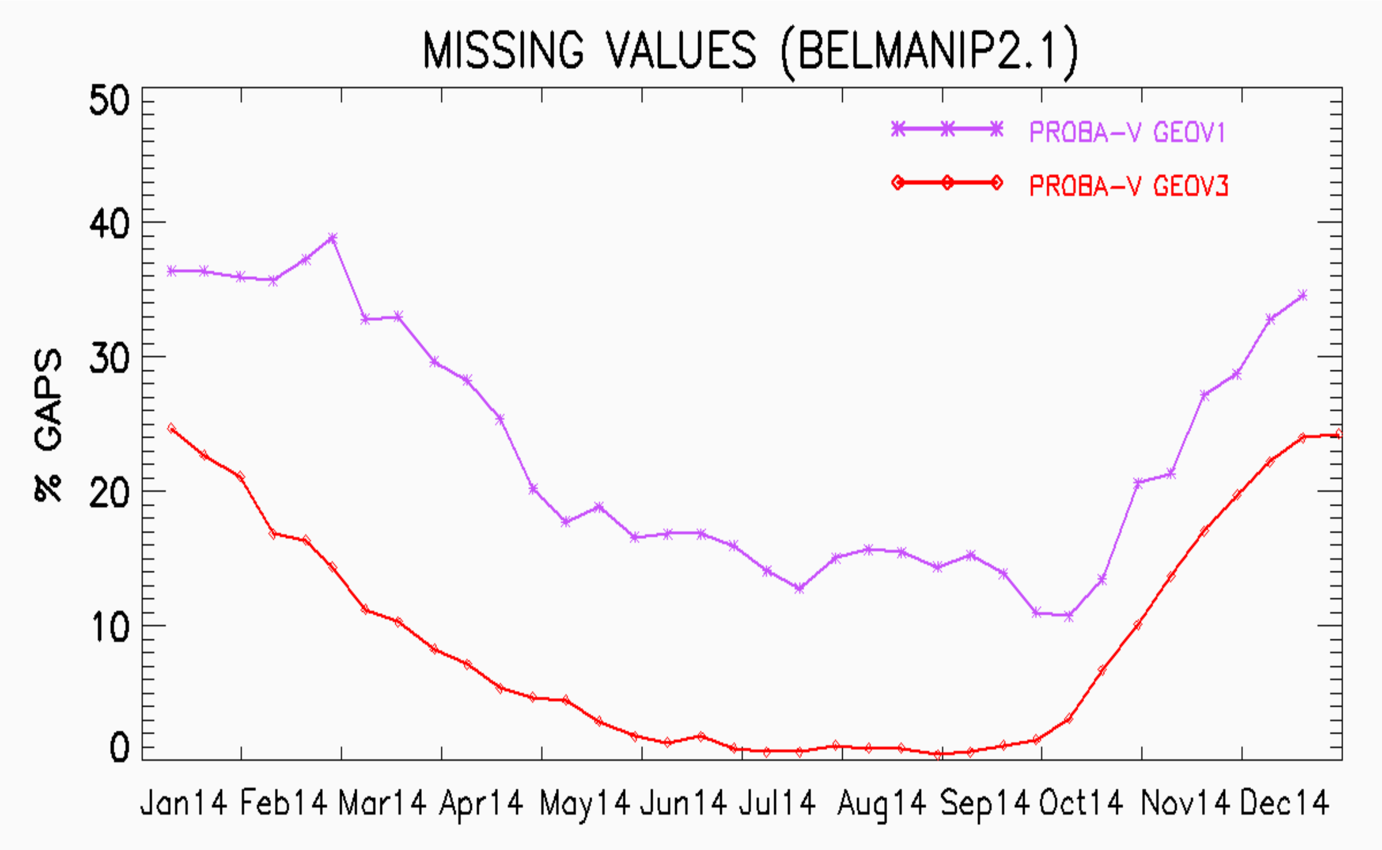
⇨ **GEOV2 /GEOV1**

- Temporal compositing at the product level
- TOA vs TOC

RESULTS : GEOV3



RESULTS – GAP FILLING



- ⇨ Polynomial fitting in GEOV3 reduce the %gaps
- ⇨ Winter period: gaps are too large because of snow & bad weather

…. AND VALIDATION

⇨2000-2005:

- 73 campaigns
- Similar to BigFoot/MODLAND
- Main limitations: spatial sampling vs man power
- Use of HR data to spatially interpolate local measurements

⇨2006:

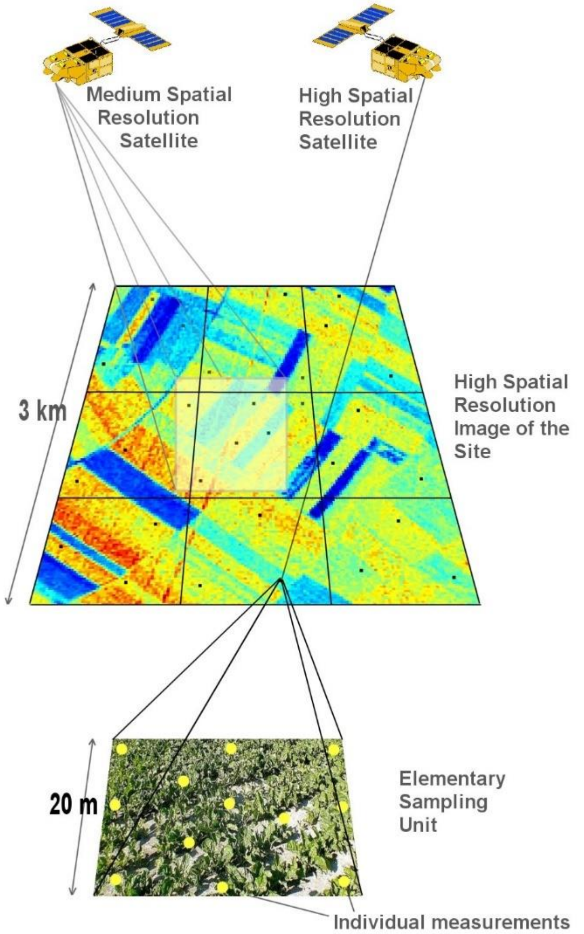
- Ground measurements: not enough
- Product inter-comparison database + machine learning

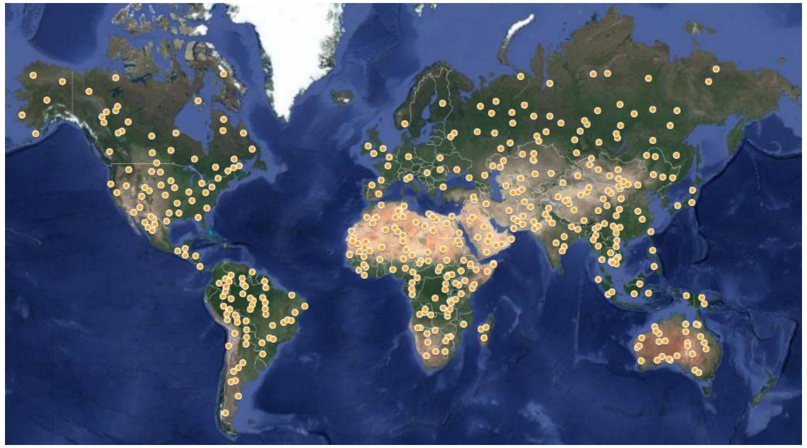
⇨2011:

- Web platform for product intercomparison
- BELMANIP2

⇨2013-2015:

- 20 ground campaigns





WHAT DID WE LEARN: biophysical algorithm

- ⇨ Cloud mask accuracy
- ⇨ TOC/TOA reflectance as inputs
  - Very good performances achieved with TOA as inputs but requires a larger training dataset
- ⇨ Class - Specific processing
  - EBF: can be identified easily and should be processed separately
    - Cloud occurrence
    - Temporal course
  - Other vegetation classes?
    - Dependence on map classification (update frequency? Mis-classification?)
- ⇨ Machine learning
  - Use of actual satellite data is better but limited by the availability of ground data (currently MODIS+CYCLOPES fused products)
- ⇨ Effective/True LAI
- ⇨ Ground truth
  - Limited by man power
  - PSF of medium resolution instruments can not be neglected in heterogeneous conditions

WHAT DID WE LEARN : temporal aspect is fundamental

⇨ Temporal consistency

- Compositing at the product level : better compromise between the temporal smoothness and the data fit
- Adaptive temporal window (function of amount of available data)

⇨Gap filling

- a priori information provides better results than mathematical fitting
- Use of climatology
  - Too long period masks possible recent evolution
  - Too short period more sensitive to atypical previous years
- Polynomial fit
  - Sensitive to noise

⇨Near Real Time :

- Not adequate at the very beginning of growing or senescent phase
- Projection is highly dependent on the amount of available data in the previous temporal window

WHAT TO DO NEXT ?

BENEFIT FROM THE AVAILABILITY OF DECAMETRIC DATA

⇨ Algorithm : Machine learning across scales

- RTM: 3D-4D modelling at very HR resolution (Fred's talk)
  - Deep learning combining accurate measurements & modelling
- Transfer to decametric products

  Machine learning (inverse model)

  Class specific algorithm : better classification accuracy, more frequent updating to capture HR phenology, especially for short vegetation cycle

- Transfer to hecto/kilometric products
  - Learning based on decametric products
  - Going backwards in time (reprocessing archive)

⇨ Validation

- Focus on the validation of decametric products

  Measurements at this scale easy to complete and more and more available

- Temporal monitoring of the vegetation cycle is mandatory

  New sensors are becoming available (IOT)

- Indirect validation of hecto/kilometric resolution through the validation of decametric products (estimate sensor PSF is mandatory)