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LAND COVER MAPPING WITH GAUSSIAN PROCESSES AT THE COUNTRY SCALE USING SPARSE AND

VARIATIONAL APPROACHES

V. BELLET^{1,2}, M. FAUVEL², J. INGLADA²

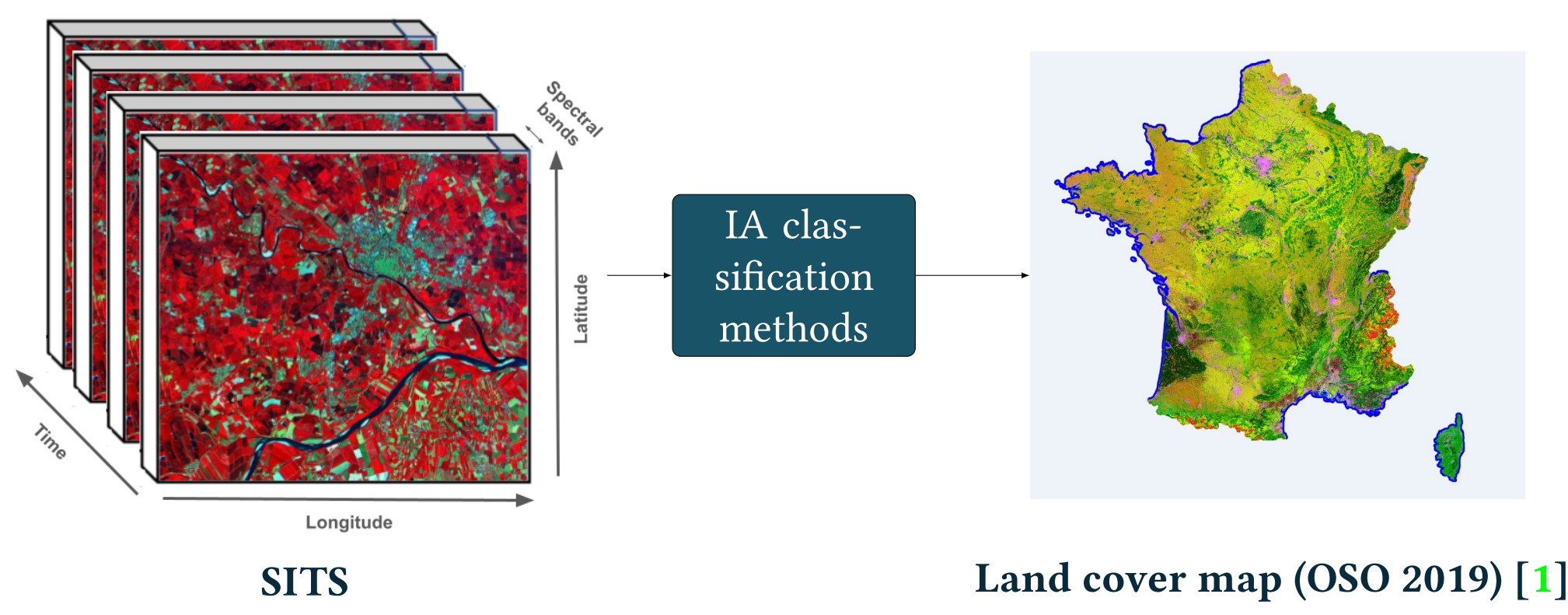
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² CESBIO, Université de Toulouse, CNES/CNRS/INRAe/IRD/UPS

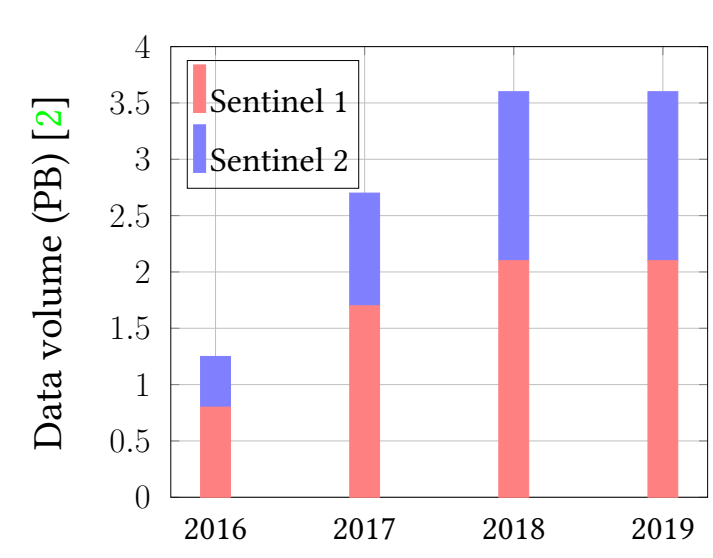


Massive Earth Observation Data

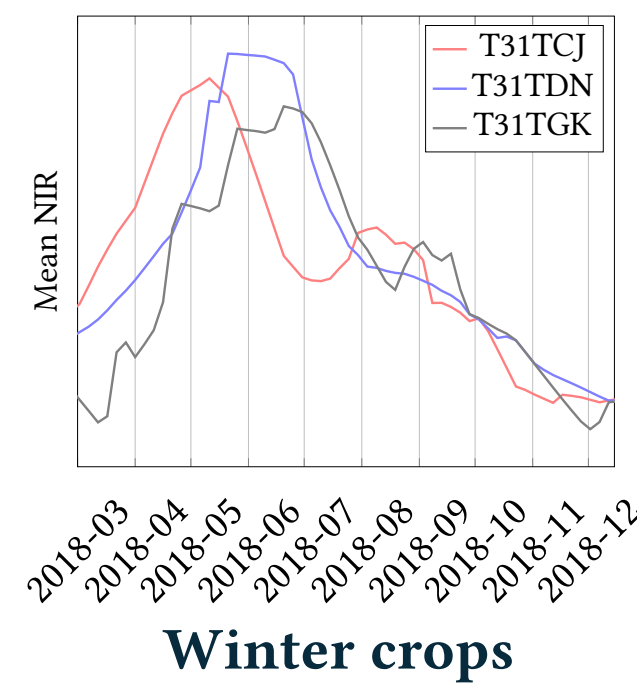
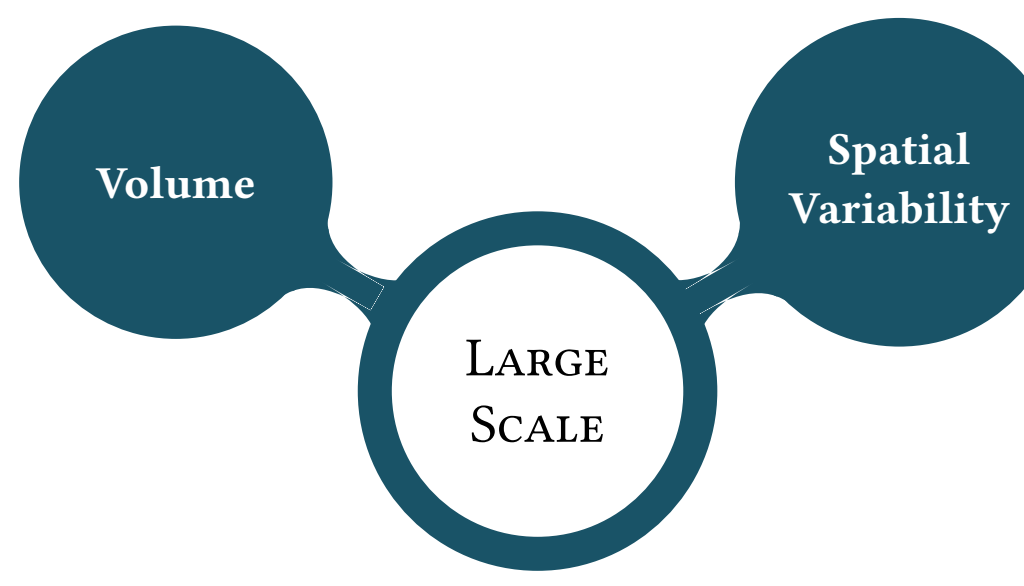
Land cover classification:



Challenges:



Annual data volume



Winter crops

Data generation:

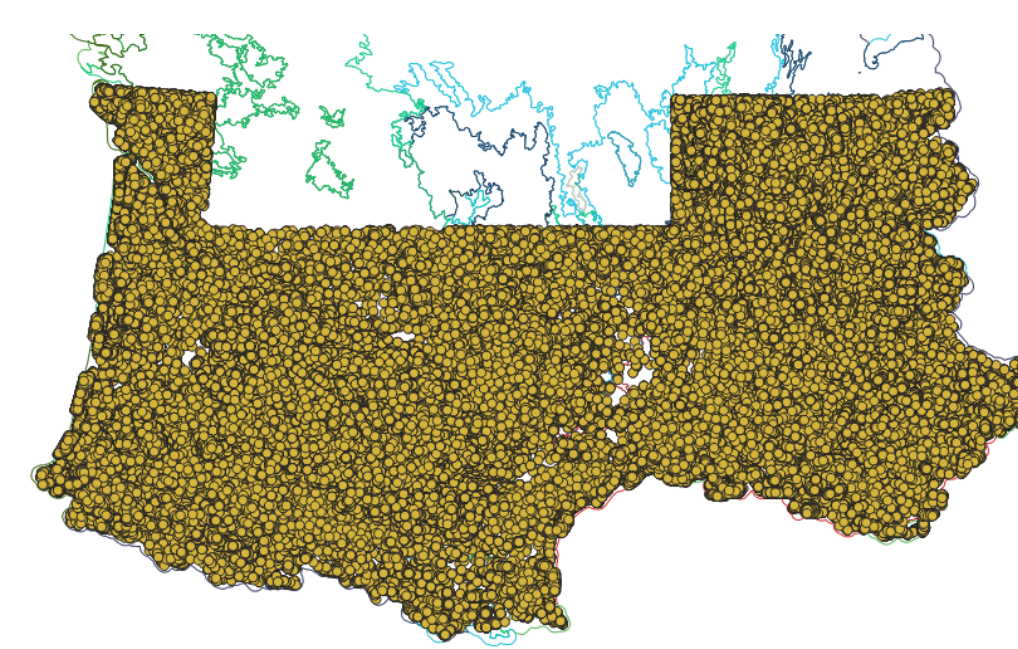
Classification dataset

- 3 distinct datasets: train, validation and test
- dataset produced for each ecoclimatic region (8 ecoclimatic regions)
- sampling repeated 11 times with different random seed
- preprocessing: feature scaling

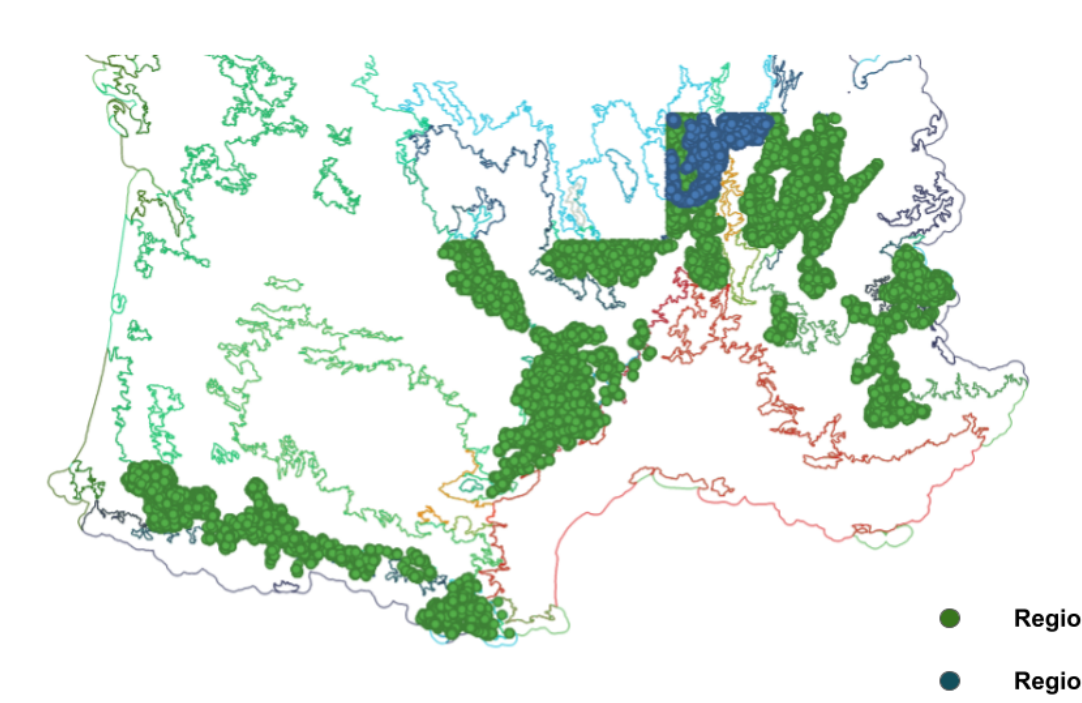
Maximum number of pixels for each class

	Region X	Global
Dataset A (train-val)	4 000-1 000	32 000 -8 000
Dataset B (train-val)	16 000-4 000	128 000-32 000
Dataset A&B (test)	10 000	80 000

Classification configuration:



Global configuration:
learn a unique model in the full area



Stratification configuration:
learn a model for each ecoclimatic region

Competitive methods:

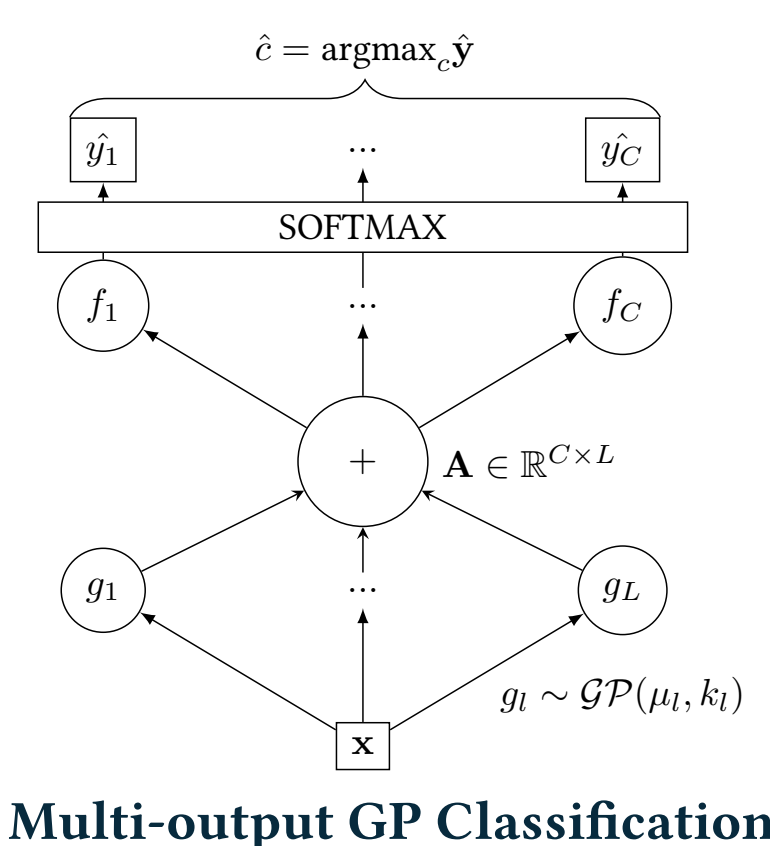
1. Random Forest (RF): 100 trees with no maximum depth and the number of features considered for splitting at each leaf node is equal to the square root of the total number of features. (*Scikit-learn*)
2. Multilayer Perceptron (MLP): four hidden layers. The number of neurons in the first layer is the number of features divided by 2 and in the last three layers: the number of classes multiplied by 3. The activation function used is the ReLU. (*Pytorch*)

Large Scale Gaussian Process Classification

Multi-output Stochastic Variational Sparse Gaussian Process Classification [3]:

To overcome large scale issues [4], Gaussian Process $f \sim \mathcal{GP}(\mu, k)$ can be approximated using inducing points $\mathbf{Z} = \{\mathbf{z}_i\}_{i=1}^m$ with $m \ll n$ (i.e. n number of training inputs $\mathbf{X} = \{\mathbf{x}_i\}_{i=1}^n$). The complexity is reduced from $\mathcal{O}(n^3)$ to $\mathcal{O}(nm^2)$. (μ and k are modeled by some parametric functions with hyperparameters θ)

These inducing points \mathbf{Z} can be learned with the hyperparameters θ using the ELBO ϵ (stochastic optimization): $\epsilon = \text{data driven term} + \text{regularization term}$ (Kullback-Leibler divergence)

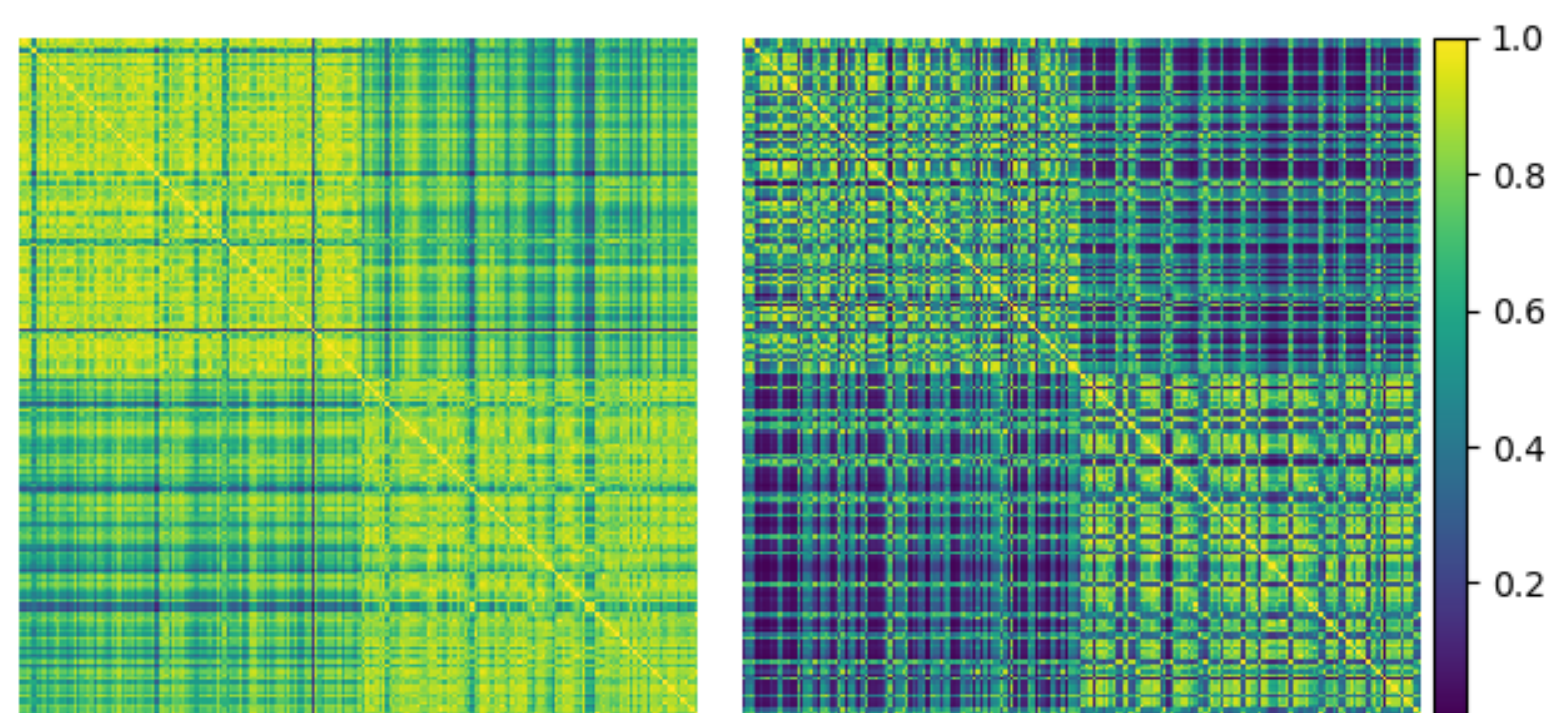


Multi-output GP Classification

Sparse GP

Stochastic Variational SGP

Spectro-temporal and spatial covariates:



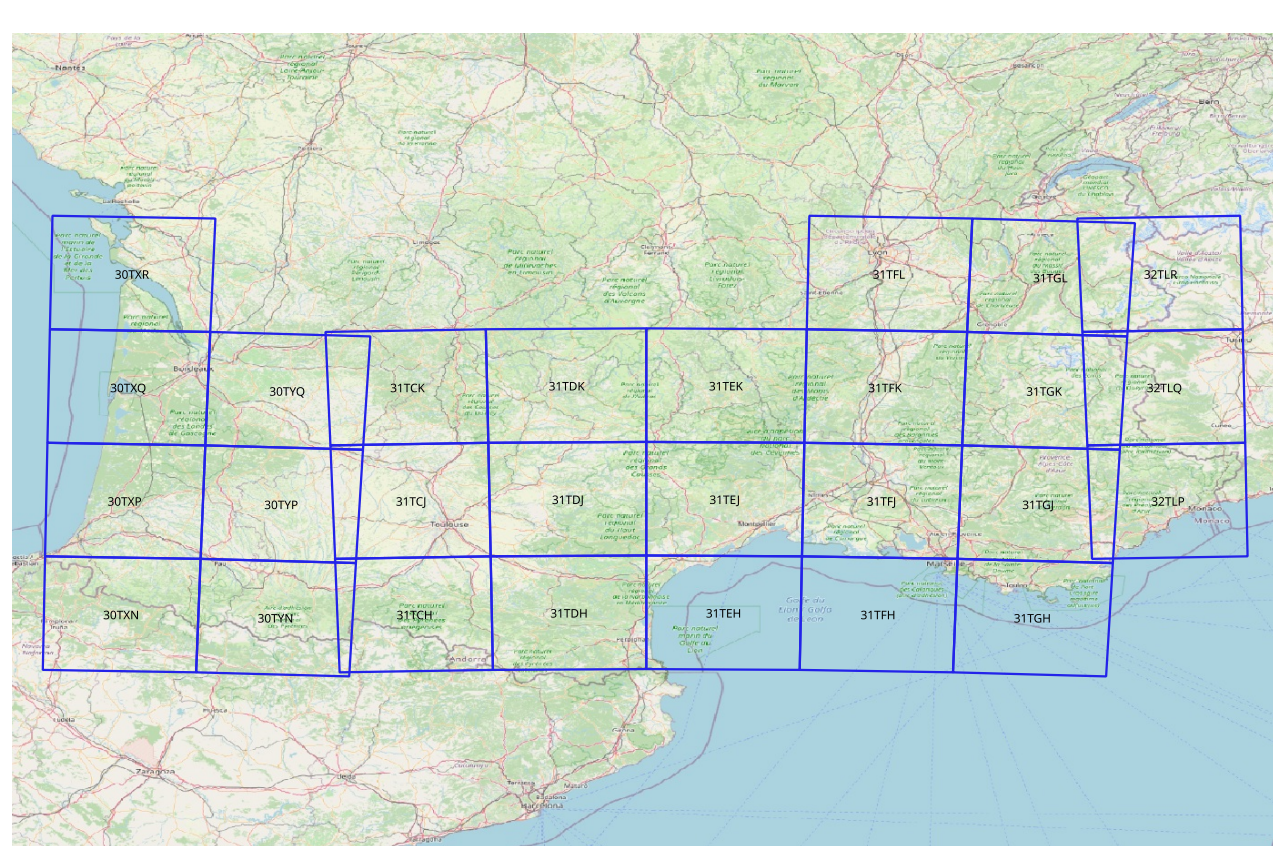
Spectro-temporal kernel Spatio-spectro-temporal kernel

1. λt -GP: $k(\mathbf{x}, \mathbf{x}') = k_M(\mathbf{x}_M, \mathbf{x}'_M)$
2. $\phi \lambda$ -GPSC: $k(\mathbf{x}, \mathbf{x}') = \alpha_0^2 \times k_\phi(\mathbf{x}_\phi, \mathbf{x}'_\phi) + \alpha_M^2 \times k_M(\mathbf{x}_M, \mathbf{x}'_M)$
3. $\phi \lambda$ -GPPC: $k(\mathbf{x}, \mathbf{x}') = k_\phi(\mathbf{x}_\phi, \mathbf{x}'_\phi) \times k_M(\mathbf{x}_M, \mathbf{x}'_M)$

$$\mathbf{x} = \{\mathbf{x}_\phi, \mathbf{x}_M\}$$

Experimental setup

Study area:



SITS and reference data

- 27 Sentinel-2 tiles
- acquisitions of level-2A from January to December 2018 linearly resampled (interval of 10 days) (total of 37 virtual dates)
- 13 spectral features λt : 10 spectral-bands (10m ground sampling distance) + 3 spectral indices (NDVI, NDWI, brightness)
- 2 spatial features ϕ : geographic coordinates (latitude, longitude) in meters in Lambert 93 projection
- 23 land cover classes ranging from artificial areas to vegetation and water bodies
- ~ 5 TB

Color	Name	Area (km ²)
Blue	Continuous urban fabric	104
Light Blue	Discontinuous urban fabric	654
Yellow	Industrial and commercial units	564
Light Green	Road surfaces	62
Green	Rapeseed	297
Light Green	Straw cereals	564
Light Green	Protein crops	150
Light Green	Soy	470
Light Green	Sunflower	1441
Light Green	Corn	1030
Light Green	Rice	77
Light Green	Tubers / roots	49

Color	Name	Area (km ²)
Light Green	Grasslands	1167
Light Green	Orchards and fruit growing	93
Light Green	Vineyards	523
Light Green	Broad-leaved forest	1593
Light Green	Coniferous forest	4934
Light Green	Natural grasslands	3386
Light Green	Woody moorlands	1713
Light Green	Natural mineral surfaces	1680
Light Green	Beaches, dunes and sand plains	126
Light Green	Glaciers and perpetual snows	164
Light Green	Water bodies	14567

Results

Quantitative results: (first line: dataset A, second line: dataset B)

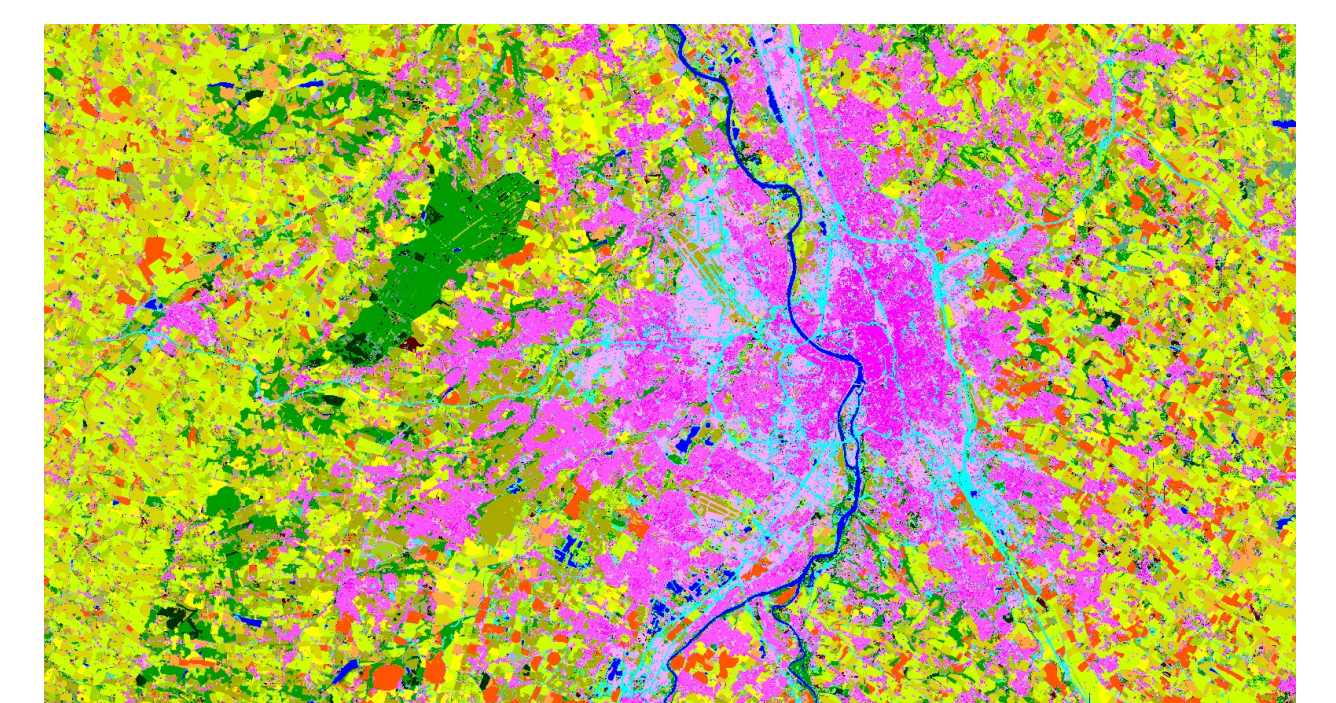
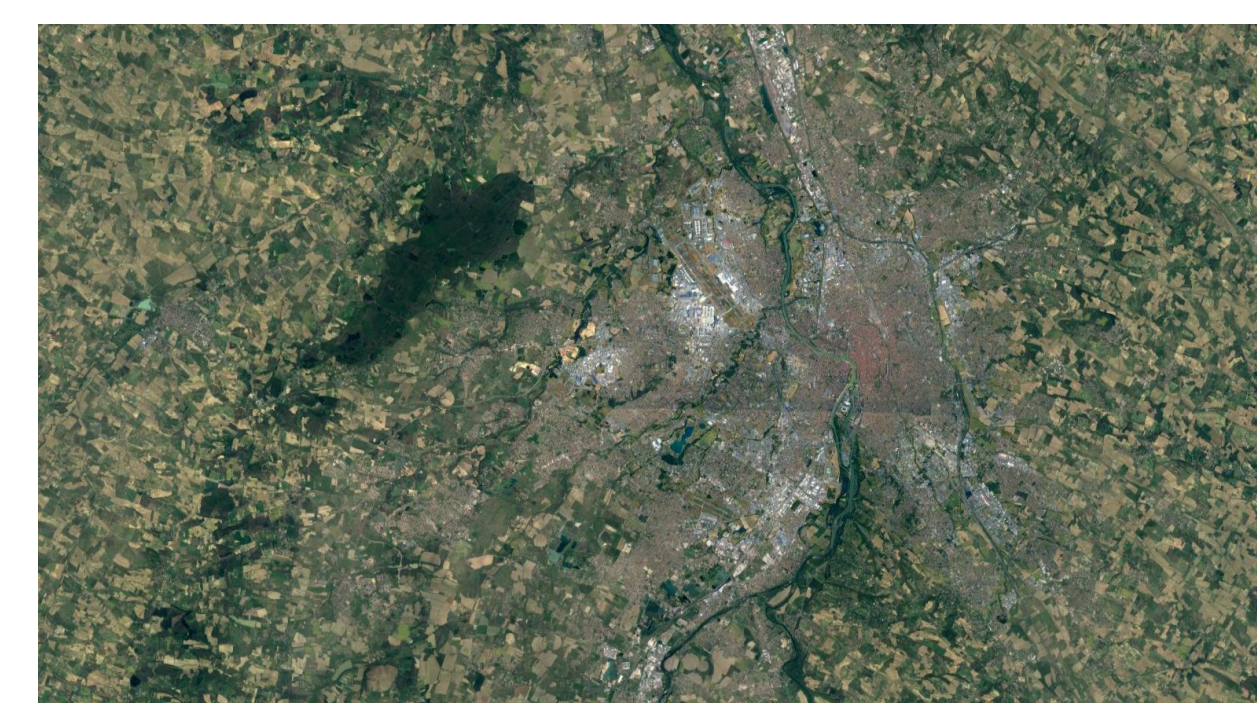
Stratification configuration

	λ -GP	$\phi \lambda$ -GPSC	$\phi \lambda$ -GPPC	λ -RF	$\phi \lambda$ -RF	λ -MLP	$\phi \lambda$ -MLP
oa	77.2 ± 0.3	78.2 ± 0.4	78.6 ± 0.3	75.6 ± 0.1	76.8 ± 0.1	75.5 ± 0.3	76.0 ± 0.2
score	77.5 ± 0.3	76.1 ± 0.4	76.7 ± 0.3	75.5 ± 0.2	76.5 ± 0.1	77.1 ± 0.3	77.6 ± 0.3

Global configuration

	λ -GP	$\phi \lambda$ -GPSC	$\phi \lambda$ -GPPC	λ -RF	$\phi \lambda$ -RF	λ -MLP	$\phi \lambda$ -MLP
oa	76.6 ± 0.6	79.3 ± 0.5	79.7 ± 0.6	75.3 ± 0.1	76.2 ± 0.1	77.7 ± 0.1	78.6 ± 0.1
score	77.5 ± 0.6	80.3 ± 0.5	80.7 ± 0.6	76.4 ± 0.2	77.4 ± 0.2	78.6 ± 0.1	79.5 ± 0.1

Qualitative results: (with stratification configuration using *iota2* chain with the model λ -GP)

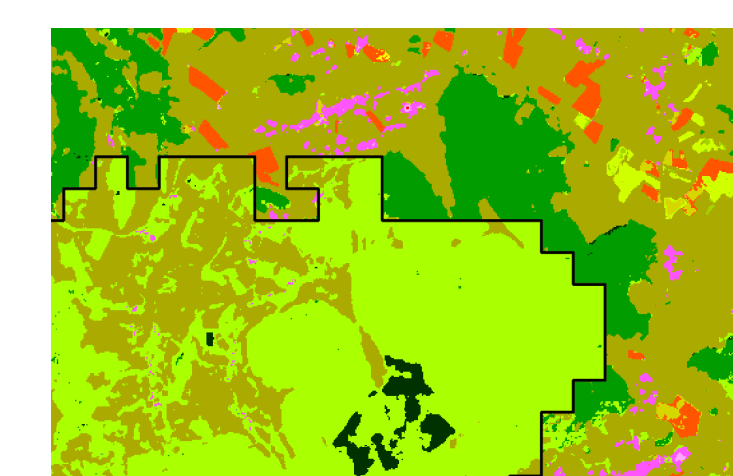
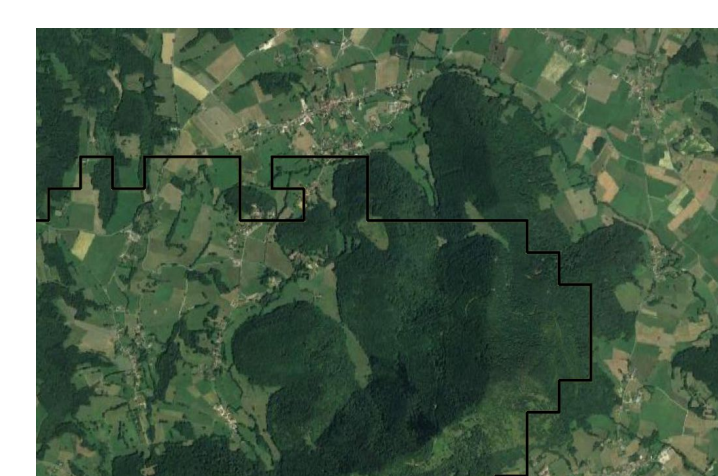


Perspectives

• Dimensionality reduction

Optimization of the inducing points $\mathbf{Z} = \{\mathbf{z}_i\}_{i=1}^m$ with $\mathbf{z}_i \in \mathbb{R}^{\phi+\lambda}$ can be difficult for large dimension: feature reduction.

• Spatial constraints in boundary zones:



Join optimization between models of 2 regions [5]:

$$\mathcal{L}_1 + \mathcal{L}_2 + \lambda R(f_1, f_2)$$

- \mathcal{L}_1 : ELBO region 1
- \mathcal{L}_2 : ELBO function region 2
- $f_1 = f_2$ in boundary zones

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Acknowledgements

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