Identification & Monitoring of Poplar Plantations with Hypertemporal Satellite Remote Sensing

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[3]IDF / Centre National de la Propriété Forestière

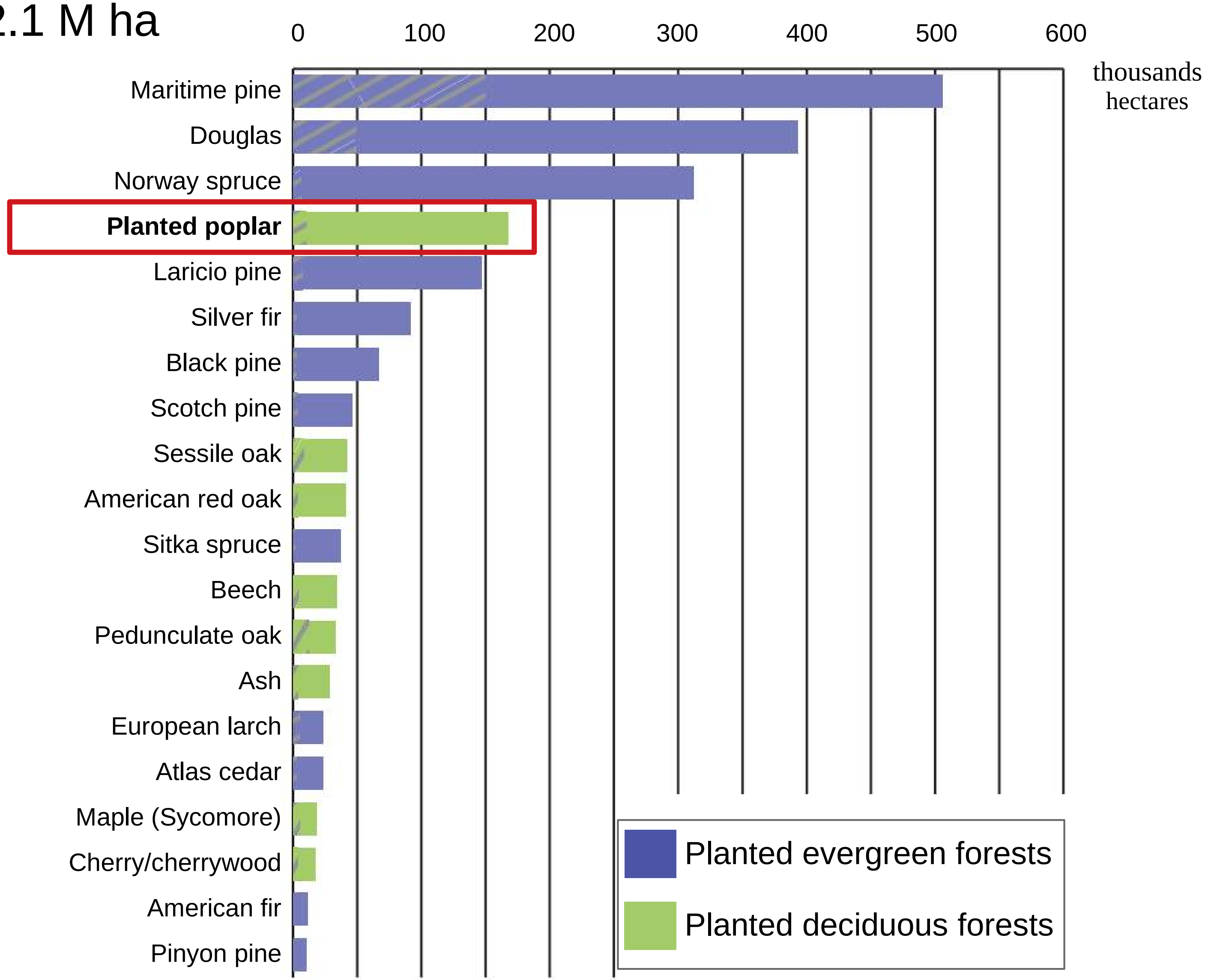
Conseil National du Peuplier

CNPF

DYNAFOR
UMR 1201 | INRA - INP TOULOUSE

Poplar: 1st deciduous tree species planted in France

- French forest= 16.9 M ha
- Planted area= 2.1 M ha
  - Poplar: 10 %



Distribution of plantation areas by main species planted (source: translated from IGN, 2017)

Poplar: 1st deciduous tree species planted in France

Natural poplars: riparian woodland

Fast growing trees (15 years)
Good wood quality
Light wood packaging

Conseil National
du Peuplier

Planted poplars: timber production

Poplar: 1st deciduous tree species planted in France

Natural poplars: riparian woodland

What is the surface area of the poplar plantations in France?

How does it change over time?

Fast growing trees (15 years)
Good wood quality
Light wood packaging

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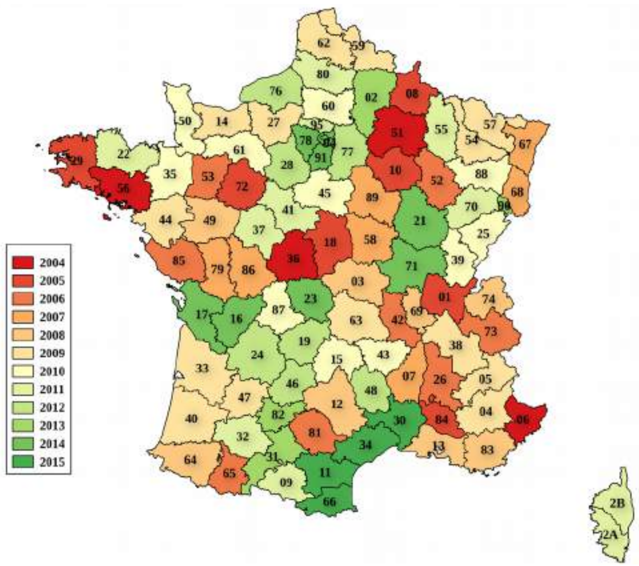
Planted poplars: timber production

Poplar area in France: high uncertainty...

1. Forest database: BD Forêt® IGN



⇒ 10 years to get a national coverage

2. Statistical forest inventory

⇒ Annual estimates but not accurate enough

3. Cadastral register

Poplar wood

Excerpts from the cadastral register of 2013

⇒ Based only on declarations

Poplar area in France: high uncertainty...

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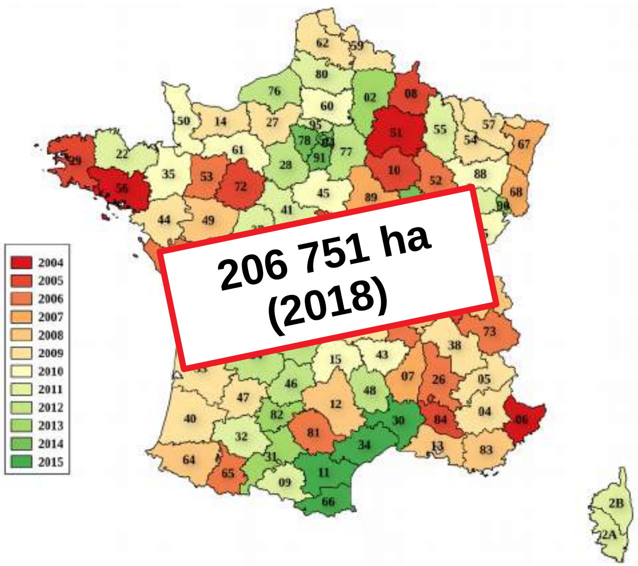

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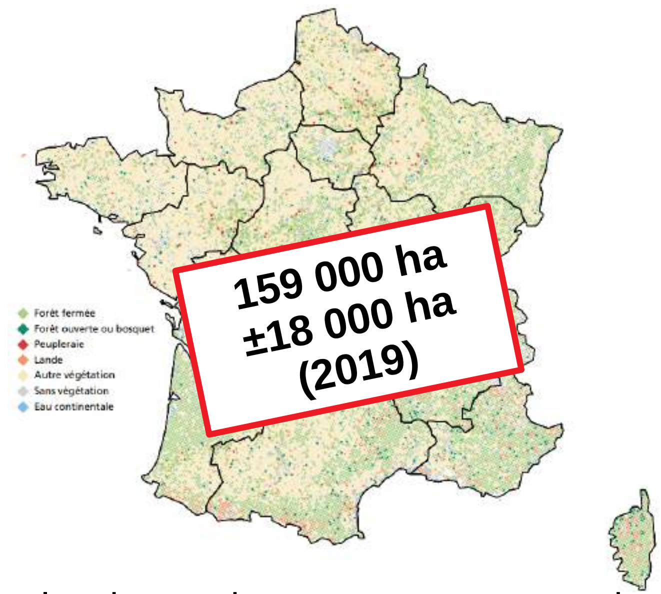

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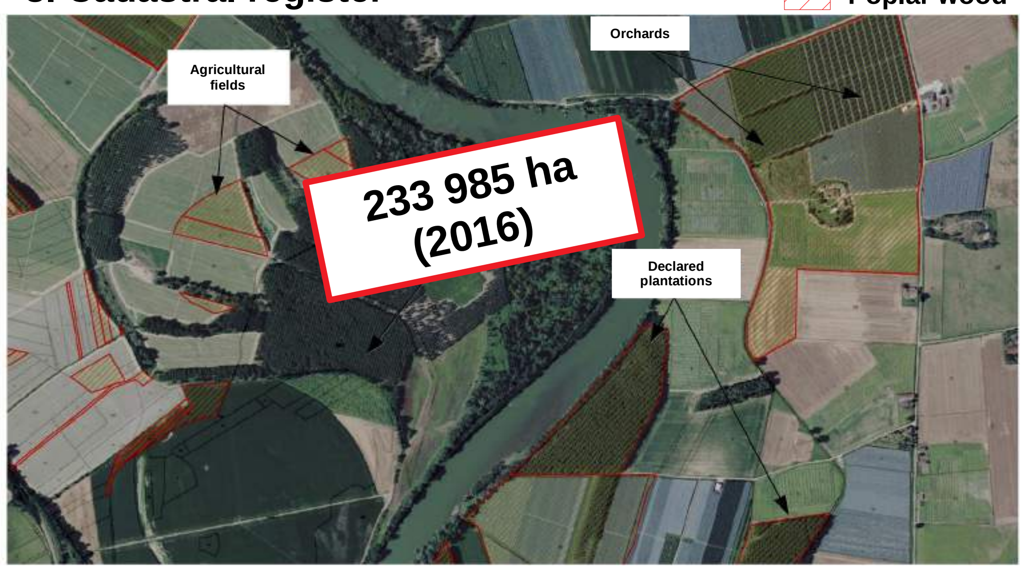

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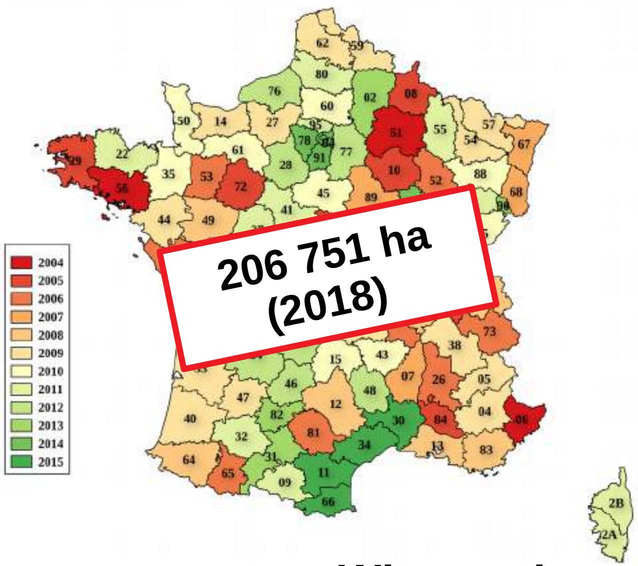

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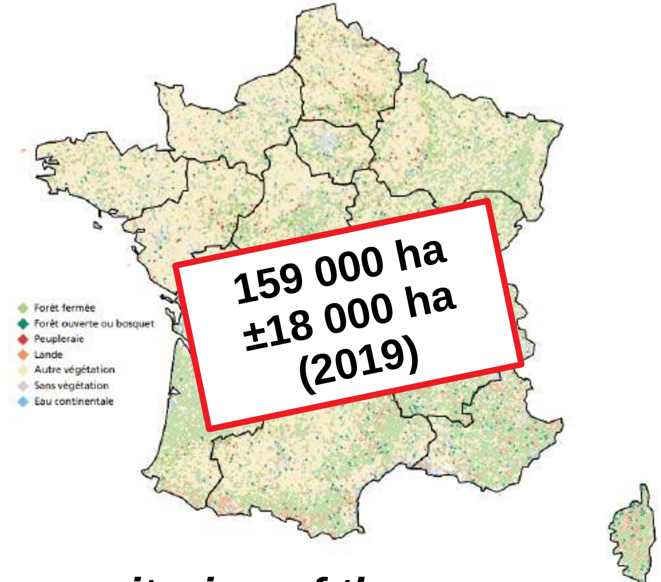
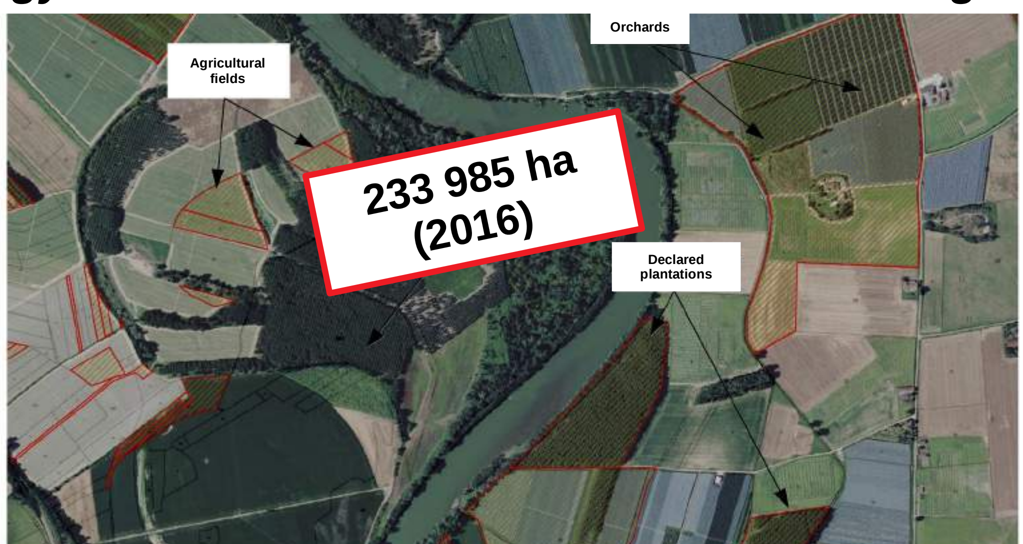


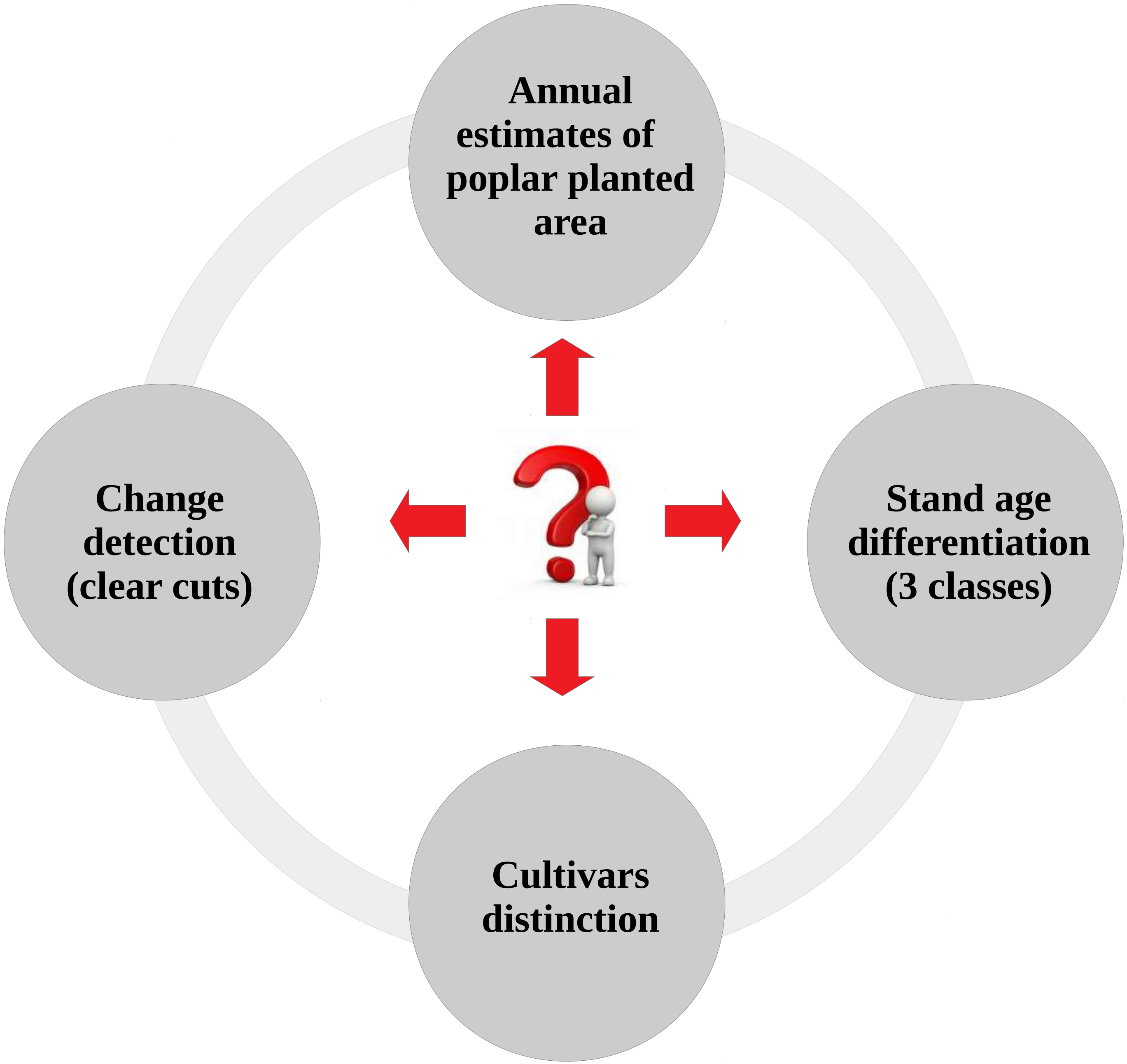
What tools are available to ensure a cost-effective monitoring of the poplar resource?

Which methodology must be followed in order to meet the large scale requirements?



Excerpts from the cadastral register of 2013

Main objective: monitoring of the poplar resource



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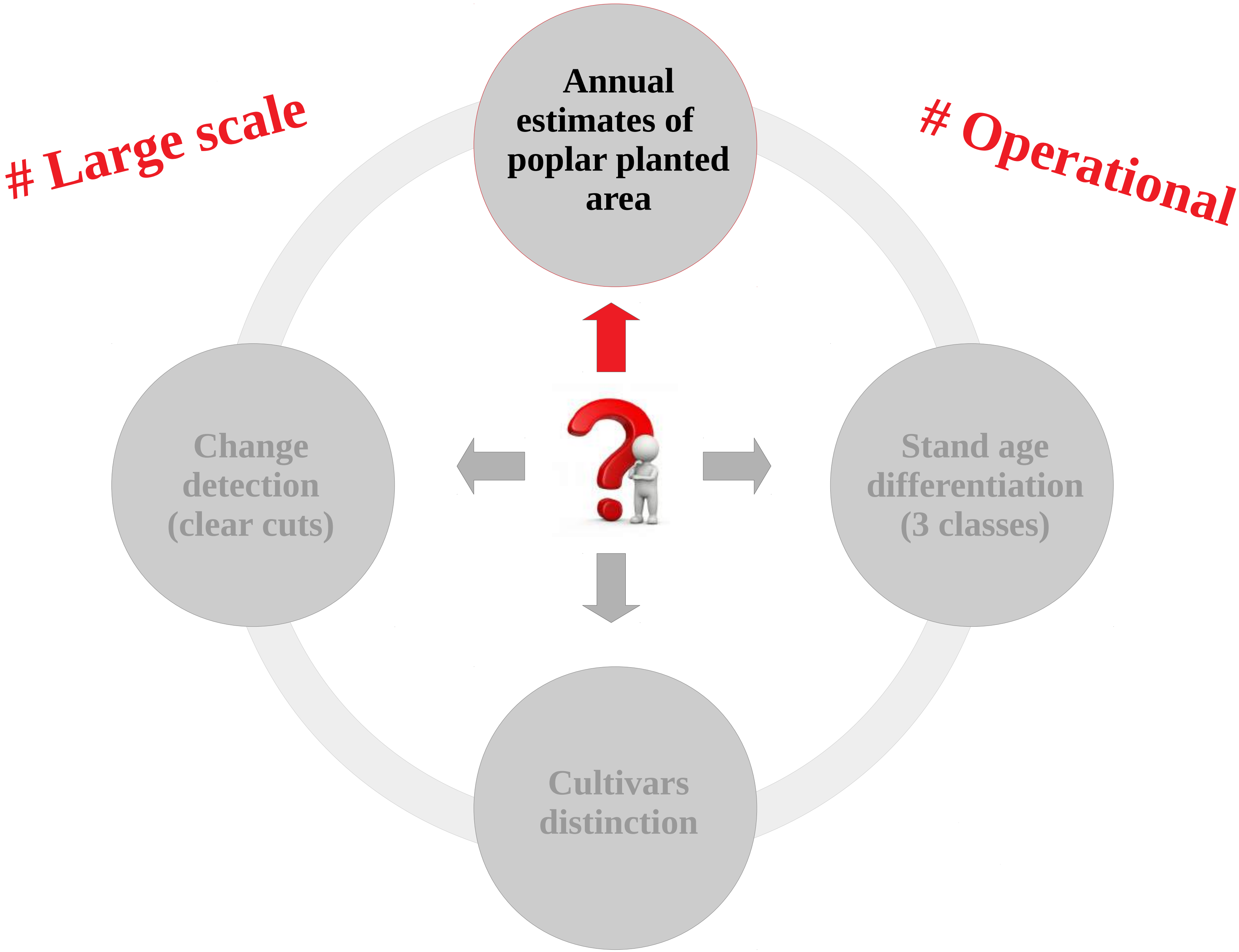
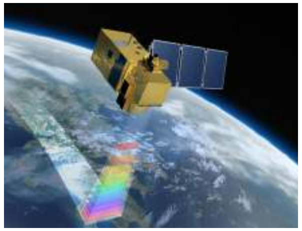


Satellite Remote Sensing: favourable context



- **Unprecedented images: Sentinel-2 time series**
  - Sentinel-2A & Sentinel-2B
  - 10 spectral bands: VIS → SWIR
  - Very high temporal resolution: 5 days
  - High spatial resolution: 10 to 20 m
  - Tiles of 100 km² area

- **Data accessible to all the community**
  - Implementation of pre-processing and dissemination infrastructures
  - Sentinel-2 images provided in level 2A (atmospheric correction)

- **Free and open source tools**
  - OrfeoToolBox, iota2, Google Earth Engine
  - Source codes, Python libraries

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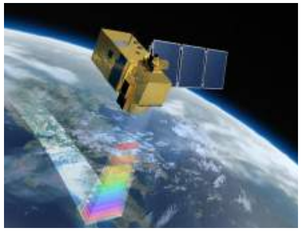

Identification of poplar plantations and annual estimates of their surfaces using Sentinel-2 time series

1. **Ability to identify poplar plantations locally ?**
2. **Ability to generalize on a large scale ?**

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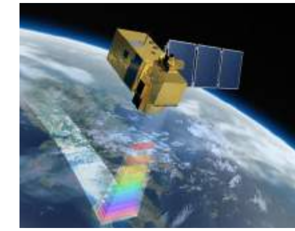

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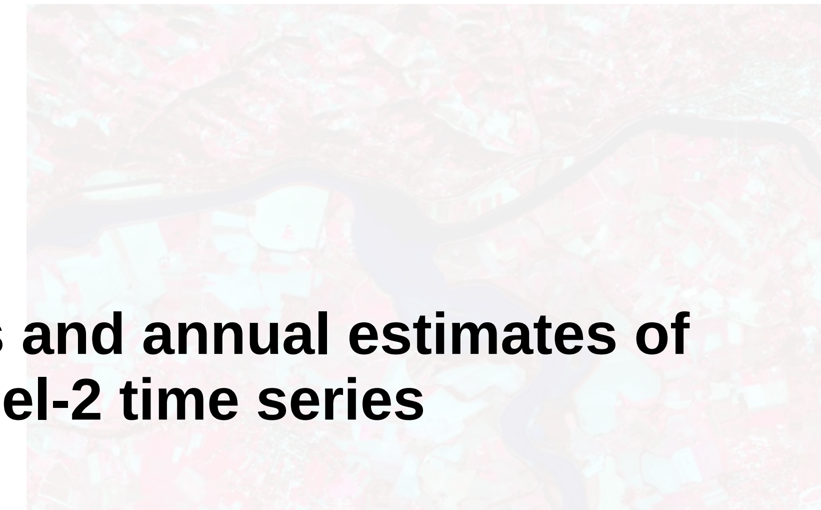

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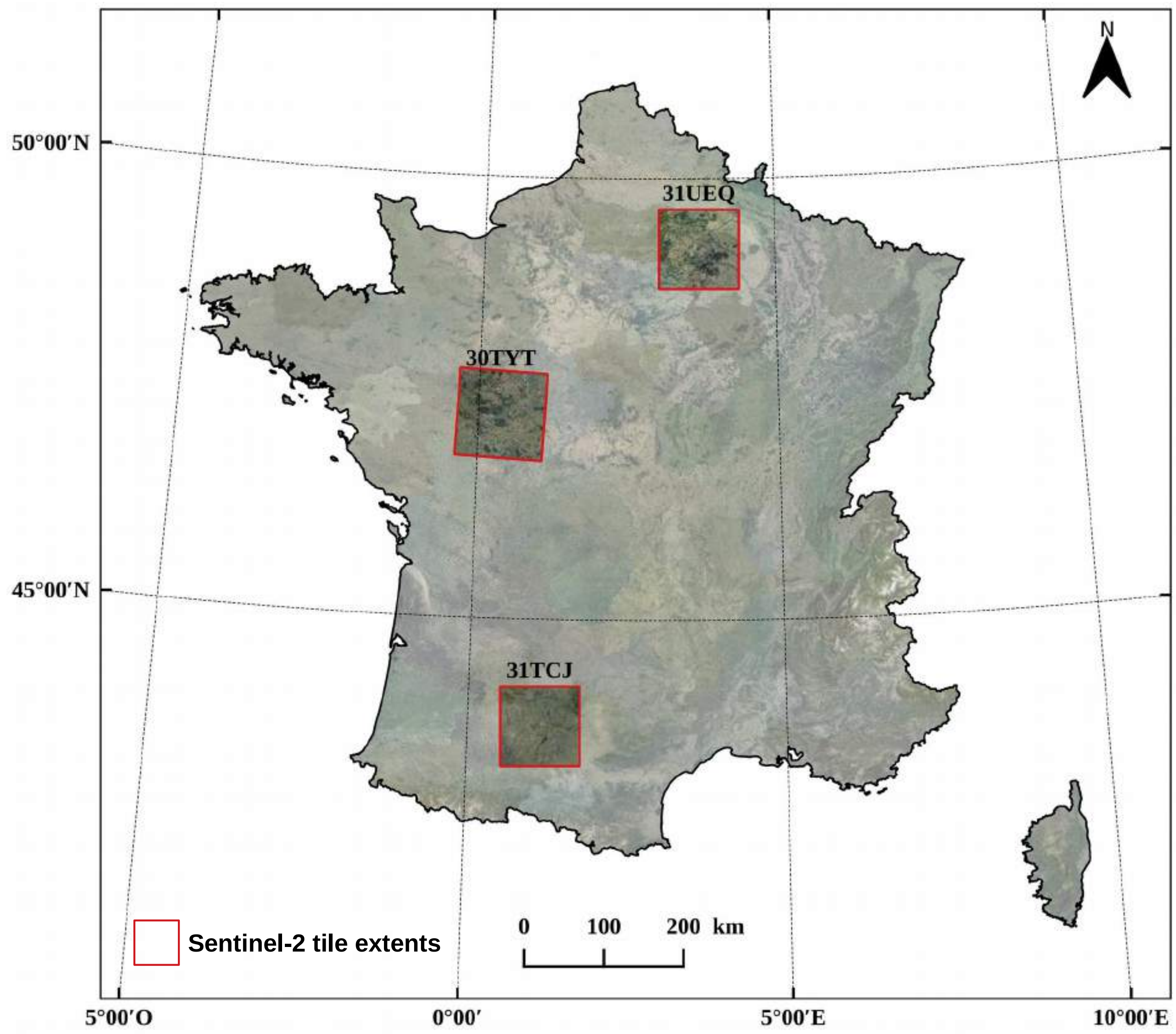
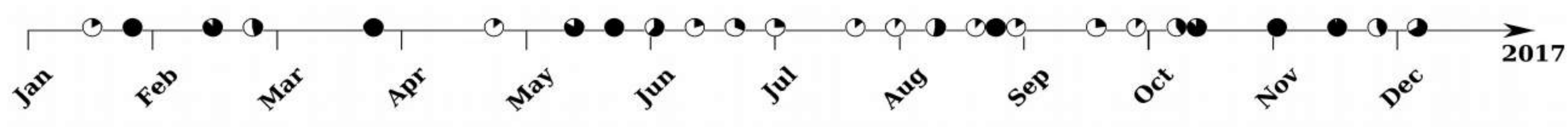
Study areas: three main poplar sites



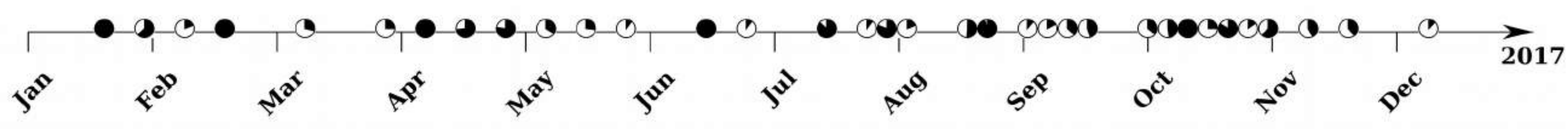
- **Three contrasting sites:** cultivars, silvicultural practices and climatic conditions

Study areas: three main poplar sites

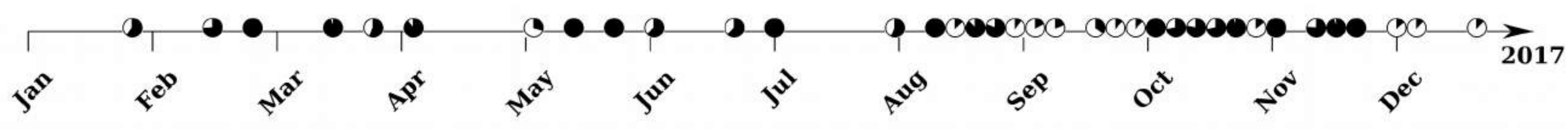
- **Sentinel-2 images from Theia plateform**: level 2A products with atmospheric correction and cloud mask
  - **Northeast:** 26 dates



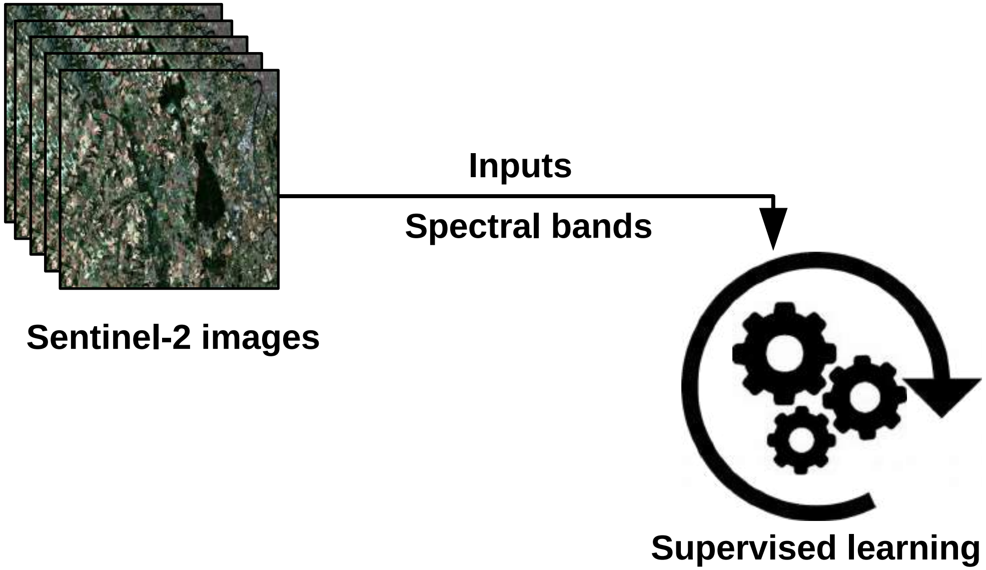
  - **Center:** 34 dates



  - **Southwest:** 36 dates



Methodology in each tile: local supervised classification



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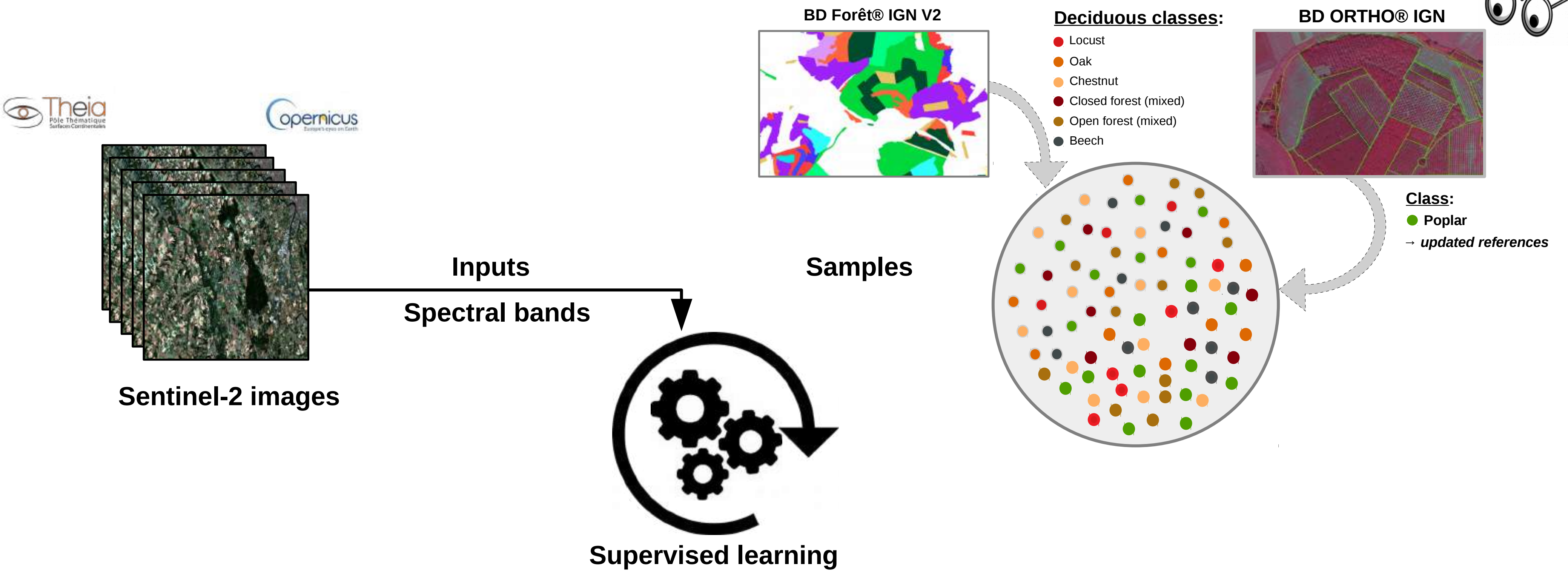

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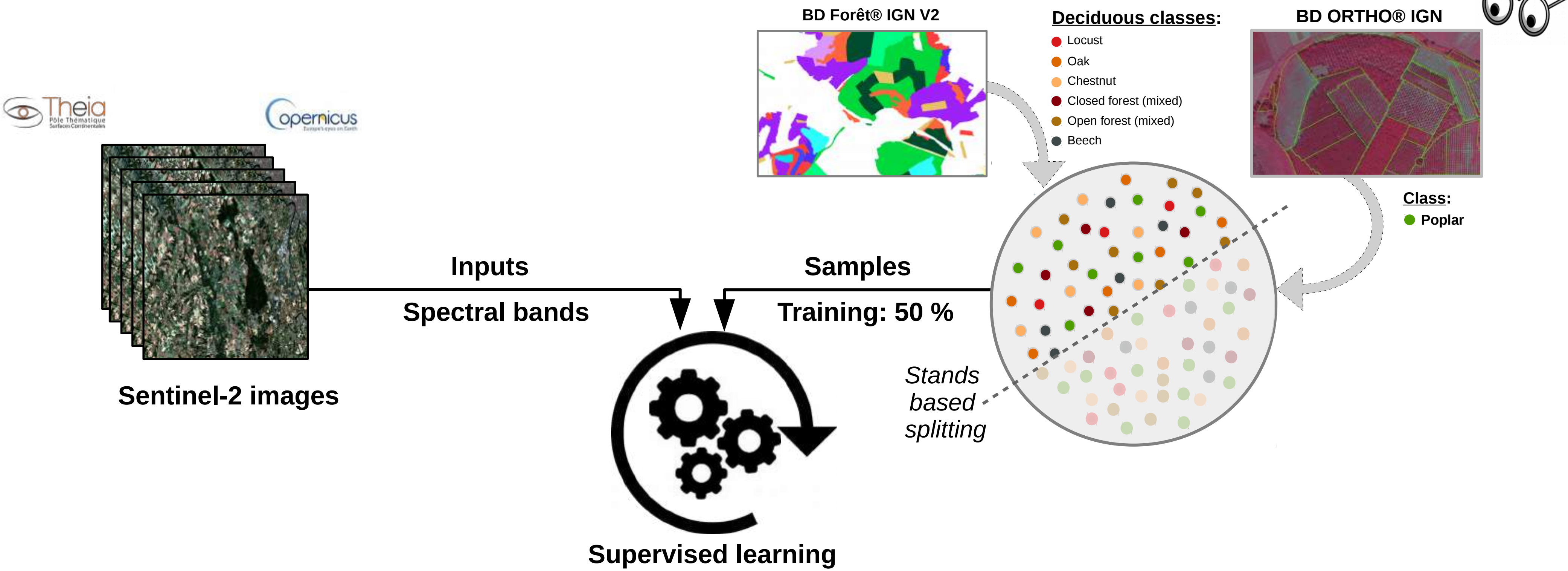

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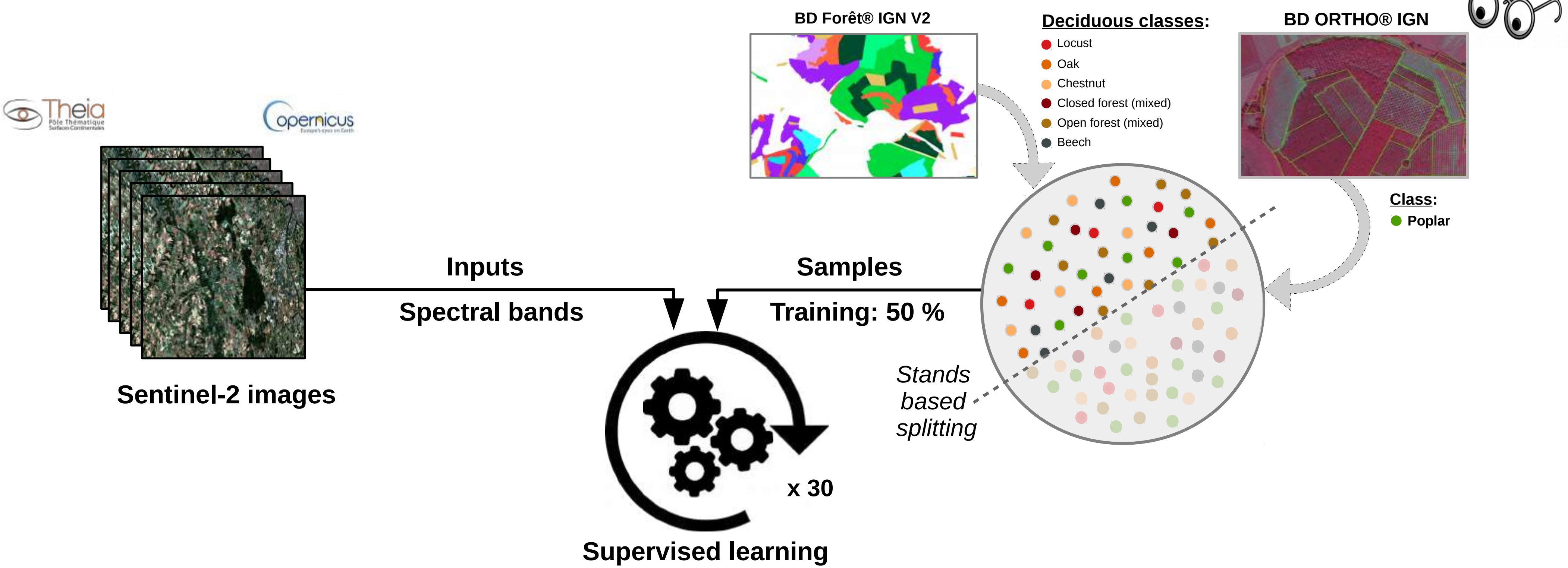

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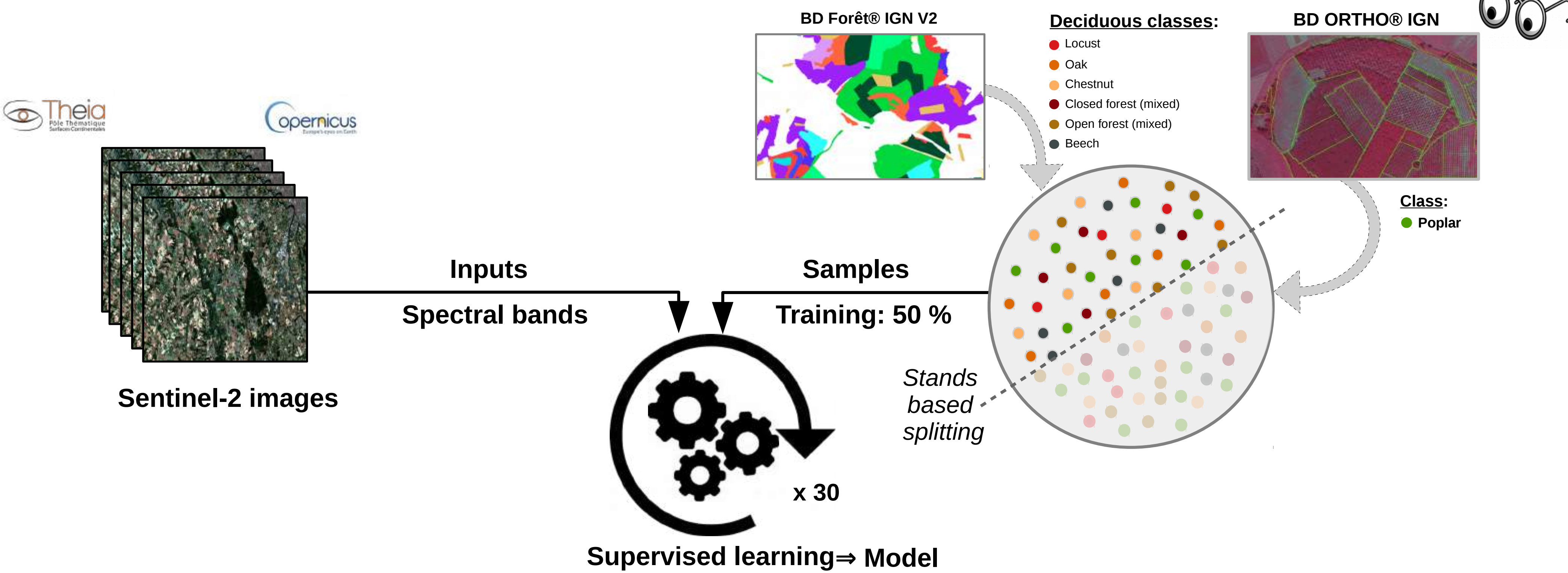

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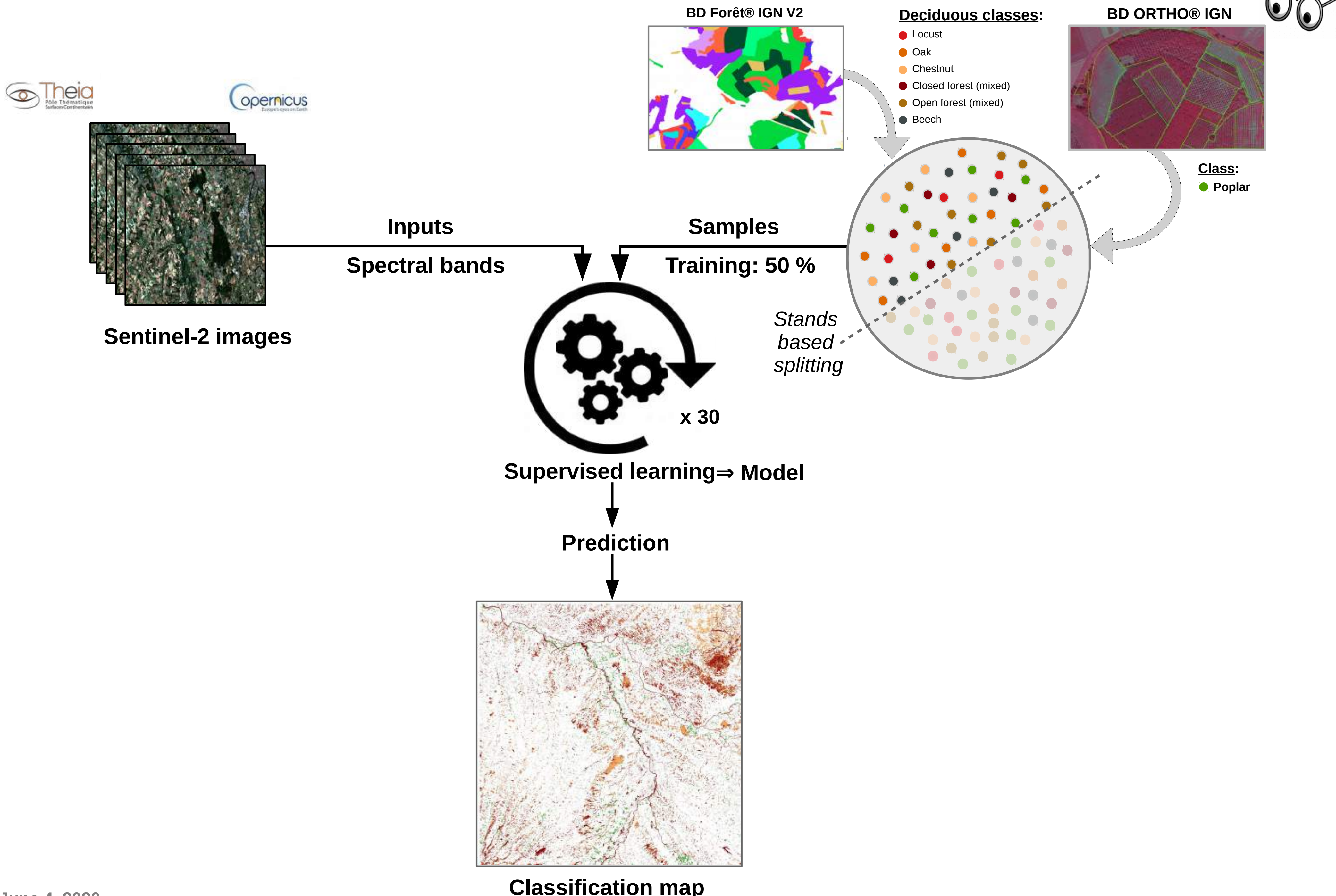

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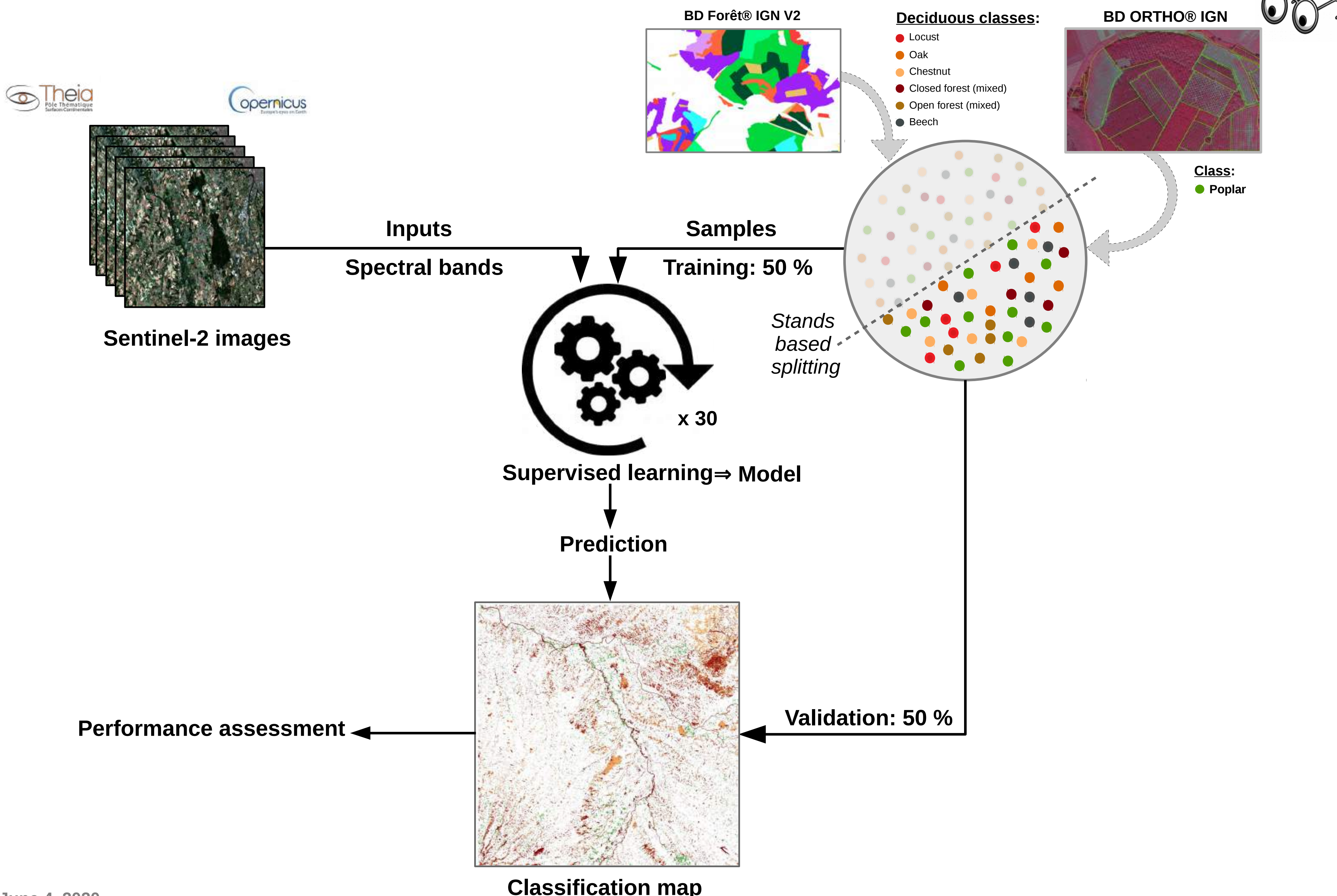

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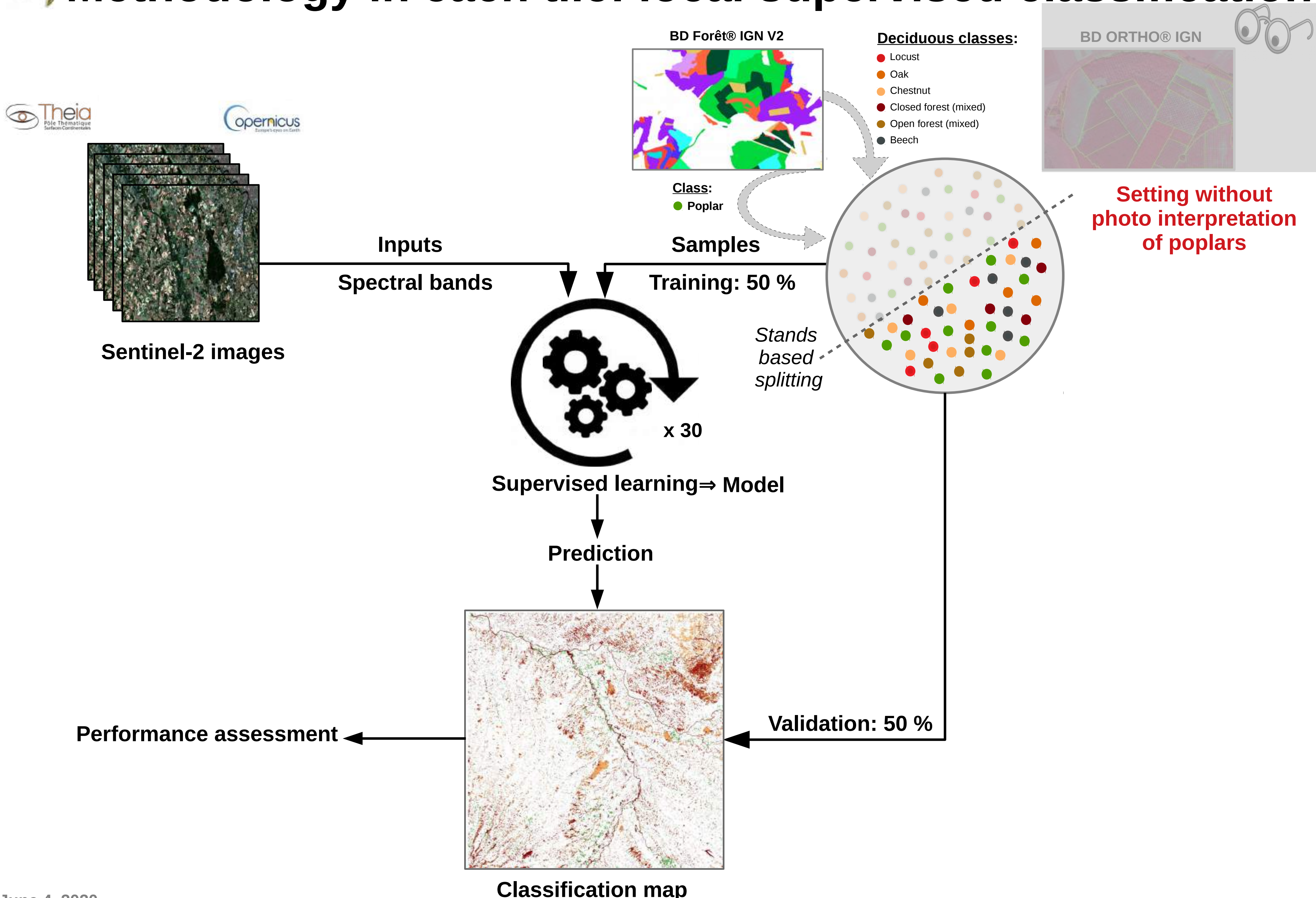

Local supervised classification: results

Tile code	Training size[1] per class in pixels	No. classes	Overall Accuracy$_{(*30)}$	Poplar F-score$_{(*30)}$
Without photo interpretation of poplars (outdated data)				
31UEQ	1250	6	65.6±6.9 %	72.6±5.7 %
30TYT	2000	6	65.8±2.2 %	86.7±1.7 %
31TCJ	3850	6	79.5±3.7 %	89.1±3.9 %

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With photo interpretation of poplars (updated data)					
31UEQ	1250	6	73.7±2.0 %	89.5±3.3 %	+17%
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31TCJ	3850	6	80.0±0.6 %	97.9±0.8 %	+9%

[1] Training samples represent 50% of the available reference data.

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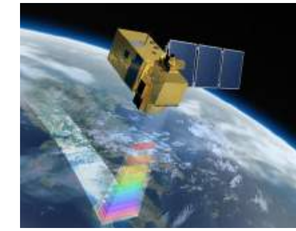
- **High capacity of Sentinel-2 identify poplar plantations at the tile scale**
- **Up to 17% loss of poplar F-score with outdated samples**
- **Importance of data update to ensure the best classification results**

Satellite Remote Sensing: favourable context



Copernicus Europe's eyes on Earth

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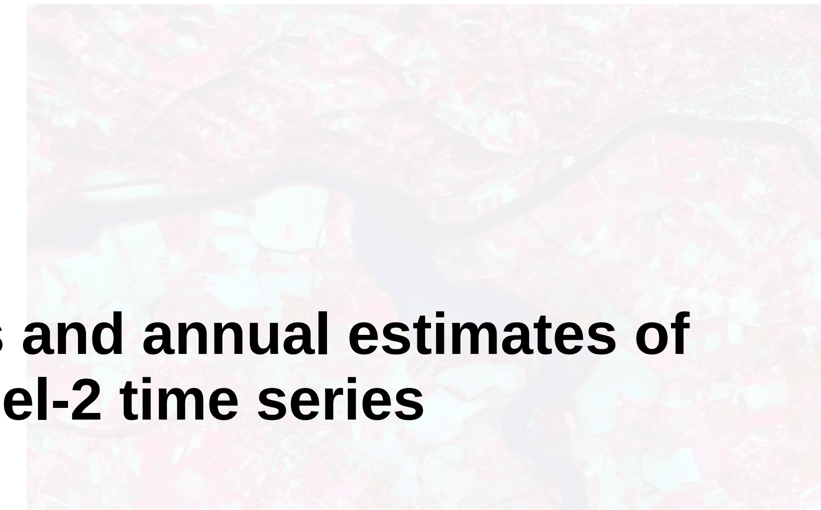

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Photo interpretation

Theia Pôle Thématique Surfaces Continentales

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- **Free and open source tools**
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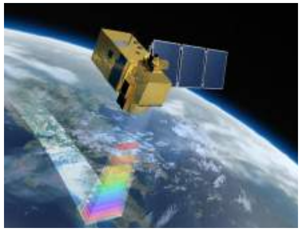

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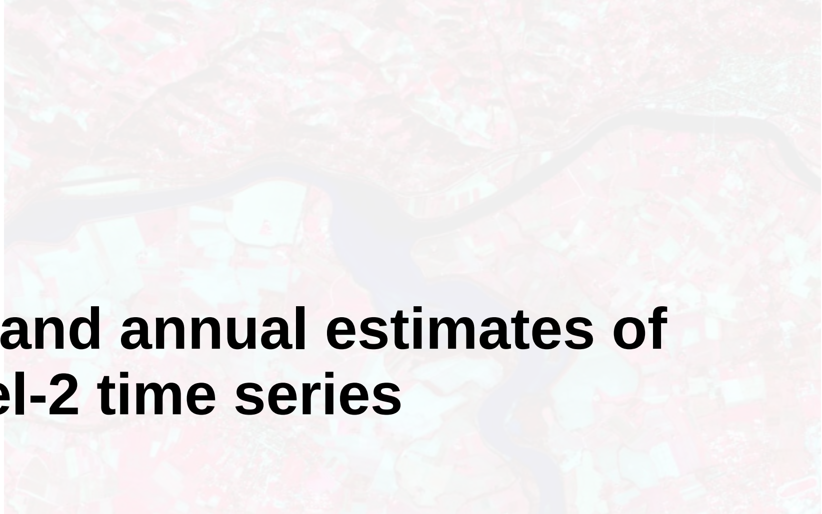

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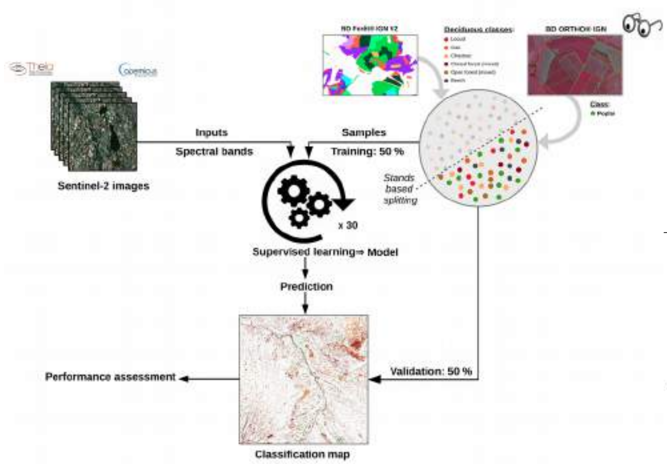
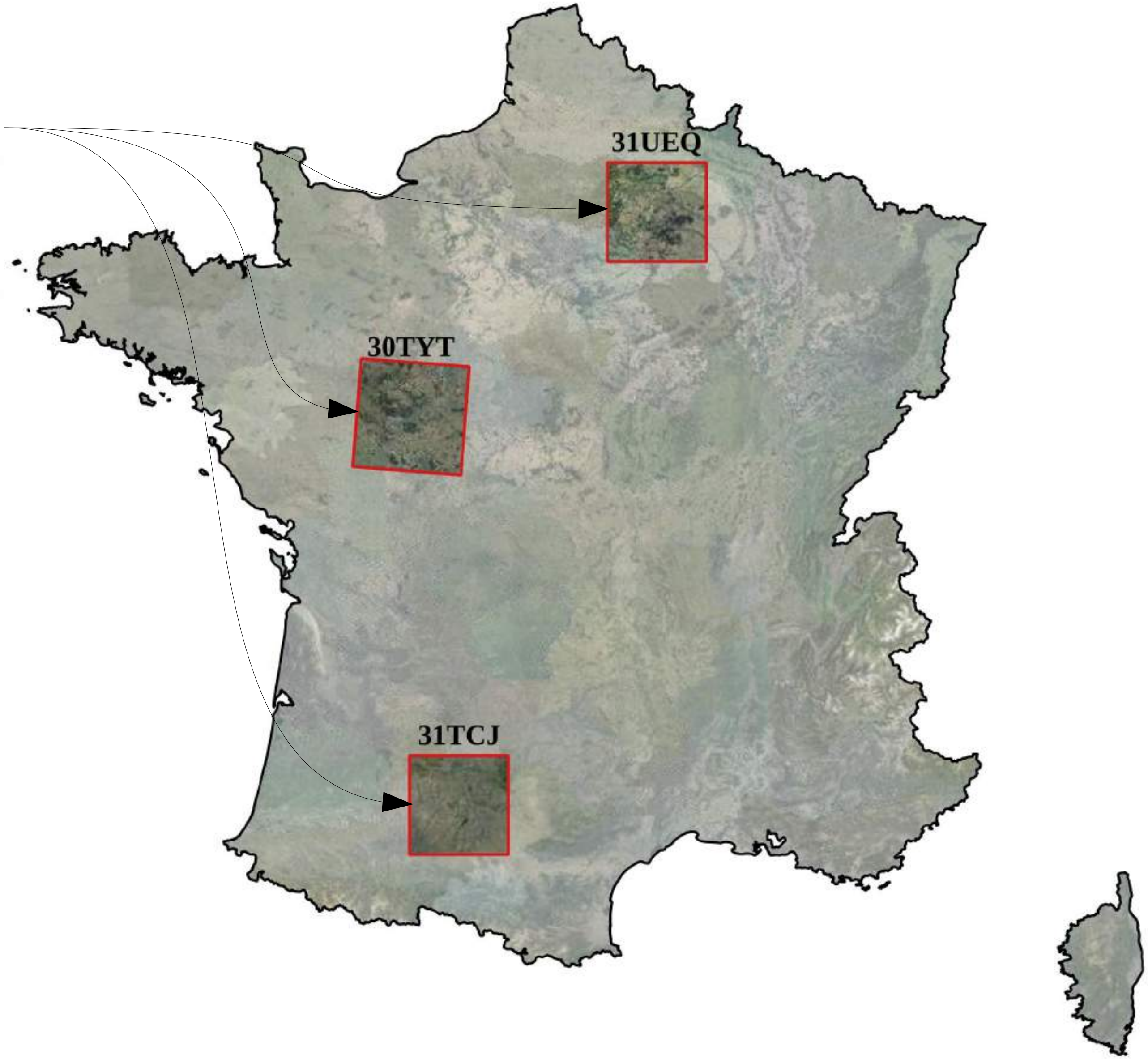




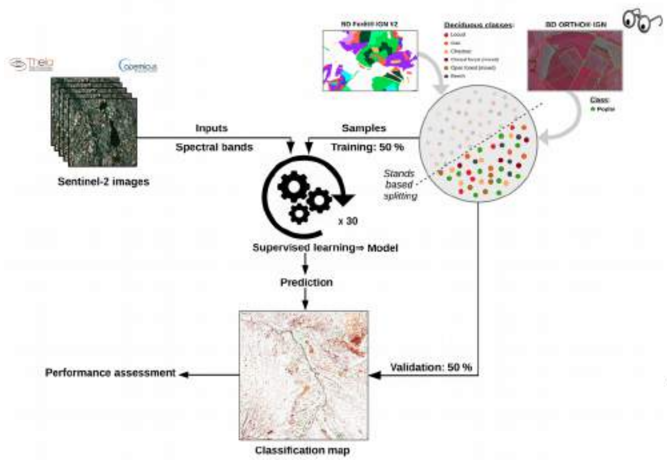
For 3 tiles:

- Local classification x3

- Photo interpretation x3

→ **3 independent models**

Reminder: local supervised classification



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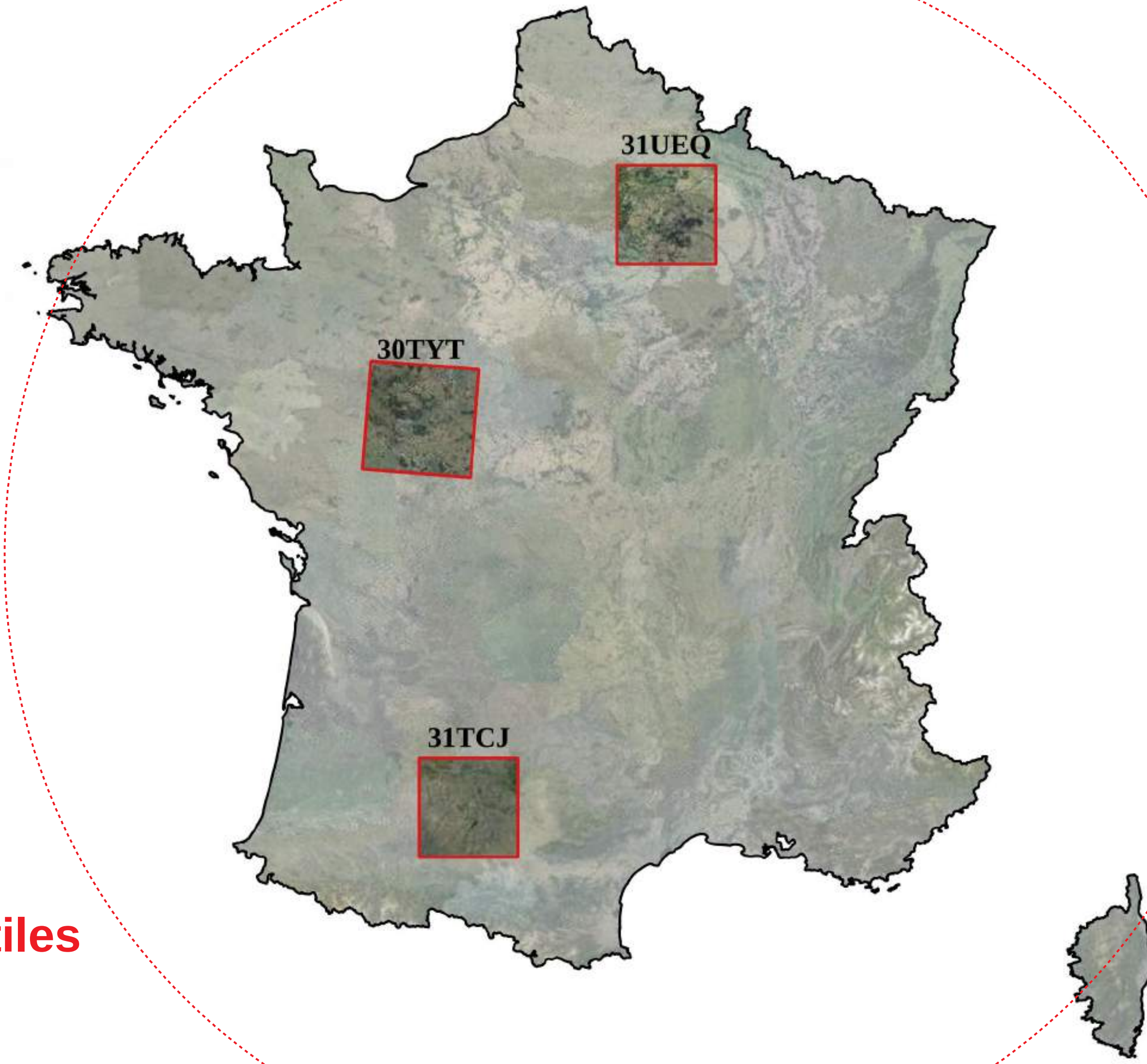
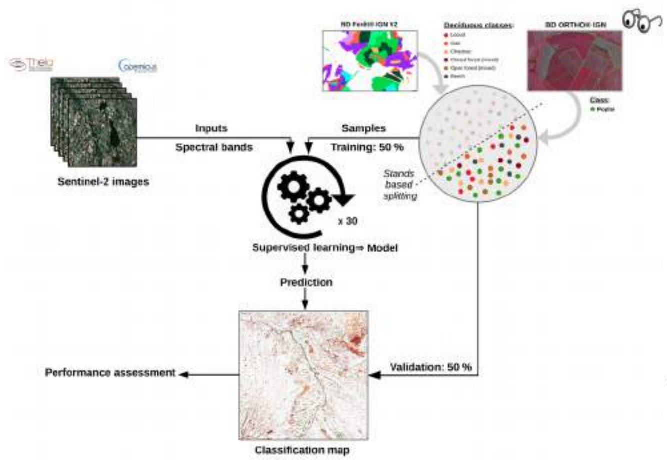


x 98 tiles

Reminder: local supervised classification



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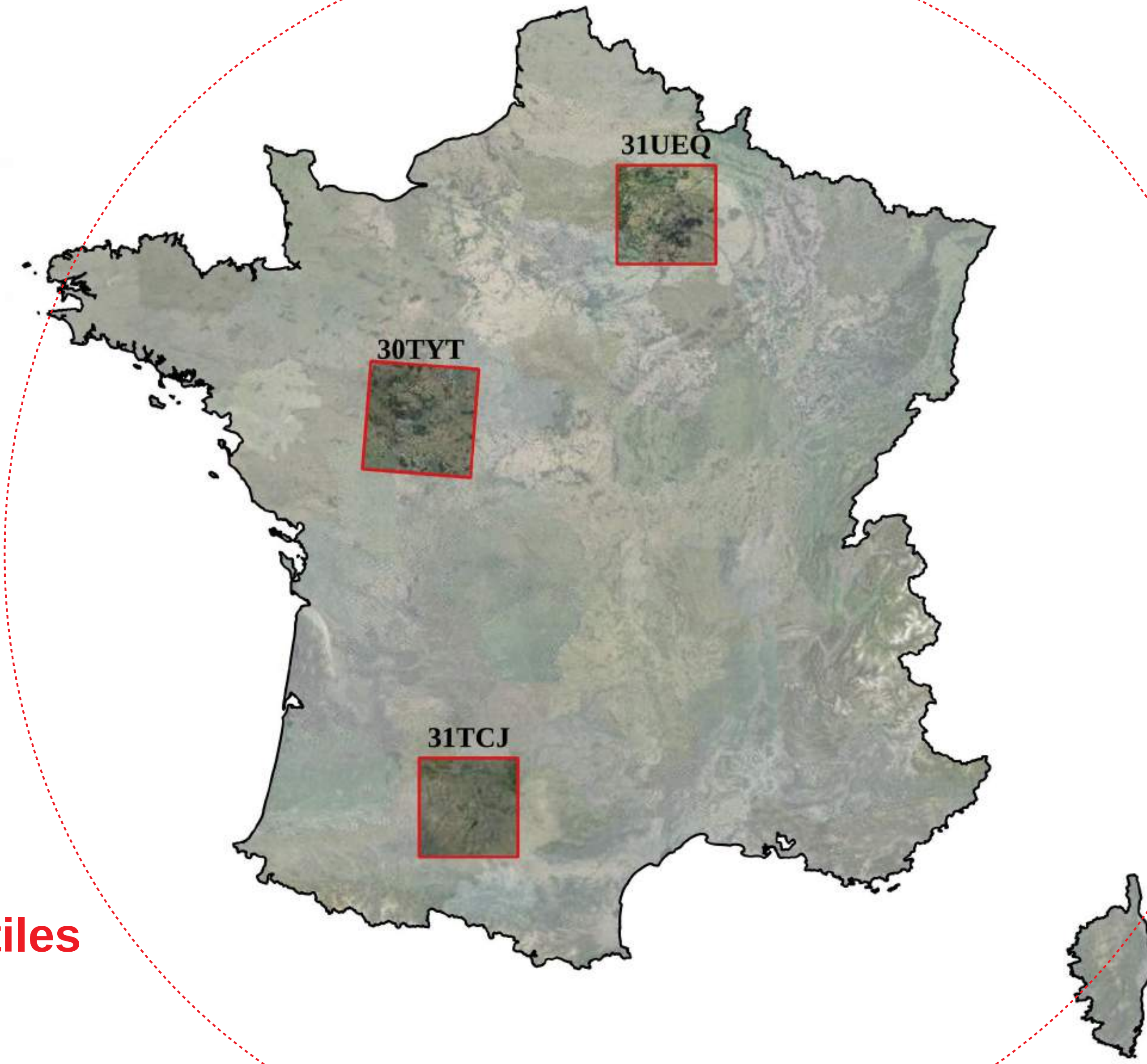
Unrealistic at national scale!

x 98 tiles



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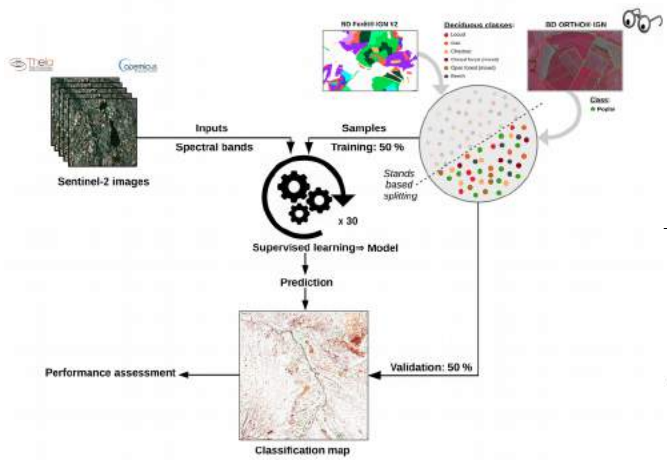

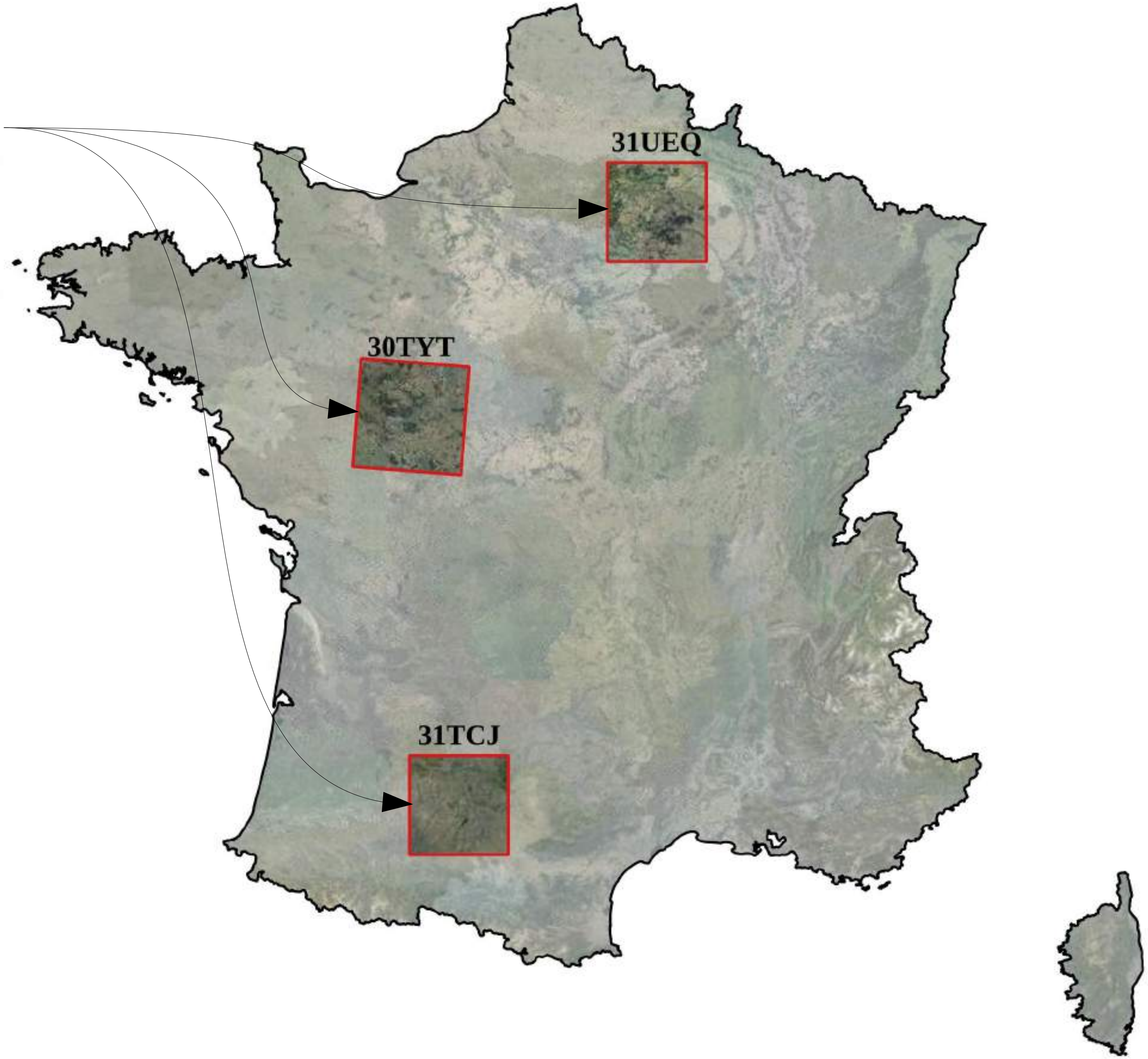

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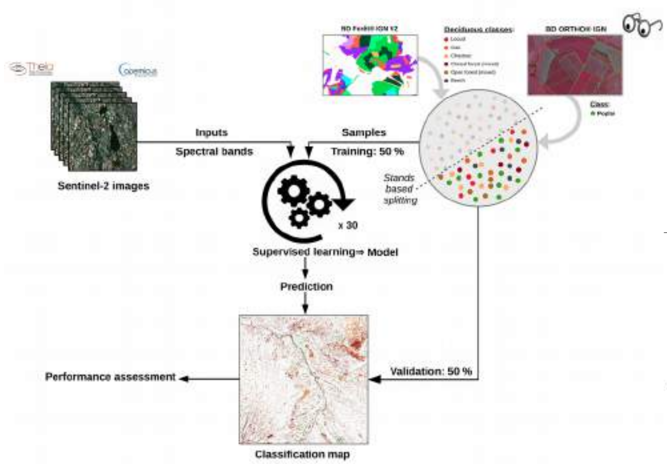
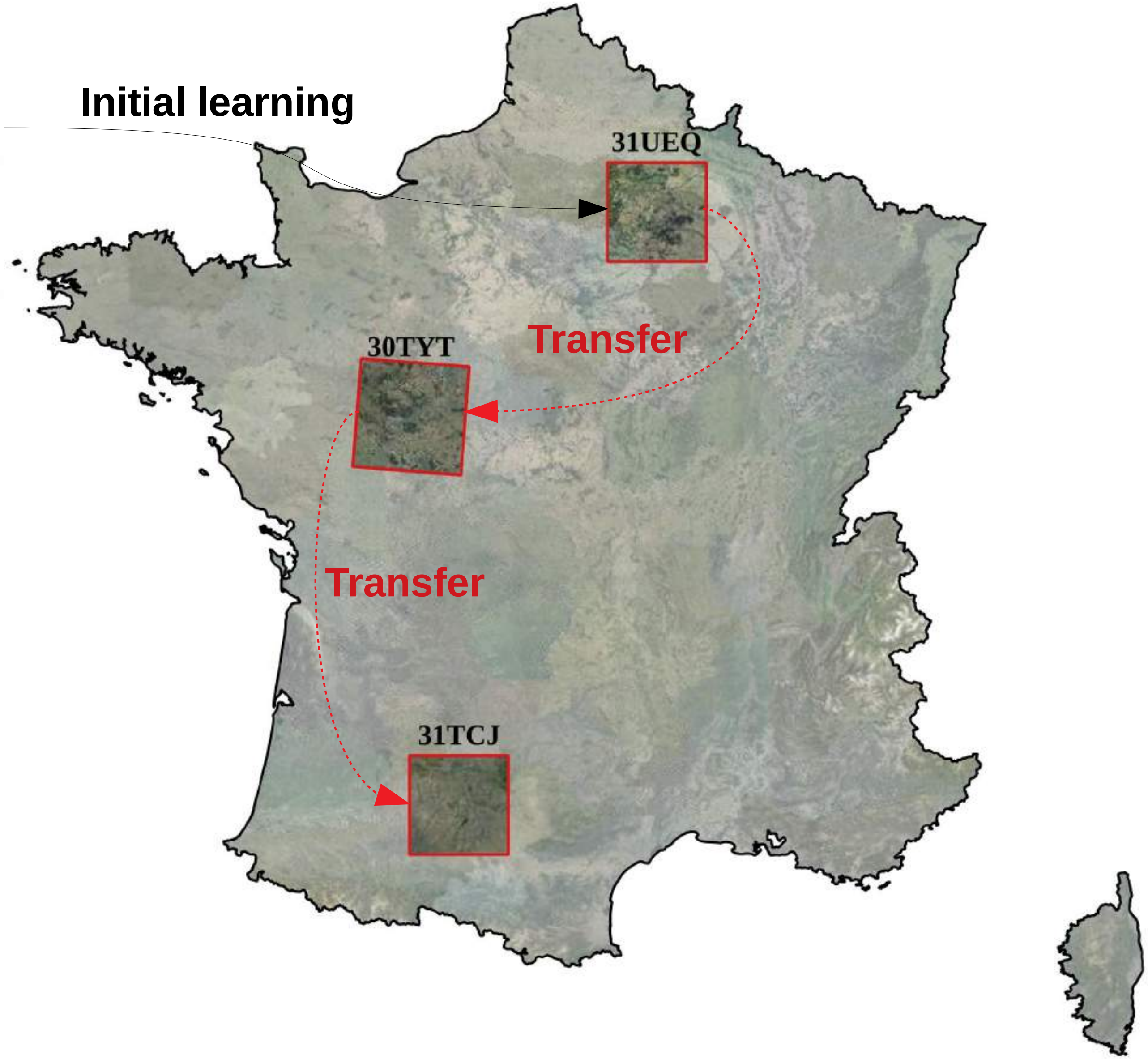
Transfer learning (TL) for large scale mapping





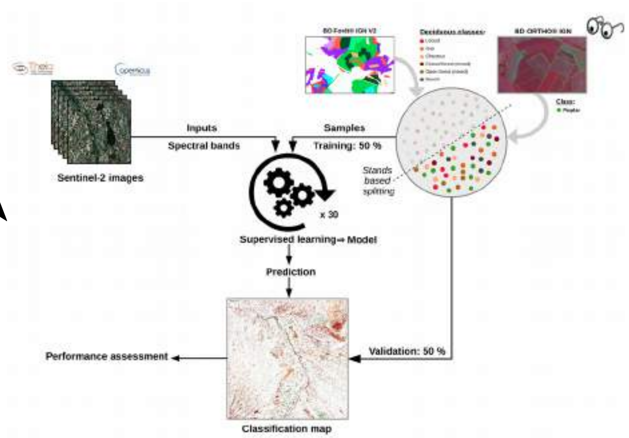
Transfer learning (TL) for large scale mapping

Tile 1

Tile 2

Tile 3

Local classification



Local model tile 1

TL

Two-tile model
tile 1+ tile 2

TL

Three-tile model:
tile 1 + tile 2 + tile 3

Global model

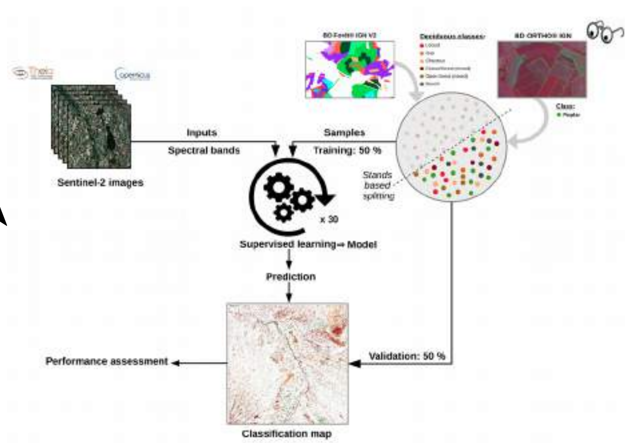
Proposed TL technique: Active Learning (AL)

Tile 1

Tile 2

Tile 3

Local classification



Local model tile 1

AL:
+samples from tile 2

Two-tile model tile 1+ tile 2

AL:
+samples from tile 3

Three-tile model: tile 1 + tile 2 + tile 3

Global model

Proposed TL technique: Active Learning (AL)

- **Principle:** AL is based on the hypothesis that a machine learning algorithm can achieve greater accuracy with fewer training labels if it is allowed to choose the data from which it learns (Settles, 2010)

- Well motivated use when training samples are scarce and difficult to collect

- Only relevant samples are queried: ranking criterion (uncertainty and/or diversity)

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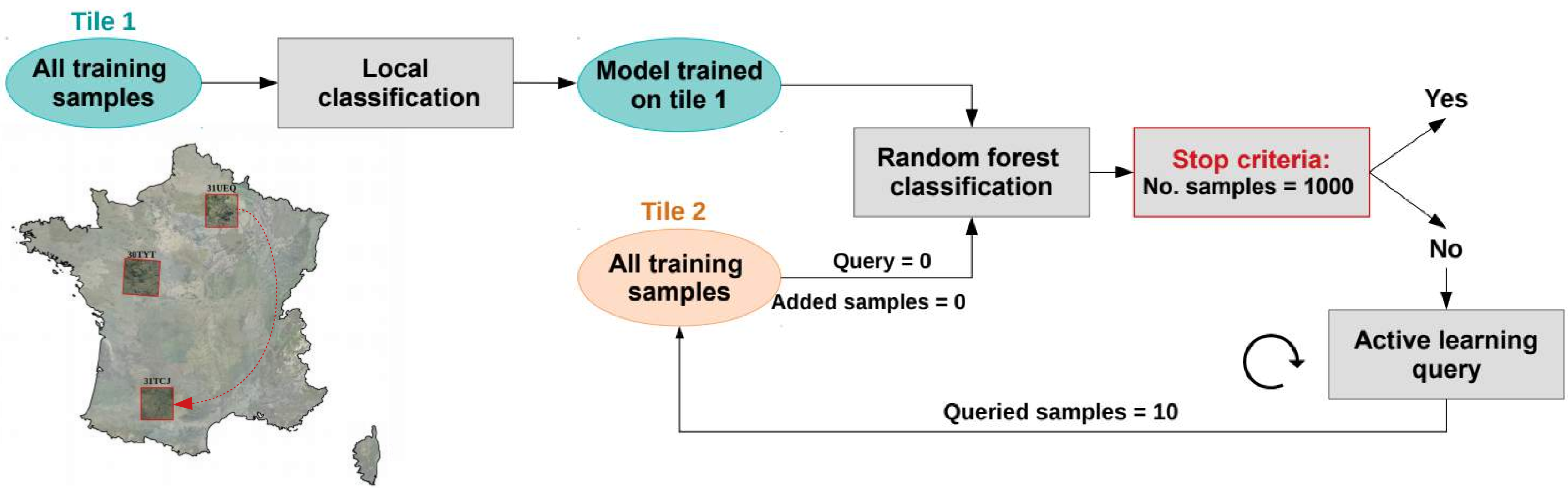
- Example with two tiles:

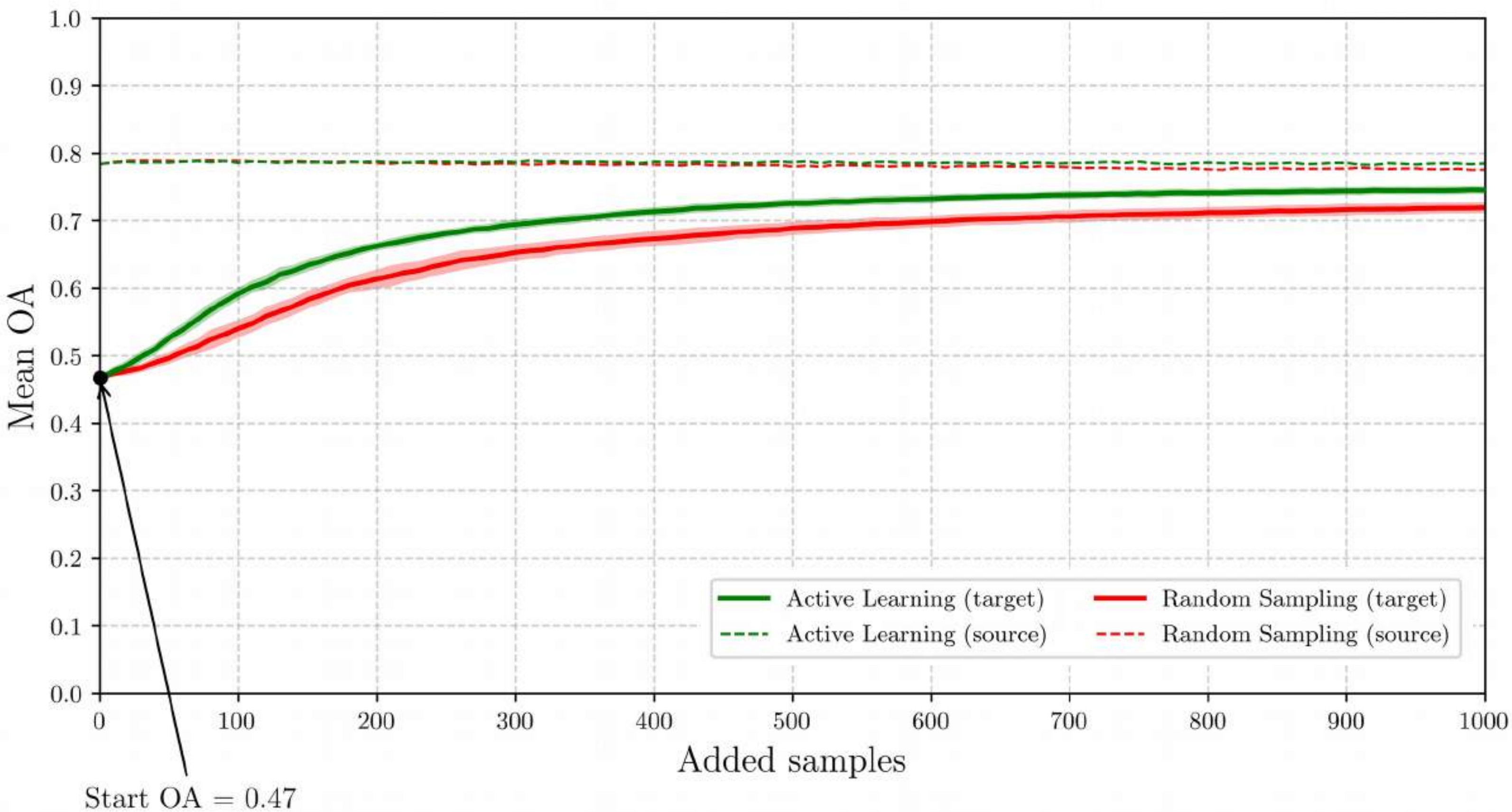


Active learning setting for large scale mapping: settings

- Active learning between the three tiles (two by two): six combinations (Nord→ South, Center→ North…):
  - Initial model: a local model learned in one tile
  - Samples addition from a second tile (10 in each iteration)
  - Stopping criterion: 1000 extra samples
  - Validation on the initial and second tile
- Active learning assessment: comparison with a “passive learning model” based on a random selection of samples
- Measurement of classification performance for all classes combined (Overall accuracy, global F-score) and also by class (Class F-score)

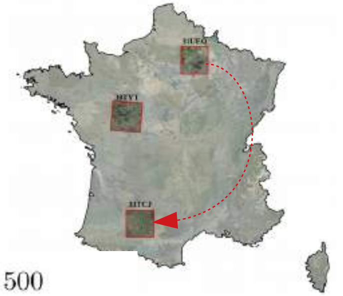
Active learning setting for large scale mapping: results

- Active learning from the north-eastern (*source)* to the south-western tile (*target*)
  - **Overall accuracy (OA) assessment: all the classes**

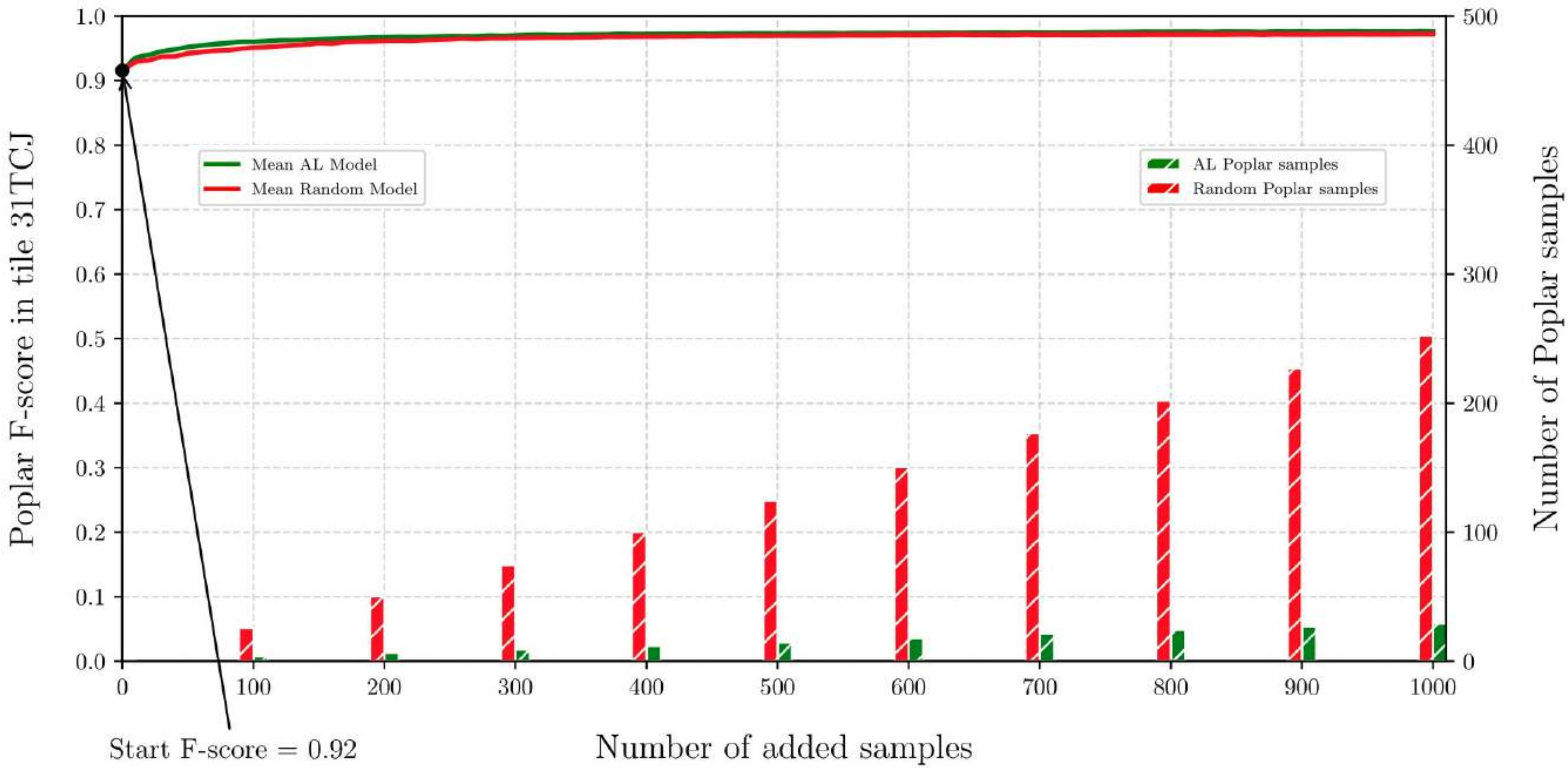


- Low OA value before Active learning adaptation & improvement with the addition of target samples
- Active learning model > Random sampling model: +5% difference on average
- The model remained valid on the source tile

Active learning setting for large scale mapping: results

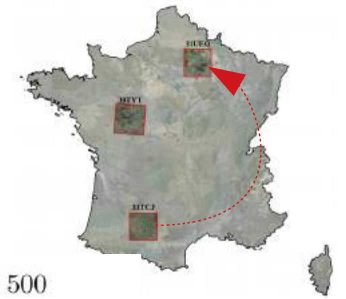


- Active learning from the north-eastern (*source)* to the south-western tile (*target*)
  - **Class F-score assessment: case of the poplar class**

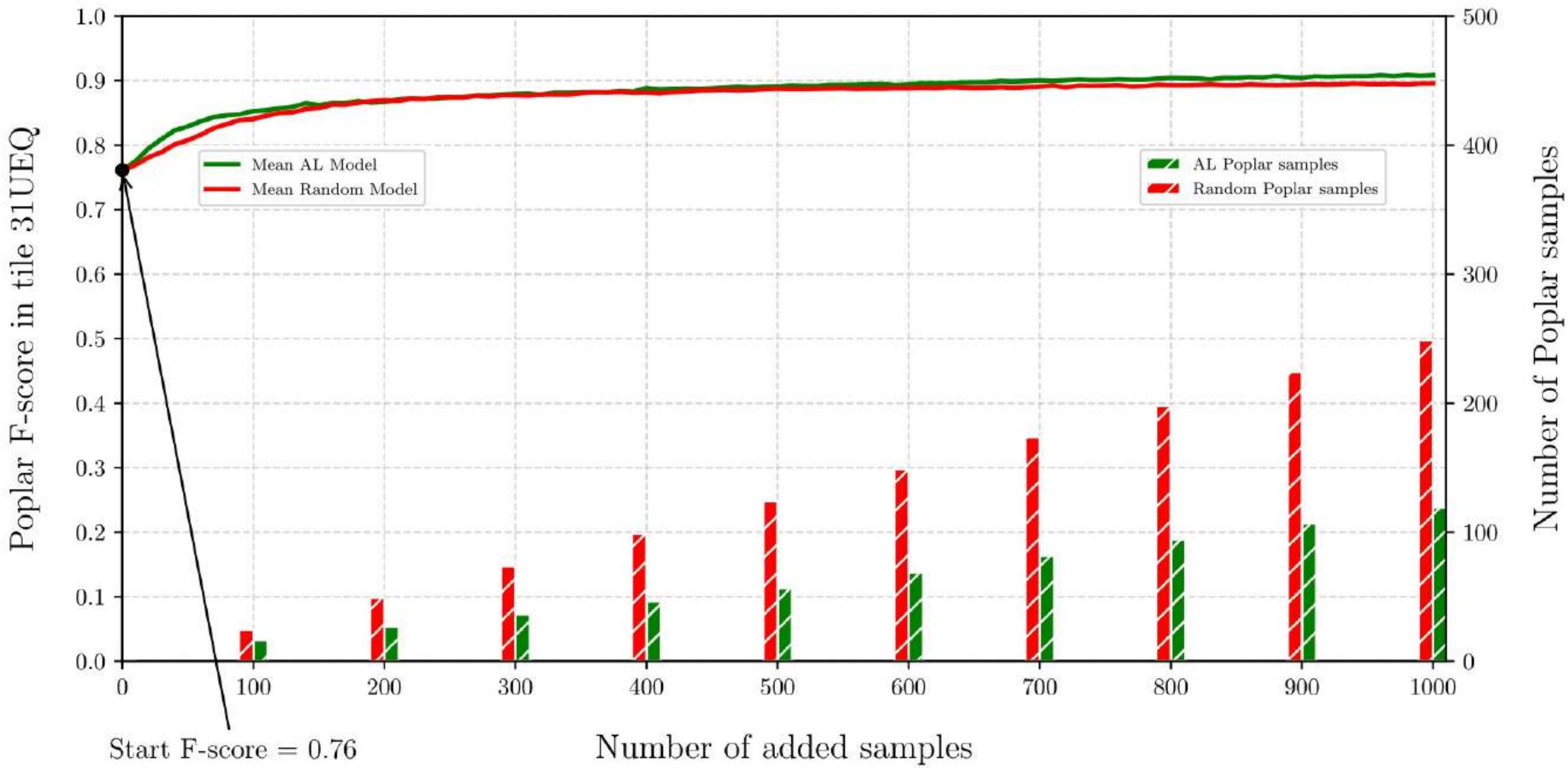


- High poplar F-score even before adaptation
- Queried random samples **~ 8x** queried active learning samples
- The north-eastern model is capable to accurately detect south-western poplars

Active learning setting for large scale mapping: results



- Active learning from the south-western (*source)* to the north-eastern tile (*target*)
  - **Class F-score assessment: case of the poplar class**

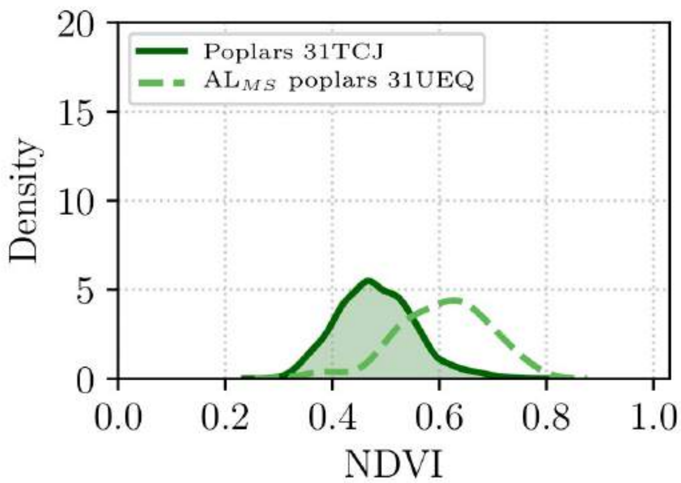


- Lower poplar F-score before samples addition compared to the opposite direction of transfer
- Queried active learning samples **~ 2x** queried random samples
- The south-western model needed extra target samples to accurately detect north-eastern poplars

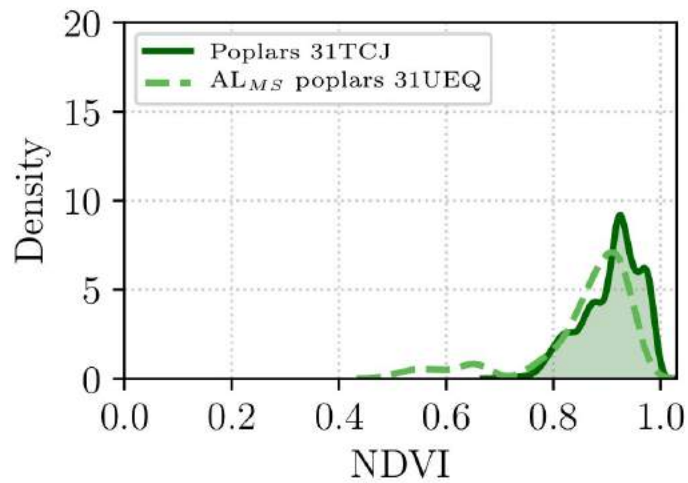
Active learning setting for large scale mapping: results

- Active learning from the south-western (*source)* to the north-eastern tile (*target*)
  - **Class F-score assessment: case of the poplar class**

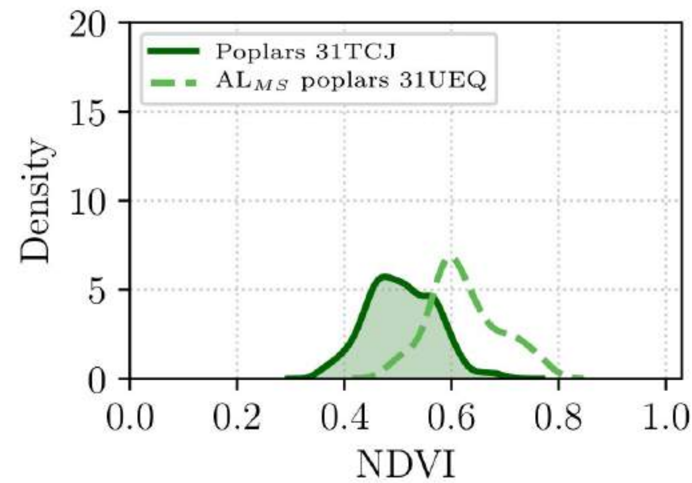
26/01/2017



16/05/2017



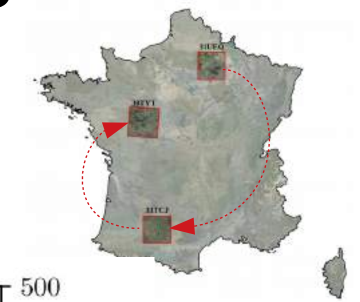
02/12/2017



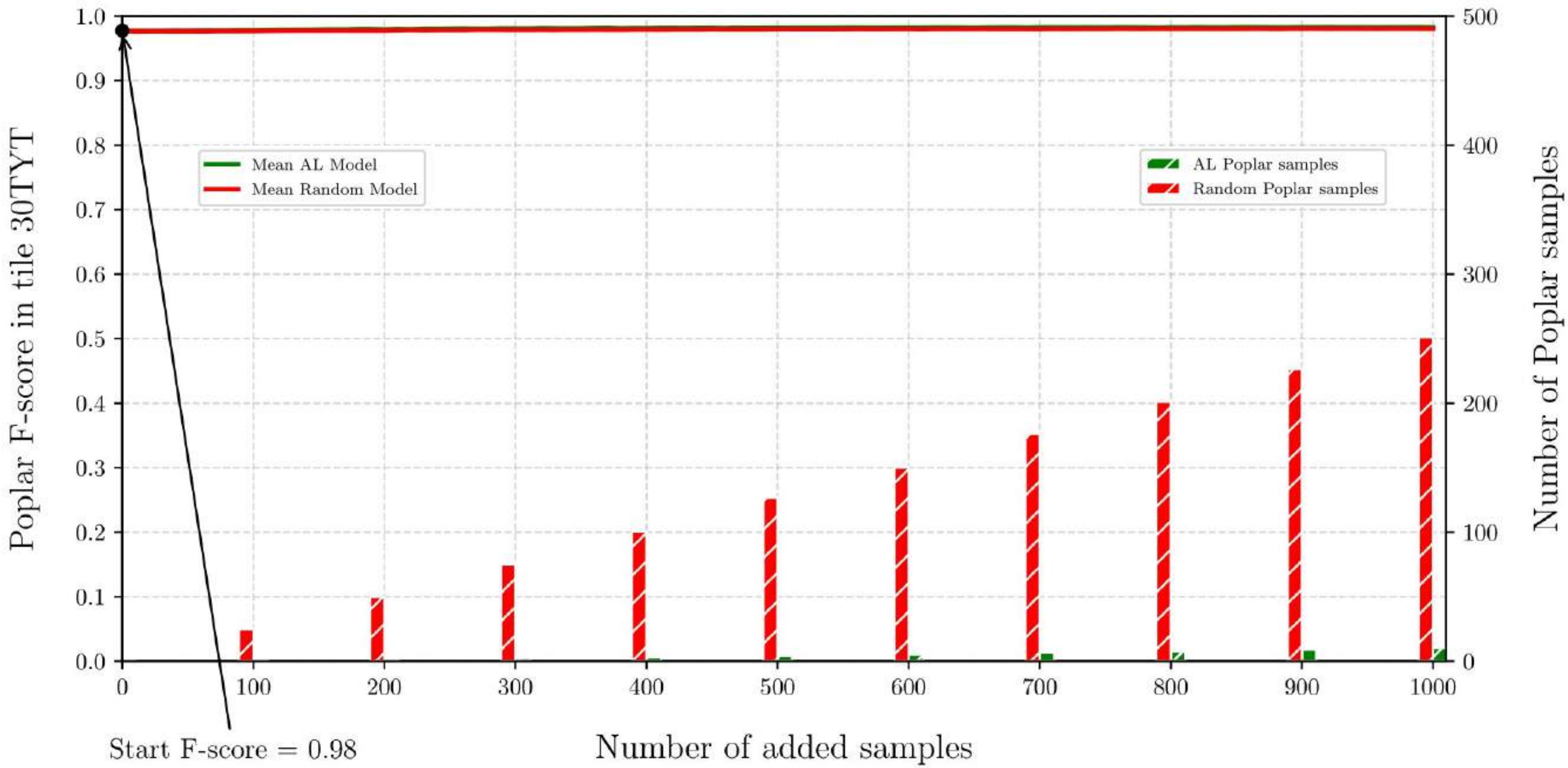
→ ***The pixels selected by AL are located in the areas of uncertainty***

- Lower poplar F-score before samples addition compared to the opposite direction of transfer
- Queried active learning samples **~ 2x** queried random samples
- The south-western model needed extra target samples to accurately detect north-eastern poplars

Active learning setting for large scale mapping: results



- Active learning using the ***two-tile*** model (south+north) to predict the central tile
  - **Class F-score assessment: case of the poplar class**



- Very high poplar F-score without any sample addition
- Queried random samples >>>>>> Queried active learning samples
- The resulting global model is well suited to all three tiles

Conclusions & future work

- Very good ability of Sentinel-2 time series to identify poplar stands at the tile scale
- Interest of active learning to quickly create a global model with a minimum of samples ⇒ approach adapted to large scale
- Contribution of active learning for poplars and the other deciduous classes
- Influence of noise on the choice of samples with active learning (undetected clouds, mixed classes….) ⇒ adapt the informativeness criterion

Work in progress

- Variable selection ⇒ reduce the dimension of the data and speed up the processing
- National mapping: configuration of the iota2 processing chain
- Yearly change detection: clear cuts and new plantations

Thank you
for your attention

Active learning: parameters

➢ Informativeness measure: uncertainty

- **Entropy**: it measures the variability of the probability of belonging to all possible classes in the model: a "disorder measure" ⇒ The higher its value, the greater the uncertainty
- **Margin sampling**: difference in probability between the two most probable classes ⇒ the lower its value, the more uncertain the model is

Example :

Class	1	2	3	4	5	Entropy	MS
Pixel A	0.4	0.45	0.1	0.03	0.02	1.14	**0.05**
Pixel B	0.4	0.2	0.25	0.12	0.03	**1.42**	0.15

➢ Transfer directions:

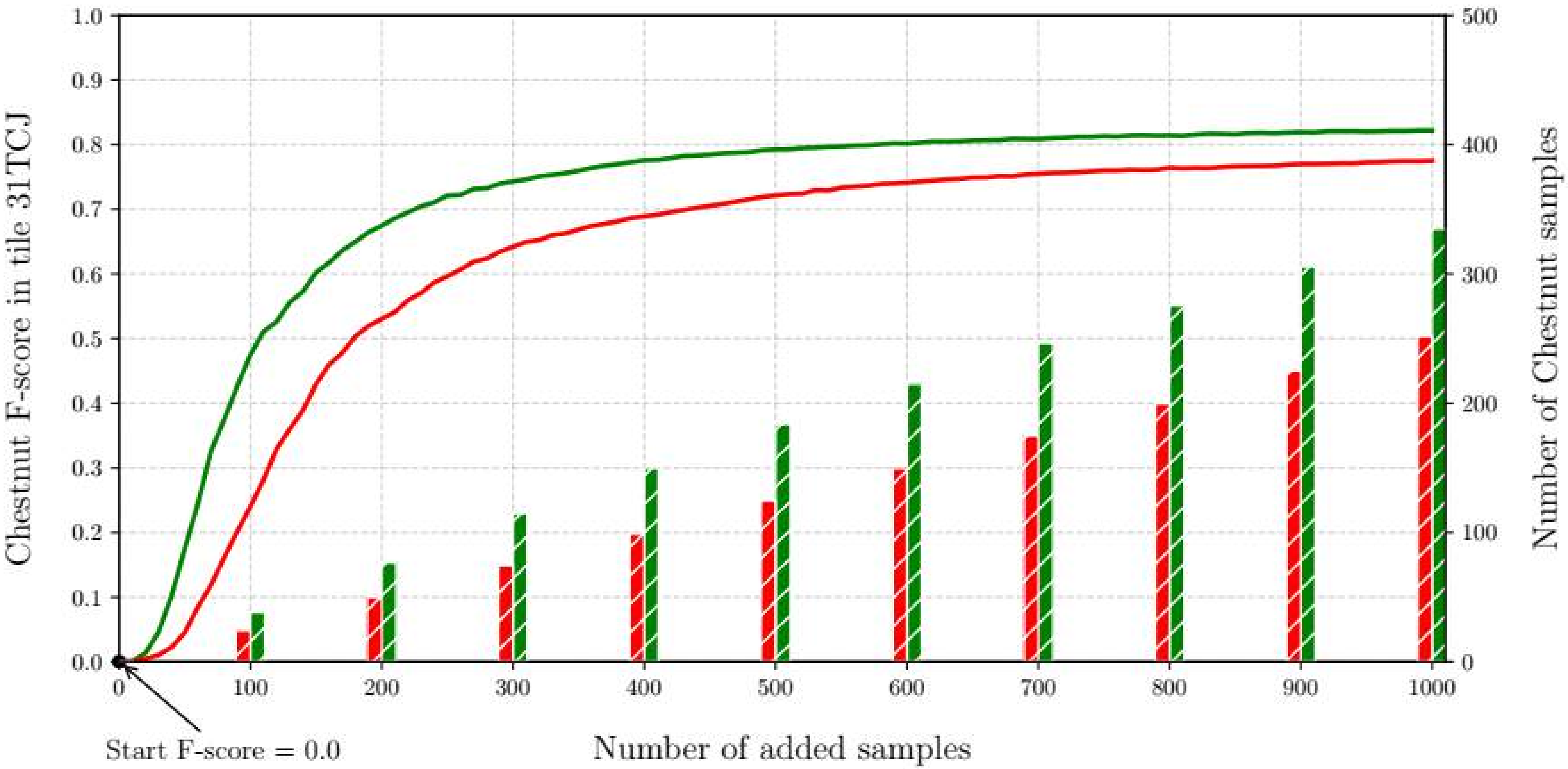
- All combinations have been tested (6): South→ North, South→ Center, North→ South .

➢ Learning classes:

- Mixed and pure classes
- Only pure classes

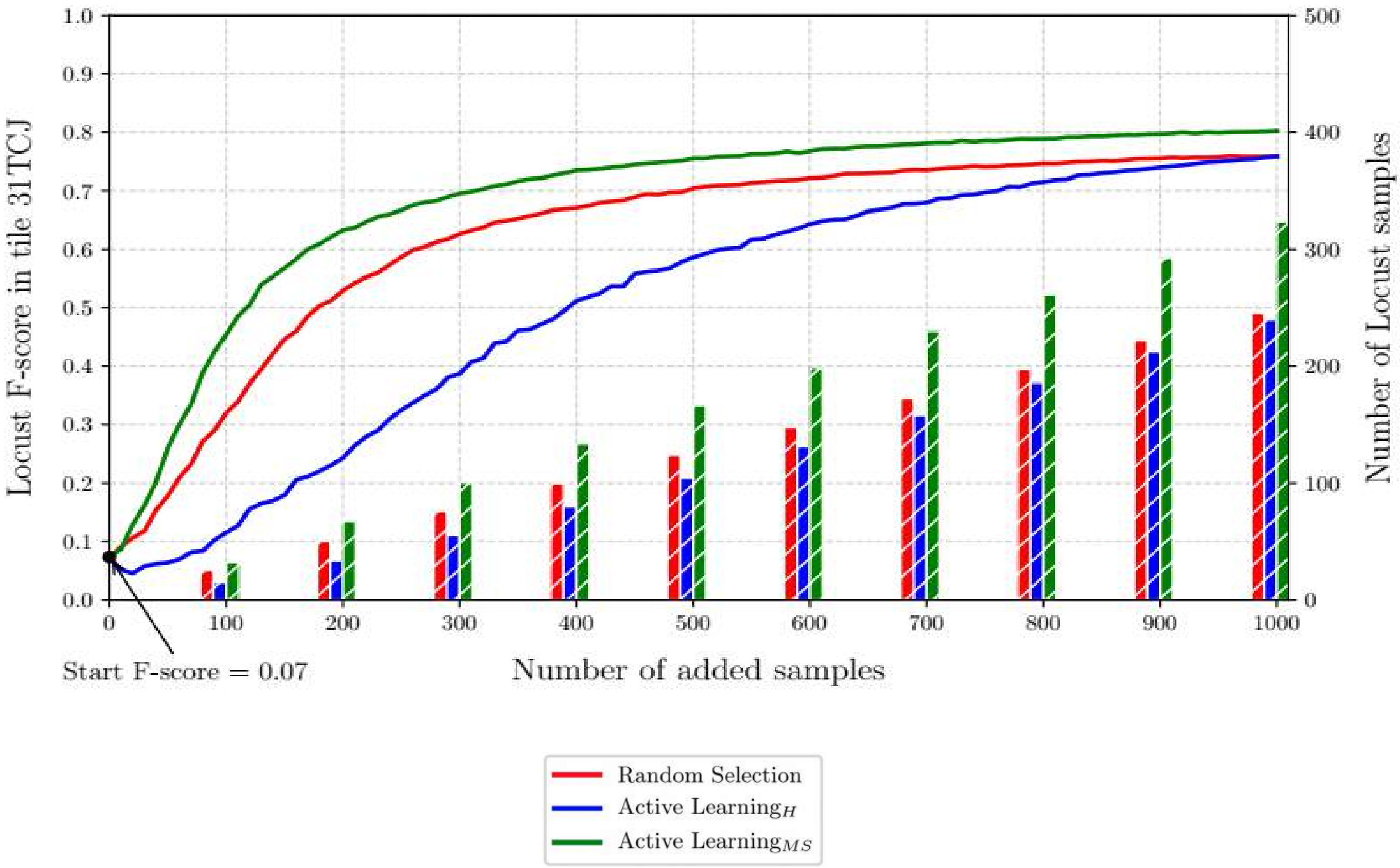
Active learning setting for large scale mapping: results

- Active learning from the north-eastern (*source)* to the south-western tile (*target*)
  - **Class F-score assessment: case of the chestnut class**
    - *Influence on the missing classes in the initial model*



Active learning setting for large scale mapping: results

- Active learning from the north-eastern (*source*) to the south-western tile (*target*)
  - **Class F-score assessment: case of the locust class**
    - *Influence of the uncertainty measure*



Active learning setting for large scale mapping: results

- Active learning from the north-eastern (*source)* to the south-western tile (*target*)
  - **Class F-score assessment: case of the locust class**
    - *Influence of the presence of mixed classes in training*