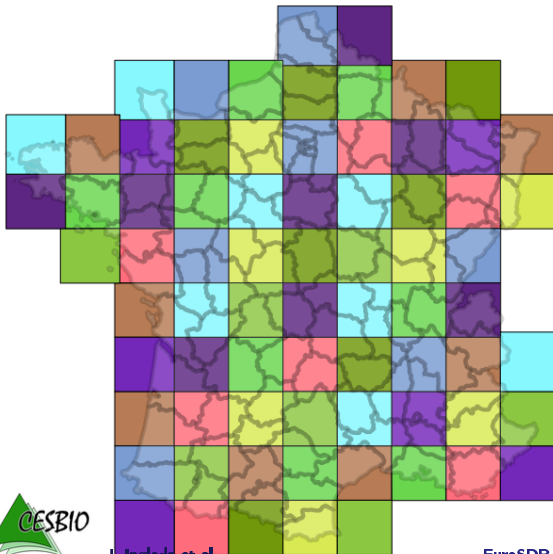


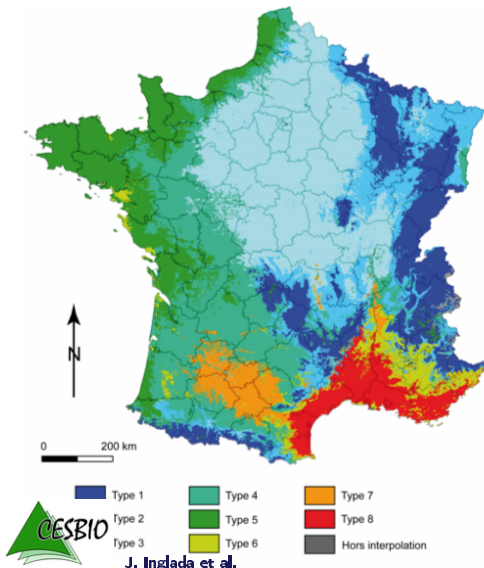
Speeding up the classification



- ▶ A different classifier per group of tiles
 - ▶ allows for parallel learning.
- ▶ Classification step
 - ▶ classifier fusion for robustness and spatial homogeneity.

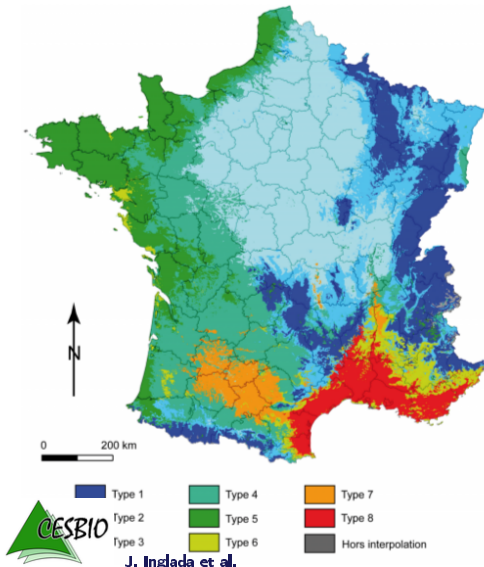
Spatial stratification

- Take into account intra-class variability.

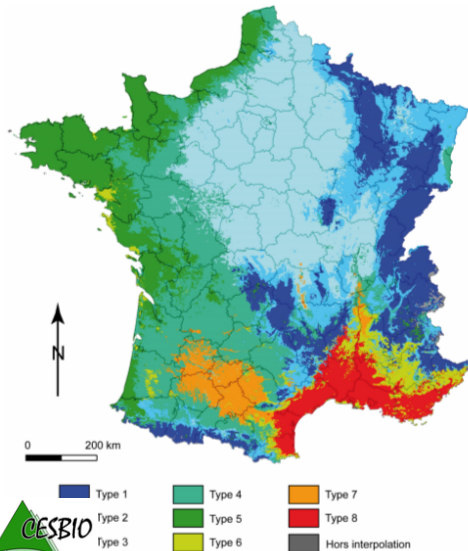


Spatial stratification

- ▶ Take into account intra-class variability.
- ▶ Like processing per tiles, but split per eco-climatic area.

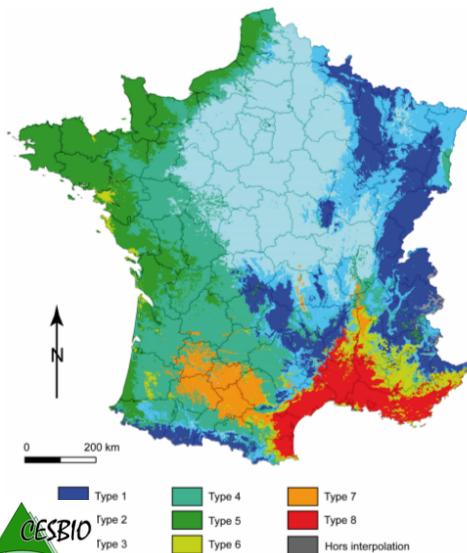


Spatial stratification



- ▶ Take into account intra-class variability.
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- ▶ Several strategies for distributed classifier fusion are available
 - ▶ majority voting;
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Spatial stratification



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- ▶ Like processing per tiles, but split per eco-climatic area.
- ▶ Several strategies for distributed classifier fusion are available
 - ▶ majority voting;
 - ▶ confidence map voting.
- ▶ Allows an average accuracy improvement of about 3%
 - ▶ small improvement for majority classes
 - ▶ up to 20% improvement for some small classes

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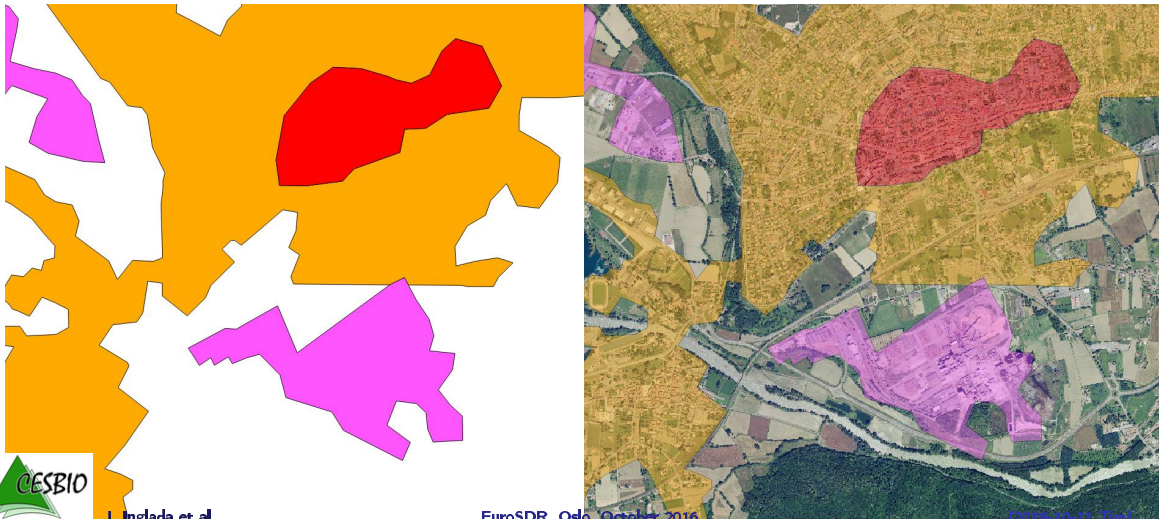
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- ▶ Classifiers with high tolerance to label noise.

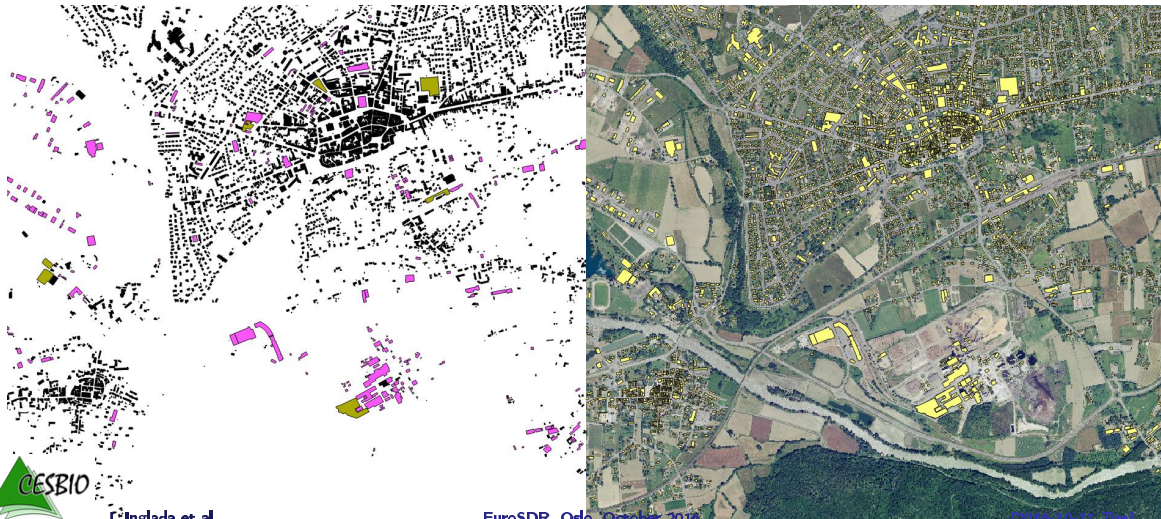
Reference data cleaning

- CLC polygons: minimum mapping unit too large



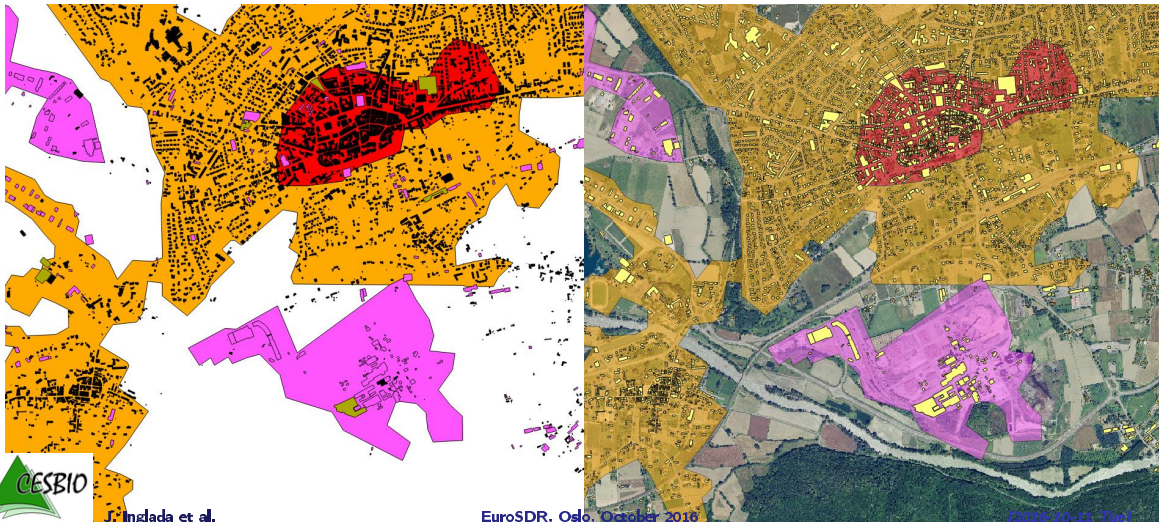
Reference data cleaning

- ▶ Topographic DB: different LC semantics, but spatially accurate



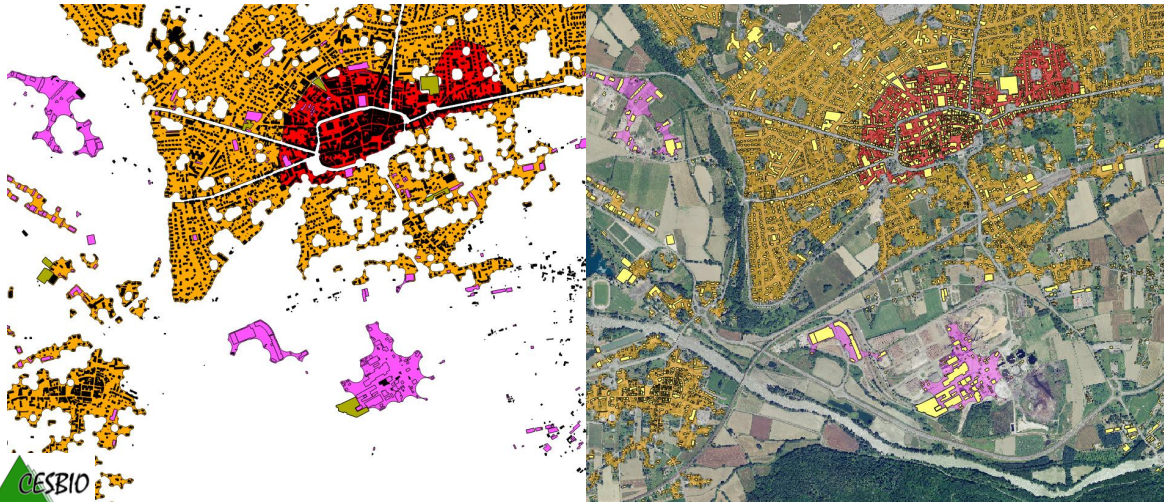
Reference data cleaning

- Fusing both data sources



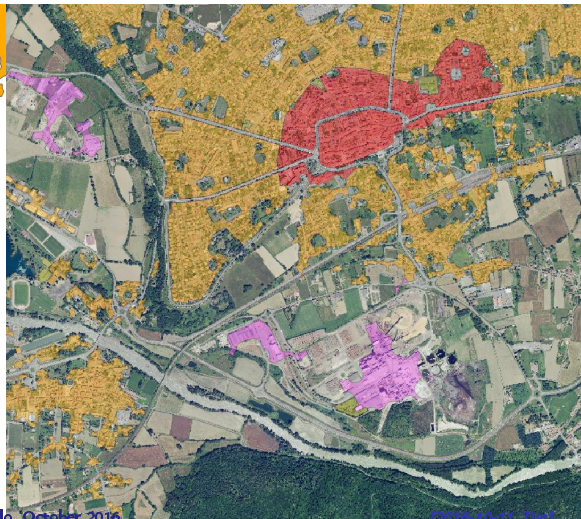
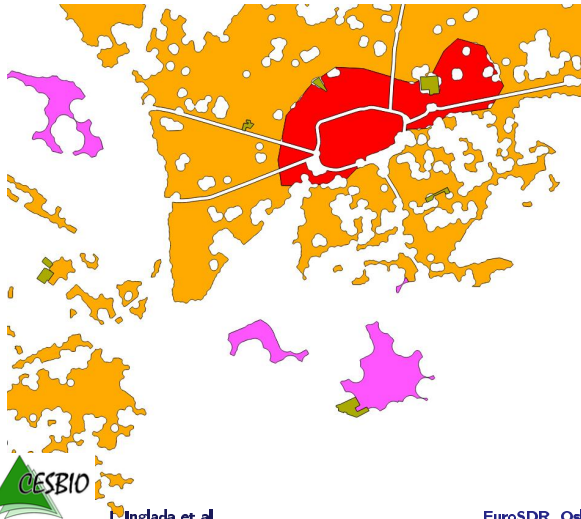
Reference data cleaning

- ▶ Spatial and semantic accuracy



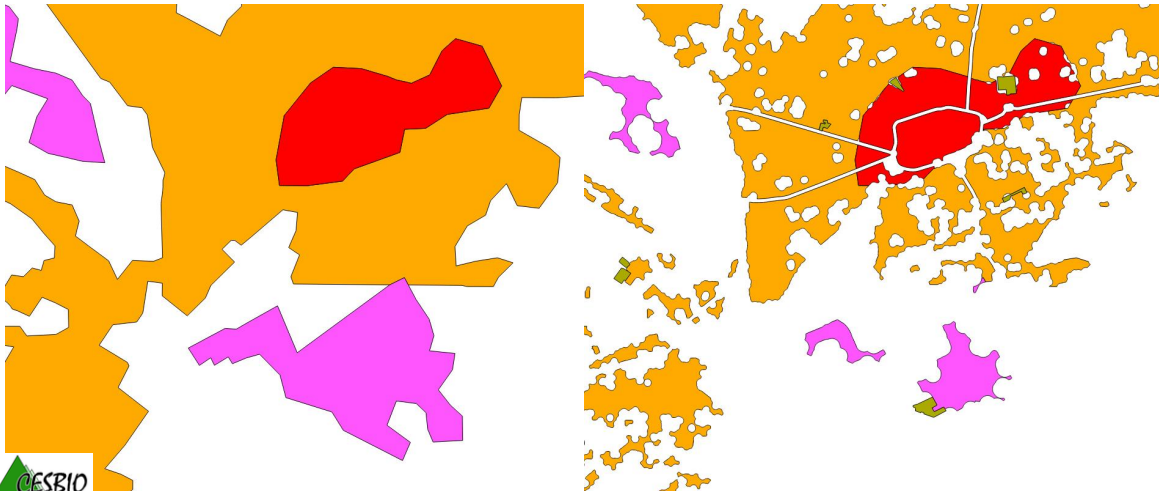
Reference data cleaning

- Spatial and semantic accuracy



Reference data cleaning

- ▶ Improved reference data



When no reference data is available (yet)

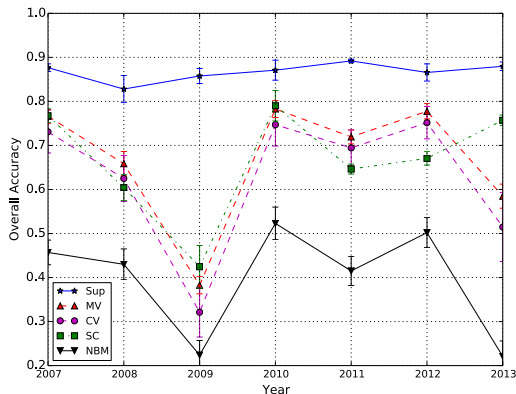
- ▶ Reference data is expensive to collect.
- ▶ Delay between collection and availability
 - ▶ CLC (3 years), LPIS (1 year delay in France)
- ▶ Use previous year's reference data?
 - ▶ OK for *stable classes* ;
 - ▶ phenology is affected by climatic variability
 - ▶ warm winter, rainy spring,
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- ▶ If your maps are good enough, previous maps are "reference data".
- ▶ Use the wisdom of crowds
 - ▶ many inaccurate but decorrelated data sources may become good *on average*.

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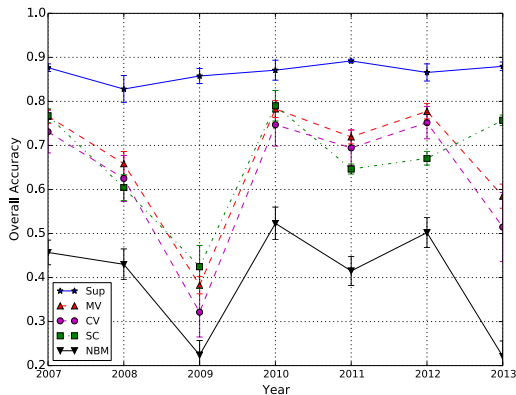
- ▶ Example using other periods (images and reference data)



- ▶ Supervised case (upper bound)

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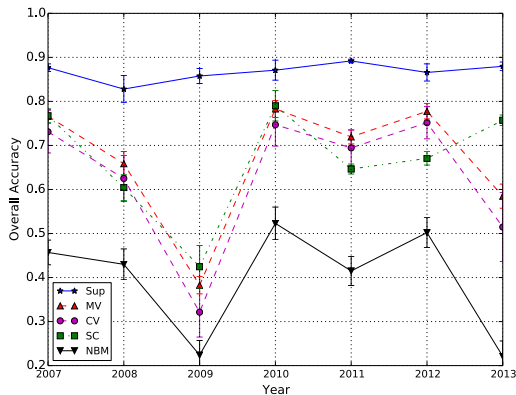
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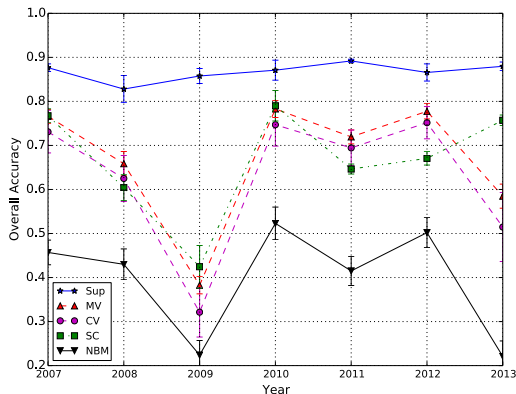
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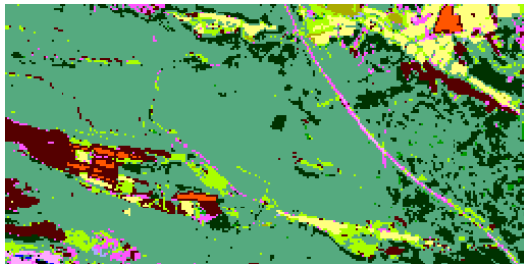
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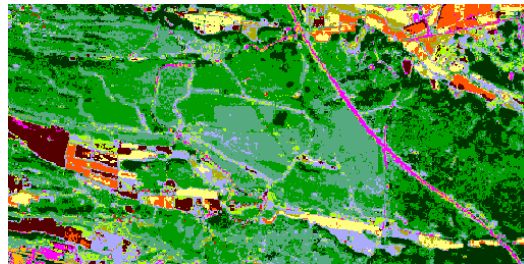
- ▶ Supervised case (upper bound)
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- ▶ Majority voting with one classifier per year
- ▶ Confidence-based fusion with one classifier per year

Main current work

- Sentinel-2 time series integration for joint use with Landsat-8



Landsat-8 (30m)



Sentinel-2 (10m)

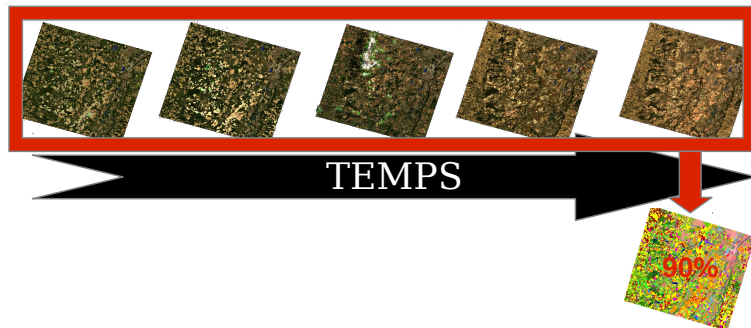
Outline

- ① Fully automatic land cover map production
- ② Examples
- ③ How we do it
- ④ Ongoing Improvements**
- ⑤ Conclusion

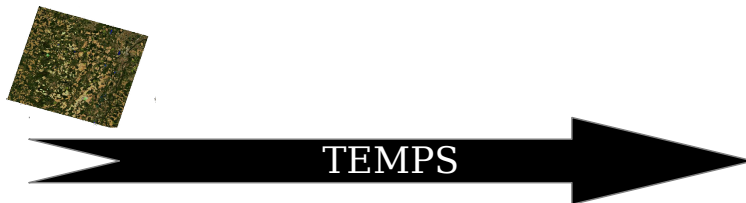
Ongoing improvements

- ▶ Integration of SAR time series (Sentinel-1)
- ▶ Multi-temporal image segmentation.
- ▶ Use of VHR optical data (SPOT6, Pléiades)
 - ▶ single date, used for object-based image analysis.

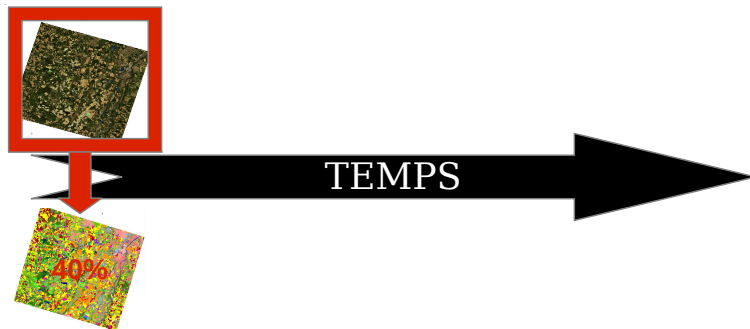
Incremental classification for early crop mapping



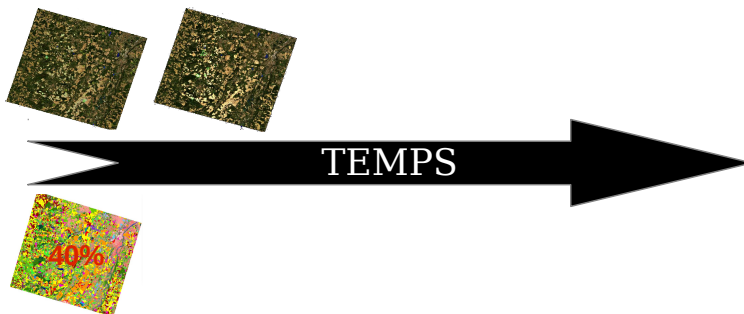
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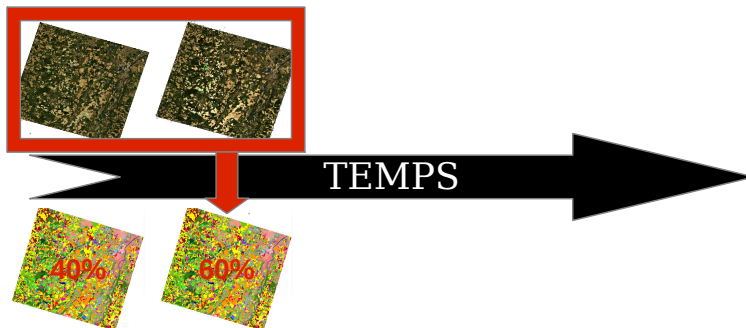
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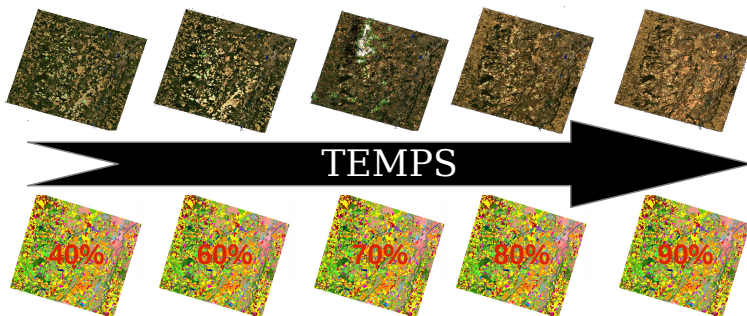
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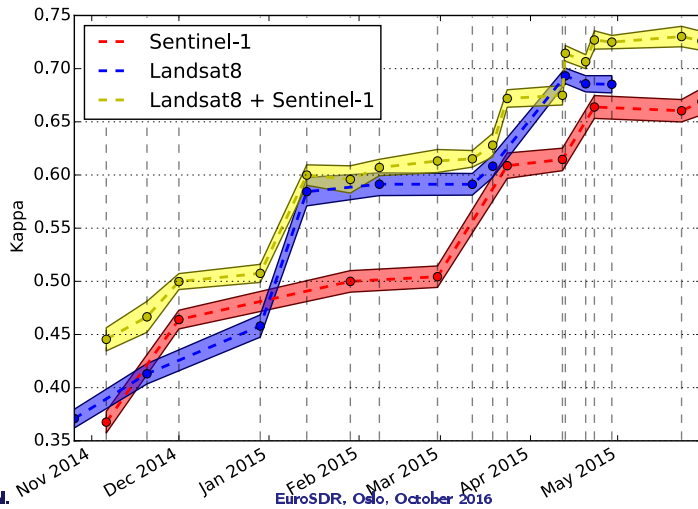
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- ▶ We are open to collaborations
 - ▶ jordi.inglada@cesbio.cnes.fr

Thanks ! (Sorry for not being Jordi)

- ▶ Get the slides : <https://frama.link/inglada-landcover>
- ▶ Get the processor : <https://frama.link/iota2>

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