Active learning for large-scale classification of poplar plantations with Sentinels time series

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INTRODUCTION

Poplar is one of the fast-growing and wood producing trees which are increasingly considered as an important resource. In France, accurate and regularly up-to-date maps of poplar plantations are not yet available at the national scale. The update rate of National Forest Maps is unsuitable for this species because of its short rotation cycle (from 15 to 20 years).

Since the availability of high spatial and temporal resolution Sentinel time series, new opportunities for monitoring poplar plantations over large areas have come up.

Objectives

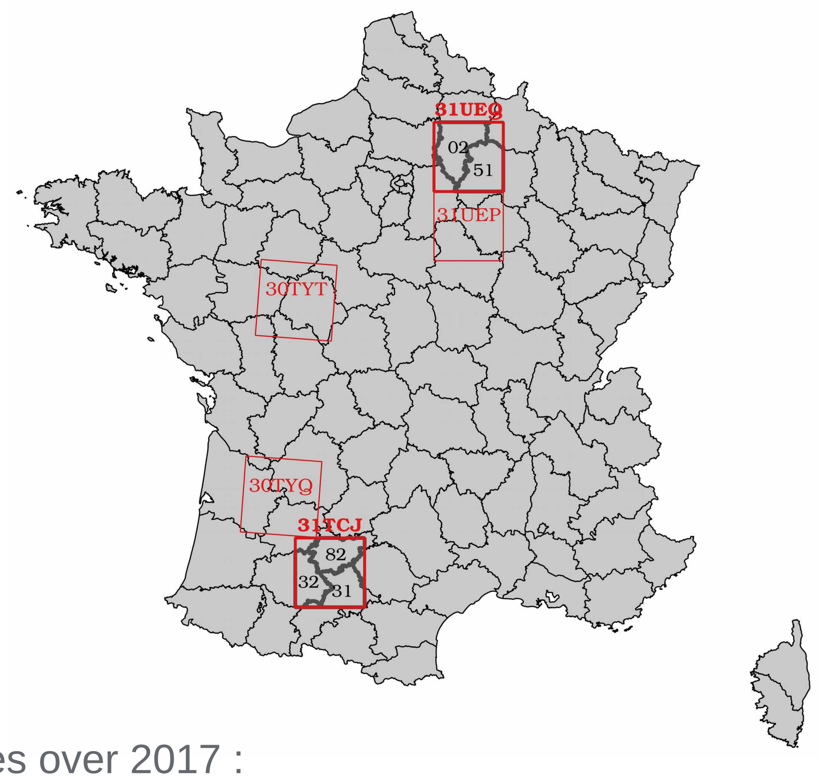
Poplar large scale mapping from Sentinel-2 time series :

- With all available reference data : 2 sampling approaches are compared
- With limited number of samples : use of Active Learning

MATERIALS

Study area

The study is focused on three different sites in France with the most contrasting poplar variability, climatic conditions and management practices.
They are represented by five Sentinel-2 tiles in the following figure. Only highlighted tiles will be presented in this work.



Data

- *Optical images*

All available Sentinel-2A and Sentinel-2B images over 2017 :

T31TCJ : 39 images (10 spectral bands)

T31UEQ : 35 images (10 spectral bands)

- *Reference data*

1st approach :

- *All deciduous species (including poplar) :* sampling from the national forest database BD Forêt® (ground reality between 2004 and 2015 depending on departments)

2nd approach :

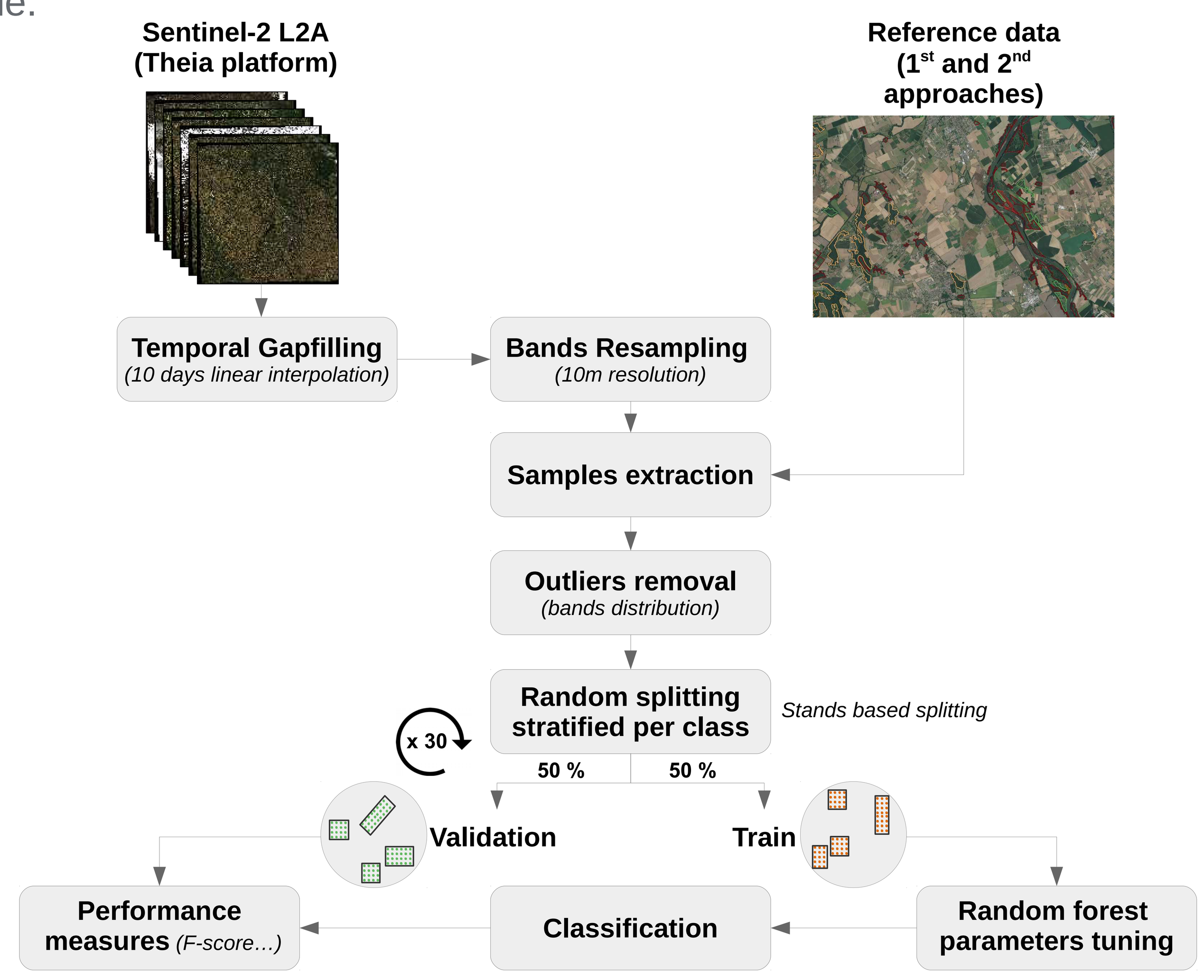
- *Poplar class* : visual interpretation from Orthophotos **+ validation with Sentinel-2 images**
- *Others deciduous classes :* sampling from the national forest database BD Forêt®

BD ORTHO® 50 cm (IGN, 2016)

METHOD 1 : site by site classification

Context 1 : all possible samples are used

The following flowchart illustrates the classification process applied to each department in each tile.



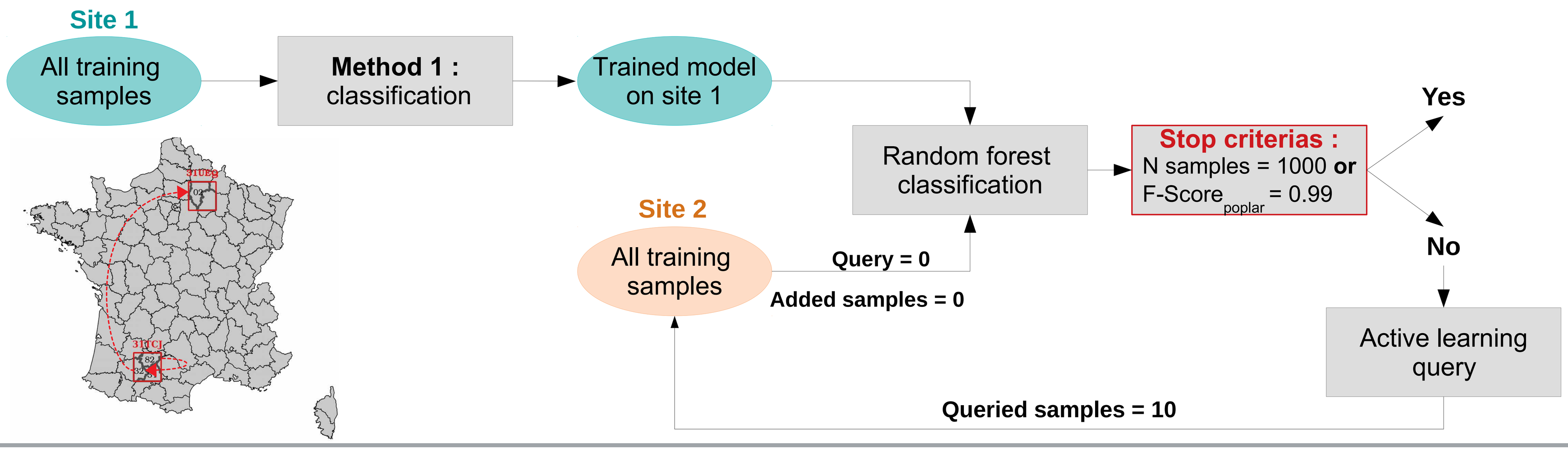
METHOD 2 : site to site classification

Context 2 : the fewest and most informative samples are used with Active learning

Active learning (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).

Its use is well-motivated since collecting appropriate training samples is an expensive and difficult task especially for large scale.

Starting from a well trained model in a **first** study site, new samples are queried with AL from a **second** site and iteratively added to the model in order to adapt it to both sites.



RESULTS

Site by site classification

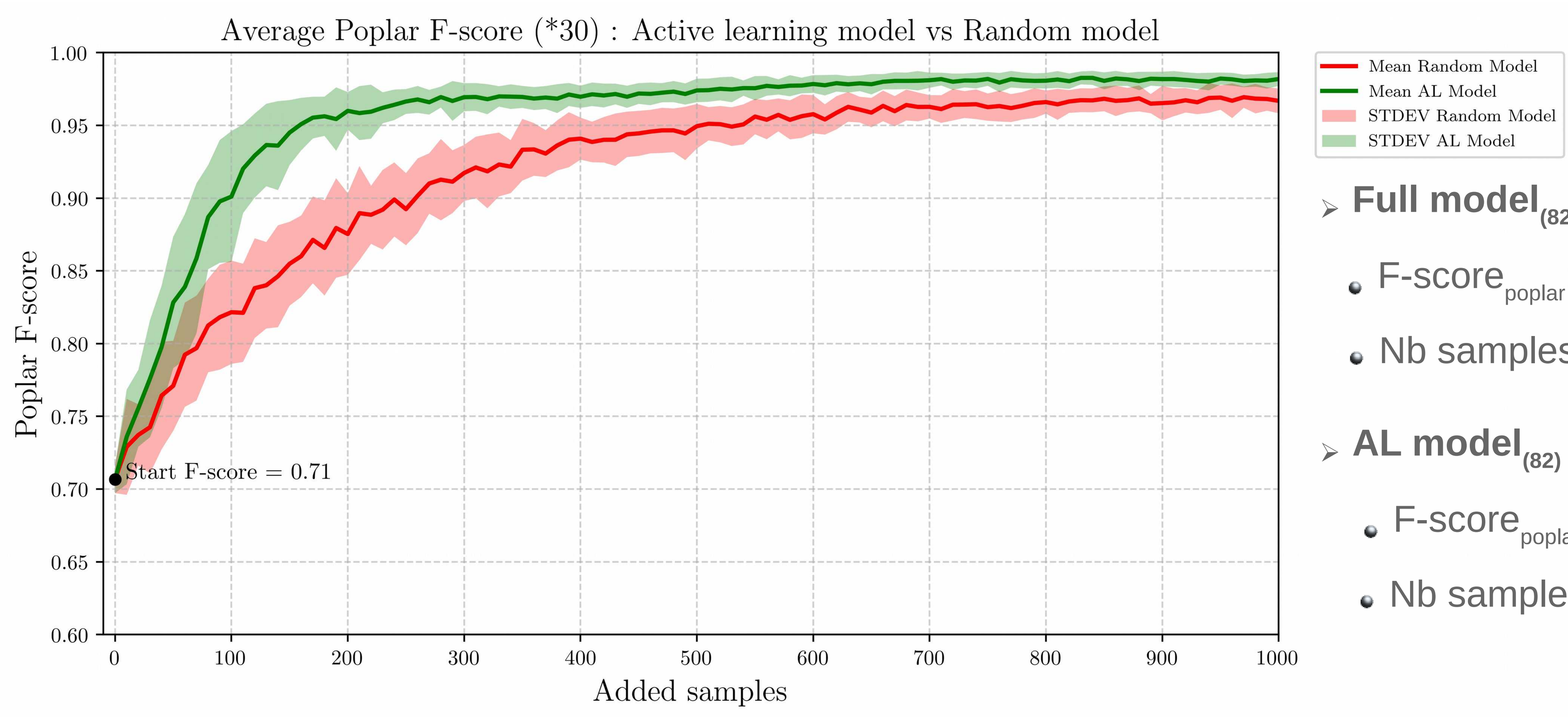
1st approach : BD Forêt®					
Tile	Department	Nb classes	Training samples per class	Mean $OA_{(*30)}$	Mean Poplar $F\text{-score}_{(*30)}$
T31TCJ (S.W)	82	6	1000	71.3	76.6 ±3.7
	32	4	1000	79.6	88.6 ±2.2
	31	4	250	80.9	84.7 ±8.3
T31UEQ (N.E)	51	4	1000	59.9	68.7 ±7.8
	02	6	1000	71.3	76.6 ±3.6

2nd approach : BD Forêt®+ Visual interpretation					
Tile	Department	Nb classes	Training samples per class	Mean $OA_{(*30)}$	Mean Poplar $F\text{-score}_{(*30)}$
T31TCJ (S.W)	82	6	1000	79.1	98.9 ±0.6
	32	4	1000	82.5	96.0 ±0.2
	31	4	250	86.4	99.6 ±0.4
T31UEQ (N.E)	51	4	1000	69.2	90.9 ±2.4
	02	6	1000	79.1	89.9 ±3.9

- **Better poplar identification with the 2nd approach (visual validation of training samples)**
- **10 to 20 % improvement of Poplar F-Score**

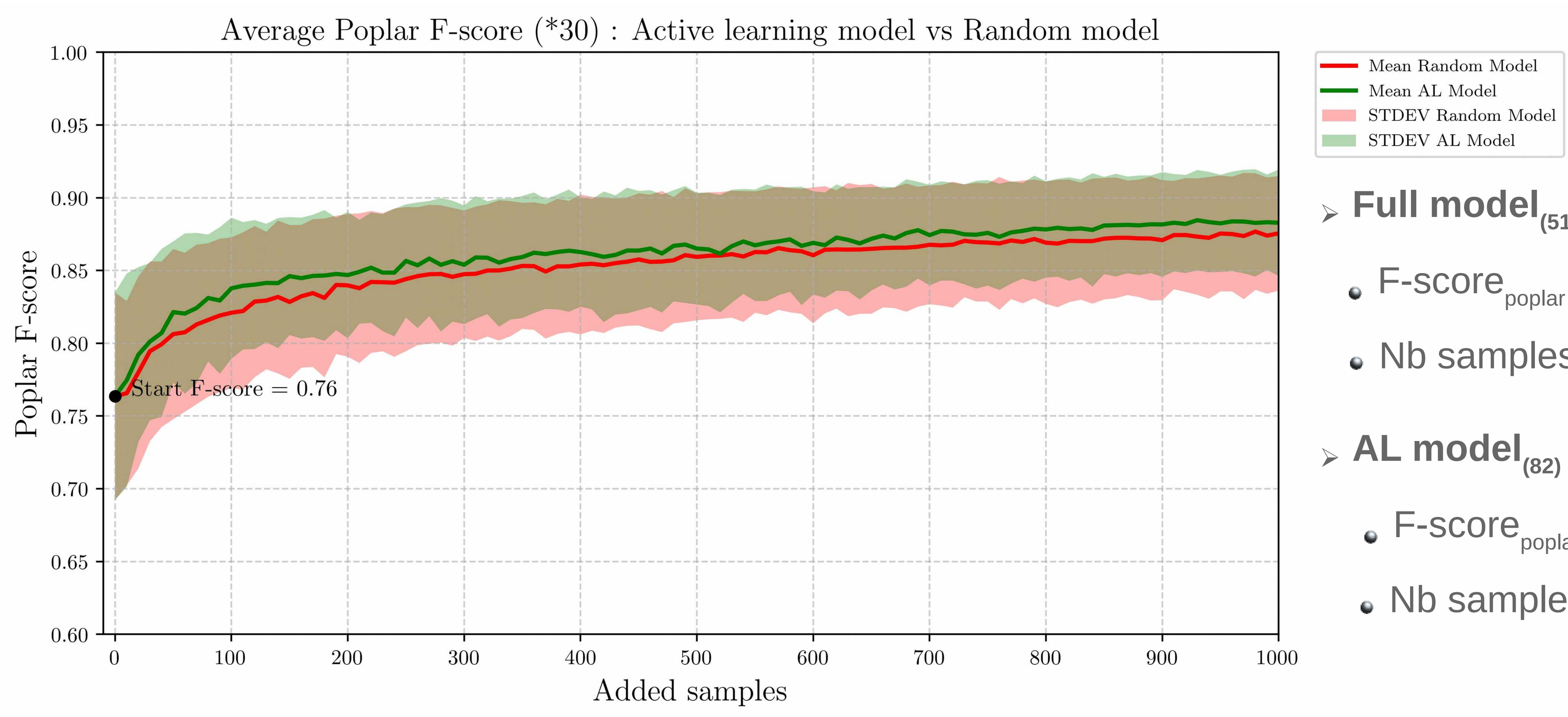
Site to site classification with Active learning

- **Department 51 (T31UEQ) to Department 82 (T31TCJ) : 4 classes → 6 classes**



- **Full model$_{(82)}$:**
  - F-score$_{poplar}$: 98.9 %
  - Nb samples : 6000
- **AL model$_{(82)}$:**
  - F-score$_{poplar}$: 96 %
  - Nb samples : 200

- **Department 82 (T31TCJ) to Department 51 (T31UEQ) : 6 classes → 4 classes**



- **Full model$_{(51)}$:**
  - F-score$_{poplar}$: 90.9 %
  - Nb samples : 4000
- **AL model$_{(82)}$:**
  - F-score$_{poplar}$: 85 %
  - Nb samples : 200

CONCLUSIONS

- Better classification results are obtained with well-created poplar samples → The national forest data base is not updated regularly enough to guarantee high accuracies.
- In the first case, the active learning model achieved high Poplar F-score with the first added samples (+20 % with 100 samples) and reached a plateau faster than a randomly trained model → Active learning technique is a suitable option where reliable and appropriate training samples are limited, time-consuming or expensive to collect.

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