Detecting land cover changes between satellite image time series by exploiting self-supervised representation learning capabilities

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Objective

⇒ Detecting land cover conversion changes using satellite image time series (SITS)

Challenges in detecting changes using a multi-temporal dataset:

- high inter- and intra-annual (i.e., seasonal) variabilities,
- irregular temporal sampling due to different acquisition dates and presence of clouds,
- high dimensional data (complex datacube),
- scarcity of reference data.

Dataset

Satellite images

- **Sentinel-2** (L2A) image time series for the consecutive years **2018 and 2019**
- collected from THEIA
- **10 spectral bands**
- correction of the atmospheric effects using the MAJA processing chain
- cloudy pixels gap-filled using linear temporal interpolation on the union of both SITS acquisition dates.

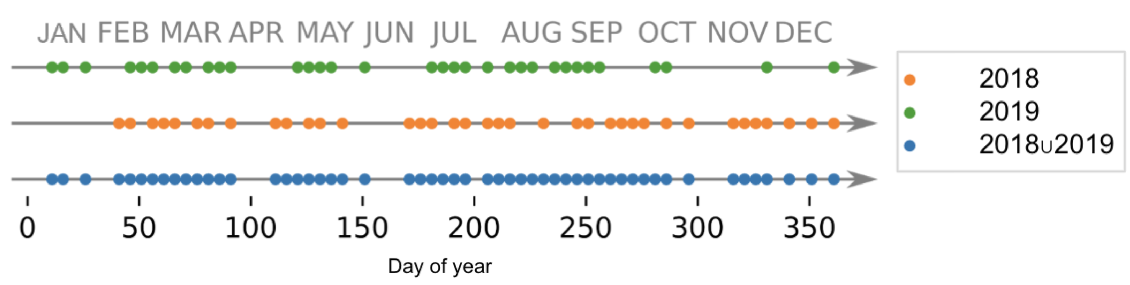

Figure 1. Sentinel-2 time-series acquisition dates with the interpolated union of both date acquisitions.

Reference data

- **French land cover reference dataset** [1] for years 2018 and 2019
- **19 land cover classes**, including four urban classes, seven annual crops, seven permanent vegetation classes, and water within the region of interest.

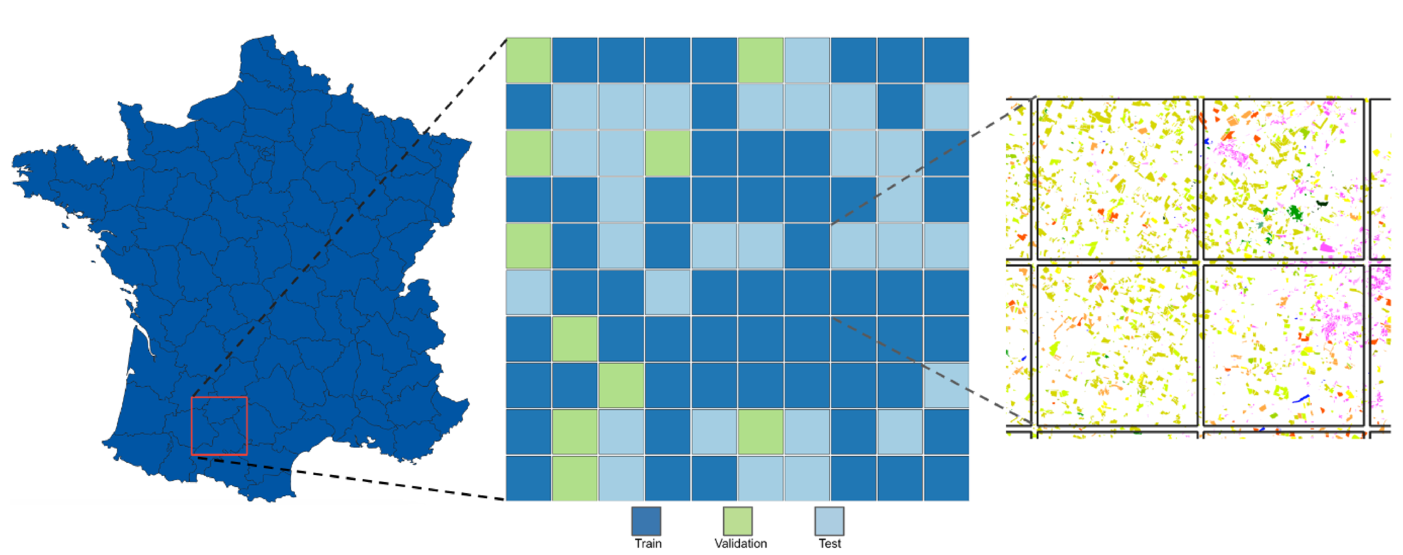

Figure 2. Left: Study area showing the map of France and Sentinel-2 tile T31TCJ in red covering Toulouse and its surroundings. Center: A grid split strategy is used to partition the data into train, validation and test sets with a ratio of $60 : 10 : 30$. Right: A close-up view of some blocks overlaying the reference dataset.

Proposed Approach

Strategy: leveraging **self-supervised learning** for change detection by taking advantage of the acquisition of Sentinel-2 satellite images over two years

A. Pre-detection of non-change areas

Goal: ensuring that the contrastive loss in the self-supervised learning is computed only between time series that have the same land cover.

1. Training a state-of-the-art SITS network (Lightweight Temporal Attention Encoder - LTAE) [2]
2. Applying post-classification to detect non-change areas. We use two strategies for the comparison:
   - hard-label comparison, i.e. predicted classes pairwise comparison
   - soft-label comparison: computing the Euclidean distance and automatic thresholding

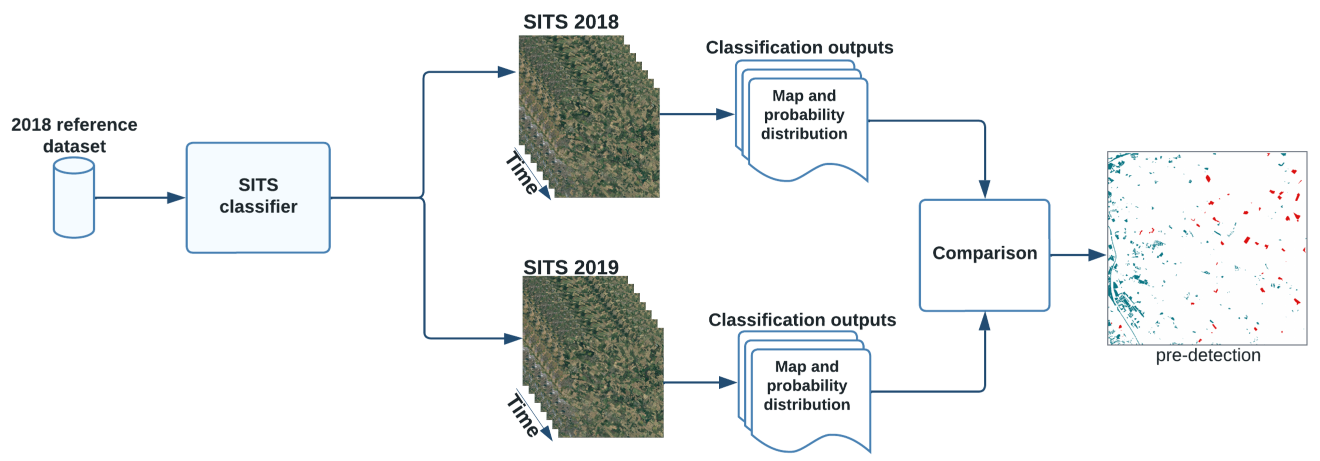

Figure 3. Framework to pre-detect non-change areas. The classifier is trained for the year in which the reference data are available; this is used to generate pseudo-labels for both years. If the classes for the labeled year and the unlabeled year are identical, then the pair of time series is used in self-supervised learning.

B. Self-supervised learning

We use Bootstrap Your Own Latent (BYOL) [3], a self-supervised learning strategy that allows learning robust data representations.

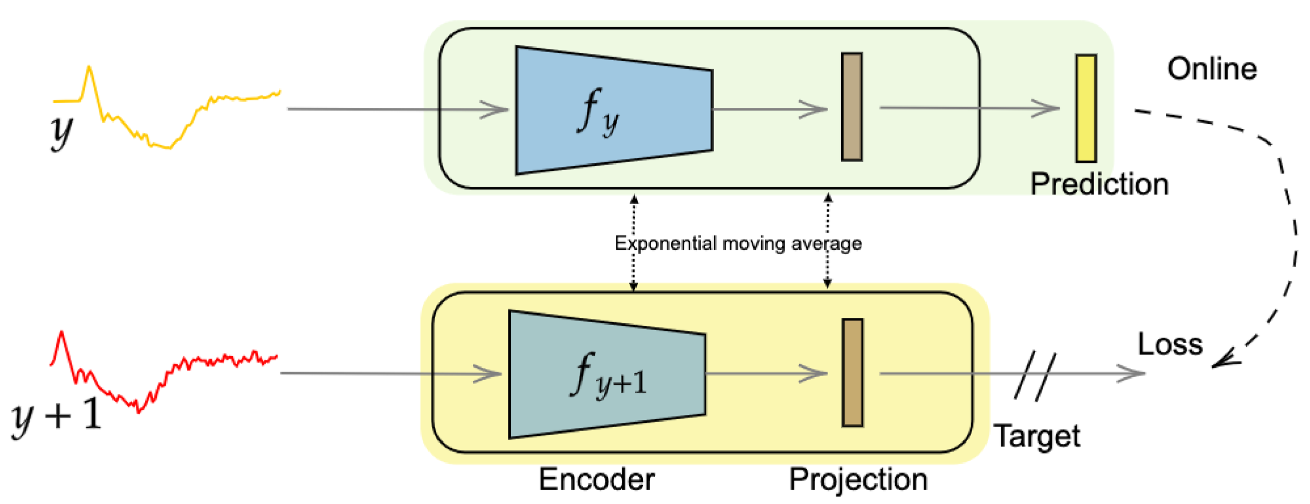

Figure 4. Framework of BYOL in the context of this study; where time series are extracted for two consecutive years y and $y+1$ represents.

C. Change detection

To obtain the change map, a classifier network is trained using the available land cover labeled data for the oldest year, similar to the pre-detection step.

We test two strategies to use the pre-train network, the encoder's parameters are either :

- frozen or
- finetuned.

Results

Table 1. Pre-detection of non-change areas. TNR: true negative rate; NC: number of pixels detected as non-changes.

	Label (%)	TNR (↑)	NC
Hard	5	79.94	491,548
	20	96.79	420,788
	100	97.98	397,760
Soft	5	84.81	498,737
	20	99.04	548,294
	100	99.34	548,285

Table 2. Change detection results. FPR: false positive rate; FNR: false negative rate; ERR: total error. (**best**)

	Label (%)	FPR (↓)	FNR (↓)	ERR (↓)	F1 (↑)
Post classification w/o SSL (soft-label)					
	5	9.63	7.22	16.85	0.827
	20	1.55	4.13	5.68	0.939
	100	1.27	3.86	5.12	0.945
Hard-label					
Finetuned	5	8.70	10.83	19.53	0.790
	20	11.24	1.97	13.21	0.874
	100	12.27	1.09	13.36	0.874
Frozen	5	14.50	9.57	24.07	0.760
	20	12.77	1.06	13.83	0.871
	100	14.86	**0.90**	15.76	0.856
Soft-label					
Finetuned	5	8.61	6.20	14.81	0.848
	20	4.40	1.99	6.39	0.934
	100	**1.17**	3.76	**4.93**	**0.947**
Frozen	5	9.28	6.87	16.15	0.835
	20	1.24	3.83	5.07	0.945
	100	1.48	4.07	5.55	0.940
All pixels					
Finetuned	5	4.54	7.13	11.67	0.873
	20	1.46	4.05	5.51	0.94
	100	1.64	4.23	5.87	0.936
Frozen	5	7.87	5.46	13.33	0.863
	20	4.29	1.88	6.18	0.936
	100	1.29	3.87	5.17	0.944

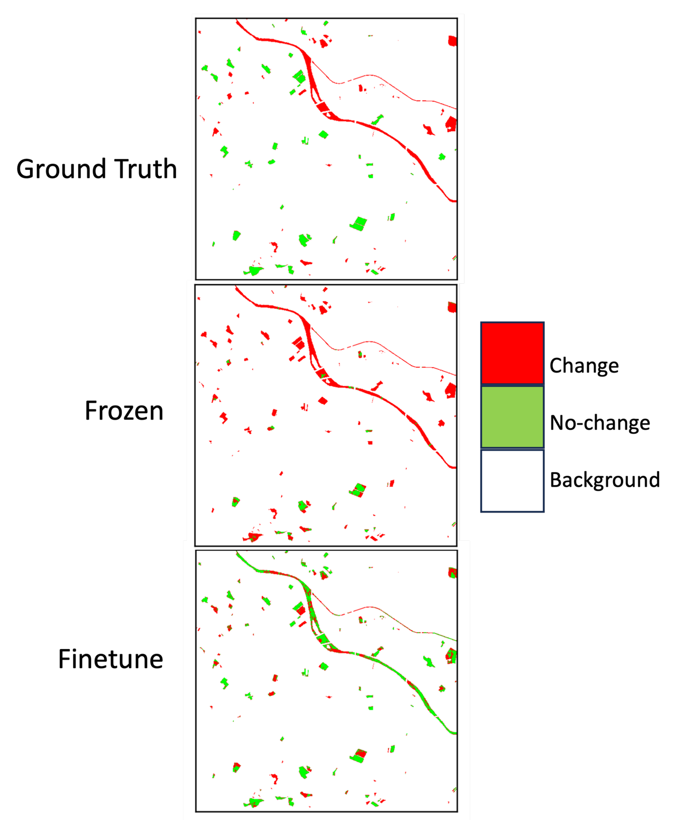

Figure 5. An example of change detection map in a test set grid, comparing the influence of Frozen and Finetuned strategies on the quality of change map. Showing that finetuning model parameters outperform a frozen strategy.

Conclusion

- Exploring the use of self-supervised learning for change detection from SITS.
- Using time series acquired at different periods as natural augmented views allows applying self-supervised learning strategies.
- Self-supervised learning shows promising results in addressing the annotation label scarcity.

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Code

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