Temporal Unsupervised Domain Adaptation for land cover mapping from satellite image time series

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Outline

Introduction

- Remote Sensing and Land Cover Mapping
- Remote Sensing and Data reuse

Domain adaptation

- Unsupervised Domain Adaptation
- Domain Adaptation and RS
- Temporal Domain Adaptation

SpADANN : Spatially Aligned Deep Adversarial NN with Self-Training

A Case Study on Koumbia (Burkina Faso)

Experimental Settings & Results

Conclusions and Future Works

Earth Observation Data (EOD)

Nowadays, many earth observation satellite missions exist:

- Sentinel [Senti]
- LandSat-8 [LandSat]
- SPOT 6/7[Spot]
- …

Acquired images have different:

- Spatial resolution (0.5 – 300 meters)
- Radiometric content (spectral bands/modality)
- **Revisit Time** (from 1 year to every 5 days - depending on weather conditions)

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i.e Sentinel Mission (Sentinel-2) allows to acquire information with high revisit time (every 5 days)

→

Information can be profitably organised as Satellite Image Time Series (SITS)

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Satellite Image Time Series

The possibility to collect **multiple satellite images** (SITS: Satellite Image Time Series), **on the same area**, with **high revisit period** and **high spatial resolution** is paving the way to new applications (especially in agricultural land monitoring).

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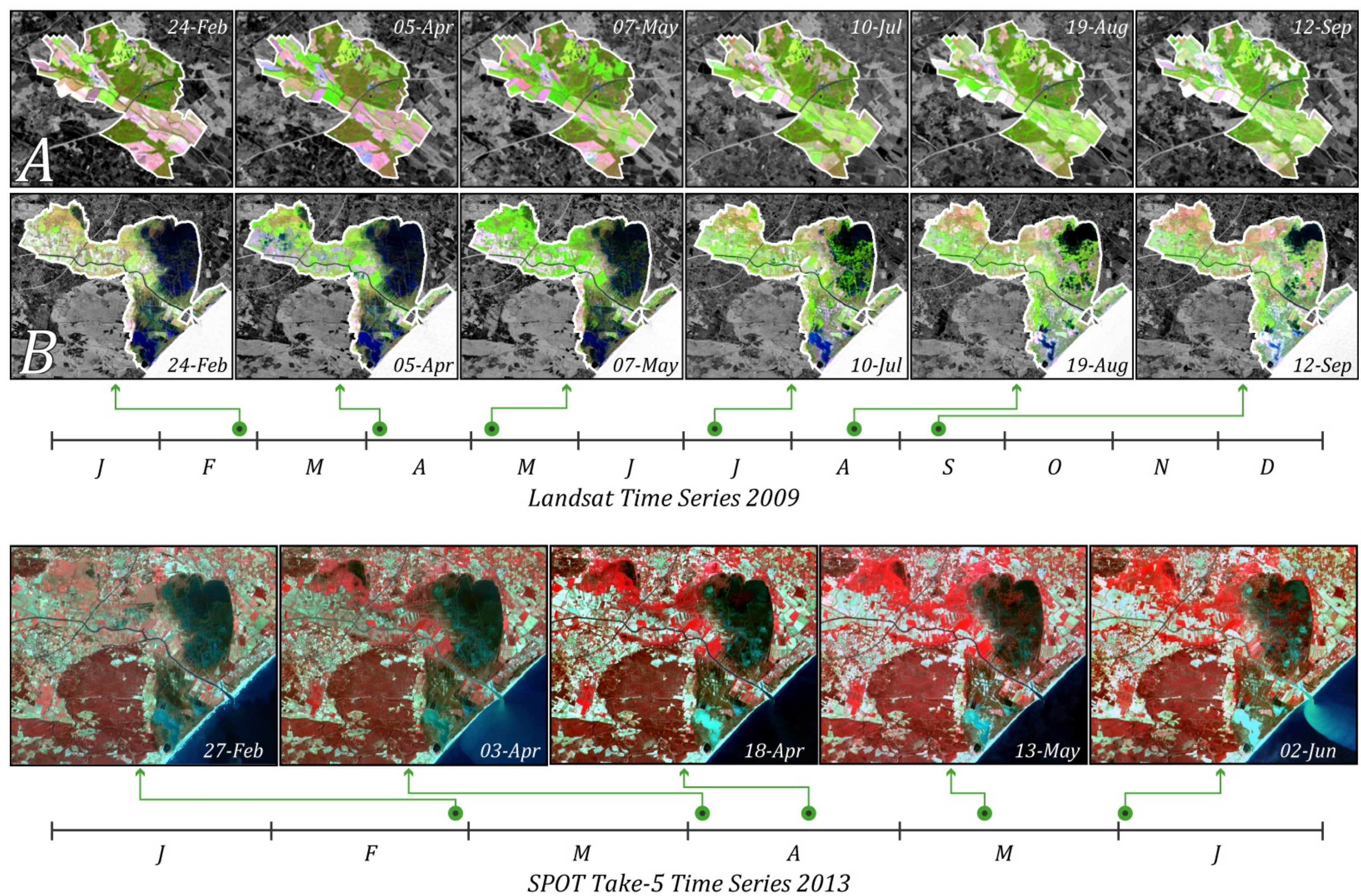
<u>In the context of agriculture SITS:</u>

- allows to **distinguish between** different crops
- captures **phenological cycle**
- supports **change detection analysis**
- helps to monitor **spatio-temporal phenomena**



Land Cover Mapping & SITS

Among the others, SITS are largely used for **land cover mapping (LCM)** [Inglada17] and [Ienco19]

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Task:

Given SITS + reference data, the goal is to map each pixel to the corresponding land cover

Common approach:

- Land cover mapping is addressed via **Machine Learning (ML)** methods.
- A ML method is **calibrated/trained on** (in season) **reference data** to classify the rest of the same study area (unlabelled data).

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Land Cover Mapping Update

The LCM process requires:

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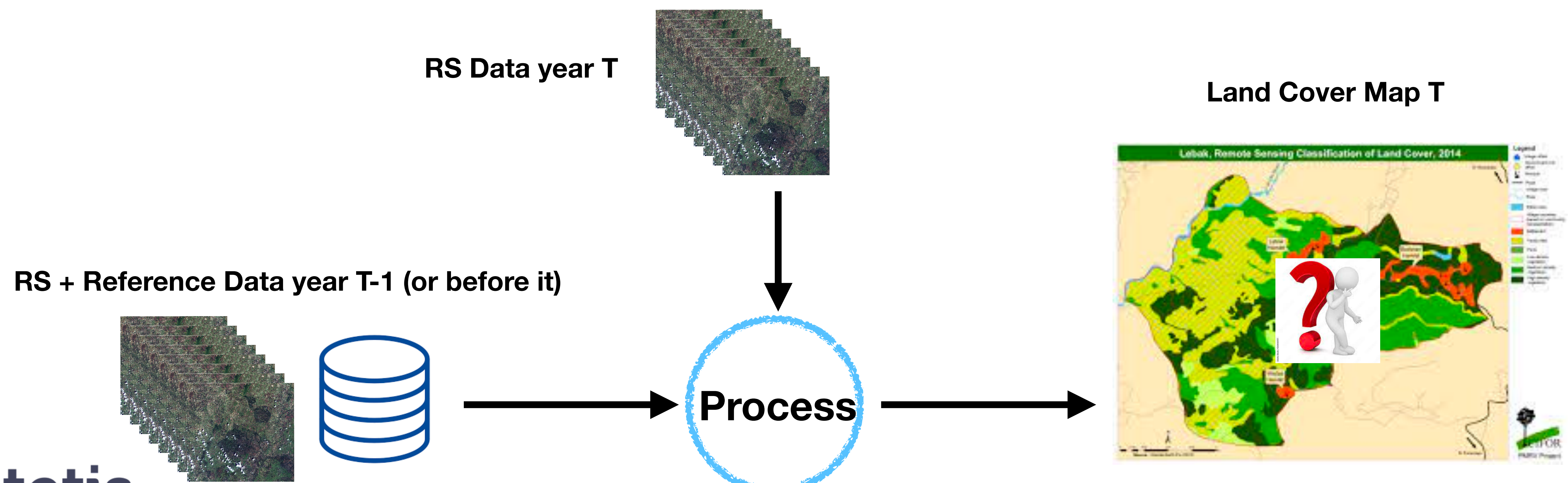

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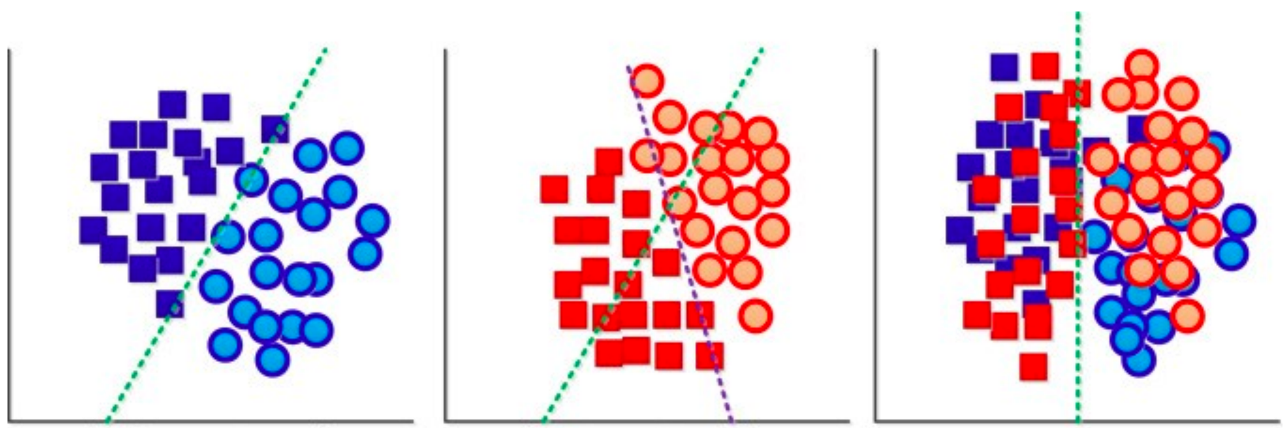

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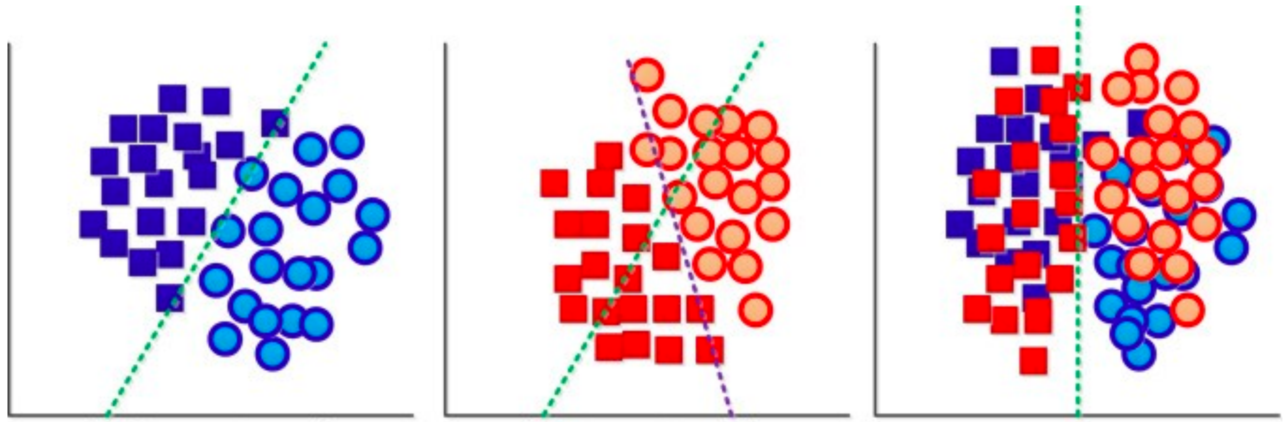
Our case: Adapt a supervised ML models from one year to another one under the same land cover nomenclature



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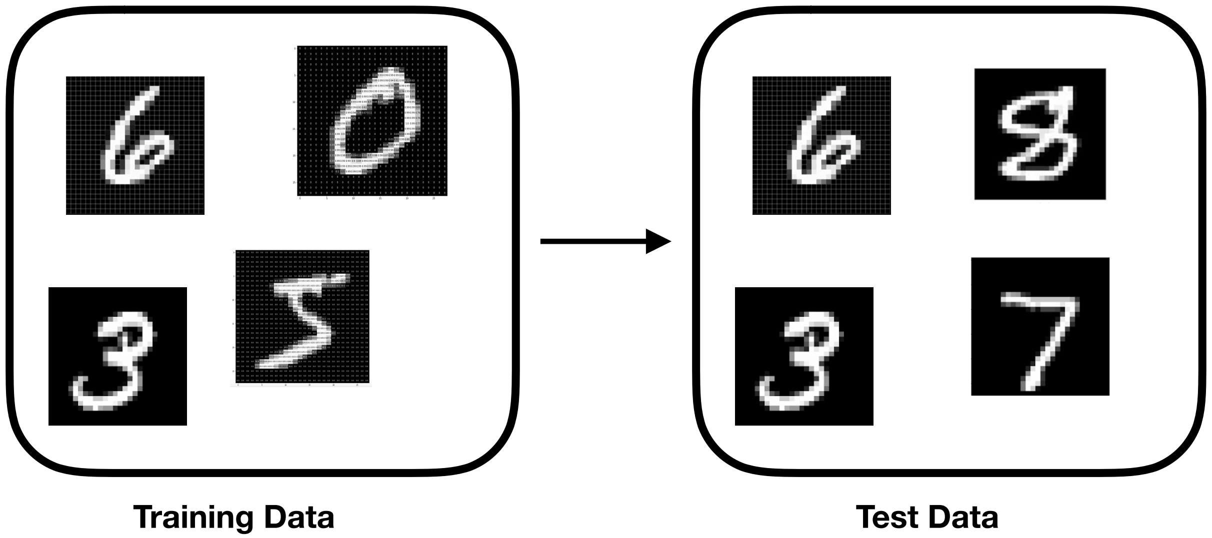

Training and Test
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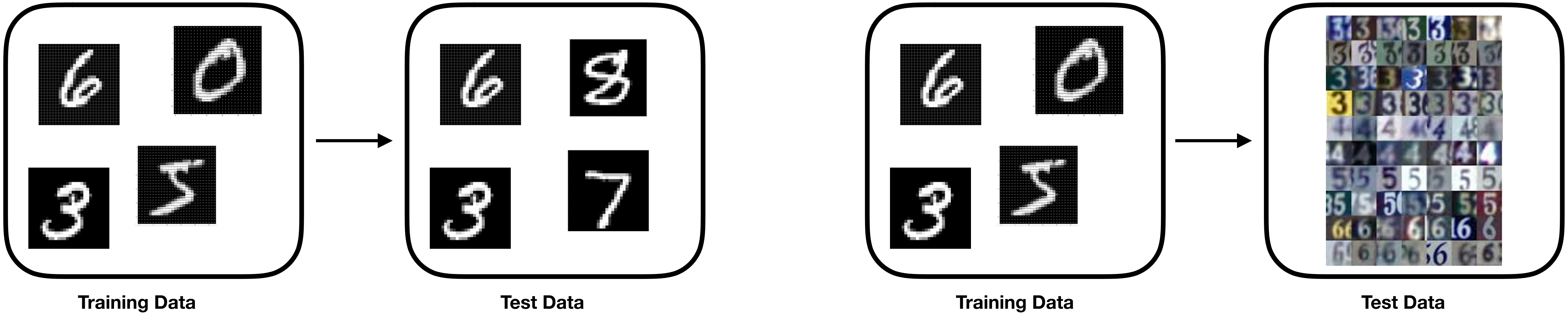

Training and Test from same distributions

Training and Test from different distributions

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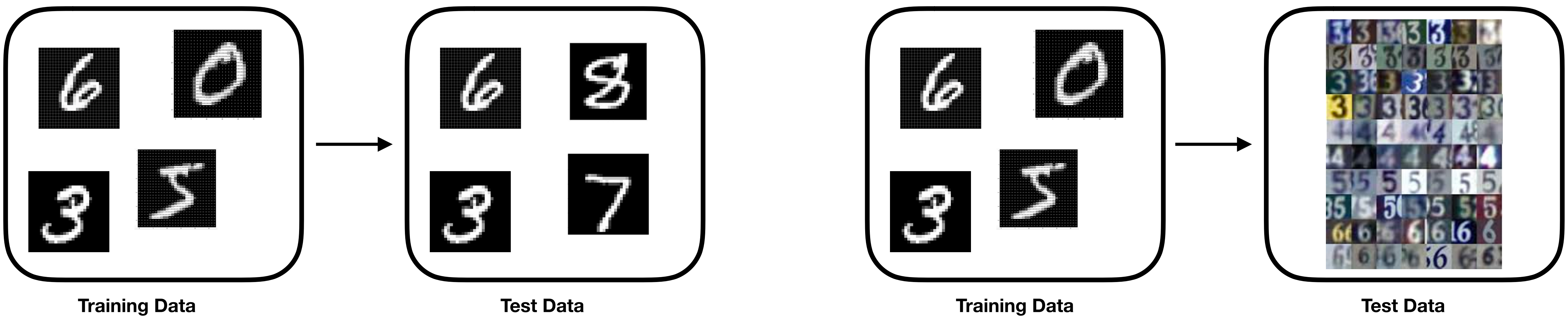

Training and Test from same distributions

Training and Test from different distributions

- Distribution from Training (Source) and Test (Target) domains can be different
- In this case standard supervised ML approaches fail to generalise, thus …
- Needs for methods dealing with distribution shift => Domain Adaptation

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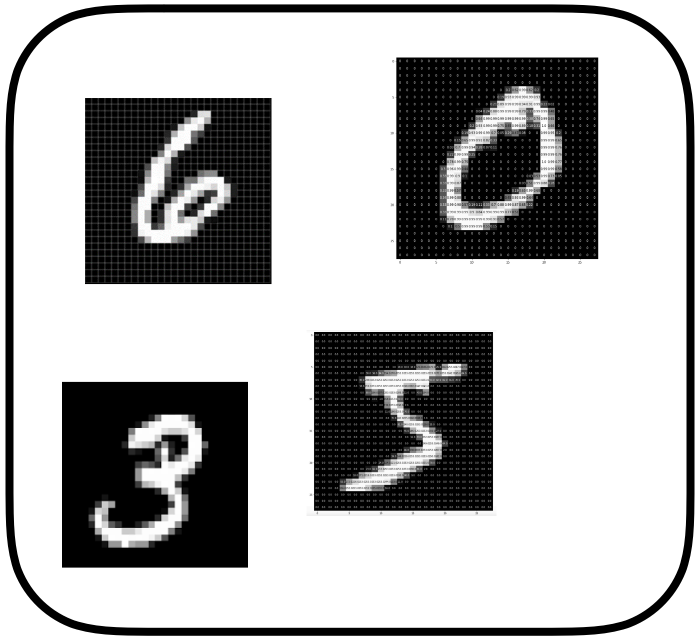

Source Data/Domain

Test Data/Domain

Generally, no (or really small amount of) reference data is available on Target domain

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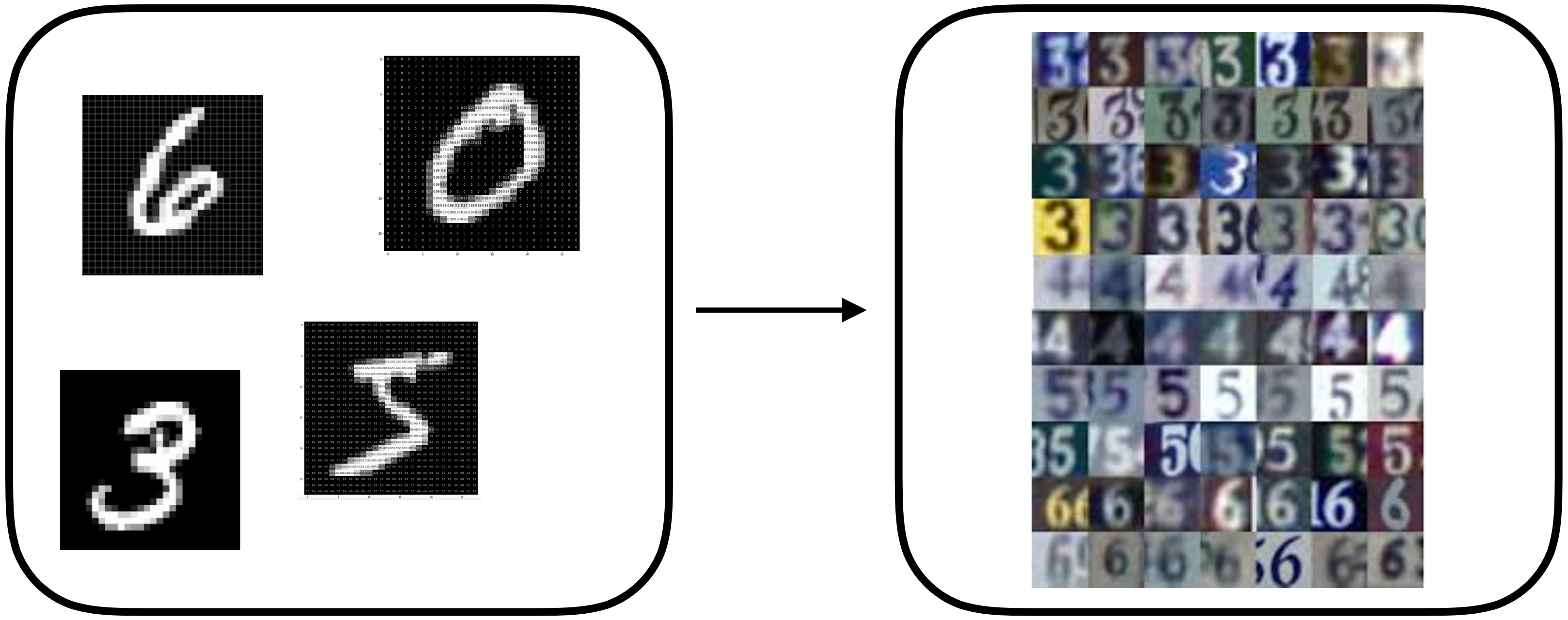

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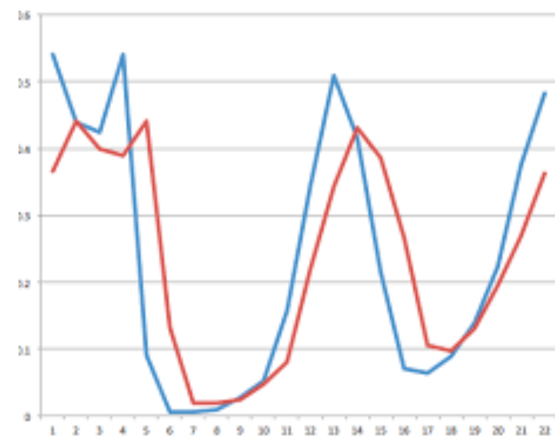
Domain Adaptation:

- Unsupervised Domain Adaptation (UDA): Build a model on Source (Data + Reference) with the aim to generalise on Target Data.
- Semi-Supervised Domain Adaptation (SS-DA): Build a model on Source + small amount of Target data to generalise on Target Data

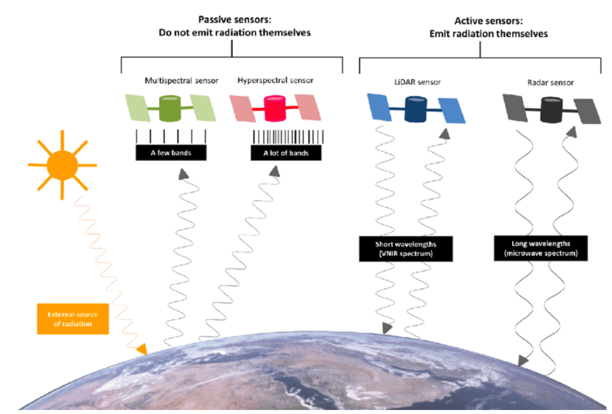
Domain Adaptation & Remote Sensing

Remote Sensing analysis can suffer, among others from:

Changes in **acquisition conditions** (i.e. climate/environment).



Temporal shifts (i.e. same study site from one year to another one or cross-site).



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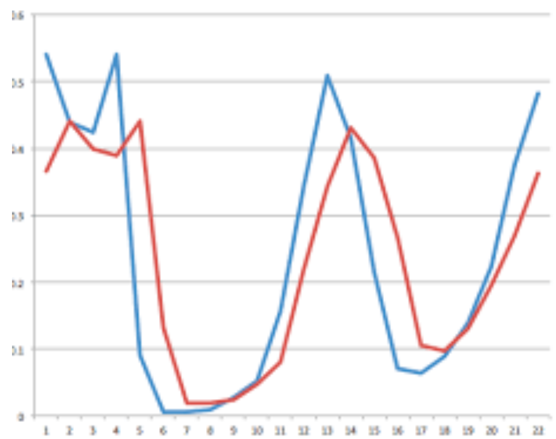

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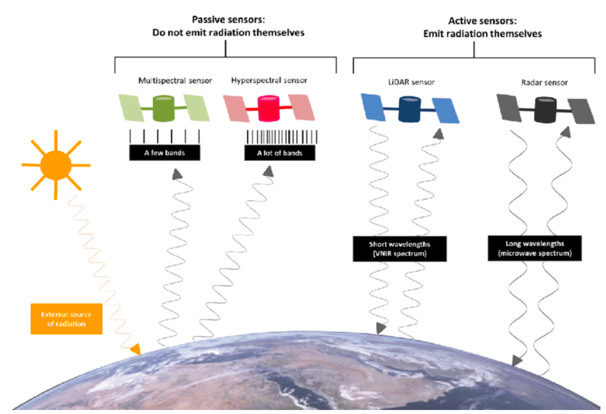

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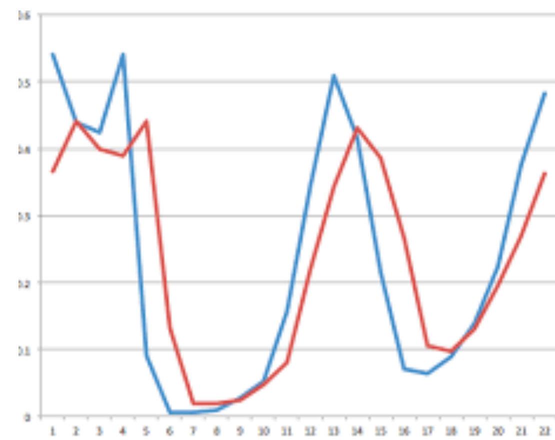

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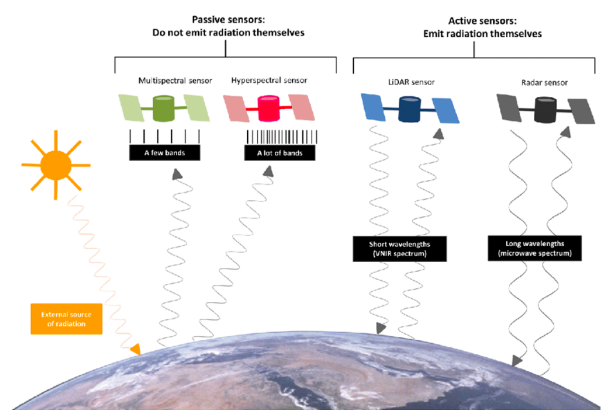

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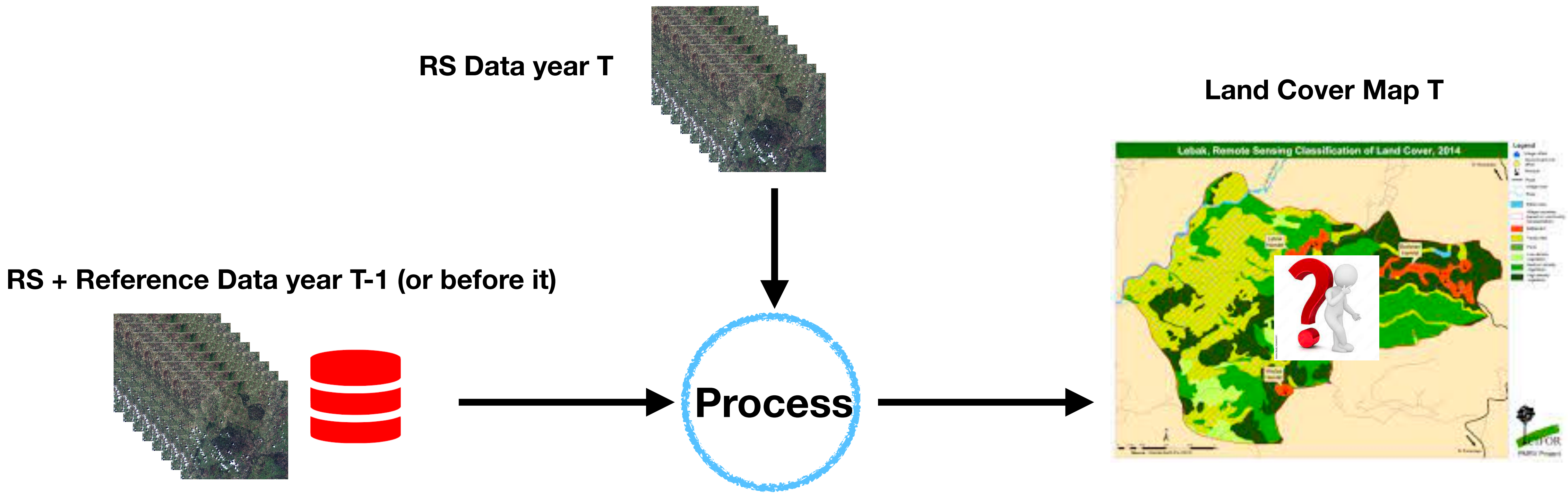
All these points clearly induce data distribution shifts (between training/source and test/target domains) that will **hinder the use of standard supervised ML methods.**

This is why **Domain Adaptation** can be an interesting **research direction** in **Remote Sensing Analysis** to directly adapt model without costly and time-consuming efforts.

Main Problem Recap



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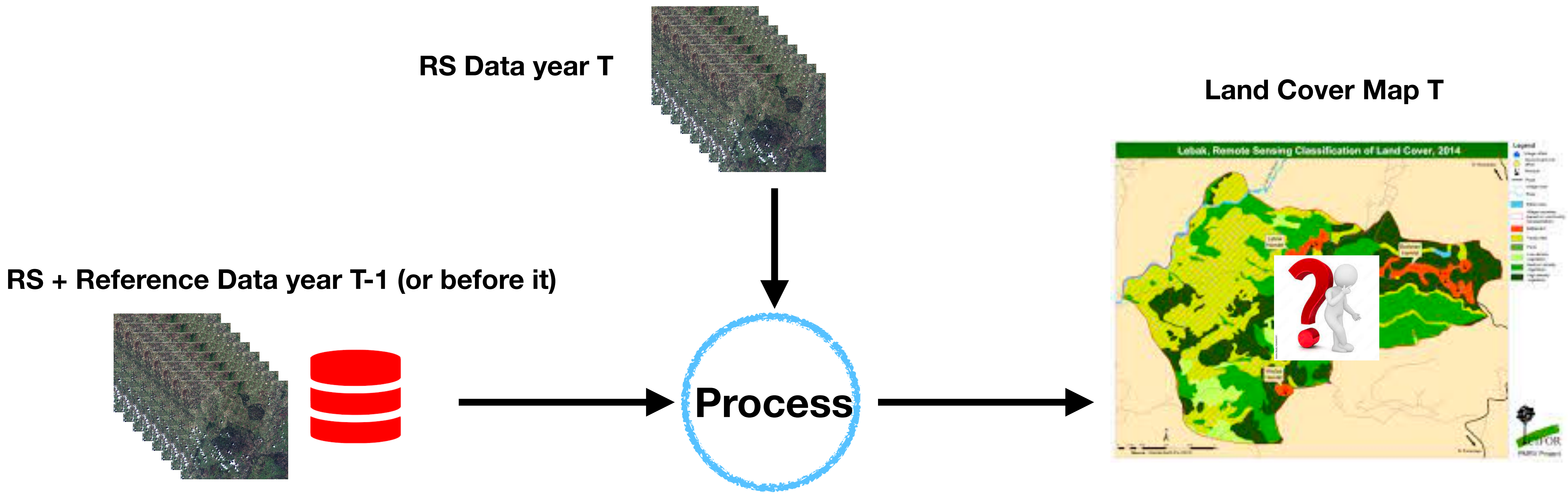

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Benefit of this process:

- **Save money** and **time** from performing (systematic/new) field campaigns;
- **Reuse** previous efforts (**acquired data**) on the same area.

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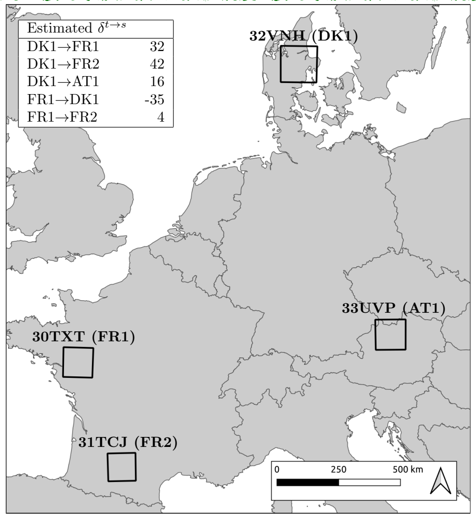
While some recent works exist combining (Semi and Unsupervised) **Domain Adaptation for Cross-Site** model adaptation [Nyborg21] and [Lucas20]



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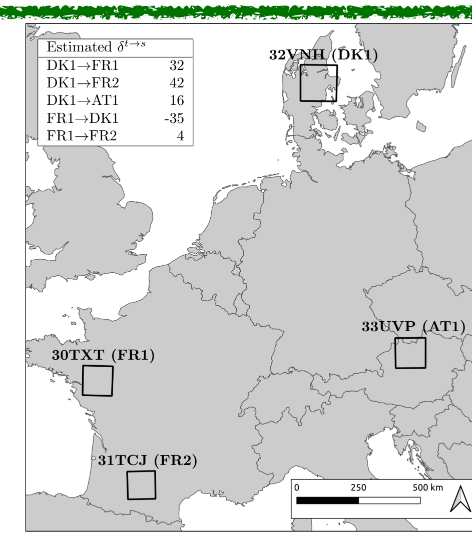

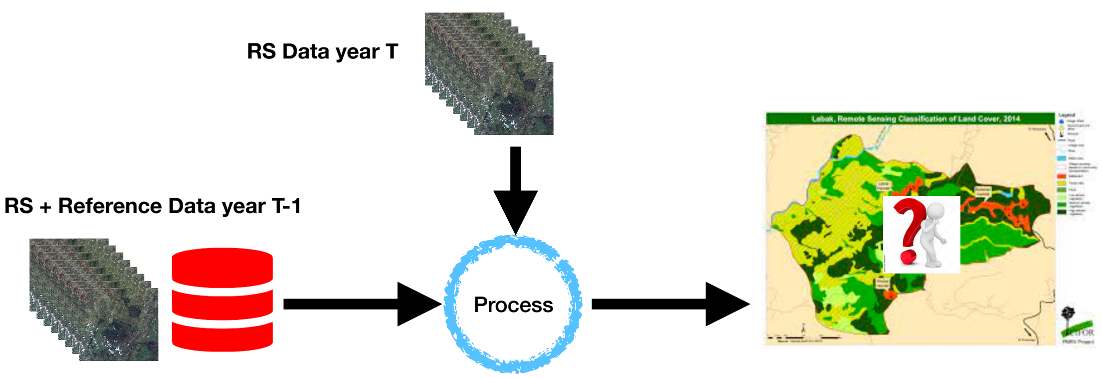

Only some preliminary attempts to cope with temporal transfer are available:

- leveraging **multiple** previous **reference data** [Tardy19];
- **Identify changes** from previous thematic map [Paris19].

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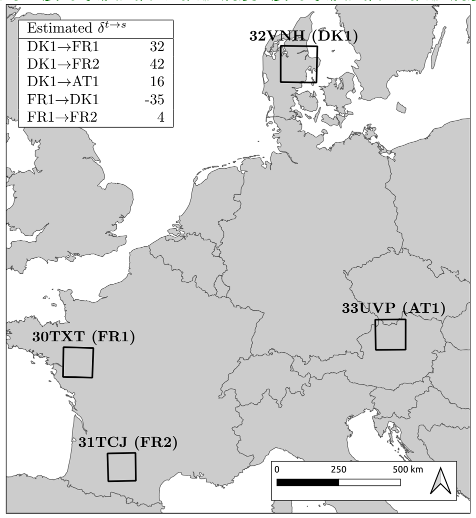

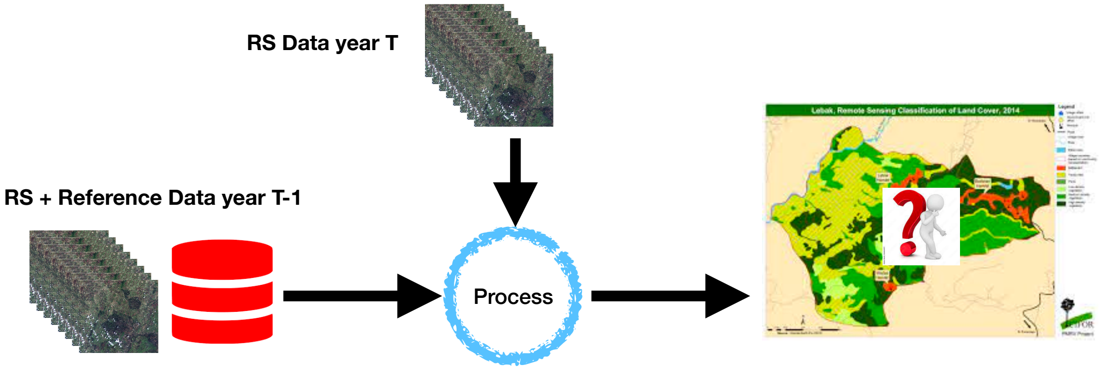

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No research study takes advantage of recent (deep-learning) DA techniques for unsupervised temporal land cover mapping/updating

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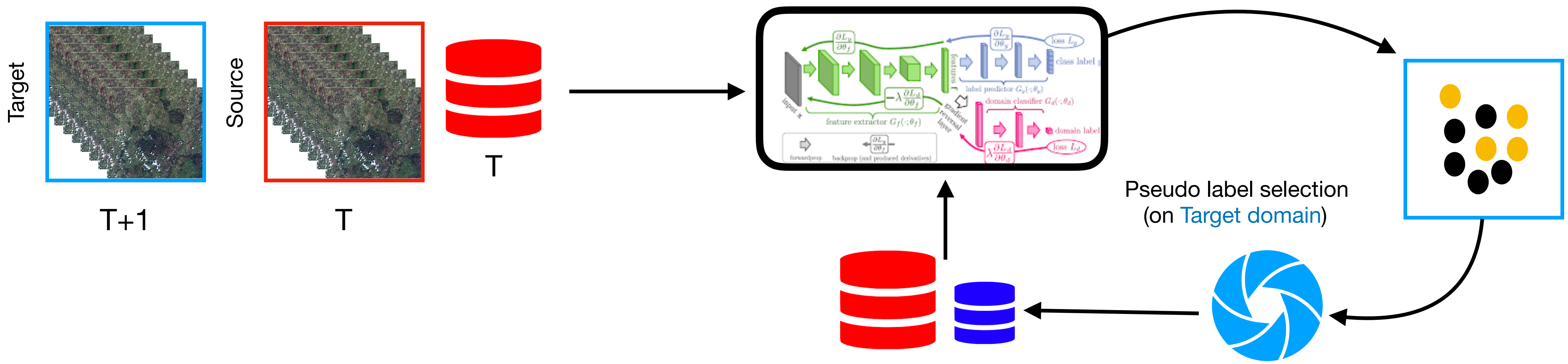

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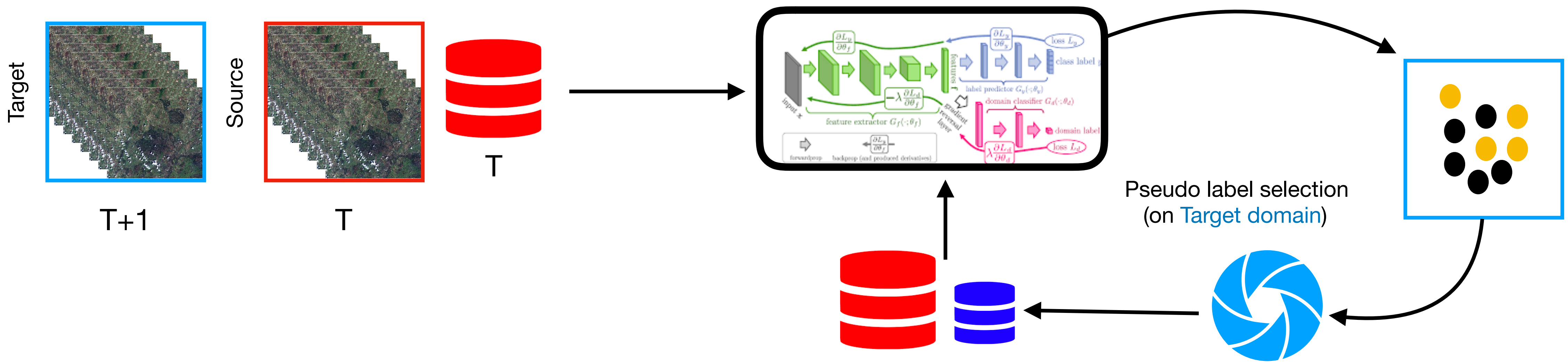

The main ideas behind **SpADANN** is to :

- Learn i**nvariant features w.r.t. distribution shifts** between source and target domain/year
- Identify reliable **areas** (pixels) **that remain stable** (in term of land cover) between domains/years
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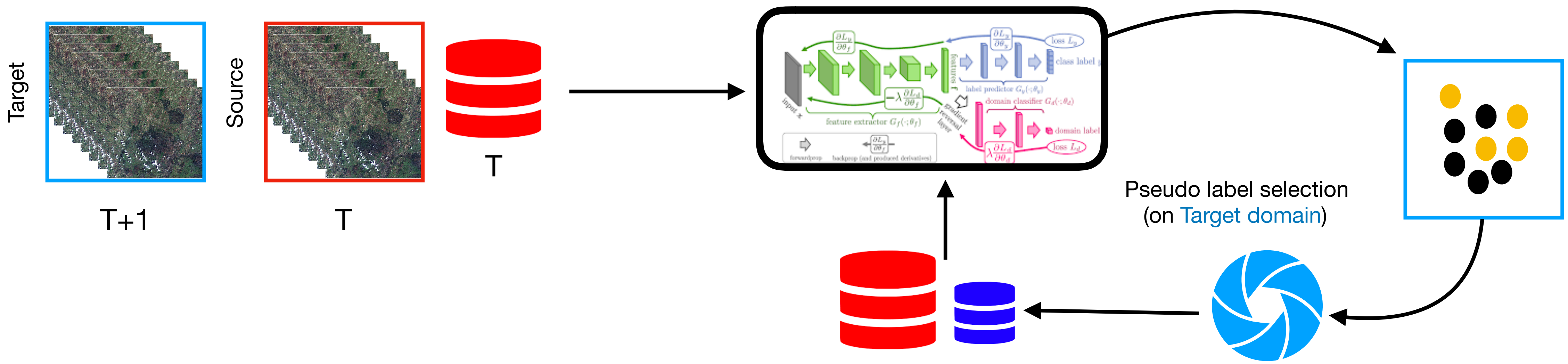

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To this end, **SpADANN** combines
- Adversarial Learning
- Self-Training with Spatial Consistency

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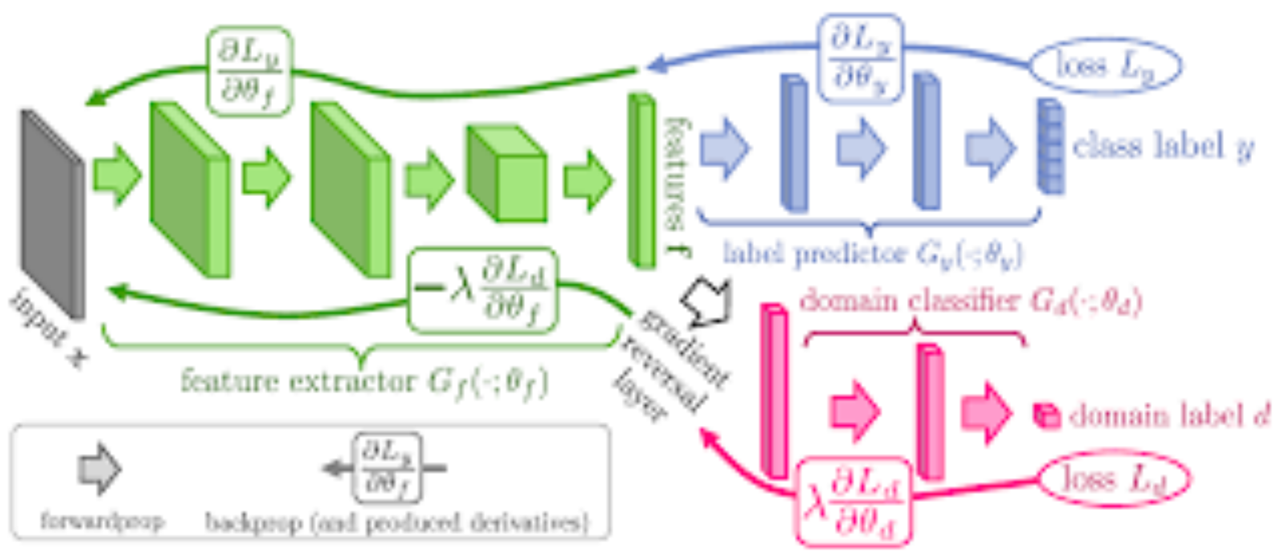
SpADANN:
Spatially Aligned Domain Adversarial NN with Self-Training

Adversarial Learning



The DANN [Ganin15] model adopts a multi-task strategy:
- An Encoder to manage input data;
- A Task Classifier to solve the multi-class classification task;
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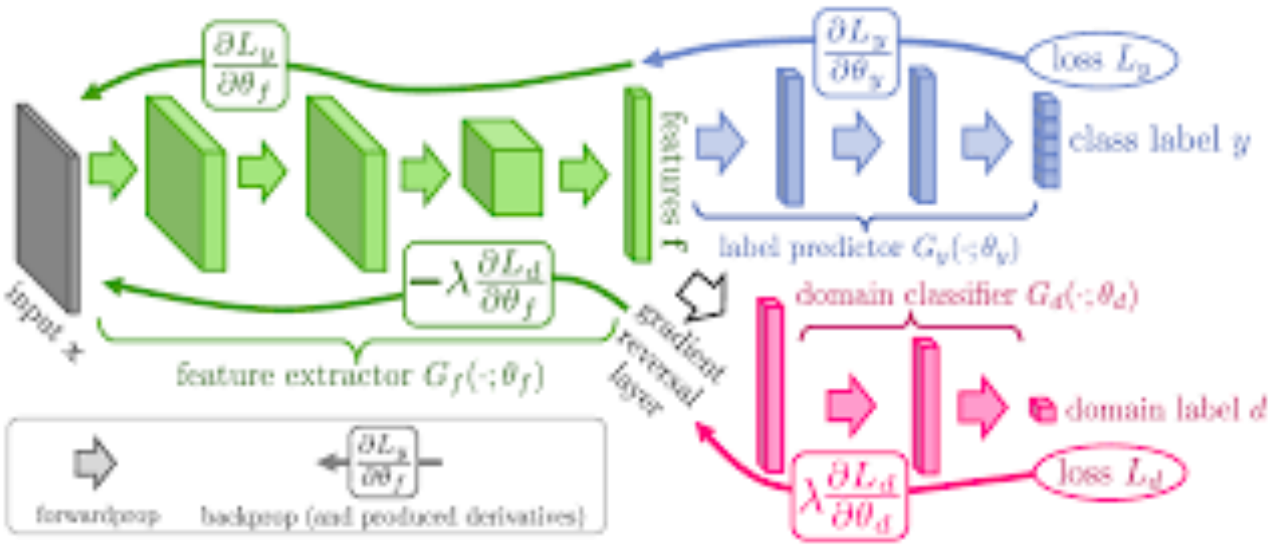

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Gradient Reversal Layer

Reverse the gradient (multiply by -1) for the Domain Classifier module with the aim to "confuse" the model and make domain indistinguishable.

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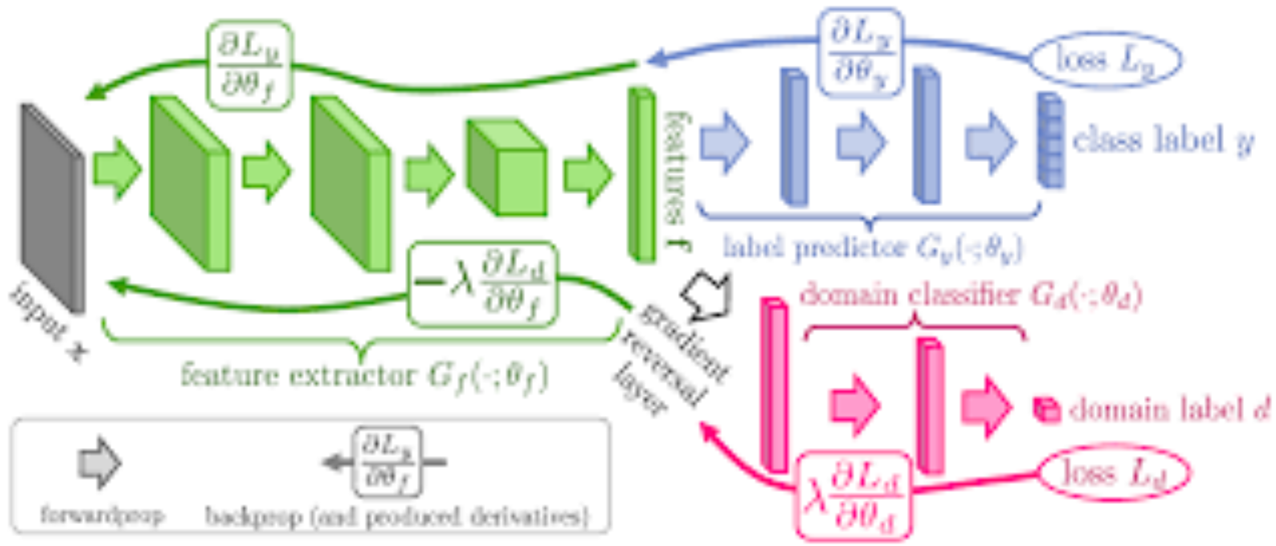

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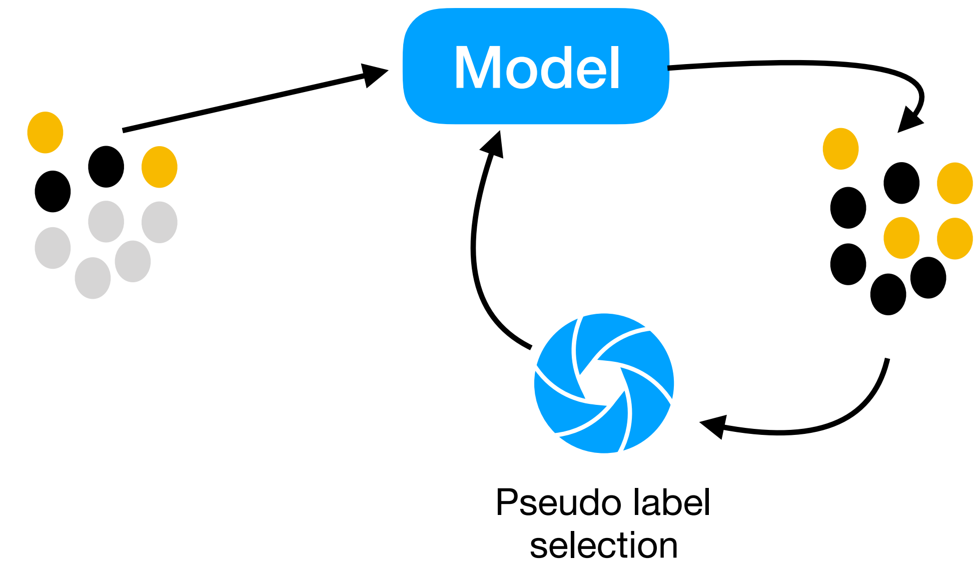

A family of techniques that can be employed to learn a model from its predictions [Yang21].

Self-training is tightly connected with the concept of **pseudo-label** (a label that is generated via the classifier prediction).

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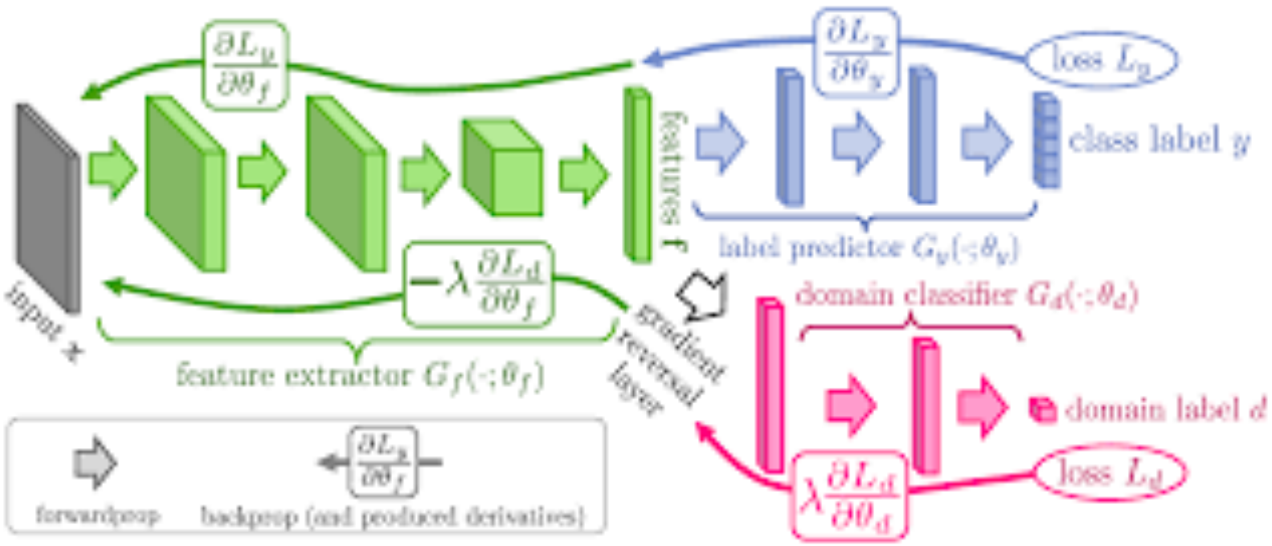

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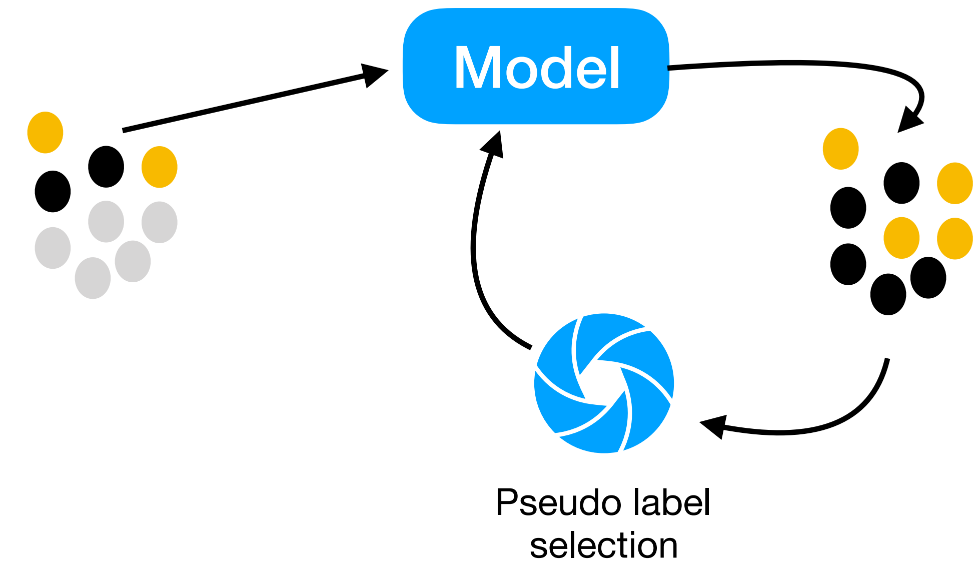

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Self-training is nowadays a widely adopted approach in:

- **Semi-supervised learning** and Low-data regime classif.
- **Domain Adaptation**
- **Few Shot Learning**
- **...**

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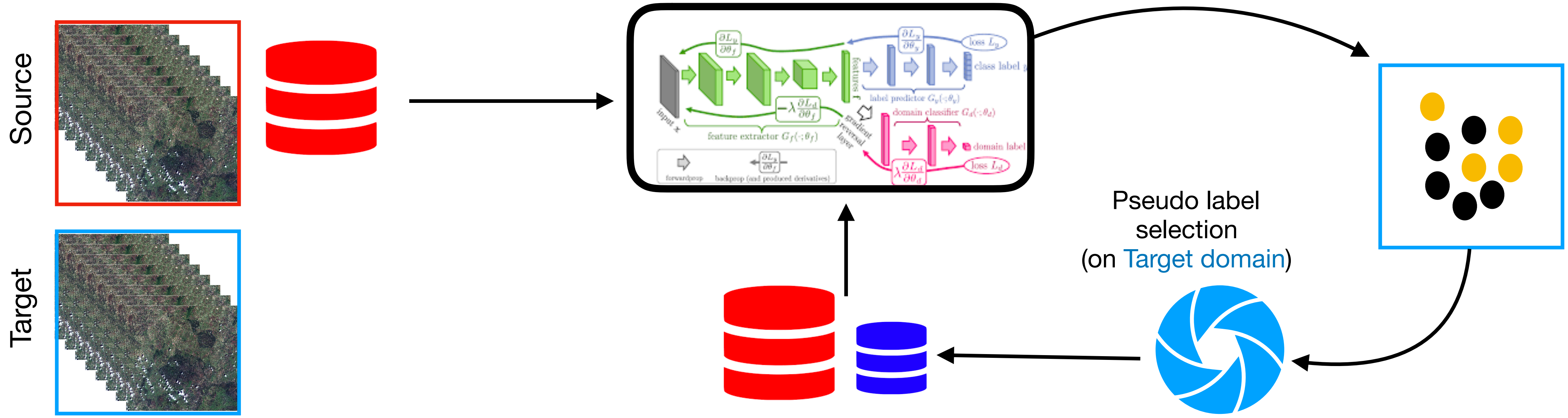

Pseudo labels are chosen according to:

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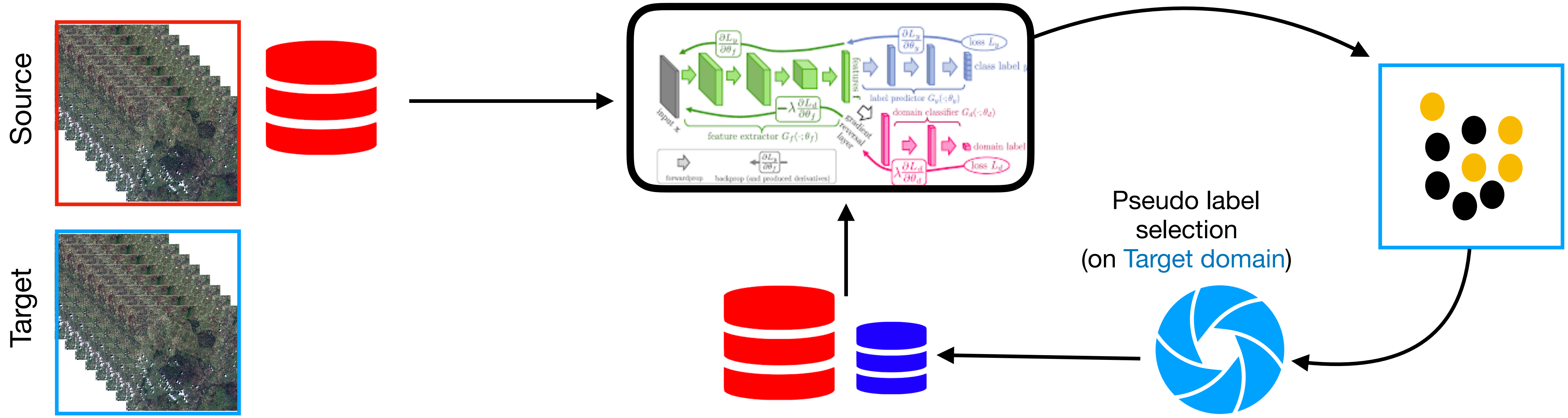

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The gradual transfer from Source to Target domain is ensured by the following loss function:

$$(1-\alpha) \times Loss(Cl(X_s), y_s) + \alpha \times Loss(Cl(X_t), \hat{y}_t)$$

Which include a weight (alpha) that increases linearly with the # of epochs in the training process

$$\alpha = \beta \times \frac{current\_epoch}{\#Epochs}$$

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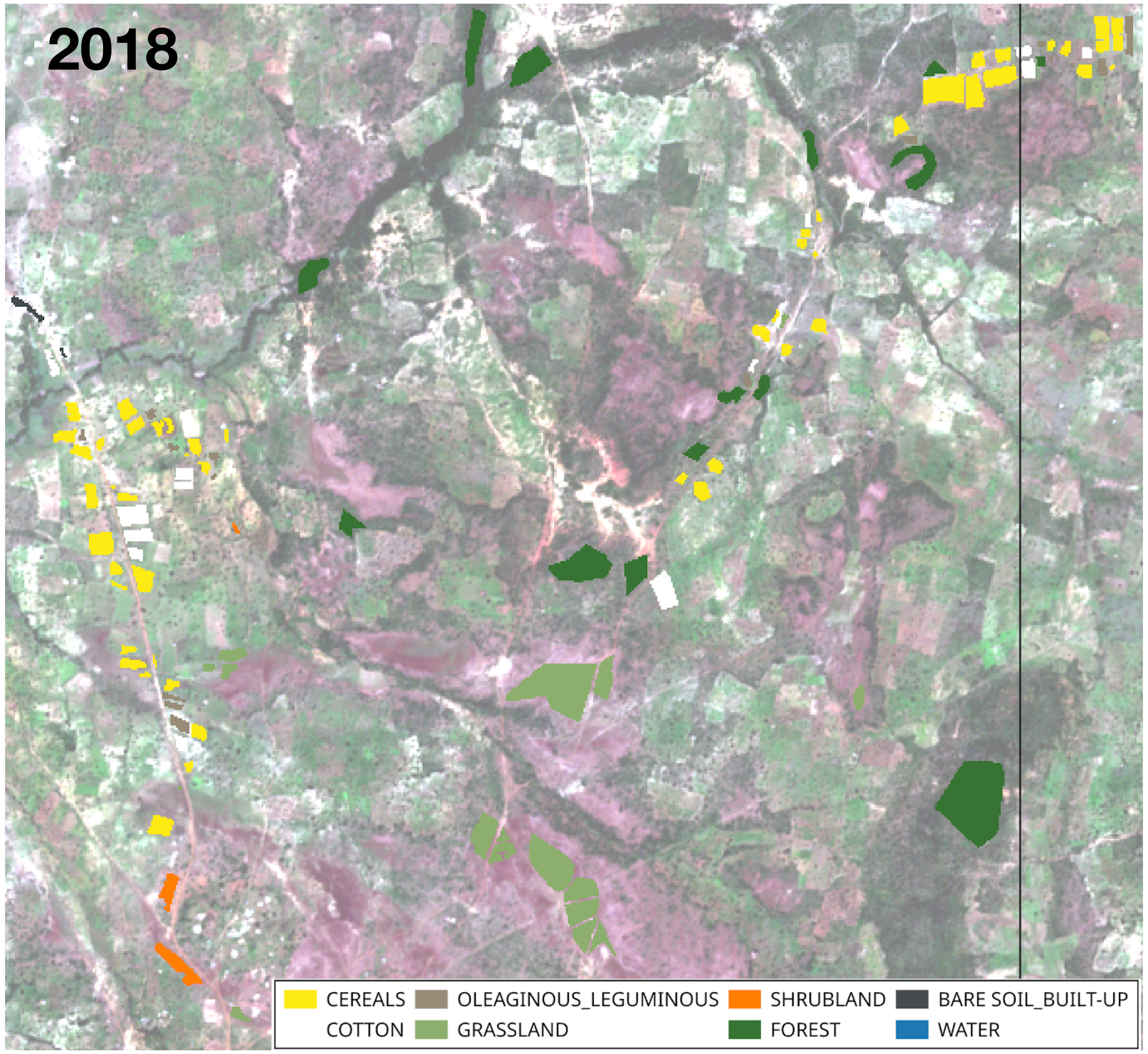
Study site : Burkina Faso (Koumbia)

Koumbia region in Burkina Faso - 2 338 km^2

We collect SITS data for **2018**, **2020** and **2021**
For each year, we select 24 images (based on cloud cover statistics) and only 10m bands.



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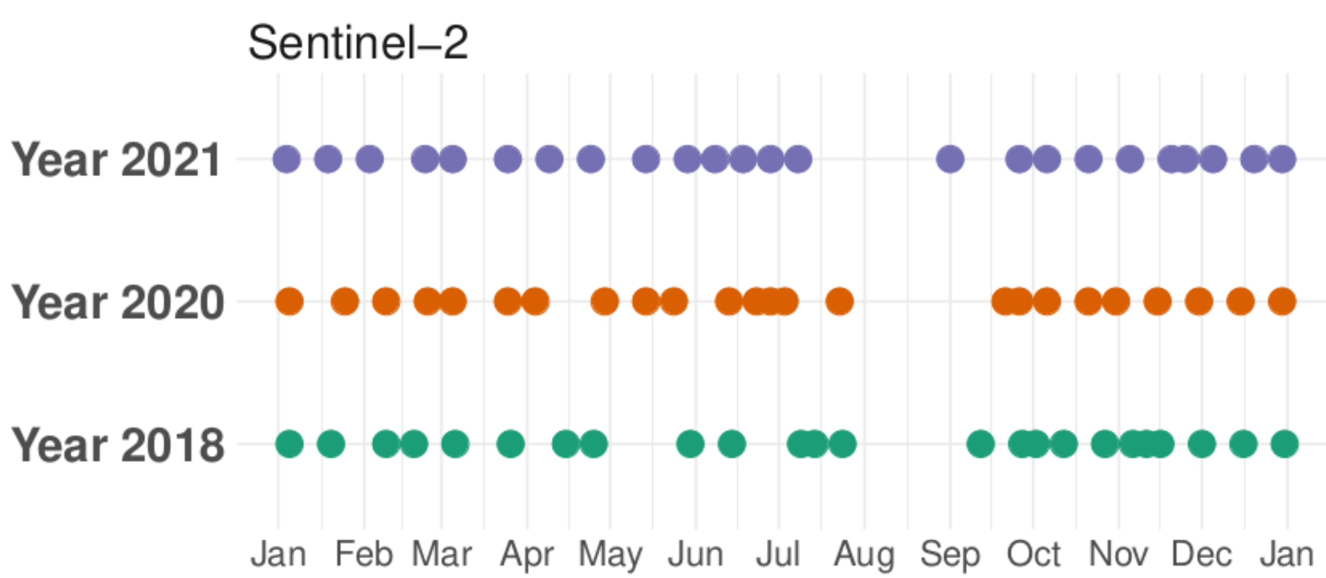
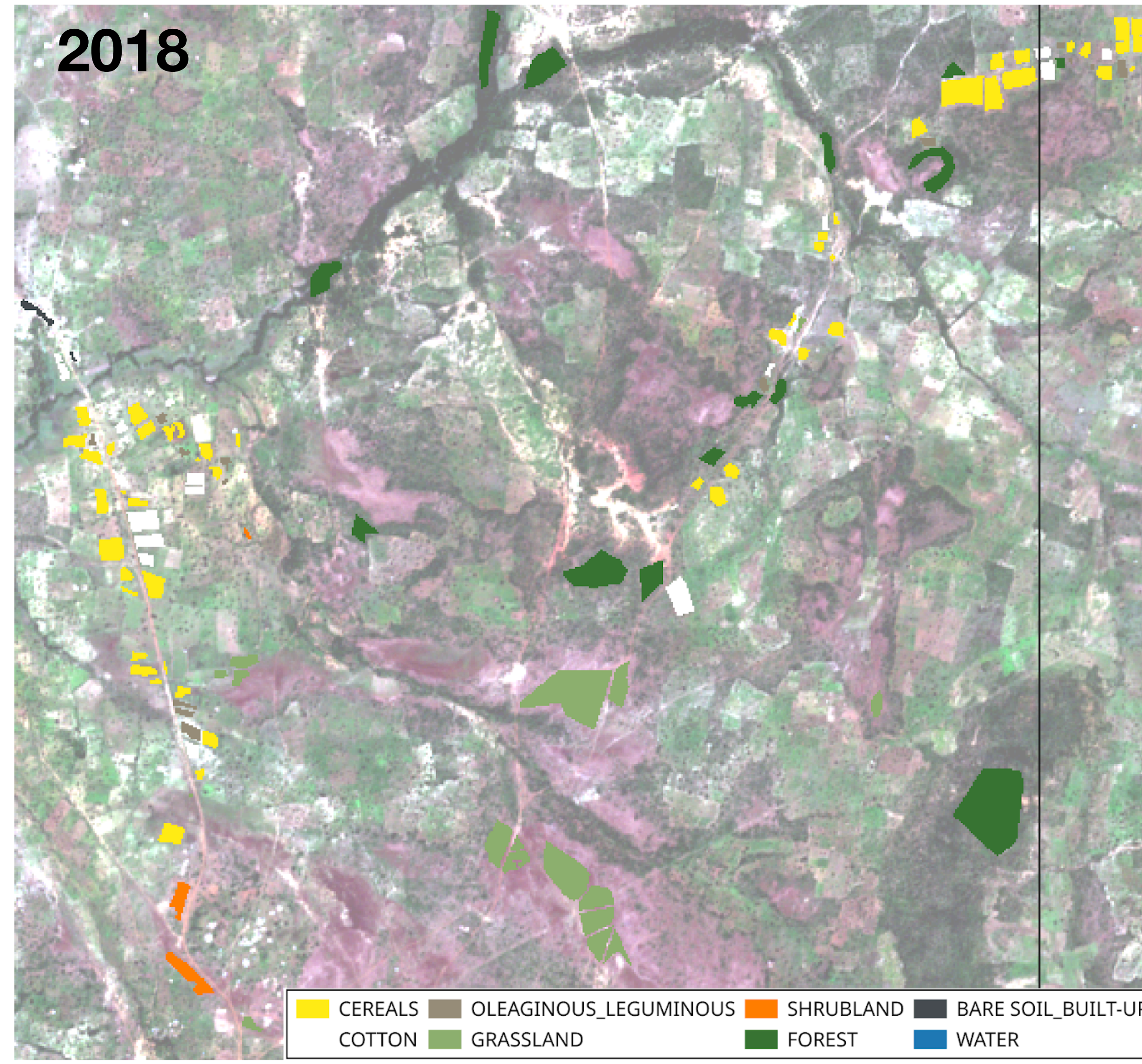


Figure 3: Acquisition dates of each Satellite Image Time Series.

Almost 1000 polygons covering varying land cover classes



Class Name	# Pixels 2018	# Pixels 2020	# Pixels 2021
CEREALS	13056	9731	11435
COTTON	7672	6971	6575
OLEAGINOUS/LEGUMINOUS	3595	7950	7316
GRASSLAND	13108	12998	11100
SHRUBLAND	23121	22546	24324
FOREST	17369	17435	16984
BARE SOIL/BUILT-UP	835	1125	1022
WATER	1205	1205	1205
Total	79961	79961	79961

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https://doi.org/10.18167/DVN1/P7OLAP

Experimental Settings

We adopt several UDA competing methods :

- **DANN** [1] (the base method on which spADANN is built on
- **ADDA** (Adversarial Discriminative Domain Adaptation) [2]
- **GFK** (Geodesic Flow Kernel) method [3]. This approach align source/target domain supplying a new data representation. Successively, we couple it with standard classifiers (RF, MLP) obtaining **GFK-RF** and **GFK-MLP**

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Additionally, we consider two baseline (supervised) scenarios:

- A supervised classifier **trained on source data** and **deployed on target data**
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In both cases we use RF and TempCNN as supervised baseline classifiers.

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Methods are evaluated by means of the **Accuracy/F1-score** on the target data

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Results - Overall Accuracy

Scenario	Method	2018 → 2020	2018 → 2021	2020 → 2021
Only $\mathcal{D}_s$	TempCNN	60.7	52.0	57.9
	RF	65.7	59.6	66.6
UDA	GFK-MLP	57.4	52.6	52.2
	GFK-RF	66.2	61.0	68.5
	ADDA	69.3	65.1	69.7
	DANN	71.9	70.7	72.4
	SpADANN	**76.5**	**80.9**	**81.0**
Only $\mathcal{D}_t$	TempCNN	77.8	72.0	72.0
	RF	78.0	74.2	74.2

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	SpADANN	**76.5**	**80.9**	**81.0**
Only $\mathcal{D}_t$	TempCNN	77.8	72.0	72.0
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SpADANN obtains:

- The **best scores** among the UDA competitors;
- Clear advantages w.r.t. the DANN approach (on which SpADANN is based on);
- Results **closer** or better than Only Target approaches;
- When target domain = 2021, it **outperforms the Only Target approaches** (we are still investigating what is happening).

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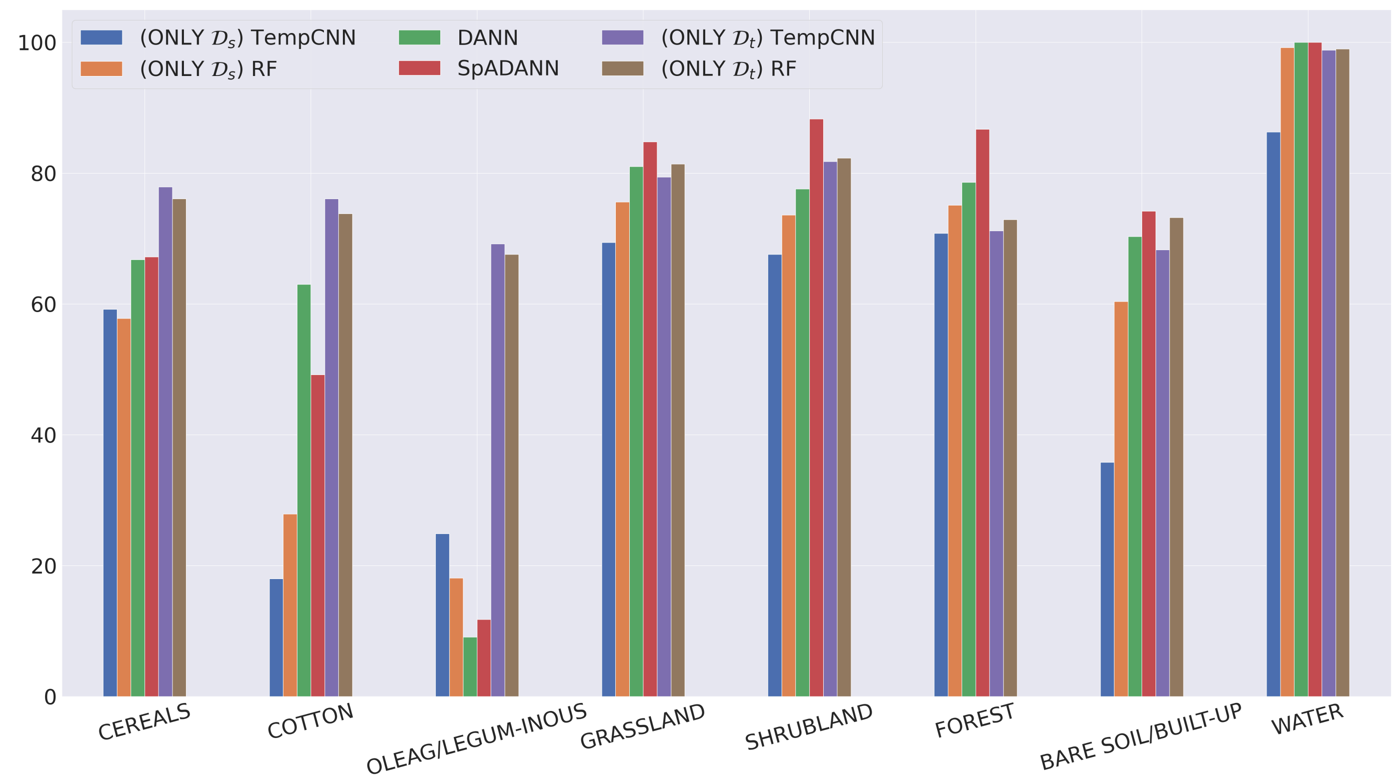
Results - F1-score per Class



D_s=2018 ; D_t = 2020

SpADANN **well transfers on non-agricultural classes**;

In this task it has **troubles to perform transfer on agri classes**, in particular on Oleaginous;

Some explanations are related to **class imbalance** and **cloud cover** in the source domain.

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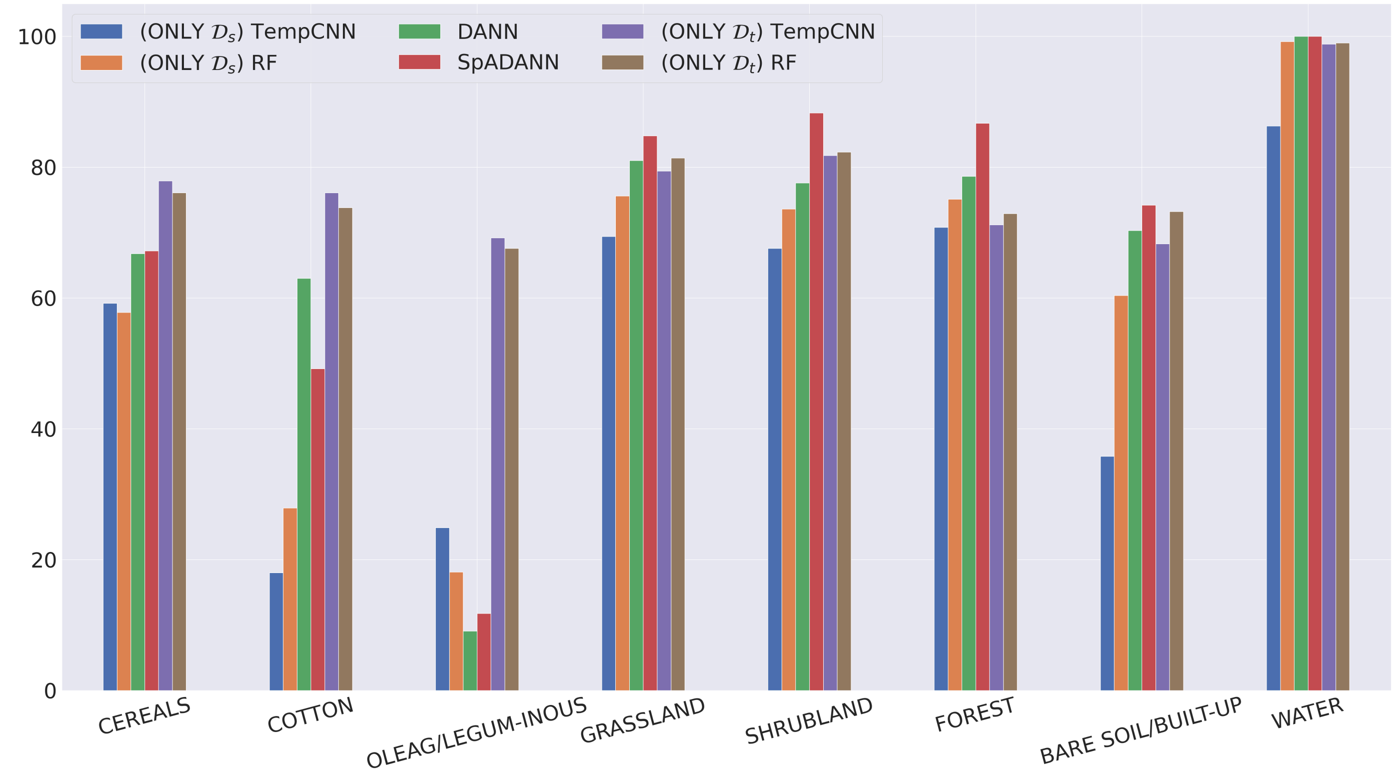

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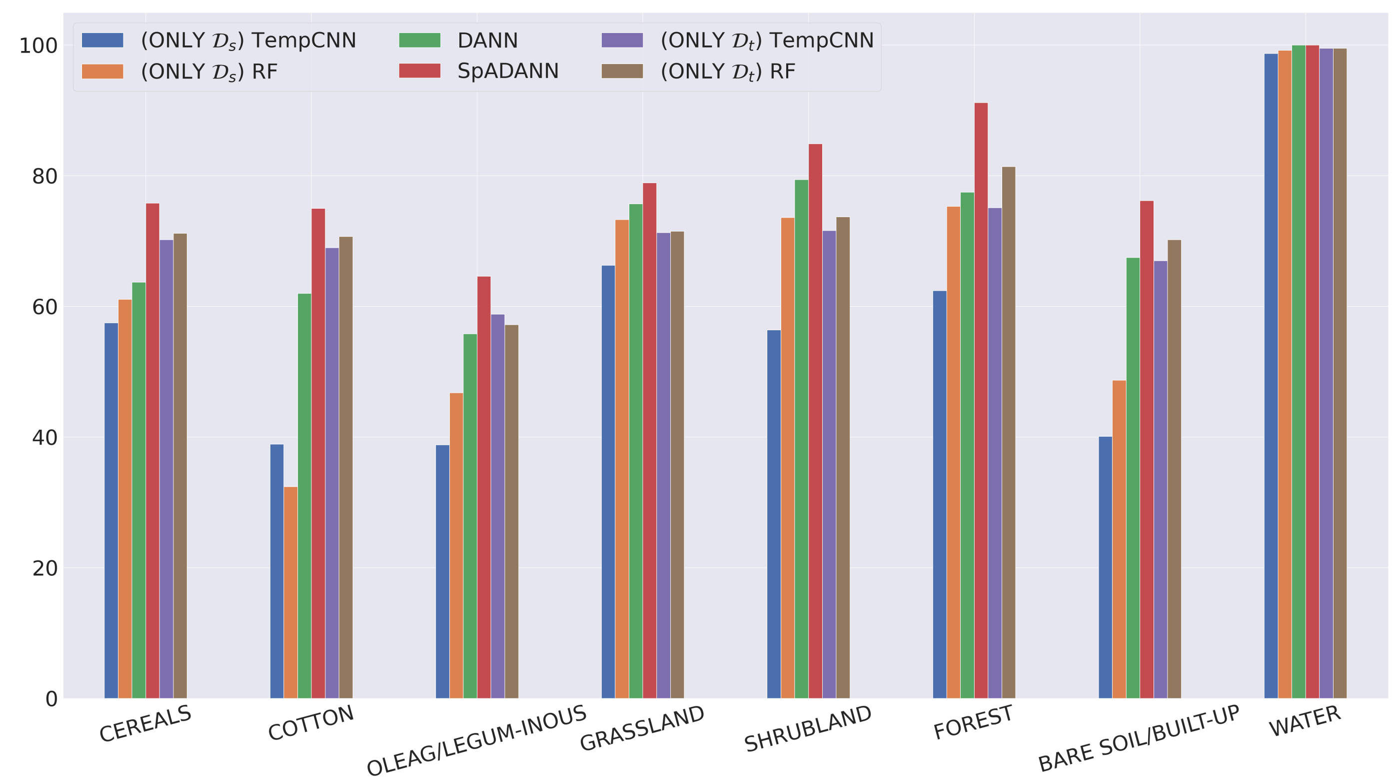
D_s=2020 ; D_t = 2021

SpADANN well transfers on all classes;

Probably **Source and Target** domains are more **related**;

The transfer heavily depends from the source/target pair (Not all transfers are equal)



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UDA techniques **seem appropriate** to cope with temporal transfer for LULC mapping

Exploiting **spatial information** to perform temporal transfer **matters**

Preliminary results associated to SpADANN are encouraging

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Perspectives

Finalize the **experimental evaluation** (Confusion matrices, ablations, sensitivity analysis)

Characterize more precisely **what happens** during transfer

Extend the evaluation on other study sites with different characteristics

The ongoing evaluation will pave the way to **new questions** …

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Thank You for your attention

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Questions