Land cover mapping from Satellite Images Time Series with Deep Learning approaches

Dino Ienco, PhD, HDR
INRAE Researcher @UMR TETIS
dino.ienco@inrae.fr

Joint collaboration with:
- Alessandro Michele Censi (INRAE)
- Yawogan Jean-Eudes Gbodjo (INRAE)
- Raffaele Gaetano (CIRAD)
- Roberto Interdonato (CIRAD)

Outline

Context

SITS and Object-based Image Analysis

Reunion Island Case Study

TASSEL: Manage intra-object heterogeneity for SITS analysis

STARCANE: How much spatial context matters for SITS analysis

Conclusions

Context

In relation to **Sustainable Development Goal** 2:

End hunger, achieve food security and improved nutrition and promote sustainable agriculture

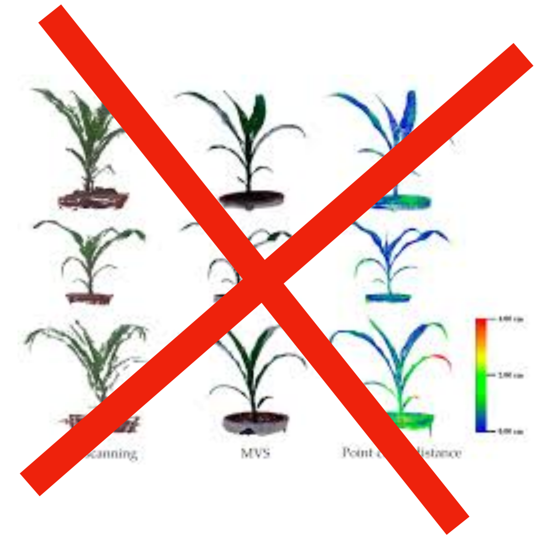
Improve agricultural monitoring systems is one of the way to promote sustainable agriculture

The target 2.4 is especially dedicated to increase agricultural production in a sustainable way (land, water, natural resources, etc…)

https://sustainabledevelopment.un.org/?menu=1300

Context

While precise and in situ information, in the context of agricultural monitoring, demands dedicated tools and investments, nowadays, Earth Observation (EO) Data are easily accessible and provide information at large and medium scale .



Context

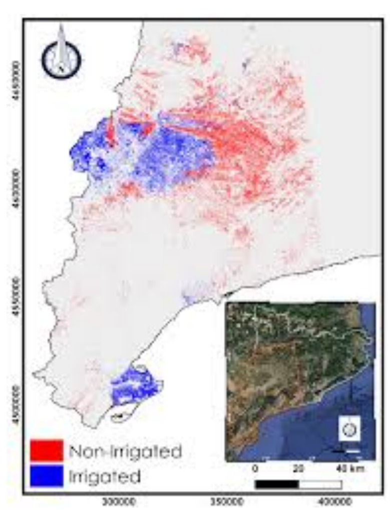
While precise and in situ information, in the context of agricultural monitoring, demands dedicated tools and investments, nowadays, Earth Observation (EO) Data are easily accessible and provide information at large and medium scale .

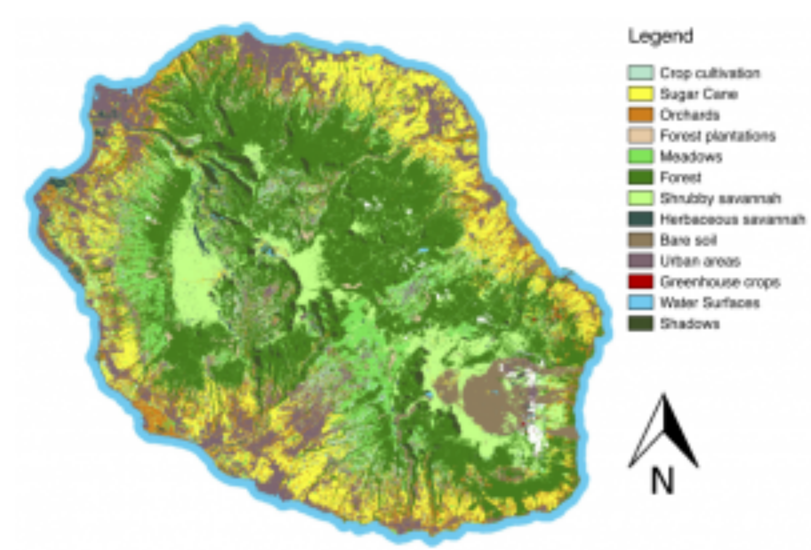
Medium and large scale can support:

- “Where/When and How grow” questions
- Public policies and private actions

Quantifying:

- Land utilisation
- Cropping intensity
- Crop production
- Resources





Context

Nowadays, many earth observation satellite missions exist:

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

Acquired images have different:

- spatial resolution (0.5 – 30 meters)
- radiometric content (spectral bands)
- temporal resolution (every 5 – 365 days)

HUGE quantity of Satellite Images Describing Earth Phenomena at different scales

Satellite Image Time Series

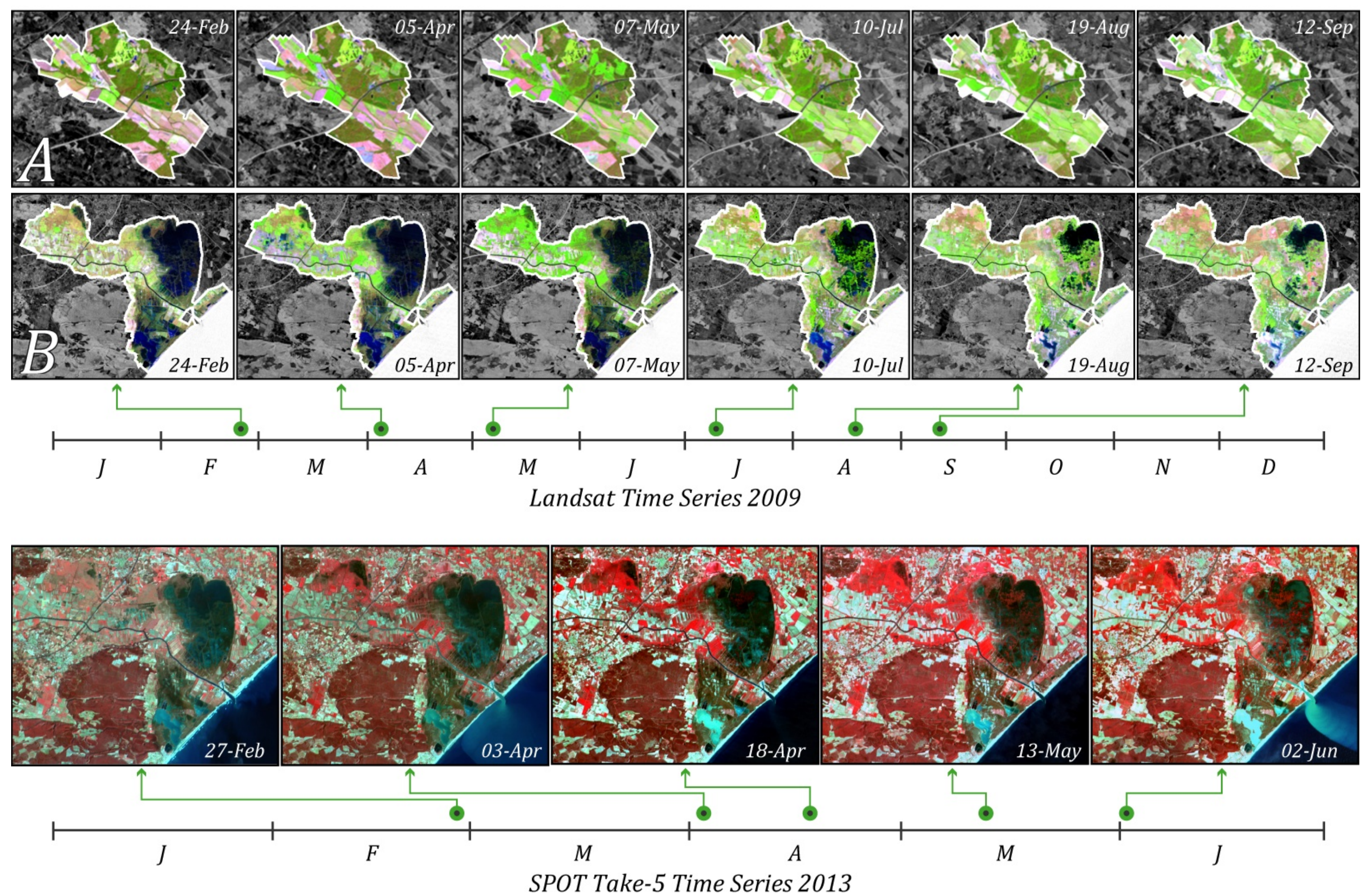
Among all the opportunities, the possibility to collect **multiple satellite images** (SITS: Satellite Image Time Series), **on the same area**, with **high revisit period** and **high spatial resolution** is paving the way to new applications (especially in agricultural land monitoring)

Satellite Image Time Series

Among all the opportunities, 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)

In the context of agriculture:

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



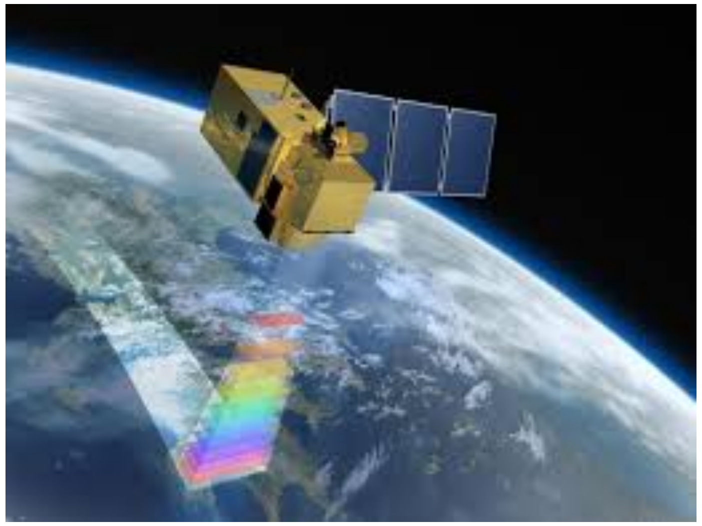
Satellite Image Time Series

Sentinel Missions belong to the **Copernicus Programme**

Copernicus Programme is provided by the **ESA** (European Space Agency)

Provide Remote Sensing data at **High Spatial/Temporal Resolution** of the **Earth**

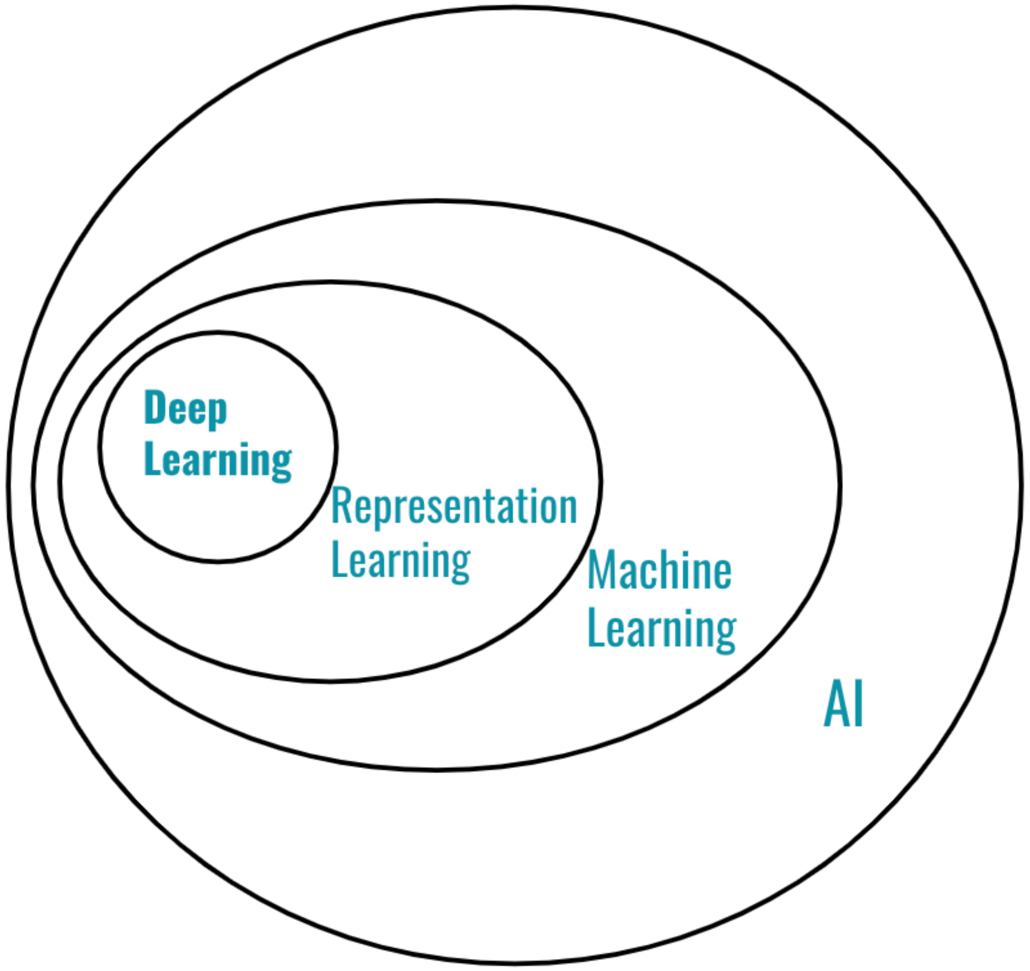
Different kind of sensors for different uses:
Sentinel-1, Sentinel-2, Sentinel-3, …

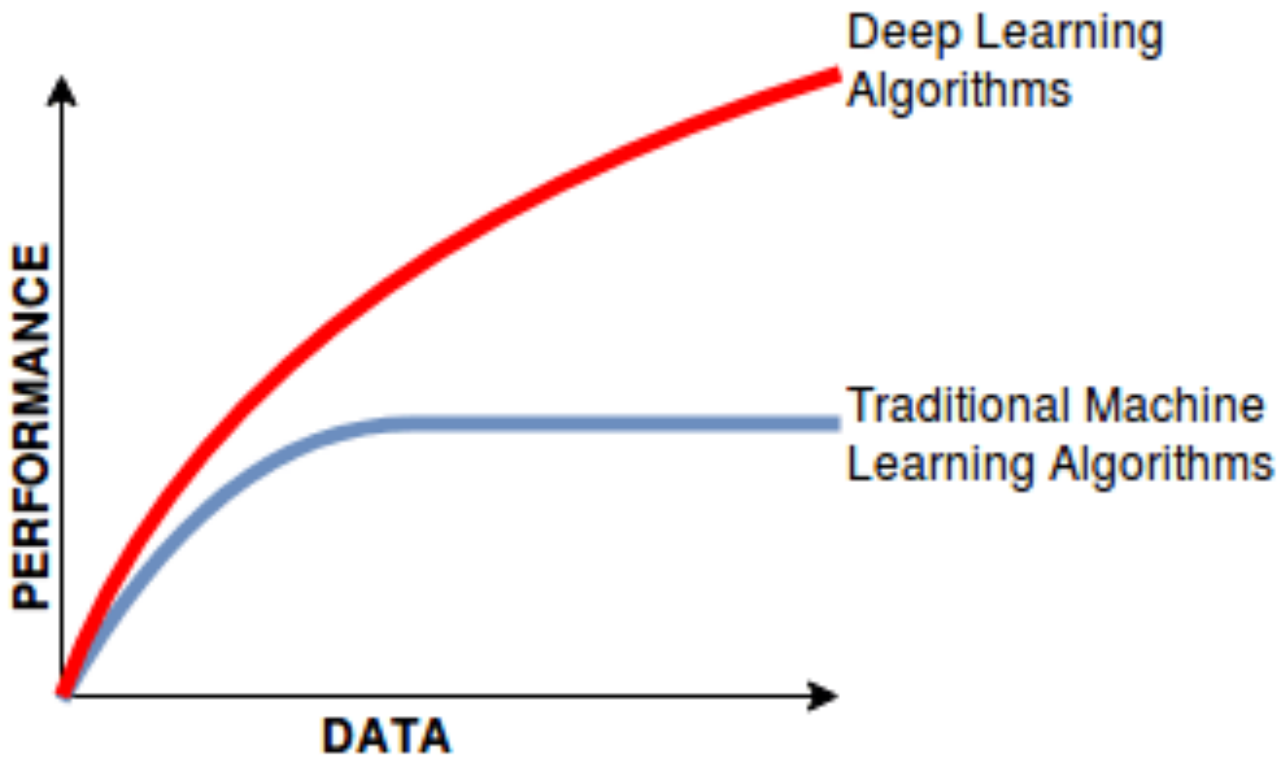


Sentinel 2: two satellites placed in the same sun-synchronous orbit supplying optical information with a revisit time period between 10 and 5 days till January 2016

Machine Learning

- Increasing application of Machine Learning approaches on signal data
- Deep Learning, Neural Networks
- Deep Learning is a subfield of Machine Learning





Source: Blog Datacamp

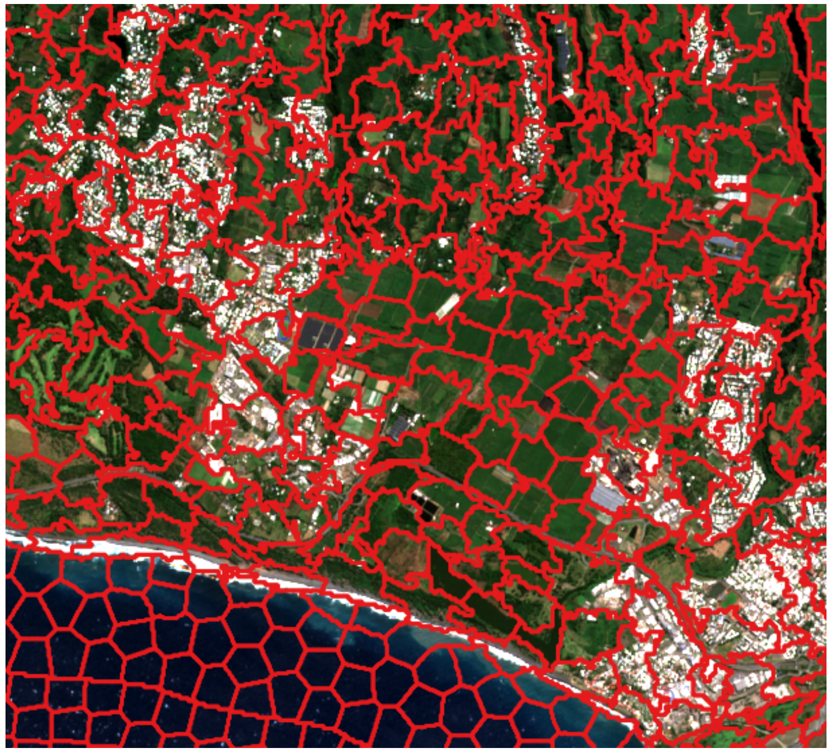
Pixel vs. Object analysis

When working on Earth Observation data, two different level of granularity:

- Pixel: the base unit of image analysis
- Object: group of pixel (land unit) with an high level of semantic
    - Needs of a preprocessing step to extract object (segmentation)

Pixel

Object



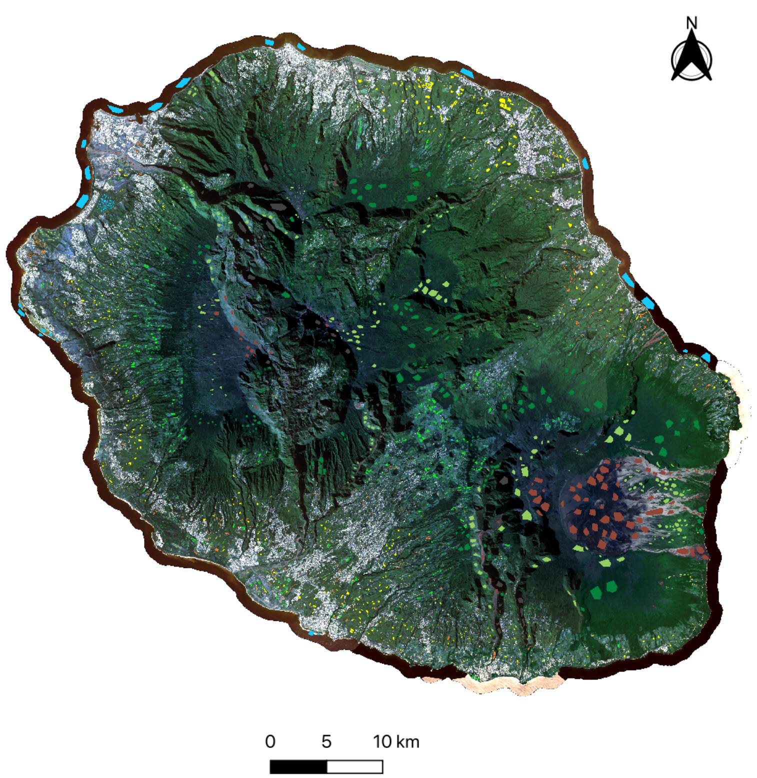
Land cover mapping task

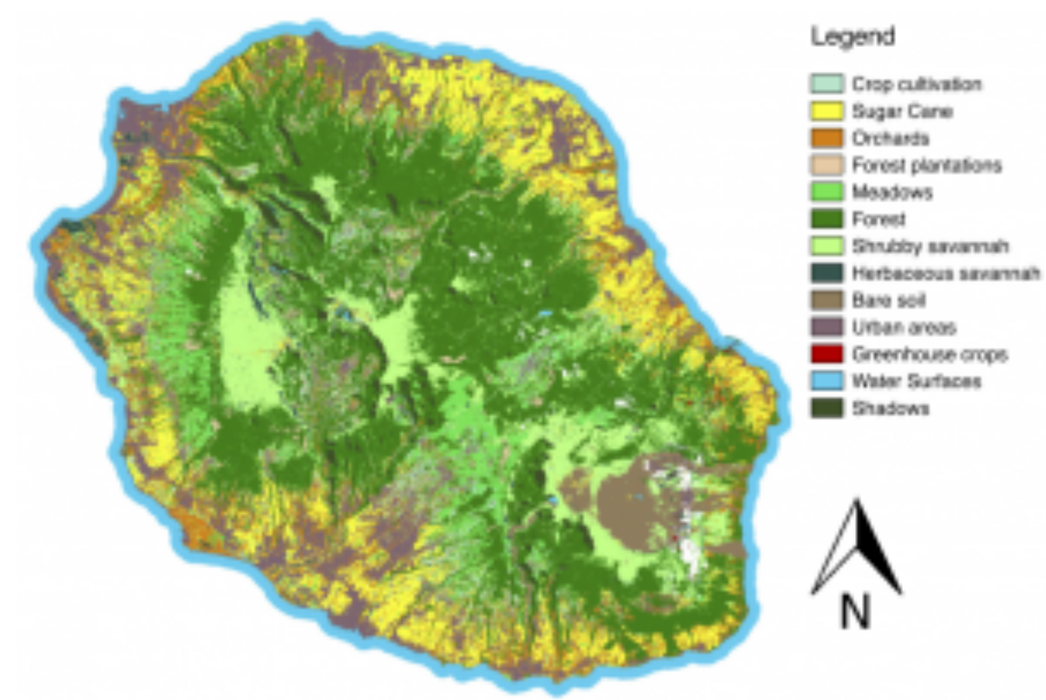
Task:

Given EO data + a limited number of reference data, the goal is to map each pixel (or object) to the corresponding land cover class

Common approach:

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





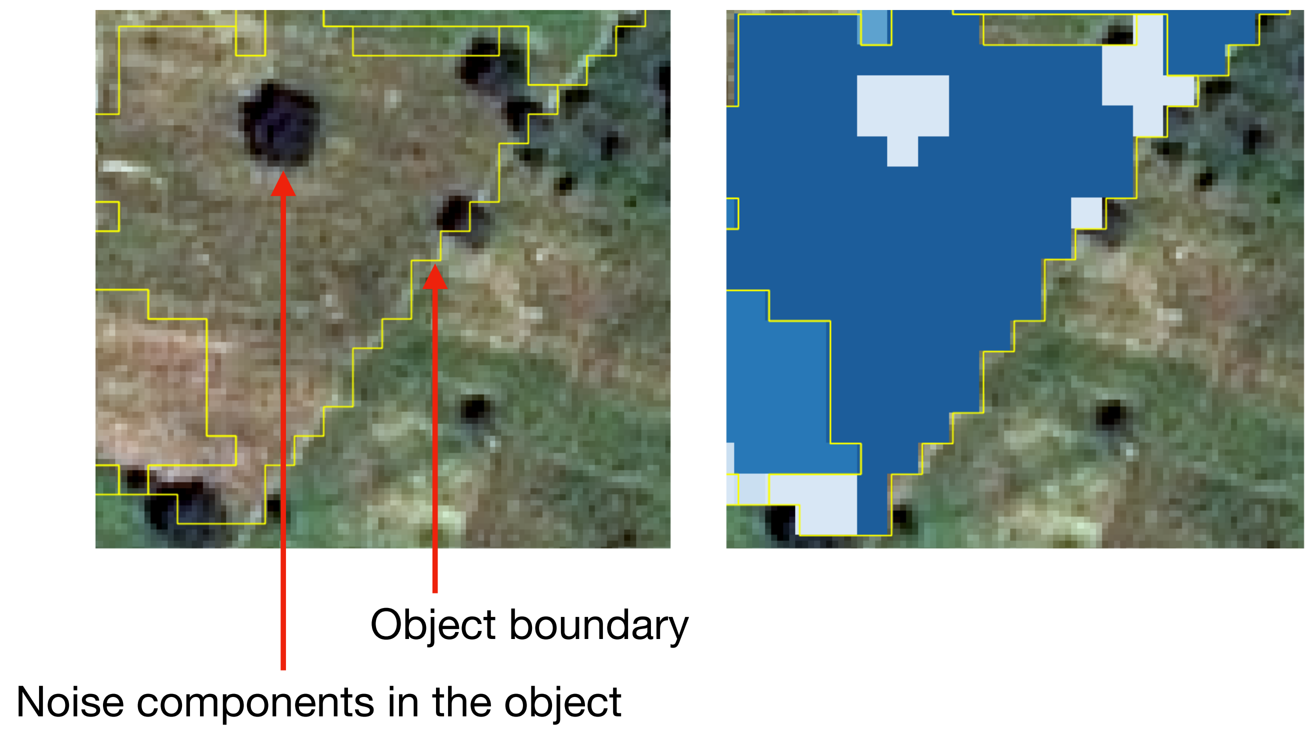
Two methodological points in object-based land cover mapping

An **Object** should be homogeneous group of pixels but it can:

- Represent complex land unit (i.e. urban areas: built-up, garden, street, etc…)
- Be approximate or contain noise components that are unrelated with the major land cover class

Problem (1): intra-object heterogeneity

Agricultural Field

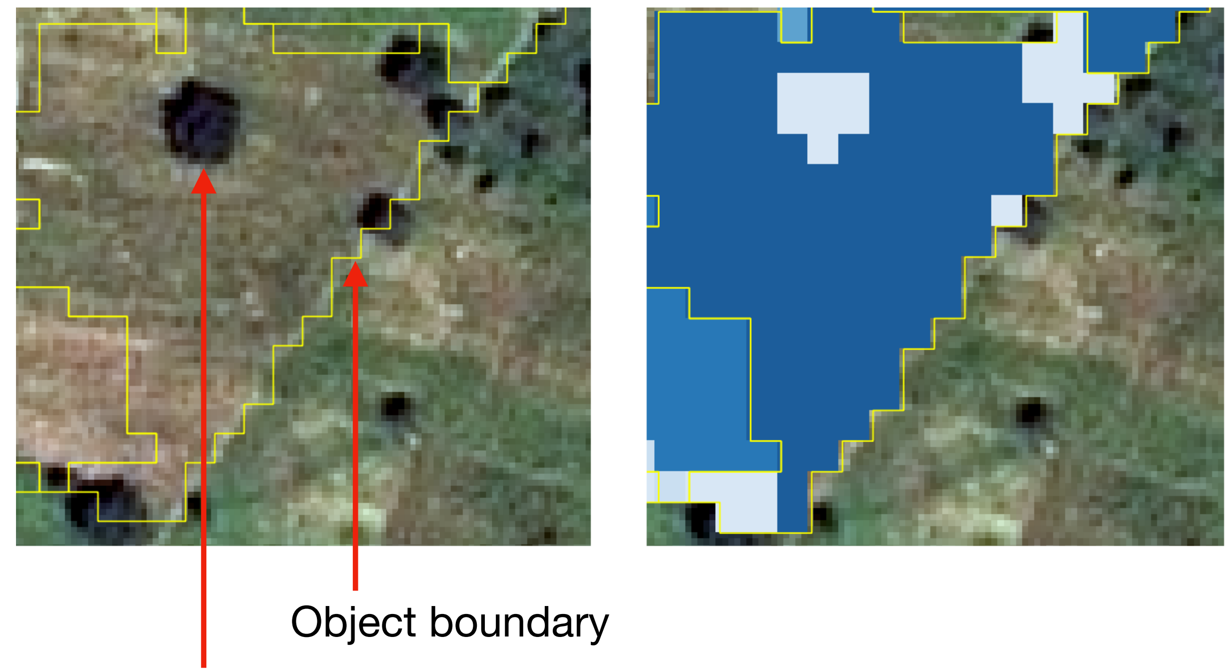


Two methodological points in object-based land cover mapping

An **Object** should be homogeneous group of pixels but it can:

- Represent complex land unit (i.e. urban areas: built-up, garden, street, etc…)
- Be approximate or contain noise components that are unrelated with the major land cover class

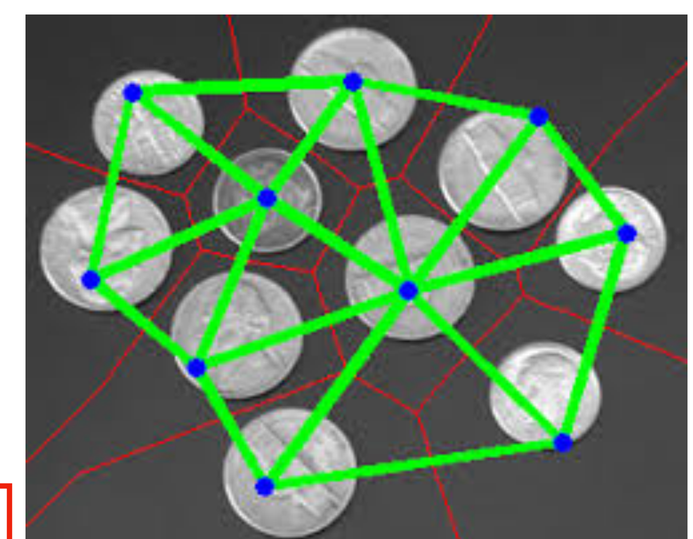
Agricultural Field



Problem (1): intra-object heterogeneity

An **Object** is embedded in a landscape (spatial context):

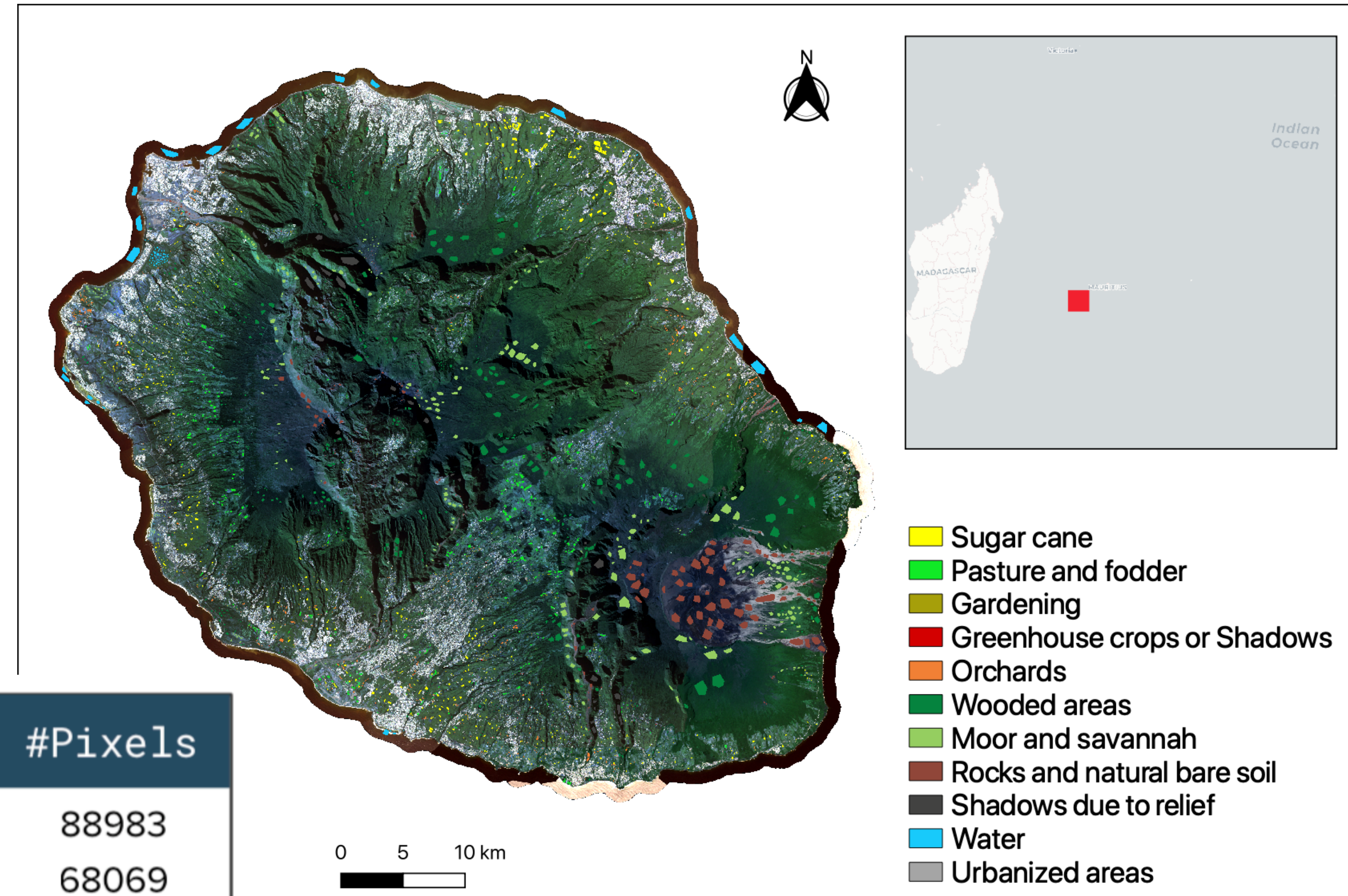
- It is usually neglected
- Difficult to manage due to the irregular neighbourhood (different number of neighbour segments)



Problem (2): How to integrate the spatial context

Reunion Island case study

Surface: around 3000km²
Sentinel-2: 21 images
Image size: 6656 x 5913
Bands: 6
LC classes: 11
Amount of data: 19Gb



Class	Label	#Polygons	#Objects	#Pixels
0	Sugar Cane	869	1466	88983
1	Pasture and fodder	582	1042	68069
2	Market Gardening	758	1038	17574
3	Green. Crops	260	308	1928
4	Orchards	767	1174	33694
5	Wooded areas	570	1467	205050
6	Moor and Savannah	506	1172	155229
7	Rocks and bare soil	299	845	154283
8	Relief shadows	81	248	54308
9	Water	177	458	82547
10	Urbanized areas	1396	1360	19004
Total		**6265**	**10578**	**880669**

TASSEL

Does intra-object variability/heterogeneity affect Satellite Image Time Series based land cover mapping?

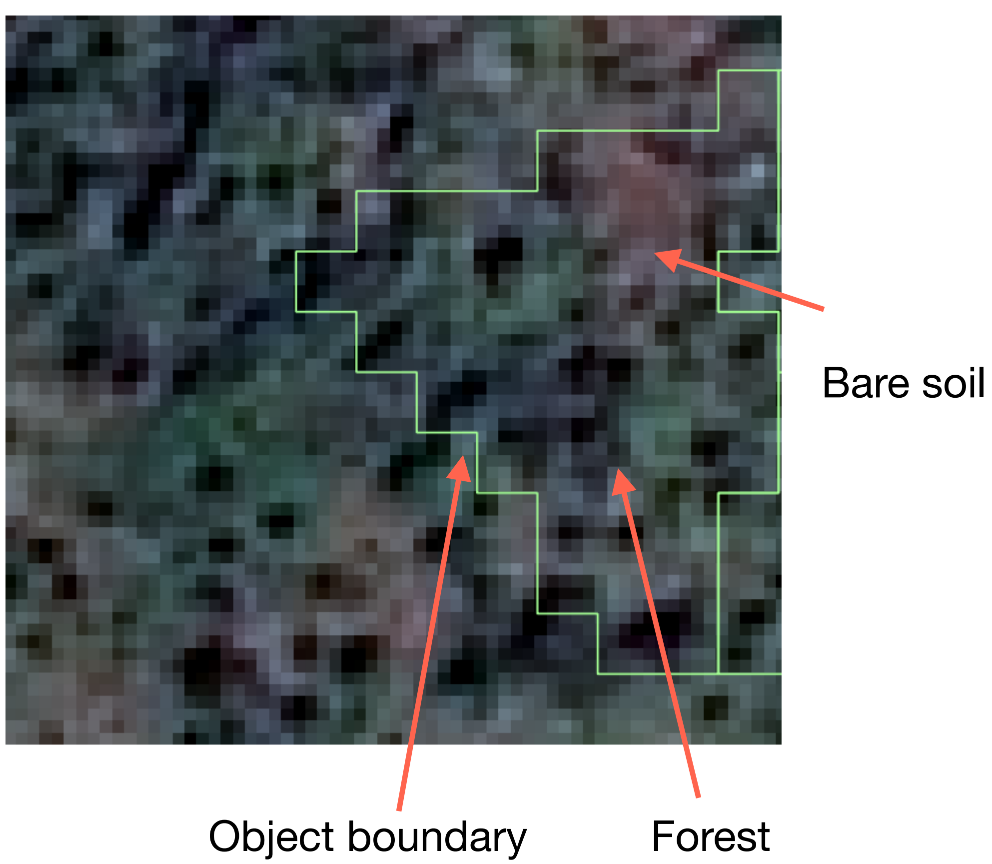
Introduction

Explicitly take into account:

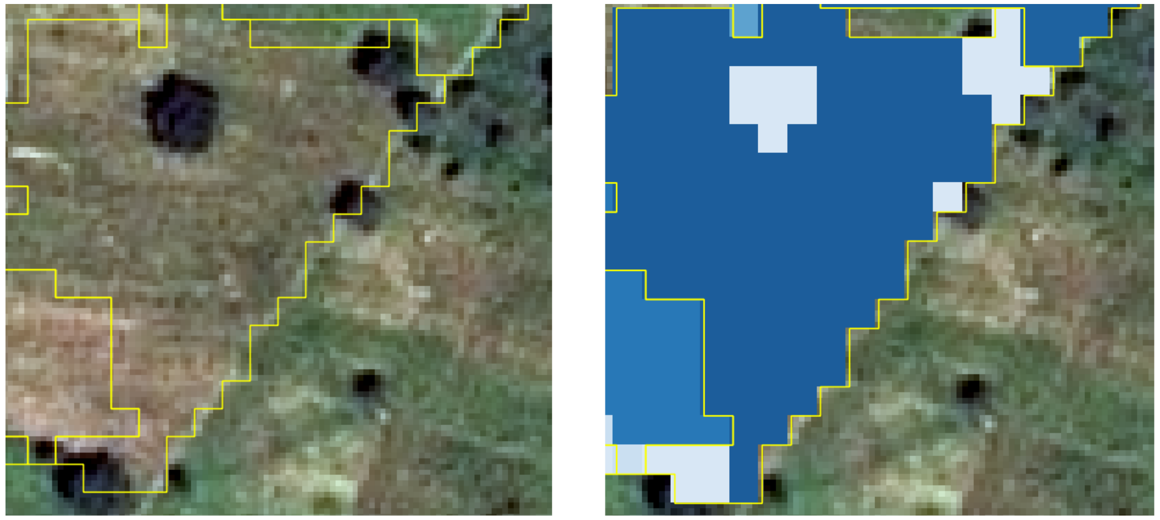
- The intra-object heterogeneity
- Problem related to approximate or inexact annotation
- Land-unit involving multifaceted information

Manage object as a set of components

Forest Object



Crop Object



Component contribution to the final decision

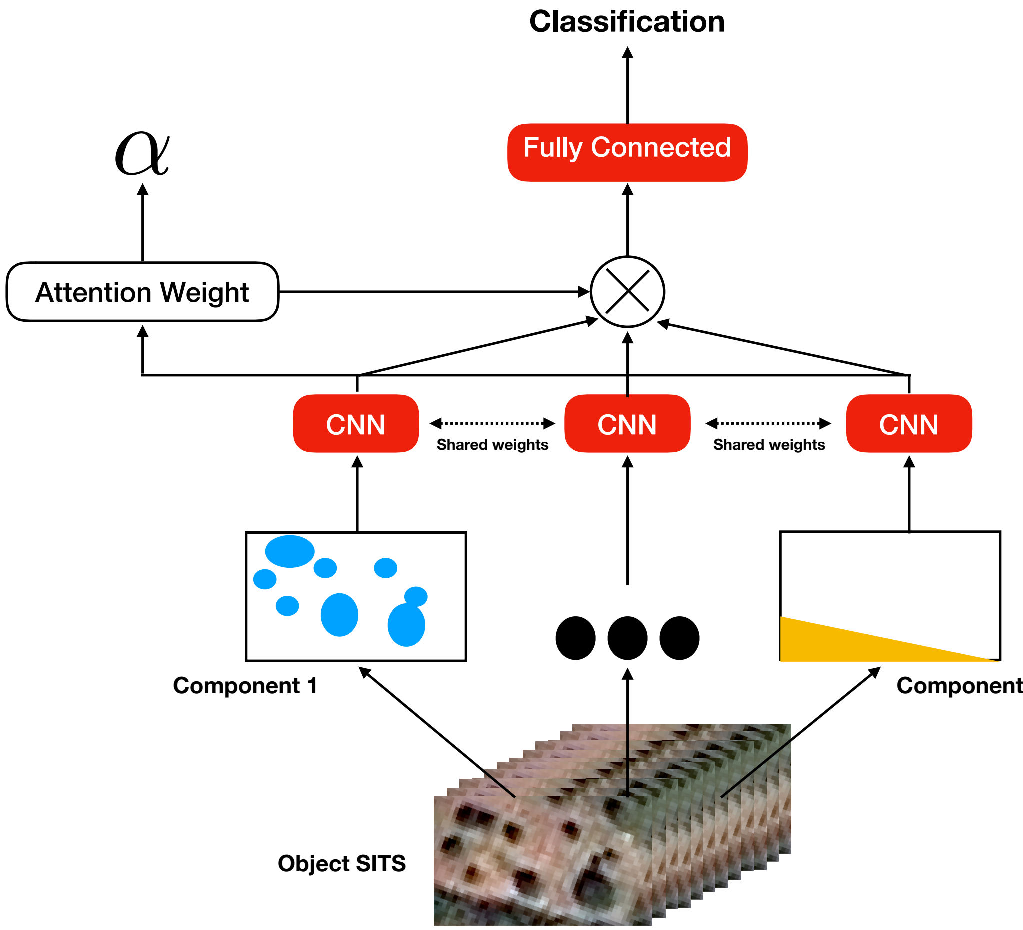
TASSEL

How to manage intra-object heterogeneity

Method

Method Description

- Identify components for each object (K-means)
- Use Convolutional Neural Networks (CNN1D) to manage per-component information
- Aggregate per-component representation to take the final decision

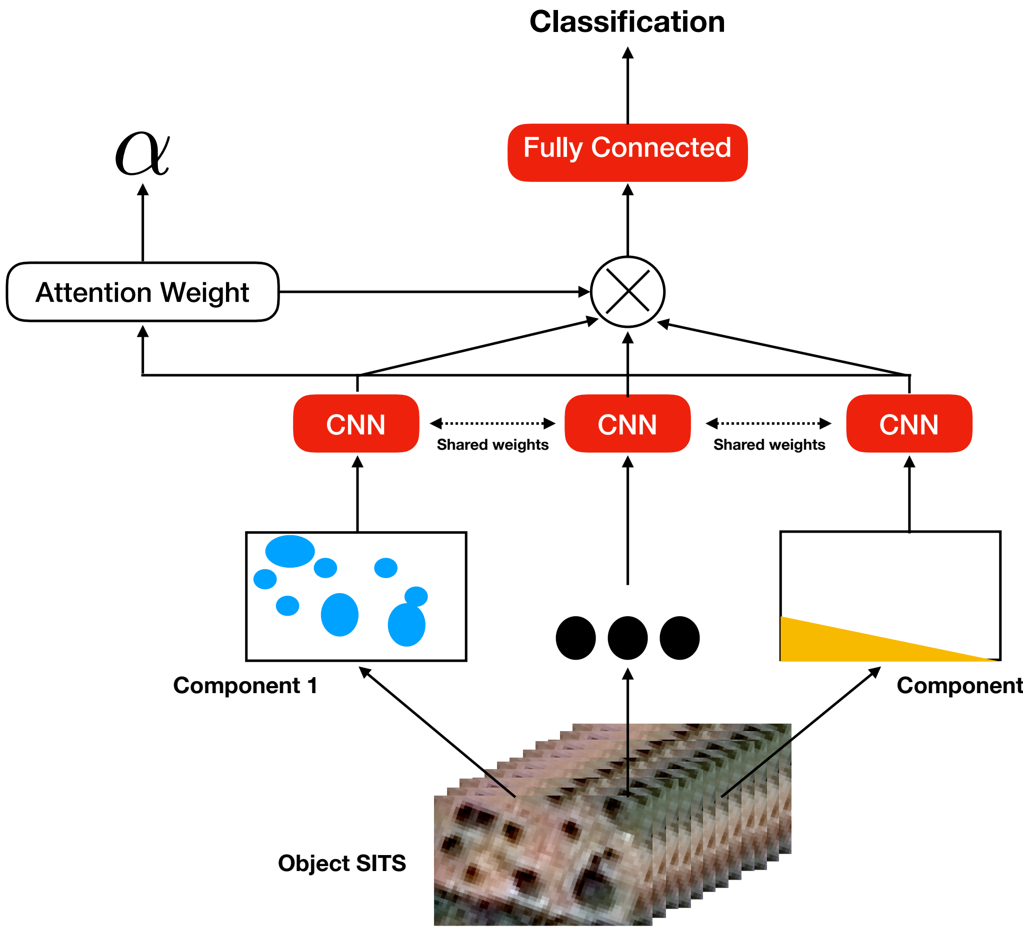


TASSEL
How to manage intra-object heterogeneity

Method

Method Description

- Identify components for each object (K-means)
- Use Convolutional Neural Networks (CNN1D) to manage per-component information
- Aggregate per-component representation to take the final decision



The output of TASSEL is twofold:

- A **classification** for each object Satellite Image Time Series
- An **attention weight** in the range [0,1] associated to each component that can be interpreted as the contribution of that component to the decision process

TASSEL

How to manage intra-object heterogeneity

Results

Experimental Settings:

- We compare TASSEL w.r.t. standard competitors: RF, LSTM, MLP, CNN
- We employ standard evaluation measures: F1-score, Kappa and Accuracy
- We divided the dataset in training/validation/test (50%/30%/20%) and repeat 5 times

Results

Experimental Settings:

- We compare TASSEL w.r.t. standard competitors: RF, LSTM, MLP, CNN
- We employ standard evaluation measures: F1-score, Kappa and Accuracy
- We divided the dataset in training/validation/test (50%/30%/20%) and repeat 5 times

Competitors work **on the average object representation** without considering object components

	F1 Score	*Kappa*	*Accuracy*
RF	81.74 ± 0.47	0.7991 ± 0.0052	82.13 ± 0.46
LSTM	82.91 ± 0.66	0.8098 ± 0.0078	83.06 ± 0.69
MLP	85.81 ± 0.60	0.8423 ± 0.0074	85.94 ± 0.66
CNN	87.11 ± 0.61	0.8565 ± 0.0068	87.20 ± 0.61
TASSEL	$\mathbf{89.13} \pm 0.62$	$\mathbf{0.8797} \pm 0.0072$	$\mathbf{89.28} \pm 0.63$

TASSEL

How to manage intra-object heterogeneity

Results

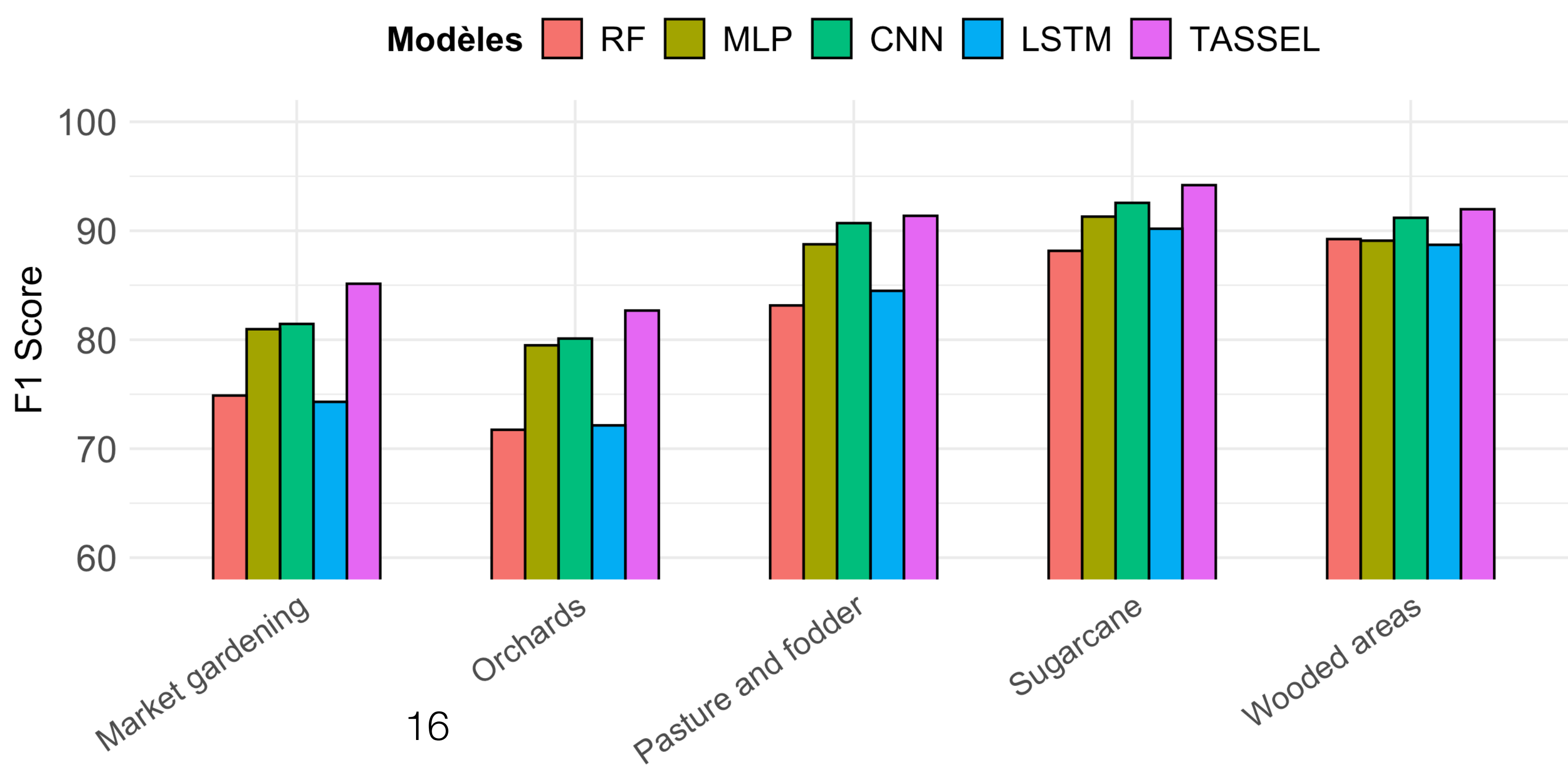
Experimental Settings:

- We compare TASSEL w.r.t. standard competitors: RF, LSTM, MLP, CNN
- We employ standard evaluation measures: F1-score, Kappa and Accuracy
- We divided the dataset in training/validation/test (50%/30%/20%) and repeat 5 times

Competitors work **on the average object representation** without considering object components

	F1 Score	*Kappa*	*Accuracy*
RF	81.74 ± 0.47	0.7991 ± 0.0052	82.13 ± 0.46
LSTM	82.91 ± 0.66	0.8098 ± 0.0078	83.06 ± 0.69
MLP	85.81 ± 0.60	0.8423 ± 0.0074	85.94 ± 0.66
CNN	87.11 ± 0.61	0.8565 ± 0.0068	87.20 ± 0.61
TASSEL	**89.13** ± 0.62	**0.8797** ± 0.0072	**89.28** ± 0.63

We observe relative improvement on all the natural/agricultural classes.

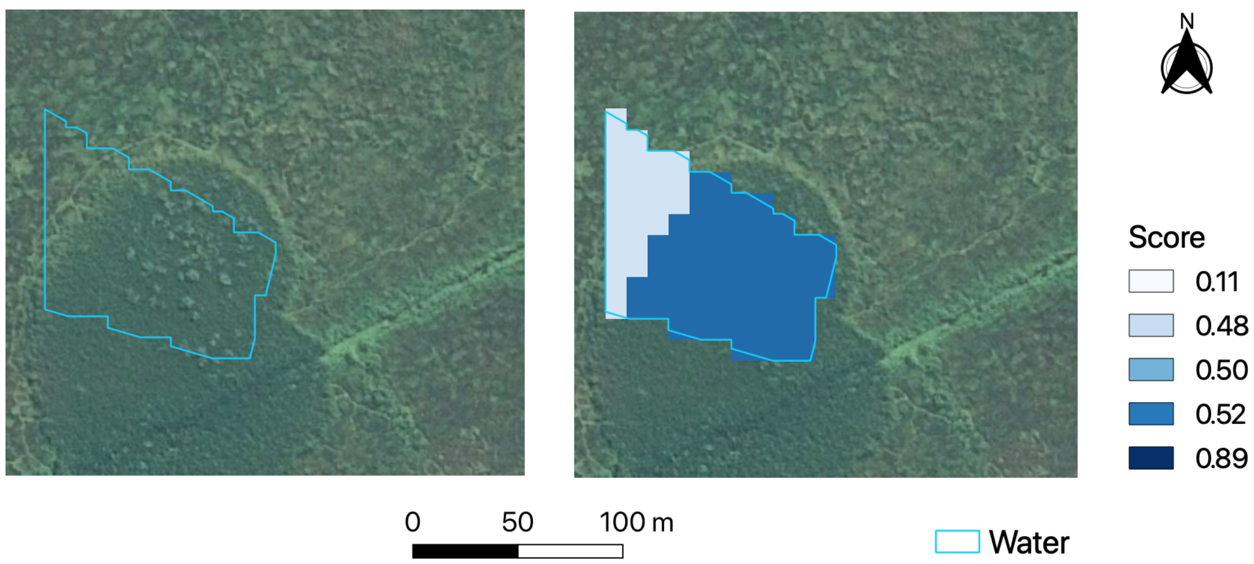


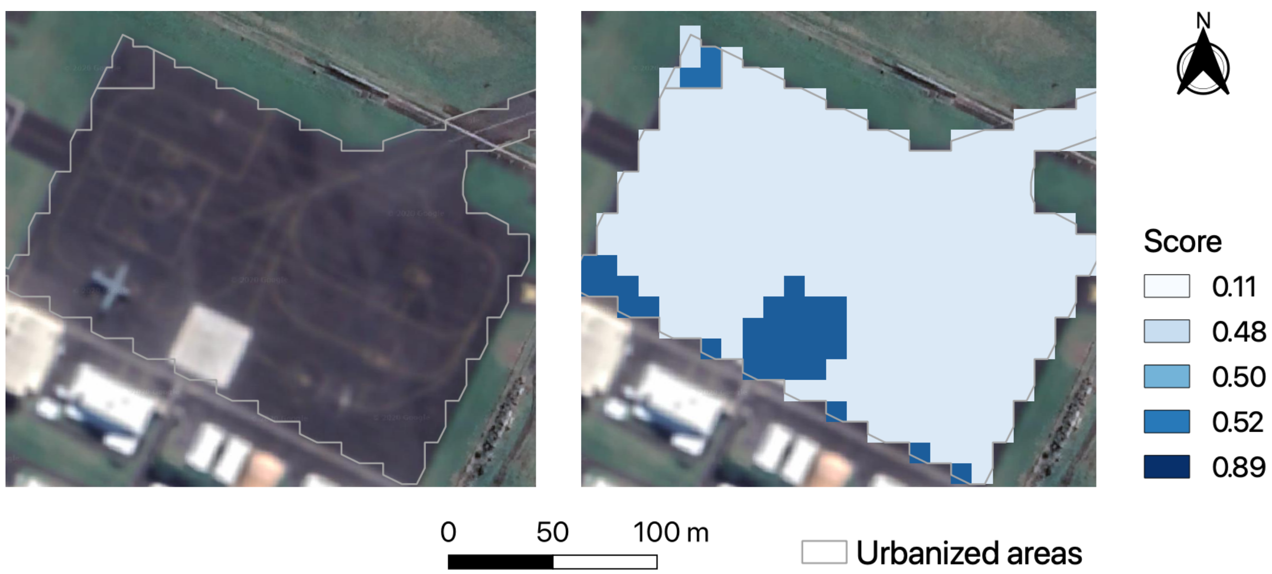
TASSEL

How to manage intra-object heterogeneity

Results

Interpret model decision by attention weight on the object components



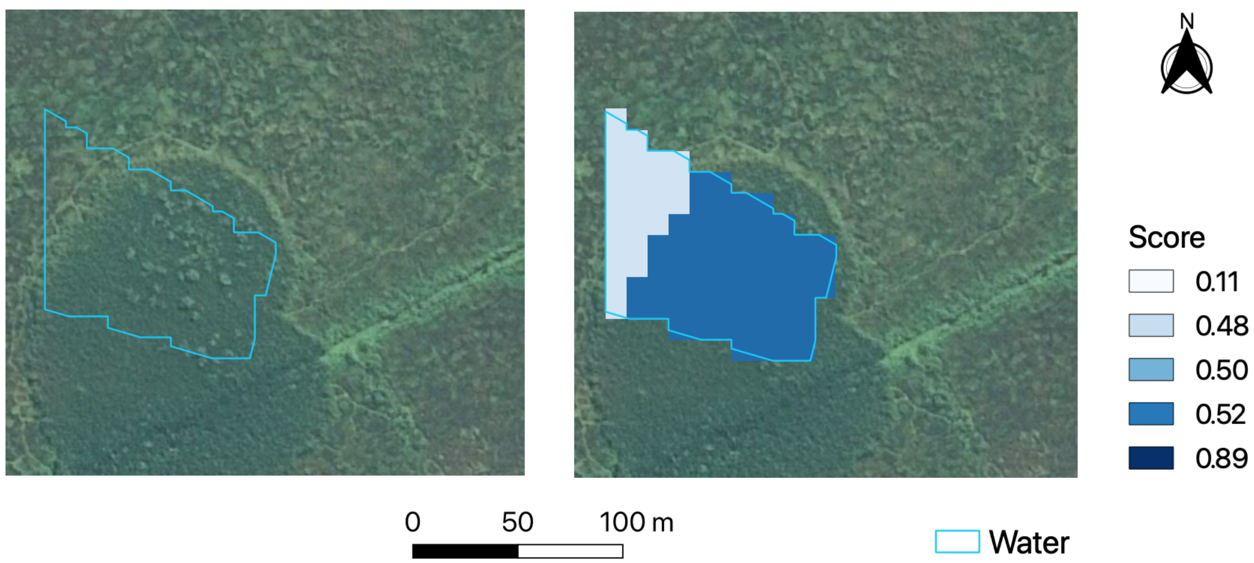


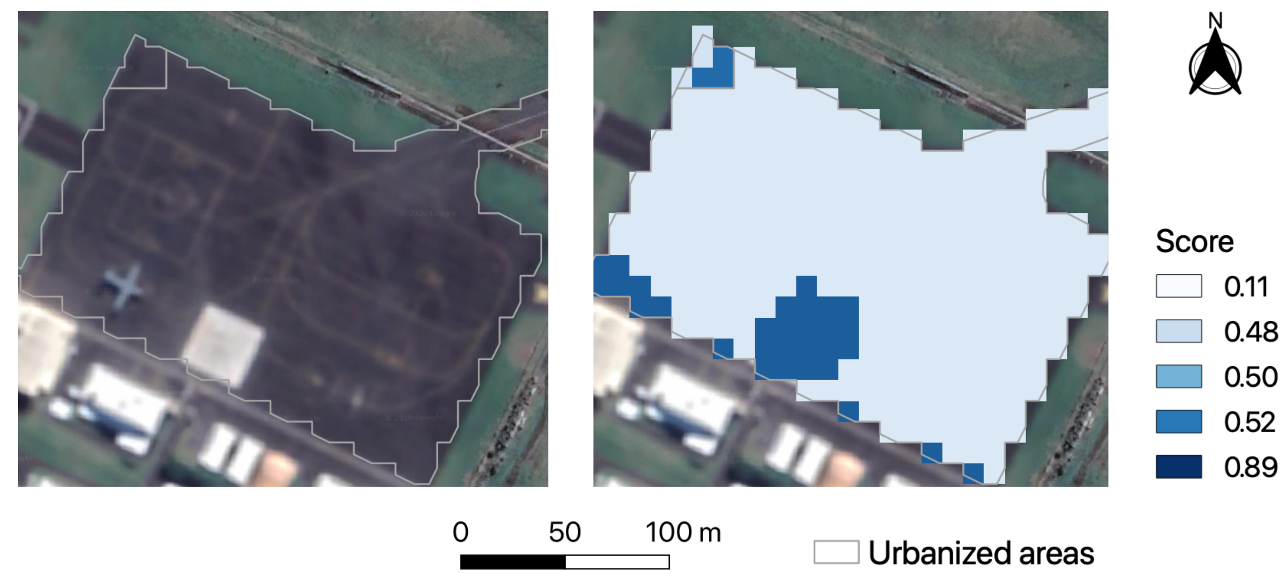
TASSEL

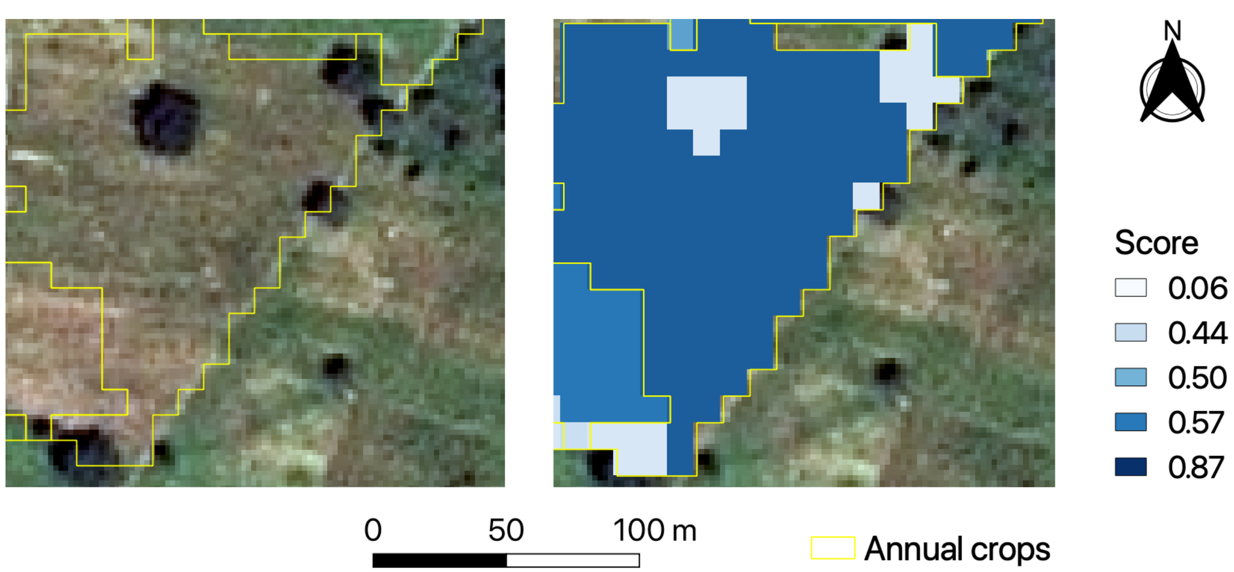
How to manage intra-object heterogeneity

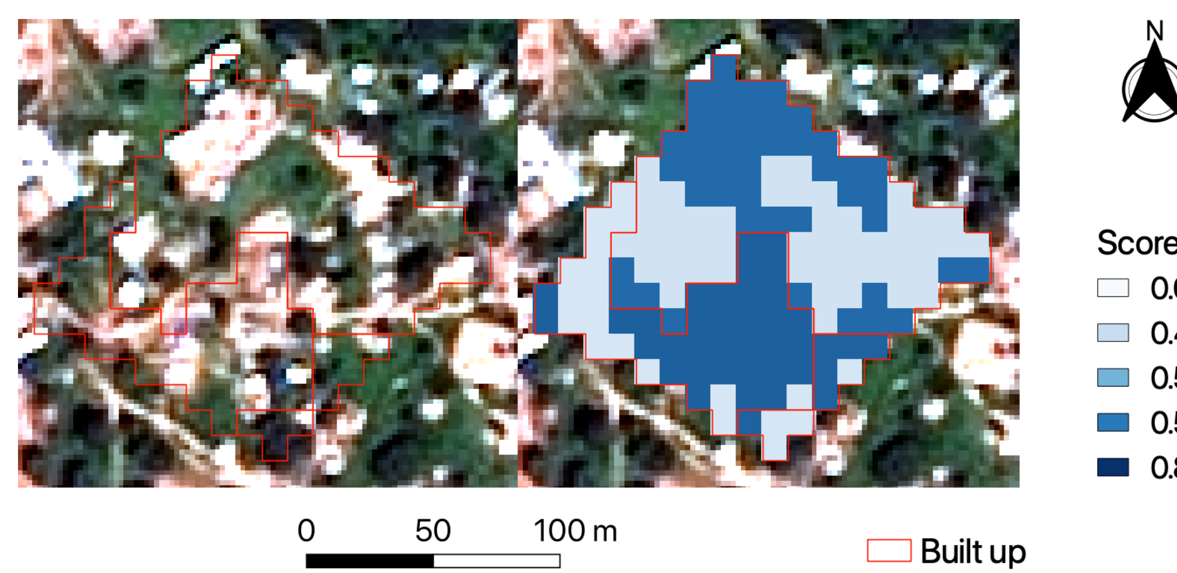
Results

Interpret model decision by attention weight on the object components









Example coming from another study sites (Bourkina Faso)

TASSEL

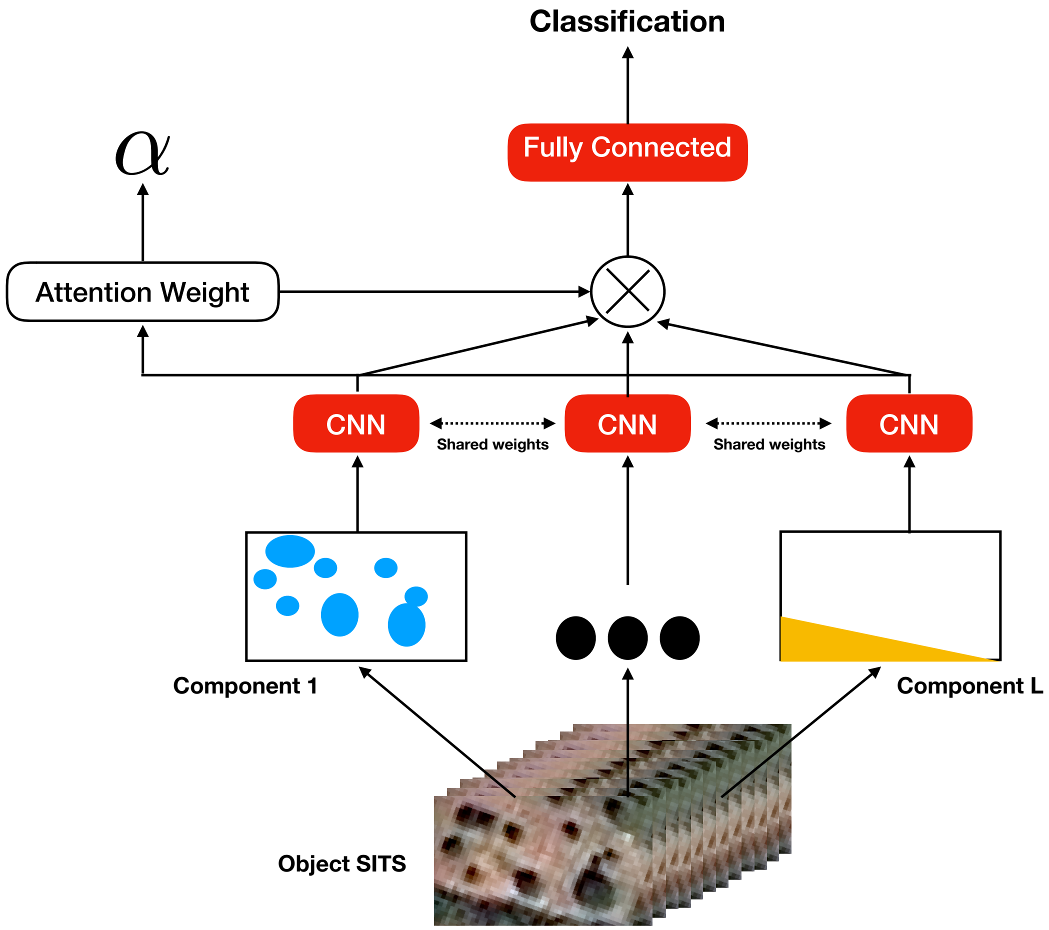
How to manage intra-object heterogeneity

Conclusions

Experimental results support the intuition to **explicitly manage intra-object heterogeneity**

The TASSEL model also supplies **“a kind of” interpretation** about its decision

The main gain are obtained considering **agricultural land cover classes** that exhibits mixed or complex spatial patterns



STARCANE

Does the spatial context matter for land cover mapping via Satellite Image Time Series data?

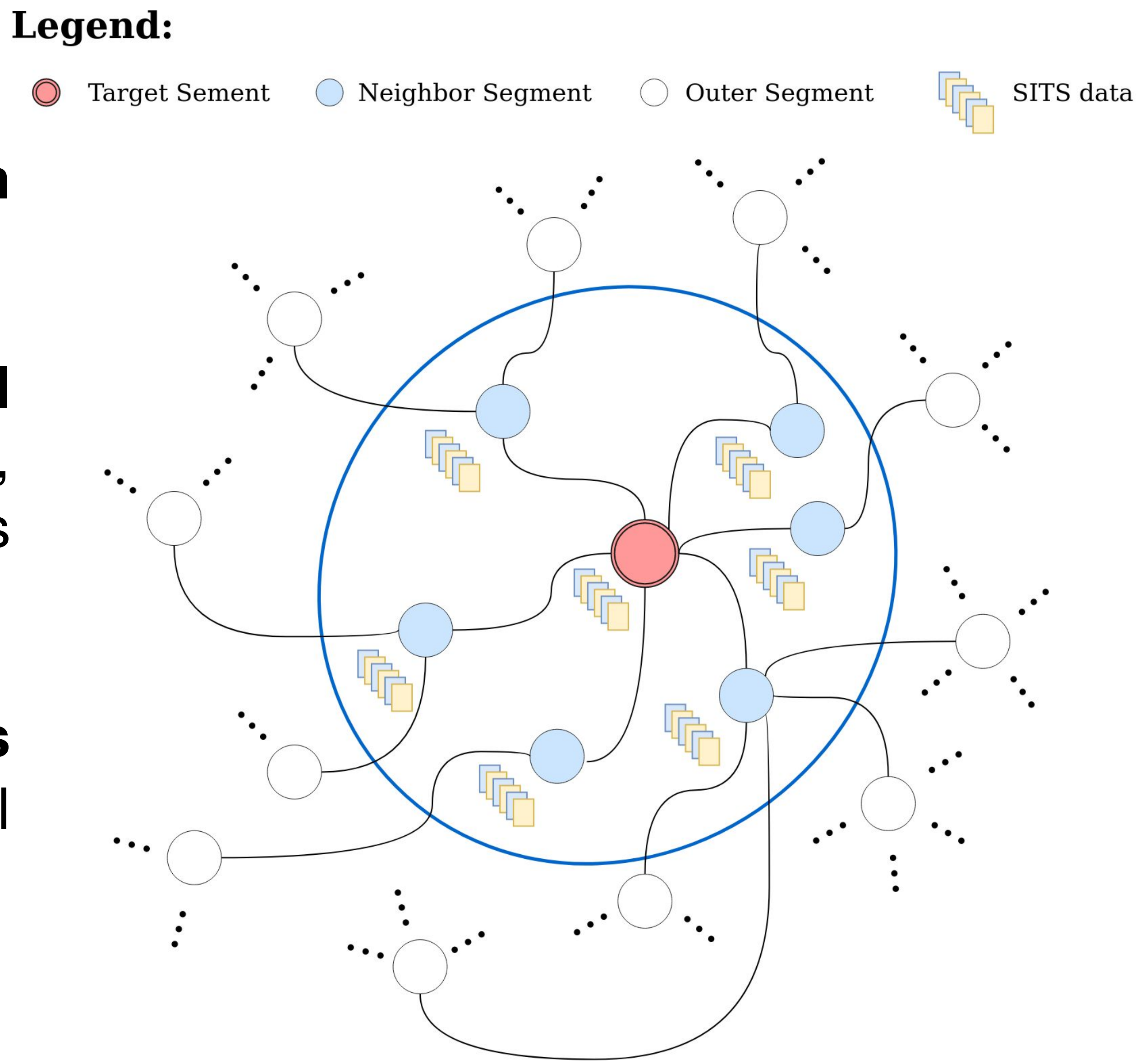
STARCANE

Does spatial context matter?

Integrate the landscape (spatial context) in which an object is embedded

Method Description

- From the segmentation derive a **Region Adjacency Graph**
- **Spatio-Temporal Graph Convolutional Neural Network** to manage, simultaneously, the target SITS object as well as the neigh. SITS objects information
- **Automatically weight** the **neigh. objects contribution** belonging to the spatial context w.r.t. the target node



Work in progress

STARCANE

Does spatial context matter?

Results

We compare STARCANE w.r.t. standard competitors: RF, LSTM, MLP, CNN that not consider spatial context
We employ standard evaluation measures: F1-score, Kappa and Accuracy
We divided the dataset in training/validation/test (50%/30%/20%) and repeat 5 times

STARCANE

Does spatial context matter?

Results

We compare STARCANE w.r.t. standard competitors: RF, LSTM, MLP, CNN that not consider spatial context

We employ standard evaluation measures: F1-score, Kappa and Accuracy

We divided the dataset in training/validation/test (50%/30%/20%) and repeat 5 times

The competing approaches does not (cannot) use the spatial context information

	F1 Score	*Kappa*	*Accuracy*
RF	82.43 ± 0.15	80.65 ± 0.17	82.79 ± 0.15
MLP	80.78 ± 0.53	78.60 ± 0.52	80.96 ± 0.46
CNN	84.40 ± 0.37	82.73 ± 0.45	84.62 ± 0.41
LSTM	83.36 ± 0.57	81.41 ± 0.71	83.44 ± 0.64
STARCANE	$\mathbf{90.50} \pm 0.1$	$\mathbf{89.37} \pm 0.08$	$\mathbf{90.52} \pm 0.08$

STARCANE

Does spatial context matter?

Results

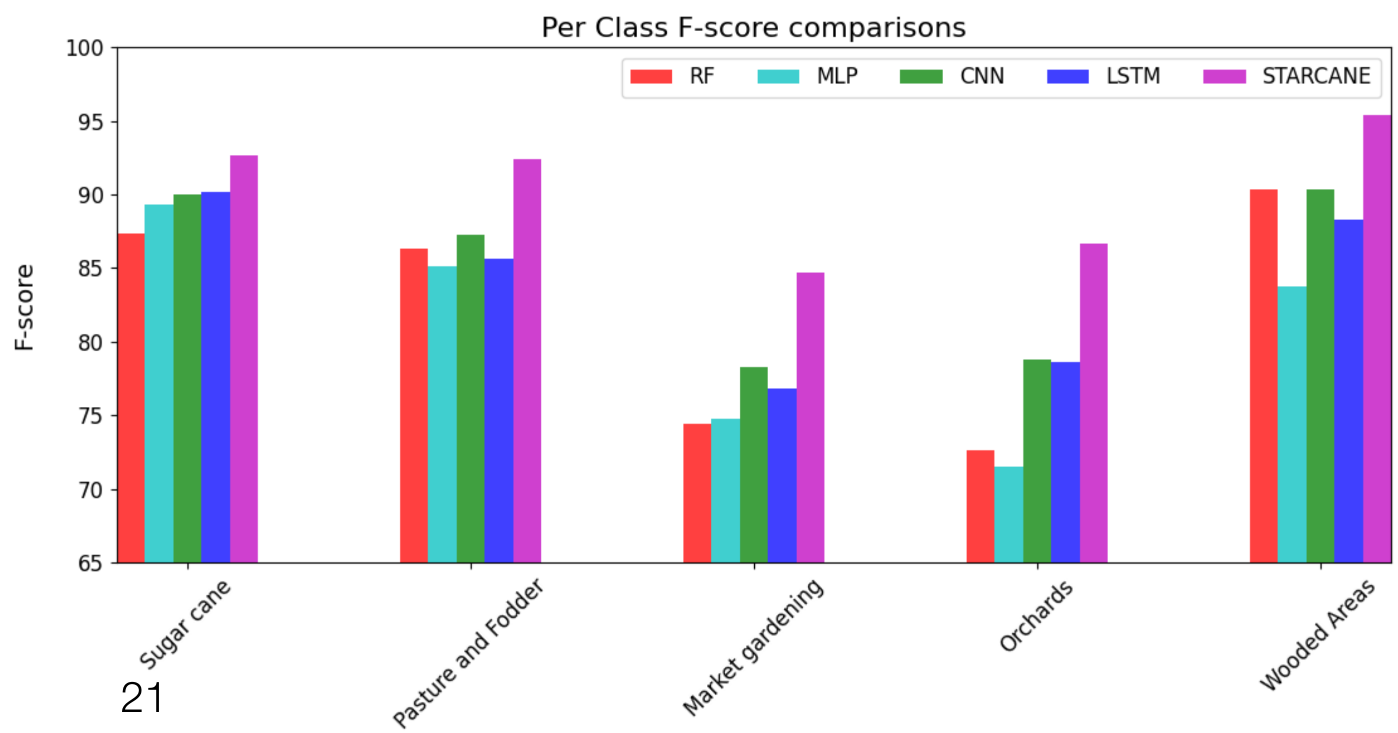
We compare STARCANE w.r.t. standard competitors: RF, LSTM, MLP, CNN that not consider spatial context

We employ standard evaluation measures: F1-score, Kappa and Accuracy

We divided the dataset in training/validation/test (50%/30%/20%) and repeat 5 times

The competing approaches does not (cannot) use the spatial context information

	F1 Score	*Kappa*	*Accuracy*
RF	82.43 ± 0.15	80.65 ± 0.17	82.79 ± 0.15
MLP	80.78 ± 0.53	78.60 ± 0.52	80.96 ± 0.46
CNN	84.40 ± 0.37	82.73 ± 0.45	84.62 ± 0.41
LSTM	83.36 ± 0.57	81.41 ± 0.71	83.44 ± 0.64
STARCANE	**90.50** ± 0.1	**89.37** ± 0.08	**90.52** ± 0.08



STARCANE

Does spatial context matter?

Results

We compare STARCANE w.r.t. standard competitors: RF, LSTM, MLP, CNN that not consider spatial context

We employ standard evaluation measures: F1-score, Kappa and Accuracy

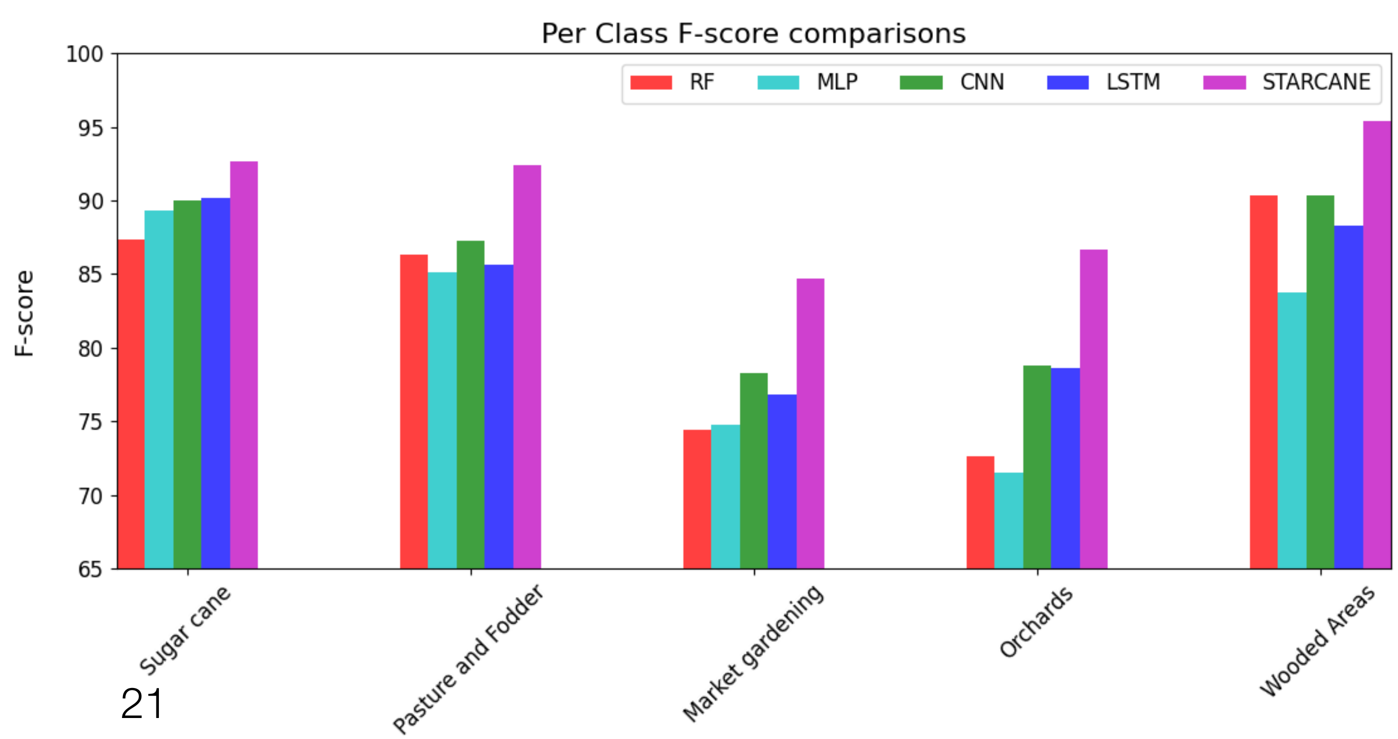
We divided the dataset in training/validation/test (50%/30%/20%) and repeat 5 times

The competing approaches does not (cannot) use the spatial context information

	F1 Score	*Kappa*	*Accuracy*
RF	82.43 ± 0.15	80.65 ± 0.17	82.79 ± 0.15
MLP	80.78 ± 0.53	78.60 ± 0.52	80.96 ± 0.46
CNN	84.40 ± 0.37	82.73 ± 0.45	84.62 ± 0.41
LSTM	83.36 ± 0.57	81.41 ± 0.71	83.44 ± 0.64
STARCANE	$\mathbf{90.50} \pm 0.1$	$\mathbf{89.37} \pm 0.08$	$\mathbf{90.52} \pm 0.08$

Gain can be observed considering **all the LC classes.**

Regarding agricultural and natural LC, STARCANE has notable improvement d**ue to the use of spatial context.**



Results

Due to the ability of STARCANE to weight the contribution of neigh. objects:

- For a land cover class, **we analyse the spatial (pattern) co-occurrence** of the land cover classes in the surrounding

- We can **sort the objects in the spatial context** considering the attention/contrib. weight

STARCANE

Does spatial context matter?

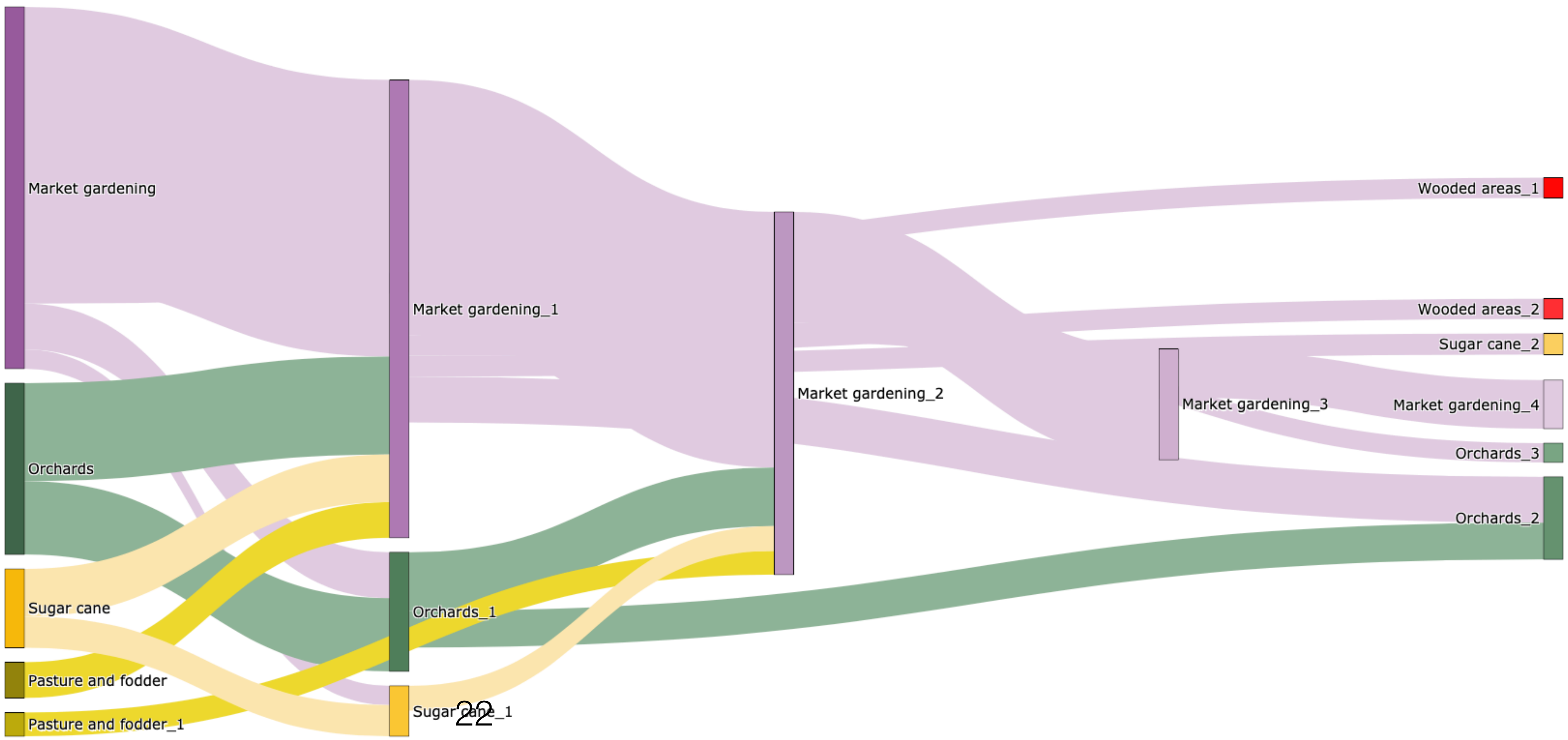
Results

Due to the ability of STARCANE to weight the contribution of neigh. objects:

- For a land cover class, **we analyse the spatial (pattern) co-occurrence** of the land cover classes in the surrounding
- We can **sort the objects in the spatial context** considering the attention/contrib. weight

<u>From the most important neighbour to the least important</u>

Spatial context related to objects classified as **Market Gardening**



STARCANE

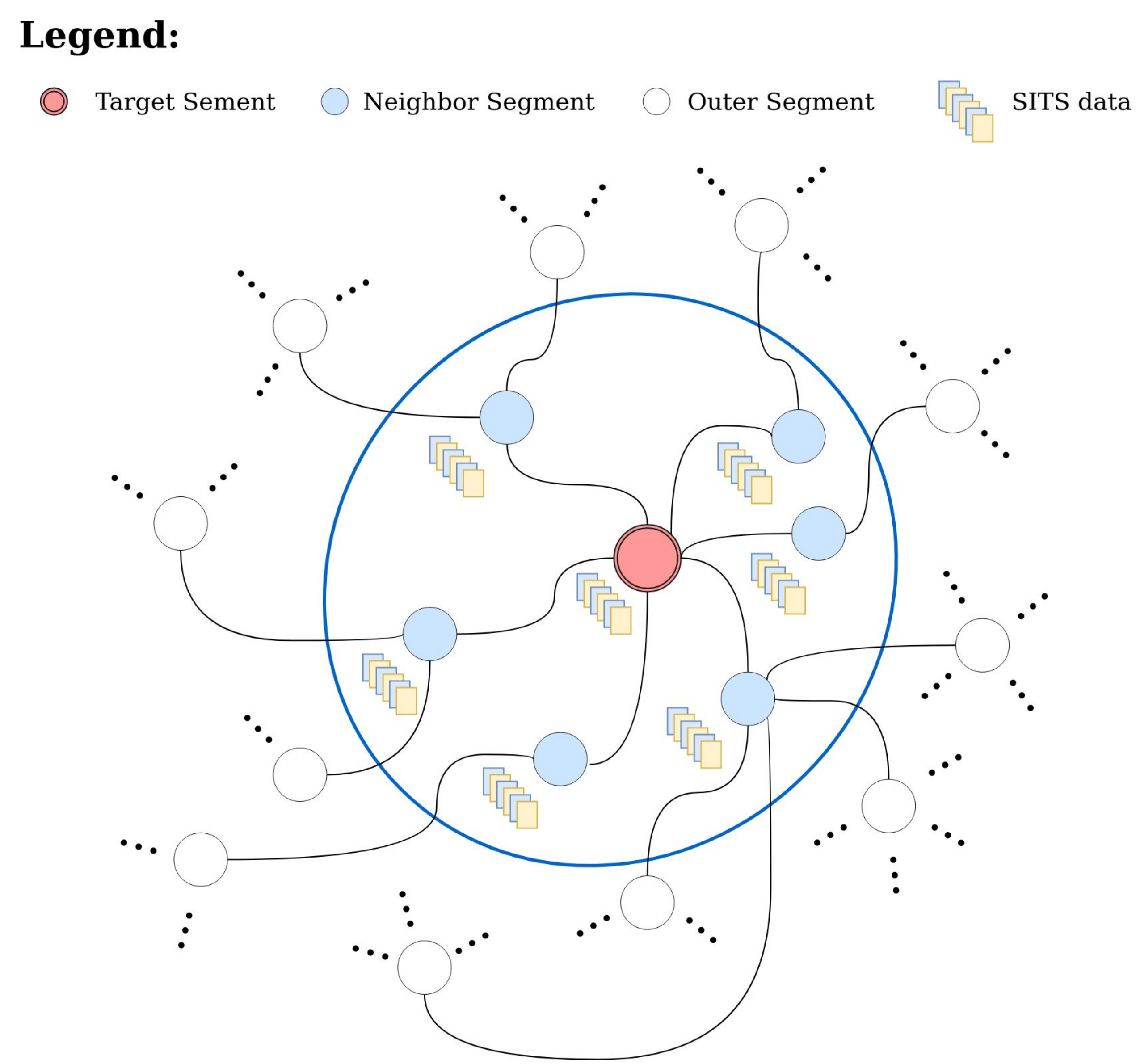
Does spatial context matter?

Conclusions

Experimental results support the intuition that **spatial context matters in land cover mapping** through SITS data

The STARCANE model provides **information** about the **neighbourhood importance in its decision**

Gain are systematically obtained on all the land cover classes. The spatial context allows to **reduce ambiguity**, in particular, on agricultural classes



To wrap up

Earth Observation data is **a valuable information source** to support agricultural monitoring systems at medium and large scale:

- Support **public policy**
- Map **natural resources**

Among all the EO data, Satellite Image Time Series offer new possibilities to monitor the Earth Surface evolution and provide insights in agricultural productions

To wrap up

Earth Observation data is **a valuable information source** to support agricultural monitoring systems at medium and large scale:

- Support **public policy**
- Map **natural resources**

Among all the EO data, Satellite Image Time Series offer new possibilities to monitor the Earth Surface evolution and provide insights in agricultural productions

In the context of EO data, **Machine Learning/DL tools** seem adequate to get the most of EO data but:

- It is mainly data-driven (some efforts are starting to combine data-driven and knowledge-based approaches)
- ML/DL is not yet fully consolidated in the contest of EO analysis and further research are still necessary
- Necessity to extract additional information that can support the model decision

Perspectives

In the context of Object-based analysis, **combine** TASSEL and STARCANE principles

Extend approach to leverage **heterogeneous EO sources** (Sentinel-2, Sentinel-1, Very High Spatial Resolution, etc..)

Towards **limited reference data** to train the model

Spatial and Temporal model transfer: from an area to another area, from a time period to another time period

Combine EO data with insitu (or proxy detection) data to combine information at extreme scales

Thank You for your attention

TERRITOIRE ENVIRONNEMENT TELEDETECTION INFORMATION SPATIALE

tetis

#DigitAg

Thank You for your attention

TERRITOIRE ENVIRONNEMENT TELEDETECTION INFORMATION SPATIALE

Questions