AI meets Remote Sensing to support the achievement of SDGs

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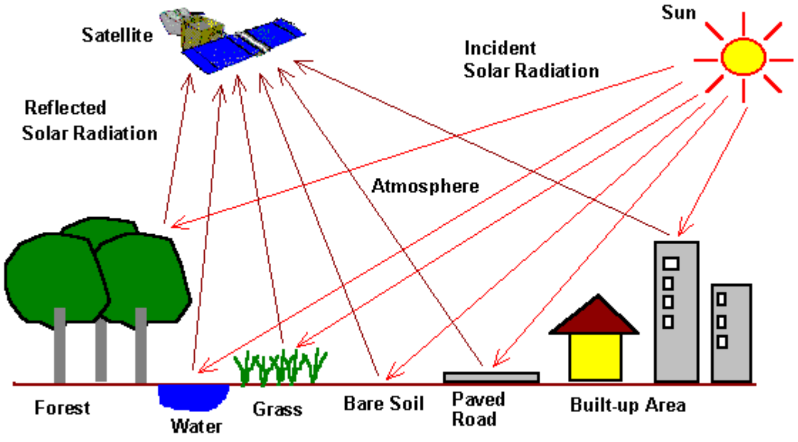
Remote Sensing/Earth Observation data (RS/EOD)

Remote sensing is the acquisition of **information** about an **object** or **phenomenon** **without making physical contact** with the object, in contrast to in situ or on-site observation.



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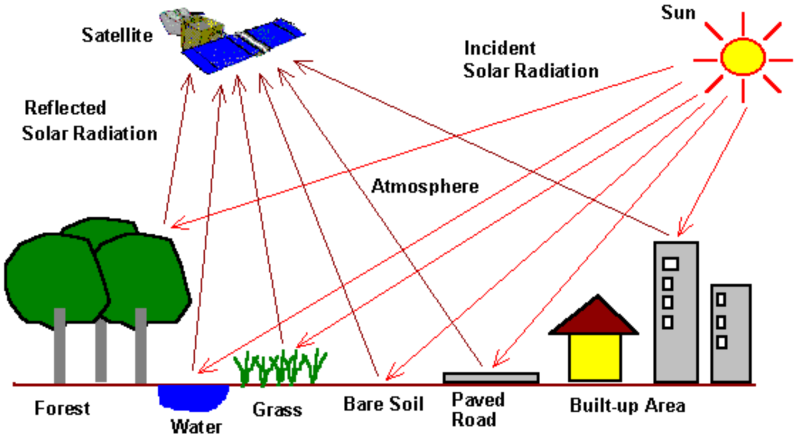

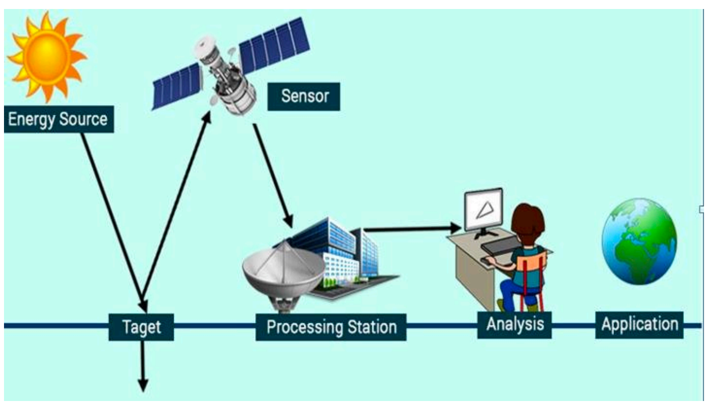

After that the data are acquired and retrieved, further **analysis** can be conducted in order to support specific **applications** related to **Earth surface monitoring.**

Why RS/EOD is an opportunity

Earth Observation Data can have practical influence on different domains:

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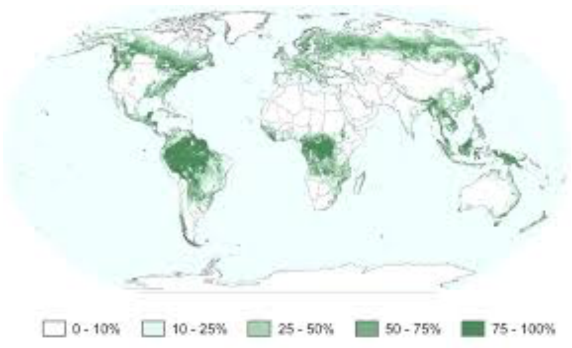
Continental and Global surfaces analysis



Sustainable Agriculture

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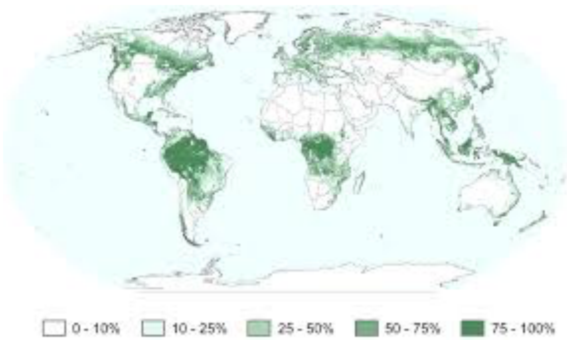

Sustainable Agriculture

Climate Changes Analysis

Biodiversity Monitoring

RS/EOD & SDGs

Earth Observation has been identified as **key information** to monitor the achievements of **SDGs** [1]:

- **Cost-effectiveness** pertaining to data acquisition
- Small / **Medium** / **Large scale** information
- Frequent **temporal revisit** time
- Cover **areas** that can be (commonly) difficult to access

[1] B. Ferreira, M. Iten & R. G. Silva : "Monitoring sustainable development by means of earth observation data and machine learning: a review" Environmental Sciences Europe volume 32, Article number: 120 (2020)

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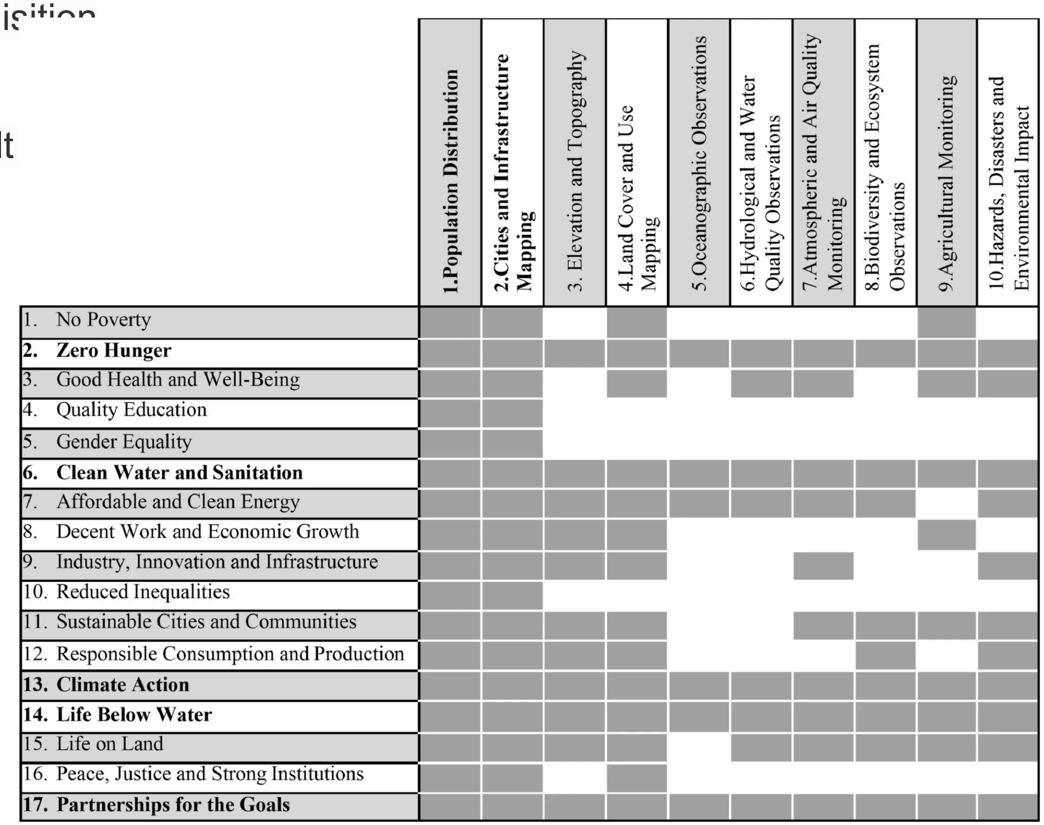

Figure from [1]

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The RS/EOD revolution

In recent years, remote sensing is living an exponential growth in terms of data availability:

- **Accessibility** (reduced cost and open access data)
- **Multiplicity** (increasing number of missions, different mode of acquisition)
- **Temporal density** (high revisit time, overlapping mission)

As a results:

- Data **volume** dramatically **increases**
- Data **diversity matters** for applications
- Data **flow/acquisition augments**

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The main question :
How to extract and synthesise valuable information/knowledge from Big Earth Observation data?

Big RS/EOD require advanced AI solutions

AI today is providing unprecedented **breakthroughs**:

- **In different domains** (image, video, 3D, text, speech, ….)
- All these domains are characterised by huge volume of available data

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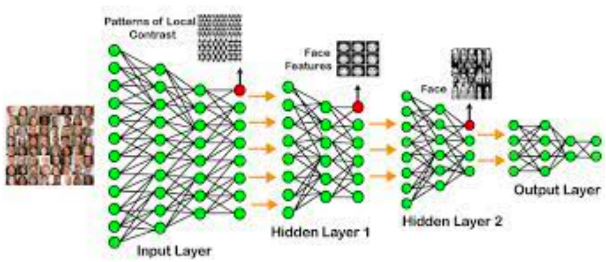
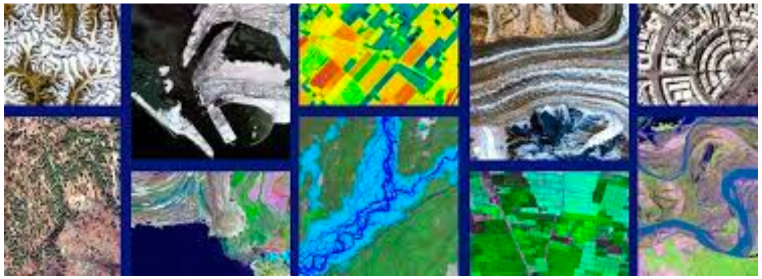


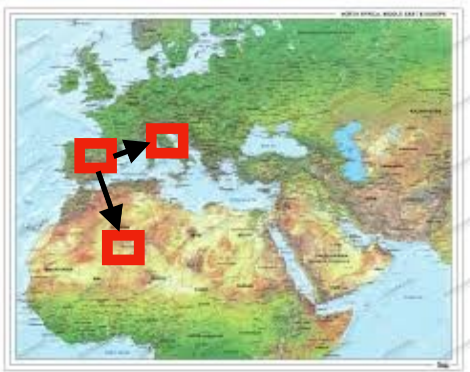
In the Remote Sensing /Earth Observation Data analysis field:

- **Increasing application** of AI
- Deep Learning to **cope with spatio-temporal dimensions**
- Especially useful to **exploit multi-modal RS/EOD**



Big RS/EOD open challenges

Spatio - Temporal Generalization



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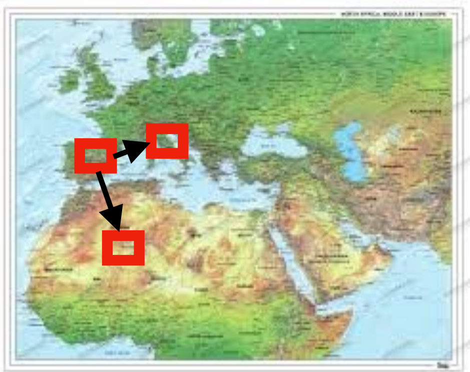

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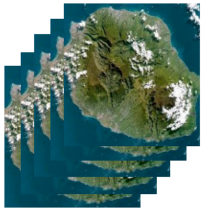
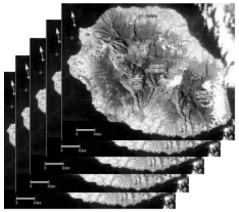
Heterogeneous data exploitation





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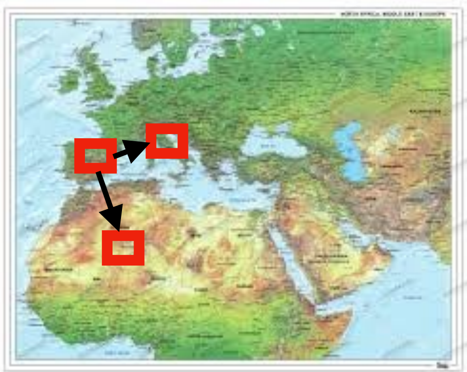

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Trustworthy AI for EO Data

How to **explain current AI models** and how to **conceive** approaches that integrate **by-design interpretability** to raise the AI acceptability.

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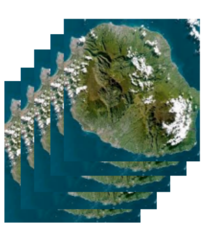

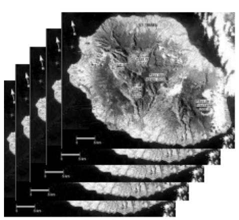

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Example related to SDGs

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Land Cover Mapping [1]

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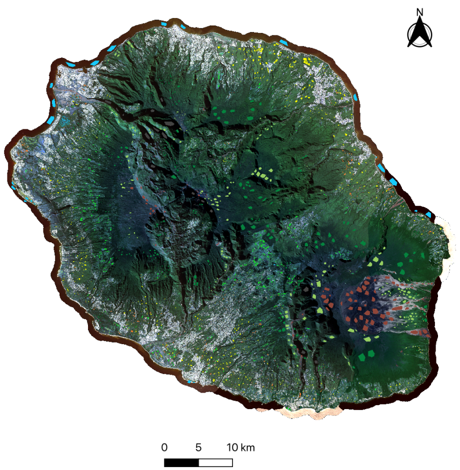

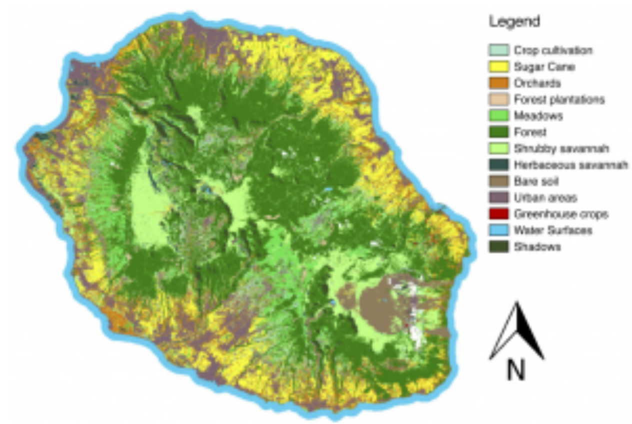

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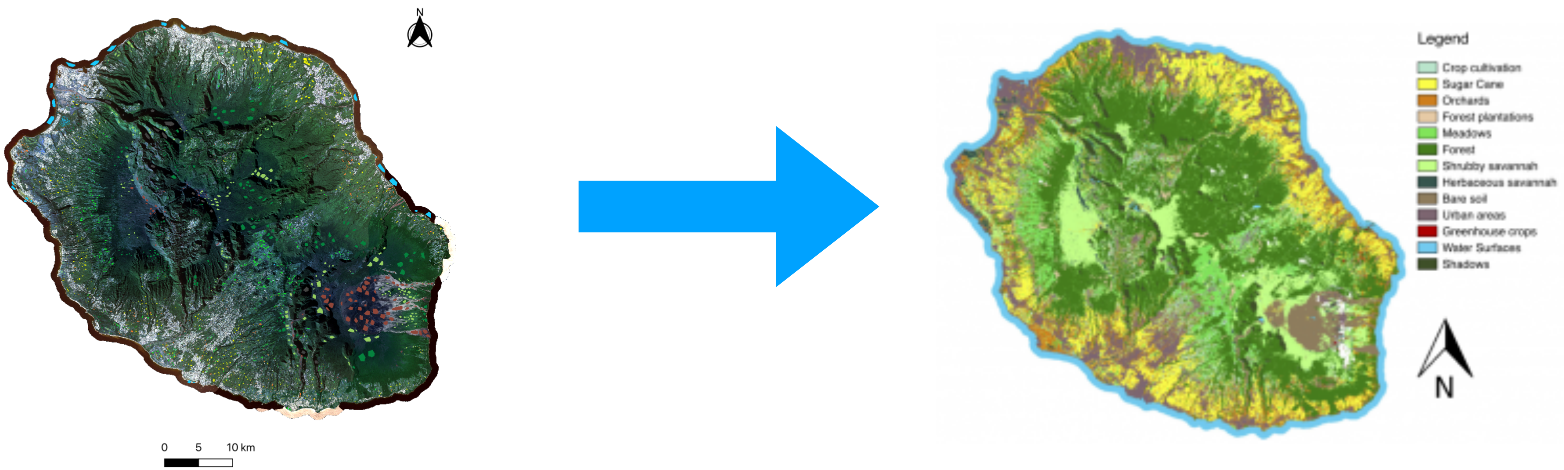

<u>Impacts</u>:

- Extract useful **spatial statistics** to quantify **agricultural** and **natural ressources** extents as well as **urban settlement**
- Support **public policies** or national agency to set up practical actions related to **land management**

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Crop Yield Estimation [1,2]

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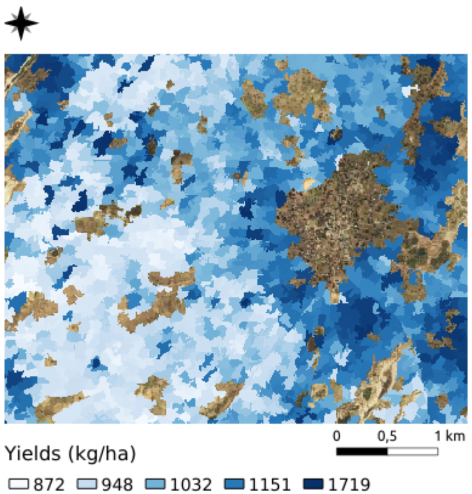

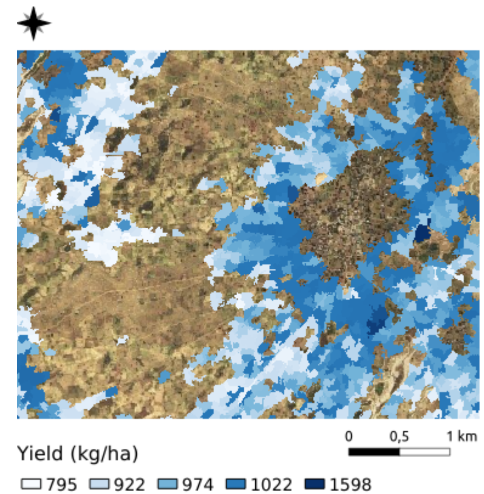

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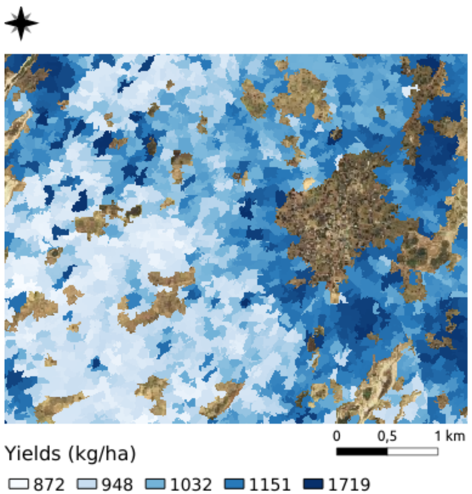

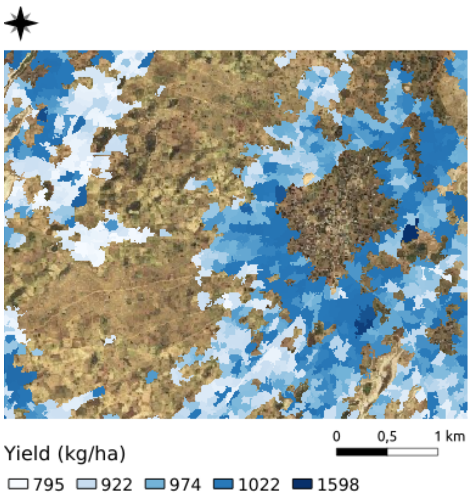

Impacts:

- Extract spatial information to quantify **agricultural production** before the harvesting date
- Support policies related to **Food Security** and planification in relationship with **financial markets**
- Reducing famine by estimating the **food availability** for the growing world population

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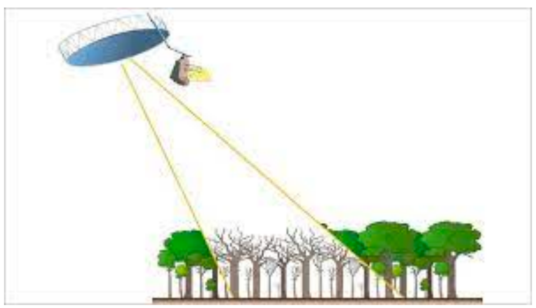
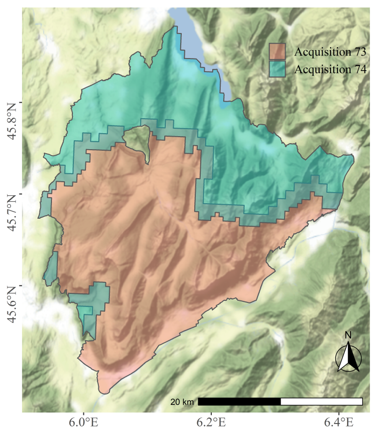
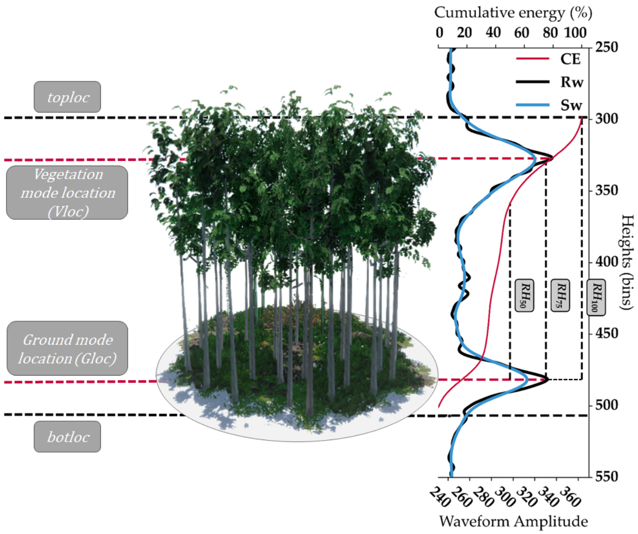
Given EO data (Lidar, Time Series, …) + Reference Data, estimate forest variables like height, biomass, basal areas, …







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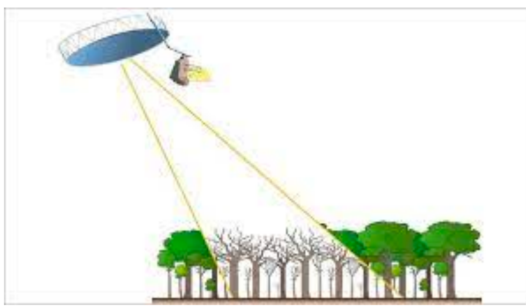

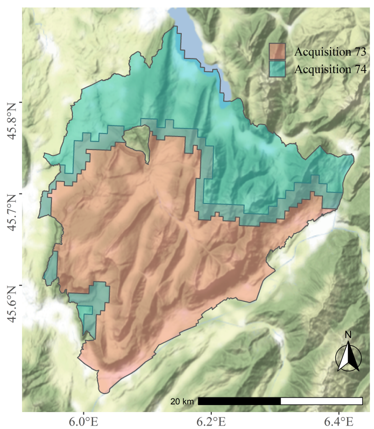

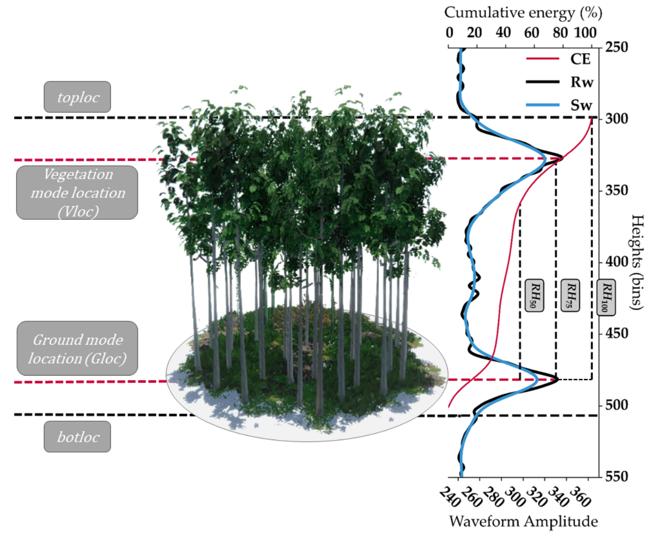

<u>**Impacts**</u>:

- **Extrapolate/Upscale Forest variables** to large scale areas
- **Quantify biomass** and other characteristics to monitor carbon stock availability
- Monitoring **forest disturbances** (fires, pests, …) and **illegal actions** (logging) on forest areas

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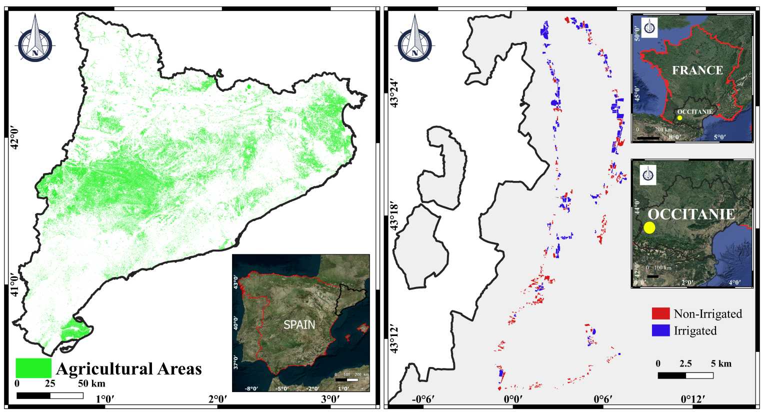
Given EO data (Optical & Radar Time Series, …) + Reference Data, estimate soil moisture and or irrigation at plot level



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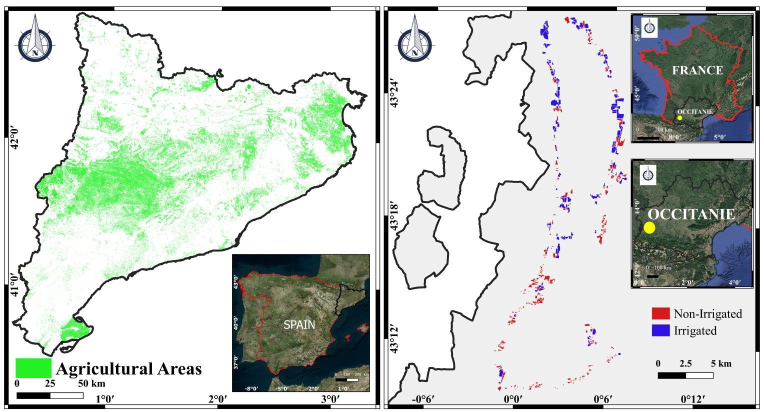

Source Dataset CATALONIA (a) | Target Dataset OCCITANIE (b)

<u>Impacts</u>:

- Monitor and Characterise **water consumption**
- Planification for **crop related irrigation** strategies
- Support a better understanding on **how the environment responds to climate/weather changes**

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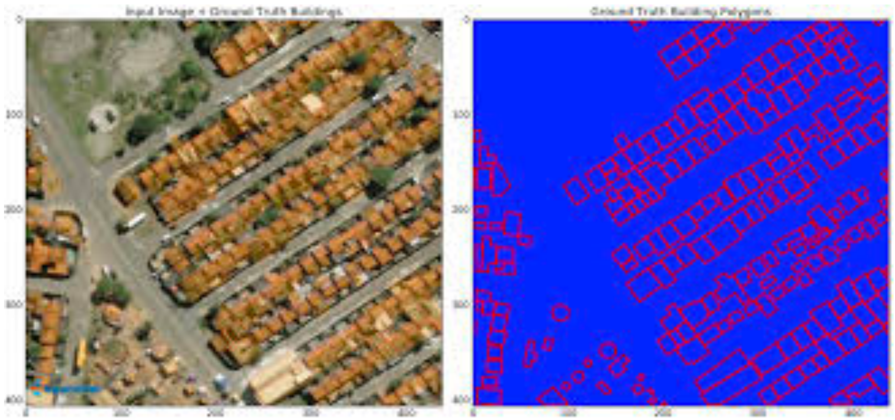

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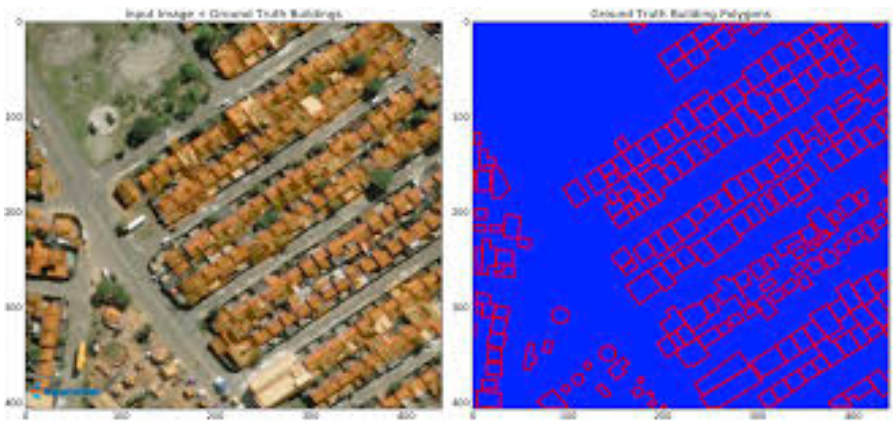

<u>Impacts</u>:

- Cadastral mapping for **uncovered areas**
- Cadastral **updates** for large areas
- **Settlement expansion** monitoring

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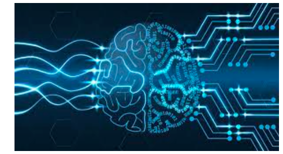
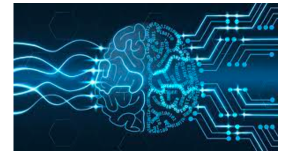


Earth Observation data is **a valuable source of information** to support environmental and agricultural monitoring/planning at medium and large scale to:

- Support **public policy makers** via spatial indicators
- Map **natural resources**
- **Monitor the evolution** of land surfaces

Exploit **several EO data** (among the others, Satellite Image Time Series) **via AI techniques** offers new opportunities to **monitor the Earth Surface** evolution and provide insights to support the achievement of many **Sustainable Development Goals**

To conclude



Earth Observation data is **a valuable source of information** to support environmental and agricultural monitoring/planning at medium and large scale to:

- Support **public policy makers** via spatial indicators
- Map **natural resources**
- **Monitor the evolution** of land surfaces

Exploit **several EO data** (among the others, Satellite Image Time Series) **via AI techniques** offers new opportunities to **monitor the Earth Surface** evolution and provide insights to support the achievement of many **Sustainable Development Goals**

Nevertheless, many actions are in progress or still necessary, among them:

- RS/EOD exploitation via modern AI tools is quite **recent** and **still at exploratory stage**
- Many **methodological challenges** are still open (method transferability, domain expert integration, interpretability/explainability, large multi-modal data integration, …)
- **Capacity building** related to AI tools for RS/EOD exploitation needs to be strengthen

Thank you for your attention

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Questions