Remote Sensing Applications on Agriculture using Machine Learning

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Outline

- Why it matters?
- Common applications
- Example cases
- Challenges / Opportunities

Why it matters

-Population growth

-Climate Change & Extreme weather events

-Pressure on resources

-Need to improve soil & water quality

-Lack of basic resources can increment disease spreading and conflicts

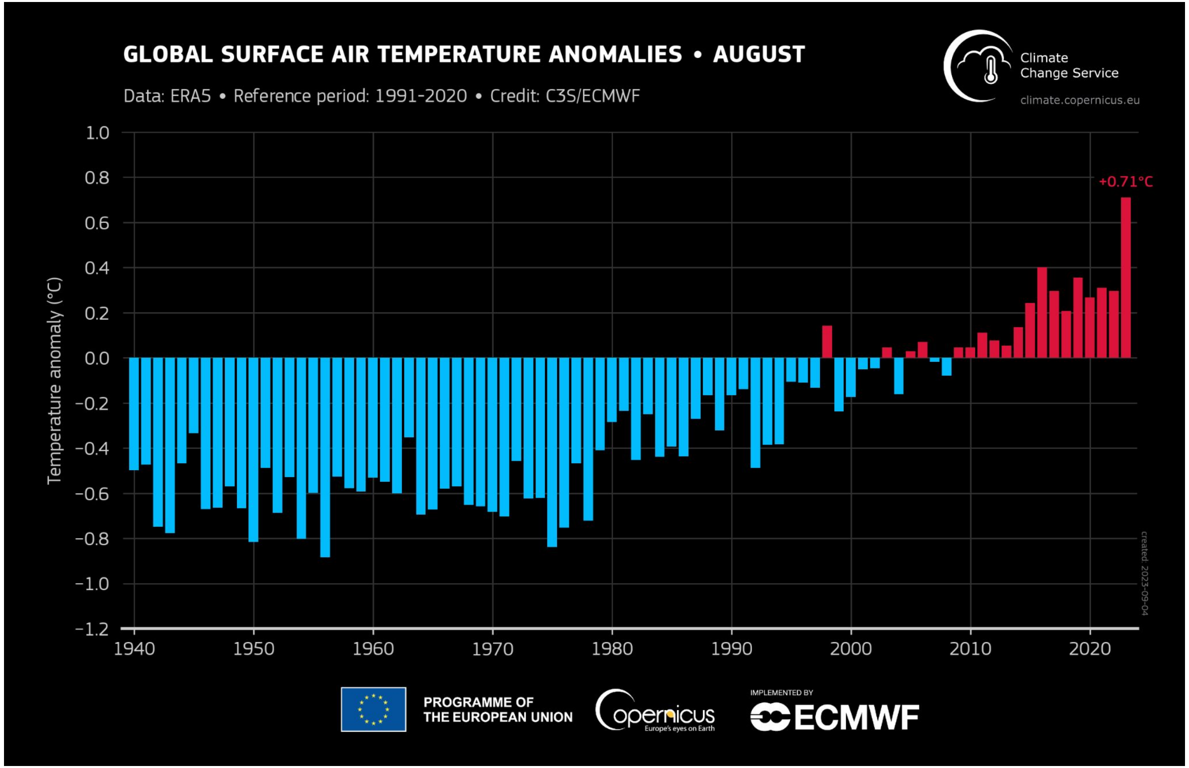


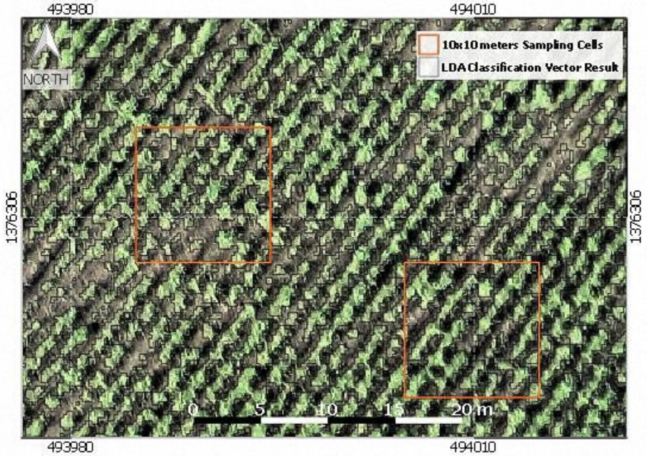
Figure taken from Climate Copernicus,2023

Common Applications

- **Scouting / Field comparison**
- **Crop Classification**
- **Management Zoning**
- **Yield estimation**
- Irrigation Management
- **Fertilizer Application**
- Pest / Disease detection
- Object Detection & Counting

CA - Crop Scouting / Field comparison

- Early Detection of problems (generic)
- Damage estimation (quantity/quality of products)
- Crop status is used for tuning operation and crop management (e.g.:re-planting)
- Allocate Resources
- Evaluate operations

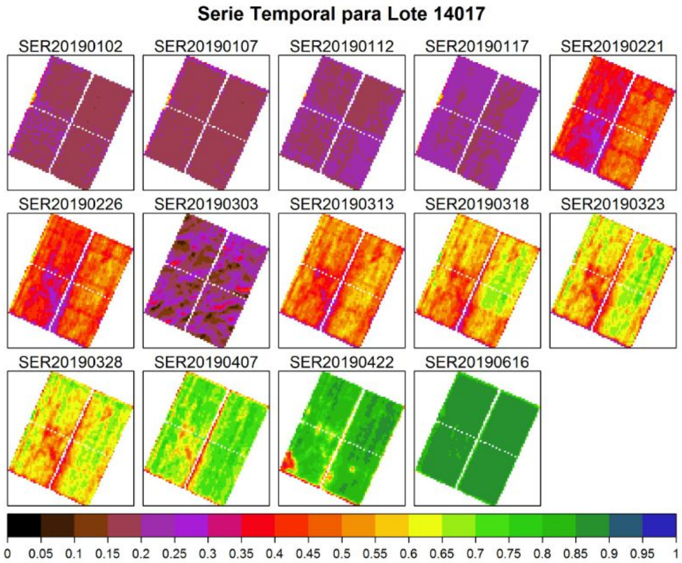


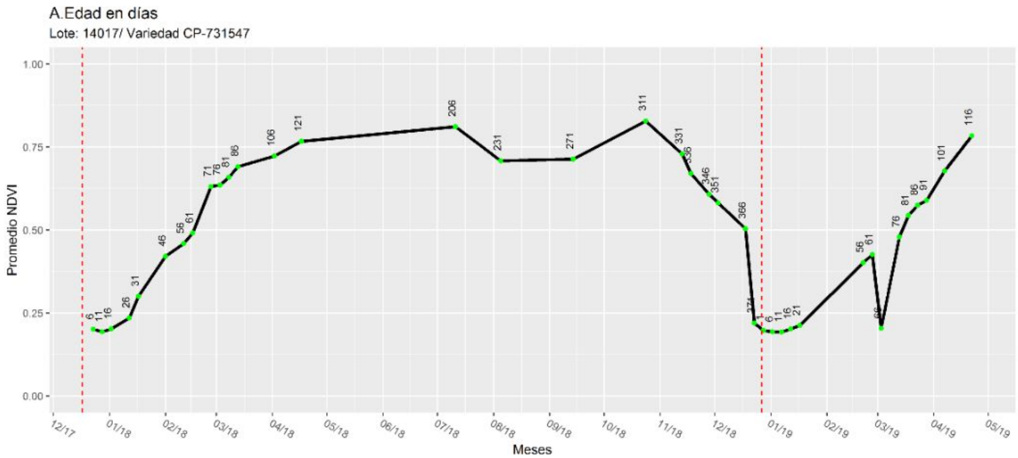
Linear Discriminant Analysis (and SVM) for sugarcane gap detection

Katy 01 UAV use to map 200-500 Ha at 10 cm/pixel with 50 minutes autonomy depending on weather conditions

Monitoring sugarcane plantations using RS

Año	Imágenes disponibles por mes con condiciones atmosféricas aceptables (nubes y bruma mínima)										
	Ene	Feb	Mar	Abr	May	Jun	Jul	Agos	Sep	Oct	Nov	Nov
2018	1	2	2	1	2	2	0	2	3	2	1	4





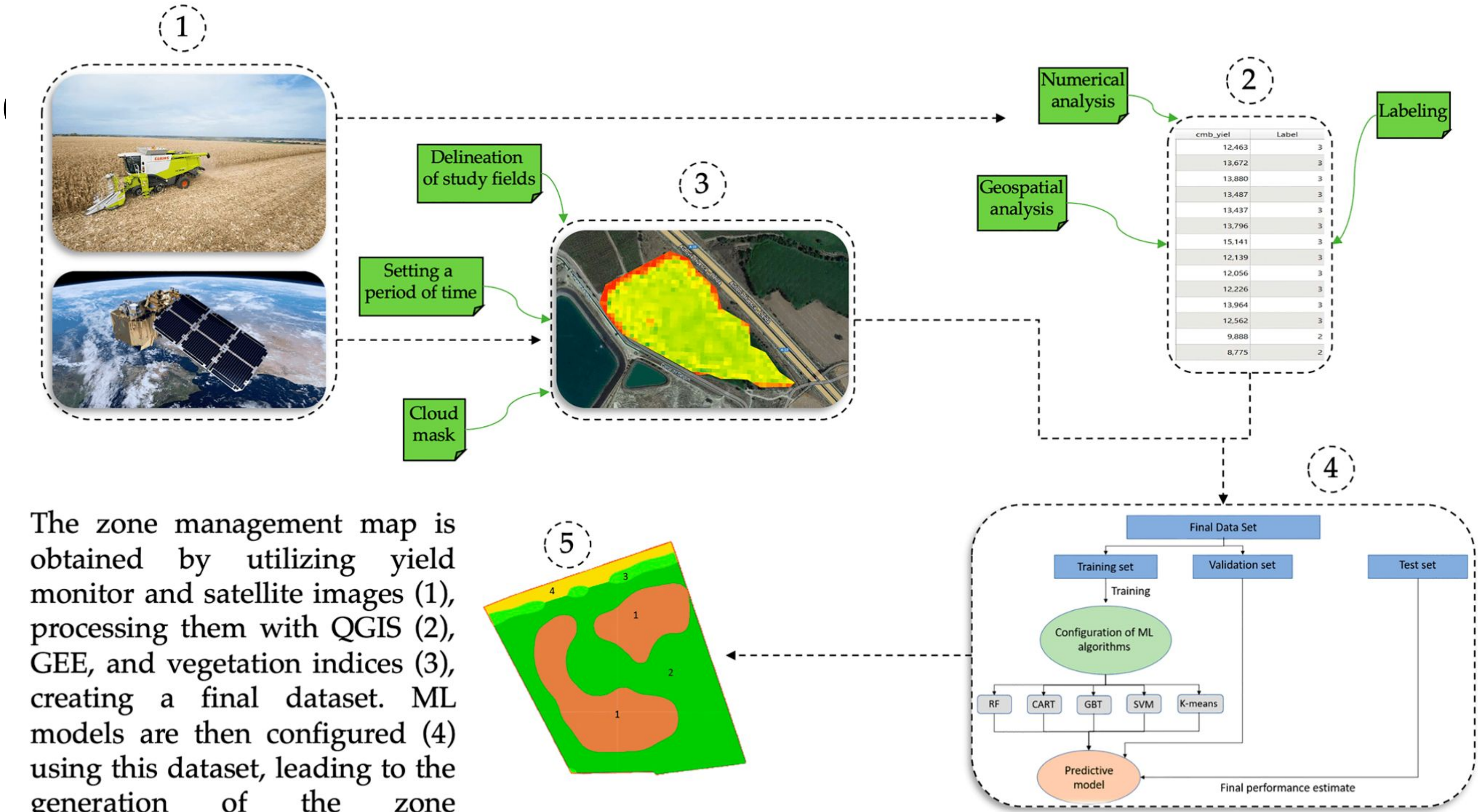
CA - Crop Classification

Why?

- Crop classification Data can be use to monitor and control resources (water)
- One step towards crop specific yield estimation
- Study land cover/use changes and drivers
- Identify specific varieties is needed when looking for seeds

CA - Field Management Zoning

- Multiple factors contributing to spatial and temporal variability in the field
- Electromagnetic soil conductivity measurements provide valuable (related with soil properties and yield) data but are expensive
- Remote sensing approach has been proved to deliver similar value by collecting several crop season´s data.
- From season imagery median Vegetation indices are calculated, ground sampling (machinery or manual) and then use machine learning algorithms for classification of “homogeneous” yield areas of other fields.



The zone management map is obtained by utilizing yield monitor and satellite images (1), processing them with QGIS (2), GEE, and vegetation indices (3), creating a final dataset. ML models are then configured (4) using this dataset, leading to the generation of the zone management map (5).

Figure taken from Gallardo-Romero et al, 2023

CA - Yield Estimation

Main factors

-Weather

-Soil properties

-Genetics

-Water and nutrient balance

Traits

-Crop Type

-Soil and plant Nitrogen

-Canopy cover

-Soil moisture

CA - Yield Estimation

Approaches

-Empirical

-Model based (LUE / WUE)

-Radiative Transfer Models

-Hybrid (Coupled)approach

Table 3. The main difference between the three methods for assimilating remote sensing data into crop models.

	Data Assimilation Method		
	Forcing	**Recalibration**	**Updating**
Number of iterations	Fewer	More	Fewer
Computational time	Less	More	Less
Flexibility	No	Yes	Yes
Propagation of uncertainty	Possibly	Minimize errors	Minimize errors
Number of parameters	Fewer	More	More
Complexity	Less	Less	More

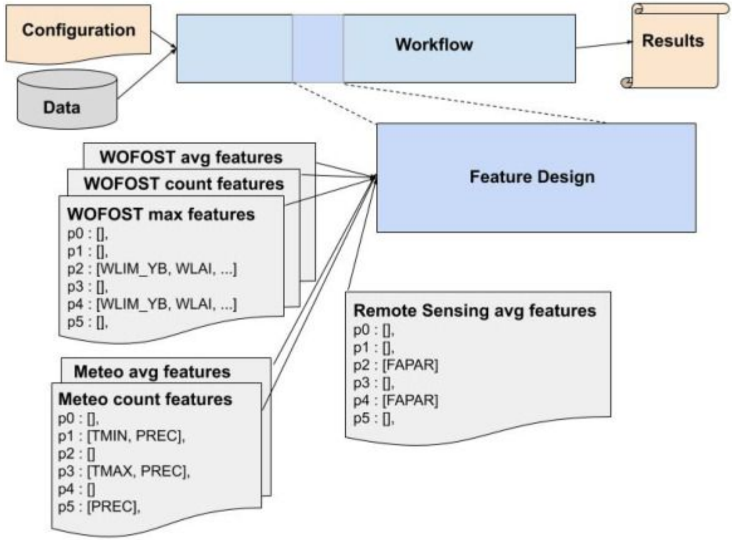
Table taken from Dlamini et al.,2023

CA - Yield Estimation

- Combining agronomic principles of crop modeling with machine learning.
- Modular Approach (reusable and open to configuration-dataset-features)
- Possible to predict yield for 5 crops at 3 countries
- Initial results are comparable to MARS Crop Yield Forecasting System (MCYFS)

Machine learning for large-scale crop yield forecasting

Dilli Paudel [a], Hendrik Boogaard [b], Allard de Wit [b], Sander Janssen [b], Sjoukje Osinga [a], Christos Pylianidis [a], Ioannis N. Athanasiadis [c]



CA - Fertilizer Application

There are different strategies to use fertilizers once management zones are known and understood:

-More fertilizer-> more yield + cost

-Less fertilizer -> same yield - cost

-Same fertilizer -> more yield

In rice, is common that farmers apply fertilizer more than once, using simple color cards.

ML and remote sensing can be used for a more precise estimation of fertilizer needs

Average nitrogen

Use efficiency in rice paddies is often very low (about 30%) -> water pollution, GHG emission & economical losses

CA - Fertilizer Application

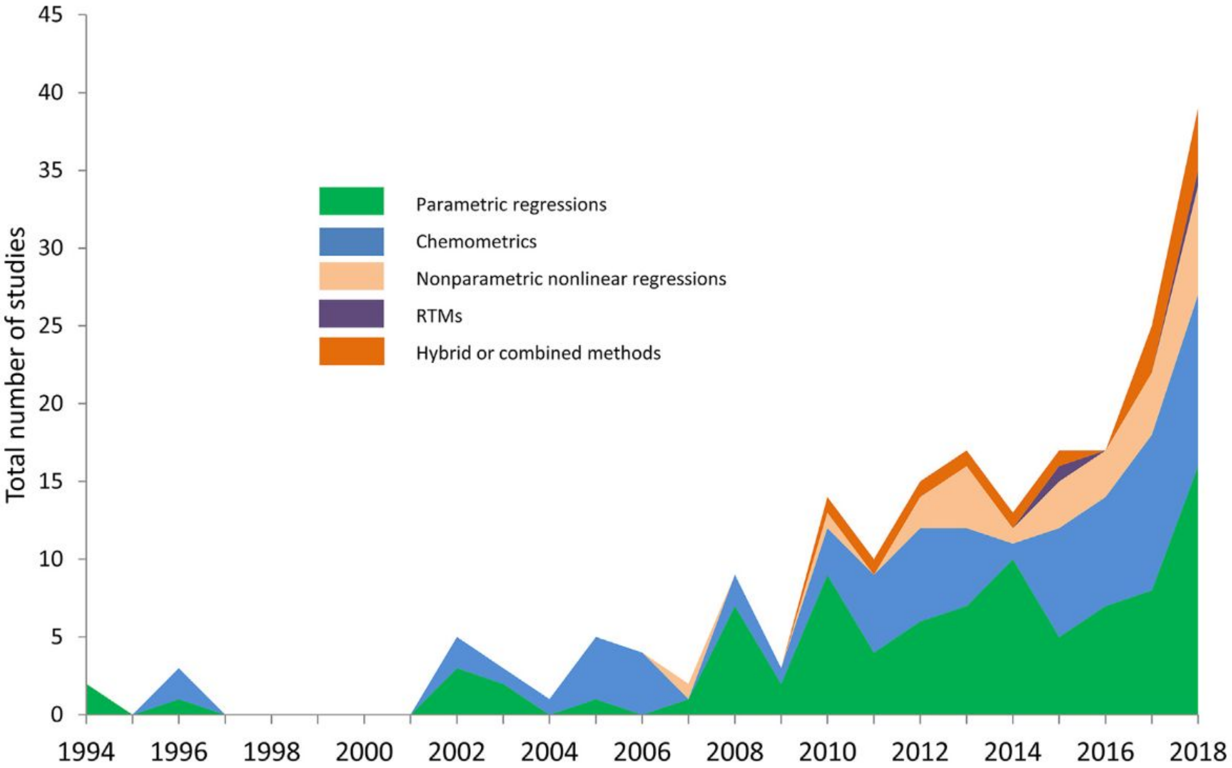


Fig. 6. Development of the five main categories of N retrieval methods in scientific studies over time (from 1994 to 2018).

Figure taken from Berger et al, 2020

Challenges / Opportunities

- Cloud cover in tropical regions
- Lack of ground reference data
- In many cases, machine learning models are specific for dataset, time and conditions
- Easy to focus only on accuracies and not understanding/building knowledge, estimate uncertainties and limitations
- Combining Biophysical models + Machine learning to overcome some limitations and extract unknown relations / parameters

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