A CROSS-CORRELATION PHENOLOGY-BASED CROP FIELDS CLASSIFICATION USING SENTINEL-2 TIME SERIES

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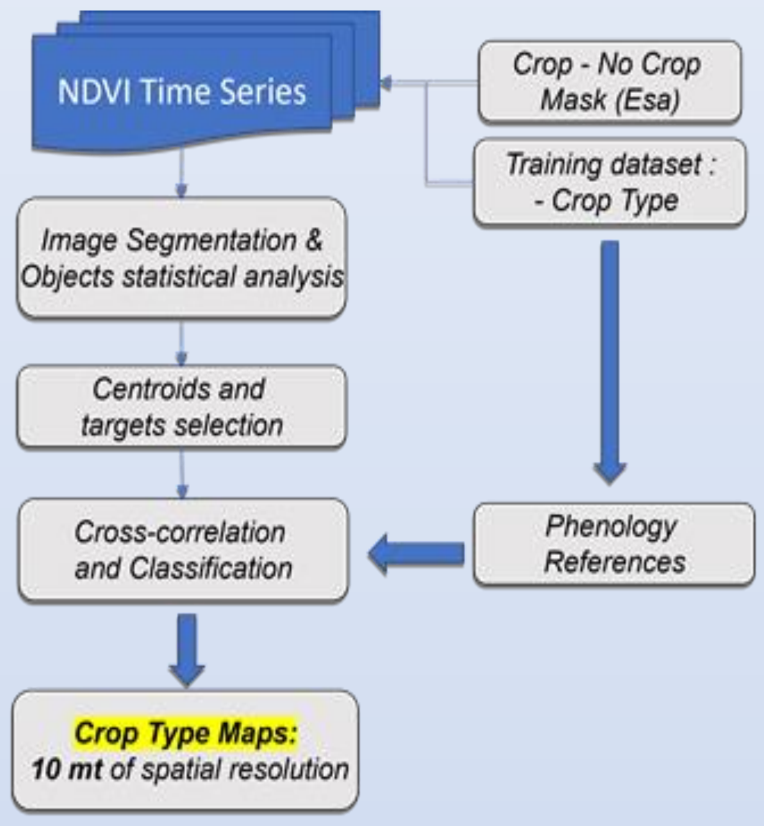
Abstract

This paper is born in the framework of the European H2020 project **AfriCultuReS**: *Enhancing **Food Security** in African agricultural systems with the support of **Remote Sensing***. The project aims at provide a decision support system for improved decision making in the field of food security in Africa. An accurate and timely crop-type map based on remote sensing data is essential for many applications, such as agro-ecological analysis to support agricultural policy and economic growth.

Agricultural areas are naturally affected by significant variations within relatively short time intervals, in accordance with the **growing season**. These **dynamics** could, in principle, be exploited to classify different types of crops. **Vegetation indices** (VI) retrieved from **Sentinel-2** imagery are evaluated to track the year-round vegetation behavior. Starting from a multi-temporal image series of the same scene, the phenological profiles can be extracted and introduced into a **supervised classification** process to detect crop fields, discriminating among different species. Following this, we propose a cross-correlation based model that, using a priori information from ground training data, searches for the best matching phenology.

Sentinel-2 Data

- Region of interest (ROI): Bothaville, South Africa
- Downloading and processing **36 Sentinel 2-A and 2-B images of one entire year**: 3 per month for tile T35JMK, the least cloudy. A total of 36 Level-2A bottom of atmosphere (BOA) reflectance images in cartographic geometry (UTM/WGS84 projection) of Sentinel-2A/B Multispectral Instrument (MSI) were collected, extracting cloud free NDVIs.
- Extract the RED and NIR bands (B04 and B08)
- Extract the SCL bands (Scene Classification Map)
- Data cleaning : Removing all the pixels saturated, shadow or cloudy using SCL's
- Calculate the NDVI's : $NDVI = \frac{B8-B4}{B8+B4}$

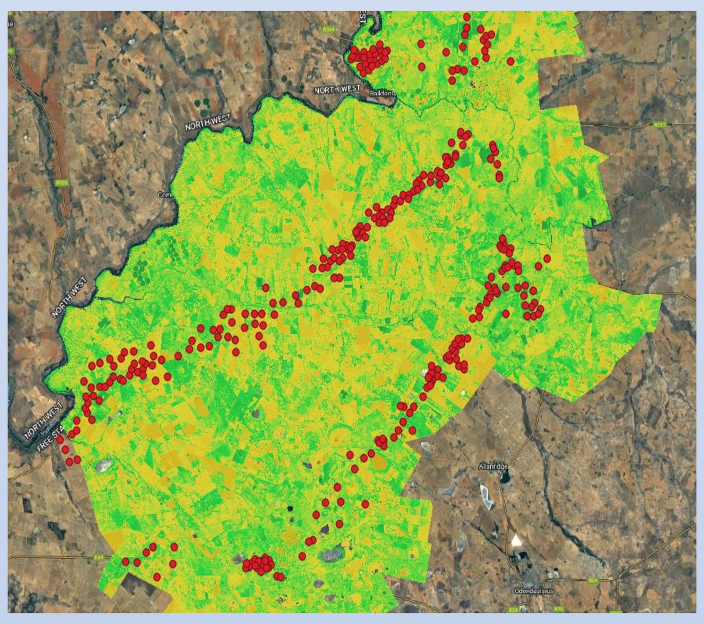


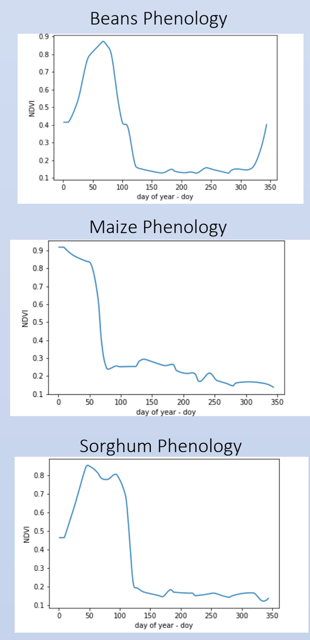
Methodology

- ✓ *S-2 High Resolution 10 mt*
- ✓ *Object Based*
- ✓ *Phenology based (1 year NDVI time series)*
- ✓ *Cross-correlation method for discrimination*

- Building a ***reference dataset*** extracting phenology for each ground data object/point
- Masking the entire NDVI collection with a *Crop-No Crop Mask* derived from *ESA World Land Cover* mask
- ***Image Segmentation*** step: discriminating polygon-like fields, boundaries and centroids
- ***Object Statistical analysis***: performing a statistical analysis on each polygon-like crop field and extracting for each polygon the mean value and standard deviation with the aim of extrapolate a single characteristic and representative phenology profile for the whole crop field
- ***Phenology extraction*** step: extracting time series NDVI for each centroid, building phenology curve with outliers' removal and noise time filtering (rolling mean), and finally interpolating.
- Comparison with the ground data phenologies: ***Cross-correlation***
- **Discrimination** rule: best matching with minimum cross-correlation coefficient of 0.90 and maximum lag of 15 days

(Reference Dataset)





Segmentation and Classification

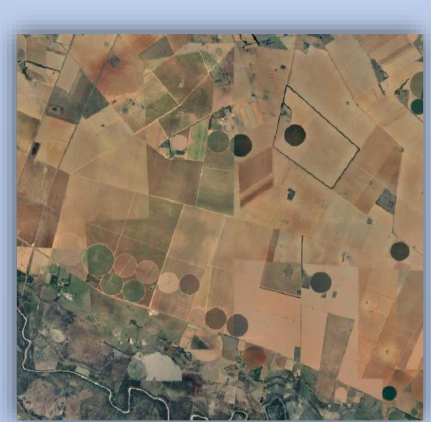
Selecting the least cloudy NDVI images over the period, a multi-image edge detection and a subsequent watershed algorithm were applied to get the image segmentation. Firstly, **Canny edge detection Algorithm** was performed on multiple images and then aggregated into one field boundary image, using as input more than one index or band: NDVI, NDWI, and Blue band reflectance.

This crucial step can be improved in the pre-watershed processing phase with morphological transformations on the edge detection, such as small objects removal, filling holes, dilation and thinning to clean the noise and closing polygon edges. Combining them was necessary to obtain a cleaner edge detection to use as the input for the watershed approach, avoiding over-segmentation and noise.

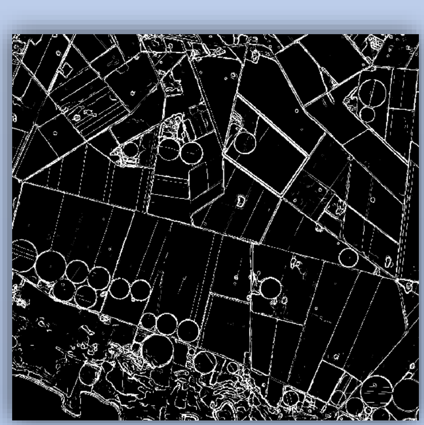
Therefore, using **Watershed Algorithm** to close the polygons. Starting from user-defined markers, the watershed algorithm treats pixels values as a local topography (elevation). It consists in calculating the distance transform of the edge detection binary image, inverting it, finding the local minima, the darkest parts of the image, that will be the objects centers, using them as markers and then applying watershed on it using the original image as mask.

	Sigma	Threshold
NDVI	4,0	0,170
NDWI	2,5	0,200
BLUE	3,5	0,035

(Canny Algorithm Parameters)



(Original)



(Edge Detection)

(Watershed Algorithm)

(Object Classification)

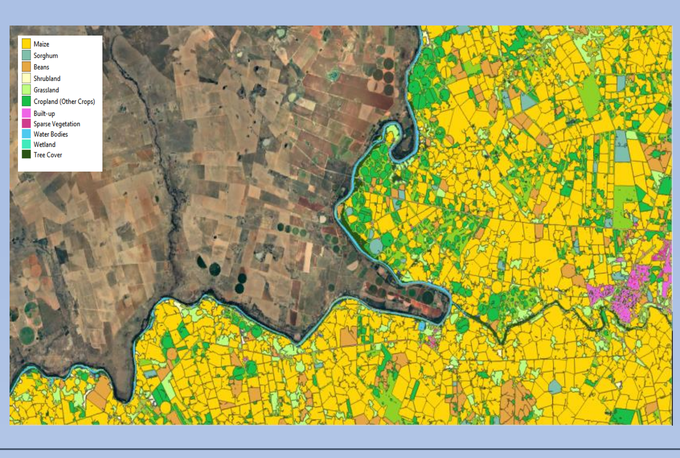
Conclusions and Results

The actual validation results for the **Bothaville** region (Nala County, **South Africa**) demonstrates a good user **accuracy** on the main crop type, **89.19 % for maize crops**. The validation was performed comparing the total number of pixels belonging on 138 fields polygons of maize of the ground campaign data available in 2021. For beans and sorghum, even if the accuracies are good, their statistics are not as significant as the maize ones because of their limited number of available ground validation data. The confusion matrix attests 93.48% of accuracy for beans and 73.66% for sorghum.

CONFUSION MATRIX (NUMBER OF PIXELS)

PREDICTED VALUES

ACTUAL VALUES (TRUE)	Maize	Sorghum	Beans
Maize	1413373	0	0
Sorghum	1166	2738	0
Beans	57386	0	51028
Other Crops	112676	979	3559
UA	**89,19%**	**73,66%**	**93,48%**



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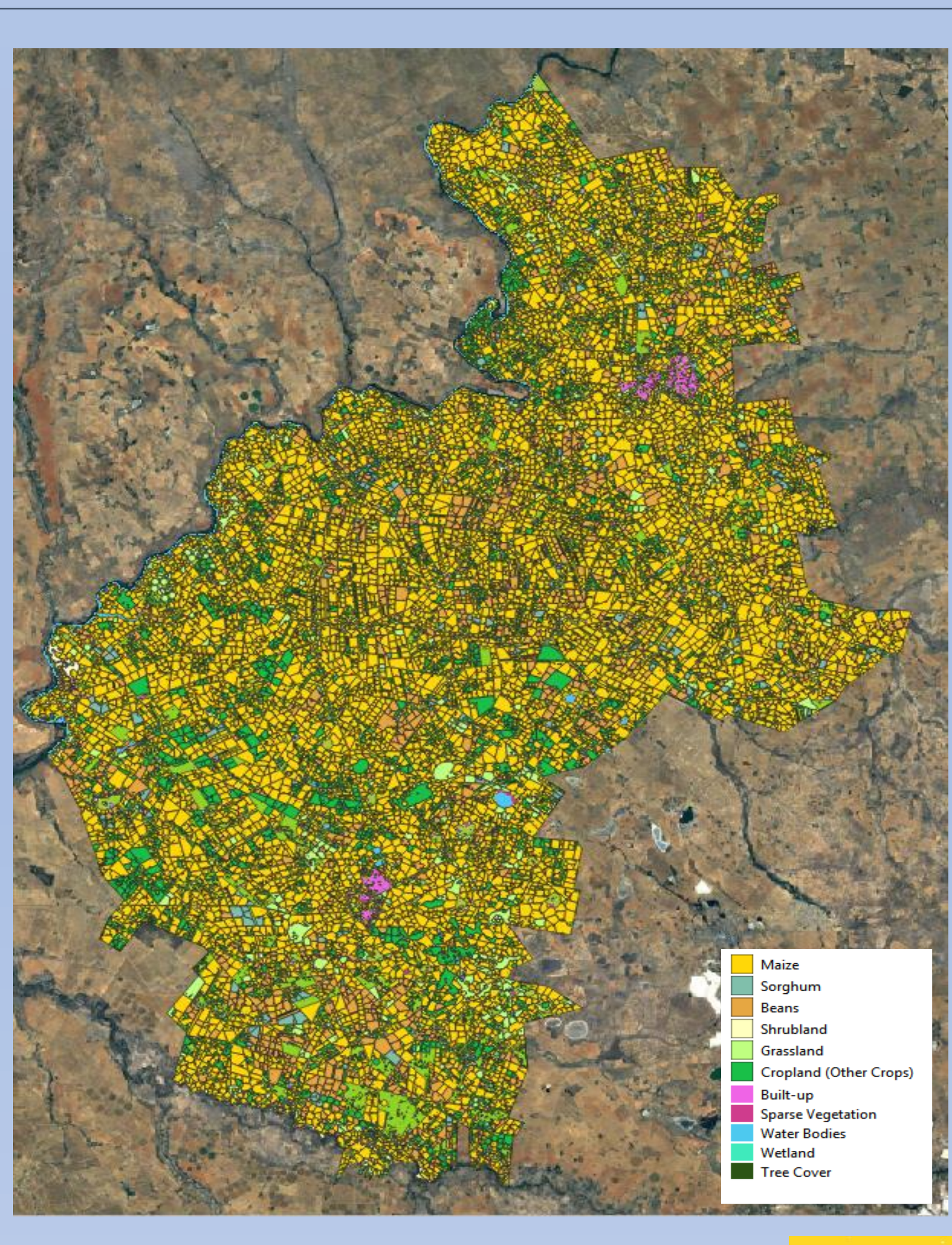

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