

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

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ABSTRACT

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. Thus, this study aims to investigate the methodologies and the results for crop types classification relative to the use of phenological information extracted from high spatial resolution satellite imagery. 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 semi-automatic 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 among phenologies. In comparison with machine learning models for crop classification, the one proposed in this study can provide useful information about phenology that can be stored and used for better monitoring spatio-temporal variations of crops species through the future years and guiding agricultural management accordingly. Our study cases are the regions of Bothaville and Harrismith, located in South Africa, and the region of Jendouba in Tunisia.

Index Terms— Sentinel-2, agriculture, classification, phenology, cross-correlation.

1. INTRODUCTION

An accurate and timely crop-type map is essential for many applications, and site-specific crop identification based on remote sensing data, is useful for agro-ecological analysis to support agricultural policy, and economic growth [1]. It's crucial for water management and food security issues, ensuring a better decision-making process at regional and country scale. At a field scale, it represents a site-specific input to improve field management practices for helping farmers.

The NDVI (Normalized Difference Vegetation Index) calculated from the red and near-infrared bands is largely used as an indicator of the photosynthesis capacity of the

vegetation embodied in each pixel. This normalized vegetation index is defined as: $N = (R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED})$, where R_{NIR} is the reflectance in the near-infrared band and R_{RED} is the reflectance in the red band. The NDVI is produced at 10 m resolution for the entire year for each scene of the study areas, and the retrieved phenology represents a potentially significant source of land cover information leading to more accurate classification maps [2, 3, 4]. In fact, in land-cover maps the croplands are usually generalized as a unique 'cropland' class or only a few classes such as winter/summer crops and irrigated/non-irrigated cropland.

Classification methods based on multi-temporal images have been well acknowledged in agriculture, since crop systems usually disclose specific and often separable seasonal trends on multi-temporal images, within a particular agro-ecological area, during the annual cycle [5, 6]. As a rule, taking advantage of a large number of sequential multi-temporal images assures to effectively describe the crop seasonality. Nevertheless, when the number of time-series images is too large and significant correlation among them exists, the dataset becomes redundant: additional images add little information but increase the computing complexity. In the field of signal detection and signal matching applications time series methods that can be classified as time-domain or frequency-domain, are commonly used: the former ones use mathematical tools such as autocorrelations, cross-correlations and convolutions [7].

The ability of **MSI Sentinel-2 10 meters NDVI time series in detecting crop seasonal variation** was investigated. A phenology-based classification (PBC) approach was developed and tested, which doesn't need to model NDVI variation with some logistic or double sigmoid fitting function [8] because the discriminating agent will be the degree of cross-correlation of the interpolated phenology profiles.

In fact, cross-correlation is widely used as effective similarity measure in matching tasks [9], to be able to discriminate for different crop species using Sentinel-2 MSI imagery. Cross-correlation analysis was selected to implement crop species discrimination.

Bothaville and Harrismith counties in South Africa, and Jendouba Governorate in Tunisia were selected as case

studies to be mapped at 10 m spatial resolution trying to detect and identify all the crop fields in those regions.

2. STUDY AREAS

The study was performed for three regions. The first one is the region of Nala local municipality in South Africa, around **Bothaville**, the city that lies in the center of the so called “maize triangle”, surrounded by vast maize lands, irrigated from the Vals and Vaal Rivers. This region is located near the Vaal River, in Lejweleputswa district of the Free State province, and lies between latitudes 27°6′ and 28°6′ South, and longitude 26°3′ and 26°51′ East. Depending on the place, the climate is classified as arid steppe cold (BSk) or arid steppe hot (BSh) based on the Köppen-Geiger climate classification: a climate whose mean annual temperature is less than 18°C (cold steppe) or more than 18°C (hot steppe) and is too dry to support a forest, but not dry enough to be a desert, usually consisting of grassland plains [10]. About 565 mm of precipitation falls annually [11].

The second region of interest is around **Harrismith**, in Maluti-a-Phofung municipality in Thabo Mofutsanyana district of the Free State province (South Africa), between latitudes 26°59′ and 28°47′ South, and longitude 27°41′ and 29°48′ East. This zone is crossed by Wilge River that is a tributary of the Vaal River, and the climate is mild, warm and temperate, categorized as ‘Cwb’ (subtropical highland climate), based on the Köppen-Geiger Climate Classification: warm temperate with dry winter and warm summer. In winter the precipitations are much less frequent than summer, with an average temperature range that goes from 8°C (June- July) to 18°C (January- March) with an average of 17°C. About 970 mm of precipitation falls annually [11]. Sorghum, Maize and beans are prominently the main cash crops grown in these two regions of South Africa.

The third region is around **Jendouba**, a city in northwestern Tunisia, between latitudes 36°3′ and 37°2′ North, and longitude 7°52′ and 9°6′ East. This city is the capital of the Jendouba Governorate, where the main economic activity is agriculture. It has a hot-summer Mediterranean climate (Köppen climate classification ‘Csa’). The winter season has much more rainfall than summer. The range of average annual temperatures goes from 4°C (January - February) to 36°C (July - August) with an annual average of 18.0 °C. About 540 mm of precipitation falls annually [11]. Wheat, maize, barley and potatoes are prominently the main cash crops grown in this region [12].

3. DATA AND MATERIALS

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 from ESA Copernicus hub for each area of interest: 3 per month during the year 2021. The selection was made using the Sentinel-API downloading tool, imported from the library Sentinel-sat in Python, with an algorithm that selects 3 images per month filtered by cloud cover percentage: only the 3 least cloudy are chosen for each month. In particular, most part of the acquired images are almost cloud-free for the regions of Bothaville and Harrismith. This limitation on the image number was necessary because of the computational time and memory needed, but actually removes a lot of unnecessary data and cloudy images. The Sentinel tiles of interest needed for this study are tile 32SMF for Jendouba, 35JMK for Bothaville, and 35JPJ, 35JPK, 35JQJ, 35JQK for Harrismith. Training points were collected during field campaigns carried out in April 2021 in the study areas previously described. The FAO crop calendars and the FAO Farm Management Handbook for Africa [13, 14] were used as first references data during the experimental setup [15], for the season knowledge about each crop. The ESA World Cover map was introduced to mask out the regions different from cropland. This map contains 11 different land cover classes at 10 m resolution, achieving 74.4 % of global overall accuracy and 81.1 % for Cropland class. It was developed and validated in almost near-real time in 2020 by ESA [16], that helps us minimize the processing time excluding the no-crop areas, that is essential for high spatial resolution applications on large areas.

4. METHODOLOGY

The first step of the crop mapping procedure is the co-registration of the entire images time series to evaluate the NDVI, masking out all the pixels that are cloudy or not vegetated or saturated, using the scene classification map provided by Sentinel-2. Each Sentinel-2 L2A image includes a classification map (SCL, Scene Classification) at 20 meters resolution which provides a first coarse classification, that gives preliminary information such as vegetated/not-vegetated pixel, cloudy/not-cloudy, and makes possible a first data-sanitation process.

To discriminate crop species using phenology, profiles of the characteristic crops of the area of interest are necessary, so a training dataset is needed to retrieve from the selected training points and from the time series images the reference phenologies for each crop type. These data are used to implement a set of phenology references to be used during the cross-correlation comparison in the classification process. With the support of FAO crop calendar and FAO Farm Management Handbook is also possible to extrapolate more seasonal information (start and end of seasons) for the training dataset, that could be used to generate phenology maps of the entire region at the end of the process, knowing the time lag.

The overall process is outlined in Fig. 1. On one side of the chain the training dataset is processed to obtain the

reference library needed for the comparison, performing a statistical analysis on each polygon-like crop field and extracting for each polygon the mean value and standard deviation with the aim to extrapolate a single characteristic and representative phenology profile for the whole crop field, taking advantage of the crop calendars as first references in the assessment of the phenology profiles.

On the other side of the chain process all the crop fields are investigated and detected. The principal processing chain goes through several steps.

Firstly, selecting the best and the clearest NDVI images, a multi-image edge detection and a subsequent watershed algorithm were applied to get the image segmentation.

Once all the crop fields are recognized and represented like isolated homogeneous objects, a statistical and morphological analysis is carried out to find and isolate a single target pixel which will be representative of the whole field analyzing its spectral variability over its geometry [15]. Centroids are representative of objects geometry, being the arithmetic mean of all pixels within the objects and the target point selected is the closest pixel to the centroid included within the field polygon perimeter. Target point phenology is derived by statistically analyzing a region of pixels centered around it, for example a 10-by-10 pixels square around the target point within the object, so that it is considered the phenology variability across a good part of the field. For classification purposes this simplification seems enough to reduce the computational time over wide areas, retaining a good accuracy provided by the previous segmentation.

The processing chain goes on with the phenology extraction step. After masking out all the out of bounds crops outside the cropland areas of the ESA World Land Cover mask, for each crop target pixel the NDVI behavior is extracted over a year and averaged over the centroid's region. Then, NDVI series is interpolated in time using a Cubic Spline interpolation method. Modified Akima cubic Hermit interpolation method is another good choice to avoid overshoots in the building process of phenology profiles.

Each target crop within the crop mask is classified by its centroid's region phenology. A cross-correlation sequence among the target crops phenology and the reference phenologies previously stored, measures the degree of similarity between the two of them [17].

By means of cross-correlation comparison, the crop type is found when the best match occurs, looking for the highest correlation value associated with the minimum time lag, choosing properly a set of thresholds to be applied on correlation and lag values, beyond which no class is associated to the target crop [15].

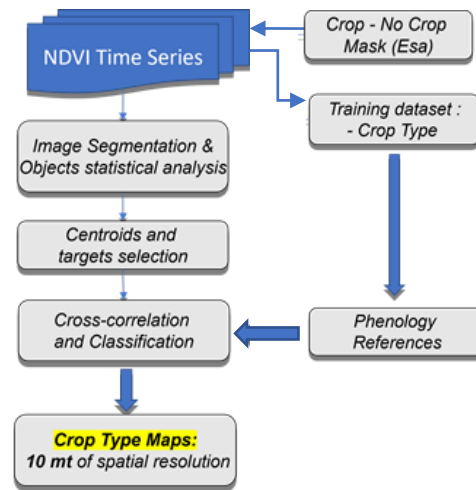


Figure 1. Outline of the overall classification process.

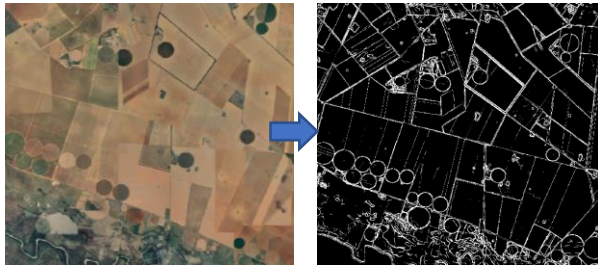
5. RESULTS AND CONCLUSIONS

The multi-temporal phenology-based cross-correlation approach has been applied to the classification problem of three regions of interest: Bothaville and Harrismith in South Africa and Jendouba in Tunisia.

Details produced from the classification map of Bothaville (Nala County) in 2021 are shown in Fig.2. The classification map, released at a spatial resolution of 10 m, comprises mainly maize and bean fields. In this study case it was used 90% as the minimum cross-correlation value and 20 as maximum lag value in days.

The actual validation results for the Bothaville region demonstrates a good user accuracy on the main crop type, 89.19 % for maize crops. It 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 their accuracy are good, their statistics are not to be considered very significant because of their limited number of available ground validation data, 6 polygons for beans, 4 for sorghum. The confusion matrix attests that for beans there is 93% of accuracy, and 74% for sorghum. A validation campaign to proper evaluate the classification accuracy of other regions is currently underway.

A parallel study to improve the segmentation precision and therefore the overall classification accuracy was performed, using algorithms in the pre-processing phase such as canny edge detection on multiple cloud-free images, with subsequent morphological transformations such as small objects removing, filling holes, dilation and thinning. Combining them was necessary to obtain a cleaner edge detection to use as the input for the watershed approach.



(Original image RGB)

(Edge detection)

Figure 2. Multi image Edge detection (Bothaville, South Africa, 2021)



Figure 3. Watershed segmentation and Classification (Bothaville, South Africa).



Figure 4. Classification map developed for Bothaville (Nala County) in 2021 with a spatial resolution of 10.

[1] Dubovyk O. et al., "Spatial targeting of land rehabilitation: A relational analysis of cropland productivity decline in arid Uzbekistan", *Erdkunde*, vol. 6, 2013.

[2] Knight J. et al., "Regional Scale Land-Cover Characterization using MODIS-NDVI 250 m MultiTemporal Imagery: A Phenology Based Approach," *GIScience and Remote Sensing*, pp. 1-23, 2006.

[3] Simonetti E. et al., "Phenology-based land cover classification using Landsat 8 time series". *EUR - Scientific and Technical Research series*, 2014.

[4] D. Bargiel, "A new method for crop classification combining time series of radar images and crop phenology information", *Remote Sens. Environ.*, vol. 198, pp. 369-383, 2017.

[5] Pax-lenney M. et al., "The status of agricultural lands in Egypt: the use of multitemporal NDVI features derived from Landsat TM", *Remote Sens. Environ.*, vol. 56, pp. 8-20, 1996.

[6] B. Tso and P. P. Mather, "Classification Methods for Remotely Sensed Data," 2nd Edition, CRC Press, Boca Raton, 2009.

[7] F. Quiero, F. Quintana, L. Bennun, "A novel method based on cross correlation maximization, for pattern matching by means of a single parameter. Application to the human voice, 2015.

[8] L. Zhong, T. et al., "A phenology-based approach to map crop types in the San Joaquin Valley, California", *International Journal of Remote Sensing* Vol. 32, 2011.

[9] Zhao, Feng & Huang, Qingming & Gao, "Image Matching by Normalized Cross-Correlation". *IEEE International Conference on Acoustics Speed and Signal Processing Proceedings*, 2006.

[10] Beck, H. E. et al., "Present and future Köppen-Geiger climate classification maps at 1-km resolution." *Sci. Data*, 2018.

[11] Climate-Data.org [online] Available: <https://en.climate-data.org/> (accessed December 16, 2021).

[12] "Les normales climatiques en Tunisie entre 1981 2010" (in French). Ministère du Transport. Archived from the original on 19 December 2019. Retrieved 25 January 2020.

[13] FAO crop calendar tool, [online] Available: <http://www.fao.org/agriculture/seed/cropcalendar/welcome.do> (accessed December 16, 2021).

[14] ESA CCI Land Cover map [online] Available: <http://www.esa-landcover-cci.org/> (accessed December 16, 2021).

[15] Luciani R. et al., "Phenology-based classification of crop fields using cross-correlation: a case study", 2021.

[16] ESA World land cover, [online] Available: <https://esa-worldcover.org/> (accessed December 16, 2021).

[17] Proakis J.G. et al., *Digital signal processing: Principles algorithms and applications*, Prentice-Hall, Newdelhi, India, 1997.