

# SINO–EU EARTH OBSERVATION DATA TO SUPPORT THE MONITORING AND MANAGEMENT OF AGRICULTURAL RESOURCES

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## ABSTRACT

This paper presents the results of a collaboration between Italian and Chinese research groups carried out under the context of the GEO work programme and AfricultuReS H2020 project. The paper encompasses three main aspects:

(a) the description of some results on the high resolution crop mapping carried out in some African countries in the framework of the AfricultuReS project;

(b) the description of the results on the crop early warning service delivered in the framework of the AfricultuReS project; and

(c) based on the multi-source data, the factors that have an important influence on the desert locust occurrence and spread process were extracted, the desert locust disaster monitoring model was constructed, and the desert locust in Somali was quantitatively monitored and analyzed.

The connection between the three points mentioned above must be sought in the fact that the combination of an accurate mapping of agricultural areas accompanied by techniques for estimating any threats to them allows to accurately estimate the possible effect in terms of production loss.

*Index Terms*— crop, pests, map, satellite, warning

## 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. 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 calculated from the red and near-infrared bands is largely used as an indicator of the photosynthetic capacity of the vegetation embodied in each pixel. The NDVI is produced at 10 m resolution for the entire year for each scene of the study area, and the retrieved phenology represents a potentially significant source of land cover

information leading to more accurate classification maps [1, 2]. In fact, on land-cover maps the croplands were usually generalized as a unique 'cropland' class or only a few classes such as winter/summer crops and irrigated/non-irrigated cropland.

The classification methods based on multi-temporal images has 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. As a rule, taking advantage of a large number of sequential multi-temporal images assures to effectively describe the crop seasonality. In the field of signal detection and signal matching applications are commonly used time series methods that can be classified as time-domain or frequency-domain: the former ones use mathematical tools such as autocorrelations, cross-correlations and convolutions [3].

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 [4] 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 [5], to be able to discriminate for different crop species using Sentinel-2 MSI imagery. Cross-correlation analysis was selected to implement crop species discrimination.

An accurate knowledge of the crop types and extent allows to design a tool capable to assess the impact of bad weather conditions or pests/diseases. One of such tools is the AfriCultuReS crop early warning that, as others warning systems [6], is based on rainfall and vegetation index anomalies computed over crop and rangeland areas. Warnings consider the timing during the crop season at which they occur using remote sensing derived phenology per-pixel. The other tool herein considered is the Desert Locust monitoring and forecasting systems [7] which integrates multi source data (e.g. meteorological data, field data, and remote sensing data such as GF series, MODIS and Landsat series, and Sentinel series) and self-developed models and algorithms to construct the 'Vegetation pests and diseases monitoring and forecasting system', which

could regularly release thematical maps and reports on desert locust.

## 2. STUDY AREAS

This study was performed on three areas:

- The Bothaville County, in the Free State province (South Africa), that is part of the so called “maize triangle”, including vast maize lands.
- The Harrismith County. This zone is crossed by Wilge River that is a tributary of the Vaal River. Sorghum, Maize and beans are prominently the main cash crops grown in these two regions of South Africa.
- The Jendouba Governorate (Tunisia). Wheat, maize, barley and potatoes are prominently the main cash crops grown in this region.
- The horn of Africa for locust invasion monitoring.

## 3. DATA AND METHODS

### 3.1. Crop mapping

A total of 36 per year Level-2A bottom of atmosphere (BOA) reflectance images in UTM/WGS84 projection of Sentinel-2A/B Multispectral Instrument (MSI) were collected from ESA Copernicus hub for each area of interest. 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 less cloudy are chosen for each month. In particular, most of the acquired images are 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. Training points were collected during field campaigns carried out by OSS (Sahara and Sahel Observatory) and SANSa (South African National Space Agency) in the study areas previously described. The ESA world cover map with a resolution of 10 meters [8], introduced to mask out the regions different from cropland, helps us to minimize the processing time excluding the no-crop areas, that is essential for high spatial resolution applications on large areas.

The first step of the crop mapping procedure is the co-registration of the entire time series of images 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 (SCL, Scene Classification, 20m spatial resolution) which provides a 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, NDVI temporal profiles of the characteristic crops of the area of interest are necessary. So, a training dataset is needed to retrieve from selected training points and from the images time series the reference phenologies for each crop type. These data were used to implement a set of reference phenologies 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. The overall process is outlined in Fig. 1.

As a support to the decision makers to monitor the vegetation status and, specifically, in the agricultural sector, following adverse climatic events such as periods of drought and high temperatures, a product has been developed that considers crop status driving factors in order to issue several levels of alert on status of the vegetation and aiming at minimizing and preventing food insecurity issues. This product, based on Sentinel-2 images, is the CRop Early Warning (CREW) which provides high resolution information (20m). Several requirements are needed to compute the CREW: the availability of an archive, covering a period of, at least, 5 years of the statistics relating to the NDVI, in particular the mean and standard deviation, and temperatures and rainfall. The statistics will be used to identify anomalies in NDVI, temperatures and precipitations. Furthermore, the crop map and phenology data of the different crops present are needed, in order to determine if the crop is in the phenological period or not. The CREW is based on an analysis procedure divided into several steps: as soon as the last Sentinel-2 image is available, the cloud cover mask will be extracted and the NDVI will be calculated.

The actual NDVI value (pixel per pixel) is compared with the mean and standard deviation relating to the same

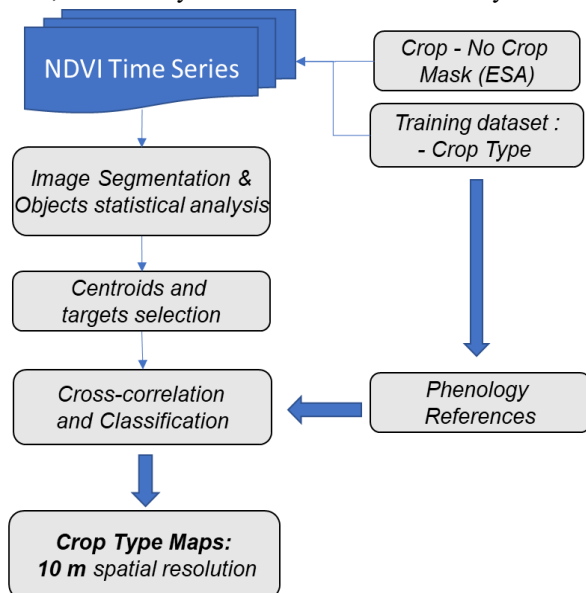


Figure 1. Outline of the overall classification process.

time period of the observation. In the event that the value indicates an anomaly in the health conditions of the crop for a certain area, and this anomaly repeats itself on at least three subsequent images (therefore, over a time period of approximately 15 days), and the crop is in its phenological phase (from the calendar of phenology), then a first level of alert will be issued.

Following this, a check will be carried out to check if, in the same time period, there is a correspondent anomaly in the temperature (higher than normal) and/or precipitations (lower than normal).

According with the occurrences of one, or both, of these conditions, higher warning levels would be obtained.

NDVI anomaly	Temperature anomaly	Rain anomaly	Warning level
X	-	-	1
X	X	-	2
X	-	X	3
X	X	X	4

### 3.2. Locust monitoring

The study area is Somalia, which is located in arid and semi-arid regions, with high temperatures all year round and less precipitation. The desert in the study area is large and sparsely populated, which provides suitable breeding habitat for desert locusts. Without timely prevention and control, locust plagues can easily occur.

Our data mainly include remote sensing data, meteorological data, basic geographic data, and other auxiliary data. The remote sensing data is mainly used to extract locust habitat information such as vegetation and soil condition. The meteorological data is mainly used to calculate and extract precipitation, temperature, wind direction, and wind speed. The basic geographic data and other auxiliary data are mainly used for desert locust monitoring modeling and verification. The specific data types and basic information are not shown for sake of space.

Based on the physiological and ecological characteristics and development conditions of desert locusts, we conduct a comprehensive analysis of the climate, vegetation, soil and other essential habitat factors for the occurrence of locusts. Combined with the natural environment and climate characteristics, five types of factors including air temperature and land surface temperature (LST), precipitation, soil moisture, vegetation greenness, and Normalized Vegetation Index (NDVI) are used as remote sensing monitoring indicators for the desert locust habitat. we use a weighted method to construct the habitat suitability index, and the quantitative extraction of large areas of locust breeding areas is realized. Subsequently, we extract the main vegetation types (such as farmland, grassland, shrub) in the study area based on land use/cover data. Combined with the crop planting calendar, comprehensively analyze the vegetation growth curve of farmland, grassland, and

shrub. For the vegetation with stable periodicity growth curves, the damage area monitoring of the locust was conducted by comparing the vegetation index after the infestation and the average vegetation index over the past years. For other vegetation, the damage area monitoring was conducted by simulating the vegetation growth index of the same meteorological conditions and the same growing period and comparing it with the actual situation after the infestation.

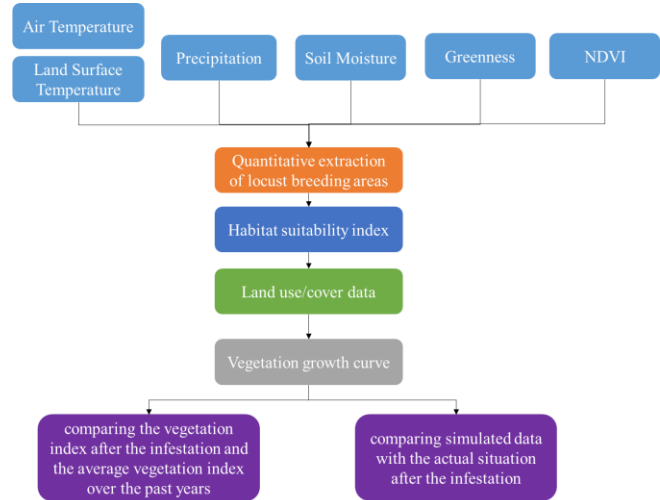


Figure 2. Monitoring process for desert locusts in Somalia.

## 4. RESULTS

### 4.1 Crop mapping

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

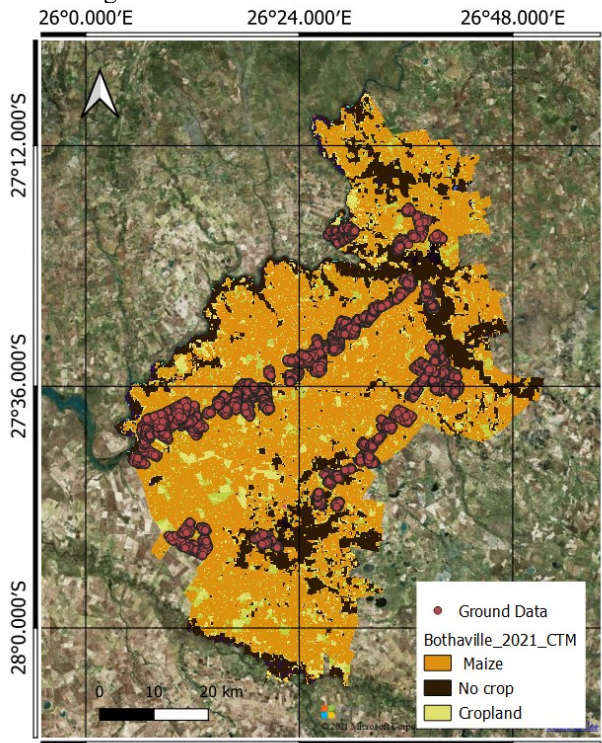
Details produced from the classification map of Bothaville (Nala County) in 2021 are shown in Fig.2. The classification map is released at a spatial resolution of 10 m, the area is mainly devoted to sorghum and maize cultivation.

The validation results for the Bothaville region, made on the 212 fields of the ground data collected in 2021, demonstrates that all the fields centroid recognized as “Maize” correspond to a true maize region. The overall accuracy on this scene is of the 87%.

### 4.2 Monitoring of desert locusts in Somalia

Desert locusts in Somalia were monitored in January to November 2020. According to the results, from January to March 2020, mature locust swarms emerged in northeastern Somalia, and native locusts continued to breed, while central and southern locusts migrated southwards to northeast Kenya, and the desert locust affected a total of 1028.7 thousand hectares of vegetation, including 1.2 thousand hectares of farmland, 203.7 thousand hectares of grassland, and 823.8 thousand hectares of shrub. In April 2020, desert

locusts in Somalia were mainly distributed in the northwest and central part of the border with Ethiopia. The monitoring results showed that the desert locust affected 596.2 thousand hectares of vegetation in April, including 1.1 thousand hectares of farmland, 190.2 thousand hectares of grassland, and 404.9 thousand hectares of shrub. Further invasions of locusts occurred in June 2020 (migrated from southern Ethiopia and southern Yemen), from July to September 2020 and from October to November 2020, locust swarms in Yemen migrated to northern Somalia.



**Figure 3.** Bothaville (Nala County) classification map for 2021 with a spatial resolution of 10 m.

## 9. CONCLUSIONS

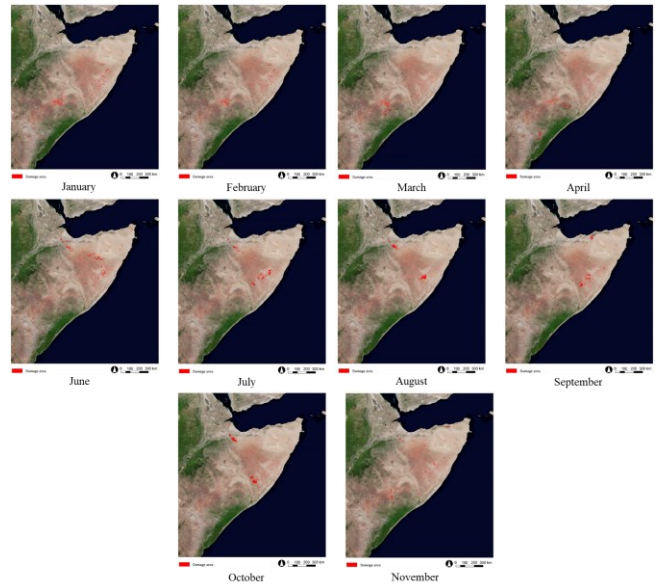
The paper describes the potentiality of combining satellite based accurate crop mapping methodology with techniques able to assess crop stress conditions with the objective of estimating the impact on food availability, mainly in developing countries.

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**Figure 4.** Monitoring results of desert locusts in Somalia from January to November 2020.

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