ANALYSIS OF PRODUCTIVITY ANOMALIES FOR FOOD SECURITY MONITORING BASED ON REMOTE SENSING DERIVED PHENOLOGY-INDICATORS

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ABSTRACT

Various institutions and organizations regularly monitor vegetation condition in food insecure regions of the world using remote sensing techniques from space mainly because of economic and security reasons. In this study, we outline a method to objectively assess the characteristics of concluded growing seasons ate the regional level on the basis of low spatial resolution optical remote sensing data only. A few key phenological indicators, derived from multi-temporal Earth observations, characterize the spatial and temporal evolution of successive growing seasons. These indicators, together with a simplified light use efficiency approach, are used to compute a proxy of the yearly gross primary production. Vegetation condition and the associated risk of food deficit are derived from a comparison of these yearly values with their long-term averages. This approach is exploited here to document the severe 2010-2011 drought in the Horn of Africa.

INTRODUCTION

The Horn of Africa (HoA: Ethiopia, Somalia, Eritrea and Djibouti) is notorious for its high risk of food insecurity. The failure of two consecutive rainy seasons in 2010 and 2011 led to a severe drought that hit the entire region. This situation resulted in poor vegetation condition, significantly reduced crop and pasture production, and a major food security crisis.

In this context, vegetation monitoring is of great importance to plan an emergency response and develop a more resilient long-term development strategy. Various organizations (e.g., FEWSNET, FAO, JRC) exploit satellite remote sensing (RS) techniques from space to generate crop and pasture status reports that are transmitted to local governments, decision makers and donors. Operationally, vegetation indices such as NDVI, or more current products like FAPAR (1), are derived from low-resolution satellite RS observations and exploited to document the state and evolution of the vegetation because these instruments (e.g., MODIS or SPOT-VEGETATION) cover large geographic areas with an adequate temporal frequency and have been operational for more than a decade.

RS-based analyses can be used to assess the current status of crops and pastures in a near real time. Also, optical remote sensing provides very valuable vegetation monitoring information in areas like the Horn of Africa where meteorological station networks are sparse and in particular the availability and quality of rainfall measurements is extremely low. The larger amount of information available at the end of a crop season can be leveraged to analyse the overall vegetation productivity of the recently concluded growing season (see Rembold et al. (3) for a review). The first type of analysis aims at detecting as early as possible vegetation anomalies that could lead to production deficiencies during the on-going season, while the latter summarises the vegetation condition and associated strain on food production resulting from the last completed season. This latter analysis may be performed by comparing the temporal profile of the selected RS variable for the season of interest (spatially averaged over both administrative and thematic layers, e.g., land cover) with the long-term average profile, to qualitatively evaluate the deviation from the typical, expected situation.

In this study, we address this second type of analysis and outline a pixel-based method to objectively assess and map the characteristics of past growing seasons. A few key phenological indicators, derived from time series of space observations, characterize the spatial and temporal evolution of successive growing seasons. These indicators, together with a simplified light use efficiency approach (4), are used to compute a proxy of the seasonal gross primary production (GPP). Vegetation conditions and the associated risk of food deficit are derived from a comparison of these yearly values with their long-term averages.

The method is exploited to document the impact of year-to-year climatic fluctuations in the HoA and in particular the very poor vegetation condition experienced between late 2010 and 2011. The case study refers to an analysis of the situation as of the 1st of November 2011. This contribution presents some examples of the anomaly analysis results focused on the description of the last two growing seasons: the one which ended in late 2010 - early 2011 and the following one which ended in mid-2011. Wherever only one growing period occurs per year, we considered only the seasons concluded in 2011.

Finally, we present a preliminary evaluation of the plausibility of these results by comparing them with seasonal calendars compiled from field observations, spatial patterns of rainfall estimate anomalies, and field assessment reports.

DATA AND METHODS

Processing proceeds in two main steps: the first one consists in characterizing the Land Surface Phenology (LSP), i.e., the spatio-temporal development of the vegetation as revealed by satellite sensors (5). Key phenological indicators such as the dates of the start (SOS) and end (EOS) of the growing season are computed using the Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) derived from the SPOT- VGT imagery.

In the second step, FAPAR values are integrated in time between SOS and EOS for each growing season, to obtain a proxy of the yearly GPP according to a simplified LUE approach where the variation in incident PAR is neglected, under the assumption that it never represents a limiting factor in the HoA.

The procedure is applied to each pixel showing seasonality and belonging to the area of interest to map the integrated FAPAR spatial distribution. The integrated values for the season of interest are then compared to the long-term averages for the same locations, and the probable causes for the deviations (especially decreases), such as a delayed start or precocious end of the growing season, or a lower than usual peak are identified.

Study area and data

The study area is located between 22° N - 5° S and 22 - 51° E, it encompasses the countries of Sudan, South Sudan and Kenya in addition to the HoA countries (Eritrea, Djibouti, Ethiopia and Somalia). The climate in most of the area is arid to semi-arid and rainfall is the most significant climatic variable affecting vegetation productivity. The region is quite heterogeneous from the agro-ecological point of view and exhibits a high temporal variability in crop seasons (6), which can be either mono- or bi-modal (i.e., one or two growing seasons per year).

This study is based on an analysis of dekadal (10-day) FAPAR products derived from SPOT-VGT data at about 1 km spatial resolution for the period 1998-2011 (7, 8).

A qualitative evaluation of the results was performed using the following ancillary data: FEWSNET (Famine Early Warning System, USA) and FAO (Food and Agriculture Organization of the United Nations) seasonal calendars (9, 10); TAMSAT satellite-based rainfall estimates v2.0 (11); and finally, several ground assessment reports published by a number of institutions active in the region (National Authorities; FAO; WFP, World Food Program; FEWSNET, FSNAU, Food Security and Nutrition Analysis Unit, Somalia; etc.).

Phenology retrieval and anomaly computation

The retrieval method consists in fitting a mathematical model to the seasonal time series and deriving the key phenological parameters from the model. The model fitting approach offers several advantages compared to the retrieval of phenological parameters directly from the observations. The time series of observations may not be continuous or complete (e.g., due to the presence of clouds) so that the assessment of a phenological event (e.g., SOS) may be biased if retrieved directly from the measurements. Measurements are always subject to uncertainties, both systematic and random, which result from a wide range of processes. Thus, individual measurements should not be taken at face value. The model acts as a smoothing operator and permits to objectively describe the variability of the canopy while taking into account the known or expected accuracy of the measurements. Finally, defining and computing the statistical characteristics of a seasonal time series on the basis of a smooth and continuous model is more precise and stable than an approach based on raw observations.

The pixel-based processing is performed in three sequential steps: statistic characterization of the time series, annual breakpoints setting and model fitting. In the first step, the algorithm exploits the full time series to extract the statistics characterising the pixel and its likely number of growing season (GS) per year (only mono- or bi-modal types are treated). The typical number of GS per year is determined by the number of relative maxima in the autocorrelogram of the FAPAR time series.

The second step aims to characterize the climatology of the pixel, that is, setting the temporal breakpoints that likely separate the periodic climatic cycles in the time-series. The yearly cycle can include one or two GS and represents the first level of segmentation of the time series before model optimization. To perform this task we compute the “median year”, i.e., the median of the FAPAR time series values for each dekad of the year. Next we define the breakpoints of the cycle (or sub-cycles in case of bi-modality) as the relative minima of the “median year” that is iteratively smoothed until the number of minima is equal the number of growing season per year.

Finally, the third step of the processing involves fitting a mathematical model to the FAPAR time series in each cycle (or sub-cycle). The model used here to simulate a single GS is the Parametric Double Hyperbolic Tangent (PDHT) model, given by:

$$f_{PDHT}(t) = a_0 + a_1\{\tanh[(t-a_2)a_3]+1\}/2 + a_4\{\tanh[(t-a_5)a_6]+1\}/2 - a_4 \quad (1)$$

where t is time and the seven parameters play the following roles: a_0 provides an overall base value; a_1 and a_4 define the amplitudes of the growth and decay phases; a_2 and a_5 allow shifting the inflexion points of the growth and decay phases along the time axis; a_3 and a_6 define the slopes of the two phases, respectively. Before model optimization, the local breakpoints defining the window in which to look for the growing season are adjusted to the time series minima, calculated on the smoothed FAPAR profile. After that, if enough valid observations (>7) and sufficient FAPAR variability (i.e., 95^{th} - 5^{th} percentile of FAPAR > 0.05) are present, the optimization is performed. Otherwise, the season is flagged as not processed or failed, respectively. Since the FAPAR values may be biased towards low values due to the presence of undetected clouds, the model optimization is adapted to the upper envelope of the observations using an iterative weighting scheme similar to that proposed by Chen et al. (12). Once the parametric model has been adjusted to the observed FAPAR time series, the phenological indicators described in Table 1 are computed and used for further analysis.

Anomaly indicators of the phenological variables have been either expressed as absolute differences with respect to the long-term average or as standard scores (Z-scores, $Z(x)=(x-\mu)/\sigma$). Under the assumption of normal distribution, Z-scores represent a convenient way to measure anomalies since deviations from the mean are weighted by their inherent variability. Anomalies at different locations and at different times can then be compared in terms of how extreme they are.

Table 1. Phenology indicators used in this study.

Metric		Definition
SF	Complete season failure	When the difference between the 95th and the 5th percentile of FAPAR data for that season doesn't exceed 0.05 units
SOS	Start of the season	Day when the modelled time series exceeds the initial base value a_0 plus 20% of the amplitude a_1
EOS	End of season	Day when the modelled time series drops below the final base value a_0+a_1-a_4 plus 20% of the amplitude a_4
LEN	Length of season	EOS-SOS
MaxV	Maximum FAPAR value during the season	Derived from the fitted model
CUM	Cumulative FAPAR during plant activity	Integral of the fitted model between SOS and EOS, assumed to be proportional to GPP

RESULTS

Anomalies in seasonal productivity are depicted in Fig. 1 and 2 as Z-scores of the CUM variable. For the bi-modal areas (Fig. 2), the anomalies are computed for the vegetation development that occurred during the most recently concluded seasons (late 2010 – beginning of 2011 and Apr. to Jul. 2011, respectively). In the mono-modal areas, the end of the season at different locations covers a wide range of dates. Therefore, to avoid ambiguities in the interpretation of the results we map only the season concluded in 2011 and provide a temporal indication of the timing of its conclusion (Fig 1).

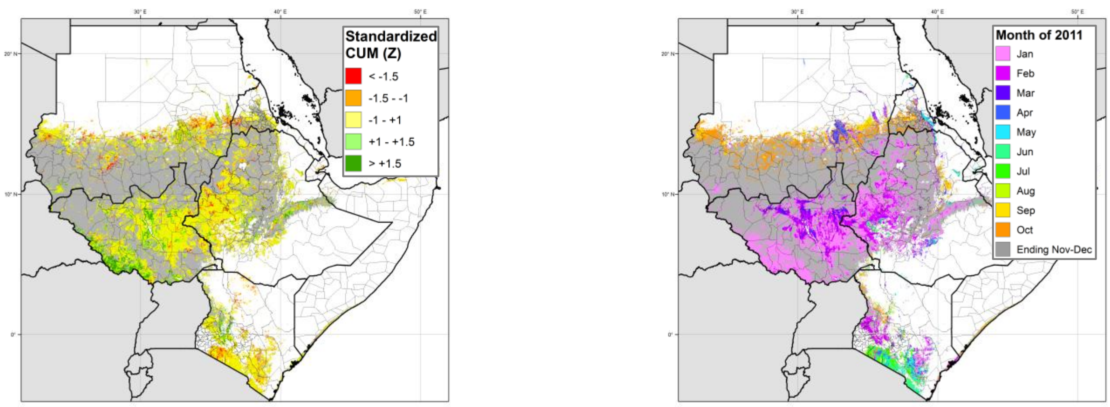

Fig. 1. CUM z-scores for areas with single growing season in 2011 (left panel) and timing of end of season to which the anomaly refers to (right panel). The areas with an on-going season expected to end in Nov. and Dec. 2011 (after the time of analysis) are mapped in dark grey.

Mono-modal areas show a limited spatial extent of negative anomalies (Fig. 1, left panel). However, spots of negative anomalies are present in a restricted area in the southwest Kenya (EOS from May 2010 to Jun. 2011) and for the most recently concluded season along the northern vegetation limit in Sudan (EOS from Aug. to Oct. 2011, Fig. 1 right). More spatially extended negative anomalies are detected for the areas showing bi-modal seasonality (Fig. 2), with very poor growing conditions observed for the first season in Kenya, Ethiopia and particularly, Somalia. Note that for simplicity we define as first season the first of the two studied, not the first in of the calendar year. Vegetation condition slightly improved during the second season that was however far below normal conditions in large areas. In Fig. 2, a large number of pixels showing high negative anomalies are characterized by complete season failure. The number of pixels where vegetation failed to develop during these last two seasons is significantly higher than the average number (15.9 % and 5.5 % of the pixels against an average failure percentage of 2.8 %).

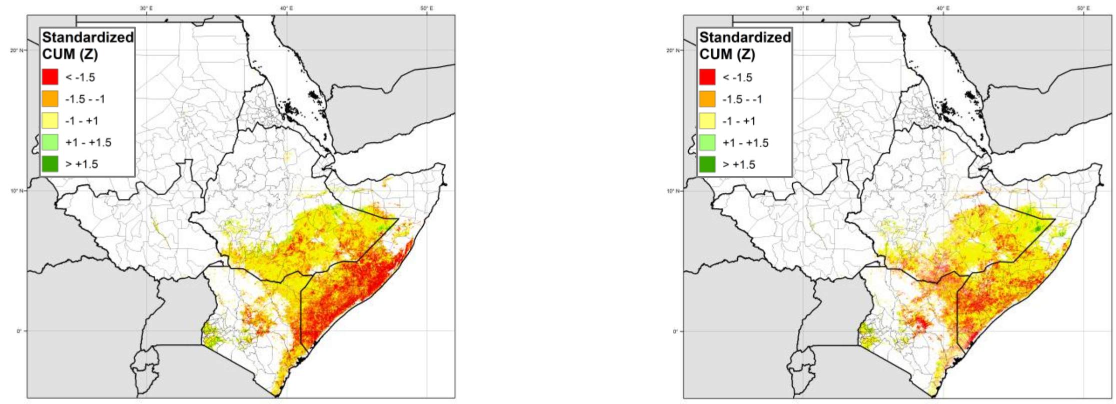

Fig. 2. CUM z-scores for areas with double growing season: left and right panels refer to the first and second season (approximately late 2010 – beginning of 2011 and Apr. to Jul. 2011, respectively).

Focusing on the areas that experienced the poorest productivity, i.e., those showing bi-modal seasonality, we identified the factors contributing to the observed development by analysing SOS, LEN and MaxV (FAPAR peak) anomalies. Even if the first growing period was not significantly delayed compared to the long-term average, it ended precociously and was therefore shorter. In addition, this season was characterized by lower vegetation development (i.e., negative anomalies of the peak FAPAR values) and by a widespread occurrence of complete failure of the vegetation growth. On the contrary, a larger delay of the onset (up to more than one month) was observed for the second season. This delay caused a shortening of the length of the growing season with exceptions of some areas in the eastern Ethiopia and central Somalia where the delay in the start was compensated by a later than usual end. The overall shortening of the growing season was accompanied by a reduction of the maximum vegetation development in part of Somalia and Kenya.

As a validation exercise, the plausibility and consistency of the results were evaluated against available independent sources of information. The climatological timing of start and end of the seasons, as retrieved by the phenological algorithm, showed a good agreement with country level crop calendars with the exception of some mono-modal areas in Kenya where the calendar indicates the presence of two rainy seasons. These areas exhibit very challenging conditions for phenology retrieval from an FAPAR profile characterized by poor periodicity (i.e., lack of a dominant temporal pattern throughout the years), predominance of one of the two growing seasons and unclear separation between them. Preliminary results of further qualitative validation show that the anomalies of cumulative FAPAR spatially matched those of rainfall estimates and are in agreement with the spatially scattered field observations summarised in the field reports elaborated by a number of institutions in the region. The main advantage of our methodology is the capacity to identify areas of major drought severity (e.g., Somalia and Kenya) as well as areas less or not impacted (e.g., in Ethiopia and South Sudan) while covering the study area exhaustively. The method provides pixel-level objective information about vegetation development also when and where local observations are not available.

CONCLUSIONS

In this paper we presented a methodology to assess the seasonal development of vegetation in semi-arid ecosystems based on phenology retrieval from satellite RS data. This provides relevant inputs for regional and national early warning systems as well as a basis for food security analysis at a given time by documenting the vegetation performances of the last few concluded seasons. The anomaly maps of the cumulative FAPAR during the growing period provide a synoptic overview of vegetation condition that is homogeneous in terms of time and method of analysis. This information can therefore complement the heterogeneous one provided by field assessments that are often carried out with different methodologies and at different periods in different countries.

With respect to existing operational methods, the use of the cumulative FAPAR during the whole growing period enables a coherent interpretation of regional anomaly maps. In fact, anomaly maps traditionally computed by comparing a RS product (e.g., NDVI or FAPAR) with its long-term average at a given dekad are not easily interpretable because the anomaly at different spatial locations may refer to different stages of vegetation growing seasons. In this way for example, shifts in the timing of the season that do not necessarily lead to abnormal vegetation development may be regarded as severe anomalies at the initial and final stages of the growing period.

Future research will aim to adapt the proposed methodology for near real time monitoring and early warning purposes. Such development could build upon the current approach to estimate the outcome of the on-going season and would require adaptation of the algorithm to detect when the current growing season starts its decay phase. In this way the cumulative FAPAR during the growing phase could represent a first integrated assessment of the current growing season.

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