Evaluation of a Satellite Drought Indicator Approach and its Potential for Agricultural Drought Prediction and Crop Loss Assessment. The Case of BEACON Project

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Abstract. BEACON is a market-led project that couples Earth Observation (EO) with weather intelligence and blockchain to deliver a toolbox for timely, cost-efficient and actionable insights for the Agricultural Insurance (AgI) sector. BEACON enables insurance companies to exploit the untapped market potential of AgI, while contributing to the redefinition of existing products and services. The Damage Assessment Calculator of BEACON employs remote sensing in order to improve the quality and cost-effectiveness of agri-insurance by: i) increasing the objectivity of the experts' field inspections; ii) reducing the cost of field visits and iii) increasing farmers' confidence in the estimation results. This paper provides an approach that employs a satellite derived agricultural drought indicator, implemented in the operational workflow of BEACON that can be used by AgI companies to improve the prediction and crop loss assessment due to drought.

Keywords: BEACON; Agricultural Insurance; Drought; NDVI-Anomaly.

1 Introduction

The agriculture sector is highly vulnerable to drought, as it depends directly on water availability (Tsakiris and Tigkas, 2007; Meng et al., 2016). Although each crop differs in its resilience to water stress, drought can cause crop failure if the weather conditions are adverse during the most sensitive stages of crop growth (Peña-Gallardo et al., 2019). Droughts are difficult to measure and quantify (Vicente-Serrano et al., 2016), and consequently a wide range of drought indices have been developed to provide tools for quantifying their effects on vegetation.

Vegetation is constantly monitored for conditions of drought using vegetation indices (VIs). Among them, NDVI is the one most often used for monitoring the environmental conditions (e.g. grassland status, land degradation, desertification, and drought) all over the world (Hassan et al., 2018). NDVI is commonly calculated using image data from polar orbiting satellites, which carry sensors detecting radiation in red

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and infrared wavelengths. The Moderate Resolution Imaging Spectroradiometer (MODIS) is most widely used for drought monitoring. There are several NDVI-based approaches for detecting and mapping drought using its long-term mean for a pixel or region at a given time. A simple and common NDVI-based approach for monitoring drought, is the relative NDVI Anomaly (NDVIA) (Anyamba and Tucker, 2012; Nanzad et al., 2019).

The use of anomaly isolates the variability in the vegetation signal and establishes meaningful historical context for the current NDVI to determine relative drought severity. NDVIA provides a powerful tool for agricultural drought monitoring to ease identify drought-sensitive areas and estimate possible crop damage. This possibility emerges from the well-established potential of remote sensing to detect change on vegetation.

This short paper presents the methodology developed in BEACON project, for crop loss assessment due to drought, based on the NDVIA and ground truth data made available by AgroSeguro, the Spanish AgI provider. The dataset consisted of drought damage percentage occurred on wheat and barley. A validation procedure was followed to test the accuracy of the developed EO product against in-situ data.

2 Materials and Methods

2.1 Satellite data

The NDVI MODIS/Terra daily Level-2G product (GMOD09Q1) was used for drought monitoring. This product is provided as a service federation of the GIMMS MODIS NASA-UMD with a spatial resolution of 250 m and as a composite 8-day product, since 2001. To develop the methodology, the MODIS NDVI datasets were downloaded and cropped to the provided parcels extent. The total period that was taken into account corresponded to the growing season from 17 November to 26 June (2017, 2018 and 2019). The number of 8-day records per growing season was 29. After image acquisition, the Relative NDVIA was calculated as follows:

$$\mathrm{NDVIA}_{i,j} = 100 \cdot (\mathrm{NDVI}_{i,j} - \mathrm{NDVI}_{ave,j}) \,/\, \mathrm{NDVI}_{ave,j} \qquad (1)$$

where i subscript denotes the year, j subscript denotes the period (8-day), and $\mathrm{NDVI}_{ave,j}$ is the average value for the same period j from a number of years (the multi-year mean of the specific 8-day). The Relative NDVIA indicates the variation of the current 8-day composite compared to the long-term average, where a positive value denotes enhanced vegetation conditions compared to the average, and a negative value indicates comparatively poor vegetation conditions (Vaani and Porchelvan, 2017). The historical average was based on the NDVI values of the corresponding 8-day period from 2001 until present.

2.2 In-situ data

In BEACON, in-situ data were made available by AgroSeguro that manages AgI on the Spanish market at national level. Drought damage originated from the rural area of Ávila and Segovia. In this region the predominant crops are rainfed barley and wheat, covering 26% and 22% of the total area, respectively. Wheat and barley growing seasons begin by the middle of December and last until early July. The most frequent damaging weather phenomena in the regions are drought and hail. Number of damaged parcels was 91 (2017), 13 (2018), 42 (2019). The parcel size ranged between 1 ha and 10 ha, with the majority of the parcels area being approximately 4 ha and an average size of ≈5.7 ha. Based on the spatial resolution of 250 m, the NDVIA pixels corresponding to each parcel ranged from 1 to 21. Damage severity caused by drought ranged between 10% and 100%. Approximately 75% of the samples were used to develop the methodology, while 25% were used to validate the developed EO product.

2.3 Indicator-impact functions

To relate the level of drought severity, expressed through NDVIA, to the number of reported impacts and the onset of drought (Naumann et al., 2014), ***indicator-impact*** functions were derived. These sigmoidal regressions are used to quantify the drought impact in terms of production (damage) or economic return (loss) (Bachmair et al., 2015). The performed regressions were based on specific crop data (winter wheat and barley crop damage) and localized climatic conditions, therefore, several agro-meteorological aspects had to be taken into account, such as:

- The developed methodology for drought applies only for winter wheat and barley.
- The crop loss assessment methodology is the same for winter wheat and barley crops.
- Vegetation stress obtained through the calculation of NDVIA for the growing seasons of wheat and barley (2017-2019) was attributed only to drought events.
- Variation of intensity of vegetation stress reflects the variation of drought severity throughout the growing season.
- Under natural conditions, the severity of vegetative drought evolves gradually in time.
- Barley and wheat yields are vulnerable to drought during spring, responding in both short drought timescales (1–3 months) and medium (4–6 months) timescales.
- Peña-Gallardo et al. (2019) found no major differences in precipitation patterns among districts in Spain during a drought study. Differences found were focused mainly in the average maximum and minimum temperatures. Therefore the methodology could be expanded to include winter wheat and barley crops in the entire Spain.

In wheat (*Triticum aestivum* L.) and barley (*Hordeum vulgare* L.), drought stress can occur at any growth stage (Sallam et al., 2019). Although barley is less dependent on water availability at germination and the grain filling stage than wheat, Peña-

Gallardo et al. (2019) found that the temporal responses of these crops to drought conditions were very similar in both space and time.

3 Results and discussion

For the development of the methodology an indicator-impact function was derived by correlating the drought severity with the in-situ assessment of the damage. The drought severity was defined as the sum of the absolute values below zero of the NDVIA during a certain period of time. Bachmair et al. (2015) and Naumann et al. (2014) proposed this approach using meteorological drought indicators. The accumulation time period was limited from the 1st of April to the end of June, corresponding to the reproductive and senescence stages. A study by Hernandez-Barrera et al. (2016) demonstrated that during spring, precipitation deficit is the most influential climate factor affecting cereal growth.

For the accumulation of the NDVIA values, the median of the pixel values, corresponding to a parcel, was selected for the regression which was considered as the most representative to be linked with the damage. An example of the procedure is illustrated in Fig. 1.

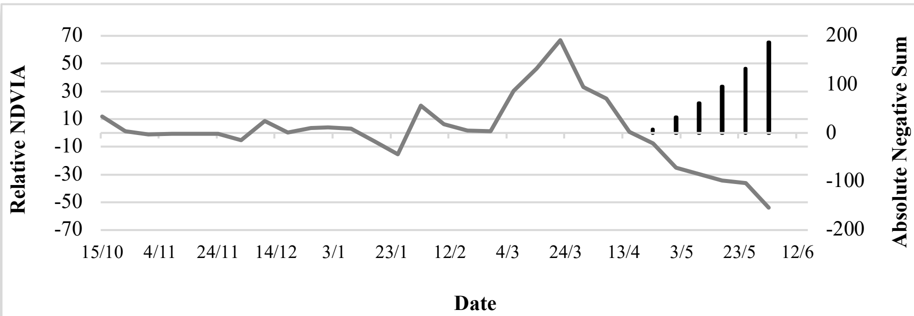

Fig. 1. Relative NDVIA and Absolute Negative Sum during the growing season 2016-2017.

Gridded datasets of the SPEI indicator were acquired for the growing seasons of 2017-2019 from the SPEIbase[1]. According to SPEI values, wheat and barley crops faced severe drought during the 2017 and 2019 seasons, justifying the small number of in-situ data provided for 2018. Mutsotso et al. (2018) found that external signs of stress expressed through the NDVI, lagged SPEI approximately one month. However, they supported that SPEI correlated well with NDVIA. SPEI values are illustrated in Fig. 2.

[1] http://spei.csic.es/map/maps.html#months=1#month=8#year=2019

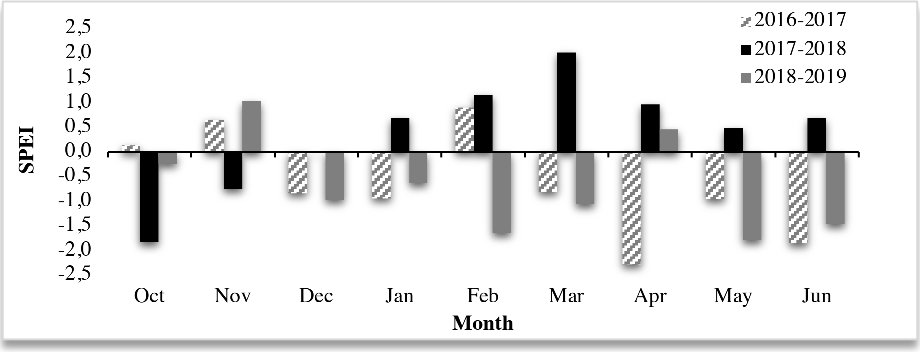

Fig. 2. Fluctuation of SPEI for Ávila and Segovia regions, during the growing seasons.

To select the best function type, the goodness of fit between the drought severity expressed as the absolute negative sum of the relative NDVIA and the damage percentage was assessed assuming linear, power-law, exponential and sigmoidal relationships. The sigmoidal relationship that provided the best explanation of variance with a correlation coefficient of r = 0.53, is the following:

$$y = (78.6 + 106.1 \cdot x^{0.31}) / (2.43 + x^{0.31}) \qquad \textbf{(2)}$$

where y is the expected impact in terms of % damage, x is the absolute negative sum of the Relative NDVIA. Fig. 3 provides the indicator-impact function plotted against the provided damage data.

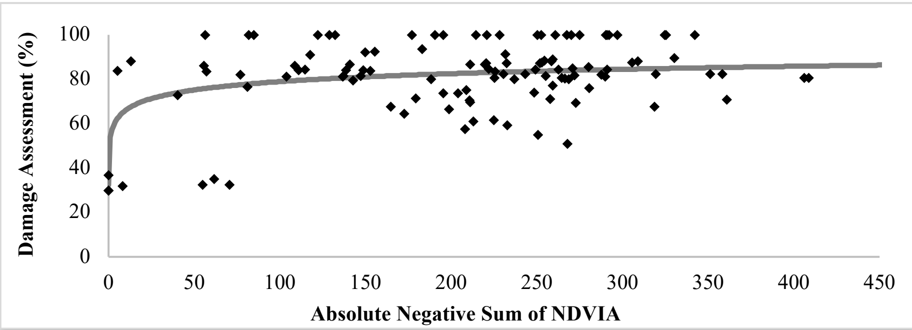

Fig. 3. Drought-damage function depicting the relationship between reduction in crop production and drought severity.

A number of 28 drought damage cases were used to characterize the accuracy of the developed methodology and evaluate the performance of the EO data product. The following statistical criteria were applied, namely i. the mean error (ME), ii. the root mean square error (RMSE), iii. the normalized RMSE (nRMSE), iv. the coefficient of residual mass (CRM) and v. the correlation coefficient (r) between the observed and predicted data (Antonopoulos, 2000). Table 1 provides the results of the statistical analysis.

Table 1. Statistical criteria between observed and calculated drought damage.

Metric	Value
ME (%)	-3.29
RMSE (%)	8.28
nRMSE%	9.88
CRM	0.04
r	0.69

4 Conclusions

According to the statistical analysis results, the following conclusions are drawn based on the performance of the indicator-impact equation to describe crop damage due to drought:

- The developed methodology slightly underestimates drought damage.
- The RMSE% value indicates good performance of the methodology to describe the drought damage.
- The nRMSE is considered acceptable and indicates relatively good correspondence between observed and predicted damage.

Overall the methodology describes fairly well the selected cases. However, the number of damage cases used for the validation cannot be considered adequate for safe results at this point. During the two-year pilot phase of the project, the algorithms for crop loss are expected to be further refined with new data that will be collected.

5 Summary

BEACON solution employs a multi-satellite approach in order to provide safe and reliable estimates on crop damage, for any type of AgI. BEACON takes into account damage by hail, floods, wild-fires and drought which are the four most devastating hazards of agricultural production worldwide. This paper presents a simple crop-specific methodology that takes advantage of the historical MODIS NDVI records to synthesize a service for drought damage quantification. The service will support AgI companies in assessing and calculating damage to proceed with indemnity payouts of claims. In-situ data that will originate from AgI companies, most of which are early adopters of the BEACON's solution, will be used to further fine-tune the algorithms.

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