Redefining Agricultural Insurance Services Using Earth Observation Data. The Case of Beacon Project

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Abstract. BEACON is a market-led project that couples cutting edge Earth Observation (EO) technology with weather intelligence and blockchain to deliver a toolbox for the Agricultural Insurance (AgI) sector with timely cost-efficient and actionable insights for the agri-insurance industry. BEACON enables insurance companies to exploit the untapped market potential of AgI, while contributing to the redefinition of existing AgI products and services. The Damage Assessment Calculator of BEACON employs remote sensing techniques 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, given the significant economic impact of erroneous estimation. This paper provides an analysis of different type of EO data and remote sensing techniques implemented in the operational workflow of BEACON that can be used by AgI companies to provide safe and reliable results on storms, floods, wildfires and droughts damage on crops.

Keywords: Agricultural Insurance, BEACON, Earth Observation Data

1 Introduction

Agricultural Insurance (AgI) sector is expanding on a global scale and is projected to grow by €50 B, by 2020. This rapid growth is driven by a set of fundamental structural changes directly affecting the agricultural sector like more frequent and severe extreme weather events, growing global population and intensification of production systems [1, 2]. Insurance solutions are set to grow in importance for agricultural management, given that agriculture will continue to be increasingly dependent on risk financing support. However, the development and provision of insurance services/products in the agricultural sector is generally low as compared to other sectors of the economy, and in their majority, suffer from low market penetration [3].

In that frame, the BEACON toolbox was born, that aims to provide insurance companies with a robust and cost-efficient set of services that will allow them i) to alleviate the effect of weather uncertainty when estimating risk of AgI products; ii) to reduce the number of on-site visits for claim verification; iii) to reduce operational and administrative costs for monitoring of insured indices and contract handling; and iv) to design more accurate and personalized contracts. Specifically, BEACON scales-up on EO data and Weather Intelligence services components, couples them with blockchain, to deliver the required functions for Weather Prediction and Assessment and Smart Contracts and offer the required services:

- Crop Monitoring, which provides contract profiling and crop monitoring data together with yield estimations.
- Damage Assessment Calculator, which supports AgI companies in better assess and calculate damage to proceed with indemnity payouts of claims.
- Anti-fraud Inspector, which allows AgI to automatically check the legitimacy of a claim submitted;
- Weather Risk Probability, which provides probabilities maps of extreme weather events that may occur in the upcoming season;
- Damage Prevention/ Prognosis – Early Warning System, which provides extreme weather alerts to AgI providers and their customers.

This paper focuses on the DAT service components. It provides an analysis of different type of EO data and remote sensing techniques implemented in the operational workflow of BEACON that can be used by AgI companies to improve the quality and cost-effectiveness of their services.

2 Materials and methods

BEACON employs a multi-satellite approach to tackle one of the main challenges of AgI, which is damage assessment and handling of claims with a greater accuracy. BEACON estimates damage occurred by hailstorms, windstorms, floods, wildfires, and drought, considered as the most devastating natural hazards of agricultural production worldwide [4]. Damage on a number of arable crops is taken into account, namely wheat, barley, maize, soybean, sunflower and cotton.

The Damage Assessment Calculator (DAC) provides visual damage maps of the affected area accompanied by the appropriate information, aiming in quantifying damage and providing a transparent basis for the indemnity pay-out process with farmers. The general framework under which the DAC is developed, is the implementation of change detection techniques between a pre- and a post- hazard available image. The concept is based on the fact that the spectral behavior of a crop in different zones of the electromagnetic spectrum can be modified by a number of means, including catastrophic phenomena, destruction or decrease in plant chlorophyll content, changes in internal leaf structure and of the morphological characteristics of plant canopy. These changes in spectral behavior can be detected by satellite sensors [5].

Satellite images utilized by BEACON in producing the appropriate vegetation indices (VIs) are: i) Sentinel-2, Level-2A, Bottom-Of Atmosphere (BOA), surface reflectance products, ii) Sentinel-1, C-band Interferometric Wide (IW) swath, TOPSAR data, in GRDH (Ground Range Detected in High resolution) format, with double polarization (VV and VH) and iii) MODIS Terra 9x9 degree Tiles, 8-day NDVI composites. Due to their sensitivity to vegetation condition and abundance, VIs are then employed in image differencing to detect changes related to extreme weather events [6]. Two aspects are critical for the change detection results: selecting suitable image bands or VIs and selecting suitable thresholds to identify the changed areas. For this reason, a number of different techniques were implemented in the DAC, based on the type of the hazardous event.

2.1 Hail and storms damage assessment

In BEACON, to overcome issues in optical data quality and therefore availability, the synergistic use of optical and synthetic aperture radar (SAR) images was included in the workflow of the DAC. Regarding optical data, the NDVI (Normalized Difference Vegetation Index) is used to perform damage assessment between a pre- and a post-hazard acquired image of an insured crop. The index results from the following equation:

$$NDVI = \left(NIR - RED \right) / \left(NIR + RED \right) \tag{1}$$

where *RED* and *NIR* stand for the spectral reflectance measurements acquired in the red and near-infrared regions, respectively. NDVI sensed values are sensitive to a number of perturbing factors including: i) atmospheric effects (with respect to water vapor and aerosols), ii) clouds (deep – optically thick and thin clouds – ubiquitous cirrus) and iii) cloud shadows, that can significantly contaminate the results and lead to misinterpretations in damage assessment. Hailstorm events are usually accompanied by prolonged cloud coverage, impeding the acquisition of cloud free optical images.

SAR sensors are independent of atmospheric and sunlight conditions and therefore can provide the means to overcome the limitations of optical sensors. SAR derived, vegetation indices proposed in the literature are the Radar Vegetation Index (RVI) [7], Radar Forest Degradation Index (RDFI) [8] and Microwave Polarization Difference Index (MPDI) [9]. In BEACON, the MPDI is employed for change detection under this type of damage. The index represents a normalized polarization, calculated from VV and VH images captured by Sentinel-1 satellites. It is expressed as follows:

$$MPDI = \left(\sigma^{o}_{VV} - \sigma^{o}_{VH} \right) / \left(\sigma^{o}_{VV} + \sigma^{o}_{VH} \right) \tag{2}$$

where $\sigma^{o}{}_{VH}$ and $\sigma^{o}{}_{VV}$ are the backscattering sigma nought values of *VH* and *VV* polarization, respectively. The values of MPDI vary between 0 and 1. Low MPDI values (<0.3) refer to high biomass and denser vegetation. Values change gradually to higher values for degraded, damaged or sparse vegetation and during crop maturation.

The MPDI was selected in BEACON for three reasons. Firstly, the numerator (*VV-VH*) reflects the depolarization ratio. This ratio has an increased sensitivity to surface roughness, as well as vegetation structure. Secondly, the normalization of the depolarization ratio demonstrates sensitivity to vegetation canopy density and water content. Therefore, structural damage caused during hailstorms (e.g. defoliation, stem breakage and uprooting) can easily be detected by MPDI. Furthermore, normalizing the depolarization ratio also serves to reduce potential outliers within the data. Thirdly, *VV* and *VH* present a high level of availability that the Sentinel-1 sensors provide, with a standard revisit time per orbit (ascending, descending) of 6 days (S1-A, S1-B).

2.2 Flood damage spatial distribution

In BEACON, SAR and optical data are utilized for flood damage assessment. SAR data assist in monitoring flood extent, damage and duration and fill the gaps of optical data acquisition [10]. Their synergistic use is intended to enable BEACON to identify the beginning, the duration and the extent of flooding with a significant accuracy.

Optical data to detect and map flooding events. In BEACON, mNDWI (modified Normalized Difference Water Index) [11] is used to map and delineate flooded areas. Research has demonstrated that mNDWI can enhance water information and extract water bodies with a significant accuracy [12, 13]. The index is expressed as follows:

$$mNDWI = \left(GREEN - SWIR\right) / \left(GREEN + SWIR\right) \tag{3}$$

where *GREEN* and *SWIR* stand for the spectral reflectance measurements acquired in the green (visible) and the Shortwave Infrared (SWIR) band, respectively. The value of mNDWI ranges from −1 to +1. The higher reflectance of built-up and lower reflectance of water in SWIR band result in negative values of built-up and positive values of water features in the mNDWI derived image. For the separation of water bodies from other land-cover features, several thresholds have been proposed for mNDWI, ranging from 0 to 0.41 [13, 14].

SAR, C-band Data Processing to detect and map flooding events. BEACON uses a methodology for flood mapping based on multi-temporal SAR data analysis and the computation of two indices, i.e. the Normalized Difference Flood Index (NDFI) for highlighting flooded areas, and the Normalized Difference Flood in Vegetated areas Index (NDFVI) for highlighting shallow water in short vegetation [15, 16]. According to the method, two SAR multi-temporal layer stacks are created. One contains only reference (pre-flood) SAR images and the other both reference and post-flooding images. Statistical analysis of the backscattering sigma nought, $\sigma°$, of each pixel is then performed in both multi-temporal image stacks ($\sigma°_{ref}$ and $\sigma°_{flood}$). For each pixel, the minimum, maximum and mean $\sigma°$ is derived. The calculated temporal statistics are used to compute the NDFI, which aims at highlighting temporary open water bodies:

$$NDFI = \left(mean\left\langle\sigma^o_{ref}\right\rangle - min\left\langle\sigma^o_{ref}, \sigma^o_{flood}\right\rangle\right) / \left(mean\left\langle\sigma^o_{ref}\right\rangle + min\left\langle\sigma^o_{ref}, \sigma^o_{flood}\right\rangle\right) \tag{4}$$

To detect shallow water in short vegetation, NDFVI is used, aiming at highlighting the increase of backscatter that happens in those circumstances. NDFVI is used for detecting and delineating flood events in well-developed crops, which is particularly important in BEACON, and is computed:

$$NDFVI = \left(max\left\langle\sigma^o_{ref}, \sigma^o_{flood}\right\rangle - mean\left\langle\sigma^o_{ref}\right\rangle\right) / \left(max\left\langle\sigma^o_{ref}, \sigma^o_{flood}\right\rangle + mean\left\langle\sigma^o_{ref}\right\rangle\right) \tag{5}$$

After the computation of the two indices, a threshold of 0.70 for NDFI and 0.75 for NDFVI is applied to extract flooded areas [15]. In BEACON, the sigma nought for *VV* polarization is used for both NDFI and NDFVI. Research suggests that *VV* polarization performs better for water body detection, providing better accuracies than *VH* [17].

In the workflow for flood detection in BEACON, SAR images, are stored and every time a new image is available, the NDFI and NDFVI are calculated. The two stacks of images contain, on the one hand, the reference image stack and on the other hand, the reference stack and the latest image (presumed as a post-flood image). After the determination of flooded or non-flooded pixels, based on the thresholds imposed, a binary algorithm will be applied. To binarize the image, band math is applied, setting as logical value (true) for values less than the chosen threshold and false for higher values, producing the final "*Water*" image [10].

This methodology adopted in BEACON, exhibits the following advantages: i) it is fully automated and non-user dependent, especially in terms of defining an appropriate threshold; ii) it is robust since the same workflow (in particular, the same threshold values) is applied to different floods in different environments by using different SAR sensors, polarizations and resolutions; iii) the use of time-series improves the robustness of the reference image allowing a more precise mapping; and iv) it reports shallow water in short vegetation, a product particularly important for flooded crops.

2.3 Wildfires damage mapping

Several methods have been proposed for mapping fire-affected areas from multitemporal or single post-fire satellite images [18, 19]. Much of the literature in remote sensing of burn severity has been based on thresholding the arithmetic difference of the Normalized Burn Ratio (dNBR) at two dates. The Normalized Burn Ratio (NBR), is a very sensitive index for burned areas enhancement and severity assessment [20]. The index combines the reflectance in the *NIR* and *SWIR* bands. The NBR and the dNBR indices, are expressed as follows:

$$NBR = \left(NIR - SWIR\right) / \left(NIR + SWIR\right) \tag{6}$$

$$dNBR = NBR_{PreFire} - NBR_{PostFire} \tag{7}$$

where $NBR_{PreFire}$ and $NBR_{PostFire}$ is the sensed NBR in the satellite image before and after the fire event, respectively. NBR values range from −1 to 1, and dNBR values can range from −2 to 2. Higher NBR values indicate healthy vegetation, and lower values, burned areas.

In BEACON, the Relativized Burn Ratio (RBR) [21] is used for fire damage assessment, mapping and severity classification. RBR is divided by an adjustment to the pre-fire NBR, as follows:

$$RBR = 1000 \cdot dNBR / \left(NBR_{PreFire} + 1.001\right) \tag{8}$$

RBR index is designed to detect change even where pre-fire vegetation cover is low. The dNBR index receives low values when burned areas are covered with low vegetation, due to low values in the change detection between the pre- and post-fire NBR [22]. This results in the underestimation of the fire severity by the dNBR. The relativized index performs better at detecting high severity effects across the full range of pre-fire vegetation cover [21]. RBR is used in BEACON because it is a robust severity metric applicable across broad geographic regions and fire regimes. Furthermore, RBR thresholds show reduced variability among fires and are more stable compared to other indices like dNBR and RdNBR (Relative dNBR) thresholds, and are thus more transferable among fire types and ecoregions. In terms of the RBR equation usability in an automated workflow, it is expected that the equation will not fail (i.e., reach infinity) for any pre-fire NBR value, will not result in extremely high or low values when pre-fire NBR is near zero, and it will retain the sign of pre-fire NBR, thereby avoiding potential arbitrary bias of taking the absolute value (e.g. RdNBR index) [21, 22].

2.4 Drought damage detection

BEACON detects drought damage by monitoring NDVI Anomaly (NDVIA) of an insured crop, throughout the growing season [23]. NDVIA is calculated from the MODIS NDVI, Level-2G product, provided in 8-day composites with a spatial resolution of 250 m (GMOD09Q1). The NDVIA is calculated as follows:

$$NDVIA_{ij} = 100 \cdot \left(NDVI_{i,j} - NDVI_{ave,j} \right) / \left(NDVI_{ave,j} \right) \tag{9}$$

where i subscript denotes the year, j subscript denotes the 8-day period, and $NDVI_{ave,j}$ is the historical average, based on NDVI values of the corresponding 8-day period from 2001 until present. NDVIA positive values indicate normal conditions while negative values indicate possible drought stress [24]. 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 [25].

3 Results and Discussion

3.1 SAR and Optical Data for hail and storms damage assessment

In change detection, image acquisition could present a significant irregularity in pre- and post- event dates due to availability issues of a proper cloud free multispectral image. The longer the time period between pre- and post- event images, the most possible it is for change detection techniques to capture different crop phenology stages (physical reduction of chlorophyll content) which will then result in biased damage estimates. For an effective event coverage, in BEACON, an image acquisition strategy is followed to ensure that the pre- and post- damage imagery are as representative as possible of the insured crop's condition. Afterwards, the Difference Percentage Index (DPI), is calculated with the VI differencing technique, by the pre- and post- hazard satellite image. DPI records the % change of the indices in the pre- and post- hazard crop status, and is used for damage spatial distribution and severity classification in the final image. Differencing is applied on NDVI and MPDI obtained before and after a damage.

$$DPI(\%) = 100 \cdot \left(NDVI_i - NDVI_j \right) / NDVI_i \tag{10}$$

$$DPI(\%) = 100 \cdot \left| \left(MPDI_i - MPDI_j \right) / MPDI_i \right| \tag{11}$$

where the subscripts i and j denote the sensed VIs values in the pre- and post-damage satellite images, respectively. The equation is applied in the two available satellite images pixel by pixel, and a third one is produced with the resulting DPI in the pixels.

Since DPI expresses the actual damage, as a percentage of change detection, the incorporation of severity levels generalizes the spatial mapping of damage, providing further information on where the natural hazard event hit the most or where the change was undetectable. From a geoprocessing point of view, the qualitative damage estimation involves the DPI raster value reclassification, into severity levels, classified as light (10-40%), moderate (40-70%) and severe damage (70-100%) [26]. Fig. 1 provides an example of hail damage estimated under regular and irregular pre- and post- event time intervals.

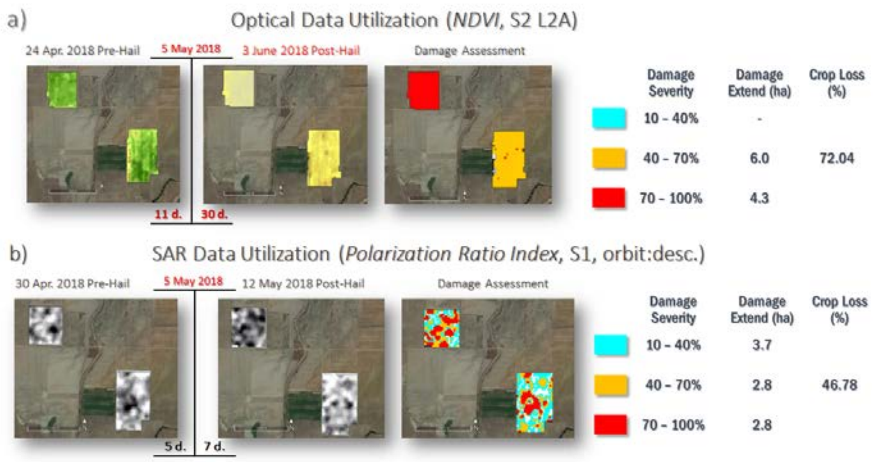

Figure 1. Wheat crop hail damage spatial distribution and severity levels in Kilkis, Central Macedonia (Greece), on 5 May 2018, estimated with the methodologies implemented in BEACON. (a) Irregular time interval between pre- and post- hazard images due to cloudiness, (b) acceptable time interval between pre- and post- hazard images.

For the validation of the methodology, hail damage in-situ data on wheat, barley, maize, soybean and cotton crops were provided by AgI companies, early adopters of the BEACON solution. Data will be used to derive regression equations between the calculated DPI and levels of damage.

3.2 Flood duration identification

Based on the adopted methodology, BEACON applies SAR image change detection for flood mapping and flood extent assessment. Using this methodology synergistically with optical satellite data the flood duration is estimated. Then, crop loss is estimated based on the duration, the crop type and the crop stage. According to the availability of SAR images, the temporal variation of surface backscattering from the pre- to the post-flooding phase is produced, delineating the flood extent by the number of pixels classified as inundated. The same is produced based on the mNDWI sensed values. Every time a new assessment is available, the flood extent is re-estimated and subtracted from the initial extent detected. The days between the pre- and post- flooding images are counted and recorded and a full report is provided to the users through BEACON. This report contains the duration of the flood between the pre- and post- flooding image, as well as, the extent of the flood, until the water fully withdraws. The short revisit cycle of Sentinel-1 satellites (6 days) enables the collection of flood data that allow mapping inundated areas accurately. Fig. 2 presents an example of a flooded area estimated with the coupled use of SAR and optical satellite data, with the methodology implemented in BEACON.

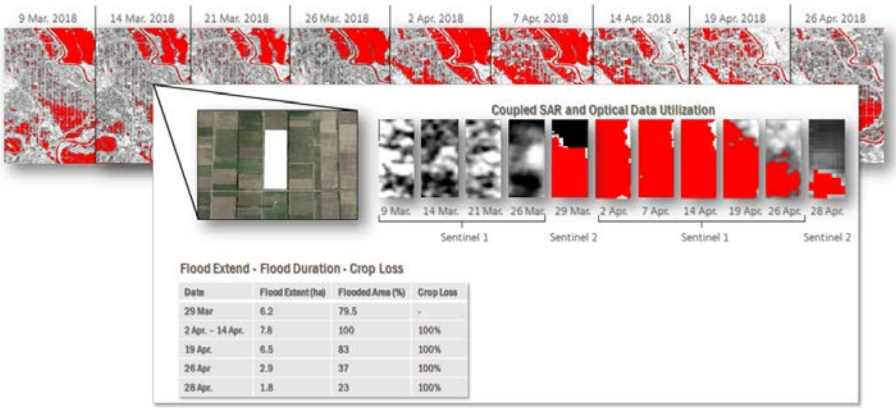

Figure 2. Wheat crop flood damage assessment (extent and duration) in Tychero, Evros River Basin (Greece), on 29 March 2018, estimated with the methodology implemented in BEACON.

For the assessment of crop loss, BEACON uses the stage-damage exponential functions [27, 28], expressed in the general form:

$$D(\%) = c_1\, exp(c_2 \cdot t) \tag{12}$$

where D is the flood damage percentage, c_1 and c_2 are coefficients specific for arable crops and t is the duration of flood, in days. These equations take into account the duration of the flood, as well as, the seasonality. Seasonality is introduced by different crop heights. Coefficients c_1 and c_2 are provided for three different crop heights, taking into account, in this way the crop growth stage. The crop heights are 0.2-0.5 m, 0.5-1 m and 1 m and above [27]. In-situ data on flood damage for wheat and barley, provided by AgI companies will be used to validate the stage-damage functions in estimating the damage on these two cereal crops.

3.3 Wildfires damage assessment

The fire severity levels are defined based on the RBR values, allowing the spatial mapping of damage intensity. This procedure involves the RBR raster value reclassification, into predefined interval classes. The disaster levels are classified as unburned, moderate-low, moderate-high and high fire severity [21, 22] reflecting the intensity of the damaging agent. RBR values range from lesser than unity to greater than 304. In the crop loss assessment of BEACON, it is assumed that when RBR values are higher than

27, the area is categorized as a burned area and crop is considered totally damaged. Fig. 3 provides an example of olive groves fire damage, estimated with the RBR index methodology.

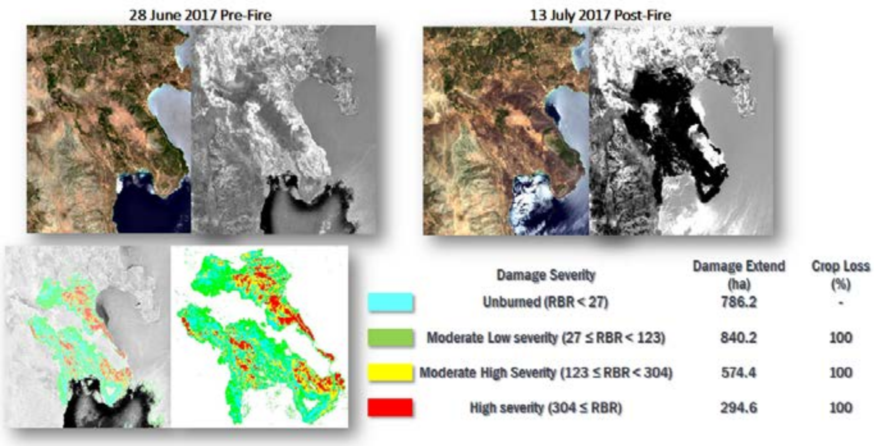

Fig. 3. Olive groves fire damage assessment (spatial mapping and severity levels) in Kotronas, Peloponnese Region, (S. Greece), on 2-5 July 2017, estimated with the methodology implemented in BEACON. $NBR_{Prefire}$, $NBR_{Postfire}$, dNBR, RBR image reclassification, visualization and zonal statistics report on fire damage severity.

3.4 Drought damage assessment

In BEACON, NDVI-A product is calculated to characterize the health of vegetation throughout the growing season of an insured crop, and is used as an indicator of declining vegetation health due to drought. BEACON uses this approach to estimate crop damage and loss by the temporal integration of the Absolute NDVI Anomaly (Fig. 4).

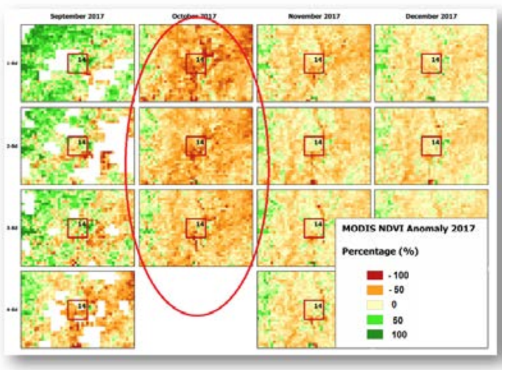

Figure 4. Niger Case Study, 2017 Growing Season, Multi-crop drought damage assessment estimated with the methodology implemented in BEACON. Crop loss is estimated by the temporal integration of Absolute NDVI-A.

For the validation of the crop loss assessment due to drought, damage data on wheat and barley crops were provided by AgI companies. Drought damage cases were classified in early and late claims, based on the date submitted by the farmers. Depending on the case, an indicator-impact exponential function was then 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, in the growing season.

4 Summary and conclusions

BEACON solution employs a multi-satellite approach and a series of change detection techniques in order to provide safe and reliable estimates on crop damage, for any type of Agricultural Insurance. BEACON takes into account damage by hail, floods, wildfires and droughts which are the four most devastating hazards of agricultural production worldwide. This paper presents the methodologies and different types of EO data that synthesize the DAT service of BEACON's toolbox. DAT, supports AgI companies in accurately assessing and calculating damage to proceed with indemnity payouts of claims. The methodologies implemented in the operational workflow of BEACON will be validated by a diverse plethora of ground truth crop damage data. In-situ data will originate from private AgI companies, most of which are early adopters of the BEACON's solution and will participate in the project's pilot phase.

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References

1. Rosenzweig, C., Iglesius, A., Yang, X.B., Epstein, P.R., Chivian, E.: Climate change and extreme weather events- Implications for food production, plant diseases, and pests. NASA Publications, 24 (2001).
2. Rüegger, M.: Trends in agricultural insurance in the European Union. Milliman (2007).
3. de Leeuw, J., Vrieling, A., Shee, A., Atzberger, C., Hadgu, K.M., Biradar, C.M., Keah, H., Turvey, C.: The Potential and Uptake of Remote Sensing in Insurance: A Review. Remote Sens, 6, 10888-10912 (2014).
4. FAO: 2017 The impact of disasters and crises on agriculture and food security. Rome (2018).

5. Nuttall, J.G., Perry, E.M., Delahunty, A.J., O'Leary, G.J., Barlow, K.M., Wallace, A.J.: Frost response in wheat and early detection using proximal sensors. J Agro Crop Sci 205, 220–234 (2019).
6. Lu, D., Mausel, P., Brondízio, E., Moran, E.: Change detection techniques. Int J Remote Sens 25(12), 2365-2407 (2004).
7. Szigarski, C., Jagdhuber, T., Baur, M., Thiel, C., Parrens, M., Wigneron, J.-P., Piles, M., Entekhabi, D.: Analysis of the Radar Vegetation Index and Potential Improvements. Remote Sens 10, 1776 (2018).
8. Saatchi, S.: SAR Methods for Mapping and Monitoring Forest Biomass. e-book: SAR Handbook: Comprehensive Methodologies for Forest Monitoring and Biomass Estimation. NASA (2019).
9. Chauhan, S., Srivastava H.S.: Comparative evaluation of the sensitivity of multi-polarised SAR and optical data for various land cover classes. IJARSGG 4(1), 1-14 (2016).
10. Zoka, M., Psomiadis, E., Dercas, N.: The complementary use of optical and SAR data in monitoring flood events and their effects. Proceedings 2, 644 (2018).
11. Xu, H.Q.: Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int. J. Remote Sens 27, 3025–3033 (2006).
12. Du, Y., Zhang, Y., Ling, F., Wang, Q., Li, W., Li, X.: Water Bodies' Mapping from Sentinel-2 Imagery with mNDWI at 10-m Spatial Resolution Produced by Sharpening the SWIR Band. Remote Sens 8, 354 (2016).
13. Singh, K.V., Setia, R., Sahoo, S., Prasad, A., Pateriya, B.: Evaluation of NDWI and MNDWI for assessment of waterlogging by integrating digital elevation model and groundwater level. Geocarto Int. 30, 650-661 (2015).
14. Kwang, C., Osei, E.M. Jr, Amoah, A.S.: Comparing of Landsat 8 and Sentinel 2A using Water Extraction Indexes over Volta River. J Geogr Geol 10(1) (2018).
15. Cian, F., Marconcini, M., Ceccato, P.: Normalized Difference Flood Index for rapid flood mapping: Taking advantage of EO big data, Remote Sens. Environ 209, 712-730 (2018).
16. Cian, F., Marconcini, M., Ceccato, P., Giupponi, C.: Flood depth estimation by means of high-resolution SAR images and lidar data. Nat. Hazards Earth Syst. Sci 18, 3063-3084 (2018).
17. Twele, A., Cao, W., Plank, S., Martinis, S.: Sentinel-1-based flood mapping: A fully automated processing chain. Int. J. Remote Sens 37, 2990-3004 (2016).
18. Roldán-Zamarrón, A., Merino-de-Miguel, S., González-Alonso, F., García-Gigorro S., Cuevas, J.M.: Minas de Riotinto (south Spain) forest fire: Burned area assessment and fire severity mapping using Landsat 5-TM, Envisat-MERIS, and Terra-MODIS postfire images. J Geophys Res 111 (2006).
19. Viana-Soto, A., Aguado, I., Martínez, S.: Assessment of Post-Fire Vegetation Recovery Using Fire Severity and Geographical Data in the Mediterranean Region (Spain). Environments 4, 90 (2017).
20. Key, C.H., Benson, N.C.: Measuring and remote sensing of burn severity: the CBI and NBR. Poster abstract. In L.F. Neuenschwander and K.C. Ryan (Eds.), Joint Fire Science Conference and Workshop, 284 pp. University of Idaho and International Association of Wildland Fire (1999).
21. Parks, S.A., Dillon, G.K., Miller, C.: A new metric for quantifying burn severity: the Relativized Burn Ratio. Remote Sens 6, 1827-1844 (2014).

22. Suresh Babu, K.V., Arijit Roy, Aggarwal, R.: Mapping of forest fire burned severity using the Sentinel datasets. ISPRS – Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci., pp. 763–769 (2018).
23. Klisch, A., Atzberger, C.: Operational drought monitoring in Kenya using MODIS NDVI time series. Remote Sens 8, 267 (2016).
24. Vaani, N., Porchelvan, P.: Assessment of long term agricultural drought in Tamilnadu, India using NDVI anomaly. Dis. Adv. 10 (10), 1–10. (2017).
25. Anyamba, A., Tucker, C.J.: Historical perspective of AVHRR NDVI and vegetation drought monitoring. In: Remote Sensing of Drought: Innovative Monitoring Approaches, pp. 23 (2012).
26. Zhao, J.L., Zhang, D.Y., Luo, J.H., Huang, S.L., Dong, Y.Y., Huang, W.J.: Detection and mapping of hail damage to corn using domestic remotely sensed data in China. Aust J Crop Sci 6(1), 101-108 (2012).
27. Herath, S.: Flood damage estimation of an urban catchment using remote sensing and GIS. International Training Program on total disaster management. 10-13 June (2003).
28. Dutta, D., Herath, S., Musiake, K.: A mathematical model for flood loss estimation. J. Hydrol, 277: 24–49 (2003).