PRELIMINARY APPROACH TO A GLOBAL DROUGHT MONITORING SYSTEM

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ABSTRACT:

Drought is one of the natural phenomena endangering population, mostly in developing countries, where specific international institutions, like WFP, are involved to manage and solve humanitarian emergencies related to food security. In order to offer technical and scientific support to such humanitarian interventions, ITHACA association is developing a global drought monitoring system mostly based on satellite data analysis.
In this paper authors describe the first phase of the project, related to the analysis of two key parameters for drought detection and monitoring: Normalized Difference Vegetation Index (NDVI) and Standardized Precipitation Index (SPI). Various studies demonstrated how temporal variations of NDVI and related anomalies are an indicator of vegetation health conditions also relatively to water availability, especially in arid and semi-arid environments. SPI index is commonly used to recognize drought onset, duration, intensity and spatial distribution. The analysis was based on historical temporal series of NDVI and precipitation data obtained from global satellite missions. Authors developed ad hoc statistical procedures and data management routines, suitable for the recognition of past drought episodes and to study their spatial and temporal development. The selected approach allow to individuate most vulnerable areas in case of water scarcity and to define, for these areas, adequate threshold values to be used for drought early warning. We describe the procedures applied to a case of study in Africa.

1. INTRODUCTION

Drought is one of the most complex natural hazards, affecting more people than any other natural phenomenon. It originates from a deficiency of precipitation with respect to normal conditions, as a consequence of climatic fluctuations interacting with several environmental aspects, and by itself does not trigger an emergency. It is a natural phenomenon occurring in almost every region of the earth, quite variable in terms of duration, intensity and spatial extension, since it can be local or regional, lasting for few months or even for several years. It is different from most of other natural or anthropic disasters due to its slow onset, and long lasting period of occurrence. Whether it becomes an emergency depends on its impact on local people (Walter, 2004). Drought impacts vary significantly among locations because of differences in economic, social, and environmental characteristics. As a consequence, it has always been difficult to find a unique, universally accepted definition of drought, and usually distinctions are made among meteorological, hydrological, agricultural or socio-economic droughts, according to which aspect is taken into consideration each time (Wilhite and Glantz, 1985).

The worst effects of drought occur mostly in developing countries, where a mixture of unfavorable environmental, social and economical factors contribute to increase the vulnerability and to compromise food security and human survival. Moreover, climate change is adding uncertainty and seems to worsen the existing threats, accelerating land degradation and desertification processes. The World Food Programme (WFP) is the most important international agency involved in the management of humanitarian emergencies related to food security. In order to offer technical and scientific support to such humanitarian interventions, the ITHACA (Information Technology for Humanitarian Assistance, Cooperation and Action) association is developing a global drought monitoring system mostly based on satellite data analysis.
The main project objective will be the development of a drought monitoring and early warning system, based on automated map production procedures, disseminated to interested users through "ad hoc" web applications. In this paper we propose the main aspects of the planned system and the first results of the preliminary studies conducted in order to define proper drought monitoring procedures.

2. METHODOLOGY

Considering the purposes of the planned system, which focuses on the global scale, the choice of suitable methodologies claimed a preliminary analysis of available datasets, possibly free of charge, with global coverage and provided in form of geographical grids.
A drought monitoring system requires the identification of a set of drought related variables. The first efforts were oriented to the monitoring of the agricultural drought, which describes all the effects related to food production, availability and accessibility. Agricultural drought is mostly related to soil moisture content available to crop growth. The concept of water balance describes this component dynamically, since it considers the flow of water in and out of a system. The meteorological component is fundamental, being rainfall the main water source to soil. Other variables which can be monitored are: vegetation condition and growth, evapotranspiration, temperature, soil moisture, and runoff.
In order to add information to the previous parameters, more detailed analysis can be performed on other related aspects, considering for example several environmental and agricultural parameters (i.e. soil parameters like water holding capacity,

crop features, agricultural techniques, irrigation status, land cover data, etc.) and socio-economical aspects, such as: population livelihoods, income, availability of mitigation measures.
In the first phase of the project, the planned activities focused on the analysis of those variables and indices considered key elements in order to detect and monitor drought conditions, and to characterize and compare different drought events.
The following model components were taken into consideration:

- Satellite-derived vegetation condition variables (mainly, the NDVI, *Normalized Difference Vegetation Index*) and derived phenological measures;
- Precipitation data, also used in order to calculate suitable meteorological drought indexes (i.e. SPI, the *Standardized Precipitation Index*);
- Historical drought events lists and datasets.

For each of the selected components, the different available base data sources, possibly derived from satellite, are identified. Table 1 shows the main base data sources.

DATASET	TIME COVERAGE	SPATIAL RESOLUTION
Vegetation		
GIMMS NDVI (G)	**1982 - Present**	**8 km x 8 km**
REAL-TIME (RG) GIMMS NDVI	**Real Time**	**8 km x 8 km**
Precipitation		
UEA CRU New	**1901 - 2002**	**0.5° x 0.5°**
NASA GPCP V2	**1979 - Present**	**2.5° x 2.5°**
NOAA CPC CAMS - OPI	**1979 - Present**	**2.5° x 2.5°**
TRMM	**1998 - Present**	**0.25° x 0.25°**
Drought Historical Events		
CRED EM-DAT	**Regionally variable**	**Tables - Involved Countries**

Table 1 – Main datasets and base data sources

3. VEGETATION CONDITION MONITORING

3.1 Introduction

In this part of the project, historical NDVI (*Normalized Difference Vegetation Index*) time-series have been analysed with the aim of investigating, with proper robust statistical techniques, spatial and temporal vegetation dynamics and their relationships with land degradation and desertification processes and, finally, with drought events. In the first phases of this activity, the whole Africa has been considered as a test area. Obtained outcomes of historical analyses will be used in order to define a near real-time monitoring procedure of vegetation conditions and for the production of maps about areas where the vegetation is subject to stress, suitable for drought detection and monitoring activities.
Satellite remote sensing techniques provide successful tools for the monitoring of vegetation productivity and ecosystems. The various data sources available through remote sensing offer the possibility of gaining environmental data over both large areas and relatively long time-periods (about three decades of satellite acquisitions), with frequent temporal revisit capabilities. (Hassan, I.M.E., 2004)
In particular, we took into consideration NDVI measures. The NDVI is the most commonly used satellite derived index of vegetation health and density, often used for vegetation monitoring, crop yield assessment, and vegetation stress detection. The NDVI is calculated using the satellite reflectance values in the near infrared and red bands. The formula is based on the fact that chlorophyll absorbs red radiation whereas the mesophyll leaf structure reflects near infrared radiation. NDVI measurements range between -1 and +1. Cloud, water, snow, ice and non-vegetated surfaces have negative NDVI values. Bare soils and other background materials produce NDVI values ranging from -0.1 to +0.1. The NDVI values for vegetation are positive and range from 0.1 to 0.7, with low values indicating poor vegetation conditions and possibly unfavourable weather impacts. The use of NDVI in drought monitoring activities or in the evaluation of land degradation processes relies on the sensitivity of the index to vegetation dryness. In general, with the development of a drought, the NDVI decreases, the surface temperature increases, and the soil moisture decreases, provided that other factors are stable.

3.2 Base data and methodology

According to a performed research about source base data, several NDVI datasets are available, with various spatial and temporal resolutions, and distinct temporal coverages. In particular, different NDVI datasets are available derived from data acquired by the Advanced Very High Resolution Radiometer (AVHRR) instrument, with differences in the corrections applied or in the spatial and temporal resolutions available. Nowadays, NOAA AVHRR NDVI dataset is the only freely available that gives daily coverage over an extensive time period (1981 - present).
In this study, 15 day maximum value NDVI composites at 8 km spatial resolution produced by the *Global Inventory Mapping and Monitoring System* (GIMMS) at NASA's Goddard Space Flight Center have been used (Herrmann, S.M., A. Anyamba and C.J. Tucker, 2005; Tucker et al 2005). The base data collected by the AVHRR instrument have been corrected by GIMMS to minimize cloud contamination using Maximum Value Compositing (MCV). Furthermore, the final GIMMS NDVI-G dataset is corrected for sensor degradation and inter-calibration differences and various contaminations using Empirical Mode Decomposition (EMD) designed for non-parametric and non-stationary data, resulting in a stable time-series, relatively consistent over time, appropriate for trend analysis (Tamavsky, Garrigues and Brown, 2008; Brown, Pinzon and Tucker, 2004~~), ~~). For these reasons, we carried out first analyses of historical NDVI time-series extracted from this dataset.
First of all, for the purposes of the proposed activities, the selected NDVI base data have been geometrically pre-processed and monthly NDVI historical time-series have been then developed and analyzed. In the definition of time-series to use, a pixel-based (8×8 km^2) approach has been chosen.
Several routines have been implemented in IDL (Interactive Data Language programming tool) with the purpose of applying

suitable statistical analysis techniques to the generated historical time-series to perform a components analysis in order to discover underlying patterns and extract the desired vegetation dynamics. In particular, using proper statistical methods (Least Square regression techniques, LS, which are very sensitive to outliers in real data, coupled with a robust technique, such as Least Median of Squares regression estimator, LMS, used for a preliminary outliers detection and removal), the parameters of the regression have been calculated in order to show the NDVI trends.

NDVI data are often affected by noise arising from different sources, including clouds, atmospheric perturbations and variable illumination and viewing geometry. All of these factors usually reduce NDVI values. For the purposes of this study the presence of residual contaminations in used time-series, due to these effects, has been considered. Therefore a preliminary and fundamental step to carry out the analyses was to define a proper outliers' detection technique. Moreover, detected outliers may also reveal anomalies in vegetation conditions; properly treated, they could be used to identify and map anomalies that can be used for vegetation stress detection and monitoring purposes.

After the robust data snooping phase, a re-estimation of regression, deprived of outliers, has been performed using regular LS regression techniques. The slope of regression was finally verified by the Student's t test, around zero values.

Moreover, the defined parameters of the LS regression, that show the long-term NDVI trends (1982-2006), have been used in order to calculate and map historical monthly NDVI deviations. Maps about historical NDVI deviations show the pixel-based spatial distribution of vegetation conditions as regards to the normal long-term NDVI behaviour, modelled by defined trends, with a procedure which allows the analysis of seasonal variations, since every month is compared with the historical trend of the same month. Positive departure from the trend indicates that the vegetation condition is better than normal in the considered month. Negative departure from the trend describes vegetation condition worse than normal.

Finally, the same approach used to study the vegetation conditions with historical NDVI data will be applied on NDVI data obtained in near real-time in order to define a proper vegetation stress monitoring procedure in the planned drought monitoring system.

3.3 Results

During a preliminary vegetation analysis, several NDVI measures (such as minimum, maximum and mean NDVI values, standard deviation and coefficient of variation) have been calculated for each year (from 1982-2006) and investigated. In particular, the annual variability of monthly NDVI values with respect to the mean annual value has been evaluated for every year and for every pixel and its temporal change during the 25 years observation window, has been investigated using the coefficients of variation (CoVs). As a matter of fact, the use of the coefficients of variation enables to evaluate and compare the spatial distribution of the annual variability of monthly values on a pixel basis. Figure 1 shows the distribution of the long-term (1982-2006) mean coefficients of variation of NDVI values; it helps to identify the areas where the vegetation has been subject to the major changes during the observed 25 years.

Figure 2 shows an example of the spatial distribution of the obtained slopes of the regressions: white and dark grey areas show, respectively, reduction or increase in vegetation greenness between 1982 and 2006; while light grey areas have not been subject to significant vegetation changes, according to the implemented Student's t test.

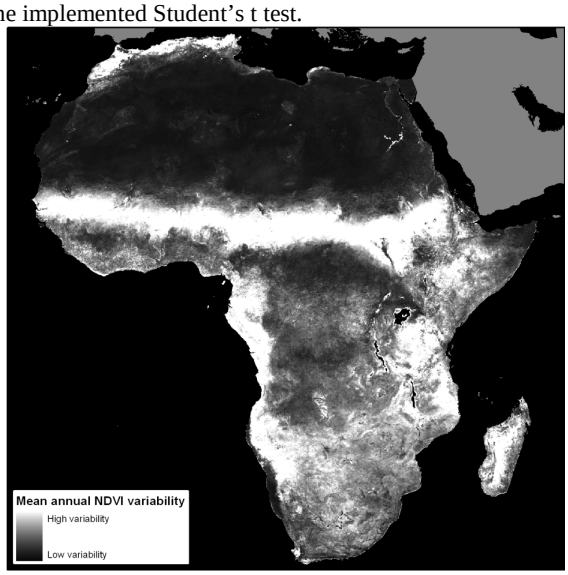

Figure 1 - Spatial distribution of long-term mean values of yearly coefficients of variation (CoVs)

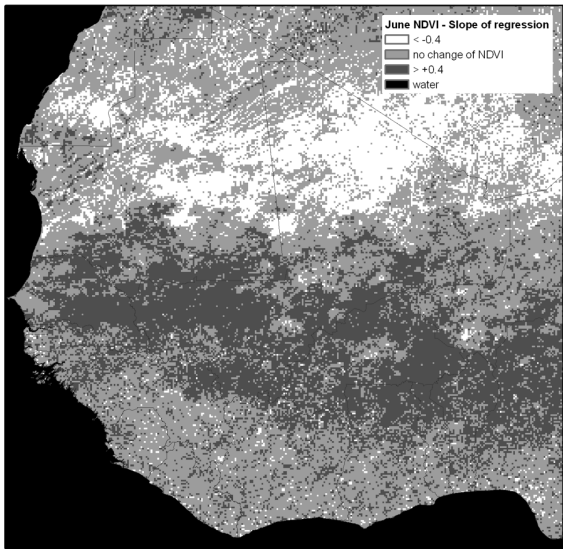

Figure 2 - Overall trends in vegetation greenness for the period 1982-2006: spatial distribution of the regression slopes for monthly NDVI values (June trends, West Africa area)

The results of this activity show the existence of clear regional trends of NDVI over the period 1982-2006, both decreasing and increasing, which can help to describe long-term vegetation dynamics and to highlight areas subject, respectively, to reduction or increase in vegetation greenness and biomass production.. The actual meaning on the ground of greening has not yet been firmly established. Therefore, the observed greening trends may be interpreted as land degradation or improvement with much caution (Bai, Dent , Olsson, and Schaepman, 2008). For these purposes, the identified patterns of vegetation degradation and improvement identified need to be further explored by comparisons with climatic, land cover, soil and terrain and socio-economic data, using also field survey data on dominant rural activities at local scale and, perhaps, finer resolution satellite data. Further results and discussions

about this part of the project can be found in Bellone, Boccardo, and Perez, (2009).
As aforementioned, a secondary result of this activity has been the detection of NDVI deviations from normal behavior in historical time-series. These deviation values, coupled with NDVI anomalies identified during the data snooping operations, can be used to identify historical vegetation stress key events.
This kind of analysis, performed on a pixel-basis, allowed to produce several maps about historical monthly vegetation conditions. These maps, that contain also the detected vegetation anomalies, are called, in the following, *Vegetation Conditions Maps* and show, on a monthly basis from 1982 to 2006, the pixel-based spatial distribution of vegetation conditions, using seven classes defined according to the deviation value from the trend:

- Anomalous vegetation conditions (positive value);
- Very favourable vegetation conditions;
- Favourable vegetation conditions
- Regular vegetation conditions;
- Unfavourable vegetation conditions;
- Very unfavourable vegetation conditions;
- Anomalous vegetation conditions (negative value).

Figure 3 shows an example of these maps.
At the moment, these maps are available through a proper web application that allows to the users to visualize the maps for the months of interest.

Finally, identified historical NDVI deviations and anomalies have been analyzed in order to extract information about the areas more prone to vegetation stress according to the historical observation period. The analysis has been performed using, as a base data, the frequency distribution of the favourable and unfavourable conditions in the 25-years considered period (1982 – 2006). The results of this analysis have been summarized in several maps that show the spatial distribution of identified critical areas on a monthly basis, distributed through the web application.

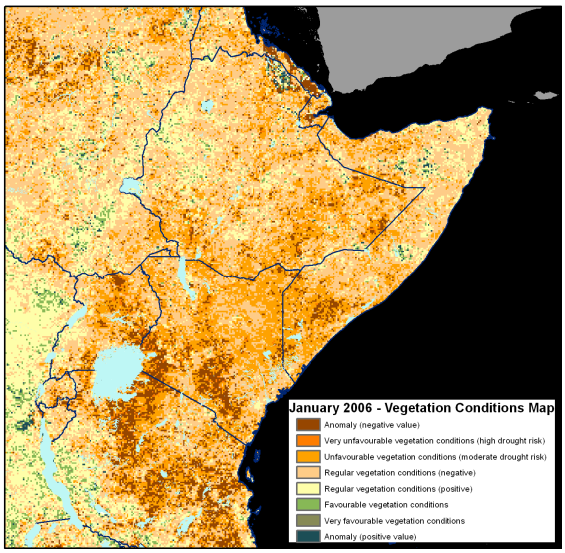

Figure 3 – January 2006, Horn of Africa, Vegetation Conditions Map: spatial distribution of the detected NDVI anomalies and deviation

3.4 Near real-time vegetation stress monitoring

In order to define a valuable vegetation stress early warning system, that produce geospatial information for a proper decision support tool, we need to use vegetation datasets developed for near real-time stress and anomalous condition identification.
The GIMMS group, together with the NOAA AVHRR GIMMS-G dataset, used for the previously described activities, produces two near real-time datasets, also obtained from the NOAA AVHRR sensor acquisitions. Like long term data records, these real time datasets must be self-consistent and calibrated. Just like all vegetation data products, most serious problem afflicting these datasets are clouds, which render any observation useless by obstructing the target, and to a lesser degree, effects of the bidirectional reflectance distribution function or BRDF. The choice of using the real time data products require to balance the need for rapid delivery with processing that improves the quality of data.

After having verified the future availability of GIMMS real time products, through a direct contact with GIMMS research group, the GIMMS RG real-time NDVI product have been incorporated in the methodology and started to be investigated.
The RG real-time NDVI product uses the same code used to produce the NDVI-G, for example an inter-calibration is applied with SPOT data and the dynamic range of NDVI is adjusted to values from –0.05 to 0.95 to match more closely that of the SPOT- and MODIS-based NDVI. Differently from the G product the calibration of the real time products is computed approximately once every six months. Furthermore, the interpolation routine to replace missing data is not applied to real time products. In the real time dataset cloud detection is obtained through a channel 5 (T5) temperature threshold technique, using 285 degrees Kelvin for Africa to detect pixels with low temperatures indicating cold cloud tops (Brown, 2008).
A first analysis was performed in order to test the incidence of the missing values factor on the near-real time NDVI product. Figure 4 shows with different gray tonalities the percentage of image, the occurrence of masking values because of the presence of clouds in the 5 years time considered period from 2002 to 2007. The 95% of African continent is masked at maximum for the 7% of the 130 composite images

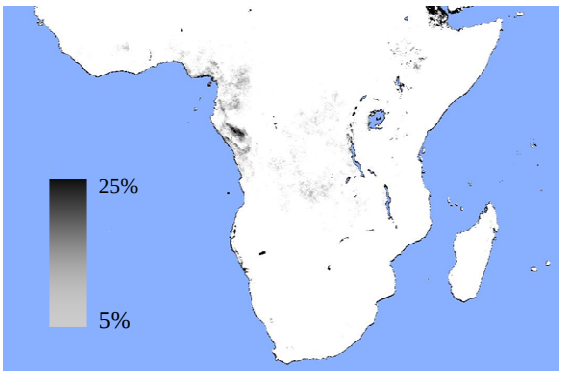

Figure 4. Percentage of the occurrence of masking values in the 15 days composite images referring to the 5 years testing period

Furthermore, an analysis was carried out to verify the possible existence of a relationship between the 15-days and monthly NDVI-G values (on a pixel basis) and the correspondent 15-days, monthly NDVI-RG ones, for all the years of overlap

available (2002 to 2007). The Pearson linear correlation coefficient, $R_{G,RG}$ was therefore calculated. The $R_{G,RG}$ values are ≥ 0.9 for all the pairs of fortnightly and monthly datasets, for all considered years, demonstrating the existence of a strong relationship between the two populations. This was a basic condition and requirement for the subsequent tests.
In order to quantify the NDVI differences for each pair of datasets, the following deviations were calculated, on a pixel basis:

$$\Delta_{G,RG} = NDVI_G - NDVI_{RG}$$

where $NDVI_{RG}$, $NDVI_G$ are the NDVI-RG and NDVI-G values in the same two weeks/month and the same year for generic pixel.
Also the relationship between these deviations $\Delta_{G,RG}$ and the NDVI-RG values was evaluated. The two classes don't seem to be correlated: the calculated Pearson linear correlation coefficients are in the range between -0.25 and 0.15.
Since the $\Delta_{G,RG}$ deviations could be interpreted as NDVI anomaly values and cause errors, a quantitative analysis of the differences has been performed.
At the moment no fixed threshold for the identification of NDVI anomaly values has been selected, but it can be reasonably thought that $\Delta_{G,RG}$ values below 0.05 would not bring to detect false anomalies.
For each 15-day composite image the $\Delta_{G,RG}$ value was calculated and some synthesis were obtained in order to understand the recurrence of consistent deviation values in the different areas of the African continent.
Figure 5 shows the most critical areas in which the occurrence of delta values greater than the established threshold overpasses the 5% of the cases. In this case it will be suitable to detect local correction factor (pixel by pixel), in order to avoid the detection of false anomalies.

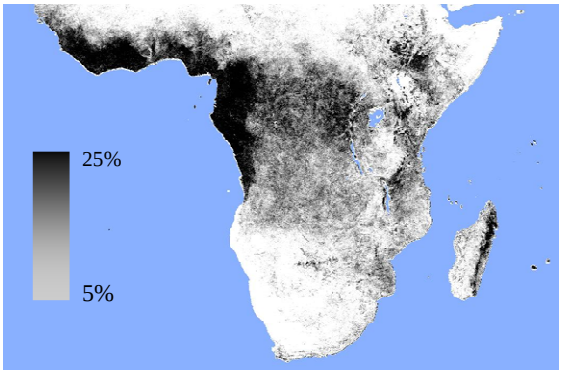

Figure 5. Percentage of the occurrence of consistent $\Delta_{G,RG}$ values in the 15 days composite images referring to the 5 years testing period

4. PRECIPITATION AND SPI

Precipitation is the main input of water available to crop growth, and was taken into consideration as one of the main parameters for monitoring purposes. Precipitation has been historically recorded by rain or snow gauges, which offer reliable estimation of precipitation values, but don't provide a sufficient spatial coverage for their inhomogeneous global distribution. The development of ground radar systems offered a strong improvement in precipitation measurements, but also their distribution is limited in terms of global coverage. Therefore, the best estimation of precipitation on a global scale is possible through the utilization of Earth Observation Satellites. There is a limited number of available global precipitation dataset suitable for the project purposes (Levizzani, Gruber, 2008). The list of chosen datasets is shown in Table 1.

Each of these datasets contains monthly combined satellite-gauge precipitation data as well as error estimates. The general approach used to create these datasets is to combine precipitation information available from each of several sources, such as microwave estimates based on radar technology, Infrared estimates from geostationary and polar-orbiting satellites, together with gauge data collected from the ground, into a final merged product, taking advantage of the strengths of each data type.

The Standardized precipitation index (SPI) is considered one of the most important indices for drought monitoring, and requires only precipitation monthly cumulates as input data (McKee, Doesken, and Kleist, 1993). Other commonly adopted drought indices, as Palmer Drought Severity Index (PDSI) or WRSI (Water Requirement Satisfaction Index) require a large variety of detailed input data, difficult to gather on a global level in a complete and homogeneous way. Moreover, these indices are usually calibrated on local specific climatic and geographic conditions, not allowing easy spatial comparisons. SPI was formulated to assign a single numeric value to precipitation, which can be compared even across different climatic and geographic regions. Technically, the SPI is the number of standard deviations that the observed value would deviate from the long-term mean, for a normally distributed random variable. Since precipitation is not normally distributed, a transformation is first applied so that the transformed precipitation values follow a normal distribution.
The Standardized Precipitation Index from one side gives a numerical value which offers quantitative information related to the deviation from normal conditions, which can be interpreted as the intensity of a drought spell in case of negative values; from the other side allows considering for every month different time scales, related to different drought conditions. In facts, it is possible to calculate the SPI for any month in the record for the previous i months where i=1, 2, 3, ..., 12, ..., 24, ..., 48, ... depending upon the time scale of interest. For example the SPI can be computed for an observation of a 3 month total of precipitation, which can be linked to soil moisture and agricultural effects, as well as a 24 or 48 month total of precipitation, which can have consequences on water reservoirs storage and ground water.
Due to its probabilistic nature, the SPI index requires long enough precipitation time series to offer good estimations, which is a strong limiting factor considering the relatively young satellite technology. Therefore, in case of datasets lesser than 50 years long, extreme SPI values will be considered carefully.

Each dataset listed in Table 1 has been considered as input precipitation data source for SPI index calculation. The International Research Institute for Climate and Society (IRI) provides already calculated SPI analyses based on some of these datasets. The only dataset which satisfies the SPI long temporal coverage requirement is the University of East Anglia dataset, provided by the Climatology Research Unit (UEA CRU); but it has some drawbacks: this dataset extends from 1901 to 2002, and only historical analyses can be performed. Moreover it is built only by spatial interpolation of the ground rain gauges,

and since their number was very low at the beginning of 20th century, the datasets inserts synthetic zero values in regions that are too far (more than 450 km) from observations. NOAA Climate Prediction Center (CPC) and NASA Global Precipitation Climatology Project (GPCP) datasets are similar, but use in part different data sources and calculation algorithms, with different final results. Tropical Rainfall Measuring Mission (TRMM) was also considered, even if its time coverage is very short, since it offers more detailed and up to date precipitation estimations, which could be particularly useful for real time monitoring purposes.

5. ONGOING ACTIVITIES

At the moment procedures for the real time NDVI dataset correction and for the real time vegetation monitoring are being tested.

Furthermore the actual efforts are oriented towards the analysis of the different available datasets, to understand how precipitation and vegetation patterns are correlated, in relationship to available information about historical drought events, as collected by EM-DAT datasets. The main purpose is the identification of suitable values or combination of values of previously described variables, to be used as triggers for early warnings of incoming drought conditions, and to map and describe the spatial extension and intensity of the event.

Other variables and parameters, as previously described, will be added, in order to improve the amount and quality of available information to final users of the monitoring product.

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