A MULTITEMPORAL AND NON-PARAMETRIC APPROACH FOR ASSESSING THE IMPACTS OF DROUGHT ON VEGETATION GREENNESS: A CASE STUDY FOR LATIN AMERICA

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ABSTRACT

In this paper, we present the first results of an on-going study that aims at evaluating the relationship between the frequency and duration of meteorological droughts in Latin America and the subsequent temporal changes on the characteristics of vegetation greenness for different land cover/use classes. An innovative non-parametric and non-supervised approach, based on the Fisher-Jenks optimal classification algorithm, is used to identify meteorological droughts on the basis of cumulative distributions of monthly precipitation totals. As input data for the classifier, we use the GPCC Full Data Reanalysis precipitation time-series raster product, which ranges from January 1901 to December 2010 and is interpolated at the spatial resolution of 1º (decimal degree). Vegetation greenness composites are derived at the spatial resolution of 1km on the basis of 10-daily SPOT-VEGETATION images. The time-series analysis of changes on vegetation green cover conditions during growing season is performed with a non-parametric method, namely the seasonal Relative Greenness (RG) of accumulated fAPAR. The study is carried out for the period between 1998 and 2010, and we present the preliminary results for rainfed croplands. The Global Land Cover map of 2000 and the GlobCover maps of 2005/2006 and 2009 are used as a reference data to setup study cases only on geographical areas that did not undergo changes during the analysis period. The multi-scale information is integrated at the lowest spatial resolution available, i.e. 1º (decimal degree), and the impacts of meteorological drought episodes on seasonal greenness of rainfed crops are assessed. Final results show that the regional agricultural cycle is more correlated with long-standing and continuous small timescale drought conditions than with discrete or short long-term timescale drought events.

INTRODUCTION

Drought originates from a deficiency of precipitation that results in water shortage for natural processes (e.g. plant growth) and human activities (e.g. agriculture). Regardless of the environment, a lack of precipitation over a certain period of time and particular region may result in reduced green vegetation cover. When drought conditions end, recovery of vegetation greenness may follow, but such a recovery process may be slow and last for longer periods of time. In natural ecosystems, long-term dry conditions cause vegetation to be more prone to forest fires, while in human-induced ecosystems they reduce the fodder available for animals and the agricultural yield, thus leading to a reduction in income.

The added-value of satellite imagery for monitoring vegetation vigour and phenology has been demonstrated (1,2). Indeed, the availability of remote sensing data covering wide regions over long periods of time has progressively strengthened the role of vegetation indices in environmental studies related to drought episodes (3,4,5,6,7,8,9,10). In this context, the use of use satellite images to directly monitor spatially-explicit patterns of drought-related changes in vegetation conditions (i.e. agricultural drought) in areas where weather stations are sparse or non-existent is increasing (5). However, it is impossible to rely solely on satellite-derived information to monitor drought, assess its duration and evaluate its impacts on green vegetation cover. The problem is that relatively poor vegetation conditions may be caused by factors other than drought, e.g.

unseasonable coolness or crop rotation. Thus, some additional background information on drought onset and end, derived from rainfall data as recorded in meteorological networks, is a priori demanded in this context, as shown by (5). Indeed, because agricultural drought is understood as a precipitation shortage sufficient to adversely affect vegetation development (11), the aim of remote sensing data can only be to measure the cumulative impacts of meteorological drought-related changes on vegetation cover over time.

To assess the usefulness of the vegetation greenness status measured by satellite images to prosecute a drought, many authors evaluated the relationship between low precipitation conditions estimated from gauge stations at a certain moment in time and the vegetation conditions at that time or at some fixed time lag, e.g. (7,9), to cite but a few. However, the attained correlations between both events are many times insignificant (e.g. only 3% to 15% of the individuals show a correlation higher than 0.4 in (9)) and can be simply explained by the art of examining the phenomenon from a discrete and near-real time viewpoint. In words, because a single isolated monthly drought occurs during the vegetation growing season, it does not imply a straightforward impact on its greenness. Indeed, one atypical monthly precipitation record can represent simply some noise in the dataset or be just a sporadic phenomenon that is harmless to the normal development of vegetation. On the other hand, it is also possible that vegetation stress continues after meteorological drought stops and be still associated to it. Correlating indiscriminately all meteorological and biophysical events without understanding their duration and time dependence (e.g. many times comparing weekly vegetation greenness with monthly precipitation records), can result in non-linear and incomprehensible relationships. Indeed, (12) highlighted that the vegetation development is not influenced by the dryness of the drought, but by its duration. Similarly, (11) stated that "the longer the rainfall deficiency is, the more likely other types of droughts [agricultural and hydrological] will occur as a result". So, before using vegetation greenness to monitor patterns of drought broadening is important to know how and when low rainfall supplies impact on the expected vegetation growth.

In this paper, we aim at evaluating the cause-effect relationship between low flow precipitation regimes and consequential vegetation greenness anomalous' values. In detail, our goal is to describe the the meteorological drought characteristics, namely time, timescale and duration, which can impart knowledge about the consequent impacts on the normal development of different types of vegetation cover in specific geographical areas. This information is lacking in the literature and is an important structural background support of any monitoring system that aims at following (agricultural) drought with satellite imagery time-series.

This study is performed in the framework of EUROCLIMA, an on-going Initiative Programme (N° DCI-ALA/2009/021-126) funded by the Directorate General for Development and Cooperation (DG DEVCO) of the European Commission (EC), which activities focuses in Latin America region. In agreement, in this paper we restrict our analysis to that region and due to progress of project activities, we focus our experiments on rainfed crops only.

INPUT DATA

The data used to perform this study are divided in: (a) existing land cover cartographies used as complementary information for reference land cover type's identification and study area selection; (b) a time series set of fAPAR (fraction of photo-synthetically active radiation absorbed by the canopy) measurements used for Relative Greenness (RG) computation; and (c) a gauge-based gridded monthly precipitation dataset used for meteorological drought estimation.

Land Cover Cartographies

The Global Agricultural Lands in the Year 2000 data set (GAL 2000). This map shows the extent and intensity of agricultural land use on Earth. In detail, GAL 2000 represents the proportion of land area used as cropland (land used for the cultivation of food) and pasture (land used for grazing) in the year 2000. Satellite data from the Moderate Resolution Imaging Spectroradiometer

(MODIS) and Satellite Pour l'Observation de la Terre (SPOT) Image Vegetation sensor were combined with agricultural inventory data to create a global data set. The data were compiled by (13) and are provided in raster GeoTiff and ESRI Grid formats, with a raster cell size of 5", or 0.08333 degree decimal (about 10 kilometers at the equator).

The Land Cover of the World in the Year 2000 (Global Land Cover 2000, GLC 2000). The GLC 2000 was developed by the Joint Research Centre (JRC) for the baseline year of 2000, which is a reference year for environmental assessment. The product was created using 14 months of pre-processed daily global data at a spatial resolution of 1 km, acquired by the VEGETATION instrument on board the SPOT 4 satellite. A bottom-up approach to product development was undertaken in which more than 30 research teams around the world contributed to 19 regional windows (14). The regional legends were derived from the United Nations (UN) Land Cover Classification System (LCCS) as a common framework to produce 22 global classes (15).

The Globcover Land Cover maps of 2005/2006 and 2009. GlobCover is a European Space Agency (ESA) initiative to develop an automatic and regionally-tuned classification system to produce a global land cover map for 2005/6, using 300 meters resolution time series of image mosaics acquired globally by the MERIS sensor on board the ENVISAT satellite (16). This product was intended to update and to complement the other existing comparable global products – GLC 2000 in particular – and to improve on their spatial resolution. The global Globcover legend is compatible with the GLC2000 global land cover classification and similarly comprises 22 land cover classes that were also defined with the UN LCCS. GlobCover 2009 was released in December 2010 and produced with a time series set of MERIS images for the year 2009; its legend is identical to that of the GlobCover 2005/2009, thus being compatible also with the GLC2000 global land cover classification.

fAPAR

fAPAR is the fraction of photosynthetically active radiation (400–700 nm) absorbed by green vegetation. It is one of the Essential Climate Variables recognized by the UN Global Climate Observing System (GCOS) as of great potential to characterize the climate of the Earth (17). Due to its sensitivity to vegetation stress, fAPAR was already proposed as a drought indicator (9). The fAPAR time series set used in this study is derived from VEGETATION sensors (18) at 10-daily temporal resolution (composited over 30-day windows), for the period between 1st of April 1998 and 31st December of 2011, and 1/112° plate–carrée spatial resolution. From now onwards, 10-daily fAPAR composites are denominated simply by fAPAR. VEGETATION sensor is characterized by a multi-temporal registration uncertainty around 150 m (1σ), which was measured by (19) and (20). The VEGETATION images used to compute fAPAR were subjected to enhanced radiometric calibration, cloud screening, atmospheric correction and BRDF normalization (18).

A Gauge-based gridded monthly precipitation

The precipitation data used in this study is derived from the Global Precipitation Climatology Centre (GPCC) Full Data Reanalysis Monthly Product Version 6 for the Latin America region at 1° (decimal degree) grid and the long-term period of January 1901 – December 2010. The GPCC has been established in 1989 and provides a global analysis of monthly precipitation on Earth's land surface based only in situ rain gauge data. The data supplies from 190 worldwide national weather services to the GPCC are regarded as primary data source, comprising observed monthly totals from more than 65,000 stations since 1901 (21). All GPCC monitoring products are available in a monthly basis at the spatial resolutions ranging from 1.0° x 1.0° to 2.5° x 2.5° (decimal degrees); non real-time products are also available in 0.5° x 0.5° resolution. GPCC is operated by Deutscher Wetterdienst (DWD) under the auspices of the World Meteorological Organization (WMO).

METHODOLOGY

This section describes in detail the study area selection, the Relative Greenness (RG) computation, the meteorological drought estimation and the correlation analysis used to evaluate the relationship between RG and meteorological drought conditions.

Before describing in detail the methodological approach, we explain that the spatial resolution of the statistical analysis performed within this study equals the coarsest dataset, i.e. the GPCC precipitation grid cell at 1° (decimal degree), which comprises 12544 fAPAR pixels. Because the fAPAR data is restricted to the period between 1st of April 1998 and 31st December of 2011, and the precipitation data ends by December 2010, we focus our correlation analysis on the period between April 1998 and December 2010.

Study area definition

To assess the hypothesis that anomalous seasonal RG values for rainfed crops correlate with preceding low flow precipitation conditions, i.e. meteorological droughts, we fix our analysis on a geographical window containing a large rainfed crop cover density and low spatial and temporal land use/ cover changes (LULCC) in the period between 1st of April 1998 and 31st December of 2010. To undertake this task, we started by overlaying the *GAL 2000* product with the GPCC fishnet and identifying the 1° (decimal degree) cell with the highest proportion of land area covered by rainfed croplands and smallest variance. In the sequence, and to avoid that temporal variations in RG are due to LULCC, we selected the regions inside the previous cell that did not undergo LULCC during the period of analysis, by using as benchmark the GLC2000 and the GlobCover maps of 2005/2006 and 2009. From now onwards, the geographical set of multitemporal stationary rainfed crop pixels used for the subsequent analyses are denominated simply by study area.

Let us now briefly evaluate the characteristics of the study area. From the viewpoint of climate and weather variability, we assume that the analysed geographical window is small enough to guarantee the homogeneity of monthly precipitation regimes inside its boundaries and that all fAPAR pixels are affected similarly by the estimated precipitation anomalies. Indeed, this assumption stands as we are not interested in precision farming or intra-field agricultural variations, but on average regional impacts of low precipitation regimes. Moreover, a study area with 1° (decimal degree) spatial resolution is large enough to evaluate the correlation between overall greenness and precipitation anomalies at the regional scale.

Relative Greenness (RG) computation

(22) introduced the concept of "Relative Greenness (RG)" as a percentage value that expresses how green each vegetation index (VI) pixel is at a given time in relation to the respective average greenness computed over the whole available historical VIs' records. The concept is the same as for the "Vegetation Condition (VC)", developed by (3) and (4), but the last is normalized for a specific intra-annual period (usually 10-daily, biweekly or monthly) on the basis of the minimum and maximum VIs' values per pixel collected among the historical multiyear image records for that specific period. In this study, we use an approach similar to (3) and (4) and compute a relative greenness ($RG_{GS,n}$) index value for the seasonal growing period of vegetation in the whole study area and each year *n* in the database, as follows:

$RG_{GS,n} = (fAPAR_{GS,n} – fAPAR_{GS,min})/(fAPAR_{GS,max} – fAPAR_{s,min})$, (1)

where: $fAPAR_{GS,n}$ is the fAPAR accumulated during the vegetation growing season period for the study area in year *n*; $fAPAR_{GS,min} = \min \{fAPAR_{GS,n}\}$; and $fAPAR_{GS,max} = \max \{fAPAR_{GS,n}\}$. Please note that:

(1) We focus our experiences on the whole set of fAPAR pixels corresponding to multitemporal stationary rainfed crop cover within the study area, in opposition to the per-pixel analysis implemented as working strategy both by (22) and (3,4). We claim that individual per-pixel analysis is subject to higher radiometric and geometric noise, thus possibly biasing the correlation analysis between meteorological drought and vegetation stresses. In addition,

and as stated before, the precipitation dataset that we are using is too coarse to evaluate the impact of low precipitation flows on within sub-study area sections. Smoothing greenness variability within study area by decreasing vegetation index pixels resolution to the spatial resolution of GPCC data will reduce also the noise in the analysis caused by differences in the spatial resolution of used datasets.

(2) We focus our experiences on seasonal accumulated fAPAR totals and not on 10-daily means, because our goal here is to assess the response of average seasonal vegetation greenness to different low flow precipitation conditions, i.e. meteorological droughts, occurring during the *a priori* growing season period, and not to monitor the temporal evolution of their interrelationship, if some.

To estimate $fAPAR_{GS,n}$, we need first to define the inter-annual common growing season (GS) for the rainfed crops in the study area. The definition of a common growing period among the several years is necessary to assure that differences in the member of $\{fAPAR_{GS,n}\}$ are only due to impacts of abnormal precipitation conditions and not to differences in the length of the greenness accumulation periods for each year *n*. The common growing season period, GS, for the study area is computed as the lowest common period among all $\{GS_n\}$, for n = 1998, …, 2010, and GS_n for year *n* can be computed as follows:

$GS_n = \{t\!: t \in t_n; \{\text{median } fAPAR_{tn}\} > fAPAR_m \}$, (2)

where $\{\text{median } fAPAR_{tn}\}$ represents the discrete time series set of median fAPAR values for the study area and year *n*, *t* represents the time indices of fAPAR images in the database, and $fAPAR_m$ represents the historical inter-annual empirical mean fAPAR estimated for the study area as:

$fAPAR_m = (\max \{\text{median } fAPAR\} + \min \{\text{median } fAPAR\})/2$. (3)

In words, GS_n equals the time period in year *n* where the respective median fAPAR values computed for the study area are above the historical inter-annual empirical mean fAPAR.

Meteorological drought estimation

Meteorological droughts are estimated in a monthly basis at the 1° (decimal degree) spatial resolution for the Latin America region from the GPCC precipitation data, which was previously described in the Input Data section. Meteorological drought can be defined as “period of more than some particular number of days with precipitation less than some specified small amount” (23). Several indicators for meteorological drought estimation have been published in the literature and their advantages, added values, limitations and drawbacks have been already presented in numerous studies, e.g. (24,25). However, all of these indicators prescribe fixed thresholds to identify precipitation conditions that correspond to meteorological droughts in a given time and location. Although these thresholds allow us to compare relative drought trends and frequencies for different geographical regions, the indicators themselves do not allow us to estimate adaptive thresholds that correspond to physical boundaries of low precipitation regimes. However, physically defined low precipitation regimes are a very important condition in the case of the intra-annual phenological development of vegetation. In fact, we expect vegetation greenness to respond to anomalies in the precipitation totals that are function of the characteristics of the climatology of the region and not to low rainfall regimes established with ad-hoc or operational thresholds.

In this manuscript, we propose an innovative method to identify monthly meteorological drought events based on precipitation time series alone and the Fisher-Jenks optimal classification algorithm. Similarly to many other approaches (26,27), we currently adopt the historical median precipitation value for each location and time period as the expected precipitation for that time and location. However, in opposition to other approaches, our method adapts to the characteristics of the climatological precipitation frequencies in the region and allows us to determine the natural breaks that separate the precipitation totals smaller than the median into drought and non-drought events. In detail, for each GPCC grid cell *k* and month *j* = 1, …, 12, we identify the median precipitation value ($P_{k,j,m}$) and the years n in the available time series where $P_{k,j,n} <= P_{k,j,m}$, and set those precipitation observations to the group $\{P_{n,1}\}_{k,j}$. In the sequence, we use the Fisher-Jenks classification algorithm to find the optimal point that divides $\{P_{n,1}\}_{k,j}$ into two groups: the set of observations $\{-1_n\}_{k,j}$ that are closer to $\min\{P_n\}_{k,j}$; and the set of observations $\{0_n\}_{k,j}$ that are closer to $P_{k,j,m}$. From a semantic view point, $\{-1_n\}_{k,j}$ are those individuals that can be considered in "physical" meteorological drought, as they approximate the minimum precipitation total that was ever registered for region k and month j between 1901 and 2010. On the other hand, the group of observations $\{0_n\}_{k,j}$, and the remaining individuals $P_{k,j,n} >= P_{k,j,m}$, are closer or above, respectively, the expected precipitation value for the region and thus cannot physically be considered in meteorological drought. Finally, we create a discrete monthly time series of drought events for each grid cell k, as $D_k = \{\{-1_n\}_{k,j}, j = 1, …, 12\}$.

Note that similarly to other drought indices, D_k can simultaneously be computed for different timescales, namely 1-, 3-, 6-, and 12-months precipitation accumulation periods. Short accumulation timescales are useful for monitoring drought impacts on agricultural yields, while long accumulation timescales are important mainly for assessing impacts on reservoirs levels and groundwater supplies (28). In this paper, we evaluate the potential usefulness of each drought timescale for assessing the preceding weather conditions that may lead to vegetation greenness shortage.

Correlation analysis between relative greenness and meteorological drought

To verify the hypothesis that specific meteorological drought conditions relate to consequential decreases on the seasonal RG values of rainfed crops, we first define the intra-annual period in which low flow precipitation regimes may affect the vegetation growth conditions in the study area. We denominate this period as Growing Season Precipitation (*GSP*) and define it as the set of months comprised between the starting of vegetation growing season (see RG computation section) and the starting month of the preceding rainy season. Then, for each timescale i, we compute the indicator $i\text{-}SD_{k,n}$ that represents the accumulated drought for the period *GSP* in region k and year n. In addition, we compute two composite seasonal meteorological drought indicators, i.e. the total sum of seasonal meteorological droughts (TSD_k) and the weighted sum of seasonal meteorological droughts (T_wSD_k), both for region k and year n, as:

$TSD_{k,n} = \sum i\text{-}SD_{k,n}$, i =1, 3, 6 and 12, (4)

$T_wSD_{k,n} = \sum 1/i * i\text{-}SD_{k,n}$, i =1, 3, 6 and 12, (5)

The weights defined for $T_wSD_{k,n}$ can be further optimized, but in this ongoing study they correspond simply to the inverse length of precipitation timescale, as recent water supplies anomalies tend to higher impact the vegetation greenness of rainfed crops.

Finally, to test our hypothesis, we compute the correlation analysis for each year n = 1998, …, 2010, between $RG_{GS,n}$ and each of the seasonal drought indicators proposed in this study, namely $i\text{-}SD_{k,n}$, $TSD_{k,n}$ and $T_wSD_{k,n}$.

RESULTS AND DISCUSSION

Following the structure of the Methodology section, we start this section by presenting the selected study area. It corresponds to a 1° (decimal degree) grid cell, located in *Cañada de la Mala Cara*, Córdoba Province, Argentina (Figure 1.a). According to some areal estimates based on the used ancillary data, 87% of the study area was occupied by rainfed crops in 2000 (Figure 1.b), from which only 5% undergo land cover changes until 2009. According to (29) and (30), this region is characterized by large agricultural areas occupied mainly by soya bean crops, wheat crops and other cash crops that grow normally between December each year and February next year.

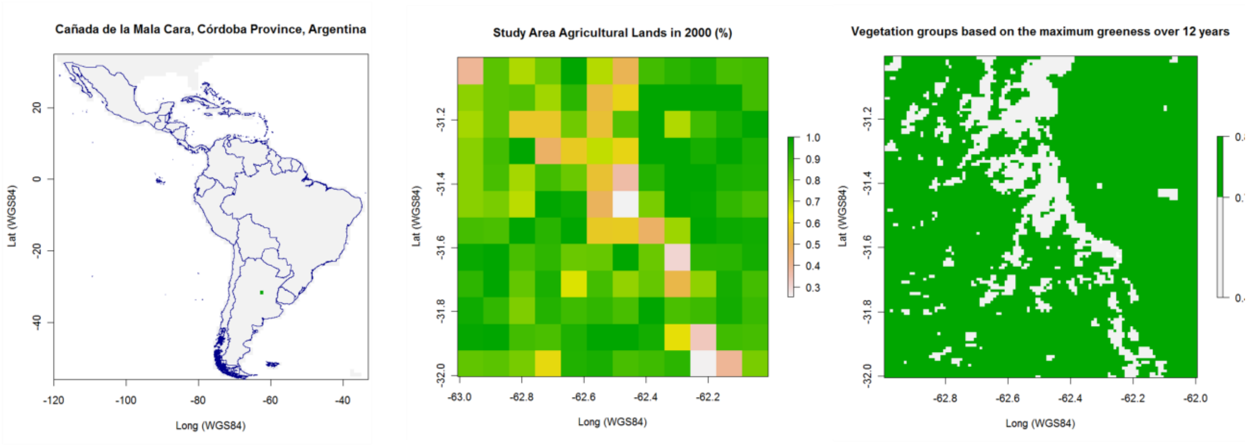


Figure 1: Study area location in Latin America (a); probability of being rainfed crops in 2000 – GAL 2000 (b); area that did not undergo changes between 2000 and 2009.

In Figure 2.a one presents the empirical mean fAPAR estimated for the study area and the median fAPAR distribution along time, and in Figure 2.b we compare the temporal distribution of 25th, 50th and 75th fAPAR percentiles for the study area. Two important points need to be detailed. Firstly, we perceive that the land cover management practices vary along time, as the amplitude of the sinusoidal harmonic function that describes the median fAPAR distribution along time increases from 1998 to 2011. Although an exhaustive noise reduction process was performed to remove possible outliers from the crops classification, it was not possible to remove changes in the agricultural practices. This shows how extremely difficult is to establish a system that depends on ancillary data, which is not always available or is not sufficiently detailed to support the necessary analysis. Secondly, we perceive that changes in the land use practices are similar along time for the whole study area, as the estimated interquartile distances are maintained. This is an important point to retain, as it suggests that time changes in the weather conditions in the region will similarly impact the whole rainfed crop types inside the study area.

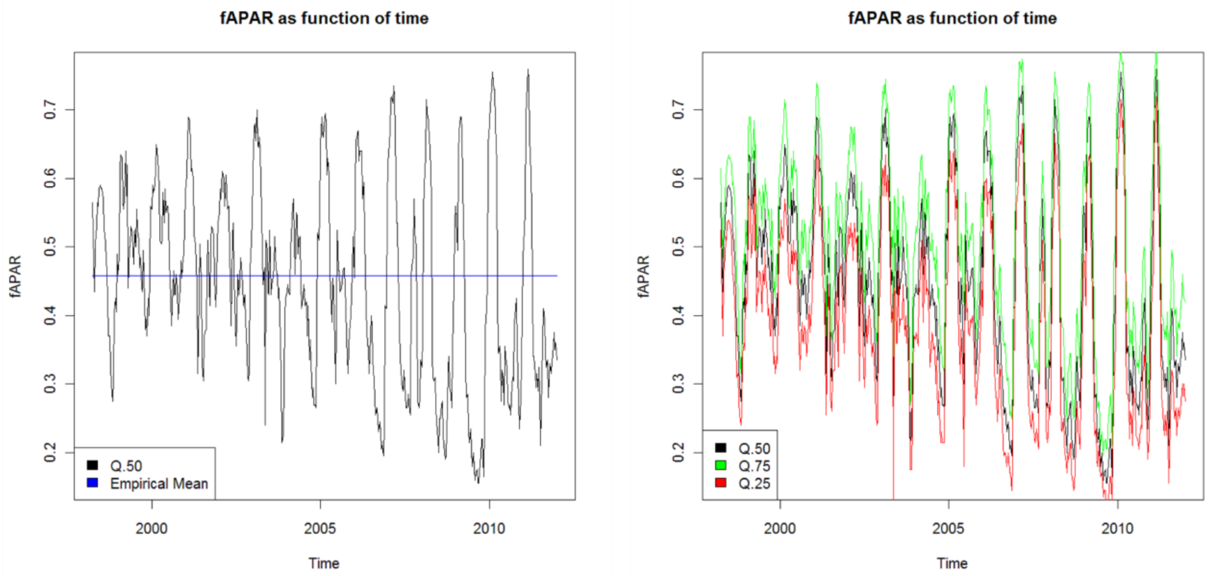


Figure 2: a) Empirical mean (blue horizontal line) and median fAPAR for the study area as function of time; b) 25th, 50th and 75th fAPAR percentiles for the study area.

Based on the information presented in Figure 2, we defined the GS for the study area as the set of 10-daily periods comprised between 21st January and 1st of April each year. Because this growing period was relatively constant – just extending at a maximum of 2 more weeks in some of the years between 1998 and 2010 – we can assume that the agricultural crops in the study area present the same phenological pattern along the period of analysis and can be used for testing our hypothesis.

In Figure 3.a, we present the accumulated fAPAR for each year ($fAPAR_{GS,n}$) and in Figure 3.b the respective seasonal relative greenness ($RG_{GS,n}$). Looking at the diagrams shown in Figure 3, we perceive immediately that there was a remarkable anomaly affecting the greenness of agricultural crops during the season of 2003-2004, as compared to the other seasons evaluated in the analysis. The first evidence is the continuous and notable increasing distance between the accumulated $fAPAR_{GS,03\text{-}04}$ (Figure 3.a) and that attained for the other years in the analysis along the growing season. Although from this figure we cannot capture the dimension of the anomaly, from Figure 3.b we perceive that the $RG_{s,03\text{-}04}$ is substantially inferior to that of the other years. This suggests that there was some phenomenon causing a notable disturbance in the normal development of the rainfed crops.

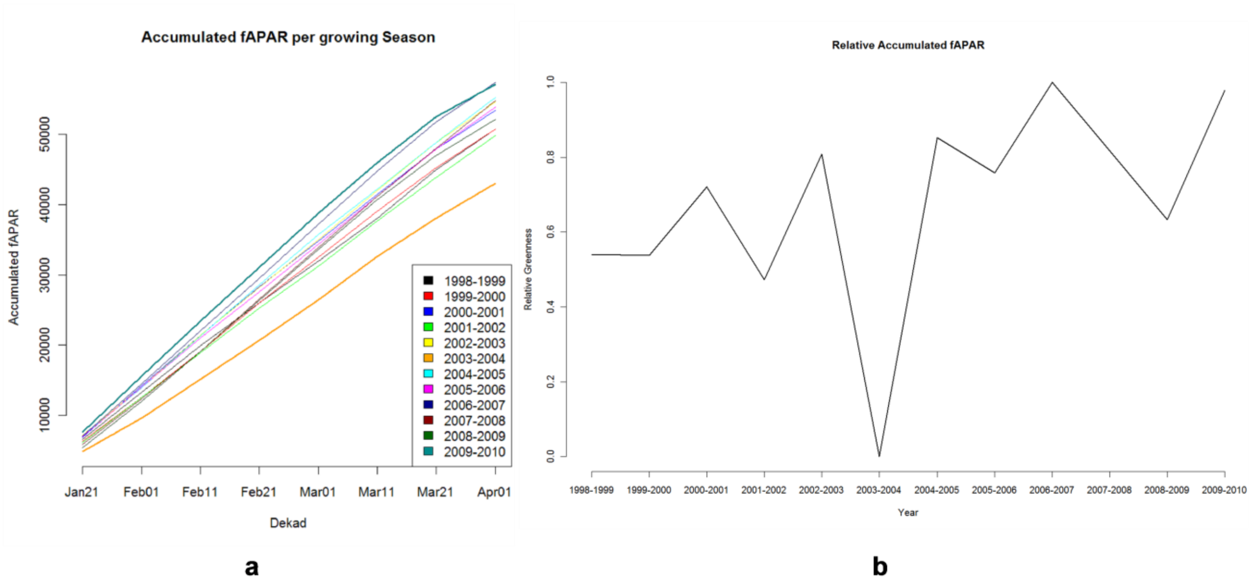
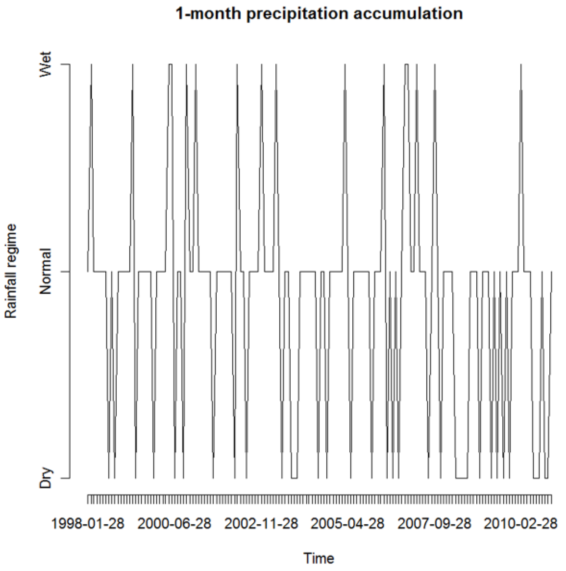
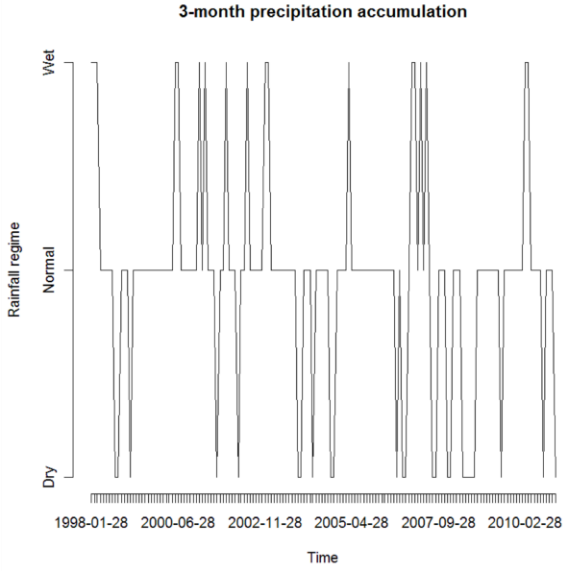


Figure 3: a) Accumulated $fAPAR_{GS,n}$ for different years along the growing season; b) $RG_{GS,n}$ computed for the years between 1998 and 2010.

Let us now look for some evidence between drought indices' values and the anomalous accumulated RG of rainfed crops during growing season of 2003-2004. In Figure 4 (a-d), we show the discrete time variation of monthly drought indices' values, i-D_k, computed for timescales of 1-, 3-, 6-, and 12-months precipitation accumulation. As expected, the number of discrete consecutive months' under drought becomes longer with the increase of the timescale of analysis, but the number of droughts occurring is smaller. Physically, this outcome verifies the validity of the proposed drought indicator, as from that viewpoint it is likely that small timescale monthly droughts recover faster than large timescale monthly droughts. In words, it takes physically more time to re-establish the "normal" water supply conditions within a system that drop down a large timescale rainfall shortage than a short one.



a



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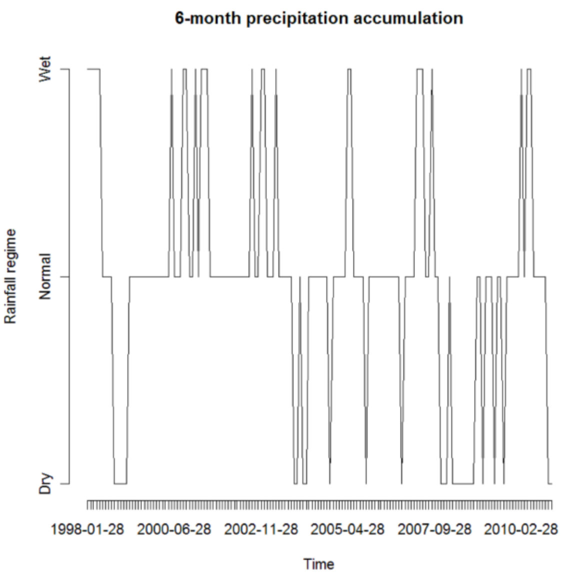

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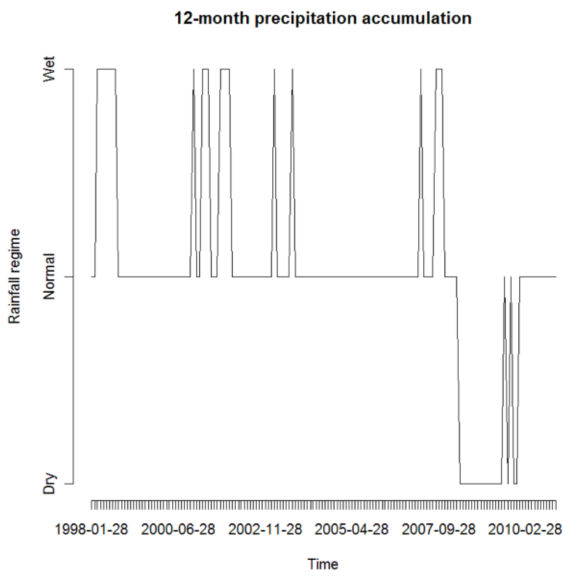


d

Figure 4: Monthly drought events as function of time for: a) 1-D_k*; b) 3-*D_k*; c) 6-*D_k*; d) 12-*D_k*.*

As the discrete time variation of monthly drought occurrences for different timescales seems not to put in evidence the shortage on RG verified for the rainfed crops in the season of 2003-2004, it is now important to evaluate if consecutive monthly meteorological drought events relate to that shortage. From Figure 5, which shows the intra-annual monthly accumulated rainfall for the years between 1998 and 2010, we perceive that the annual rainfall period averagely begins in September/October each year and ends by the end of March next year. Thus, we used the period between October to December to evaluate the impact of accumulated meteorological drought on seasonal relative greenness of rainfed crops and define it as the *GSP* for the study area. Please remember that we defined January as the staring month of the growing season for rainfed crops in the study area.

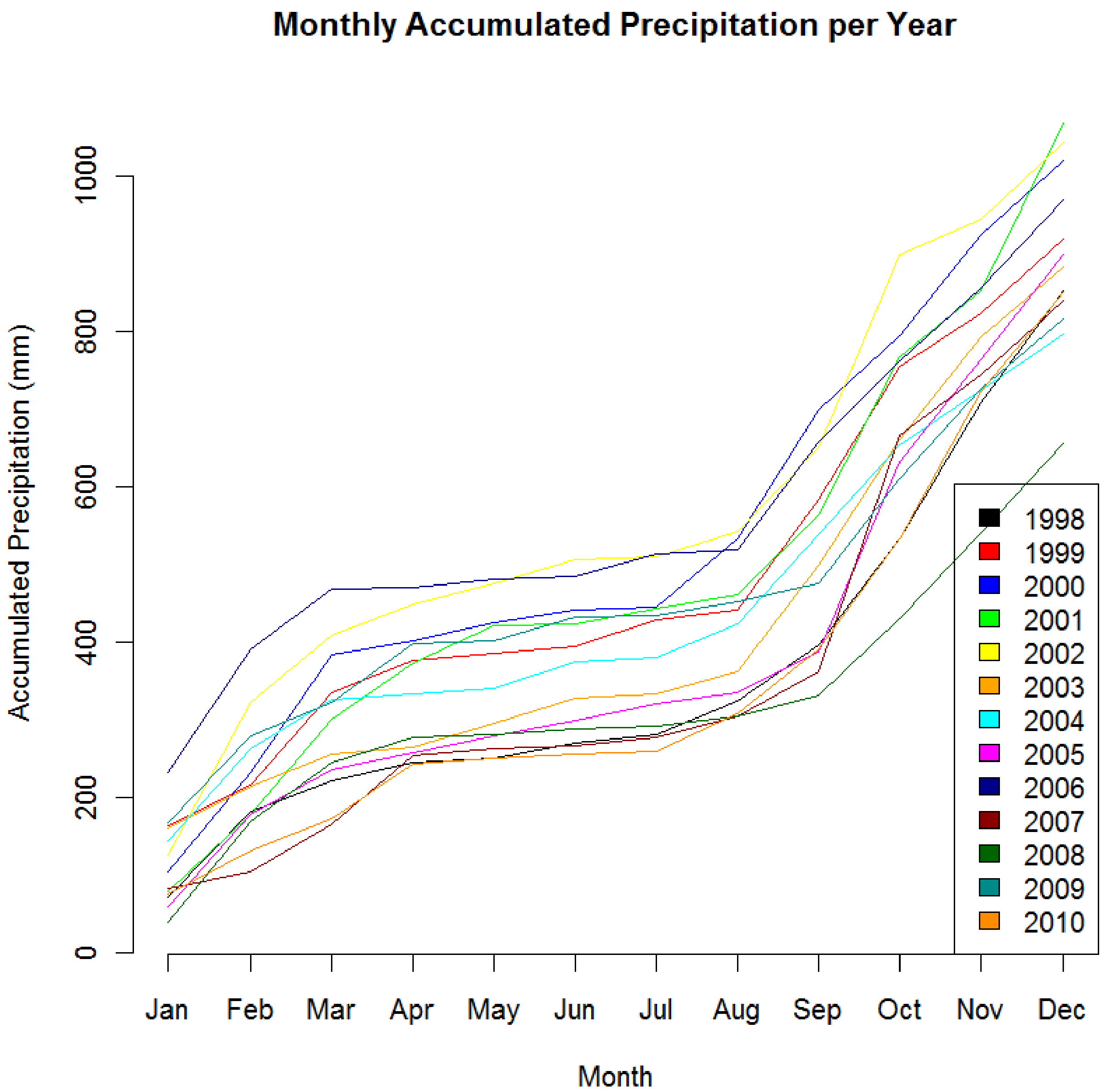
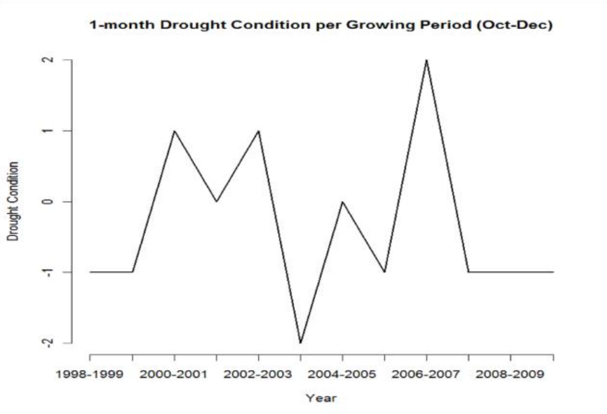
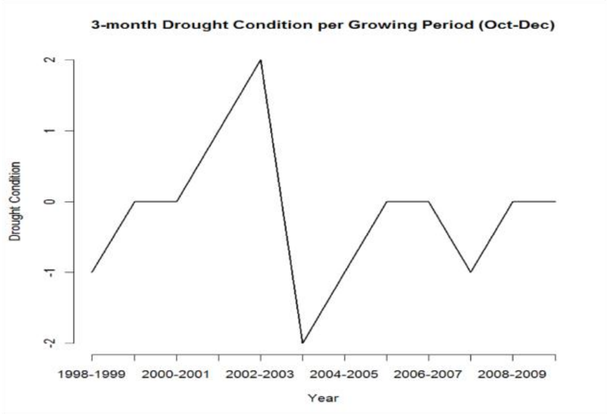


Figure 5: Intra-annual monthly accumulated rainfall for the years between 1998 and 2010.

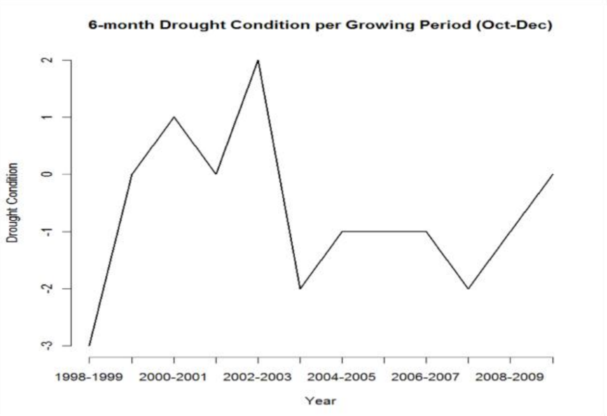
In Figure 6 (a-f), we present the time distribution of accumulated drought indices' values for the seasons between 1998-1999 and 2009-2010, as well as the correlation coefficient (r) measuring the strength of the linear relationship between each accumulated indicator and the $RG_{s,n}$ presented in Figure 3.b. From a general viewpoint, it is worth mention that all indicators, with the exception of *6-SD* and *12-SD*, show a relevant accumulated drought event for the season 2003-2004, which matches the highest shortage on accumulated relative greenness for the study area. Indeed, according to (31) and (32), there was a remarkable meteorological drought in this season, that extended between January 2003 and March 2004 and largely affected the crops in the region. In fact, the crops in 2003 were not affected, as the rainfall deficit started after vegetation growing period. However, because there were continuous short timescale monthly droughts occurring in the *GSP* period of 2003-2004, the crops in 2004 were affected.



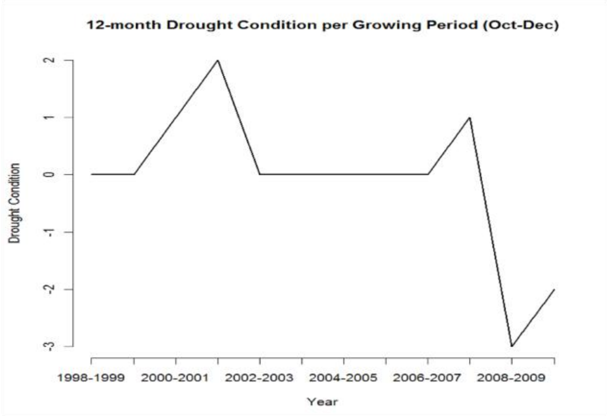
***r* = 0.57** **a**



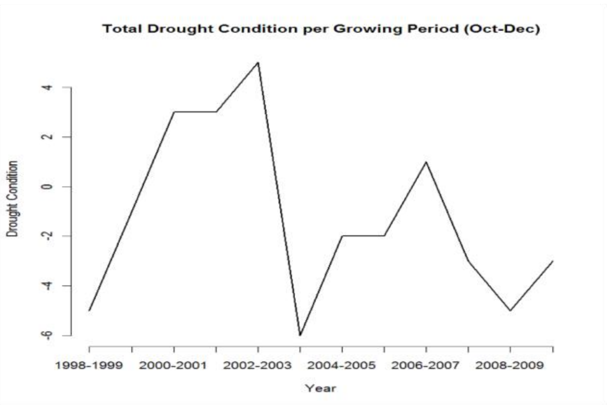
***r* = 0.40** **b**



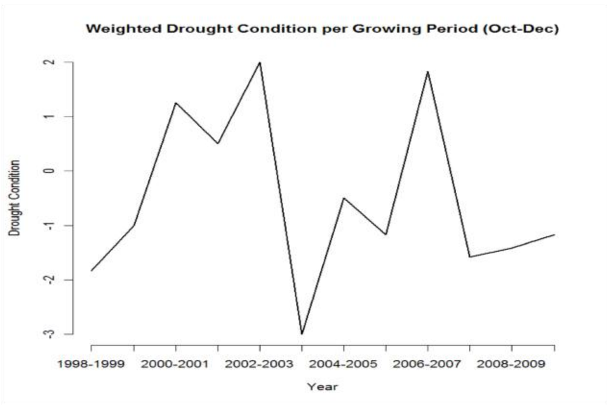
***r* = 0.30** **c**



***r* = -0.2** **d**



***r* = 0.35** **e**



***r* = 0.54** **f**

Figure 6: Accumulated monthly meteorological drought values for: a) 1-SD_k; b) 3-SD_k; c) 6-SD_k; d) 12-SD_k; e) TSD_k; f) T_wSD_k.

In the sequence, we perceive also that there is a decrease in the correlation coefficient *r* as long as we increase the timescale of the accumulated drought indicator, i.e. from Figure 6.a to 6.d. This outcome suggests that short, independent and continuous meteorological droughts accumulated during the period preceding the time of vegetation growing is the type of water shortage that most affects the normal phenological conditions of rainfed crops vegetation. The reason is evident: large timescale accumulated monthly droughts may be the result of independent longstanding short timescale monthly droughts that are no longer affecting the vegetation conditions, but just now visible at a lower temporal resolution.

Looking now at Figures 6.e and 6.f, i.e. the accumulated monthly drought values that combine all available timescales, we perceive again that small timescale drought patterns contribute more than those at larger timescales to a match with the seasonal relative greenness. Thus, the results suggest that for an a priori evaluation of the impacts of meteorological droughts on vegetation greenness, it is more useful to rely on accumulated and consecutive short-term drought events than on larger ones.

CONCLUSIONS

In this paper we aimed at evaluating the cause-effect relationship between long-lasting meteorological droughts and the regional vegetation greenness accumulated during growing season, which can serve as *a priori* information to predict the impacts of low precipitation supplies on the expected seasonal development of vegetation.

We introduced the concept of seasonal accumulated relative greenness. The proposed indicator was evaluated on a rainfed crop area in Latin America and it was computed from a time-series set of 10-daily fAPAR images derived from SPOT-VEGETATION data collected between 1998 and 2010. The results show that our approach was successful on accurately exposing the regional impacts of meteorological drought on the normal growth of rainfed crops, by identifying the drought pattern that affected the crop production in the study area during the growing season of 2003-2004 in the study area.

In the sequence, we presented an innovative and non-parametric meteorological drought indicator. Its main advantage is the ability to adapt to the climatological characteristics of the geographical region when defining the drought thresholds from historical rainfall records. The results show a physical coherence between drought timescales and their average duration, thus giving us confidence on the validity of the indicator. Moreover, using the cumulative values of monthly droughts preceding the vegetation growing season as *a priori* knowledge for assessing its consequential greenness development, we were able to clearly identify by three months in advance the decrease in the rainfed crops production in 2003-2004. In fact, the results showed that the agricultural cycle is more correlated with long-standing and continuous small timescale drought conditions than with discrete or short long-term timescale drought events.

This is an on-going study that reports only the case of rainfed crops, but we expect to compare these outcomes with those attained with other types of vegetation, namely forest, shrubland and grassland. Similarly, it would be appreciated to confirm the relationship attained in this study for different study areas with the same land use/cover type, but different climatic and topographic conditions. In this study, we focused on fAPAR derived from SPOT-VEGETATION satellite images. Although the results are optimistic, there is still in the research community a long discussion about different vegetation indices and their usefulness for drought assessment and monitoring. It would be interesting to evaluate the behaviour of different data on this study case scenario in order to select the most adequate dataset to monitor agricultural drought events.

Regarding the estimation of drought, several improvements and modifications to the methodology can still be performed in order to improve it. The quality of input data should be optimized, as the number of stations used to compute GPCC products are highly variable in space and time. The spatial resolution of the input precipitation records can be enhanced with other datasets, namely Tropical Rainfall Measuring Mission (TRMM) remote sensing images. At this moment, the baseline statistics for characterizing the climatology of the region are based on a continuous period between 1901 and 2010. However, it is important to evaluate the impacts of the ENSO (El Niño Southern Oscillation) events on the baseline statistics for meteorological drought computation – and even on relative greenness estimation. Regarding the accumulated drought indicators, we think that a scheme with different weights can be tested and further optimized based on more detailed information about the weather variability in the region and phenological characteristics of different types of vegetation.

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