MONITORING DROUGHT USING MULT-SENSOR REMOTE SENSING DATA IN CROPLAND OF GANSU PROVINCE

Linglin ZENG [1]**, Jie SHAN** [2,3]**, Daxiang Xiang**[4]

[1]State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China

[2]School of Remote Sensing and Information Engineering, Wuhan University, Wuhan, China

[3]School of Civil Engineering, Purdue University, USA

[4]Changjiang River Scientific Research Institute, Changjiang River Water Resources Commission, Wuhan, China

Email: zenglinglin@whu.edu.cn

Abstract: Various drought monitoring models have been developed from different perspectives, as drought is impacted by various factors (precipitation, evaporation, runoff) and usually reflected in various aspects (vegetation condition, temperature). Cloud not only plays an important role in the earth's energy balance and climate change, but also directly impacts the regional precipitation and evaporation. As a result, the change of cloud cover and cloud type can be used to monitor drought. This paper proposes a new drought composite index, the Drought Composite Index (DCI), for drought monitoring based on multi-sensor remote sensing data in cropland of Gansu Province. This index combines the cloud classification data (CLS) from FY satellite and Vegetation Condition Index (VCI) which was calculated using the maximum and minimum NDVI values for the same time period from Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. Pearson correlation was performed to correlate NDVI, VCI, CLS and DCI values to precipitation data and soil moisture (SM) data collected from 20 meteorological stations during the growing season of 2011 and 2012. Better agreement was observed between DCI and precipitation as compared with that between NDVI/VCI and precipitation, especially the one-month precipitation, and there is an obvious time lag in the response of vegetation to precipitation. In addition, the results indicated that DCI well reflected precipitation fluctuations in the study area promising a possibility for early drought awareness necessary and near real-time drought monitoring.

1. Introduction

Drought is a recurrent complex phenomenon that affects nearly all climatic zones in the world, the semi-arid regions being especially susceptible because of their low annual precipitation [1]. Many of the indices are used to measure meteorological drought, such as the Palmer Drought Severity Index (PDSI) and the Moisture Anomaly Index (Z-index) [2], the Standardized Precipitation Index (SPI) [3], etc. Remote sensing, with continuous measurements across large geographic areas, frequent revisit time for image acquisition and long series of historical data, can be an effective technology in assessing a wide

range of critical drought indicators. Normalized Difference Vegetation Index (NDVI), detecting drought on the basis that vegetation vigor is closely related to moisture condition, is the most widely used satellite-based drought indices. NDVI is an effective indicator of vegetation moisture conditions but seasonal changes should be considered when monitoring drought [4]. And NDVI-based Vegetation Condition Index (VCI) is considered to be a better indicator of drought than NDVI, as it reflects the vegetation vigor in comparison with the best and worst conditions over the same period in different years [4][5][6]. However, vegetation responds to water deficit with a striking time lag. Such observations have been made by Malo[7], Liu and Ferreira [8], Cihlar et al. [9], Di et al. [10], Vogt et al.[11], Karabulut [12], Bajgiran et al. [13], who found different time lags for different vegetation covers and ecosystems.

Cloud not only plays an important role in the earth's energy balance and climate change, but also directly impacts the regional precipitation and evaporation. As a result, the change of cloud cover and cloud type can be used to monitor drought. Liu [14][15] proposed cloud index method based on three cloud parameters, which could reflect near real-time soil moisture fluctuations in the study area, promising a possibility for early drought awareness necessary for drought risk management, as cloud directly affect the short term rainfall and evaporation. However, in this model, all types of cloud were treated as the same weight, and actually, different cloud types play very different roles in rainfall.

The objective of this study was to conduct satellite-derived methods for monitoring drought in croplands over Gansu province in China during the growing season of 2011 and 2012, respectively the dry year and wet year of the cropland in Gansu, through the combination of vegetation index and improved cloud index to build a new composite model, so as to take advantage of the two single models. Additionally, this study includes the evaluation of the suitability of the NDVI and VCI and the establishment and verification of the new model for monitoring meteorological drought (e.g., precipitation deficits) as well as agricultural drought (e.g., soil moisture deficits).

2.   Materials and methods

2.1 Study area
Drought is one of the most happened natural disasters in the Gansu province which is located in Northwest China. Affected by monsoon, the 50%-70% of precipitation gets concentrated among July to September. So Gansu is susceptible to spring droughts, when wheat is beginning to grow. The cropland of Gansu, most of which is covered by wheat in spring and summer, was selected to validate the drought monitoring approach. The average annual precipitation in Gansu is 36.6-734.9 mm and the average temperature of a year is 4–14 degrees centigrade.

2.2 In-situ data
Ground-measured soil moisture and precipitation data in Gansu province were used to validate the drought monitoring approach in this study. As seen in Figure 1, there are 20 agriculture meteorological stations which are located in the cropland.

2.2.1 SPI
McKee et al. (1993) developed the SPI, which is based on statistical probability and was designed to be a spatially invariant indicator of drought SPI can be calculated by standardizing the probability of observed precipitation for any duration of interest (e.g., weeks, months, or years).Durations of weeks or months can be used to apply the SPI for agricultural or meteorological purposes, and longer durations of years can be used to apply it for hydrological and water management purposes [16]. And in this study, to discuss the timeless of the satellite-derived drought monitoring index, the 1-, 2- and 3- month SPI are calculated for the 20 agriculture meteorological stations based on the precipitation data in Gansu during recent two

decades from the China Meteorological Data Sharing Service System (CMDSSS) Website (http://cdc.cma.gov.cn/home.do).

2.2.2 Soil moisture
Soil moisture contents are measured at depths of 0-10, 0–20 and 0–50 cm on days 8, 18 and 28 of each month, respectively. In this study, 0-10 cm depth soil moisture is selected and obtained from CMDSSS.

2.3 Remote sensing data
The products of Terra MODIS (Moderate Resolution Imaging Spectroradiometer): Sixteen-day vegetation indices with 250m resolution (MOD13A1) were obtained using the Warehouse Inventory Search Tool (Reverb; http://reverb.echo.nasa.gov/reverb/) covering the study area. The product of FY2D: 5-minite cloud classification data was obtained from the National Satellite Meteorological Center (NSMC) website (http://nsmc.cma.gov.cn/NewSite/NSMC/Home/Index.html), among which the images at 5 o'clock (UTC time) of each day was selected as the representation of the cloud condition of that day. And then the improved cloud index model based on the model proposed by Liu [14][15] was established and calculated through giving different weight to different kind of cloud types according to the possibility of rainfall. The FROM-GLC (Finer Resolution Observation and Monitoring of Global Land Cover) 30 m resolution global land cover maps was used in Figure 1, which is obtained from FROM-GLC website (http://data.ess.tsinghua.edu.cn/modLikeDataRef.html).

2.4 Data processing and analysis
The eight-year period NDVI data of 2005–2012 at the end of the growing season months: March to August, was used to calculate VCI using maximum and minimum NDVI values over the eight-year study period according to the equation 1. The drought composite index (DCI) is the composition of the VCI and cloud classification data (CLS) values. The CLS and land cover data was resized as the 250m resolution, and then the values for individual stations were averaged over 250 pixels centered at each station. As the 250 pixel square is big enough for accuracy of geo-referencing but small enough for the square to receive a similar rainfall amount.

$$VCI = \frac{NDVI - NDVImin}{NDVImax - NDVImin} \tag{1}$$

Where NDVI, NDVImax and NDVImin are the smoothed sixteen-day NDVI, multi-year maximum NDVI and multi-year minimum NDVI, respectively, for each grid cell. VCI changes from 0 to 1, corresponding to changes in vegetation condition from extremely unfavorable to optimal [5].
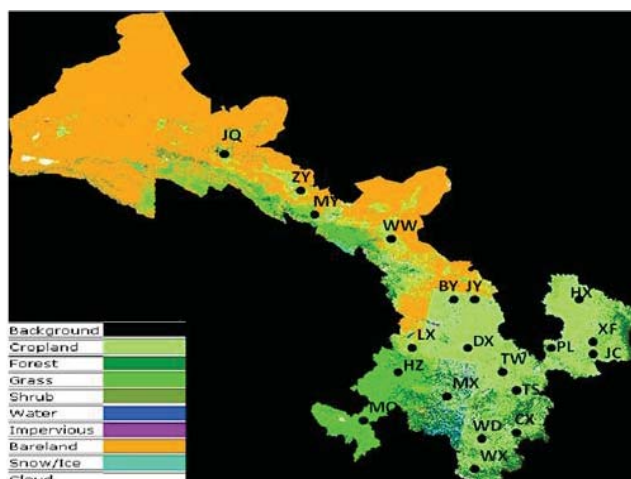
Figure 1. Land cover and agriculture stations of study area. (The capital letters on the map are the acronym of the station names.)
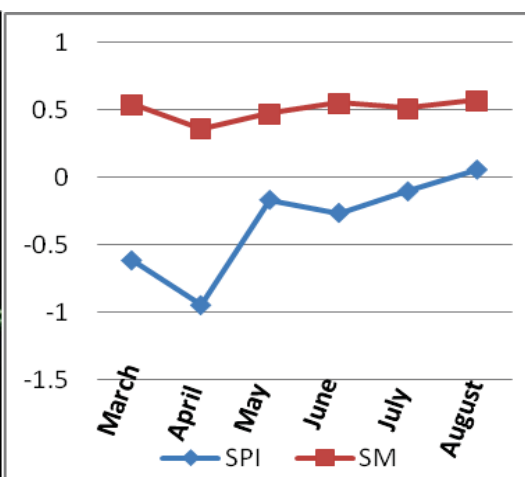

Figure 2. The average one-month-SPI and SM of each month during the growing season of 2011.

3.   Results and discussion

3.1 Variation of NDVI time series

What is shown in Figure 3 is the monthly time series (from March to August) NDVI of the 20 stations in 2011 and 2012. The NDVI values vary considerably over time and space, accordingly, it is difficult to detect drought by a single NDVI image, as a result VCI, instead of NDVI, is chosen to be combined with DCI which is calculated according to the equation 2. It can be seen from Figure 3 that the difference between dry year 2011 and wet year 2012 of the peak NDVI value or the point after peak point in each station is larger than the points before peak point. While as demonstrated in Figure2, the average SM, especially the average one-month SPI, in March and April is relatively lower, while it is relatively high in peak points: May, June or July. Collectively, it is shown that there is an obvious time lag in the response of vegetation to drought, because the water deficits on vegetation are cumulative.

$$DCI = 0.5*VCI + 0.5*CLS \tag{2}$$

3.2 Correlation and regression analyses

Pearson correlation analysis was performed to correlate NDVI, VCI and CLS values with precipitation data and soil moisture data (Table 1). It is shown from Table 1 that DCI combined with vegetation indices (VCI) and cloud condition (CLS) performed better than the indices with only VCI or CLS value, when correlated with 1-, 2-, 3-month SPI. Although DCI produced the lowest correlation coefficient with SPI1, 0.46, compared to SPI2 and SPI3, 0.52 and 0.54 respectively, it is much higher than that of NDVI and VCI with SPI1, 0.29 and 0.20 respectively.
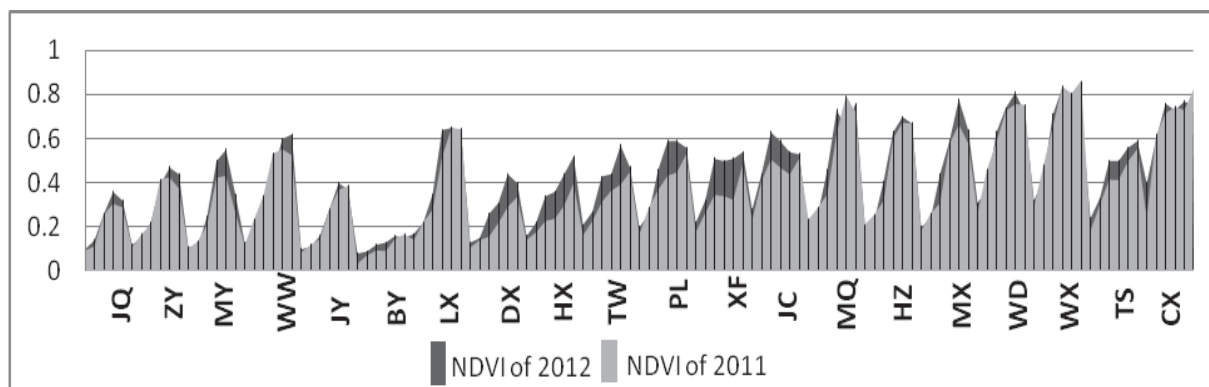
Figure 3. Time-series NDVI of 2011 and 2012

Table 1. Linear correlation coefficients between NDVI, VCI, CLS and DCI in the study area during March to August in 2011 and 2012.

	SPI1	SPI2	SPI3	SM
NDVI	0.29	0.40	0.38	0.19
VCI	0.20	0.46	0.49	0.24
CLS	0.38	0.25	0.22	0.1
DCI	**0.46**	**0.52**	**0.54**	**0.20**

Due to the difference of other factors, like human activity, climate pattern, soil type, etc., the correlation between remote sensing indices and SPIs varies with space, while as for the individual station, the correlation is stronger. Regression analyses were conducted for the DCI vs. 1-month SPI for individual stations. Scatter plots, correlation coefficients and their p-values for the SPI1 and CCI during the growing season months can be seen in Figure 4. The p-value refers to the probability of rejecting the null hypothesis that there is no correlation between two variables. It can be noted from these plots there is good relevance between SPI1 and DCI, as DCI is closely related with predication.

3.3 Drought monitoring experiment and mapping

In 2011, there were droughts in most part of Gansu from the beginning of the year, due to shortage of rainfall. However, according to the reports of Gansudaily website (http://gansu.gansudaily.com.cn/system/2011/05/27/012009376.shtml), in May, several round of rain fall on most parts of Gansu, especially, on middle and southeast of Gansu province where drought was relatively serious, thereby nearly alleviating the drought. Seen from Figure 5, there is little difference from the VCI of April and May, while, the drought detecting based on DCI, which includes localized cloud information, shows that drought was significantly relieved in May, compared to that in April. So DCI enables not only the description of drought but also near real-time drought conditions than only vegetation indices.
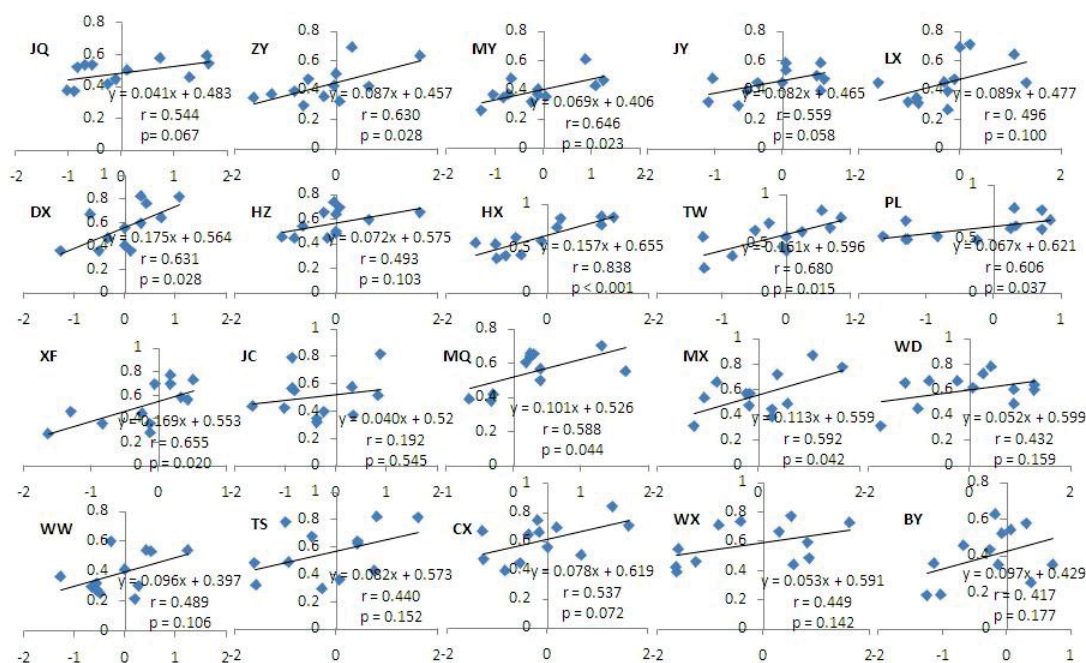
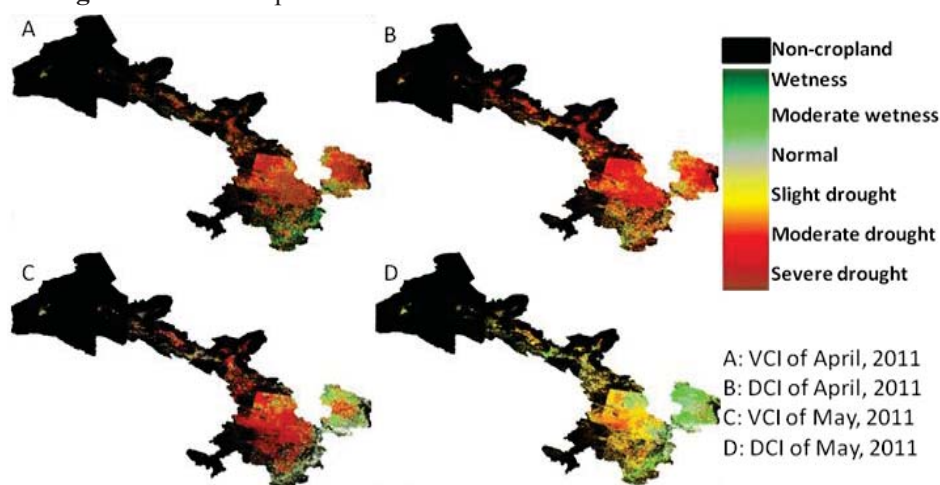**Figure 4.**   Scatter plots with SPI1 as the abscissa and CDI as the ordinate.

Figure 5. VCI and DCI of April - May, 2011

4.   Conclusions

We concluded that the time-series NDVI is a good indicator of moisture condition and can be an important data source when used for detecting and monitoring drought in this area, but it is difficult to detecting drought from single NDVI image, as many other factors like seasonality, spatial variability, vegetation type, etc. have very significant effects on NDVI values. In addition, of the multi-scale SPIs from 1 to 3 months, the 3-month SPI has the highest correlation to the NDVI and VCI in the Gansu province. This is because vegetation response to precipitation has a time lag, and the impact of water deficits on vegetation is cumulative.

The most important finding of this research is that drought composite indices combined with vegetation index and cloud parameters have stronger correlation with SPI1 than drought indices with only vegetation index have, as cloud directly impacts the regional precipitation and evaporation and the changes of cloud cover and cloud type have a good relevance with regional precipitation and evaporation. In addition, drought condition is often most directly affected by precipitation, and based on DCI, the change of drought can be detected more timely than VCI, thereby enhancing the timeliness of drought monitoring.

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