EVALUATING THE RESPONSE OF THE VEGETATION CONDITION INDEX (VCI) TO METEOROLOGICAL DROUGHT IN AN AGRICULTURAL REGION OF CHINA NORTH PLANE

Yuanyuan Wang[1]

1. National Satellite Meteorological Center, China Meteorological Administration, Beijing, China; wangyuany@cma.gov.cn

ABSTRACT

Although Satellites based drought indices (such as Vegetation Condition Index, VCI) has been intensively used for drought monitoring, the drought information provided by satellite technique is quite different from traditional station-based meteorological drought indices (such as Standard Precipitation Index, SPI). The relationship between VCI and SPI is influenced by many factors including climate, land cover, soil properties, etc. In this study, we explored the relationship between VCI and SPI for an intensive agriculture area in China North Plane during 12 growing seasons (2000-2011). Our aim is to identify key factors influencing the relationship between VCI and SPI for this local region with relatively high homogeneity in terms of climate and land cover. Results indicated that regional mean VCI agrees well with SPI at medium time scales (8-24 weeks), and double cropping could be a factor impacting the seasonal variation in the correlation between VCI and SPI. Significant spatial variations are observed both in the strength and the time lag of the relationship between VCI and SPI. The correlation coefficients, with a range of 0.11-0.48, are strongly affected by annual mean temperature, accumulated NDVI during growing season, and irrigation percentage, and 58.3% variations can be explained with a linear model based on the three variables. The time scale of SPI at which VCI shows the strongest correlation is influenced by percent of groundwater irrigation, annual precipitation and soil Available Water Capacity, with 59.8% variations explained using a linear model incorporating the three variables. Our results demonstrated that besides climatic and soil prosperities, human activities (double cropping, groundwater irrigation) and vegetation dynamics (not just vegetation type) should also be considered in interpretation of meteorological drought with VCI.

INTRODUCTION

Agriculture management needs efficient drought information. Although meteorological drought indices (such as Standard Precipitation Index, SPI) are useful in drought measurement, they often have limited spatial resolution since they rely on in situ data (1). Satellites based drought indices (such as Vegetation Condition Index, VCI) can provide drought information over large areas at a higher spatial resolution, but in a way that is quite different from station-based meteorological drought indices (2). It has been recognized that the existing satellite-based drought indices are more associated with agricultural drought (e.g., crop yield, soil moisture, etc), and the response of vegetation to meteorological drought (precipitation deficits) varies depending on the seasonal timing, land cover type, climate, soil properties, irrigation, and other factors (3,4,5,6,7,8). More specifically, strong correlations between VCI and SPI are more likely to occur when the time is in growing season, the land is covered with grass/shrub/crop, the climate is arid/semi-arid, the soil Available Water Capacity (AWC) is low, or the land is not irrigated.

Previous researches often focused on a large area that spanned a range of climatic and ecological zones. In this paper, the response of the VCI to meteorological drought indices was studied over a small agricultural region (with an area of about 47,000 km2) in China North Plane where drought hits frequently and irrigation farming is very prevalent (Figure 1). Main land cover in this region is crop land, scattered with residential area. Annual mean temperature is 13℃, and annual mean precipitation amount is 497 mm. We want to understand how VCI responses to SPI temporally and spatially when the climatic and environmental features are relatively uniform, and what factors could account for the spatial variability in the relationship between VCI and SPI in this local region.

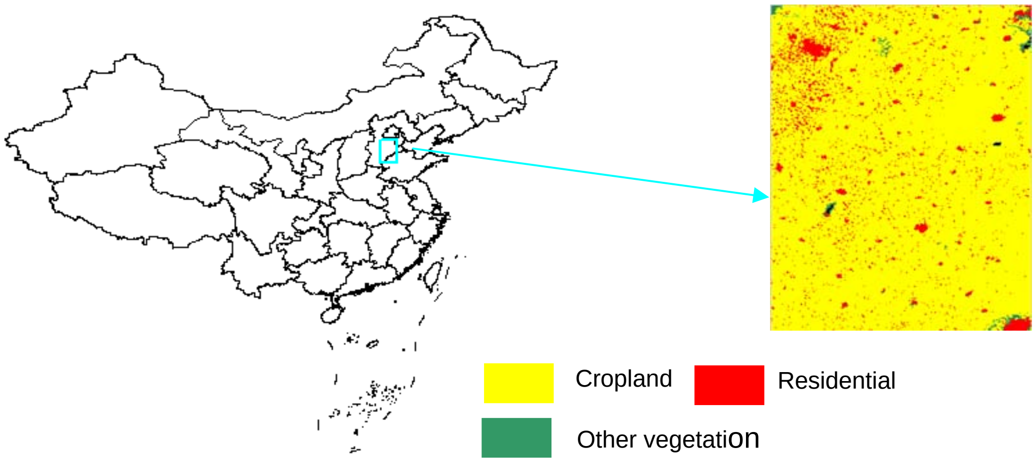


Figure 1: The location and main land cover type of our study region.

METHODS

SPI calculation

The SPI was proposed by McKee (9) and it is calculated by standardizing the probability of observed precipitation for any duration of interest (e.g., weeks, months, or years) (2). Due to the flexibility in time scales, SPI is very useful for separating different types of drought. SPI at short time scales (weeks or months) is more related to meteorological and agricultural drought; while SPI at longer time scales (years) is more related to hydrological drought and socioeconomic drought. SPI at short time scales responds to precipitation very fast, and it can identify drought many months earlier than PDSI (6). Another advantage is that SPI is spatially and temporally comparable. SPI values of -0.5 or lower is indicative of drought status. In this study, 21 meteorological stations with a long-term precipitation record (1965-2011) in the study region were used to calculate the SPI at 10 time scales (2-, 4-, 8-, 12-, 16-, 24-, 32-, 40-, 48-, 52-week).

VCI calculation

VCI proposed by Kogan (10) is a pixel-wise normalization of NDVI and it is calculated as follows:

$$VCI = \frac{NDVI_i - NDVI_{i,\min}}{NDVI_{i,\max} - NDVI_{i,\min}}$$

in which $NDVI_i$ is the NDVI of pixel *i*, and $NDVI_{i,\max}$ and $NDVI_{i,\min}$ are the historical maximum and minimum values of NDVI for the pixel *i*. VCI is very useful for making relative assessments of vegetation vigour because the contribution of local geographic resources (such as climate, land cover, etc) to the spatial variability of NDVI is filtered out (2). Many researches have demonstrated high correlations between VCI and crop yield in different regions (4,11).

In this study, MODIS NDVI products (MOD13A2) during 2000-2011 were used to calculate VCI. The product is composited over 16 days and has a spatial resolution of 1 km. Although the Maximum Value Composite method has removed most cloud contamination, residual data noise and other artefacts still exist in the NDVI products. Therefore we used the weighted least squares regression technique proposed by Swets et al (1999) (12) to smooth the NDVI time series prior to VCI calculation.

Data analysis method

First we calculated the correlation coefficients between the regional averaged VCI and SPI at different time scales to get a general view of correlation characteristics. Then we calculated the correlation coefficients between VCI and SPI during 12 growing seasons (DOY 73-297, 2000-2011) for each meteorological station. The highest correlation and the time scale at which the highest correlation occurs were extracted. To explain the spatial variations in the relationship, we investigated some ancillary variables of interest, such as the soil AWC (13), irrigation data (14), and accumulated NDVI during growing season, etc.

RESULTS

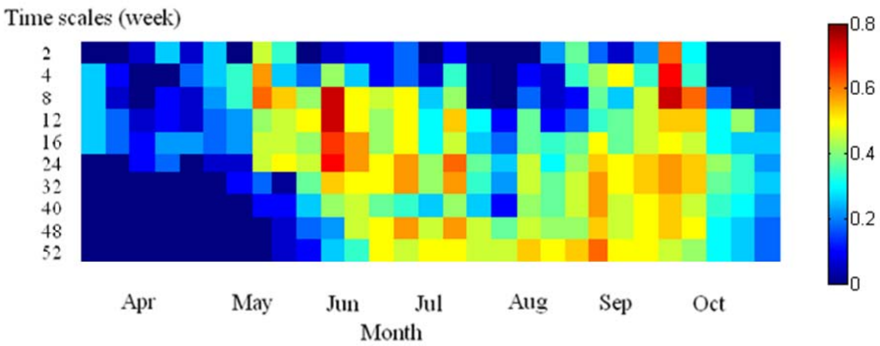
Correlation coefficients between regional mean VCI and SPI

Figure 2(a) shows the weekly correlations between regional mean VCI and the SPI at different time scales. High correlations (R>0.4) are found from May-September considering time scales shorter than 24-week and longer than 8-week except in late July, which means drought information conveyed by VCI is in general consistency with SPI at medium time scales. Correlations before June are especially low at longer time scales, whereas after October the correlations are very low at short time scales. There are clear seasonal differences in the response of VCI to SPI at different time scales. Figure 2(b) illustrates an example. It can be seen that the correlation coefficient between VCI and 8-week SPI is the highest in early June and late September, but is the lowest in late July. For the 52-week SPI, the correlation first increased steadily from May to June, then levelled from July to September, and decreased again in October. SPI at long time scales changes more gently so the temporal variation in the correlation coefficient is smaller.

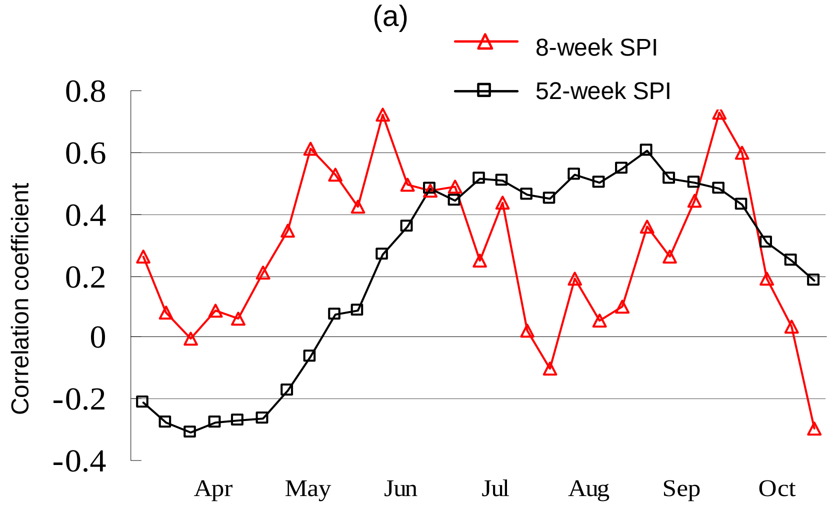
The seasonal variation in the VCI response to SPI can also be partially attributed to double cropping in the study region. It is reasonable that the lag between precipitation occurrence and vegetation response is related to the crop type and growing stage. After winter wheat is harvested in June, corn is the main crop. Growth of winter wheat during May-June responds to 8-week SPI more obviously (Figure 2a). From June to middle July (the early growing stage of Corn), VCI responds to 24-week SPI more obviously. From middle July to late September, VCI responds to 52-week SPI most strongly. After corn is harvested in late September winter wheat is planted, and the VCI again show a strong correlation coefficient with 8-week scale SPI.

Spatial variations in the strength of the relationship between VCI and SPI

The highest correlation coefficients (denoted by r hereafter) between VCI and SPI and the corresponding time scale for each of the 21 meteorological stations are shown in Table 1. For 6 stations, VCI shows weak correlations with SPI; r is less than 0.2 irrespective of times scales. For the other 15 stations, VCI is correlated with medium or long term precipitation deficits (16-, 24-, 32-week SPI) with r values varying between 0.2 and 0.48. To explain the spatial variability in r, we investigated stations' climatic, soil and vegetation characteristics, and found that the temperature, accumulated NDVI in growing season, and irrigation percent play the most important roles in determining the r value. Linear model incorporating the three variables can explain 58.3% variations in r values. Contribution from temperature is the largest, which is a little unexpected since precipitation is usually considered to be a key factor. The lower the temperature is, the higher the value of r is. It is assumed that station with higher annual mean temperature is located in the southern part of the study region which has higher relative humidity and denser vegetation, so the vegetation status has a relatively weaker relationship with precipitation. Moreover, higher temperature is related to an earlier time in the green-up onset which could also impact the relationship between VCI and SPI. More in-depth research is needed in this respect. Accumulated NDVI, which was calculated by averaging the NDVI values during growing season after subtracting NDVI background values at the start of growing season, is the second important variable impacting r. Higher accumulated NDVI means the seasonal change of vegetation is large, leading to a bigger contrast between historical maximum and minimum NDVI values which is helpful to using VCI value to evaluate the relative vigour of vegetation. A region with smaller dynamic ranges in NDVI could easily result in dramatic VCI values, although the absolute difference might be small. Perhaps the strength of the relationship between VCI and SPI is weakened due to the inability of describing vegetation condition accurately using VCI in those regions. Another probable reason is that higher accumulated NDVI is resulted from higher water use efficiency which will further enhance sensitivity of vegetation growth to precipitation. Irrigation percent is the third important factor and influences the r value negatively. This is reasonable since vegetation growth on irrigated land only depends on precipitation partly.



(a)



(b)

Figure 2: (a) Correlation coefficients between spatially averaged VCI and SPI at different time scales. (b) Comparison for the Temporal changes of the correlation coefficients between VCI, 8-week SPI, 52-week SPI.

Table 1: Correlation coefficients, climatic, and environmental variables of meteorological stations

No.	Precipita-tion (mm)	Temper -ature (℃)	Growing season mean relative humidity (%)	Percent of groundwater irrigation (%)	Irrigation percent (%)	Soil AWC (mm)	Accumulated NDVI	Highest correlation (r)	Time scale with highest correlation (week)
1	481.48	12.87	63.07	84.81	49.46	260.25	0.29	0.237	8
2	469.03	12.91	67.91	84.81	59.75	242.29	0.45	0.208	16
3	503.77	12.84	66.54	84.81	73.76	242.29	0.54	0.408	12
4	503.74	12.96	63.81	84.81	43.15	249.68	0.38	0.282	32
5	493.81	12.63	66.85	84.81	38.34	249.68	0.39	0.482	32
6	497.27	12.87	67.35	84.81	79.17	242.29	0.34	0.216	24
7	515.02	12.91	65.89	84.81	2.17	242.29	0.39	0.331	16

8	537.02	12.53	63.37	34.29	43.72	249.68	0.49	0.386	48
9	471.35	12.78	67.96	84.81	76.37	242.29	0.51	0.358	16
10	465.32	12.84	68.71	84.81	82.48	242.29	0.45	0.36	16
11	504.97	12.74	67.87	84.81	64.85	242.29	0.45	0.448	16
12	454.15	13.35	67.34	84.81	24.8	242.29	0.36	0.123	48
13	480.09	13.13	66.3	84.81	72.94	242.29	0.33	0.112	4
14	470.59	13.36	66.45	84.81	37.26	242.29	0.35	0.302	24
15	423.83	13.31	67.7	48.16	67.4	242.29	0.35	0.175	48
16	523.24	13.03	66.16	84.81	77.75	242.29	0.48	0.2	12
17	513.79	13.12	67.14	84.81	12.94	249.68	0.45	0.121	8
18	535.74	13.01	69.18	84.81	49.95	249.68	0.48	0.297	48
19	555.15	13.14	69.77	48.16	68.17	257.84	0.44	0.247	52
20	518.47	13.36	70.88	69.65	64.94	242.29	0.4	0.154	16
21	521.24	13.16	72.29	48.16	70.49	242.29	0.5	0.182	52

Spatial variations in the scale showing strongest correlation

The scale at which the highest correlation coefficient occurs also has a spatial variation. Because some stations have very low values of r irrespective of scales, we only focused on the 15 stations whose r values exceeding 0.2. Partial correlation analysis was carried out between the scale and the environmental factors, and it was found that the three most important factors are the percentage of groundwater irrigation, the annual precipitation, and soil AWC. Linear model incorporating the three variables explains 59.8% variations in the values of the time scale. All the three factors impacting time lags are about water conditions. Higher percentage of groundwater irrigation is indicative of drier condition on land surface (*e.g.* fewer water bodies), so VCI will responds to SPI at shorter time scales. For humid locations with more annual precipitation, the lag between precipitation occurrence and vegetation response tends to be longer. Lower soil AWC will also enhances the sensitivity of vegetation to precipitation, so precipitation deficits at shorter time scales can be readily reflected by vegetation.

CONCLUSIONS

In this study we analyzed the relationship between VCI and SPI using long time-series MODIS data and climatic data for an intensive agriculture region located in China North Plane. Main findings are as follows. (1) The double cropping practice influences the seasonal change of correlation coefficients with varying magnitudes depending on the time scales of SPI. (2) Temperature, accumulated NDVI during growing season and irrigation percent were found to be the most important features impacting spatial variation of the correlation strength. (3) Percentage of groundwater irrigation, annual precipitation, and soil AWC were the most important features impacting the lag between VCI and SPI.

Similar to other studies, we confirmed that precipitation, soil properties and irrigation percent are key factors impacting the relationship between VCI and SPI, despite relatively high homogeneity in the study region. Moreover, we found that vegetation seasonal changes and percent of groundwater irrigation contribute greatly to the relationship between VCI and SPI. About 58% variations in the relationship between VCI and SPI can be explained using spatially varying environmental factors. The percentage is not very high mainly because the study region is small and some environmental factors (soil and irrigation data) have very low spatial resolution (10 km).

Based on the results of this study, we will try to propose a method combining VCI and SPI to obtain more accurate drought evaluations, taking into account growing stage, irrigation practice and other ancillary variables.

ACKNOWLEDGEMENTS

This work was supported by the National Natural Science Foundation of China (41301461) and the R&D Special Fund for Public Welfare Industry (Meteorology, GYHY201206041).

REFERENCES

1 Brown J F, B D Wardlow, T Tadesse, M J Hayes, B C Reed, 2008. The Vegetation Drought Response Index (VegDRI): a new integrated approach for monitoring drought stress in vegetation. GIScience & Remote Sensing, 45: 16–46.

2 Quiring S M, S Ganesh, 2010. Evaluating the utility of the Vegetation Condition Index (VCI) for monitoring meteorological drought in Texas. Agricultural and Forest Meteorology, 150: 330–339.

3 Bhuiyan C, R P Singh, F N Kogan, 2006. Monitoring drought dynamics in the Aravalli region (India) using different indices based on ground and remote sensing data. International Journal of Applied Earth Observation and Geoinformation. 8: 289–302.

4 Gitelson A A, F N Kogan, E Zakarin, L Spivak, L Lebed, 1998. Using AVHRR data for quantitative estimation of vegetation conditions: calibration and validation. Advances in Space Research, 22: 673–676.

5 Ji L. A Peters, 2003. Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices. Remote Sensing of Environment, 87: 85–89.

6 Vicente-Serrano S M, 2007. Evaluating the impact of drought using remote sensing in a Mediterranean, semi-arid region. Natural Hazards, 40: 173–208.

7 Singh R P, S Roy, F N Kogan, 2003. Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. International Journal of Remote Sensing, 24: 4393–4402.

8 Bayarjargal Y, A Karnieli, M Bayasgalan, S Khudulmur, C Gandush, C J Tucker, 2006. A comparative study of NOAA AVHRR derived drought indices using change vector analysis. Remote Sensing of Environment, 105: 9–22.

9 McKee T B, N J Doesken, and J Kleist, 1993. The relationship of drought frequency and duration to time scales. Eighth Conference on Applied Climatology, Anaheim, California.

10 Kogan F N, 1995. Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. Bulletin of the American Meteorological Society 76 (5): 655–668.

11 Kogan, F.N., 1997. Global drought watch from space. Bulletin of the AmericanMeteorological Society 78 (4), 621–636.

12 Swets D L, B C Reed, J R Rowland, S E Marko, 1999. A Weighted Least-Squares Approach to Temporal Smoothing of NDVI," in Proceedings of the 1999 ASPRS Annual Conference, from Image to Information, Portland, Oregon, May 17–21, 1999 (CD-ROM, 1 disc).

13 http://www.igbp.net/

14 Global Map of Irrigation Areas, version 5, downloaded from the page: http://www.fao.org/nr/water/aquastat/irrigationmap/index10.stm