USING A NEW INTEGRATED DROUGHT MONITORING INDEX TO IMPROVE DROUGHT DETECTION IN MID-EASTERN CHINA

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ABSTRACT

Using data-mining technology, this paper established a new method, named the Integrated Surface Drought Index (ISDI). ISDI integrates traditional meteorological data, remotely sensed indices, and biophysical data, and attempt to describe drought from a more comprehensive perspective. The evaluation results indicated that the construction models for three phases of growth season have very high regression accuracy. The drought condition can be predicted using the independent variables. The practical application of ISDI in mid-eastern china also demonstrated that ISDI has good application accuracy in mid-eastern China. ISDI results were corresponding to the disaster observation records of agro-meteorological sites. It can be potentially extended to nationwide near real time drought monitoring.

Index Terms**—** Drought, ISDI, remote sensing, data mining

1. INTRODUCTION

Drought affects a large number of people and cause more losses to society compared to other natural disasters[1]. Researches on drought receive more and more attention from scientists since 20th century. China is a drought disaster-prone country. The frequent occurrence of drought poses an increasingly severe threat to the Chinese agricultural production[2].

Since the beginning of 20th century, a lot of drought indices have been developed for monitoring the occurrence and variation of drought. The first developed indices are meteorological drought indices such as Standard Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI). Most of the early established meteorological drought indices are calculated from station-based measurements of temperature and precipitation. The SPI was one of the drought indices been widely used worldwide, which is designed to be a spatially invariant indicator (spatially and temporally comparable) only based on in-situ precipitation data[3]. The statistical probability of precipitation compared to historical average level was calculated and standardized to get the final SPI values. The PDSI is calculated using historical temperature and precipitation, and information of the available water content of the soil based on a soil moisture/water balance equation[4]. Although the meteorological drought indices can get more accurate and spatially and temporally comparable drought conditions, their utilization is enslaved to the density and distribution of the station network[5]. This type of indices also can not reflect the vegetation condition induced by the water deficit.

Satellite-based drought indices have obvious advantages compared to station-based meteorological drought indices in spatial resolution. More and more indices are established since the appearance of remote sensing technology. The Normalized Difference Vegetation Index (NDVI) is one of the early developed and most widely used satellite-based indices[6]. NDVI is the best indicator of the vegetation growth condition and the vegetation coverage, which has been widely used to estimate vegetation biomass and assess the environmental condition[7]. Based on NDVI, Vegetation Condition Index (VCI) has proved to be a useful means for detecting the vegetation condition deterioration caused by drought[8-9]. Besides, Percent of Average Seasonal Greenness (PASG) is another typical drought index. PASG provides a measure for vegetation conditions by calculating the percentage between the greenness in the specific period and the average greenness over the same period[5].

Land surface temperature (LST) is also closely related with drought. Temperature Condition Index (TCI) is

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developed to monitor the drought through land surface temperature anomalies based on remote sensed LST data[10]. In addition to temperature increases caused by water deficit, the vegetation index decreases along with the vegetation growth status suppressed[11]. Therefore, the ratios of vegetation index and LST such as the Temperature/Vegetation Index (TVI) and the Vegetation Supply Water Index (VSWI) have been successfully used to detect drought[12].

Although the remote sensed drought indices can provide near real time drought condition detection over the global at a relatively high spatial resolution, it is often difficult to distinguish drought-related vegetation stress from vegetation changes caused by other factors without additional information[5]. Therefore, no single drought index can be used to adequately monitor the onset of drought and measure drought intensity, duration and impact[13]. Vegetation Drought Response Index (VegDRI) was developed based on data mining technology namely decision-making regression tree model[5]. VegDRI can integrated both station based meteorological drought indices, satellite-based regional drought indices, and biophysical data. The accuracy of VegDRI has been validated by the field observation data, and this index has been used to national wide drought monitoring in America.

The objective of this paper is to establish a new integrated drought monitoring index name Integrated Surface Drought Index (ISDI) based on data mining technology. ISDI integrates land surface water and thermal environment condition, vegetation growth condition and biophysical information. Mid-eastern china was selected as pilot study area and ISDI drought monitoring results in this area from 2000-2009 was evaluated.

2. MATERIAL AND DATA

The meteorological data namely daily precipitation and temperature data during 50 years (1960–2009) from 130 weather stations in mid-eastern china are derived from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). High quality, consistent and well-calibrated Moderate Resolution Imaging Spectroradiometer data (MODIS) provides a means for quantifying land surface characteristics such as NDVI, LST, and land cover type. This remote sensed data is necessary for near real time regional drought detection. In our investigation, the 16-day interval MODIS NDVI products (MOD13A2, 1km×1km) were used to monitor vegetation dynamics. The LST data is derived from 8-day interval MODIS products (MOD11A2, 1km×1km). The NDVI and LST products are both from 2000 to 2009. MODIS land cover data (MOD12Q2, 1km×1km) for 2008 was used to distinguish the drought characteristic differences in various land cover types. Besides, the biophysical data inputs include ecological zoning data (Eco-region), Available Water-holding Capacity (AWC) data, and the irrigation water management distribution data and Digital Elevation Data (DEM). The Eco-region data is obtained from a Chinese eco-geographical zoning map[14]. AWC is provided by the International Geosphere-Biosphere Programme (IGBP). DEM data is derived from the "China Western Environment and Ecology Science Data Center" (http://westdc.westgis.ac.cn) with a spatial resolution of 1 km.

3. METHODOLOGY

3.1. ISDI input parameters

The 16-day interval self-calibrated PDSI and multi-scale SPI (9-month and 12-month) based on observed meteorological data at sites were calculated. Rigorous pre-treatment has been applied to the meteorological data before they are used to build SPI and PDSI. SPI provides a measure of precipitation deficit compared to historical precipitation record. PDSI accounts for the effect of both precipitation and temperature and their combine effect on soil water available to drought conditions. PDSI was selected as the dependent variable in ISDI model.

Drought indices derived from remote sensed data include NDVI, VCI, PASG, and Start of Season Anomaly (SOSA). VCI, PASG, and SOSA indices are established using time series NDVI[15-16]. The VSWI, which integrated vegetation and temperature information, was selected to reflect the vegetation, surface thermal and water content conditions. Besides, all the biophysical data mentioned in section 2 are selected as inputs to comprehensively describe drought characteristics in different regions. Through comparison of the remote sensed drought indices[16], 8 independent variables namely VSWI, SOSA, SPI, elevation, Landcover, AWC, GIAM, Eco_region were determined as a combination inputs of ISDI.

3.2 Data mining technology

A commercial Supervised Classification and Regression-Tree (CART) algorithm called cubist 2.07 was used in this investigation to analyze historical drought indices and biophysical variables and build the three seasonal, rule-based, linear regression models. This approach can handle a variety of data types (e.g., discrete and continuous), so it suitable for constructing ISDI which integrates site-scale meteorological drought indices and regional scale remote sensed data.

3.3 ISDI construction method

For the same vegetation type, the vulnerability under drought condition is significant different in different phases of growth season. Therefore, we divide the growing season into three seasonal phases namely spring, summer, and fall and ISDI was constructed for the three phases separately. The multi-scale SPI and self-calibrated PDSI data for 130 meteorological stations were collected from 2000 to 2009. Spatial continuous variables were extracted from the 9km× 9km pixel window centered on each station location, and the average value from the window was calculated for the continuous variables and the dominant (or majority) class for the categorical variables. All the extracted variable for three phases were sequentially ordered to build the training dataset and imported into the Cubist 2.07. Then, a series of three seasonal, rule-based and piecewise linear regression rules were generated and they were used to calculate drought condition pixel by pixel from 2000 through 2009 in the study area.

4. RESULTS

4.1 Regression accuracy of ISDI

The scatter plots of IDSI consruction results using regression and the decision tree model based on all samples of the dataset are shown in Fig. 1.

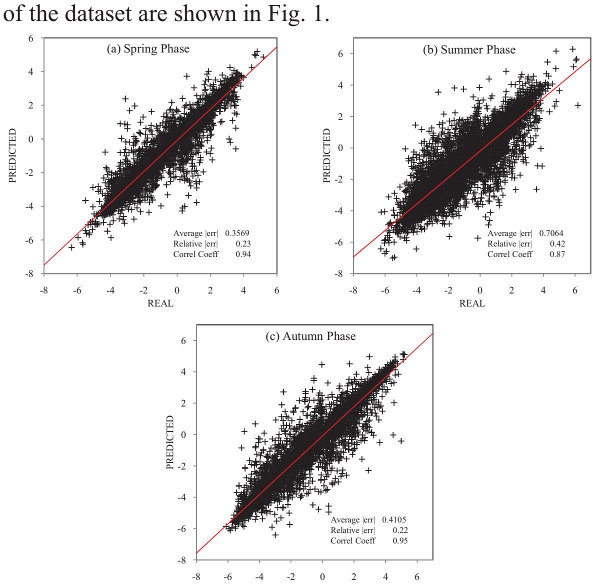

Figure 1. Scatter plots for plan 7 predicted values and real values

The average error, relative error, and correlation coefficients were also calculated to evaluate the accuracy of ISDI. It should be noted that the relative error is the ratio of the average error magnitude to the error magnitude that would result from always predicting the mean value. The smaller the values indicate that the higher accuracy of the models and the values less than 1 proved the models are useful. We found that the models for three phases have very high prediction accuracy. The relative errors for spring and autumn phases are higher than summer phase, reached 0.23 and 0.22 respectively. The relative error for summer phase is 0.42, also has high precision. The correlation coefficients for the three phases are reached 0.94, 0.87, and 0.95 respectively. All the evaluation results proved that the drought condition can be predicted using the independent variarbles.

4.2 Monitoring results of ISDI

We calculated the spatial ISDI drought monitoring results with 16-day intervals in the period 2000-2009 for mid-eastern china. 2009 Was chosen as the typical dry year to evaluate the regional scale drought monitored results. This is because the northern China experienced severe drought in early 2009. Shaanxi, Hebei, Inner Mongolia and other places in northern china were lack of precipitation for a long time and caused widespread drought in 2009. Some places developed to autumn drought in this year (http://news.163.com/special/000135UP/090205ganhan.html#7). The ISDI results for DOY 2009193 (Jul 12 to Jul 28, 2009) are shown in Figure 2. The disaster observations of agro-meteorological stations (http://cdc.cma.gov.cn/) in mid-Jul 2009 were used to test the accuracy of ISDI results (Table 1).

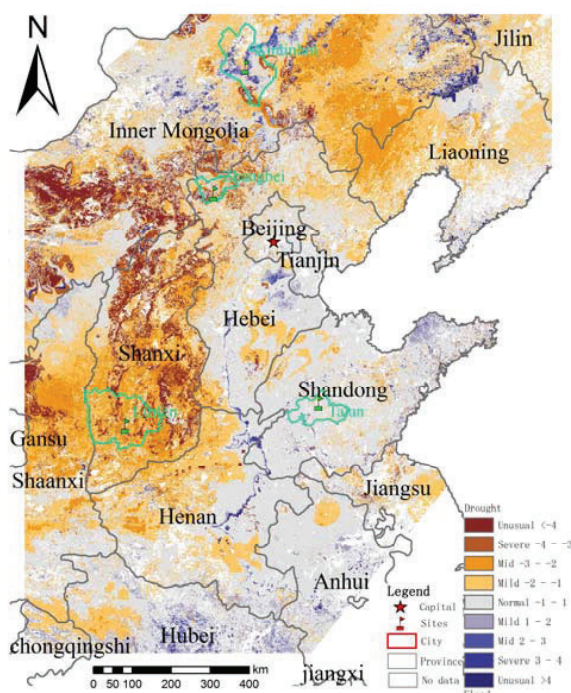

Figure 2. ISDI monitored results for 2009193 (Jul 12 to Jul 28, 2009)

Figure 2 indicated that the mid-eastern china experienced various levels of drought during mid-Jul 2009. The northern china, especially Shanxi, Shaanxi, and central Inner Mongolia experienced serious drought. This is consistent with the reported results (http://news.163.com/special/000135UP/090205ganhan.html#7). For local scales (county region), ISDI results were corresponding to the disaster observations of four representative agro-meteorological sites, namely Xilinhot, Zhangbei, Linfen and Taian. Zhangbei, Linfen and Xilinhot suffered a moderate drought during mid-Jul 2009 according to Table 1, but Jinan was not affected by drought. According to ISDI, most area of Zhangbei, Linfen, and Xilinhot also experienced mild to severe drought during the same time, but most area of Jinan were in normal condition.

Table 1 Comparison of the drought field observations and the ISDI monitoring results in 2006

Site Name	Intensity	Affected area (ha)	Observed percentage
Xilinhot	Mid	>66666	90-100%
Zhangbei	Mid	>66666	70-79%
Linfen	Mid	13333	30-39%
Taian	Normal	-	-

Mid: the dry soil depth is 3-6cm. The leaves of crop wilt during the day because of drought persistence.
Affected Area (ha): is crop area affected by drought.
Percentage: is the ratio of drought affected crop area and sown area in the county where the agro-meteorological site located in. The values are estimated results through observation.

5. CONCLUSIONS

In our study, a new drought index named ISDI was established based on data-mining technology. This index integrates traditional meteorological data, remotely sensed indices, and biophysical data, and attempt to describe drought from a more comprehensive perspective. Chosen PDSI as the dependent variable and 8 data as independent variables, ISDI not only have good mechanism, but also integrate many features of drought. Correlation coefficient analysis proved that the regression accuracy is very high and the drought condition can be accurately portrayed using the independent variables.

By using ISDI model for drought monitoring in mid-eastern china during 2000-2009, we conclude that ISDI has good accuracy for both large scale and local scale drought monitoring. ISDI results were corresponding to the disaster observations of agro-meteorological sites. This demonstrates that ISDI is suitable for near real time drought monitoring in mid-eastern china and it has potential applications all over the country.

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7. REFERENCES

[1] D. A. Wilhite, "Drought as a natrural hazard: concepts and definitions," in *Drought : a global assessment*, D. A. Wilhite, Ed., ed London & New York: Routledge, 2000, pp. 3-8.
[2] K. Li, Q. guo, and J. Zhang, *China drought research and disaster mitigation measures*, Henan Science and Technology Press, Zhengzhou, China, 1999. (In Chinese)
[3] T. B. McKee, N. J. Doesken, and J. Kleist, "The relationship of drought frequency and duration to time scales," in *Eighth Conference on Applied Climatology*, Anaheim, California, America, 1993, pp. 179-184.
[4] W. C. Palmer, "Meteorological drought," *US. Weather Bureau Research Paper,* p. 58, 1965.
[5] J. Brown*, et al.*, "The Vegetation Drought Response Index (VegDRI): a new integrated approach for monitoring drought stress in vegetation," *GIScience & Remote Sensing,* vol. 45, pp. 16-46, 2008.
[6] C. J. Tucker and P. J. Sellers, "Satellite remote sensing of primary production," *International Journal of Remote Sensing,* vol. 7, pp. 1395-1416, 1986.
[7] G. G. Gutman, "Towards monitoring droughts from space," *Journal of Climate,* vol. 3, pp. 282-295, 1990.
[8] F. N. Kogan, "Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data," *Bulletin of the American Meteorological Society,* vol. 76, pp. 655-668, 1995.
[9] W. T. Liu and F. N. Kogan, "Monitoring regional drought using the Vegetation Condition Index," *International Journal of Remote Sensing,* vol. 17, pp. 2761-2782, 1996.
[10] R. D. Jackson, S. B. Idso, and R. J. Reginato, "Canopy temperature as a crop water stress indicator," *Water Resources Research,* vol. 17, pp. 1133-1138, 1981.
[11] T. R. McVicar and D. L. B. Jupp, "The current and potential operational uses of remote sensing to aid decisions on drought exceptional circumstances in Australia: a review," *Agricultural Systems,* vol. 57, pp. 399-468, 1998.
[12] Y. Bayarjargal*, et al.*, "A comparative study of NOAA-AVHRR derived drought indices using change vector analysis," *Remote Sensing of Environment,* vol. 105, pp. 9-22, 2006.
[13] S. M. Quiring and S. Ganesh, "Evaluating the utility of the Vegetation Condition Index (VCI) for monitoring meteorological drought in Texas," *Agricultural and Forest Meteorology,* vol. 150, pp. 330-339, 2010.
[14] D. Zheng and B. Li, *Study on eco-geographic regional systems of china*, The Commercial Press, Beijing, China, 2008. (In Chinese)
[15] L. Zhou*, et al.*, "Assessing the drought monitoring characteristic of time-series NDVI indices in crop growing season," in *IEEE International Geoscience and Remote Sensing Symposium*, Honolulu, Hawaii, USA, 2010, pp. 2063-2066.
[16] L. Zhou*, et al.*, "Comparison of Remote Sensed and Meteorological Data Derived Drought Indices in Mid-Eastern China," *International Journal of Remote Sensing,* vol. 33, pp. 1755-1779, 2012.