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# Study on the construction of multi-dimensional Remote Sensing feature space for hydrological drought

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Abstract. Hydrological drought refers to an abnormal water shortage caused by precipitation and surface water shortages or a groundwater imbalance. Hydrological drought is reflected in a drop of surface water, decrease of vegetation productivity, increase of temperature difference between day and night and so on. Remote sensing permits the observation of surface water, vegetation, temperature and other information from a macro perspective. This paper analyzes the correlation relationship and differentiation of both remote sensing and surface measured indicators, after the selection and extraction a series of representative remote sensing characteristic parameters according to the spectral characterization of surface features in remote sensing imagery, such as vegetation index, surface temperature and surface water from HJ-1A/B CCD/IRS data. Finally, multi-dimensional remote sensing features such as hydrological drought are built on a intelligent collaborative model. Further, for the Dong-ting lake area, two drought events are analyzed for verification of multi-dimensional features using remote sensing data with different phases and field observation data. The experiments results proved that multi-dimensional features are a good method for hydrological drought.

#### **1. Introduction**

Hydrological drought is a phenomenon of lower streamflow than its normal value or aquifer drawdown[1]. Its main feature is the shortage of available water in a particular area and a specific period of time. It has the common characteristics of drought: multiple, regional, seasonal and persistence and the occurrence indicates less rainfall, anomaly serious decline of groundwater level, added difficulties of soil moisture and plant physiological water[2]. At present, hydrological drought monitoring is to measure the changes of the surface runoff[3]. The development of remote sensing technology provides new opportunities for the hydrological drought monitoring. It is the continuation of meteorological drought and agriculture drought, as the ultimate, most serious drought.

In the essay, the relevant characteristic parameters in meteorological drought and agricultural drought monitoring are introduced and multi-dimensional remote sensing feature space for hydrological drought are constructed through the analysis of the relationship between remote sensing data and ground measured data.

#### 2. Materials

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# 2.1. HJ-1A/B CCD/IRS data

HJ-1A/B satellite is designed for the environment and disaster monitoring in China. Because of this, it is mainly used for dynamic monitoring of the ecological environment and disasters in a wide range day and night, reflecting the occurrence and development of ecological environment and disasters timely, forecasting development trend of ecological environment and disasters, conducting fast disaster assessment, and providing scientific basis for emergency rescue, disaster relief and reconstruction work. The parameters of visible and infrared detectors are introduced in the following table:

# Table 1. Detector parameters table.

Detect	or Items	Band1	Band2	Band3	Band4		
CCD	Resolution(m)	30	30	30	30		
	Wavelength(µm)	0.43-0.52	0.52-0.60	0.63-0.69	0.76-0.90		
IRS	Resolution(m)	150	150	150	300		
	Wavelength(µm)	0.75-1.10	1.55-1.75	3.50-3.90	10.5-12.5		

It can be found in Table 1 that CCD/IRS data has visible, near-infrared and thermal infrared channels, so the remote sensing characteristic parameters can be extracted, including vegetation index, cloud information, water area, and land surface temperature, and so on, which used to analysis hydrological drought condition. In this paper, the drought during Sep. to Nov. of 2009 and Mar. to May of 2011 was studied. The HJ-1A/B CCD/IRS data and the water level field data in these periods were used.

# 2.2. Study area

The study area focused on the Dongting Lake region, including the East, West, south of Dongting Lake, 110.6 to 113.2 degrees east longitude, 28.5 to 30.3 degrees north latitude. Lake area is 18780 square kilometers, including 2740 square kilometers natural lake and 1200 square kilometers enclosed lake. In this area, the annual rainfall of 1400-1500 mm is abundant,. The average level of this lake is 25.57 meters, but the variation is large. The Water of Dongting Lake valley which is the vast area of Dongting lake system accounts for about 21% of surface water resources in the Yangtze River Basin[4].

The measured data from 2009 to 2011 were used in this experiment, including water level and flow data of the part of the measured site in Dongting Lake basin area. These sites consist of zizhiju, shadaoguan, mituosi, guanyuan, shiguishan, caowei, niubitan, nanju, xiaoheju, zhouwenmiao, yuanjiang, xiangyin, shatou, chenglingji site.

# 3. Result and discussion

# 3.1. Water area detection

Water can absorb most of the incident energy in the near infrared and mid-infrared channels, as a result the reflectivities are very low. While the vegetation and soil objects have highly reflectivities. The different spectral characteristics of water and background feature were used to establish spectral water extraction model. As the water reflectivity in the green band is higher than the near-infrared band and the vegetation have the strongest reflectivity in the near-infrared band[5]. Normal Differential Water Index(NDWI), the ratio of green and near-infrared channels, were constructed to , highlight the water information and suppress vegetation and other background information at the same time [6].

OTSU is one of the best automatical threshold methods, based on the principle that the class variances were considered as a criterion and the maximum class variance, as the optimal threshold, was used to conduct image segmentation. Because of the complexity of the remote sensing image gray level, the OTSU method, is not a good target segmentation method when applied in global threshold segmentation. In this study, the dynamic-global threshold image segmentation method, which introduced the Particle Swarm optimization(PSO), was proposed in order to improve the OTSU algorithm in automatical threshold selection and high algorithm efficiency. The calculation steps

including:(1) Obtaining the optimal global threshold through the OSTU algorithm by the PSO algorithm optimization; (2) The target image was divided into sub-images of moderate size, and theinter-class variance method was used to determine the threshold of each sub-image; (3) Constructing dynamic-global threshold matrix.(4) Selecting a suitable threshold to segment NDWI image. Most of the water area can be detected (figure 1).

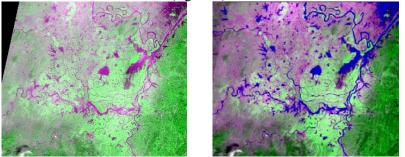


Figure 1. Water detection result of Oct. 5th.

# 3.2. Water level time-series data analysis

The run theoretical method is one of the existing mature hydrological drought monitoring methods[7]. And the main idea of the run theoretical is using a truncated horizontal value to truncate the runoff time series, and the drought duration, drought degree and drought intensity information according to the truncation level. Accordingly, the qualitative relationship of water level changes and drought was analysed through the time series of actual water level data in this study.

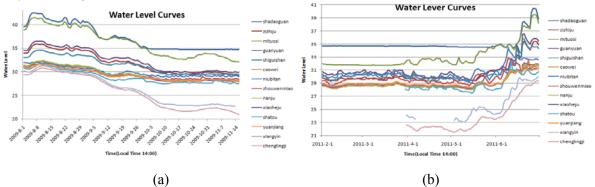


Figure 2. Water level change curves:(a) Aug. to Nov. in 2009;(b) Feb. to Jun. in 2011.

Serious drought occurred in Dongting Lake Basin during the autumn of 2009. It began in September, and became the most severe in October, but was relieved in in November. It can be seen from the figure 2(a), in August of 2009, the water level of Dongting Lake remained steady with minor fluctuation. From the early of September, the water level of each site showed a sustained downward trend, and reached to the lowest point in October and continued for a period of time. Then, there was a degree of rebound in the part of the sites in November. Thus, it is can be drawn that water level change curves have an identical tendency with the drought event.

From March to May 2011, there was a severe drought happening in the Dongting Lake Basin because of the shortage of rainfall and the reduction of runoff in upper reaches of the Yangtze River. The control flow of the Yangtze River was less than normal by 25-70% compared to the same period of the year in May of 2011. And the water area of Dongting Lake decreased by approximately 73%, compared to the same period of 2010. As it can be seen from the figure 2(b), from February to April 2011, each monitoring site water level remained steady near the bottom of water level. The drought began from the dry season and developed in the spring, and became the most serious in mid-May. Up to the end of May and early June, the drought was relieved, and water level of each site began to rise

and then reached normal levels. Accordingly, it can be concluded that the curve of water level data can be considered as an important indicator for hydrological drought detection in real time.

#### 3.3. NDVI-LST feature space

Normal Differential Vegetation index(NDVI) and Land Surface Temperature(LST) are the two most important index for meteorological and agricultural drought remote sensing monitoring. The existing mature drought monitoring models are divided into three types, including vegetation index class, temperature class, and vegetation and temperature combined class. To conduct agricultural drought monitoring, the NDVI-LST two-dimensional feature space was used to analysis the soil moisture conditions in related study. Some experiments results showed that the NDVI-LST two-dimensional feature space was a good indicator to the precipitation and soil moisture situation.

LST is calculated by single-window algorithm, and LSTmax, LSTmin of different NDVI conditions is extracted on the basis of 0.01 NDVI step (NDVI is among 0.3 to 0.7 for medium vegetation coverage), and then NDVI-LST feature space is obtained (Figure 3).

It is shown in Figure 3 that LSTmax and LSTmin have good correlation with NDVI in HJ-1A/B CCD/IRS data. Based on the principle of least squares fitting, the relationship functions are regressed in the NDVI-LST feature space. Because wet and dry side fitting is quite instable in the low and high vegetation coverage (with NDVI ranging from 0 to 0.30 and from 0.70 to 1 respectively), only middle NDVI of 0.30 to 0.70 is used in regression.

The fitting equations of wet and dry sides based on Oct.5th of 2009 are as follows:

$$LST_{max} = -13.33 + 31.83 NDVI \quad R^2 = 0.6313$$
(1)

$$LST_{min} = 39.92 - 12.98 NDVI R^2 = 0.7142$$
 (2)

The above formulas demonstrate that if the slope of dry side is less than zero, LSTmax will decrease with the increase of vegetation coverage. The minimum LST is vice versa. The R-squares of in wet and dry sides fitting are 0.6313 and 0.7142 respectively, in Oct.5th of 2009. It shows that changes of LSTmax and LSTmin are quite consistent with the changes of NDVI, and the mechanism of drought is well demonstrated.

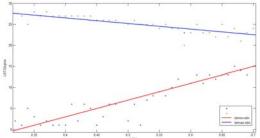
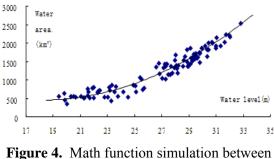


Figure 3. The wet and dry sides in feature space for Oct. 5th of 2009.



water area and water level.

#### *3.4. WA-WL feature space*

Generally, there is a close function relationship between the water area and the water level, of a lake. The water area can be obtained from the remote sensing image directly, and exploring the relationship of water area and the water level is necessary for the real-time monitoring of lake water level. The correlation coefficients between the water level and the water area were enumerated in the following table, including chenglingji, nanju, xiaoheju and shiguishan sites from 2009 to 2011.

As can be seen from the above table, the correlation coefficients between in-situ water level and remote sensing water area were high higher during the period from 2009 to 2011, reaching over 85%. In terms of sites, chenglingji station have the highest correlation coefficient and the best function fitting, followed by nanju, xiaoheju and shiguishan station. In terms of time, the correlation coefficients of 2009 is generally higher than 2010 and 2011.

Year	Chenglingji	Nanju	Shiguishan	Xiaoheju
2009	92.34	90.26	88.35	89.23
2010	91.56	89.93	90.75	88.52
2011	89.96	89.66	85.9	86.69

Table 2. The correlation cofficients between water level and water area.

Due to the less of remote sensing data, the water area and water level data from 2009 to 2011 were used together to conduct functional simulation. As can be seen from the figure 4, the function of the water area data and water level, the fitting function can be drawn as the follow:

$$S = 10.32Z^2 - 323.46Z + 2905.77 \tag{3}$$

It can be concluded that the water area from remote sensing image can be used to estimate the water level, and to serve the hydrological drought monitoring.

#### 3.5. NDVI-WA feature space

Because hydrological drought is a continuation and development of the agricultural drought, the agricultural drought remote sensing monitoring indicators can be introduced into the hydrological drought monitoring[8]. While vegetation index is an important indicator in the monitoring of agricultural drought, vegetation index can be considered as an important indicator of hydrological drought remote sensing monitoring. When hydrological drought occurs, the vegetation growth and water supply is negatively affected and vegetation index will change accordingly. In other words, the vegetation index changes indicate the intensity of hydrological drought in some extent.

In this study, the Dongting lake region was divided into a number of plaques, and the average vegetation index of each plaque was calculated, and then the maximum and minimum values of the average vegetation index of each plaque was extracted in every images. Finnaly, the relationship function between the maximum & minimum value and the water area was established to construct NDVI-WA two-dimensional feature space for simulation.

### 3.6. Discussion on multi-dimensional feature space

By analyzing the several two-dimensional feature spaces, the results can be showed that:

(1) In-situ water level time series data is one of the best indicators of hydrological drought, which is also consistent with traditional hydrological drought monitoring model. Therefore, the water level time-series data can be considered as a link between traditional and remote sensing hydrological drought monitoring.

(2) NDVI and LST are the two typical indicators of remote sensing of agricultural drought. Meanwhile, the two parameters can be regarded as indicators hydrological drought monitoring. So combining the two remote sensing indexes to a new monitoring index is reasonable to be introduced into hydrological drought monitoring model.

(3) The water surface area from remote sensing image was the direct hydrological parameters, as well as the important parameters of the hydrological drought modelling. Therefore, the water area can be considered as the most important indicator of the remote sensing hydrological drought monitoring model.

The intuitive of the water level time-series data, the sensitivity of NDVI-LST two-dimensional feature space for soil moisture, the highly estimate accuracy of WA-WL two-dimensional feature space and the accurate definition of soil moisture in NDVI-WA two-dimensional feature space, could all contribute to the construction of multi-dimensional feature space for hydrological drought together. The NDVI-LST two-dimensional feature space includes the best and the worst conditions of soil moisture, and combining them with WA, which was as well extracted from the remote sensing image, to construct three-dimensional feature space to establish the hydrological drought evaluation model.

### 4. Conclusion

Through this study, the following conclusions can be drawn:

(1) Through analysising the water level time-series data, NDVI-LST feature space, WA-WL feature space and NDVI-WA feature space, each feature space function fitting have high precision and physical meaningful.

(2) Through the organic combination of several groups of the two-dimensional feature space, a multi-dimensional feature space was formed for hydrological drought monitoring. The expression of the multi-dimensional feature space can be a good indicator for hydrological drought and used for hydrological drought monitoring.

(3) The NDVI and LST are 30 meters and 300 meters spatial resolution raster data, while the water level and water area data are dotted data. Therefore, the inconsistencies of the spatial scale and the larger space variability of water level data will affect the precision of the feature space.

(4) Although the quality was controlled, in two-dimensional feature space, there were still some poor pixels which affected the fitting precision of the multi-dimensional feature space. Therefore, it is very important to exclude the invalid pixels in the subsequent studies.

#### Acknowledgment

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#### References

- [1] Kogan F N 1990 Remote sensing of weather impacts on vegetation in non-homogenous areas *Int. J. Re. Sens.* B **11** 1405-19
- [2] Feng Q and Tian G L 2004 Drought monitoring based on VCI Arid Land Geo. B 27
- [3] Bastiaanssen W GM, Menenti M, Feddes R A 1998 A remote sensing surface energy balance algorithmfor land (SEBAL) 1.Formulation *J. Hydro*. B (**212-213**) 198 -229
- [4] Du Yun, Cai Shuming, Zhang Xiaoyang, 2001 Interpretion of the environmental change of Dongting Lake, middle reach of Yangtze River, China Measur. Sat. imag. Analy. Geo. B 41 171-81
- [5] Conrad C, Dech S W, Hafeez M 2007 Mapping and assessing water use in a Central Asian irrigation system by ultilizing MODIS remote sensing products *Irri. Drain. Syst.* B **21** 197-218
- [6] McFeeters S K 1996 The Use of Normalized Difference Water Index (NDWI) in the Delineation of Open Water Features *Int. J. Re. Sens.* B **17** 1425-32
- [7] Shresha R, Takara K, Tachikawa Y 2004 Water resources assessment in a poorly gauged mountainous catchment using a geographical information system and remote sensing *Hydro*. *Pro.* B 18 3061-79
- [8] Chen DY, Huang JF, Jacksom T J 2005 Vegetation water content estimation for corn and soybeans using spectral indices derived from MODIS near- and short wave infrared bands *Re. Sens. Envir.* B 98 225-36