Bangladesh J. Bot. **49**(3): 735-742, 2020 (September) Special

SOIL MOISTURE MONITORING BASED ON LONG-TERM TIME SERIES LAND SURFACE TEMPERATURE (LST) DATA - A CASE STUDY IN HEBI CITY, HENAN PROVINCE

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Keywords: Land surface temperature, Soil moisture, Temperature vegetation dryness index

Abstract

Long time-series land surface temperature (LST) data acquired by moderate-resolution imaging spectroradiometer (MODIS) were used to calculate temperature vegetation dryness index ($TVDI_{time}$) data. Results showed that predicted soil water contents fit well with the data measured by 12 meteorological sites and 25 manually measured data, with identical variation tendency. It indicates that the soil moisture prediction method presented in this paper is highly effective. This method will help to provide scientific and technical supports for making intelligent decisions, guiding measures of the agricultural irrigation and enhancing grain yield.

Introduction

Drought is one of the most serious natural disasters in agricultural production, and it is also a kind of natural phenomenon in specific areas with insufficient water in the near-surface ecosystem (Wang *et al.* 2010). Long-period drought changes may have formed different types of arid zones around the world. According to the estimations by the Food and Agriculture Organization of the United Nations (UNFAO), drought-induced loss in global agriculture can be as high as billions of dollars per year, and more than 56 billion yuan is lost each year in China. Traditional drought monitoring mainly relies on the measurement of soil water content in the drought monitoring stations for representing small-scale soil moisture (Wang *et al.* 2008). Remote sensing (RS) monitoring exhibits a series of advantages such as fast monitoring velocity, large-area coverage, and low cost. Therefore, it is of significant economic value and practical significance to monitor agricultural drought and soil moisture based on RS monitoring data.

A number of studies have been conducted and proposed multiple agricultural drought RS monitoring indices from different angles (Sun *et al.* 2012, Yang *et al.* 2010). However, due to the difference in climate, soil and crop planting among various areas, the monitoring indices exhibit apparent difference in space-time adaptability, thereby resulting in the lack of uniform and eurytopic models and methods. The reasons lie in the following two aspects. Firstly, the distribution and development of agricultural droughts differ greatly in both space and time. Secondly, crops reflect different agricultural drought characteristics in different regions at different growth phases (Mu *et al.* 2006, Li *et al.* 2013, Wang *et al.* 2013, Ezzine *et al.* 2014, Dong *et al.* 2015, Huang *et al.* 2015). By contrast, temperature vegetation dryness index (TVDI) now witnesses extensively applications since it takes vegetation index and surface temperature into overall consideration (Sandholt *et al.* 2002). TVDI should be solved on the basis of assumption that smaller soil moisture content corresponds to higher land surface temperature (LST) under a

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same NDVI (Li *et al.* 2019). In actual applications, since two types of data (NVDI and LST) should be prepared simultaneously, data preparation process is quite complex and basic assumption condition generally is invalid. On account of significant field micro-climate difference, the negative correlation between LST and soil water content is not significant. The related model should be further modified.

In this work, taking Hebi city, Henan province, a main grain-producing area in China, a drought index only based on long time series LST data, denoted as temperature vegetation dryness index ($TVDI_{time}$) was proposed. The data preparation is relatively simple and it makes full use of long-term land surface monitoring data obtained by agricultural Internet of Things (IoT).

Materials and Methods

Hebi city, located in the north of Henan, China, is a typical agricultural planting area. It covers a total area of 2299 km^2 (113°59′E~114°45′E, 35°26′N~36°02′N) (Wu *et al.* 2019), including 119,600 ha of cultivated land. Fig. 1 displays the location map of the survey area. (http://jyj.hebi.gov.cn/zghb/zghb_page_key/index.html)

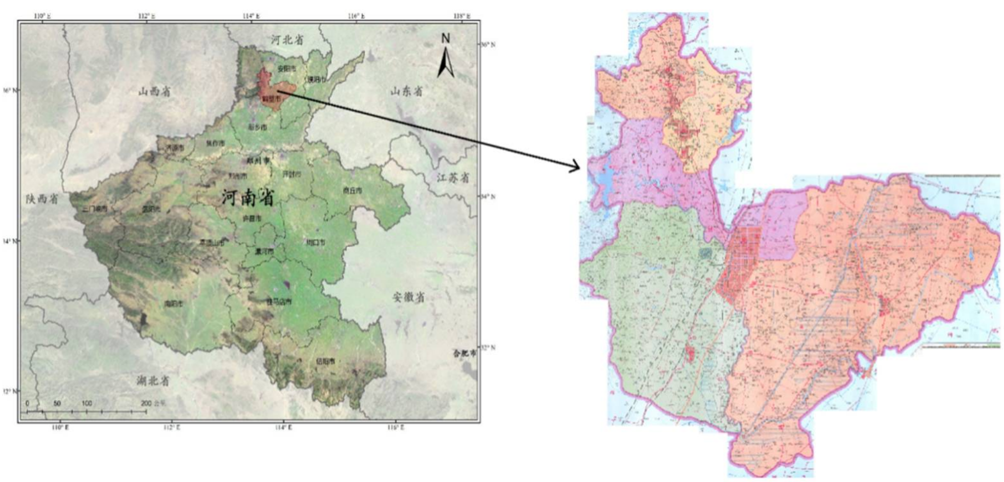

Fig. 1. Location map of the survey area in Hebi city.

Four types of data, including crop phenological information, surface meteorological sites data, artificial measurement data and RS data in Hebi, were used in this study.

(1) Phenology information of winter wheat: Winter wheat in Hebi is generally sown in early October, and harvested approximately in early June at maturity. Meanwhile, corn is sown and harvested in late September or early October. To be intuitive, the enhanced vegetation index (EVI) of the crops in the whole growth period is displayed in Fig. 2, and the linear significance coefficient (p) and the correlation coefficient (R^2) between soil temperature and soil water content in different months are shown in Table 1. From Fig. 2, it is apparent that May - March and July - August are the key periods in the growth of winter wheat and summer corn, respectively. This study emphases on soil moisture in March - May, because during this period soil temperature and soil water content exhibits significantly negative correlation (Table 1).

(2) Surface meteorological site data: The surface meteorological site data were automatically acquired via field acquisition devices based on Internet of Things (IoT). Actually, two national

standard meteorological sites and 10 meteorological sites in Hebi are included in this paper. Meteorological data, from 1 January, 2014 to 20 June, 2019, mainly includes air temperature, LST, precipitation, and soil moisture content at a depth of 10 cm. The distribution of meteorological sites is depicted in Fig. 3.

(3) Artificial measurement data: The data at 25 measuring points in Hebi were randomly measured during the period from 1 May to 5 May, 2019, including the same parameters as stated above.

(4) RS data: RS data mainly includes MODIS LST 8-day synthetic images from March to May each year from 2001 to 2018, with a spatial resolution of 500 m. All the data were provided by NASA Land Processes Distributed Active Archive Center User Services, which can be downloaded from: https://search.earthdata.nasa.gov/search?m=-0.0703125!0!2!1!0!0%2C2.

All experimental measurement data and the monitoring data from meteorological sites were registered with RS data space via GPS information spatialization. In order to match with MODIS LST 8-day synthetic data, soil temperatures and soil moisture contents obtained from surface meteorological sites were averaged at an interval of 8 days. The surface measurement data were used for deriving model, which can be used as the true values for validating the inversion precision of the model.

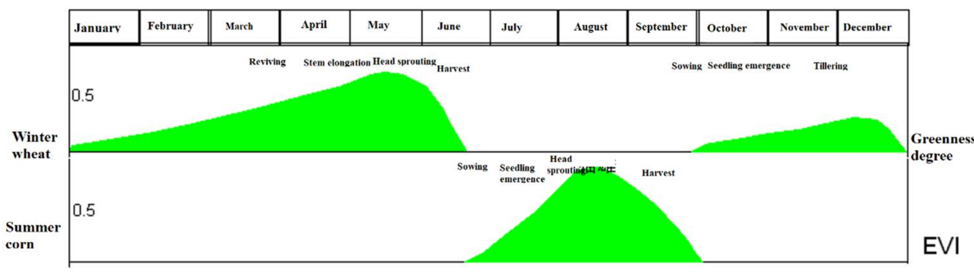

Fig. 2. Phenological greenness degrees of crops (via literature consultation).

Table 1. T-test results of the correlation between soil temperature and soil water content in different months.

Month	Crop phenology	p	R
June - October	Bare land	0.094	-
July - September	Corn	0.6	-
November - January in the next year	Winter wheat before the winter	< 0.05	> 0
March - May	Winter wheat after the winter	< 0.05	–0.437

$p < 0.05$ suggests significant linear correlation at a confidence level of 95%.

In this study, a method using $TVDI_{time}$ to monitor soil moisture based on existing models and algorithms was proposed. The method includes the following procedures: (1) RS data acquisition and LST maximum/minimum composite; (2) calculating long time-series drought index $TVDI_{time}$; (3) meteorological site and manual measurement data acquisition and screening; (4) establishment of regression equation; (5) soil moisture monitoring results and precision validation; (6) application of results. Fig. 4 illustrates the detailed research idea.

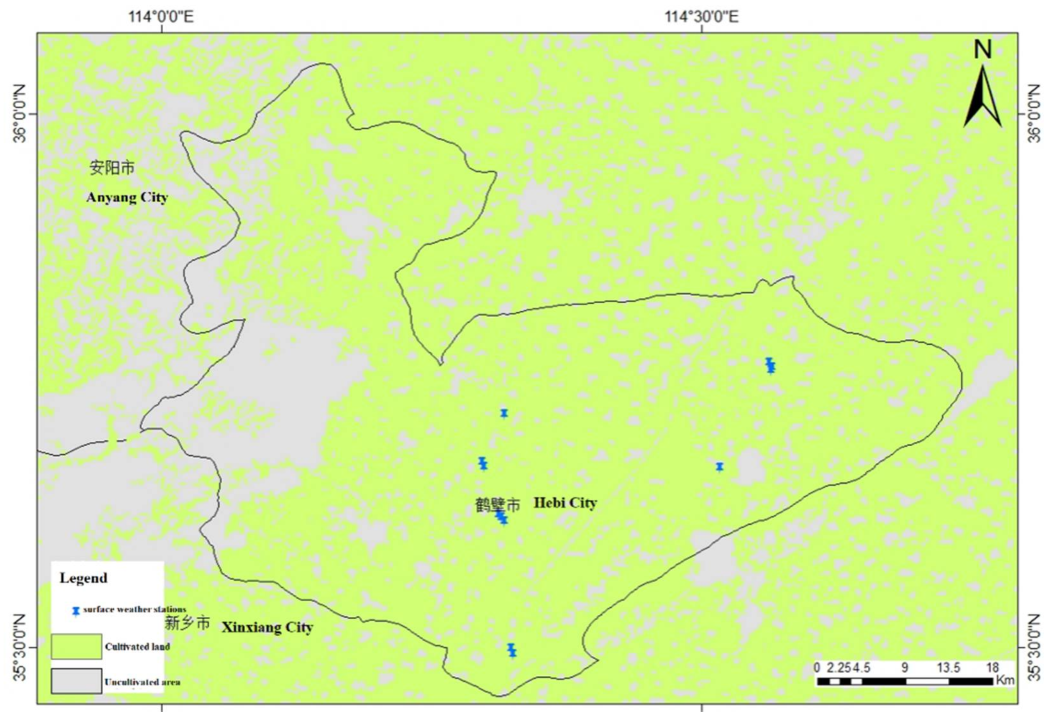

Fig. 3. Distribution of surface meteorological sites.

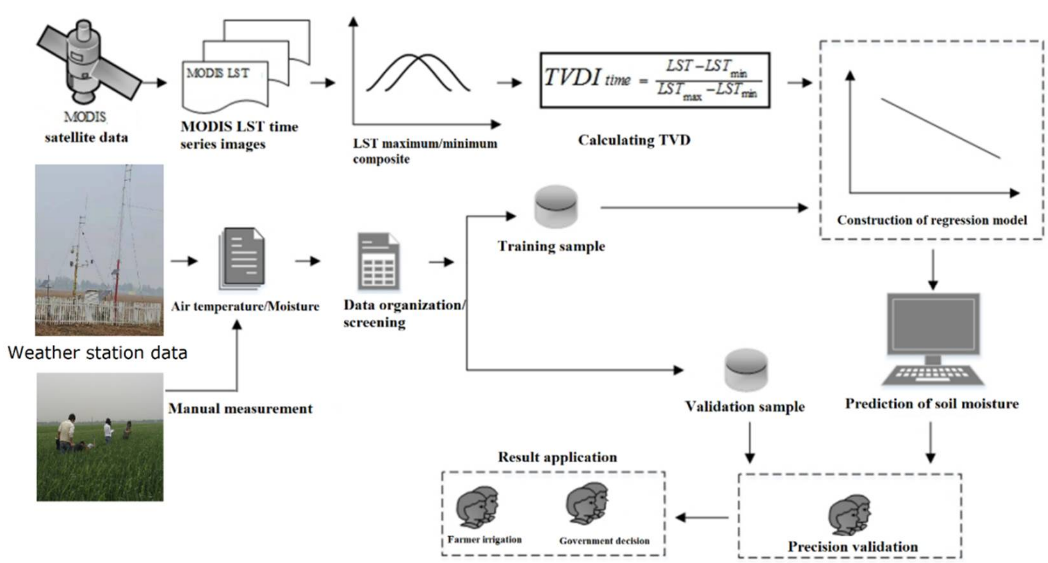

Fig. 4. Research technical route.

Maximum (LST_{max}) and minimum (LST_{min}) LST of MODIS data from 2001 to 2018 were obtained and composited via the plug-in 'maximum value composites' in ENVI. And $TVDI_{time}$ can be calculated as:

$$TVDI_{time} = \frac{LST - LST_{min}}{LST_{max} - LST_{min}} \qquad (1)$$

where, LST denotes actual surface temperature from 2001 to 2019, LST_{min} and LST_{max} are the maximum and maximum of surface temperature of the survey area from 2001 to 2019, respectively.

The regression relation was established using $TVDI_{time}$ and soil moisture content. Meanwhile, two-dimensional (2D) scatter diagram was plotted based on the data in 2014, 2016 and 2018, and the following linear regression equation can be established as:

$$M = -42.926 * TVDI + 114.03 \qquad (2)$$

where, M is soil moisture content and TVDI refers to the drought index at certain time.

Based on $TVDI_{time}$, the water content of the whole study area can be calculated according to the regression equation. The calculated results were also compared with the data from 12 surface meteorological sites in 2015 and 2019, and also manual measurement data in May, 2019 for precision validation.

Results and Discussion

By means of LST maximum/minimum composite, the maximum and minimum images of land surface temperature from 2001 to 2009 were obtained and TVDI data from March to May in 2014 - 2019 (i.e., on the 65th, 73rd, 81st, 89th, 97th, 105th, 113rd, 121rd, 129th, 137th and 145th day) were calculated according to Eq. 1. A larger value of TVDI (redder) suggests drier condition, as some results are shown in Fig. 5. It can be observed from Fig. 5 that Hebi suffered from most severe drought on May 9th, 2019 (i.e., the 129th day) and least drought on March 6th, 2019 (i.e., the 65th day), during the planting of winter wheat. The drought degree was moderate in the other periods. Various meteorological sites varied greatly in drought degree.

Table 2. Monitoring results and the corresponding measured water contents.

Period	Monitoring data by the meteorological sites	
	Monitoring results	Mean measured water content (%)
March 6th	Mild drought	72.07
March 14th	"	79.56
March 22nd	Moderate drought	78.44
March 30th	"	74.93
April 7th	Heavy drought	66.97
May 9th	"	65.11

The $TVDI_{time}$ data inverted by MODIS images were used as the drought monitoring results in different periods. Table 2 lists the monitoring results and the corresponding soil water content data measured by surface meteorological sites. As listed in Table 2, the monitoring drought degree data observed by meteorological sites are in good consistency with the inverted drought results. In the meanwhile, the present research team also performed field survey on May 5th, and the field investigation results also fit well with the measured data.

The data measured by 12 meteorological sites, TVDI data on 11 days (specifically, on 65th, 73rd, 81st, 89th, 97th, 105th, 113nd, 121st, 129th, 137th, and 145th day) each year from 2014 to 2018 were used in this study to form 110 data pairs of TVDI and the monitored soil water content. Soil moisture monitoring precision evaluation mainly includes the following two conditions. The precision of the monitoring results during the establishment of regression equation was evaluated, as shown in Fig. 7. The precision of the monitoring results according to the established regression equation was evaluated (Fig. 8).

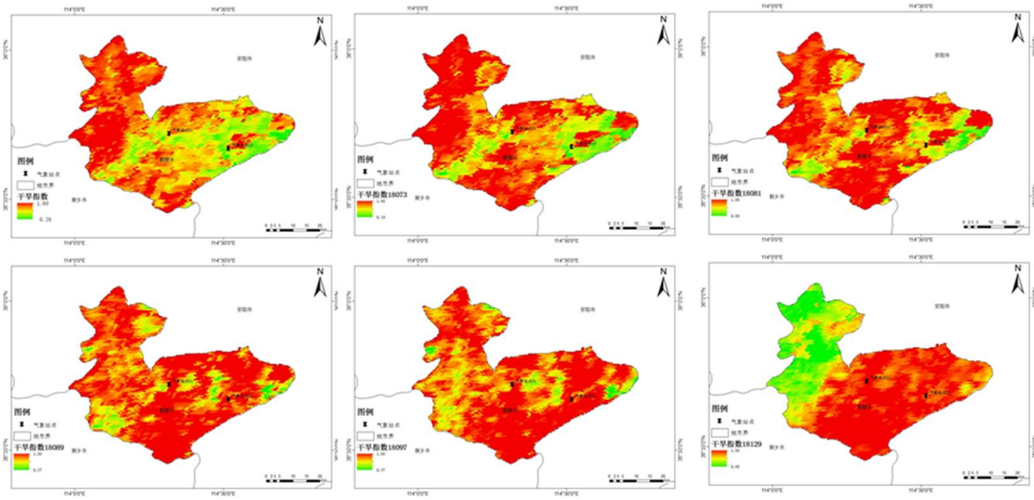

Fig. 5. Soil moisture monitoring results in 2019 (upper left: on March 6th; upper middle: on March 14th; upper right: on March 22nd; lower left: on March 30th; lower middle: on April 7th; lower right: on May 9th).

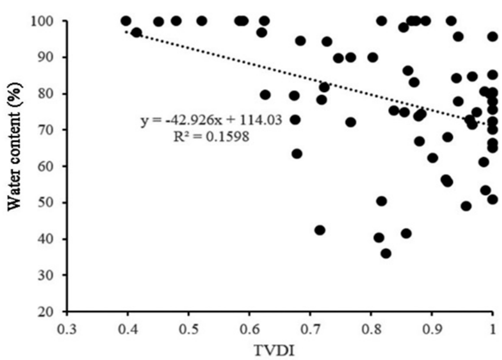

Fig. 7. Linear regression equation between drought index and soil water content.

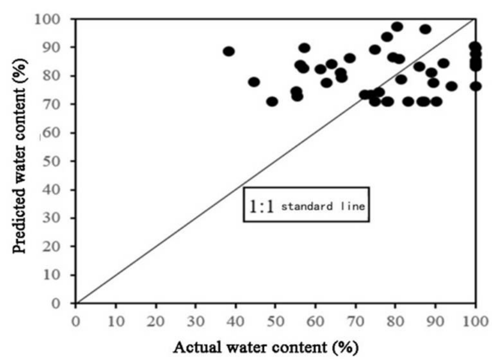

Fig. 8. Evaluation of prediction precision of soil water content predicted water content (%)/ actual water content (%) 1 : 1 standard line.

The 66 data in the even years (2014, 2016 and 2018) were selected as the training samples. Using the established linear regression equation Eq. 2, the t-test results suggested that linear significance coefficient ($p = 0.001 < 0.05$), i.e., these two factors exhibit significant linear correlation at a confidence interval of 95%, while the correlation coefficient $R = -0.4$, suggesting no negative correlation between two factors. Based on TVDI images, soil water contents were predicted according to Eq. 2. The 44 data in odd-numbered years were selected for precision validation, and results are shown in Fig. 8. It can be also seen from Fig. 8 that the predicted data and the observed water content are roughly distributed on the both two sides of 1:1 standard line, suggesting favorable prediction precision and completely right tendency. The prediction is more accurate at high water content.

Henan province is China’s main grain producing area. Hebi city adopts typical grain production pattern on North China Plain. By taking full advantages of agricultural IoT and fast RS data acquisition, the algorithm and model for business monitoring were established, which can realize rapid continuous monitoring of soil moisture. Moreover, the monitoring results were applied to farmer production and irrigation guidance. In addition, some results can also be used for directing government decision-making such as grain yield consultation and agricultural disaster subsidy, exhibiting significant social and economic values.

Based on the present experimental and research results, the following conclusion can be drawn.

(i) By analyzing crop planting phenological rules in the survey area, the key periods of soil moisture monitoring for the planting of winter wheat and summer corn were determined as March ~ May and July - August each year. These two key periods also significantly affect crop output.

(ii) By reviewing international soil moisture monitoring data based on RS data, surface temperature vegetation drought index (TVDI) based on time series was constructed and improved. Using favorable data measured by surface meteorological sites, effective regression equation between TVDI and soil water content was established, which can give accurate prediction results. In addition, the required data in monitoring can be simplified so as to satisfy the business requirement.

Acknowledgements

The study was supported by National Key Research and Development Plan ‘Research and Development and Product Creation of Meteorological Disaster Prevention and Control Technology for Major Cash Crops (2019YFD1002205)'. And National Basic Conditions for Science and Technology Platform: National Agricultural Science Data Center (NASDC 2020XM05)

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(Manuscript received on 17 June, 2020; revised on 10 November, 2020)