STUDY ON REMOTE SENSING MONITORING MODEL OF AGRICULTURAL DROUGHT BASED ON RANDOM FOREST DEVIATION CORRECTION
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基于随机森林偏差校正的农业干旱遥感监测模型研究

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ABSTRACT
Using remote sensing data to monitor large area drought is one of the important methods of drought monitoring at present. However, the traditional remote sensing drought monitoring methods mainly focus on monitoring single drought response factors such as soil moisture or vegetation status, and the research on comprehensive multi-factor drought monitoring is limited. In order to improve the ability to resist drought events, this paper takes Henan Province of China as an example, takes multi-source remote sensing data as data sources, considers various disaster-causing factors, adopts random forest method to model, and explores the method of regional remote sensing comprehensive drought monitoring using various remote sensing data sources. Compared with neural network, classification regression tree and linear regression, the performance of random forest is more stable and tolerant to noise and outliers. In order to provide a new method for comprehensive assessment of regional drought, a comprehensive drought monitoring model was established based on multi-source remote sensing data, which comprehensively considered the drought factors such as soil water stress, vegetation growth status and meteorological precipitation profit and loss in the process of drought occurrence and development.

摘要
利用遥感数据进行大面积干旱监测是目前干旱监测的重要方法之一。然而，传统的遥感干旱监测方法主要侧重于监测土壤水分或植被状况等单一干旱响应因子，而对多因子干旱综合监测的研究却十分有限。为了提高抗旱能力，本文以河南省为例，以多源遥感数据为数据源，考虑各种致灾因素，采用随机森林法进行建模，探讨了利用各种遥感数据源进行区域遥感综合干旱监测的方法。与神经网络、分类回归树和线性回归相比，随机森林的性能更稳定，对噪声和离群点的容忍度更高。为了为区域干旱综合评价提供一种新的方法，综合考虑土壤水分胁迫等干旱因素，建立了基于多源遥感数据的干旱综合监测模型，干旱发生发展过程中植被生长状况与气象降水盈亏。

INTRODUCTION
Agricultural drought refers to the imbalance of water supply and demand in the process of crop growth due to insufficient water supply, which hinders the normal growth of crops *(Bao Q. L. et al., 2019)*. Agricultural drought is mainly related to soil temperature, effective precipitation and crop water demand. The frequent occurrence of drought has a serious impact on the ecological environment, agricultural production and socio-economic situation. Since ancient times, mankind has suffered from drought disasters. Drought has become the most serious natural disaster affecting agricultural production due to its high frequency, long duration, wide range of impact and great delayed impact. As a common and frequent disaster, drought has always posed a serious threat to agricultural production, food security, ecological environment and economic and social development *(Carolyn Q. et al., 2019)*. The direct cause of agricultural drought is water deficit. When drought develops to a certain extent, vegetation will show the characteristics of increasing canopy temperature and decreasing vegetation index. Meteorological monitoring and remote sensing monitoring are the main drought monitoring methods at present, although the meteorological drought monitoring methods are relatively mature. However, due to the limited number of stations, uneven spatial distribution, and the lack of consideration on the response of surface and vegetation to drought in monitoring mechanism, drought monitoring has limitations *(Elena G. et al., 2021)*.

Conventional soil moisture monitoring methods have few measuring points and poor representativeness, so it is difficult to achieve large-scale, real-time and dynamic drought monitoring. Remote sensing has the advantages of macro, large area, real-time dynamic monitoring, and is widely used in agricultural drought monitoring.

Drought is one of the most serious meteorological disasters in the world, which is characterized by high frequency, large influence range and long duration *(Dietz K. J. et al., 2019)*. Its frequent occurrence has brought huge economic losses to the national economy, especially agricultural production. Drought refers to the situation that during the growth period of crops, the soil water in the farming layer is not supplied by precipitation, groundwater and irrigation water, the soil water supply is constantly consumed, the water absorbed by crops from the soil cannot meet the normal physiological needs, and the growth of crops is restricted by water conditions *(Hassan M. A. et al., 2019).* Remote sensing drought monitoring has the advantages of macroscopical, fast and continuous data in time and space, but it mainly monitors the vegetation growth or soil moisture and other single factors, which cannot fully reflect the drought information. Traditional agricultural drought monitoring methods are not only time-consuming and labour-intensive, but also have certain limitations in terms of spatial representation and sampling period. Remote sensing has the advantages of macroscopic, large-area, and real-time dynamic monitoring, and is currently widely used in agricultural drought monitoring. Random forest is a relatively new machine learning algorithm with fast learning process, fast calculation speed, good stability, high efficiency in processing large data sets, high prediction accuracy, and not easy to produce over-fitting *(Hirayama H. et al., 2019)*. This paper takes multi-source remote sensing data as the data source, considers multiple hazards, uses random forest method to model, and explores the use of multiple remote sensing data sources for regional remote sensing comprehensive drought monitoring methods. The research comprehensively considers the drought-causing factors such as soil water stress, vegetation growth status and meteorological precipitation surplus and loss during the occurrence and development of drought, and establishes a comprehensive drought monitoring model based on multi-source remote sensing data in order to provide a new method for comprehensive regional drought assessment *(Wu M. Y. et al., 2018).*

Drought is a hot scientific issue in global climate change research. As a major meteorological disaster, drought has a great impact on China's economic and social development and agricultural production. Therefore, research on drought monitoring technologies and assessment methods will improve the government's ability to respond to natural disasters. It has important practical significance *(Kumar K. C. A. et al., 2021)*. Constructing an accurate drought monitoring model can not only reflect the occurrence of drought events in a timely manner, but also provide scientific support and guarantee for local governments to formulate disaster reduction and production measures *(Shah D. et al., 2021)*. Abnormal precipitation change, vegetation growth, abnormal evaporation and soil moisture are important indicators reflecting drought degree from different levels, which have been widely used in drought monitoring *(Tirivarombo S. et al., 2018)*. However, drought is a slow process involving many aspects such as precipitation, and the drought evaluation results relying on a single index are different from the actual situation. As a major meteorological disaster affecting China, drought seriously threatens China's economic and social development and food security. Therefore, in order to enhance the ability to resist drought events, it is of practical significance to study drought monitoring technology and evaluation methods. Compared with neural network, classification regression tree and linear regression, the performance of random forest is more stable and tolerant to noise and outliers.

Drought refers to a disaster in which crops suffer from drought during the growth period. Agricultural drought monitoring includes agricultural drought monitoring, early warning and post-disaster assessment *(Javed T. et al., 2021)*. The direct inducement of agricultural drought is water shortage. When drought develops to a certain extent, vegetation will show the characteristics of canopy temperature rising and vegetation index falling *(Chaitanya D. N. V. et al., 2018)*. Literature *(Haekyung P. et al., 2019)* uses RF, Cubist and Bagging methods to build a comprehensive drought index, and the results show that RF algorithm has better fitting ability. Literature shows that RF algorithm is more accurate in drought prediction than enhanced regression tree and Cubist method. The RF algorithm is based on the average results of several decision trees, and its results are relatively accurate and credible, but at the same time it will lead to certain deviations, especially its ability to predict extreme values is weak.

For drought disasters, extreme conditions often bring greater losses, which should be paid more attention to. *(Javed T. et al., 2021)* comprehensively considered the drought factors of soil moisture and meteorological precipitation, weighted the vegetation water supply index and the precipitation anomaly drought index to add linearly, the agricultural drought index is put forward, and the monitoring effect of agricultural drought index is good in practical application, which will avoid greater losses due to extreme conditions.

Based on the above principles, remote sensing drought monitoring generally considers the extraction of drought information from the temporal and spatial characteristics of soil moisture, canopy temperature, vegetation index and other elements. Literature proposed a comprehensive drought monitoring index (DMI) based on the combination of temperature vegetation index (TVDI) and precipitation anomaly index (PPAI). It was applied to drought monitoring in the main winter wheat producing areas in China *(Khalili K. et al., 2019)*.

Other authors combines traditional meteorological drought monitoring indicators, remote sensing monitoring indicators, and other biophysical information to develop a vegetation drought response index VegDRI, which takes into account vegetation growth conditions, precipitation surplus, and ecological environment parameters, including surface cover types and topography *(Lee S. J. et al., 2021)* and other factors *(Sadri S. et al., 2018).*

Remote sensing drought monitoring methods are widely used because of their high temporal and spatial resolution and the ability to obtain regional continuous spatial drought conditions. However, the previous remote sensing drought monitoring methods mostly focused on considering single factors such as soil and vegetation, especially most remote sensing drought monitoring methods, which cannot reflect the precipitation profit and loss information in the drought-causing factors. Literature established a comprehensive drought monitoring model based on the idea of classification regression tree, and put forward a comprehensive drought index SDI, which was applied to drought monitoring in Henan Province, and could quantitatively monitor the spatial-temporal evolution and development characteristics of regional actual drought and historical drought. Literature proposes to combine remote sensing monitoring with traditional meteorological monitoring, and obtain agricultural drought index by using the linear weighting of crop water supply index and precipitation anomaly index *(Yan L. et al., 2021)*

MATERIALS AND METHODS

Research area survey

Henan Province is located in the middle east of China, between 110°22′E-116°37′E, 31°24′N-36°23′N. The terrain gradually decreases from west to east, and plains account for about 53.2% of the province's total area. Henan Province belongs to the transitional climate of northern subtropical humid climate and warm temperate semi-humid monsoon climate. The annual average temperature from south to north is 10.5-16.50ºC, the average annual precipitation is 406.5-1290.5 mm, and the seasonal distribution of precipitation is uneven, 50% of the annual precipitation is concentrated in summer, with an average annual sunshine of 128.6-2290.8 hours and a frost-free period of 200 to 280 days throughout the year, which is suitable for the growth of a variety of crops. The terrain is high in the west and low in the east, with mountains in the north, west and south, plains in the east and basins in the southwest, spanning the Yellow River, Haihe River, Huaihe River and Yangtze River.

The planting structure in Henan Province is relatively simple, mainly including summer harvest crops and autumn harvest crops. Winter wheat is the main summer harvest crop, and autumn harvest crops include corn, cotton and so on. Considering the different responses of different crops to drought under the same conditions such as meteorological conditions and topography. The topography of Henan is high in the west and low in the east, and the northern, western and southern sides are distributed in a semi-circular shape along the provincial boundary by Taihang Mountain, Funiu Mountain, Tongbai Mountain and Dabie Mountain. The central and eastern parts are Huang-Huai-Hai alluvial plain. Nanyang Basin is located in the southwest. Plains and basins, mountains and hills account for 55.7%, 26.6% and 17.7% of the total area respectively. According to topography, Henan is mainly divided into five areas: western mountainous and hilly area, southern border area mountainous and hilly area, loess area, southwest Nanyang Basin, and eastern and northern Henan Plain.

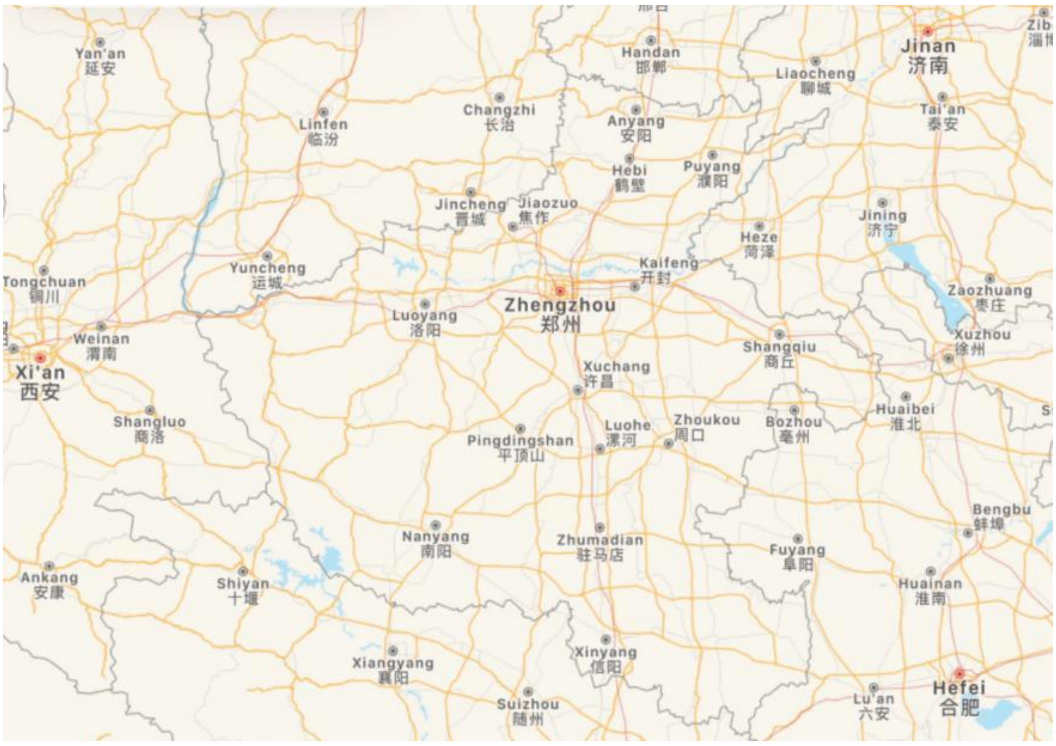

Fig. 1 - Administrative area map of the study area

As a major agricultural province in China, Henan Province is the largest commodity grain base in China, so it is of great significance to prevent drought for food security in Henan Province. The unique geographical location and climatic characteristics of Henan Province have made the meteorological disasters in Henan Province frequent, such as drought, flood, wind, hail, earthquake, thunder, snow, etc., which are characterized by many kinds of natural disasters, high frequency of occurrence, wide influence range and serious harm. The main agrometeorological disasters in Henan Province are drought, waterlogging, hail and freezing. Among them, drought is the most frequent disaster in the province and has a serious impact on agricultural production, and there is a saying of "nine droughts in ten years" in history. Drought basically occurs in every season. Because Henan is located in the temperate monsoon climate zone, there is less precipitation in spring, coupled with the rapid rise of temperature, the increase of gale days and evaporation, spring drought occurs most frequently. In recent years, the drought situation in Henan Province has gradually intensified, which has seriously threatened human daily life and agricultural production. Therefore, it is of great significance to build a suitable drought monitoring index for the development of agriculture and the protection of people's life in Henan Province.

Data sources and processing

At present, Palmer drought index PDSI and standardized precipitation index SPI are widely used and mature in monitoring and analysing regional drought, both of which can be used to characterize the probability of regional drought and flood disasters under different climate and soil characteristics. The water supply of crops mainly comes from soil moisture, and the growing season of crops is the key period of water demand of crops. The essence of drought monitoring is to monitor soil water content. The distribution range and degree of drought can be reflected by the amount and distribution of soil water content. Soil water evaporation is large, soil water loss is serious, and drought will develop rapidly. PDSI is a meteorological drought index based on the balance equation of water supply and demand. Its calculation begins with estimating the difference between actual precipitation and climate suitable precipitation (CAFC-P) to determine the deviation degree between drought and flood in the study area and the average monthly level for many years. Then, the monthly water anomaly is transformed into a water anomaly index by adding and multiplying weight factors. Finally, the severity of drought and flood can be inferred from the monthly water anomaly index and PDSI value of the previous month and the study month. Standardized precipitation index only needs precipitation data, which is simple in calculation and comparable in different time and space scales. It is widely used in meteorological drought monitoring at home and abroad.

Assuming that precipitation at a certain time scale is a random variable x, the probability density function of its Gamma distribution is:

$$g(x)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{a-1}e^{-x/\beta} \quad (x>0) \tag{1}$$

$$\Gamma(\alpha)=\int_{0}^{\infty}x^{a-1}e^{-x}dx \tag{2}$$

Where: α is the shape parameter of the Γ distribution function; β is the scale parameter, and $\Gamma(\alpha)$ is the gamma function. α and β can be estimated by the maximum likelihood method, see equations (3) and (4).

$$\hat{s}=\frac{1+\sqrt{1+4A/3}}{4A} \tag{3}$$

$$\hat{\beta}=\frac{\bar{x}}{\hat{a}} \tag{4}$$

$$A=\ln(\bar{x})-\frac{\sum \ln x}{n} \tag{5}$$

In the formula: $\bar{x}$ is the average value of precipitation for many years, and n is the length of the sample sequence. Because x>0 in the Gamma function, and precipitation can be 0 in actual conditions, $\bar{x}$ is the average value of non-zero items in the multi-year precipitation series. Assuming that there are n zero items in the precipitation sequence and the total length is m, the cumulative probability of a certain time scale is calculated by equation (6):

$$SPI=S\left(1-\frac{c_2k^2+c_1k+c_0}{d_3k^3+d_2k^2+d_1k+1}\right) \tag{6}$$

Where: $k=\sqrt{\ln\frac{1}{F(x)^2}}$. When $F(x)>0.5$, S=1, when $F(x)\le 0.5$, S=-1.

In this paper, MODIS vegetation index products (MOD13A3), surface temperature products (MOD11A2), land cover type products (MCD12Q1), TRMM 3B43 products and SRTM-DEM data from 2011 to 2021 are taken as the main remote sensing data sources. MOD13A3 is a monthly land vegetation index product, MOD11A2 is a land temperature product synthesized every 8 days, the spatial resolution of MODIS products is 1km, and MCD12Q1 is an annual land cover type product with a spatial resolution of 500m. This paper adopts the meteorological data of 20 main meteorological stations and 10 agrometeorological stations in Henan Province from 2001 to 2021, such as monthly average temperature, precipitation data, and relative soil humidity. The data has passed quality control. In addition, in order to calculate the effective soil water content (AWC), the Chinese soil particle size distribution data set released by Beijing Normal University was adopted with a spatial resolution of 1km. The TRMM3B43 data is converted from hourly precipitation to monthly precipitation, and projected with MODIS data and SRTM-DEM data into WGS84/Geographic system, resampled to 0.0059°×0.0059°. For mod13a3 and mod11a2 data, the normalized vegetation index (NDVI) and land surface temperature (LST) were extracted, and the invalid values in the images were removed by using the quality control file, and the data of other years in the same month were used for filling.

Construction of comprehensive drought model

Agricultural drought is due to the abnormal shortage of precipitation for a long time, and the soil moisture cannot meet the water demand for crop growth, which leads to the stress of crop growth. It can be seen that the agricultural drought is essentially caused by the imbalance between the environmental water supply and the normal growth of vegetation. In order to extract the vegetation index with reliable quality, the study uses the quality information file of the data set, writes an algorithm to control the quality of MOD13A3 data after projection transformation and cutting in the study area, eliminates low-quality pixels, and fills with the average values of vegetation index of the same month in other years. On the one hand, the environmental water supply comes from atmospheric precipitation, on the other hand, it comes from the water content of soil itself. Therefore, when insufficient atmospheric precipitation causes meteorological drought, if the soil water can meet the water demand of crops, it will not cause agricultural drought. The random forest method randomly selects n sample sets in the original data set by bootstrap self-help method. The data of 2 / 3 sample capacity are taken as the data in the bag each time, n decision trees are built to construct the random forest, and the average value of regression results of N decision trees is used to predict.

Drought is a natural disaster caused by precipitation. Traditional agricultural drought is only a single vegetation information obtained from remote sensing to obtain and monitor drought. Because of the lag of vegetation response to drought, this leads to a certain lag in the traditional agricultural drought monitoring. Although the 8-D surface temperature data can eliminate some invalid values in the process of synthesizing monthly surface temperature data, there are still some invalid value areas in the synthetic data. Therefore, the average algorithm is used to repair the invalid value of monthly surface temperature data. The integrated drought monitoring process is shown in Figure 2.

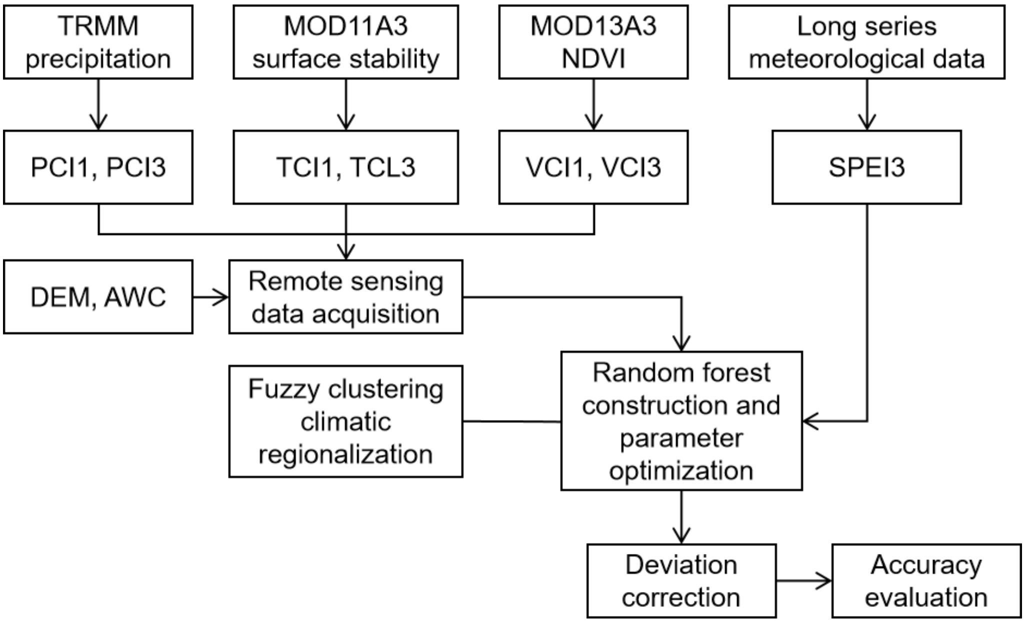

Fig. 2 - Integrated drought monitoring process

The linear relationship between the predicted value of the data in the bag and the actual value is established, and the linear relationship is used to correct the predicted value of the sample data outside the bag to achieve the effect of deviation correction. The calculation formula is:

$$y_{obs} = a + b\hat{y}_{pre} \tag{7}$$

In the formula: y_{obs} is the actual value, y_{pre} is the predicted value, and a and b are coefficients.

Dry early is a complex and changeable process, and many droughts may occur within one month. Although short-term dry early disasters cannot be monitored by the dry early index based on the monthly scale, short-term drought will directly lead to the reduction of grain production during the flowering and growth period of crops. The MOD11A2 surface temperature data also uses the quality control algorithm to eliminate some filling values and low-quality pixels in the synthesis process and fill them with invalid values. Since MODIS does not have monthly synthetic LST products with 1km resolution, this study synthesized monthly LST products with 8D LST products. In order to build the agricultural drought monitoring model with multiple drought factors, the standardized precipitation evapotranspiration index (spei), vegetation state index (VCI), temperature state index (TCI) and Temperature Vegetation Drought Index (TVDI) from 2011 to 2021 were input into the model as eigenvalues based on decision tree classification.

RESULTS

In the process of modeling, firstly, vegetation state index VCI, temperature state index TCI and temperature vegetation drought index TVDI are extracted in ENVI software according to each index calculation formula. Then, according to the longitude and latitude information of the ground meteorological stations in Henan Province, the values of the coordinate positions of the above-mentioned spatial data in each meteorological station are extracted.

The agricultural drought process is determined by a variety of disaster-causing factors, which are not only related to atmospheric precipitation, vegetation growth status and soil water stress, but also related to evaporation, soil effective water holding capacity and other factors. A single index has insufficient reflection on drought, and the coupling relationship between hazards is complicated. Due to the limitation of data and the complexity of drought causes, it cannot fully reflect the relationship between agricultural drought and meteorological drought, soil drought, and evaporation. To make up for the deficiencies of the data itself and improve the drought monitoring mechanism, drought monitoring research tends to be a comprehensive method of multi-source information. Figure 3 shows the remote sensing detection of agricultural drought in Henan Province.

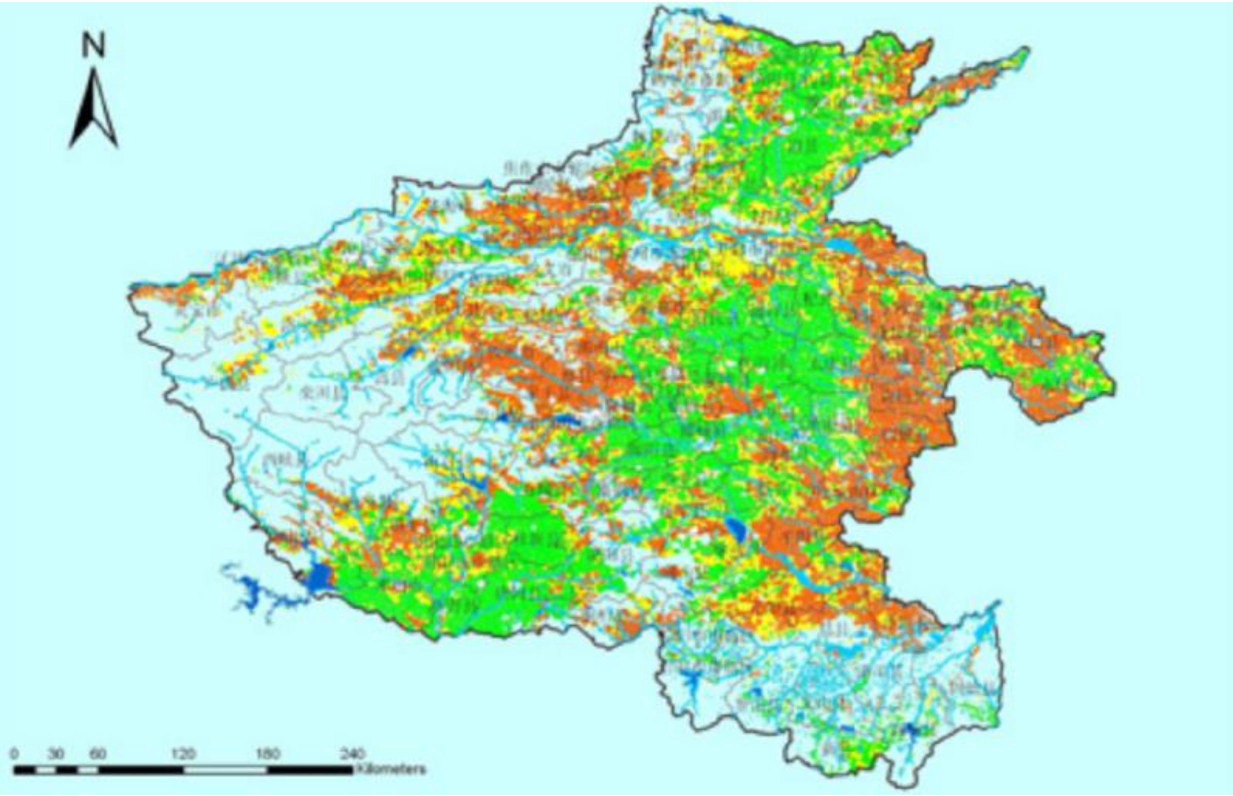

Fig. 3 - Remote sensing detection of agricultural drought in Henan Province

In this study, the data from the training set and the test set are input into the model respectively, and the predicted values of the model are obtained. The mean relative error absolute value (MRE), root mean square error (RMSE) and correlation coefficient R between the predicted values of the model and the actual comprehensive meteorological drought index (CI) are calculated.

- As shown in Table 1 and Table 2, the correlation coefficient of training sets in each season is above 0.975. The correlation coefficient of the test set is slightly lower than that of the training set, but it also reaches more than 0.75, and both have a significant correlation. However, the root mean square error (RMSE) of training set and test set is small, and the simulation accuracy of the model is high. The mean absolute relative error (MRE) of the test set does not exceed that of the training set, which shows that the model has good generalization performance and strong applicability to new data.

Table 1

Accuracy analysis of training set model

	Absolute value of average relative error %	Root-mean-square error	Correlation coefficient
Spring	0.581	0.345	0.975**
Summer	0.501	0.328	0.980**
Autumn	0.478	0.310	0.990**
Winter	0.521	0.325	0.975**

Table 2
(continuation)

Accuracy analysis of test set model

	Absolute value of average relative error %	Root-mean-square error	Correlation coefficient
Spring	1.436	0.751	0.765**
Summer	1.613	0.748	0.753**
Autumn	1.248	0.698	0.886**
Winter	1.376	0.732	0.769**

In order to verify the applicability of the drought classification of the model, the classification results of the training set and the test set were compared with the actual drought. The calculation method is as follows:

$$\text{Overall coincidence rate} = \frac{\text{Number of sites with the same rank}}{\text{Research Year} \times \text{Number of Sites}} \tag{8}$$

$$\text{Empty evaluation rate} = \frac{\text{The number of stations with drought monitoring results but no actual drought}}{\text{The actual number of stations with drought above light drought}} \tag{9}$$

$$\text{Leakage evaluation rate} = \frac{\text{The monitoring result is the number of stations without drought but with actual drought}}{\text{The actual number of stations with drought above light drought}} \tag{10}$$

The status of crops under drought stress can be measured by the change of the vegetation index at this time relative to the vegetation index under normal conditions. Such remote sensing monitoring indexes include Anomaly Vegetation Index (AVI) and Conditional Vegetation Index (VCI). The algorithm is as follows:

$$AVI = NDVI - \overline{NDVI} \tag{11}$$

$$VCI = \frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \tag{12}$$

Agricultural drought is defined as crop water shortage caused by the failure of soil water supply to meet crop water demand. It usually first shows the lack of soil moisture caused by the decrease of precipitation. At the same time, with the continuous loss of water from crop transpiration, the water in the crop cannot meet the normal physiological activities, which is manifested by inhibiting crop growth, resulting in crop yield reduction or crop failure, and the effects of drought on different growth periods of crops are significantly different. The correlation between the drought affected area calculated by the integrated remote sensing drought monitoring model and the disaster affected area in the statistical yearbook is higher than that of the disaster affected area, which indicates that the drought monitoring situation of the integrated remote sensing drought monitoring model can well monitor the area caused by drought in the Huaihe River Basin [21]. The correlation between the comprehensive remote sensing drought monitoring model and the agricultural drought disaster area is higher than that of the disaster area, which also shows that the comprehensive remote sensing drought monitoring model can better monitor the drought disaster area and accurately evaluate the drought situation of Huaihe River Basin.

CONCLUSIONS

The correlation between drought-affected areas and disaster-affected areas calculated by the remote sensing integrated drought monitoring model in Statistical Yearbook is higher than that in disaster areas, which indicates that the drought monitoring situation of the remote sensing integrated drought monitoring model can monitor the arid areas of Huaihe River Basin well. The correlation between the integrated remote sensing drought monitoring model and agricultural drought-stricken areas is higher than that in the disaster areas, which also shows that the integrated remote sensing drought monitoring model can better monitor the drought-stricken areas and accurately evaluate the drought situation in Huaihe River Basin. Remote sensing and geographic information system (GIS), as effective means to obtain information on a large scale and effective tools to manage spatial data, have been widely used in drought monitoring and forecasting research.

Agricultural drought involves precipitation, vegetation, temperature and environmental factors, and its drought process is very complex. Monitoring with multi-source remote sensing data can effectively explain the complexity of agricultural drought. In this paper, a remote sensing drought monitoring model based on random forest algorithm is established by using MODIS, TRMM and other multi-source remote sensing data, and the model is verified. The drought index improved in this paper can only detect and monitor the drought accurately and timely, but cannot predict the drought. Therefore, drought forecasting is an urgent problem to be solved in future work. The agricultural drought process is determined by various disaster factors, which are not only related to atmospheric precipitation, vegetation growth and soil water stress, but also related to evaporation, soil effective water retention capacity and other factors.

The reflection of drought by a single index is insufficient, and the coupling relationship between disasters is complicated. Because of the limitation of data and the complexity of drought causes, it cannot fully reflect the relationship between agricultural drought and meteorological drought, soil drought and evaporation. From the perspective of energy balance, the occurrence and development of agricultural drought are discussed by making full use of the underlying surface information obtained by remote sensing, combined with atmospheric model and hydrological model, and the occurrence and development of agricultural drought are monitored and predicted to achieve the goal of disaster reduction and prevention. This is the development direction and goal of agricultural drought monitoring by remote sensing in the future.

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