

# Spatiotemporal Analysis of Drought Characteristics Based on MODIS and GEE

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**Abstract:** Drought is a major agricultural disaster that has long posed significant challenges to China's agriculture and ecological environment. Its latent, widespread, and vulnerability characteristics make it crucial to obtain effective large-scale, long-term remote sensing data for spatiotemporal analysis and drought forecasting. With the advancement of remote sensing technology, the spatiotemporal resolution of remote sensing data has improved, providing robust support for analyzing drought spatiotemporal variations. However, traditional remote sensing data analysis methods require extensive preprocessing, involve high computational costs, and face difficulties in data acquisition. These challenges highlight the need for remote sensing big data platforms. Google Earth Engine (GEE), a cloud-based platform, offers powerful data storage and analytical capabilities that effectively support large-scale remote sensing data processing. The Vegetation Supply Water Index (VSWI), which integrates vegetation conditions and surface temperature information, is a simple yet effective tool for drought assessment and demonstrates good correlation with the widely used Palmer Drought Severity Index (PDSI). In this study, we used the GEE platform to construct VSWI based on MODIS datasets, utilizing Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) data to conduct a temporal analysis of drought conditions in the three northeastern provinces of China from 2010 to 2020. A comparative analysis with PDSI revealed that VSWI effectively captures the trends in drought variation in the region, demonstrating good spatial and temporal consistency. The findings indicate that the VSWI drought index constructed on the GEE platform provides a simple and efficient method for drought assessment in the region, laying the foundation for developing more complex drought assessment models in the future.

**Keywords:** GEE; Drought Monitoring; Spatiotemporal Variation; VSWI.

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## 1. Introduction

Drought has long been one of the most significant natural disasters threatening human survival, characterized by its latent onset, widespread impact, and high vulnerability [1]. The causes of drought are highly complex, and it exerts a significant influence on various aspects of development in China. In the future, it is bound to become a critical factor restricting the nation's economic progress[2]. Currently, drought is defined in various ways. Based on its causes, it can be broadly categorized into four primary types: meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought [3]. Agricultural drought refers to the phenomenon where insufficient atmospheric precipitation, low soil moisture, and inadequate or untimely artificial irrigation during the growing season fail to meet the water requirements of crops, resulting in reduced yields or even total crop failure[4].

Since ancient times, China has been an agrarian nation, and agriculture remains one of its most important industries today[5].

However, research indicates that China is one of the countries most severely affected by drought worldwide. Among its regions, Northeast China is particularly vulnerable, experiencing the longest drought durations, the highest frequency of occurrences, and the most severe drought levels in the country[6]. Statistics show that drought accounts for 50% of the total crop losses caused by natural disasters in China each year[7]. Northeast China, primarily comprising Heilongjiang, Jilin, and Liaoning provinces, serves as a crucial production base for staple and cash crops in the country. However, it is highly susceptible to the impacts of abnormal precipitation and drought[8]. With global warming,

Northeast China has experienced rising temperatures and decreasing precipitation, leading to an increased frequency of drought events[9]. This has severely disrupted the agricultural ecological balance. Therefore, conducting in-depth research and monitoring drought conditions in the three provinces of Northeast China holds profound significance.

Remote sensing technology has become the mainstream method for monitoring drought in contemporary research [10]. However, as the volume and diversity of remote sensing data continue to grow, efficiently processing, analyzing, and utilizing these resources has become a significant challenge in research. For instance, conducting a dynamic analysis of drought characteristics in Northeast China requires long-term time-series remote sensing data, highlighting the critical role of cloud platforms for managing remote sensing big data. Google Earth Engine (GEE) is an integrated platform that combines remote sensing image storage and analysis, enabling the efficient retrieval and extraction of remote sensing data and information[11]. With the continuous advancements of GEE, an increasing number of remote sensing data processing and analysis tasks can be accomplished. Using the GEE platform to analyze agricultural drought offers numerous advantages, including access to an extensive range of data, streamlined data processing, and integrated visualization and computation capabilities[12]. Leveraging its extensive remote sensing data products and powerful cloud-based computing capabilities, GEE can meet the diverse data processing requirements of various analytical needs. As a result, GEE has garnered increasing attention from researchers, offering a new perspective for tackling the challenges of massive remote sensing data analysis and addressing real-world problems.

## 2. Data Sources and Research Methods

### 2.1. Study Area

Heilongjiang Province, abbreviated as "Hei," is located in the northeasternmost part of China, covering a total area of 473,000 square kilometers, making it the sixth largest province in the country. Bordered by Russia across the river to the east, Inner Mongolia to the west, and Jilin Province to the south, Heilongjiang is characterized by a cold climate and fragile ecological environment. It serves as a vital region for agriculture and ecological conservation[13].

Jilin Province, abbreviated as "Ji," is situated in the central part of Northeast China, covering a total area of 187,000 square kilometers. It shares a border with Russia to the east and faces North Korea across the river to the southeast. To the south, it borders Liaoning Province; to the west, Inner Mongolia; and to the north, Heilongjiang Province. Jilin has a temperate monsoon climate and is a key base for agriculture and forestry.

Liaoning Province, abbreviated as "Liao," is located in the southern part of Northeast China, covering a total area of 148,600 square kilometers. It borders the Bohai Sea and Yellow Sea to the south, Hebei Province to the southwest, and Jilin Province to the northeast, while facing North Korea across the Yalu River to the southeast. With a temperate monsoon climate, Liaoning is a crucial province for both industry and agriculture in China.

### 2.2. Google Earth Engine

Google Earth Engine (GEE) is a cloud computing platform jointly developed in 2015 by Google, Carnegie Mellon

University, and the United States Geological Survey (USGS)[14]. It is designed to process satellite remote sensing imagery and other Earth observation data.

The development of GEE was facilitated by the gradual opening of global remote sensing data, particularly the decision by USGS in 2008 to provide over 40 years of Landsat data to the public for free. Subsequently, other satellite programs, such as the Sentinel series under ESA's Copernicus Program and NOAA's MODIS, also made their spatial data publicly available. This open data policy laid a solid foundation for the establishment of the GEE platform.

As a resource integration platform, GEE brings together a vast array of publicly available geospatial datasets, including satellite imagery, climate products, surface reflectance, land use, nighttime light data, topography, and socioeconomic data. Leveraging Google's powerful server computing capabilities and extensive remote sensing resources, the platform enables efficient data processing and analysis. Users can not only conduct extensive remote sensing research using the platform's existing data but also upload local datasets via the provided API to perform customized analyses in combination with available resources. This offers innovative solutions to address major challenges such as global climate change, drought monitoring, and environmental disaster assessment.

### 2.3. Data

The NDVI data used in this study is derived from the MODIS/MOD09GA\_006\_NDVI product, which is generated from the MODIS/006/MOD09GA surface reflectance composites. This product provides daily normalized difference vegetation index (NDVI) data at a global resolution of 500 meters. Details of the product are presented in Table 1.

**Table 1. MOD09GA Product**

NAME	MIN	MAX	PIXEL SIZE	DESCRIPTION
NDVI	-1	1	463.313meters	Normalized Difference Vegetation Index

The LST data used in this study is obtained from the MODIS/061/MOD11A1 product. The MOD11A1 V6.1 product provides global daily land surface temperature (LST)

and emissivity values within a 1200 x 1200 km grid. It has a spatial resolution of 1 km, with detailed product information provided in Table 2.

**Table 2. MOD11A1 Product**

NAME	UNITS	MIN	MAX	SCALE	OFFSET	DESCRIPTION
LST_DAY_1KM	Kelvin	7500	65535	0.02		Daytime Land Surface Temperature
QC_DAY						Daytime LST Quality Indicators

To construct the drought monitoring model, appropriate MODIS datasets were retrieved from the GEE platform and subjected to a series of preprocessing steps, including vector clipping, quality control, conditional filtering, reprojection and resampling, and standardization. The specific steps carried out for this study are outlined as follows:

(1) The MODIS\_LST data used in this study is derived from the MODIS/006/MOD11A1 product, with a spatial resolution of 1 km. The key bands utilized are LST\_Day\_1km and LST\_Night\_1km. The daily mean land surface temperature (LST) was calculated by iterating through these two bands and deriving the surface temperature. The monthly

LST median was then computed to exclude outliers and represent the average monthly values. The processed data was further clipped and standardized for subsequent use.

(2) The MODIS\_NDVI data used in this study is sourced from the MODIS/MOD09GA\_006\_NDVI product. Similarly, the monthly median was calculated to eliminate anomalies. Since this product has a spatial resolution of 500 meters and contains only a single NDVI band, spatial resampling was performed to unify the resolution to 1 km. The data was also reprojected to align its coordinate system with that of the LST product. Standardization was then applied to prepare the data for subsequent analysis.

## 2.4. Method

### 2.4.1. Palmer Drought Severity Index

The Palmer Drought Severity Index (PDSI) is a widely used meteorological indicator for quantifying drought and wet conditions. It was introduced by Wayne Palmer in 1965 and primarily assesses long-term drought conditions by considering the balance between soil moisture supply and demand. PDSI has been extensively applied in various fields, such as drought comparison, spatiotemporal distribution analysis, drought area assessment, climate evaluation, and disaster assessment. In the United States, it is recognized as a semi-official drought indicator by state government agencies.

The core concept of PDSI is to determine drought or wet conditions by calculating the soil moisture balance, which represents the difference between supply and demand. The water balance equation is as follows:

$$D = P - PET - R - RO \quad (1)$$

Where,  $D$  represents the moisture deficit or surplus,  $P$  is the actual precipitation,  $PET$  is the potential evapotranspiration,  $R$  is the soil moisture recharge, and  $RO$  is the surface runoff.

The PDSI not only takes into account factors such as precipitation, temperature, and soil moisture but also incorporates evapotranspiration and soil moisture recharge rates. This makes it highly effective for identifying and assessing long-term drought conditions.

### 2.4.2. Vegetation Supply Water Index

The Vegetation Supply Water Index (VSWI) is a remote sensing-based indicator designed to assess vegetation water status. It is particularly suitable for monitoring drought and evaluating water supply conditions in agricultural vegetation.

In vegetated areas, the remotely sensed land surface temperature (LST) effectively represents the canopy temperature of vegetation. During drought conditions, crops reduce transpiration by partially closing their stomata to minimize water loss. This reduction in transpiration leads to an increase in canopy temperature, making it a useful indicator of crop water supply status. In areas with high vegetation coverage, LST is commonly used as a proxy for canopy temperature. Additionally, the Normalized Difference Vegetation Index (NDVI), obtained from meteorological satellite remote sensing, is a widely used indicator for assessing vegetation growth status [15].

The Vegetation Supply Water Index (VSWI) integrates the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) to infer vegetation water supply status based on their relationship. The calculation formula is as follows:

$$VSWI = \frac{NDVI}{LST} \quad (2)$$

Where,

By combining NDVI and LST, the VSWI effectively reflects the health status of vegetation under varying water supply conditions. When the VSWI value is high, it indicates a high NDVI and low LST, suggesting healthy vegetation with sufficient water supply. Conversely, a low VSWI value reflects low NDVI or high LST, indicating water stress or insufficient supply. Since this index integrates factors from both biological and physical domains, it is particularly suitable for drought monitoring in areas with high vegetation

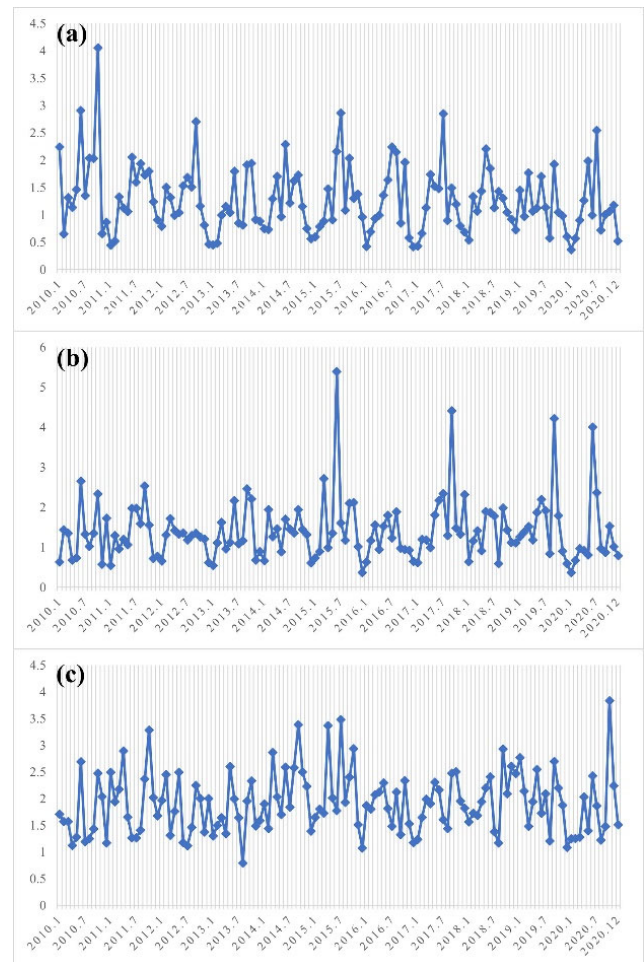
coverage.

For the three northeastern provinces, where croplands exhibit good vegetation coverage, the VSWI is well-suited for drought assessment.

## 3. Result

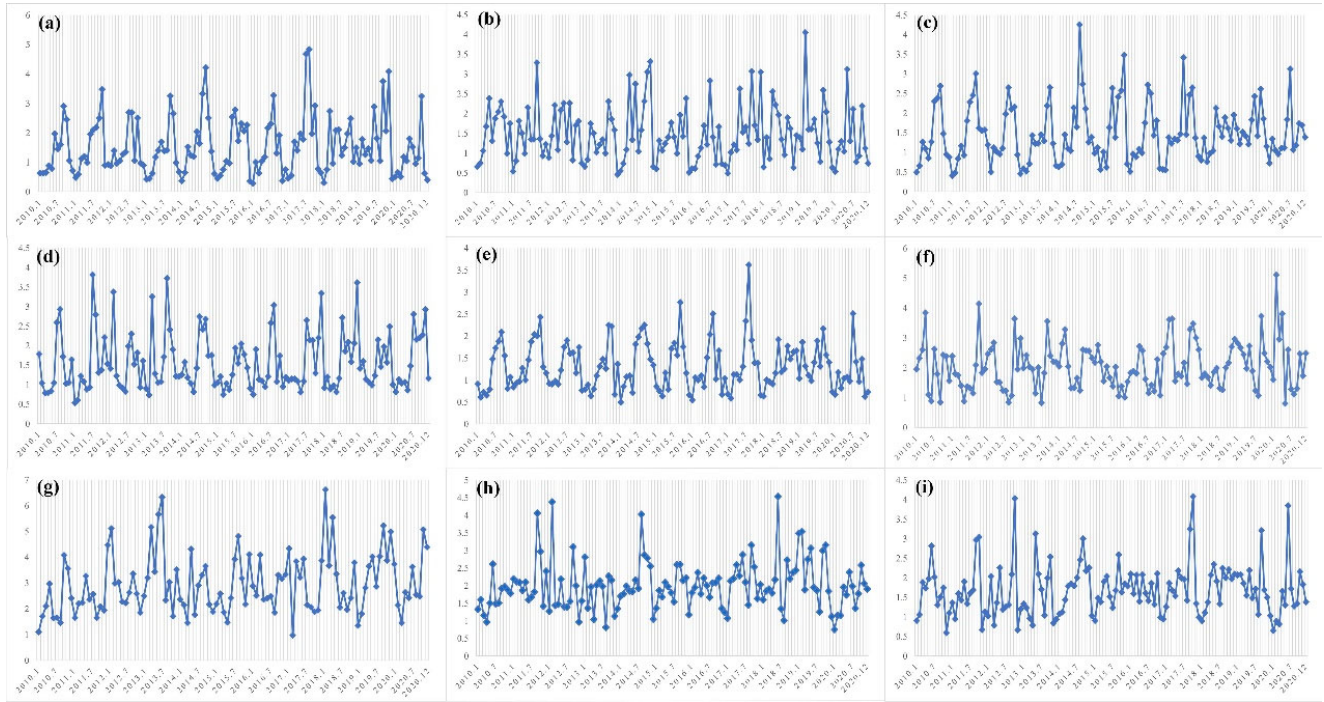
### 3.1. Temporal Variation Characteristics of Drought in the Study Area

From Fig 1 show the analysis of the monthly average VSWI values across the provinces, fluctuations in VSWI have been observed in Northeast China over the past decade. The monthly average VSWI in Heilongjiang Province generally ranged between 0.5 and 3, while in Jilin Province, most values also concentrated within the 0.5 to 3 range. In contrast, Liaoning Province exhibited a broader fluctuation range, spanning from 1 to 3.5. Overall, the temporal variation of VSWI in each province remained relatively stable without significant seasonal fluctuations.



**Figure 1.** Temporal Variation of VSWI in Northeast China (2010–2020):(a) Heilongjiang, (b) Jilin, and (c) Liaoning.

To further investigate the spatiotemporal characteristics of drought, key meteorological stations in major agricultural areas of each province were selected. Around these stations, 3x3 analysis windows were established for small-scale drought time series analysis (Fig.2). The statistical results of monthly average VSWI in localized areas revealed more pronounced patterns in temporal variation.



**Figure 2.** Temporal Analysis of VSWI in Key Agricultural Regions of Northeast China: (a) Harbin, (b) Jiamusi, (c) Qiqihar, (d) Baicheng, (e) Changchun, (f) Yanji, (g) Fuxin County, (h) Shenyang, (i) Fushun.

In Heilongjiang Province, three meteorological stations—Harbin, Jiamusi, and Qiqihar—were selected to analyze the monthly average VSWI values for their surrounding areas. The analysis results revealed a generally consistent trend across these regions: VSWI slightly increased from January to March, showed a slight decline in April and May, significantly rose from June to September, and then dropped sharply from October to December. However, during 2018, the typical significant increase in VSWI values from June to September was not observed in Harbin and Qiqihar, indicating poor crop growth in these areas.

Further investigation found that the precipitation in Harbin and Qiqihar during the spring of 2018 was significantly below normal. Specifically, precipitation in Heilongjiang Province during April and May was 39% lower than the historical average and 51% less compared to 2017. This provides a plausible meteorological explanation for the anomalous fluctuations in VSWI observed in 2018.

In Jilin Province, three meteorological stations—Baicheng, Changchun, and Yanji—were selected to analyze the monthly average VSWI values. The spatiotemporal characteristics of drought varied across the stations. Changchun's VSWI trend was similar to that of Harbin, likely due to their close geographic proximity and comparable climatic and drought conditions. Baicheng and Yanji, located in the western and eastern parts of Jilin Province, respectively, exhibited distinct drought characteristics.

Overall, winter drought conditions alleviated to some extent, while drought intensified from July to September. Specifically, from April to June, drought frequency was higher in Yanji, whereas Baicheng experienced peak drought conditions from July to September. Additionally, from January to March, VSWI values in both Yanji and Baicheng were generally low.

In Liaoning Province, meteorological stations in Fuxin County, Shenyang, and Fushun were selected for monthly

average VSWI analysis. For these three areas, the variation in the VSWI index was generally not significant during most periods. However, starting in July, all stations showed a marked downward trend, indicating a higher frequency of droughts in autumn compared to other seasons.

Overall, the spatiotemporal characteristics of drought varied across different regions within each province, but seasonal fluctuations were generally observed, with a notably higher frequency of droughts in summer and autumn. Detailed time-series analysis of monthly average VSWI provides a more precise understanding of the spatiotemporal dynamics of drought, offering scientific support for drought assessment and the development of early warning and response strategies.

### 3.2. Qualitative Evaluation of Drought Assessment Index Results Based on GEE

Using monthly PDSI data from meteorological stations as ground truth, a random selection of stations previously used for long-term vegetation drought index statistics was made. The original VSWI and PDSI data were subjected to intra-annual temporal correlation analysis to evaluate the consistency between the remote sensing monitoring model (VSWI) and PDSI in capturing drought variations within a year. The results are presented in Fig.3.

From the correlation analysis of the line charts, it can be observed that the VSWI and PDSI exhibit good agreement, with high consistency in their trends when describing intra-annual drought variations. This indicates that the vegetation drought index derived from MODIS effectively reflects drought dynamics.



**Figure 3.** Temporal Analysis of PDSI Ground Truth and VSWI in Northeast China (2010): (a) Jiamusi, (b) Yanji, (c) Fuxin.

## 4. Conclusion

The study focused on analyzing the spatiotemporal characteristics of drought in Northeast China's three provinces from 2010 to 2020. Using time-series MODIS data products and leveraging the GEE platform, an appropriate remote sensing drought index, the Vegetation Supply Water Index (VSWI), was applied to analyze drought patterns in the target area. Additionally, the study examined the correlation between the VSWI and meteorological station data (PDSI) to assess its feasibility. The main conclusions are as follows:

(1) As a cloud computing platform for storing and processing global satellite remote sensing imagery and other Earth observation data, GEE offers significant advantages, including high computational power and diverse, multi-source remote sensing data. Researchers can import customized data and write scripts to achieve spatial analysis and data processing for specific study areas. GEE demonstrates efficiency and speed in monitoring drought temporal characteristics over long time periods.

(2) The VSWI used in this study showed strong regularity in describing the spatiotemporal characteristics of drought in Heilongjiang Province, effectively capturing drought patterns. For Jilin and Liaoning provinces, the regularity was slightly weaker. A temporal correlation analysis with PDSI data

qualitatively revealed a good correlation, indicating that the VSWI constructed using GEE and MODIS data can effectively reflect temporal drought variations.

(3) While the VSWI as a single index is effective for analyzing long-term drought characteristics, it has certain limitations in reflecting overall drought variability. Future studies should integrate additional indices to conduct more comprehensive drought analyses. Moreover, since the VSWI is derived from the coupling of NDVI and canopy temperature, its accuracy is highly time-sensitive. Using monthly averages reduces data precision, potentially impacting subsequent research accuracy.

This study aims to explore whether remote sensing drought models based on big data platforms like GEE can serve as an alternative to traditional methods for analyzing spatiotemporal drought characteristics. It is hoped that this research contributes to advancing the development of more complex and refined remote sensing drought monitoring models using big data and cloud computing platforms in the future.

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