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Developing and Validating a Liaoning Drought Monitor with Multi-Source Remote Sensing Downscaling and Land-Surface Thermal Correction

Bihao Gao¹ , Songshi Zhao¹ , Xiaolei Yang² , Wei Xu¹ , Dali Guo¹ , Hongyu Zhang¹ , Maosen Lin^{1*} 

¹ College of Water Conservancy, Shenyang Agricultural University, Shenyang 110161, China

² Architectural Engineering Institute, City Institute, Dalian University of Technology, Dalian 116600, China

ABSTRACT

The low spatial resolution of the Integrated Multi-satellite Retrievals for Global Precipitation Measurement (IMERG), a mainstream Global Precipitation Measurement (GPM) product, limits its use in refined drought analysis over complex monsoon underlying surfaces. To resolve this issue, this study proposes an integrated meteorological drought monitoring framework (SPTI), which enhances accuracy by coupling 0.05° downscaled IMERG precipitation data with Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) data. First, a Normalized Difference Vegetation Index (NDVI)-topography guided multivariate regression kriging downscaling scheme was built using monthly precipitation data from 23 Liaoning stations (2010–2018), geographic-topographic factors, and NDVI covariates, downscaling original 0.1° IMERG data to 0.05° (achieving $R^2 > 0.7$ in ten months, except for June and July). Second, a high-performance multi-source drought model was established via regression of Standardized Precipitation Evapotranspiration Index (SPEI) against downscaled IMERG-Z Index (derived from IMERG precipitation using the drought Z-index method) and Temperature Condition Index (TCI). Finally, SPTI was validated with four typical Liaoning drought events during 2014, 2015, 2017, and 2018. Results show that: (1) 0.05° precipitation data captures fine spatial details, clearly depicting Liaoning's southeast-to-northwest precipitation gradient and central plain rainfall zones; (2) SPTI outperforms standalone IMERG-Z—it accurately identifies severe/extreme droughts, mitigates IMERG-Z's underestimation bias, and reasonably characterizes drought alleviation after heavy rains by integrating TCI, avoiding IMERG-Z's “abrupt drought-to-waterlogging” misjudgment; (3)

*CORRESPONDING AUTHOR:

Maosen Lin, College of Water Conservancy, Shenyang Agricultural University, Shenyang 110161, China; Email: imsen2007@126.com

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SPTI results align well with the Liaoning Meteorological Disaster Bulletin, confirming its suitability for refined monsoon drought monitoring.

Keywords: Drought Monitoring; Multiple Regression; IMERG Downscaling; Standardized Precipitation Evapotranspiration Index; Liaoning Region

1. Introduction

Drought, as a long-term climatic phenomenon, is typically characterized by precipitation levels significantly below normal^[1]. As one of the most widespread, prolonged, and economically damaging climate-related hazards globally, drought imposes systemic impacts on ecological balance, agricultural production, water resource security, and sustainable socio-economic development^[2,3]. Against the backdrop of global warming, adjustments in atmospheric circulation patterns further exacerbate drought risk, leading not only to a significant increase in the frequency, duration, and intensity of drought events^[4] but also intensifying derivative issues such as ecological degradation^[5], crop yield reduction^[6], and water scarcity, posing a serious threat to regional sustainable development. Therefore, establishing accurate drought monitoring is crucial for early warning of droughts and also facilitates the rational utilization of resources and the protection of the ecological environment.

Current drought monitoring research primarily relies on various drought indices^[7], which can be categorized into two main types based on data sources: drought indices based on ground observations (meteorological stations, agro-ecological stations) and those based on remote sensing data^[3]. To overcome the limitations of single-index monitoring, scholars have increasingly explored multi-factor integration methods, forming two main technical approaches: weight-based methods and machine learning methods^[8,9]. In the application of weight-based methods, Rhee et al.^[10] employed the Analytic Hierarchy Process (AHP) to subjectively assign weights to the Precipitation Condition Index (PCI), TCI, and Vegetation Condition Index (VCI), constructing the Scaled Drought Condition Index (SDCI) for drought monitoring in the southeastern United States. While this method achieved preliminary integration of multiple factors, the subjective weighting is prone to introducing human bias, and the static weighting system cannot adapt to the dynamic evolution characteristics of drought across different regions

and periods, making it difficult to accurately capture drought response differences over complex underlying surfaces^[11]. To enhance model objectivity, Liu et al.^[12] utilized multiple linear regression to integrate PCI, GLDAS soil moisture data, TCI, and VCI, constructing the Multi-sensor Comprehensive Drought Index (MCDIs) and successfully applying it to drought monitoring in Shandong Province. This approach not only avoids the defects of subjective weighting but also offers clear physical interpretability, enabling the identification of the contribution of each driving factor to drought formation and providing direct support for drought cause analysis and response decision-making. However, traditional linear regression models struggle to capture potential nonlinear relationships among drought factors. In complex scenarios such as monsoon regions characterized by high temperatures, humidity, and significant precipitation variability, their monitoring accuracy can be limited^[13]. With the advancement of artificial intelligence technologies, Danandeh Mehr et al.^[14] introduced machine learning methods, developing a Genetic Random Forest (GeRF) model based on meteorological station precipitation and temperature data to predict dry and wet events using the SPEI-3 and SPEI-6 indices. Machine learning methods demonstrate significant advantages in handling complex data relationships due to their powerful nonlinear fitting capabilities. However, they also have inherent limitations, relying heavily on high-quality, large-sample training data. In regions with sparse meteorological stations or poor data continuity, they are prone to overfitting or prediction bias^[15]. In comparison, multiple linear regression offers distinct advantages in terms of interpretability, data requirements, and stability. To address its limitations regarding linear assumptions, existing studies often optimize model input by introducing high-resolution data or supplementing key driving factors, thereby enhancing its representational capacity while maintaining model simplicity and interpretability^[16,17]. Following this approach, this study chooses to construct the final drought monitoring model within the multiple linear regression framework by

integrating optimized high-resolution data. However, the acquisition of high-resolution data relies on high-quality satellite precipitation products and efficient downscaling techniques.

Current global precipitation products exhibit diverse characteristics, ranging from earlier series products like the Tropical Rainfall Measuring Mission (TRMM) to subsequent products such as the Fengyun-3 (FY-3) precipitation series. Different products have their own emphases in terms of spatiotemporal resolution, coverage, and accuracy^[18,19]. Among them, the series of satellites launched by the GPM mission in 2014 have significantly enhanced the precipitation retrieval accuracy and performance stability of various sensors by integrating multi-satellite observation data with ground calibration information^[20]. Its core product, IMERG, has become a preferred data source for drought research due to its prominent advantages and has been widely applied^[21–23]. However, most existing studies use the original 0.1° resolution IMERG data, which is insufficient for fine-scale drought monitoring needs. Research on applying downscaling techniques to enhance its resolution for drought monitoring remains relatively limited.

Spatial downscaling techniques can generate precipitation products with improved accuracy and resolution compared to the original data by leveraging information from high-resolution auxiliary variables^[24,25]. These techniques are mainly divided into two categories: dynamics-based and statistics-based methods. Among them, statistical downscaling methods are more widely applied in drought monitoring-related studies due to their operational flexibility, lower computational resource requirements, and ability to effectively integrate regional characteristic information such as topography and vegetation. Among various statistical downscaling models, combination schemes integrating multiple regression and Kriging interpolation perform particularly well, as they balance global fitting with local error correction. For example, Sun et al.^[26] successfully downscaled monthly GPM/IMERG precipitation data from 0.1° to 1 km in Hubei Province, China, by integrating Geographically Weighted Regression with a Multifractal model using topographic and temperature variables. This approach not only enhanced spatial resolution but also effectively corrected systematic biases. In the complex terrain of southern Syria, Alsafadi et al.^[27] incorporated novel covariates such as cloud cover frequency

and employed a Regression Kriging framework. Their study demonstrated the superior capability of this hybrid method to generate high-precision, physically interpretable precipitation fields in data-sparse regions, offering a practical and robust solution for fine-scale precipitation modeling in topographically challenging areas. It served as a reliable technical reference for obtaining high-resolution precipitation data in this study.

In addressing the challenges of global climate change, timely and accurate drought monitoring is a crucial theoretical foundation for drought prevention and disaster reduction in Liaoning Province. The specific objective of this study is to develop a comprehensive drought monitoring model suitable for Liaoning and validate the monitoring results of this model. The main research questions are: (a) to construct a downscaling model for IMERG and perform a consistency test for the IMERG-Z index; (b) to develop a comprehensive drought monitoring model for Liaoning Province using meteorological station and remote sensing data; (c) to validate the accuracy and reliability of the drought monitoring model's results.

2. Materials and Methods

2.1. Overview of the Study Area

Liaoning Province is situated in northeastern China (38°43′–43°26′ N, 118°53′–125°46′ E) and serves as one of the country's major grain-producing regions. Characterized by a temperate continental monsoon climate, the terrain exhibits a northeast–southwest orientation, featuring higher elevations in the east, gentle slopes in the west, and a relatively flat central plain. Precipitation is unevenly distributed throughout the year, with the majority concentrated in summer, aligning with high temperatures in a typical “rain-heat synchrony” pattern. Annual precipitation ranges from 450 to 1150 mm, generally decreasing from southeast to northwest^[28]. The mean annual temperature varies between 5.6 °C and 10.9 °C. These specific climatic and topographic conditions contribute to frequent regional drought disasters, which have become a major meteorological hazard constraining agricultural production and ecological security. Drought in Liaoning occurs primarily in spring, accounting for over 70% of annual drought events. Summer occasionally experiences “high-temperature and low-rainfall” drought, which

can coincide with spring drought to form prolonged dry spells, thereby amplifying disaster impacts—a phenomenon often summarized as “nine droughts in ten years.” Vegetation cover in Liaoning is dominated by deciduous broadleaf forests, which are most abundant and widely distributed in the eastern mountainous areas. From southwest to northeast in western Liaoning, vegetation gradually transitions from arboreal to grassland types. Major land cover categories include cropland, forest, grassland, water bodies, built-up areas, and bare land. Approximately 70% of the cropland is concentrated in the central region^[29]. During droughts, insufficient soil moisture readily threatens grain production security, underscoring the necessity for precise drought monitoring research in this area.

2.2. Data Sources and Processing

2.2.1. Data Sources

The datasets selected for this study mainly include meteorological station data, remote sensing data, and statistical data. The meteorological station data consists of monthly measured precipitation values from 23 meteorological

stations in Liaoning Province from 1960 to 2018, obtained from the National Meteorological Information Center (<http://data.cma.cn/>). The spatial distribution of the meteorological stations is shown in **Figure 1**. The remote sensing datasets include GPM IMERG, MODIS, NDVI, and SRTM datasets. The IMERG Version 06 monthly precipitation product used in this study was released on March 13, 2019, with a temporal resolution of one month and a spatial resolution of 0.1° , covering the period from 2010 to 2018. The MODIS data comprises the MOD13C2 V6 dataset and the MOD11C3 V6 dataset. MOD13C2 is an NDVI monthly composite dataset created using a maximum value composite of the original NDVI data over the 30 days of the month, with a resolution of $0.05^\circ \times 0.05^\circ$ ^[30,31]. MOD11C3 is a monthly dataset of land surface temperature (LST), with global imagery acquired monthly at a resolution of $0.05^\circ \times 0.05^\circ$. The elevation data is from the SRTM DEM V4.1 dataset, with a spatial resolution of $90\text{ m} \times 90\text{ m}$. A description of the data and their sources is provided in **Table 1**. Additionally, statistical data includes drought records for Liaoning Province from 2014, 2015, 2017, and 2018 and the “Liaoning Province Meteorological Disaster Bulletin.”

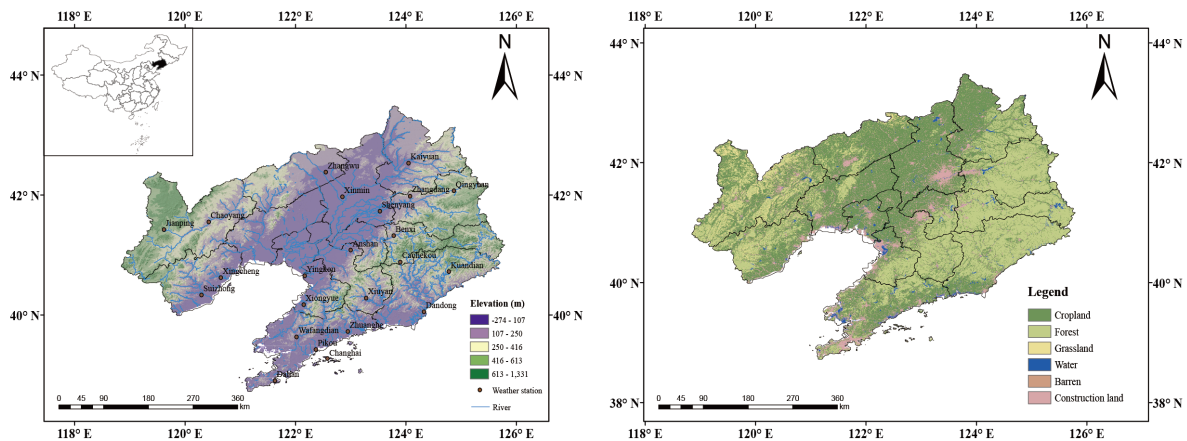


Figure 1. Map of topography, rivers, weather stations and land cover in Liaoning region.

Table 1. Description and sources of remotely sensed data.

Data	Description	Source
Meteorological data	Monthly precipitation data	National Meteorological Information Center (http://data.cma.cn/)
GPM IMERG ($0.1^\circ \times 0.1^\circ$)	Monthly precipitation dataset	NASA Precipitation Measurement Mission website (https://pmm.nasa.gov)
MOD11C3 V6 ($0.05^\circ \times 0.05^\circ$)	Monthly land surface temperature dataset	NASA LAADS website (https://ladsweb.modaps.eosdis.nasa.gov)
MOD13C2 V6 ($0.05^\circ \times 0.05^\circ$)	NDVI monthly composite dataset	
SRTM DEM ($90\text{ m} \times 90\text{ m}$)	Elevation data	Geospatial Data Cloud (http://www.gscloud.cn/)

2.2.2. Processing of Remote Sensing Data

The IMERG remote sensing precipitation data is expressed in units of precipitation rate (mm/h), and a raster image of monthly precipitation (in units of mm) is obtained by converting the units using the ArcGIS 10.2 (a Geographic Information System software, version 10.2) raster calculator. The region vector boundary is then used to clip the precipitation data to obtain the precipitation information for Liaoning Province. The latitude and longitude coordinates of the 23 meteorological stations in Liaoning Province are imported into ArcGIS, and the pixel values for each station's corresponding raster position on the IMERG monthly precipitation map from 2010 to 2018 are extracted to obtain the remote sensing precipitation data for each meteorological station. The MOD13C2 and MOD11C3 datasets were transformed into the commonly used GCS_WGS_1984 coordinate system

using ArcGIS, and the NDVI and LST images of each month were clipped to obtain the NDVI and LST values for each month in Liaoning Province. The NDVI values for each meteorological station were standardized. Since there may be missing or anomalous values in the surface temperature data due to weather conditions such as clouds or other adverse factors during satellite overpasses, the surface temperature data must be checked and the missing data and anomalous values removed^[32]. In addition, using the DEM data and the latitude and longitude coordinates of the meteorological stations in Liaoning Province, the 3D Analyst and Appatial Analyst tools in the ArcGIS toolbox were utilized to extract the pixel elevation and slope values corresponding to the raster position on the elevation map and slope map, thereby obtaining the elevation and slope data for each meteorological station in Liaoning Province based on the remote sensing data. The detailed workflow is illustrated in **Figure 2**.

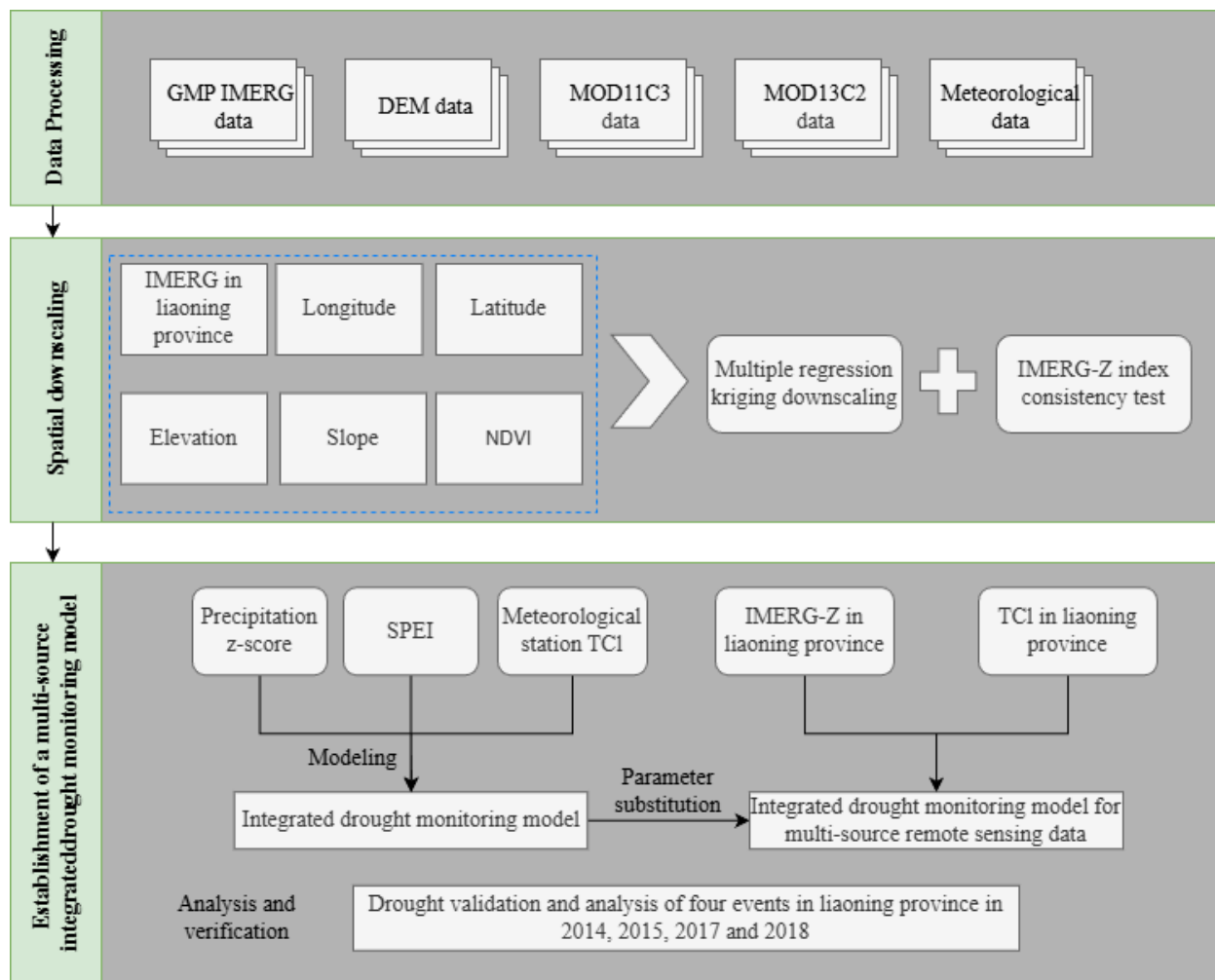


Figure 2. Flowchart of this approach.

3. Research Methods

3.1. IMERG Monthly Downscaling Study

Through extensive research, scholars, both domestically and internationally, have found that factors such as geographic location, topography, climate, and vegetation indices significantly influence precipitation's spatial and temporal distribution^[33]. This study uses a multiple stepwise regression method, utilizing SPSS analysis software to comprehensively analyze the impact of geographic factors (longitude lon , latitude lat), topographic factors (elevation DEM , slope), and monthly vegetation factors ($NDVI$, $NDVI_2$, $NDVI_3$) on precipitation. The aim is to establish the optimal relationship between GPM IMERG precipitation data and precipitation influencing factors and to construct a downscaling model that downscales the GPM IMERG data to a resolution of $0.05^\circ \times 0.05^\circ$. The formula is as follows Equation (1).

$$\begin{aligned} IMERG = & \alpha_0 + \alpha_1 \cdot NDVI + \alpha_2 \cdot NDVI^2 \\ & + \alpha_3 \cdot NDVI^3 + \alpha_4 \cdot lon + \alpha_5 \cdot lat \quad (1) \\ & + \alpha_6 \cdot DEM + \alpha_7 \cdot slope \end{aligned}$$

In the equation: $IMERG$ represents the downscaled precipitation values, α_i denotes the fitting coefficient, lon represents longitude, lat represents latitude, DEM represents elevation, and $slope$ represents slope.

The specific downscaling method is as follows: First, the $NDVI$ and DEM are resampled to the corresponding resolution of the GPM IMERG data, where 0.1° corresponds to a resolution of LR and 0.05° corresponds to a resolution of HR.

Then, a multiple linear regression equation is established at a resolution of 0.1° (low resolution):

$$\begin{aligned} P_{LR} = & \alpha_0 + \alpha_1 \cdot NDVI_{LR} + \alpha_2 \cdot NDVI_{LR}^2 \\ & + \alpha_3 \cdot NDVI_{LR}^3 + \alpha_4 \cdot lon + \alpha_5 \cdot lat \quad (2) \\ & + \alpha_6 \cdot DEM_{LR} + \alpha_7 \cdot slope_{LR} \end{aligned}$$

$$\Delta_{LR} = IMERG_{LR} - P_{LR} \quad (3)$$

In the equation, Δ_{LR} represents the residual between the predicted precipitation value from the model and the

GPM IMERG remote sensing precipitation data. The residual value Δ_{HR} at a resolution of $0.05^\circ \times 0.05^\circ$ is obtained using the Kriging interpolation method.

The high-resolution precipitation prediction value P_{HR} (mm) is estimated using Equation (4), and the downscaled precipitation data is corrected using the high-resolution residual value Δ_{HR} , ultimately resulting in the high-resolution GPM IMERG remote sensing precipitation data D:

$$\begin{aligned} P_{HR} = & \alpha_0 + \alpha_1 \cdot NDVI_{HR} + \alpha_2 \cdot NDVI_{HR}^2 \\ & + \alpha_3 \cdot NDVI_{HR}^3 + \alpha_4 \cdot lon + \alpha_5 \cdot lat \quad (4) \\ & + \alpha_6 \cdot DEM_{HR} + \alpha_7 \cdot slope_{HR} \end{aligned}$$

$$IMERG_{HR} = P_{HR} + \Delta_{HR} \quad (5)$$

In the equation, $NDVI_{HR}$, DEM_{HR} , and $slope_{HR}$ represent the high-resolution ($0.05^\circ \times 0.05^\circ$) $NDVI$ data, DEM data, and slope data, respectively.

3.2. Calculation of Drought Index

(1) Precipitation Z index

The precipitation Z index indicates the severity and spatial distribution of drought and flood conditions^[34,35]. It assumes that precipitation over a specific period follows a P-III type distribution. Normalizing the precipitation data transforms the probability density function into a standard normal distribution with respect to the Z variable^[36]. Based on the precipitation characteristics of Liaoning Province and referencing the corrected boundary values of the Z index drought and flood levels proposed by other scholars for different regions^[37,38], which can correspond to the SPI drought levels, the adjusted drought and flood severity levels are shown in

Table 2. The calculation formula is as follows:

$$Z_i = \frac{6}{C_S} \left(\frac{C_S}{2} \phi_i + 1 \right)^{\frac{1}{3}} - \frac{6}{C_S} + \frac{6}{C_S} \quad (6)$$

In the equation, C_S represents the skewness coefficient, and ϕ_i represents the standard variable, which can be calculated from the monthly precipitation sequence.

Table 2. Z index of drought and flood levels.

Level	Z Value	Drought/Flood Severity
1	$Z > 1.602$	Severe flood
2	$1.037 < Z \leq 1.602$	Moderate flood

Table 2. Cont.

Level	Z Value	Drought/Flood Severity
3	$0.552 < Z \leq 1.037$	Mild flood
4	$-0.552 \leq Z \leq 0.552$	Normal
5	$-0.84 \leq Z < -0.552$	Mild drought
6	$-1.10 \leq Z < -0.84$	Moderate drought
7	$-1.602 \leq Z < -1.10$	Severe drought
8	$Z < -1.602$	Extreme drought

$$C_S = \frac{\sum_{i=1}^n (x_i - \bar{x})^3}{n\delta^3} \quad (7)$$

$$\phi_i = \frac{x_i - \bar{x}}{\delta} \quad (8)$$

$$\delta = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (9)$$

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (10)$$

In the equations, δ represents the standard deviation, x_i represents the monthly precipitation sequence, and $\bar{x}$ is the mean monthly precipitation, with all units in mm. If $\bar{x} > 60$ mm, no correction is needed; if $\bar{x} < 60$ mm, then $\bar{x}$ is set to 60 mm.

(2) Standardized precipitation index

The calculation of the Standardized Precipitation Index (SPI)^[39] first involves transforming the Gamma distribution probability of precipitation over a given period,

followed by normalization to a standard normal distribution, and finally dividing the probability distribution of standardized precipitation accumulation levels into drought categories^[40,41]. Based on the “Meteorological Drought Levels GB/T 20481-2017” standard, the SPI drought levels are shown in **Table 3**. The calculation steps are as follows:

$$SPI = S \left\{ t - \frac{(c_2 t + c_1)t + c_0}{[(d_3 t + d_2)t + d_1]t + 1.0} \right\} \quad (11)$$

In the above formula, $t = \sqrt{\ln \frac{1}{F^2}}$, F is the precipitation distribution probability associated with the Gamma function, and S is the positive and negative coefficient of the probability density function. Specifically, when $F > 0.5$, $S = 1$; when $F \leq 0.5$, $S = -1$. $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

Table 3. SPI and SPEI drought classification levels.

Level	SPI Value	SPEI Value	Type
1	$-0.5 < SPI$	$-0.5 < SPEI$	Normal
2	$-1.0 < SPI \leq -0.5$	$-1.0 < SPEI \leq -0.5$	Mild drought
3	$-1.5 < SPI \leq -1.0$	$-1.5 < SPEI \leq -1.0$	Moderate drought
4	$-2.0 < SPI \leq -1.5$	$-2.0 < SPEI \leq -1.5$	Severe drought
5	$SPI \leq -2.0$	$SPEI \leq -2.0$	Extreme drought

The probability density integration formula for the Gamma distribution function is used to calculate F , and the formula is as follows:

$$F(x < x_0) = \frac{1}{\beta^\gamma \Gamma(\gamma)} \int_0^{x_0} x^{\gamma-1} e^{-x/\beta} dx, \quad x > 0 \quad (12)$$

In the equation, $\beta > 0$ represents the scale parameter, and $\gamma > 0$ represents the shape parameter, both of which can be estimated using the maximum likelihood estimation method. The calculation formulas are as follows:

$$\hat{\gamma} = \frac{1 + \sqrt{1 + 4A/3}}{4A} \quad (13)$$

$$\hat{\beta} = \bar{x} / \hat{\gamma} \quad (14)$$

$$A = \lg \bar{x} - \frac{1}{n} \sum_{i=1}^n \lg x_i \quad (15)$$

In the equations, x_i represents the precipitation data sample, and $\bar{x}$ represents the average precipitation, with units in mm.

(3) Standardized precipitation evapotranspiration index

The Standardized Precipitation Evapotranspiration Index (SPEI) characterizes the degree of drought by calculating the deviation from the mean difference between precipitation and potential evapotranspiration. Firstly, the difference between monthly precipitation and potential evapotranspiration is calculated and normalized using a 3-parameter log-logistic probability distribution^[40]. Finally, the probability distribution of standardized precipitation and evapotranspiration difference levels is divided into drought categories (see **Table 3**). The calculation formula is as follows:

The difference between monthly precipitation and evapotranspiration:

$$D_i = P_i - PET_i \quad (16)$$

In the equation, P_i represents monthly precipitation, and PET_i represents potential evapotranspiration. This study calculates potential evapotranspiration using the Thornthwaite method. The specific calculation process can be found in the studies of Xia et al.^[42–45].

Normalization is performed using a 3-parameter log-logistic probability distribution:

$$F(x) = \left[1 + \left(\frac{\alpha}{x - r} \right)^\beta \right]^{-1} \quad (17)$$

In the equation, α is the scale parameter, β is the shape parameter, and γ is the location parameter. The parameters are fitted using the method of linear moments.

The probability density is then standardized:

$$W = \sqrt{-2 \ln(P)} \quad (18)$$

$$SPEI = W - \frac{c_0 - c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad (19)$$

When $P \leq 0.5$, $P = 1 - F(x)$; when $P > 0.5$, $P = 1 - P$, and the sign of SPEI is reversed. The constant values are $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

(4) IMERG-Z index

The IMERG-Z index is calculated based on the precipitation Z index algorithm using the IMERG remote sensing precipitation data from 2010–2018.

(5) Temperature condition index (TCI)

The Temperature Condition Index (TCI) is a thermodynamic remote sensing index based on land surface

temperature (LST)^[46], which characterizes drought phenomena about temperature. The TCI index calculation method is based on a time series of maximum and minimum land surface temperature values. The TCI calculation formula is as follows:

$$TCI_i = \frac{LST_{i_{max}}}{LST_{i_{min}}} \quad (20)$$

In the equation, TCI_i represents the TCI index of the i -th pixel; LST_i represents the land surface temperature of the i -th pixel; LST_{max} and LST_{min} are the maximum and minimum land surface temperatures of that pixel for each month from 2010 to 2018, with units in °C. It is generally believed that the closer the TCI is to 0, the more severe the drought conditions are. This study calculated the Temperature Condition Index (TCI) for each month corresponding to 23 meteorological stations in Liaoning Province from 2010 to 2018.

3.3. Construction of Integrated Drought Monitoring Model

Considering that the time series of IMERG remote sensing precipitation data is relatively short, this study is based on a drought monitoring model calculated using long-term observational data from meteorological stations. We utilized meteorological data from 23 stations in Liaoning Province from 1960 to 2018 to compute the SPEI, SPI, and the precipitation Z-index. Additionally, we extracted IMERG-Z indices corresponding to the precipitation data from 2010 to 2018 for these 23 meteorological stations in Liaoning Province and the corresponding TCI for each month. First, based on the methods for classifying drought levels using the SPI and Z indices, we statistically analyzed the frequency of drought occurrences and the number of different drought levels in each meteorological station from 2010 to 2018. This comparison was conducted to evaluate whether the IMERG-Z index can effectively represent the drought conditions in Liaoning Province. Next, we established an optimal correlation model using multiple stepwise regression analysis, with the SPEI series as the dependent variable and the precipitation Z index and TCI series as independent variables. Based on the previous accuracy assessment of GPM IMERG remote sensing precipitation data, it was confirmed that the IMERG data is highly applicable for monitoring droughts in Liaoning Province^[47]. The IMERG-Z index, based on

IMERG remote sensing precipitation data, was employed in place of the precipitation Z index in the model, ultimately resulting in the development of the Integrated Meteorological Drought Monitoring Index (SPTI) for Liaoning Province, using multi-source remote sensing data.

4. Results

4.1. Downscaling Analysis of Monthly Precipitation from IMERG Data

We conducted linear regression analysis using the monthly precipitation sequences extracted from IMERG data for various meteorological stations from 2010 to 2018, along with geographic factors (longitude, latitude), topographic

factors (elevation, slope), and vegetation factors (NDVI). The parameters of the regression models for each month are presented in **Table 4** below.

In **Table 4**, the fitting coefficient $\alpha_i = 0.000$ indicates an excluded variable. All monthly stepwise regression models passed the significance test ($P < 0.01$). The test statistics for the regression models for each month are presented in **Table 5**. A higher goodness-of-fit (R^2) value, closer to 1, along with a larger F-value and a P -value below the significance level (0.05), indicates that the established regression equations are more significant. From the table, it can be observed that, except for June and July, the goodness-of-fit (R^2) for the other months is above 0.7, with February exhibiting the highest goodness-of-fit ($R^2 = 0.968$).

Table 4. Parameters of the optimal model for each month.

Month	α_0	α_1	α_2	α_3	α_4	α_5	α_6	α_7
January	-87.739	36.533	-278.059	562.345	1.161	-1.212	0.002	-0.007
February	-388.947	17.104	0.000	-144.653	4.177	-2.694	0.004	-0.014
March	-364.525	23.818	-59.472	0.000	3.072	0.000	0.005	0.000
April	-368.429	51.466	-222.678	257.692	5.114	-5.355	0.000	0.000
May	-726.118	-15.762	43.407	-40.115	7.194	-2.014	0.000	0.000
June	-90.269	0.000	0.000	16.518	1.815	-0.815	0.012	0.000
July	-963.904	0.000	47.876	0.000	17.194	-23.916	0.020	0.248
August	-1377.641	0.000	26.391	0.000	25.143	-37.263	0.009	0.348
September	-381.245	-80.045	149.842	-84.660	5.990	-6.954	0.018	0.000
October	-396.052	0.000	15.473	0.000	3.885	-0.963	0.002	0.000
November	-524.489	0.000	0.000	0.000	7.496	-8.784	0.014	-0.083
December	-524.489	37.920	-199.747	295.352	3.212	-1.231	0.005	0.000

Table 5. Model R^2 and test statistics of each month.

Month	R^2	F
January	0.936	3328.898
February	0.968	7938.544
March	0.912	4145.844
April	0.930	3501.276
May	0.885	2440.424
June	0.436	308.491
July	0.698	735.802
August	0.928	4080.686
September	0.762	850.230
October	0.725	1050.648
November	0.942	6447.539
December	0.943	4383.803

Using August 2018 as an example, the downscaling process was employed to obtain the IMERG remotely sensed precipitation value and the high-resolution ($0.05^\circ \times 0.05^\circ$) remotely sensed precipitation value (**Figure 3**) with a resolution of $0.1^\circ \times 0.1^\circ$. Comparing the two, it's evident that the overall spatial distribution of precipitation data before and after downscaling is consistent, showing a decreasing trend from south to north, with some areas in central Liaoning and

southeast Liaoning experiencing relatively abundant rainfall. The spatial resolution of data before downscaling was low, resulting in unclear local spatial precipitation characteristics. However, the spatial resolution of data after downscaling was significantly increased to $0.05^\circ \times 0.05^\circ$, indicating a substantial improvement in the field, with more detailed spatial precipitation characteristics than the original data, particularly in regions with higher precipitation.

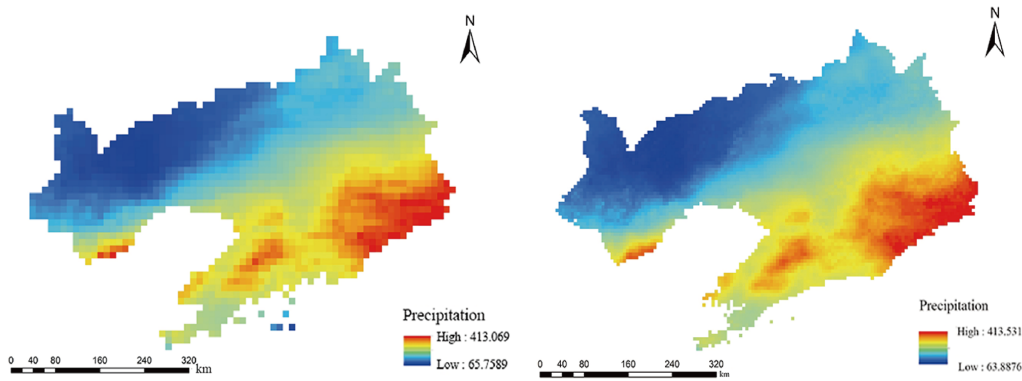


Figure 3. Raw 0.1° IMERG precipitation data and 0.05° downscaled precipitation data.

4.2. Consistency Test of IMERG-Z Index

Table 6 presents the frequency of drought occurrences and the number of different drought levels as indicated by the IMERG-Z index and the SPI index at various meteorological stations in Liaoning Province from 2010 to 2018. It can be observed that the total number of drought events and their frequencies reported by the IMERG-Z index are comparable to those reported by the SPI index, indicating that the IMERG-Z index can broadly reflect the drought conditions at different stations in Liaoning Province. However, the drought severity

reflected by the IMERG-Z index is generally weaker than that indicated by the SPI index. The frequencies of extreme and severe drought occurrences are relatively low, with some instances not occurring, while moderate drought and mild drought events are recorded more frequently. The IMERG-Z index estimates extreme and severe droughts as moderate or mild, leading to an underestimation of the drought severity at the stations. This suggests that the current IMERG-Z data may be ineffective for monitoring significant drought events in Liaoning Province.

Table 6. Frequency and frequency of drought occurrence of IMERG-Z index and SPI index in meteorological stations of Liaoning province.

Station Name	Extreme Drought	Severe Drought	Moderate Drought	Mild Drought	Total	Frequency (%)	Extreme Drought	Severe Drought	Moderate Drought	Mild Drought	Total	Frequency (%)
Zhangwu	1	3	24	18	46	43	3	2	8	18	31	29
Kaiyuan	1	1	7	25	34	31	5	4	5	21	35	32
Qingyuan	2	1	6	24	33	31	5	4	5	21	35	32
Chaoyang	3	5	21	18	47	44	3	3	7	16	29	27
Jianping	0	4	25	14	43	40	1	2	9	13	25	23
Xinmin	1	3	8	23	35	32	3	5	10	14	32	30
Anshan	2	2	7	19	30	28	3	5	6	15	29	27
Shenyang	0	1	11	19	31	29	2	9	2	26	39	36
Benxi	0	0	9	19	28	26	1	2	10	16	29	27
Zhangdang	0	2	8	23	33	31	1	4	10	21	36	33
Suizhong	1	2	13	24	40	37	3	5	10	18	36	33
Xingcheng	2	3	15	21	41	38	7	3	11	15	36	33
Yingkou	0	0	6	29	35	32	4	3	11	13	31	29
Xiongyue	2	4	6	18	30	28	3	6	8	15	32	30
Caohekou	1	1	5	21	28	26	4	3	11	16	34	31
Xiuyan	0	0	3	24	27	25	3	5	8	21	37	34
Kuandian	3	2	5	22	32	30	5	2	8	18	33	31
Dandong	0	1	4	25	30	28	2	3	10	14	29	27
Wafangdian	0	2	10	20	32	30	2	5	7	17	31	29
Pikou	0	0	2	26	28	26	2	0	3	16	21	19
Changhai	0	4	8	25	37	34	3	5	11	12	31	29
Zhuanghe	2	4	5	24	35	32	4	3	8	21	36	33
Dalian	0	2	8	22	32	30	2	9	6	19	36	33

To further analyze the ability of the IMERG-Z index to represent drought conditions in Liaoning Province, we selected the actual drought events that occurred in 2014 for comparative analysis. **Figure 3** shows the drought distribution in Liaoning Province from April to October 2014 based on the IMERG-Z index. Varying degrees of drought

occurred in Liaoning Province during this period. Drought conditions began manifesting in April, and there was some amelioration in May. Flooding appeared in northern Liaoning in June, with the drought being most severe in July and August. Notably, in August, most areas of Liaoning Province experienced moderate drought or worse, with regions such

as Shenyang, Dalian, and Liaoyang facing severe drought conditions. By September, drought conditions in central and western Liaoning had eased; by October, they had returned to near-normal levels.

Historical drought data and the “Meteorological Disaster Bulletin of Liaoning Province in 2014” indicate that 2014 experienced the most severe summer and autumn drought since 1951 in Liaoning Province, with the drought area and the scale of moderate to severe drought ranking first in the nation. From June 21 to September 10, 2014, the average precipitation in Liaoning Province was 195.7 mm, a reduction of 48.3% compared to the historical average precipitation during the same period (378.6 mm) and a decrease of 13.3% compared to the severe drought event in 2009 (225.8 mm). This was the lowest value recorded during the same period since comprehensive meteorological observations began in 1951. In early July, drought conditions emerged in western Liaoning, rapidly spreading across the province. By mid-to-late July, light to moderate drought was evident throughout the province, with severe drought occurring in parts of Dalian, Liaoyang, and Huludao. In August, much of Liaoning Province escalated to a moderate to severe drought, with the severity and extent of the drought rapidly expanding. Areas including Shenyang, Dalian, and Anshan saw extreme drought conditions. Following two rainfall events from August 23 to 25 and September 1 to 2, significant meteorological drought alleviated across the province, with marked reductions in areas experiencing severe and extreme drought.

From the drought situation depicted in **Figure 4** using the IMERG-Z index and the comparative analysis with actual drought events in Liaoning Province, it can be concluded that while the IMERG-Z index possesses a certain level of reliability, it tends to underestimate the severity of droughts.

Extreme and severe droughts in Liaoning Province are often classified as moderate or mild. Additionally, when regional precipitation levels are relatively high, the results may indicate flooding conditions. This is particularly evident in the monitoring of summer droughts. If only precipitation factors are considered, the IMERG-Z index struggles to accurately represent drought severity due to the typically high precipitation levels during summer. In high-temperature, low-rainfall areas, the average value of the precipitation series in the Z index calculation is relatively low, leading to a less pronounced indication of drought severity. Therefore, this study integrates the TCI into the subsequent comprehensive drought monitoring model, aiming to enhance the robustness and accuracy of the drought monitoring framework.

4.3. Results of the Integrated Drought Model

Through multiple stepwise regression analysis, we obtained the fitting results, where the correlation coefficient (CC) is 0.931, the goodness-of-fit (R^2) is 0.866, the F-value is 4001.914, and $P < 0.01$, satisfying the criteria for significance testing. This indicates that the model can effectively monitor drought in Liaoning Province. Given the excellent applicability of IMERG remote sensing precipitation data in Liaoning Province, we replaced the precipitation Z-index based on meteorological station observational data with the IMERG-Z index derived from IMERG remote sensing precipitation data in the integrated meteorological drought model. This led to the optimal fitting equation (**Table 7**) and the development of the Integrated Meteorological Drought Monitoring Index (SPTI) for Liaoning Province, which is based on multi-source remote sensing data. Furthermore, we classified the index into five levels of drought severity (**Table 8**).

Table 7. Drought monitoring regression equations.

Precipitation Index	Regression Formula
Precipitation Z Index	$SPEI = -0.774 + 1.703Z - 0.093Z^3 + 3.87TCI - 2.694TCI^2$
IMERG-Z Index	$SPTI = -0.774 + 1.703Z_{IMERG} - 0.093Z_{IMERG}^3 + 3.87TCI - 2.694TCI^2$

Table 8. SPTI drought classification table.

Level	SPTI Value	Type
1	$0.5 < SPTI$	Normal
2	$0 < SPTI \leq 0.5$	Mild drought
3	$-0.5 < SPTI \leq 0$	Moderate drought
4	$-1.0 < SPTI \leq -0.5$	Severe drought
5	$SPTI \leq -1.0$	Extreme drought

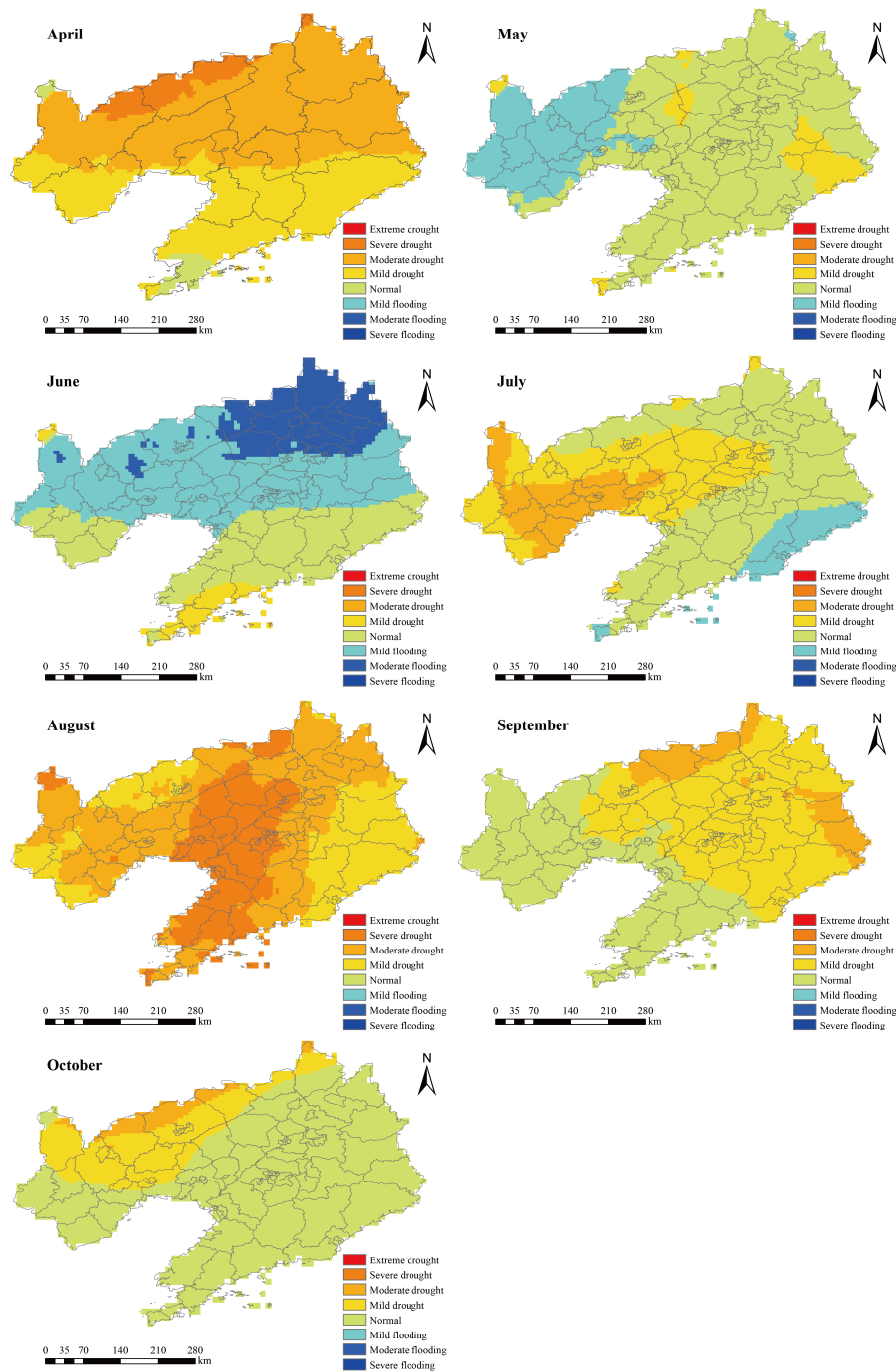


Figure 4. Spatial Distribution of IMERG-Z Drought Levels in Liaoning Province in 2014.

4.4. Comparison and Analysis of Monitoring Results

4.4.1. Comparison of Drought Monitoring Results in Liaoning Province for 2014

By calculating the SPTI index from April to October 2014, we can observe (**Figure 5**) that different degrees of

drought occurred in Liaoning Province during this timeframe. Drought conditions began to emerge in April, with most areas experiencing light and moderate drought. There was slight alleviation in May, and most regions shifted to light drought conditions. In June, drought appeared in southern Liaoning, with moderate and light drought occurring in the entire Dalian area and the southern regions of Yingkou, Anshan, and

Dandong. The severity of the drought intensified in July, primarily concentrated in the western and central areas of Liaoning. Western Liaoning experienced predominantly severe and moderate drought, while most of the central region faced light drought. August and September saw significant drought throughout almost all of Liaoning Province. In August, areas in Yingkou and Panjin experienced extreme drought, with drought conditions spreading outward. Surrounding regions

such as Huludao, Jinzhou, Shenyang, Liaoyang, Anshan, and parts of Dalian experienced severe and moderate drought. By September, except for light drought in some areas of Chaoyang, Huludao, and Dalian, most other regions faced severe or moderate drought conditions. In October, drought conditions eased, with only light drought appearing in western Liaoning, while most other areas returned to near-normal levels.

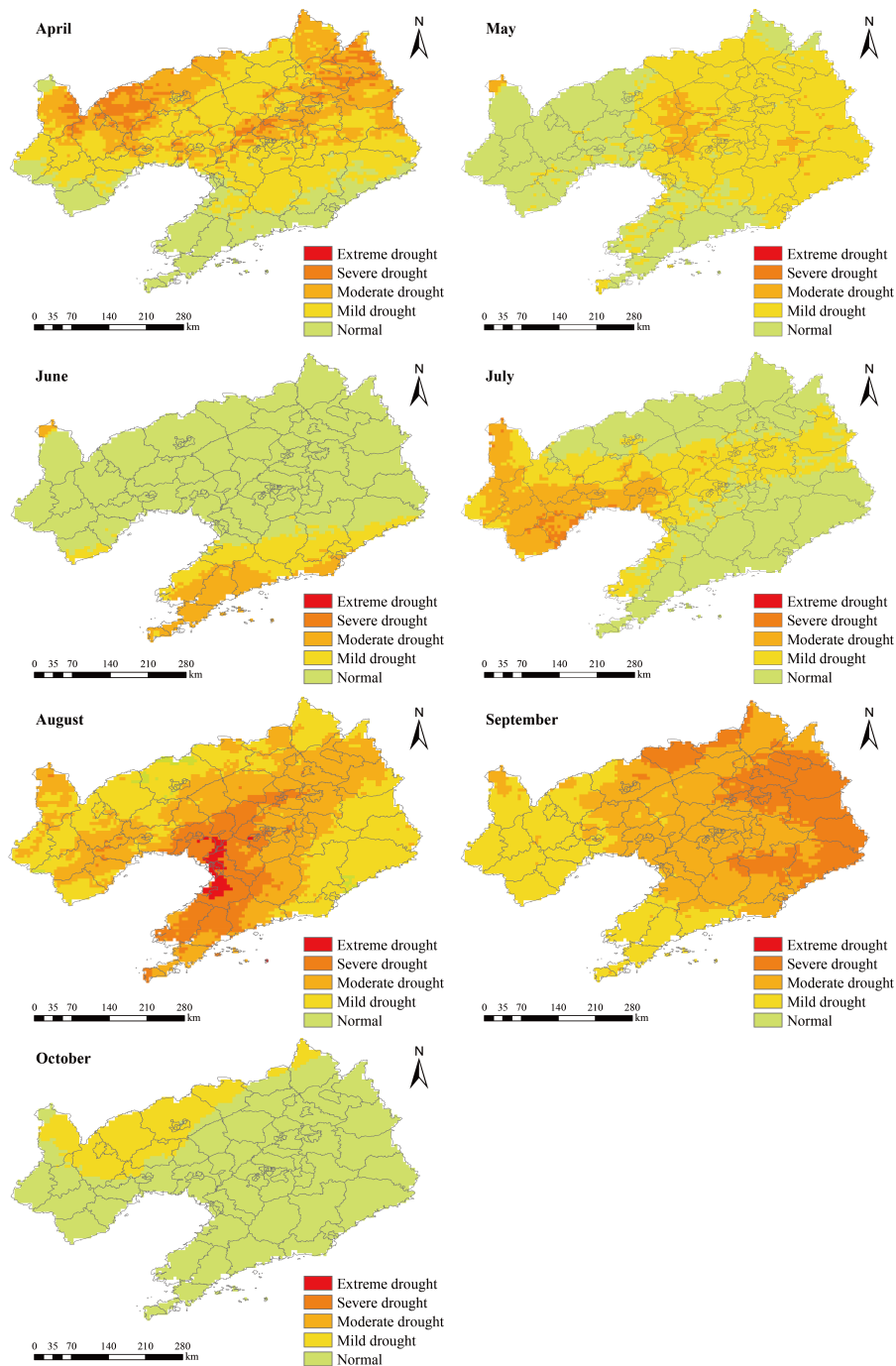


Figure 5. Spatial distribution of summer and fall SPTI drought classes in Liaoning Province in 2014.

Additionally, the SPTI index exhibited a more reliable representation of drought conditions than the IMERG-Z index. Compared to the actual drought events in Liaoning Province in 2014, the SPTI index more accurately reflected severe drought conditions and above, demonstrating a significant improvement over the IMERG-Z index. This enhancement addressed the issue of the IMERG-Z being weak in describing drought severity. By incorporating the TCI, the SPTI index effectively describes drought severity even in scenarios with considerable precipitation. When substantial rainfall occurs in a region, drought alleviation will be evident without experiencing the abrupt transition from drought to flooding characteristic of the IMERG-Z index.

4.4.2. Comparison of Drought Monitoring Results in Liaoning Province for 2015

Figure 6 illustrates the summer drought conditions in Liaoning Province for 2015 as monitored by the SPTI index. In July, widespread drought of varying degrees affected

the entire province, with most areas experiencing moderate drought. Severe drought occurred in regions such as Fuxin, Jinzhou, Shenyang, and eastern Chaoyang, as well as parts of Dalian and Yingkou. Following rainfall in August, the drought conditions improved, with the northwestern region of Liaoning, southern Shenyang, and western Fushun revised to light drought conditions. Central Chaoyang experienced moderate drought, while other areas returned to normal conditions. According to the “Meteorological Disaster Bulletin of Liaoning Province in 2015,” from July 1 to 28, the average precipitation across the province was 41 mm, which is a 72% decrease compared to the standard value for the same period (146 mm), marking the lowest value since 1951. During this period, moderate drought or worse was observed in most parts of the province, with severe drought reported in regions of Dalian, central Fushun, Yingkou, Liaoyang, and southern Panjin. The monitoring results from the SPTI align closely with these observations.

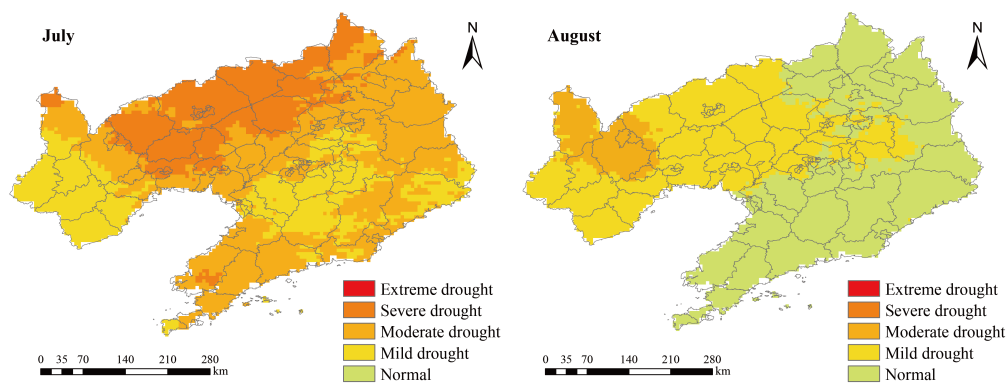


Figure 6. Spatial distribution of summer SPTI drought classes in Liaoning Province in 2015.

4.4.3. Comparison of Drought Monitoring Results in Liaoning Province for 2017

Figure 7 shows the monitoring results of the SPTI index for the spring and summer drought in Liaoning Province in 2017. Since April, most areas of Liaoning Province have experienced mild to moderate drought, with severe drought occurring in parts of Chaoyang, Fuxin, and Jinzhou. In May, the drought intensified, and the mild to moderate drought areas expanded to the whole province. Northwestern Liaoning Province changed from moderate to severe drought, and areas like Chaoyang experienced extreme drought. In June, the drought peaked, and most areas of the province experienced moderate to severe drought, with special drought

occurring in Fuxin, Dalian, Anshan, and Dandong. In July, the drought in western Liaoning Province eased slightly, but the drought in areas like Dalian and Fuxin remained severe. According to historical drought data and the “2017 Meteorological Disaster Bulletin of Liaoning Province,” from March to July, the average precipitation in Liaoning Province was 205 mm, 43% lower than the same period in a normal year and the lowest value since 1972. The average precipitation days were 24 and 33 days lower than the same period in a normal year and the lowest value since 1951. At the same time, the relatively high temperature in the spring of 2017 (the average temperature was 10.1 °C) and the continuous lack of rain led to a drought situation in most areas of the province,

causing varying degrees of drought disasters. From March to mid-May, the average precipitation in Jinzhou, Fuxin, Chaoyang, Panjin, and Huludao was only 8 mm, 88% lower than in a normal year. There were 61 consecutive days of no precipitation in Jinzhou, Heishan, Yixian, Linghai, Dawu, and Huludao's national meteorological observation stations. On April 8, the soil moisture content in the western Fuxin and eastern Chaoyang areas was less than 40%, indicating

severe drought. On April 22, there was mild to moderate drought in the Shenyang and Jinzhou areas, and Fuxin was the hardest hit area. From March to June 17, there were more than 100 consecutive days of no effective precipitation, and by June 18, the affected area in Fuxin had reached 503,000 hectares. It can be seen that the SPTI index describes the drought situation, which is consistent with the actual drought situation.

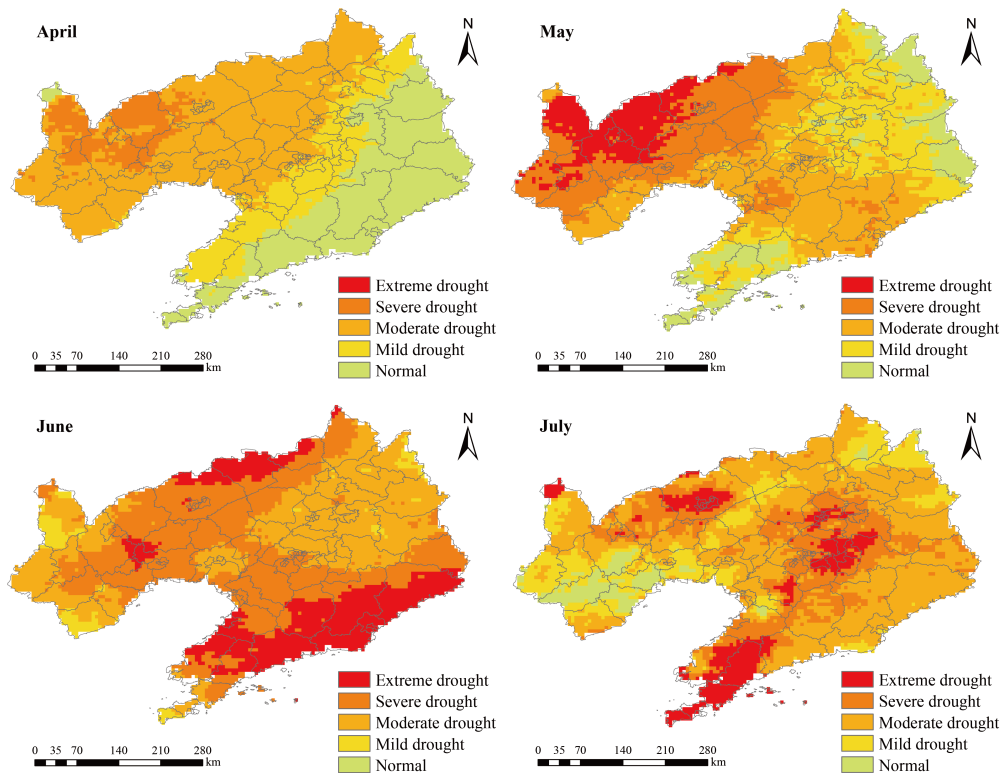


Figure 7. Spatial distribution of spring and summer SPTI drought classes in Liaoning Province in 2017.

4.4.4. Comparison of Drought Monitoring Results in Liaoning Province for 2018

Figure 8 shows the monitoring results of the SPTI index for the summer drought in Liaoning Province in 2018. In July, a large-scale drought occurred in Liaoning Province, with areas other than some of Huludao and Chaoyang experiencing moderate to severe drought. Dalian, Fuxin, the eastern part of Chaoyang, Shenyang, Tieling, and Fushun had extreme drought. The drought eased in August, with areas other than Chaoyang (moderate drought) experiencing mild to moderate drought. According to historical drought data and the “2018 Meteorological Disaster Bulletin of Liaoning Province,” in 2018, most areas of Liaoning Province experi-

enced the longest-lasting, most severe, and widest-ranging summer drought since 2001. From early July to early August, the average precipitation in the province was 127 mm, which was 47% lower than the same period in a typical year (244 mm). Due to the sustained high temperatures and unusually low rainfall, severe summer drought occurred in most areas of the province except for Chaoyang and Huludao. A total of 40 cities and counties in the province experienced severe drought, with 22 cities and counties in Shenyang, Dalian, Anshan, Benxi, Dandong, Jinzhou, and Tieling experiencing extreme drought, with Dalian being the most brutal hit. It can be seen that the SPTI index accurately describes the summer drought situation in Liaoning Province in 2018.

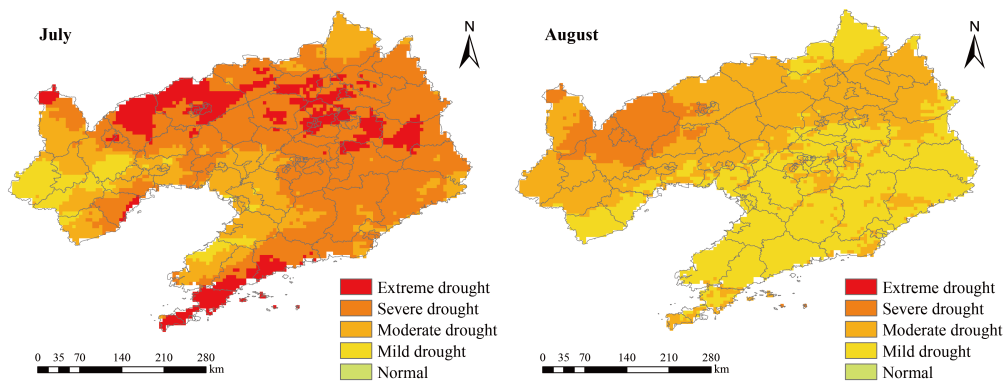


Figure 8. Spatial distribution of summer SPTI drought classes in Liaoning Province in 2018.

5. Discussion

5.1. Analysis of Downscaling for Drought Monitoring

The NDVI-topography guided multivariate regression kriging downscaling scheme adopted in this study successfully enhanced the spatial resolution of IMERG precipitation data from 0.1° to 0.05° , achieving satisfactory fitting performance with $R^2 > 0.7$ for most months. This result is consistent with the findings of Du et al. [48], who employed a similar method to downscale IMERG data from 0.1° to 0.05° in the Yangtze River Basin, thereby validating the effectiveness of statistical downscaling methods in improving the spatial resolution of satellite precipitation products and their applicability in monsoon regions. However, a noticeable decline in performance was observed during the summer months (June and July) in this study, which contrasts sharply with the maintained high accuracy of the downscaling model in summer as reported in the Yangtze River Basin study. This discrepancy primarily stems from differences in regional precipitation characteristics. While summer precipitation in the Yangtze River Basin is also influenced by the monsoon, it is often more closely associated with large-scale weather systems such as the Meiyu front, resulting in relatively better spatial continuity and more stable correlations with topography and vegetation. In contrast, summer precipitation in Liaoning Province is predominantly driven by localized convective activities, where short-duration heavy rainfall and thunderstorms exhibit high spatial randomness and heterogeneity. Consequently, the statistical relationship between its spatial distribution and monthly-scale covariates such as NDVI and topography is weaker, leading to limited

efficacy of statistical downscaling models based on these covariates during this period. This finding partially aligns with the conclusions of Tu and Duan [49]. In their comparative study of different downscaling methods in the Yellow River Basin, they noted that statistical downscaling models exhibit increased uncertainty in regions with high spatiotemporal variability in precipitation. However, this study further clarifies that such uncertainty in Liaoning is primarily manifested as a decline in model explanatory power during summer, rather than a general fluctuation in annual performance. Despite the limitations in summer accuracy, the downscaling results of this study still demonstrate significant value for drought monitoring. Compared to using the original 0.1° data, the 0.05° downscaled data not only more clearly depicts the southeast-to-northwest precipitation gradient but also reveals finer precipitation patterns in key agricultural areas such as the central plains. This is crucial for drought monitoring, particularly for identifying the initial occurrence areas and spatial evolution pathways of droughts.

5.2. Special Value of the SPTI Model for Drought Monitoring

The SPTI model achieved significant improvements in monitoring droughts in Liaoning Province compared to using the precipitation-based IMERG-Z index alone. This enhancement aligns with the widely recognized principle in drought monitoring that multi-source information integration is superior to single-factor approaches. However, the SPTI model developed in this study diverges in important ways. First, in terms of factor selection, SPTI focuses on the two most fundamental meteorological elements—precipitation and temperature—without incorporating soil moisture or veg-

etation indices as seen in models like MCDIs or SDCI^[50]. This is not an oversight but rather a consideration based on the specific mechanisms of agricultural drought in Liaoning Province and the operational feasibility of data. Agricultural drought in Liaoning, particularly the summer drought that poses the greatest threat to major crops such as corn, often manifests as a combined effect of high temperature and water deficit^[51]. High temperatures exacerbate soil evaporation and crop transpiration, directly leading to water stress. Therefore, temperature in this region is not merely an accompanying phenomenon of drought but a key driver that intensifies drought hazards. By assigning significant weight to the TCI through regression analysis, the SPTI model essentially quantifies the contribution of temperature stress to the overall severity of drought. This allows for earlier warnings of drought risks triggered by high temperatures compared to using soil moisture or vegetation indices alone, providing a longer lead time for agricultural drought mitigation. Second, compared to using IMERG-Z alone, the improvement of SPTI is profoundly reflected in its ability to distinguish drought types. While IMERG-Z only reflects precipitation deficits, SPTI, by integrating TCI, can effectively identify drought events characterized primarily by high temperatures, which are often more destructive to agricultural production. This has direct implications for agricultural management in Liaoning Province. When SPTI indicates a high-temperature synergistic drought, agricultural departments not only need to allocate water resources for irrigation but should also consider adopting agronomic measures such as sprinkler irrigation for cooling and foliar fertilization to alleviate high-temperature stress. In contrast, for water-deficit droughts, the focus should be on ensuring irrigation water supply. This preliminary differentiation of drought types based on causation, which is difficult to achieve with single precipitation indices or certain composite indices, highlights the unique advantage of the SPTI model in serving precision agricultural drought mitigation.

5.3. Research Limitations and Future Directions

This study constructed and validated a comprehensive meteorological drought monitoring model (SPTI) suitable for Liaoning Province, providing an effective tool for regional refined drought monitoring. However, the analytical frame-

work of this study still has the following limitations. First, the model is primarily based on meteorological elements and has not yet directly incorporated key agricultural drought factors such as soil moisture and crop types^[52], which limits its direct application in supporting precision agricultural drought decision-making. Additionally, the IMERG data used in the study have a relatively short time series, which may affect the model's stability under long-term climate change scenarios. Future research could deepen the work in the following aspects: first, building upon the existing SPTI framework, integrate soil moisture remote sensing products such as SMAP and crop phenology data to construct a meteorological-soil-crop integrated drought impact assessment model, thereby enhancing the agronomic application value of the findings^[53]. Second, utilize longer time series of remote sensing data and climate model outputs to test and optimize the model's monitoring stability under different climate scenarios.

6. Conclusions

- (1) The IMERG data downscaling model developed in this study improves precipitation data's spatial resolution and accuracy. The model parameters have passed significance tests, and the goodness of fit (R^2) for all months, except June and July, is above 0.7.
- (2) The IMERG-Z index's consistency test indicates a certain degree of reliability for drought monitoring in Liaoning Province. However, it was also found that the drought conditions detected by the IMERG-Z index are generally milder than the actual drought conditions.
- (3) The comprehensive drought monitoring model can objectively describe the drought severity in Liaoning Province. The SPTI index calculated by this model was validated and compared with four drought events in 2014, 2015, 2017, and 2018. The results show that the monitoring outcomes agree with the actual drought severity and spatial distribution. Therefore, the model developed in this study is suitable for drought monitoring in Liaoning Province.

Author Contributions

Conceptualization, B.G. and M.L.; data curation, B.G., X.Y. and M.L.; formal analysis, B.G., S.Z., W.X. and

M.L.; funding acquisition, X.Y., W.X. and M.L.; methodology, B.G., X.Y. and M.L.; software, B.G., S.Z. and W.X.; writing—original draft, B.G. and M.L.; writing—review and editing, H.Z., W.X., D.G. and M.L. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the restriction policy of the co-authors' affiliations.

Conflicts of Interest

The authors declare no conflict of interest.

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