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Meteorological Drought Trends in Ordos (1961-2020) Based on Precipitation Anomaly Percentage: Postprint

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Abstract

Due to frequent drought events in Ordos, local economic development has been severely affected. Investigating the spatiotemporal evolution characteristics of drought in Ordos is essential for drought resistance and disaster mitigation efforts. This study employs monthly precipitation data from 85 grid points in Ordos from 1961 to 2020, utilizes run theory to analyze the applicability of the Standardized Precipitation Index (SPI) and Precipitation Anomaly Percentage (Pa) index in this region, and further adopts inverse distance interpolation and other methods to analyze the spatiotemporal evolution characteristics of drought. The results indicate: (1) The Pa index exhibits strong sensitivity and accuracy in describing drought in Ordos. (2) Drought shows high interannual variation frequency, with summer drought having the highest occurrence frequency at 16.7% and winter drought the lowest at 13.3%; furthermore, drought occurrence rate gradually decreases as drought severity level increases. (3) The western part of Ordos is more prone to severe drought than the eastern part, with the probability of being unaffected by drought gradually increasing from 42% to 75%. (4) Drought conditions in spring and summer have the greatest impact on annual drought conditions, while drought situations in autumn and winter show improvement, with winter demonstrating more pronounced improvement.

Full Text

Abstract

Due to the frequent occurrence of drought events in Ordos, local economic development has been seriously affected. Studying the spatiotemporal evolution characteristics of drought in this region is essential for effective drought resistance and disaster mitigation. This study utilized monthly precipitation data from 85 grid points in Ordos from 1961 to 2020. Using run theory, we analyzed the applicability of the Standardized Precipitation Index (SPI) and Precipitation Anomaly Percentage (Pa) in the region, and further employed inverse distance interpolation to examine drought spatiotemporal evolution characteristics. The results indicate: (1) The Pa index exhibits strong sensitivity and accuracy for drought characterization. (2) Interannual drought variation shows high frequency, with summer drought occurring most frequently at 16.7%; drought incidence gradually decreases as drought severity increases. (3) The western part of Ordos is more prone to severe drought than the eastern part, with the probability of being unaffected by drought gradually increasing from west to east. (4) Drought conditions in spring and summer have the greatest impact on annual drought patterns, while drought conditions in autumn and winter show improvement, with winter showing more obvious improvement.

Keywords: gridded dataset; drought characteristic; run theory; standardized precipitation index; precipitation anomaly percentage

Introduction

Drought is one of the natural disasters causing the greatest losses to agriculture and animal husbandry worldwide. It is estimated that annual global economic losses from drought far exceed those from other meteorological disasters [?]. As the economy develops rapidly, population grows, and climate changes, the affected areas of drought are also changing. Drought characteristics are typically described using drought indices, which convert one or more meteorological variables such as precipitation and evapotranspiration into a single numerical value to represent drought intensity and magnitude [?].

With increasingly sophisticated research on drought indices, numerous studies have used different drought indices to analyze spatiotemporal evolution characteristics of drought worldwide, thereby revealing drought occurrence patterns and impacts [?]. For example, in Inner Mongolia, Wu et al. [?] used the Precipitation Anomaly Percentage (Pa) to study spatiotemporal distribution characteristics of precipitation and drought, concluding that precipitation is the main factor causing meteorological drought in Inner Mongolia. Xie et al. [?] used the Standardized Precipitation Evapotranspiration Index (SPEI) to study drought characteristics in Inner Mongolia at different time scales, finding that drought conditions in central and western Inner Mongolia are gradually intensifying. Zhang et al. [?] used standardized precipitation indices at different time scales to study drought characteristics in Damao Grassland, discovering that the sensitivity of SPI to precipitation identification decreases as the time scale increases. These studies demonstrate that both Pa and SPI indices are suitable for drought research in Inner Mongolia, but their applicability to other regions requires further investigation. Therefore, this paper selects the Pa index to analyze drought spatiotemporal evolution characteristics in Ordos.

McKee et al. [?] proposed the Standardized Precipitation Index (SPI), which requires only precipitation data and can identify drought at multiple time scales, including drought onset, termination, intensity, and magnitude. Currently, over 100 drought indices have been applied to drought characteristic analysis, drought prediction, emergency planning, and impact assessment [?]. Drought is classified into meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought based on impact type. Meteorological drought occurs due to persistent abnormal dry weather causing water shortage and severe hydrological imbalance. Consequently, meteorological drought indices are typically calculated based on precipitation data, such as Precipitation Anomaly Percentage and Standardized Precipitation Index.

Run Theory is a method for analyzing time series that has been widely applied to drought event identification [?]. Wang et al. [?] used run theory to extract drought duration and intensity on the Loess Plateau of northern Shaanxi. Zuo et al. [?] used run theory to isolate drought events, frequency, duration, and intensity in southwestern China from SPI sequences. These studies demonstrate that run theory is effective for separating drought characteristics. However, in drought research on Inner Mongolia, effective application of run theory is still lacking. Therefore, this paper employs run theory to isolate drought characteristics from SPI3, SPI12, and Pa sequences in Ordos.

Based on monthly precipitation data from 85 grid points in Ordos, this study first evaluates the applicability of SPI3, SPI12, and Pa sequences using run theory. It then analyzes spatiotemporal evolution and variation of drought in Ordos over the past 60 years using inverse distance interpolation and other methods, providing references for understanding climate change patterns, drought monitoring and forecasting, and drought risk assessment.

1. Materials and Methods

1.1 Study Area

Ordos is located in southwestern Inner Mongolia, adjacent to Shanxi, Shaanxi, and Ningxia provinces, in the hinterland of the Ordos Plateau. Its geographic coordinates are 37°35 24 -40°51 40 N, 106°42 40 -111°27 20 E, with a north-south width of about 340 km and an east-west length of about 400 km. The region has a typical temperate arid and semi-arid continental climate with large seasonal temperature variations. The multi-year average temperature is 6.2 °C, with a daily minimum temperature of -31.4 °C. The multi-year average precipitation is 348.3 mm, with uneven spatiotemporal distribution—precipitation gradually decreases from southeast to northwest, and is concentrated in June-September, accounting for 70-80% of annual precipitation. Ordos is a typical farming-pastoral ecotone with a fragile ecological environment; drought and low rainfall are the most basic climate characteristics.

The terrain is undulating, generally higher in the northwest and lower in the southeast, with complex topography and diverse landforms. Desert and sandy land account for 28.81% of the total area, hilly mountainous areas account for

18.91%, and plains account for only 4.33%, mostly concentrated in the northern Yellow River alluvial plain.

1.2 Data Sources

1.2.1 Grid Data Monthly precipitation data from 85 grid points in Ordos were selected for analysis. Station precipitation data were obtained from the China Meteorological Administration' s National Meteorological Information Center' s China Surface Climate Data Daily Dataset and monthly precipitation data provided by Shaanxi Meteorological Information Center, with a spatial resolution of 0.5°$×$0.5°. The geographic locations are shown in [Figure 1: see original paper]. Before use, the grid point data were processed through data collection and classification, forming continuous precipitation time series from 1961 to 2020.

To verify the reliability of grid data, Dong Sheng and Otuq Qin meteorological stations were selected for comparison. Daily observation data from 1961–2020 and monthly observation data from 1961–2020 were integrated. Actual observed data from the two stations were compared with data from the nearest grid points. Correlation analysis showed that correlations between grid data and observed data were significant at the 0.01 level, confirming that the grid data are authentic, valid, and meet the scientific requirements of this study.

1.2.2 Historical Drought Disaster Data According to drought records in the *China Meteorological Disaster Canon (Inner Mongolia Volume)*, Ordos experienced 23 drought disasters from 1961 to 2020, including 5 severe and catastrophic droughts, and 18 moderate and mild droughts. Specifically, spring 1962 had extremely low precipitation; spring 1965 experienced severe spring drought with the smallest precipitation on record in most areas, and Otuq Qin Banner was dry throughout the year; summer 1972 had reduced June–July precipitation, with severe disasters in eastern Ordos; spring 1980 had drought in most areas, which continued into summer with less rainfall, causing severe damage in western pastoral areas; several droughts also occurred after 2000. Detailed drought occurrence times in Ordos are shown in and .

1.3 Drought Indices

1.3.1 Standardized Precipitation Index (SPI) The Standardized Precipitation Index (SPI) was proposed by McKee et al. [?] and offers simple, rapid calculation and multi-time scale analysis capabilities. The calculation principle assumes that precipitation over a certain time scale follows a Gamma distribution. The corresponding cumulative probability function is derived and then transformed into a standard normal distribution. After transformation, the SPI value for a sample is the value on the x-axis of the standard normal distribution corresponding to the cumulative probability of that sample' s precipitation.

Assuming precipitation in a certain period is x, the Gamma distribution probability density function is:

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

where β and γ are scale and shape parameters, respectively, and $\Gamma(\gamma)$ is the Gamma function. The cumulative probability for a determined time scale is:

$$G(x) = \int_0^x g(x) dx$$

Since the Gamma function is undefined at $x = 0$, the probability of zero precipitation events is calculated as:

$$P(x = 0) = \frac{m}{n}$$

where m is the number of samples with zero precipitation and n is the total number of samples.

The cumulative probability distribution is then normalized. Substituting the probability value P into the standardized normal distribution function yields:

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right)$$

where $t = \sqrt{\ln \frac{1}{P^2}}$, and coefficients are: $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

The Z value is the Standardized Precipitation Index (SPI). Drought classification based on SPI values is shown in .

1.3.2 Precipitation Anomaly Percentage (Pa) Precipitation Anomaly Percentage (Pa) refers to the percentage relative deviation of precipitation in a certain period compared to the average precipitation in the same period. It evaluates precipitation anomalies and deviation from normal patterns. Pa is calculated as:

$$Pa = \frac{P - \bar{P}}{\bar{P}} \times 100\%$$

where P is precipitation in a certain period (mm), and $\bar{P}$ is the average precipitation in the same period (mm), calculated as:

$$\bar{P} = \frac{1}{n}\sum_{i=1}^{n} P_i$$

where n generally takes 30 years, and P_i is precipitation on day i (month or year). Drought classification based on Pa values is shown in .

1.4 Run Theory

Run Theory is a method for analyzing time series by identifying the number of consecutive occurrences of similar events to measure the intensity of specific events in a sequence. For example, in precipitation analysis, the monthly precipitation series is treated as a discrete time series, and the multi-year average precipitation $\bar{P}$ is calculated. According to Run Theory, if a month' s precipitation x_i is less than $\bar{P}$ ($x_i - \bar{P}$ is negative), it represents a dry month; conversely, if $x_i - \bar{P}$ is positive, it represents a wet month. When negative deviations occur consecutively, a series of drought events appears, called a negative run. When positive deviations occur consecutively, it is called a positive run. The number of runs indicates event frequency, while run duration indicates event persistence.

The sum of m consecutive negative (positive) deviation terms is called a negative (positive) run sum S. In a drought event, the time span d between $x_i - \bar{P}$ moments represents the event duration, while the negative run value S represents drought intensity. [Figure 3: see original paper] shows a schematic diagram of Run Theory, where the horizontal axis represents drought index values and the vertical axis represents time.

Based on Run Theory and drought classification, three thresholds are set: for SPI, $S_1 = -0.3$, $S_2 = -0.5$; for Pa, $S_1 = -20$, $S_2 = -40$. When $S_1 < \text{index} < 0$, it indicates a possible drought event; when index $\leq S_2$, it is recorded as a drought event. When two drought events are separated by only one month and that month' s index is between S_1 and S_2, the two events can be merged into one, with combined duration $d = d_1 + d_2 + 1$, where d_1 and d_2 are the durations of the first and second events, respectively.

1.5 Wavelet Analysis

Morlet et al. [?] proposed an analysis tool with time-frequency multi-resolution capabilities, named wavelet analysis. Wavelet analysis has good localization properties in both time and frequency domains and is a powerful data analysis tool [?]. A notable feature is multi-frequency analysis, making it effective for image fusion, denoising, and edge feature extraction.

Wavelet analysis, developed from Fourier transform, uses a family of wavelet functions to represent or approximate a signal. In practice, it is mainly used for denoising, filtering, detecting abrupt change points, identifying periodic components, and multi-time scale analysis. Wavelet transform includes Discrete

Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT), commonly used to extract time-domain and frequency-domain features.

The wavelet function (mother wavelet) is defined as:

$$\psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right)$$

where a is the scaling factor and b is the translation factor. The key to wavelet analysis is selecting the mother wavelet. Common wavelets include Haar, Daubechies, and Morlet wavelets. This study uses the Morlet wavelet for periodic drought analysis. The Morlet wavelet expression is:

$$\psi(t) = \exp(i\omega_0 t)\exp\left(-\frac{t^2}{2}\right)$$

For a given sub-wavelet function $f(t)$, the continuous wavelet transform is:

$$W_f(a,b) = \langle f(t), \psi_{a,b}(t)\rangle = |a|^{-1/2}\int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-b}{a}\right)dt$$

where ψ^* is the complex conjugate of ψ, and $W_f(a,b)$ is the wavelet coefficient.

Using continuous wavelet transform for drought periodicity analysis, wavelet coefficients are obtained through continuous scaling and translation. The wavelet variance is calculated by integrating the squared wavelet coefficients over time:

$$\mathrm{Var}(a) = \int_{-\infty}^{+\infty} |W_f(a,b)|^2 db$$

Finally, by analyzing and comparing wavelet variances, the main periods of meteorological drought in Ordos are determined.

2. Results

2.1 Applicability of Drought Indices

To compare average annual drought duration and average duration per drought event at different time scales, run theory was applied to SPI3, SPI12, and Pa sequences from 1961-2020. The annual average drought duration and annual average duration per event were calculated.

[Figure 4: see original paper] shows that drought frequency calculated by the three methods follows similar trends, but with regional differences. SPI3 has the highest frequency (15.7 times per grid point), followed by Pa (12.3 times), while SPI12 has the lowest (8.7 times). [Figure 5: see original paper] shows that except for SPI3' s large fluctuations, SPI12' s annual average drought duration is generally higher than other indices, with Pa and SPI3 showing similar fluctuation ranges. In terms of trends, Pa and SPI3 show higher similarity. For extreme drought years, SPI12 and Pa share the same longest drought duration year (1965), with durations of 11.2 and 8.7 months, respectively. SPI3' s longest drought year is 1980 (7.3 months), while Pa' s longest drought year is 2000 (6.8 months). The shortest drought years for SPI12 and Pa are both 1967, with durations of 1.3 and 0.8 months, respectively, while SPI3' s shortest drought years are 1978 and 1992.

[Figure 6: see original paper] shows that the average duration per drought event follows similar trends with distinct fluctuation ranges, ordered from high to low as: SPI12 > Pa > SPI3. This indicates that SPI12 has the longest drought events but lowest frequency, while SPI3 has the shortest events but highest frequency, showing poor continuity. Pa shows moderate continuity.

Historical drought identification accuracy was evaluated by comparing monitored drought grades with actual drought conditions from . The results show that Pa has the highest drought frequency and annual average duration, with moderate average duration per event, matching actual drought conditions well. SPI12 has the lowest accuracy, while SPI3 shows varying errors. Overall, Pa demonstrates higher sensitivity and accuracy than SPI indices at different time scales. Therefore, the Pa index was selected for spatiotemporal drought evolution analysis in Ordos.

2.2 Temporal Evolution of Drought

Due to large interannual precipitation variation and uneven spatiotemporal distribution, Ordos has experienced multiple droughts of varying severity. shows drought identification by different indices. The most droughts occurred in 1961–1970 (9 times), with 1965 being an extreme spring drought year.

Drought frequency by season shows that summer drought occurred in 10 years (16.67%), with dispersed occurrence but high frequency, though generally low severity. Spring drought occurred in 9 years (15.00%), with concentrated occurrence in 1961–1970. Autumn drought occurred in 9 years (15.00%), with higher severity. Winter drought occurred in 8 years (13.30%), with the lowest frequency but highest severity. Continuous seasonal droughts were common, including summer-autumn drought in 1962, autumn-winter drought in 1965, and summer-autumn-winter drought in 1980.

[Figure 7: see original paper] shows Pa values from 1961–2020. Based on annual-scale Pa drought classification, 17 years experienced drought (28.3%), including 11 light drought years (18.3%) and 6 moderate or higher drought years (10.0%). This indicates that interannual drought variation in Ordos is characterized by high frequency, low intensity, and strong continuity.

Wavelet analysis of annual-scale Pa values reveals three main periods: 3–5 years, 8–12 years, and 18–22 years, corresponding to peaks in [Figure 8: see original paper]. Wavelet coefficient plots at these time scales ([Figure 9: see original paper]) show that all have periodicity, though cycles and patterns differ. Combined with historical drought timing, drought occurrence in Ordos shows periodic behavior.

2.3 Spatial Evolution of Drought

Spatial analysis shows that central-western Ordos has the highest drought probability, decreasing gradually outward. Light drought probability is highest in the southwest and east ([Figure 10a: see original paper]). Moderate drought is more likely in central-western and northern regions ([Figure 10b: see original paper]). Severe drought is most frequent in southwestern areas ([Figure 10c: see original paper]), while extreme drought affects the northwestern region most, decreasing from northwest to southeast ([Figure 10d: see original paper]).

Overall, light and moderate drought probabilities are relatively high, decreasing with drought severity. Except for light drought, which occurs more in eastern Ordos, moderate, severe, and extreme drought probabilities are highest in western Ordos, indicating the west is more susceptible to higher-grade drought. The probability of being unaffected by drought also follows this pattern, increasing from west (40%) to east (75%).

Linear regression of annual Pa values at each station, interpolated using Kriging, shows change rate distributions ([Figure 11: see original paper]). Annual change rates show decreasing trends in western and central regions (minimum -0.8%/year), indicating worsening drought, while other areas show increasing trends, especially in southeastern Ordos (maximum +0.6%/year), indicating improving conditions.

Seasonal analysis reveals that spring Pa change rates show a stepwise increase from south to north, with most areas increasing (maximum +0.9%/year) and only southern areas decreasing slightly (-0.1%/year), indicating reduced spring drought severity except in the south. Summer shows a clear stepwise pattern, but with most areas decreasing (minimum -0.7%/year) in western, eastern, and central-northern regions, indicating worsening summer drought, while central-southern areas improve. Autumn shows overall increasing trends, with faster improvement from south to north (maximum +1.2%/year). Winter shows similar increasing trends but more pronounced (maximum +1.5%/year), indicating more obvious winter drought improvement, with a pattern of low change in western and eastern areas but high change in central and southwestern areas.

3. Discussion

This study found significant differences between Pa and SPI indices in identifying drought frequency and characteristics. As time scale increases, drought frequency decreases while drought duration increases. SPI12 shows the largest fluctuations, indicating the strongest randomness, while SPI' s sensitivity decreases with increasing time scale. Pa shows higher sensitivity and accuracy, and better matches actual drought disasters, making it suitable for spatiotemporal drought evolution analysis in Ordos.

Future research could consider using Copula functions to jointly analyze drought intensity and duration [?]. The drought evolution characteristics obtained in this study are consistent with previous research [?], indicating high credibility and providing a scientific basis for drought management decisions.

4. Conclusions

Based on monthly precipitation data from 85 grid points in Ordos from 1961-2020, this study used SPI and Pa indices at different time scales to analyze drought spatiotemporal evolution characteristics. The main conclusions are:

(1) The Pa index shows high sensitivity and accuracy for drought description in Ordos. In terms of temporal evolution, drought occurred in 17 years (28.3%) from 1961-2020, with light drought most frequent (18.3%), followed by moderate drought (10.0%). Summer drought frequency is highest (16.7%), while winter drought frequency is lowest (13.3%). Interannual drought variation is characterized by high frequency, low intensity, and strong continuity, with periodic patterns. Seasonal variation shows summer drought is most frequent but least severe, winter drought is least frequent but most severe, and autumn drought is more severe than spring drought.

(2) In terms of spatial evolution, western Ordos is more prone to higher-grade drought than eastern Ordos. The probability of being unaffected by drought increases from west to east (from 40% to 75%). Annual, spring, and summer Pa change rates mostly decrease with local increases, indicating that spring and summer drought conditions most affect annual patterns. Autumn and winter Pa change rates increase, with winter increase (maximum +1.5%/year) more obvious than autumn (maximum +1.2%/year), indicating improving drought conditions in autumn and winter, with more obvious winter improvement.

References

[?] Li Xinzhou, Liu Xiaodong, Ma Zhuguo. Analysis on the drought characteristics in the main arid regions in the world since recent hundred odd years. *Arid Zone Research*, 2004, 21(2): 97-103.

[?] Chun Lan, Qin Fuying, Bao Lu, et al. Spatiotemporal variation of extreme precipitation indices in Inner Mongolia in recent 55 years. *Arid Zone Research*, 2019, 36(4): 963-972.

[?] Xie Min, Gao Julin, Sun Jiying, et al. Spatiotemporal variation of drought in Inner Mongolia estimated based on the standardized precipitation evapotranspiration index. *Journal of Irrigation and Drainage*, 2022, 41(6): 140-146.

[?] Zhang Weijie, Zhou Guangsheng. Comparison between standardized precipitation index and Z index in China. *Safety and Environmental Engineering*, 2020, 27(5): 32-37.

[?] Yuan Wenping, Chen Xiaojun, Wang Wenjun, et al. Drought characteristics of desert steppe in recent 56 years based on standardized precipitation index of different time scales—A case study of Damao Grassland in Baotou, Inner Mongolia. *Safety and Environmental Engineering*, 2020, 27(5): 32-37.

[?] Yuan Wenping, Zhou Guangsheng. Theoratical study and research prospect on drought indices. *Advances in Earth Science*, 2004, 19(6): 985-991.

[?] Zargar A, Sadiq R, Naser B, et al. A review of drought indices. *Environmental Reviews*, 2011, 19: 333-349.

[?] McKee T B, Doesken N J, Kleist J. The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology*, 1993, 17(22): 179-183.

[?] Gebrehiwot T, Van der Veen A, Maathuis B. Spatial and temporal assessment of drought in the northern highlands of Ethiopia. *International Journal of Applied Earth Observation and Geoinformation*, 2011, 13(3): 309-321.

[?] Guo H, Bao A, Liu T, et al. Spatial and temporal characteristics of droughts in Central Asia during 1966-2015. *Science of the Total Environment*, 2018, 624(1): 1523-1538.

[?] Potop V, Boroneanţ C, Možn M, et al. Observed spatiotemporal characteristics of drought on various time scales over the Czech Republic. *Theoretical and Applied Climatology*, 2014, 115(1): 1-18.

[?] Santos J F, Pulido Calvo I, Portela M M. Spatial and temporal variability of droughts in Portugal. *Water Resources Research*, 2010, 46(3).

[?] Tabari H, Abghari H, Hosseinzadeh Talaee P. Temporal trends and spatial characteristics of drought and rainfall in arid and semi-arid regions of Iran. *Hydrological Processes*, 2012, 26(22): 3352-3361.

[?] Zarch M A A, Sivakumar B, Sharma A. Droughts in a warming climate: A global assessment of Standardized Precipitation Index (SPI) and Reconnaissance Drought Index (RDI). *Journal of Hydrology*, 2015, 526(1): 183-195.

[?] Wang Chenghai, Li Jian, Li Xiaolan, et al. Analysis on quasi periodic characteristics of precipitation in recent 50 years and trend in next 20 years in China. *Arid Zone Research*, 2012, 29(1): 1-10.

[?] Wu Yingjie, Li Wei, Wang Wenjun, et al. Drought characteristic in Inner Mongolia based on precipitation anomaly percentage. *Arid Zone Research*, 2019, 36(4): 943-952.

[?] Wang Pengxin, Gong Jianya, Li Xiaowen, et al. Advances in drought monitoring by using remotely sensed normalized difference vegetation index and land surface temperature products. *Advances in Earth Science*, 2003, 18(4): 527-533.

[?] Yuan Wenping, Zhou Guangsheng. Comparison between standardized precipitation index and Z index in China. *Chinese Journal of Plant Ecology*, 2004, 50(4): 523-529.

[?] Chen Zaiqing, Hou Wei, Zuo Dongdong, et al. Research on drought characteristics in China based on the revised Copula function. *Journal of Arid Meteorology*, 2016, 34(2): 213-222.

[?] Wang Xiaofeng, Zhang Yuan, Feng Xiaoming, et al. Analysis and application of drought characteristics based on run theory and Copula function. *Transactions of the Chinese Society of Agricultural Engineering*, 2017, 33(10): 206-214.

[?] Zuo Dongdong, Hou Wei, Yan Pengcheng, et al. Research on drought in Southwest China based on the theory of run and two-dimensional joint distribution theory. *Acta Physica Sinica*, 2014, 63(23): 53-64.

[?] Luo D, Li L. Spatiotemporal evolution analysis and prediction of drought in Henan Province based on standardized precipitation evapotranspiration index. *Water Supply*, 2023, 23(1): 410-427.

[?] Morlet D, Peyrin F, Desseigne P, et al. Time scale analysis of high resolution signal averaged surface ECG using wavelet transformation. *Proceedings Computers in Cardiology*, IEEE, 1991: 393-396.

[?] Mokarram M, Taripanah F. Prediction drought using CA Markov model and neural networks and its relationship to landforms. *Arabian Journal of Geosciences*, 2023, 16(5): 342.

[?] Chen Qingjiang, Shi Xiaohan, Chai Yuzhou. Image denoising algorithm based on wavelet transform and convolutional neural network. *Journal of Applied Optics*, 2020, 41(2): 288-295.

[?] Mei Xiaodan, Mao Xuegang, Wang Qiang, et al. Analysis of drought influencing factors in Xiaoxing' anling area of Heilongjiang Province based on SPEI. *Geomatics & Spatial Information Technology*, 2023, 46(8): 16-20.

[?] Xu Xiaojun, Wang Youren, Chen Shuai. Novel image fusion method based on down sampling fractional wavelet transform. *Chinese Journal of Scientific Instrument*, 2014, 35(9): 2061-2069.

[?] Wang Xiaozhu, Niu Saisai, Zhang Kai, et al. Image fusion of infrared weak small target based on wavelet transform and feature extraction. *Journal of Northwestern Polytechnical University*, 2020, 38(4): 723-732.

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