Propagation characteristics from meteorological drought to agricultural drought over the Heihe River Basin, Northwest China (Postprint)

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Abstract

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Full Text

Preamble

Propagation Characteristics from Meteorological Drought to Agricultural Drought over the Heihe River Basin, Northwest China

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Abstract: In the context of global warming, drought events occur with increasing frequency. To better understand the processes and mechanisms of drought occurrence and evolution, scholars have devoted considerable attention to drought propagation, focusing primarily on propagation time and probability. However, relatively few studies have examined the sensitivities of drought propagation to seasons and drought levels. Therefore, we selected the Heihe River Basin (HRB) in Northwest China as a case study area to quantify the propagation time and probability from meteorological drought to agricultural drought during 1981–2020, and subsequently explore their sensitivities to seasons (irrigation and non-irrigation seasons) and drought levels. The correlation coefficient method and a Copula-based interval conditional probability model were employed to determine drought propagation time and probability. The results identified an average drought propagation time of 8 months across the entire basin, which was reduced by 2 months (i.e., 6 months) during the irrigation season and prolonged by 2 months (i.e., 10 months) during the non-irrigation season. Propagation probability was sensitive to both seasons and drought levels, with noticeable spatial differences across the basin. In the upstream, midstream, and southern downstream regions of the HRB, the propagation probability of agricultural drought at different levels generally increased with meteorological drought severity. Lesser agricultural droughts were more likely to be triggered during the irrigation season, while severer agricultural droughts occurred mostly during the non-irrigation season. These results enhance understanding of drought propagation characteristics and provide a scientific basis for drought prevention and control. This study is of great significance for rational water resources planning and maintaining a healthy ecological environment in the HRB.

Keywords: meteorological drought; agricultural drought; drought propagation time; drought propagation probability; Copula function; interval conditional probability; Heihe River Basin

1 Introduction

Drought has become one of the most common natural disasters worldwide (Mishra and Singh, 2012; Liu et al., 2018), typically inducing negative effects on the economy, agriculture, society, and environment (Cheng et al., 2013; Gu et al., 2020; Dahal et al., 2021; Zhang et al., 2022a). Economic losses caused by droughts in China during 1987–2006 accounted for more than 50% of all meteorological disaster losses (Wang et al., 2012). Under extreme drought conditions, the probability of corn yield reduction was estimated to exceed 80% in Shandong Province of North China and 86% in Jiangsu Province of East China (Zhang et al., 2022a). With global warming, drought assessment has become increasingly important for establishing drought prevention and early warning systems.

The American Meteorological Society classifies drought into four types: meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought (Heim, 2002). Meteorological drought generally occurs earlier than hydrological and agricultural drought. Once meteorological drought occurs, the other two types can easily follow (Huang et al., 2015; Guo et al., 2020). Although droughts differ in onset time, their direct impacts and disasters are often manifested through agricultural and hydrological drought (Guo et al., 2020; Zhou et al., 2021b). The propagation of water deficit signals between different drought types is defined as drought propagation (Apurv et al., 2017). Current research on drought propagation primarily focuses on propagation time and probability.

Drought propagation time is typically derived from correlation analysis between two drought types (Abbas et al., 2021; Um et al., 2022). It is determined by the maximum correlation coefficient between a drought type on an n-month time scale and another drought type on a 1-month time scale; the accumulation period n is generally defined as the drought propagation time (Li et al., 2016; Bayer Altin and Altin, 2021; Liu et al., 2021b; Xu et al., 2021). Using this method, scholars found that propagation time from meteorological to agricultural drought in the Yellow River Basin was 0–3 months (Wang, 2020), while propagation from meteorological to hydrological drought in the Pearl River Basin was 2–6 months (Zhou et al., 2021b), both in China. Significant spatiotemporal differences in drought propagation time have also been identified (Huang et al., 2017; Li et al., 2020; Xu et al., 2021; Zhou et al., 2021b). For example, Xu et al. (2021) evaluated propagation time from meteorological to agricultural drought and found it gradually increased from 2 to 7 months from southern to northern China. Huang et al. (2017) concluded that propagation time from meteorological to hydrological drought exhibited noticeable seasonal characteristics in the Weihe River Basin, China, being shorter in spring and summer and longer in autumn and winter, while Li et al. (2020) found longer durations in spring and winter and shorter durations in summer and autumn in the upper Shaying River Basin. Ding et al. (2021) revealed stronger propagation relationships from agricultural to hydrological drought in summer and autumn compared to spring in North China.

Drought propagation probability is generally determined using either conditional probability with copula functions or Bayesian network models (Shin et al., 2018; Sattar et al., 2019; Xu et al., 2019; Sun, 2021). Shin et al. (2018) employed the former method and found that propagation probability from meteorological to hydrological drought in Korea was 33% and 48% based on the Standardized Precipitation Evapotranspiration Index (SPEI) at 3- and 6-month time scales, respectively. Sattar et al. (2019) used a Bayesian network model to predict propagation probability of hydrological drought triggered by meteorological drought in Korea, determining probabilities ranging from 27% to 60%. The propagation probability of different drought levels has attracted attention in recent years. For example, Dehghani et al. (2019) found that extreme and severe meteorological drought led to hydrological drought with 70% propagation probability in the Karun Basin of Iran, while other levels of meteorological drought resulted in normal hydrological drought with less than 50% probability. Jehanzaib and Kim (2020) employed Bayesian network models and Markov random fields to examine propagation probability from meteorological and agricultural drought to hydrological drought in the Nakdong River Basin of Korea, revealing that joint propagation probability from severe and extreme meteorological and agricultural drought to severe and extreme hydrological drought ranged from 49% to 83% on average. Xu et al. (2021) concluded that agricultural drought propagation probability in China increased in parallel with meteorological drought severity. Zhu et al. (2021) detected increasing propagation probability of soil moisture drought globally with rising meteorological drought levels.

While these studies have advanced understanding of drought propagation time and probability across different regions, and some scholars have examined seasonal sensitivity of propagation time and drought level sensitivity of propagation probability (e.g., Huang et al., 2017; Dehghani et al., 2019; Jehanzaib and Kim, 2020; Li et al., 2020; Ding et al., 2021; Xu et al., 2021; Zhu et al., 2021), further research is needed to enrich understanding of drought propagation laws, particularly regarding propagation probability and its sensitivity to seasons and drought levels.

The Heihe River Basin (HRB) in Northwest China is characterized by sparse, concentrated precipitation and intense solar radiation, making local drought problems particularly prominent. Drought and its propagation across the basin not only aggravate the fragile ecological environment but also affect water security, food security, and socio-economic development. Taking the HRB as the study area, this research aims to explore propagation characteristics from meteorological drought to agricultural drought from two perspectives—propagation time and propagation probability—and analyze their sensitivities to seasons and drought levels. This work provides a scientific basis for water resources management and planning in the HRB and offers decision-making support for early warning and drought prediction in this region.

2.1 Study Area

The HRB, the second-largest inland river basin in Northwest China, is located in the arid zone of Northwest China (37°44′–42°40′N, 97°37′E–102°06′E). The basin covers an area of 142,900 km^2 and can be divided into upstream, midstream, and downstream regions from south to north according to the locations of Yingluoxia and Zhengyixia hydrological stations (the outlets of the upstream and midstream regions, respectively). The upstream region is the runoff-producing area, generating 90% of the basin's water (Wang, 2019). The midstream region is a runoff utilization area and one of China's top ten commodity grain bases, with cultivated land accounting for nearly 20% of the total area. It also serves as an essential ecological safety barrier and transportation hub along the Silk Road Economic Belt. The downstream region is a runoff consumption area with a vulnerable ecological environment.

The multi-year average annual precipitation and air temperature over the basin are 122.0 mm and 5.1°C, respectively, estimated from observed data at gauge stations from 1981 to 2015 using the Thiessen polygon method. Precipitation gradually decreases from upstream to downstream, while air temperature increases from upstream to downstream. Due to climatic characteristics and water withdrawal for irrigation in the midstream region, the downstream region frequently suffers from droughts and water shortages (Feng and Su, 2020), making the ecological environment of Ejina Oasis—a national ecological reserve—particularly fragile. Topographically, the upstream region has high elevations with peaks above 4000 m, the midstream region is relatively flat with elevations of 1200–2000 m, and the downstream region is open and flat with elevations below 1200 m [Figure 1: see original paper].

2.2 Global Land Data Assimilation System (GLDAS)

GLDAS is a joint development of NASA's Goddard Space Flight Center and NOAA's National Centers for Environmental Prediction, designed to simulate land surface fluxes and storage of water and energy (Rodell et al., 2004). GLDAS has been updated to version 2 (GLDAS-2), which includes 3-hourly, daily, and monthly products at spatial scales of 0.25° and 1.0° (https://earthdata.nasa.gov/). GLDAS-2 comprises GLDAS-2.0 and GLDAS-2.1 versions, with the former covering 1948–2014 and the latter covering 2000–2020. Since both versions include data from 2000 to 2014, we compared the overlapping precipitation data in the HRB [Figure 2: see original paper].

The two curves representing each version are essentially consistent, with only slight differences in extremes for individual years, indicating the datasets are largely comparable and consistent. Therefore, GLDAS-2.0 data for 1981–1999 and GLDAS-2.1 data for 2000–2020 were used in this study.

While GLDAS datasets inevitably involve some uncertainties (e.g., Liu et al., 2021a; Wu et al., 2021; Zhang et al., 2021a; Zhou et al., 2021a), such as GLDAS-2.1 slightly underestimating climatology values in northern China and overestimating values during summer and autumn in southern China (Wu et al., 2021), GLDAS-2 provides substantial research data, particularly in areas with scarce measured data. Several studies have verified the reliability of GLDAS-2 datasets in specific regions. For example, Liu et al. (2019) used Noah products from GLDAS-2.1 (1982–2015) to investigate spatiotemporal characteristics of dry-wet regimes and vegetation dynamics in the Yarlung Zangbo River Basin, showing that GLDAS-Noah simulated precipitation and air temperature patterns fitted well with in-situ data. Li et al. (2022) used Noah products from GLDAS-2.1 to investigate vegetation dynamics and environmental responses in the same basin. Zhu et al. (2021) compared GLDAS-2.0 data with global observed data, finding GLDAS-2.0 data objective and reasonable for global drought propagation analysis. To assess GLDAS-2 data applicability in our study, we compared precipitation and air temperature data from GLDAS-2 and HRB gauge stations for the same period (1981–2015). Results showed GLDAS-2 data was essentially consistent with observed data in spatial trends, with better performance on the regional average scale, although precipitation and air temperature in the upstream region were underestimated. Therefore, GLDAS-2.0 and GLDAS-2.1 data were selected as the basic data for analysis.

More specifically, precipitation, air temperature, and soil moisture data from 1981 to 2020 provided by Noah in GLDAS-2.0 and GLDAS-2.1 (https://earthdata.nasa.gov/) were selected as data sources. Table 1 reports key information for these data. Soil moisture data include values at depths of 0–10, 10–40, and 40–100 cm. Data were pre-processed prior to drought analysis, including re-projection and unit conversion. Figure 3a–c [Figure 3: see original paper] presents spatial distributions of multi-year average precipitation, air temperature, and soil moisture. Drought indices were calculated based on processed data (Vicente-Serrano et al., 2010; Martínez-Fernández et al., 2015). Additionally, land use and land cover change data for 2015 were provided by Landsat 8 (https://landsat.gsfc.nasa.gov/satellites/landsat-8/). According to the current land use classification (Ministry of Agriculture of the People's Republic of China, 2017), there are 23 land use and land cover types in the HRB, including forest, low-coverage grassland, cultivated land, desert, Gobi, etc. The distribution of each type is shown in Figure 3d [Figure 3: see original paper].

3.1 Framework

This research aims to explore propagation time and probability from meteorological drought to agricultural drought over the HRB. Regarding propagation time, besides seasonal sensitivity, dynamic characteristics were also considered since propagation time may not remain stable due to climate change and human activities (Liu et al., 2021b). For propagation probability, both seasonal sensitivity and drought level sensitivity (i.e., probabilities of agricultural drought at different levels triggered by meteorological drought at different levels) were investigated.

The framework is presented in Figure 4 [Figure 4: see original paper]. Specifically, we focus on three issues: (1) spatial characteristics of meteorological and agricultural drought across the basin from 1981 to 2020; (2) seasonal sensitivity and dynamic characteristics of drought propagation time; and (3) seasonal and drought level sensitivity of drought propagation probability.

Meteorological and agricultural drought were characterized by SPEI and Soil Water Deficit Index (SWDI), respectively. As SPEI has multiple time scales, we used SPEI at 1-, 3-, 6-, and 12-month time scales (denoted as SPEI-1, SPEI-3, SPEI-6, and SPEI-12) to investigate spatial patterns of meteorological drought. Seasonal sensitivity and dynamic characteristics of propagation time were evaluated using the correlation coefficient method, sliding windows, and Mann-Kendall test. Propagation probability and its sensitivities to seasons and drought levels were quantified using a Copula-based interval conditional probability model. All data were from GLDAS-2.0 and GLDAS-2.1.

Unlike the conventional four seasons (spring, summer, autumn, winter), this study considers only two seasons due to high irrigation frequency in the study area: (1) the irrigation season from April to September, and (2) the non-irrigation season from October to March of the following year.

3.2.1 Standardized Precipitation Evapotranspiration Index (SPEI)

SPEI, proposed by Vicente-Serrano et al. (2010), is a drought index based on the Standardized Precipitation Index (SPI) that incorporates potential evapotranspiration. The Thornthwaite approach, which requires only monthly precipitation and air temperature data, is recommended for calculating potential evapotranspiration (Li et al., 2016). SPEI is obtained through normalization using Equations 1 and 2:

$$\omega = \sqrt{-2\ln(F(D))} \tag{1}$$

$$\mathrm{SPEI} = \omega - \frac{c_0 + c_1\omega + c_2\omega^2}{1 + d_1\omega + d_2\omega^2 + d_3\omega^3} \quad (0 < F(D) \leq 1) \tag{2}$$

where ω is a function of $F(D)$, and $F(D)$ is the probability distribution function of D, which is the difference series between precipitation and potential evapotranspiration; and c_0, c_1, c_2, d_1, d_2, and d_3 are constants with values of 2.515517, 0.802853, 0.010328, 1.432788, 0.189269, and 0.001308, respectively. Further calculation details can be found in Vicente-Serrano et al. (2010). Table 2 shows meteorological drought classification according to SPEI values.

3.2.2 Soil Water Deficit Index (SWDI)

Unlike many drought indices based on meteorological variables or water balance equations, SWDI is based on a previous water deficit index (Martínez-Fernández et al., 2015). It considers the relationship between plant physiological state and soil moisture, making it more suitable for monitoring agricultural drought (Zhu et al., 2019; Wu et al., 2020). SWDI is calculated as:

$$\text{SWDI} = \frac{\theta - \theta_{FC}}{\theta_{AWC}}$$

where θ is soil moisture (g/cm^3), and θ_{FC}, θ_{WP}, and θ_{AWC} represent field capacity (g/cm^3), wilting point (g/cm^3), and available water capacity (g/cm^3), respectively. Long-term minimum and maximum values from the soil moisture time series serve as estimators of θ_{FC} and θ_{WP} (Bai et al., 2018). Table 3 lists agricultural drought categories based on SWDI values (Martínez-Fernández et al., 2015).

3.3.1 Pearson Correlation Coefficient

Propagation time can be defined as the duration from meteorological drought onset to agricultural drought beginning, simplified into a mathematical linkage between SPEI and SWDI across different accumulation periods. The time scale for meteorological drought is n months (n = 1, 2, …, 12), while for agricultural drought it is 1 month. The maximum Pearson correlation coefficient between SPEI-n and SWDI-1 represents the connection between meteorological and agricultural drought, with accumulation period n defined as drought propagation time (Xu et al., 2021).

3.3.2 Mann-Kendall Test and Sliding Windows

The Mann-Kendall test is a nonparametric statistical test used to quantitatively detect significant trends in long-term series. It does not require samples to follow a specific distribution and is less affected by outliers, making it widely used for trend and mutation testing in hydrology and meteorology (e.g., Sun, 2021). Sen's slope estimator is often used with the Mann-Kendall test to quantify change magnitude, with the former testing trend direction and the latter determining trend magnitude (Bazrafshan, 2017; Moral et al., 2017).

The sliding window algorithm includes two key elements: sliding distance and window length. By assigning values to these elements, new series are generated in a certain direction according to a fixed sliding distance and length (Shao et al., 2019). In this study, sliding distance was set to 1 year and window length to 20 years. Based on these settings, the index series from 1981 to 2020 was divided into 21 new series, and dynamic changes in drought propagation time were determined by calculating Sen's slope estimator values for these series.

3.4 Copula Function and Conditional Probability

Two commonly used Copula functions are Archimedean Copula and Elliptical Copula (Sun, 2021). Archimedean Copula is highly representative and easy to construct, while Elliptical Copula can establish non-normal relationships and better describe extreme events. The Copula function is calculated as:

$$C(F_1(u), F_2(v)) = P(U \le u, V \le v)$$

where $C(F_1(u), F_2(v))$ is the Copula function combining two random variables u and v; F denotes the marginal distribution function; and F_1 and F_2 represent the marginal distribution functions of the two random variables.

Five Copula functions (four Archimedean and one Elliptical) were selected to establish joint distributions of meteorological and agricultural drought indices. Table 4 details their formulas and parameters. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to evaluate goodness-of-fit, with the Copula function having the smallest AIC or BIC value considered the best fit for SPEI and SWDI series. Before establishing the Copula function, five alternative marginal distribution functions (normal, logistic, Weibull, General Extreme Value (GEV), and Pearson-III (P3)) were chosen to fit SPEI and SWDI series, with the Kolmogorov-Smirnov (K-S) test evaluating each marginal distribution function's performance.

An interval conditional probability model can characterize relationships between conditionally restricted random variables (Sattar et al., 2019). The interval conditional probability models of SPEI and SWDI were used to explore probabilities of different agricultural drought levels caused by different meteorological drought levels. The corresponding formulas are:

$$P(v_1 < V \le v_2 \mid u_1 < U \le u_2) = \frac{C(F_1(u_2), F_2(v_2)) - C(F_1(u_2), F_2(v_1)) - C(F_1(u_1), F_2(v_2)) + C(F_1(u_1), F_2(v}{F_1(u_2) - F_1(u_1)}$$

where P is the conditional probability value; U and V represent SPEI and SWDI series, respectively; v_1 and u_1 are lower limits of variables v and u; v_2 and u_2 are upper limits; F_1 and F_2 represent marginal distribution functions of variables u and v; and $C(F_1(u_1), F_2(v_1))$, $C(F_1(u_1), F_2(v_2))$, $C(F_1(u_2), F_2(v_1))$, and $C(F_1(u_2), F_2(v_2))$ are the corresponding Copula functions.

4.1 Meteorological Drought and Agricultural Drought over the Study Area

Figure 5a–d [Figure 5: see original paper] shows spatial distribution of multi-year average meteorological drought based on SPEI across the HRB at different time scales from 1981 to 2020. The study area was generally dominated by non-drought conditions at the multi-year average scale, although SPEI values differed across time scales. Larger SPEI values were observed for SPEI-1 (mainly green and yellow colors) with only 1% negative values, while smaller values were observed for SPEI-3, SPEI-6, and SPEI-12 (mainly orange and red colors), exhibiting more negative values (37%, 31%, and 25% of total values, respectively).

Figure 5e [Figure 5: see original paper] exhibits agricultural drought spatial distribution characterized by SWDI. Blue and green colors indicate non-drought conditions (SWDI > 0), while yellow and red colors indicate drought (SWDI < 0). Except for the river system and its surroundings in midstream and downstream regions, most of the study area was dominated by orange, light green, and red colors, indicating agricultural drought presence. Extreme agricultural drought was detected in the eastern downstream region (red color), likely related to low soil moisture. Extreme agricultural drought was also detected in some upstream regions (orange color), though less severe than in the eastern downstream region. The river system and surrounding areas (blue color) were categorized as non-drought, likely due to high soil moisture.

4.2.1 Drought Propagation Time and Its Seasonal Sensitivity

Figure 6 [Figure 6: see original paper] shows spatial distribution of drought propagation time for year-round, irrigation season, and non-irrigation season in the HRB. Redder tones indicate longer propagation time. Propagation time varied across basin regions. For example, in Figure 6a, midstream and southern downstream regions experienced short propagation time (<2 months), while other regions experienced longer time, particularly upstream and northern downstream regions (>11 months). The average propagation time across the whole basin was about 8 months, with the upstream region having the longest time (average 12 months), followed by midstream (8 months) and downstream (6 months) [Figure 6: see original paper].

Figures 6b and 6c reveal seasonal characteristics of propagation time. During the irrigation season, drought propagated much faster, taking less than 2 months to transform from meteorological to agricultural drought in midstream and downstream regions, compared to more than 7 months during the non-irrigation season. On average, propagation time was shorter during the irrigation season (6 months basin-wide, with 9, 5, and 3 months in upstream, midstream, and downstream regions, respectively) [Figure 6: see original paper]. During the non-irrigation season, propagation time became longer (10 months basin-wide, 11 months in both upstream and midstream regions, and 9 months in downstream region) [Figure 6: see original paper].

4.2.2 Dynamic Characteristics of Drought Propagation Time

To explore dynamic characteristics, we set a sliding window of 20 years and divided the study period (1981–2020) into 21 time series. Trends in propagation time for each grid were detected using Sen's slope estimator and Mann-Kendall test. Figure 7 [Figure 7: see original paper] depicts spatial distribution of temporal trends for propagation time. All tests exceeded the 95% confidence level, indicating significance at the 0.05 level. Green color indicates Sen's slope estimator values >0 (upward trend), while red color indicates values <0 (downward trend).

At the year-round scale, upstream and northern downstream regions (red color; 56% of basin) exhibited downward trends, indicating shortening propagation time. Midstream and southern downstream regions (green color; 44% of basin) showed upward trends, revealing lengthening propagation time [Figure 7: see original paper]. During the irrigation season, more regions (78% of basin) presented upward trends (green color) [Figure 7: see original paper]. Conversely, during the non-irrigation season, nearly 98% of the basin exhibited downward trends (red color) [Figure 7: see original paper], indicating that propagation time from meteorological to agricultural drought became shorter in most regions. Thus, over time, agricultural drought triggered by meteorological drought occurred more quickly during the non-irrigation season than during the irrigation season.

4.3.1 Selection of Optimal Marginal Distribution and Copula Functions

Drought propagation probability was calculated using the Copula-based interval conditional probability model. Normal, logistic, Weibull, GEV, and P3 marginal distribution functions were used to fit SPEI and SWDI series. Figure 8 [Figure 8: see original paper] shows the percentage of each marginal distribution function across all grids. GEV ranked first for SPEI-1, SPEI-6, and SPEI-12 series (64%, 48%, and 54%, respectively) and second for SPEI-3 series (28%). For SWDI, P3 ranked first. To maintain consistency in selecting optimal marginal distribution functions, we selected GEV and P3 as marginal distributions for SPEI (including SPEI-1, SPEI-3, SPEI-6, and SPEI-12) and SWDI series, respectively.

To ensure reliability, we performed K-S tests for each grid. For SPEI series, >94% of grids could be fitted by GEV, and for SWDI series, 82% of grids could be fitted by P3, according to K-S test results in Table 5 . Thus, GEV and P3 were finally determined as optimal marginal distribution functions for SPEI and SWDI series.

Copula functions were fitted using R (v.4.1.1) (R Development Core Team, 2022), and the function with the highest percentage across all grids was selected as optimal. Figures 9 and 10 [FIGURE:9-10] show the percentage of each Copula function under AIC and BIC. The Clayton Copula function accounted for the highest percentage for SPEI-1-SWDI, SPEI-3-SWDI, and SPEI-6-SWDI combinations, and the second-highest percentage for SPEI-12-SWDI (slightly inferior to Gumbel Copula). Thus, the Clayton Copula function was chosen as the optimal Copula function for SPEI and SWDI series.

4.3.2 Drought Propagation Probability and Its Drought Level Sensitivity

Propagation probability was calculated using Equations 5 and 6 and the Clayton Copula function. SPEI-6 was selected for calculating propagation probability because the average propagation time from meteorological to agricultural drought in the HRB was estimated at 8 months, close to 6 months. This medium time scale is suitable for characterizing water deficit signal propagation from atmosphere to soil (Xu et al., 2021; Yang et al., 2021; Zhang et al., 2021b).

Figure 11 [Figure 11: see original paper] shows propagation probability of different agricultural drought levels induced by varying meteorological drought levels. Probability ranged from 0.00 to 1.00, with redder tones indicating higher values. Generally, agricultural drought caused by meteorological drought exhibited varying spatial trends.

In the upstream region, when meteorological drought occurred, severe agricultural drought propagation probability was about 0.60 (mainly blue color), and extreme agricultural drought probability was 0.40–0.85 (green and purple colors), slightly greater than mild and moderate agricultural droughts (0.20 and 0.40, respectively). In the eastern upstream region, extreme agricultural drought was more likely to be triggered, with propagation probability >0.80. Propagation probability of agricultural drought at different levels increased with meteorological drought severity. For example, when meteorological drought increased from moderate to severe, agricultural drought propagation probability increased from 0.40 (moderate level) to 0.60 (severe level).

In the midstream region, propagation probability of agricultural drought at different levels also increased with meteorological drought severity. For example, severe agricultural drought probability increased from 0.80 to >0.90 when meteorological drought increased from moderate to severe. In the upstream-midstream junction region, severe and moderate agricultural droughts were more likely to occur, with propagation probability >0.80.

The downstream region was mainly dominated by mild, moderate, and extreme agricultural droughts induced by meteorological drought. Extreme drought was most likely in the east of the river system, while moderate agricultural drought was more probable in the west, with propagation probability >0.90. In the southern downstream region (near midstream), propagation probability of mild and moderate agricultural droughts increased with meteorological drought levels. For example, moderate agricultural drought probability increased from 0.40 to 0.80 and subsequently exceeded 0.90 when meteorological drought increased from mild to moderate and then to extreme levels. Note that propagation probability values near the river system were extremely close to zero because soil moisture near the mainstream region was always high, implying low agricultural drought propagation probability.

In short, except for regions close to the river, different agricultural drought levels in the HRB were sensitive to different meteorological drought levels, with noticeable spatial differences in sensitivity.

4.3.3 Seasonal Sensitivity of Drought Propagation Probability

Figures 12 and 13 [FIGURE:12-13] present spatial distributions of seasonal sensitivity of propagation probability across the basin. Meteorological drought was more likely to trigger low-level agricultural drought during the irrigation season and severe-level agricultural drought during the non-irrigation season. This seasonal sensitivity also exhibited noticeable spatial differences.

In the western downstream region, only mild and moderate agricultural droughts were triggered during the irrigation season, with propagation probability values of 0.20–0.40 and >0.90, respectively [Figure 12: see original paper], while moderate and severe agricultural droughts were triggered during the non-irrigation season, both with propagation probability >0.85 [Figure 13: see original paper]. In the southern downstream region, only mild agricultural drought was triggered, with propagation probability >0.90 during the irrigation season [Figure 12: see original paper], while mild and moderate agricultural droughts were triggered during the non-irrigation season, with propagation probability >0.85 [Figure 13: see original paper]. In the eastern downstream region, extreme agricultural drought was most likely to occur, with propagation probability exceeding 0.90 regardless of season.

In the midstream region, mild, moderate, severe, and extreme agricultural droughts (probability values ranging from 0.20 to >0.90) occurred during both irrigation and non-irrigation seasons. However, the area of severe agricultural drought triggered during the non-irrigation season was larger than during the irrigation season [FIGURE:12-13]. In the upstream region, minimal changes were detected in propagation probability of agricultural drought at varying levels during both seasons [FIGURE:12-13].

5 Discussion

The water and energy link between meteorological and agricultural drought involves a phase difference in time, with propagation inseparable from the water cycle (Xu et al., 2021; Li et al., 2022). This study analyzed propagation time and probability from meteorological to agricultural drought and their sensitivities to seasons and drought levels in the HRB. Drought propagation characteristics and corresponding sensitivities exhibited great spatial differences, likely related to local climate, topography, vegetation cover, etc. (Xu et al., 2019; Zhou et al., 2021a; Zhu et al., 2021; Zhang et al., 2022b).

5.1 Drought Propagation Time

The upstream region experienced longer propagation time from meteorological to agricultural drought, likely related to land use and land cover type. As shown in Figure 3d [Figure 3: see original paper], the upstream region is mainly forested with good water holding capacity. In the short term, precipitation changes have limited effects on soil moisture, resulting in slow agricultural drought response to short-term precipitation changes and thus longer propagation time.

In midstream and southern downstream regions, propagation time was only 1–2 months, possibly related to climate and geographical conditions. The midstream is an agricultural planting region requiring substantial irrigation water to maintain soil moisture and ensure crop growth. The southern downstream region is dominated by marshland, saline land, and desert with relatively low soil moisture, making precipitation particularly important for soil moisture replenishment. Thus, these regions are more sensitive to climate changes. If precipitation scarcity continues (without artificial diversion irrigation), soil moisture decreases, quickening agricultural drought response. The northern downstream region contains an inland lake and grassland with relatively high soil moisture and minimal average annual precipitation (<50.0 mm) (Ding et al., 2009; Yang et al., 2022), leading to weak sensitivity to climate changes and slow agricultural drought response. Other factors including wind, radiation, and altitude could also affect soil moisture availability by influencing evapotranspiration and runoff processes (Van den Hoof and Lambert, 2016).

The HRB irrigation season experienced shorter propagation time than the non-irrigation season, indicating agricultural drought is more sensitive to meteorological drought during irrigation season. Over 70% of precipitation is concentrated in June–September (irrigation season), and continued precipitation lack decreases soil moisture accordingly. Additionally, June–August is the growing season when vegetation requires more water from soil (Qian et al., 2016). Agricultural drought is more likely triggered by precipitation deficiency and high water demand. Thus, relatively shorter propagation time occurs during the irrigation season.

Figure 6b–c [Figure 6: see original paper] reveals that regardless of season, the upstream region always experienced longer propagation time than other regions, possibly because forest vegetation has deep, well-developed roots, leading to higher resistance to surface soil moisture reduction compared to crops, grassland, and marshland in midstream and downstream regions. Moreover, propagation time during the irrigation season in the upstream region was slightly shorter than during the non-irrigation season, possibly due to snow and ice cover in the basin (Chen et al., 2018; Li et al., 2021). As temperatures increase, snow and permafrost melt, replenishing soil moisture (LYU et al., 2020) and shortening propagation time during the irrigation season.

Few studies have investigated seasonal sensitivity of propagation time from meteorological to agricultural drought in the HRB, but relevant cases in other basins provide reference (e.g., Huang et al., 2015; Bhardwaj et al., 2020; Li et al., 2022). Huang et al. (2015) concluded that propagation time from meteorological to agricultural drought in the Weihe River Basin is shorter in summer and longer in autumn. Liang et al. (2021) estimated propagation time from meteorological to agricultural drought in the Jinta River Basin of Northwest China was concentrated in 2 months during summer and 6–12 months in autumn and winter. Li et al. (2022) found propagation time from meteorological to agricultural drought was shorter (1–3 months) in summer and autumn but longer (5–12 months) in spring and winter over an arid region of Northeast Asia. Previous literature shows propagation time from meteorological to agricultural drought is relatively shorter in summer, similar to our findings for the HRB irrigation season.

5.2 Drought Propagation Probability

Propagation probability of agricultural drought at different levels increased with meteorological drought severity in the upstream and midstream regions, possibly related to vegetation cover and evapotranspiration. When mild meteorological drought occurs, vegetation's excellent water retention capacity can withstand effects. However, extreme precipitation reduction can induce water-stressed vegetation states, consuming more water through evapotranspiration during droughts, which may exacerbate droughts and induce higher agricultural drought propagation probability (Zhu et al., 2021). Propagation probability in the midstream region was always higher than in the upstream region, likely due to different vegetation types. Upstream forests are more drought-tolerant because well-developed root systems can absorb deep soil water, while midstream grasses and crops have shorter, less developed root systems requiring more shallow soil water (Zhou et al., 2021a). In the downstream region, agricultural drought levels varied spatially, largely related to soil moisture. Low soil moisture in western and eastern downstream regions increased propagation probability of moderate and extreme agricultural droughts, while high soil moisture near the river system made agricultural drought less likely to be triggered.

At the seasonal scale, lesser agricultural droughts were more likely during the irrigation season in midstream and downstream regions, while severer agricultural droughts occurred mostly during the non-irrigation season. This implies irrigation-induced soil moisture increases could delay and mitigate meteorological drought effects on agricultural drought. Irrigation affects water and energy balance near the ground, making the atmosphere wetter near the surface (Zhu et al., 2021). Therefore, the same level of meteorological drought is more likely to trigger lower-level agricultural drought during the irrigation season, consistent with Fang et al. (2019). In contrast, no obvious propagation probability differences were observed in the upstream region between seasons [FIGURE:12-13] since upstream soil moisture was not affected by irrigation.

6 Conclusions

This study investigated propagation time and probability from meteorological to agricultural drought in the HRB from 1981 to 2020, together with their spatial variations and sensitivities to seasons and drought levels. The correlation coefficient method and Copula-based interval conditional probability model were employed. The following conclusions can be drawn:

(1) Larger SPEI values were observed for SPEI-1, while smaller SPEI values were observed for SPEI-3, SPEI-6, and SPEI-12. Spatially, smaller SPEI values occurred in midstream and northern downstream regions. Agricultural drought characterized by SWDI exhibited the most serious level in the eastern downstream region, followed by the upstream region.

(2) Average drought propagation time was estimated at 8 months basin-wide at the year-round scale, 6 months during the irrigation season, and 10 months during the non-irrigation season. Propagation time showed obvious spatial differences in the HRB. Dynamic characteristic analysis revealed increasing trends in 78% of the basin during the irrigation season and decreasing trends in 98% of the basin during the non-irrigation season.

(3) Propagation probability was sensitive to seasons and drought levels, with noticeable spatial differences. In upstream, midstream, and southern downstream regions, propagation probability of agricultural drought at different levels increased with meteorological drought severity. In western and eastern downstream regions, moderate and extreme agricultural droughts were more easily triggered by meteorological drought, with propagation probability >0.90. Regarding seasonal sensitivity, lesser agricultural droughts were more likely triggered during the irrigation season, while severer agricultural droughts occurred mostly during the non-irrigation season.

These results improve understanding of drought propagation among different drought types and provide a useful reference for monitoring meteorological and agricultural drought and rational water resources use in the HRB. However, this study has limitations. For example, influencing factors of drought propagation characteristics were only explained through qualitative analysis. Quantitative analysis of climate, land use, soil moisture, and irrigation effects on drought propagation will be the focus of future work.

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