Clarifying the Propagation Dynamics from Meteorological to Hydrological Drought Induced by Climate Change and Direct Human Activities

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ABSTRACT: An understanding of the propagation process from meteorological to hydrological drought contributes to accurate prediction of hydrological drought. However, the comprehensive influence of direct human activities involved in drought propagation is not well understood. In this study, an identification framework for drought propagation time was constructed to quantify the effects of direct human activities (i.e., reservoir storage, irrigation, industrial, domestic, and agricultural water consumption) on drought propagation. Subsequently, the effects of meteorological and underlying surface factors on the drought propagation process were clarified based on random forest method, and the driving effect of teleconnection factors was investigated from top to bottom. The Wei River basin (WRB), the largest tributary of the Yellow River basin, was selected as the case study. Results disclosed that the propagation time from meteorological to hydrological drought was short in summer (approximately 2 months) and autumn (approximately 3 months), while long in spring (approximately 3–5 months) and winter (approximately 3–8 months), exhibiting noticeable spatial variability. In a changing environment, the propagation time generally showed a decreasing trend in spring and winter, while increasing propagation time was observed in summer and autumn. The dynamic drought propagation time of each season was all jointly controlled by the different extent variation of meteorological and underlying surface conditions, and the basic flow is all relatively significant throughout the period. Direct human activities had an effect on the seasonal dynamics of drought propagation, especially during the winter of the nonflood season, which alleviated the severity of winter hydrological drought to some extent, thus delaying the transmission of meteorological signals to hydrological systems. Sunspots, the dominant direct teleconnection driving force in the WRB, could indirectly affect the local precipitation and base flow in spring, autumn, and winter and interfere with the drought propagation process. This study sheds new insights into the attribution of drought propagation dynamics in a changing environment.

KEYWORDS: Rivers; Drought; Dynamics; Statistics; Time series; Stochastic models

1. Introduction

Worldwide, drought occurs in almost all climatic zones and are one of the most frequent natural disasters. Due to the characteristics of high frequency, long duration, and wide range, drought impacts affect almost all parts of the ecological environment security, as well as social and economic development (Hao and AghaKouchak 2014). Between 1980 and 2009, the economic losses associated with drought disasters worldwide averaged $17.33 billion (U.S. dollars) per year, far more than other meteorological disasters; since then, the world has witnessed a continued escalation of economic damages from drought, averaging $23.125 billion (U.S. dollars) per year from 2010 to 2017 (Wilhite 2000; Su et al. 2018; Zhang et al. 2020). As the global water cycle intensifies under a warming climate, the water balance, made up of processes like plant transpiration and surface evapotranspiration, is made to adjust, further increasing drought risk. Meanwhile, existing studies have shown that the frequency and intensity of drought disasters have increased in recent years, especially in the midlatitude region (Dai 2011), making the characteristics of drought disasters more abnormal and increasing the potential harm to human production and life; in particular, major drought disasters can directly threaten a country’s long-term food security and social stability (Cruz et al. 2007; X. Li et al. 2018). China is located in the east of Asia and the west coast of the Pacific Ocean, which is a fragile climate zone with a complex geographical environment. Due to the influence of specific climatic conditions and water resource conditions, drought in China, in sync with the global trend, has become increasingly serious and frequent (Su et al. 2018). Since the twenty-first century, droughts have continued to occur frequently in northern China; however, the frequency of droughts in southern China has also increased significantly, and the increase in seasonal droughts has been particularly significant (Sun and Yang 2012; Chen and Sun 2015). The complexity of China’s drought problem is showing an increasing trend under the influence of climate warming and rapid social development (Xu et al. 2015), which requires researchers to further strengthen drought-related research. As such, improving the understanding of the causes (depending on the climate and
human settings) of drought processes is of great importance because it has the potential to improve drought-forecasting skills and, thus, drought preparedness and management (Kingston et al. 2013).

Owing to the complexity of the drought occurrence, development, and influence process, droughts are currently divided into meteorological, agricultural, hydrological, and socioeconomic, based on the water cycle components (Mishra and Singh 2010). Meteorological drought, caused by inadequate rainfall, is the first stage of the four drought types with relatively rapid occurrence and termination, and is thus the most common and basic type of drought which is often characterized by standardized precipitation index (SPI), standardized evapotranspiration index (SPEI), and Palmer drought severity index (PDSI) (Palmer 1965; McKee et al. 1993; Vicente-Serrano et al. 2010). Compared with SPEI and PDSI, the SPI has lower data requirements, is simple to calculate, covers multiple time periods, and is recommended by the World Meteorological Organization (WMO), so it is widely used in the depiction of meteorological drought and reliably monitors the development of meteorological drought (Wu et al. 2017). Because the water supply is mainly in the form of runoff after the completion of all physical processes on the underlying surface, hydrological drought based on insufficient runoff is considered to be a thorough drought (Barker et al. 2016; Wu et al. 2017). Hydrological drought is often characterized by the standardized streamflow index (SSI), which is similar to SPI and has also been widely verified worldwide (Huang et al. 2017; Li et al. 2016). Meteorological and hydrological droughts usually do not occur simultaneously during a drought duration. The long-term precipitation deficit, combined with water consumption through evapotranspiration and human activities, to a certain extent, will ensure that the surface water and groundwater cannot be replenished in a certain period, resulting in hydrological drought. Therefore, the formation and termination of hydrological drought has a certain lag relative to meteorological drought; that is, it takes time for drought to propagate from meteorological to hydrological, which is the basis for establishing a hydrological drought early warning system based on meteorological drought information.

Recent research projects have carried out comprehensive studies on the propagation mechanism from meteorological to hydrological drought in terms of the propagation process (Van Loon and Van Lanen 2012; Yu et al. 2020), propagation characteristics (Sattar et al. 2019), propagation influencing factors (Huang et al. 2017), temporal and spatial changes in propagation (Barker et al. 2016), and the relationship between these two types of droughts (Wu et al. 2017; Wang et al. 2020), thus improving the scientific understanding of the evolution from meteorological to hydrological drought to a certain extent. When studying the propagation mechanism from meteorological to hydrological drought, the main methods used include hydrological model simulation and data analysis. Hydrological model simulation can apply hydrological models to understand the physical mechanisms of drought propagation under different climate and watershed characteristics, and has advantages in analyzing spatial variation laws among different drought types (Apurv et al. 2017; Apurv and Cai 2020; J. Li et al. 2018). However, uncertainty surrounding the ideal model parameters and outputs involved limits the ability of this method to reflect the complexity of a real watershed; thus, it is typically applied to basin-specific exploration (Fang et al. 2020; Apurv and Cai 2020). In contrast, statistical analysis methods often involve fewer assumptions and have been widely applied to areas with abundant atmospheric and hydrological variables, which are more reliable and easier to use in different spatial ranges (Fang et al. 2020). Meanwhile, the time lag effect of meteorological drought on hydrological drought can be effectively quantified based on the response time between the two droughts. Barker et al. (2016) analyzed the propagation behavior of 121 natural watersheds in the United Kingdom based on the cross-correlation results of 1-month SSI with various SPI accumulation periods and found that longer SPI accumulation periods were strongly correlated with the 1-month SSI. Zhao et al. (2014) identified the duration of meteorological and hydrological drought in the Jing River basin and determined that the response time was approximately 4 months, and proposed that the impact of rainfall intensity, temperature, vegetation coverage, underlying surfaces, and human activities on the time lag needed further analysis.

In particular, as the occurrence of drought is closely related to the hydrological cycle, current studies have explored the dynamics of drought response time, as well as their dominant drivers from the perspective of climate change and human activities (Van Lanen et al. 2013; Xu et al. 2019; Wang et al. 2019). Huang et al. (2017) explored the El Niño Southern Oscillation (ENSO)/Arctic Oscillation (AO) and underlying surface characteristics as potential factors for drought propagation time. Barker et al. (2016) explored the relationship between meteorological drought and hydrological drought in the United Kingdom and its links with climate and catchment properties. They found that in the south and east, catchment properties describing storage (such as the percentage of highly productive fractured rock, base flow index, and typical soil wetness) were more influential on hydrological drought duration, severity, and propagation. By analyzing the relationship between meteorological drought and hydrological drought before and after dam construction, Wu et al. (2017) found that the construction of a reservoir shortened the propagation time from meteorological to hydrological drought. Apurv and Cai (2020) showed that the relationship between storage and discharge, which was a key watershed property, affected the drought propagation process. Nevertheless, our understanding of drought propagation mechanisms is still limited because of the time difference between meteorological and hydrological droughts, as well as the variability of basic conditions and climate variables related to drought propagation processes (Mishra and Cherkauer 2010; Sattar et al. 2019). The extent to which climate change and human activities affect drought propagation mechanisms remains a challenging and unsolved problem, and one which is not conducive to understanding hydrological drought formation mechanisms, as well as accurate hydrological drought prediction. Especially in this “human-influenced changing era” the impact of human activities on the process of drought propagation cannot be ignored. At the basin scale, human activities mainly change the storage
status of rivers and hydraulic connections (mainly through storage, diversion, lifting, and water transfer projects), causing changes in the regulation and storage functions of rivers and groundwater systems, or by changing the temporal and spatial structure and distribution of water use (highlighted in the aspects of irrigation, agriculture, and urbanization), causing changes in surface runoff production conditions, consumption, and discharge conditions, which directly affect the propagation process of meteorological drought to hydrological drought and the development process of hydrological drought. Previous studies on the effects of human activities on drought propagation have emphasized that different human factors (such as reservoir storage, irrigation, industrial, domestic, and agricultural water consumption) should be integrated to analyze drought propagation characteristics (Ma et al. 2019; Xu et al. 2019). Hence, this paper comprehensively quantifies the impact of direct human activities (water resources development and utilization such as reservoir storage, irrigation, and artificial water extraction) on drought propagation on a monthly and seasonal scale in the study basin. Likewise, because the drought process is affected by many factors (such as underlying climatic and physiographic settings) and there may be linear or nonlinear responses between these factors, the precipitation deficit and the change in local water storage in the basin will intensify the drought propagation process from meteorological to hydrological drought (Kingston et al. 2013; Y. Liu et al. 2019; Zhou et al. 2021). Unlike most previous efforts that identified the drought propagation time exclusively considering the linear Pearson’s correlation between the two kinds of studied droughts (Ma et al. 2019; Barker et al. 2020), we apply the Spearman method as a metric of nonlinear dependence in view of casual meteorological droughts possibly transmitting to hydrological droughts in a nonlinear manner. When determining the propagation time, other nonlinear analysis methods (such as mutual information and maximal information coefficient) can also be used, or even a combination of linear and nonlinear analysis methods (Fang et al. 2020). Concurrently, the use of the Spearman correlation coefficient to measure the relationship between two different types of drought or one drought and its influencing factors has been verified in case studies (Kazemzadeh and Malekian 2016; López-Moreno et al. 2013; da Rocha et al. 2020; Sattar et al. 2019). Furthermore, we use random forest (RF) technology, which has advantages in solving nonlinear system problems (Breiman 2001; J. Li et al. 2020). Therefore, it is an effective technology for exploring the driving factors and related mechanisms behind the dynamic propagation from meteorological to hydrological drought. If these potential driving factors and related mechanisms are revealed properly, it will lay a solid foundation for the establishment of a monitoring and forecasting system for hydrological drought based on meteorological drought, thereby increasing the forecast period for hydrological drought. To a certain extent, the adverse effects of hydrological drought on regional social and economic development can be alleviated. Hence, investigating the propagation mechanism from meteorological to hydrological drought has important theoretical significance and application value.

The Wei River basin (WRB), and the Guanzhong area in particular, has served as a bridgehead for China’s western development in recent years, especially after the establishment of the Xixian New Area and has become a new growth pole for the country. Currently, frequent droughts have a great impact on the sustainable development of the economy and society in the region, and even affect the overall situation of a regional coordinated development of the country.

Considering the spatial heterogeneity of climate and topography, this study selected the WRB and its two major tributaries, the Jing River and Beiluo River, as the study area. Based on the time–frequency space exploration of the relationship between meteorological drought and hydrological drought, the propagation time from meteorological to hydrological drought and its dynamic change characteristics were quantified, and the drought-controlling mechanisms affecting the propagation process were analyzed to determine the relative role of climate (such as precipitation, potential evapotranspiration, and teleconnection factors) and underlying surface conditions on the development of hydrological drought in a changing environment. This study adds to previous works by performing a comprehensive and systematic analysis of hydrological drought, including a comprehensive quantification of the contribution of direct human activities on the process. The research results are expected to develop a drought reduction mechanism, in terms of formation and propagation, to effectively guide local watershed planning and drought risk management.

2. Study area and data

2.1. Study area

The WRB is the largest tributary of the Yellow River with a length of 818 km, covering a drainage area of approximately 134,800 km², and originates from the northern side of the Niaoshu Mountains in Weiyuan County of Gansu Province. The WRB flows from west to east through the three provinces (or autonomous regions) of Gansu, Ningxia, and Shaanxi, and merges into the Yellow River in Tongguan County, Weinan City, Shaanxi Province (Fig. 1). The terrain of the basin gradually slows down from west to east, and the river channel widens; thus, the flow velocity decreases. The watershed landform is complex and mainly manifests as a loess area, which is composed of hill areas, earth rock areas, terrace areas, and valley alluvial plain areas. The watershed is located at the junction of arid and humid regions and has a continental monsoon climate. There are significant differences in the temporal and spatial distribution of precipitation across the basin, with more precipitation in the southeast and less precipitation in the northwest and more in the mountainous and less in the basins. The average annual precipitation is approximately 580 mm, and with precipitation from July to October accounting for approximately 60% of the annual total (Huang et al. 2017; Zuo et al. 2014). Since the 1970s, large-scale water conservancy construction began in the WRB and since the 1980s, comprehensive treatment projects have been carried out, with 24,647 million mu (1 mu = 666.67 m²) of basic
farmland and 27.756 million mu of forest and grassland planted for soil and water conservation and since the 1990s, a number of urban water supply projects have been successively built to meet the increasing demand in residential water consumption (Wang et al. 2006). By the end of 2000, a total of 302 reservoirs [including large, medium, and small (I) type], 2631 water diversion projects, 6578 water lifting projects, and 1.21 million hm² of effective irrigation area (from storage, diversion, and lifting project) were built in the WRB. There are nine large-scale irrigation districts, such as the Baojixia Tableland irrigation completed in 1971, which increased the irrigated area to more than 1 million mu, compared to 270 000 mu in 1949 (Chen 2017).

There are many tributaries in the WRB, and the two largest tributaries are the Jing River basin (JRB) and the Beiluo River basin (BRB), with approximate areas of 45 400 and 26 900 km², respectively. The JRB, with a total length of 455 km, is the largest tributary of the WRB. The average annual temperature is approximately 10°C, the average annual precipitation is 550 mm, and the distribution of runoff during the year is extremely uneven, which leads to frequent floods and droughts, aggravated soil erosion, and increased sand content. Thus, floods and sediments in the WRB are mainly produced in the JRB. The BRB, the second largest tributary of the WRB, originates from the Caoliang Mountain at the southern foot of the Baiy Mountain in Dingbian County, Shaanxi Province, and empties into the Wei River at the mouth of the Sanhekou, southeast of Dali County, with a total length of 680 km. The average annual temperature in the basin is approximately 9°C, and the average annual precipitation is approximately 520 mm. The topography of the BRB is generally higher in the northwest and lower in the southeast. Approximately 71% of the basin is characterized as a loess hilly area, mostly in the upper reaches, with deep gullies, steep slopes, and sparse vegetation; the Loess Plateau area accounts for 25%, distributed in the middle reaches, and the lower reaches, belonging to the Guanzhong basin, which has relatively good natural conditions in the basin. In the upper and middle reaches of the BRB, long-term serious soil erosion has caused vegetation destruction, farmland degradation, massive siltation of rivers, and frequent droughts and floods, restricting the sustainable economic and social development of the region.

Drought hazards in the WRB have caused huge losses to the socioeconomic fabric and grain production and in recent years (Zou et al. 2017). A total of 255 drought events occurred in the JRB between 1470 and 1979, of which 103 were severe or extreme (Guo and Zha 2009). From 1949 to 1995, 32 drought disasters occurred in the WRB, which restricted the sustainable development of agriculture. In addition, continuous drought events were more prominent, such as from 1960 to 1962, from 1971 to 1972, from 1978 to 1980, from 1986 to 1987, and from 1994 to 1997 (Lei et al. 2014). According to Y. Liu et al. (2019), over the past 200 years (1813–2017) in the WRB, of which mild droughts occurred the most, and major droughts occurred the least.

b. Data

Data for meteorological, hydrological, digital elevation model (DEM), teleconnection, soil moisture (SM), and base flow (Bf) were mainly utilized in this study. Daily meteorological data from 1960 to 2010, including precipitation P, relative humidity, sunshine duration, air pressure, wind velocity, and mean, maximum, and minimum air temperature, were collected from 28 meteorological stations (Lintao, Minxian, Huajialing, Xiji, etc.) in the WRB and the surrounding areas, which were provided by the China Meteorological Data Sharing Service System (http://www.cma.gov.cn). Monthly natural and observed streamflow data were obtained from the Zhangjiashan, Zhuangtou, and Huaxian hydrological stations in the WRB, which were derived from the Yellow River Commission and the Hydrological Yearbook of the People’s Republic of China, respectively. Data quality was strictly controlled before publication. The natural streamflow here is the observed streamflow plus the water use quantity, which
eliminates the influence of water resource development and utilization (i.e., direct human activities) such as reservoir impoundment, irrigation, and industrial, domestic, and agricultural water consumption (Y. Li et al. 2020). In the results of “Revision on hydrological design results in the Yellow River basin,” the calculation process of the natural streamflow and the verification of its accuracy and rationality were recorded in detail (H. Liu et al. 2019). In addition, based on the same set of data, Wang and Zhao (2019) explored the strategy of harnessing the Yellow River in the new period, and Peng et al. (2019) demonstrated the advantages of the constructed model for the synergetic optimal operation of cascade reservoirs in mainstream. Y. Li et al. (2020) also carried out research on the hydrological drought in the whole Yellow River basin. The DEM dataset with a spatial resolution of 90 m was derived from the geospatial data cloud. The teleconnection data of sunspot, ENSO, and AO during 1960–2010 were mainly used in this study. The monthly sunspot data were obtained from the International Council of Scientific Unions (ICSU). World Data System (WDS), and the long-term solar observation website (http://sidc.oma.be/silso/dayssnplot), the monthly Niño 3.4 index data used to characterize the ENSO events were collected from the National Oceanic and Atmospheric Administration (NOAA) Earth System Research Laboratory (http://www.esrl.noaa.gov/psd/data/correlation/nina34.data), and the monthly AO data were acquired from the climate data center of NOAA (http://www.ncdc.noaa.gov/teleconnections/ao.php). The monthly SM data for 0–2-m soil layer thickness in the WRB were gathered from the data center of the Global Land Data Assimilation System (GLDAS) (https://search.earthdata.nasa.gov/search?q=GLDAS). The GLDAS provides data on a large quantity of land surface states and fluxes. The reliability of the GLDAS dataset in the study area was verified by earlier studies through a comparison with the in situ measurements (Feng et al. 2016; Wu et al. 2019). Furthermore, Bf data were calculated using the Lyne–Hollick filtering method (the relevant calculation formula can be obtained by referring to the paper by Zhang et al. (2017), and the potential evapotranspiration (PET) data were calculated based on the Penman formula (Guo et al. 2019; Zhou et al. 2020) revised by the Food and Agricultural Organization (FAO). The geographical location of the study watershed and the spatial distribution of hydro-meteorological stations are shown in Fig. 1. Based on the daily data from the 28 meteorological stations, the monthly averaged areal PET of each subwatershed were estimated by using the Thiessen polygon method.

3. Methodology

a. Determination of propagation time from meteorological to hydrological drought

To identify the propagation time from meteorological to hydrological drought, it is necessary to select a reasonable standardized drought index to represent meteorological drought and hydrological drought. The SPI can effectively characterize the meteorological drought. It was first proposed by McKee et al. (1993) and applied to the assessment of drought conditions in Colorado. SPI is used to characterize the probability of precipitation occurrence in a certain period of time, and has the ability to detect drought at different time scales. Therefore, it can meet the need for multi-time-scale meteorological drought calculations. As it cannot only characterize the change in precipitation drop over a short time scale, but also characterize the evolution characteristics of water resources on a long time scale, it can reveal the correlation between the climate characteristics and lack of precipitation over a certain period of time. In line with earlier efforts (Barker et al. 2016; Zhao et al. 2014), the current study makes use of the multiscalar characteristic of the SPI. Considering the availability of precipitation data and the simplicity and wide use of the SPI index, this study was based on SPI to identify the characteristics of meteorological drought changes in the WRB. The hydrological drought index can be characterized by the SSI, which was first proposed by Shukla and Wood (2008). Owing to the high bias of the streamflow series, the probability distribution type of the fitting cumulative data is different from that of the SPI series. In this study, the lognormal distribution which had performed well in similar watersheds in northwest China, was used to calculate the SSI (Gao and Zhang 2016). Meanwhile, an SPI time scale capable of gaining a relatively high SPI–SSI correlation is defined as the propagation time of meteorological to hydrological droughts. This definition is essentially based on the concept that the development of hydrological droughts is a response to the persistence of meteorological drought conditions (quantified by the accumulated precipitation deficits over a long time) rather than simply a response to a particular timing (mainly the onset, peak severity, and termination) of antecedent meteorological droughts. This definition has been widely applied in drought propagation studies (Dash et al. 2019; Ma et al. 2019; Fang et al. 2020). Therefore, the drought propagation time obtained in this study is in a generalized sense, which highlights the cumulative effects of meteorological droughts and represents the average accumulation period during which insufficient precipitation is sufficient to trigger the development of hydrological drought (Fang et al. 2020).

The specific calculation steps for the propagation time from meteorological to hydrological drought are shown in Fig. 2. First, based on the monthly SPI and SSI sequences, the Spearman method was used to calculate the correlation coefficient between meteorological drought and hydrological drought. Readers interested in the theoretical details of the Spearman method can refer to da Rocha et al. (2020). Second, the SPI time scale corresponding to the first correlation maximum was chosen as the propagation time from meteorological to hydrological drought. Finally, based on the average propagation time of 3 months from a particular season, the drought propagation time of the season was obtained (e.g., the summer drought propagation time was the average of the drought propagation time from June to August).

b. Random forest method

The RF method was proposed by Breiman (2001), who used bootstrap resampling technology to extract multiple subsamples from original samples, modeled the decision tree of each bootstrap subsample, and then determined the final prediction
result by combining the prediction results of multiple decision trees by voting or averaging. Compared with neural networks, support vector machines, decision trees, etc., RF has better noise tolerance and higher prediction accuracy, and is not prone to overfitting problems (Cai et al. 2019; Sutanto et al. 2020). RF regression can model continuous dependent variables, which are formed by the growth of a decision tree related to the random vector $\mathbf{u}$. Therefore, in this study, RF regression was used to analyze the drivers of drought propagation dynamics from meteorological to hydrological drought in a changing environment. The main procedures of the random regression algorithm constructed are as follows:

- Step 1: The dataset $N$ of drought propagation time at the required time scale was derived from the determined drought propagation time database and used to generate a random vector sequence $\mathbf{u}_i$ ($i = 1, 2, \ldots, n$). Meanwhile, a bootstrap was applied to randomly sample a subdataset of $n$ samples with replacement, which was recorded as $[N_i]$ ($i = 1, 2, \ldots, n$, where $n$ represents the number of regression trees constructed).
- Step 2: For each bootstrap sample set $[N_i]$ ($i = 1, 2, \ldots, n$), the drought propagation time tree regression model $[h_i(\mathbf{X}, \mathbf{\theta})]$, $i = 1, 2, \ldots, n$ was established, where the matrix $\mathbf{X}$ was the independent variable used for modeling, which was the influence factor related to the drought propagation process in this study.
- Step 3: Through $n$ rounds of training, a decision tree regression sequence $[h_1(\mathbf{X}), h_2(\mathbf{X}), \ldots, h_n(\mathbf{X})]$ could be obtained. Then, this sequence was used to construct a model composed of multiple decision tree regressions. The final prediction results of the model were the average summary of the results of the above $n$ rounds.

The RF obtains different sample sets by the resampling method and uses these sample sets to construct the decision tree regression model separately, thus enhancing its extrapolation forecast ability. In the RF, “ntree” and “mtry” are two important parameters, where ntree is the number of decision

Fig. 2. Structural diagram for identifying the propagation time from meteorological to hydrological drought.
trees in RF, mtry is the number of candidate variables in node, and mtry = sqrt(number of variables). To make the simulated results closer to the measured values, the performance of the random forest regression model was evaluated using the Nash–Sutcliffe efficiency (NSE) and coefficient of determination (R²) (Gupta et al. 2009; Nash and Sutcliffe 1970; Z. Li et al. 2020):

\[
\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (T_{\text{obs},i} - T_{\text{sim}})^2}{\sum_{i=1}^{n} (T_{\text{obs},i} - T_{\text{obs}})^2}, \quad (1)
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (T_{\text{obs},i} - T_{\text{sim}})(T_{\text{obs},i} - T_{\text{obs}})^2}{\sum_{i=1}^{n} (T_{\text{obs},i} - T_{\text{obs}})^2}, \quad (2)
\]

where \(T_{\text{sim},i}\) and \(T_{\text{obs},i}\) are the simulated drought propagation time and the observed drought propagation time in period \(i\), respectively; \(T_{\text{sim}}\) and \(T_{\text{obs}}\) are the average simulated drought propagation time and observed drought propagation time, respectively; and \(n\) is the total number of data points.

When evaluating the importance of input variables, the RF regression method uses a heuristic to determine the importance of variables by comparing the accuracy of the variables before and after they are added to the noise (Breiman 2001). Because the variables (i.e., the propagation time from meteorological to hydrological drought) were continuous data, the variable importance score (VIM) in the RF regression was measured by the percentage of increased mean-squared error (%IncMSE).

In addition, the cross-wavelet method was used to explore the relationship and significance of meteorological drought and hydrological drought in the time–frequency space, and the partial correlation coefficient was used to analyze the influence of teleconnection factors on the drought propagation process. The specific introduction of these methods is not detailed here, and those interested can refer to the articles by Labat (2010), Maraun and Kurths (2004), and Shan et al. (2020). The main reason for the adoption of the partial correlation coefficient here was that the driving effect of teleconnection factors in this study was investigated based on the top-down strategy with two stages. In the first stage, the teleconnection factors affecting the drought propagation process in each season were determined. In the second stage, the relationship between these teleconnection factors and the corresponding local factors, including meteorological and underlying surface factors, was further analyzed. It is well known that the teleconnection factor has a relatively small impact on the drought propagation process compared to local factors. However, if the RF model was used in the first stage, it could only utilize the teleconnection factor as the input variable, which makes it difficult to obtain a good performance of drought propagation time. Meanwhile, to ensure the unity of the two-stage method, we utilized the partial correlation analysis method, which has the advantage of excluding the interference between factors in the correlation analysis.

4. Results and discussion

a. Correlation analysis of meteorological drought and hydrological drought

Based on the cross-wavelet method, the correlation and response relationships between meteorological drought and hydrological drought were explored. The identification results of the relationship and its significance in the time–frequency space are displayed in Fig. 3. Here, meteorological drought was characterized by the monthly standardized precipitation index (SPI) from 1960 to 2010, and hydrological drought in the same period was characterized by the SSI\textsubscript{natural} and SSI\textsubscript{observed} indices, which were obtained from natural streamflow and observed streamflow, respectively. The differences between the SPI\textsubscript{1} and SSI\textsubscript{natural} and SPI\textsubscript{1} and SSI\textsubscript{observed} correlations can be considered as the relationship between meteorological drought and hydrological drought caused by direct human activities, at least in part, and can be used to understand the drought system processes under a “human-influenced changing era.”

In the WRB, there were strong correlations between the SPI\textsubscript{1} and SSI\textsubscript{natural} as well as that between the SPI\textsubscript{1} and SSI\textsubscript{observed}, and they all had intermittent resonance periods in the low-frequency region. Moreover, SPI\textsubscript{1} and SSI\textsubscript{observed} in the high-frequency region showed a positive correlation with eight resonance periods, especially about 6–8 years from 1976 to 1988, and it was obvious that SPI\textsubscript{1} precedes SSI\textsubscript{observed} (Fig. 3a1). Furthermore, SPI\textsubscript{1} and SSI\textsubscript{natural} appeared in about seven resonance periods in the high-frequency region, and a positive correlation for approximately 5–7 years appeared around 1978–90. In the interim, SPI\textsubscript{1} was ahead of SSI\textsubscript{natural} in most regions (Fig. 3b1). In the JRB, there were approximately four larger resonance periods in the high-frequency region between monthly SPI and SSI (i.e., SSI\textsubscript{natural} and SSI\textsubscript{observed}). Meanwhile, the positive correlation between SPI\textsubscript{1} and SSI\textsubscript{observed} was observed for approximately 5–8 years around 1973–93, the positive correlation between SPI\textsubscript{1} and SSI\textsubscript{natural} was approximately for 7–11 years around 1965–93, and the majority of regions showed that SPI\textsubscript{1} was ahead of SSI\textsubscript{natural} and SSI\textsubscript{observed} (Figs. 3a2–b2). In addition, in the BRB, the positive correlation between SPI\textsubscript{1} and SSI\textsubscript{observed} was about 6–8 years from 1981 to 1989, and the positive correlation between SPI\textsubscript{1} and SSI\textsubscript{natural} was about 5–9 years from 1979 to 1989. Most areas of the watershed also showed that SPI\textsubscript{1} was ahead of SSI\textsubscript{natural} and SSI\textsubscript{observed} (Figs. 3a3–b3).

In summary, there was a close connection between meteorological drought and hydrological drought in the study area, and meteorological drought preceded hydrological drought. Therefore, according to the multiscale nature of the SPI series, this study further explored the relationship between SPI series at various time scales (spanning 1–24 months, i.e., SPI\textsubscript{1–SPI}\textsubscript{24}) and the monthly SSI series to determine the propagation time from meteorological to hydrological drought.

b. Propagation time from meteorological to hydrological drought

Figure 4 exhibits the calculation results of the correlation coefficient between variable-scale SPI and monthly SSI.
(including SSInatural and SSIobserved obtained from natural streamflow and observed streamflow, respectively) from 1962 to 2010, and it can be seen that the high correlation coefficient (>0.6) mainly appears in the basin from June to November (summer and autumn) ranging from one to four months. Hydrological drought had a time lag effect on meteorological drought, with different time lags in each subzone of the WRB. Based on the response characteristics between the multiscale SPI and monthly SSIobserved, the propagation time of the WRB and the BRB was the fastest in August (i.e., one month), and the corresponding correlation coefficients were 0.77 and 0.65, respectively. Moreover, the propagation time of the JRB was the fastest in July and August (i.e., one month), and the correlation coefficients were 0.70 and 0.75, respectively. Furthermore, based on the response characteristics between the multiscale SPI and monthly SSInatural series, the drought propagation time without direct human activities could be obtained, which was still the fastest in August in the WRB and in July and August in the JRB. However, in the BRB, the propagation time was accelerated to one month in July.

Figure 5 exhibits the propagation time from meteorological to hydrological drought in the WRB and its two subzones.
Based on the observed streamflow, the propagation times in the WRB in spring, summer, autumn, and winter were approximately 3, 2, 3, and 6 months, respectively; in the JRB, the propagation times in spring, summer, autumn, and winter were approximately 3, 2, 3, and 8 months, respectively; and in the BRB, the propagation times in spring, summer, autumn, and winter were approximately 5, 2, 3, and 6 months, respectively. The corresponding monthly propagation time was the longest in January for the WRB, in February for the JRB, and in March for the BRB. Compared with the observed streamflow in the three basins, the propagation time based on the natural streamflow was basically unchanged in summer and autumn, but was relatively more varied in spring and winter, especially in winter. The propagation time in winter reduced to three months in the WRB, seven months in the JRB and five months in the BRB. This indicated that the direct human activities such as water storage and artificial water intake had more influence on streamflow in winter than in other seasons, and these direct human activities might alleviate the severe hydrological drought to a certain extent, thus the propagation time from meteorological

Fig. 4. Correlation between monthly SSI and SPI at multiple time scales ranging from 1 to 12 months.

Fig. 5. Annual variation of propagation time from meteorological to hydrological drought.
FIG. 6. (a) The change trend of precipitation, (b) potential evapotranspiration, (c) soil moisture, and (d) base flow in the study area from 1962 to 2010.
FIG. 6. (Continued)
drought to hydrological drought was prolonged. The findings of Zhang et al. (2012), Wang et al. (2019), and Wu et al. (2017) also reflected the rationality of the abovementioned perspective attribution. Zhang et al. (2012) pointed out that upstream reservoirs significantly altered the natural inflow of the reservoir, causing higher inflow during the dry season. According to Wang et al. (2019), with the regulation of the reservoirs and water diversion, the lag time from the meteorological to hydrological drought was longer for termination and most of the meteorological drought did not transform into a hydrological drought. Wu et al. (2017) concluded that, when only the influence of the reservoir operation was taken into account, the duration or magnitude of hydrological drought in the reservoir-influenced period became significantly smaller than that in the natural-influenced period under similar meteorological drought conditions. The above findings can also be summarized as follows: the regulation effect of the reservoir can alleviate the severity of hydrological drought to a certain extent, especially in the dry season. Overall, the propagation time from meteorological to hydrological drought was shorter in summer and autumn, and longer in spring and winter.

To better analyze the physical mechanism behind the seasonal difference phenomenon and provide a reference for further quantitative research on the impact of seasonal climate change and direct human activities on drought propagation, this study investigated the time-scale variation characteristics of key variables of meteorological ($P$, $PET$) and underlying surface ($SM$, $Bf$) factors in the process of drought propagation. Figure 6 represents the analysis results of the $P$, $PET$, $SM$ (0–2 m), and $Bf$ series in the study area from 1962 to 2010, and Table 1 summarizes the statistical results of related hydrometeorological characteristics in the same period. By comprehensive analysis, in summer, due to the high temperature and rainy as well as the increasing precipitation, once sufficient precipitation was insufficient then the response of summer streamflow to precipitation tended to be faster than that of other seasons. With the decreasing trend of SM, the recharge time of $P$ to streamflow might become longer and the drought propagation time might lengthen. Moreover, although the $PET$ decreased in autumn (approximately 160 mm), the average SM of the WRB, BRB, and JRB were still high, at 490.59, 482.15, and 444.88 mm, respectively. Therefore, hydrological drought can also respond to meteorological drought in a short time period. However, with the decrease in $P$, $Bf$, and SM and the increase in PET over time, more $P$ would be consumed for evapotranspiration and recharge of soil water or groundwater for a longer time after the $P$ falls on the ground, which could lengthen the propagation time of drought. Furthermore, the precipitation value in winter was significantly reduced, where the average precipitation of WRB, JRB, and BRB was 15.44, 14.12, and 16.8 mm, respectively. With the production of snow in winter, the groundwater replenishment capacity decreased, which made the propagation time of drought longer; however, the $Z$ statistics of $P$ in this season obtained by the Mann–Kendall (MK) method (Mann 1945; Kendall 1975) in the WRB, JRB, and BRB were 1.90, 2.25, and 1.59, respectively, indicating that precipitation emerged an upward trend, which might make this propagation faster. In addition, although precipitation increased gradually in spring, water consumption increased due to the growth of plants, decreasing soil water storage in the WRB ($Z$ statistic of −2.46), JRB ($Z$ statistic of −3.35), and BRB ($Z$ statistic of −2.49) and thereby using more precipitation to replenish the soil water consumption, which in turn reduced the surface runoff. Thus, the propagation time from meteorological to hydrological drought is relatively long in spring. Meanwhile, the decreasing trend of precipitation in this season was less than that of $Bf$ and SM, indicating that spring precipitation could quickly replenish the soil water deficit, which might shorten the propagation time of drought.

Based on the above results, in order to better determine the dynamic change characteristics of drought propagation, it is necessary to calculate and analyze the driving force of the dynamic changes in the propagation time from meteorological to hydrological drought in different seasons.

c. Dynamic changes of the propagation time from meteorological to hydrological drought in different seasons

A sliding window correlation analysis can be used to analyze shorter-term trends in time series that may be hidden by long-term correlation analysis. To better analyze the temporal dynamics of drought propagation from meteorological to hydrological drought and reveal the temporal dynamics of drought propagation in different seasons, this study was based on a monthly series from December 1961 to November 2010, using 21 years as a sliding window with a 1-yr time step, which was divided into 29 subsequences to calculate the corresponding propagation time series. Simultaneously, the MK method was used to analyze the trend of propagation time in different seasons. The first sliding window was the first subsequence, corresponding to December 1961–November 1982, the second sliding window was the second subsequence, corresponding to December 1962–November 1983, and so on to the 29th sliding window, corresponding to December 1989–November 2010. Here, the selection strategy of the sliding window was mainly to ensure that the sample size of the

---

**Table 1. Hydrometeorological characteristics (1962–2010; mm) of the study basins.**

<table>
<thead>
<tr>
<th></th>
<th>WRB</th>
<th>JRB</th>
<th>BRB</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$</td>
<td>106.05</td>
<td>97.06</td>
<td>99.99</td>
</tr>
<tr>
<td>$PET$</td>
<td>272.39</td>
<td>280.63</td>
<td>289.10</td>
</tr>
<tr>
<td>$SM$</td>
<td>460.95</td>
<td>452.37</td>
<td>426.60</td>
</tr>
<tr>
<td>$P$</td>
<td>265.97</td>
<td>256.11</td>
<td>279.74</td>
</tr>
<tr>
<td>$PET$</td>
<td>364.14</td>
<td>374.23</td>
<td>376.78</td>
</tr>
<tr>
<td>$SM$</td>
<td>490.59</td>
<td>482.15</td>
<td>444.88</td>
</tr>
<tr>
<td>$P$</td>
<td>147.13</td>
<td>137.93</td>
<td>142.29</td>
</tr>
<tr>
<td>$PET$</td>
<td>159.73</td>
<td>161.16</td>
<td>167.54</td>
</tr>
<tr>
<td>$SM$</td>
<td>490.59</td>
<td>482.15</td>
<td>444.88</td>
</tr>
<tr>
<td>$P$</td>
<td>14.44</td>
<td>14.12</td>
<td>16.80</td>
</tr>
<tr>
<td>$PET$</td>
<td>92.32</td>
<td>92.34</td>
<td>93.13</td>
</tr>
<tr>
<td>$SM$</td>
<td>478.28</td>
<td>467.91</td>
<td>439.32</td>
</tr>
</tbody>
</table>
propagation dynamic time analysis was relatively sufficient in the early stage; in the later stage, when the RF modeling is used to analyze the potential influencing factors of the drought propagation process, it can also ensure that the sample size of the input elements is as large as possible. Moreover, previous case studies have also applied a similar sliding window (Bartels et al. 2020; Meng et al. 2014; Fang et al. 2020).

The quantitative impact of direct human activities on drought propagation time in different seasons can be seen from the dynamic difference of drought propagation in Table 2. The propagation from meteorological to hydrological drought based on observed streamflow in the WRB changed significantly in autumn and winter, while based on natural streamflow changed significantly in summer and autumn. Concurrently, the propagation from meteorological to hydrological drought in the JRB based on the natural streamflow and observed streamflow was significant in summer and autumn. The propagation based on observed streamflow in the BRB was significant in spring and summer, while the propagation based on natural streamflow changed significantly in summer and winter. The results showed that direct human activities affected the seasonal dynamics of drought propagation, exhibiting noticeable spatial variability. Overall, the propagation time of the three study areas showed a decreasing trend in spring and winter, but an increasing trend in summer and autumn.

A faster or slower propagation time of drought reflects the disturbance of the hydrological cycle of the basin caused by the changing environment. Based on this, this study further explored the driving force and physical mechanism of the propagation time from meteorological to hydrological drought (based on observed streamflow) in different seasons under changing environments.

d. Discussion

The RF method has the advantages of strong over fitting and generalization ability in solving nonlinear systems, and does not need to give a mathematical form assumption of the model in advance. At the same time, the RF method has good estimation performance for solving classification and regression in advance. At the same time, the RF method has good estimation performance for solving classification and regression in advance. This study quantified informaton performance for solving classification and regression in advance. At the same time, the RF method has good estimation performance for solving classification and regression in advance. The RF model has the advantages of strong over fitting and generalization ability in solving nonlinear systems, and does not need to give a mathematical form assumption of the model in advance. At the same time, the RF method has good estimation performance for solving classification and regression in advance. This study quantified informaton performance for solving classification and regression in advance. At the same time, the RF method has good estimation performance for solving classification and regression in advance. Therefore, further clarification of the influence of remote correlation factors such as sunspot and AO on drought propagation time is helpful to improve the understanding of the drought propagation process and the accuracy of its prediction and supervision.

1) Analysis of Simulation Results of Drought Propagation Time Based on RF Model

Based on the meteorological and underlying surface factors, the first 21 groups of data were selected as the training sample set (calibration period), and the remaining eight groups were used as the verification sample set (validation period). Breiman (2001) suggested that the number of random characteristic variables should be equal to the root of the total number of characteristic variables, and the number of decision trees should be 100. Therefore, the parameter ntree was 100 and mtry was 2 here.

Figure 7 displays performance evaluation results of drought propagation time during the calibration and validation periods of the RF model and it can be seen that the $R^2$ of the drought propagation time in natural and observed periods are greater than 0.84. At the same time, the precision for most of the seasons in the calibration period was better than that of the validation period, and in validation period, $R^2$ was greater than 0.93 in spring, 0.85 in summer, 0.85 in autumn and 0.96 in winter. In addition, the simulation accuracy of the validation period was better than the calibration period in spring and autumn for the BRB, and winter for WRB and JRB, and the NSE in their validation periods were as high as 0.95, 0.90, 0.89, and 0.78, respectively. This means that the simulation accuracy of the RF regression model constructed for the study area reached a satisfactory result, and the generalization ability was strong, which could be used to reflect the quantitative assessment of the drought propagation process of the watershed.

2) A Preliminary Analysis of Drought Propagation Mechanism Under Meteorological and Underlying Surface Characteristics

The RF model cannot only evaluate the drought propagation time, but also the importance of the factors (input variables) that affect it. This section of the paper combines meteorological ($P$, PET), and underlying surface (SM, Bf) factors in the study area in the same sliding window to determine the importance of drought propagation time in RF regression and allow better analysis of the dynamic change of the drought response process in different seasons from the perspective of physical mechanisms.

### Table 2. Results of MK trend statistics of the propagation time from meteorological to hydrological drought in different seasons.

<table>
<thead>
<tr>
<th>Basin</th>
<th>Sources of data</th>
<th>Spring</th>
<th>Summer</th>
<th>Autumn</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>WRB</td>
<td>Observed</td>
<td>-0.26</td>
<td>0.13</td>
<td>4.31**</td>
<td>-3.96**</td>
</tr>
<tr>
<td></td>
<td>Natural</td>
<td>0.99</td>
<td>2.83**</td>
<td>4.28**</td>
<td>-1.26</td>
</tr>
<tr>
<td>JRB</td>
<td>Observed</td>
<td>-0.90</td>
<td>2.96**</td>
<td>3.94**</td>
<td>-0.71</td>
</tr>
<tr>
<td></td>
<td>Natural</td>
<td>-0.32</td>
<td>5.01**</td>
<td>4.13**</td>
<td>-1.24</td>
</tr>
<tr>
<td>BRB</td>
<td>Observed</td>
<td>-2.16*</td>
<td>3.92**</td>
<td>1.28</td>
<td>1.54</td>
</tr>
<tr>
<td></td>
<td>Natural</td>
<td>-1.52</td>
<td>4.54**</td>
<td>-1.03</td>
<td>-2.29*</td>
</tr>
</tbody>
</table>
In spring, the propagation time from meteorological to hydrological drought in the three watersheds showed a decreasing trend. The propagation time of drought in the BRB decreased significantly, while in the other two watersheds, the change in drought propagation time was not significant (Table 2). Spring precipitation in the BRB was the most sensitive factor to drought propagation, followed by SM and Bf (Fig. 9c), and all three of these factors showed a significant downward trend. Meanwhile, PET showed a weak downward trend (Fig. 8c), which means that it is possible that the water consumption of crops in the watershed in spring reduced the amount of water transported to aquifers or directly reduced the runoff, leading to runoff deficits. In addition, insufficient supply of $P$ was highly sensitive to drought propagation, allowing $P$ loss signals to be transmitted earlier into the hydrological system, which in turn caused drought propagation faster in the BRB than in other basins. Bf and PET were more sensitive to drought propagation than other factors in spring in the WRB (Fig. 9a) and the SM and Bf showed a significant decreasing trend in spring, while the PET showed an increasing trend (Fig. 8a). It made the lower the water content of the basin, the weaker the resistance to the insufficient precipitation (or evaporation consumption) and the faster the propagation speed of meteorological drought in the terrestrial ecosystem, and therefore, the faster the drought propagation from meteorological to hydrological drought. The spring PET of the JRB was more important than the other factors in the regression analysis of drought propagation time (Fig. 9b). As a result, after precipitation falls to the ground, it compensates for the evaporation, thus, the streamflow would take longer to supplement. This increases the likelihood of hydrological drought as it causes meteorological drought to spread to hydrological drought more quickly.

In summer, the propagation time from meteorological drought to hydrological drought in the three basins showed an increasing trend, and the propagation time of drought in the
JRB and BRB was significantly longer, while that of the WRB was not significant (Table 2). The PET and Bf in summer in JRB and WRB were more sensitive to the impact of drought propagation than other factors (Fig. 9), and both showed a significant downward trend, which meant that with the decrease in evapotranspiration demand, precipitation could increase the supply of soil and groundwater deficit, and thus penetrate into the hydrological system, so that the propagation time from meteorological to hydrological drought in a changing environment gradually lengthened during the season. At the same time, the P in the JRB showed a significant upward trend, while that in the WRB showed an insignificant upward trend, which to a certain extent alleviated the severity of summer meteorological drought in these two basins, which

![Fig. 8. MK trend statistics of meteorological and underlying surface factors under sliding window.](image)

![Fig. 9. Importance score of different seasonal meteorological and underlying surface factors on drought propagation time under sliding window.](image)
resulting in a significantly increased trend of drought propagation time in the JRB and an insignificant increasing trend in the WRB. In addition, the summer P and Bf in the BRB were sensitive to the propagation of drought (Fig. 9c), and the Bf showed a significant downward trend, indicating that with the loss of groundwater, the water supply to the Bf in the basin decreased, and the water transported to the aquifer decreased accordingly, possibly leading to a faster and faster occurrence of hydrological drought. However, as P did not decrease significantly, the water deficit in the soil was compensated to a certain extent, thus, the propagation time from meteorological to hydrological drought appeared to be increase.

In autumn, the propagation time from meteorological to hydrological drought in the three watersheds showed an increasing trend, with the trend of the WRB and JRB being significant, while that of the BRB was not (Table 2). The PET, Bf, and SM in the three watersheds had relatively more important effects on the propagation time of drought. As PET increased, SM and Bf showed a downward trend (Fig. 8), meaning that after precipitation reached the ground, it took longer to compensate for the evaporation of soil water or groundwater loss, thereby prolonging the replenishment time for runoff. This indicates that as the degree of meteorological loss increased, runoff deficit was more likely to occur, and the response of hydrological to meteorological drought was accelerated to a certain extent, which was unfavorable to explain the phenomenon that the propagation time from meteorological to hydrological drought in autumn showed a longer trend. However, the SM in the three watersheds in this season all showed high levels (Table 1). Although they continued to decrease, they were resistant to meteorological drought to a certain extent and could resist a certain degree of meteorological drought. Thus, in autumn, the hydrological drought was alleviated, and the meteorological drought signal needed a longer time to transmit to the hydrological system.

In winter, the propagation time from meteorological to hydrological drought in the three river basins presented a decreasing trend, while the propagation time of drought in the WRB was more obvious than that in the other two river basins (Table 2). The P and Bf values in winter were relatively sensitive to drought propagation in the three watersheds (Fig. 9). Although winter P increased, runoff volume was small and less water traveled deeper to recharge groundwater (Table 1), resulting in decreased storage in the aquifer. Meanwhile, SM and Bf decreased significantly during the winter, indicating that the basin could not tolerate a relatively long-term water shortage. With the passage of time, the water transported to the aquifer decreased gradually, which caused winter hydrological droughts to respond to precipitation variability at shorter time scales.

3) A PRELIMINARY ANALYSIS OF DROUGHT PROPAGATION MECHANISM UNDER TELECONNECTION CHARACTERISTICS

In the process from meteorological to hydrological drought, teleconnection factors may affect the local meteorological and underlying surface factors to a certain extent, thus indirectly disturbing the dynamic changes in the drought propagation process. Therefore, this section first explored the influence degree of teleconnection factors in the WRB, JRB, and BRB on the propagation process from meteorological to hydrological drought in different seasons under changing environments, and then further analyzed the correlation between teleconnection factors and local meteorological as well as underlying surface factors to explain the influence mechanism of teleconnection factors on the drought propagation process. Solar variability is the process by which changes in cosmic ray fluxes affect changes in cloud cover over Earth and ultimately climate change. Sunspot is the most striking feature of solar activity (Fu et al. 2012). ENSO is the strongest interannual change signal in the tropical air–sea coupled system at low latitudes, and the abnormal changes in sea temperature play an important role in atmospheric circulation and the variability of weather and climate in China (Dong et al. 2021). The sea temperature of the Niño-3.4 area is the characteristic index of ENSO (Deo et al. 2017). AO is the main mode of low-rate atmospheric changes outside the tropics of the Northern Hemisphere, and the climate anomalies in northern China are closely related to AO (Wu et al. 2013).

Based on the above, in this section, partial correlation coefficients were used to analyze the driving forces of the lag time of hydrological to meteorological drought in different seasons, including sunspot and atmospheric circulation anomaly factors such as ENSO and AO. Table 3 reveals the results of the partial correlation coefficient and significance of seasonal propagation time and teleconnection factors in the WRB, JRB, and BRB. Sunspots had the largest effect on the lag time of drought in spring, followed by winter and autumn in the WRB, and passed the 95% significance test. Only the spring propagation time of drought in the JRB passed the 95% significance test, moreover, sunspots had the greatest impact on the winter drought propagation time in the BRB, followed by spring, and both passed the 95% significance test. Simultaneously, the effects of ENSO on the drought propagation time of the WRB in autumn, the JRB in autumn and the BRB in summer passed the 95% significance test. The effect of AO on the propagation time of spring drought

| TABLE 3. Partial correlation coefficient and significance statistical results of drought propagation time and remote correlation factors in different seasons. Note: one asterisk (*) indicates a test of confidence exceeding 95%, and two asterisks (**) indicate a test of confidence exceeding 99%. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                  | Spring          | Summer          | Autumn          | Winter          |
| **WRB**          |                 |                 |                 |                 |
| Sunspot          | −0.60**        | −0.30           | −0.43*          | 0.53*           |
| ENSO             | −0.11           | 0.10            | 0.65**          | −0.24           |
| AO               | −0.42*          | −0.14           | 0.09            | −0.33           |
| **JRB**          |                 |                 |                 |                 |
| Sunspot          | −0.47*          | −0.36           | −0.41           | 0.01            |
| ENSO             | −0.23           | 0.31            | 0.49*           | −0.11           |
| AO               | −0.26           | 0.04            | 0.19            | 0.00            |
| **BRB**          |                 |                 |                 |                 |
| Sunspot          | 0.51*           | −0.06           | 0.26            | −0.55**         |
| ENSO             | −0.34           | 0.44*           | 0.27            | −0.20           |
| AO               | 0.19            | −0.05           | −0.23           | 0.47*           |
in the WRB and winter drought in the BRB passed the 95% significance test.

Next, we analyzed the internal relationship between the teleconnection factors that had a greater impact on the propagation time from meteorological to hydrological drought, and local meteorology (P, PET, SM, and Bf) in the three study areas also showed obvious seasonal variations. For the WRB, sunspots, which were closely related to the propagation time from meteorological to hydrological drought in spring, autumn, and winter, affected the PET in spring, P and Bf in autumn, and P in winter, respectively. Meanwhile, AO, which was closely related to the propagation time of spring drought, mainly affected the PET, SM, and Bf, while ENSO, which was closely related to the propagation time of autumn drought, mainly affected P. Moreover, for JRB, the sunspots closely related to the propagation time of the spring drought to the hydrological drought mainly affected the Bf, while the ENSO closely related to the propagation time of the autumn drought mainly affected P. Furthermore, for BRB, the sunspots closely related to the propagation time of spring and winter meteorological drought to hydrological drought mainly affected the Bf in spring, and P, SM, and Bf in winter. Meanwhile, ENSO, which was closely related to the propagation time of summer drought, mainly affected the PET and Bf, while AO, which was closely related to the propagation time of winter drought, mainly affected the PET, SM, and Bf.

Through comparison, it was found that among the teleconnection factors, their overall influence on the propagation time of meteorological to hydrological drought from large to small was as follows: sunspot, AO, and ENSO in the WRB, and sunspot, ENSO, and AO in the JRB and BRB. Teleconnection factors not only had a direct impact on the propagation time of drought, but also had an indirect impact on the propagation time of drought by affecting local weather and underlying surface factors. It can be seen that the teleconnection factors affected the change in the propagation time from meteorological to hydrological drought in the WRB to a certain extent, and the sunspot was the main teleconnection driving force that affected the drought lag time in the entire Wei River basin.

5. Conclusions

Quantifying the relative effects of climate change and direct human activities on the dynamic changes in drought propagation is essential. In this study, the WRB and its two tributaries were used as the research objects. Based on the static and dynamic differences in drought propagation obtained by the natural and observed streamflow, the quantitative impact of direct human activities (reservoir storage, irrigation, artificial water extraction, etc.) on drought propagation time in different seasons was obtained. At the same time, the RF method was used to clarify the influence of meteorological factors and underlying surface factors on the process of drought propagation under changing environments and analyze their influence on drought propagation from the perspective of physical mechanisms. In addition, the driving effect of teleconnection factors on the process of drought propagation was investigated from top to bottom, which enhanced the understanding of hydrological drought formation from the perspective of meteorological drought propagation. The main conclusions are as follows.

The propagation time from meteorological to hydrological drought in the WRB, JRB, and BRB was shorter in summer and autumn, while longer in spring and winter. Compared with observed streamflow in the three basins, the propagation time based on the natural streamflow was basically unchanged in summer and autumn, while relatively more varied in spring and winter, especially in winter, which were reduced across all three basins to three months in the WRB, seven months in the JRB, and five months in the BRB. This indicates that direct human activities such as water storage, irrigation, and artificial water intake had an effect on the seasonal dynamics of drought propagation, especially in the winter of the nonflood season, which alleviated the severity of winter hydrological drought to some extent, and delayed the transmission of meteorological signals to hydrological systems. Thus, the propagation time from meteorological to hydrological drought was prolonged.

### Table 4. Partial correlation coefficient and significance statistical results of teleconnection factors and local meteorology, underlying surface factors in different seasons. Note: one asterisk (*) indicates a test of confidence exceeding 95%, and two asterisks (**) indicate a test of confidence exceeding 99%.

<table>
<thead>
<tr>
<th>Partial correlation coefficient</th>
<th>Teleconnection factor</th>
<th>WRB</th>
<th>JRB</th>
<th>BRB</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>P</td>
<td>PET</td>
<td>SM</td>
</tr>
<tr>
<td>WRB</td>
<td>Sunspot</td>
<td>0.06</td>
<td>-0.69**</td>
<td>-0.25</td>
</tr>
<tr>
<td></td>
<td>AO</td>
<td>0.10</td>
<td>0.54**</td>
<td>0.63**</td>
</tr>
<tr>
<td>Autumn</td>
<td>Sunspot</td>
<td>-0.71**</td>
<td>0.28</td>
<td>-0.17</td>
</tr>
<tr>
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<td>ENSO</td>
<td>-0.55**</td>
<td>0.09</td>
<td>0.07</td>
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<td>JRB</td>
<td>Sunspot</td>
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<td>ENSO</td>
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<td>0.13</td>
</tr>
<tr>
<td>BRB</td>
<td>Sunspot</td>
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<td>-0.21</td>
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<td>ENSO</td>
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<td>-0.80**</td>
<td>0.22</td>
</tr>
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<td></td>
<td>AO</td>
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<td>-0.67**</td>
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<tr>
<td></td>
<td></td>
<td>-0.21</td>
<td>-0.59**</td>
<td>-0.79**</td>
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</tbody>
</table>
Under the changing environment, the propagation time of drought generally showed a decreasing trend in spring and winter, while an increasing propagation time was noticed in summer and autumn. In view of this change feature, the importance of the attribution factors in the process of drought propagation was effectively evaluated based on the constructed RF regression model. In the changing environment, the dynamic propagation time was affected by different factors in each season, but they were all jointly controlled by the variation of meteorological and underlying surface conditions, which was helpful in understanding the dynamic evolution of drought and improving the accuracy of drought decision-making. In addition to local impact factors, teleconnection factors directly or indirectly affected the drought propagation. Sunspots, as the main teleconnection driving factor of the variation of meteorological and underlying surface conditions, in each season, but they were all jointly controlled by the dynamic propagation time was affected by different factors in each season, but they were all jointly controlled by the variation of meteorological and underlying surface conditions, which was helpful in understanding the dynamic evolution of drought and improving the accuracy of drought decision-making. In addition to local impact factors, teleconnection factors directly or indirectly affected the drought propagation. Sunspots, as the main teleconnection driving factor of the changing environment, the propagation time of the forecast season can be selected as input data of this model. In general, the findings of this study help to reveal the propagation process from meteorological to hydrological drought under changing environments, and thus, at least to a certain extent, could be valuable for the establishment of an accurate monitoring and forecasting hydrological drought system based on meteorological drought for local drought preparedness.

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