Application of a Hybrid ARIMA–SVR Model Based on the SPI for the Forecast of Drought—A Case Study in Henan Province, China

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ABSTRACT

Drought forecasts could effectively reduce the risk of drought. Data-driven models are suitable forecast tools because of their minimal information requirements. The motivation for this study is that because most data-driven models, such as autoregressive integrated moving average (ARIMA) models, can capture linear relationships but cannot capture nonlinear relationships they are insufficient for long-term prediction. The hybrid ARIMA–support vector regression (SVR) model proposed in this paper is based on the advantages of a linear model and a nonlinear model. The multiscale standard precipitation indices (SPI: SPI1, SPI3, SPI6, and SPI12) were forecast and compared using the ARIMA model and the hybrid ARIMA–SVR model. The performance of all models was compared using measures of persistence, such as the coefficient of determination, root-mean-square error, mean absolute error, Nash–Sutcliffe coefficient, and kriging interpolation method in the ArcGIS software. The results show that the prediction accuracies of the multiscale SPI of the combined ARIMA–SVR model and the single ARIMA model were related to the time scale of the index, and they gradually increase with an increase in time scale. The predicted value decreases with increase in lead time. Comparing the measured data with the predicted data from the model shows that the combined ARIMA–SVR model had higher prediction accuracy than the single ARIMA model and that the predicted results 1–2 months ahead show reasonably good agreement with the actual data.

1. Introduction

Drought is a water shortage that is caused by an imbalance between supply and demand. As one of the most severe natural disasters, drought exerts relatively widespread effects on human society that usually last for several months or even a few years, causing huge economic loss, reductions in food yield, starvation, and land degradation (Piao et al. 2010; Lobell et al. 2012; Asseng et al. 2015). China is located in the East Asian monsoon region, with complex geographical conditions, complex

climate changes, and frequent climate disasters. As climate warming and drying become increasingly apparent, the occurrence of natural disasters has increased significantly. Affected by specific climatic conditions, topographical features, and water resources, China is one of the countries with the most frequent and severe drought in the world. Local or regional drought occurs almost every year (Chen and Sun 2015; Wang et al. 2016). Global warming and excessive carbon emissions will lead to the continued warming of agricultural lands in the future (Allen and Ingram 2002). Global food production, including in China, has been seriously threatened. Therefore, quantitative studies on drought could facilitate research regarding the spatiotemporal changes in drought characteristics, improve drought monitoring ability, aid in the performance of drought

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forecasting work, and help identify drought management and coping strategies. It has important significance for future agricultural production, drought prevention, and drought resistance in China.

Droughts are generally categorized into five types: meteorological droughts, agricultural droughts, hydrological droughts, socioeconomical droughts, and droughts that impact stream health (Esfahanian et al. 2017; Heim 2002; McKee et al. 1993). Because of the wide range of applications of drought indicators and the variation in the understanding of drought across different professions and disciplines, various drought indicators have emerged. More than 100 drought definitions and indicators exist worldwide. Different angle definitions and the use of different criteria to measure drought will result in variation in the understanding of drought. There are many meteorological drought indices (Tarpley et al. 1984; Wang et al. 2015), such as the standardized precipitation index (SPI), Palmer drought severity index (PDSI) (Ortega-Gómez et al. 2018), and standardized precipitation evapotranspiration index (SPEI). Among them, the PDSI is calculated with monthly temperature and precipitation data and soil water-holding capacity information, and the main application is to identify droughts that affect agriculture (Belayneh et al. 2014; Aiguo et al. 2004; Zhang et al. 2017). Similarly, the SPEI requires the inclusion of temperature and precipitation data so that the index can take into account the effect of temperature on drought development, but compared to the SPI, it is more computationally expensive and is not widely applicable. The SPI drought index, which was first proposed by McKee (1993) in the study of drought in Colorado, United States, is the quantile of the standard normal distribution transformed from the precipitation distribution function, and it can be used to characterize the probability of precipitation occurring during a certain period of time.

The SPI is a powerful, flexible index that is sample to calculate. In fact, precipitation is the only required input parameter. In addition, it is as effective in analyzing wet periods/cycles as it is in analyzing dry periods/cycles (Watanabe et al. 1987). The SPI can be applied to all climatic conditions and can compare climatically different SPI values (Chen and Sun 2015; Wang et al. 2016, 2015). Huang et al. (2016) used SPI and effective drought index (EDI) to determine the severity of future potential drought durations in their study on drought severity of the Langat River basin in Malaysia, and compared the two indices to get a more operational index between SPI1, SPI6, SPI12, and EDI outlook for representing Malaysia drought events. To provide an overall view of drought conditions across the Loess Plateau of China, Liu et al. (2016) used SPI and SPEI, two multiscalar drought indices, to identify the regional

spatiotemporal characteristics of drought conditions from 1957 to 2012. Therefore, the SPI drought index was chosen to forecast drought in this study.

It is important to strengthen research on drought prediction to prevent drought disasters and reduce the loss caused by drought disasters. To date, the most commonly used methods to assess and predict drought are data-driven methods. Data-driven models have rapid development times and have traditionally been used for drought forecasting (Adamowski 2008; Karthika et al. 2017; Mossad and Alazba 2015; Fung et al. 2020b; Rafiei-Sardooi et al. 2018). Fung et al.'s (2020b) paper aims to review drought forecasting approaches, including their input requirements and performance measures, for 2007–17 and shows that machine-learning models have better performance in modeling nonlinear data than do stochastic models. For example, autoregressive integrated moving-average (ARIMA) models (Mishra and Desai 2005, 2006; Mishra et al. 2007; Han et al. 2010) have been the most widely used stochastic models for drought forecasting. The principal objective of the Karthika et al. (2017) study is to carry out short-term annual forecasting of meteorological drought using the ARIMA model in the lower Thirumanimuthar subbasin located in the semiarid region of Tamil Nadu. The results showed that the best ARIMA models are compared with the observed data for model validation purposes in which the predicted data show reasonably good agreement with the actual data. Mossad and Alazba (2015) use ARIMA as a suitable tool to forecast drought, and several ARIMA models are developed for drought forecasting using the SPEI in hyperarid climates. The results reveal that all developed ARIMA models demonstrate the potential ability to forecast drought over different time scales. Stochastic models are linear models with limited ability to predict nonlinear data. To effectively predict nonlinear data, an increasing number of researchers have begun to use artificial neural networks (ANNs) to predict hydrological data in the past decade (Kousari et al. 2017; Seibert et al. 2017; Marj and Meijerink 2011; Ochoa-Rivera 2008; Sigaroodi et al. 2013). Artificial neural networks have been used as drought prediction tools in many studies (Seibert et al. 2017; Borji et al. 2016; Deo and Şahin 2015; Chen et al. 2017; Belayneh and Adamowski 2012; Belayneh et al. 2016) and achieved good results.

Support vector machines (SVMs), such as the ANN model, are machine-learning techniques that have been successfully applied in classification, regression, and forecasting in the field of hydrology (Tabari et al. 2012; Ganguli and Janga Reddy 2014). Support vector machines can be divided into support vector classification (SVC) and support vector regression (SVR), which

solve classification and regression problems, respectively. Several studies have used SVR in hydrological and drought forecasting (Khan and Coulibaly 2006; Belayneh et al. 2016, 2014; Belayneh and Adamowski 2012). Borji et al. (2016) used two models including the SVR and ANN to forecast the streamflow drought index (SDI) of different time scales in Larian watershed, Iran, which is one of the most important sources of water for the large metropolitan Tehran. The results showed, that the SVR approach showed a better efficiency in the forecast of long-term droughts compared to the ANN. When predicting the drought conditions in the Awash River basin of Ethiopia, Belayneh et al. (2016) developed ANN and SVR models, in addition, combined with wavelet analysis to improve drought prediction. By taking root-mean-square error (RMSE), mean absolute error (MAE), and coefficient of determination R^2 as model evaluation indices, it is found that the wavelet-boosting ANN (WBS-ANN) and wavelet-boosting SVR (WBS-SVR) models provided better prediction results than did the other model types that were evaluated.

To improve prediction accuracy in time series forecasting, Choubin et al. (2016) demonstrated the effectiveness of the adaptive neuro-fuzzy inference system (ANFIS) model in forecasting the SPI across different time scales. Apart from that, ARIMA-ANN, wavelet-ANN (WANN), and wavelet-adaptive neuro-fuzzy inference system (WANFIS) are also effective forecasting tools among the hybrid models (Belayneh et al. 2014). A study by Soh et al. (2018) adopts the proposed wavelet-ARIMA-ANN (WAANN) model and the latest WANFIS model to predict the SPEI at the Langat River basin for different time scales and found that the hybrid model gives better accuracy than single model. It is also found that the WANFIS model has a good prediction effect on midterm drought forecast, while the WAANN model has better accuracy on short-term and midterm drought forecast. A study by Fung et al. (2020a) used SVR model and two of its enhanced variants, namely, fuzzy-support vector regression (F-SVR) and boosted-support vector regression (BS-SVR) models, for predicting the SPEI with a lead time of 1 month. By applying the MAE, RMSE, mean bias error (MBE), and R^2 as model assessments, it was found that the F-SVR model was best with the trend of improving accuracy when the time scales of the SPEIs increased. Using similar methods, Fung et al. (2019) also discussed the wavelet-boosting-support vector regression (W-BS-SVR), multi-input wavelet-fuzzy-support vector regression (multi-input W-F-SVR), and weighted wavelet-fuzzy-support vector regression (weighted W-F-SVR) models for meteorological drought predictions downstream of the Langat River basin, with lead times of 1, 3, and 6 months. The similarity

between this study and Soh et al.'s (2018) study is that the hybrid model is used to predict the drought index, and the difference is this study used the SVR model with high long-term prediction accuracy (Borji et al. 2016) to replace the ANN model.

The purpose of this paper is to propose a hybrid model to improve the application of a single linear or nonlinear model in drought prediction. Taking Henan Province as an example, based on the SPI values of 19 meteorological stations from 1951 to 2017, this study compares the effectiveness of two models in forecasting drought conditions in Henan Province. The multiscale SPI was forecast and compared using a traditional ARIMA model and a hybrid ARIMA-SVR model for 1–6-month lead time. Because ArcGIS has a powerful function in spatial analysis, the kriging interpolation method is commonly used for interpolation analysis of drought index and rainfall (Cai et al. 2019; Karavitis et al. 2012; Manatsa et al. 2008; Afzali et al. 2016; Jain and Flannigan 2017). When Afzali et al. (2016) interpolated the SPI of the Zayandehroud River basin of Iran, they adopted various methods for interpolation analysis, and the results showed that kriging methods were chosen as the best method for spatial analysis of the drought indices. Karavitis et al. (2012) and Manatsa et al. (2008) also performed interpolation analysis on the drought index such as SPI and obtained the same conclusion. Similar research has also used Cai et al. (2019) to interpolate rainfall with the kriging method and achieved good results. This paper will describe the use of the kriging interpolation method in the ArcGIS software to conduct a visual analysis of the SPI3 observed values and fitted values of the two models in 2017. The performance of all models is compared using measures of persistence, such as the R^2 , RMSE, MAE, and Nash–Sutcliffe coefficient (NSE).

2. Study area

As a province located in the middle and lower reaches of the Yellow River, a midlatitude zone in China, Henan Province is an important food-crop-producing area and a major agricultural province. It plays a vital role in ensuring national food security (Shi et al. 2017). As a province situated in the warm temperate and subtropical region, Henan is characterized by a dry spring with frequent wind, a hot summer with abundant rainfall, a clear autumn with plenty of sunshine, and a cold winter with light snow. However, due to its special topography and geographical location, meteorological disasters are frequent occurrences; drought is one of the most frequent natural disasters, with a long duration, including spring droughts and summer droughts, as well as spring and summer or summer and autumn droughts. Due to the large

FIG. 1. Location of Henan Province, the 19 meteorological stations, and the five example stations.

area of Henan Province, the terrain features are high in the west and low in the east. Therefore, according to the research needs, this paper selected five meteorological stations representing the eastern, western, southern, northern, and central Henan Province as examples to carry out multiscale SPI (SPI1, SPI3, SPI6, and SPI12) calculation and model prediction process description. This paper uses daily precipitation data from 19 national meteorological stations (Fig. 1) in Henan Province from 1951 to 2017. The original data were derived from the National Meteorological Information Center (http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_MON.html).

3. Research methods

a. SPI

The SPI was developed by McKee et al. (1993) at Colorado State University in 1992. The results of his work were first presented at the Eighth Congress of Applied Climatology in January 1993. The index is based on the relationships between drought and frequency, duration, and time scale. The SPI can be applied to all climatic conditions, and the calculated SPI values indicating large climatic differences can be compared and analyzed. Because of the flexibility of the SPI, it can be calculated using data missing from the recording cycle at a given location. Ideally, the time series should be as complete as possible, but if there are not sufficient data to compute a value, the SPI will compute a value of “zero,” and when the data are available, the SPI will begin to compute output again. Typically calculated on a 24-month time scale, the

index is flexible and can be used for a variety of purposes, including for events affecting agriculture, water resources and other industries. Usually, SPI values of less than 3 months may be used for basic drought monitoring, while SPI values of less than 6 months may be used for monitoring agricultural impacts, and SPI values of more than 12 months may be used for hydrological impacts (Tsakiris and Vangelis 2004; Mishra and Desai 2006; Cacciamani et al. 2007). The use of precipitation data is the greatest advantage of the SPI because it makes it extremely easy to use and calculate (Cacciamani et al. 2007). The SPI can be calculated as follows (Asadi Zarch et al. 2015):

$$SPI = S \frac{t - (c_2 t + c_1)t + c_0}{[(d_3 t + d_2)t + d_1]t + 1}, \quad \text{with} \quad (1)$$

$$t = \sqrt{\ln \frac{1}{G(x)^2}}, \quad (2)$$

where $G(x)^2$ is the probability distribution of precipitation associated with the gamma (Γ) function; x is the precipitation sample value; S is the probability density positive and negative coefficient; and C_0 , C_1 , and C_2 and d_1 , d_2 , and d_3 are the calculation parameters for the Γ distribution function to convert to the cumulative frequency simplified approximate solution formula. The specific values are as follows: $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$. When $G(x) > 0.5$ or $G(x) \leq 0.5$, $S = -1$. Here, $G(x)$ is obtained by the Γ function, and the formula is

$$G(x) = \frac{2}{\beta\gamma\Gamma(\gamma_0)} \int_0^x x^{\gamma-1} e^{-x/\beta} dx, \quad x > 0, \quad (3)$$

where γ and β are the shape and scale parameters of the Γ distribution function, respectively.

The classification of dry and wet spells resulting from the values of the SPI is shown in Table 1.

b. ARIMA

The ARIMA model is the stochastic model and has been widely used in hydrologic forecasting over recent decades according to the well-known Box–Jenkins methodology (Kisi et al. 2015; Choubin and Malekian 2017). The ARIMA model is divided into the autoregressive model (AR), moving-average model (MA), and autoregressive moving-average model (ARMA), which is also classified as an “ARIMA (p, d, q)” model and is a traditional time series forecast model, where p is the number of autoregressive terms, d is the number of differences needed for stationarity, and q is the number of lagged forecast errors in the prediction equation. The modeling process is first to judge the smoothness of the model, then to use the difference method to smooth the nonstationary time series, and then to select AR(p) and MA(q) to classify the model; the number of differences is

TABLE 1. Drought classification based on SPI.

Level	Type	Range of SPI
0	Wet	$0.5 \leq \text{SPI}$
1	No drought	$-0.5 \leq \text{SPI} < 0.5$
2	Mild drought	$-1.0 \leq \text{SPI} < -0.5$
3	Moderate drought	$-1.5 \leq \text{SPI} < -1.0$
4	Severe drought	$-2.0 \leq \text{SPI} < -1.5$
5	Extreme drought	$\text{SPI} \leq -2.0$

recorded as d , which will be determined. The ARIMA (q, d, p)–selected time segments are used as training sets and test sets for predictive analysis. The ARIMA can be calculated as follows: Equation (4) is the AR formula, where u_t is a white noise sequence and δ is a constant,

$$x_t = \delta + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + u_t. \quad (4)$$

Equation (5) is the MA formula; MA is constructed with the weighted average of u_t itself and q lag terms of u_t ,

$$\begin{aligned} x_t &= \mu + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} \\ x_t - \mu &= (1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q) u_t = \Theta(L) u_t. \end{aligned} \quad (5)$$

Equation (6) is the ARMA formula,

$$\begin{aligned} x_t &= \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \delta + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} \\ \phi(L)x_t &= (1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p) x_t = \delta + (1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q) u_t = \delta + \Theta(L) u_t \\ \phi(L)x_1 &= \delta + \Theta(L) u_1. \end{aligned} \quad (6)$$

Whether ARMA (p, q) satisfies the stationarity depends on whether the root of the equation $\phi(L) = 0$ is outside the unit circle. The difference operator in ARIMA(p, d, q) is

$$\begin{aligned} \Delta x_t &= x_t - x_{t-1} x_t - L x_t = (1 - L) x_t \\ \Delta^2 x_t &= \Delta x_t - \Delta x_{t-1} = (1 - L) x_t - (1 - L) x_{t-1} = (1 - L)^2 x_t \\ \Delta^d x_t &= (1 - L)^d x_t. \end{aligned} \quad (7)$$

For the d -order single-integer sequence $x_t \sim I(d)$,

$$w_t = \Delta^d x_t = (1 - L)^d x_t, \quad (8)$$

where w_t is a stationary sequence. For the ARIMA model of w_t , the result is $x_t \sim \text{ARIMA}(p, d, q)$, and the model form is

$$\begin{aligned} w_t &= \phi_1 w_{t-1} + \phi_2 w_{t-2} + \cdots + \phi_p w_{t-p} \\ &+ \varphi + u_t - \theta_1 u_{t-1} - \theta_2 u_{t-2} - \cdots - \theta_q u_{t-q} \\ \phi(L)\Delta^d x_t &= \delta + \Theta(L) u_t. \end{aligned} \quad (9)$$

Among them, the p, q order is determined by the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). When the number of samples N is fixed, the minimum AIC and BIC are selected to determine p and q . The formula is as follows:

$$\begin{aligned} \text{AIC}(p, q) &= N \ln \sigma^2(p, q) + 2(p + q + 1) \quad \text{and} \\ \text{BIC}(p, q) &= N \ln \sigma^2(p, q) + (p + q + 1) \ln N. \end{aligned} \quad (10)$$

c. SVM

The current SVM was proposed by Cortes and Vapnik (1995). The basic idea of the SVM is to construct a hyperplane in a high-dimensional space used for classification or regression. Its characteristic is to transform the nonlinear classification problem or original sample attribute space into a linear convex quadratic programming problem of high-dimensional space by introducing the kernel function mapping method. This method guarantees the uniqueness and global optimality of the

FIG. 2. SPI values at different time scales of five example stations (Zhengzhou, Anyang, Xinyang, Sanmenxia, and Shangqiu) in Henan Province from 1951 to 2017.

understanding and solves the local extremum problem, which is difficult to avoid in the neural network method, and the algorithm complexity is independent of the sample dimension. The core of the SVM method is to find the classification surface in the case of a linear separable. For the linear separable training set T , $T = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_l, y_l)\} \in (\mathbf{x} \times y)^l$, among them $\mathbf{x}_i \in R^n$ and $y_i \in \{-1, 1\}$, $i = 1, \dots, l$.

The optimization problem can be solved, as shown in Eq. (11):

$$\min_{\mathbf{w}, b} \frac{1}{2} \|\mathbf{w}\|^2, \quad \text{s.t. } y_i[(\mathbf{w} \cdot \mathbf{x}_i) + b] \geq 1, \quad i = 1, \dots, l, \quad (11)$$

where “s.t.” indicates “subject to.” The classification surface determined by the optimal solutions $\mathbf{w}^*$ and b^* is

$$(\mathbf{w}^* \cdot \mathbf{x}) + b^* = 0, \quad f(\mathbf{x}) = \text{sgn}[(\mathbf{w}^* \cdot \mathbf{x}) + b^*]. \quad (12)$$

TABLE 2. Unit root test of five example meteorological stations at four time scales of the SPI original sequence.

SPI series	Zhengzhou		Anyang		Xinyang		Sanmenxia		Shangqiu	
	ADF	<i>P</i> value	ADF	<i>P</i> value	ADF	<i>P</i> value	ADF	<i>P</i> value	ADF	<i>P</i> value
SPI1	−9.995	2.41×10^{-17}	−23.809	0	−24.194	0	−3.941	0.0145	−7.686	1.46×10^{-11}
SPI3	−7.778	6.58×10^{-12}	−10.506	1.05×10^{-18}	−8.268	4.87×10^{-13}	−3.916	0.002	−7.537	3.44×10^{-11}
SPI6	−7.567	2.9×10^{-11}	−7.101	4.16×10^{-10}	−7.148	3.19×10^{-10}	−3.297	0.002	−4.976	2.47×10^{-05}
SPI12	4.656	0.0001	−4.820	4.97×10^{-05}	−4.857	4.22×10^{-05}	−3.564	0.006	−5.524	1.84×10^{-06}

FIG. 3. (a) ACF and PACF of (a) SPI1 (b) SPI3, (c) SPI6, and (d) SPI12 of Zhengzhou meteorological station.

The SVM model uses a small number of support vectors to represent the decision function, which has sparse characteristics. When extending the SVM method to the regression problem—namely, SVR—it is necessary to

introduce a loss function to maintain this important property. Taking the ε loss function based on the standard proposed by Vapnik as an example, the ε loss model is written as follows:

TABLE 3. AIC, BIC, and $P_{\text{Ljung-Box}}$ test comparisons of selected models at four time scale of SPI for five example meteorological stations.

SPI series	Example stations	Model	AIC	BIC	$P_{\text{Ljung-Box}}$
SPI1	Zhengzhou	ARIMA (4, 0, 4)(1, 1, 0) ₁	2545.261	2559.321	0.979
	Anyang	ARIMA (2, 0, 3)(1, 1, 0) ₁	2516.561	2530.622	0.986
	Xinyang	ARIMA (3, 0, 3)(0, 1, 1) ₁	2268.631	2282.693	0.985
	Sanmenxia	ARIMA (1, 0, 1) ₁	1968.821	1987.569	0.913
	Shangqiu	ARIMA (3, 0, 3)(1, 1, 1) ₁	2137.781	2156.529	0.978
SPI3	Zhengzhou	ARIMA (3, 0, 4)(0, 0, 2) ₃	1811.951	1830.703	0.875
	Anyang	ARIMA (2, 0, 4)(0, 0, 2) ₃	1892.275	1911.028	0.698
	Xinyang	ARIMA (4, 0, 3)(0, 0, 2) ₃	1815.702	1834.456	0.901
	Sanmenxia	ARIMA (1, 0, 3) ₃	1598.346	1626.476	0.822
	Shangqiu	ARIMA (1, 0, 3)(0, 0, 2) ₃	1663.728	1682.482	0.710
SPI6	Zhengzhou	ARIMA (4, 0, 4) ₆	1562.672	1590.802	0.810
	Anyang	ARIMA (4, 0, 4)(2, 0, 1) ₆	1662.521	1690.652	0.939
	Xinyang	ARIMA (4, 0, 4) ₆	1585.461	1613.591	0.853
	Sanmenxia	ARIMA (3, 0, 4) ₆	1314.681	1356.877	0.853
	Shangqiu	ARIMA (4, 0, 4)(3, 0, 4) ₆	1454.268	1496.464	0.966
SPI12	Zhengzhou	ARIMA (4, 0, 4)(4, 0, 3) ₁₂	831.100	859.240	0.985
	Anyang	ARIMA (4, 0, 4)(4, 0, 3) ₁₂	827.363	855.493	0.989
	Xinyang	ARIMA (4, 0, 4) ₁₂	913.555	941.685	0.877
	Sanmenxia	ARIMA (4, 0, 3)(3, 0, 2) ₁₂	672.718	705.537	0.784
	Shangqiu	ARIMA (4, 0, 4)(4, 0, 3) ₁₂	902.140	930.270	0.957

FIG. 4. Forecast of multitime-scale SPI value of Shangqiu (east) meteorological station of the ARIMA model and hybrid ARIMA–SVR model.

$$\begin{aligned} \min & \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^m (\xi_i + \xi_i^*), \\ \text{s.t.} & \begin{cases} y_i - \mathbf{w} \cdot \mathbf{x}_i - b \leq \varepsilon + \xi_i \\ \mathbf{w} \cdot \mathbf{x}_i + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, \end{cases} \end{aligned} \quad (13)$$

where ξ_i and ξ_i^* are slack variables that specify the error requirements of the model; C is the penalty parameter, and the decision boundary of the support vector increases as C increases; σ is the nuclear density. The relationship between sigma and gamma in the radial basis function (RBF) formula is as follows:

$$\begin{aligned} K(\mathbf{x}_i, y_i) &= \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right) \\ &= \exp[-\text{gamma} \times d(\mathbf{x}_i, \mathbf{x}_j)^2], \quad i = 1, 2, \dots, n, \end{aligned} \quad (14)$$

where $K(\mathbf{x}_i, y_i)$ is the RBF kernel function and σ is the kernel density. The relationship between sigma and gamma in the RBF is calculated as follows:

$$\text{gamma} = \frac{1}{2\sigma^2}. \quad (15)$$

Therefore, an increase in gamma or a decrease in σ will narrow the width of the RBF.

d. Hybrid ARIMA–SVR model

The ARIMA model and the SVR model have different advantages in linear and nonlinear prediction (Che and Wang 2010). Therefore, the hybrid model ARIMA–SVR was established using the advantages of both the ARIMA and SVR models. It was assumed that the time series Y_t can be regarded as a combination of the linear autocorrelation part L_t and the nonlinear residual N_t . First, the ARIMA model was used to predict the SPI values, and then the result was subtracted from the actual value to obtain the residual, which was recorded as a nonlinear part. Second,

FIG. 5. As in Fig. 4, but of Sanmenxia (west) meteorological station.

the residual was brought into the SVR model for prediction. Last, the two prediction results were added to obtain the combined result:

$$Y_t = L_t + N_t. \quad (16)$$

e. Evaluation verification index

In this study, the RMSE, MAE, R^2 , and NSE (Nash 1970) were used to evaluate the model's accuracy between the measured and predicted values. RMSE is used to measure the deviation between the observed value and the real value. MAE is the mean value of the absolute error, which can better reflect the actual situation of the error of the predicted value. The R^2 method is typically used in regression models to evaluate the degree to which a predicted value matches the actual value, using the mean value as the error baseline to determine whether the prediction error is greater than or less than the mean. The interval is usually (0, 1); 0 means not predictable at all, directly taking the mean, and 1 means that all forecasts match the real result

perfectly. The NSE method is typically used in hydrological simulation of hydrology, as well as in the test of model simulation effect of studying the relationship between climate, environment, soil, ecology, and hydrological process.

The formulas are as follows (Belayneh et al. 2016; Deo and Şahin 2016):

$$\text{RMSE} = \sqrt{\frac{\text{SSE}}{N}}, \quad (17)$$

where SSE is the sum of squared errors and N is the number of samples used. SSE is given by

$$\text{SSE} = \sum_{i=1}^N (y_i - \hat{y}_i)^2, \quad (18)$$

with the variables already having been defined. The

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i|. \quad (19)$$

FIG. 6. As in Fig. 4, but of Xinyang (south) meteorological station.

The closer that the RMSE and MAE are to 0, the higher is the proximity of the two samples (predictor to observation). The coefficient of determination is

$$R^2 = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}, \quad (20)$$

where

$$\bar{y} = \frac{\sum_{i=1}^N y_i}{N}. \quad (21)$$

The

$$NSE = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}, \quad (22)$$

where y_i is the observed value at time i ($i = 1, \dots, N$), $\bar{y}$ is the mean value taken over N , N is the total data size of y_i ($i = 1, \dots, N$), and $\hat{y}_i$ is the forecast value at time i .

4. Data and measures

a. Calculation of the SPI

In this study, the original data were derived from the daily data from China's surface climate database, which was provided by the National Meteorological Information Center. Based on the daily precipitation data from 19 national meteorological stations from 1951 to 2017 in Henan Province, the SPI calculation program was written with MATLAB mathematical modeling software. The time scales of the SPI values were calculated as every 1, 3, 6, and 12 months from 1951 to 2017 and recorded as SPI1, SPI3, SPI6, and SPI12, respectively. Then, the drought conditions were characterized by the drought grading standards (Table 1) specified in the National Standard Meteorological Drought Rating

FIG. 7. As in Fig. 4, but of Anyang (north) meteorological station.

(GB/T20481–2006). The matplotlib visualization library in Python 3.6 was used to visualize the multiscale SPI calculation results. Because there were too many meteorological station sites, this paper selects five meteorological stations in east, west, south, north, and middle of Henan Province as examples to carry out the calculation and demonstration of multiscale SPI, as shown in Fig. 2.

b. ARIMA modeling steps

1) STABILIZATION AND ARIMA ORDERING

The ARIMA model is a stationary time series ARMA model with d differences, and it is typically modeled for stationary time series (Durdu 2010). Choubin and Malekian (2017) used the ARIMA model for groundwater-level forecasting to 4 months ahead in the Shiraz basin of southwestern Iran. Using augmented Dickey–Fuller (ADF) to test the stationarity of time series and analysis is conducted according to the Box–Jenkins method the same way as in this paper. The

ADF test was adopted in this paper to evaluate the stationarity of the time series. In the ADF test, the original hypothesis was that of a nonstationary time series, and there was a unit root. Given a significance level of 0.05, the null hypothesis was rejected if the probability value P corresponding to the test statistic was less than 0. Taking five meteorological stations as examples, the P values of SPI1, SPI3, SPI6, and SPI12 were all less than 0.05 (Table 2), so it was judged that SPI1, SPI3, SPI6, and SPI12 are stationary time series. If the P value is greater than 0.05, they were considered to be nonstationary time series, and a difference method was required for stabilization. Therefore, the difference for the stationary time series, after adopting the Ljung–Box test white noise inspection procedure, smoothed the white noise sequence, and then the autocorrelation function (ACF) and partial autocorrelation function (PACF) were used to classify the ARIMA (p, d, q) model. Because there are too many stations, only the ACF and PACF diagrams of the four-time-scale SPI values of Zhengzhou station were shown in Fig. 3.

FIG. 8. As in Fig. 4, but of Zhengzhou (middle) meteorological station.

2) ARIMA APPLICABILITY TEST AND RESULT

Because of the use of the ACF and PACF set order, there were multiple values. This article uses the AIC and BIC to select the optimal model. The results are shown in Table 3 along with the optimal model selection and residual test results. The Ljung–Box test was used to evaluate the stability of the model at four time scales, if the P value of a Ljung–Box test of residual is greater than 0.05, it indicates white noise sequence. As can be seen from Table 3, the P value obtained by a Ljung–Box test of all models was greater than 0.05, indicating that the residual of each selected model conforms to the characteristics of white noise sequence, indicating that each selected model was suitable for forecasting the SPI values of this scale. Using the cross-validation method, data from 1951 to 2003 (80%) were selected as the training set and data from 2004 to 2017 (20%) were selected as the test set to predict SPI values at four time scales. The results of 1-month lead time are shown in Figs. 4–8, and the results of 1–6-month lead time are

shown in Tables 4–7. In Figs. 4–8, the solid black line represents SPI observations, and the solid blue line represents ARIMA predictions.

c. SVR modeling steps

Before using the SVR model to predict the residuals of the ARIMA model, it was necessary to understand the SVR model residual order and that the residuals of the past few periods will affect the residuals in the next period. Thus, beginning at the start time, k time-ordered residual data were obtained at each time point and arranged in sequence. The aligned matrix was used as the input for the SVR model, and $k + 1$ data were used as the output of the model, and the data error was retained. Using the cross-validation method, 80% of the data were randomly taken as the training set of the model, and the remaining 20% were used as the test set. The results of the test set were predicted by SVR model training. If the selected order was k and the RKE k th order was less than the $k + 1$ th order, then

TABLE 4. Performance measures for comparison of observed and predicted data for SPI1 for different lead times.

Example stations	Model	Performance measures	1-month lead time	2-month lead time	3-month lead time	4-month lead time	5-month lead time	6-month lead time
Zhengzhou	ARIMA	R^2	0.398	0.374	0.303	0.224	0.157	0.098
		RMSE	0.691	0.726	0.804	0.987	1.237	1.459
		MAE	0.547	0.607	0.697	0.817	1.027	1.134
		NSE	0.381	0.366	0.289	0.217	0.154	0.081
	ARIMA-SVR	R^2	0.714	0.687	0.601	0.528	0.433	0.327
		RMSE	0.586	0.624	0.724	0.807	0.899	0.927
		MAE	0.477	0.508	0.654	0.728	0.812	0.874
		NSE	0.708	0.671	0.585	0.514	0.429	0.310
Anyang	ARIMA	R^2	0.357	0.324	0.287	0.207	0.156	0.085
		RMSE	0.668	0.687	0.784	0.857	1.024	1.578
		MAE	0.532	0.559	0.678	0.754	0.947	1.347
		NSE	0.348	0.328	0.277	0.187	0.142	0.044
	ARIMA-SVR	R^2	0.728	0.717	0.687	0.553	0.458	0.339
		RMSE	0.503	0.554	0.628	0.765	0.824	0.987
		MAE	0.389	0.413	0.567	0.701	0.754	0.837
		NSE	0.716	0.709	0.685	0.547	0.449	0.317
Xinyang	ARIMA	R^2	0.377	0.351	0.297	0.221	0.167	0.097
		RMSE	0.684	0.705	0.864	0.927	1.062	1.687
		MAE	0.538	0.647	0.833	0.905	0.959	1.457
		NSE	0.361	0.340	0.284	0.21	0.154	0.086
	ARIMA-SVR	R^2	0.714	0.685	0.664	0.547	0.422	0.325
		RMSE	0.518	0.684	0.702	0.769	0.824	0.973
		MAE	0.404	0.527	0.654	0.724	0.796	0.861
		NSE	0.705	0.675	0.655	0.539	0.417	0.315
Sanmenxia	ARIMA	R^2	0.381	0.358	0.318	0.233	0.179	0.101
		RMSE	0.668	0.674	0.784	0.861	0.988	1.547
		MAE	0.579	0.608	0.749	0.948	0.974	1.387
		NSE	0.379	0.348	0.308	0.227	0.165	0.094
	ARIMA-SVR	R^2	0.711	0.687	0.656	0.537	0.411	0.318
		RMSE	0.524	0.607	0.694	0.728	0.826	0.962
		MAE	0.377	0.455	0.662	0.709	0.791	0.866
		NSE	0.709	0.674	0.648	0.529	0.394	0.307
Shangqiu	ARIMA	R^2	0.401	0.389	0.347	0.255	0.198	0.104
		RMSE	0.680	0.701	0.865	0.946	1.267	1.662
		MAE	0.564	0.587	0.849	0.925	1.087	1.428
		NSE	0.387	0.374	0.335	0.244	0.197	0.094
	ARIMA-SVR	R^2	0.738	0.721	0.668	0.548	0.427	0.329
		RMSE	0.467	0.578	0.643	0.761	0.854	0.964
		MAE	0.328	0.412	0.628	0.744	0.829	0.866
		NSE	0.729	0.704	0.653	0.534	0.419	0.311

the loop was stopped and k was output. Otherwise, the order continued to increase. For the penalty parameter C in the SVR model and the parameter gamma in the RBF, the grid-search algorithm was used for calibration, and the SVR model was modeled. The data from 1951 to 1995 were used as the training set, and those from 1996 to 2017 were used as the test set. The SVR model was used to predict the residuals of the SPI1, SPI3, SPI6, and SPI12 values predicted by the ARIMA model.

d. Hybrid ARIMA-SVR model

There are usually two ways to use the ARIMA model with the SVR model for combined forecasting. One is a

parallel type, which is obtained by recombining the prediction results of the two models with weights. The other type is tandem. In the tandem type, the residual correction value of the SVR output (the residual value obtained by the ARIMA model was input into the SVR model and then predicted) was combined with the ARIMA prediction value to obtain the final combined model. ARIMA and ARIMA-SVR had respective advantages in linear and nonlinear prediction. When the ARIMA model weights were assigned by the parallel combination, the results could not be changed with an increase in the length of time. Therefore, this paper uses the tandem type for combined forecasting and the flowchart is shown in Fig. 9. Four-time-scale SPI values

TABLE 5. As in Table 4, but for SPI3.

Example stations	Model	Performance measures	1-month lead time	2-month lead time	3-month lead time	4-month lead time	5-month lead time	6-month lead time
Zhengzhou	ARIMA	R^2	0.407	0.387	0.309	0.264	0.218	0.139
		RMSE	0.710	0.767	0.852	0.974	1.038	1.685
		MAE	0.552	0.745	0.836	0.954	0.996	1.421
	ARIMA-SVR	NSE	0.404	0.380	0.295	0.247	0.204	0.125
		R^2	0.678	0.657	0.564	0.508	0.427	0.381
		RMSE	0.504	0.548	0.634	0.716	0.781	0.864
		MAE	0.421	0.467	0.568	0.664	0.766	0.841
		NSE	0.657	0.642	0.543	0.507	0.408	0.369
		R^2	0.420	0.394	0.289	0.242	0.198	0.106
Anyang	ARIMA	RMSE	0.736	0.784	0.864	0.982	1.056	1.724
		MAE	0.574	0.739	0.817	0.944	1.015	1.410
		NSE	0.411	0.388	0.279	0.238	0.184	0.104
	ARIMA-SVR	R^2	0.701	0.681	0.573	0.519	0.433	0.39
		RMSE	0.601	0.584	0.654	0.735	0.804	0.889
		MAE	0.408	0.452	0.627	0.708	0.769	0.840
		NSE	0.685	0.677	0.568	0.509	0.424	0.385
		R^2	0.427	0.409	0.293	0.256	0.203	0.164
		RMSE	0.663	0.694	0.851	0.967	1.029	1.348
		MAE	0.517	0.673	0.801	0.924	1.009	1.347
Xinyang	ARIMA	NSE	0.411	0.401	0.282	0.243	0.186	0.157
		R^2	0.704	0.676	0.583	0.522	0.446	0.407
		RMSE	0.578	0.608	0.647	0.709	0.793	0.827
	ARIMA-SVR	MAE	0.501	0.448	0.618	0.692	0.745	0.804
		NSE	0.703	0.662	0.573	0.508	0.427	0.389
		R^2	0.372	0.369	0.268	0.206	0.148	0.101
		RMSE	0.687	0.701	0.869	0.982	1.128	1.560
		MAE	0.518	0.687	0.818	0.938	1.024	1.368
		NSE	0.367	0.359	0.244	0.195	0.136	0.091
		R^2	0.679	0.658	0.566	0.509	0.428	0.364
Sanmenxia	ARIMA	RMSE	0.547	0.604	0.638	0.693	0.782	0.817
		MAE	0.483	0.529	0.584	0.673	0.739	0.801
		NSE	0.677	0.654	0.551	0.487	0.406	0.344
	ARIMA-SVR	R^2	0.389	0.371	0.276	0.228	0.154	0.121
		RMSE	0.662	0.694	0.841	0.973	1.089	1.367
		MAE	0.508	0.677	0.808	0.922	1.011	1.283
		NSE	0.364	0.366	0.251	0.216	0.137	0.108
		R^2	0.682	0.673	0.576	0.511	0.429	0.358
		RMSE	0.587	0.598	0.634	0.687	0.765	0.855
		MAE	0.429	0.489	0.534	0.649	0.702	0.778
Shangqiu	ARIMA	NSE	0.673	0.661	0.565	0.508	0.407	0.344

from 1951 to 2003 of five meteorological stations were selected as training sets, and data from 2004 to 2017 were selected as a test set. Take the selected five meteorological stations as examples, the ARIMA model and hybrid ARIMA-SVR model were used to forecast the SPI values of four time scale with 1–6-month lead time. The forecast results were shown in Tables 4–7. The prediction chart of one-month lead time was shown in Figs. 4–8. The solid black line represents SPI observations, and the solid red line represents hybrid ARIMA-SVR predictions.

Drought disasters are frequent occurrences with long durations in Henan Province. They were considered at the monthly scale (SPI1), seasonal scale

(SPI3), half-year scale (SPI6), and annual scale (SPI12). According to the introduction of SPI by the World Meteorological Organization (WMO) and the literature of McKee et al. (1993), a 3-month SPI reflects short- and medium-term moisture conditions and provides a seasonal estimation of precipitation. In primary agricultural regions, a 3-month SPI might be more effective in highlight available hydrological indices. According to WMO, take 6-month SPI as an example, a 6-month SPI at the end of March would give a very good indication of the amount of precipitation that has fallen during the very important wet season period from October through March for certain Mediterranean locales. In terms of seasonality of

TABLE 6. As in Table 4, but for SPI6.

Example stations	Model	Performance measures	1-month lead time	2-month lead time	3-month lead time	4-month lead time	5-month lead time	6-month lead time
Zhengzhou	ARIMA	R^2	0.561	0.508	0.437	0.286	0.154	0.089
		RMSE	0.643	0.683	0.768	0.829	1.348	1.864
		MAE	0.474	0.564	0.668	0.794	1.084	1.467
		NSE	0.557	0.452	0.423	0.266	0.107	0.071
	ARIMA-SVR	R^2	0.803	0.784	0.702	0.634	0.518	0.421
		RMSE	0.537	0.567	0.648	0.701	0.788	0.812
		MAE	0.408	0.429	0.567	0.68	0.721	0.786
		NSE	0.758	0.735	0.664	0.567	0.463	0.406
Anyang	ARIMA	R^2	0.461	0.428	0.364	0.244	0.106	0.096
		RMSE	0.676	0.698	0.786	0.849	1.364	1.892
		MAE	0.467	0.578	0.671	0.809	1.024	1.287
		NSE	0.358	0.327	0.298	0.201	0.101	0.069
	ARIMA-SVR	R^2	0.847	0.804	0.734	0.668	0.529	0.457
		RMSE	0.521	0.549	0.627	0.689	0.763	0.804
		MAE	0.404	0.418	0.559	0.644	0.708	0.755
		NSE	0.844	0.799	0.713	0.637	0.504	0.441
Xinyang	ARIMA	R^2	0.502	0.486	0.407	0.328	0.247	0.101
		RMSE	0.614	0.634	0.725	0.807	0.989	1.543
		MAE	0.440	0.521	0.657	0.788	0.946	1.354
		NSE	0.498	0.472	0.391	0.303	0.238	0.091
	ARIMA-SVR	R^2	0.817	0.795	0.715	0.649	0.511	0.442
		RMSE	0.576	0.594	0.646	0.712	0.791	0.827
		MAE	0.407	0.429	0.581	0.669	0.721	0.778
		NSE	0.804	0.781	0.687	0.621	0.498	0.404
Sanmenxia	ARIMA	R^2	0.560	0.519	0.428	0.337	0.266	0.187
		RMSE	0.568	0.611	0.708	0.764	0.891	1.269
		MAE	0.395	0.499	0.627	0.734	0.835	0.987
		NSE	0.544	0.498	0.387	0.237	0.219	0.165
	ARIMA-SVR	R^2	0.837	0.807	0.735	0.681	0.559	0.482
		RMSE	0.479	0.506	0.594	0.657	0.762	0.809
		MAE	0.342	0.417	0.556	0.648	0.709	0.755
		NSE	0.808	0.786	0.704	0.659	0.528	0.461
Shangqiu	ARIMA	R^2	0.457	0.418	0.385	0.297	0.167	0.085
		RMSE	0.619	0.688	0.756	0.847	0.962	1.546
		MAE	0.436	0.508	0.654	0.769	0.878	0.986
		NSE	0.429	0.401	0.372	0.267	0.154	0.076
	ARIMA-SVR	R^2	0.798	0.775	0.689	0.607	0.521	0.453
		RMSE	0.544	0.568	0.627	0.725	0.849	0.923
		MAE	0.401	0.537	0.607	0.684	0.817	0.898
		NSE	0.797	0.762	0.664	0.583	0.489	0.431

the drought in Henan Province, they were divided into winter drought (at the end of February, 1 December 2016–28 February 2017), spring drought (at the end of May, 1 March 2017–31 May 2017), summer drought (at the end of August, 1 June 2017–31 August 2017), and autumn drought (at the end of November, 1 September 2017–30 November 2017). Because of the seasonal continuity of drought disasters in Henan Province and because the growth cycle of crops is usually 3 months, the seasonal-scale classification selected in this paper was the most realistic. By using the kriging interpolation method in the ArcGIS software, the predicted SPI3 values of 19 meteorological stations of the two models were compared with the observed values. In

Fig. 10, the first values listed are SPI observations, the second are ARIMA fitting values, and the third are ARIMA-SVR fitting values, and the fitting precision of the hybrid model is superior to that of the single model. The RMSE, MAE, R^2 , and NSE evaluation indicators were used to evaluate the prediction results of five example meteorological stations of the two models at the four time scales in 1–6-month lead time. The results are shown in Tables 4–7. According to the data in the table, it can be seen that the two models have the best predictive effect at 1–2-month lead time and decreases with increase in lead time. The worst predictive effect at the SPI1 time scale. The ARIMA model has the best predictive ability at

TABLE 7. As in Table 4, but for SPI12.

Example Stations	Model	Performance measures	1-month lead time	2-month lead time	3-month lead time	4-month lead time	5-month lead time	6-month lead time
Zhengzhou	ARIMA	R^2	0.816	0.707	0.557	0.419	0.387	0.276
		RMSE	0.434	0.571	0.689	0.728	0.801	1.081
		MAE	0.273	0.458	0.654	0.709	0.798	1.077
	ARIMA-SVR	NSE	0.798	0.694	0.538	0.408	0.37	0.255
		R^2	0.905	0.812	0.726	0.684	0.512	0.404
		RMSE	0.327	0.404	0.521	0.645	0.789	0.854
Anyang	ARIMA	MAE	0.214	0.389	0.51	0.601	0.771	0.842
		NSE	0.885	0.811	0.714	0.667	0.507	0.398
		R^2	0.708	0.627	0.557	0.471	0.322	0.281
	ARIMA-SVR	RMSE	0.398	0.423	0.588	0.701	0.825	1.254
		MAE	0.238	0.397	0.496	0.647	0.762	1.168
		NSE	0.689	0.611	0.541	0.462	0.303	0.261
Xinyang	ARIMA	R^2	0.857	0.814	0.725	0.682	0.591	0.401
		RMSE	0.301	0.452	0.581	0.689	0.801	0.886
		MAE	0.287	0.402	0.542	0.598	0.788	0.854
	ARIMA-SVR	NSE	0.842	0.804	0.722	0.657	0.584	0.394
		R^2	0.756	0.684	0.581	0.473	0.396	0.219
		RMSE	0.429	0.561	0.688	0.75	0.857	1.013
Sanmenxia	ARIMA	MAE	0.271	0.387	0.451	0.601	0.784	0.957
		NSE	0.755	0.672	0.564	0.454	0.387	0.198
		R^2	0.886	0.824	0.708	0.683	0.588	0.427
	ARIMA-SVR	RMSE	0.305	0.448	0.573	0.691	0.821	0.897
		MAE	0.297	0.401	0.567	0.684	0.792	0.887
		NSE	0.748	0.798	0.701	0.671	0.574	0.41
Shangqiu	ARIMA	R^2	0.75	0.677	0.576	0.469	0.388	0.264
		RMSE	0.426	0.574	0.692	0.764	0.869	1.001
		MAE	0.252	0.455	0.509	0.591	0.856	0.921
	ARIMA-SVR	NSE	0.749	0.666	0.564	0.457	0.371	0.198
		R^2	0.867	0.831	0.715	0.694	0.598	0.487
		RMSE	0.312	0.398	0.467	0.517	0.687	0.808
Shangqiu	ARIMA	MAE	0.298	0.344	0.408	0.497	0.587	0.743
		NSE	0.861	0.821	0.678	0.689	0.597	0.454
		R^2	0.582	0.577	0.465	0.398	0.302	0.219
	ARIMA-SVR	RMSE	0.403	0.527	0.668	0.714	0.855	1.234
		MAE	0.259	0.451	0.586	0.661	0.799	0.998
		NSE	0.581	0.521	0.448	0.375	0.287	0.167
Shangqiu	ARIMA	R^2	0.784	0.765	0.641	0.587	0.499	0.336
		RMSE	0.35	0.388	0.471	0.579	0.662	0.754
		MAE	0.303	0.367	0.458	0.501	0.654	0.722
	ARIMA-SVR	NSE	0.771	0.755	0.612	0.585	0.467	0.301

the SPI12 scale, and the predictive ability at the SPI3 and SPI6 time scales was second to that at the SPI12 time scale. However, the hybrid model shows better prediction results at all time scales than the single ARIMA model.

5. Discussion and conclusions

Strengthening research on drought monitoring and prediction is of great significance for relevant governmental departments to prevent drought disasters and reduce losses from drought disasters. In this paper, the SPI index, which is easy to calculate and widely applicable, was selected as the drought index,

and the rainfall at 19 national meteorological stations from 1951 to 2017 in Henan Province was calculated. The SPI at four time scales was obtained; these time scales were SPI1, SPI3, SPI6, and SPI12. Data from 1951 to 2003 were selected as the training set, and data from 2004 to 2017 were selected as the test set. Two models were used to predict SPI values at four time scales for 1–6-month lead time, and the R^2 , RMSE, MAE, and NSE were used to evaluate the prediction accuracy of the two models.

First, the most common time series prediction model, the ARIMA model, was used to predict the SPI values at the four time scales of five example meteorological stations. As shown in Figs. 4–8, the prediction accuracy

FIG. 9. Hybrid ARIMA-SVR model forecast flowchart.

of the ARIMA model for short time scales of SPI was significantly lower than that for long time scales. This is because the ARIMA model is essentially an overall linear autoregressive model that predicts a trend that tends to stabilize as the test set grows (Yurekli et al. 2005; Hu et al. 2007). Since SPI1 has the lowest P value during the stability test (ADF test) relative to the other three time scales, the overall trend is strict and stable (the distribution of strict and stable representation does not change with time), so the prediction accuracy was the lowest. Similarly, the time scales of SPI3, SPI6, and SPI12 gradually increased, and it tended to be weak and stable (the expectation and the correlation coefficient were unchanged, and the future time value depended on the value of the past time); thus, the overall fitting accuracy gradually improved.

Since the linear ARIMA model cannot handle nonlinear relationships, SVR has recently been used in many applications, including drought prediction, because it is capable of describing nonlinear relationships

(Belayneh et al. 2014; Belayneh and Adamowski 2012). Lima et al. (2013) found in their study that SVR has advantages in regard to nonlinear model prediction. Studies by Shin et al. (2005) and Chevalier et al. (2011) found that the application of the SVR model in time series forecasting was comparable to that of ANN models. This paper presents a new drought prediction method based on the SPI with higher accuracy than traditional methods. By combining the advantages of the linear ARIMA model and nonlinear SVR model, a hybrid ARIMA-SVR model was proposed to predict SPI values of five example stations at four time scales for 1-6-month lead time, and the result was more accurate than that of a single ARIMA model. Comparing the measured data with the predicted data of the model shows that the two models have the best predictive effect at 1-2-month lead time and decreases with increase in lead time. The hybrid ARIMA-SVR model had higher prediction accuracy than the single ARIMA model in 1-6-month lead time and could well fit the SPI values at different time scales.

FIG. 10. Spatial distributions of seasonal drought levels at 19 national meteorological stations in 2017, using the two forecasting models ARIMA and hybrid ARIMA-SVR model.

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