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Long-Term Streamflow Forecasting Based on Relevance Vector Machine Model

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Academic Editor: Marco Franchini
Received: 26 September 2016; Accepted: 21 December 2016; Published: 28 December 2016

Abstract: Long-term streamflow forecasting is crucial to reservoir scheduling and water resources management. However, due to the complexity of internally physical mechanisms in streamflow process and the influence of many random factors, long-term streamflow forecasting is a difficult issue. In the article, we mainly investigated the ability of the Relevance Vector Machine (RVM) model and its applicability for long-term streamflow forecasting. We chose the Dahuofang (DHF) Reservoir in Northern China and the Danjiangkou (DJK) Reservoir in Central China as the study sites, and selected the 500 hpa geopotential height in the northern hemisphere and the sea surface temperatures in the North Pacific as the predictor factors of the RVM model and the Support Vector Machine (SVM) model, and then conducted annual streamflow forecasting. Results indicate that forecasting results in the DHF Reservoir is much better than that in the DJK Reservoir when using SVM, because streamflow process in the latter basin has a magnitude bigger than 1000 m^3/s. Comparatively, accurate forecasting results in both the two basins can be gotten using the RVM model, with the Nash Sutcliffe efficiency coefficient bigger than 0.7, and they are much better than those gotten from the SVM model. As a result, the RVM model can be an effective approach for long-term streamflow forecasting, and it also has a wide applicability for the streamflow process with a discharge magnitude from dozen to thousand cubic meter per second.

Keywords: long-term streamflow forecasting; relevance vector machine; support vector machine; hydrological process

1. Introduction

Conducting streamflow forecasting, especially long-term streamflow forecasting at monthly, annual, inter-annual or even decadal scales, is an important precondition for reservoir scheduling, water resources management, flood control and many other practical water activities [1,2]. However, it is a difficult task in practice due to the stochastic and nonlinear characteristics of streamflow process at multi-time scales [3,4]. During the recent decades, a large number of methods have been developed and improved for the streamflow forecasting. They can be generally divided into two types: process-driven methods and data-driven methods [5]. The former are based on mathematical simulation of streamflow process and the internally physical mechanisms that contribute to the hydrological cycle [6]. Process-driven methods usually require a large number of data inputs and parameter calibration. Comparatively, data-driven methods usually identify and describe the correlation between inputs and outputs, without considering the physical mechanisms of hydrological process in a watershed, and thus they have two advantages of low quantitative demand of data and simple formulation.

Owing to the complexity of physical mechanism in streamflow process and the influences of many random factors, the results gotten from process-driven methods cannot meet practical needs enough in some situations, especially in those data-ungauged basins. Comparatively, data-driven methods are an effective alternative, and they have been more widely used for long-term streamflow forecasting [7]. Data-driven methods generally include times series analysis-based and artificial intelligence (AI)-based methods [8–11]. They are simple and can be easily implemented, and so play an important role in hydrology research. However, the data should be stationary and follow normal distribution when using traditional times series analysis-based methods, which perform poorly in predicting extreme (both peak and small) streamflow values. Recently, AI technique has become increasingly popular in hydrology. Artificial neural networks (ANNs) model, one type of AI models, has gained more popularity for hydrological forecasting [12,13]. An extensive review about the model type can be found in the references [7,8]. However, a hard problem for ANNs is underfitting or overfitting [14], which would influence their fault-tolerant capability.

Another type of AI-based methods, called Support Vector Machine (SVM), has attracted the concerns from many researchers [15–20]. SVM is based on the structural risk minimization (SRM) principle and is an approximation implementation of SRM, with a good generalization capability [15]. It is considered as a kernel-based learning system rooted in the statistical learning theory, and has been applied widely for streamflow forecasting. For example, Asefa et al. used SVM to forecast flows at seasonal and hourly scales in the Sevier River Basin [17]; Lu et al. indicated a superior SVM performance over ANN in forecasting annual runoff [18]; and Li et al. predicted runoff by coupling SVM with the chaos analysis [19]. An improved SVM model, called Relevance Vector Machine (RVM), was proposed by Tipping [21,22]. It has the identical functional form as SVM [23,24]. RVM introduces a general Bayesian framework for obtaining sparse solution, and can derive accurate prediction models which typically utilize fewer basis functions than SVM; further, it can offer a number of additional advantages such as the benefit of probabilistic prediction, automatic estimation of parameters, and the facility to utilize arbitrary basis functions. The RVM model has been successfully applied for the pattern recognition and regression in different fields, including power load forecast and quality inspection [25]. However, there are relatively fewer applications of RVM in hydrology compared with other AI-based methods.

The objective of this study is therefore to investigate the performance of the RVM model in long-term streamflow forecasting, and further demonstrate its applicability for different basins. To achieve the goal, we chose the Dahuofang (DHF) Reservoir in North China and the Danjiangkou (DJK) Reservoir in Central China, which have obviously different underlying surface conditions and climate conditions, as the study areas and conduct long-term streamflow forecasting. Before it is feasible, how to identify proper physical factors which influence runoff is an important task for developing reliable model. Many researchers have investigated the statistical relationship between hydrological variables and ocean-atmospheric signals, such as the El Nino-Southern Oscillation, sea surface temperature (SST) and others [9,26–32]. Because ocean-atmospheric signals have time-lag effect on hydrological variables, models based on these factors could extend the forecasting period. Here the ocean-atmospheric signals, including the atmospheric circulation patterns of 500 hpa geopotential height in the northern hemisphere and the sea surface temperatures (SSTs) in the North Pacific, are used as the predictor factors, and the RVM model is applied for annual streamflow forecasting in the DHF and DJK basins.

2. The RVM Model

A brief description of the RVM model is provided here. The idea of the learning machine was first proposed by Turing [33]; after then, Vapnik discussed the feature of learning machine and proposed SVM, based on the statistical learning [16]. Tipping put forward a Sparse Bayesian learning model called RVM [21]. It can give more accurate prediction and utilize much fewer basis functions than SVM; further, the RVM model can describe the distribution function of the predicting variable under the Bayesian probabilistic framework.

Given a set of training data $\{x_n, t_n\}_{n=1}^{N}$, where x_n is the input vector and t_n is the target vector with the total number of N, the output for the RVM model is given as:

$$t_n = y(w_n; w) + \varepsilon_n \text{ with } y(x;\omega) = \sum_{i=1}^{N} \omega_i K(x, x_i) + \omega_0 \tag{1}$$

where $w = (\omega_1, \omega_2, \cdots, \omega_N)^T$ are parameters, ε_n are independent samples following a Gaussian distribution $\varepsilon_n \sim N(0, \sigma^2)$, and $K(x, x_i)$ is a kernel function. Here the Gauss radial basis function $G(x, x_i) = \exp(-\frac{\|x-x_i\|^2}{\sigma^2})$, which has low complexity and has been used widely, is used as the kernel for the study of two cases. The parameters are estimated by the maximum likelihood method:

$$p(t\Big|w, \sigma^2) = (2\pi\sigma^2)^{-N/2} \exp\left\{-\frac{1}{2\sigma^2}|t - \phi w|^2\right\} \tag{2}$$

where $t = (t_1 \cdots t_N)^T$, $w = (\omega_0 \cdots \omega_N)^T$; $\phi = [\varphi(x_1), \varphi(x_2), \cdots, \varphi(x_N)]^T$ is a $N \times (N+1)$ designed matrix, with $\varphi(x_N) = [1, K(x_n, x_1), K(x_n, x_2), \cdots, K(x_n, x_1)]^T$. All parameters in Equation (2) compose a vector of hyperparameters, with the total number of N + 1. Following the general practice, we chose the Gamma distribution as the hyperpriors of all parameters α:

$$Gamma \quad (\alpha|a, b) = \Gamma(a)^{-1} b^a \alpha^{a-1} e^{-b\alpha} \tag{3}$$

with $\Gamma(a) = \int_0^\infty t^{a-1} e^{-t} dt$. In order to gain the same hyperpriors, here we fix the intimal values of those parameters in Equation (3) as 0.001. Then, following the Bayesian inference the posterior of all parameters can be described as:

$$p(\omega, \alpha, \sigma^2 | t) = \frac{p(t|\omega, \alpha, \sigma^2) p(\omega, \alpha, \sigma^2)}{p(t)} \tag{4}$$

For a new test point x_*, predictions can be made at the corresponding target t_* in terms of the predictive distribution:

$$p(t_*|t) = \int p(t_*|w, \alpha, \sigma^2) p(w, \alpha, \sigma^2|t) dwd\,\alpha d\sigma^2 \tag{5}$$

After determining the optimal hyperparameters α_{MP} and σ^2_{MP}, we can describe the predictive distribution as:

$$p(t_*|t,\ \alpha_{MP}, \sigma^2_{MP}) = \int p(t_*|w, \alpha, \sigma^2_{MP}) p(w|t, \alpha_{MP}, \sigma^2_{MP}) dw \tag{6}$$

Because both terms in the above integrand function are the Gaussian distribution, they can also be expressed as:

$$p(t_*|t,\ \alpha_{MP}, \sigma^2_{MP}) = N(t_*\Big|y_*, \sigma^2_*) \tag{7}$$

with $y_* = \mu^T \phi(x_*)$ and $\sigma^2_* = \sigma^2_{MP} + \phi(x_*)^T \Sigma \phi(x_*)$. Finally, the predictive mean is $y(x_*; \mu)$.

More detailed description of the RVM model can be found in [21,22]. The forecasting process of hydrological variables by RVM can also be found in the flow chart in Figure 1.

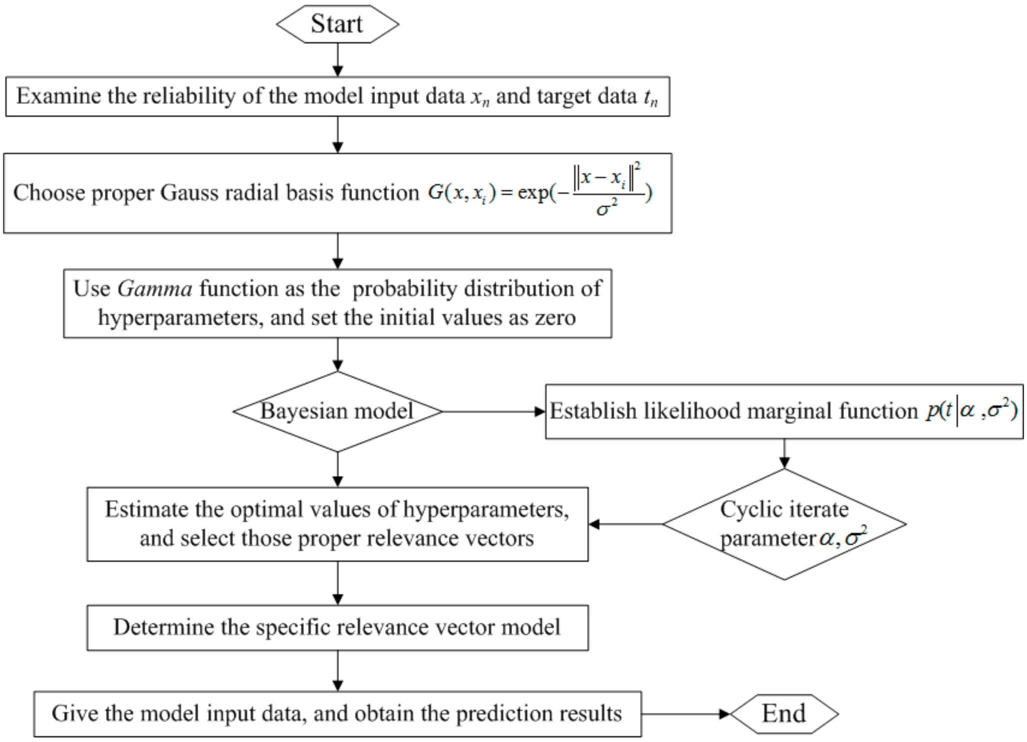

Start
Examine the reliability of the model input data x_n and target data t_n
Choose proper Gauss radial basis function $G(x,x_i)=\exp(-\frac{\|x-x_i\|^2}{\sigma^2})$
Use *Gamma* function as the probability distribution of hyperparameters, and set the initial values as zero
Bayesian model
Establish likelihood marginal function $p(t|\alpha,\sigma^2)$
Cyclic iterate parameter α,σ^2
Estimate the optimal values of hyperparameters, and select those proper relevance vectors
Determine the specific relevance vector model
Give the model input data, and obtain the prediction results
End

Figure 1. Flow chart of the forecasting process of hydrological variables using the Relevance Vector Machine (RVM) model.

3. Materials

3.1. Study Area

The Dahuofang (DHF) Reservoir and the Danjiangkou (DJK) Reservoir are chosen as the study sites (Figure 2), with an average annual precipitation of 800 mm and 870 mm respectively. The DHF Reservoir is located in the mid reaches of the Hun River, China, with a basin area of 5437 km^2 and a water capacity of 2.27 billion m^3. It supplies water to the Shenyang and Fushun cities, provides water resources for the agriculture in the Liaoning Province, and protects the downstream regions from flood disasters. The DJK Reservoir, as a tributary of the Yangtze River, is located in the upper reaches of the Hanjiang River, with a basin area of 96,217 km^2 and a water capacity of 30 billion m^3. The DJK Reservoir aims at flood control, power generation, irrigation and shipping functions. Because the two reservoirs were designed as annual regulation, annual streamflow forecasting has socioeconomic significance for local regions.

3.2. Data Sets

The data sets used for long-term streamflow forecasting include the oceanic-atmospheric signals and the naturalized annual streamflow data at the DHF and DJK Reservoir. The annual streamflow data were measured from 1962 to 2006 in the DHF Reservoir, and those were measured from 1957 to 2006 in the DJK Reservoir. These runoff data were gotten from the Chinese Hydrological Yearbook.

The oceanic-atmospheric signals include the atmospheric circulation patterns of 500 hpa geopotential height (Z_{500}) in the northern hemisphere and SSTs in the North Pacific. The data of Z_{500} in the northern hemisphere are a product of the NCEP/NCAR reanalysis 40-year Project and were obtained from the NOAA Physical Sciences Center (http://www.cdc.noaa.-gov/cgi-bin/Composites/printpage.pl). The data of the Z_{500} index are given on a 2.5° by 2.5° latitude and longitude grid, and are available from 1948 to present. The region with the latitude 0° N–90° N and longitude 0° W–2.5° W was considered for the study. The data of SSTs in the North Pacific were obtained from the National

Climatic Data Center (http://www.cdc.noaa.gov/cdc/data.noaa.ersst.html). The SSTs data consist of average monthly values for a 2° by 2° grid. The extended reconstructed global SSTs were based on the comprehensive ocean-atmosphere data set from 1854 to present. The region of the North Pacific Ocean (120° E–80° W and 10° S–50° N) was also considered for the study.

In the modelling practice, both the Z_{500} and SSTs are used as the predictor factors, that is, the input data of model; the streamflow data at each reservoir are the output data of model.

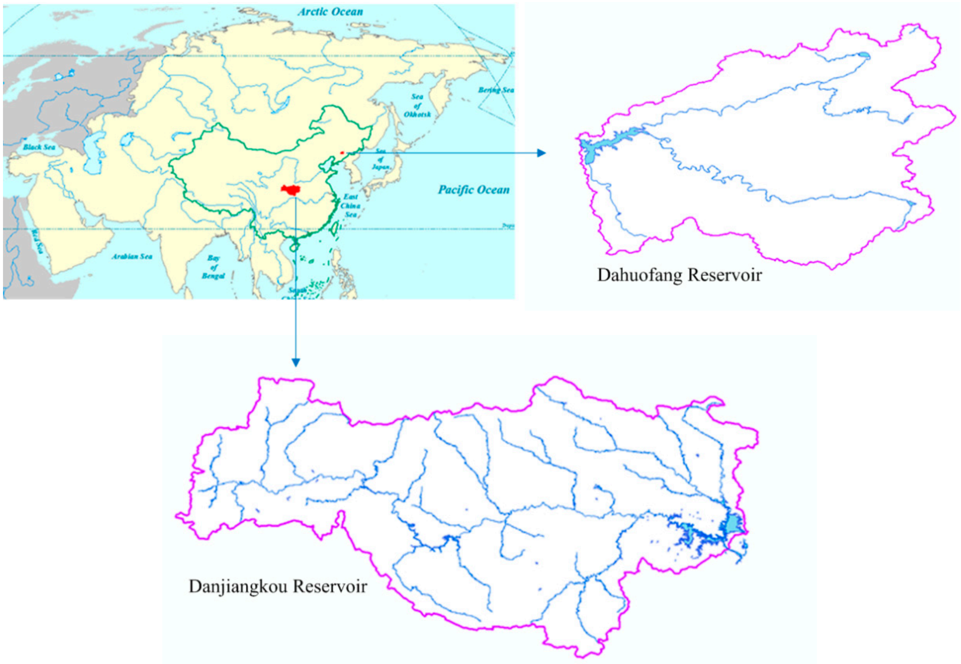


Figure 2. Location of the Dahuofang Reservoir Basin and the Danjiangkou Reservoir Basin in China.

4. Results and Discussion

4.1. Selection of Predictor Factors

How to select proper predictor factors is the first task in streamflow forecasting by the RVM model. Several methods are commonly used to describe the relationship of spatiotemporal variability between climate variables and streamflow data. Here we used the correlation analysis method to investigate the major predictor factors which influence the annual streamflow process in the DHF and DJK Reservoir. The main steps are explained as follows. First, we calculate the correlations between the average annual streamflow and the average monthly indices of Z_{500} and SSTs from January to December at last year; and then, we select those variables which have stably high correlation (with a confidence level bigger than 0.95) as the predictor factors.

Those predictor factors selected above show good correlations (i.e., multi-collinearity), which would influence the generalization ability of the RVM model. Therefore, useful information included in these predictor factors cannot be utilized simultaneously. To solve this problem, we further employed the two-step stepwise regression method to pick the effectively primary predictors, and reduce the impact of multi-collinearity. Finally, we selected 6 predictor factors for the annual streamflow forecasting in the DHF Reservoir (Table 1), and selected 7 predictor factors for the DJK Reservoir (Table 2). From Table 3 we can see that the multiple correlations using all selected factors in the first step exceed 0.8. However, the multiple correlations using those selected factors in the second step, with the values bigger than 0.92, become much better. It indicates that the combination of these predictor factors would have better forecasting performance, and they are used for the RVM modelling. Besides, these selected factors are also considered as the input signals of SVM.

Table 1. Predictor factors used for annual shreamflow forecasting in the Dahuofang Reservoir.

Order	Predictor Factor	Correlation Coefficient	Description of Factor
1	500 hpa_4_218	−0.457	Z_{500} in the grid 218 in April of the last year
2	500 hpa_3_260	−0.397	Z_{500} in the grid 260 in March of the last year
3	500 hpa_8_164	0.456	Z_{500} in the grid 164 in August of the last year
4	SST_9_591	0.490	SSTs in the grid 591 in September of the last year
5	SST_5_409	0.411	SSTs in the grid 409 in May of the last year
6	SST_3_418	−0.408	SSTs in the grid 418 in March of the last year

Table 2. Predictor factors used for annual shreamflow forecasting in the Danjiangkou Reservoir.

Order	Predictor Factor	Correlation Coefficient	Description of Factor
1	500 hpa_6_193	0.337	Z_{500} in the grid 193 in June of the last year
2	500 hPa_4_182	0.471	Z_{500} in the grid 182 in April of the last year
3	500 hpa_11_126	−0.468	Z_{500} in the grid 126 in November of the last year
4	500 hpa_7_221	0.451	Z_{500} in the grid 221 in July of the last year
5	SST_9_187	−0.522	SSTs in the grid 187 in September of the last year
6	SST_7_189	−0.395	SSTs in the grid 189 in July of the last year
7	SST_6_412	−0.417	SSTs in the grid 412 in June of the last year

Table 3. Number of predictor factors in the first- and two-step stepwise regression and the multiple correlations for the Dahuofang (DHF) and Danjiangkou (DJK) Reservoir.

Step	Predictor Factor	Factor Number		Multiple Correlation	
		DJK	DHF	DJK	DHF
First step	Z_{500}	7	6	0.90	0.85
	SST	4	5	0.79	0.81
Second step	Factor set	7	6	0.92	0.94

After selecting the predictor factors for the annual streamflow forecasting in the DHF and DJK Reservoir, we determine the specific RVM model through the training and testing practice using different data (Table 4). The Gauss radial basis function (RBF) is used as the Kernel function of RVM here. Various studies have indicated the favorable performance of the RBF kernel in hydrological forecasting [17,34–36]. In the RVM model, the "leave-one-out" cross validation is used to optimize parameters σ, as the width of the RBF kernel. Through calculation, the optimal value 2.25 and 3.00 of parameter σ is determined for the DHF and DJK Reservoir respectively. Furthermore, we also compare the results gotten from RVM with those from SVM.

Table 4. Data used for training and testing the relevance vector machine (RVM) model and support vector machine (SVM) model in the Dahuofang (DHF) and Danjiangkou (DJK) Reservoir.

Area	Data for Model Training	Data for Model Testing
DJK	1962–2000	2001–2006
DHF	1957–2000	2001–2006

4.2. Model Performance Evaluation

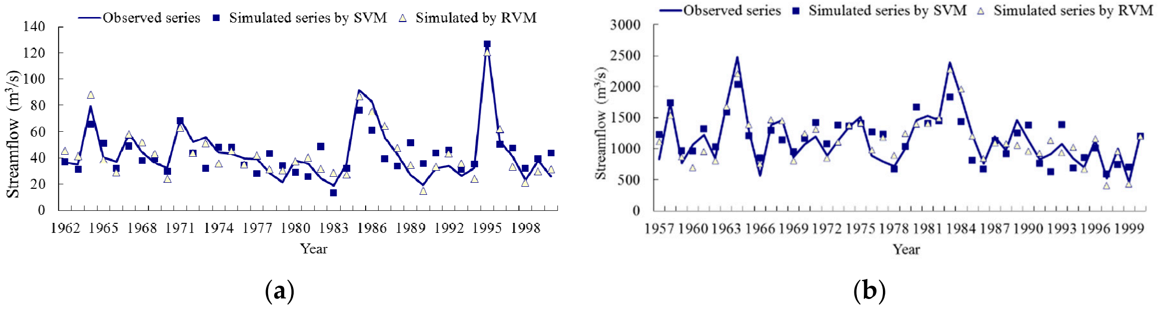
Three quantitative indexes are used to evaluate the effectiveness of the RVM and SVM model, including correlation coefficient (R), root means squared error (RMSE) and Nash Sutcliffe Efficiency Coefficient (E), with the computation equations as:

$$\begin{aligned}
\mathrm{R} &= \frac{\frac{1}{n}\sum\limits_{i=1}^{n}(Q_0(i)-\overline{Q_o})(Q_f(i)-\overline{Q_f})}{\sqrt{\frac{1}{n}\sum\limits_{i=1}^{n}(Q_0(i)-\overline{Q_o})^2}\sqrt{\frac{1}{n}\sum\limits_{i=1}^{n}(Q_f(i)-\overline{Q_f})^2}} \\
\mathrm{RMSE} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_f(i)-Q_0(i)\right)^2} \qquad (8) \\
\mathrm{E} &= 1-\frac{\sum\limits_{i=1}^{n}(Q_0(i)-Q_f(i))^2}{\sum\limits_{i=1}^{n}(Q_0(i)-Q_0)^2}
\end{aligned}$$

where n is the number of years, $Q_0(i)$ are the observed values, $\overline{Q_o}$ is the average observed values, $Q_f(i)$ are the predicted values and $\overline{Q_f}$ is the average predicted values. The R is an index used commonly to describe the correlation of two series. The RMSE can measure the difference between the observation and simulated data. The E coefficient is widely used for the evaluation of model's performance. Generally, high NSE and R values, and small RMSE values, reflect good modeling performance [37].

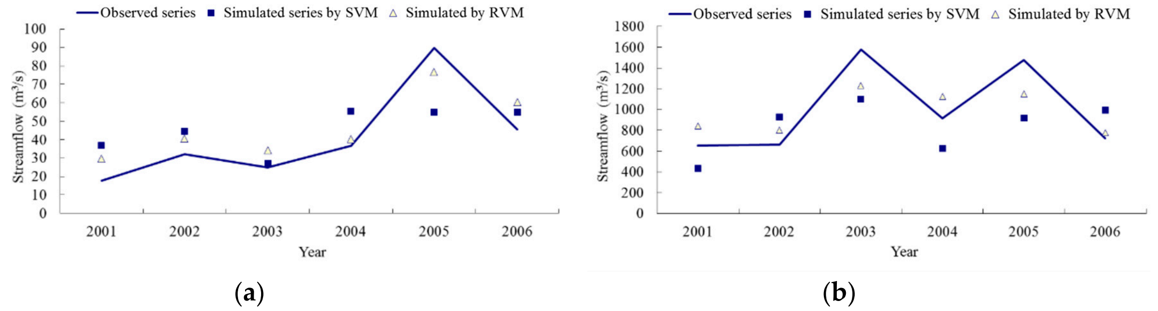
4.3. Results Discussion

The observed streamflow data and the simulated data by SVM and RVM during the training period are shown in Figure 3 (left, DHF Reservoir; right, DJK Reservoir). The observed data and the simulated streamflow data by SVM and RVM during the testing period can be found in Figure 4 (left, DHF Reservoir; right, DJK Reservoir). In Figures 3 and 4 the solid line represents the observed data, and the hollow triangle shows the simulated data gotten from the RVM model, with the solid square indicating the simulated data by SVM. Table 5 shows the forecasting performance of different models for the DHF Reservoir, and the results of the DJK Reservoir are presented Table 6.



(**a**) (**b**)

Figure 3. Observed and simulated streamflow data in the Dahuofang Reservoir (**a**) and Danjiangkou Reservoir (**b**) during the training period by the RVM and SVM model.



(**a**) (**b**)

Figure 4. Observed and simulated streamflow data in the Dahuofang Reservoir (**a**) and Danjiangkou Reservoir (**b**) during the testing period by the RVM and SVM model.

From Table 5 we can find that for the streamflow forecasting in the DHF Reservoir, the values of three indices R, RMSE and E in the training period, gotten from the SVM model, are 0.91, 7.58 m^3/s and 0.89, which are similar as those gotten from the RVM model, with the R, RMSE and E value of 0.95, 6.78 m^3/s and 0.90. However, the RVM model performs much better than the SVM model during the testing period. To be specific, the indices R and E in the testing period gotten from the SVM model is 0.74 and 0.63, which are much smaller than those of 0.83 and 0.78 for the RVM model, but the index RMSE value of 19.01 m^3/s for the SVM model is much bigger than that of 13.76 m^3/s for the RVM model. The results from the DHF Reservoir indicate the better performance of the RVM model compared with SVM. Many previous studies used the traditional auto-regression models and the ANN, wavelet-based ANN models to conduct streamflow forecasting in the DHF reservoir [38,39]. Those results indicated the poor performance of the auto-regression models, which are just based on linear characteristics and long-memories of time series, and cannot deal with the decadal variability of streamflow process; besides, although those results gotten from the ANN or wavelet-based ANN models considered the influences of climate factors, they had the relative errors bigger than 20%. Comparatively, the results gotten form the RVM model in this study have higher accuracy, thus it is thought that RVM also performs better than those traditional auto-regression models and ANN models.

Table 5. Results of indices used to evaluate the performance of the relevance vector machine (RVM) and support vector machine (SVM) model for streamflow forecasting in the Dahuofang Reservoir.

Model	Training			Testing		
	R	RMSE (m^3/s)	E	R	RMSE (m^3/s)	E
SVM	0.91	7.58	0.89	0.74	19.01	0.63
RVM	0.95	6.78	0.90	0.83	13.76	0.78

Table 6. Results of indices used to evaluate the performance of the relevance vector machine (RVM) and support vector machine (SVM) model for streamflow forecasting in the Danjiangkou Reservoir.

Model	Training			Testing		
	R	RMSE (m^3/s)	E	R	RMSE (m^3/s)	E
SVM	0.84	191.18	0.81	0.67	339.01	0.57
RVM	0.92	163.06	0.85	0.88	231.92	0.68

As for the DJK Reservoir, the results gotten from the RVM model are also much better than those of the SVM model, no matter considering the training period or testing period. In the training period, the RVM model reduces the RMSE value with respect to SVM by 14.7% (163.06 m^3/s compared to 191.18 m^3/s), and increase the R and E value by 9.5% (0.92 compared to 0.84) and 4.9% (0.85 compared to 0.81) respectively. In the testing period, the RVM model reduces the RMSE value by 31.6% (231.92 m^3/s compared to 339.01 m^3/s) compared with SVM, and increase the R and E value by 31.3% (0.88 compared to 0.67) and 19.3% (0.68 compared to 0.57) respectively. Previous studies have compared the different capabilities of the traditional auto-regression models and ANN models with that of the SVM model [40], and indicated that the forecasting results gotten from the later have high accuracy, more stability and reliability. By comprehensively analyzing the results here and the previous study results, it can be found that the RVM model performs the best among these models for the streamflow forecasting in the DJK reservoir.

Presently the SVM model has been widely applied in the streamflow simulation and forecasting, and a great number of studies have verified the ability of the SVM model in vast majority of cases; especially, its better performance compared with conventional auto-regression models or ANN models has been clearly verified in the DJK reservoir basin. Therefore, SVM can be taken as the reference to evaluate the ability of the RVM model, while other data-driven models and the results gotten from them, as discussed above, were not considered and compared again. On the whole, all the results in the two reservoirs indicate the better performance of RVM compared with SVM for long-term streamflow forecasting, although the results in the testing period is a little worse compared with those in the training period. In addition, our previous study results also indicated the better performance of the RVM model for monthly and seasonal streamflow forecasting in the two reservoirs, compared with the SVM model [41,42]. Because the RVM model is based on the Bayesian theory, posterior distributions of all parameters and characteristics of hydrological variables can be accurately and reasonably evaluated, following which more accurate forecasting results can be gotten, but the SVM model cannot do this. Thereby, it is thought that the RVM model can be effective method for long-term streamflow forecasting.

Besides, the two reservoir basins chosen for the study have obviously different underlying surface conditions and climate conditions; further, the average streamflow magnitudes in the two basins are about 40 m^3/s and 1000 m^3/s, also showing obvious difference. It can be found that the results in the DHF Reservoir is better that that in the DJK Reservoir when using the SVM model, indicating the worse performance of the SVM model for those streamflow process with big magnitudes. From Figure 3 we know that both the RVM and SVM model show good performance for the forecasting of peak and small values of streamflow process in the DHF Reservoir; however, peak values of streamflow process in the DJK Reservoir can only been accurately simulated by the RVM model, which cannot be achieved by the SVM model. Especially, for those peak values bigger than 2000 m^3/s in the streamflow process in the DJK Reservoir, the relative errors gotten from RVM are about 20% in 2003 and 2005, but the results of SVM are much worse, with the relative errors bigger than 40%. As a result, it is thought here that the limited ability of forecasting peak magnitudes of streamflow process cause the poor performance of the SVM model. Comparatively, all the results gotten from the RVM model are stable and accurate, not matter analyzing the DHF or DJK Reservoir. Therefore, it is thought that the RVM model also has a wide applicability for long-term forecasting of streamflow process with a magnitude of dozens to thousands discharge units.

5. Conclusions

Long-term streamflow forecasting is an important issue for the reservoir scheduling and water resources management, but it is also a difficult task due to the complexity in streamflow process. In the article, we presented a data-driven model, called RVM, for annual streamflow forecasting. The RVM model was applied to the DHF Reservoir in Northern China and the DJK Reservoir in Central China. Results indicate the better performance of the RVM model compared with the SVM model which has been widely used for hydrological forecasting. Therefore, RVM can be a more reliable and effective model for long-term streamflow forecasting rather than SVM. Compared with SVM, the RVM model has relatively limited applications in the hydrology and water resources studies. Through this study, we can find the RVM model is suitable for the forecasting of annual streamflow process with obviously different magnitudes in two different basins, thus it is thought that the RVM model has a widely applicable scopes for long-term hydrological forecasting. In the future, more studies can focus on the RVM model by applying it to various basins with different climatic conditions.

Acknowledgments: The authors gratefully acknowledged the most appropriate comments and suggestions given by the editors and the anonymous reviewers. This study was financially supported by the National Natural Science Foundation of China (No. 91647110), the "Bingwei" Excellent Talents from the Institute of Geographic Sciences and Natural Resources Research, CAS, the Youth Innovation Promotion Association CAS, the Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (WL2015003), and the Water Resources Public-welfare Project of China (Y515010, Y516012).

Author Contributions: Yong Liu did the data analysis work and wrote the paper; Yan-Fang Sang provided the method and guided the entire study; Xinxin Li contributed to the discussion part; Jian Hu and Kang Liang helped analyzing the data.

Conflicts of Interest: The authors declare no conflict of interest.

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