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Research on Reference Crop Evapotranspiration Forecast Based on FOA-GRNN

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Abstract

In order to achieve high-precision prediction of reference crop evapotranspiration (ET0) in the absence of meteorological factors, this paper firstly analyzes the sensitivity of each meteorological factor, and then selects the appropriate combination of meteorological factors as input parameters, using FAO-56 Penman-Monteith The ET0 calculated by the formula is used as the prediction standard value, and an ET0 prediction model based on the fruit fly optimization algorithm (FOA) optimized generalized regression neural network (GRNN) is established. The research results show that: (1) In Yibin City, Sichuan Province, the sensitivity of meteorological factors to reference crop evapotranspiration is: RHmean >Ra> Tmax> Tmean >n> Tmin> u2; (2) FOA-GRNN model simulation accuracy Relatively high level. Among them, the R2 and NSE of the FOA-GRNNA, FOA-GRNNB and FOA-GRNNH models are all greater than 0.97, and the RMSE and MAE are also less than 0.29mm/d and 0.21mm/d, respectively, and their overall evaluation index rankings are 1, 2, 3; (3) The simulation accuracy of FOA-GRNN model is higher than that of Irmark-Allen model, Hargreaves-Samani model and Iramk model under the same input condition. Therefore, in the absence of meteorological factors, the FOA-GRNN model can be used as a recommended model for ET0 calculation in Sichuan Province, providing a scientific basis for intelligent agricultural precision irrigation forecasts.

Keywords

Reference Crop Evapotranspiration; Prediction; Drosophila Optimization Algorithm; Neural Network.

1. Introduction

Reference crop evapotranspiration (Reference crop evapotranspiration, ET0) is an internationally accepted theoretical basis for evaluating hydrological resources and calculating crop water requirements, and it is also an important indicator of intelligent irrigation and irrigation water use efficiency for smart agriculture [1]. At present, many scholars have conducted research on the simplified calculation of ET0. Lou Zhongqiu et al. [2] compared the calculation accuracy of 6 simplified algorithm models in Dujiangyan Irrigation District. Ladlani et al. [3] used GRNN and radial basis function neural network (radial basis function neural network, RBFNN) to model and compare the daily ET0 in northern Algeria, and the results showed that the GRNN model was significantly better than the RBFNN model. Existing studies mostly use empirical methods for the selection of input meteorological factors without analysis; for the application of neural network prediction models, people have introduced bionic optimization algorithms such as ant colony algorithm and particle swarm algorithm, but these algorithms cannot always converge to Globally optimal, and the number of iterations is large, the convergence speed is slow [4].

In response to the above problems, many researchers have used the good global optimization ability of the fruit fly optimization algorithm (FOA) and the excellent processing ability of GRNN for nonlinear problems to establish a generalized regression nerve for the optimization of the fruit fly

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optimization algorithm. The network prediction model (FOA-GRNN) improves the prediction accuracy of the GRNN model, and is used for tunnel surrounding rock deformation prediction, bullet mark depth prediction, converter steelmaking end point prediction, automatic welding obstacle prediction, power load prediction, etc. This article first analyzes the sensitivity of various meteorological factors (daily average temperature (Tmean), daily maximum temperature (Tmax), daily minimum temperature (Tmin), average relative humidity (RHmean), sunshine hours (n) and 2m high wind speed (u2)), and then selects different combinations of meteorological factors as Model input, establish ET0 prediction model based on FOA-GRNN.

2. Meteorological factor sensitivity of ET0

The sensitivity coefficient of ET0 is a quantitative parameter that characterizes the degree of influence of the change of one or several related meteorological factors on the change of ET0. It is defined as the ratio of the rate of change of ET0 to the rate of change of meteorological factors [5]. The calculation formula is as follows:

$$S_{V_i} = \lim_{V_i \to 0}\left(\frac{\Delta ET_0 / ET_0}{\Delta V_i / V_i}\right) = \frac{\partial ET_0}{\partial V_i} \cdot \frac{V_i}{ET_0}$$

In the formula: SV_i is the sensitivity coefficient; ET0 and ΔET0 are the reference crop evapotranspiration and its variation respectively; V_i and ΔV_i are the meteorological factors and its variation respectively. SV_i is a positive value, indicating that ET0 has the same change as the meteorological factor, and vice versa, the change trend is opposite; the greater the absolute value of SV_i, the greater the impact on ET0.

The 6 meteorological factors, Tmean, Tmax, Tmin, Ra, RHmean, n, and u2, were selected to calculate their sensitivity to ET0 in Yibin City, Sichuan Province. The calculation results show that the sensitivity coefficient of RHmean is negative, and the average value of the city is -1.522. The sensitivity coefficients of the other 6 meteorological factors are all positive values, and the absolute value of the sensitivity coefficient of RHmean is the largest, which is the same as that of Chen Dongdong [6] The conclusion that the average relative humidity of Sichuan is most sensitive to ET0 is consistent with the conclusion that the sensitivity coefficient of u2 is the smallest (Table 1).

Table 1. Sensitivity coefficients of various meteorological factors in Yibin City

Yibin annual average	S_{Ra}	S_{Tmean}	S_{Tmax}	S_{Tmin}	S_{RHmean}	S_{u2}	S_n
Sensitivity factor	0.864	0.196	0.203	0.085	-1.522	0.024	0.144

The analysis shows that RHmean is the main meteorological factor that causes the change of ET0 in Yibin City, Sichuan Province. A 10% change in RHmean may cause a change of up to 15.22% in ET0; the sensitivity of meteorological factors to ET0 is: RHmean >Ra> Tmax> Tmean >n> Tmin> u2. Existing model temperature factors often use the combination of Tmax and Tmin. The sensitivity analysis of Yibin City, Sichuan Province shows that Tmean is more sensitive to ET0 than Tmin, so Tmin is discarded and Tmean is selected, and RHmean, Tmax, Tmean, n, and u2 are used as Input to the model.

3. Principle

3.1 Reference crop evapotranspiration calculation model

The Penman-Monteith combination method recommended by the International Food and Agriculture Organization's reviewing experts is a standard method for determining the reference crop evapotranspiration. It is defined as "a hypothetical reference crop with an assumed height of 0.12m, a fixed surface resistance of 70s/m, and reflectivity 0.23", it is established based on the principles of aerodynamics and energy balance, fully considering the influence factor of calculating ET0, and is

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applicable to different climates. Therefore, the ET0 calculated by the P-M model [7] is used as the standard value to verify the feasibility of the model. The calculation formula is:

$$ET_0=\frac{0.408\Delta(R_n-G)+\gamma\frac{900}{T+273}u_2(e_s-e_a)}{\Delta+\gamma(1+0.34u_2)}$$

In the formula: ET0 is the reference crop evapotranspiration (mm/day), Rn is the net radiation on the surface of the crop (MJ/(m2•day)), and G is the soil heat flux (this text is taken as 0) (MJ/(m2) •Day)), u2 is the wind speed (m/s) at a height of 2m, es is the saturated vapor pressure (kPa), ea is the actual vapor pressure (kPa), es-ea is the saturated vapor pressure difference (kPa), and Δ is Saturated water vapor pressure curve slope (kPa/℃), gamma hygrometer constant (kPa/℃), T is the average temperature (℃) in the calculation period, u2 is 2m high wind speed (m/s), the same below.

In order to test the prediction accuracy of the FOA-GRNN model, the Irmark-Allen, Hargreaves-Samani and Iramk calculation models are selected to compare with the FOA-GRNN model. The specific models and calculation formulas are shown in Table 2.

Table 2. The specific models and calculation formulas

model	Calculation formula	Enter meteorological factors
Irmark-Allen[8] (I-A)	ET_0=0.480+0.289R_n + 0.023T_{mean}	T_{mean}, T_{max}, n
Hargreaves-Samani[9](H-S)	$ET_0 = 0.00133R_a(T_{mean}+17.8)(T_{max}-T_{mean})^{0.5}$	T_{mean}, T_{max}
Iramk [10]	ET_0=-0.611+0.149R_s+0.079T_{mean}	T_{mean}, n

3.2 FOA-GRNN calculation principle

GRNN consists of four layers, which are input layer, mode layer, summation layer and output layer. GRNN has strong nonlinear mapping ability and high robustness, and is suitable for solving nonlinear problems, and when the data sample is small, the prediction effect is also better. For details of its theoretical basis, see reference [11]. The GRNN function is called in Matlab, and the calling format is:

Net=newgrnn(P,T,SPREAD)

Among them, P is the R*Q-dimensional matrix composed of Q groups of input vectors; S*Q-dimensional matrix composed of T-dimensional Q groups of target classification vectors; SPEEAD is the expansion speed of the radial basis function, and the default value is 1.

The Fruit Fly Optimization Algorithm (FOA) is a new method of seeking global optimization based on the foraging behavior of fruit flies. Drosophila itself is superior to other species in sensory perception, especially in terms of smell and vision. Drosophila's olfactory function collects various odors floating in the air very well, and can even smell food sources 40 kilometers away. After the food is close to the position, you can also use keen vision to find the location where the food and the companions gather, and fly in that direction [12]. The calculation steps are as follows:

(1) Random initial flies population position Init X_axis, Init Y_axis.

(2) Give the fruit fly individual a random direction and distance to search for food by smell, and get the coordinate (Xi, Yi) of the fruit fly after it has moved.

$$\begin{cases}X_i=X_{\_axis}+RandomValue\\Y_i=Y_{\_axis}+RandomValue\end{cases}$$

(3) Since the food location cannot be known, first calculate the distance (Dist) between (Xi, Yi) and the origin, and then calculate the taste density judgment value (S), which is the reciprocal of the distance.

$$Dist_i=\sqrt{{X_i}^2+{Y_i}^2};\ S_i=1/D_i$$

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(4) The taste concentration determination value (Si) is substituted into the taste concentration determination function to obtain the taste concentration (Smelli) of the individual position of the fruit fly. This paper uses the root mean square error RMSE in the model as the taste concentration determination function, namely:

$$Smell_i = Function(S_i)$$

(5) Find the fruit flies with the lowest taste concentration in this fruit flies group (such as finding the minimum value).

(6) Keep the best taste concentration and X and Y coordinates. At this time, the fruit fly colony uses vision to fly to this position.

(7) Enter iterative optimization, repeat steps (2)-(5), and judge whether the taste concentration is better than the previous iteration taste concentration, if it is, perform step (6).

Using FOA to optimize the GRNN smoothing factor can greatly reduce the time for GRNN to find the smoothing factor and improve the accuracy of the model.

4. Results and analysis

4.1 Model performance testing indicators

The root mean square error (RMSE), coefficient of determination (R2), Nash coefficient (NSE) and overall evaluation index (GPI) [13] are selected to evaluate the applicability of the model. RMSE is used to measure the deviation between the predicted value and the standard value; NSE is an evaluation parameter used to evaluate the quality of the model; R2 is the joint influence degree of all the explanatory variables included in the model on the dependent variable. The smaller the RMSE, the smaller the model deviation; the closer the R2 is to 1, the higher the fit of the model simulation; the closer the NSE is to 1, the better the model quality and the higher the credibility. The higher the GPI, the better the overall simulation effect of the model (this article is presented in a ranking way). The calculation formula is:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{y}_{\_\mathrm{predict(i)}} - \mathrm{y}_{\_\mathrm{P-M(i)}})^2}$$

$$R^2 = \frac{[\sum_{i=1}^{N}(y_{\_predict(i)} - \bar{y}_{\_predict})(y_{\_P-M(i)} - \bar{y}_{\_P-M})]^2}{\sum_{i=1}^{N}(y_{\_predict(i)} - \bar{y}_{\_predict})^2 \sum_{i=1}^{N}(y_{\_P-M(i)} - \bar{y}_{\_P-M})^2}$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(y_{\_predict(i)} - y_{\_P-M(i)})^2}{\sum_{i=1}^{N}(y_{\_P-M(i)} - \bar{y}_{\_P-M})^2}$$

$$GPI = \sum_{i=1}^{4}\alpha_i(\mathrm{T_i} - \bar{\mathrm{T}}_i)$$

Where is the predicted value of the i-th day simulated by the model; is the standard value of the i-th day calculated by the PM model;, is the average value; N is the number of samples in the test set; is the normalized value of RMSE, MAE, R2, and NSE Value; is the median of the corresponding parameter. Ai is -1 when Ti is RMSE, and αi is 1 when other parameters are used.

4.2 Simulation of FOA-GRNN model under different meteorological factors input

Based on sensitivity analysis, five meteorological factors, Tmean, Tmax, RHmean, n, and u2, are selected as model inputs, and different meteorological factors are randomly combined to form different input situations, and the corresponding FOA-GRNN model is established. Taking the daily meteorological data of Yibin City, Sichuan Province from 2014 to 2018 and the ET0 calculated by PM as the training set, the 2019 meteorological data and the ET0 calculated by PM as the validation set, the initial parameters of the FOA-GRNN model are set as: fruit fly population size It is 40, the maximum number of iterations is 200, the initial position of the fruit fly is [0, 10], and the flight direction and radius of the fruit fly are set to [0, 1].

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Table 3. FOA-GRNN model ET0 simulation accuracy under different meteorological factors input

Number	FOA-GRNN model	Enter meteorological factors	RMSE/(mm/d)	R^2	NSE	GPI
6	FOA-GRNNA	R_a, T_{mean}, T_{max}, RH_{mean}, n, u_2	0.1728	0.9908**	0.9898	1
5	FOA-GRNNB	R_a, T_{mean}, T_{max}, RH_{mean}, n	0.2623	0.9847**	0.9764	2
	FOA-GRNNC	R_a, T_{mean}, T_{max}, RH_{mean}, u_2	0.5168	0.9174**	0.9083	10
	FOA-GRNND	R_a, T_{mean}, T_{max}, n, u_2	0.3438	0.9635**	0.9595	5
4	FOA-GRNNE	R_a, T_{mean}, T_{max}, RH_{mean}	0.6224	0.9186**	0.8670	11
	FOA-GRNNF	R_a, T_{mean}, T_{max}, n	0.3558	0.9619**	0.9565	6
	FOA-GRNNG	R_a, T_{mean}, T_{max}, u_2	0.8665	0.7504**	0.7423	15
	FOA-GRNNH	R_a, RH_{mean}, n, u_2	0.2928	0.9723**	0.9706	3
3	FOA-GRNNI	R_a, T_{mean}, T_{max}	0.7909	0.7970**	0.7853	14
	FOA-GRNNJ	R_a, RH_{mean}, n	0.3560	0.9640**	0.9565	4
	FOA-GRNNK	R_a, RH_{mean}, u_2	0.7296	0.8290**	0.8173	13
	FOA-GRNNL	R_a, n, u_2	0.4186	0.9447**	0.9399	9
	FOA-GRNNM	T_{mean}, T_{max}, n	0.3936	0.9520**	0.9468	7
2	FOA-GRNNN	T_{mean}, T_{max}	0.6982	0.9438**	0.8327	12
	FOA-GRNNO	T_{mean}, n	0.4087	0.9475**	0.9427	8

Note: ** means extremely significant correlation at the level of 0.01, the same below.

When 6 meteorological factors are input, the RMSE of FOA-GRNNA is 0.1728mm/d, R2 and NSE are both greater than 0.98, and GPI ranks first. It shows that FOA-GRNNA can accurately predict ET0 through meteorological factors, and the model has good reliability.

When inputting 5 meteorological factors, the simulation accuracy of FOA-GRNNB (lack of u2) and FOA-GRNND (lack of RHmean) is higher than FOA-GRNNC (lack of n), and the GPI rankings are 2, 5, and 10 respectively. Comparing FOA-GRNNC and FOA-GRNNA, it is found that when n is present, the RMSE of the model decreases by 66.6%, the NSE increases by 8.97%, and the GPI increases from 9 to 1, indicating that n has a greater influence on the calculation of ET0 in Yibin City, Sichuan Province.

When 4 meteorological factors are input, the GPI of FOA-GRNNH (lack of Tmean, Tmax and u2) ranks third, and its simulation accuracy is generally better than the other 3 models. Comparing FOA-GRNNH and FOA-GRNNA, it is found that when Tmean and Tmax are present, RMSE is reduced by 41%, but NSE is only increased by 1.9%, and the model optimization effect is not obvious. Therefore, when there are only meteorological factors such as Ra, RHmean, n and u2, FOA-GRNNH can be used as the recommended model for ET0 simulation in Sichuan Province.

When three meteorological factors are input, the GPI of FOA-GRNNJ (lack of Tmean, Tmax and u2) ranks fourth, and its simulation accuracy is significantly higher than the other four models. Comparing FOA-GRNNJ with FOA-GRNNC, FOA-GRNNE (lack of n and u2), and FOA-GRNNG (lack of RHmean and n) respectively, it is found that the number of meteorological factors input by FOA-GRNNJ is less, and the simulation accuracy is obviously improved. . FOA-GRNNJ reduces the input of Tmean, Tmax and u2, the RMSE is still less than 0.36mm/d, and the NSE remains above 0.95. Therefore, when only the meteorological factors of Ra, RHmean, and n are available, FOA-GRNNJ can be used as the ET0 simulation in Sichuan Province The recommended model also shows that humidity and sunshine hours are the key factors driving ET0 in Sichuan Province.

When two meteorological factors are input, the GPI of FOA-GRNNO (input Tmean and n) ranks 8th, and its simulation accuracy is higher than FOA-GRNNN (input Tmean and Tmax). It shows that FOA-GRNNO has higher simulation accuracy when only two meteorological factors are input.

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4.3 Portability analysis of FOA-GRNN model

Four models, FOA-GRNNA, FOA-GRNNB, FOA-GRNNH and FOA-GRNNJ, simulate ET0 with high accuracy in Yibin City, Sichuan Province. In order to explore the portability of the FOA-GRNN model, choose Yibin City, Sichuan Province as the training site P, and other typical sites in Sichuan Province as the test site T, forming 6 sets of test set and training set samples to construct FOA-GRNNA and FOA-GRNNB , FOA-GRNNH and FOA-GRNNJ 4 models, the simulation results are shown in Table 4.

Table 4. Results of FOA-GRNN portability between different sites in Sichuan Province

model	Site P	Site T	RMSE/(mm/d)	R^2	NSE
FOA-GRNNA	Yibin	Aba	0.2228	0.9641^{**}	0.9566
		Liangshan	0.3143	0.9550^{**}	0.9535
		Luzhou	0.1802	0.9894^{**}	0.9892
		Leshan	0.1461	0.9921^{**}	0.9903
		Dazhou	0.1558	0.9909^{**}	0.9905
		Guangyuan	0.1929	0.9840^{**}	0.9836
FOA-GRNNB	Yibin	Aba	0.2593	0.9472^{**}	0.9412
		Liangshan	0.3431	0.9458^{**}	0.9447
		Luzhou	0.2133	0.9855^{**}	0.9849
		Leshan	0.1860	0.9862^{**}	0.9843
		Dazhou	0.1928	0.9870^{**}	0.9854
		Guangyuan	0.2299	0.9771^{**}	0.9768
FOA-GRNNH	Yibin	Aba	0.5126	0.8013^{**}	0.7701
		Liangshan	0.4477	0.9061^{**}	0.9058
		Luzhou	0.3012	0.9766^{**}	0.9699
		Leshan	0.2376	0.9744^{**}	0.9743
		Dazhou	0.2855	0.9702^{**}	0.9680
		Guangyuan	0.3804	0.9368^{**}	0.9364
FOA-GRNNJ	Yibin	Aba	0.5978	0.7509^{**}	0.6873
		Liangshan	0.4930	0.8883^{**}	0.8857
		Luzhou	0.3070	0.9693^{**}	0.9688
		Leshan	0.3131	0.9570^{**}	0.9554
		Dazhou	0.3334	0.9571^{**}	0.9563
		Guangyuan	0.4212	0.9246^{**}	0.9220

It can be seen from Table 4 that the 4 models have strong portability between different sites. The portability analysis shows that: except for the FOA-GRNNH and FOA-GRNNJ models, the simulation accuracy of the Yibin and Aba sites is relatively low. The accuracy is very high, R2 and NSE are both above 0.88, and R2 reaches a very significant level ($P<0.01$), and the RMSE is below 0.5mm/d. This study shows that in Sichuan Province, the FOA-GRNNA, FOA-GRNNB, FOA-GRNNH and FOA-GRNNJ models are used at various sites to simulate and predict with high accuracy and strong applicability.

Table 5. Accuracy comparison between FOA-GRNN model and other models with the same meteorological factor input

Enter meteorological factors	Calculation model	RMSE/ (mm/d)	R^2	NSE	GPI
T_{mean}, T_{max}, n	FOA-GRNNM	0.3936	0.9520^{**}	0.9468	1
	Irmark-Allen (I-A)	0.9059	0.9472^{**}	0.7183	6
T_{mean}, T_{max}	FOA-GRNNN	0.6982	0.9438^{**}	0.8327	3
	Hargreaves-Samani (H-S)	0.8451	0.7932^{**}	0.7549	5
T_{mean}, n	FOA-GRNNO	0.4087	0.9475^{**}	0.9427	2
	Iramk	0.6164	0.9106^{**}	0.8696	4

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4.4 Comparison of simulation accuracy between FOA-GRNN model and other models

When Tmean, Tmax, n are input items, compare FOA-GRNNM and Irmark-Allen (IA) models; when Tmean, Tmax are input items, compare FOA-GRNNN and Hargreaves-Samani (HS) models; When Tmean and n are used as input items, compare the FOA-GRNNO and Iramk models. The specific results are shown in Table 5. Then plot the simulation errors of these 6 models (Figure 1).

It can be seen from Table 5 that under the same meteorological factor input, the simulation accuracy of the FOA-GRNN model is always higher than the corresponding other empirical models. When Tmean, Tmax and n meteorological factors are input, the RMSE of the FOA-GRNNM model is 56.6% lower than that of the Irmark-Allen (IA) model, and the NSE is 24.03% higher than the IA model, and the GPI ranking is also higher than that of the IA model, indicating that FOA-GRNNM The simulation accuracy is higher than the IA model. When Tmean and Tmax meteorological factors are input, the RMSE of the FOA-GRNNN model is 39% lower than that of the Hargreaves-Samani (HS) model, R2 and NSE are 19% and 10% higher than the HS model, respectively, GPI rankings are 3 and 5, respectively, FOA -The simulation accuracy of GRNNN is generally higher than that of HS model. When only Tmean and n are input, the RMSE of the FOA-GRNNO model is 33.7% lower than that of the Iramk model, R2 and NSE are 4.1% and 8.4% higher than the Iramk model respectively, and the GPI ranking is also higher than that of the Iramk model, indicating that FOA-GRNNO has high simulation accuracy Based on the Iramk model.

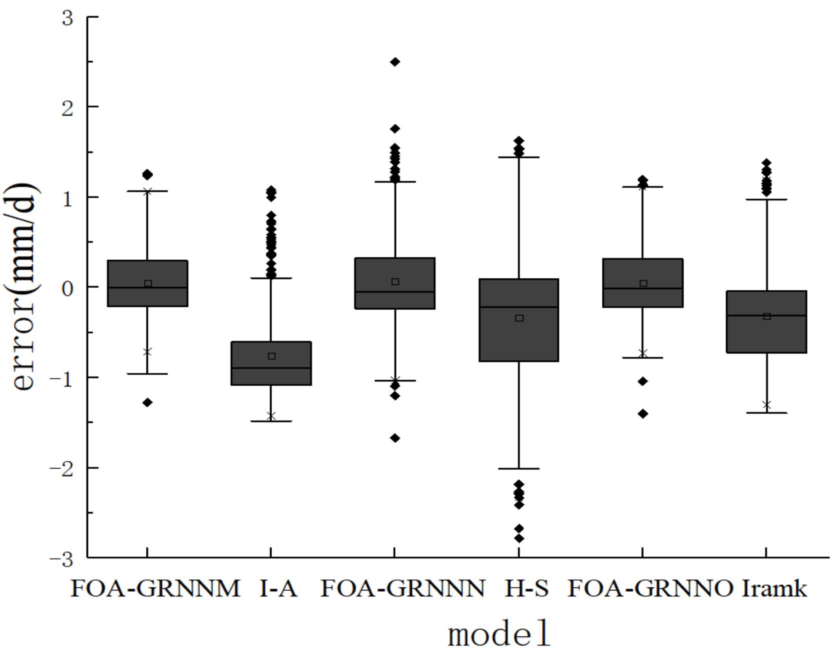

Figure 1. Comparison of simulation errors between FOA-GRNN model and other empirical models

It can be seen from Figure 1 that the error in the figure is the ET0 standard value calculated by the PM model minus the ET0 value predicted by each model. The error of FOA-GRNNM is the smallest, most of which are between -1 and 1mm/d, FOA-GRNNN and FOA The error of GRNN3 is also small, most of the errors are between -1~1.5mm/d. Other models have relatively large errors. Among them, the IA model errors are almost all below 0mm/d, indicating that the IA model predicts ET0 values in Sichuan Province are generally too large, and there are more outliers than FOA-GRNN1; the HS model has the largest simulation error, most of which are -2~2mm/d, indicating that the HS model estimates that ET0 has a larger error compared to FOA-GRNNN in Sichuan Province; the simulation error of the Iramk model is not significantly different from the simulation error of FOA-GRNNO.

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5. Conclusion

A reference crop evapotranspiration prediction model based on the Drosophila optimization algorithm optimized generalized regression neural network (FOA-GRNN) was established, and the model was applied to the prediction research of ET0 in Yibin City, Sichuan Province. The results show that the FOA-GRNN ET0 prediction model can still obtain high simulation accuracy and strong portability in the absence of meteorological factors. In the absence of meteorological factors, the simulation accuracy of the FOA-GRNN model is always higher than that in the absence of meteorological factors. Other models under the same meteorological factor input.

(1) After analyzing the sensitivity of meteorological factors to ET0 in Yibin City, Sichuan Province, the sensitivity is as follows: average relative humidity RHmean>atmospheric top layer radiation Ra> Tmax> Tmean> n> Tmin> u2.

(2) Comparing and analyzing the FOA-GRNN model with Irmark-Allen, Hargreaves-Samani and Iramk models with higher simulation accuracy in Sichuan Province, it can be found that when the same meteorological factors are input, the simulation accuracy of the FOA-GRNN model is always Higher than other models. It shows that in the absence of meteorological factors, the FOA-GRNN model has high simulation accuracy, and can be used as a recommended model for ET0 prediction in Sichuan Province in the absence of meteorological factors.

(3) The portability analysis of the FOA-GRNN model shows that, except for the Yibin site to Aba site, the simulation accuracy of Yibin's other representative sites in Sichuan Province are all very high, R2 and NSE are both above 0.88, and R2 reaches a very significant level (P <0.01), RMSE is below 0.5mm/d. Therefore, the FOA-GRNN model has a strong generalization ability in areas with similar climate characteristics, and the FOA-GRNN model can be established for ET0 prediction using the data of nearby stations in the area when the station data is missing.

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