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Application of meta-heuristic algorithms to estimate daily evaporation rate

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Accurate estimation of daily evaporation is fundamental in the sustainable management of water resources. Therefore, the purpose of this study was to investigate the application of the artificial neural network model with wavelet and firefly meta-heuristic algorithms of to estimate daily ET0. To achieve this goal, two combined W-ANN and FA-ANN models were investigated for daily estimation of ET0 in two Mediterranean climates in the west of Iran as a case study. Daily climatic parameters including maximum and minimum temperature (T max and T min), sunshine duration (n), relative humidity (RH), wind speed (U), and evaporation ET0 were collected from two weather stations from 2012-2022 and during four combined scenarios, which were used from 2012 to 2019 for model training and from 2022 to 2019 for model testing. To compare and evaluate the models, statistical indicators of the correlation coefficient, root mean square error, mean absolute value of error, normalized root mean square error, and Nash Sutcliffe coefficient were used. The results showed that all the investigated models performed better in combined input scenarios. The results of the evaluation criteria showed that the W-ANN hybrid model has the highest daily estimation accuracy.

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Introduction

Population growth and the increasing demand for freshwater have created significant challenges in achieving sustainable water resources. In response, experts have focused on two primary strategies: water production and the optimal utilization of existing water resources. Effective planning, optimization, and simulation of water resource systems at the basin level require accurate identification and estimation of key parameters, including evapotranspiration (ET). Evaporation is a critical component of the hydrological cycle and is essential for calculating plant water requirements, managing water resources, assessing agricultural systems, and determining the water balance (Allen et al., 1998).

Meteorological variables such as air temperature, relative humidity, solar radiation, and wind speed significantly influence ET (Kim et al., 2012). Numerous empirical equations have been developed to estimate ET based on these climatic factors. Among them, the FAO-56 Penman-Monteith equation is widely recognized as a reference method across different regions and climates (Wang et al., 2016). However, given that evaporation is a complex and nonlinear process, models capable of capturing nonlinear hydrological relationships are crucial. Recent research has demonstrated that artificial intelligence (AI) and soft computing techniques provide accurate modeling of such complex phenomena (Liu & Sun, 2016).

For instance, Karthika et al. (2016) predicted the average daily temperature in the Shimoga Basin, India, using inputs such as wind speed, relative humidity, sunshine duration, and precipitation through a fuzzy model and a wavelet neural network (WNN). Their findings indicated that the WNN outperformed the fuzzy model in temperature prediction. Similarly, Seifi and Soroush (2020) evaluated the performance of metaheuristic algorithms—Gray Wolf, Genetic Algorithm, and Whale Optimization Algorithm—combined with an artificial neural network (ANN) to estimate evaporation in five distinct Iranian climates. The results demonstrated that the ANN–Genetic Algorithm hybrid model yielded the highest performance across all five climates.

In another study, Sahi et al. (2021) applied an ANN to estimate daily evaporation in Damghan City using meteorological data—including daily minimum and maximum temperature, average relative humidity, wind speed, sunshine hours, and evaporation—collected over 16 years (2002–2018). The ANN model demonstrated high accuracy and low error in evaporation estimation. Dehghani and Dehghani (2022) utilized WNN and ANN models to estimate air temperature in northern Iran, using inputs such as relative humidity, maximum and minimum temperature, wind speed, and evaporation at a daily time scale for the years 1382–1392 (2003–2013). Their results confirmed the superior accuracy of the WNN in most cases.

Alempour Rajabi et al. (2024) developed a hybrid ANN–COOT model to predict monthly evaporation rates at three stations in Shiraz, Kish, and Gorgan. Using monthly data from 2002 to 2022—including minimum and maximum temperature, sunshine hours, wind speed, and relative humidity—they found that the hybrid model performed better than the standalone ANN model. In a similar study, Bidabadi et al. (2024) predicted monthly evaporation at the Sirjan station in Kerman province using hybrid models including ANN, adaptive neuro-fuzzy inference system (ANFIS), and ANN–Gray Wolf Optimization (ANN–GWO). Input parameters included minimum and maximum temperature, ET_0, and wind speed from adjacent stations during 2002–2022. The results indicated that the ANN–GWO model yielded the highest accuracy among all evaluated models.

Based on these studies, the use of metaheuristic algorithms in conjunction with ANN models has become increasingly prevalent in recent years to enhance accuracy. In the present study, a hybrid ANN approach is employed to reduce model error and improve estimation accuracy. The data were obtained from the Khorramabad hydrometric station in Lorestan province, Iran—one of the country's most important agricultural regions. The province's strategic geographical position also influences tourism and regional development planning, making it a relevant case study.

Despite the widespread use of ANN for evaporation estimation, no study has yet explored or compared metaheuristic algorithms—such as Wavelet and Firefly Algorithm (FA)—within a Mediterranean climate context. Therefore, this study employs optimization models in combination with ANN to estimate evaporation in the Mediterranean climate of Khorramabad, Iran. Furthermore, there is currently no specific formula or relationship for estimating evaporation using ANN. To enhance the ANN model's performance, two nature-inspired metaheuristic algorithms—Wavelet and FA—are applied for optimization.

Objectives of the Study

The main objectives of this research are:

1. To accurately estimate daily evaporation rates in a Mediterranean climate using a hybrid model based on ANN combined with Wavelet and Firefly algorithms.
2. To evaluate the effectiveness of various input structures on model performance.
3. To provide a methodological framework for evaporation prediction using AI and optimization in data-scarce Mediterranean regions.

Materials and methods

Study area

Khorramabad Plain is located in the center of Lorestan Province of Iran, with a Mediterranean climate between latitudes 33 degrees and 13 minutes to 33 degrees and 35 degrees north and longitudes from 47 degrees and 52 minutes to 48 degrees and 46 minutes east. The maximum height of the area is 1903 meters and the minimum is 929 meters, with an area of 2517 square kilometers. The average annual precipitation of the study area is 509 mm and its average temperature is 17.2 degrees Celsius. In Figure 1, the geographical location of the meteorological station can be seen. We used relative humidity (RH), maximum temperature (T.max), minimum temperature (T.min), wind speed (WV) and sunshine hours (SSH) as input and evaporation (ET) as output parameters of the model in the form of daily data for the period 2012-2022.

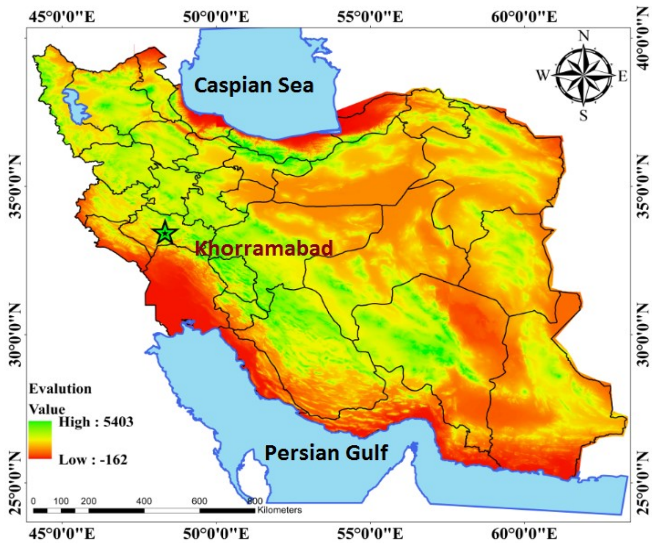

Figure 1. The study area

Artificial neural network

Artificial neural networks (ANNs) have numerous applications in geohydrology and hydrological processes (Nourani et al., 2011). A typical ANN consists of three main layers: the input layer, the hidden (intermediate) layer, and the output layer. The input layer is responsible for receiving and preprocessing data; the hidden layer contains neurons with activation functions that process the data; and the output layer produces the final results of the network. Among the various types of ANNs, the multilayer perceptron (MLP) is one of the most widely used. In MLP networks, activation functions such as the sigmoid, hyperbolic tangent, and linear hyperbolic tangent are commonly applied. When combined with the backpropagation learning algorithm and a feedforward network structure, MLPs demonstrate strong performance in solving complex problems related to hydrogeology and hydrological simulations (Nourani et al., 2009).

Wavelet transform

The wavelet transform is introduced as an alternative to the short-time Fourier transform (STFT), primarily to address the limitations related to frequency resolution in STFT. Similar to STFT, the wavelet transform divides the target signal into segments or windows, and the transformation is applied to each segment individually (Wang et al., 2000). However, the key distinction lies in how frequency and time resolution are managed. In wavelet transform, unlike STFT where the window size remains fixed, the window size—or scale—varies depending on the frequency content of the signal. This means that high-frequency components are analyzed with narrower windows, providing better time resolution, while low-frequency components are analyzed with wider windows, offering better frequency resolution.

In essence, the wavelet transform is a time–scale transform rather than a time–frequency transform. At high scales, the signal is expanded to analyze detailed features, while at low scales, it is compressed to capture the overall structure. A wavelet itself is a small wave—a localized portion of the original signal whose energy is concentrated in time. Through wavelet transformation, a signal (or mother time series) can be decomposed into wavelet components at various scales and resolution levels. These wavelets are scaled and shifted versions of the mother wavelet, exhibiting finite length and significant attenuation, which makes them suitable for analyzing transient, non-stationary, and localized signal features (Nourani et al., 2018).

Firefly Algorithm

Metaheuristic algorithms are considered effective methods for solving complex problems, as they do not require the calculation of the gradient of the objective function and do not assume specific conditions such as linearity or continuity. Typically, they provide satisfactory solutions. The Firefly Algorithm is one of the metaheuristic algorithms based on a collective and group approach, using the bioluminescence behavior of fireflies to solve optimization problems (Yang, 2009).

In the Firefly Algorithm, each solution to a problem is represented as a firefly, and the fireflies can emit light and attract other fireflies based on their fitness levels. This algorithm is a population-based and stochastic optimization method first introduced to the scientific community by Yang (Yang and He, 2013). It operates based on the mating behavior of fireflies. The three fundamental assumptions of this algorithm are as follows:

1. No specific gender is assigned to fireflies.
2. Each firefly is attracted to other fireflies according to the intensity of their light.
3. In maximization problems, the intensity of light has a direct relationship with the objective function, while in minimization problems, the intensity of light has an inverse relationship.

The attractiveness of fireflies is relative and depends on the distance between two fireflies and the light absorption coefficient, which can be calculated using the following equation:

$\beta(r) = \beta_0 e^{-\gamma r_{ij}^2}$ (1)

where β is the attractiveness at r=0, where r is the distance between the dimmer firefly and the brighter firefly. The position of firefly i after moving towards the brighter firefly j is calculated using the following formula:

$$X_{id}(t+1) = X_{id}(t) + \beta_0 e^{-\gamma r_{ij}^2}\left(X_{jd}(t) - X_{id}(t)\right) + \alpha\left(rand - \frac{1}{2}\right) \quad (2)$$

$$\boldsymbol{r_{ij}} = \left\|\boldsymbol{X_i} - \boldsymbol{X_j}\right\| \quad (3)$$

where Rand is a random number between 0 and 1, and α is a randomization parameter between 0 and 1. The flowchart of this algorithm is illustrated below.

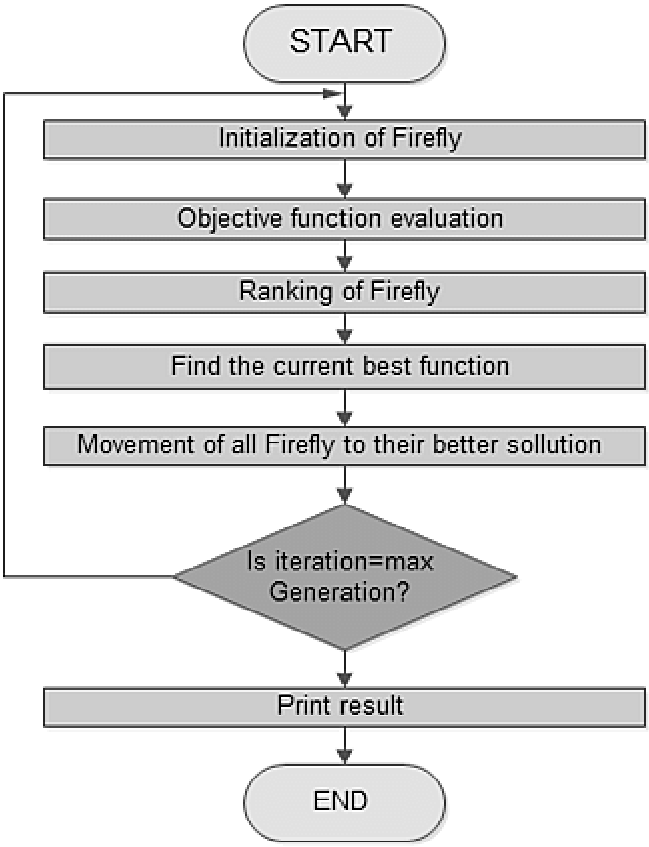

Figure 2. Flowchart of firefly algorithm

Evaluation Criteria

In this research, the accuracy and capability of the models in simulating daily evaporation rates were evaluated based on observed and calculated values using the correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE), and Nash-Sutcliffe (NS) indices according to the following relations. The best values for these four criteria are, respectively, one, zero, zero, and one. In the above relations, CC is the correlation coefficient, RMSE is the root mean square error in mm, NS is the Nash-Sutcliffe criterion, x_i, and y_i are the observed and calculated values at the i-th time step, N is the number of time steps, and $\bar{x}$ and $\bar{y}$ represent the mean of the observational and computational values, respectively. In addition to the above criteria, scatter plots and time series graphs of the observational and computational values over time will also be utilized for further comparison and analysis.

$$R = \frac{\sum_{i=1}^{N}(x_i-\bar{x})\,(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2\,\sum_{i=1}^{N}\,(y_i-\bar{y})^2}} \quad 1 \leq R \leq 1 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\,(x_i - y_i)^2} \quad (5)$$

$$MAE = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n} \quad (6)$$

$$NRMSE = \frac{RMSE \times 100}{\bar{X}} \quad (7)$$

$$NS = 1 - \frac{\sum_{i=1}^{N} (x_i - y_i)^2}{\sum_{i=1}^{N} (x_i - \bar{y})^2} \quad \infty \leq NS \leq 1 \quad (8)$$

Results and discussion

In this research, an ANN model with wavelet and firefly algorithms was used in order to model the daily evaporation rate of Khorramabad with a Mediterranean climate. Relative humidity parameter (RH), maximum temperature (T.max), minimum temperature (T.min), wind speed (WV), and sunshine hours (SSH) as input and evaporation rate (ET) as an output parameter of the model in the daily period, 1392-1402 was used for Khorramabad meteorological station. The general purpose of these intelligent models is to express the relationship between variables whose complexity is difficult to find in nature with high uncertainty. Daily evaporation is one of the most important meteorological parameters, whose estimation is of great importance in the future time steps. For this purpose, in order to reduce the error and estimate the evaporation parameter with high accuracy, using the lowest input parameters, the mentioned method was used, which provides much better performance compared to the approximate methods. The purpose of this research is to understand this natural complexity between meteorological parameters and provide a model for future prediction, and since the daily evaporation rate is more important than other parameters, this parameter was chosen as the target variable. Table 1 presents the statistical characteristics of the parameters used. It should be noted that for modeling, 70% of the data for training and the remaining 30% for testing were randomly selected to cover a wide range of data types (Kisi and Karhan, 2006; Nagy et al., 2002; Dehghani et al., 2020).

One of the most important steps in modeling is choosing a suitable combination of input variables. In smart models, choosing appropriate and effective initial inputs in the phenomenon in order to teach the nature of the mechanism governing the phenomenon will improve the performance, therefore, in modeling the daily evaporation rate, we tried to select the most effective observational data as training data (Dehghani and Torabi., 2021). For this purpose, different combinations of input parameters were used in order to achieve the optimal model for estimating evaporation, which is shown in Table 2.

In order to model the daily evaporation rate of Khorramabad, an artificial neural network model with wavelet and firefly algorithms was used. For this purpose, the values of the meteorological parameters of Khorramabad meteorological station, which is located in the western regions of Iran, are normalized and then entered into the ANN model. In recent years, due to the fact that the values of weights and bias are chosen randomly in the ANN model, optimization algorithms have been used to increase the accuracy and reduce the model error (Zayd Alinejad and Dehghani, 2023: Dehghani et al., 2022). In this research, in order to increase the performance of the model, wavelet and firefly algorithms were used to optimize the values of weights and bias. Therefore, in this research, after entering the information of meteorological parameters into the model and optimizing the weights and bias, the structure of the hybrid model is formed and it leads to the computational response of the model, since the stop criterion in training artificial intelligence models is the error rate, so the model has the lowest error rate. stop and output is obtained.

The ANN used in this research was a multi-layer perceptron network with hidden layers with different numbers of neurons. Hyperbolic tangent function is the most common form of stimulus function, which was used in this research to construct the output layer of artificial neural networks. The training of multi-layer perceptron networks was done using the error back propagation training algorithm called the Lunberg-Marquardt algorithm due to faster convergence in network training. The input data is entered into the model according to different scenarios, then the weights and bias values of the ANN model are estimated to the best possible values by meta-heuristic algorithms and entered into the model, and the overall structure of the combined model is formed. The number of necessary repetitions in the learning process of the network is considered to be 1000, and the performance of the network is evaluated with the help of the mean square error criterion. The number of neurons in the input and output layers is determined according to the nature of the problem under investigation, while the number of neurons in the hidden layer is determined by trial and error in order to reduce the amount of error and ultimately lead to the output. Its results were analyzed using an evaluation index and qualitative charts.

As shown in Table 3, the W-ANN (Wavelet–Artificial Neural Network) model yields satisfactory results in simulating daily evaporation rates. After selecting the optimal input combination for each model, evaluation of the predictive models (as presented in Table 3) indicates that, across all hybrid models investigated, the use of a hyperbolic tangent activation function in the hidden layer and a linear activation function in the output layer provides better performance due to faster convergence during optimization.

Specifically, the W-ANN model demonstrates superior performance in the validation stage, achieving the highest correlation coefficient (0.934), the lowest root mean square error (RMSE) of 0.171 mm, the lowest mean absolute error (MAE) of 0.107 mm, a normalized RMSE of 2.676, and the highest Nash–Sutcliffe efficiency coefficient (NSE) of 0.935.

Figure 3 displays the time series plot of observed and predicted evaporation values. As illustrated, the W-ANN model outperforms the FA-ANN (Firefly Algorithm–Artificial Neural Network) model in estimating a wider range of values, including minimum, maximum, and intermediate points, with acceptable accuracy across both test regions. In contrast, while the FA-ANN model performs relatively well in estimating mid-range values, it shows lower accuracy in predicting extreme values.

These results can be explained by the fact that wavelet decomposition separates the time series into high-pass and low-pass components. The high-pass components capture detailed variations in the signal, thereby enhancing the resolution and improving the accuracy of the W-ANN model. As reported in the studies by Alempour Rajabi et al. (2024) and Bidabadi et al. (2024), hybrid ANN models generally exhibit higher accuracy and lower error than their standalone counterparts—a conclusion also supported by the findings of this study.

Table 1. The range of parameters used for training and validation of the data

Khorramabad							
Parameters		Training			Testing		
		Minimum	Mean	Maximum	Minimum	Mean	Maximum
Input	RH(%)	14	23.3	69	5	12.2	69
	T.max(^{0}C)	-31	57.9	125	-47	66.9	124
	T.min(^{0}C)	-66	14.5	85	-56	43.8	84
	WV(km/h)	3	26.7	95	4	14.4	54
	SSH(hr)	0	21.1	120	0	10.6	58
Output	ET(mm)	0	6.39	19.20	0	2.85	9.6

Table 2. Selected combinations of input parameters for the hybrid models

Number	Input	Model	
1	$T_{min}(t),T_{max}(t)$	WANN-1	FA-ANN-1
2	$RH(t),T_{min}(t),T_{max}(t)$	WANN-2	FA-ANN-2
3	$RH(t),T_{min}(t),T_{max}(t),WV(t)$	WANN-3	FA-ANN-3
4	$RH(t),T_{min}(t),T_{max}(t),WV(t),SSH(t)$	WANN-4	FA-ANN-4

Table 3. Evaluation of the performance of the investigated simulation models

Khorramabad										
Model	Training									
	R	RMSE(mm)	MAE(mm)	NRMSE	NS	R	RMSE(mm)	MAE(mm)	NRMSE	NS
WANN-1	0.9	0.273	0.168	4.272	0.895	0.905	0.198	0.136	3.099	0.91
FA-ANN-1	0.885	0.3	0.19	4.695	0.88	0.895	0.217	0.158	3.396	0.895
WANN-2	0.908	0.27	0.158	4.225	0.9	0.918	0.192	0.13	3.005	0.917
FA-ANN-2	0.89	0.293	0.176	4.585	0.885	0.9	0.211	0.152	3.302	0.902
WANN-3	0.92	0.258	0.148	4.038	0.908	0.928	0.182	0.118	2.848	0.925
FA-ANN-3	0.9	0.282	0.167	4.413	0.895	0.911	0.2	0.137	3.130	0.911
WANN-4	0.93	0.247	0.142	3.865	0.918	0.934	0.171	0.107	2.676	0.935
FA-ANN-4	0.917	0.271	0.158	4.241	0.9	0.917	0.194	0.125	3.036	0.92

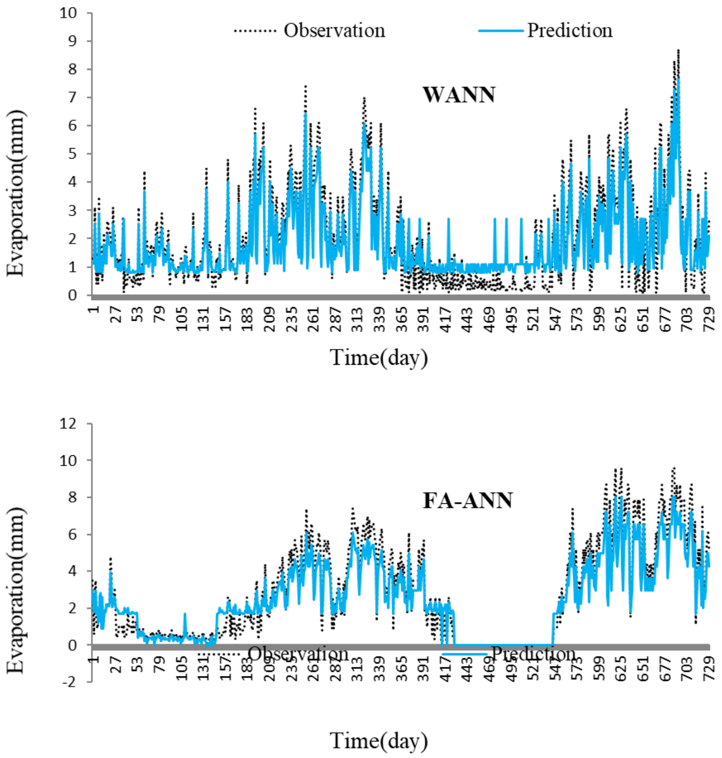

Figure 3. Time series chart of the models in the validation step

Conclusion

Estimation of daily evaporation by new hybrid models based on artificial neural networks can provide an effective tool in designing hydrological systems. In the current research, a case study was conducted to evaluate the performance of the meta-heuristic hybrid artificial neural network model to estimate evaporation in the Mediterranean climate of Khorramabad, located in Iran. For this purpose, algorithms inspired by nature including wavelet and firefly combined with the ANN model were used. In the process, the relative humidity (RH), maximum temperature (T.max), minimum temperature (T.min), wind speed (WV), and sunshine hours (SSH) parameters were used as input and ET as model output for modeling. The research results showed that in all the investigated models, increasing the number of effective parameters in different simulation models leads to better performance in estimating daily evaporation. In addition, it was observed that the W-ANN model has high accuracy and negligible error in the investigated area. Also, the results showed that the ANN hybrid model has a better performance than its single model. In general, the results of this research show that the use of the W-ANN model can be used to estimate the daily evaporation rate during 10 statistical years. The method can be used for other regions of the country with results that may help make appropriate management decisions. Ultimately, the results can improve water resources and land management, and economic investment attempts.

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