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Study on Real-Time Water Demand Prediction of Winter Wheat–Summer Corn Based on Convolutional Neural Network–Informer Combined Modeling

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Abstract: The accurate prediction of crops' water requirements is an important reference for real-time irrigation decisions on farmland. In order to achieve precise control of irrigation and improve irrigation water utilization, a real-time crop water requirement prediction model combining convolutional neural networks (CNNs) and the Informer model is presented in this paper, taking the real-time water demand of winter wheat–summer maize from 2017 to 2021 as the research object. The CNN model was used to extract the depth features of the day-by-day meteorological data of the crops, and the extracted feature values were inputted into the Informer model according to the time series for training and prediction to obtain the predicted water demand of winter wheat and summer maize. The results showed that the prediction accuracy of the constructed CNN–Informer combination model was higher compared to CNN, BP, and LSTM models, with an improvement of 1.2%, 25.1%, and 21.9% for winter wheat and 0.4%, 37.4%, and 20.3% for summer maize; based on the good performance of the model in capturing the long-term dependency relationship, the irrigation analysis using the model prediction data showed a significant water-saving effect compared with the traditional irrigation mode, with an average annual water saving of about 1004.3 m^3/hm^2, or 18.4%, which verified the validity of the model, and it can provide a basis for the prediction of crops' water demand and sustainable agricultural development.

Keywords: CNN–informer combined model; real-time water demand forecasting; long time series; winter wheat; summer corn; sustainable agricultural development

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1. Introduction

With the continuous development of society and the economy, agricultural water resources are increasingly scarce, exacerbated by the frequent incidence of extreme weather events. In this context, the accurate prediction of crops' water demand holds paramount importance in ensuring the sustainable development of agriculture [1,2]. The current winter wheat–summer corn planting mode, a principal grain production approach in Henan Province, still faces challenges in traditional irrigation areas. These challenges include a low utilization of water resources and increasingly prominent conflicts between agricultural water use and other industrial water demands [3]. To alleviate water resource constraints and foster the healthy, sustainable development of agriculture, there is an urgent need to conduct research on predicting crops' water demand. This entails accurately forecasting the water requirements of winter wheat and summer maize across various growth stages [4].

The traditional calculation of crops' water requirements primarily relies on crop evapotranspiration (ET_0) and crop coefficients (Kc). The Penman method uses crop evapotranspiration to predict crops' water requirements. Monteith and others, based on the principles of energy balance and aerodynamics, simplified and modified the Penman formula to derive the FAO Penman–Monteith equation [5]. The incorporation of surface resistance in this equation enhances its calculation accuracy and regional applicability without requiring extensive parameter calibration [6]. Although these semi-empirical and semi-theoretical models can better capture the characteristics of time series data with clear periodicity and gradual changes, they exhibit a high dependency on data correlation and may not effectively capture complex nonlinear relationships. In recent years, driven by the rapid advancements in computer technology and artificial intelligence, researchers both domestically and internationally have begun to explore the application of time series prediction models in the domain of crop water demand forecasting. These models aim to enhance the accuracy of predicting crops' water demand by establishing a relationship between measured values and predicted values. Research in this field can be broadly categorized into three main approaches: traditional machine learning algorithms, deep learning algorithms, and hybrid modeling algorithms. In traditional machine learning algorithms, Jingran Liu et al. proposed a neural network prediction model that integrates radial basis function networks and backpropagation neural networks to forecast crops' water requirements using meteorological data. This approach has been shown to improve the convergence speed and accuracy of the model [7]. Meng Wei et al. introduced an artificial bee colony algorithm as an enhancement to the radial basis neural network. They utilized this improved model to construct a predictive radial basis neural network model for estimating the daily reference crop water requirement of plants. The simulation results demonstrated a significantly closer alignment with calculations compared with standard methods [8].

However, the accurate prediction of dynamic real-time crop water demand has become increasingly challenging due to the susceptibility of crops' water demand to uncertainties such as meteorological changes [9]. The traditional model for water demand prediction often relies heavily on meteorological data. However, when this information is incomplete, achieving accurate predictions of future water demand becomes challenging. Additionally, traditional neural network models typically require a substantial amount of data for training, which can lead to issues such as gradient disappearance or explosion during the training process. Particularly when faced with long prediction series, the inference speed and prediction accuracy can rapidly decline, leading to a sharp increase in prediction errors [10]. Therefore, hybrid models have been applied in this context. Aitazaz Ahsan Farooque et al. integrated neural network architectures such as 1D-CNN and LSTM into a combined ConvLSTM model. Through calibration and validation assessments of ET_0 prediction, the hybrid ConvLSTM model demonstrated smaller errors compared to standalone CNN and LSTM models, thereby confirming the accuracy of ET_0 prediction [11,12]. I Pulido-Calvo et al. employed a CNN for water demand prediction, where they corrected the predictions of individual models using a fuzzy logic approach. They further optimized the parameters of these models using genetic algorithms. Their study demonstrated that the hybrid model significantly outperformed both univariate and multivariate autoregressive CNN models [13].

The prediction of crops' water demand, being a long time series, is vulnerable to challenges like poor prediction accuracy and low water use efficiency when implemented in irrigated agriculture. These issues arise due to various factors such as environmental changes and the adaptation of models. In this paper, we introduce an innovative approach by proposing a combined CNN–Informer deep learning model, integrating a convolutional neural network (CNN) with a probabilistic sparse self-attention mechanism. This model is applied to predict the water demand of winter wheat and summer maize, considering day-to-day meteorological factors such as temperature, sunshine duration, and humidity as input signals. The CNN component is utilized to capture global patterns in the data and extract in-depth features, which are then fed into the Informer model for prediction [14–17]. And we then apply the prediction results to a water-saving irrigation model, aiming to provide guidance for optimizing field water management in northern semi-arid regions.

2. Methodology

2.1. Research Area

The irrigation experiments were conducted at the Agricultural Efficient Water Use Irrigation Test Site, Longzi Lake Campus, North China University of Water Resources and Hydropower, located in Zhengzhou City, China (Figure 1), between October 2017 and June 2021. The Zhengzhou area features a warm temperate continental climate, characterized by four distinct seasons, with an average annual temperature of 15.4 °C and an average annual precipitation of 632.4 mm. Rainfall is concentrated mainly between June and September, with a frost-free period lasting approximately 220 days. The annual sunshine duration is around 2400 h. This climate is suitable for cultivating winter wheat and summer maize. The experimental area covered 0.24 hm^2 and predominantly consisted of sandy loam soil, with an average field water-holding capacity of 32%. The soil's physicochemical properties before planting are shown in Table 1 below.

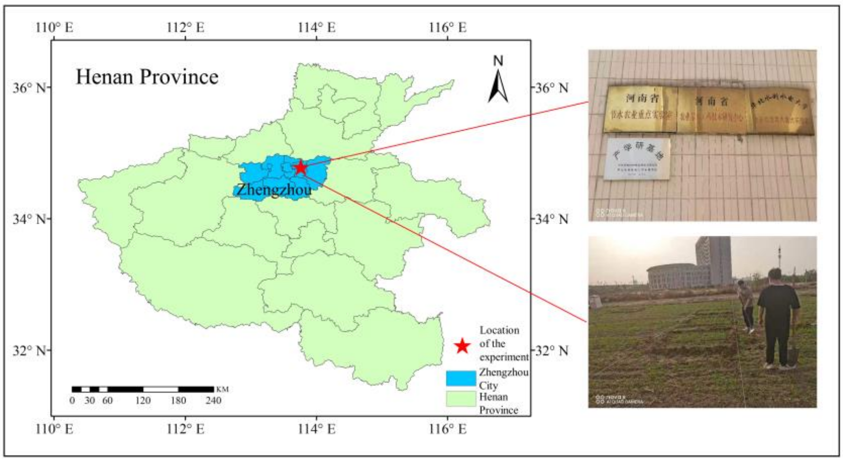


Figure 1. Location of the test area.

Table 1. Physical and chemical properties of soil.

Physical and Chemical Properties of Soil before Irrigation	Depths/cm						
	0~10	10~20	20~30	30~40	40~60	60~80	80~100
Dry weight/ ($g{\cdot}cm^{-3}$)	1.42	1.45	1.45	1.42	1.48	1.44	1.41
Field water-holding capacity/(%)	25.54	28.07	29.33	28.03	27.05	23.58	22.06

The experimental area is arranged with 2 replicates for each treatment. Each experimental plot is 2.2 m wide and 3 m long, with a longitudinal total length of 35.4 m and a transverse total length of 7 m. The spacing between rows is 60 cm (row width), with a row spacing of 60 cm. Winter wheat is planted in a 5-row planting pattern with dense planting, while summer corn is planted in a 4-row pattern, with a plant spacing of 30 cm. Soil moisture is monitored in real-time using soil moisture monitoring devices. Sensors are installed at depths of 5 cm, 15 cm, 25 cm, 35 cm, 50 cm, 70 cm, and 90 cm, placed within the root zone of the crops. The monitoring frequency is every 30 min, enabling continuous monitoring and data transmission throughout the day. A field-based miniature weather station is used to monitor variables such as sunshine duration, maximum and minimum temperatures, relative humidity, wind speed, vapor pressure, etc. Meteorological data are utilized to calculate the crop's water requirements.

2.2. CNN Neural Network Model

The CNN model, as a deep feed-forward neural network structural model, primarily comprises the following layers: data input layer, convolutional computation layer, maximum pooling layer, fully connected layer, and output layer.

The convolutional layer is activated using the ReLU function. During the convolutional operation, the input weather information is fused with the convolutional kernel, and the resulting receptive field represents the region where the pixel points on the feature map, output from each layer of the convolutional neural network, are mapped on the input picture [18]. The operation of the convolutional layer can be expressed as follows:

$$\mathrm{S(i,j)(i*k)(i,j)} = \sum \mathrm{m} \sum \mathrm{n}\ \mathrm{I(i-m,j-n)K(m,n)} \tag{1}$$

In the formula, S is the output value of the convolution operation; I is the original data input matrix; K is the convolution kernel; i and j represent the positions of the output rows and columns; and m and n represent the offsets in the row and column directions of the input data.

After multiple convolution operations, the data are passed to the pooling layer. This layer decomposes the input data features into numerous pixel points and employs statistical operations to aggregate each pixel point with its surrounding data points. This aggregation helps reduce the size of the data by taking the mean or maximum value of its neighboring regions, thereby further reducing the number of parameters [19–21].

2.3. Informer Model

Drawing inspiration from the Transformer model, the Informer model introduces a ProbSparse self-attention mechanism, which effectively reduces the computational and spatial complexity associated with conventional self-attention mechanisms. Additionally, the Informer model employs self-attention distillation operations to reduce the dimensionality of feature vectors and, consequently, decrease the number of model parameters. Furthermore, the Informer model adopts alternative decoding methods for one-step output results and incorporates other techniques to enhance prediction accuracy [22].

The Encoder part of the Informer model receives ultra-long sequence inputs, and the input feature vector of the model consists of a feature scalar αU_i^t, a fixed-position embedding PE, and a learnable stamp embedding, SE, expressed as follows:

$$X_{feet[i]}^{t} = \alpha U_i^t + PE_{(LX*(t-1)+i)} + \sum_p \left[SE_{(L_x*(t-1)+i)} \right]_p \tag{2}$$

In the formula, $\mathrm{i} \in \{1, \ldots\ldots, \mathrm{L_X}\}$, and α is the factor balancing the magnitude between the scalar projection and local/global embeddings.

In order to further improve the ability to take long sequence inputs into distant dependency relationships, the Encoder module introduces the Cov1d + Self-Attention Distilling operation to reduce the feature dimensions to improve the robustness of the algorithm. The input representation of the main sequence's input token and timestamp, after a convolutional layer Conv1d to obtain a representation of the size L * d, and then the two being added as the input of the Attention Block, and after a number of repetitive operations, the final scaled-down representation Feature Map can be obtained. Self-Attention Distilling stacks multiple stacks at the same time, and each stack reduces the input length to 1/2 of the previous one through the Conv1d convolutional layer during embedding, while the latter stack reduces one Attention Block in turn to ensure the same output dimension, and finally, the Feature Map obtained from multiple stacks is combined to obtain the final output representation of the Encoder [23].

In addition, the Informer model replaces the traditional Self-Attention layer with the ProbSparse Self-Attention layer. In this layer, for each query, a subset of keys is randomly sampled after computing the probability distribution of sparsity for each query and the similarity to a uniform distribution $\mathrm{M(q_i, K)}$. Subsequently, the subset of values with the highest sparsity score is selected to perform the dot product operation with the keys, while the remaining queries directly utilize the input of the Self-Attention layer to compute the mean (V) as the output. Finally, the attention result is obtained using the following formula:

$$\mathrm{A}(\mathrm{Q},\mathrm{K},\mathrm{V}) = \mathrm{softmax}\left(\frac{\overline{\mathrm{Q}}\mathrm{k}^{\mathrm{T}}}{\sqrt{\mathrm{d}}}\right)\mathrm{V} \tag{3}$$

In the formula, Q is the number of sparse matrices with the highest sparsity scores; d is the input dimension.

The Decoder module processes a series of long sequence inputs by dividing the input sequence into two parts: a known sequence before the time point that is to be predicted and a sequence of zeros for the time points that are to be predicted. Subsequently, it passes through the Attention layer with masking to generate the predicted output at the final step.

2.4. Water Balance Equation

Without considering the crop recharge from groundwater in the test area, the water balance equation for the time period of day was calculated as follows:

$$W_i = W_{i-1} + P_{0i} + W_{Ti} - ET_i + M_i \tag{4}$$

In the formula, $\mathrm{W_i}$ is the soil's water content at the end of day i, mm; $\mathrm{W_{i-1}}$ is the soil's water content at the beginning of day i, mm; $\mathrm{P_{0i}}$ is the effective rainfall on day i; $\mathrm{W_{Ti}}$ is the increase in water volume due to the increase in the planned wet layer on day i, mm; $\mathrm{ET_i}$ is day's crop water requirement, m; and $\mathrm{M_i}$ is the water volume on day i, mm.

3. Model Building

3.1. CNN–Informer Crop Water Demand Prediction Modeling

The CNN–Informer model presented in this study is composed of a CNN feature extraction component and an Informer prediction component. The CNN component utilizes a convolutional neural network to extract feature information from weather sequence data. The extracted features are then input into the Encoder part of the Informer model [24]. The input data undergo a ProbSpare Self-Attention layer to reduce the complexity of the self-attention dot product operations and Self-Attention distilling operations to compress features. After several stacking operations, the data are input into the Decoder part. The input of the Decoder includes the back part of the Encoder input, along with a zero matrix that has the same shape as the predicted target. During ProbSpare Self-Attention operations, the input data are used to predict the back part of the data using the front part of the data. The Attention of the Encoder part of the input is calculated after the Attention has been calculated. Finally, the prediction results are generated in one step through a fully connected layer [25]. The basic structure of the CNN–Informer model is illustrated in Figure 2.

The CNN feature extraction module employs multiple convolutions to extract data features. This module consists of a convolutional layer, followed by an activation layer and a maximum pooling layer, with this operation repeated twice. The first convolutional layer is configured with 32 filters, each with a size of 3. The second convolutional layer is designed with 64 filters, also with a size of 3. The maximum pooling layer uses average pooling, and the fully connected layer contains 128 neurons. The Informer model's Encoder and Decoder steps are set to 16 and 8, respectively, and both models are activated using the ReLU function. The model's parameter settings are summarized in Table 2.

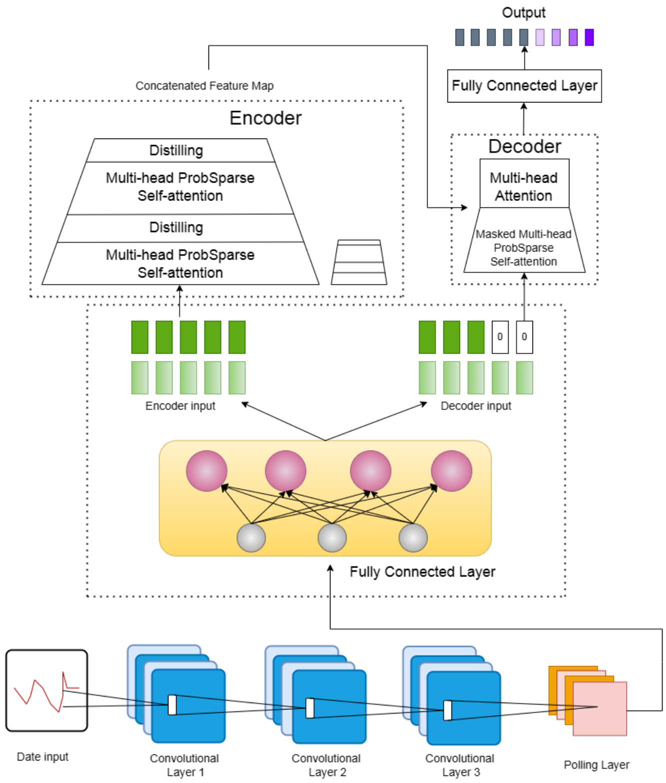


Figure 2. CNN–Informer schematic diagram.

Table 2. CNN–Informer model's hyper-parameters.

Mold	Name	Parameters	Clarification
CNN	sequence input layer	data structure	(974, 1)/(372, 1)
	convolutional layer	convolution kernel size	3 × 3
		number of convolution kernels	32
	convolutional layer	convolution kernel size	3 × 3
		number of convolution kernels	64
	convolutional layer	convolution kernel size	3 × 3
		number of convolution kernels	64
	activation layer	activation function	ReLU
	ponding layer	pooling method	Average Polling
	full connectivity layer	number of neurons	128
Informer	Encoder	Encoder step	16
	Decoder	Decoder step	8
	activation layer	activation function	ReLU

3.2. Data Preprocessing

In this study, the CNN–Informer model was employed to predict the water demand of winter wheat and summer corn crops. Meteorological data from October 2017 to June 2021 from the experimental field of efficient agricultural water use irrigation at Longzi Lake Campus of North China University of Water Resources and Hydropower were utilized. To ensure the quality of the experimental data and achieve a good prediction effect, this paper conducted data preprocessing on the original samples.

(1) Missing value processing. The data collection process from small automatic weather stations in the field may lead to missing data records, which can reduce the accuracy of model predictions. To address this issue, missing weather information in the time series is filled in using linear interpolation to obtain a complete dataset.

(2) Irrelevant value processing. In this paper, after analyzing the original samples, a large number of experimentally irrelevant attribute data that are present in the collected data are directly deleted.
(3) Data normalization. In this paper, the collected data are standardized to make the indicators comparable and eliminate the influence of dimensionality. This process improves the consistency and manipulability of the data.

3.3. Dataset Segmentation

The dataset was divided on a daily basis, arranging the water demand dataset as a time series during the growing period of winter wheat from October to May each year and during the growing period of summer maize from June to September each year. Before training the model, the data were further divided, with the first three years' data for winter wheat and summer maize selected as the training set, and the data from the last year as the testing set. This division resulted in the training set accounting for 75% of the data and the testing set accounting for 25% [26]. The divisions are illustrated in Figure 3.

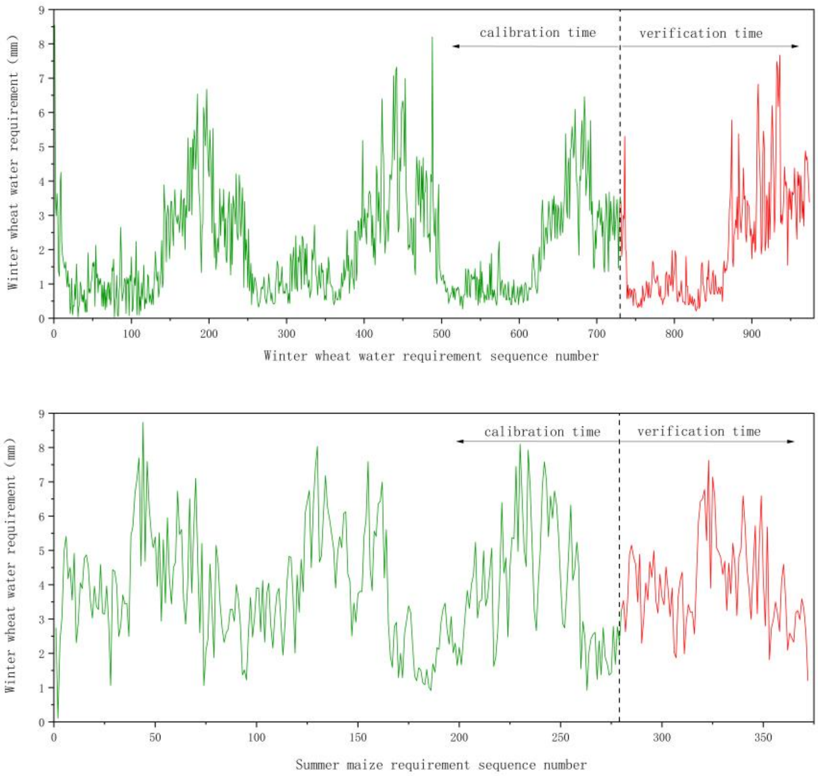


Figure 3. Growth sequence number of crops. The *x*-axis represents the growth sequence of crops, starting from 1 and arranged according to the growth dates of the crops over four years. The green area represents data from the first three years, which serve as training data. The red area represents data from the last year, which serve as prediction data.

3.4. Model Evaluation Indicators

The accuracy assessment of the CNN–Informer crop water demand prediction model utilizes Nash–Sutcliffe Efficiency (NSE), Mean Absolute Error (MAE), root mean square error (rMSE), and Mean Absolute Percentage Error (MAPE). These metrics are used to measure the degree of agreement between predicted values and actual values, the average of the absolute differences, the precision of the prediction data, and the accuracy of the model's predictions, respectively. The formulas for NSE, MAE, RMSE, and MAPE are as follows:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(y_i - y_{ik})^2}{\sum_{i=1}^{n}(y_{ik} - \overline{y}_{ik})^2} \quad (5)$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - y_{ik}|}{n} \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_{ik})^2} \tag{7}$$

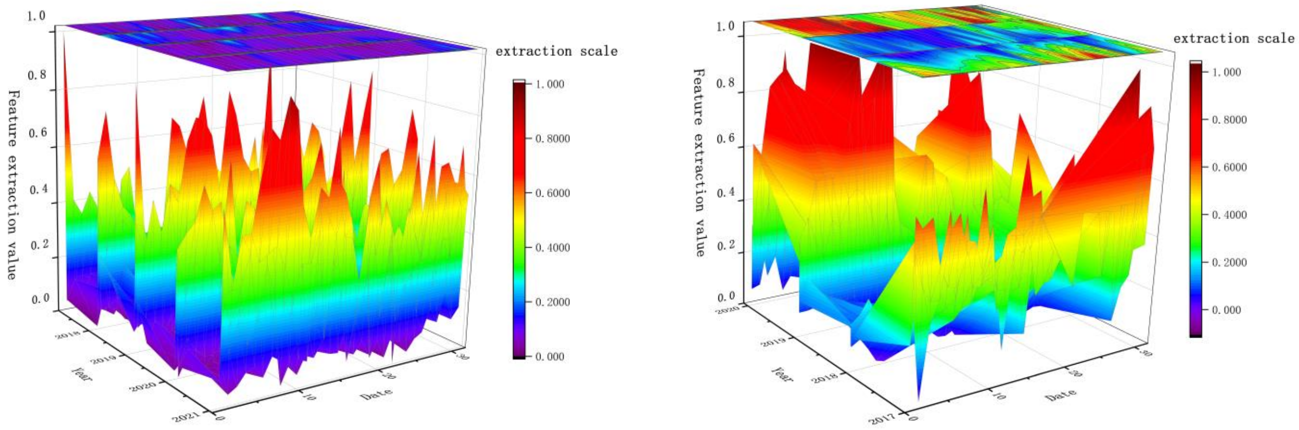
$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_{ik}}{y_{ik}}\right| \tag{8}$$

In the formula, n denotes the number of predicted samples; y_i is the ith predicted value of water demand for the model; and y_{ik} is the ith measured value of water demand for the model.

4. Experiment and Results

4.1. Model Prediction Accuracy Analysis

In this paper, meteorological data from the growing periods of winter wheat and summer maize from 2017 to 2021 are selected. A CNN is then employed for feature extraction, and the extraction results are illustrated in Figure 4.



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

Figure 4. Deep feature extraction of meteorological data: (**a**) characterization of winter wheat meteorological data; (**b**) characterization of meteorological data for summer corn.

From Figure 4, it can be observed that there is a certain similarity in the overall change patterns between the extracted values of the meteorological data features for winter wheat and summer maize and the measured values. The data features generally exhibit cyclical changes over the three years, with a trend of a lower water demand in the early stage and higher demand in the later stage of each year. After sowing, the water demand for winter wheat is relatively high and then slows down during the overwintering period when crop growth is slower, resulting in a lower level of water demand. Around the 150th day of the growing season, the crop growth rate and biomass reach their peak, leading to a significant increase in water demand. Moreover, extreme data points are more likely to occur during the later stages of winter wheat cultivation due to climatic factors, with these extreme data points most often appearing in the summer. Similarly, the annual water demand for summer maize also roughly follows a cyclical pattern of troughs and peaks. However, due to the variable climate during the planting period of summer maize, its water demand exhibits unstable fluctuations.

The error in feature extraction primarily stems from the influence of consecutive extreme weather events on the crops' water demand. The error is more pronounced near these extreme weather conditions and can impact subsequent feature extraction. However, overall, the feature extraction values for winter wheat and summer maize align well with the measured values. They more comprehensively reflect the changes in water demand during the reproductive periods of winter wheat and summer maize.

To validate the effectiveness of the CNN–Informer model, the extracted feature values were inputted into the Informer model to obtain predicted water demand values for winter wheat and summer maize crops. These predictions were then compared with those of the BP neural network model, the CNN convolutional neural network, and the LSTM prediction model. For a more realistic and effective comparison, all models utilized measured meteorological data as input and were configured with the same parameters. Tables 3 and 4 present the fitting degree and error of the two crop predictions, with the prediction results displayed in these tables.

Table 3. Model prediction error for winter wheat.

Predictive Model	Calibration Time				Verification Time			
	NSE	MAE	RMSE	MAPE, %	NSE	MAE	RMSE	MAPE, %
CNN	0.982	0.149	0.200	17.637	0.121	1.151	1.553	37.281
BP	0.743	0.511	0.749	36.580	0.467	0.822	1.190	29.115
LSTM	0.775	0.490	0.698	33.134	0.514	0.793	1.095	28.308
CNN–Informer	0.994	0.089	0.123	5.903	0.994	0.083	0.124	5.629

Table 4. Model prediction error for summer maize.

Predictive Model	Calibration Time				Verification Time			
	NSE	MAE	RMSE	MAPE, %	NSE	MAE	RMSE	MAPE, %
CNN	0.990	0.103	0.148	9.669	−0.194	1.151	1.649	72.673
BP	0.620	0.775	0.960	39.218	0.316	1.011	1.213	45.921
LSTM	0.791	0.533	0.713	29.761	0.386	0.754	1.150	57.326
CNN–Informer	0.994	0.087	0.123	5.839	0.993	0.088	0.122	5.886

From Tables 3 and 4, it is clear that for winter wheat's periodic rates, the CNN–Informer combined model showed a 1.2% improvement in NSE and achieved 6.0%, 7.7%, and 11.7% reductions in MAE, RMSE, and MAPE, respectively, relative to the CNN model. Compared with the BP and LSTM models, this combined model further reduces the error and improves the prediction accuracy, especially on the NSE, by 25.1% and 21.9%, respectively. During the validation period, the combined model is even more effective in prediction, with an 87.3% improvement in NSE relative to the single CNN model, and resulting in 106.8%, 142.9%, and 31.6% reductions in MAE, RMSE, and MAPE, respectively. Compared with the BP and LSTM models, the error reduction is more obvious compared to the NSE improvement, with improvements of 73.9%, 106.6%, and 23.5% and 71.0%, 97.1%, and 22.7%, respectively.

The results of the water demand predictions for each model for summer maize were compared with those for winter wheat, and the results were generally the same. In the rate period, the CNN model performs better, but in the validation period, the model prediction accuracy decreases dramatically, and the combined CNN–Informer model improves the NSE by 118.7% and reduces the MAE, RMSE, and MAPE by 106.3%, 152.7%, and 66.8%, respectively. The BP and LSTM models perform more stably, and in general, the prediction accuracy in the rate period is greater than the prediction accuracy in the validation period, and the combined CNN–Informer model improves the NSE by 37.4% and 20.3% in the rate period and 67.7% and 60.7% in the validation period, respectively.

Figure 5 illustrates the prediction effects of the four models for winter wheat and summer maize during the validation period. The CNN prediction model, utilizing multiple causal convolutions, demonstrates a high prediction accuracy during the rate period. However, its prediction accuracy significantly decreases in the validation period due to factors such as local precipitation characteristics. The prediction results of the BP and LSTM models exhibit large errors compared to the measured values, with the prediction errors during the rate period being smaller than those in the validation period. In comparison with the other models, the CNN–Informer model shows clear advantages in terms of prediction accuracy. It particularly excels in long-term prediction, maintaining higher stability and accuracy.

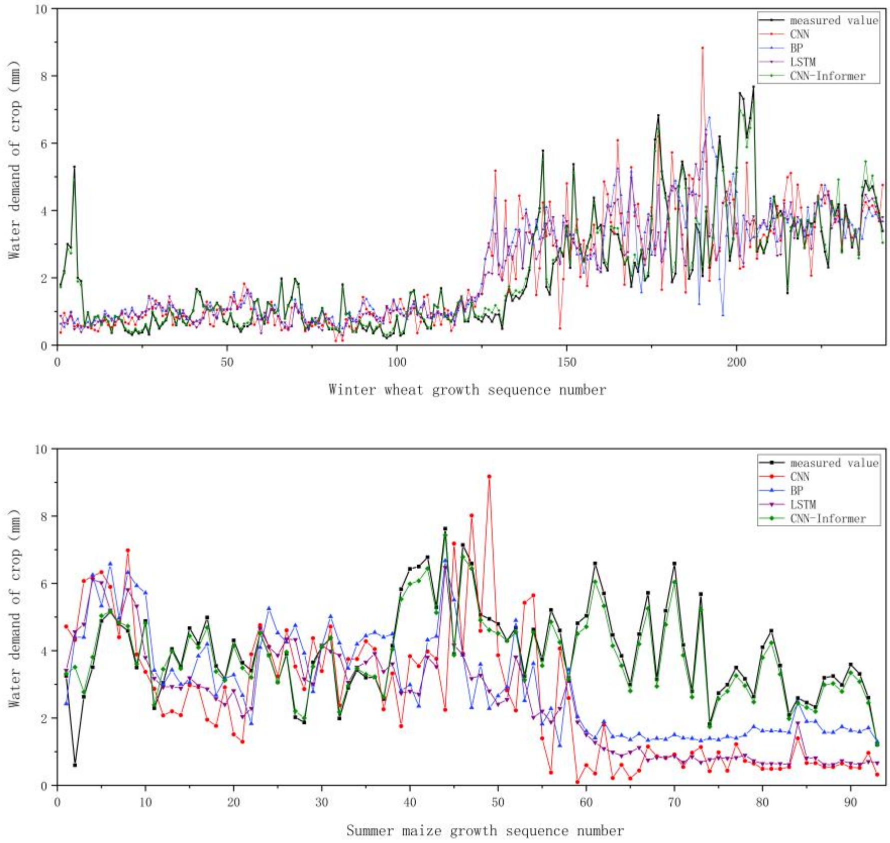


Figure 5. Comparison of model predictions.

A crop's water demand is significantly influenced by weather changes, and extreme values in water demand are prone to occur during consecutive droughts or floods. From the box plots of winter wheat and summer maize, it can be seen that in the prediction of the water demand of winter wheat, the CNN–Informer model's maximum and minimum values are closer to the measured values compared to the CNN, BP, and LSTM models. The predictive results are superior to other models, and they are also closest to the measured values in predicting outliers, except for extreme values. In the prediction of the water demand of summer maize, the CNN model, BP model, and LSTM model have large differences in maximum and minimum values and median values compared to the measured values, and some extreme values are not accurately predicted. In contrast, the CNN–Informer model exhibits extremely high stability. Therefore, it can be concluded that the CNN–Informer model predicts the water demand of crops in long sequences more accurately, especially for predictions with extreme values. It has the ability to capture the changing characteristics of the time series of crops' water demand more comprehensively (Figure 6).

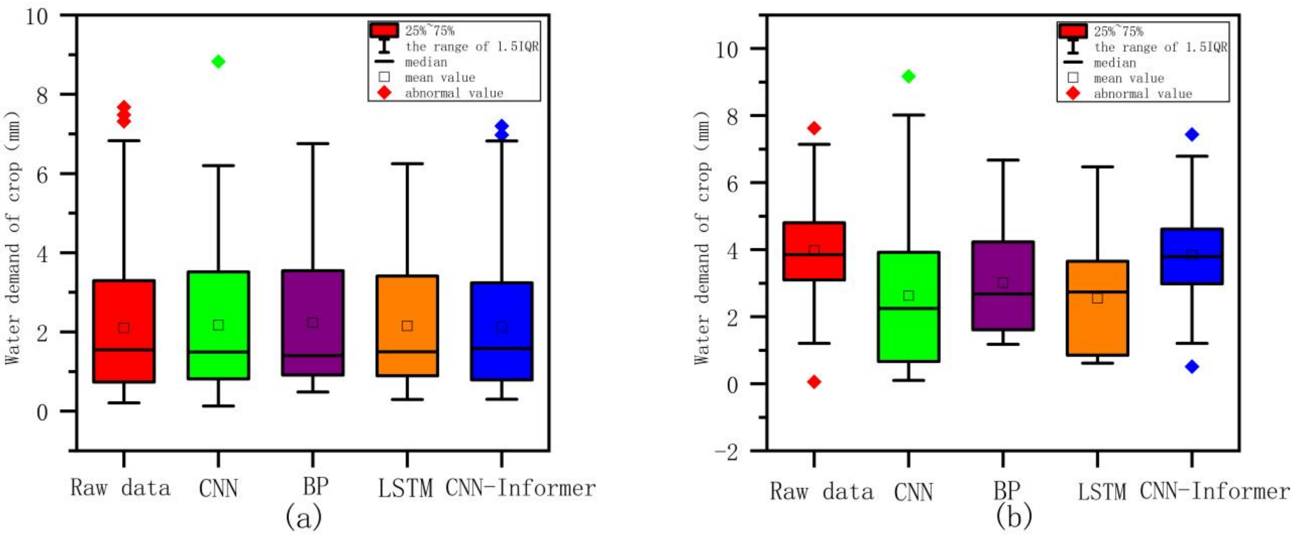


Figure 6. Box plots comparing the forecasts of the models: (**a**) comparative box plots of winter wheat predictions across models; (**b**) characterization of meteorological data for summer corn. The legend uses the original data as an example, and all other models represent the same meaning.

4.2. Analysis of Model's Water-Saving Effect

Using the CNN–Informer model to predict crops' water demand, we combined soil moisture monitoring data and meteorological data. By integrating these into the water balance equation, we calculated the net irrigation water consumption for winter wheat and summer maize during each growth stage. Using reference crops' evapotranspiration, we determined the crop irrigation water demand, which was then divided by the irrigation water utilization rate to obtain the crop irrigation quota. Comparing the net irrigation water use with the irrigation quota [27–29], we evaluated the water-saving effect, as illustrated in Figure 7 below.

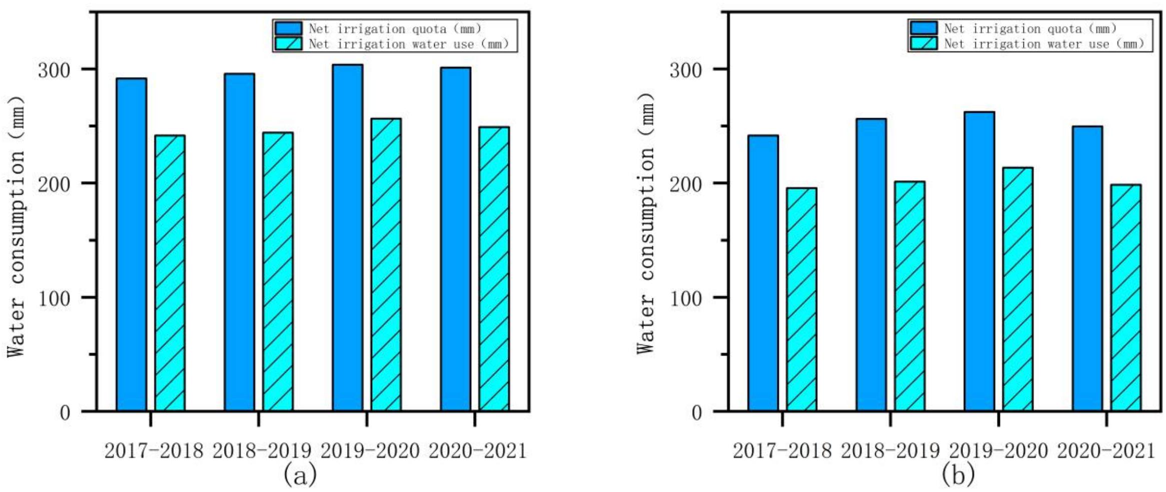


Figure 7. Analysis of water-saving effect of combined model: (**a**) analysis of water-saving effect in winter wheat; (**b**) analysis of water-saving effect in summer corn.

The 2017–2021 net irrigation quotas for winter wheat were 291.6 mm, 295.7 mm, 303.8 mm, and 301.2 mm, and the actual net irrigation water use was 241.6 mm, 244.3 mm, 256.5 mm, and 249.1 mm; for summer maize, the net irrigation quotas were 241.6 mm, 256.2 mm, 262.4 mm, and 249.7 mm, and the actual net irrigation water consumption was 195.6 mm, 201.3 mm, 213.5 mm, and 198.6 mm, respectively. Based on the principle of soil moisture and water balance, using the CNN–Informer model to predict the crops' water demand and combining the predicted data on irrigating can achieve an average annual saving of 1004.3 m^3/hm^2 of irrigation water, with an average annual saving of 18.4%, which is good for achieving water savings and reducing the intensive use of water resources.

Figures 4–7 show the comparison of prediction effects of the four different models. It is evident that a single neural network exhibits a high degree of dispersion between the predicted and measured values in ultra-long sequence prediction. In contrast, the combined CNN–Informer model leverages convolutional neural networks to extract deep features from meteorological data, giving it a significant advantage in predicting individual long-term dependencies between the output and input in long sequence time series. This advantage substantially improves the prediction accuracy and optimizes the fitting effect. When applying the CNN–Informer combination model to water-saving irrigation, it outperforms a single neural network like the CNN. The combination model is more representative in predicting time periods of large changes in crops' water demand caused by weather factors [30]. Additionally, the prediction effect is more stable, leading to a significant water-saving effect.

5. Conclusions

In order to improve the accuracy of predictions of crops' water demand, this paper innovatively establishes a long sequence crop water demand prediction model based on meteorological data and deep learning, with optimization of the Informer module based on CNN feature extraction. Firstly, meteorological information is collected using small-scale field weather stations to calculate the daily crop water demand. Secondly, the daily crop water demand is arranged as a time series and divided into training and testing sets. Then, the CNN module of the newly established model is used to extract features from the time series data, thereby effectively reducing the complexity of the original sequence. Finally, the Informer model is employed to predict the extracted features and output the results in one step, which are then compared with the predictions of the BP, CNN, and LSTM models. The main conclusions are as follows:

(1) The CNN–Informer combined model effectively replaces the conventional Self-Attention Mechanism with the ProbSparse Self-Attention Mechanism by extracting global features from meteorological data. This mechanism learns the long-distance dependencies in the time series of crops' water demand. By capturing the dependencies between the long sequence inputs and outputs, it achieves accurate prediction of crops' water demand. Additionally, the Self-Attention Distilling operation is utilized for feature compression, reducing the length of input sequences and greatly improving the computational efficiency. This demonstrates the effectiveness of the model in solving long sequence prediction problems.

(2) The combined CNN–Informer model was utilized to predict the water demand of winter wheat and summer maize, achieving remarkable fitting accuracies of 99.4% and 99.3% in the rate and validation periods, respectively. This represents a significant improvement in prediction accuracy compared to other models. The root mean square error of the model stabilized at about 12.3%, indicating its effectiveness in capturing the specific data on crop water requirement changes. The water-saving analysis based on the prediction results revealed that the average annual water saving for winter wheat was 502.0 m^3/hm^2, and for summer maize, it was 502.3 m^3/hm^2, amounting to a saving of 18.4%. This achievement realizes the efficient use of water resources and enables dynamic prediction and management of irrigation water use in farmland.

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