Study on Winter Wheat Water Requirement Prediction based on CNN-BiLSTM-Attention Model

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Abstract

Accurate prediction of winter wheat water requirements is crucial for improving water resource utilization efficiency,increasing farmers' income,and ensuring national food security.To enhance the accuracy of winter wheat water requirement prediction,a CNN-BiLSTM neural network prediction model incorporating an attention mechanism (CNN-BiLSTM-Attention) is proposed in this paper.This model utilizes a convolutional neural network to extract spatial features of meteorological factors,employs a bidirectional long short-term memory network to learn long-term temporal dependencies of water requirements,and introduces an attention mechanism to focus on key growth stages influencing water demand formation.To validate the model's performance,a study was conducted based on daily meteorological data from Zhengzhou.The results indicate that the predictions of the CNN-BiLSTM-Attention model are closer to the benchmark truth and outperform five comparison models,including BP,LSTM,and BiLSTM,across various evaluation metrics.This demonstrates higher prediction accuracy and indicates that the model has good regional applicability,providing a basis for crop water requirement forecasting and sustainable agricultural development.

Keywords

Attention Mechanism; BiLSTM; CNN; Winter Wheat Water Demand.

1. Introduction

Prediction of crop water requirements is not only the foundation for formulating precise irrigation strategies, but also a key scientific support for optimizing agricultural water resource allocation and improving water use efficiency. Traditional methods for predicting crop water requirements, such as the water balance method and the Penman formula [1], are widely used in practice. However, their calculation processes are relatively complex, relying on a large amount of meteorological and crop parameters, and they do not effectively reflect the dynamic soil moisture and the complex non-linear interactions among multiple meteorological factors during crop growth stages. In recent years, with the rapid advancement of artificial intelligence technology, machine learning-based methods for predicting water demand have gradually become a research hotspot. Li Zhixin [2] et al. constructed a crop water requirement prediction model based on an Elman neural network optimized by a genetic algorithm and verified its feasibility. Meng Wei [3] et al. optimized a radial basis function neural network model using an artificial bee colony algorithm to construct a prediction model for daily reference crop water requirements in orchards irrigated by water storage pits. Results indicate that this optimized model achieves higher prediction accuracy than traditional radial basis function neural network models. Ma Shijiao [4] et al. designed a crop water requirement prediction model based on a BP neural network and a fuzzy-controlled wheat irrigation system according to the growth environment and water demand during the wheat growth period. Researchers have discovered that, in response to the limitations of single neural network models in predictive accuracy, a construction strategy based on hybrid machine learning models can significantly enhance the precision of predictions. Ma [5] et al. developed the CNN-Informer hybrid model, which integrates spatial feature extraction with long-term temporal dependency modeling, achieving higher accuracy in predicting water requirements for winter wheat-summer maize. The CNN-BiLSTM model developed by Du Yun [6] et al. enhances the accuracy of wheat water requirement prediction through multi-source inputs and structural optimization. Ma [7] et al. found that when constructing crop water requirement models, the EEMD-Attention-LSTM model incorporating an attention mechanism demonstrated superior predictive accuracy compared to both standalone models and combined models without attention mechanisms, demonstrating the effectiveness of model structure optimization in enhancing performance.

Crop water requirement prediction is influenced by multiple factors, and prediction accuracy is often not high due to issues such as environmental changes and model applicability. Therefore, this paper constructs a crop water requirement prediction model based on a convolutional-bidirectional long short-term memory network with an attention mechanism (CNN-BiLSTM-Attention), leveraging the advantages of ensemble models in time series prediction. Compared to ensemble deep learning models based on signal decomposition, this model takes into account potential issues such as information loss and reconstruction errors that may be caused by the preprocessing decomposition stage. It directly extracts spatial features from the raw data using a convolutional neural network (CNN), employs a bidirectional long short-term memory network (BiLSTM) to capture temporal dependencies, and finally introduces an attention mechanism (Attention) to adaptively allocate weights, focusing on the critical growth stages that influence crop water requirements. Finally, using winter wheat as the research subject, the daily water requirement of winter wheat was calculated based on the FAO56-PM formula and the crop coefficient method. Modeling was carried out using multidimensional meteorological data, and the effectiveness of the CNN-BiLSTM-Attention model in predicting crop water requirements was verified by comparing it with various other models.

2. Materials and Methods

2.1. CNN Neural Network

Convolutional Neural Networks (CNNs) are a common algorithm in deep learning, primarily composed of five components: the input layer, convolutional layers, pooling layers, activation functions, and fully connected layers. CNNs extract local features through sliding convolutional layers, reducing parameters while capturing key information; pooling layers compress features and prevent overfitting; fully connected layers map the output. Their basic structure is shown in Figure 1.

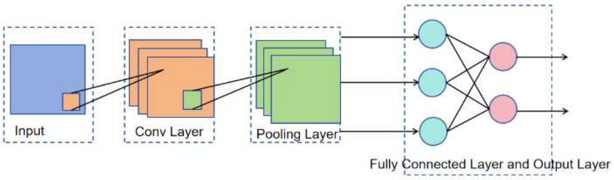

Figure 1. CNN Architecture Diagram

2.2. BiLSTM Neural Network

Long Short-Term Memory (LSTM) Networks represent an enhancement of Recurrent Neural Network (RNN) algorithms, designed to address the challenge of learning long-range dependencies in RNN models caused by gradient vanishing. By introducing three gating mechanisms-the forget gate, input gate, and output gate-LSTMs effectively modulate the influence of historical information on current data [8]. Its structure is illustrated in Figure 2.

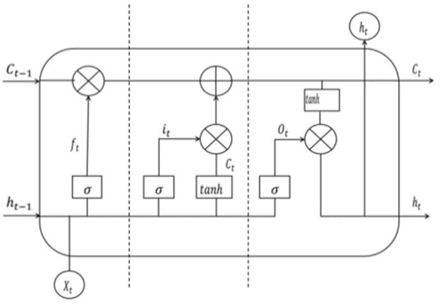

Figure 2. LSTM Architecture Diagram

Bidirectional Long Short-Term Memory (BiLSTM) networks build upon the LSTM model by incorporating two LSTM layers that propagate information along both the forward and backward directions of the time series. This enables the network to capture contextual information within sequential data, allowing the architecture to fully utilize input data and further enhance prediction completeness and accuracy [9]. Its structure is illustrated in Figure 3.

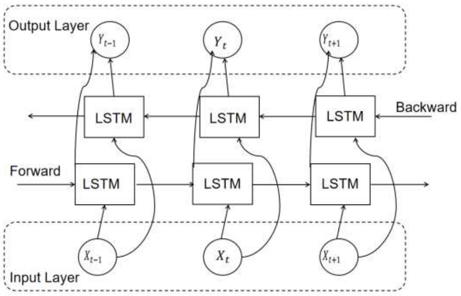

Figure 3. BiLSTM Architecture Diagram

The BiLSTM formulas are expressed as follows:

$$\overrightarrow{h_t} = LSTM\left(X_{\mathrm{t}}, \overrightarrow{h_{t-1}}\right) \tag{1}$$

$$\overleftarrow{h_t} = LSTM\left(X_{\mathrm{t}}, \overleftarrow{h_{t-1}}\right) \tag{2}$$

$$Y_{\mathrm{t}} = \sigma\left(W_{\mathrm{y}}\left[\overrightarrow{h_t}, \overleftarrow{h_t}\right] + b_y\right) \tag{3}$$

In the formula, the LSTM unit represents the computational process of a traditional LSTM network; σ is the Sigmoid function; $\overrightarrow{h_t}$ denotes the forward LSTM hidden layer state at time step t, $\overleftarrow{h_t}$ denotes the backward LSTM hidden layer state at time step t, W_y and b_y represent the weight matrix and bias term, X_t represents the input data at time t, and Y_t represents the output data at time t.

2.3. Attention Mechanism

In the CNN-BiLSTM-Attention ensemble model, the attention mechanism operates on the outputs of the BiLSTM layer to effectively capture information features. By quantifying the importance of features at each time step and assigning weights, it enhances the contribution of key information to prediction results, thereby optimizing model accuracy [10]. The specific calculation process is as follows:

$$S_i = v^T \cdot \tanh\left(W_q Q + W_k K_i + b\right) \tag{4}$$

$$\alpha_i = soft\max\left(S_i\right) = \frac{\exp\left(S_i\right)}{\sum_{j=1}^{T} \exp\left(S_j\right)} \tag{5}$$

$$C = \sum_{i=1}^{T} \alpha_i V_i \tag{6}$$

In the formula, Q is the query vector; K_i is the key vector; S_i is the correlation score between them; W_q and v are trainable weights; b is the bias term; the tanh function maps the calculation result to the interval $[-1,1]$, preventing extreme values from influencing the outcome. α_i represents the attention weight, T denotes the time step of the input sequence, and C is the feature vector optimized through the attention mechanism.

2.4. CNN-BiLSTM-Attention Prediction Model

In the CNN-BiLSTM-Attention hybrid neural network model constructed herein, the CNN serves as the front-end feature extractor, capturing local features and spatial dependencies from multivariate meteorological time series. The BiLSTM receives the high-level features output by the CNN and, through its bidirectional gating mechanism, captures the long-term temporal dynamics of water demand from both forward and backward directions, thereby comprehensively understanding the entire crop growth cycle. The attention mechanism further applies differential weights to the BiLSTM hidden states, enabling the model to focus on critical growth stages significantly influencing water demand and mitigating the “selective forgetting” issue in long sequences. By integrating the CNN's local feature extraction capability, the BiLSTM's bidirectional temporal modeling capability, and the attention mechanism's critical information focusing ability, the model ultimately generates prediction results. The model structure is shown in Figure 4.

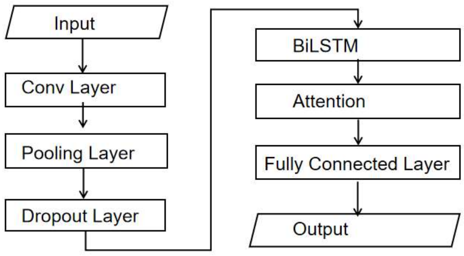

Figure 4. CNN-BiLSTM-Attention Water Demand Forecasting Model

2.5. Model Evaluation Indicators

To comprehensively evaluate the accuracy of the CNN-BiLSTM-Attention crop water requirement prediction model, four metrics-the coefficient of determination (R^2), root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE)-were employed to quantify model performance and compare the discrepancy between predicted and reference values. The calculation formulas are as follows:

$$R^2=1-\frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{\sum_{i=1}^{n}(X_i-\overline{X})^2} \tag{7}$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{n}} \tag{8}$$

$$MSE=\frac{\sum_{i=1}^{n}(X_i-\overline{X})^2}{n} \tag{9}$$

$$MAE=\frac{\sum_{i=1}^{n}|X_i-\overline{X}|}{n} \tag{10}$$

In the formula, X_i denotes the measured value from the i-th experiment; Y_i denotes the predicted value of the i-th model; n represents the total number of observations; and $\overline{X}$ is the mean of the actual data. The higher the modeling accuracy, the larger the value of R^2, and the smaller the RMSE, MSE, and MAE.

3. Examples and Analysis

3.1. Data Sources and Preprocessing

The data originates from the Era5 reanalysis dataset released by the European Centre for Medium-Range Weather Forecasts (ECMWF), comprising daily meteorological data for Zhengzhou City, Henan Province, from 2015 to 2024. It includes daily mean temperature, minimum temperature, maximum temperature, wind speed, relative humidity, precipitation, sunshine duration, surface air pressure, net solar radiation, surface temperature, and evaporation.The daily crop water requirement ET calculated using the FAO56-PM formula combined with locally adjusted crop coefficients serves as the benchmark reference value for prediction. To avoid model training biases caused by dimensional differences among meteorological variables, the raw data undergoes normalization processing.

$$X_i^{'}=\frac{X_i-X_{\min}}{X_{\max}-X_{\min}} \tag{11}$$

In the formula, x_i denotes the raw data of the i-th sample; $x_i^{'}$ represents the normalized data; x_{max} is the maximum value in the dataset; and x_{min} is the minimum value.

3.2. Water Requirement Calculation

Calculate the reference crop water requirement ET_0 using the FAO56-Penman-Monteith formula amended by the Food and Agriculture Organization of the United Nations (FAO) [11]:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{12}$$

In the formula, ET_0 is the reference crop water requirement; R_n represents net radiation at the crop surface; G signifies the soil heat flux; T denotes the daily average temperature at a height of 2 meters; u_2 is the wind speed at the height of 2 meters; e_s denotes the saturated vapor pressure; e_a denotes the actual vapor pressure; e_s-e_a denotes the saturated vapor pressure difference; Δ is the slope of the saturated vapor pressure curve; and γ denotes the hygrometer constant.

Crop water requirement ET is calculated by multiplying the reference crop water requirement ET_0 by the crop coefficient K_c.

$$ET = K_c \cdot ET_0 \tag{13}$$

Based on the winter wheat crop coefficient calculation methods provided by FAO56-PM and Li Ying [12] et al., the growth period of winter wheat is divided into four stages: Seeding-reviving period (early October to late February of the following year), Reviving-booting period (late February to mid-April), Booting-filling period (mid-April to late May), and Filling-maturity period (late May to early June), as shown in Table 1.

Table 1. Duration of Each Growth Stage of Winter Wheat

Growth period	**Seeding-reviving period**	**Reviving-booting period**	**Booting-filling period**	**Filling-maturity period**	**Whole growth period**
Day	130	50	40	20	240

The crop coefficient K_c used in this study was determined by Wang Qiang [13] et al. through modifications based on the winter wheat crop coefficients provided by the FAO56-PM equation, specifically for the research in Henan Province, as shown in Table 2.

Table 2. Crop Coefficients for Each Growth Stage of Winter Wheat in Henan Province

Growth period	**Seeding-reviving period**	**Reviving-booting period**	**Booting-filling period**	**Filling-maturity period**
K_c	0.40	1.05	1.15	0.40

3.3. Model Input Parameter Selection

Using winter wheat water requirement data from 2015 to 2022 as the training set and data from 2023 to 2024 as the test set, the CNN-BiLSTM-Attention model was trained, and its prediction accuracy was evaluated post-training. Parameter categories included the number of convolutional layers, the number of BiLSTM neurons, learning rate, number of iterations, dropout rate, etc. The primary parameter values determined through model training are shown in Table 3.

Table 3. Parameter Settings for the CNN-BiLSTM-Attention Model.

Parameter	**No.of Conv layers**	**No.of BiLSTM unit count**	**Learning rate**	**No.of iterations**	**Dropout rate**
Value	2	128	0.001	200	0.2

3.4. Water Demand Forecast Results

The experimental results indicate that the CNN-BiLSTM-Attention model proposed in this paper demonstrates high prediction accuracy on the test set, specifically manifested as: coefficient of determination R^2=0.8741, root mean square error RMSE=0.8367, mean squared error MSE=0.7, and mean absolute error MAE=0.5282. These metrics indicate that the model accurately reflects the dynamic changes in winter wheat water requirements. Compared with the results obtained using the crop coefficient method combined with the FAO56-PM formula, this model shows smaller prediction deviations under the same input conditions and is more reliable in calculating water requirements. A comparison of the model's predicted values and the calculated values on the test set is shown in Figure 5.

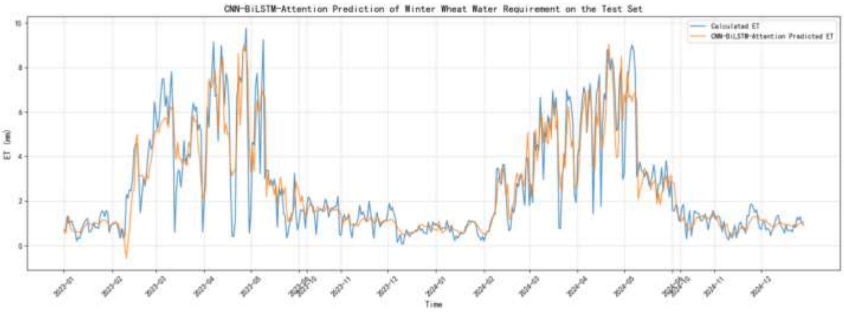

Figure 5. CNN-BiLSTM-Attention Model Prediction Results

The test dataset comprises winter wheat growth cycle data from the complete 2023–2024 growing season. As shown in Figure 5, the predicted values from the CNN-BiLSTM-Attention model exhibit significant consistency with evapotranspiration (ET) values calculated using the FAO56-PM formula and crop coefficient method throughout the entire growth period. During periods of relatively stable water demand (corresponding to the winter wheat seeding and maturity phases in the early, middle, and late segments of the time series in the figure), the predicted curve closely aligns with the calculated value curve. Even during growth stages with more pronounced fluctuations in water demand (namely the winter wheat heading and grain filling phases), the model accurately captures the dynamic characteristics, precisely fitting both the peak magnitude and timing of occurrence, while maintaining strong tracking capability during the subsequent decline phase.

3.5. Comparison of Water Demand Forecasting Models

Five models-BP,LSTM,BiLSTM,CNN-LSTM,and CNN-BiLSTM-were selected to compare predicted values against calculated values on the test set, as shown in Figures 6–10.

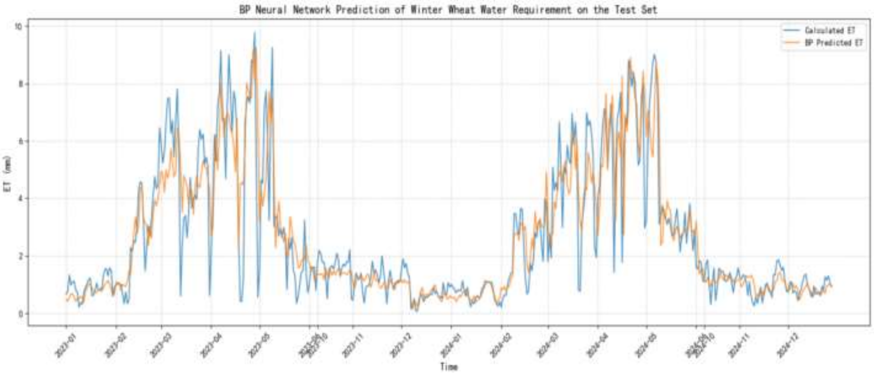

Figure 6. BP Neural Network Prediction Results for Winter Wheat Water Requirements

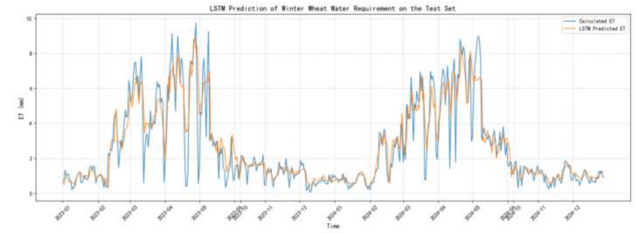

Figure 7. LSTM Prediction Results for Winter Wheat Water Requirements

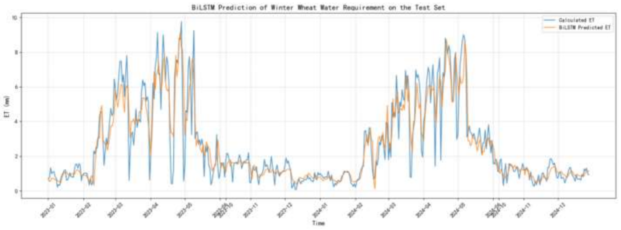

Figure 8. BiLSTM Prediction Results for Winter Wheat Water Requirements

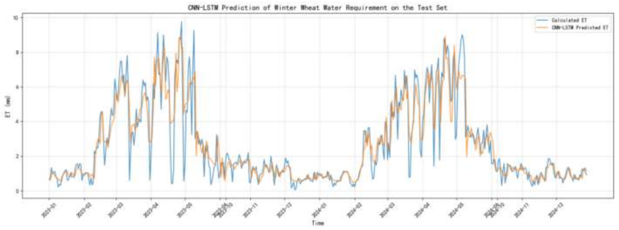

Figure 9. CNN-LSTM Prediction Results for Winter Wheat Water Requirements

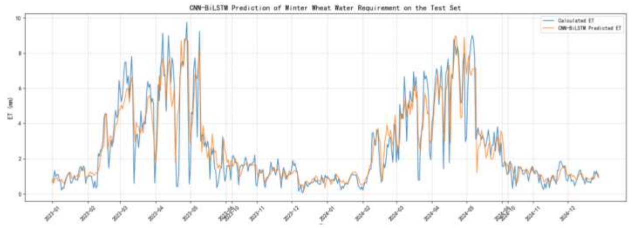

Figure 10. CNN-BiLSTM Prediction Results for Winter Wheat Water Requirements

Table 4. Comparison of Parameters in Prediction Results Across Different Models

Model	R^2	MAE	MSE	RMSE
BP Neural Network	0.7835	0.6695	1.2039	1.0972
LSTM	0.8359	0.5952	0.9126	0.9553
BiLSTM	0.8379	0.6130	0.9012	0.9493
CNN-LSTM	0.8389	0.5805	0.8958	0.9465
CNN-BiLSTM	0.8378	0.5813	0.9018	0.9496
CNN-BiLSTM-Attention	0.8741	0.5282	0.7000	0.8367

As shown in Figures 6–10 and Table 4, the BP neural network model exhibits the poorest predictive performance, while both the LSTM and BiLSTM models demonstrate superior predictive capabilities compared to the BP neural network. After incorporating the Convolutional Neural Network (CNN), the CNN module effectively extracts spatial features from the input data, complementing the time series processing capabilities of LSTM and BiLSTM. Consequently, both the CNN-LSTM and CNN-BiLSTM models outperform the standalone LSTM and BiLSTM models. Furthermore, the CNN-BiLSTM-Attention model, which integrates an attention mechanism into the CNN-BiLSTM framework, demonstrates superior performance metrics across all evaluation metrics compared to the other models. It exhibits enhanced predictive capability specifically for forecasting winter wheat water requirements.

4. Conclusion and Discussion

Water scarcity has become a prominent bottleneck constraining agricultural production in arid and semi-arid regions of northern China. Accurate forecasting of winter wheat water requirements holds significant strategic importance for refined agricultural water resource management, ensuring stable and increased grain production, enhancing quality, and promoting green and sustainable agricultural development. Based on the aforementioned research, the main conclusions are summarized as follows:

(1) The model construction demonstrates advanced capabilities and regional applicability. Using Zhengzhou as a representative region, the study employed the FAO56-PM formula combined with locally adjusted crop coefficients to calculate daily winter wheat water requirements as the benchmark reference values for prediction. Daily meteorological features were used as inputs to construct the CNN-BiLSTM-Attention prediction model. This model effectively integrates the feature extraction capabilities of convolutional neural networks, the temporal dependency capture ability of bidirectional long short-term memory networks, and the reinforcement effect of attention mechanisms on key information, significantly enhancing prediction accuracy and feature learning flexibility.

(2) Model prediction performance has been significantly enhanced. Experimental results demonstrate that the proposed hybrid model excels in forecasting winter wheat water requirements. It accurately captures locally significant features within the time series that substantially influence water demand, while assigning greater weight to key characteristics. This enables highly precise water requirement predictions, providing reliable support for agricultural irrigation decision-making.

(3) Future research directions are clearly defined. Subsequent studies will focus on the following areas: advancing the practical application of the model in real agricultural settings to validate its reliability and utility in precision irrigation practices, thereby providing pathway support for sustainable water resource management; simultaneously, integrating multi-source data to construct a comprehensive driving mechanism, further enhancing prediction accuracy and generalization capabilities.

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