

Article

Short-Term Temperature Prediction of Farmland Microclimate Based on a GABP-Net Model

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Abstract

In response to the challenge of insufficient accuracy in short-term air temperature prediction under severe changes in agricultural microclimate, a hybrid prediction model based on GABP-Net (Gated-Attention and BP Parallel Network) neural network and attention mechanism is proposed. The proposed GABP-Net provides a comprehensive feature fusion framework through two parallel branches: the Gated-Attention branch, built on a GRU followed by multi-head attention, captures local temporal dependencies, with the multi-head attention component adaptively reweighting the GRU outputs across multiple heads to capture diverse temporal patterns; meanwhile, the BP branch, a Backpropagation neural network operating on the flattened input, extracts global contextual features. Their parallel combination enables the model to simultaneously leverage both local dynamics and global representations. Taking 28.2 hectares of farmland in Pingdu, Qingdao as the research object, based on observation data collected every 2 h from September to October 2025, combined with meteorological station measurements and background meteorological prediction data, key meteorological factors such as temperature, radiation, and pressure were selected as input features. The results showed that in the 6-h, 12 h, and 24-h prediction tasks, the model's R^2 reached 0.9654, 0.9759, and 0.9622, respectively. The MAE was 0.95 °C, 0.84 °C, and 1.04 °C, respectively, and the RMSE was ≤ 1.32 °C, significantly better than the single BP (Backpropagation) and GRU (Gated Recurrent Unit) models. Research has shown that this hybrid model effectively improves prediction stability under realistic field conditions with naturally imperfect sensor data and wide temperature variations (overall range 39 °C, maximum diurnal difference 21.6 °C), providing reliable technical support for microclimate regulation in precision agriculture.

Keywords: farmland microclimate; temperature prediction; GABP-Net hybrid model; multi-head attention mechanism



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1. Introduction

In recent years, global climate change has continued to intensify. Unpredictable anomalous changes in local microclimate conditions can affect the growth cycle and quality of crops. Among these factors, air temperature in farmlands serves as the most direct and critical indicator [1]. Either excessively high or low air temperature adversely affects crop growth, as well as the photosynthesis and transpiration rates of crop leaves, thereby hindering crop growth and development and ultimately exerting a direct impact on crop yield and quality [2–4].

Air temperature simulation for microclimates primarily employs the energy balance method, linear regression, and neural network approaches [5]. The energy balance method, a physical modeling approach based on the first law of thermodynamics, enables dynamic simulation of the microclimate temperature field by quantifying the energy exchange between the land surface and the atmosphere. Compared with empirical methods, it is tightly coupled with spatial characteristics, providing more accurate connections between microclimate variations and site features. Studies have shown that combining continuous observations with energy balance calculations can effectively evaluate the impact of different soil and irrigation treatments on water use efficiency. In addition, hybrid models integrating the energy balance method with machine learning algorithms such as random forests have demonstrated high accuracy in predicting key water temperature and evaporation parameters in arid environments, with exceeding 0.94 and low root mean square errors (RMSE) [6,7]. However, the energy balance method involves numerous parameters, resulting in a substantial and complex simulation workload [8–10].

Linear regression is widely applied. Huang Lüwen et al. used multi-year meteorological data of canopy regions, integrated multi-source environmental factors via the Informer architecture and long short-term memory (LSTM) network, and established a canopy regional temperature prediction model. The model achieved a coefficient of determination (R^2) of 0.978, enabling accurate medium- and short-term forecasting of regional meteorological temperatures. Tao Yao et al. constructed temperature estimation models under different weather types using linear regression based on data from Wuyuan tea plantations from March to September 2020. The results showed that the atmospheric temperature estimation model for the tea plantation yielded RMSE of 0.628 °C, a mean absolute error (MAE) of 0.799 °C, and an accuracy of 95.3%. Linear models can effectively correlate meteorological parameters inside and outside facilities under conventional conditions [11–13], yet they lack robustness to complex multi-factor interactions and sudden anomalies, and are prone to systematic prediction deviations triggered by abrupt changes in a single variable [14,15].

Neural networks have been widely applied in microclimate environmental simulation, particularly in time-series prediction tasks. Among these, recurrent neural networks (RNNs) and their improved variants have shown remarkable advantages. Attention-enhanced LSTM models have been applied for greenhouse temperature prediction, achieving high-precision 48-h forecasts with $R^2 \geq 0.95$ and $RMSE \leq 1.34$ °C. Compared with traditional RNN and GRU models, root-mean-square errors were reduced by 37.3–57.6%, and mean absolute percentage errors decreased to a minimum of 4.26% [16]. Machine learning approaches, including Extreme Gradient Boosting (XGBoost), have similarly been applied for high-resolution near-surface air temperature inversion and crop productivity modeling [17]. Enhanced LSTM models optimized using improved particle swarm algorithms have demonstrated reductions in Mean Squared Error (MSE), RMSE, and MAE compared with standard LSTM, with greater error reductions than BP and RNN models [18]. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)-GRU frameworks have been applied to short-term forecasting, achieving $R^2 = 0.791$ and $MAE = 0.053$ in 1-h predictions, with errors reduced by 6.19–56.24% relative to multiple benchmark models [19]. Data-driven predictive control models integrating GRU and LSTM architectures have also been explored for controlled-environment cultivation; GRU-based models reduced temperature–humidity violations by 5% and computation time by 40% compared with LSTM, while maintaining comparable economic performance and crop yield [20].

Previous studies applying neural networks to agricultural microclimate simulation have mostly focused on specific seasons and tended to select periods with stable weather for investigation. Such research usually involves long time spans, low data sampling density, or the deliberate exclusion of extreme weather samples, which prevents the models

from fully demonstrating their microclimate simulation performance across different time scales [15,21–24].

Several studies have demonstrated the challenges neural networks face in meteorological prediction under variable temporal conditions. Overfitting has been identified as a critical bottleneck in ANN(Artificial Neural Network)-based weather forecasting, where models trained on limited temporal samples often fail to generalize—the optimal fitting precision for training data cannot be predetermined, resulting in unstable prediction performance on unseen periods [25]. At extended forecast horizons, deep neural networks for seasonal precipitation prediction achieved a five-year average prediction skill score of 76.0, illustrating the inherent difficulty of maintaining accuracy as the prediction window lengthens [26]. For short-term temperature forecasting, a 1DCNN-LSTM hybrid model was proposed and compared with standalone LSTM, One-Dimensional Convolutional Neural Network (1DCNN), and BP networks. The hybrid approach reduced RMSE by 5.2%, 19.4%, and 9.3%, and MAE by 4.4%, 17.5%, and 8.1%, respectively, demonstrating that fusing complementary architectures can substantially outperform single-branch models [27]. However, existing hybrid models typically employ sequential rather than parallel fusion, which may still constrain the independent preservation of global features. These findings motivate the proposed GABP-Net, Gated-Attention and BP Parallel Network, whose parallel architecture is designed to simultaneously capture local temporal dynamics and global contextual information without mutual interference.

To overcome this shortcoming of neural networks in agricultural microclimate prediction, this paper selects 55-day high-frequency microclimate observation data (recorded at 2-h intervals) from a 28.2-hectare farmland in Pingdu, Qingdao, along with synchronous meteorological data from nearby weather stations. A hybrid prediction model named GABP-Net (Gated-Attention and BP Parallel Network) fusing gated recurrent units (GRU) and backpropagation (BP) branches is proposed. Through multi-branch feature extraction and a dynamic attention fusion mechanism, the model realizes effective modeling of multi-scale features in time series.

Unlike existing serial GRU-Attention hybrids, where attention operates solely on the sequentially processed GRU outputs, the novelty of GABP-Net lies in its parallel architecture: the BP branch independently processes the raw flattened input to extract global features, while the Gated-Attention branch captures local temporal dynamics. These complementary representations are then fused, ensuring that global structural information is preserved for the final prediction. The main contributions of this study are as follows:

1. A parallel hybrid architecture is designed, integrating a Gated-Attention branch for local temporal feature extraction and a BP branch for global contextual representation, enabling complementary learning from the same input sequence.
2. A dynamic attention fusion mechanism is employed to adaptively weight the importance of different historical time steps, enhancing the model's ability to capture multi-scale temporal dependencies.
3. The model is validated on real-world farmland microclimate data with natural sensor imperfections and diverse temperature conditions, demonstrating its practicality for precision agriculture applications.
4. Experimental results across different forecast lengths show that GABP-Net achieves consistently higher accuracy and stability compared to single-branch baseline models.

2. Materials and Methods

2.1. Data Sources

Field observation data were collected from a farmland site located in western Pingdu City, Qingdao, 119.99° E, 36.61° N, covering an area of 28.2 hectares. The site practices

an annual winter wheat-summer maize double-cropping system. Real-time observations were conducted using seven Micro Weather Stations, monitoring ambient temperature and light intensity with measurement accuracies of ± 0.1 °C and $\pm 5\%$, respectively. Deviated data within the same sampling cycle were removed, and averaged values were retained. Data were collected over a 55-day period from September to October, with observations recorded every 2 h. Predictive data were sourced from the Global Forecast System (GFS) provided by the China Weather Network. Meteorological observational data were obtained from The Weather Company, collected via ground-based weather station measurements. These include 24-h temperature forecasts, average temperature, precipitation, wind speed, and wind direction angle.

2.2. Experimental Methods

2.2.1. Selection of Key Influencing Factors

As illustrated in Figure 1, the strength and direction of linear correlation between meteorological variables were quantified using the Pearson correlation coefficient in this study. The correlation coefficients and significance levels between 15 parameters, including temperature, air pressure, humidity, radiation, and meteorological forecast data, were calculated. During the period of 4 September to 30 October 2025, sensors in the study area recorded measured temperature and light intensity, as well as hourly meteorological data from ground weather stations, including temperature, precipitation, wind speed, wind direction angle, air pressure, humidity, visibility, cloud cover, dew point temperature, shortwave radiation, and predicted temperature values for 6, 12, and 24 h.

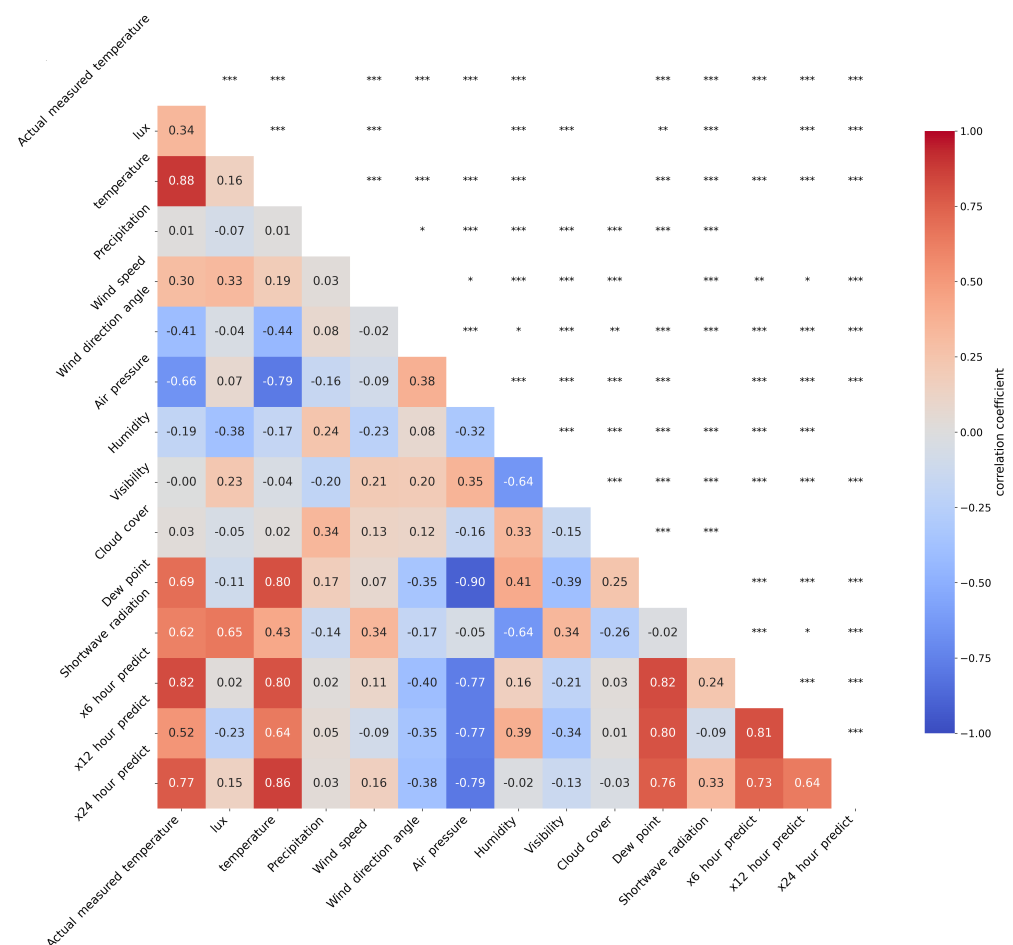


Figure 1. Pearson correlation heatmap of correlation between meteorological elements in Qingdao farmland from September to October 2025. Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Based on the correlation analysis, a threshold of $|r| < 0.1$ was applied for feature selection. Three variables—precipitation, visibility, and cloud cover—were excluded from model input due to their negligible linear correlation with the target temperature. The remaining 12 variables were retained as model inputs. This low threshold was chosen to exclude only variables with virtually no direct linear relationship, while preserving features that may contribute through indirect interactions or nonlinear transformations.

In response to the problem of 0° and 360° abrupt changes in wind direction angles near due north, this study adopts a nonlinear preprocessing method of absolute value transformation after angle halving. This processing effectively eliminates the interruption of linear correlation and numerical oscillation caused by the cyclic characteristics of azimuth angles, enabling the wind direction data that were originally divided into extreme values to achieve numerical continuity after transformation. Although this method sacrifices the ability to identify the east-west wind direction, considering that the research area is affected by the East Asian monsoon during the experimental period, the dominant background wind direction is concentrated in the southeast–northwest quadrant. Therefore, such directional information loss does not have a significant impact on the prediction accuracy of the conclusions of this study.

This time period is a critical agricultural period for planting wheat after corn harvest, and temperature changes directly affect the growth cycle of crops, sowing timing, and core environmental parameters of field management. Its dynamic changes have important guiding significance for various aspects of agricultural production.

2.2.2. Experimental Model

The Backpropagation (BP) neural network is a critical implementation framework of feedforward neural networks. Its core architecture comprises a hierarchical topology of input layer, hidden layers, and output layer, with parameter optimization achieved through the error backpropagation algorithm [24,28]. The model employs nonlinear activation functions such as Sigmoid or ReLU to construct a multilayer perceptron structure. During forward propagation, predictions are computed, and gradients are subsequently backpropagated based on prediction errors using the chain rule to calculate gradients for network parameters layer by layer. The training process utilizes gradient descent optimization algorithms, with MSE or cross-entropy loss functions defining the objective function. Gradients derived from backpropagation iteratively update weights across layers [29,30]. However, the BP neural network training process is prone to getting trapped in local minima, leading to slow convergence or failure to reach global optimal solutions [25]. In the model described in this paper, this module first flattens the input sequence into a $[B, T \times F]$ vector, eliminating temporal dimension constraints. Subsequently, two linear transformations with ReLU activation functions generate a $[B, H]$ global feature representation.

The Gated Recurrent Unit (GRU) neural network, a simplified variant of LSTM, also belongs to the recurrent neural network framework. The GRU integrates the forget gate and input gate into a single update gate, while eliminating independent memory cell structures, significantly reducing model complexity [31]. Its core mechanism employs a reset gate to control the degree of historical state forgetting and an update gate to dynamically regulate the fusion ratio between current inputs and historical information. The final output is a hidden state processed through nonlinear activation. Training still utilizes the Backpropagation Through Time (BPTT) algorithm. However, due to reduced parameters, the GRU generally converges faster than LSTM [32]. In the model described in this paper, this module dynamically filters historical information through the update gate and reset gate mechanisms.

A hybrid neural network model integrating temporal modeling and global feature extraction is proposed. Its core architecture is composed of a 2-layer GRU, a multi-head attention mechanism with 4 heads, a backpropagation branch, and a feature fusion layer. The specific workflow is illustrated in Figure 2. The model input is defined as a temporal feature matrix of shape $[B, T, F]$, where B denotes batch size, T sequence length, and F feature dimension.

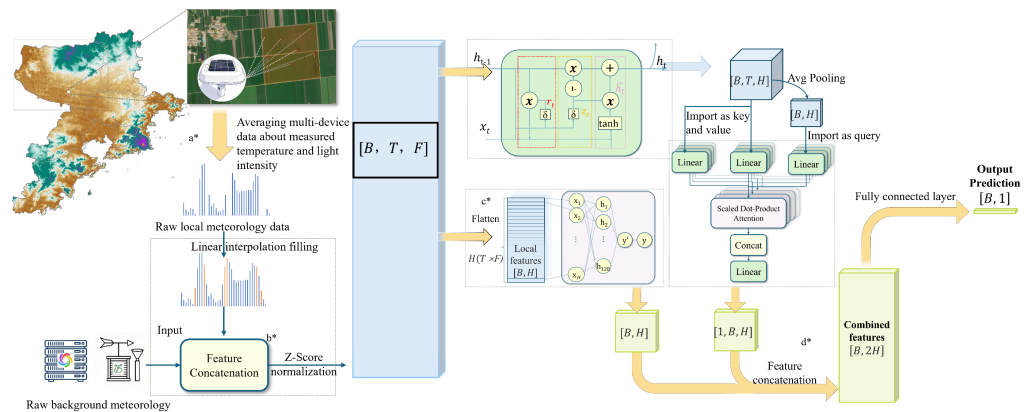


Figure 2. Architecture of the GABP-Net Hybrid Neural Network Farmland Microclimate Prediction Model Based on Multi-Source Data Fusion. Note: The input is a temporal feature matrix of shape $[B, T, F]$, where B denotes batch size, T sequence length, and F feature dimension. a^* : Local farmland observations are collected from field micro-meteorological instruments with multi-device synchronized acquisition, outlier removal, and averaging; background meteorological and forecast data are sourced from The Weather Company and China Weather Network. b^* : Z-Score normalization standardizes all features to a distribution with mean = 0 and standard deviation = 1, eliminating dimensional discrepancies among multi-source data. c^* : In the upper branch, a 2-layer GRU processes the temporal sequence $[B, T, F] \rightarrow [B, T, H]$, followed by 4-head multi-head attention that uses the average-pooled GRU output as Query and the full GRU output as Key and Value, producing an attention context vector $[1, B, H]$. d^* : In the parallel lower branch, a flattening operation converts the raw input $[B, T, F]$ into a global feature vector $[B, T \times F]$, which is mapped through two fully connected layers with ReLU activation to $[B, H]$.

- **Step One: Local Temporal Feature Extraction via GRU Branch**
The input matrix is processed by the GRU branch for local temporal feature extraction. At each time step, the GRU unit processes the input, outputting a hidden state sequence $[B, T, H]$ containing temporal dependencies, where H is the hidden layer dimension. Subsequently, the multi-head attention mechanism uses the average-pooled result of the GRU output as the Query, with shape $[1, B, H]$. The complete GRU output sequence serves as Key and Value, with shape $[T, B, H]$. By calculating the similarity between Query and all Keys and weighting the Values, an attention-weighted context vector is generated, retaining shape $[1, B, H]$.
- **Step Two: Global Feature Extraction via BP Branch**
Simultaneously, the BP branch independently processes the raw input sequence. This branch flattens the 2D temporal matrix $[B, T, F]$ into a global feature vector $[B, T \times F]$, removing temporal dimension constraints. The vector is then mapped through two fully connected layers to generate a $[B, H]$ global feature representation.
- **Step Three: Feature Concatenation and Final Prediction Output**
The attention context vector $[1, B, H]$ and the BP branch global feature $[B, H]$ are concatenated along the feature dimension, expanding the fused feature dimension to $[B, 2H]$. This fused feature retains both local temporal dynamics and global contextual information. After nonlinear mapping through a fully connected layer, the final prediction $[B, 1]$ is output.

2.2.3. Experimental Process

In the dataset, occasional data loss during rare time intervals caused by network fluctuations or device offline events was addressed using linear interpolation (MATLAB R2024a (MathWorks Inc., Natick, MA, USA) interp1 function, default ‘linear’ method). Missing values were estimated and supplemented based on neighboring time points. For denoising, temperature data from multiple co-located sensors were averaged at each time step. Before averaging, individual sensor readings falling outside the physically valid range of [−10 °C, 50 °C] were filtered out as anomalous. These extreme values, typically caused by occasional sensor malfunctions or transient environmental interference, were excluded to prevent distortion of the averaged result. All features were then normalized using Z-Score normalization based on training set statistics. The dataset was split into training, validation, and testing sets using random shuffling rather than chronological division, as each sample represents a fixed-length sliding window treated as an independent input–output pair. Time-series modeling transformed raw data into a supervised learning format via a sliding window mechanism. Input sequence length was defined as a fixed-length time window, and the prediction target was the fixed-step value at the next time point. Standardization parameters and sequence construction logic were encapsulated in independent modules and persistently stored. Details on data partitioning, training configurations, and output settings are summarized in Table 1. The experiment was implemented in Python 3.10.18 (Python Software Foundation, Wilmington, DE, USA), leveraging pandas 2.3.2 and NumPy 2.2.6 (NumFOCUS, Austin, TX, USA) for data preprocessing and numerical calculations, with deep learning models built using PyTorch 2.7.1 (Meta AI, Menlo Park, CA, USA).

Table 1. Model Configuration Parameters.

Category	Parameter/Method	Description
Data Splitting	Training:Validation:Test	7:1.5:1.5
Training Config	Optimizer	Adam
	Learning Rate	0.001
	Loss Function	MSE
	Training Epochs	200
	Early Stopping	Stop if no improvement for 15 epochs
Input Config	Input Sequence Length	3, 6, 12 (each step = 2 h)
	Batch Size	10
	Hidden Layer Dimension	128

Note: Hidden layer dimension was set to 128 after preliminary tests with values of 64 (underfitting) and 256 (no significant improvement but longer training time). Batch size was set to 10 to allow frequent gradient updates given the modest dataset size. Input sequence lengths of 3, 6, and 12 correspond to 6 h, 12 h, and 24 h forecast horizons. Learning rate, optimizer, and loss function follow standard practices for time-series regression. Training epochs were capped at 200 with early stopping (patience = 15) to prevent overfitting.

2.2.4. Evaluation Metric

To assess and compare the model accuracy, the RMSE, MAE, and R^2 were employed as evaluation metrics. RMSE is derived by averaging the squared differences between the true and predicted values and then taking the square root. This metric offers an intuitive measure when true and predicted values share the same order of magnitude, with a smaller RMSE indicating higher average predictive accuracy. MAE is computed by averaging the absolute differences between the true and predicted values, where a lower value corresponds to greater prediction accuracy. R^2 reflects the proportion of variance in the true data explained by the model, representing the ratio of the dispersion of predicted

values relative to the true mean to the dispersion of true values relative to their mean. A value closer to 1 signifies a better model fit. The specific formulas for these metrics are given below:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (1)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (3)$$

Among them, y_i represents the true value of the i sample, $\hat{y}_i$ represents the corresponding predicted value, n is the total number of samples, and $\bar{y}$ represents the average of the true values.

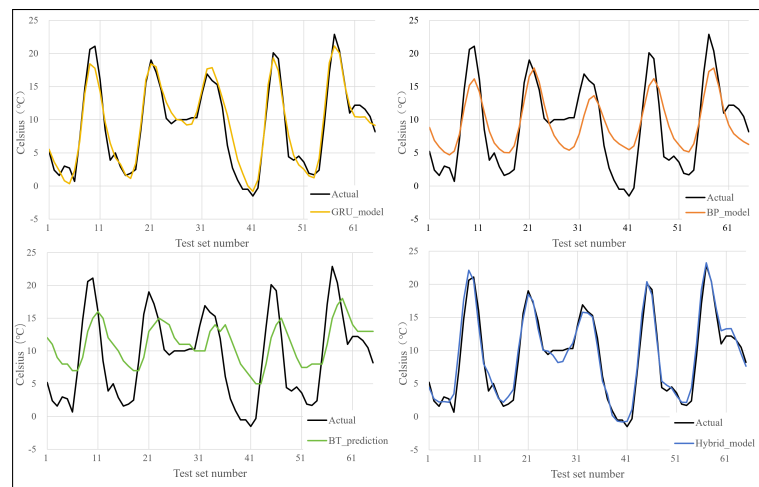
3. Results

Multiple models were compared on a prediction time scale, including background temperature prediction (BT_prediction), BP, GRU and hybrid neural network (hereinafter referred to as Hybrid). From 4 September to 30 October 2025, a portion of the test set data was selected from a crop field in Pingdu City, Qingdao, Shandong Province for generating prediction results. The error comparison chart and the comparison between the measured values and the predicted values of each model are shown in Figure 3, the scatter relationship between the measured data and the predicted values is shown in Figure 4, and the error distribution feature of each model is shown in Figure 5.

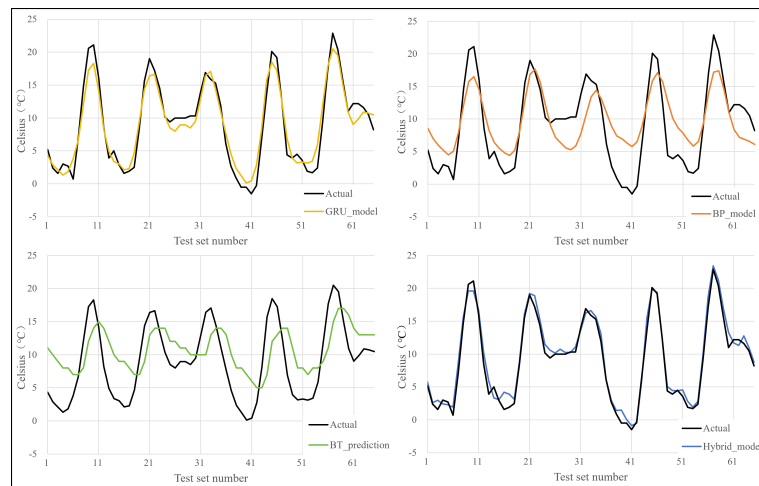
The correlation heatmap reveals a strong negative correlation between air pressure and temperature in Figure 1. This likely reflects the alternating influence of high- and low-pressure systems during the experimental period, where sunny conditions under high pressure contrast with rainy conditions under low pressure at the test site.

As can be seen from Figure 3, for the 6-h forecast horizon, BP shows a peak of 17.27 °C and a valley of 5.61 °C, underestimating rapid rises and overestimating drops, resulting in moderate short-term errors. GRU captures the overall trend well, with a peak-to-valley range of 17.46 °C (18.76–1.30 °C). The BT_prediction provides a baseline trend, with a smaller peak-to-valley range of 9.00 °C (15.00–6.00 °C), smoothing sharp changes and leading to noticeable discrepancies at high and low temperature points. Overall, for the 6-h forecast, the Hybrid model showed the closest alignment with observed values in both timing and magnitude among all models; For the 12-h forecast horizon, deviations between predicted and actual temperatures become more pronounced. The Hybrid model accurately reproduces peaks and valleys with minimal deviation, preserving the general waveform of temperature changes. BP exhibits peaks up to 17.26 °C and valleys down to 5.83 °C, showing underestimation of rapid rises and overestimation of drops. GRU's peak-to-valley range is 15.31 °C (16.48–1.17 °C). BT_prediction shows a peak-to-valley range of 12.00 °C (15.00–3.00 °C), capturing the overall trend but failing to reproduce sharper fluctuations. The Hybrid model maintained the closest alignment with observations, while GRU, BP, and BT_prediction showed larger deviations than at the 6-h horizon; For the 24-h forecast horizon, prediction errors increase across all models due to the extended forecast horizon. The Hybrid model still demonstrates the closest alignment with observed temperatures, with minor deviations in peak magnitude and timing. BP exhibits peaks of 16.66 °C and valleys of 7.26 °C, underestimating high-temperature peaks and overestimating low-temperature valleys. GRU shows a pronounced peak-to-valley range of 19.64 °C (22.55–2.91 °C). BT_prediction captures general trends with a peak-to-valley range of 12.00 °C (17.00–5.00 °C) but fails to represent sharp fluctuations effectively. At the 24-h

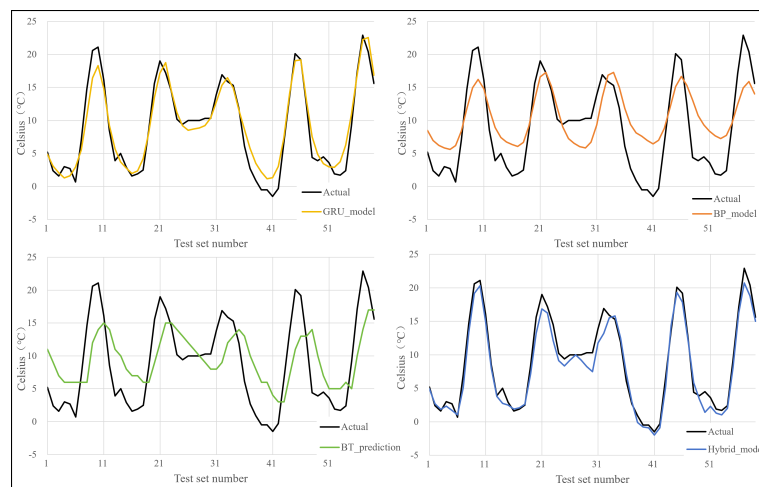
forecast, the Hybrid model maintained the smallest deviation among all models, with GRU showing the largest errors at extreme temperatures.



(a)



(b)



(c)

Figure 3. Line Chart and Error Comparison of Predicted vs. Actual Values for Models in Multi-Timescale Forecasting Tasks. Note: (a), (b), and (c) denote 6 h, 12 h, and 24 h forecasts, respectively.

Figure 4 displays the scatter plots of predicted versus actual temperature values for the Hybrid model, BP_model, GRU_model, and BT_prediction across the 6-h, 12-h, and 24-h forecast horizons. The grey solid line represents the actual value reference line ($y = x$). The linear regression equations and coefficients of determination (R^2) for the Hybrid model are annotated in the upper-left corner of each subplot. For the 6-h forecast, the Hybrid model scatter points cluster tightly along the reference line across the full temperature range, with a regression equation of $y = 0.9683x + 0.569$ and $R^2 = 0.9672$. The BP_model points show moderate dispersion, with predicted values generally lower than the reference line at high actual temperatures (e.g., actual 22.90 °C, predicted 17.30 °C) and higher than the reference line at low actual temperatures (e.g., actual −1.50 °C, predicted 5.46 °C). The GRU_model points exhibit a distribution closer to the reference line than BP_model, with minor deviations at the extremes. The BT_prediction points are concentrated within the 5–15 °C range, showing substantial vertical deviation from the reference line, with predicted values ranging from 5 to 18 °C across all actual temperature values. For the 12-h forecast, deviations from the reference line increase across all models. The Hybrid model maintains the closest clustering along the diagonal, with a regression equation of $y = 0.9774x + 0.7694$ and $R^2 = 0.9825$. The BP_model continues to show under-prediction at high temperatures (e.g., actual 22.90 °C, predicted 17.19 °C) and over-prediction at low temperatures (e.g., actual −1.50 °C, predicted 5.76 °C). The GRU_model points show increased spread compared with the 6-h forecast, particularly at temperatures above 15 °C and below 5 °C. The BT_prediction points remain concentrated within a narrow predicted range (5–17 °C), with deviations from the reference line at both high and low actual temperatures. For the 24-h forecast, the overall dispersion of scatter points further increases. The Hybrid model, while showing some deviation from the diagonal at extreme temperatures, yields a regression equation of $y = 0.9402x - 0.2969$ and $R^2 = 0.9787$. The GRU_model exhibits the widest spread at high temperatures (e.g., actual 20.40 °C, predicted 22.55 °C; actual 22.90 °C, predicted 22.23 °C). The BP_model shows a general downward shift relative to the diagonal, with predicted values consistently below actual values at high temperatures (e.g., actual 20.40 °C, predicted 15.87 °C). The BT_prediction points are primarily distributed within the 3–17 °C predicted range, with large deviations from the reference line at extreme actual temperatures.

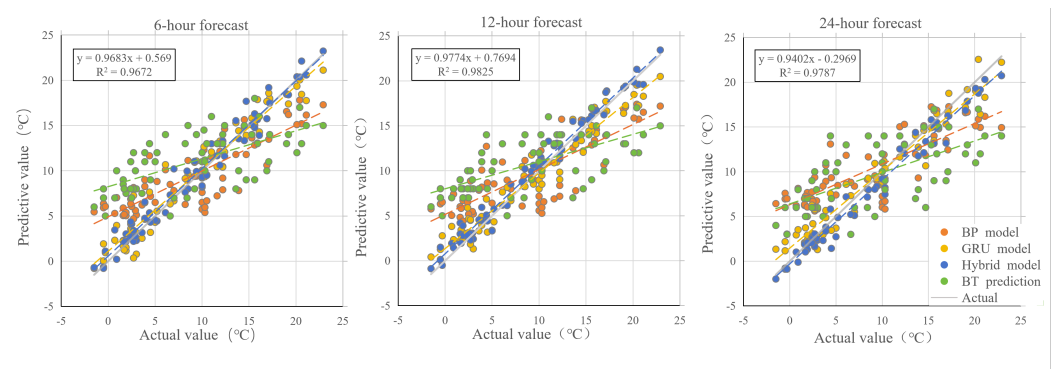


Figure 4. Scatter Plot Comparison of Predicted vs. Actual Values for Models in Multi-Timescale Forecasting Tasks.

Figure 5 displays the histogram comparison of forecast errors for the Hybrid model, BP_model, GRU_model, and BT_prediction across the 6-h, 12-h, and 24-h forecast horizons. The horizontal axis represents the prediction error (°C), and the vertical axis represents the frequency count. For the 6-h forecast, the Hybrid model exhibited the most concentrated error distribution, with errors predominantly within ± 2 °C and a peak frequency of 13 at +0.40 °C. The GRU_model showed a slightly wider spread, with errors mainly between

−3.20 °C and +2.00 °C. The BP_model displayed a broader distribution ranging from −6.00 °C to +8.40 °C, with notable positive skew. The BT_prediction presented the widest error range, extending from −8.00 °C to +9.60 °C, with multiple modes across both positive and negative error bins. For the 12-h forecast, the error distributions broadened across all models. The Hybrid model maintained the narrowest spread, with the highest frequency (11) at −0.80 °C and most errors within ± 2 °C. The GRU_model showed a bimodal distribution with peaks at −1.60 °C (frequency 6) and +0.40 °C (frequency 6). The BP_model exhibited a broader range from −6.00 °C to +9.20 °C, with a visible negative skew. The BT_prediction continued to display the widest dispersion, with errors reaching +7.60 °C and −6.40 °C. For the 24-h forecast, the dispersion further increased for all models. The Hybrid model maintained the most concentrated distribution, with errors largely between −2.00 °C and +2.00 °C and peak frequencies of 7 at both −0.40 °C and 0.00 °C. The GRU_model exhibited a widened range from −3.60 °C to +3.20 °C, with multiple modes. The BP_model showed a pronounced negative skew, with errors extending from −6.00 °C to +9.20 °C. The BT_prediction displayed the largest error range, spanning from −8.80 °C to +7.60 °C, with elevated frequencies at the extreme bins.

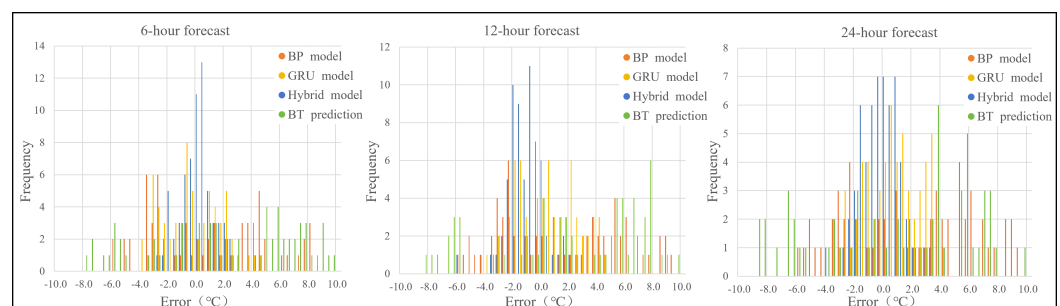


Figure 5. Histogram Comparison of Forecast Errors for Models in Multi-Timescale Temperature Forecasting Tasks.

As presented in Table 2, the hybrid model consistently outperformed the other models across all forecast horizons. In terms of R^2 values, the hybrid model achieved 0.9654, 0.9759, and 0.9622 for 6-h, 12-h, and 24-h predictions, consistently remaining above 0.96. The GRU model ranked second, with R^2 values of 0.9392, 0.9356, and 0.9329, showing relatively small fluctuations but falling 2.8–4.0% below the hybrid model. The BP model exhibited a continuous decline from 0.6514 to 0.5596, explaining only 56–65% of temperature variations, with predictive reliability decreasing significantly as the horizon extended. Horizontal comparisons reveal that the hybrid model outperformed GRU by 2.8%, 4.0%, and 3.0%, and surpassed BP by 48.2%, 58.8%, and 67.9% across the three timeframes. BT_prediction exhibited the lowest R^2 values, ranging from 0.3317 to 0.4086, indicating limited predictive capacity; For MAE, the hybrid model achieved errors of 0.95 °C, 0.84 °C, and 1.04 °C for 6-h, 12-h, and 24-h forecasts, respectively, indicating high predictive accuracy. The GRU model followed with MAE values of 1.27 °C, 1.37 °C, and 1.41 °C, while the BP model showed larger errors increasing from 3.38 °C to 3.96 °C, and BT_prediction displayed the highest errors of 4.60–4.78 °C. Comparatively, the hybrid model reduced MAE by 25–28% relative to GRU and by 72–76% relative to BP across all time horizons; Regarding RMSE, the hybrid model maintained the lowest errors of 1.21 °C, 1.01 °C, and 1.32 °C for 6-h, 12-h, and 24-h forecasts. The GRU model followed with RMSE values of 1.60 °C, 1.65 °C, and 1.76 °C, exhibiting modest increases in mid-term forecasts. The BP model's RMSE increased markedly from 3.84 °C to 4.50 °C, while BT_prediction consistently showed the highest errors (5.22–5.47 °C). Horizontal comparisons demonstrate that the hybrid model reduced RMSE by 24–28% compared to GRU and by 63–75% compared to BP, highlighting its superior stability and predictive performance.

Table 2. Model Performance Comparison of Three Models in Multi-Timescale Forecasting Tasks.

Evaluation Metric	Model	6-h Forecast	12-h Forecast	24-h Forecast
R^2	GABP-Net	0.9654	0.9759	0.9622
	BP	0.6514	0.6147	0.5596
	GRU	0.9392	0.9356	0.9329
	BT_prediction	0.3618	0.3317	0.4086
MAE (°C)	GABP-Net	0.95	0.84	1.04
	BP	3.38	3.51	3.96
	GRU	1.27	1.37	1.41
	BT_prediction	4.78	4.62	4.60
RMSE (°C)	GABP-Net	1.21	1.01	1.32
	BP	3.84	4.04	4.50
	GRU	1.60	1.65	1.76
	BT_prediction	5.47	5.32	5.22

4. Discussion

The predictive performance of neural networks for farmland microclimate was evaluated across 6-h, 12-h, and 24-h forecast horizons. A hybrid model integrating GRU for temporal dependency modeling, multi-head attention for feature interaction optimization, and BP for global feature extraction was established based on extensive meteorological observation data from farmland in Qingdao. As shown in Table 2, the hybrid model consistently outperformed the other models in short-term temperature prediction. Its R^2 values were 0.9654, 0.9759, and 0.9622 for 6-h, 12-h, and 24-h forecasts, respectively, maintaining high predictive reliability (≥ 0.96). The GRU model ranked second with R^2 values of 0.9392, 0.9356, and 0.9329, demonstrating relatively small fluctuations but consistently 2.8–4.0% lower than the hybrid model. In contrast, the BP model exhibited a significant decline in performance over longer horizons, with R^2 decreasing from 0.6514 to 0.5596 and RMSE increasing from 3.84 °C to 4.50 °C, indicating difficulty in capturing nonlinear temporal dependencies. BT_prediction, representing background weather forecast data, exhibited the lowest R^2 (0.3317–0.4086) and highest errors, reflecting its inherent delay in responding to rapid microclimate changes, though it serves as a useful reference baseline. Recent reviews have shown that deep learning models for greenhouse temperature prediction typically achieve R^2 values of 0.96–0.99 and RMSE values of 0.3–1.3 °C [33]. Our GABP-Net falls within this range, confirming its competitiveness with state-of-the-art approaches.

The results also reveal distinct behavioral patterns among the models. GRU captured the overall temperature trend reasonably well but exhibited slightly higher sensitivity with minor overshoot at extremes, particularly at the 24-h horizon where its peak-to-valley range reached 19.64 °C and peak errors were amplified. This behavior likely reflects the gating mechanism's responsiveness to recent temporal changes, which is beneficial for tracking rapid fluctuations but can amplify errors when the prediction horizon extends and the input signal weakens. The relative deterioration of GRU, BP, and BT_prediction as the forecast horizon extended from 6 h to 24 h highlights the challenge of mid- to longer-range prediction using single-branch architectures. The Hybrid model, by contrast, maintained superior stability across all horizons, confirming that the parallel fusion of local temporal and global contextual features effectively addresses this limitation. This finding is consistent with recent studies showing that hybrid architectures generally outperform single-branch models in agricultural time-series forecasting [34–36].

The superior performance of the hybrid model can be attributed to its parallel architecture. Unlike a standalone GRU that relies solely on sequentially processed hidden

states—where global context can be gradually diluted—GABP-Net preserves global structural information through the independent BP branch while the GRU-attention branch captures local temporal dynamics. The multi-head attention mechanism further enhances this by adaptively weighting critical time steps, and the BP branch extracts global patterns that complement the local features. This integrated design enables the hybrid model to adapt to complex and rapidly changing microclimatic conditions in farmland. This parallel design philosophy is supported by emerging work in both agricultural and general time-series forecasting. Some recent reviews on hybrid deep learning models for greenhouse environmental prediction identified parallel architectures as a promising direction for improving robustness [33,37]. In a similar vein, a parallel multi-scale dynamic graph neural network that uses multiple branches to capture complementary temporal characteristics has been proposed, demonstrating that parallel designs effectively enhance prediction stability [38]. This principle has since been extended to agricultural temperature forecasting: an attention-enhanced multi-scale convolutional network with a dendritic architecture has been developed for greenhouse temperature prediction [39], and a dual-branch spatio-temporal network that separately captures short-term fluctuations and long-term dependencies from multisensor data has also been designed [40]. The GABP-Net follows the same principle, with its GRU-attention branch handling local dynamics and its BP branch preserving global context. Microclimate variations are influenced not only by weather but also by local topography, radiation, crop distribution, and soil conditions. Incorporating such factors can further improve model accuracy.

Several limitations of this study should be acknowledged. First, the dataset is limited to a 55-day period (September–October 2025), representing a single agricultural season. Model performance under other seasons, interannual variability, or extreme weather events has not been evaluated. Second, the data were collected from a single site in Pingdu, Qingdao; generalizability to other regions with different microclimatic characteristics remains untested. Third, while 12 meteorological variables were used as inputs, the model does not incorporate additional factors such as soil moisture, crop canopy temperature, or evapotranspiration that may influence microclimate dynamics. Fourth, the current model exhibits a notable decline in prediction accuracy when the forecast horizon extends to 48 h. This performance degradation likely reflects the limits of the learned temporal dependencies over longer intervals, where the predictive signal from historical data weakens and the influence of unobserved external factors increases. Fifth, computational efficiency metrics—such as the number of trainable parameters, training time, and inference latency—were not systematically recorded in this study, as the primary research objective was prediction accuracy rather than lightweight deployment. A quantitative comparison of computational cost between GABP-Net and baseline models is warranted in future work.

Future work will introduce crop height, soil evapotranspiration, and other field parameters into the model. Additionally, to overcome the limitations of external background forecast data, small-scale autonomous numerical weather prediction systems will be deployed to provide more detailed and controllable input parameters.

5. Conclusions

This study presents a hybrid neural network approach for predicting farmland air temperature in a winter wheat–summer maize rotation system in Pingdu, Qingdao. The dataset integrates micro-weather station observations, China Weather Network forecasts, and in-situ measurements from The Weather Company, covering 55 days with 2-h interval observations. The model architecture combines GRU for temporal dependency capture, BP for global feature extraction, and multi-head attention for enhanced feature fusion. Data were

split into training, validation, and testing sets in a 7:1.5:1.5 ratio, with input sequences of 3, 6, and 12 time steps. Evaluation metrics included R^2 , MAE, and RMSE.

The key findings are as follows. The hybrid model achieved R^2 values above 0.96 across all forecast horizons, with MAE ranging from 0.84 °C to 1.04 °C and RMSE from 1.01 °C to 1.32 °C, significantly outperforming standalone GRU and BP models. Its error growth remained moderate, demonstrating superior accuracy and stability, particularly in longer-term forecasts. The results demonstrate that the hybrid model effectively handles complex temporal interactions and nonlinear feature dynamics through its parallel architecture, showing strong potential for short-term temperature prediction in farmland microclimates under the tested conditions. While BT_prediction provides a background reference, its lower R^2 and higher error highlight the limitations of traditional forecast data in capturing rapid microclimate changes.

A key limitation of this study is that the model was validated on a single site in Qingdao over a 55-day period, and prediction accuracy declines notably when the forecast horizon extends to 48 h. Further validation across multiple sites and seasons is warranted to confirm its broader applicability. Future developments will integrate additional crop and soil parameters and deploy mesoscale numerical weather prediction systems to enhance model robustness and operational applicability, further supporting precision agriculture and informed farm management decisions.

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