Theory and Practice of Science and Technology
2026, VOL. 7, NO. 6, 10-15
DOI: 10.47297/taposatWSP2633-456902.20260706

A Study on a Model for Assessing and Predicting Climate Comfort in Chengdu Based on Multi-Source Meteorological Data Fusion and LSTM-FNN

Zijie Liu

School of Computer Science, Sichuan University Jinjiang College, Meishan, Sichuan, 620860, China

ABSTRACT

Climate comfort is a key indicator for measuring urban livability and the tourism experience. This study focuses on Chengdu as the research area and integrates multi-source data—including ground-based meteorological observations, satellite remote sensing data, and radar data—to construct a comprehensive climate comfort assessment model based on the Temperature-Humidity Index (THI), Wind Effect Index (WEI), and Clothing Index (ICL), enabling detailed evaluations on a monthly and seasonal scale. For daily mean temperature, relative humidity, and daily mean wind speed, a combined prediction model (LSTM-FNN) was proposed, consisting of a four-layer Long Short-Term Memory (LSTM) network and a single-hidden-layer feedforward neural network (FNN). The model was trained and tested using daily meteorological data from 2015 to 2023, with Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as evaluation metrics, and compared with LSTM, BiLSTM, and BRNN models. The results indicate that in Chengdu, spring and autumn are "comfortable" or "fairly comfortable," summer is "somewhat uncomfortable," and winter is "uncomfortable"; the RMSE values of the LSTM-FNN for temperature, humidity, and wind speed forecasts were 1.82°C, 5.37%, and 0.41 m/s, respectively, significantly outperforming the comparison models, demonstrating a distinct advantage in multivariate nonlinear fitting. This study provides a quantifiable technical solution for urban climate assessment and forecasting.

KEYWORDS

Climate comfort; Multi-source meteorological data fusion; LSTM-FNN; Chengdu; Time series forecasting

1 Introduction

As urbanization accelerates, climate comfort in Chengdu has drawn increasing attention, and it has become a key factor influencing the quality of life and livability of urban residents. The development of livable, resilient, and smart cities has become a vital goal for contemporary urban construction worldwide. As the capital of Sichuan Province, Chengdu has distinct climatic characteristics, featuring moderate temperatures and humidity, though certain trends of change are also emerging. Chengdu's climatic conditions are jointly influenced by its geographical location, topography, and human activities. Meteorological factors such as temperature, humidity, wind speed, and solar radiation have a direct impact on residents' daily lives, health, and psychological comfort. At the same time, extreme weather phenomena caused by climate change—such as heat waves and torrential rains—may further exacerbate the pressures of urban life and affect the city's ecological environment as well as its socioeconomic development. The integration of multi-source meteorological data—combining satellite remote sensing, weather station data, and meteorological models—can provide more comprehensive and real-time climate information. Through climate comfort assessment models, combined with intelligent analysis technologies such as deep learning and machine learning, valuable patterns and trends can be extracted to comprehensively evaluate the current state of climate comfort in Chengdu and its future trends. This not only helps government and city administrators better understand the impact of climate change on residents' lives but also provides strong support for government decision-making, urban planning, and public health.

Research on climatic comfort has a history of nearly a century. Scholars both domestically and internationally have proposed more than 100 models, including the Temperature-Humidity Index (THI), Wind Effect Index (WEI), Physiologically Equivalent Temperature (PET), Universal Thermal Climate Index (UTCI), and Outdoor Weather Comfort Index (OWCI) [1-3]. In China, extensive research on human climatic comfort has been conducted since the 1980s. Domestic scholars such as Ma Lijun and Liu Qingchun employed expert scoring and the Analytic Hierarchy Process (AHP) to develop a widely used comprehensive climate comfort evaluation model by weighting and integrating the THI, WEI, and the Clothing Index (ICL) [4]; Tan Kaiyan and colleagues, meanwhile, proposed the OWCI model based on China's climatic characteristics [5]. Existing research has largely focused on the evaluation of tourism climate resources or single-point comfort calculations; systematic assessments and future projections specifically for Chengdu remain unexplored.

In the field of meteorological parameter forecasting, machine learning and deep learning methods have been widely applied to the time-series forecasting of temperature, humidity, and wind speed. Tao Ye et al. proposed a Random Forest-based Long Short-Term Memory Network (RF-LSTM), which outperformed Backpropagation (BP) neural networks and Support Vector Machines (SVMs) [6]; Zhang et al. combined Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) to form a CRNN for daily average temperature forecasting [7]; and Dong Zhiqiang combined Dynamic Time Warping (DTW) with LSTM for ultra-short-term wind speed forecasting [8]. However, most existing models rely on univariate or simple multivariate inputs, have limited capabilities for extracting features from multi-source data fusion, and lack the ability to model the nonlinear coupling relationships among meteorological variables. This paper integrates multi-source meteorological data, including ground observations and satellite remote sensing data from Chengdu, to

construct a localized THI-WEI-ICL comprehensive comfort assessment model for evaluating monthly and seasonal comfort levels in Chengdu; At the same time, we propose a prediction model (LSTM-FNN) that combines a four-layer LSTM with a single-hidden-layer FNN. By fully leveraging the temporal memory capabilities of LSTM and the feature integration capabilities of FNN, this model achieves accurate predictions of daily average temperature, relative humidity, and daily average wind speed, providing a scientific basis for urban livability planning and tourism services.

2 Study Area and Data

2.1 Overview of the Study Area

Chengdu (102°54′–104°53′ E, 30°05′–31°26′ N) is located in the western part of the Sichuan Basin at an elevation of approximately 500 m and has a humid subtropical monsoon climate. The long-term average temperature is 16.2°C; the average temperature in the hottest month (July) is 25.6°C, and in the coldest month (January) it is 5.6°C. The annual average relative humidity is approximately 82%; the annual average wind speed is 1.2 m/s; and the annual average sunshine duration is approximately 1,100 hours. The unique topography and climatic conditions result in high sensitivity of human comfort to temperature, humidity, and wind.

2.2 Raw Data

This study collected daily meteorological data covering a total of nine full years, from January 1, 2015, to December 31, 2023. The data sources included ground-based observations, satellite remote sensing, radar observations, and multi-source fusion products. Specifically, ground-based meteorological observation data were obtained from the Wenjiang National Reference Climate Station in Chengdu (station number 56187), including daily average temperature (°C), relative humidity (%), average wind speed (m/s), and hours of sunshine (h); Satellite remote sensing inversion data utilized the total surface solar radiation (W/m^2) derived from the Fengyun-3 (FY-3D) MERSI-II inversion, with a spatial resolution of 0.05° × 0.05°, from which the average values for the Chengdu metropolitan area were extracted; radar data were sourced from the Doppler weather radar network in Chengdu and its surrounding areas, providing precipitation and wind field information; For the gridded fusion products, daily temperature, humidity, and wind speed gridded products (resolution of 0.0625°) from the China Meteorological Administration's Land Surface Data Assimilation System (CLDAS-V2.0) were selected. Through the integration of multi-source data fusion and assimilation techniques, a harmonized dataset describing the meteorological conditions in Chengdu was generated, including key characteristics affecting climate comfort such as temperature, humidity, wind speed, radiation, and sunshine duration.

2.3 Data Preprocessing

To address missing and anomalous values in the raw multi-source meteorological data, this study conducted systematic preprocessing. The proportion of missing daily data from ground stations was approximately 3.2%; linear interpolation was performed using corresponding pixel values from the CLDAS gridded product. The proportion of missing satellite radiation data was approximately 5.7%; these gaps were filled using a three-day moving average method. Outliers were detected based on the 3σ principle, and records with air temperatures >40°C or <−5°C, relative humidity >100% or <10%, and wind speeds >15 m/s were excluded, resulting in the removal of 17 records (accounting for 0.05% of the total data set). For data fusion, the Kalman filter algorithm was used to fuse data from ground-based observation stations with CLDAS grid products. Using the ground-based stations as the observed values and the grid products as the background field, the final temperature, humidity, and wind speed time series were updated on a daily basis. The fusion formula is as follows:

$$X_{fusion} = X_{obs} + K \cdot (X_{grid} - X_{obs}$$

K represents the Kalman gain, which is dynamically adjusted based on observation errors and background errors. The correlation coefficients between the fused data and an independent validation station (Shuangliu Station) reached 0.98 for air temperature, 0.92 for humidity, and 0.85 for wind speed, respectively—significantly outperforming a single data source. Data from 2015 to 2022 (a total of 8 years, accounting for 70% of the dataset, or 2,557 days) was used as the training set, while the entire year of 2023 (accounting for 30%, or 1,095 days) was used as the test set. To eliminate the impact of different units on model training, all features were subjected to Min-Max normalization, linearly mapping them to the interval [0,1]. The final dataset comprises five features: daily mean temperature (T), relative humidity (RH), daily mean wind speed (WS), sunshine duration (SSD), and total solar radiation (SR). Of these, all five features are used for climate comfort assessment, while the prediction model uses daily mean temperature, relative humidity, and daily mean wind speed as direct prediction targets.

3 Research Methods

3.1 Comprehensive Climate Comfort Assessment Model

To date, scholars both in China and abroad have proposed numerous models for evaluating climatic comfort. This paper comprehensively considers various meteorological indicators that influence climatic comfort and adopts the comprehensive climatic comfort model proposed by Ma Lijun et al., which is expressed as follows:

$$C = 0.6X_{THI} + 0.3X_{WEI} + 0.1X_{ICL}$$

C represents the comprehensive comfort index; XTHI, XWEI, and XICL are the normalized values of the temperature-humidity index, wind-effect index, and clothing index, respectively (all normalized to the range of 1–10). The methods for calculating and normalizing each sub-index are as follows:

3.1.1 Thermal Humidity Index (THI)

$$THI = T - 0.55 \times (1 - RH/100) \times (T - 14.4)$$

T represents temperature (°C) and RH represents relative humidity (%). The raw THI values range from 0 to 30 and are mapped in intervals to a scale of 1 to 10, as described in Reference [4] (1 being the least comfortable and 10 being the most comfortable).

3.1.2 Wind Efficiency Index (WEI)

$$WEI = -(10\sqrt{v} + 10.45 - v)(33 - T)$$

Where v is the wind speed (m/s). WEI is a negative value; the larger the absolute value, the less comfortable the wind conditions are. It is empirically normalized in intervals to a range of 1–10.

3.1.3 Clothing Index (ICL)

$$ICL = \frac{33 - T}{0.155 \cdot H} - \frac{v + 2.1}{0.62} \cdot \frac{1 - RH/100}{3.6}$$

H represents the human metabolic rate (set at 58.15 W/m^2 for light activity). The ICL unit is Clo (1 Clo = 0.155 m^2·K/W), normalized to a range of 1–10.

The classification criteria, human perception, symbols, and score assignments for the temperature-humidity index, wind chill index, and clothing index are shown in Table 1. The criteria for the comprehensive comfort rating are as follows: C ∈ [7, 9] indicates comfort, [5, 7) indicates relatively comfortable, [3, 5) indicates relatively uncomfortable, and [1, 3) indicates uncomfortable.

Table 1 Classification Standards for the Temperature-Humidity Index, Wind-Cold Index, and Clothing Index

THI		WCI		ICL		Symbols and Assignments	
Scope	People's Perceptions	Scope	People's Perceptions	Scope	Clothing	Level	Assignment
<40	Extremely cold and very uncomfortable	⩽-1000	Strong cold wind	＞2.5	Various Winter Wool Sweaters	e	1
40~45	Cold, uncomfortable	-800~-1000	Cold Wind	1.8~2.5	Everyday casual clothes paired with a sturdy jacket	d	3
45~55	A bit chilly, not very comfortable	-600~-800	A slight chill in the wind	1.5~1.8	Traditional Winter Clothing	c	5
55~60	Cool and comfortable	-300~-600	Cool Breeze	1.3~1.5	Casual attire that includes a cotton jacket	b	7
60~65	Cool—very comfortable	-200~-300	A Gentle Breeze	0.7~1.3	Casual Outfits That Include a Shirt	A	9
65~70	Warm, comfortable	-50~-200	Warm Breeze	0.5~0.7	Lightweight Summer Clothing	B	7
70~75	A bit warm, but quite comfortable	+80~-50	Light breeze	0.3~0.5	Short-Sleeved Cardigan	C	5
75~80	Stuffy and uncomfortable	+160~+80	Hot breeze	0.1~0.3	Tropical Attire	D	3
>80	Extremely stuffy and uncomfortable	⩾+160	Sensitive to Wind	＜0.1	Mini Skirt	E	1

3.2 LSTM-FNN Hybrid Forecasting Model

3.2.1 Model Design

Meteorological time series exhibit significant long-term dependence and multivariate nonlinear interactions. Taking Chengdu as an example, meteorological variables such as daily average temperature, relative humidity, and wind speed are not only influenced by long-term trends such as seasonal cycles and weather processes but also exhibit strong inter-daily autocorrelation; simultaneously, complex nonlinear coupling relationships exist between temperature and humidity, as well as between wind speed and temperature. These characteristics make it difficult for a single forecasting model to fully extract the underlying information from multi-source meteorological data.

Long Short-Term Memory (LSTM) networks, by introducing forget gates, input gates, output gates, and memory cells, can effectively capture long-term dependencies in time series and mitigate the vanishing or exploding gradients issues inherent in traditional RNNs; therefore, they possess a natural advantage in the time-series modeling of meteorological variables. However, the core mechanism of LSTM focuses on information propagation along the temporal dimension and lacks the explicit feature fusion capability required for nonlinear interactions between different features (such as air temperature, humidity, and wind speed). It often relies on subsequent fully connected layers for simple linear combinations, making it difficult to fully extract the deep coupling features among multiple variables. Feedforward neural networks (FNNs) possess general-purpose function approximation capabilities and can, in theory, fit any nonlinear mapping relationship; they are particularly adept at nonlinearly reorganizing and integrating high-dimensional input features. However, FNNs themselves lack the ability to process sequential data; directly flattening the raw time-series data for input results in the loss of temporal order information, leading to a decline in predictive performance.

This paper proposes a serially combined LSTM-FNN architecture. A four-layer stacked LSTM is used to extract deep temporal features from multivariate time series data via sliding windows, compressing high-dimensional temporal

information into hidden state vectors rich in contextual dependencies; This vector is then fed into a single-hidden-layer FNN, which leverages the FNN's powerful nonlinear mapping capabilities to remap and reorganize the LSTM output, thereby enhancing the model's ability to capture the nonlinear couplings among multiple meteorological variables. The model ultimately outputs daily forecasts for air temperature, humidity, and wind speed.

3.2.2 Model Construction

Based on the model design described above, this paper constructed a serial-combined LSTM-FNN prediction model, as shown in Figure 1. The specific construction steps are as follows:

Step 1: Input layer design. A sliding window technique is used to construct the input samples, with a window length set to 7 days. Specifically, five meteorological features—the daily average temperature, relative humidity, daily average wind speed, hours of sunshine, and total solar radiation from the past seven consecutive days—are used to predict the daily average temperature, relative humidity, and daily average wind speed for the eighth day. The sliding window converts continuous time-series data into supervised learning samples while preserving short-term dependencies among variables.

Step 2: Stacking LSTM Layers. Four LSTM layers were configured, with the number of units per layer set to 64, 128, 128, and 64, respectively. The activation function was set to tanh, and the dropout rate was 0.2 for all layers. A hierarchical structure from low to high was adopted: the first two layers (64 and 128) extract low-level time-series patterns (such as diurnal variations and weather trend processes), while the latter two layers (128 and 64) further abstract high-dimensional time-series features. For the first three layers, `return_sequences=True` is set to pass the complete sequence to the next layer and maintain the flow of temporal information; for the last layer, `return_sequences=False` is set to return only the hidden state at the final time step, compressing the information from the entire time window into a feature vector of fixed dimension. The stacked structure enhances the model's ability to represent long-term dependencies, while dropout regularization effectively suppresses overfitting.

Step 3: FNN Layer Integration. A single-hidden-layer FNN is added, with 32 neurons and the ReLU activation function. This layer receives the feature vector output by the LSTM and reorganizes information across dimensions through nonlinear transformations, enhancing the model's ability to capture the complex coupling relationships among temperature, humidity, and wind speed. The sparse activation characteristics of the ReLU function help mitigate gradient vanishing and accelerate convergence.

Step 4: Output Layer Configuration. A fully connected output layer is connected, with 3 neurons corresponding to the predicted values for temperature, humidity, and wind speed, respectively. No activation function is set (linear regression) to ensure the output range is unrestricted.

Step 5: Training Configuration. The loss function is Mean Squared Error (MSE), and the optimizer is Adam, with an initial learning rate of 0.001 and exponential decay (coefficient 0.9). The batch size is set to 32, the number of training epochs to 200, and early stopping is implemented (patience=15), meaning training is terminated early if the validation set loss does not decrease for 15 consecutive epochs to prevent overfitting.

In this paper, for the Chengdu daily average temperature, relative humidity, and daily average wind speed datasets, the first 70% of the data is used as the training set, and the remaining 30% as the test set. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are calculated by comparing the predicted values with the actual values.

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

4 Experimental Results and Analysis

4.1 Results of the Climate Comfort Assessment for Chengdu

Based on the fused daily data from 2015 to 2023, the monthly and seasonal average comprehensive comfort index C was calculated. The specific results are shown in Table 1 and Figure 1.

Seasonal statistics show that in spring (March–May), the average comprehensive comfort index C was 6.17, classified as "fairly comfortable"; in summer (June–August), the average C was 5.90, also classified as "fairly comfortable," although the index for July was close to the threshold (5.0) for the "fairly comfortable" range; In autumn (September–November), the average C was 5.87, also falling into the "fairly comfortable" category; whereas in winter (December–February), the average C was only 2.50, classified as "uncomfortable."

The most comfortable months in Chengdu are May and September (C > 7), primarily due to moderate temperatures (21–22°C) and relatively low humidity (70%–78%). Although temperatures are higher in summer, high humidity and low wind speeds create a noticeable feeling of stifling heat, reducing comfort levels. In winter, low temperatures combined with high humidity result in a chilly, damp sensation, making it the least comfortable season. These findings align with the subjective experiences of Chengdu residents.

Table 1 Monthly and Seasonal Average Comprehensive Comfort Index for Chengdu (Average Values for 2015–2023)

Month	Average Temperature(℃)	Relative Humidity(%)	Wind Speed(m/s)	Composite IndexC	Comfort Level
January	5.6	83	1.1	2.3	Uncomfortable
February	7.8	80	1.2	3.1	Less comfortable
March	11.5	76	1.3	4.8	Less comfortable
April	16.8	72	1.4	6.2	More comfortable
May	21.2	70	1.3	7.5	Comfortable
June	24.5	75	1.2	6.8	More comfortable
July	25.6	82	1.1	5.3	More comfortable
August	25.1	80	1.1	5.6	More comfortable
September	21.3	78	1.2	7.2	Comfortable
October	16.5	79	1.1	6.5	More comfortable
November	11.8	81	1.1	3.9	Less comfortable
December	6.2	84	1.0	2.1	Uncomfortable

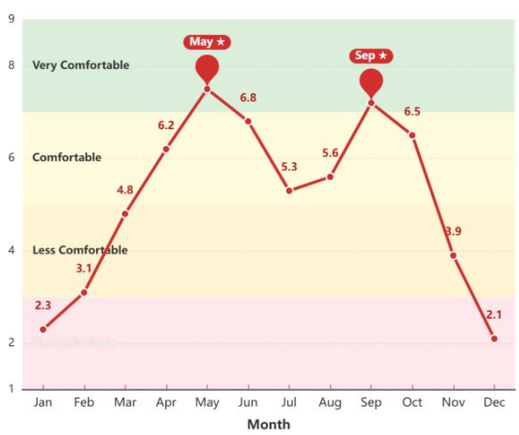


Figure 1 Monthly and Seasonal Average Comprehensive Comfort Index for Chengdu (2015–2023 Average)

4.2 Results of Meteorological Indicator Forecasts

4.2.1 Performance Comparison

We compared the performance of the algorithm described in this paper with that of the commonly used original LSTM, original BiLSTM, and original bidirectional recurrent neural network (Bi-directional RNN, BRNN). Table 2 shows the prediction errors for daily average temperature, relative humidity, and daily average wind speed for each model on the 2023 test set (1,095 samples).

Table 2 Comparison of Prediction Errors Across Models (Test Set)

Model	Temperature RMSE(℃)	Temperature MAE(℃)	Humidity RMSE(%)	Humidity MAE(%)	Wind Speed RMSE(m/s)	Wind Speed MAE(m/s)
LSTM	2.54	1.98	7.82	5.96	0.63	0.48
BiLSTM	2.31	1.75	7.15	5.43	0.58	0.44
BRNN	2.43	1.87	7.43	5.67	0.61	0.46
LSTM-FNN	1.82	1.41	5.37	4.02	0.41	0.31

The results show that LSTM-FNN achieved the best performance across all three prediction targets. Compared with the original LSTM, the RMSE for temperature was reduced by 28.3%, the RMSE for humidity by 31.3%, and the RMSE for wind speed by 34.9%. Although BiLSTM and BRNN utilize bidirectional information, they lack the ability to integrate nonlinear features, and their performance falls between that of LSTM and LSTM-FNN.

4.2.2 Detailed Analysis of Temperature Forecasts

Figure 2 shows a comparison of daily temperature forecasts for July 2023 (a typical summer month) and January 2023 (a typical winter month). LSTM-FNN accurately captured both high- and low-temperature events, particularly the peak of the heatwave in mid-July—a five-day stretch with temperatures above 35°C (actual: 36.2°C; forecast: 35.8°C)—whereas LSTM underestimated the temperature by 4.2°C. In winter, all three models tracked temperature changes well, but LSTM-FNN responded more quickly at the inflection point of the temperature drop. For LSTM-FNN, 68.2% of samples had a prediction error of ⩽1°C, and 89.5% had an error of ⩽2°C; for LSTM, these proportions were 51.3% and 74.6%, respectively. The primary sources of error were days with the passage of strong cold air (24-hour temperature drop >8°C) and days with frontal precipitation.

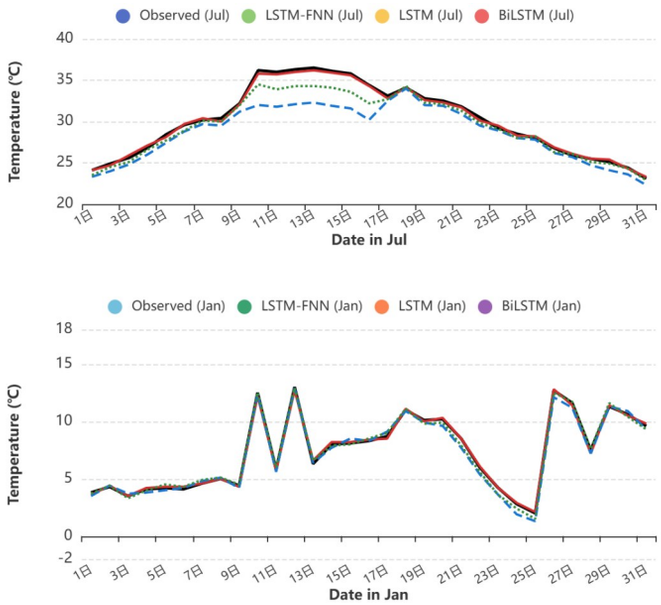


Figure 2 Comparison of Daily Temperature Forecasts for July 2023 (Summer) and January 2023 (Winter)

4.2.3 Analysis of Humidity and Wind Speed Predictions

Relative humidity prediction is the most challenging of the three variables due to its high volatility and significant influence from local evaporation and precipitation. The LSTM-FNN achieved an MAE of 4.02% on the test set, outperforming the LSTM's 5.96%. Typical errors occurred following rainfall events: humidity on the day after rainfall is typically close to saturation (above 95%), but the model's predicted values ranged from approximately 88% to 92%, which were slightly low. Incorporating a precipitation factor (which may be considered in the future) is expected to improve these results.

Regarding wind speed forecasting, the daily average wind speed in Chengdu is generally low (1.0–1.5 m/s), but strong winds exceeding 5 m/s occasionally occur. The LSTM-FNN successfully predicted a thunderstorm-induced strong wind event on August 2, 2023 (actual 5.2 m/s, predicted 4.9 m/s), whereas the LSTM predicted only 2.1 m/s.

5 Conclusions and Outlook

A comprehensive comfort assessment based on the fusion of multi-source meteorological data indicates that Chengdu is rated as "comfortable" (C > 7) in May and September, "uncomfortable" (C < 3) in winter, and generally comfortable in spring and autumn. The proposed four-layer LSTM-FNN hybrid model significantly outperformed LSTM, BiLSTM, and BRNN in forecasting daily mean temperature, relative humidity, and daily mean wind speed. The RMSE for temperature was reduced to 1.82 °C, the RMSE for humidity to 5.37%, and the RMSE for wind speed to 0.41 m/s, validating the effectiveness of the nonlinear integration provided by the FNN layers. This study has established an integrated "assessment-forecasting" technical workflow that can be extended to cities with similar climate types in the southwestern region. In the future, we plan to further incorporate spatial information such as satellite cloud imagery and radar reflectivity to construct a ConvLSTM model, apply transfer learning to data-scarce regions, and develop a WebGIS platform for real-time dynamic visualization and early warning to support public health and tourism decision-making.

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