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An Improved iTransformer with RevIN and SSA for Greenhouse Soil Temperature Prediction

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Abstract: In contemporary agricultural practices, greenhouses serve as a critical component of infrastructure, where soil temperature plays a vital role in enhancing pest management and regulating crop growth. However, achieving precise greenhouse environmental control continues to pose a significant challenge. In this context, the present study proposes ReSSA-iTransformer, an advanced predictive model engineered to accurately forecast soil temperatures within greenhouses across diverse temporal scales, encompassing both long-term and short-term horizons. This model capitalizes on the iTransformer time-series forecasting framework and integrates Singular Spectrum Analysis (SSA) to decompose environmental variables, thereby augmenting the extraction of pivotal features, such as soil temperature. Furthermore, to mitigate the prevalent distribution shift issues inherent in time-series data, Reversible Instance Normalization (RevIN) is incorporated within the model architecture. ReSSA-iTransformer is adept at executing multi-step forecasts for both extended and immediate future intervals, thereby offering comprehensive predictive capabilities. Empirical evaluations substantiate that ReSSA-iTransformer surpasses conventional models, including LSTM, Informer, and Autoformer, across all assessed metrics. Specifically, it attained R^2 coefficients of 98.51%, 97.03%, 97.26%, and 94.83%, alongside MAE values of 0.271, 0.501, 0.648, and 1.633 for predictions at 3 h, 6 h, 24 h, and 48 h intervals, respectively. These results highlight the model's superior accuracy and robustness. Ultimately, ReSSA-iTransformer not only provides dependable soil temperature forecasts but also delivers actionable insights, thereby facilitating enhanced greenhouse management practices.

Keywords: time-series prediction; iTransformer; singular spectrum analysis; reversible instance normalization; greenhouse control

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1. Introduction

Severe climate change, coupled with a rapidly expanding global population, presents significant challenges to the sustainability of agricultural systems [1]. Increasingly frequent extreme weather events and rising food demand necessitate more resilient and efficient production strategies. Agricultural production is particularly susceptible to environmental fluctuations [2]. Facility agriculture, equipped with intelligent control systems, can maintain optimal growing environments year-round, thus improving yields, resource utilization, and environmental sustainability. These controlled conditions also expand viable cultivation areas and reduce geographical constraints. Advanced predictive models further enhance facility agriculture by providing scientific decision support, accurate early warnings, and precise automation of the production environment [3]. As a result, the development of robust predictive models is urgently needed to ensure future food security and sustainable agricultural practices.

Greenhouses create controlled microclimates conducive to crop growth by integrating various regulatory measures. However, their climate is inherently complex, shaped by external weather conditions, internal management strategies, and numerous interdependent parameters that interact nonlinearly. Traditional predictive models typically use system dynamics or material flow transfer methods to forecast environmental changes [4]. Among these factors, maintaining optimal soil temperature and moisture is crucial for greenhouse production [5]. These conditions influence nutrient distribution, soil fertility, microbial activity, and plant development, directly impacting yield and profitability. Accurate soil-condition predictions further enhance irrigation efficiency and resource utilization [6].

Cucumbers are sensitive to fluctuations in soil temperature due to their relatively large leaf area and shallow root distribution. In greenhouse cultivation, maintaining an optimal soil temperature is crucial for fostering a robust root system, enhancing mineral and water absorption, and improving the overall vitality of the plant [7]. When soil temperatures are maintained within the range of 20–25 °C, the growth rate of cucumber roots and the level of enzymatic activity are optimized [8], which in turn enhances the photosynthetic rate and assimilate accumulation in the aboveground parts, ultimately improving fruit yield and quality [9]. Conversely, excessively low temperatures can inhibit the activity of root-related enzymes; reduce nutrient absorption efficiency; and lead to typical stress symptoms, such as leaf wilting and curling. On the other hand, excessively high temperatures can accelerate root respiration and increase transpiration rates, making cucumbers more susceptible to water deficiency. This can result in problems such as fruit deformity or elevated levels of bitter compounds [10–12]. The internal greenhouse soil temperature and air temperature reflect a complex interplay of external conditions, internal materials, and historical environmental patterns [13]. Recent machine-learning approaches have capitalized on historical time-series data to model these intricate dynamics with increasing accuracy. For example, Li et al. [14]. employed an extreme gradient-boosting algorithm to predict greenhouse temperature and humidity, subsequently informing greenhouse film-rolling decisions. Zhao et al. [15]. integrated convolutional neural networks (CNNs) with gated recurrent units (GRUs), improving temperature and humidity forecasts beyond what conventional backpropagation (BP) neural networks, long short-term memory (LSTM) networks, or standalone GRUs could achieve. Jung et al. [16]. combined recurrent neural networks (RNNs) with LSTMs to mitigate gradient explosion issues, outperforming artificial neural networks (ANNs) and nonlinear autoregressive exogenous (NARX) models, though the resulting model remained complex and less effective for humidity prediction. T. Petrakis et al. [17]. proposed a multilayer perceptron (MLP) model to estimate indoor temperature and relative humidity of the greenhouse climate. Vyas et al. [18]. introduced a semi-supervised dynamic graph neural network for soil moisture prediction, demonstrating robustness to missing data and strong performance on real-world datasets. As variants of the Transformer architecture, Informer, Autoformer and iTransformer have demonstrated strong performance across various fields. Informer introduces a probabilistic sparse attention mechanism to address the high computational cost associated with self-attention, thereby enhancing the predictive accuracy of long-sequence time series. Autoformer, on the other hand, models trend components through moving averages in seasonal trend decomposition, effectively separating the changing trend and seasonal components from the hidden variables. It alternates between optimizing prediction results and decomposing the sequence, achieving mutual reinforcement in the process. Without modifying the original components, iTransformer redesigns the architecture to enhance its timing-prediction performance. However, a single prediction model still has certain limitations. When confronted with short-period time-series data, these models often struggle to effectively capture the sequence characteristics, making them susceptible to overfitting during training.

Although these methodologies demonstrate proficiency in accurately predicting short-term temperatures, they often encounter difficulties in multi-step temperature forecasting. Specifically, they perform well in predicting a singular instance but face challenges in forecasting temperatures at multiple distinct time intervals [19]. Furthermore, there exist inherent limitations in the relationship between the volume of data and the implementation of algorithms. Many forecasting techniques depend on sparse data points, which may be inadequate for short-term or precise predictions. The temporal characteristics of changes in greenhouse soil temperature are evident, and the internal climate of a greenhouse differs significantly from traditional meteorological forecasts. This is because both air and soil temperatures are greatly influenced by complex environmental factors and structural properties [20]. Relying solely on simple variables, such as temperature, for forecasting cannot adequately account for the temperature fluctuations caused by multiple interacting variables.

This study examines the limitations of current time-series forecasting models in the context of multivariate long-term forecasting. We propose an iTransformer time-series forecasting model that combines singular spectrum analysis (SSA) [21] with reversible instance normalization (RevIN) [22], referred to as ReSSA-iTransformer. The model aims to deliver more accurate forecasts for variables such as soil temperature in cucumber greenhouses. The main contributions of this study are summarized as follows:

- The environmental-factor data obtained from the cucumber greenhouse are analyzed using SSA to decompose the greenhouse soil-temperature data, in conjunction with strongly correlated predictive variables, into subsequences. This methodology enhances the significance of features within the predictive model, thereby facilitating a more precise representation of the characteristics and trends present in the time-series data.
- The ReSSA-iTransformer greenhouse soil temperature prediction model is the first to integrate the SSA and RevIN methods within the iTransformer prediction framework, enabling both long- and short-term multi-step predictions of greenhouse soil temperature. In this model, subsequences derived from the SSA decomposition serve as the input for the prediction process. To address the distribution shift problem in the model's prediction results, RevIN technology is employed, enhancing the overall prediction performance.
- Comprehensive experiments validate the effectiveness of the SSA decomposition algorithm in time-series prediction models through comparative testing. The model developed in this study demonstrates superior performance compared to traditional models in predicting soil temperature in cucumber greenhouses across various forecasting-time horizons.

The remainder of this paper is organized as follows: Section 2 introduces the materials and methods, including data collection, dataset preprocessing, and the algorithms employed in this study. Section 3 presents the experiments and result analysis, which includes numerous experiments. Finally, Sections 4 and 5 provide an analysis and summary of the findings in this study.

2. Materials and Methods

2.1. Dataset Construction and Preprocessing Process

2.1.1. Greenhouse Environment Dataset Construction

The cultivation environment of cucumbers is a critical factor influencing the quality of production, as it directly affects their growth cycle, susceptibility to diseases, and overall yield. To enhance the production quality of greenhouse cucumbers, it is imperative to analyze the environmental variables that affect cucumber growth and implement appropriate measures to regulate the greenhouse conditions. Establishing optimal growing conditions and mitigating the spread of diseases caused by adverse environmental factors will contribute to improved production quality.

In order to accurately predict soil temperature within the cucumber greenhouse, key environmental parameters were collected from a greenhouse situated at the No. 7 planting shed of the National Precision Agriculture Research Demonstration Base in Changping District, Beijing. The experimental greenhouse is designed as a solar greenhouse, measuring 30 × 7.5 × 3 m, and is utilized for the cultivation of two cucumber crops. The overall configuration is illustrated in Figure 1. To more accurately represent the climate-change characteristics within the greenhouse, the sensor was positioned in the central area of the room, at a height of 1.5 m from the ground, 15 m from both the front and back of the greenhouse, and 3.75 m from each side. The environmental dataset for the cucumber greenhouse developed in this study encompasses data on soil temperature, soil moisture, air temperature, air humidity, light intensity, outdoor evapotranspiration, and soil salinity. All data were collected from NX-XLB01 Green Cloud Greenhouse Environmental Monitoring Equipment(Beijing Academy of Agricultural and Forestry Sciences Information Technology Research Center, Beijing, China). A total of 17,570 data items were collected at 10-min intervals, as presented in Table 1.

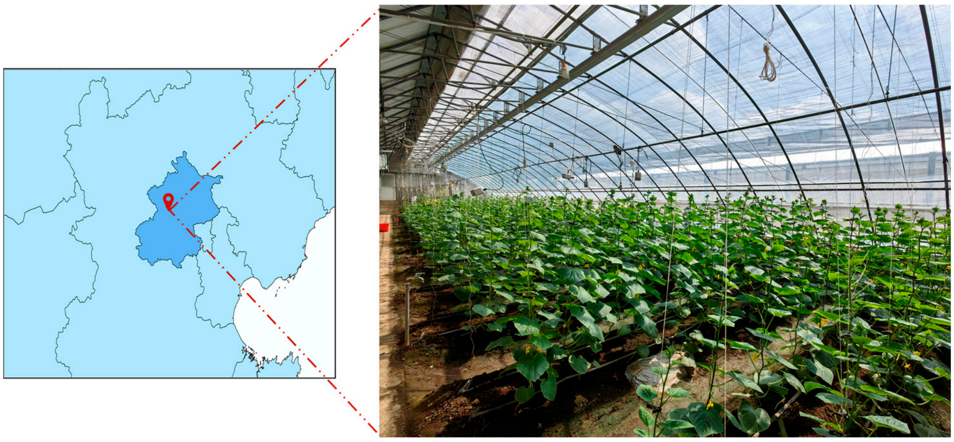

Figure 1. Overall situation of the experimental greenhouse.

Table 1. Main data collected in cucumber greenhouse.

Acquisition Parameters	ParameterUnit	Measuring Range	Accuracy	Resolution	Data Cycle
Soil temperature	°C	−50~80	±0.5 °C	0.1 °C	10 min
Soil moisture	RH	0~100%	±3%RH	0.1% RH	10 min
Air temperature	°C	−40~60	±0.5 °C	0.1 °C	10 min
Air humidity	RH	0~100%	±3%RH	0.1% RH	10 min
Light intensity	Lux	0~56,500	±5%	0.1 Lux	10 min
Salt content	mg/L	0~10,000	±10%	0.1 mg/L	10 min
Evapotranspiration	mm	0–200	±5%	0.001 mm	10 min

2.1.2. Experimental Data Preprocessing

When training a model, the presence of numerous outliers and missing values in the training data can impede the model's ability to learn robust time-dependent features. The model may focus excessively on these anomalies, which can introduce unnecessary complexity during the training iterations. Sensor limitations, manual greenhouse operations, and extreme weather conditions can lead to missing or anomalous data, posing challenges in building reliable cucumber greenhouse datasets. Unstable sensor networks and packet loss further exacerbate these issues by causing short-term omissions in environmental parameters. To ensure robust predictive models, it is crucial to preprocess the collected data, removing parameters with substantial missing values and eliminating outliers that deviate significantly from expected ranges. This approach preserves data integrity and enhances model performance.

The data-preparation phase encompasses two primary steps: outlier removal and missing value imputation. Outliers are defined as non-positive values and are excluded from the dataset. Missing values are addressed through various interpolation methods, contingent upon their position within the data sequence. It is a widely accepted practice to impute missing values between two valid data points through the method of linear interpolation. In instances where a sequence exhibits missing values at the beginning, the first valid downstream value is employed for imputation. Conversely, if the series contains missing values at the end, the first valid upstream value is utilized for this purpose. In experiments, the dataset is divided into training, validation, and test sets in a 7:1:2 ratio.

2.2. iTransformer

The iTransformer represents a variant of the Transformer framework, specifically designed to address the challenges encountered by autoregressive models when generating sequences in reverse order [23]. This innovative time-series prediction model enhances performance by overcoming the limitations of traditional Transformers, particularly in managing large-scale backtracking windows and conventional embedding strategies. As illustrated in Figure 2, the traditional Transformer model fails to adequately represent the intrinsic correlations among variables at the same time step within a time series. In contrast, the iTransformer adopts an inverted perspective of the time series, mapping each time series to a variable label. This approach enables the model to not only focus on temporal dependencies but also to effectively capture the inter-variable correlations. By employing a self-attention mechanism on the variable tokens, the iTransformer adeptly extracts dependencies across multiple variables. This methodology is particularly advantageous for multivariate time series, where the intricate interconnections between variables often pose challenges for traditional Transformers. Moreover, the iTransformer mitigates the high computational costs typically associated with extended backtracking windows. In conventional Transformers, increasing the backtracking window often results in diminished performance and heightened computational demands. The iTransformer addresses this concern by reengineering the attention and feedforward network components, thereby reducing the complexity of the attention mechanism to a linear scale, which efficiently accommodates longer backtracking windows [24]. The architecture of the iTransformer proficiently resolves the task of generating output sequences in reverse order, offering tailored solutions for specific sequence generation requirements. Initially, the entire sequence of a given variable is transformed by the iTransformer into variable tokens, which generate feature vectors that encapsulate the variable and independently reflect its historical changes. Subsequently, the attention module identifies the correlations among multiple variables, while the feedforward network encodes historical observation features layer by layer along the temporal dimension, mapping these features to future prediction outcomes.

The variation in greenhouse soil temperature exhibits a short periodicity and is significantly influenced by diurnal meteorological conditions. The iTransformer model is capable of mapping the time-series characteristics of each influencing factor to a uniform variable label within the time-series analysis of the dataset utilized in this study. This approach effectively captures the interrelationships among variables, thereby enhancing the predictive accuracy regarding trends in greenhouse soil temperature changes.

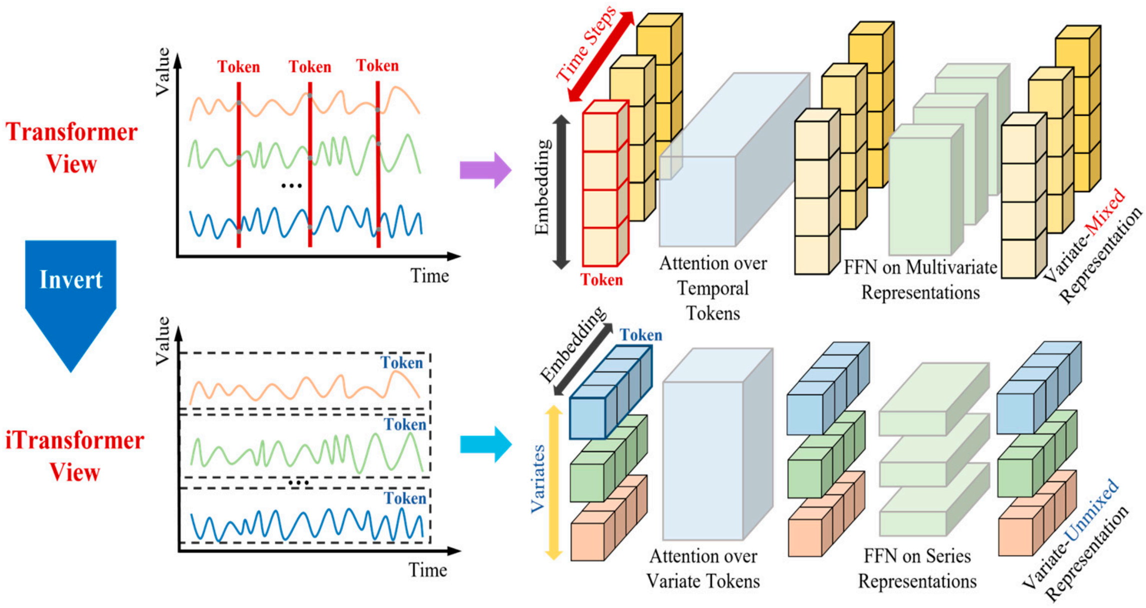

Figure 2. Comparative of traditional Transformers (**top**) and iTransformer (**bottom**).

The iTransformer framework is composed of an embedding layer, a projection layer, and multiple stackable Transformer modules. Initially, the iTransformer maps the entire sequence, $\boldsymbol{X}_{:,n}$, of each variable into a high-dimensional feature representation, h_n^0, through the embedding layer. Subsequently, the feature set $H = \{h^1, h^2, \ldots, h^N\} \in R^{N\times D}$ is input into the TrmBlock module to model the correlations between variables, where H contains N feature vectors of dimension, D [25]. The output, H^l, from the l-th layer is then fed into the subsequent TrmBlock module to continue modeling the relationships among the variables. The feedforward network encodes historical observation features layer by layer along the time dimension and maps the learned features, h_l^N, to future prediction outcomes, where $\hat{\mathbf{Y}}_{:,n}$ represents the predicted value for each variable. The entire process can be articulated through Equations (1)–(3).

$$h_n^{\mathbf{0}} = \text{Embedding}\,(\boldsymbol{X}_{:,n}) \tag{1}$$

$$\boldsymbol{H}^{l+1} = \text{TrmBlock}\left(\boldsymbol{H}^l\right), (l = 0, \ldots, L-1) \tag{2}$$

$$\hat{\mathbf{Y}}_{:,n} = \text{Projection}\left(h_n^L\right) \tag{3}$$

2.3. SSA Signal Decomposition

SSA can accurately decompose highly variable time-series data without obscuring key signal trends or smoothing out mutations [26]. It effectively separates the primary trend and periodic components within the time series, facilitating efficient calculations in the feature extraction for forecasting model changes. This study employs SSA as an auxiliary preprocessing technique to eliminate noise and decompose signals. SSA is a non-parametric time-series analysis method that is widely used in signal extraction, periodic analysis, and data dimensionality reduction [27]. Given that this algorithm does not impose assumptions regarding parameters and does not necessitate specific conditions for the stationarity of the time series, it has found extensive application in tasks related to time-series decomposition. SSA effectively extracts and reconstructs signals from the original time series while accurately identifying periodic and oscillatory components [28]. The SSA process consists of four key steps: embedding, decomposition, grouping, and reconstruction.

2.3.1. Signal Embedding

The primary time series is transformed into a matrix format to facilitate further analysis through the embedding process. This transformation allows the time series to be represented in a multi-dimensional matrix form by selecting appropriate embedding dimensions and delay factors. Transforming the original signal, x_n, into a two-dimensional trajectory matrix, X, is the main objective of embedding. The fundamental aspect of the embedding process is determined by the length of the moving window, ψ, which satisfies $2 \leq \psi \leq \frac{N}{2}$.The one-dimensional original sequence, $X_{ori} = \{x_1, x_2, \ldots, x_N\}$, is divided into several overlapping segments of equal length using the moving window. By embedding these segmented signals into a matrix, the trajectory matrix, $x_i = (x_i, \ldots, x_{i+\psi-1})^T$, is generated. The definition of the trajectory matrix, X, is given by Equation (4), where the parameters ψ and β satisfy the conditions $\psi < \beta$ and $N = \beta + \psi - 1$.

$$X = [X_1, \cdots, X_\beta] = (X_{ij})_{i,j=1}^{\psi,\beta} \begin{bmatrix} x_1 & x_2 & \cdots & x_\beta \\ x_2 & x_3 & \cdots & x_{\beta+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_\psi & x_{\psi+1} & \cdots & x_{\mathcal{N}} \end{bmatrix} \tag{4}$$

2.3.2. Signal Decomposition

In SSA, the most critical stage is performing Singular Value Decomposition on the normalized embedded trajectory matrix, X. The main objective of this procedure is to minimize noise present in the original dataset and to identify the principal components. These components consist of the left eigenvector, U_i; the right eigenvector, V_i; the left singular matrix, U; the right singular matrix, V; and the diagonal matrix, Σ, where $i \in \{1, 2, \ldots, \psi\}$. The calculation formula for V_i is shown in Equation (5), where the singular value, $\sqrt{\lambda_i}$, is used to construct the diagonal matrix, Σ. The matrix Σ satisfies the condition $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_\psi$, and $\lambda_\psi \to 0$, with the specific definition provided in Equation (6). The original matrix, $\mathcal{T}_i$, is shown in Equation (7). The trajectory matrix, X, can then be decomposed using the original matrix, $\mathcal{T}_i$, and the decomposition result is shown in Equation (8).

$$V_i = \frac{X^T U_i}{\sqrt{\lambda_i}} \tag{5}$$

$$\Sigma = \mathrm{diag}\left(\sqrt{\lambda_1}, \sqrt{\lambda_2}, \cdots, \sqrt{\lambda_i}\right) \tag{6}$$

$$\mathcal{T}_i = \sqrt{\lambda_i}\, U_i\, V_i \tag{7}$$

$$X = \mathcal{T}_1 + \mathcal{T}_2 + \cdots + \mathcal{T}_d, d = \max(i, \lambda_i > 0) \tag{8}$$

2.3.3. Signal Grouping

The process of decomposing the embedded trajectory matrix, X, into various singular spectral components is conducted in accordance with the chosen singular values. The contribution rate, α, determines the value of r, and its calculation formula is shown in Equation (9). In the grouping stage, by ignoring smaller singular values, noise can be effectively removed, thus improving feature extraction. The refinement process of the trajectory matrix, X, is shown in Equation (10).

$$\alpha = \frac{\lambda_i}{\sum\limits_{i=0}^{d} \lambda_i} \tag{9}$$

$$\mathrm{X} = \mathrm{X}_{I_1} + \cdots + \mathrm{X}_{I_m} \tag{10}$$

2.3.4. Signal Reconstruction

The goal of reconstruction is to approximate the original time series by recombining the extracted singular spectral components. Each grouped matrix is transformed using Equation (11) to produce a time series of length, N. x_{ij} is an element of the matrix which has ψ rows and β columns, where $1 \leq i \leq \psi$, an $1 \leq j \leq \beta$. The matrix, X_{Ii}, is transformed into the time series $Y_i = \{y_1, y_2, \cdots, y_N\}$, as defined in the formula, where $d' = \min(\psi, \beta)$, $f' = \max(\psi, \beta)$. The original time series, X_{ori}, is decomposed into m subsequences, as specifically defined in Formula (12).

$$y_k = \begin{cases} \frac{1}{k} \sum\limits_{m=1}^{k} x_{m,k-m+1}, 1 \leq k < d' \\ \frac{1}{d'} \sum\limits_{m=1}^{d'} x_{m,k-m+1}, d' \leq k < f' \\ \frac{1}{N-k+1} \sum\limits_{m=k-f'+1}^{N-f'+1} x_{m,k-m+1}, f' \leq k \leq N \end{cases} \tag{11}$$

$$\mathrm{X}_{\mathrm{ori}} = \sum_{k=1}^{m} \mathrm{Y}_i \tag{12}$$

2.4. Reversible Instance Normalization

Long-term time-series forecasting tasks frequently encounter the challenge of distribution shift, which arises from temporal changes in the mean and variance [29]. Such distribution shifts create a discrepancy between the distributions of training and testing data, resulting in input sequences that possess different underlying distributions. This discrepancy can significantly diminish the predictive performance of the model. During the forecasting process, models often struggle to extract meaningful features from non-stationary sequences [30]. Normalizing the original data can help stabilize their statistical properties, thereby enhancing their suitability for model training. However, this normalization process may lead to the loss of critical non-stationary information present in the original sequence [31]. Consequently, after normalization, the model learns exclusively from the standardized data, neglecting the non-stationary information inherent in the original data, which may further exacerbate the distribution shift issue.

To address the identified issue, this study employs the RevIN method. Figure 3 presents a schematic representation of the RevIN structure, which is composed of two symmetrical components: a normalization layer and a denormalization layer. Within the normalization layer, translation and scaling techniques are utilized to adjust the input instances, thereby mitigating the distributional discrepancies among instances [32]. This approach aids in alleviating the effects of distribution shift on the predictive model. Cucumber greenhouse prediction is considered a multivariate time-series forecasting task. The objective is to generate an output, $X \in R^{pre\_len \times l}$, based on an input sequence, $X \in R^{T_X \times l}$, where T_x represents the length of the input sequence, l denotes the number of variables, and *pre_len* indicates the length of the forecast sequence. After normalizing the input data, X, the mean and standard deviation are calculated using Formula (13). Through the statistical data, the input data are normalized, as demonstrated in Formula (14), where the learnable affine parameter vectors are denoted as γ and β. The transformed data, denoted as $\hat{X}$, will serve as the input for the prediction model to forecast future values.

$$y_k = \begin{cases} \mathrm{E}_t[X_{lt}] = \dfrac{1}{T_x}\sum\limits_{j=1}^{T_x} X_{lj} \\ \mathrm{Var}[X_{lt}] = \dfrac{1}{T_x}\sum\limits_{j=1}^{T_x}\left(X_{lj} - \mathrm{E}_t[X_{lt}]\right)^2 \end{cases} \tag{13}$$

$$\hat{X}_{lt} = \gamma_l\left(\frac{x_{lt}^{(i)} - \mathrm{E}_t[X_{lt}]}{\sqrt{\mathrm{Var}[X_{lt}] + \varepsilon}}\right) + \beta_l \tag{14}$$

RevIN proficiently removes non-stationary information from data related to cucumber greenhouse environments and reinstates it as required, thereby mitigating the problem of distribution drift in soil temperature. As a result, this approach improves the precision and reliability of multi-step soil temperature predictions, and this improvement is crucial for optimizing temperature forecasting in greenhouse environments.

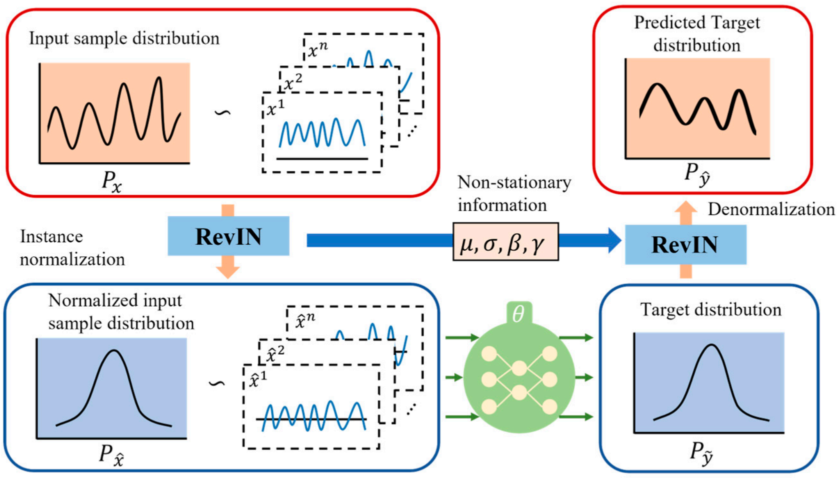

Figure 3. The reversible instance normalization structure diagram.

2.5. *ReSSA-iTransformer Model Combination Process*

The multi-parameter greenhouse environment dataset undergoes initial processing through a preprocessing layer, during which outliers are eliminated and missing values are imputed. By determining the ideal quantity of subsequences for SSA decomposition, this approach effectively filters out data noise, thereby enhancing the model's ability to accurately capture the features and trends inherent in the time-series data, and in turn, this enhancement improves prediction accuracy [33]. Each complete subsequence is processed through the embedding layer of the iTransformer, where the entire sequence corresponding to the same variable is converted into high-dimensional feature representations. Following the analysis of variable correlations, the RevIN method is employed to address distributional discrepancies among variables through layer normalization. Subsequently, a linear feedforward network is utilized to extract deep features from the time-series data. The learned features are projected through the projection layer to yield future prediction results for each subsequence that are ultimately aggregated to produce the overall prediction outcome. The greenhouse-environment data are characterized as a non-smooth sequence with a distribution that evolves over time, displaying pronounced long-term trends and seasonality. In the context of predicting soil temperature in cucumber greenhouses, the RevIN method preserves the benefits of conventional normalization techniques, which enhance the optimization of neural network parameters and improve generalization performance. Simultaneously, it mitigates the adverse effects associated with the direct omission of information on the predictive performance of the model. The primary workflow for predicting soil temperature in cucumber greenhouses is illustrated in Figure 4.

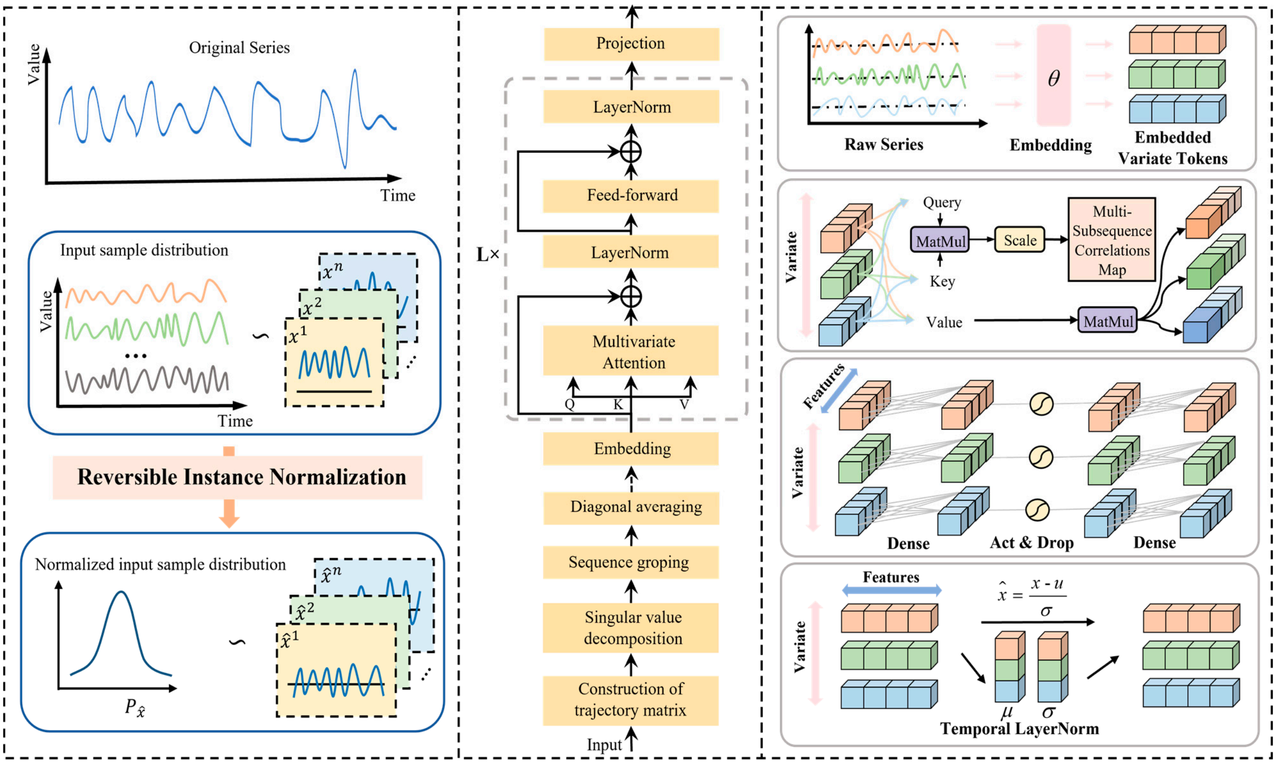

Figure 4. ReSSA-iTransformer greenhouse soil temperature prediction process.

3. Results

3.1. Experimental Setup and Results

3.1.1. Experimental Evaluation Indicators

This study utilizes four assessment measures to evaluate the efficacy of various time-series forecasting techniques from multiple perspectives, thereby confirming the superiority of the proposed strategy. In the following formulas, $y = \{y_1, y_2, \cdots, y_n\}$ represents the actual values; $\hat{y} = \{\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_n\}$ represents the predicted values; and $\overline{y}$ denotes the mean value.

The Mean Absolute Error (MAE) is determined by aggregating and averaging the absolute discrepancies between the observed values and the forecasted values. The mathematical representation of MAE is provided in Equation (15).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \quad (15)$$

The Root Mean Squared Error (RMSE) is a statistical metric employed to evaluate the deviation between anticipated and observed outcomes. It is calculated as the square root of the mean of the squared differences between the expected and actual values. The formula for RMSE is presented in Equation (16).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (16)$$

Mean Absolute Percentage Error (MAPE) is a metric that calculates the average absolute difference between observed values and predicted values, expressed as a percentage. The formula for MAPE is given by Equation (17).

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{17}$$

Coefficient of Determination (R^2) is a metric used to evaluate the goodness of fit of a model. When data have different scales, metrics such as RMSE, MAE, and MAPE may not adequately reflect model performance, in which case R^2 can be a more suitable evaluation criterion. It represents how well the regression line fits the observed data. The formula for R^2 is given by Equation (18).

$$R^2(y,\hat{y}) = \frac{\sum_{i=1}^{n}(\hat{y}_i - \overline{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \tag{18}$$

3.1.2. Experimental Environment Setup

The experimental software environment is based on Python 3.8.0 and the PyTorch 1.9.0 deep-learning framework. The hardware environment uses an RTX 3090 GPU with 24 GB of memory. This study's experiments mainly cover three areas. Initially, the influence of distinct signal decomposition subsequences on prediction accuracy is assessed to evaluate the effectiveness of the proposed adaptive signal decomposition algorithm. Subsequently, the performance of various methods on greenhouse environmental datasets across different temporal scales is evaluated, while also assessing the effectiveness of various signal decomposition algorithms in time-series forecasting. Both experiments employ MAE, RMSE, MAPE, and R^2 as evaluation metrics.

3.2. Validation of the SSA Signal Decomposition Method

Using the SSA algorithm, the primary variable of the prediction model, namely soil temperature, is subjected to decomposition. The embedding window is established at a size of 10, and the resulting reconstructed component sequence is illustrated in Figure 5. The experimental findings are summarized in Table 2, where the optimal number of subsequences for prediction within the greenhouse dataset is emphasized in bold. Testing across multiple sliced datasets revealed that the optimal number of subsequences fluctuates across different temporal intervals. This variability is attributed to seasonal factors that exert distinct influences on soil temperature throughout the year. Consequently, this underscores the necessity for an adaptive approach to determine the optimal number of subsequences, tailored to the specific characteristics of the data. The model is capable of extracting the most significant feature information pertinent to soil temperature prediction under varying conditions. By employing this method for subsequence selection, the iTransformer prediction model attained optimal results across diverse factors within the greenhouse environmental slice data. This further corroborates the efficacy of the SSA technique. The prediction performance metrics for each decomposed subsequence are presented in Figure 6.

Research on time-series forecasting in agricultural contexts underscores the necessity for robust signal decomposition methods, particularly when handling unstable and highly variable data, such as soil temperatures. The Stationary Wavelet Transform (SWT) effectively captures subtle fluctuations in greenhouse temperature datasets; however, it may introduce errors by excessively decomposing low-frequency components, which can fragment essential signal trends, and by inadequately representing high-frequency spikes caused by external factors, like rapid ventilation changes. Variational Mode Decomposition (VMD) demonstrates stable performance across varying time steps, making it advantageous in greenhouse environments where sampling rates may fluctuate due to sensor limitations. Nonetheless, VMD can smooth out abrupt cooling or heating events, leading to delayed predictions. In contrast, Empirical Mode Decomposition (EMD) enhances prediction accuracy by iteratively extracting Intrinsic Mode Functions (IMFs) to address strongly fluctuating data [34]. However, the sequential extraction process of EMD requires significant computational time, hindering its applicability in real-time agricultural settings and resulting in large oscillations in forecasts under high noise levels. This emphasizes the need for robust noise filtering during preprocessing stages. Furthermore, the Ensemble Wavelet Transform (EWT) captures multi-scale features of temperature data but may lead to substantial prediction fluctuations and pronounced lag when addressing abrupt changes in greenhouse conditions. These limitations indicate that while each decomposition method offers unique advantages, the effectiveness of each is contingent upon the specific characteristics of the dataset and the operational requirements of the forecasting application.

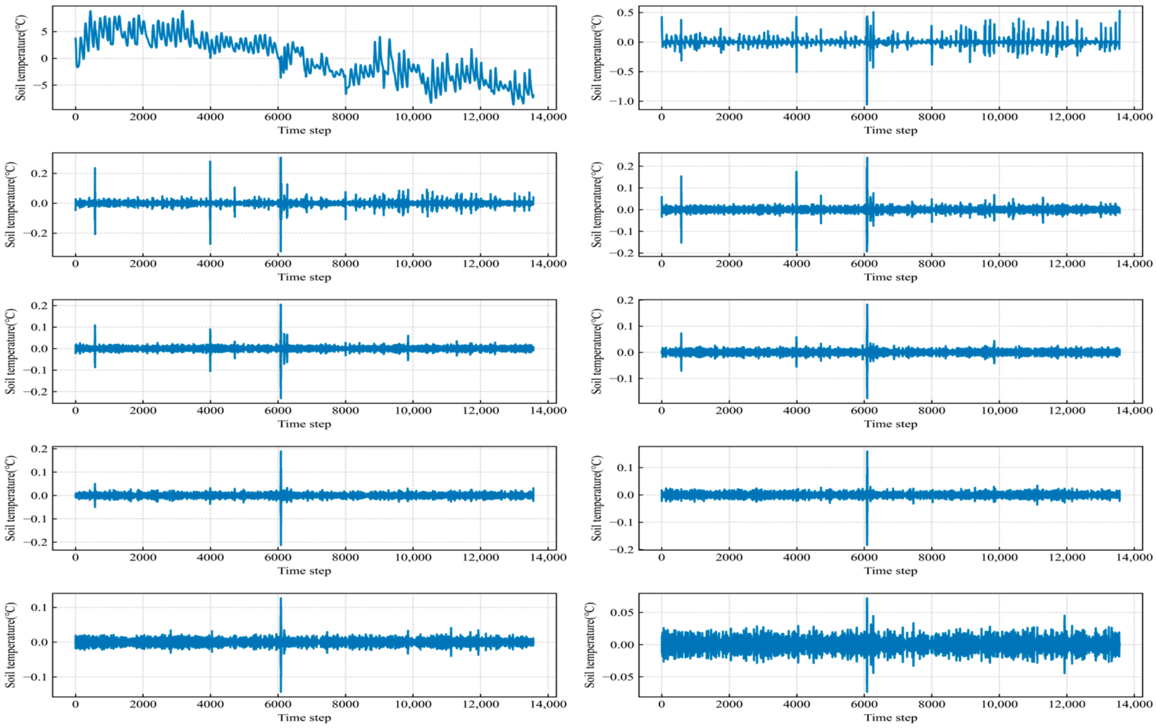

Figure 5. Sequential components of soil temperature after SSA decomposition.

Table 2. Prediction results for different subsequence numbers.

Subsequence No.	MAE	MAPE	RMSE	R^2
1	0.72	0.019	1.054	0.9418
2	0.994	0.028	1.263	0.8471
3	0.704	0.016	0.889	0.9527
4	0.623	0.015	0.875	0.9711
5	0.619	0.016	0.877	0.9752
6	**0.613**	**0.015**	**0.855**	**0.9884**
7	0.627	0.016	0.928	0.9782
8	0.645	0.017	0.905	0.9823
9	0.645	0.017	0.976	0.9765
10	0.694	0.021	0.984	0.9611

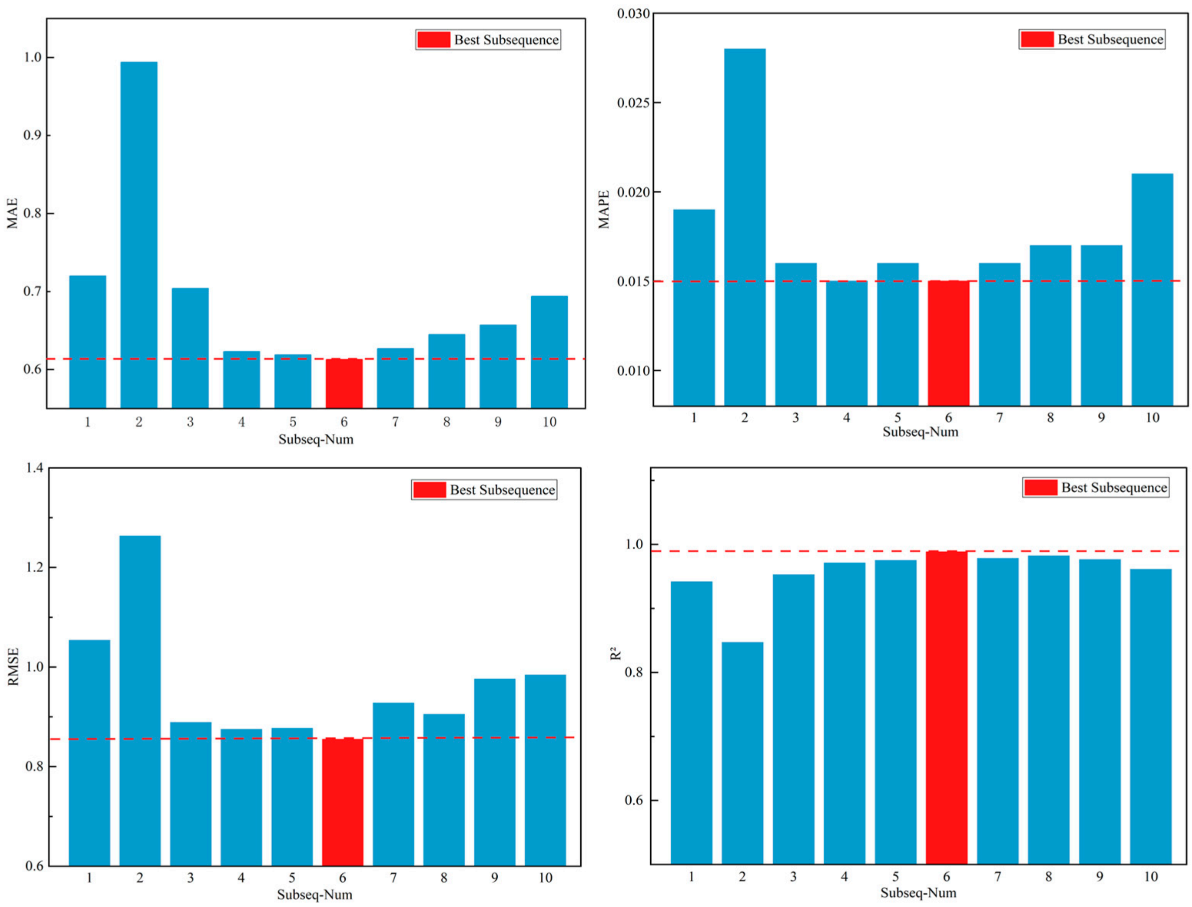

Figure 6. The impact of different numbers of subsequences on prediction performance.

Table 3 provides a quantitative comparison of the performance of these methods within the iTransformer model, utilizing error metrics such as MAE and RMSE to emphasize differences in accuracy and computational requirements. The indicators that demonstrate the highest performance are presented in bold font. Additionally, Figure 7 illustrates a comparative analysis of the prediction outcomes of different methodologies concerning the one-hour soil temperature in cucumber greenhouses. In conclusion, the overall efficacy of the different signal decomposition techniques can be ranked as follows: EMD < VMD < SWT < EWT < SSA.

Table 3. Performance comparison of various signal decomposition algorithms.

Model	MAE	MAPE	RMSE	R^2
EMD-iTf	1.121	0.028	1.563	0.7448
VMD-iTf	0.78	0.026	1.054	0.9192
SWT-iTf	0.704	0.016	0.889	0.9523
EWT-iTf	0.725	0.024	0.965	0.8515
SSA-iTf	**0.613**	**0.015**	**0.855**	**0.9864**

Through comparison study, the superiority of the SSA approach over other signal decomposition approaches may be shown. The performance advantage of this approach is derived from the robust mathematical theory that underpins it. The performance of the SSA method is significantly affected by the choice of the number of decomposed subsequences. The prediction model developed in this study effectively mitigates this challenge, leading to substantial enhancements in the accuracy and adaptability of the algorithm.

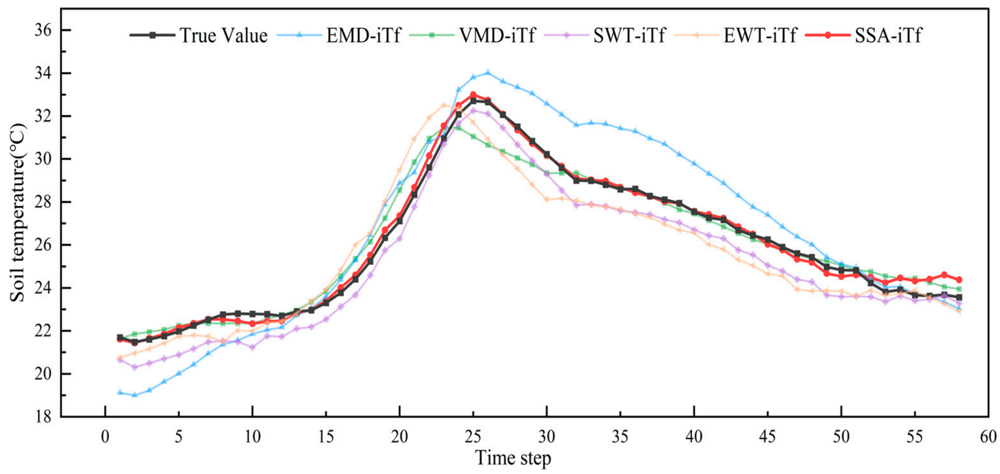

Figure 7. Prediction results of various decomposition signal algorithms.

3.3. Comparison of the Effectiveness of Prediction Results of Soil Temperature in Cucumber Greenhouse

This section presents the quantitative evaluation results of ReSSA-iTransformer compared to other baseline algorithms, including MAE, MAPE, RMSE, and R^2. To validate the advancement of the constructed model, long- and short-term multi-step predictions of cucumber greenhouse soil temperature were compared using time steps of 3 h, 6 h, 24 h, and 48 h. The model performance comparison results are shown in Tables 4–7, while Figures 8–11 illustrate the prediction performance comparison between ReSSA-iTransformer and other models at the four time steps. Notably, the proposed model consistently achieved the best results across different time steps, demonstrating its ability to effectively reduce the impact of outliers and inaccurate data on prediction outcomes. It also successfully extracted subsequence components beneficial for prediction and further uncovered rich time-series information through the iTransformer framework.

Table 4. Comparison of short-term forecast (3 h) results of various models.

Model	MAE	MAPE	RMSE	R^2
LSTM	1.421	0.89	1.916	0.4568
Informer	1.211	0.602	1.103	0.8687
Autoformer	0.704	0.38	1.137	0.9274
iTransformer	0.476	0.336	0.481	0.9436
Proposed	0.271	0.304	0.375	0.9851

Table 5. Comparison of short-term forecast (6 h) results of various models.

Model	MAE	MAPE	RMSE	R^2
LSTM	1.928	0.112	2.471	0.5649
Informer	1.634	0.093	2.137	0.8592
Autoformer	1.449	0.083	1.967	0.9116
iTransformer	0.877	0.052	1.314	0.9325
Proposed	0.501	0.029	0.831	0.9703

Table 6. Comparison of long-term prediction (24 h) results of various models.

Model	MAE	MAPE	RMSE	R^2
LSTM	2.195	0.128	2.599	0.6235
Informer	1.829	0.107	2.341	0.7174
Autoformer	1.577	0.094	2.165	0.9283
iTransformer	1.115	0.065	1.788	0.8957
Proposed	0.648	0.041	0.856	0.9726

Table 7. Comparison of long-term prediction (48 h) results of various models.

Model	MAE	MAPE	RMSE	R^2
LSTM	4.024	0.256	4.630	0.4218
Informer	2.054	0.119	2.545	0.6528
Autoformer	1.808	0.104	2.323	0.8821
iTransformer	1.752	0.101	2.256	0.9044
Proposed	1.633	0.094	2.177	0.9483

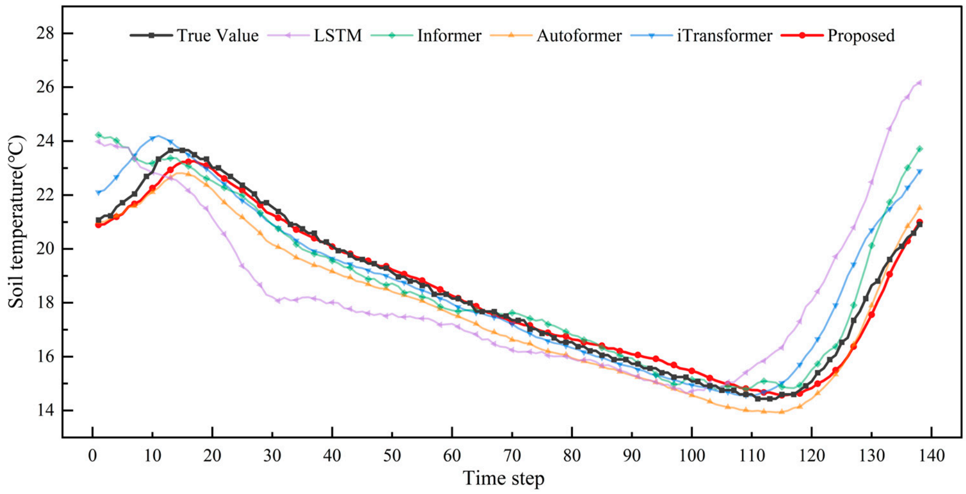

Figure 8. Comparison of model prediction results for 3 h.

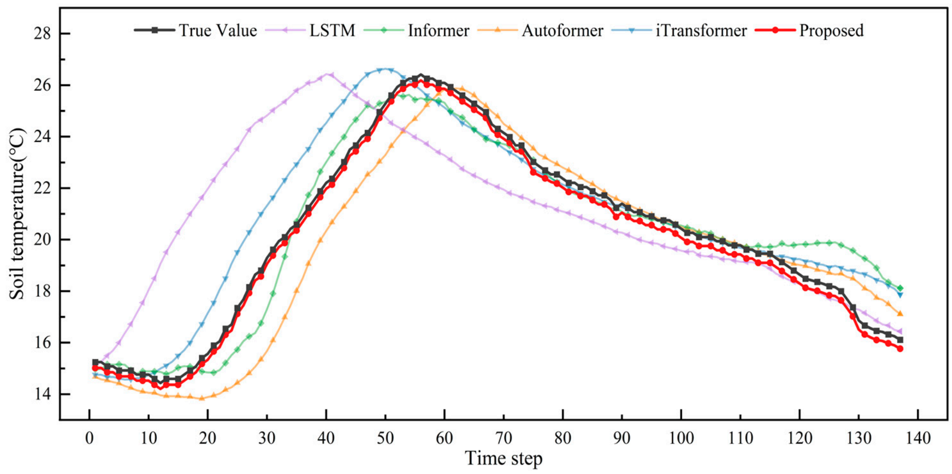

Figure 9. Comparison of model prediction results for 6 h.

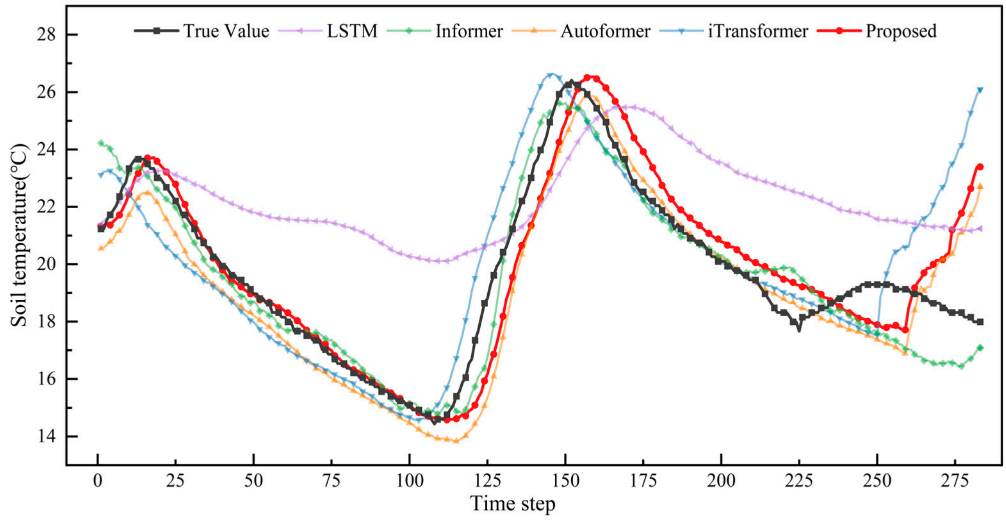

Figure 10. Comparison of model prediction results for 24 h.

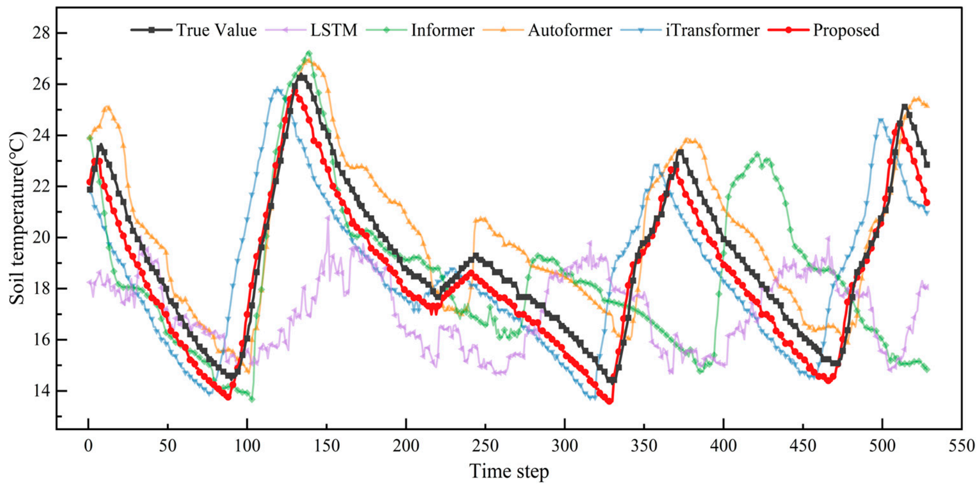

Figure 11. Comparison of model prediction results for 48 h.

The experimental findings indicate that, although there is variability in the performance of the comparison algorithms at various time intervals, the predictive model established in this research consistently surpasses the performance of the other models in most instances. Specifically, the average R^2 value of the ReSSA-iTransformer in the greenhouse soil temperature prediction dataset is 96.91%, indicating outstanding performance in accurately fitting the true values and suggesting significant potential for broad applications. ReSSA-iTransformer achieved an average performance improvement of 48.89% in MAE, 37.76% in MAPE, and 47.59% in RMSE compared to Transformer-based prediction models across the four time-step forecasts. In contrast, the LSTM model exhibits inferior predictive performance, primarily due to its difficulty in capturing correlations between variables when processing long time-series data, thus hampering its ability to identify the complex patterns and trends inherent in such data. Additionally, Autoformer and other Transformer-based models, while designed to handle long-term dependencies through attention mechanisms, often face challenges related to computational complexity and may struggle with scalability in real-time agricultural applications. These models can also be prone to overfitting, especially when dealing with noisy and highly variable agricultural data, thereby reducing their generalization capabilities. By integrating the SSA and RevIN methods, the predictive accuracy of the iTransformer on the greenhouse environment dataset has been significantly enhanced. All evaluation metrics showed significant improvement, with MAE improving by an average of 33.66%, MAPE by 24.41%, and RMSE by 28.61% in time-series forecasting performance across different time steps.

In order to offer a more intuitive representation of the accuracy of the variations associated with each method across different time steps, this paper presents charts illustrating the evaluation metrics, as depicted in Figure 12. The horizontal axis on the right shows the names of the compared models, while the left side lists the different evaluation metrics. The vertical axis represents the values of the four-evaluation metrics. Among them, lower values of MAE, MAPE, and RMSE, and higher values of R^2 indicate better model performance.

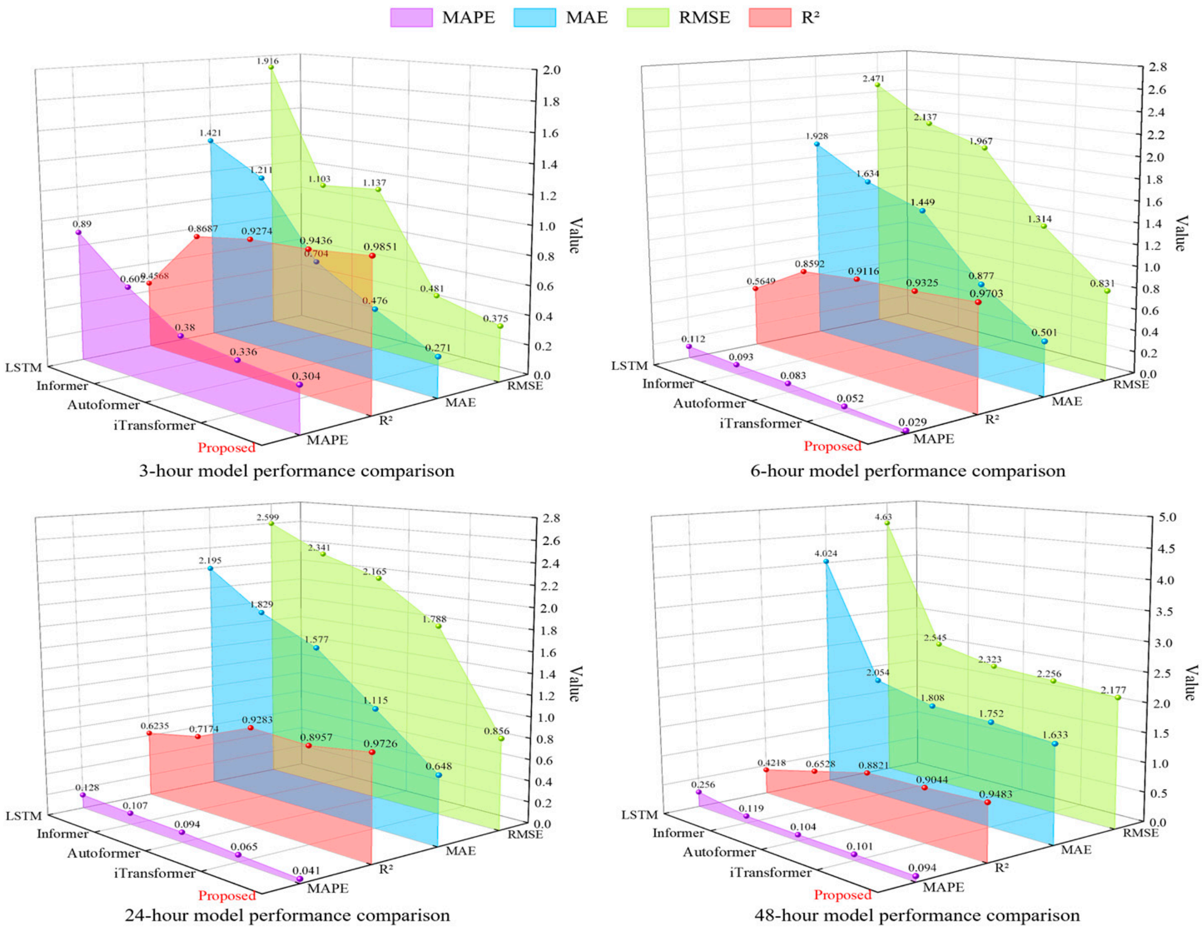

Figure 12. Comparison of model performance based on soil temperature.

4. Discussion

Through comprehensive experimental validation, the following conclusions were derived from the greenhouse soil temperature hybrid prediction model developed in this study:

In comparative experiments, the hybrid model consistently demonstrated superior performance compared to the individual models. This outcome can be attributed to the time-lag effects observed in greenhouse environmental data, which arise from the interactions among various environmental factors. Among various time-series prediction frameworks, the iTransformer-based method surpasses other models within the Transformer series, thereby validating the efficacy of the iTransformer's transpose structure in facilitating the extraction of deeper temporal information. When integrated with adaptive signal decomposition, the iTransformer significantly enhances the model's predictive performance for univariate data, resulting in improved computational efficiency. In the context of greenhouse environment data, the SSA method introduced in this study demonstrates a marked superiority over alternative signal decomposition techniques. This finding underscores the importance of optimizing the number of optimal subsequences through parameter tuning to fully leverage the benefits of SSA decomposition.

The ReSSA-iTransformer demonstrates superior performance across various temporal dimensions and datasets. As the prediction horizon extends, the prediction errors for all models tend to increase; nevertheless, the ReSSA-iTransformer consistently surpasses other baseline models at every time step. In comparison to the baseline models, the ReSSA-iTransformer exhibits enhancements across all evaluation metrics, highlighting its exceptional learning capacity and nonlinear modeling proficiency. Furthermore, it delivers stable and reliable predictive outcomes for datasets characterized by differing sequence lengths.

While the ReSSA-iTransformer model demonstrates commendable efficacy in predicting greenhouse soil temperature, several limitations persist. Specifically, under conditions of extreme weather, the model is capable of forecasting the general trend of soil temperature fluctuations; however, its precision in predicting soil temperature amidst substantial variations remains inadequate. Additionally, it is imperative to account for the robust correlation with the time-series characteristics inherent in anomalous changes. The integration of greenhouse-monitoring data or remote-sensing data necessitates a thorough evaluation of the model's performance and efficiency in handling complex, large-scale datasets. This is particularly crucial to ensure that computational efficiency is maintained without compromising the high accuracy of predictions.

5. Conclusions

The greenhouse environment is characterized by its complexity and variability, rendering precise predictions of soil temperature essential for the successful cultivation of greenhouse crops. Accurate soil temperature forecasting not only facilitates optimal growth conditions for crops but also enhances overall yield. This study introduces the long- and short-term sequence prediction model, ReSSA-iTransformer, which is designed to extract pertinent features of soil temperature within the cucumber greenhouse environment. The model utilizes SSA to decompose various fluctuating factors into distinct signals, thereby enhancing the identification of key feature factors. Furthermore, by integrating the RevIN method into the iTransformer framework, this research effectively mitigates the issue of distribution shift in prediction outcomes, resulting in accurate soil temperature forecasts across different temporal sequences. The model developed herein supports both short-term and long-term multi-step predictions of soil temperature in cucumber greenhouses. When compared to several baseline methods, the proposed model demonstrates superior performance in terms of accuracy, generalization capability, and response time, thereby providing a viable solution for forecasting conditions within greenhouse environments.

Significant opportunities exist to enhance greenhouse soil prediction models by addressing the dynamic agricultural environment and regional climatic variations that influence outcomes. Developing models that integrate multi-source data can improve predictive performance without increasing complexity or data volume. Additionally, incorporating the effects of extreme weather events into data selection is crucial for capturing environmental dynamics. These advancements will result in more robust and accurate soil prediction models, thereby facilitating informed decision-making in agricultural management.

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W.C. and C.Z.; project administration, Y.W. and W.C.; funding acquisition, W.C. All authors have read and agreed to the published version of the manuscript.

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