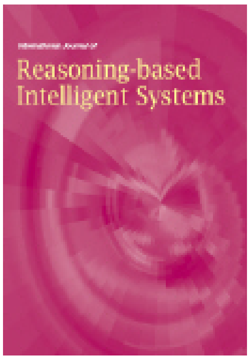

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Region-specific multi-scale meteorological forecasting based on data assimilation and reinforcement learning

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Region-specific multi-scale meteorological forecasting based on data assimilation and reinforcement learning

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Abstract: Accurate meteorological forecasting is vital for disaster prevention. However, existing approaches often suffer from significant heterogeneity in meteorological data. To address these challenges, this paper introduces a data assimilation method based on particle swarm optimisation and particle filtering to derive assimilated meteorological observation variables. Subsequently, the seasonal-trend decomposition using LOESS is applied to disaggregate meteorological series. The trend component is predicted using a gated recurrent unit model, while the seasonal and residual components are formulated as state variables. This reformulation transforms forecasting problems into the multi-dimensional decision-making task, facilitating the training of a reinforcement learning model to improve forecasting accuracy. Experimental results show that the proposed model reduces the root mean square error by at least 13.93% and 15.21% for forecast lead times of 6 and 24 days, respectively, demonstrating its potential as an effective technical solution for high-precision meteorological forecasting across diverse climatic regions.

Keywords: multi-scale meteorological forecasting; data assimilation; reinforcement learning; seasonal-trend decomposition using LOESS; gated recurrent unit.

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1 Introduction

Meteorology refers to various elements that indicate the physical state and phenomena of the atmosphere, directly affecting the formation and changes of regional meteorological and climate, thus having a significant impact on human production and life (Fathi et al., 2022). Therefore, accurate short-term meteorological forecasting is crucial for various practical applications (Biswas et al., 2018), such as disaster prevention, agricultural production, and environmental monitoring. Traditional meteorological forecasting methods often employ unified forecasting models and parameter settings, which find it difficult to fully consider the differences in geographical environment, climate characteristics, and meteorological elements across different regions, making it impossible to meet the needs of region-specific meteorological forecasting (Neal et al., 2016). To address this challenge, artificial intelligence algorithms have been used for fine-grained modelling of specific areas to improve the accuracy and timeliness of meteorological forecasting. However, the heterogeneity of meteorological data also poses challenges for the application of artificial intelligence algorithms (Conti, 2024). The heterogeneity of meteorological data is reflected in its enormous differences in form and scale, increasing the difficulty of parsing and fusing these data (Aalto et al., 2017). Given this, it is particularly important to develop a region-specific meteorological forecasting model that can uniformly process multiple types of data and deeply mine the intrinsic relationships between them.

Traditional meteorological forecasting methods mainly analyse long-term historical data to establish functional models between the historical data and the target for prediction, including statistical analysis methods such as autoregressive models (Abdallah et al., 2020), moving average models (Rigby et al., 2024), autoregressive moving average models (Lai and Dzombak, 2020), etc. Al-Hajj (2025) used the Nadaraya-Watson estimator to further propose a time-adaptive kernel density estimation method for wind speed forecasting; however, there was considerable error in meteorological forecasting. Eberle et al. (2022) suggested a forecasting model in light of enhanced Hidden Markov models (HMM), using fuzzy smoothing methods to overcome performance degradation and adopting roulette selection methods to determine probabilities for the predicted results, thereby handling uncertainty. Małolepsza et al. (2024) adopted adaptive resampling combined with fuzzy reasoning to construct prediction intervals, obtaining a complete probability distribution of meteorological forecasts by simultaneously generating prediction intervals at different confidence levels. Statistical methods have advantages such as simplicity, ease of implementation, and strong interpretability (Finkel et al., 2023).

Artificial intelligence methods refer to meteorological forecasting approaches based on machine learning and deep learning. These methods, based on historical data, establish neural networks that describe the relationship between historical inputs and outputs through various machine learning and deep learning rules, and further use this model to predict future meteorological conditions. Helmert et al. (2018) introduced a data assimilation method to improve the heterogeneity of meteorological data and integrated random forests, support vector machines, and neural networks for predicting extreme temperatures in the coming day. Gyamerah and Owusu (2024) proposed a regional meteorological forecasting approach based on feedforward neural networks, combining upper-lower bound estimation and bootstrap methods to quantify uncertainty. Veeramsetty et al. (2023) combined chaos theory with an artificial bee colony algorithm to optimise radial basis function neural networks for meteorological prediction, significantly improving the prediction accuracy. Suleman and Shridevi (2022) used long short-term memory (LSTM) neural network to predict uncertainties in meteorological and employed a Gaussian mixture model to analyse the distribution characteristics of prediction errors. Utku and Can (2023) utilised wavelet transforms to decompose original meteorological sequences into sub-sequences with different frequencies, using multi-scale convolutional neural networks (CNN) to learn nonlinear features in each component for multiscale probabilistic predictions of meteorological data. Hewage et al. (2020) proposed a decomposition-aggregation temporal convolutional network-based meteorological forecasting model and conducted analysis and prediction on Beijing meteorological station data, achieving smaller prediction errors compared to individual models. Liu et al. (2020) developed a wind speed prediction method based on CNN and LSTM, and introduced deep reinforcement learning for error compensation prediction, significantly improving prediction accuracy. Zhao et al. (2024) utilised reinforcement learning to combine predictions from multiple neural networks to obtain future meteorological conditions. Jethva (2025) employed particle filter algorithms for meteorological observation data assimilation and proposed an integrated model dynamic weighting forecasting method based on reinforcement learning, which can dynamically allocate and update the weight of each model at different times according to the characteristics of the data and individual model predictions.

Based on the analysis of the aforementioned studies related to meteorological forecasting, it is evident that current meteorological models are often affected by initial field error accumulation, complex multi-scale meteorological system coupling mechanisms, and element heterogeneity, making it difficult to meet customised prediction needs across different regions. To address this issue, this paper proposes a region-specific, multi-scale meteorological prediction model based on data assimilation and reinforcement learning. The main work of this model can be summarised in the following four aspects.

1 To address the dependency on future observations in particle filter data assimilation algorithms, a particle filter data assimilation method based on particle swarm optimisation (PSO) is proposed. This approach utilises historical reanalysis data to replace future observations. Leveraging the PSO algorithm's capability to adjust particle positions, particles are guided toward observations. The resulting assimilated meteorological variables serve as input for subsequent forecast models.

2 Decompose the assimilated meteorological sequence using the seasonal-trend decomposition using LOESS (STL) algorithm. Separate the sequence into trend, seasonal, and residual components, selecting different components for learning based on the characteristics of deep learning and reinforcement learning.

3 The GRU model is employed to forecast the distinct trend component, while the remaining seasonal component and residual component are treated as states. This reframes the meteorological sequence forecasting problem as a Markov decision process (MDP) decision problem, enabling learning through reinforcement learning models. By integrating the strengths of deep learning and reinforcement learning, the accuracy of multi-scale meteorological forecasting is enhanced.

4 The experimental results show that when the prediction lengths are 6 and 24, the RMSE of the proposed model is 14.58 and 18.25 respectively. The prediction error is significantly lower than that of the benchmark model, and it can accurately achieve multi-scale meteorological prediction, opening up a new idea for realising regional customised multi-scale meteorological prediction.

2 Relevant theory

2.1 Particle filter data assimilation method

The particle filter data assimilation method is a nonlinear, non-Gaussian data assimilation technique based on Bayesian estimation (Maclean and Van, 2021), which uses Monte Carlo simulations to generate a large number of weighted particles to approximate the posterior probability distribution, thereby achieving dynamic data estimation.

The particle filter is a sequential data assimilation method where particles represent model states and a collection of particles forms a model state ensemble (Rémy et al., 2012). Assuming the initial state of the particles is x_i^n and the number of particles in the set is N, then the prior probability density function (PDF) is as follows.

$$p\left(x^n\right) \approx \sum_{i=1}^{N} \frac{1}{N} \delta\left(x^n - x_i^n\right) \tag{1}$$

Between two observations, the states of these particles are integrated from time to time according to model equations, and this integration process is represented as follows.

$$x^n = f\left(x^{n-1}\right) + \beta^n \tag{2}$$

where $f(x)$ he model integration function, and β^n represents discretisation error. It is generally assumed that model errors follow a distribution $N(0, Q)$. Observations are essential in the assimilation process. Therefore, observations are represented as y^n, where observation errors follow a distribution $N(0, R)$. These observational values y^n achieve assimilation by multiplying the above prior PDF with the likelihood of each possible state. According to Bayes' theorem, the posterior PDF is as follows.

$$p\left(x^n \mid y^n\right) = \frac{p\left(y^n \mid x^n\right)}{p\left(y^n\right)} p\left(x^n\right) \tag{3}$$

where $p(x^n|y^n)$ is the probability density of the observation vector, for a given state x^n, the observation y^n equals the observation error ε translated as follows.

$$p\left(y^n \mid x^n\right) = p_\varepsilon\left\{y^n - H\left(x^n\right)\right\} \tag{4}$$

From the above equation it can be seen that all terms are known values; therefore the particle weights form a number. After normalising the particle weights, they represent the posterior probability density.

Compared to the ensemble Kalman filter method, the particle filter approach has a simpler computational process. Moreover, during algorithm computation, particle states are not adjusted but only their weights are modified. However, this method may suffer from particle degeneracy.

2.2 Reinforcement Learning

Reinforcement learning emphasises trial-and-error learning through interaction, with the goal of taking an action in the current environment to maximise the numerical reward signal. It is also different from unsupervised learning; its purpose is not to find specific structures hidden in unlabeled data but rather to identify actions that maximise rewards. Therefore, reinforcement learning involves continuous trial-and-error and weighing each decision step-by-step. Therefore, reinforcement learning is regarded as the third major machine learning paradigm alongside supervised learning and unsupervised learning.

Reinforcement learning problems are typically formulated as MDP for policy learning (Mehta, 2020). The MDP includes a state space S, actions A, strategies π, reward function R, and discount factor γ. The discount factor is used to calculate the total return. In reinforcement learning formulated as an MDP, agents obtain the next state s_{t+1} after taking action a_t in a given state s_t by using the state transition probability function P.

$$P\left(s_{t+1} \mid S = s_t, A = a_t\right) \tag{5}$$

When transitioning to state s_{t+1}, rewards $r_{t+1} = R(a_t, s_t, s_{t+1})$ will be obtained based on reward function $R(a_t, s_t, s_{t+1})$.

The reward depends on the current state, the next state, and the action taken. The target policy learned by the reinforcement learning agent is π, which maximises the expected return under the initial distribution. The state visitation distribution represented as ρ^π indicates π. The value function $Q^\pi(s_t, a_t)$ describes the expected return after taking actions according to π.

$$Q^\pi\left(s_t, a_t\right) = E_{r_i \geq t, s_i \geq t \sim E, a_i > t \sim \pi}\left[R_t \mid s_t, a_t\right] \tag{6}$$

3 Regional meteorological observation data assimilation based on an improved particle filter data assimilation method

3.1 Overview of meteorological observation data assimilation method

Data assimilation is a general method used to estimate meteorological variables. This method aims to combine any type of measurement data with estimates from geophysical models. The acquisition of key atmospheric variables via data assimilation enhances the accuracy of predictions when applied to subsequent applications such as meteorological forecasting. The particle filter's capability to manage nonlinear and non-Gaussian features has led to its growing prominence as a topic of study in data assimilation. Therefore, how to effectively integrate sparse and unevenly distributed observational data with meteorological numerical models using the particle filter method to improve the accuracy of meteorological element analysis and forecasting is an urgent problem that needs to be addressed. This study is based on the particle filter method and combines it with the characteristic of the PSO algorithm (Wang et al., 2021) to search for global optimal solutions. It investigates and analyses the shortcomings of conventional particle filter approaches, which rely on future observation information to adjust particles. A particle filter data assimilation approach in light of the PSO algorithm is proposed to improve the assimilation efficiency of nonlinear and non-Gaussian meteorological element information.

PSO and the particle filter algorithm share certain common principles. First, the PSO algorithm updates a particle's position by assigning it a velocity in order to find a global optimal solution, while the particle filter algorithm adjusts particles' weights through proposal density to approximate the posterior probability density; both methods approach an optimal target through adjustments to the particles. Finally, in the PSO algorithm, particles' velocities and positions are updated based on their fitness values to search for global optimal solutions, while in the equally weighted particle filter algorithm, particle weights are updated through the computed proposal density to guide particles toward observation information. The aforementioned similarities indicate that it is feasible to apply the PSO algorithm to address the issue where the particle filter algorithm relies on future meteorological observation information to compute the proposal density and guide particles toward meteorological observations.

3.2 Particle filter data assimilation method based on PSO improvement

When the PSO algorithm is combined with the particle filter algorithm, premature phenomena often occur. Therefore, weight self-adaptive adjustments are necessary for the PSO algorithm to avoid its problem of local convergence. Compared to the standard PSO algorithm, the PSO algorithm used in this study introduces adaptive adjustment of inertia weight and learning factors, while also employing a mutation algorithm to enhance particle diversity.

The fitness value of each particle is calculated using traditional PSO. Then, each particle's fitness value is compared with the overall average fitness of the entire particle set. The self-adaptive adjustment method for inertia weight is as follows.

$$\begin{cases} w(t) = w_{\min} + \dfrac{\left(f_{\max} - F\right) * \left(w_{\max} - w_{\min}\right)}{f_{mean} - f_{\min}}, & F \leqslant f_{mean} \\ w(t) = w_{\min} + \left(w_{\max} - w_{\min}\right) * (iter - t) / iter, & F > f_{mean} \end{cases} \tag{7}$$

where f_{min} is the minimum fitness value among particles in the swarm, f_{max} is the average fitness of the particle swarm, and F is the fitness value of this particle. w_{max} and w_{min} represent the maximum and minimum values of inertia weight in the particle swarm, respectively; *iter* represents the maximum number of iterations, and t represents the current iteration count.

Adjusting the learning factors adaptively can change the ability of particles to move toward an optimal target point. In this study, exponential curves are used to update the learning factors c_1 and c_2. During the early stage of algorithm iterations, it enhances the global search capability of particles, avoiding them from falling into local optima. In the later stage of algorithm iterations, it improves the speed at which particles move toward an optimal target point to achieve higher-quality solutions. The update formulas for c_1 and c_2 are as follows, where iter represents the maximum number of iterations and t represents the current iteration count. By adaptively updating c_1 and c_2, particles possess strong global search capabilities during the early stage of algorithm iterations, quickly locating a global optimal solution. During the later stage of algorithm iterations, they have stronger local search capabilities, enabling them to rapidly find an optimal solution in their vicinity.

$$c_1 = 1.5 + \frac{\exp\dfrac{10(t-1)}{iter-1} - 1}{\exp(10) - 1} \tag{8}$$

$$c_2 = 2.5 - \frac{\exp\dfrac{10(t-1)}{iter-1} - 1}{\exp(10) - 1} \tag{9}$$

To improve the diversity of particles after algorithm optimisation, mutation operations are introduced to randomly mutate the particles. First, set a random function rand and then establish a threshold; if the random function exceeds this threshold, the particle positions are updated randomly, making the particles more dispersed and avoiding loss of diversity due to concentrated particle positions. Particle position updates follow the equation below, where R_{max} is the maximum radius of the particle search space.

$$x(t) = R_{\max} * rand \tag{10}$$

The main steps of the particle filter algorithm based on improved PSO optimisation are as follows.

1 Initialisation. Randomly draw a set of particles $\{x_n, n = 1, 2, \ldots, N\}$ from the prior PDF and randomly assign initial velocities $V_1, V_2, \ldots, V_n$ to these particles.

2 Use the improved PSO algorithm to adjust particle positions and use fitness values to evaluate the distance between particles and meteorological observation information, as shown below.

$$P(y) = \exp\left[-\frac{1}{2R}\left(z_n - z_{n|n-1}\right)^2\right] \tag{11}$$

where R is the measurement noise variance, z_n is the particle's measured value, and $z_{n|n-1}$ is the predicted measurement value. Compare the calculated current fitness value with the individual optimal solution of this particle and also compare it with the global optimal solution. The inertial weight is adaptively updated by comparing the fitness value and the average swarm fitness. Meanwhile, update c_1 and c_2. After parameter adjustment, update the velocity and position of the particles. Subsequently, if the particles are overly concentrated, randomly mutate them using a mutation method. Continuously loop and iterate this step until reaching the maximum number of iterations or achieving an ideal precision for the global optimal solution; at that point, use the updated particle positions to replace the original ones.

3 Weight update. Update the particle weights based on the latest measurement information and normalise them as follows, where ω_n^i and ω_{n-1}^i are the weights.

$$\omega_n^i \infty \omega_{n-1}^i \frac{p\left(z_n \mid x_n^i\right) p\left(x_n \mid x_n^i\right)}{q\left(x_n^i \mid x_{n-1}, z_n\right)} \tag{12}$$

4 Resampling. After updating the particle weights and states, resample the entire set of particles and re-sample 20% of the particles in the set that do not reach the target weight.

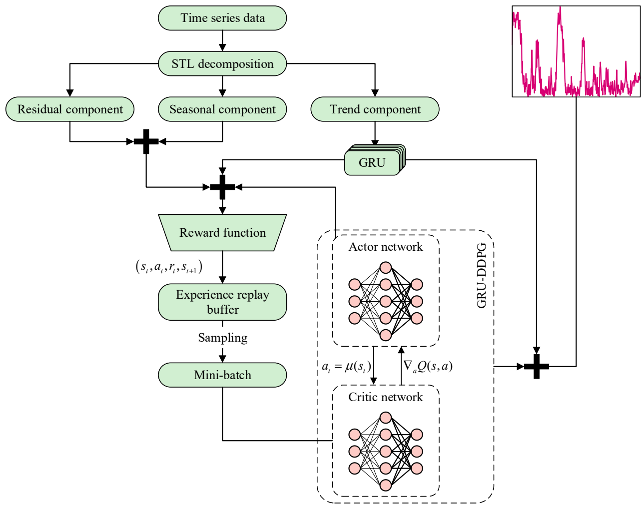
5 State output. According to the state output formula from the particle filter method, output the system's state estimate and error statistics to obtain meteorological observation variables after assimilation for input into subsequent forecasting models.

4 Regional customised meteorological multiscale forecasting based on data decomposition and reinforcement learning

4.1 Meteorological observation sequence decomposition based on STL algorithm

Traditional meteorological forecasting models have issues like insufficient dynamic error correction capability and low prediction accuracy, making it difficult to meet the needs for customised predictions in different regions. To address these challenges, this paper proposes a regionally customised multiscale meteorological forecasting method that integrates data decomposition and reinforcement learning based on meteorological observation data assimilation. The overall model framework of the suggested method is shown in Figure 1. Firstly, the STL algorithm (Krake et al., 2024) is adopted to decompose the meteorological sequence into trend, seasonal, and residual components. Based on the characteristics of deep learning and reinforcement learning, different components are selected for learning. Finally, the prediction results are combined to further improve the accuracy of multiscale meteorological forecasting.

Figure 1 The overall model framework of the suggested prediction method (see online version for colours)



For the trends, seasonal patterns, and residuals in a meteorological sequence, this proposed model uses the STL algorithm to decompose the meteorological observation sequences. The STL algorithm is one of the most commonly used decomposition algorithms (Gordan et al., 2024). Compared to other decomposition methods, it has strong robustness against outliers in the data, thereby generating robust sub-sequences. The robustness of these component sequences can further improve the accuracy of forecasting using those subsequences.

The STL algorithm is a filtering process for decomposing meteorological sequences Y_t into three components: trend, seasonal, and residual. These are represented as follows with T_t, S_t, and R_t.

$$Y_t = T_t + S_t + R_t \tag{13}$$

STL consists of two recursive processes: an inner loop nested within the outer loop. Each iteration of the inner loop comprises a seasonal smoothing step to refine the seasonal component, followed by a subsequent trend smoothing step to update the trend component. The calculation process for the k^{th} iteration of the inner loop is as bellow.

1 Detrending. A new sequence $Y_t^{\text{detrend}} = Y_t - T_t^{(k)}$ is achieved through subtracting the trend component $T_t^{(k)}$ from the original meteorological sequence values Y_t.

2 Cyclic subseries smoothing. Smooth each cyclic subsequence of the detrended sequences using a loess smoother to obtain an initial seasonal sequence $C_t^{(k+l)}$.

3 Low-pass filtering. The preliminary seasonal sequence obtained in Step (2) is processed by a low-pass filter and then smoothed with a loess smoother to gain the residual trend sequence $L_t^{(k+1)}$.

4 Detrending. The seasonal component $S_t^{(k+1)} = C_t^{(k+1)} - L_t^{(k+1)}$ is obtained by subtracting the remaining part $L_t^{(k+1)}$ from $C_t^{(k+1)}$.

5 Deseasonalising. A deseasonalised sequence $X_t^{\text{deseason}} = Y_t - S_t^{(k+l)}$ is obtained by subtracting $S_t^{(k+1)}$ from Y_t.

6 Smoothing trend: The trend sequence $T_t^{(k+1)}$ is obtained by applying a loess smoother to $X_t^{deseason}$.

In every outer loop, an inner loop is executed first, followed by the determination of robustness weights. These weights are utilised in the next inner iteration to suppress short-lived or irregular effects in the trend and seasonal elements. Through the initial operation of the inner loop, T_t and S_t are obtained, while R_t is expressed as $R_t = Y_t – T_t – S_t$.

4.2 Regional customised meteorological multi-scale forecasting based on GRU model and reinforcement learning

After decomposing the meteorological variable sequence using the STL decomposition algorithm above, a GRU model (Wu et al., 2020) is used to predict the feature-rich trend component, while the remaining seasonal component and residual component are used as states. The meteorological sequence prediction problem is reconstructed as an MDP decision-making problem, and a reinforcement learning model is used for learning. By combining the advantages of deep learning and reinforcement learning, the accuracy of forecasting is improved.

In terms of environment state construction, first use the STL algorithm to decompose the meteorological sequence Y_t, obtaining T_t, S_t and R_t. A GRU network is used to predict the decomposed trend sequence T_t. Since the action selection of an agent in reinforcement learning is affected by a constantly changing environment, agents are used to predict the remaining fluctuations. Therefore, the state of reinforcement learning is the residual fluctuation sequence of the meteorological variable sequence, namely the seasonal component and the residual component, that is $state = S_t + R_t$.

The action output by the agent is not the direct meteorological sequence value corresponding to the next time step, but rather the prediction of the remaining fluctuation part after the GRU network model predicts the trend t_t of the decomposed T_t. That is, the fluctuation value of the meteorological sequence. Therefore, the agent action is defined as a continuous action in the action space, where the action space is the normalised fluctuation range. The reward function for the agent is designed as follows: r_t is the reward value, a_t is the action value of the agent on meteorological element t, t_t is the trend value, and l_t is the corresponding meteorological variable sequence value at meteorological element t. In addition, in order to allow the agent to gain sufficient experience to learn, a noise parameter k is added; during the first k episodes, noise is added to the agent's actions, then removed so that the agent can focus more on improving prediction accuracy.

$$r_t = -|a_t + t_t - l_t| \tag{14}$$

For the state transition corresponding to the environment, since meteorological sequence data are continuous, the states start and end in time order. That is, after the agent makes an action response to the current state, it transitions to the next state in chronological order. To learn more experience, the start and end of environmental states are selected according to the following equation.

$$state_{start} = random\left(state_0, state_{max}\right) \tag{15}$$

$$state_{end} = min\left(\left(state_{start} + step_{max}\right), state_{max}\right) \tag{16}$$

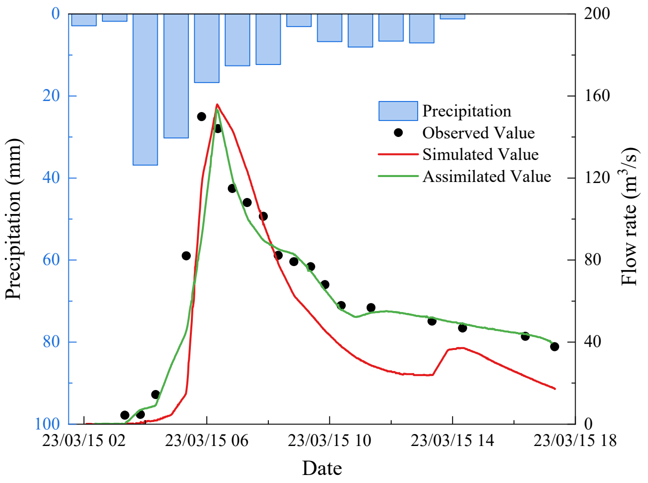
where $state_{start}$ represents the start state for agent exploration, and rando' is a random function indicating that a position is randomly selected between $state_0$ and $state_{max}$ as the starting state for agent exploration. $state_0$ and $state_{max}$ indicate the beginning and end of the meteorological sequence state space, respectively. $step_{max}$ represents the maximum number of steps an agent can explore within a single episode.

5 Analysis of experimental results

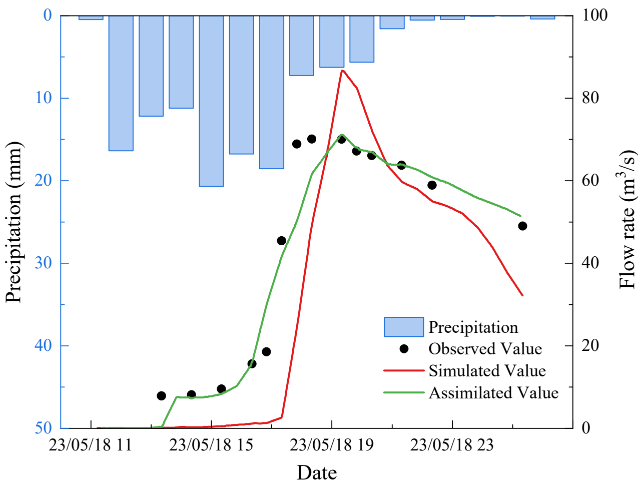
5.1 Analysis of meteorological observation data assimilation effect

This paper selects coastal and plain meteorological data collected in 2023 from the literature (Rasp et al., 2020) as the dataset, which contains 5,691 records of precipitation, humidity, and temperature data. The dataset is based on global land data assimilation system (GLDAS) data, Global Energy and water cycle experiment-surface radiation BUDGET (GEWEX-SRB) radiation data, and tropical rainfall measuring mission (TRMM) precipitation data, combined with conventional meteorological observation data produced by China's meteorological administration. It was divided into training sets, test sets, and validation sets in a 6:3:1 ratio. Experiments were conducted using an AMD 5900X processor, 24GB memory, and an NVIDIA RTX 3090 GPU, with PyTorch used to implement the model presented in this paper. During network training, each batch size was set to 64, learning rate at 0.0001, embedding dimension at 4, and Adam optimiser applied for optimisation.

Figure 2 Results of data assimilation for precipitation, (a) 20230315, (b) 20230518 (see online version for colours)



(a)



(b)

Table 1 Meteorological forecast results after data assimilation

Date	*Precipitation amount*			*Peak time difference/ h*	*Determination coefficient*
	Measured value/ (m^3/s)	*Assimilation value/ (m^3/s)*	*Relative error/ %*		
20230315	150	154.486	2.99	0.5	0.868
20230518	70.2	71.598	1.991	0.5	0.951

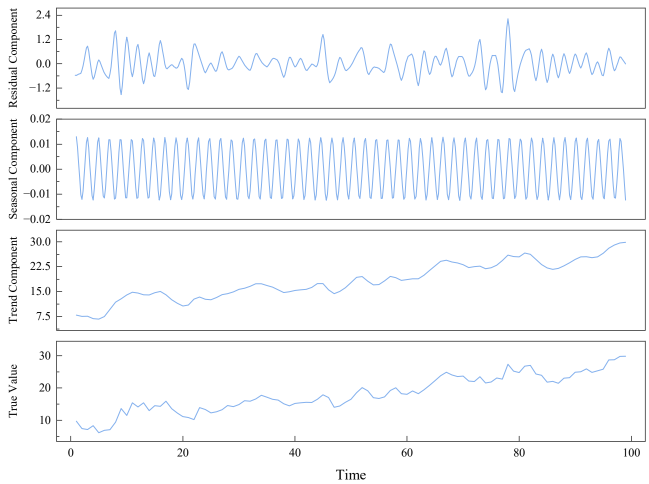
The assimilation calculation of the rainfall-runoff simulation results and measured flow data for coastal areas in 2023 using the method proposed in this paper, OURS, was performed to assimilate update two field runoff events. The assimilation results are shown in Table 1 and Figure 2. Taking daily precipitation as an example to analyse the meteorological forecasting results after data assimilation according to Table 1, the flow volume of precipitation on March 15th, 2023 after assimilation differs from the measured one by only 4.486m³/s with an error of 2.990%. The peak occurrence time is 0.5h later than the measurement; however, the determination coefficient is merely 0.868. The data assimilation method proposed in this paper significantly improves the forecast precipitation flow without any sudden proximity to observational information and can achieve better assimilation results with fewer particles. This confirms the feasibility of the proposed method and lays a foundation for further experiments on subsequent multi-scale meteorological predictions.

5.2 *Effectiveness of meteorological sequence decomposition*

To assess the effectiveness of the STL sequence decomposition algorithm, the selected dataset was decomposed using the STL decomposition algorithm and the results after decomposition were analysed. The first 100 data points of the decomposed data are used to draw curves as shown in Figure 3.

As shown in Figure 3, after the meteorological sequence data is decomposed by the STL time series decomposition algorithm, the overall trend of the true value curve and the trend component curve are consistent; however, the trend component curve becomes smoother after decomposition. The seasonal component curve shows uniform oscillation around zero, and the fluctuation part in the residual component curve demonstrates that there is a stronger effect when the smoothness between its true value curve and the trend curve differs more. Through this analysis, it verifies that after using the STL decomposition algorithm for decomposition, multi-scale meteorological observation sequences successfully separate their trends from fluctuations, making it convenient to apply deep learning and reinforcement learning models afterward to learn based on these characteristics.

Figure 3 Component curves after STL decomposition (see online version for colours)



5.3 *Meteorological prediction accuracy analysis*

To analyse the outcome of the meteorological forecasting approach OURS suggested in this paper, multi-scale meteorological prediction experiments are conducted on the plain dataset. The evaluation indicators selected include RMSE, mean absolute percentage error (MAPE), and determination coefficient R^2. Comparative models are TCN-EWF (Hewage et al., 2020), CLS-RL (Liu et al., 2020), NW-DRL (Zhao et al., 2024), PFA-RL (Jethva, 2025). The humidity prediction error results for different models with forecast lengths of 6 and 24 are implied in Table 2 and Table 3, individually.

Table 2 Comparison of prediction performance at a length of 6

Model	*RMSE*	*MAPE*	R^2
TCN-EWF	27.61	39.62	0.8524
CLS-RL	25.84	35.38	0.8862
NW-DRL	21.43	33.46	0.9054
PFA-RL	16.94	27.75	0.9428
OURS	14.58	23.53	0.9715

Table 3 Comparison of prediction performance at a length of 24

Model	*RMSE*	*MAPE*	R^2
TCN-EWF	32.66	45.29	0.7951
CLS-RL	29.51	41.66	0.8208
NW-DRL	25.08	38.17	0.8715
PFA-RL	23.48	33.53	0.9208
OURS	18.25	30.47	0.9422

As shown in Table 2 and Table 3, the OURS method performs well on various metrics under different forecast length settings. When the prediction lengths are 6 and 24, the RMSE of OURS is 14.58 and 18.25 respectively, which reduces by at least 13.93% and 15.21% compared to contrast models. The R^2 of OURS is 0.9715 and 0.9422 respectively, which increases by 13.97%, 18.5% compared to TCN-EWF, 9.63%, 14.79% compared to CLS-RL, 7.3%, 8.11% compared to NW-DRL, and 3.04%, 2.32% compared to PFA-RL respectively. The OURS method performs well in meteorological multi-scale forecasting tasks. The OURS method decomposes the meteorological sequence by ST with local weighted regression, predicts the features of clear trend components using GRU, and takes the remaining seasonal components and residual components as states. It reconstructs the meteorological forecast problem into an MDP decision-making problem and improves prediction accuracy through learning with a reinforcement learning model.

6 Conclusions

Conventional meteorological forecasting models are often challenged by the complex coupling of multi-scale meteorological systems and data heterogeneity, limiting their ability to provide region-specific predictions. To address this, we propose a customised multi-scale forecasting model that integrates data assimilation and reinforcement learning. A PSO-enhanced particle filter is introduced to overcome the dependency on future observations in traditional data assimilation. By leveraging historical reanalysis data and adaptively guiding particles toward observations via PSO, the method produces improved assimilated meteorological variables. The time series is decomposed using STL algorithm to extract trend, seasonal, and residual components, enhancing feature representation. A GRU model predicts the trend, while a reinforcement learning framework incorporates seasonal and residual elements as state variables for multi-scale fluctuation forecasting. This hybrid approach combines the temporal modelling capability of deep learning with the adaptive decision-making of reinforcement learning. Experimental results show that the proposed model achieves lower RMSE and MAPE, demonstrating high accuracy. It effectively handles meteorological multi-scale forecasting adaptively, consistently outperforming baseline models. These findings offer valuable insights for developing next-generation intelligent meteorological forecasting systems.

This paper has certain limitations in research, as the reinforcement learning model adopted requires interaction with the environment to obtain data for each learning process, resulting in longer training times compared to traditional deep learning methods. For applications involving large amounts of data, more training time is needed. In future time series tasks using reinforcement learning, multiple agents can be employed to work together to further improve exploration efficiency within the environment and make faster adjustments to search strategies through timely feedback, enabling the model to handle more complex scenarios.

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Declarations

All authors declare that they have no conflicts of interest.

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