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Dynamic correction of forest fire spread prediction using observation error covariance matrix estimation technique based on FLC-GRU

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Abstract

Background Data assimilation (DA) techniques have played a significant role in improving the prediction accuracy of forest fire spread. The dynamic correction technique weights the predicted and observed values to obtain an analytical value that better reflects the position of the fire perimeter. The weighted importance of each contribution is determined by the magnitude of its associated error. However, as a crucial parameter affecting prediction accuracy, the covariance matrix of observation errors is often inaccurate and neglects its own temporal correlation. This is unfriendly to spread prediction results. To address this issue, we proposed a targeted technique for estimating the observation error covariance matrix (R matrix) based on the Fire Line Convolutional Gated Recurrent Unit (FLC-GRU).

Results We integrated this method into the DA framework and validated its applicability and accuracy using Observing System Simulation Experiment (OSSE). Through comparisons with traditional methods, the results indicate that using the FLC-GRU estimated R matrix for correction calculations leads to wildfire prediction locations that are closer to the true values.

Conclusions The proposed approach learns the covariance matrix directly from time-series observed fire line data, without requiring any prior knowledge or assumptions about the error distribution, in contrast to classical posterior tuning methods. The proposed method significantly improves the rationality and accuracy of R matrix estimation, enhances the utility of observational data, and thereby improves the correction accuracy of forest fire spread predictions. Moreover, the study also demonstrates the applicability of the proposed method within the DA framework.

Keywords Forest fires, Spread prediction, Data assimilation, Observation error covariance matrix, Neural networks

Resumen

Antecedentes Las técnicas de asimilación de datos (DA) han jugado un rol significativo en el mejoramiento de la exactitud en la predicción de la propagación de fuegos de vegetación. La técnica de corrección dinámica sopesa los valores predichos y los observados para obtener un valor analítico que refleja la posición del perímetro del fuego. La importancia balanceada de cada contribución es determinada por la magnitud de su error asociado. Desde luego, como un parámetro crucial que afecta la exactitud de la predicción, el error de observación de la matriz de covarianza es frecuentemente inexacta y reniega de su propia correlación temporal. Esto aparece como poco amigable para

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diseminar los resultados predichos. Para afrontar este tema, proponemos una técnica enfocada a estimar el error de observación de la matriz de covarianza (Matriz R), basada en la unidad de línea de fuego convolucional cerrada.

Resultados Integramos este método en el marco de trabajo DA y validamos su aplicabilidad y exactitud usando el Experimento de Observación del Sistema de Simulación (OSSE). A través de comparaciones con métodos tradicionales, los resultados indican que usando la matriz R estimada (FLC-GRU) para la corrección de cálculos, se llega a predicciones de ubicación de los fuegos que son cercanas a los valores reales.

Conclusiones La propuesta presentada toma la matriz de covarianza directamente de los datos de las series de tiempo observadas en la línea de fuego, sin la necesidad de un conocimiento previo o de suposiciones sobre el error de la distribución, en contraste con los métodos clásicos de ajuste a posteriori. El método propuesto mejora significativamente la racionalidad y exactitud de la estimación de la Matriz R, aumenta la utilidad de los datos observacionales, y por lo tanto mejora la corrección en la exactitud de las predicciones de la propagación de fuegos de vegetación. Además, el estudio también demuestra la aplicabilidad del método propuesto dentro del marco de trabajo de la técnica DA.

Background

Accurately predicting the development of forest fire spread is one of the most crucial aspects in emergency management of forest fires. To address the issue of low prediction accuracy in traditional computer simulation due to errors in input data or the model itself, data assimilation (DA) techniques have been applied in this field. The main idea is to assimilate observed values into the predicted values obtained through methods like physical models. This is achieved by weighting the predicted values and observed values to obtain analytical values that better reflect the system state. Mandel et al. first applied the idea of DA to the field of forest fire spread prediction (Mandel et al. 2008). Subsequently, scholars such as Rochoux and Trouvé conducted extensive research on ensemble Kalman filter (EnKF) algorithms (Rochoux et al. 2014, 2015; Zhang et al. 2019), which became one of the mainstream correction methods in the field of forest fire spread prediction. In recent studies, Zhou et al. first applied the ensemble transform Kalman filter (ETKF) to forest fire spread prediction, improving the correction effect (Zhou et al. 2019). Building upon this, Zhou et al. explored improvements to the correction algorithm under conditions of large observation data errors or missing data (Zhou et al. 2021). In a recent study, the author's research team found that the deterministic ensemble Kalman filter (DEnKF) has a superior correction ability for forest fire spread prediction compared to EnKF. In summary, the forest fire spread prediction method based on DA has achieved widespread development and research results.

In the computation of data assimilation techniques, the weighted importance of predicted values and observed values is determined by their respective error covariances, corresponding to the background error covariance matrix (Q matrix) and the observation error covariance matrix (R matrix). Moreover, the weighted results directly influence the outcome of the final analysis values. However, in practical engineering, the unavailability of true values makes it impossible to directly calculate the magnitude and distribution of errors, posing a challenge in the estimation of error covariances. In the research on dynamic correction of forest fire spread prediction, error covariance is often simplified. Specifically, regarding the estimation of the Q matrix, using the Ensemble Kalman Filter (EnKF) algorithm as an example, the sample covariance matrix is commonly employed to represent the Q matrix. This step avoids the direct calculation of errors by implicitly advancing the ensemble forecast. However, unlike the Q matrix, the R matrix cannot be empirically estimated from the ensemble of simulated trajectories. Therefore, the treatment of the R matrix is typically more straightforward, often defined empirically as a scalar matrix, lacking theoretical rigor and potentially adversely affecting the accuracy of analytical values. Furthermore, research has indicated that observation errors are correlated and exhibit dependence on both time and state. Considering these correlated observation errors in DA can lead to more accurate analysis results (Stewart et al. 2008; Li et al. 2009; Miyoshi et al. 2013; Waller et al. 2014).

In recent years, significant research on error handling methods has been conducted in various fields applying DA techniques (Stewart et al. 2013; Liu et al. 2019; Cheng et al. 2019). One of the most representative methods is the posterior diagnostic method proposed by Desroziers et al. (known as DI01, D05) (Desroziers and Ivanov 2001; Desroziers et al. 2005). Among them, D05 estimates observation error covariance using deviations (innovations statistics) between observation values and background and analysis values. In subsequent studies, some scholars have used this method to improve filtering accuracy, thereby obtaining more accurate state estimation values (Miyoshi et al. 2013; El Gharamti 2018). In a recent comprehensive review by Pierre Tandeo, existing methods are categorized into two main classes: (1) innovation-based methods, such as the method of moments, which assumes equality between theoretical and observed moments of innovations, and (2) likelihood-based methods, which utilize the likelihood of the observations contained in the innovations. The mentioned methods fall under traditional posterior tuning methods, and more details can be found in (Tandeo et al. 2020). Additionally, some covariance estimation techniques based on neural network algorithms have been proposed and achieved good results (Cheng et al. 2023). Cheng et al. introduced an observation error covariance specification based on Long Short-Term Memory (LSTM) and demonstrated its good performance in the Lorenz twin experiment and shallow water equations, commonly used for testing DA algorithms (Cheng and Qiu 2022). However, for the estimation of the R matrix in predicting forest fire spread, there is still a lack of targeted research and validation.

In this study, we propose a technique for estimating the R matrix based on the Fire Line Convolutional Gated Recurrent Unit (FLC-GRU). This aims to enhance the accuracy and efficiency of R matrix estimation while improving the correction accuracy of forest fire spread predictions. In contrast to traditional posterior tuning methods, this new approach does not require prior knowledge of either the background or the observation matrix. In the network design, we chose to use the more efficient GRU over LSTM to learn the error distribution. Additionally, before training, we utilized a convolutional network to not only retain the temporal information of the observed fire line data but also extract its spatial information, enhancing the network's performance. To validate the accuracy of the proposed method in correcting forest fire spread predictions, we utilize actual terrain and fuel data from the Idaho Panhandle National Forests and conduct Observing System Simulation Experiment (OSSE).

Methodology

The R matrix estimation technique based on Fire Line Convolutional Gated Recurrent Unit (FLC-GRU)

Convolutional Neural Networks (CNN) are commonly employed for image processing (Krizhevsky et al. 2017; Lin et al. 2019; Huo et al. 2022), effectively reducing large volumes of image data to smaller datasets while retaining essential features, aligning with principles in image processing. In 2014, Cho et al. introduced the Gated Recurrent Unit (GRU), a simplified version of Long Short-Term Memory (LSTM) (Cho et al. 2014). GRU maintains robust memory capabilities for sequential data while enhancing computational efficiency. Leveraging the high sensitivity of convolutional Networks and GRU networks to spatial and temporal features, respectively, we aim to better provide a better solution to the estimation problem of the observation error covariance matrix in the context of forest fire spread. To achieve this, we propose the Fire Line Convolutional Gated Recurrent Unit (FLC-GRU) network, encompassing dataset generation, data preprocessing, convolutional processes, and GRU processes. The FLC-GRU network structure is illustrated in Fig. 1.

We initiate the process by employing FARSITE, a commonly used forest fire spread tool based on the

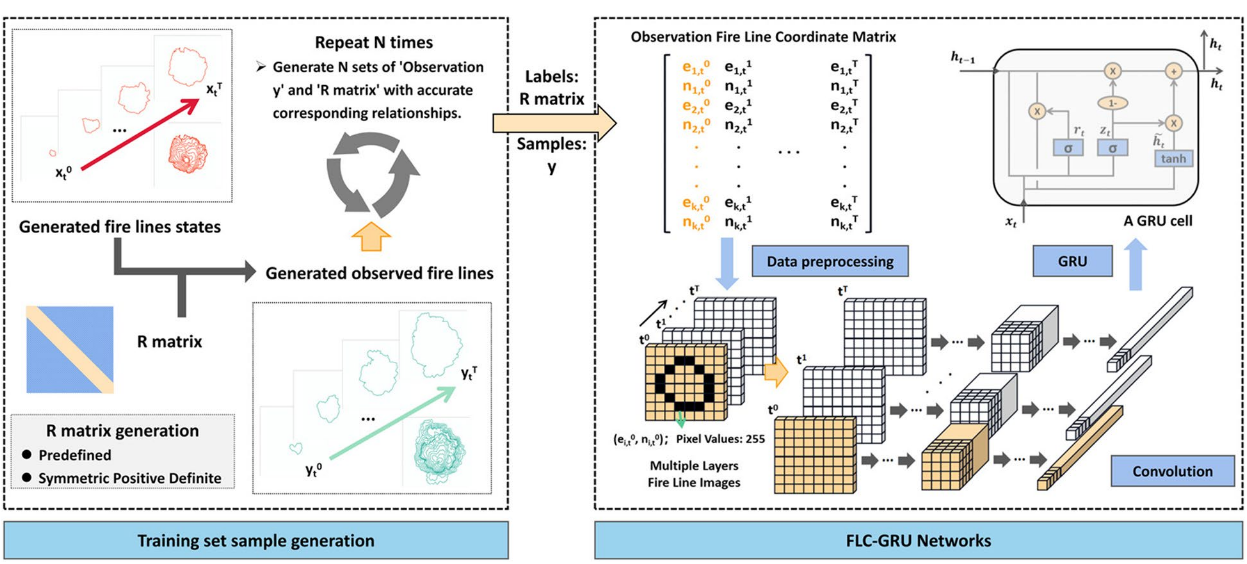

Fig. 1 Schematic diagram of the FLC-GRU network

Rothermel model and Huygens theory. This tool generates a set of fire line position state values $X_t = [X_t^0, X_t^1, \ldots, X_t^i, \ldots, X_t^T]$.

$$X_t = M(X_{t-1}, \theta_{t-1}), \tag{1}$$

where M is the nonlinear forecast operator, i.e., the FARSITE fire growth model; θ denotes the related parameters, which include the topography, fuel, weather, and wind parameters.

Concurrently, we pre-generate a Symmetric Positive Definite (SPD) matrix R, representing the specific properties of the R matrix. Subsequently, we augment X_t by introducing observation errors ϵ that follow a Gaussian distribution, resulting in the generation of observed data $y_t = [y_t^0, y_t^1, \ldots, y_t^i, \ldots, y_t^T]$. It should be noted that, as with DI01 and D05, we assume that the R matrix is time-invariant, at least for a sufficiently long time.

$$y_t = H(X_t) + \epsilon, \tag{2}$$

where H can be simply viewed as a selection operator that pairs each marker in the simulated fire fronts with its closest neighbor along the observed fire fronts, and $\epsilon \sim N(0, R)$.

This process is iterated N times to produce N sets of "Observation y_t" and "R matrix" with exact corresponding relationships.

In this study, T is set to 20 h, and the fireline state X_t^i at each time step is composed of a set of $k = 100$ fire points, i.e., $X_t^i = [e_{i,1}, n_{i,1}, e_{i,2}, n_{i,2}, \ldots, e_{i,j}, n_{i,j}, \ldots, e_{i,100}, n_{i,100}]^T$, where $(e_{i,j}, n_{i,j})$ represents the coordinates of the jth observed fire point at time i. In accordance with the requirements of the DA analysis steps, it is stipulated that the generated R matrix is a SPD matrix of size 2 k*2 k, i.e., 200*200. The values of the diagonal elements follow a random distribution in the range of (0, 200).

The above N sets of "Observation y_t" and "R matrix" with exact correspondence constitute the training set of the FLC-GRU network in this study. A total of 14,000 data sets were generated, with 11,200 sets allocated for training and 2800 for validation. The network's input is $y_t = [y_t^0, y_t^1, \ldots, y_t^i, \ldots, y_t^T]$, and the output is the R matrix. As mentioned earlier, GRU possesses the capability to handle time-series data and often significantly improves training efficiency compared to LSTM while maintaining similar training effectiveness. Therefore, we aim to utilize the GRU network to learn the distribution of observation errors. Before that, our goal is to retain the temporal information of the observed fire line data while fully leveraging the spatial information contained in the data. To achieve this, before initiating the training of the GRU network, we applied convolutional processing to the observed fire line data to extract its spatial features. Building upon this, given the suitability of convolutional networks for extracting image features, prior to the convolution operation, we remapped the observed data, represented as y_t, to multiple layers of fire images by transforming the coordinate matrix at time T. In this study, Stochastic Gradient Descent (SGD) is employed as the weight update algorithm, with a learning rate of 1e−5, exponential learning rate decay strategy, the application of weight decay, beta set to 0.8, and the mean squared error (MSE) as the loss function. Ultimately, given a set of observation data with an unknown error distribution, the network can output the predicted R matrix.

The core idea of the method

In summary, the core of this method is to address the challenge of accurately estimating the R matrix when observing the fire line in forest fire incidents, given the inherent uncertainty in determining the true fire line positions. To tackle this issue, the method adopts a reverse-thinking approach to identify the exact correspondence between observation data and the R matrix. By pre-generating a specific R matrix and generating observation data following the distribution specified by this matrix, a training set is established. Subsequently, the FLC-GRU network can learn such error distributions, improving the efficiency and accuracy of estimating the R matrix in dynamic correction for predicting forest fire spread. This approach involves a proactive generation of observation error covariance matrices, creating a training set that facilitates the learning of error distributions through convolutional and GRU networks.

Forest fire spread prediction dynamic correction system based on FLC-GRU

Typically, traditional forest fire spread models/tools are used to predict the forest fire spread position. For research on traditional forest fire spread models, refer to (Sullivan 2009a, b, c). In this study, we use FARSITE as the forest fire spread prediction tool(Finney 1998). This requires us to input the landscape file of the forest fire area, the input fire lines position, and other input parameters. Other input parameters include (I) the data that can reflect the situation of the forest fire scene, including wind conditions, weather data, and so on. (II) The input data required for computer simulators, including start time, end time, time step and so on. Through FARSITE simulations, we can obtain the simulated values of the forest fire spread position.

Based on the concept of DA, we aim to use the observed values of the fire perimeters position to correct the simulated values. Regarding the choice of DA method, as mentioned earlier, EnKF has become one of the mainstream correction methods in the field of forest fire spread prediction. Compared to the KF, the EnKF effectively address the limitation of KF not being applicable to nonlinear systems. The EnKF estimates the covariance between the state variables and observation variables based on the ensemble forecast results, and then uses the observation data and covariance to update the analysis, obtaining an analysis ensemble for further forecasting. Unfortunately, the standard EnKF requires artificial perturbation of the observation data, which introduces additional errors, making it a suboptimal filter. To address this, Sakov P and Oke PR proposed DEnKF, a deterministic data assimilation method without observation perturbation (Sakov and Oke 2008). In previous studies by our team, we found that DEnKF has superior correction capabilities in forest fire spread prediction. Therefore, this paper uses the DEnKF as the DA method.

As for observational data, we can obtain real-time observations of the fire scene through satellite remote sensing, drones, or human observation. Subsequently, the FLC-GRU network proposed in this paper is employed to estimate the observation error covariance matrix for assimilation calculations, yielding improved estimates of the fire line's position. The output of the current time's fire line position serves as the input for the next moment's prediction of forest fire spread, enhancing the results for the next time step. This process forms a rational and comprehensive dynamic correction method for predicting forest fire spread, as shown in Fig. 2. It is noteworthy that in this study, FARSITE is utilized as the tool for predicting forest fire spread, and the DA method employs the DEnKF algorithm, serving as an example. The applicability of this method remains unaffected by the choice of other forest fire spread prediction models or tools, as well as alternative DA algorithms.

In this study, we utilized FARSITE's LINUX 1.0 version, running FARSITE in command-line mode. The DEnKF algorithms were implemented using MATLAB 2020b for Linux. The FLC-GRU network was run on an i5-8600 K processor with a GeForce RTX 2080Ti GPU. The code compilation environment included Python 3.9, PyTorch 1.11.0, and CUDA 11.3. Through multiple tests, we found that the average computation time for the DA algorithm was approximately 0.2 s, while the computation time for the FLC-GRU to estimate the R matrix was about 30 s. It is important to note that the time required to run DA computations is much less than the time needed for forest fire spread predictions using FARSITE. The average computation time for a single FARSITE run is about 120 s. This means that traditional simulation accounts for a significant portion of the total computation time.

Experimental designs

Study area

Taking into consideration the variations in terrain, we selected the Idaho Panhandle National Forests located in the state of Idaho, United States (latitude 47.5° N to 48° N, longitude 115.7° W to 116.7° W) as our research focus. This region experiences a warm climate and substantial fuel accumulation, posing a higher risk of forest fire incidents. We obtained the landscape file (.LCP) for the study area from LANDFIRE (http://landfire.gov/), encompassing topographical and fuel data essential for conducting forest fire spread predictions based on FARSITE. The study area is depicted in Fig. 3.

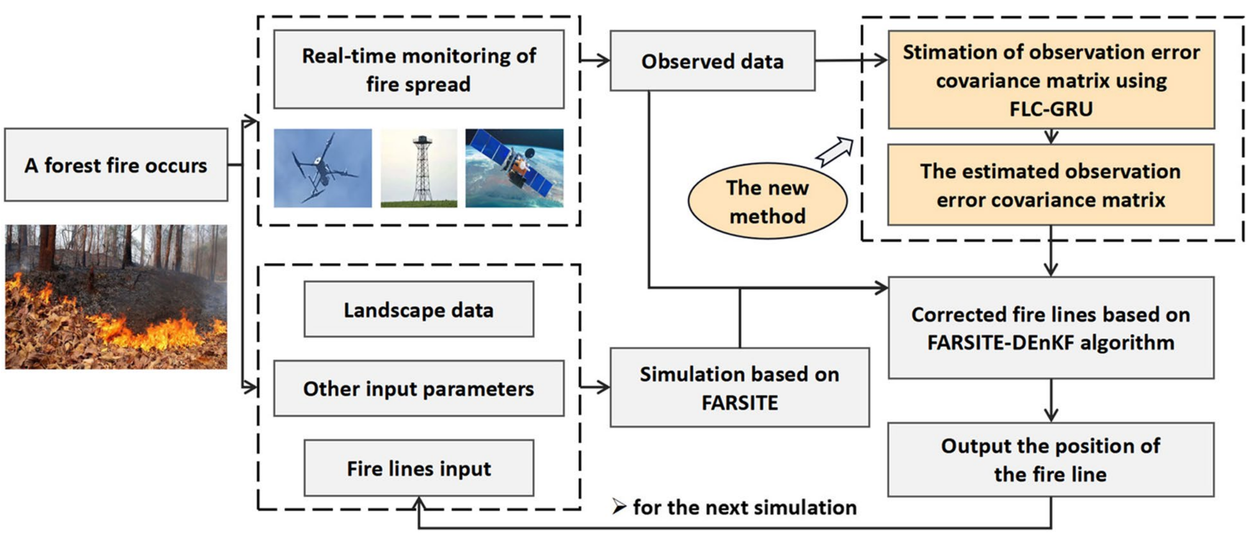

Fig. 2 Flowchart of the forest fire spread prediction dynamic correction system based on FLC-GRU

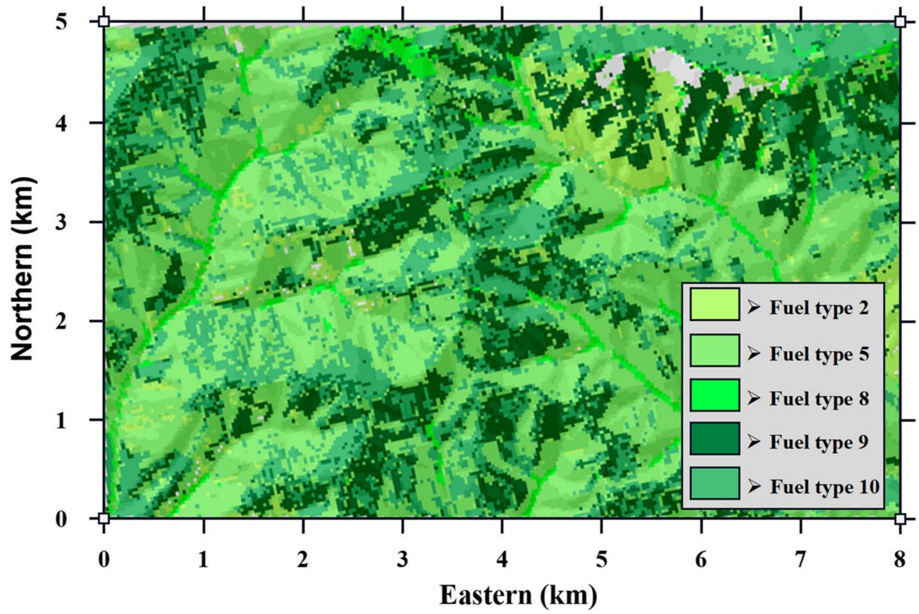

Fig. 3 Study area

Experiment set up

To validate the applicability of the proposed method, we designed an Observing System Simulation Experiment (OSSE), which is one of the most commonly used methods to assess the performance of DA algorithms. The OSSE for this study comprised four groups: (1) Real group: Simulating without input errors to generate a simulation result that serves as the true fire lines. (2) Simulation group: Introducing input errors to simulate real-world scenarios where, due to errors in input data and the model, only uncorrected predictions can be obtained. (3) DA group (Data Assimilation group): Applying DA algorithms to correct the results of the simulation group. However, common rough handling methods were used for the R matrix. (4) FLC-GRU group (Data Assimilation with Fire Line Convolutional Gated Recurrent Unit group): Employing DA for correction while utilizing the R matrix estimation method proposed in this paper. See Table 1 for details.

In this study, we adopted the Deterministic Ensemble Kalman Filter (DEnKF) as the DA method, with a set ensemble size of 20. The duration of the forest fire spread simulation experiment based on FARSITE was set at 20 h, with assimilation performed every 1 h. We assumed a spatially uniform distribution of wind, with a globally set southeastern wind speed of 3.5 m/s. It is important to note that the primary focus of this paper is to validate the applicability and accuracy of the proposed new method in dynamic correction of forest fire spread predictions by comparing it with traditional methods. Therefore, some simplifications were made in the experimental settings for certain parameters, which is a reasonable approach.

In this experiment, observational data is derived from the Real group, where we added errors following an unknown R matrix to generate observational data based on the real fire line. In the DA group, we assume observation errors to be random noise with a standard deviation of 200 m. The R matrix is empirically defined as a scalar matrix, which is a common practice in DA for correcting forest fire spread predictions. This setup is also designed to address the fact that in previous approaches, people typically assigned values to the R matrix based

Table 1 Experimental designs

	Input fire source	DA method	R matrix
Real group	No error	No	No
Simulation group	With error	No	No
DA group	With error	DEnKF	Defining a scalar matrix
FLC-GRU group	With error	DEnKF	Estimating based on FLC-GRU

on empirical considerations, lacking a certain degree of theoretical basis. In the DA with the FLC-GRU group, we employed the FLC-GRU network proposed in this study to compute the R matrix.

Evaluation criteria

In this study, we will utilize the Otsuka-Ochiai Similarity Index (OOSI) to assess the improvement in forest fire spread prediction accuracy achieved by the proposed method. OOSI is primarily employed for comparing the similarity between two sets, commonly used in the field of image analysis. Zhou et al. (Zhou et al. 2020, 2021) applied this metric to the domain of forest fire research. Assuming Sf and St represent the burned surfaces enclosed by the simulated fire perimeter and true fire perimeter, respectively. OOSI is defined as the intersection area of Sf and St divided by the geometric mean of the two, with values ranging between 0 and 1. A value closer to 1 indicates a higher degree of similarity between the two sets. The calculation formula is as follows.

$$OOSI = \frac{|S^f \cap S^t|}{\sqrt{|S^f| \times |S^t|}}, \tag{3}$$

Result and discussion

Results

To assess the performance of the proposed method, in this section, we compare the fire spread prediction results of the four control groups from both qualitative and quantitative perspectives.

The results of the four control groups at $T=1$, 7, 13, and 20 h are illustrated in Fig. 4. A comparison between the real group and the simulation group reveals significant deviations in the predicted results, with simulation errors gradually increasing over simulation time. This discrepancy is attributed to errors in the input ignition source. Furthermore, as time progresses, the errors accumulate, making predictions challenging for guiding on-site emergency management of forest fires. This underscores the inherent limitations of traditional methods or tools for predicting forest fire spread. In comparison to the simulation group, both the DA group and the FLC-GRU group exhibit predictions that are closer to the real fire line position. This suggests that DA techniques, through the incorporation of observational data, correct the simulated predictions and yield positive feedback.

Building upon this, the FLC-GRU group demonstrates superior correction effects compared to the DA group. This is particularly evident in regions of the fire line where significant discrepancies exist between the simulation and real groups (highlighted by black dashed rectangles in Fig. 4). Analysis attributes this difference to the

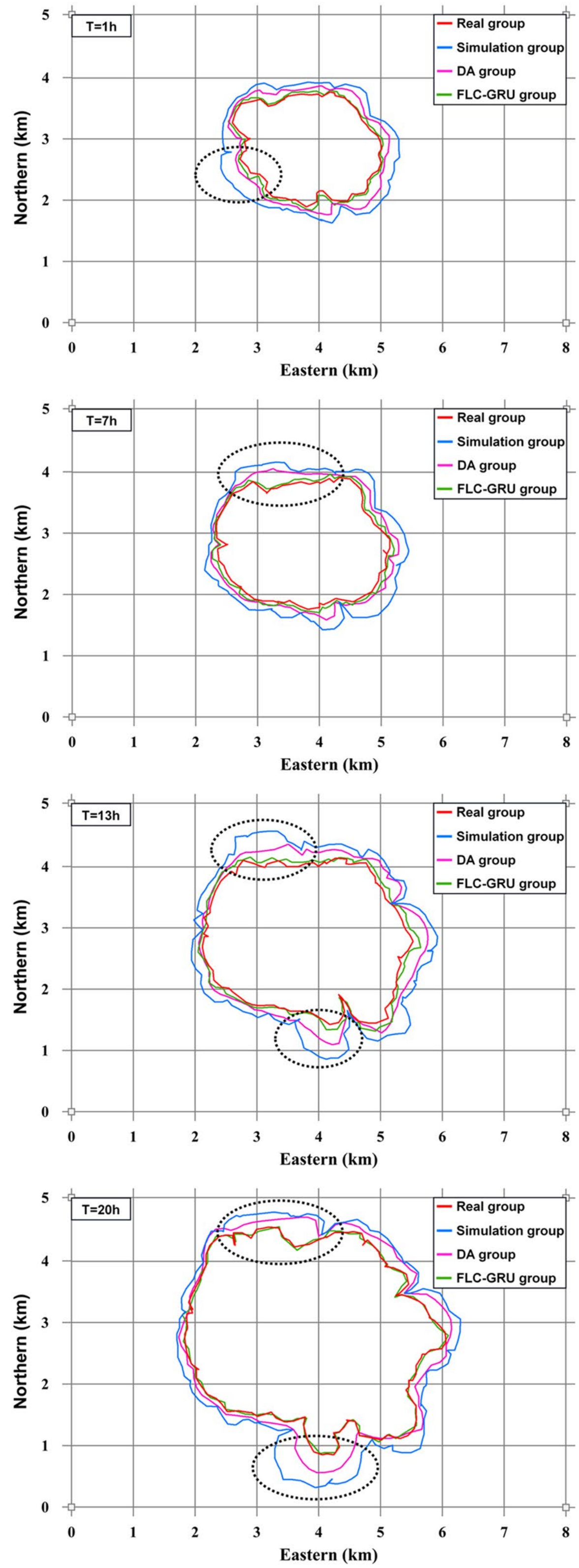

Fig. 4 Comparison of the fire perimeter predictions at 1, 7, 13, and 20 h of the real group, simulation group, DA group, and FLC-GRU group

nature of DA technology, which fundamentally involves the fusion of prior and posterior knowledge. In this study, the DA group achieves ideal predictions by weighting simulated and observed values. However, due to the inability of the R matrix involved in the calculations to accurately reflect the weighted importance of observational contributions, the DA group struggles to effectively merge prior and posterior knowledge when computing analysis values. In contrast, the FLC-GRU group, utilizing the FLC-GRU network proposed in this study, successfully predicts the R matrix corresponding to observational data, enhancing the value of the observational data and directly improving the correction results.

Subsequently, using the real group as a baseline, we calculate the OOSI between the predicted results of the remaining three groups and the true fire perimeter, quantitatively comparing the prediction results. As shown in Fig. 5, with the increase in simulation time, the similarity between the uncorrected simulation results and the spread results of the real group shows a decreasing trend. It is foreseeable that as time progresses, the similarity will decrease, rendering it less valuable as a reference. The first correction of the DA group and FLC-GRU group yielded good results and consistently maintained high similarity. Specifically, the OOSI of the DA group remained around 90%, while the OOSI of the FLC-GRU group remained above 95%. This further illustrates that based on the proposed method in this paper, the advantages of DA in the dynamic correction of forest fire spread predictions can be better utilized, enhancing prediction accuracy and assisting in the organizational scheduling of forest fire extinguishment.

Discussion

In summary, utilizing the FLC-GRU network for R matrix estimation has enhanced both the theoretical foundation and the accuracy of the estimates. In the testing conducted through OSSE, the involvement of the estimated R matrix in DA calculations demonstrated an improvement in the corrective impact of DA compared to defining the R matrix empirically as a scalar matrix. This enhancement is advantageous for the dynamic correction of forest fire spread predictions, providing valuable guidance for emergency management in the context of forest fires.

This study indicates that the proposed method is beneficial for the estimation of the R matrix and improves the predictions of forest fire spread. However, the limitation of this work is that we assume the R matrix is time-invariant, at least over a sufficiently long period. Therefore, the dimension of the R matrix is predefined to ensure that the observation data y and the R matrix share the same horizontal dimension, which is a requirement of the DA computation framework. This leads to converting each observed fire line into a finite number of point coordinates for computation, which may overlook critical observation information. Particularly for forest fires, as the fire line perimeter increases over time, more observation information is needed to guide the prediction of forest fire spread. Therefore, the current approach

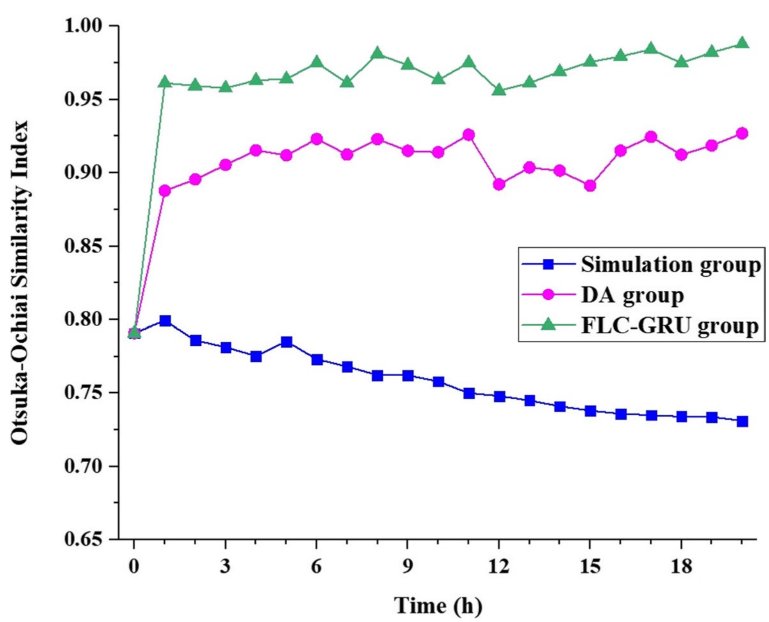

Fig. 5 The Otsuka-Ochiai Similarity Index (OOSI) between the predicted results of the simulation group, DA group, and FLC-GRU group, and the predictions of the real group, respectively

is limited to larger-scale forest fire spread predictions, highlighting the need for an improved data preprocessing method that allows more observational information to be incorporated into the correction calculations. For instance, exploring ways to represent observational data in the form of "lines" to contribute to the network's learning process could be beneficial.

On the other hand, the current network outputs a single time-invariant R matrix for a set of observation data to preserve the spatiotemporal information of the data. However, in actual forest fire observation work, time-varying observations are more meaningful. This suggests that it might be more advantageous to perform a separate R matrix estimation for each observation time point. Therefore, this may require designing a more complex network that can increase the frequency of R matrix estimation while retaining the temporal information of the observation errors.

The current research suggests that the novel method proposed in this paper has the potential to enhance the accuracy of forest fire spread prediction corrections. Despite areas mentioned above that could benefit from improvement, the method effectively advances existing approaches. By leveraging the characteristics of forest fire spread and incorporating neural network principles, it enhances the rationale and accuracy of R matrix estimation. Furthermore, this study integrates the method into the DA framework, exploring its applicability within the DA context, which is beneficial.

Conclusion

In this study, to enhance the dynamic correction accuracy in predicting forest fire spread, we purposefully designed a novel FLC-GRU network based on neural network principles. Initially, we preprocessed and extracted spatial features from the observed fire line data with temporal information. Subsequently, we utilized GRU to learn the distribution of observation errors for estimating R matrix. We conducted OSSE tests to assess the impact of this method on the correction of forest fire spread predictions. The results of the tests indicate that the R matrix predicted through the FLC-GRU network contributes beneficially to the improvement of forest fire spread prediction accuracy compared to commonly used simplified approaches. The experimental tests also highlight the applicability of the proposed method within the DA framework.

Authors' contributions

First author's contributions: designed research, performed research, wrote the paper. Second author's contribution: designed research, reviewed and wrote the paper. Third author's contribution: reviewed and wrote the paper. Fourth author's contribution: designed the neural network. Fifth author's contribution: constructed the neural network. Sixth author's contribution: reviewed the paper.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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