Research on green trade data prediction under global economic shock based on ConvLSTM model oriented towards reducing carbon emissions

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Abstract: Existing green trade data prediction models focus only on the temporal characteristics of the data, while ignoring the spatial relationships of the data, resulting in large prediction errors for trade volume (M and X). This paper takes Sino-Korean trade as the main research object, and uses the convolutional long short-term memory (ConvLSTM) model to predict trade volume (M and X) data by combining the advantages of spatiotemporal

features. This paper first collects and preprocesses relevant green trade data, then constructs a ConvLSTM model, and finally uses the model to output the predicted values of trade volumes M and X for the next year and compares them with the actual data. Experimental results show that the RMSE and MAE of the ConvLSTM model are 16,300 and 20,500, respectively, which are 1900 and 2300 lower than those of the LSTM model.

Keywords: economic shock; green trade; data prediction; ConvLSTM model; spatial features; low-carbon economy; trade volume.

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1   Introduction

With the promotion of global climate change and a low-carbon economy, green trade has gradually become an important part of international trade (Sun et al., 2023; Tan and Wang, 2023; He et al., 2025). The implementation of low-carbon policies has promoted the import and export (M and X) of green products, but global economic shocks such as trade wars (TW) and epidemics have had complex and uncertain effects on green trade (Hayat et al., 2024; Zhang et al., 2023). Green trade data has spatiotemporal characteristics (Aggarwal and Reddie, 2021), but most existing prediction methods focus on time series characteristics and ignore spatial factors, which limits the accuracy of green trade data prediction. An important issue in current research is to accurately predict green trade data, especially under the dual effects of a low-carbon background and global economic shocks.

With the advancement of global sustainable development goals and the accelerated implementation of carbon neutrality commitments, green trade has become a key path for countries to promote economic structural transformation and achieve high-quality

development. While the demand for various green products in the international market continues to grow, they are also deeply affected by new trade policies such as carbon border adjustment mechanisms, green tariffs, and environmental technical barriers. In addition, the global industrial chain and supply chain present a complex and changeable pattern due to geopolitical conflicts, energy crises, and commodity price fluctuations, further exacerbating the uncertainty of green trade development. The combined effect of these multi-dimensional background factors makes the dynamic change characteristics and spatiotemporal coupling relationship of green trade data more significant, and puts higher requirements on the accuracy and adaptability of data prediction methods.

This paper adopts a green trade data prediction method based on the convolutional long short-term memory (ConvLSTM) model to solve the problem that the existing model ignores spatiotemporal characteristics. This paper uses green trade data from 2015 to 2024, preprocesses the data, and then builds a ConvLSTM model to extract spatial features through the convolution layer, and combines the long short-term memory (LSTM) layer to capture the long-term dependencies in the time series, so as to achieve accurate prediction of green trade data. The experiment was compared with the traditional LSTM model. The experimental results show that the ConvLSTM model has a significant advantage in prediction accuracy, provides a more accurate prediction of green trade volume, and provides an effective tool for international trade analysis in the context of a low-carbon economy.

Paper contributions:

1   This paper applies the ConvLSTM model to green trade data prediction for the first time. It combines the convolutional layer to extract spatial features and the LSTM layer to capture the long-term dependencies of time series, significantly improving the model's ability to capture spatiotemporal features and breaking through the limitation of traditional models that only consider temporal features.

2   This paper considers traditional economic indicators and also incorporates various economic shock factors such as the Sino-US TW, the epidemic and changes in carbon emission policies into the model, which improves the prediction ability of green trade fluctuations and enhances the model's real-world adaptability.

3   The experiment uses a comparison with advanced models and finds that the ConvLSTM model has obvious advantages in the accuracy of M and X volume prediction, significantly reduces the prediction error, and provides a more accurate tool for international trade analysis in the context of a low-carbon economy.

2   Related works

In the prediction of green trade data, existing research mainly focuses on the time series prediction of green trade data. In the context of the pandemic, Zhu (2023) used support vector regression (SVR) to predict the oil demand of importing and exporting countries, achieving good and stable prediction results. Ozispa et al. (2024) and Sarfiah and Aripulis (2023) applied the autoregressive integrated moving average (ARIMA) model to the forecast of seaborne cargo volume and oil M and X, which better adapted to the

changes in global trade. For the green trade data forecasting model, the gated recurrent unit (GRU) model (Turkoglu et al., 2024; Saputra et al., 2024) and the LSTM (Aggarwal, 2023; Veronica et al., 2023) model are widely used in M and X and trade exchange rates, which have improved the forecasting effect to a certain extent. In the hybrid model, Pradana and Pratama (2024) used the CatBoost and XGBoost hybrid model to predict the M and X of Indonesia's oil and natural gas, with an RMSE value of only 0.046. Ghiffary et al. (2025) applied Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors (SARIMAX) to the prediction of milk, butter and egg imports, and found that the SARIMAX model had a better prediction effect than the LSTM model. Scholars use GRU, LSTM and other methods to ignore the potential spatial dependence in the data, resulting in poor accuracy of prediction results in the face of a changing international trade environment.

In recent years, with the rapid impact of the TW, the supply chain, demand and the flow of international trade have been greatly affected, especially the demand for green products, which can be affected by other non-green factors, such as economic crises and commodity price fluctuations. Studies have found that spatial characteristics such as green trade patterns and trade policies of different countries and regions play an important role in the prediction of green trade data and have a huge impact (Wang et al., 2024; Ridley and Devadoss, 2023). Maharsi et al. (2024) used the back propagation deep neural networks (DNN) method to predict Indonesia's M and X volume, and the MAPE was only 13.63%. Zhou and Zhu (2025) considered spatial features and used convolutional neural networks-long short-term memory (CNN-LSTM) to predict trade exchange rates and commodity prices, reducing the prediction error. However, it is difficult to handle spatial and temporal dependencies at the same time in each time step. Studies have shown that ConvLSTM has unique advantages in dealing with prediction problems involving spatial and temporal factors (Liu et al., 2023). ConvLSTM has been successfully applied to fields such as economic forecasting. It can effectively extract spatiotemporal features and improve forecasting accuracy (Ampountolas, 2024; Sugiartawan et al., 2023). Some scholars use convolutional neural networks (CNN) to predict trade data, which captures spatial features to a certain extent, but they have not been able to consider both temporal and spatial features for trade data prediction.

In summary, existing research on green trade data forecasting mainly focuses on time series methods, such as SVR, ARIMA, GRU and LSTM, which have achieved certain results in capturing time dependencies, but generally ignore the spatial correlation of data. As green trade becomes increasingly complex due to global economic fluctuations and policy changes, the role of spatial factors in trade patterns has become increasingly prominent, prompting researchers to try to introduce deep learning models such as CNN that can capture spatiotemporal features at the same time. Although some hybrid models have improved forecasting performance, how to efficiently integrate time and space information and solve the challenges brought by spatiotemporal dependencies is still an important direction that needs to be broken through in the current field of green trade data forecasting.

3   Data collection and preprocessing

3.1   Data collection

The experimental data in this paper come from the statistical reports and relevant policy reports of the United Nations Commodity Trade Statistics Database UN Comtrade and the total trade volume between China and South Korea and the World Bank data from 2015 to 2024. Among them, 2018 to 2022 is the key period of the Sino-US TW, which has a significant impact on the global economy. The data includes the M and X volumes of green products, M and X trade volume, carbon emission data, and macroeconomic data. The M and X volume of green products includes the annual M and X volume of green products, category distribution, and the proportion of each green product in the trade between the two countries. The M and X trade volume includes the total annual trade volume of green products between China and South Korea, the trade volume by product classification, and the market share of each category. Carbon emission data include the annual carbon emission and emission reduction effects of China and South Korea in green products, while macroeconomic data include GDP (Gross Domestic Product), foreign exchange rates, trade policies, and various economic shocks, such as the impact of TW on international trade. The World Bank uses an annual frequency to extract macroeconomic data, mainly because annual data is more stable and has a higher degree of data integrity, which helps reduce the noise impact caused by short-term fluctuations. At the same time, indicators such as green trade and carbon emissions have strong annual variation patterns. The use of annual data can more accurately reflect the long-term impact of the macroeconomic environment on green trade and ensure the scientificity and effectiveness of the analysis. The relevant data on the M and X volumes of some green products from 2015 to 2024 are shown in Figure 1. Green products include photovoltaic panels, wind turbines, biomass generators, lithium batteries, high-efficiency insulation materials, low-carbon building materials, energy-saving and environmentally friendly lamps, electric vehicles, plastic recycling machines, and water purifiers.

Figure 1   M and X volume of green trade products: (a) import volume of green trade products and (b) export volume of green trade products (see online version for colours)
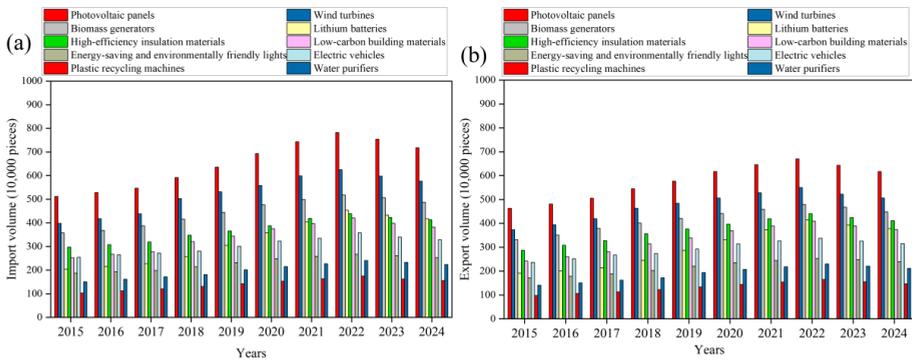
In this paper, the screening of green product classification in the UN Comtrade database from 2015 to 2024 is mainly based on the 'List of Environmental Products' issued by the World Trade Organization and the International Organization for Standardization's Green

Product Certification Catalog as the basic screening criteria. In the screening process, the products selected for inclusion must meet the following conditions at the same time:

1 Meet green, low-carbon, and environmentally friendly characteristics, such as renewable energy equipment (such as photovoltaic modules, wind turbines), energy-saving products (such as high-efficiency motors, LED lighting), and resource recycling equipment (such as plastic recycling machines, wastewater treatment devices).

2 The products have clear commodity codes in China-South Korea trade, and can be accurately matched and extracted from the UN Comtrade database. The corresponding import and export data.

3 Exclude products with environmental disputes or unclear classification (such as some mixed-use chemicals) to ensure the scientificity and consistency of the data source and the representativeness and accuracy of the research on green trade data.

In Figure 1, it can be seen that during the Sino-US TW from 2018 to 2022, the M and X volume of green products between China and South Korea showed an upward trend, especially green industry-related products such as photovoltaic panels, wind turbines, lithium batteries and electric vehicles. From 2023 to 2024, the global economy gradually recovered, but due to a certain easing of Sino-US trade, but the Sino-US TW has great uncertainty. The overall M and X volume between China and South Korea gradually stabilised, and even showed a slight decline.

3.2 Data preprocessing

3.2.1 Missing value and outlier processing

For time series data such as annual green product M and X volume, this paper uses the data of the previous time point to fill in the missing values. In order to ensure the accuracy of the data, the experiment uses the interquartile range interquartile range (IQR) method to detect outliers (Appaia and Palraj, 2023; Alabrah, 2023). In the IQR method, the quartiles and interquartile distances of the data are calculated, and the range of outliers is defined based on the IQR. The IQR definition is shown in formula (1).

$$x < Q_1 - 1.5 * IQR \ OR \ x > Q_3 + 1.5 * IQR \tag{1}$$

x represents data. When *x* meets formula (1), it is an outlier and is replaced by its mean.

3.2.2 Data standardisation

For variables with different units and dimensions, such as M and X volume, trade volume, GDP, etc., the experiment uses Z-score (Al-Mekhlafi et al., 2024; Penney, 2023) to standardise the data and convert variables of different scales into a unified scale range to ensure that the model can learn effectively. The Z-score calculation formula is shown in formula (2).

$$\bar{x} = \frac{x - \beta}{\alpha} \tag{2}$$

3.2.3 *Stabilisation and data merging operations*

Green trade data is time series data, and ensuring the stability of the data is crucial to the effectiveness of the prediction model. In order to make the time series data stable, this paper uses the difference method to eliminate the trend component of the data and turn it into a stable series. For data that grows exponentially, a logarithmic transformation is used to narrow its fluctuation range, reduce the nonlinear characteristics of the data, and make it more stable.

After preprocessing, this paper merges green trade data, carbon emission data, macroeconomic data, etc., from different data sources into a unified dataset based on timestamps. In order to avoid errors caused by time alignment of different data sources, this paper first resamples each data stream uniformly according to the annual timestamp during the merging process, uses linear interpolation or forward filling to fill in the missing time nodes, and performs a left join with the timestamp as the primary key when merging to ensure that each row corresponds to the same time point; for time misalignment caused by delayed policy reports or UN Comtrade updates, moving average smoothing window correction is further applied to key indicators involving the lag period, such as carbon emissions data, and a residual test is performed on the alignment error after the merge to confirm the temporal consistency and integrity of the overall dataset.

4   Construction and training optimisation of green trade data prediction model

4.1   *Construction of ConvLSTM model*

The ConvLSTM model is a network structure that combines CNN and LSTM, which can effectively extract features from spatiotemporal data (Tu et al., 2024; Ahmad et al., 2023; Khan et al., 2024). In ConvLSTM, the state transfer mechanism of LSTM is combined with the convolutional layer, which enables it to capture both temporal dependencies in time series and local dependencies in spatial data. In this study, green trade data not only have time series characteristics, but also include spatial relationships between different product categories and regions.

For the ConvLSTM model, the structure includes an input layer, a convolution layer, an LSTM layer, and an output layer. Each layer combines a convolution operation with time series data processing. This paper converts the M and X volumes of each category in a year into a two-dimensional matrix and sends it to the convolution layer for processing.

In this paper, the ConvLSTM model input constructs the annual M and X data of different categories of green products into a two-dimensional matrix by product category and major trade region dimensions, where the rows of the matrix represent different green product categories and the columns represent the corresponding major trade regions or policy scenarios. The assumption of this spatial mapping is that green trade data has a certain spatial dependence between different product categories and regions. For example, the trade distribution, carbon emission contribution and policy response of various green products in different regions are different. The two-dimensional matrix form can more intuitively express such spatial structural relationships, facilitate the convolution layer to capture local spatial correlations, and enhance the model's ability to extract spatial features of green trade data.

4.1.1 Construction of the convolution layer

In the convolution layer, the spatial features in the data are mainly extracted, especially the interdependence between products, regions, and trade policies. The convolution operation captures the feature association between adjacent products or regions by defining the size of the convolution kernel. The study uses a two-dimensional convolution kernel to convolve the data, and the convolution operation is shown in formula (3).

$$y_t^c = \sigma(U_c * \bar{x} + \gamma_c) \tag{3}$$

y_t^c represents the feature map of the output after convolution, U_c represents the convolution kernel, and γ_c represents the bias term.

In order to feed the feature map output by the convolution layer into the LSTM unit, this paper flattens and splits it into time steps.

1   The study expands all channel information of each pixel in the three-dimensional feature map output by the convolution layer into a long vector, as shown in formula (4).

$$z = Flatten(y_t^c) \tag{4}$$

z represents the flattened vector.

2   In order to combine the spatial information of the feature map with the time series modelling capability of LSTM, this paper divides the flattened feature map into multiple time steps. In the case of time series data, the input of each time step is a vector. Now, each flattened feature map is regarded as the input of a time step, and the flattened vector is divided into multiple sub-vectors, each of which contains specific spatial region information, expressed as z_t.

The combined feature maps are shown in Figure 2.

In Figure 2, the first map shows the spatial characteristics of the distribution of green product categories, showing the changes in the trade volume and categories of green products in different times or regions. The second map shows the spatial characteristics of the trade volume of green products between regions, reflecting the distribution and intensity of green product trade between different regions. The third figure shows the spatial relationship between green product trade and carbon emissions, revealing the mutual influence between trade volume and carbon emissions. The last figure shows how policy changes affect green trade in different regions and time points through the spatial impact characteristics of policy changes on green trade.

4.1.2 Construction of LSTM layer

In the ConvLSTM model, the main function of the LSTM layer is to process long-term dependencies in time series. The LSTM network unit is a neural network specifically used for time series data processing, which can effectively solve the problem of gradient disappearance and explosion through the gating mechanism (Cui et al., 2023; Gupta, 2024). The LSTM unit consists of three gating structures: input gate, forget gate and output gate, which determine how to update and transmit state information.

Figure 2   Combined characteristic map (see online version for colours)
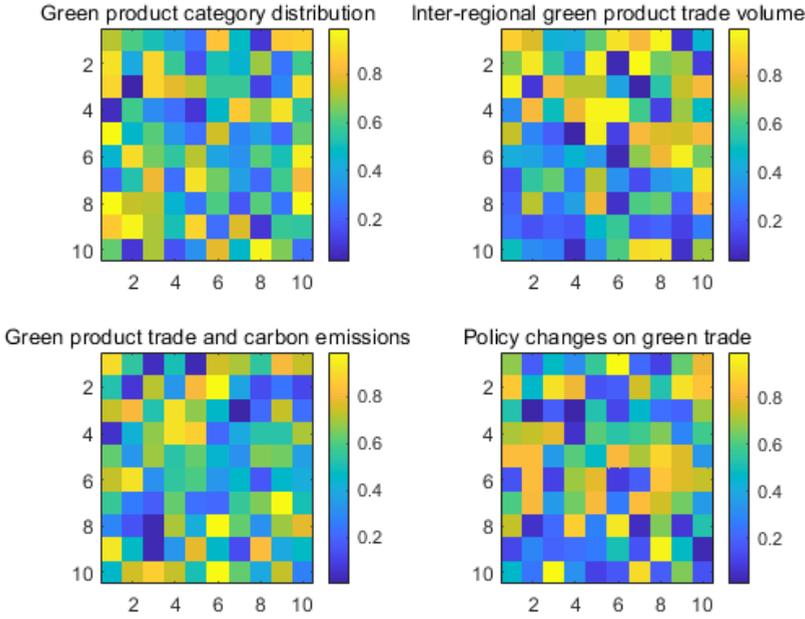
In this model, the LSTM network (Ju et al., 2024) uses the green trade data features extracted and flattened from the convolutional layer and processed into time periods as input for time series modelling. The forget gate is shown in formula (5).

$$g_t = \sigma(U_{zg} * z_t + U_{hg} * h_{t-1} + U_{dg} \odot d_{t-1} + \delta_g) \tag{5}$$

Among them, U_{zg}, U_{hg}, and U_{dg} represent the weight matrices, h_{t-1} represents the hidden state at the previous moment. z_t represents the current input, and δ_g represents the bias term.

The input gate is shown in formula (6).

$$e_t = \sigma(U_{ze} * z_t + U_{he} * h_{t-1} + U_{de} \odot d_{t-1} + \delta_e) \tag{6}$$

$*$ represents the convolution operation and $\odot$ represents the Hadamard product.

The updated memory unit state is shown in formula (7).

$$D_t = g_t \odot D_{t-1} + e_t \odot tanh(U_{zd} * z_t + U_{hd} * h_{t-1} + \delta_D) \tag{7}$$

D_{t-1} represents the memory state at the previous moment.

The output gate is shown in formula (8).

$$p_t = \sigma(U_{zp} * z_t + U_{hp} * h_{t-1} + U_{dp} \odot d_{t-1} + \delta_p) \tag{8}$$

The current hidden state is shown in formula (9).

$$h_t = p_t \odot tanh(D_t) \tag{9}$$

h_t represents the current hidden state.

The ConvLSTM model can effectively fuse spatiotemporal features between the convolutional layer and the LSTM layer, where the convolutional layer processes spatial dependencies and the LSTM layer processes temporal dependencies. Through this fusion, this paper uses ConvLSTM to capture both temporal and spatial features in green trade data in the same network, especially in the prediction of trade M and X volume, where the interaction between space and time cannot be ignored.

4.1.3 Construction of the output layer

In the output layer of ConvLSTM, this paper uses a fully connected layer to generate the final prediction results. The fully connected layer maps the spatiotemporal features output by the LSTM layer to the predicted M and X volume of green trade, as shown in formula (10).

$$y_t = U_y h_t + \delta_y \tag{10}$$

y_t represents the prediction result at a certain moment.

The ConvLSTM structure diagram is shown in Figure 3.

Figure 3 ConvLSTM structure diagram (see online version for colours)
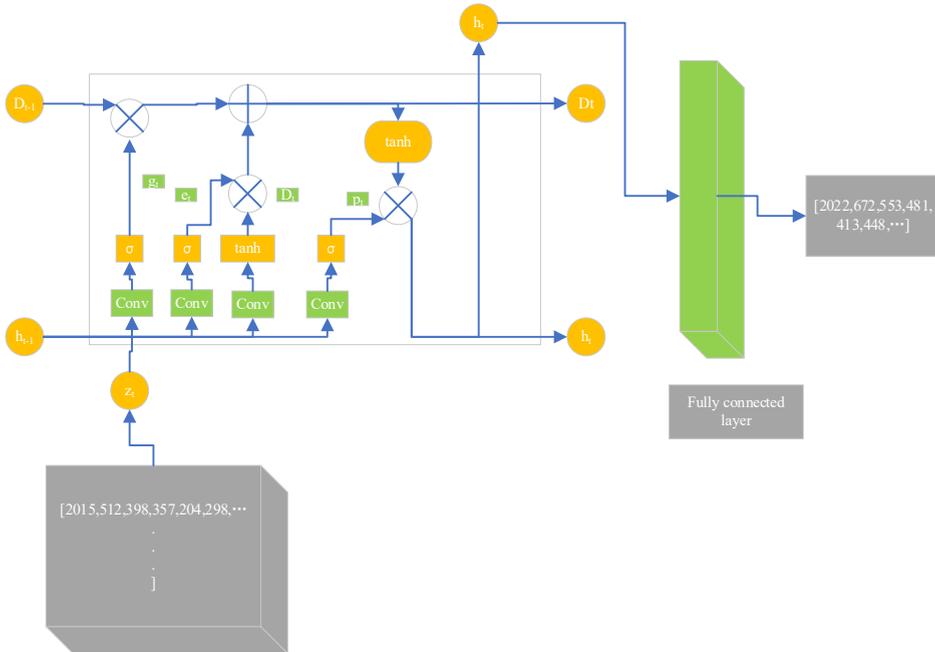
In Figure 3, it can be seen that the input trade M and X volume and other related data are sent to ConvLSTM. In each time step, after being processed by the convolution layer, it is sent to the LSTM unit to capture the temporal relationship. Finally, the fully connected layer is used to map the result to the trade M and X volume and output the result.

4.2   Model training and optimisation

4.2.1   Loss function design

This paper uses MSE as the loss function to measure the degree of fit of the model in terms of temporal and spatial features. The calculation of mean squared error (MSE) is shown in formula (11).

$$L1 = \frac{1}{T}\sum_{t=1}^{T}(y_t^p - y_t^t)^2 \tag{11}$$

T represents the time step, y_t^p represents the predicted value of the model at time t, and y_t^t represents the true value.

On the weights of the LSTM layer and the convolution layer, the experiment applies L2 regularisation to increase the penalty term of the weights to avoid overfitting caused by excessive weights. The calculation of the regularisation term is shown in formula (12).

$$L2 = \lambda\sum_{i}\theta_i^2 \tag{12}$$

θ_i represents the weight of the model and λ represents the regularisation strength.

The comprehensive loss function is shown in formula (13).

$$L = L1 + L2 \tag{13}$$

4.2.2   Optimiser selection

In order to enable the ConvLSTM model to learn and converge efficiently, the experiment selected the Adam optimiser (Reyad et al., 2023; Mehmood et al., 2023) as the optimisation tool for the model. The Adam optimiser combines the advantages of the momentum method and the adaptive learning rate, and can converge quickly and stably with fewer parameter adjustments. The update of the Adam optimiser is shown in formula (14).

$$\rho_{t+1} = \rho_t - \zeta \cdot \frac{\eta_t}{\sqrt{\iota_t} + \kappa} \tag{14}$$

ρ_t represents the model parameters, and ζ represents the learning rate.

4.2.3   Hyperparameter tuning

In the ConvLSTM model, the training efficiency is affected by multiple hyperparameters, including learning rate, batch size, number of LSTM units, convolution kernel size, etc. The experiment uses a combination of grid search and random search (Rimal et al., 2024) to find the optimal hyperparameter combination. First, grid search is used to perform a coarse-grained scan of key hyperparameters to determine the approximate parameter range and combination; on this basis, random search is combined to perform a fine-grained exploration of the parameter space to capture more potential high-quality parameter configurations.

As for the learning rate, it is a crucial parameter in the optimisation process. This paper selects it in the range of 0.0001, 0.001, and 0.01 to ensure that the model does not

converge too fast or too slow. As for the batch size, it determines the amount of data used for each parameter update. This experiment tries different batch sizes, such as 32, 64, and 128, and selects the most appropriate size through cross-validation.

In terms of the selection of convolution kernel size, this paper mainly compares the commonly used 3×3 and 5×5 square convolution kernels, but also considers the impact of non-square convolution kernels (such as 3×5) on spatial features. Non-square convolution kernels have advantages in capturing features with directionality or asymmetric spatial distribution, but because the spatial features of green trade data are relatively uniform and have no obvious directionality, this study gives priority to square convolution kernels with higher computational efficiency and stable effects. The number of LSTM units controls the expressiveness of the model. This paper selected 128 and 256 as candidates, and finally selected 128 units. The size of the convolution kernel affects the perception of local features of the convolution layer. The experiment selected 3×3 and 5×5 convolution kernels. The results show that the 3×3 convolution kernel provides a good balance in most cases.

The experiment performed multiple rounds of optimisation on the above hyperparameters through grid search, and finally obtained the best hyperparameter combination, ensuring the efficiency and accuracy of the ConvLSTM model in green trade data prediction. The hyperparameters are shown in Table 1.

Table 1 Hyperparameters

Parameters	Value	Parameters	Value
Learning rate	0.001	Number of convolution kernels	64
Batch size	32	Number of LSTM units	128
Number of iterations	50	Dropout ratio	0.3
Convolution kernel size	3×3	Loss function	Adam

Table 1 shows the main hyperparameters and their values for the ConvLSTM model in this experiment. These parameters directly affect the training effect and prediction performance of the model. The learning rate is set to 0.001 to ensure the stability of the model parameter update; the batch size is 32, taking into account both training efficiency and memory usage; the number of iterations is 50 to ensure that the model fully learns the data features. The number of convolution kernels is 64, and the convolution kernel size is 3×3, which is used to extract spatial features from the input data; the number of LSTM units is set to 128 to enhance the model's ability to capture time series dependencies. The Dropout rate is 0.3, which effectively prevents overfitting. The loss function uses the Adam optimiser to improve the convergence speed and accuracy of training.

4.2.4 *Overfitting prevention*

In this paper, Dropout is introduced into the ConvLSTM model to randomly discard the activation values of some neurons to avoid the model's over-reliance on certain features and enhance the model's generalisation ability. Dropout is shown in formula (15).

$$\bar{\varpi}_t = \varpi_t \cdot B(q) \tag{15}$$

$\bar{\varpi}_t$ represents the activation value after Dropout processing, and q represents the retention rate.

During the training process, the experiment uses the early stopping method to monitor the loss function value of the validation set. When the loss of the validation set does not decrease significantly within several training cycles, the training is stopped to avoid overfitting of the model on the training set.

5   Green trade data prediction experiment

5.1   Evaluation indicators

Root mean squared error (RMSE):

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

y_i represents the true value and $\hat{y}_i$ represents the predicted value.

Mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$ (17)

Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \hat{y}_i}{y_i}|*100\%$$ (18)

5.2   Experimental design

This experiment uses the ConvLSTM model to predict China-Korea green trade data, verify the effectiveness of the model in capturing temporal and spatial features, and compare it with other traditional time series prediction models. The baseline models for comparison include ARIMA, GRU, LSTM, CNN, and CNN-LSTM.

The global economic shocks include the Sino-US TW, the large-scale spread of the epidemic, and changes in carbon emission trade policies. According to statistics, the Sino-US TW started around 2018, the large-scale spread of the epidemic started in 2020, and the carbon emission trade policy started to have an impact on the world in 2021. Based on this, the experiment is designed to verify the prediction effect of trade M and X under different economic shocks. For the prediction of trade M and X under the Sino-US TW, this paper uses the data from 2015 to 2019 for training and predicts the M and X volume in the next year of 2020. For the prediction of trade M and X under the Sino-US TW + epidemic, this paper uses the data from 2015 to 2020 for training and predicts the M and X volume in the next year of 2021. In the context of the Sino-US TW + epidemic + changes in carbon emission trade policies, this paper uses data from 2015 to 2021 for training and predicts the M and X volume in 2022.

The carbon emission policies in the global economic shocks in this paper mainly cover the typical carbon emission and low-carbon development-related policies issued by

China, South Korea, the European Union and the USA between 2018 and 2021. These countries and regions have an important influence on global trade and carbon emission governance. The experiment selected three scenarios from 2018 to 2021, mainly because this stage is a critical period of the Sino-US trade war, the accelerated promotion of global carbon neutrality goals and the impact of the epidemic. Carbon emission policies change frequently and have a significant impact on green trade fluctuations, which is helpful to study the adaptability and predictive ability of the model under multiple economic shocks.

To ensure the generalisation ability of the model and the temporal consistency of the evaluation, this paper adopts a strict time series division principle in the training process: the overall data is divided into a training set (accounting for 70% of the total samples), a validation set (accounting for 15%) and a test set (accounting for 15%) in chronological order. The data is not randomly shuffled to avoid future information leakage. The same proportion of division is used under each economic shock scenario. The training set is used for model parameter learning, the validation set is used for hyperparameter tuning and early stopping judgement, and the test set is used for final performance evaluation to ensure the robustness and comparability of the model under different time periods and shock conditions.

5.3   Experimental results

5.3.1   M and X forecast

In the context of the Sino-US TW, this paper compares the ConvLSTM model with other models, and statistically compares the M and X forecast results of green products. The M and X forecast is shown in Figure 4.

Figure 4   M and X forecast: (a) import volume forecast and (b) export volume forecast
(see online version for colours)
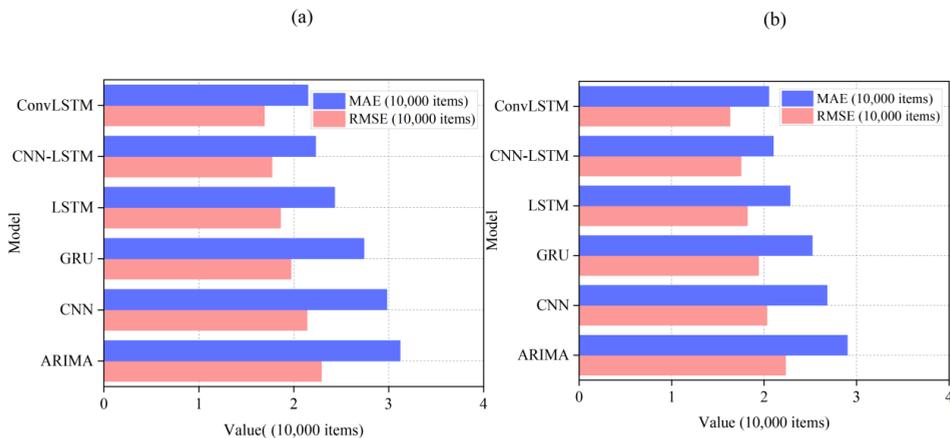
In Figure 4(a), the ConvLSTM model performs best in forecasting performance, with an RMSE of only 16,900 pieces and a MAE of 21,500 pieces. The RMSE of the ARIMA model reached 22,900 and the MAE reached 31,200, which shows that its prediction accuracy for the import volume of green products is the lowest. The RMSE of CNN is

21,400 and the MAE is 29,800, while the RMSE of GRU is 19,700 and the MAE is 27,400. The LSTM and CNN-LSTM models are relatively stable, with RMSE of 18,600 and 17,700 pieces, and MAE of 24,300 and 22,300 pieces, respectively.

In terms of export volume forecast, the corresponding figure is Figure 4(b). The ARIMA model has the worst performance with an RMSE of 22,300 and a MAE of 29,000. This is because the ARIMA model has limited predictive power for time series, especially when faced with multiple factors. The ConvLSTM model performs well, showing the smallest prediction error, with RMSE and MAE of 16,300 and 20,500, respectively, which are 1900 and 2300 lower than those of LSTM, respectively, and are closer to actual values. This shows the importance of introducing convolutional layers. The RMSE of the CNN and GRU models are 20,300 and 19,400 respectively, and the MAE are 26,800 and 25,200 respectively. The RMSE of CNN-LSTM is 17,500 and the MAE is 21,000. Overall, the ConvLSTM model considers both temporal characteristics and spatial information, making more accurate predictions for complex green trade data and economic fluctuations.

5.3.2 *Prediction curves for different green products*

In this experiment, green products are diverse. The experiment uses the ConvLSTM model to visualise the actual and predicted values of different green products under the impact of Sino-US trade, as shown in Figure 5. In Figure 5, for the convenience of representation, photovoltaic panels, wind turbines, biomass generators, lithium batteries, high-efficiency thermal insulation materials, low-carbon building materials, energy-saving and environmentally friendly lamps, electric vehicles, plastic recycling machines, and water purifiers among the green products are represented by LS1 to LS10 respectively.

Figure 5   Prediction curve under different green products (unit: 10,000): (a) prediction curve of import volume under different green products and (b) prediction curve of export volume under different green products (see online version for colours)
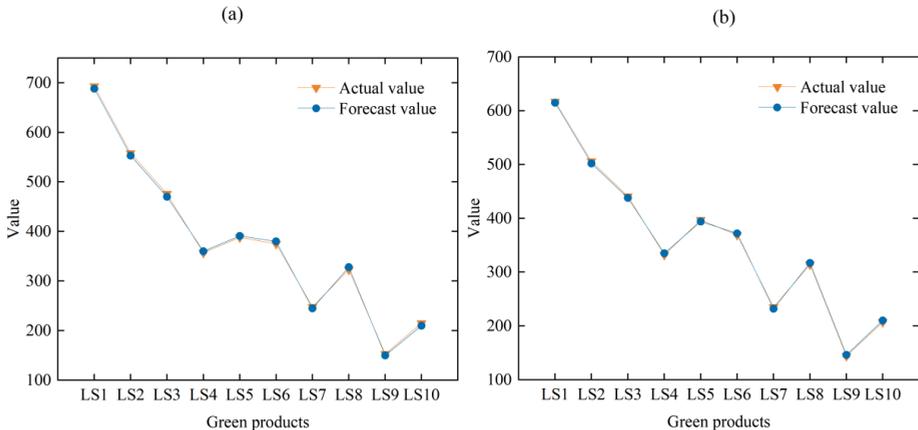
Judging from the import volume forecast results, the ConvLSTM model has a small forecast error for most green products, and the difference between the actual value and the forecast value is small. The actual value of photovoltaic panels is 6.93 million pieces,

and the forecast value is 6.88 million pieces, with a difference of only 50,000 pieces, indicating that the model has a very strong forecasting ability. The actual value of wind turbines is 5.58 million pieces, and the predicted value is 5.53 million pieces, with a difference of 50,000 pieces. The actual value of biomass generators is 4.76 million pieces, and the predicted value is 4.70 million pieces, with a difference of 60,000 pieces, indicating that the ConvLSTM model can better capture the changing trend of the import volume of green products. The forecast errors of other products such as lithium batteries and high-efficiency thermal insulation materials are also kept within a small range. The ConvLSTM model can effectively capture the temporal fluctuations of green product imports and can adapt to external shocks more accurately.

In terms of export volume forecast, the actual value of photovoltaic panels is 6.17 million units, and the predicted value is 6.15 million units, with a difference of 20,000 units. The actual value of wind turbines is 5.06 million units, and the predicted value is 5.02 million units, with a difference of 40,000 units. It can be seen that the ConvLSTM model is highly sensitive to export volume. The actual value of biomass generators is 4.41 million pieces, and the predicted value is 4.38 million pieces. The actual value of lithium batteries is 3.32 million pieces, and the predicted value is 3.35 million pieces. The predicted differences are also maintained within a small range of 30,000 pieces. This shows that the ConvLSTM model has a strong adaptability in complex trade data, especially for product categories with relatively stable or mature changes, and its prediction effect is more accurate.

### 5.3.3 *Comparison of prediction performance under different economic shocks*

At present, economic shocks include the Sino-US TW, the epidemic, and changes in carbon emission trade policies, which have a certain global impact on the M and X volume of China-South Korea trade. This paper takes exports as an example to compare the impacts of the following three situations: Sino-US TW, Sino-US TW + epidemic, and Sino-US TW + epidemic + carbon emission trade policy changes. The comparison results of prediction performance under different economic shocks are shown in Figure 6.

In Figure 6(a), in the context of the Sino-US TW, the ConvLSTM model performs best among all models, with an RMSE of only 16,300 pieces, a MAE of only 20,500 pieces, and a MAPE of 4.62%. The results show that ConvLSTM can accurately predict the changing trend of export volume under the influence of the Sino-US TW, especially when the data has large fluctuations. The ARIMA model has the worst performance with an RMSE of 22,300 pieces, a MAE of 29,000 pieces, and a MAPE of 6.12%. Its model structure is relatively simple and cannot fully capture complex spatiotemporal relationships and nonlinear factors. For the LSTM model, MAPE reaches 5.01%. The performance of other models such as CNN, GRU, and CNN-LSTM is worse than ConvLSTM.

In Figure 6(b), after adding the impact of the epidemic, the prediction performance generally decreases. The ConvLSTM model maintained a strong performance, with an RMSE of 17,600 pieces, a MAE of 21,500 pieces, and a MAPE of 5.03%, which was only slightly lower than the performance when the Sino-US TW existed alone. This shows that under the combined effects of the Sino-US TW and the epidemic, the ConvLSTM model can still effectively predict changes in trade volume. The prediction performance of other models such as ARIMA, CNN and GRU declined significantly, with the RMSE of ARIMA rising to 22,600, MAE to 30,200 and MAPE to 6.5%. The

sudden outbreak of the epidemic brought about unforeseen trade fluctuations, and many models were unable to fully adapt to this new complex situation, and a prediction error increased significantly.

Figure 6   Comparison of prediction performance under different economic shocks: (a) comparison of prediction performance under the Sino-US TW; (b) comparison of prediction performance under the Sino-US TW + epidemic and (c) comparison of prediction performance under the Sino-US TW + epidemic + carbon emission trade policy changes (see online version for colours)
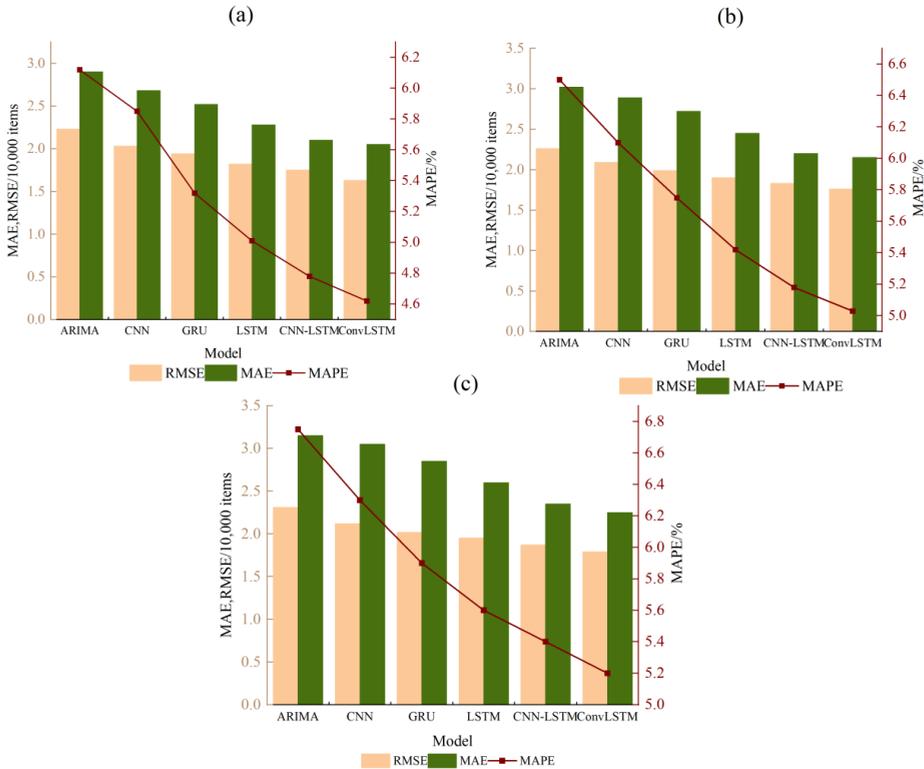
In Figure 6(c), when the carbon emissions trading policy changes are added, the overall prediction performance drops again. The RMSE of ConvLSTM is 17,900, the MAE is 22,500, and the MAPE is 5.2%, which is the best performance among all models, but its error has increased to a certain extent compared with the first two cases. The implementation of carbon emission policies has brought new policy uncertainties and adjustments to international trade rules, and the model's predictive ability has declined in response to these new changes. The ARIMA model, with an RMSE of 23,100, MAE of 31,500, and MAPE of 6.75%, failed to effectively adjust parameters to adapt to changes under multiple economic shocks. The above results show that with the increase of different economic impact factors in recent years, the prediction error of the ConvLSTM model has fluctuated to a certain extent, but it still shows good robustness and the overall error is low.

In the scenario of Sino-US trade war + epidemic + carbon emission trade policy changes, in order to further compare the differences between each model and ConvLSTM in MAPE indicators, the results are shown in Table 2.

Table 2   T-test results

Model	t-statistic	p-value	significance
ARIMA	6.12	<0.001	***
CNN	5.23	<0.001	***
GRU	4.05	0.002	**
LSTM	3.10	0.012	*
CNN-LSTM	2.15	0.045	*

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

In Table 2, the error differences of all models in the MAPE index have reached a statistically significant level, among which ARIMA and CNN have the highest t statistics, both exceeding 5 ($p < 0.001$), indicating that the performance gap between these two traditional methods and ConvLSTM is the largest; the difference of GRU is also extremely significant ($t = 4.05$, $p = 0.002$), while the difference between LSTM and CNN-LSTM is relatively small, but it is still verified at the 5% significance level ($p < 0.05$). Overall, the paired t-test further proves that ConvLSTM has a significant and sustained error advantage under the background of multiple economic shocks, and its ability to capture complex spatiotemporal features is significantly better than various baseline models.

### 5.3.4   Feature importance analysis

The experiment uses Shapley Additive exPlanations (SHAP) to interpret the features, including the M and X volume of green products, M and X trade volume, carbon emission data, GDP, foreign exchange rate, trade policy, and various economic shocks. The results of the feature importance analysis are shown in Figure 7.

In Figure 7, the M and X volume of green products is the most important feature, contributing 30.5% to the importance. This shows that the M and X volume of green products plays a core role in predicting green trade data, directly reflecting the actual transaction volume changes of green trade, and have an important impact on the prediction of future trends. The M and X trade volume is of great importance, contributing 25% of the weight. It can be seen that the trade volume, as an important indicator to measure the scale of trade and market demand, has a significant effect on the prediction results. The high weight between the two indicates that in the global trade environment and policy changes, the actual M and X quantity and trade volume changes are the most important basis for the prediction model.

Among other features, the importance of carbon emission data is 15.2%. In the context of low-carbon economic transformation, carbon emissions directly affect the country's environmental protection policies and trade flows. The contribution of GDP is 10.8%, and its impact is mainly reflected in the role of economic growth in promoting green trade demand. Foreign exchange rates, trade policies and various economic shocks contribute less to the forecast results, at 8.7%, 5.5% and 4.3% respectively. It can be seen

that these factors can affect M and X volumes and trade volume to a certain extent, but their direct impact on green trade data is relatively indirect and more susceptible to fluctuations in the macroeconomic environment.

Figure 7   Analysis results of feature importance (see online version for colours)
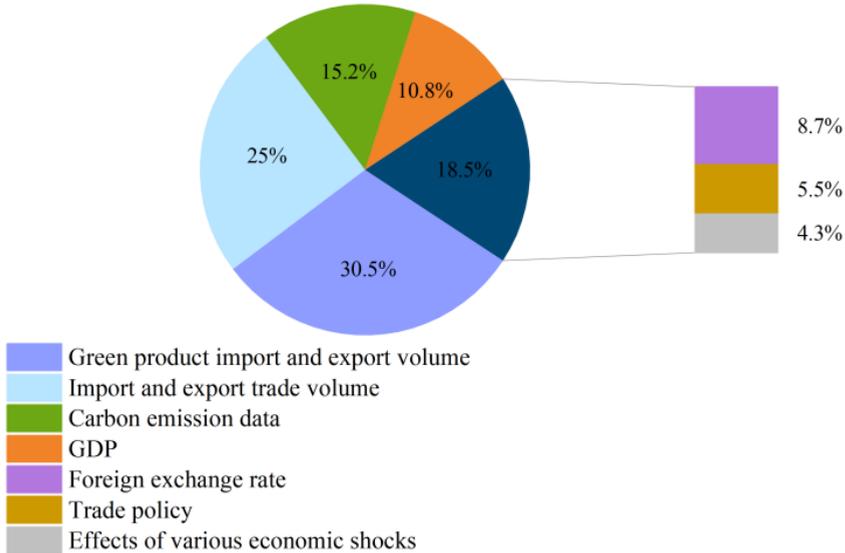
5.3.5 *Real-time analysis*

Green trade data has strong dynamic changes, and good real-time prediction can provide better guidance for trade M and X. The experiment quantified the real-time prediction by training time, training speed, number of parameters, and CPU (Central Processing Unit) utilisation. The results are shown in Table 3.

Table 3   Real-time results

Model	Training time (h)	Training speed (samples/s)	Number of parameters (M)	CPU utilisation (%)
ARIMA	0.5	150	15.2	45.2
CNN	3.2	120	20.8	70.3
GRU	2.8	110	18.5	65.0
LSTM	4.1	95	22.2	75.5
CNN-LSTM	6.3	70	30.3	85.9
ConvLSTM	5	80	27.6	80.8

In Table 3, in terms of training time and training speed, the ARIMA model has the shortest training time, which is only 0.5 h, and has a higher training speed, reaching 150 samples/s. The ARIMA model is relatively simple, has a small amount of calculation, and a relatively fast training process. The training time of CNN and GRU models is 3.2 h and 2.8 h respectively, and the training speed is 120 samples/s and

110 samples/s respectively, which is slightly slower. The training time of LSTM, CNN-LSTM and ConvLSTM models is longer, especially CNN-LSTM, which takes 6.3 h and has a training speed of 70 samples/s. The training time of the ConvLSTM model recommended in this paper is 5 h and the training speed is 80 samples/s.

In terms of parameter volume and CPU utilisation, the CNN-LSTM model has the highest parameter volume, which is 30.3M. The parameter volume of the ARIMA model is only 15.2M, which is significantly lower than that of other deep learning models. In terms of CPU utilisation, the CPU utilisation of LSTM and CNN-LSTM is relatively high, at 75.5% and 85.9% respectively, which shows that they require more computing resources to process a large number of parameters and complex network structures during training. The CPU utilisation of ARIMA is only 45.2%, because it has a small amount of calculation and does not require too many computing resources. The number of parameters and CPU utilisation of ConvLSTM are 27.6M and 80.8% respectively, which are lower than CNN-LSTM, but require more computing resources than LSTM. In summary, the prediction error of ConvLSTM is low, but its real-time performance is average. In the future, it can be further optimised by combining lightweight processing.

6 Further discussion

In the experimental results of this paper, the comprehensive performance of the ConvLSTM model is the best. When processing green trade data, it can consider time series characteristics and spatial information at the same time, and better capture the fluctuations in trade volume and the impact of external economic shocks. ConvLSTM enhances the expression of local spatial relationships of features through convolution operations, further improving the ability to predict complex data. However, the traditional time series model ARIMA is too dependent on the linear relationship of historical data and cannot effectively cope with data fluctuations under the combined effect of multiple factors. Deep learning models such as CNN, LSTM and their combination CNN-LSTM perform worse than ConvLSTM in integrating spatiotemporal features, resulting in larger prediction errors. Overall, the ConvLSTM model can provide more accurate prediction results in the context of multiple economic shocks, especially when faced with large-scale, complex data with spatiotemporal dependencies.

In addition to ConvLSTM's ability to effectively integrate temporal and spatial features, it also stems from the model's unique ability to capture local spatial dependencies. The convolution operation not only extracts relevant information from neighbouring areas, but also avoids the problem of long-distance dependencies being difficult to model in traditional sequence models, thereby enhancing the robustness of feature expression. ConvLSTM dynamically adjusts information flow through a gating mechanism, effectively suppresses noise interference, and improves the model's adaptability to sudden economic events and policy changes. This enables the model to more flexibly reflect the nonlinear changes in green trade under the influence of multiple complex factors, making up for the shortcomings of a single time series model or spatial model in processing multidimensional data, and reflecting the potential and advantages of deep spatiotemporal modelling methods in real economic forecasting.

This study has important practical significance. By introducing the ConvLSTM model, this study constructs a green trade data prediction method that can simultaneously process time series characteristics and spatial characteristics, filling the gap in existing

research that ignores spatial factors. In the context of low-carbon transformation, green trade is increasingly becoming an important part of the global economy. Accurate green trade prediction is of great value to policy-making and corporate decision-making. The researchers can use the experiment in this paper to better understand the changing trends of green products under multiple economic shocks, and provide data support for the formulation of green trade support measures, carbon emission control policies and other economic policies at the policy level. The study also revealed the advantages of the ConvLSTM model in predictive performance, stability and multi-shock adaptability, providing a new methodology for future green trade research.

The method in this paper is not limited to annual data, but can also be used for monthly or weekly high-frequency data. When applying ConvLSTM to monthly or weekly high-frequency data, it is necessary to first build a more fine-grained time series pane at the input end, such as splicing various green product indicators of each month or week into a longer time step sequence; at the same time, the time step parameters of the convolution layer and LSTM layer should be adjusted to adapt to the new sequence length, and smaller convolution kernels or multi-scale convolutions (such as dilated convolutions) should be introduced to capture spatial dependencies in the shorter term; to prevent overfitting and accelerate training, appropriate regularisation should be increased (such as a higher Dropout ratio or early stopping threshold adjustment) and the search for time steps and learning rates should be added to the hyperparameter optimisation to ensure that the model can extract short-term fluctuations in high-frequency data while maintaining a grasp of long-term trends.

In addition to green trade, ConvLSTM's spatiotemporal feature learning capabilities are also applicable to other economic and trade fields, such as international commodity price fluctuation forecasts, cross-border e-commerce transaction volume trend analysis, and supply chain logistics flow estimation. In the commodity market, ConvLSTM can combine regional inventory distribution with historical price time series to capture supply, demand, and seasonal patterns; in cross-border e-commerce scenarios, the order volumes of different categories and regions can be mapped into a spatiotemporal matrix to identify transaction peaks and valleys caused by promotions, e-commerce festivals, or policy adjustments; in logistics network optimisation, the spatial layout of storage nodes and transportation routes and real-time throughput changes can be integrated to achieve high-precision predictions of logistics flows. The above applications not only verify the versatility of ConvLSTM in dealing with complex spatiotemporal dependency problems, but also demonstrate its strong expansion potential in supporting diversified economic and trade decision-making.

This paper has made some achievements, but there are still some shortcomings:

1   The data used in this paper mainly come from the M and X data of China-South Korea trade and green products. Due to the availability of data, the generalisation ability of the model is limited to a certain extent. Future research can consider combining green trade data from more countries to expand the scope of the model and explore how to further improve the accuracy of the model by supplementing more dimensions of economic data.

2   This paper has considered a variety of economic shocks, such as the Sino-US TW, the epidemic, and changes in carbon emission policies, but there are still other unknown or unpredictable economic shocks that affect green trade. Future research can further explore how to deal with highly uncertain economic events and how to

incorporate more dynamic factors, such as climate change and changes in the global epidemic, into the model to improve the robustness of the forecast.

3 The ConvLSTM model shows excellent prediction performance, but its training time and computing resource requirements are high, especially when processing large-scale data. The real-time performance of the model becomes a bottleneck in the application. Future research can focus on how to optimise the model structure and combine lightweight processing such as pruning and quantisation to improve the real-time performance and computing efficiency of the model.

7 Conclusions

This paper adopts a green trade data prediction method based on the ConvLSTM model, which overcomes the defect of traditional models that ignore spatial information by combining temporal and spatial characteristics. The study used China-South Korea green trade data to construct a ConvLSTM model, and extracted spatial features through the convolution layer and captured time series dependencies through the LSTM layer, achieving more accurate prediction results than traditional LSTM. Experiments show that the ConvLSTM model effectively improves the prediction accuracy of green trade data and provides a new research tool for international trade analysis in the context of a low-carbon economy. This paper has made some achievements, but still faces some limitations. The single data source limits the generalisation ability of the model, and the diversity and unpredictability of economic shocks also bring challenges to the model. Future research can expand data sources, introduce more dynamic economic factors, and optimise the model structure to improve real-time performance and computing efficiency, thereby enhancing the adaptability and practicality of the model. At the same time, explore the integration of multi-source heterogeneous data, such as remote sensing and satellite imagery, and apply ConvLSTM to achieve more comprehensive and accurate predictions of the green trade environment.

Conflicts of interest

The authors declare no conflict of interest.

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