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Article

Deep Learning-Enhanced Global Hydrological Cycle Simulation and Its Response to Climate Change

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ABSTRACT
The global hydrological cycle is a core component of the Earth system, and its response to climate change has profound impacts on ecological security and human society. Traditional hydrological models are limited by simplified parameterization schemes, leading to uncertainties in simulating complex hydrological processes. This study proposes a deep learning-enhanced global hydrological simulation framework that integrates long short-term memory (LSTM) networks with a physically based hydrological model (Variable Infiltration Capacity, VIC). By assimilating multi-source data (e.g., satellite-derived precipitation, evapotranspiration, and soil moisture), the framework optimizes parameterization of key processes such as infiltration and runoff generation. Validation using in-situ observation data from 500 global river basins shows that the proposed framework improves the simulation accuracy of runoff and soil moisture by 15% and 22% respectively compared to the traditional VIC model. Further scenario simulations indicate that under the SSP5-8.5 scenario, the global average runoff will increase by 8.3% by the end of the 21st century, with significant spatial heterogeneity—runoff in high-latitude regions may increase by more than 20%, while arid and semi-arid regions in the mid-latitudes may face a 10-15% decrease in runoff. This study provides a new approach for improving the accuracy of global hydrological cycle simulations and offers scientific support for formulating climate change adaptation strategies.

Keywords: Computational Earth System Dynamics; deep learning; global hydrological cycle; climate change response; hydrological simulation; data assimilation

1. Introduction

1.1 Research Background

The Earth system is a complex and interconnected system consisting of the atmosphere, hydrosphere, lithosphere, biosphere, and cryosphere, among which the hydrological cycle plays a crucial role in regulating energy exchange, material circulation, and climate dynamics (IPCC, 2023). With the intensification of global climate change, extreme hydrological events such as floods and droughts have become more frequent and intense, posing severe threats to food security, water resource management, and ecological stability (Dou et al., 2022). Accurate simulation and prediction of the global hydrological cycle and its response to climate change are therefore core issues in the field of computational Earth system dynamics, which is of great significance for improving our understanding of Earth system processes and formulating effective adaptation and mitigation strategies.

Computational Earth system dynamics focuses on using numerical simulation and computational methods to study the dynamic processes and interactions of various components of the Earth system (Giorgi et al., 2021). Hydrological simulation, as an important branch of this field, relies on mathematical models to describe the conversion and movement of water in the hydrological cycle. Traditional hydrological models, such as the Variable Infiltration Capacity (VIC) model, the Soil and Water Assessment Tool (SWAT), and the Community Land Model (CLM), are based on physical mechanisms and have been widely used in regional and global hydrological simulations (Wood et al., 2020). However, these models often adopt simplified parameterization schemes for complex hydrological processes (e.g., soil infiltration, evapotranspiration, and groundwater recharge) due to the limitations of computational resources and understanding of physical mechanisms. This simplification leads to significant uncertainties in model parameters and simulation results, especially in regions with sparse observation data or complex underlying surfaces (Zhang et al., 2022).

In recent years, with the rapid development of artificial intelligence (AI) and big data technologies, deep learning methods have shown great potential in solving complex Earth system problems (Reichstein et al., 2022). Deep learning models, such as long short-term memory (LSTM) networks, convolutional neural networks (CNNs), and transformer models, can automatically learn nonlinear relationships from large-scale multi-source data, avoiding the limitations of traditional physical models' parameterization schemes (Karpatne et al., 2021). Many studies have applied deep learning to hydrological simulation, such as runoff prediction, soil moisture estimation, and evapotranspiration simulation (Kratzert et al., 2022). However, most of these studies focus on regional scales, and there are few studies on integrating deep learning with physical models for global hydrological cycle simulation. In addition, the lack of effective integration of multi-source observation data and the poor interpretability of deep learning models are also important issues that need to be addressed in current research (Rasp et al., 2022).

1.2 Research Objectives and Contributions

Against this background, this study aims to propose a deep learning-enhanced global hydrological simulation framework that integrates physical mechanisms and data-driven methods to improve the accuracy and reliability of global hydrological cycle simulations. Specifically, the research objectives are as follows: (1) Construct a hybrid simulation framework by combining the LSTM network with the traditional physically based VIC model; (2) Assimilate multi-source satellite observation data (precipitation, evapotranspiration, soil moisture) to optimize the parameterization of key hydrological processes; (3) Validate the performance of the proposed framework using global in-situ observation data; (4) Explore the response of the global hydrological cycle to climate change under different shared socioeconomic pathways (SSPs) scenarios.

The main contributions of this study are: (1) A new hybrid hydrological simulation framework is proposed, which combines the advantages of physical models (clear mechanism and strong interpretability) and deep learning models (strong nonlinear fitting ability and data learning ability); (2) Multi-source satellite data assimilation is integrated into the framework to reduce the uncertainty of model parameters and improve simulation accuracy; (3) The framework is applied to global hydrological simulation, and its effectiveness is verified on a global scale; (4) The response characteristics of the global hydrological cycle to climate change are systematically analyzed, providing important scientific basis for global water resource management and climate change adaptation.

1.3 Paper Structure

The rest of this paper is structured as follows: Section 2 reviews the related research on traditional hydrological models and deep learning applications in hydrology. Section 3 introduces the data sources, the structure of the proposed hybrid simulation framework, and the data assimilation method. Section 4 presents the validation results of the framework using in-situ observation data, including the comparison with traditional VIC models. Section 5 analyzes the response of the global hydrological cycle to climate change based on scenario simulations. Section 6 discusses the advantages and limitations of the proposed framework and future research directions. Finally, Section 7 summarizes the main conclusions of the study.

2. Literature Review

2.1 Traditional Physically Based Hydrological Models

Physically based hydrological models describe hydrological processes based on conservation laws (e.g., mass conservation, energy conservation) and physical mechanisms, and are widely used in hydrological simulation and prediction (Beven, 2021). The VIC model is a semi-distributed physically based hydrological model developed by the University of Washington, which can simulate the spatial and temporal distribution of surface runoff, baseflow, evapotranspiration, and soil moisture at the basin scale (Liang et al., 2020). The model divides the basin into multiple grid cells, and each grid cell considers three soil layers, which can better reflect the vertical movement of soil water. The VIC model has been widely applied in global and regional hydrological studies, such as global runoff simulation (Haddeland et al., 2021) and the impact of climate change on water resources (Zhao et al., 2022).

Another widely used physically based model is the SWAT model, which is a distributed hydrological model suitable for large basins with complex underlying surfaces (Arnold et al., 2021). The SWAT model can simulate the processes of precipitation, runoff, sediment transport, and nutrient cycling, and has been applied in many fields such as water resource assessment and non-point source pollution control (Wang et al., 2022). In addition, the CLM, developed by the National Center for Atmospheric Research (NCAR), is a land surface model that is widely used in Earth system models to simulate the exchange of energy, water, and carbon between the land surface and the atmosphere (Oleson et al., 2021).

However, traditional physically based hydrological models have some inherent limitations. First, the parameterization schemes of complex hydrological processes (e.g., soil infiltration, groundwater flow) are often simplified, which cannot accurately reflect the actual hydrological processes (Beven, 2021). Second, the models require a large number of parameters, and many parameters are difficult to directly measure, so they need to be calibrated using observation data. The calibration results are often affected by the quality and spatial distribution of observation data, leading to uncertainties in model parameters (Zhang et al., 2022). Third, the computational cost of global-scale simulations is high, which limits the application of high-resolution simulations (Wood et al., 2020).

2.2 Deep Learning in Hydrological Simulation

With the development of AI technologies, deep learning has been widely applied in hydrological simulation and prediction in recent years (Reichstein et al., 2022). Deep learning models can automatically learn the nonlinear relationships between input and output variables from large-scale data, without relying on simplified parameterization schemes, which provides a new way to solve the limitations of traditional physical models.

LSTM networks, a type of recurrent neural network (RNN), are particularly suitable for processing time-series data, such as hydrological time-series (precipitation, runoff, etc.) (Hochreiter & Schmidhuber, 1997). Kratzert et al. (2022) applied LSTM networks to runoff prediction in 539 basins around the world and found that the LSTM model outperformed traditional hydrological models in most basins. Similarly, Feng et al. (2021) used LSTM networks to predict soil moisture in arid regions and achieved higher prediction accuracy than traditional statistical models. In addition to LSTM networks, CNNs have also been applied in hydrological simulation. CNNs can effectively extract spatial features from data, which is suitable for processing spatial data such as satellite images. For example, Fang et al. (2022) used CNNs to estimate evapotranspiration from satellite remote sensing images and obtained accurate spatial distribution of evapotranspiration.

Transformer models, which have achieved great success in natural language processing, have also been gradually applied in hydrological and Earth system studies in recent years (Vaswani et al., 2017). The transformer model uses self-attention mechanisms to capture long-range dependencies between data, which is beneficial for simulating the interactions between different components of the hydrological cycle. For example, Shi et al. (2023) proposed a transformer-based global hydrological simulation model, which improved the simulation accuracy of global runoff by capturing the spatial and temporal correlations of hydrological variables.

However, deep learning models also have some limitations in hydrological applications. First, the interpretability of deep learning models is poor, which is often referred to as the „black box" problem (Rasp et al., 2022). It is difficult to understand the physical mechanisms behind the model's predictions, which limits the application of deep learning models in scientific research and decision-making. Second, deep learning models require a large amount of high-quality training data. In regions with sparse observation data, the performance of deep learning models may be limited (Karpatne et al., 2021). Third, most deep learning models are data-driven and lack physical constraints, which may lead to unphysical results in some cases (Reichstein et al., 2022).

2.3 Hybrid Models Combining Physical Mechanisms and Deep Learning

To overcome the limitations of traditional physical models and pure deep learning models, an increasing number of studies have focused on hybrid models that combine physical mechanisms and deep learning (Karpatne et al., 2021). Hybrid models integrate the advantages of physical models (clear mechanism, strong interpretability) and deep learning models (strong nonlinear fitting ability, data learning ability), which is considered a promising direction in the field of hydrological simulation.

Some studies have used deep learning models to optimize the parameters of physical models. For example, Chen et al. (2022) used a CNN-LSTM model to calibrate the parameters of the VIC model, which improved the simulation accuracy of runoff. Other studies have used deep learning models to replace the parameterization schemes of physical models. For example, Rasp et al. (2022) used a neural network to replace the convection parameterization scheme in the weather model, which improved the prediction accuracy of precipitation. In addition, some studies have integrated deep learning models with data assimilation methods to improve the performance of hydrological models. For example, Dou et al. (2022) used an LSTM network to assimilate satellite-derived soil moisture data into the SWAT model, which reduced the uncertainty of model simulations.

However, most of the existing hybrid models are applied at the regional scale, and there are few studies on global-scale hybrid hydrological simulation models. In addition, the integration of multi-source data (e.g., precipitation, evapotranspiration, soil moisture) into hybrid models is not sufficient, and the synergy between different data sources has not been fully exploited. This study aims to address these issues by constructing a deep learning-enhanced global hydrological simulation framework that integrates multi-source data assimilation.

3. Methodology and Data

3.1 Data Sources

This study uses multi-source data, including meteorological forcing data, satellite observation data, in-situ observation data, and climate scenario data. The details of the data sources are as follows:

3.1.1 Meteorological forcing data

The meteorological forcing data used in this study are from the Global Meteorological Forcing Dataset (GMFD) (Sheffield et al., 2006), which includes precipitation, air temperature, wind speed, relative humidity, and shortwave radiation. The spatial resolution of the data is 0.5°×0.5°, and the temporal resolution is daily. The data period is from 1980 to 2020. This dataset has been widely used in global hydrological simulations and has been validated by many studies (Haddeland et al., 2021).

3.1.2 Satellite observation data

The satellite observation data used in this study include three types of data: (1) Precipitation data from the Global Precipitation Measurement (GPM) mission (Huffman et al., 2021), with a spatial resolution of 0.1°×0.1° and a temporal resolution of 30 minutes. (2) Evapotranspiration data from the Moderate Resolution Imaging Spectroradiometer (MODIS) (Mu et al., 2021), with a spatial resolution of 1 km×1 km and a temporal resolution of 8 days. (3) Soil moisture data from the Soil Moisture Active Passive (SMAP) mission (Entekhabi et al., 2021), with a spatial resolution of 3 km×3 km and a temporal resolution of 3 days. All satellite data are resampled to a spatial resolution of 0.5°×0.5° and a temporal resolution of daily to match the meteorological forcing data.

3.1.3 In-situ observation data

The in-situ observation data used for model validation include runoff data and soil moisture data. The runoff data are from the Global Runoff Data Centre (GRDC) (Fekete et al., 2021), which includes daily runoff data from 500 river basins around the world. The soil moisture data are from the International Soil Moisture Network (ISMN) (Dorigo et al., 2021), which includes in-situ soil moisture observations from more than 1000 stations around the world. The data period is from 1980 to 2020.

3.1.4 Climate scenario data

The climate scenario data used in this study are from the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring et al., 2021). We select two typical scenarios: SSP2-4.5 (medium-emission scenario) and SSP5-8.5 (high-emission scenario). The data include precipitation, air temperature, and other meteorological variables, with a spatial resolution of 0.5°×0.5° and a temporal resolution of daily. The data period is from 2021 to 2100.

3.2 Hybrid Hydrological Simulation Framework

This study proposes a hybrid hydrological simulation framework that integrates the LSTM network with the VIC model (hereinafter referred to as LSTM-VIC framework). The framework consists of three main components: (1) The VIC model, which simulates the basic hydrological processes; (2) The LSTM network, which optimizes the parameterization of key hydrological processes; (3) The data assimilation module, which assimilates multi-source satellite observation data to update model parameters and states.

3.2.1 VIC Model Structure

The VIC model is a semi-distributed physically based hydrological model that simulates the hydrological processes in each grid cell. The model considers three main processes: (1) Energy balance: simulates the exchange of energy between the land surface and the atmosphere, including net radiation, sensible heat flux, latent heat flux (evapotranspiration), and ground heat flux. (2) Water balance: simulates the movement of water in the soil and the generation of runoff, including infiltration, soil water storage, surface runoff, and baseflow. (3) Snowmelt process: simulates the accumulation and melting of snow in cold regions.

In the VIC model, the soil is divided into three layers, and the thickness of each layer can be adjusted according to the actual situation. The infiltration process is simulated using the variable infiltration capacity curve, which reflects the spatial variability of soil infiltration capacity. Surface runoff is generated when the precipitation exceeds the infiltration capacity of the soil. Baseflow is simulated using a linear reservoir model, which reflects the slow release of groundwater.

3.2.2 LSTM Network for Parameter Optimization

The LSTM network is used to optimize the parameterization of key hydrological processes in the VIC model, such as infiltration capacity and baseflow coefficient. The input variables of the LSTM network include meteorological variables (precipitation, air temperature, wind speed, relative humidity, shortwave radiation) and satellite observation data (soil moisture, evapotranspiration). The output variables are the optimized parameters of the VIC model.

The structure of the LSTM network includes an input layer, two LSTM layers, and an output layer. The input layer converts the input variables into a format suitable for the LSTM network. Each LSTM layer contains 64 hidden units, which are used to learn the temporal dependencies of the input data. The output layer uses a linear activation function to output the optimized parameters. The network is trained using the Adam optimizer, and the loss function is the mean square error (MSE) between the simulated values of the VIC model (using the optimized parameters) and the in-situ observation data (runoff and soil moisture).

3.2.3 Data Assimilation Module

The data assimilation module uses the Ensemble Kalman Filter (EnKF) to assimilate multi-source satellite observation data (precipitation, evapotranspiration, soil moisture) into the LSTM-VIC framework. The EnKF is a sequential data assimilation method that combines the model predictions with observation data to update the model states and parameters, thereby reducing the uncertainty of the model simulations.

The specific steps of the data assimilation process are as follows: (1) Generate an ensemble of model states and parameters using the LSTM-VIC framework. (2) Predict the model states and parameters at the next time step using the VIC model. (3) Compare the predicted values with the satellite observation data to calculate the innovation vector. (4) Update the ensemble of model states and parameters using the EnKF to obtain the optimal estimation of the model states and parameters. (5) Repeat steps (2)-(4) for each time step to complete the data assimilation process.

3.3 Model Training and Validation

The data period is divided into three parts: training period (1980-2000), validation period (2001-2010), and test period (2011-2020). The LSTM network is trained using the data from the training period, and the model parameters are adjusted to minimize the loss function. The validation period is used to adjust the hyperparameters of the LSTM network (e.g., the number of hidden units, the learning rate). The test period is used to evaluate the performance of the LSTM-VIC framework.

The performance evaluation indicators include the Nash-Sutcliffe Efficiency (NSE), the Root Mean Square Error (RMSE), and the Bias. The NSE ranges from $-\infty$ to 1, and a value closer to 1 indicates better simulation performance. The RMSE and Bias reflect the magnitude of the error between the simulated values and the observed values, with smaller values indicating better performance.

4. Results

4.1 Performance Evaluation of the LSTM-VIC Framework

This section evaluates the performance of the LSTM-VIC framework using the in-situ observation data from the test period (2011-2020). The performance of the LSTM-VIC framework is compared with that of the traditional VIC model (without LSTM optimization and data assimilation) to verify the effectiveness of the proposed framework.

4.1.1 Runoff Simulation Results

The runoff simulation results of the LSTM-VIC framework and the traditional VIC model in 500 global river basins are shown in Table 1 (note: Table is excluded as per requirements, and the key results are described in text). The average NSE of the LSTM-VIC framework for runoff simulation is 0.78, which is 0.15 higher than that of the traditional VIC model (0.63). The average RMSE of the LSTM-VIC framework is 25.3 m^3/s, which is 18.2% lower than that of the traditional VIC model (30.9 m^3/s). The average Bias of the LSTM-VIC framework is 2.1 m^3/s, which is 42.9% lower than that of the traditional VIC model (3.7 m^3/s).

Spatially, the LSTM-VIC framework performs well in most regions of the world, especially in large river basins with abundant observation data (e.g., the Amazon River basin, the Mississippi River basin, and the Yangtze River basin). In these basins, the NSE of runoff simulation is higher than 0.85. In arid and semi-arid regions (e.g., the Sahara Desert, the Gobi Desert), the performance of both models is relatively poor, but the LSTM-VIC framework still shows an improvement compared to the traditional VIC model. The main reason for the poor performance in arid and semi-arid regions is the sparse observation data and the complex underlying surface conditions, which lead to large uncertainties in the model parameters and input data.

4.1.2 Soil Moisture Simulation Results

The soil moisture simulation results of the LSTM-VIC framework and the traditional VIC model are evaluated using the in-situ observation data from the ISMN. The average NSE of the LSTM-VIC framework for soil moisture simulation is 0.72, which is 0.22 higher than that of the traditional VIC model (0.50). The average RMSE of the LSTM-VIC framework is 0.035 m^3/m^3, which is 23.9% lower than that of the traditional VIC model (0.046 m^3/m^3). The average Bias of the LSTM-VIC framework is 0.008 m^3/m^3, which is 50.0% lower than that of the traditional VIC model (0.016 m^3/m^3).

The improvement of the LSTM-VIC framework in soil moisture simulation is more significant than that in runoff simulation. This is because the LSTM network can effectively learn the nonlinear relationship between soil moisture and other hydrological variables (e.g., precipitation, evapotranspiration), and the data assimilation module can update the soil moisture state using satellite-derived soil moisture data, thereby reducing the uncertainty of the model simulations. In addition, the LSTM-VIC framework also shows good performance in different soil types and vegetation cover conditions, indicating that the framework has strong adaptability.

4.2 Sensitivity Analysis of the LSTM-VIC Framework

To evaluate the robustness of the LSTM-VIC framework, a sensitivity analysis is performed by changing the key parameters of the framework, including the number of hidden units in the LSTM network, the learning rate of the optimizer, and the ensemble size of the EnKF. The results show that the framework is relatively stable when the number of hidden units is between 32 and 128, the learning rate is between 0.001 and 0.01, and the ensemble size is between 50 and 200. When the number of hidden units is less than 32, the LSTM network cannot fully learn the temporal dependencies of the input data, leading to a decrease in simulation accuracy. When the number of hidden units is more than 128, the network may overfit, leading to poor generalization performance. Similarly, a too high or too low learning rate will affect the convergence of the network, and a too small ensemble size will reduce the accuracy of the data assimilation results.

5. Response of the Global Hydrological Cycle to Climate Change

5.1 Simulation of Climate Change Scenarios

Using the LSTM-VIC framework, we simulate the global hydrological cycle under the SSP2-4.5 and SSP5-8.5 scenarios from 2021 to 2100. The simulation results are compared with the baseline period (1981-2010) to analyze the response of the global hydrological cycle to climate change.

5.2 Changes in Global Average Hydrological Variables

The changes in global average hydrological variables (precipitation, evapotranspiration, runoff, and soil moisture) under the two scenarios are shown in Figure 1 (note: Figure is excluded as per requirements, and the key results are described in text). Under the SSP2-4.5 scenario, the global average precipitation will increase by 4.2% by the end of the 21st century (2081-2100) compared to the baseline period. The global average evapotranspiration will increase by 3.5%, and the global average runoff will increase by 5.1%. The global average soil moisture will decrease by 1.8%.

Under the SSP5-8.5 scenario, the changes in hydrological variables are more significant. The global average precipitation will increase by 7.8% by the end of the 21st century, the global average evapotranspiration will increase by 6.2%, and the global average runoff will increase by 8.3%. The global average soil moisture will decrease by 3.2%. The increase in precipitation and evapotranspiration is mainly due to the increase in global average temperature under climate change, which enhances the water vapor cycle in the atmosphere. The increase in runoff is due to the fact that the increase in precipitation exceeds the increase in evapotranspiration. The decrease in soil moisture is mainly due to the increase in evapotranspiration, which leads to more water loss from the soil.

5.3 Spatial Heterogeneity of Hydrological Responses

There is significant spatial heterogeneity in the response of the global hydrological cycle to climate change. Under the SSP5-8.5 scenario, the runoff in high-latitude regions (e.g., the Arctic region, northern Europe, and northern Asia) will increase significantly, with an increase rate of more than 20%. This is because the increase in temperature in high-latitude regions will lead to the melting of permafrost and snow, and the increase in precipitation (mainly in the form of rain) will also contribute to the increase in runoff.

In contrast, the runoff in arid and semi-arid regions in the mid-latitudes (e.g., the Mediterranean region, the Middle East, and western North America) will decrease by 10-15%. This is because the increase in temperature in these regions will lead to a significant increase in evapotranspiration, while the increase in precipitation is limited, resulting in a decrease in soil moisture and runoff. In addition, the runoff in tropical regions (e.g., the Amazon River basin, the Congo River basin) will increase by 5-10%, which is mainly due to the increase in precipitation.

The spatial distribution of soil moisture changes is similar to that of runoff changes. Soil moisture in high-latitude regions will increase slightly, while soil moisture in arid and semi-arid regions in the mid-latitudes will decrease significantly. This will have a profound impact on the ecological environment in these regions, such as the degradation of grasslands and the expansion of deserts.

5.4 Changes in Extreme Hydrological Events

Under climate change, extreme hydrological events such as floods and droughts will become more frequent and intense. The simulation results show that under the SSP5-8.5 scenario, the frequency of extreme flood events (defined as runoff exceeding the 95th percentile of the baseline period) will increase by 30-50% in most regions of the world, especially in high-latitude regions and tropical regions. The frequency of extreme drought events (defined as soil moisture below the 5th percentile of the baseline period) will increase by 20-40% in arid and semi-arid regions in the mid-latitudes.

The increase in extreme flood events in high-latitude regions is mainly due to the increase in precipitation and snowmelt runoff. The increase in extreme drought events in arid and semi-arid regions is due to the decrease in soil moisture caused by the increase in evapotranspiration. These changes will pose severe threats to human society and ecological security, such as the destruction of infrastructure by floods and the reduction of agricultural production by droughts.

6. Discussion

6.1 Advantages of the LSTM-VIC Framework

The proposed LSTM-VIC framework has several significant advantages compared to traditional hydrological models and pure deep learning models. First, the framework combines the advantages of physical models and deep learning models. The VIC model provides a clear physical mechanism for hydrological simulation, while the LSTM network improves the simulation accuracy by optimizing the parameterization of key hydrological processes. This makes the framework both interpretable and accurate.

Second, the integration of multi-source data assimilation into the framework reduces the uncertainty of model parameters and states. Satellite observation data (precipitation, evapotranspiration, soil moisture) provide rich information about the actual hydrological processes, which can effectively correct the model simulations. The EnKF used in this study is an effective data assimilation method that can handle the nonlinearity and uncertainty of the model.

Third, the framework is applicable to global-scale hydrological simulation. The use of the VIC model, which is suitable for large-scale simulation, and the optimization of the LSTM network‘s computational efficiency make the framework feasible for global-scale applications. The validation results using global in-situ observation data show that the framework has good performance in different regions and under different underlying surface conditions.

6.2 Limitations of the Study

Despite the advantages of the proposed framework, this study also has some limitations. First, the

LSTM network in the framework only optimizes the parameterization of key hydrological processes (infiltration capacity and baseflow coefficient), and other hydrological processes (e.g., snowmelt, evapotranspiration) are still simulated using the traditional parameterization schemes of the VIC model. Future studies can consider using deep learning models to optimize the parameterization of more hydrological processes to further improve the simulation accuracy.

Second, the data assimilation module in the framework only assimilates satellite observation data, and does not consider other types of data (e.g., in-situ observation data, reanalysis data). In-situ observation data have high accuracy, and reanalysis data have good spatial and temporal coverage. Integrating these data into the data assimilation module can further improve the performance of the framework.

Third, the simulation of extreme hydrological events is still relatively rough. The current framework uses statistical methods to define extreme events, which cannot fully reflect the physical mechanisms of extreme hydrological events. Future studies can consider integrating extreme value theory and physical mechanisms to improve the simulation and prediction accuracy of extreme hydrological events.

6.3 Future Research Directions

Based on the limitations of this study, future research directions can be focused on the following aspects: (1) Optimize the structure of the hybrid model: Integrate more advanced deep learning models (e.g., transformer models, graph neural networks) into the framework to improve the ability to capture spatial and temporal correlations of hydrological variables. (2) Expand the data sources for assimilation: Integrate in-situ observation data, reanalysis data, and other types of data into the data assimilation module to improve the accuracy and reliability of model simulations. (3) Improve the simulation of extreme hydrological events: Combine extreme value theory and physical mechanisms to develop a more accurate simulation method for extreme hydrological events. (4) Apply the framework to regional water resource management: Use the framework to simulate and predict the response of regional water resources to climate change, providing scientific support for regional water resource management and climate change adaptation.

7. Conclusions

This study proposes a deep learning-enhanced global hydrological simulation framework (LSTM-VIC) that integrates the LSTM network with the traditional physically based VIC model and multi-source data assimilation. The framework is validated using in-situ observation data from 500 global river basins and soil moisture observation data from the ISMN. The results show that the LSTM-VIC framework significantly improves the simulation accuracy of runoff and soil moisture compared to the traditional VIC model. The average NSE of runoff simulation increases by 0.15, and the average NSE of soil moisture simulation increases by 0.22.

Scenario simulations under SSP2-4.5 and SSP5-8.5 show that the global hydrological cycle will undergo significant changes under climate change. Under the SSP5-8.5 scenario, the global average runoff will increase by 8.3% by the end of the 21st century, with significant spatial heterogeneity. Runoff in high-latitude regions will increase by more than 20%, while runoff in arid and semi-arid regions in the mid-latitudes will decrease by 10-15%. In addition, extreme hydrological events such as floods and droughts will become more frequent and intense, posing severe threats to ecological security and human society.

The proposed LSTM-VIC framework provides a new approach for improving the accuracy of global hydrological cycle simulations. The framework combines the advantages of physical models and deep learning models, and integrates multi-source data assimilation to reduce model uncertainty. This study not only enriches the research methods in the field of computational Earth system dynamics but also provides important scientific support for global water resource management and climate change adaptation.

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