

Interpretable Physics-Informed Neural Network Groundwater Level Simulation Model: A Case Study of Linyi, Shandong Province, China

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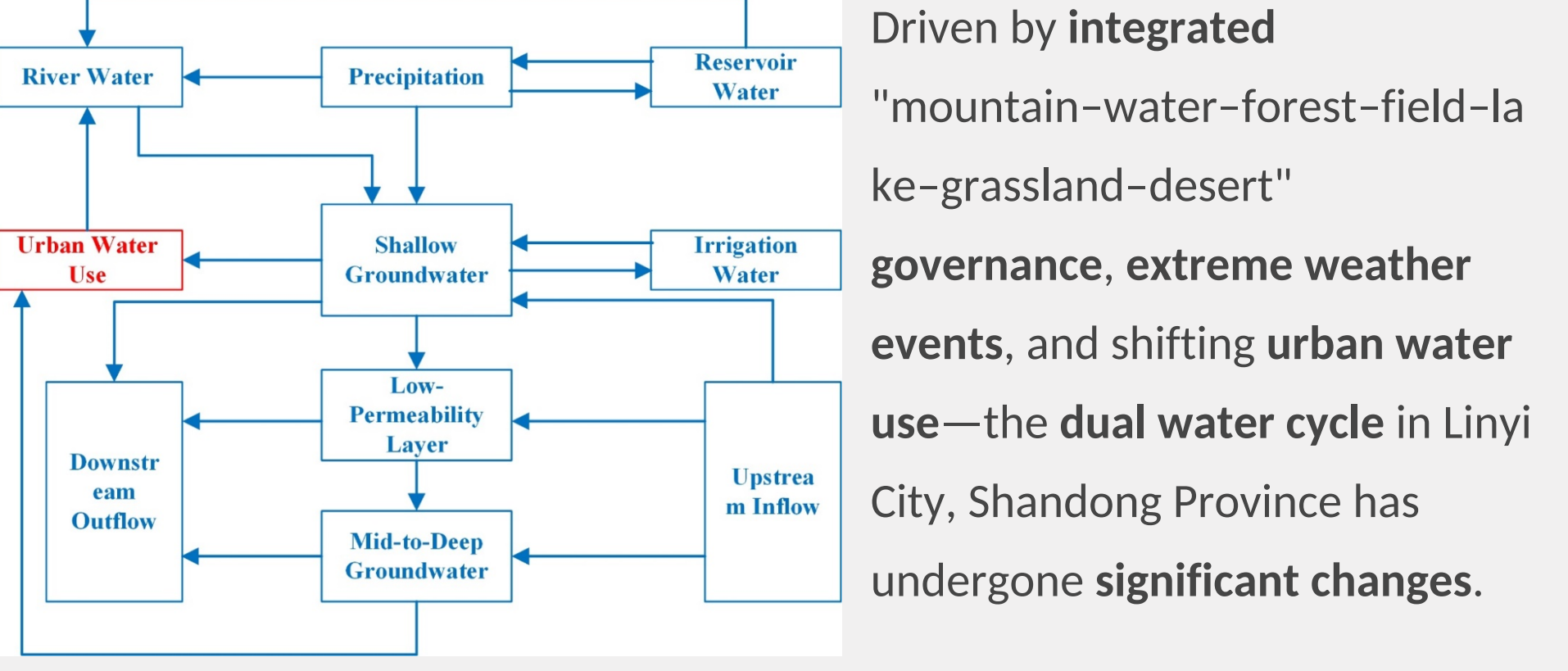
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1. Abstract

Climate change, extreme weather events, and human activities have significantly influenced regional dual water cycle processes, triggering geological hazards such as karst collapses and land subsidence. To address the urgent need for accurate groundwater level simulation and prediction, this study applies a Physics-Informed Neural Network (PINN) model to the Linyi monocline hydrogeological unit. The model incorporates the two-dimensional unsteady groundwater flow equation as a physical constraint into the loss function, ensuring that the model satisfies the governing physical laws during training. Results show that the PINN model achieves high accuracy in groundwater level simulation, with an R^2 of 0.87 and RMSE of 1.98 m. By solving physical equations during training, the importance of hydrological parameters to the PINN model is significantly enhanced, with hydraulic conductivity making the greatest contribution to the model. Moreover, the PINN model is capable of simultaneously achieving accurate groundwater level simulation and dynamic inversion of hydrogeological parameters even when some system parameters are missing. This study provides a novel and transferable approach to groundwater level modeling and offers scientific guidance for the sustainable management and protection of groundwater resources.

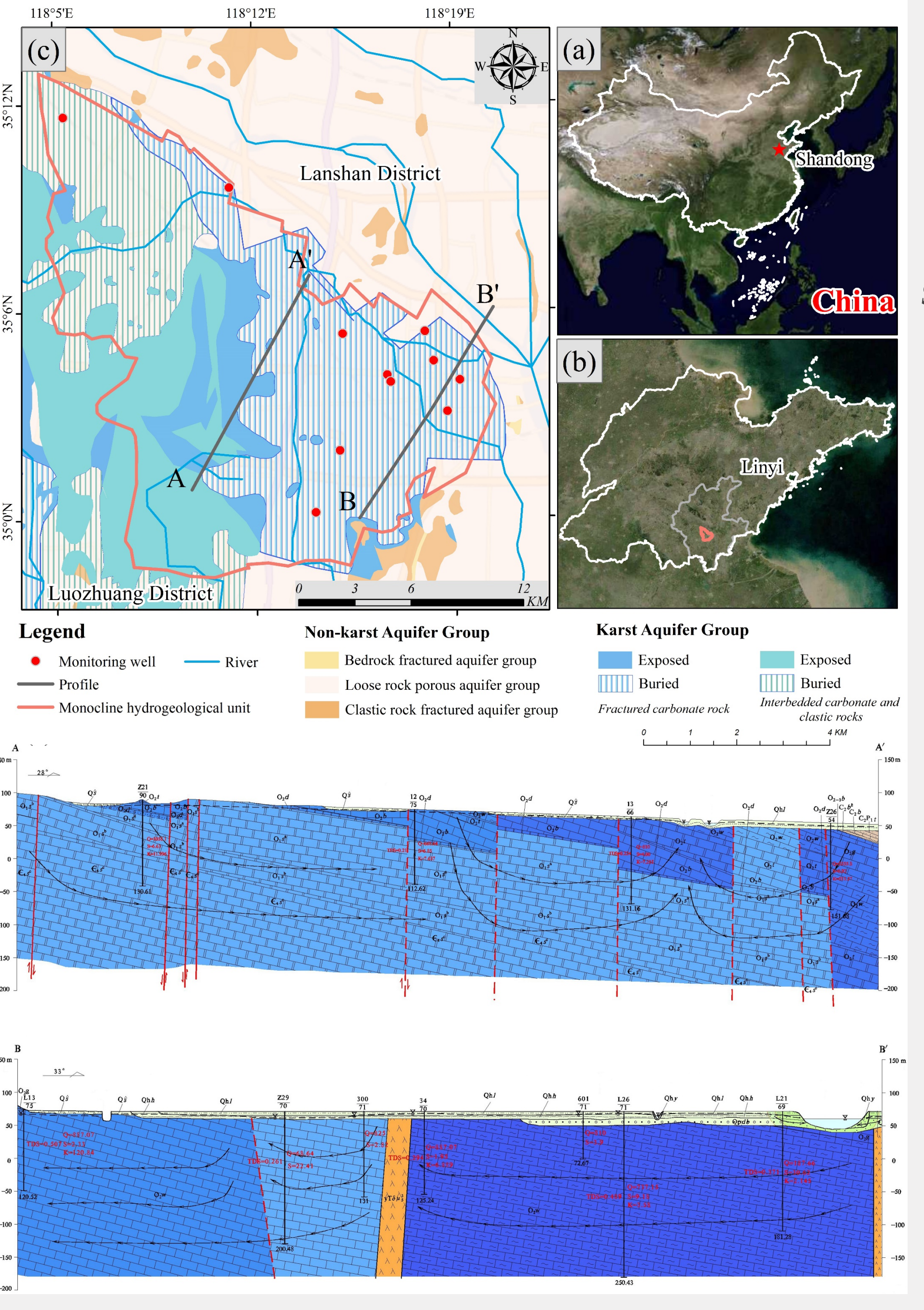
2. Introduction

- Traditional numerical models are typically grounded in **water balance** and **hydraulic theories**. These methods requires **detailed geological and hydrogeological parameters** to accurately represent complex stratigraphic structures, boundary conditions, and other critical features.
- Machine learning** provide significant advantages in addressing **nonlinear problems**. These methods are predominantly **data-driven** and often **lack** the incorporation of **physical constraints**.
- Physics-Informed Neural Network (PINN) is a computational framework that **combines** neural networks with physical laws, aiming to mitigate the **"black-box" property** of traditional neural networks by **incorporating** physical constraints and thereby enhancing the **interpretability** of the models.



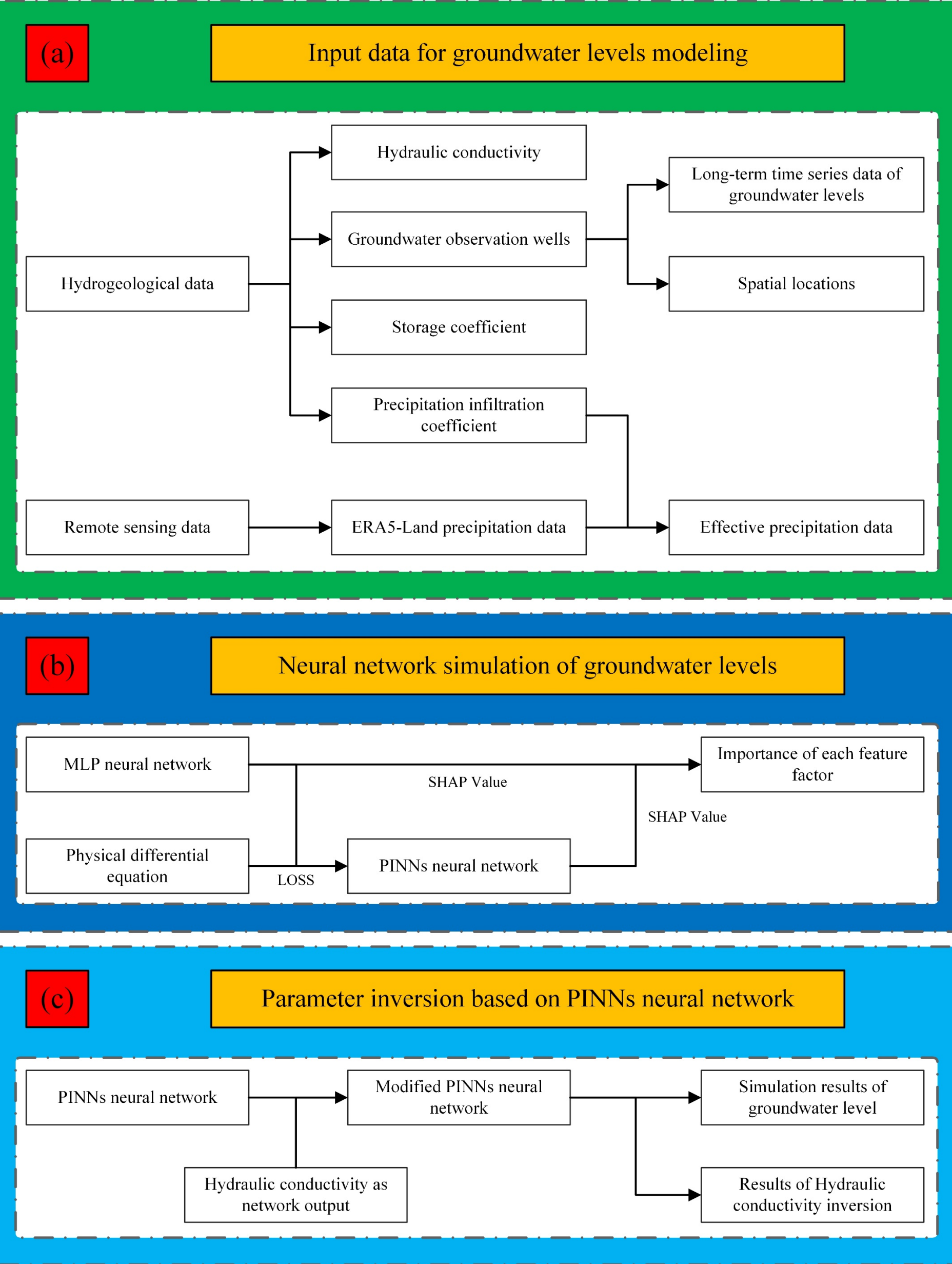
3. Objective

Case study area: Linyi monocline hydrogeological unit

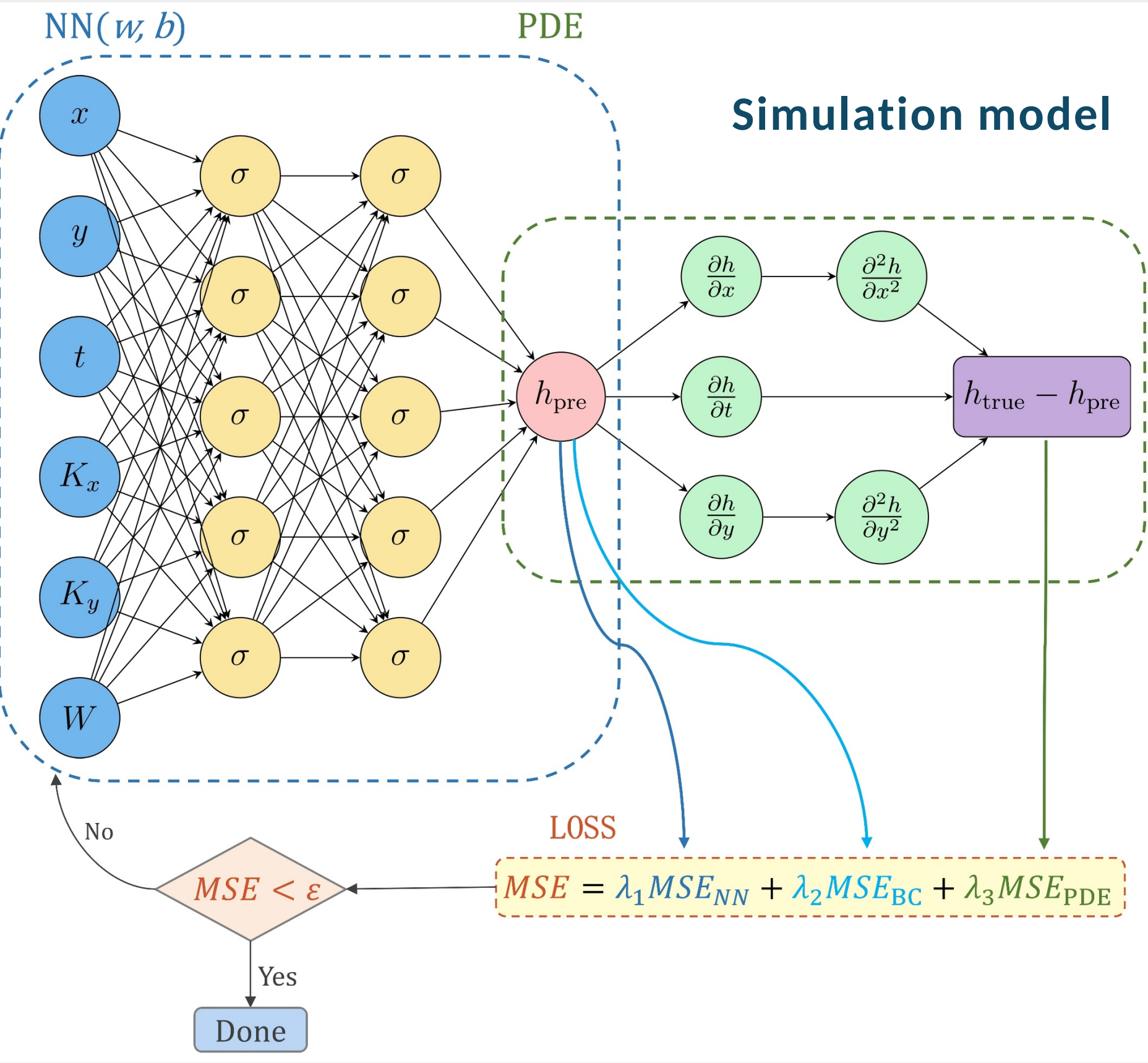


4. Methods

Framework of groundwater modeling using the PINN



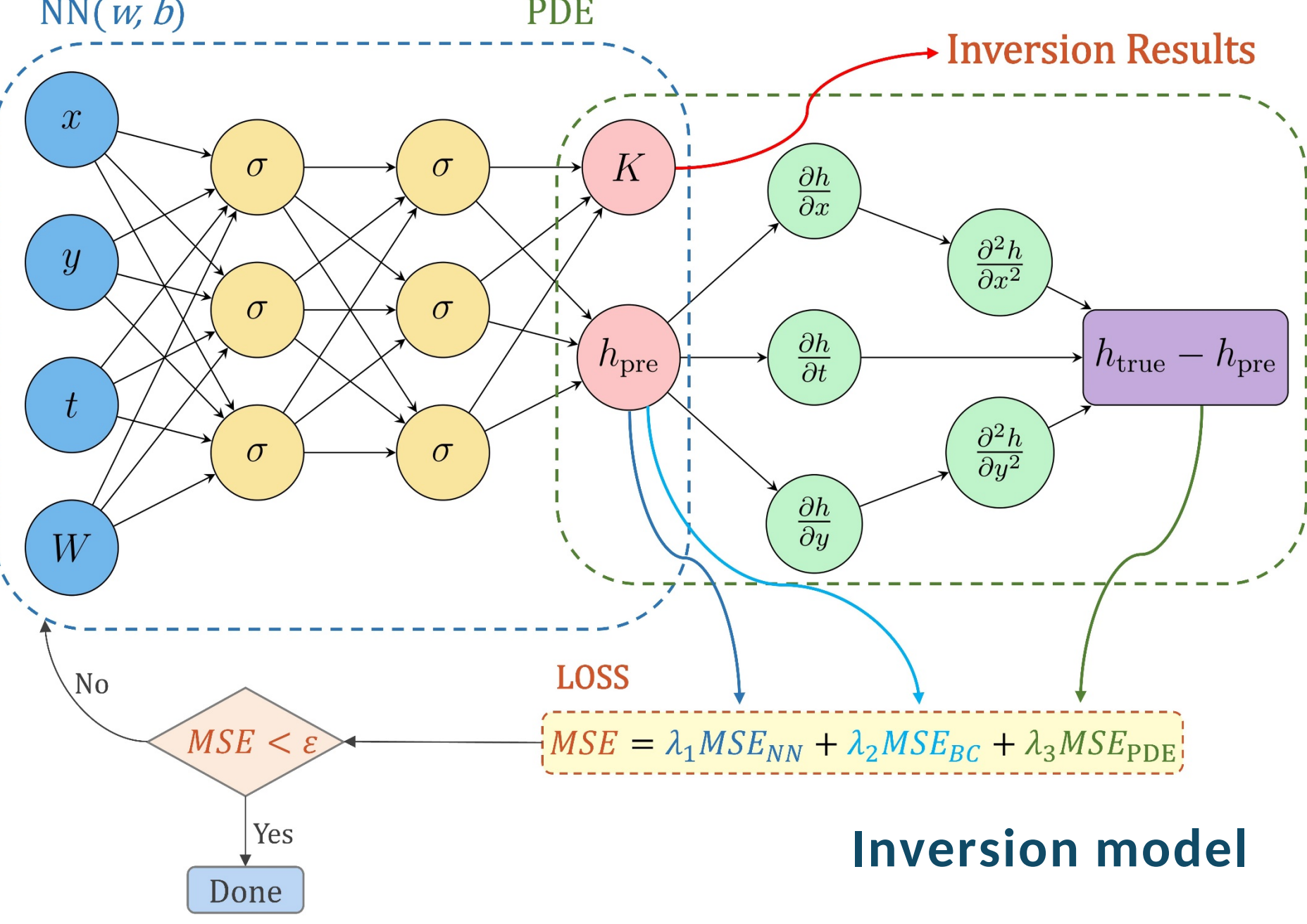
Architecture of Physics-Informed Neural Network



- Model input:
 1. Location information of groundwater level points (x, y, t)
 2. Hydraulic conductivity (K_x and K_y)
 3. Source/sink term (W)
- Model output:
 - Groundwater levels (h)
- The governing equation for **two-dimensional unsteady groundwater flow**:
$$S_s \frac{\partial h}{\partial t} = \frac{\partial}{\partial x} \left(K_x \frac{\partial h}{\partial x} \right) + \frac{\partial}{\partial y} \left(K_y \frac{\partial h}{\partial y} \right) + W$$
- Loss function:

The loss function of a PINN model consists of **three components**:

 1. The residual between the network output and the **training data**.
 2. The **PDE residual loss**.
 3. The **boundary condition loss**.



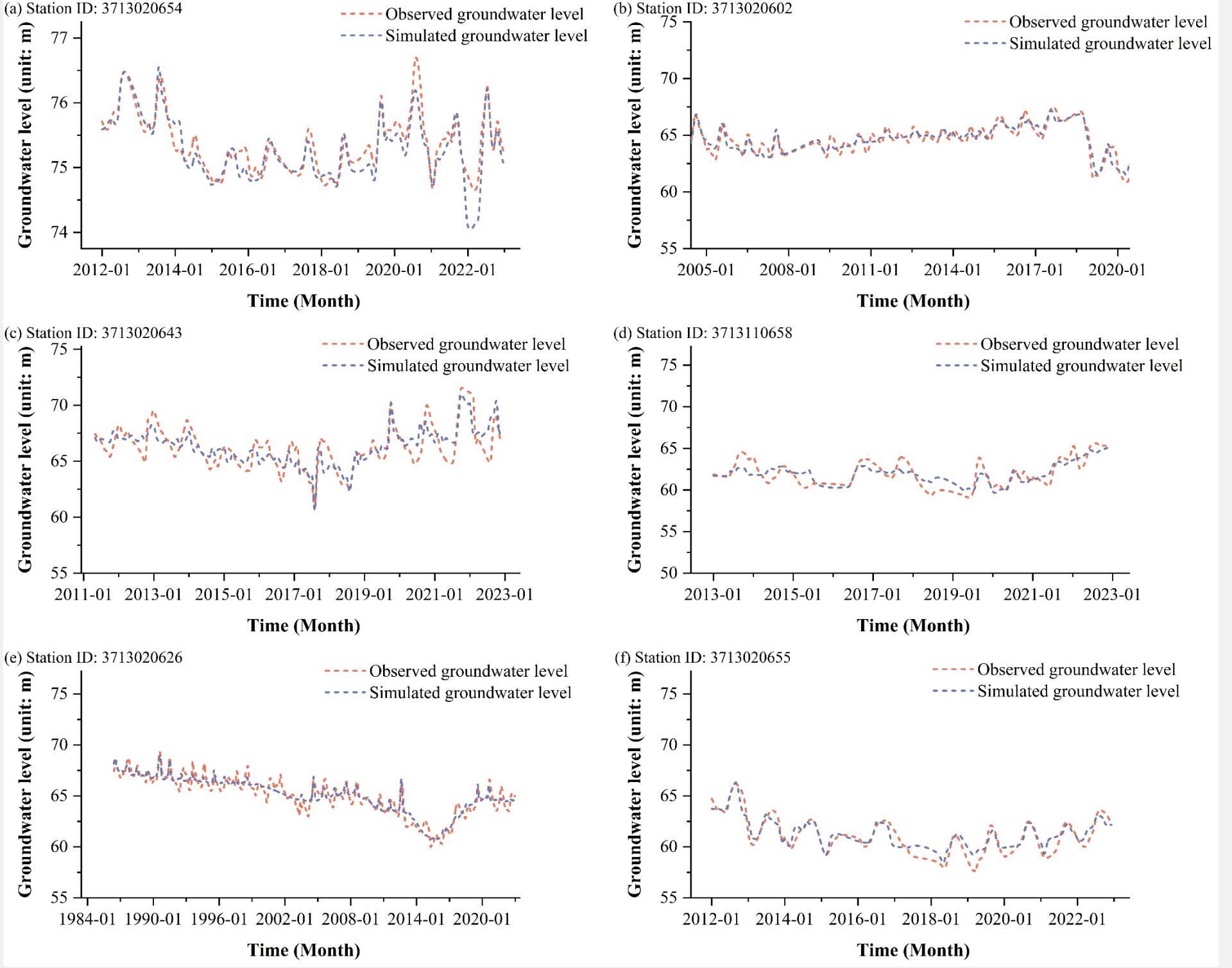
Architecture of the improved PINN for hydrological parameter inversion

5. Results and Discussion

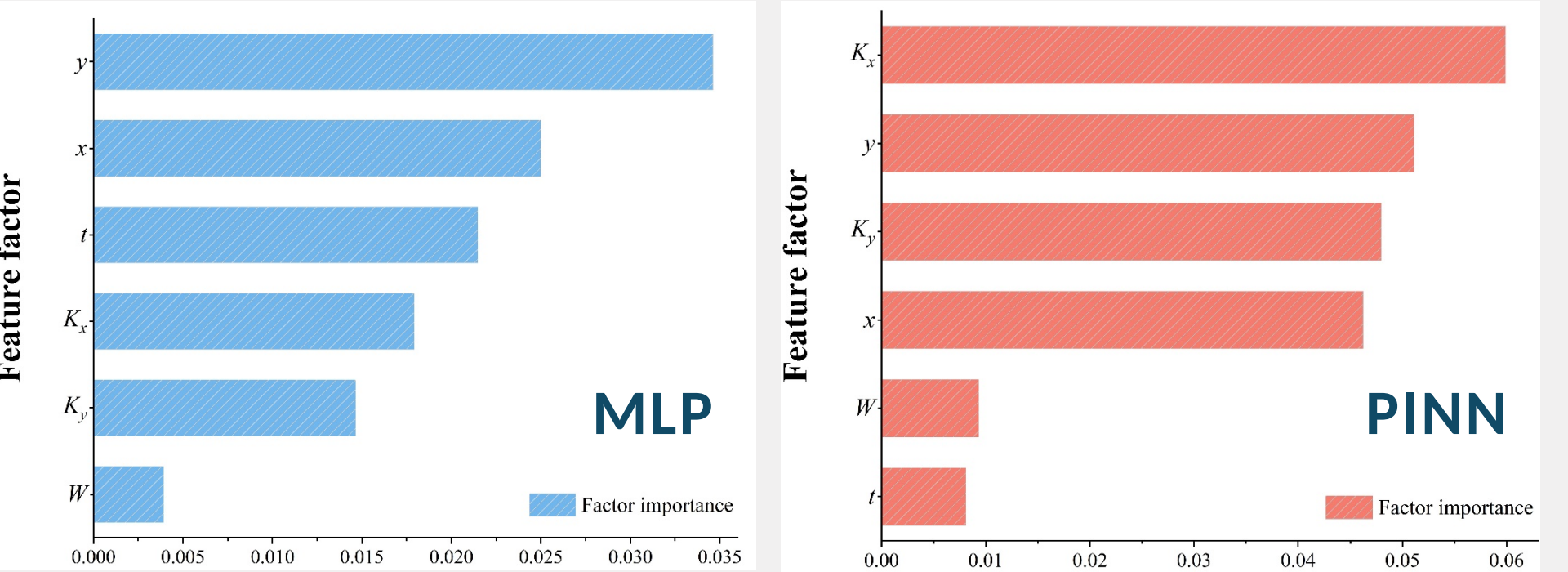
Accuracy of groundwater level simulation models

Model	Simulation Time Range	R-squared	RMSE
MLP	1984.01-2022.12	0.92	1.49 m
PINN	1984.01-2022.12	0.87	1.98 m

Groundwater level simulation results using PINN

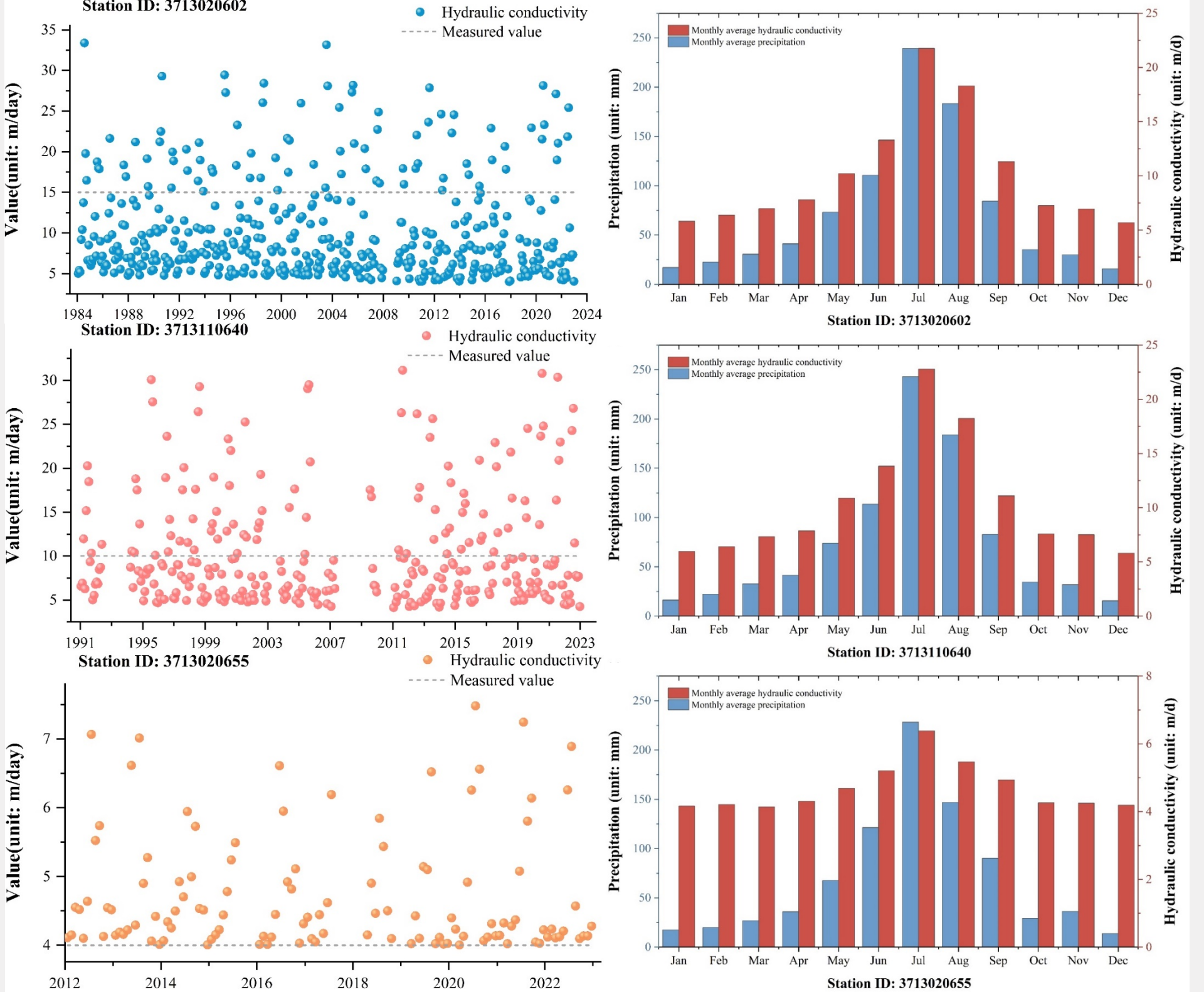


Importance of input features in MLP and PINN models



- The spatial location variables (x, y) have the highest importance to the MLP model.
- The PINN model not only accurately captures the spatial patterns of groundwater level variations but also significantly enhances its sensitivity to hydraulic conductivity.

Results of hydraulic conductivity inversion



- Results show a significant correlation between variations in hydraulic conductivity and precipitation events.
- Results demonstrate that the PINN model possesses physical interpretability

6. Conclusion

- This study proposes a novel groundwater level simulation model based on Physics-Informed Neural Networks (PINNs), which achieves high accuracy in simulating groundwater level variations.
- The proposed PINN model demonstrates strong physical interpretability by embedding governing equations into the learning process.
- The model can not only accurately simulate groundwater levels but also enables the inversion of missing hydrogeological parameter values.

Major References

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