Enhancing Long-Term River Flow Prediction for Effective Water Resource Management under Intensifying Drought Risks and Climate Change

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01 Abstract

The intensification of climate change has exacerbated the frequency and severity of extreme hydrological events, particularly droughts, posing critical challenges to global water resource management. The Zhuoshui River Basin, as a vital water supply region in Taiwan, has recently faced increasing extremes in rainfall and drought, highlighting the urgent need for effective management strategies. To address these challenges, this study develops a deep learning-based model for long-term monthly river flow prediction, emphasizing its significance in supporting water resource management and decision-making under worsening drought conditions.

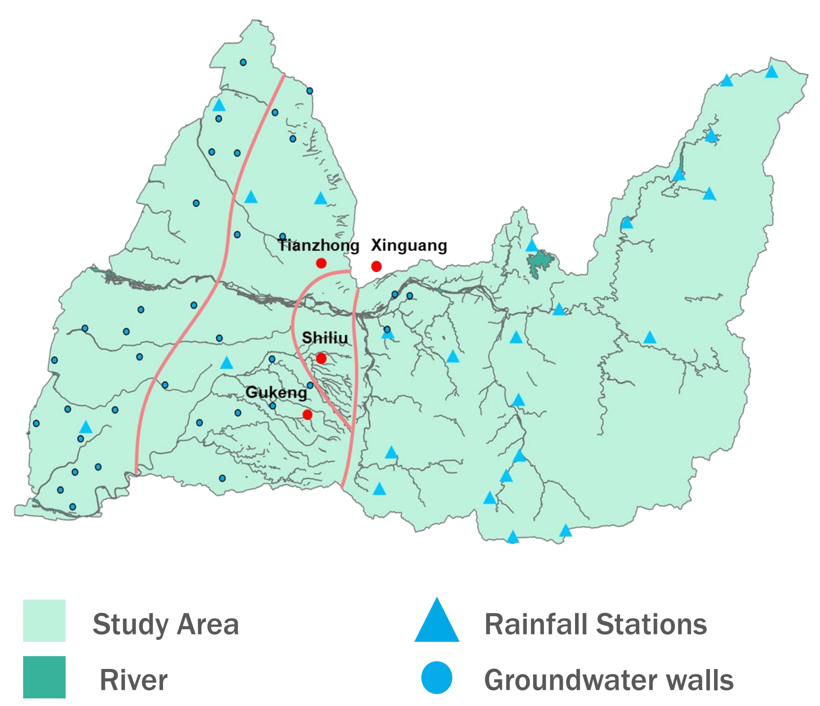
Using historical hydrological data, the model was trained and optimized with input variables such as rainfall, evapotranspiration, and groundwater levels to explore their interactions with river flow and assess their influence on predictive performance. Future climate scenarios provided by the IPCC AR6 (Sixth Assessment Report) were employed to project river flow and groundwater levels over the next 80 years, offering insights into potential drought risks.

By combining the predicted river flow and groundwater levels with established drought assessment indices, the study quantifies drought severity and provides a scientific foundation for developing sustainable water resource management strategies in the Zhuoshui River Basin under the impact of climate change.

Keywords: Long-term streamflow forecasting, Deep learning, Drought Risk, Climate Change

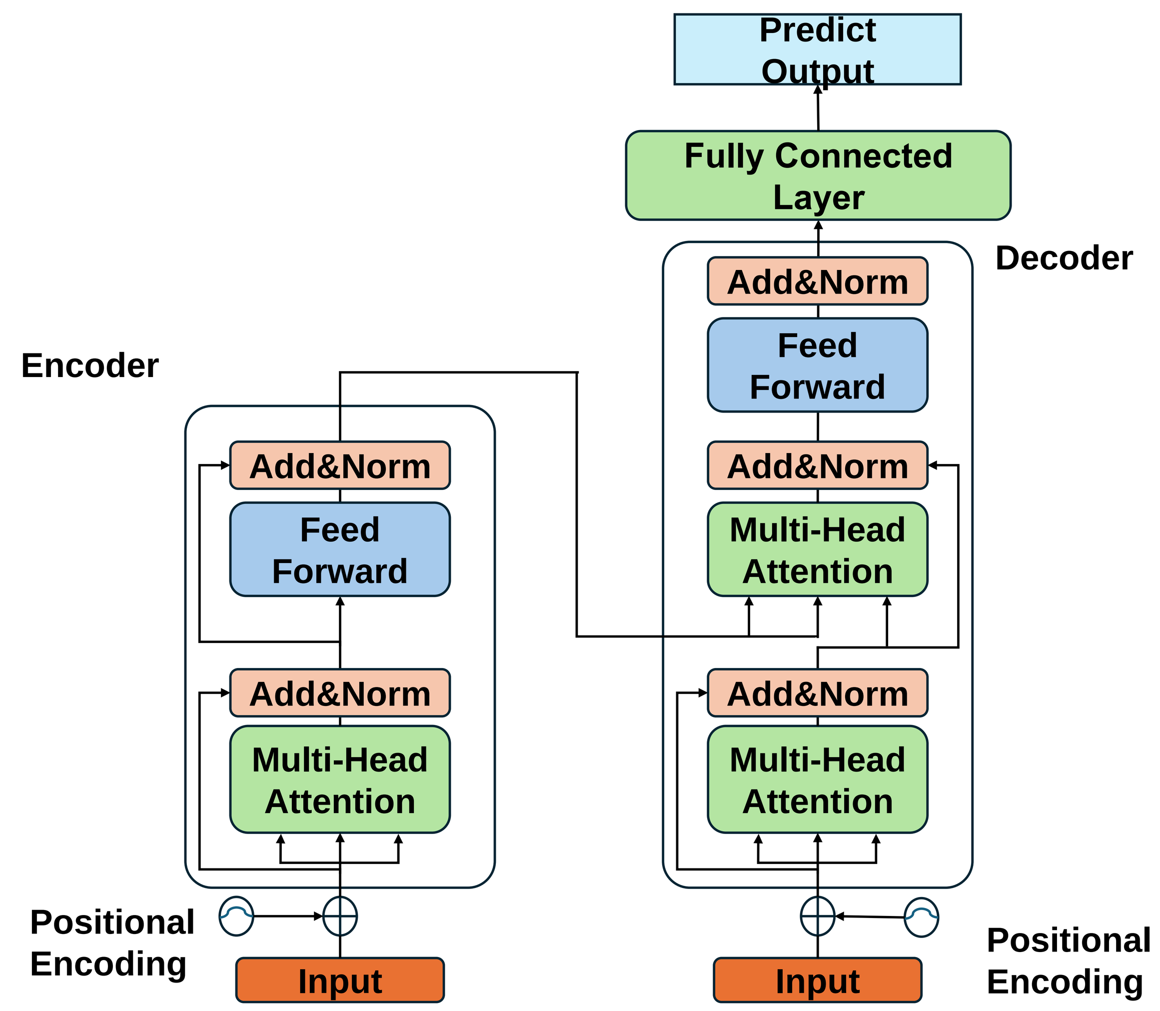
02 Study Area

Name: Zhuoshui River Basin
Location: Central Taiwan, Taiwan
Area: 3,156.9 km²



03 Methodology

The Transformer is a deep learning architecture based on the attention mechanism, originally proposed by Vaswani et al. (2017). It has shown remarkable performance in tasks involving sequential data, such as natural language processing and time-series forecasting. In this study, we adapt the Transformer model to forecast multi-site groundwater levels over time.



Encoder
The encoder processes historical multivariate input sequences. It consists of stacked layers combining **Multi-Head Self-Attention and Feedforward Neural Networks** to capture temporal patterns and inter-feature dependencies.
Decoder
The decoder generates the future groundwater level predictions by integrating the encoded context with partially known target sequences. It enables autoregressive forecasting by attending to both input history and past outputs.
Attention Mechanism
The core component of the model is the attention mechanism, which dynamically computes the relevance between different time steps. This allows the model to focus on important time-dependent patterns and enhances the learning of long-range dependencies.

04 Input Configuration

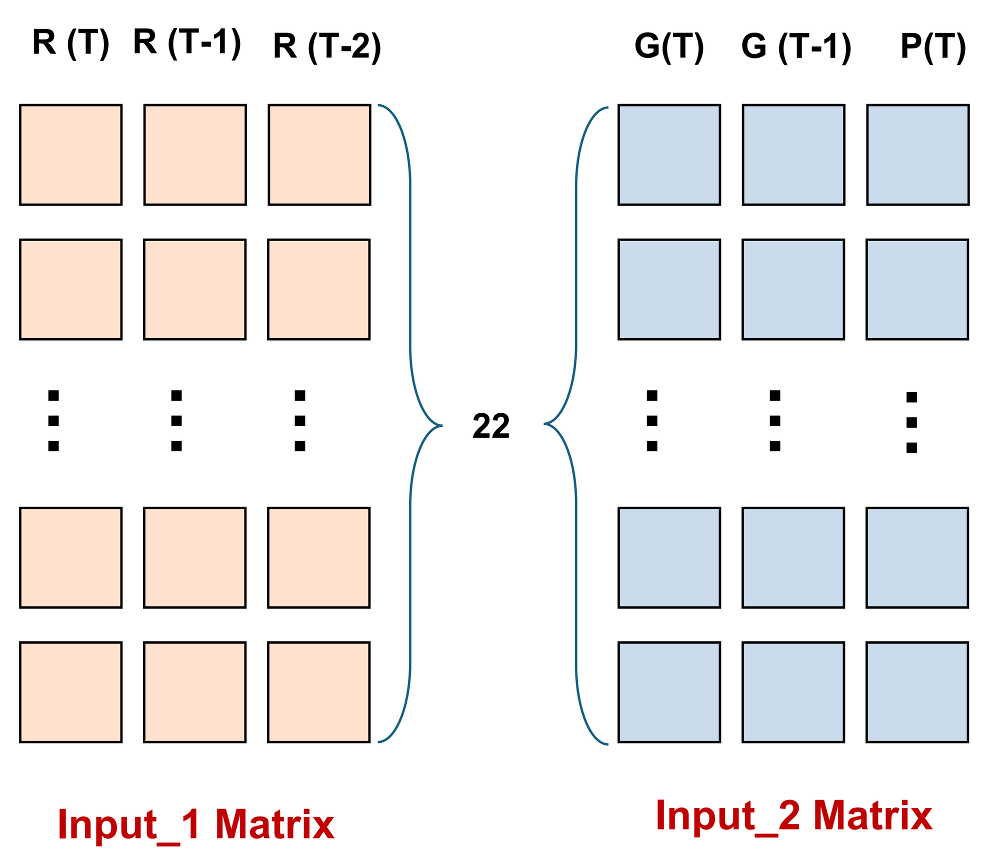
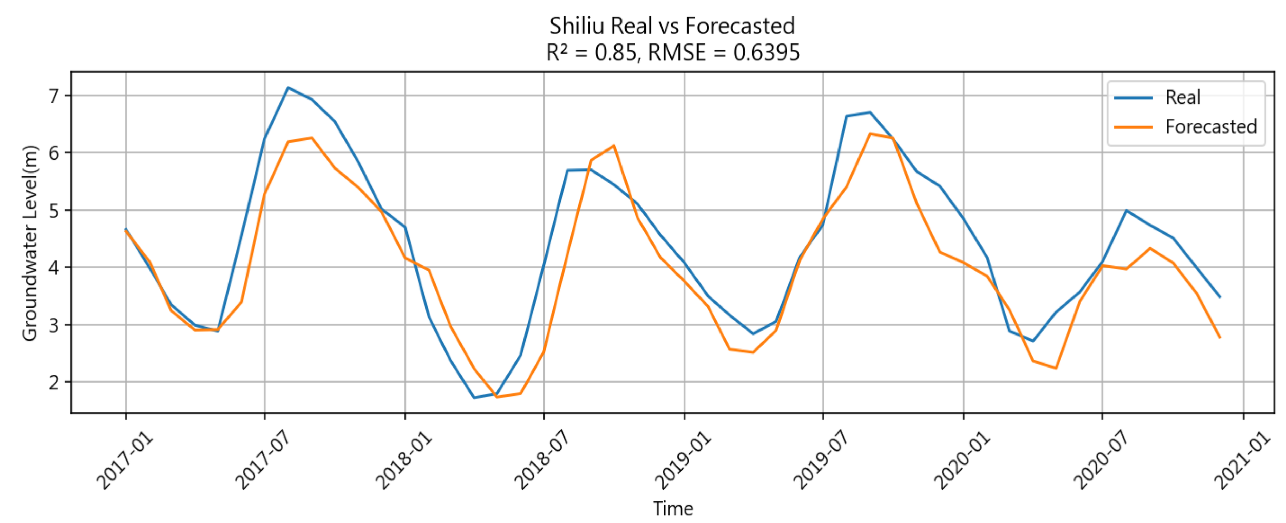


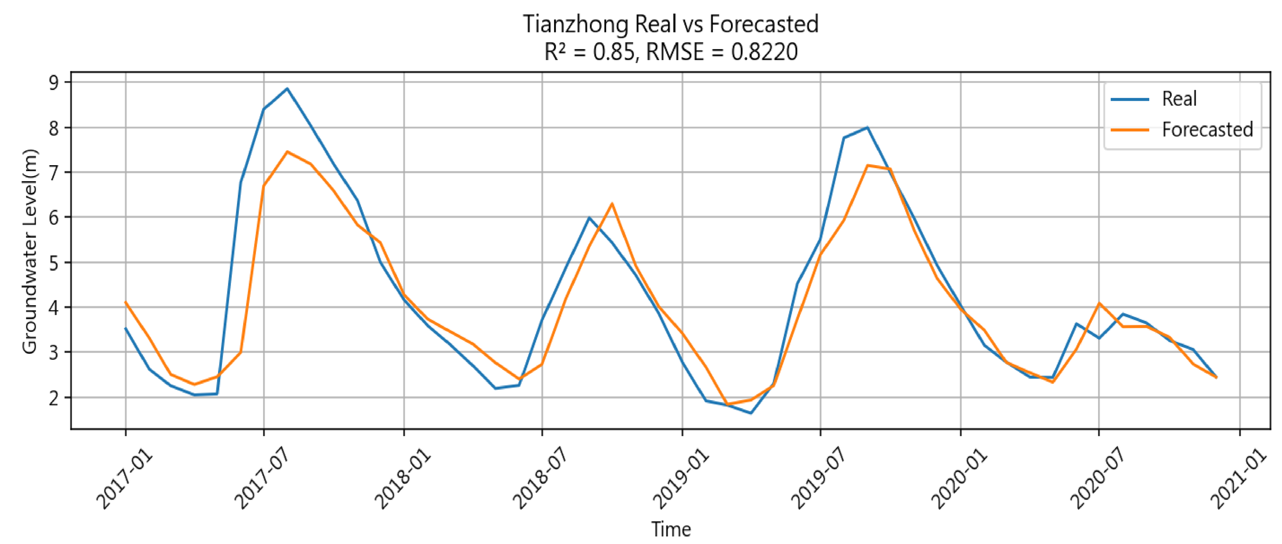
Figure 3 Dual-Matrix Input Design for Transformer-Based Forecasting

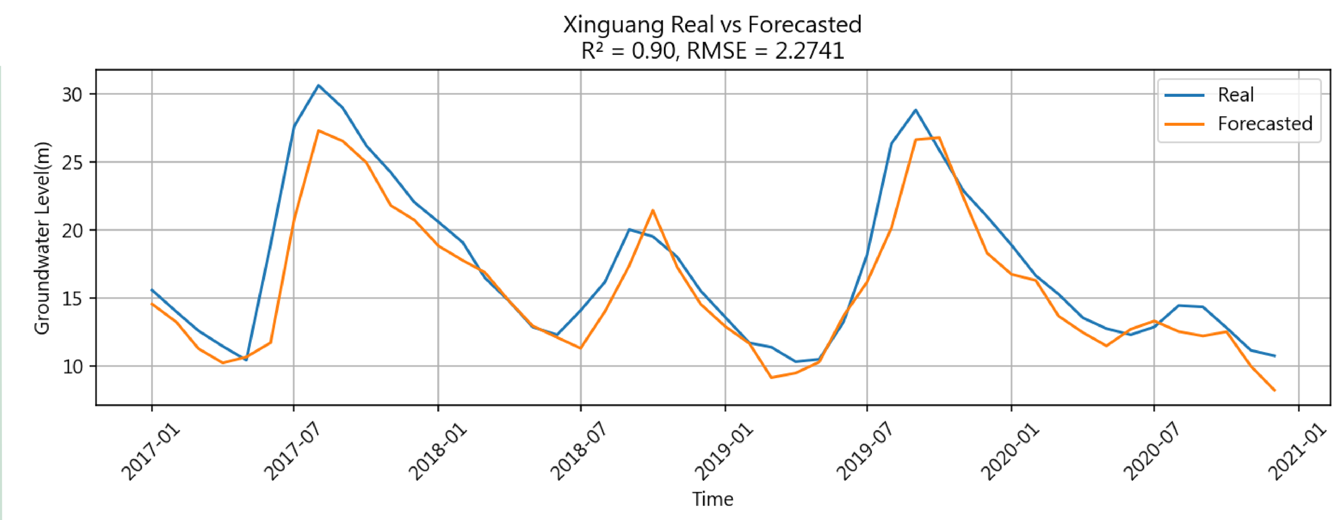
In this study, the Transformer's data input consists of two matrices:
Rainfall Matrix
Rows: 22 rainfall stations
Columns: R(T), R(T-1), R(T-2) represent rainfall at current time, one step before, and two steps before, respectively.
Groundwater Matrix
Rows: 22 groundwater monitoring stations
Column: G(T), G(T − 1), P(T) represent Groundwater level at current time and previous time, and pumping factor at current time, respectively.
Prediction Target
The model is trained to simultaneously forecast the next-month groundwater level G(T + 1) for **all 22 monitoring wells**, allowing spatially consistent and scalable inference.

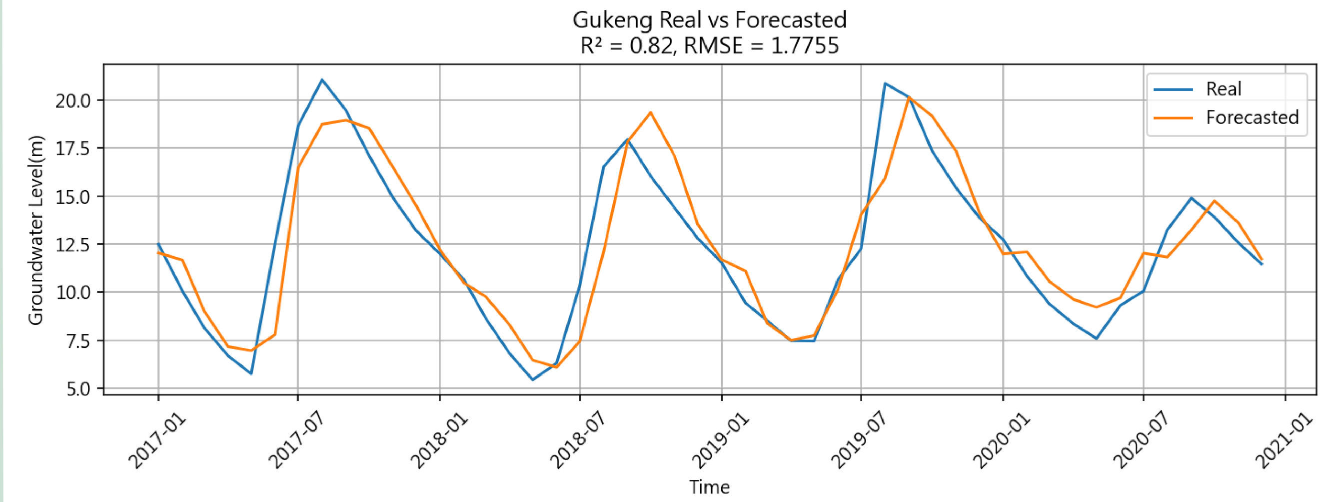
05 Results

The results shown here focus on four representative stations from the total of 22 groundwater stations. These stations, **Shiliu**, **Tianzhong**, **Gukeng**, and **Xinguang**, were chosen to reflect a diversity of hydrological behaviors and model performance.
The Transformer model exhibited stable and accurate forecasting performance. next-month groundwater level forecasts across the 22 stations. Notably, at **Shiliu** and **Tianzhong**, the model attained high consistency with observed data, reaching **R^2 values of 0.85** and **low RMSE values of 0.639 and 0.822**, respectively. These results highlight the model's effectiveness in capturing seasonal patterns and moderate groundwater fluctuations.
For stations characterized by more dynamic conditions, such as **Gukeng** and **Xinguang**, performance decreased, with RMSEs increasing to 1.776 and 2.274, respectively. Although R^2 values remained acceptable (0.82–0.90), the model tended to **underestimate peak levels**, especially during high interannual variability periods. This suggests that while the model handles typical hydrological regimes well, its ability to simulate extreme groundwater dynamics remains limited.
In summary, the proposed framework offers reliable support for **regional-scale** groundwater monitoring and early warning, though future enhancements, such as the integration of land use, soil moisture, or climate anomaly indicators, may further improve performance under extreme scenarios.









Station	R2	RMSE	NRMSE	G-Bench
Xinguang	0.90	2.274	0.112	8.075
Tianzhong	0.85	0.822	0.114	7.464
Shiliu	0.85	0.639	0.118	7.221
Gukeng	0.82	1.776	0.114	7.186

06 Conclusions

The results show that the model performs **particularly well in stations exhibiting regular seasonal stability**, achieving high R^2 and low RMSE values. In more complex environments, such as areas with high variability or anthropogenic stress the model still maintains reasonable accuracy, though further refinements are needed to improve the simulation of extreme peaks and nonlinear dynamics.

This scalable and data-driven forecasting framework offers valuable decision support for **groundwater monitoring**, **early warning systems**, and **regional water management**. Its ability to generate simultaneous forecasts across multiple wells enhances spatial coherence and operational feasibility.
Importantly, the integration of such groundwater forecasts with **river flow models** can significantly improve predictions during **drought periods**, when streamflow becomes increasingly dependent on **baseflow contributions from aquifers**. As climate change intensifies drought risk, these linked models will play a crucial role in **ensuring water security and managing environmental flows**.
Future research directions include:
- ◆ Incorporating additional predictors such as soil moisture, evapotranspiration, and land use.
- ◆ Testing attention-based variants and hybrid architectures.
- ◆ Extending forecasts to **multi-month horizons** for **drought preparedness and river basin-scale planning.**

08 Acknowledgements

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