Prediction of Groundwater from Principal Hydrological Elements Utilizing Vision Transformer

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Abstract: Groundwater levels (GL) monitoring is an essential aspect of the hydrological cycle, and it serves as an indicator for various resource management methods in a watershed. Predominant techniques have shown that GL can be predicted for any geographic region if sufficient data exists for computation through sophisticated algorithms. One of the major issues in water governance is the lack of reliable and complete data for estimating and studying the GL decline trend. Hence, using reliable artificial intelligence (AI) models known for low informational needs and high prediction accuracy is more practical. This research aims to estimate groundwater prediction using a Vision Transformer (VTf) based on principal hydrological elements (PHE). PHE from 2017 to 2024 included flow level, velocity, rainfall, humidity level, average temperature, transpiration, and warm days. Traditional deep learning (DL) models need a fixed size of data, which greatly restricts their flexibility to analyze data of varying scales; hence, they fail to capture persistent dependencies. Overcoming these constraints is where VTf excels through the use of the Individual Attention Mechanism (IAM) of the transformer concept. VTf gives the best results when estimating GL to achieve the best accuracy.

Keywords: Groundwater; Hydrology; Elements; Vision Transformer; Individual Attention Mechanisms.

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I. Overview of the Study

Water resource management requires hydrometric prediction for servicing relevant to the citizens' well-being, financial interests, and ecological conservation. Hydrometric modeling GL prediction features due to its prompt and far-reaching impact (Liu et al., 2025). Accurate forecasting allows for timely intervention in flood control, protection of reservoirs and infrastructure, and improved water supply for irrigation, industrial, and residential activities. Moreover, anticipating water levels is crucial for preserving aquatic habitats and ecological diversity (Bai & Tahmasebi, 2022).

Variations in GL at watershed levels transpire over a long period, and the consequent compounded impacts on water flow degradation may not be completely understood for years. Consequently, recovering the GL infrastructure from water flow reduction due to inconsistent circulation may take many years, contingent upon the proximity of the circulating station from the watershed and the geological properties of the groundwater source (Zhu et al., 2025). The surface and subterranean PHE elements within a watershed, namely the flow of streams and GL supply, are interrelated, rendering the connection between streams and aquifers a fundamental process that dictates the GL flow structure within a water basin. Variations in GL influence water flow and vice versa since extraction from wells intercepts GL that would typically flow into interconnected river systems, streams, and additional shallow water basins (Wang & Zha, 2024).

Water resources display fluctuations in time affected by periodic cycles, meteorological events, and long-term climate patterns. These seasonal fluctuations influence the pace of flow, the quantity of water, and the ultimate PHE function over various periods. At the same time, comprehending spatial relationships is essential for forecasting how alterations in one region disseminate across the hydrological ecosystem (Zheng, Hou, & Qin, 2024). Forecasting water circulation in hydrological networks poses a challenge in its spatial and temporal aspects, capturing the range of time changes and spatial relations within the GL system to provide accurate projections and insight into watershed activity (Suresh et al., 2024).

The spatial relation of steps of the hydrological system is determined by the change in the relief's altitude, which controls the rate at which water moves over the surface. This feature is important because it determines the speed and direction of movement of water runoff, where steep slopes result in rapid runoff and high water levels in some areas (Sun, Chang, & Chang, 2024). This also affects the collection and movement of water from one place to another, affecting the overall operation of the hydrological system.

II. Prediction of Groundwater based on PHE using a VTf

1.1 Data gathering

Two observation water sources were chosen for the acquisition of real-time GL information. Daily GL readings from these two observation water sources for eight years (2017–2024) and meteorological data from adjacent weather stations were acquired. PHE for the time frame of 2017–2024 included flow level, velocity, rainfall, humidity level, average temperature, transpiration, and warm days.

1.2 VTf-based GL prediction

The discipline of DL has historically relied on convolutional neural networks until the advent of transformers, which exhibit remarkable performance. VTf utilizes the standard transformer encoder framework for data-related activities, as seen in Fig. 1. The data is first partitioned into many parts, undergoing element embedding and geographical encoding before incorporating into the encoder using class embedding. After geographical encoding and linear transformation, the data is first partitioned into multiple input sections for the encoding process. Eventually, information is sent to the Multi-Layer Perceptron (MLP) for GL prediction. IAM serves as the foundational architecture of the encoding.

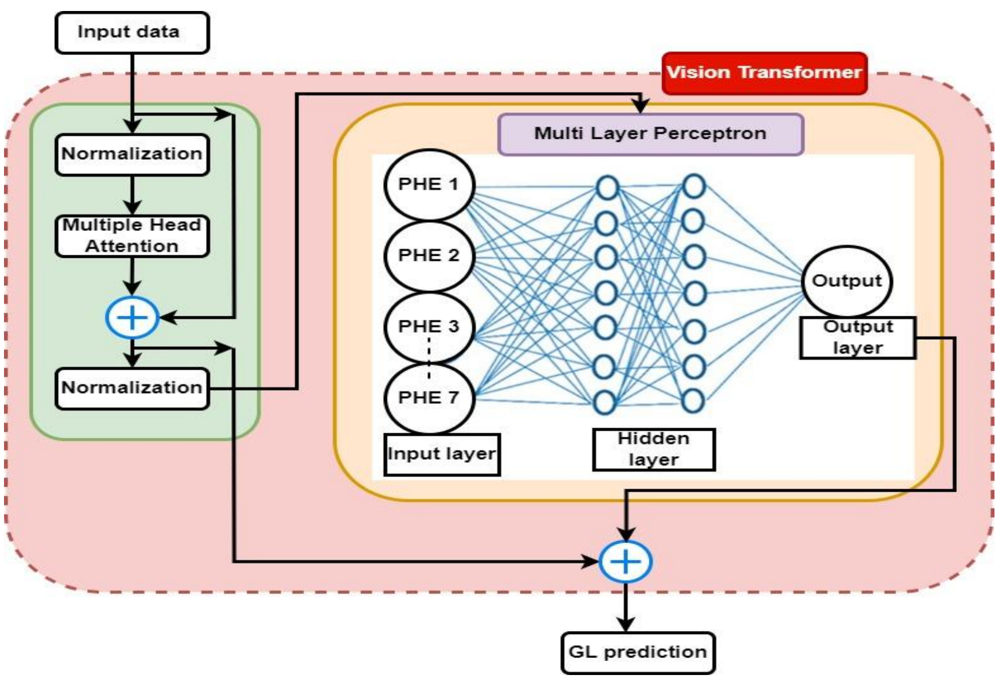
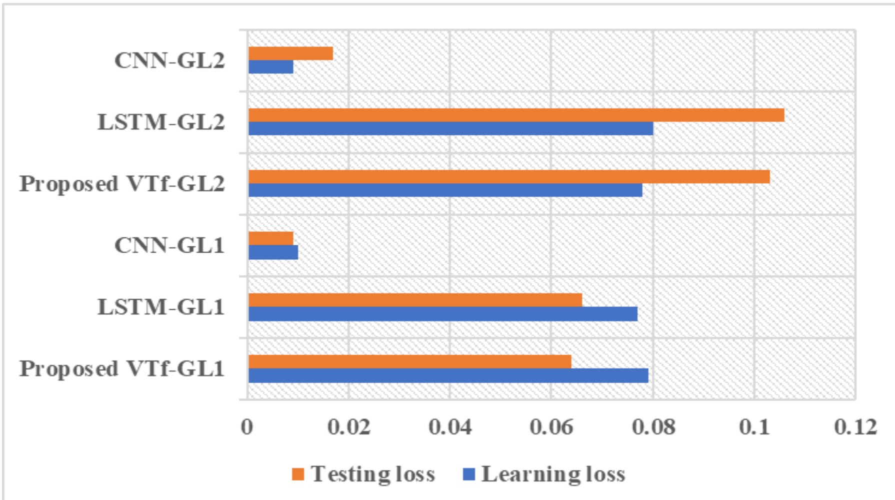


Figure 1: VTf-based GL Prediction using PHE

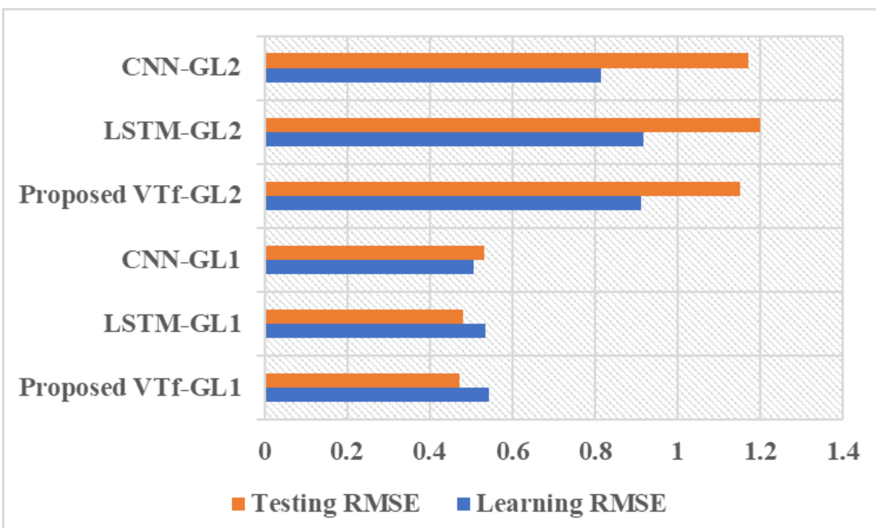
The procedure starts with the normalization and moving average of incoming hydrological data, allowing the model to discern complex connections across many temporal and geographical attributes. This improved representation is fed into an MLP that concurrently processes many PHEs, each denoted by nodes in the input layer. The model acquires intricate nonlinear associations between PHEs and GL via several concealed layers. The output layer generates predictions combined with preceding layers via residual links to improve durability and accuracy. The ultimate GL prediction is derived from synthesizing the acquired features and outputs, showcasing the VTf's robust capacity to model changing GL behavior via attention mechanisms and DL methodologies.

III. Results and Discussion

Learning and testing losses and the root mean square error (RMSE) of the DL networks (Proposed VTf, LSTM, and CNN) used in this research for the two observed water sources. Seven PHEs have been provided as input to VTf.



(a) Learning and testing loss for two observed water sources



(b) Learning and testing RMSE for two observed water sources

Figure 2: Performance Analysis for Prediction of Groundwater Levels based on PHE using a VTf

Fig. 2 compares the efficacy of several deep learning models—VTf, LSTM, and CNN—in forecasting GL based on PHE from two sources: GL1 and GL2. The proposed VTf model for GL1 has a balanced performance, achieving a testing loss of 0.064 and a testing RMSE of 0.471, comparable to the LSTM model's 0.066 testing loss and 0.48 RMSE. In this case, it seems to have better generalization capabilities. Even though the CNN model has the best training and testing losses of 0.01 and 0.009, respectively, its high testing RMSE of 0.532 suggests that, unlike VTf and LSTM, CNN suffers from severe overfitting and poor generalization performance.

In the source, GL2, the proposed VTf model showed greater generalization than LSTM with lower learning and testing losses of 0.078 and 0.103 against 0.08 and 0.106 and better testing RMSE (1.15, compared to 1.2). CNN once again achieves the lowest training error with 0.009 learning loss, yet the higher testing RMSE of 1.17 indicates that he is also subject to overfitting. These results demonstrate that the VTf-based model balances training accuracy and a moderate level of normalization, proving effective for predicting GL over multiple hydrological variables.

IV. Conclusion

This study offers a GL prediction model using primary hydrological elements (PHE) via a Vision Transformer (VTf). The PHE for 2017–2024 included flow level, velocity, precipitation, humidity, average temperature, transpiration, and warm days. Conventional deep learning (DL) models have difficulties capturing enduring relationships and need uniform input sizes, rendering them less adaptable to data of varying dimensions. The VTf mitigates these limits using the Individual Attention Mechanisms (IAM) inherent to the transformer architecture. The suggested VTf model for GL1 has a balanced performance, exhibiting a low testing loss of 0.064 and a testing RMSE of 0.471. In the GL2 source, the suggested VTf model exhibits superior generalization relative to LSTM, shown by marginally reduced learning and testing losses, along with enhanced testing RMSE.

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