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CLIMATE-HYDROLOGY INTERACTIONS AND THEIR INFLUENCE ON STREAMFLOW VARIABILITY IN CHANGING ENVIRONMENTAL CONDITIONS

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Abstract

Climate variability affects hydrological processes and functions through variations in precipitation, groundwater recharge and streamflow regimes, which make water resource management more difficult. This research aimed to study climate-hydrology interactions and impacts on streamflow variations in the Yanglou catchment based on 5479 daily hydrological data from 2004 to 2018. Precipitation, groundwater table depth, calculated groundwater recharge and streamflow were evaluated using descriptive statistics, trend analysis, Mann-Kendall, correlation analysis, Spearman and predictive modeling with multiple linear regression and Random Forest regression models. The results indicated a significant temporal and seasonal hydrological variability and around 92.41% of the observations showed that streamflow was zero. The annual precipitation did not show a statistically significant trend while the recharge of the groundwater decreased and the depth of groundwater table increased. Correlation analysis revealed positive relationship between precipitation and streamflow ($\rho = 0.1405$), groundwater recharge and streamflow ($\rho = 0.1641$) and negative between groundwater table depth and streamflow ($\rho = -0.2984$). The multiple linear regression model obtained an R^2 of 0.2506 while the RMSE was 1.7362 mm/day. The random forest model had a lower MAE of 0.2163 mm/day. Antecedent precipitation (AP) became the most significant predictor. Results highlight the need for integrated monitoring of both precipitation and groundwater to characterize intermittent streamflow, and to inform catchment management decisions for water resources, but with some limitations in the predictability of streamflow during periods of positive flow.

Keywords: Climate Variability; Streamflow Variability;
Groundwater Recharge; Hydrological Modeling; Precipitation–
Streamflow Relationships.

1. Introduction

Climate variability plays a major role in hydrological processes, affecting precipitation, groundwater recharge, water availability and river discharge. Rainfall intensity, frequency and seasonal distribution modify the water balance of the catchment and thus adds to the streamflow fluctuations. Watershed characteristics, vegetation, and human activities add to this complexity, resulting in complicated hydrological responses to altered environmental conditions (Jones et al., 2012). Groundwater recharge changes due to climate change also impact groundwater storage in the subsurface and the long-term availability of groundwater resources, especially where water levels have been dropping for an extended time (Al Atawneh et al., 2021). The knowledge of these processes is vital for sustainable management of water resources, assessment of floods and droughts and hydrological planning. Recent hydrological modeling studies highlight the need to consider changes in groundwater resources from a climate perspective in order to better account for changes in water availability (Ali et al., 2020). Moreover, integrated hydrological modelling offers valuable insights for the development of climate adaptation strategies and enhances catchment management under variable environmental conditions (Banda et al., 2022).

Climate-hydrology interactions are interrelated processes whereby the climate controls runoff, infiltration, recharge, and streamflow generation at the land surface. Precipitation is a large hydrological input and groundwater storage and recharge control the timing and quantity of flow of water through catchment systems. Research from around the world shows that groundwater recharge is tightly coupled to fluxes at the surface, highlighting the role of subsurface fluxes in catchment water balance (Berghuijs et al., 2022). In addition, the long-term dryness also affects groundwater recharge, meaning that changes in the climatic moisture availability impact groundwater recharge and resultant hydrological responses (Berghuijs et al., 2024).

Groundwater dynamics also vary considerably in space and time due to variations in climatic conditions, geological properties and catchment characteristics. Groundwater systems, globally, have proven to be sensitive to climate variability in a variety of ways, depending on environmental and hydrogeological conditions (Cuthbert, Gleeson, et al., 2019). Likewise, the evidence from sub-Saharan Africa suggests that groundwater resilience is related to recharge processes and hydroclimatic regionality (Cuthbert, Taylor, et al., 2019). Precipitation variability is thus an important determinant of groundwater storage and the dynamics of groundwater recharge and streamflow persistence. It is essential to integrate the assessment of climatic inputs and hydrological responses on adequate temporal scales to understand these relationships.

Although hydrology has advanced significantly, the ability to understand the joint effects of precipitation variability and groundwater dynamics on streamflow is still difficult. Nonlinearities, lags, and multi-temporal-scale interactions within hydrological systems make the identification of dominant streamflow controls difficult. These challenges are an expression of more general issues of hydrological processes, variability and prediction in the context of environmental change (Blöschl et al., 2019). The long-term rainfall–runoff work has emphasized the need to consider multidecadal hydrological variability in addition to the short-term relationships (Brigode & Oudin, 2025). Additionally, decreasing groundwater storage worsen streamflow reductions, highlighting the need to account for subsurface hydrological processes when estimating water supply (Carroll et al., 2024).

Catchment comparisons have been facilitated by large-sample hydrological datasets, which have enabled systematic studies of hydroclimatic variability with different geographical conditions (Alvarez-Garretón et al., 2018; Chagas et al., 2020). Comparable developments in Great Britain have improved hydrometeorological assessments and enhanced knowledge of catchment characteristics and streamflow responses (Coxon et al., 2020). However, large-scale hydrology studies highlight the importance of detailed catchment-level studies in addition to regional-scale comparisons (Clerc-Schwarzenbach et al., 2024). Therefore, the integrated analysis of precipitation, groundwater recharge, groundwater levels, and streamflow in individual catchments is still useful for the understanding of hydrological variability.

The present study proposes to examine climate-hydrology linkages and the impacts on streamflow variability based on the daily hydrological observations in Yanglou catchment from 2004 to 2018. In particular, the study aims to quantify temporal and seasonal variation in precipitation and streamflow, assess correlation between precipitation, groundwater recharge, groundwater table depth, and streamflow, and determine which hydrological variables are best predictors of discharge variability. To describe hydrological relationships and evaluate streamflow responses, descriptive statistics, temporal trend analysis, correlation techniques and predictive modeling are used. The study will deliver catchment-specific insights to enhance understanding of rainfall–groundwater–streamflow relationships and guide water resource management in the face of changing hydroclimatic conditions.

2. Materials and Methods

2.1 Study Area and Research Design

A quantitative, observational research design was used in this study to examine the interactions between climate and hydrology and the variation of streamflow in the Yanglou catchment, total area of which is ca. 265 km². The hydrological records for the period 2004 to 2018 were used to investigate the precipitation variability, groundwater variability and streamflow responses. Temporal patterns and hydrological relationships were assessed with descriptive statistics, trend analysis, correlation analysis and predictive modeling.

2.2 Dataset Description and Variables

A total of 5,479 daily observations over a 15-year period was used. The variables that were used were the average precipitation (P_avg_mm), the groundwater table depth (WTD_avg_m), calculated groundwater recharge (calculated_GR_mm), and observed streamflow (Q_mm). Other variables were simulated groundwater table depth (sim_WTD_m) and groundwater condition recharge (calculated_sim_GR_mm). Precipitation, groundwater table depth and recharge were chosen as explanatory variables, and streamflow was chosen as dependent variable. The variables observed, calculated and simulated were differentiated during analysis (Gao et al., 2024).

2.3 Data Preprocessing

Data pre-processing included missing value checking, duplicate checking, chronological consistency checking and variable format checking. The blank column was deleted and any

missing recharge measurements were omitted from the appropriate analyses. All precipitation and streamflow data were assigned a "zero" value if they were measured as zero. Precipitation and streamflow data where observed as "zero" were left as such. Records of each day were converted to monthly, seasonal and annual data summaries. An attempt was made to examine delayed streamflow responses through the use of lagged variables and antecedent precipitation totals.

2.4 Assessment of Temporal Climate and Hydrological Variability

Hydrological variability was characterized by descriptive statistics such as coefficient of variation (CV), minimum, maximum, and mean and median. Precipitation, groundwater recharge, groundwater table depth and streamflow were analyzed for their seasonal and annual patterns. Due to the possible presence of serial dependence, the Mann–Kendall test and Sen's slope estimator were chosen to determine the direction and the size of these trends. The intermittent streamflow conditions were also described by zero-flow frequency.

2.5 Climate-Hydrology Relationship Analysis

Spearman correlation analysis was used to examine the relationships between precipitation, water recharge, ground water table depth, and streamflow because of the skewed distributions and the fact that there were often zero values. Where appropriate, linear relationships were used with Pearson correlation. Lagged correlation analysis was used to examine hydrological responses over 0–7 days and 3-day and 7-day antecedent precipitation totals to determine delayed rainfall–runoff relationships.

2.6 Streamflow Variability and Predictive Modeling

Multiple linear regression and Random Forest regression were chosen to predict streamflow on diurnal basis based on precipitation, groundwater level depth, recharge, and antecedent hydrological variables. To avoid the temporal leakage, this data set was split into training (2004–2014), validation (2015–2016), and test (2017–2018) sets based on time. Multiple linear regression was used as a baseline and Random forest was used to capture the nonlinear relationships. The contributions of predictors were analyzed using regression coefficients and permutation feature importance.

2.7 Model Evaluation and Statistical Analysis

The model performance was assessed through the coefficient of determination (R^2), mean absolute error (MAE) and root mean squared error (RMSE). The R^2 and the error were smaller, suggesting better predictive ability. Streamflow observations were largely zero, so there was a particular need to assess the accuracy of predictions for positive flows only. The analyses were carried out at a p-value of less than 0.05 with temporal dependence if applicable.

3. Results

3.1 Descriptive Characteristics of the Hydrological Dataset

The descriptive analysis revealed substantial differences in precipitation, groundwater dynamics,

and streamflow characteristics. As shown in Table 1, mean daily precipitation was 2.1411 mm, with a maximum of 252.2683 mm, indicating considerable rainfall variability. Mean groundwater table depth was 2.5109 m, while calculated groundwater recharge averaged 0.4079 mm/day. Streamflow exhibited a considerably lower daily mean of 0.0884 mm, with a median of zero, reflecting predominantly intermittent discharge conditions. The relatively high standard deviations of precipitation and streamflow indicated strongly uneven hydrological distributions.

Table 1. Descriptive Statistics of Hydrological Variables in the Yanglou Catchment (2004–2018)

Variable	N	Mean	SD	Median	Minimum	Maximum
Precipitation (mm/day)	5,479	2.1411	8.8672	0.0000	0.0000	252.2683
Groundwater table depth (m)	5,479	2.5109	0.7394	2.5556	0.5922	5.0033
Groundwater recharge (mm/day)	5,478	0.4079	1.5895	0.0000	0.0000	37.8000
Streamflow (mm/day)	5,479	0.0884	0.8228	0.0000	0.0000	27.5842

Note. SD = standard deviation; N = number of valid observations. Groundwater recharge was derived from groundwater table measurements.

3.2 Temporal Variability in Precipitation

Precipitation showed significant temporal and interannual variation during the entire period of record. Annual precipitation ranged from approximately 647.29 mm in 2009 to 1,107.54 mm in 2018. Monthly rainfall trends showed significant variability and rainfall mainly occurred during summer months. As shown in Figure 1, during those years with higher precipitation, the wettest years were found and several years were also observed with lower annual precipitation totals. The Mann–Kendall analysis showed no statistically significant monotonic trend in annual precipitation ($\tau = 0.0667$, $p = 0.771$), which means that annual precipitation fluctuated widely with no discernible long-term directionality during the study period.

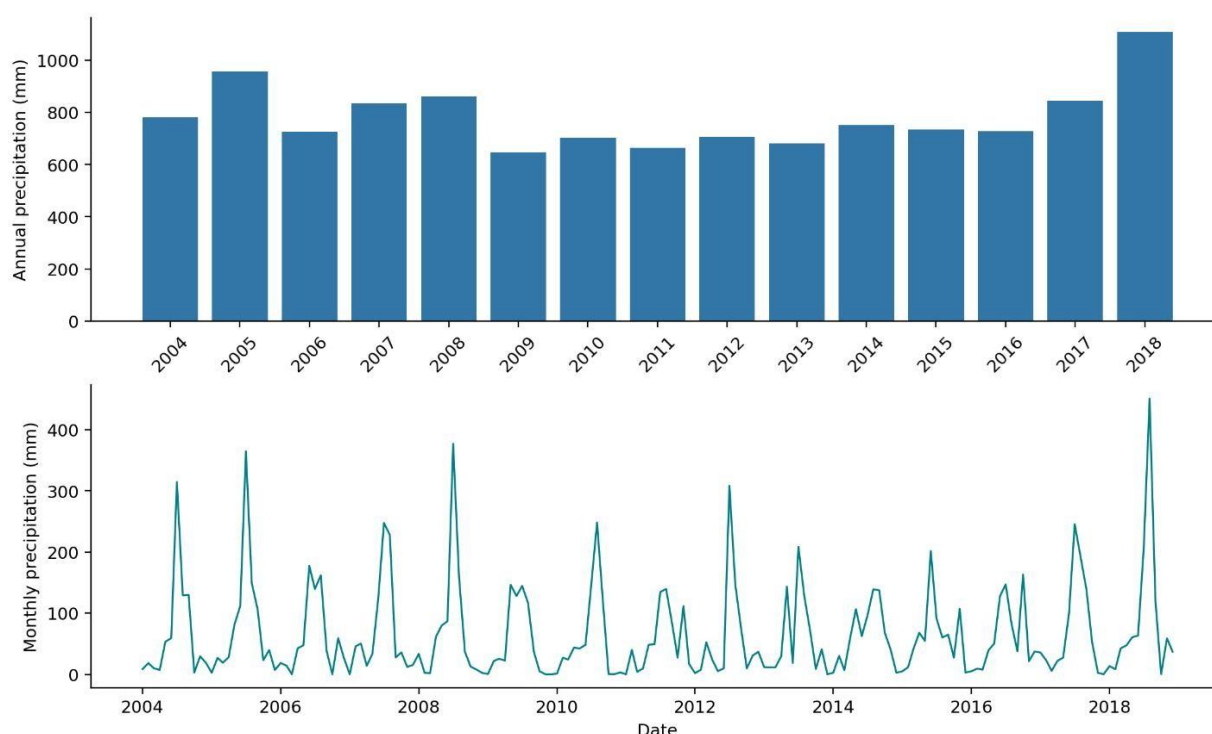


Figure 1. Annual and Monthly Precipitation Variability in the Yanglou Catchment (2004–2018)

3.3 Temporal and Seasonal Streamflow Variability

The streamflow was very intermittent and highly seasonal. Of the 5,479 daily observations, 5,063 had no discharge, which made up about 92.41% of the observations. Only 416 days had positive streamflow. Refer to Table 2, the streamflow during the summer (June-August) was the highest with around 399.76 mm of streamflow accumulated. The second largest contribution was from autumn while no positive discharge was observed in the spring. These results indicate that streamflow generation occurred over relatively short time periods, not continuously throughout the year.

Season	Observations	Positive-flow days	Positive-flow frequency (%)	Cumulative streamflow (mm)
Winter (DJF)	1,354	2	0.15	1.28
Spring (MAM)	1,380	0	0.00	0.00

Summer (JJA)	1,380	297	21.52	399.76
Autumn (SON)	1,365	117	8.57	83.48
Total	5,479	416	7.59	484.52

Note. DJF = December–February; MAM = March–May; JJA = June–August; SON = September–November. Streamflow totals represent cumulative discharge depths over all observations in each season.

3.4 Groundwater Dynamics and Recharge Variability

The depth of the groundwater table and groundwater recharge significantly changed over time. The groundwater table depths varied from 0.5922 m to 5.0033 m, reflecting the variation in subsurface water conditions during the study period. The recharge was highly variable annually with values of about 226.95 mm in 2005 and 77.90 mm in 2013. Groundwater table changes and recharge pulses did not have uniform temporal responses as shown in Figure 2. The groundwater table depth and the calculated recharge were found to increase with depth ($\tau = 0.5048$, $p = 0.008$) and decrease ($\tau = -0.3905$, $p = 0.046$) respectively by annual trend analysis. The results indicate that groundwater conditions changed progressively over the observation period, but the significance and levels of the trends should be viewed in the context of the limitations of the 15-year record.

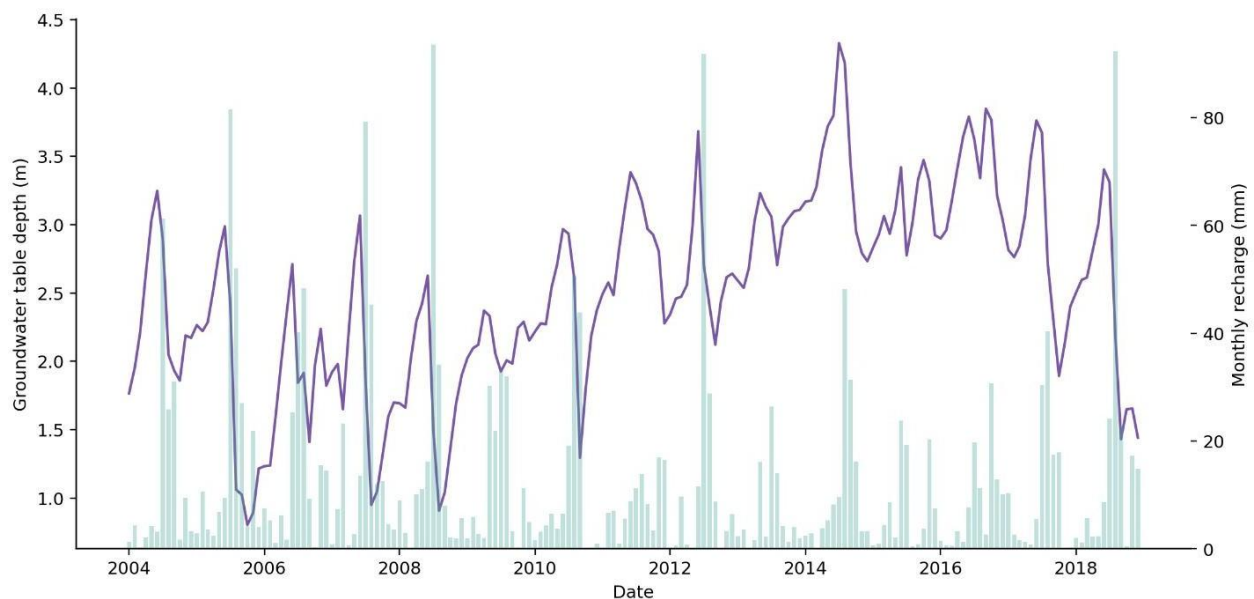


Figure 2. Monthly Groundwater Table Depth and Calculated Recharge Variability (2004–2018)

3.5 Relationships Between Precipitation and Streamflow

The correlation analysis revealed statistically significant correlation between precipitation and groundwater recharge and groundwater table depth and streamflow. As shown in Table 3, the greatest same-day Spearman correlation was between groundwater table depth and streamflow (- 0.2984, $p = 0.001$). The positive relationships between precipitation and groundwater recharge and discharge were less strong. Lagged analysis showed that the strongest correlations were observed when antecedent hydrological conditions were factored in and precipitation had its highest correlation at a six days lag (0.1987). These results indicate that the delayed precipitation responses are involved in streamflow variability, but the observed correlations were not very strong.

Table 3. Correlation and Lagged Relationships Among Hydrological Variables

Hydrological relationship	Spearman ρ	p-value	Interpretation
Precipitation–streamflow	0.1405	<0.001	Weak positive
Recharge–streamflow	0.1641	<0.001	Weak positive
Groundwater depth–streamflow	–0.2984	<0.001	Weak negative
Precipitation–recharge	0.2910	<0.001	Weak positive
Precipitation (6-day lag)–streamflow	0.1987	<0.001	Weak positive
Recharge (7-day lag)–streamflow	0.2239	<0.001	Weak positive

Note. Spearman ρ represents the rank correlation coefficient. Lagged relationships compare earlier precipitation or recharge with subsequent streamflow. Reported p-values are unadjusted and should be interpreted cautiously because of serial dependence and multiple testing.

3.6 Groundwater–Streamflow Interactions

Groundwater-streamflow analysis revealed quantifiable relationships between underlying hydrological conditions and discharge variability. The fact that there was a negative linear relationship between the depth of the groundwater table and streamflow showed that conditions of more shallow groundwater were usually associated with a higher discharge. This was a positive same-day correlation between groundwater recharge and streamflow that increased with time lag. Figure 3 shows that there was significant scatter in positive-flow observations, and that the correlation of lagged recharge went up over the seven days of the analysis period. The highest recharge association value was at a seven-day lag (0.2239) indicating delayed hydrological connectivity. However, the magnitude of the correlation coefficients is not that strong, which means that the variation of streamflow cannot be attributed to the conditions of groundwater only.

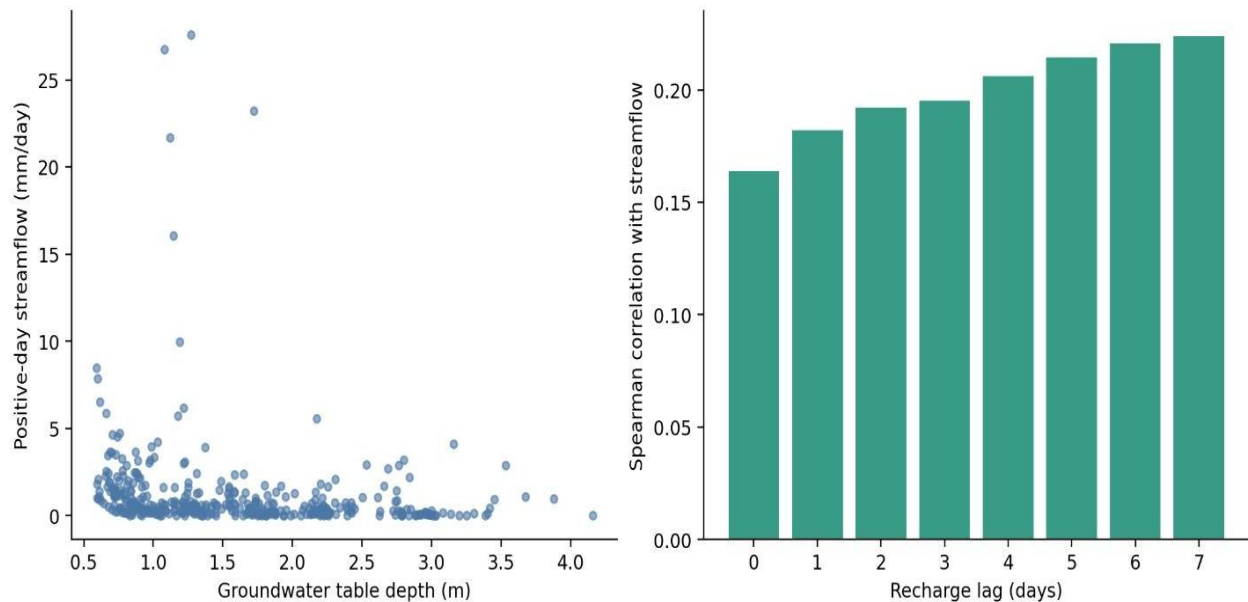


Figure 3. Groundwater Table Depth–Streamflow Relationships and Lagged Recharge Correlations

3.7 Predictive Model Performance

The chronological data partition was used to evaluate multiple linear regression and Random Forest regression. The models were calibrated on 4,010 observations, verified on 731 observations and applied independently to 730 observations with no missing lagged predictors. Multiple linear regression as shown in table 4 performed better in terms of test R^2 (0.2506) and RMSE (1.7362 mm/day) compared to Random Forest. Random Forest, however, resulted in a lower overall MAE (0.2163 mm/day), indicating that the model was more likely to make small prediction errors. Substantial differences in the errors were observed for both models in the positive flow case. However, validation-period R^2 values were very negative, due to the low variability in discharge in the validation period and the presence of only eight positive flow observations. These results suggest that the predictive robustness is not very strong, especially for rare discharge events.

Table 4. Comparative Performance of Streamflow Prediction Models

Model	Validation RMSE	Test R^2	Test MAE	Test RMS E	Positive-flow MAE
Multiple linear regression	0.1625	0.2506	0.3068	1.9154	1.9154
Random Forest regression	0.0251	0.2123	0.2163	1.7800	1.9407

Note. MAE = mean absolute error; RMSE = root mean squared error; error units are mm/day. Test metrics were calculated on 730 observations, including 76 positive-flow days. The Random Forest configuration was selected using validation RMSE. Positive-flow MAE was calculated only on days with observed discharge greater than zero.

3.8 Key Predictors of Streamflow Variability

Antecedent precipitation was recognized as the most important predictor in the Random Forest model through the permutation-based feature importance analysis. The highest increase in test MAE was observed for cumulative precipitation over the previous 7 days (0.0253 mm/day) followed by three-day antecedent precipitation (0.0074 mm/day), one-day lagged groundwater recharge (0.0071 mm/day), groundwater table depth (0.0070 mm/day), and same-day calculated recharge (0.0070 mm/day) when tested for permutation as shown in Figure 4. The results from this study indicate that the accumulated rainfall conditions provided more information for the prediction of streamflow than daily precipitation measurements. Groundwater-related variables also contributed some predictive information, but the small contribution to the model, measured by the model performance and the low importance values, should be taken with a pinch of salt.

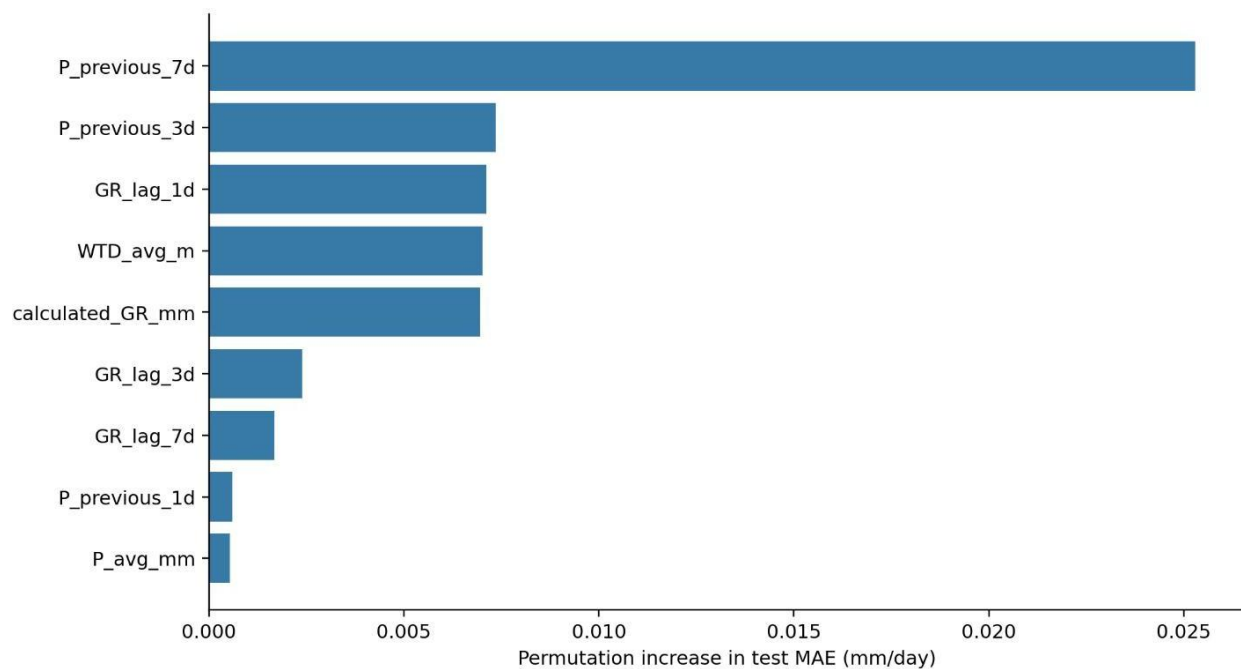


Figure 4. Permutation-Based Importance of Hydrological Predictors in Random Forest Streamflow Modeling

General interpretation: The findings show that the streamflow in the Yanglou catchment was

very intermittent, seasonally focused and related to precipitation as well as the state of ground water. The most informative predictor of the analysis based on the Random Forest was the antecedent precipitation with additional predictive information offered by groundwater table depth and groundwater recharge. Nonetheless, the poor correlations and low accuracy of positive-flow models suggest that the hydrological response is hard to predict with any certainty.

4. Discussion

The results indicate significant temporal variability of precipitation, groundwater recharge, groundwater table depth and streamflow within the Yanglou catchment. Flow was very intermittent, with about 92.41% of the observations having no flow. The discharge patterns, and the role of seasonal rainfall variability and groundwater conditions, illustrate the complexity of catchment hydrological responses. The results call for a coupling between climatic and subsurface processes for better understanding of hydrological variability. Hydrological memory and antecedent conditions have been highlighted as factors of influence on catchment responses over several time scales in similar studies (De Lavenne et al., 2022).

Precipitation was highly variable between years but no annual trend was found. Good seasonal rainfall–runoff relationship, with streamflow occurring mostly in summer. A delayed response of the catchments showed a higher correlation between precipitation and streamflow (1405 to 1987) indicating a possible delayed catchment response. The relationship is similar to the one found in hydrological prediction, where temporal rainfall data are important and where rainfall influences discharge on several timescales (Gauch et al., 2021). The modeling of precipitation-driven runoff processes is also highlighted in the case of hydrologically informed modeling approaches (Herath et al., 2021).

Groundwater depth was negatively correlated with streamflow ($\rho = -0.2984$), meaning that the shallower the depth of the groundwater, the greater the streamflow. Recharge was found to be positively correlated with streamflow and the correlation increased when one was lagged behind the other. These findings indicate that delayed hydrological responses are caused by groundwater dynamics. Groundwater–surface water connectivity has been shown to affect discharge and environmental flow in rivers in previous studies (de Graaf et al., 2019). Groundwater–river interactions, however, occur in both directions, as streamflow can filter into underlying aquifers under certain hydrogeological conditions (Jasechko et al., 2021).

Temporal analysis revealed temporal variations in rainfall, groundwater recharge and groundwater table depth for 2004–2018. Both groundwater recharge and groundwater table increases showed a decreasing trend. However, the lack of a significant trend in annual precipitation shows that hydrological variations are not solely due to precipitation variability. Studies around the world have also shown that river discharge changes in response to changing climate, in a non-uniform way (Gudmundsson et al., 2021). The only way to account for catchment-scale variability is to account for local hydrological characteristics and processes over time.

The values of test R^2 (0.2506) and RMSE (1.7362 mm/day) were slightly higher than those of Random Forest, while the value of MAE (0.2163 mm/day) was low for Random Forest. The variation in these scores suggests that neither of them performed better than the other on all measures. The most important Random Forest predictor was antecedent precipitation, reflecting

the importance of accumulated rainfall. The power of machine-learning techniques to capture the complex relationship of hydrology has been shown previously (Kratzert et al., 2019). Model benchmarking is still important, however, as advanced algorithms do not necessarily perform better than simpler ones for all hydrological conditions (Knoben, 2024).

An important antecedent precipitation was observed, which is consistent with studies showing that incorporating temporal meteorological data enhances rainfall-runoff forecasting (Kratzert et al., 2021). In the present study however, the low predictive capability is not as remarkable as in some larger size hydrological applications. Benchmarking research has revealed that the performance of models varies between catchments and modeling methods (Lees et al., 2021). The variations could be caused by catchment characteristics, intermittency of streamflow, availability of predictors, and hydrological complexity.

The results highlight the need for ongoing monitoring of precipitation, ground water, and streamflow for catchment-scale water management. The seasonal changes in flow, with a high proportion of zero flows, indicate that water availability should be based on seasonality and groundwater fluctuations. Integrated hydrometeorological data contribute to better catchment characterization and comparative hydrological assessment (Klingler et al., 2021). Likewise, standardized catchment data can be used to estimate hydrological similarities and enhance water-resource planning in various environmental contexts as done by Höge et al. (2023).

There are a few restrictions to be noted. Data limitations prevented detailed attribution of hydrological variability to changes in land use and temperature and evapotranspiration data were unavailable. In addition, the single catchment design limited the generalizability of the study geographically. In addition, the lack of observations during positive-flow conditions limited predictive ability of positive-flow conditions. Further study should consider other climatic parameters, longer periods of observation and several catchments. Advanced modeling approaches such as hybrid hydrological–machine-learning models can be used to better represent these delayed and nonlinear hydrological responses. Additional studies should also include uncertainty in calculated groundwater recharge and create prediction models tailored to intermittent streamflow systems.

5. Conclusion

The streamflow variability at the Yanglou catchment was explored by examining the interactions between climate and hydrology and the resultant impacts on streamflow variability over a 15-year period between 2004 and 2018, based on 5,479 daily observations. The results showed that there was significant temporal variation in precipitation, ground water recharge, water table depth and streamflow, which indicates the complexity of the relationships between catchment hydrological responses. The flow was highly intermittent, with about 92.41% of the observations showing no flow, and flows occurring mainly during the summer months. While there was no statistically significant trend in annual precipitation, trends in groundwater recharge and groundwater table depth suggested changes in subsurface hydrological conditions. Correlation analysis showed that there was a positive correlation between precipitation, groundwater recharge and streamflow while the groundwater table depth had a negative association with discharge. The role of the hydrologic antecedents in affecting streamflow variability was further illustrated by lagged relationships. The predictive modeling revealed that multiple linear

regression had a slightly higher R^2 and RMSE, and a lower MAE than Random Forest. Antecedent precipitation proved to be an important predictor, but both models were found to be less reliable for positive-flow events. The results highlight the need for incorporating precipitation and groundwater measurements to enhance hydrological assessment and water resource management. To further improve predictive accuracy and understanding of hydrological responses to changing environmental conditions, future investigations should include temperature, evapotranspiration, land use attributes and longer monitoring records.

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