Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Declining Spring-Water Availability Despite Persistent Rainfall–Discharge Responsiveness in a Tropical Fractured Volcanic System

Mahdika Putra Nanda
Sebelas Maret University
Rintis Hadiani
rintis@staff.uns.ac.id

Sebelas Maret University
Sobriyah Sobriyah
Sebelas Maret University
Yusep Muslih Purwana
Sebelas Maret University

Research Article

Keywords: Spring-water availability, Rainfall–discharge responsiveness, Antecedent rainfall, Low-availability conditions, Volcanic aquifer

Posted Date: November 13th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11334422/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Declining Spring-Water Availability Despite Persistent Rainfall–Discharge Responsiveness in a Tropical Fractured Volcanic System

Mahdika Putra Nanda[1], Rintis Hadiani[1]*, Sobriyah[1], and Yusep Muslih Purwana[1]

[1]Department of Civil Engineering, Faculty of Engineering, Sebelas Maret University, Jl. Ir. Sutami 36 A, Surakarta, Central Java, 57126, Indonesia

*Corresponding author: E-mail: rintis@staff.uns.ac.id

Abstract

Spring-water availability in tropical fractured volcanic systems may deteriorate without a corresponding loss of rainfall–discharge responsiveness. This study examined whether long-term hydroclimatic deterioration at Tlogorejo Spring, Central Java, Indonesia, was expressed primarily as weakening rainfall–discharge responsiveness or as a downward shift in the discharge regime with recurrent low-availability conditions. Monthly observations from 2010–2025 were analysed using trend, correlation, change-point, threshold, logistic, and recession analyses. Rainfall and discharge declined significantly (Sen's slopes: −5.87 mm yr^{-1} and −0.377 L s^{-1} yr^{-1}; mean reductions: 22.9% and 23.1%), while their monthly association remained positive (r = 0.700). After removing the shared seasonal cycle, the association weakened (r = 0.334), with no difference between periods. Low-availability frequency increased from 10.42% to 46.88% of months, with a detected shift around 2018. A 100-mm increase in the 12-month antecedent rainfall anomaly was associated with lower odds of low-availability onset (OR = 0.807 per 100-mm increase; HAC-adjusted $p = 2.29 \times 10^{-5}$), but out-of-sample discrimination was limited (area under the receiver operating characteristic curve (AUC) = 0.612). El Niño–Southern Oscillation (ENSO) was associated with antecedent rainfall but not directly with low-availability onset. These results indicate that declining spring-water reliability can emerge through a downward shift in the discharge regime even when a positive monthly rainfall–discharge association remains evident, supporting monitoring frameworks that integrate discharge trends with low-availability recurrence rather than relying on rainfall–discharge correlation alone.

Keywords: Spring-water availability · Rainfall–discharge responsiveness · Antecedent rainfall · Low-availability conditions · Volcanic aquifer

Introduction

Spring water is an important component of freshwater resources and provides a locally accessible source of water, particularly in regions where communities depend on springs for domestic and other water uses (Dass et al. 2021). The sustainability of spring-water resources depends not only on discharge magnitude but also on the reliability of water availability over time. Long-term changes in spring discharge can therefore affect the temporal reliability of a freshwater source, even when the spring continues to respond to climatic inputs. The importance of maintaining spring discharge is also reflected in groundwater-management approaches that explicitly consider the protection of spring flows alongside human, cultural, and ecological uses (Burnett et al. 2020). In many regions, springs support domestic and agricultural water uses in surrounding communities, making their reliability directly relevant to local water security and livelihoods.

Rainfall is a primary climatic input to many spring systems, although its translation into spring discharge varies with catchment characteristics, recharge processes, hydrogeological conditions, and subsurface flow pathways. Long-term observations have shown that spring-discharge responses to climatic variability and change differ across climatic and hydrogeological settings (Fan et al. 2023; Lamacova et al. 2024). Research on precipitation-driven karst springs has further demonstrated that rainfall–discharge behaviour reflects spatial differences in recharge contributions and subsurface flow processes (Song et al. 2022). Studies of groundwater springs in the Eastern Himalaya have likewise documented the influence of precipitation and hydrogeological conditions on discharge variability (Kumar et al. 2024). These findings indicate that climatic inputs alone do not fully describe spring behaviour and that the implications of hydroclimatic change for groundwater-resource sustainability need to be assessed in relation to the characteristics of individual spring systems (Klaas et al. 2020).

Rainfall–discharge responsiveness and the stability of spring-water availability represent distinct aspects of spring behaviour. A statistically detectable rainfall–discharge association indicates that discharge varies in association with rainfall, but it does not establish whether the prevailing discharge regime remains stable over time. A spring may continue to respond to rainfall while its discharge regime shifts towards lower values. Consequently, rainfall–discharge association alone cannot determine whether the temporal availability of spring water is being maintained. Assessing water-resource conditions therefore requires consideration of both the relationship between rainfall and discharge and the occurrence and persistence of low-availability conditions. This distinction is

relevant to spring-water sustainability because continued hydrological responsiveness does not necessarily imply that the amount of water available through time remains unchanged.

Previous research has examined climate-related changes in spring discharge, long-term hydrological trends, groundwater drought indicators, and low-flow conditions (Fan et al. 2023; Gullacher et al. 2023) . quantified historical and projected climatic influences on karst spring discharge, while Giese et al. (2025) examined long-term hydrological trends in European karst areas in relation to groundwater recharge evaluation. Groundwater drought research has also investigated climate and hydrological indicators for identifying deteriorating groundwater conditions (Gullacher et al. 2023). In addition, studies have assessed the effects of climatic and anthropogenic forcing on spring discharge (Sivelle et al. 2021), as well as changes in the frequency of low-discharge conditions under projected climate scenarios (Muhumure et al. 2024). Together, these studies provide complementary perspectives on hydrological response, long-term change, and deteriorating water availability. Assessing these dimensions together can help determine whether changes in rainfall–discharge association coincide with shifts in the discharge regime and changes in the recurrence of low-availability conditions.

This study applies an integrated assessment to examine the distinction between hydrological responsiveness and the temporal reliability of spring-water availability. Long-term rainfall and discharge records are analysed to evaluate hydroclimatic trends and rainfall–discharge association, while an empirical low-discharge reference is used to characterize changes in the frequency of low-availability conditions. Antecedent rainfall anomalies are examined in relation to the onset of these conditions, and the El Niño–Southern Oscillation (ENSO) is considered as an upstream hydroclimatic context for antecedent rainfall variability. This treatment is consistent with research documenting ENSO-related rainfall variability in Sumatra and the Malay Peninsula and ENSO–streamflow teleconnections in Java, Indonesia (Qian 2020; Nugroho et al. 2022). it does not assume a direct causal effect of ENSO on low-availability onset. Episode duration, cumulative discharge deficit, and within-episode recession behaviour are further examined to characterize the persistence and magnitude of low-availability episodes. Tlogorejo Spring, a tropical fractured volcanic spring system in Central Java, Indonesia, provides the empirical setting for this assessment. The study evaluates how changes in spring-water availability are expressed through rainfall–discharge responsiveness, shifts in the discharge regime, and the recurrence of low-availability conditions. Because the low-availability reference and episode characteristics are derived from observations at

Tlogorejo Spring, their application to other hydrogeological and climatic settings requires locally appropriate assessment and calibration.

Materials and methods

Conceptual framework

This study conceptualizes spring-water availability as the outcome of interactions among hydroclimatic forcing, spring hydrological response, and antecedent hydroclimatic conditions. The framework also incorporates low-availability conditions and recession characteristics to link hydroclimatic variability with the temporal occurrence and severity of water-availability constraints. The relationships among these components are illustrated in Fig. 1.

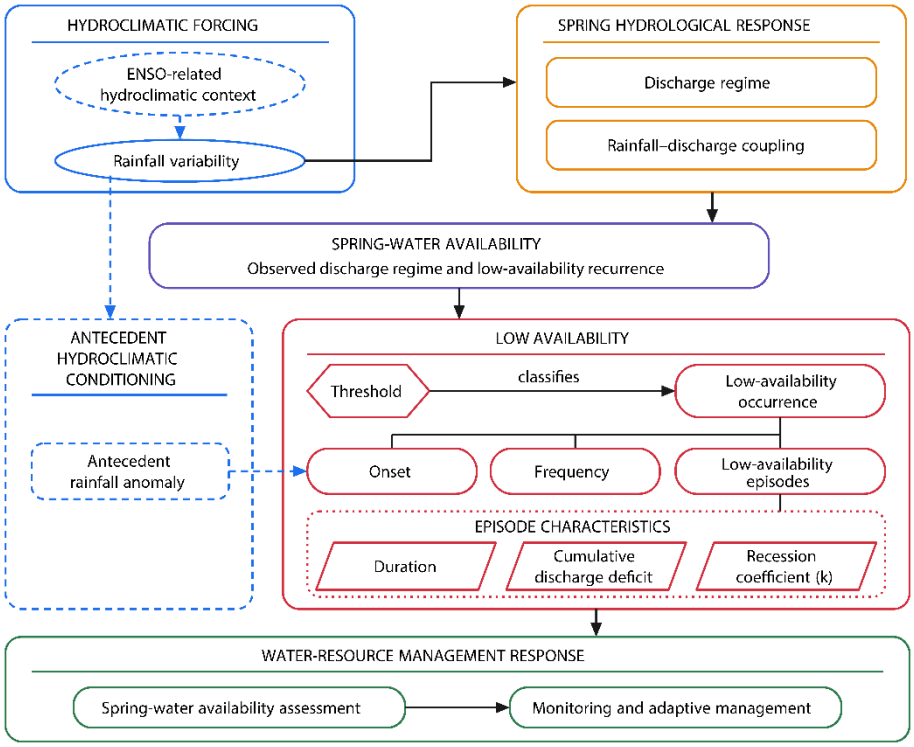


Fig. 1 Conceptual framework of hydroclimatic controls on spring-water availability in a tropical fractured-volcanic system

Hydroclimatic forcing is represented by rainfall variability and ENSO-related climate variability, whereas spring hydrological response is characterized by discharge variability and rainfall–discharge coupling. Water availability is evaluated using an empirical discharge reference, allowing changes in the recurrence of low-availability conditions to be identified. Antecedent rainfall conditions are examined as a potential conditioning factor for low-availability onset, with ENSO evaluated as an upstream hydroclimatic context affecting antecedent rainfall.

Recession characteristics are used to describe the persistence and severity of low-availability episodes. This framework provides the basis for the subsequent hydroclimatic, threshold, antecedent-condition, ENSO, and recession analyses.

Study area

The study was conducted at Tlogorejo Spring in Tlogorejo Village, Grabag District, Magelang Regency, Central Java Province, Indonesia (approximately 7°21′S, 110°22′E; 682 m above sea level) (Fig. 2). Regionally, the spring lies within the Quaternary Andong–Telomoyo–Gilipetung volcanic complex. The dominant rock unit is Holocene volcanic deposits of the Merbabu Formation, composed of andesitic lava, volcanic breccia, and pyroclastic material, which overlie older Pleistocene volcanic formations (Telomoyo, Andong–Kancil, and Gilipetung) that are generally more compact and less permeable (Thaden et al. 1975) . Tlogorejo Spring emerges at a lithological contact between relatively permeable young volcanic rocks and more compact older rocks, and is classified as a contact spring with depression-spring characteristics. The aquifer is a fractured volcanic system in which fracture networks serve as main flow paths and the rock matrix provides groundwater storage. The spring catchment encompasses the western and southwestern slopes of Mount Telomoyo, extending from elevations of approximately 1,500 m down to the spring outlet at 682 m above sea level. The catchment is dominated by protected forest, dense vegetation, and coffee plantations in Pagergunung Village (Ngablak District), which borders Tlogorejo to the east. The area experiences a tropical monsoon climate with distinct wet and dry seasons. Monthly rainfall and spring-discharge records from January 2010 to December 2025 (n = 192) were used in this study.

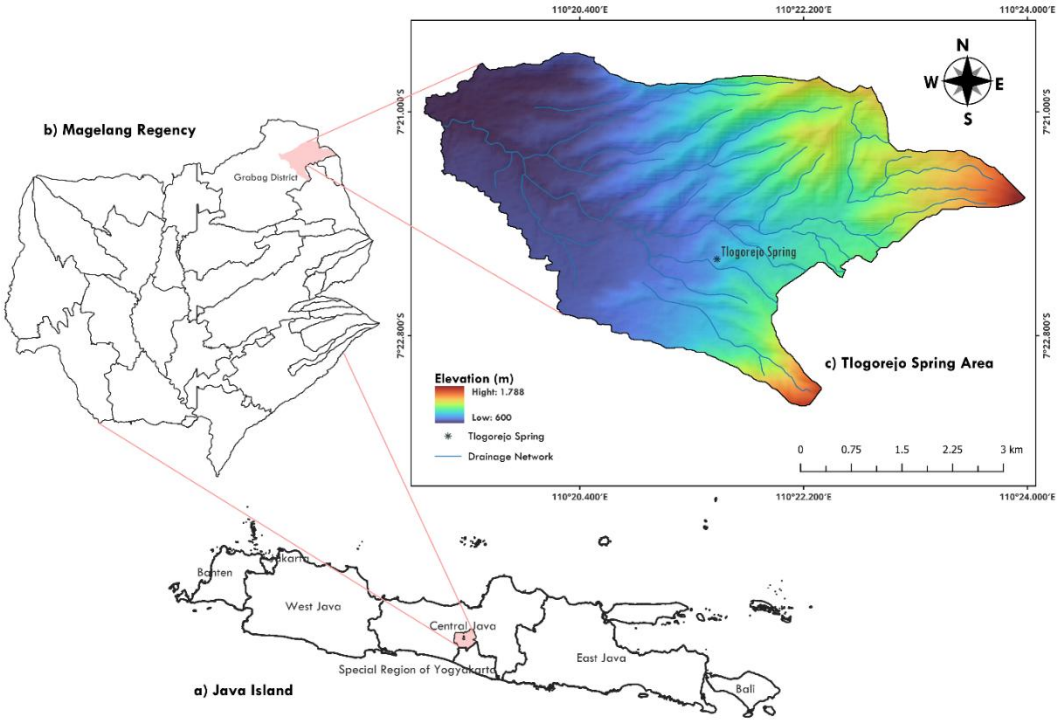


Fig. 2 . Location of Tlogorejo Spring and rainfall-monitoring stations in Central Java, Indonesia. (a) Java Island. (b) Magelang Regency. (c) Tlogorejo Spring Area with elevation and drainage network

Data requirements

The analysis used a continuous monthly record from January 2010 to December 2025, comprising 192 monthly observations of spring discharge, rainfall, and the Oceanic Niño Index (ONI). Monthly spring discharge Q_t was expressed in L s^{-1} and represents the observed discharge at the Tlogorejo spring outlet, measured using the volumetric method and obtained from Perumda Air Minum Tirta Gemilang, Kabupaten Magelang. Monthly rainfall P_t represented the principal local hydroclimatic forcing and was obtained from BBWS Serayu Opak for three stations: Caturanom, Poncol Gelangan, and Badran. Rainfall was represented by the arithmetic mean of observations from the three stations:

$$P_t = \frac{P_{C,t} + P_{PG,t} + P_{B,t}}{3} \quad (1)$$

where $P_{C,t}$, $P_{PG,t}$, and $P_{B,t}$ denote monthly rainfall at the Caturanom, Poncol Gelangan, and Badran stations, respectively. The arithmetic mean was used as the primary rainfall series rather than Thiessen-weighted averaging; a Thiessen-weighted sensitivity analysis was also considered, with weights of 0.2312 for Badran, 0.4308 for Caturanom, and 0.3380 for Poncol Gelangan. The ONI series was obtained from the NOAA Climate Prediction Center (NOAA CPC) and was used to represent large-scale ENSO-related hydroclimatic variability. Two ONI

144 measures were used: the official three-month running mean ONI series, and a 12-month antecedent ONI measure
145 ($ONI_{12,t}$) calculated as the mean of the preceding 12 monthly ONI observations, excluding the current month. The
146 analyses retained the original monthly observations and used the same verified dataset throughout all calculations.
147
148 **Methods of analysis**
149 Hydroclimatic variability was quantified using the coefficient of variation (CV), calculated as:

$$CV = \frac{s}{\bar{X}} \times 100\% \quad (2)$$

150 where s is the sample standard deviation and $\bar{x}$ is the sample mean. Monotonic trends in rainfall and discharge
151 were evaluated using the two-sided Mann–Kendall test (Kendall 1975), and their magnitudes were estimated using
152 Sen's slope (Sen 1968), calculated as the median of all pairwise slopes:

$$\beta_{\text{Sen}} = \text{median}\left(\frac{X_j - X_i}{j - i}\right), \quad j > i \quad (3)$$

153 where x_i and x_j are observations at times i and j, respectively. The estimated monthly trend was expressed on an
154 annual basis where appropriate. Trend robustness was assessed using the seasonal Kendall test and the Hamed–
155 Rao modified Mann–Kendall test applied to seasonally adjusted anomaly series. The seasonal Kendall test
156 evaluates monotonic trends within calendar months, whereas the Hamed–Rao procedure adjusts the variance of
157 the Mann–Kendall statistic for serial dependence. Results are reported in Table S4.
158
159 Mean rainfall and discharge were also compared between 2010–2017 and 2018–2025. The relative change
160 between the two periods was calculated as:

$$\Delta X(\%) = \frac{\bar{X}_{2018-2025} - \bar{X}_{2010-2017}}{\bar{X}_{2010-2017}} \times 100 \quad (4)$$

161 where $\bar{X}$denotes the period mean of the variable under consideration. The contemporaneous rainfall–discharge
162 relationship was assessed using Pearson's correlation coefficient and ordinary least-squares regression:

$$Q_t = \beta_0 + \beta_1 P_t + \varepsilon_t \quad (5)$$

163 where $Q_t$is monthly spring discharge, $P_t$is monthly rainfall, $\beta_0$is the intercept, $\beta_1$is the rainfall coefficient, and
164 $\varepsilon_t$is the residual. The coefficient of determination (R^2) was used to describe the proportion of discharge variance
165 explained by the fitted regression. Cross-correlation was evaluated at non-negative lags from 0 to 12 months to
166 identify the lag associated with the strongest rainfall–discharge correspondence. Monthly rainfall and discharge
167 anomalies were calculated relative to their corresponding calendar-month climatologies over 2010–2025. The

anomaly correlation was also evaluated separately for 2010–2017 and 2018–2025, and the difference between the period-specific correlations was assessed using Fisher's r-to-z transformation. Uncertainty was assessed using a circular moving-block bootstrap with a 12-month block length and 5,000 resamples. After removing the shared seasonal cycle, the association weakened (r = 0.334; R^2 = 0.111; 95% CI: 0.164–0.480). After additionally removing the long-term trend, the residual association was weak and not statistically robust (r = 0.129; R^2 = 0.017; 95% CI: −0.013 to 0.267).

Low spring-water availability was defined using an empirical discharge reference derived from the 2010–2017 period, preceding the identified change around 2018. The primary reference was the 10th percentile of monthly discharge in that period, $Q_c = 10.490$ L s^{-1}. Monthly conditions were classified as.

$$C_t = \begin{cases} 1, & Q_t < Q_c \\ 0, & Q_t \geq Q_c \end{cases} \quad (6)$$

where $C_t = 1$ indicates a low-availability month. Annual low-availability frequency was calculated as the proportion of observed months in each year classified as low availability. Its temporal association with year was assessed using Kendall's rank correlation (Kendall 1975). Pettitt's test was applied separately to annual low-availability frequency and annual mean discharge to identify potential change points (Pettitt 1979) . Fisher's exact test was used as a supplementary comparison of low-availability occurrence between the 2010–2017 and 2018–2025 periods. Threshold sensitivity was examined by recalculating the reference using the 15th and 20th percentiles of the same 2010–2017 discharge distribution. The resulting thresholds were 11.0425 and 11.6500 L s^{-1}, respectively, and the frequencies of months below each threshold were compared across the two periods (Table S1).

The arithmetic mean of the three rainfall stations was retained as the primary rainfall series. As a sensitivity analysis, a Thiessen-weighted series was reconstructed using station weights of 0.4308, 0.3380, and 0.2312 for Caturanom, Poncol Gelangan, and Badran, respectively. The weighted series yielded a similar downward rainfall trend (Sen's slope = −5.499 mm year^{-1}; Kendall trend p = 0.0221) and a similar rainfall–discharge correlation (r = 0.691) to the arithmetic-mean series (Sen's slope = −5.871 mm year^{-1}; p = 0.0117; r = 0.700). Results are reported in Table S2.

Antecedent rainfall conditioning was evaluated using monthly rainfall anomalies relative to the corresponding calendar-month climatology over 2010–2025. The anomaly for month $t$was calculated as:

$$P'_t = P_t - \overline{P}_{m(t)} \tag{7}$$

where P_t is observed rainfall and $\bar{P}_{m(t)}$ is the mean rainfall for the corresponding calendar month. Cumulative antecedent rainfall anomalies were calculated over 1-, 3-, 6-, and 12-month windows, excluding the month being evaluated:

$$A_{k,t} = \sum_{j=0}^{k-1} P'_{t-j}, \quad k \in \{1,3,6,12\} \tag{8}$$

with $k = 1,3,6,$ and 12 months. Low-availability onset was defined as a transition from a non-low-availability month to a low-availability month,

$$O_t = \begin{cases} 1, & C_{t-1} = 0 \text{ and } C_t = 1 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

The onset risk set included only months preceded by a non-low-availability month and with complete antecedent rainfall data for the relevant window. Differences in antecedent rainfall anomalies between onset and non-onset observations were evaluated using the Mann–Whitney U test (Mann and Whitney 1947). (Holm 1979) was applied to the four window-specific p-values to control the family-wise error rate. The association between the 12-month cumulative rainfall anomaly and onset was further evaluated using binary logistic regression:

$$\log\left(\frac{p_t}{1-p_t}\right) = \beta_0 + \beta_1 A_{12,t} \tag{10}$$

where p_t is the probability of onset at month t. The effect was expressed as an odds ratio for a 100-mm increase in cumulative antecedent rainfall anomaly:

$$OR_{100} = e^{100\beta_1} \tag{11}$$

Model discrimination was summarized using the area under the receiver operating characteristic curve (AUC). The AUC calculated from the fitted observations was treated as apparent, in-sample discrimination. Heteroskedasticity- and autocorrelation-consistent (HAC) standard errors were used for inference, with a maximum lag of 12 months. Temporal discrimination was evaluated separately using an expanding-window procedure over 2018–2025.

ENSO-related conditions were examined using the Oceanic Niño Index (ONI) and the 12-month antecedent rainfall anomaly. The association between ONI and $A_{12,t}$ was evaluated using Pearson's correlation and linear regression. To distinguish the rainfall association from the direct statistical association with ENSO, a logistic model was fitted with ONI as the explanatory variable, followed by a joint model including both ONI and the 12-month rainfall anomaly:

$$\log\left(\frac{p_t}{1-p_t}\right) = \gamma_0 + \gamma_1 ONI_{12,t} + \gamma_2 A_{12,t} \quad (12)$$

where $ONI_{12,t}$ denotes the 12-month antecedent ONI measure used in the analysis. Heteroskedasticity- and autocorrelation-consistent (HAC) standard errors with a maximum lag of 12 months were used for inference in both the direct and joint models.

Low-availability episodes were identified as consecutive months satisfying $Q_t < Q_c$. Each episode was characterized by its start and end months, duration, minimum monthly discharge, and cumulative discharge deficit relative to the empirical reference. The deficit for episode $e$was calculated as:

$$D_e = \sum_{t \in e} (Q_c - Q_t) \quad (13)$$

where $D_e$is the accumulated discharge difference over all months in episode e, expressed in L s^{-1} month. The total deficit was obtained by summing $D_e$across all episodes. Recession behaviour was evaluated separately using qualifying discharge segments containing at least three consecutive monthly observations and at least two consecutive declines. The exponential recession model (Maillet 1905) was expressed as:

$$Q(t) = Q_0 e^{-kt} \quad (14)$$

where $Q(t)$is discharge at elapsed time t, $Q_0$is discharge at the start of the fitted segment, and $k$is the recession coefficient in month^{-1}. The model was linearized as:

$$\ln Q\,(t) = \ln Q_0 - kt \quad (15)$$

and k was estimated from the negative slope of the fitted linear relationship between log-transformed discharge and elapsed time. The coefficient of determination was used to describe the fit of each qualifying segment. All statistical tests were two-sided unless otherwise specified, with a nominal significance level of $\alpha = 0.05$. Holm-adjusted p-values were used for the four antecedent-window comparisons.

Results

Hydroclimatic change and rainfall–spring discharge relationship

Rainfall and spring discharge showed a declining tendency during 2010–2025, with a comparable percentage reduction but a more consistent downward trend in spring discharge. Mean monthly rainfall was 218.887 mm, with a coefficient of variation (CV) of 71.727%, whereas mean spring discharge was 12.593 L s^{-1} with a CV of 25.000%. The mean rainfall decreased from 247.168 mm month^{-1} during 2010–2017 to 190.607 mm month^{-1} during 2018–2025, corresponding to a 22.884% reduction. Over the same periods, mean spring discharge

decreased from 14.235 to 10.951 L s^{-1}, equivalent to a 23.073% reduction. The Mann–Kendall test indicated a significant decreasing trend for both rainfall (Z = −2.521, p = 0.0117) and spring discharge (Z = −8.290, p < 0.001). The corresponding Sen's slopes were −5.871 mm $month^{-1}$ $year^{-1}$ for rainfall and −0.377 L s^{-1} $year^{-1}$ for spring discharge, which are detailed in Table 1. The seasonal Kendall test and the Hamed–Rao modified Mann–Kendall test confirmed the direction and significance of both trends (Table S4).

Table 1 Hydroclimatic variability and trend statistics during 2010–2025

Variable	Mean, 2010–2025	CV (%)	Change (%)	Mann–Kendall Z	*p*-value	Sen's slope
Rainfall (mm $month^{-1}$)	218.887	71.727	−22.884	−2.52	0.012	−5.871 $month^{-1}$ $year^{-1}$
Spring discharge (L s^{-1})	12.593	25.000	−23.073	−8.29	<0.001	−0.377 L s^{-1} yr^{-1}

The monthly series showed that the decline in spring discharge occurred alongside substantial temporal variability in rainfall. The rainfall series remained highly variable throughout the observation period, whereas the spring-discharge series exhibited a lower coefficient of variation but a stronger monotonic decline. The temporal patterns of both variables and their fitted Sen trends are shown in Fig. 3.

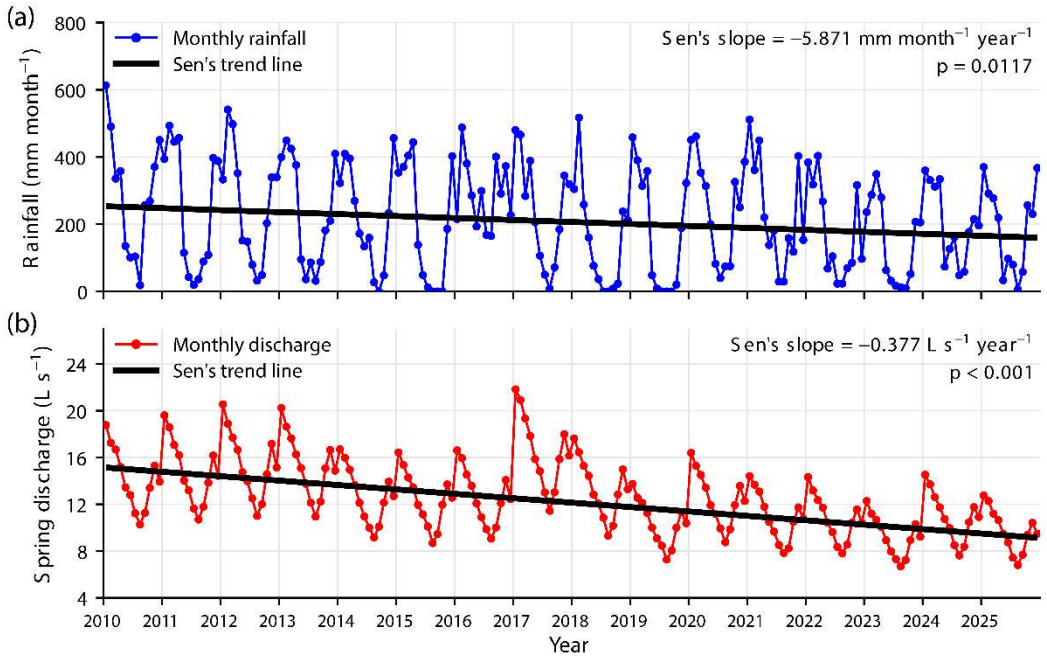


Fig. 3 Hydroclimatic variability and rainfall–spring discharge relationship. (a) Monthly rainfall and spring discharge during 2010–2025. (b) Relationship between monthly rainfall and spring discharge.

Rainfall and spring discharge were positively associated over the full observation period. Pearson correlation analysis yielded $r = 0.700$ ($R^2 = 0.490$, $p < 0.001$), with the fitted relationship expressed as $Q = 9.522 + 0.01403P$, where Q is spring discharge (L s^{-1}) and P is rainfall (mm $month^{-1}$). Cross-correlation analysis over lags of 0–12 months also produced its maximum coefficient at lag 0 (r = 0.700), indicating that the strongest monthly correspondence occurred without an identified temporal lag. After removing the shared seasonal cycle, the association weakened (r = 0.334; $R^2 = 0.111$; 95% CI: 0.164–0.480) (Table S3).

Increasing recurrence of low spring-water availability

Low spring-water availability was defined empirically as monthly spring discharge below the 10th percentile of the 2010–2017 discharge series, yielding a reference threshold of 10.490 L s^{-1}. Across the full 2010–2025 record, 55 of 192 months (28.65%) were classified as low-availability months. The annual frequency of low-availability months increased over the observation period, as indicated by a Kendall's tau of 0.662 ($p < 0.001$). The annual low-availability frequency was zero during 2010–2013, increased intermittently from 2014 onward, and reached 58.33% in both 2023 and 2025, as illustrated in Fig. 4.

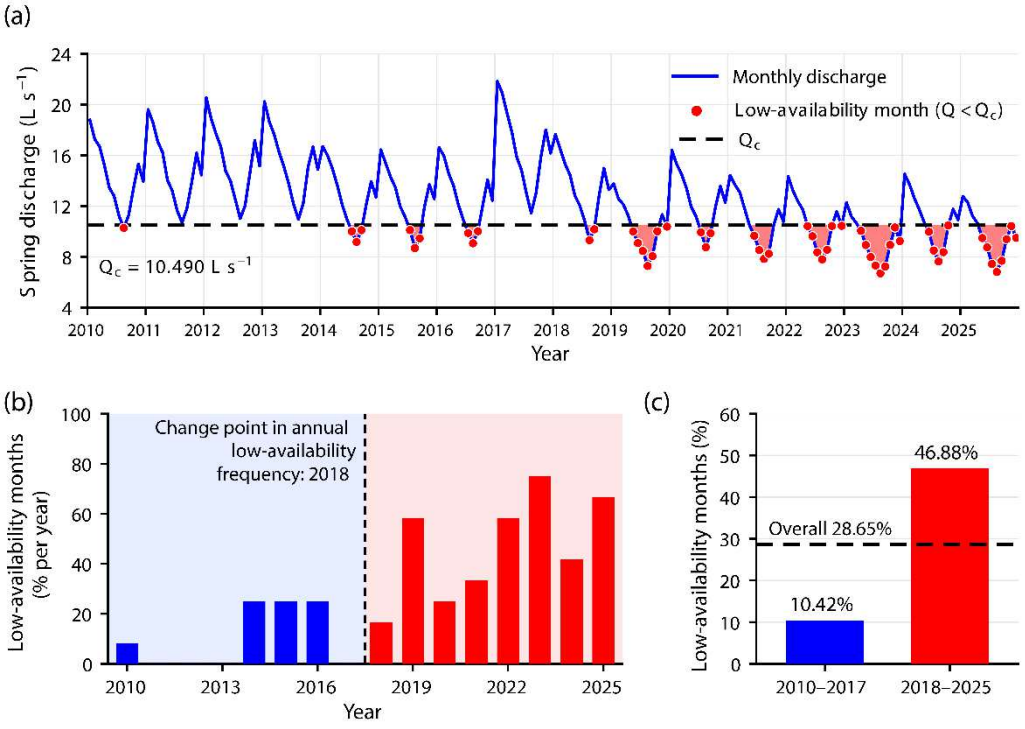


Fig. 4 Temporal distribution and annual frequency of low spring-water availability. (a) Monthly occurrence of low-availability states. (b) Annual frequency of low-availability states during 2010–2025.

The frequency of low-availability conditions differed substantially between the two eight-year periods. During 2010–2017, 10 of 96 months (10.42%) were classified as low-availability months, compared with 45 of 96 months (46.88%) during 2018–2025. This corresponds to a 4.5-fold increase in the proportion of low-availability months. The difference between the two periods was statistically significant (Fisher's exact test, $p = 2.47 \times 10^{-8}$). The Pettitt test identified 2018 as the change point in annual low-availability frequency ($p = 0.014$). The annual mean spring discharge also showed a significant change point in 2018 ($p = 0.008$). Thus, the increase in low-availability month recurrence coincided temporally with the shift in the annual discharge regime identified in the preceding analysis. Threshold sensitivity analyses using the 15th (11.0425 L s^{-1}) and 20th (11.6500 L s^{-1}) percentiles yielded similar patterns of increasing recurrence (Table S1).

Antecedent rainfall conditioning of low-availability onset

Low-availability onset was defined as a transition from a non-low-availability month to a month with spring discharge below the empirical low-availability threshold. Restricting the analysis to months with a non-low-availability preceding month and complete antecedent rainfall records resulted in risk sets that varied across antecedent windows because of differences in data availability. The number of observations ranged from 137 for the 1-month window to 127 for the 12-month window. The number of onset months was 14 for the 1-, 3-, and 6-month windows and 13 for the 12-month window, as one onset month lacked complete 12-month antecedent rainfall data. Antecedent rainfall anomalies were lower during low-availability onset than during non-onset months across all four tested windows. The difference increased with the length of the antecedent window, from −12.902 mm for the 1-month window to −437.739 mm for the 12-month window. After Holm adjustment, only the 12-month window showed a statistically significant difference ($p = 0.00663$; Table 2).

Table 2 Antecedent rainfall conditions preceding low-availability onset

Antecedent window	Onsen (n)	Non-onsen (n)	Onset mean (mm)	Non-onset mean (mm)	Difference (mm)	Holm-adjusted *p*
1 month	14	123	−4.958	7.944	−12.902	0.3879
3 months	14	121	−62.384	22.526	−84.910	0.1368
6 months	14	118	−133.727	61.528	−195.255	0.1105
12 months	13	114	−284.838	152.902	−437.739	0.00663

The 12-month antecedent rainfall anomaly was subsequently evaluated for its association with low-availability onset. Logistic regression produced a coefficient of −0.002141 per mm. Expressed per 100-mm increase in antecedent rainfall anomaly, the odds ratio was 0.807 (95% CI: 0.698–0.934; p = 0.00406), with an apparent AUC of 0.767. Using heteroskedasticity- and autocorrelation-consistent standard errors, the odds ratio remained 0.807 (95% CI: 0.731–0.891; $p = 2.29 \times 10^{-5}$). Logistic model diagnostics are reported in Table S5.

The 12-month antecedent rainfall anomaly was also examined in relation to the broader ENSO signal within the 12-month risk set (n = 127). The anomaly was negatively correlated with ONI (r = −0.466, $p = 3.47 \times 10^{-8}$), with a regression slope of −317.55 mm per ONI unit. In the direct model, the ONI term was not statistically significant ($\delta_1 = 0.2878$; p = 0.471). In the joint model, the ONI term was also not statistically significant ($\theta_1 = -0.3769$; p = 0.309), whereas the 12-month rainfall anomaly remained statistically significant after HAC adjustment ($\theta_2 = -0.002428$; $p = 3.09 \times 10^{-5}$). The antecedent rainfall and ENSO relationships are presented in Fig. 5.

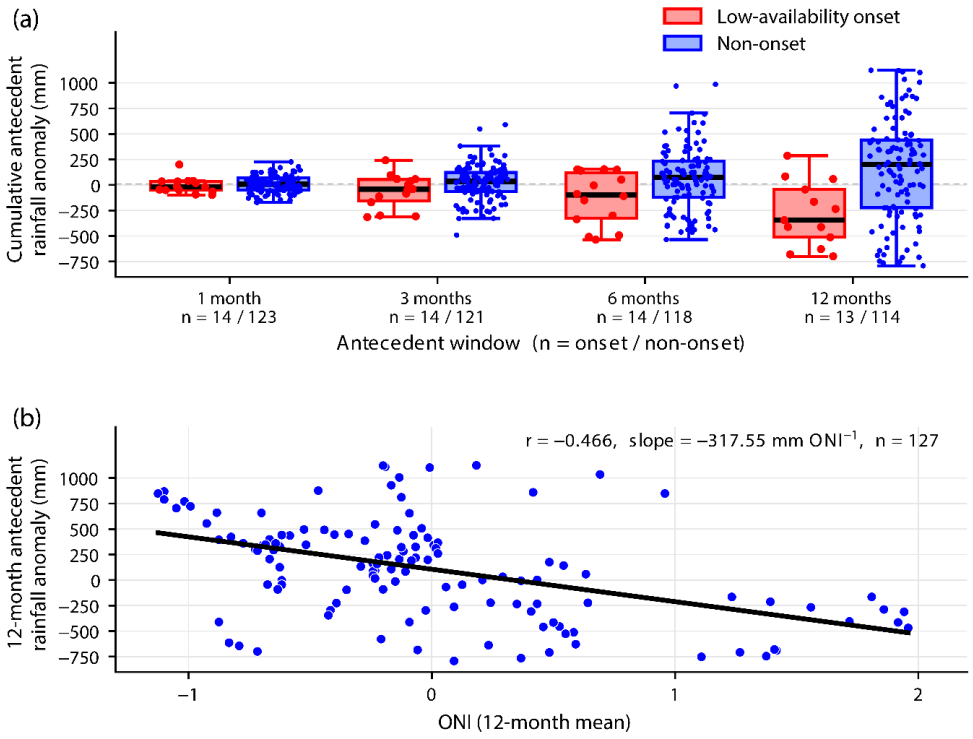


Fig. 5 Antecedent rainfall anomalies associated with low-availability onset and their relationship with ENSO. (a) Distributions of cumulative antecedent rainfall anomalies for onset and non-onset observations across 1-, 3-, 6-, and 12-month antecedent windows. (b) Relationship between the 12-month mean Oceanic Niño Index (ONI) and the 12-month antecedent rainfall anomaly; the solid line represents the fitted linear regression.

Low-availability episode persistence and recession characteristics

The 55 low-availability months identified during 2010–2025 formed 14 distinct episodes, with durations ranging from 1 to 9 months (Table 3). The shortest episodes consisted of a single low-availability month, whereas the longest episode extended from April to December 2023, lasting 9 months. Other prolonged episodes occurred during May–October 2019, May–October 2022, and May–December 2025, with durations of 6, 6, and 8 months, respectively.

Table 3 Characteristics of low-availability episodes during 2010–2025

Episode	Start	End	Duration (months)	Minimum discharge ($L\ s^{-1}$)	Cumulative deficit ($L\ s^{-1}$ month)
E1	Aug 2010	Aug 2010	1	10.28	0.21
E2	Jul 2014	Sep 2014	3	9.17	2.19
E3	Jul 2015	Sep 2015	3	8.69	3.22
E4	Jul 2016	Sep 2016	3	9.07	2.50
E5	Aug 2018	Sep 2018	2	9.31	1.50
E6	May 2019	Oct 2019	6	7.28	10.06
E7	Dec 2019	Dec 2019	1	10.38	0.11
E8	Jul 2020	Sep 2020	3	8.76	2.91
E9	Jun 2021	Sep 2021	4	7.84	7.69
E10	May 2022	Oct 2022	6	7.80	7.77
E11	Dec 2022	Dec 2022	1	10.44	0.05
E12	Apr 2023	Dec 2023	9	6.70	17.69
E13	Jun 2024	Oct 2024	5	7.63	7.51
E14	May 2025	Dec 2025	8	6.81	14.45

The cumulative discharge deficit across the 14 episodes was 77.86 $L\ s^{-1}$ month, with a mean of 5.56 $L\ s^{-1}$ month per episode. The mean episode duration was 3.93 months. The largest cumulative deficit occurred during April–December 2023 (17.69 $L\ s^{-1}$ month), followed by May–December 2025 (14.45 $L\ s^{-1}$ month). The temporal distribution of episode duration and cumulative discharge deficit is presented in Fig. 6.

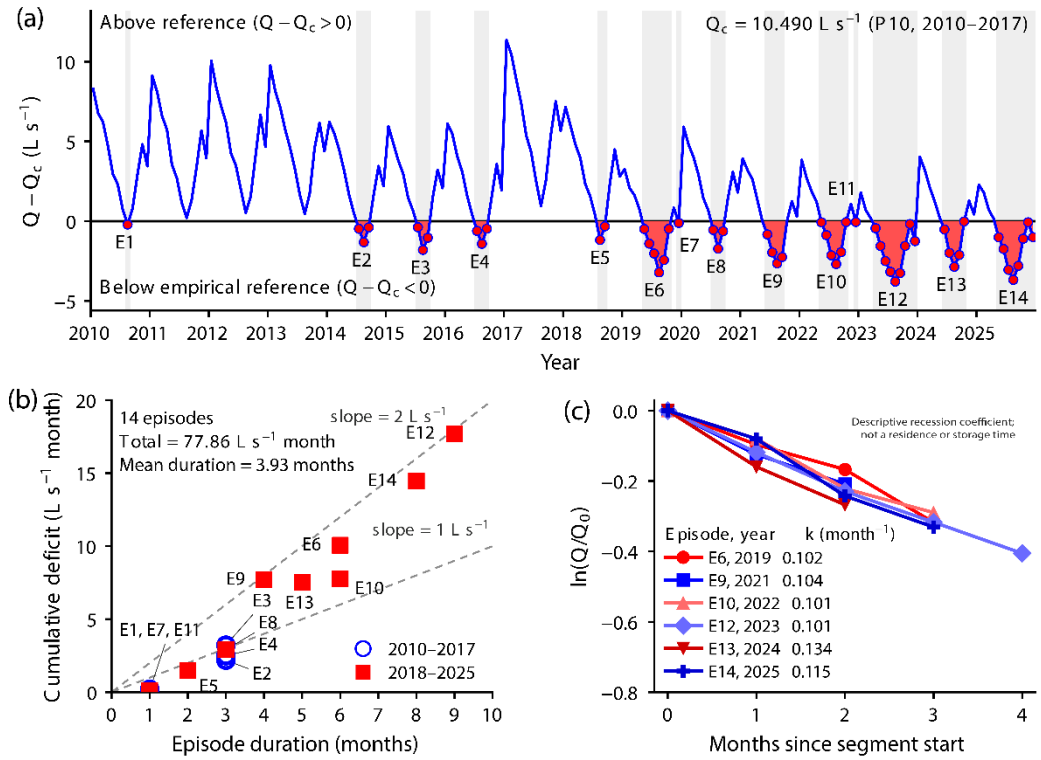


Fig. 6 Duration and cumulative discharge deficit of low-availability episodes during 2010–2025. (a) Temporal distribution and duration of the 14 low-availability episodes. (b) Relationship between episode duration and cumulative discharge deficit; dashed lines indicate reference slopes of 1 and 2 L s^{-1} month per month of episode duration.

Six discharge segments met the predefined recession criterion, requiring at least three consecutive monthly observations with at least two consecutive declines. The qualifying segments occurred during May–August 2019, June–August 2021, May–August 2022, April–August 2023, June–August 2024, and May–August 2025. The fitted recession coefficients ranged from 0.101 to 0.134 $month^{-1}$, with coefficients of determination ranging from R^2 = 0.976 to 0.995. The estimated coefficients were 0.1023, 0.1044, 0.1010, 0.1010, 0.1337, and 0.1155 $month^{-1}$, respectively. The recession segments did not necessarily span the full duration of the corresponding low-availability episodes because recession fitting was restricted to segments satisfying the predefined monotonic-decline criterion. Recession segment details are reported in Table S6.

Discussion

Declining Spring-Water Availability Despite a Persistent Rainfall–Discharge Association

The decline in spring-water availability at Tlogorejo reflects a shift towards a lower discharge regime rather than a demonstrated breakdown in rainfall–discharge association. Although rainfall and spring discharge decreased over the observation period, their contemporaneous relationship remained positive. This distinction matters for water-resource assessment because a spring can retain a measurable response to rainfall while providing less water overall and experiencing low-availability conditions more frequently. Hydrological responsiveness therefore cannot be interpreted as evidence of stable water availability.

Long-term observations from other groundwater-dependent systems demonstrate why discharge trends should be interpreted alongside multiple hydroclimatic and hydrogeological influences. An analysis of more than 50 European karst springs showed that discharge trends were not consistently explained by precipitation changes alone, highlighting the need to consider other factors affecting recharge and groundwater conditions (Giese et al. 2025) . Similarly, groundwater-resource assessments in Kumamoto, Japan, evaluated discharge and groundwater-level trends alongside climatic variables and other potential influences (Yu et al. 2024). These studies caution against attributing discharge changes exclusively to rainfall. At Tlogorejo, the concurrent decline in rainfall and discharge is consistent with changing hydroclimatic conditions, but the available observations cannot isolate the respective contributions of evapotranspiration, recharge efficiency, land-cover change, or groundwater abstraction.

Beyond the attribution of discharge trends, a separate question concerns how these changes affect the reliability of water availability. Climate-scenario modelling in Rwanda and research on a tropical karst catchment in Indonesia demonstrate the relevance of evaluating projected discharge changes in relation to water-resource availability, sustainability, and management (Klaas et al. 2020; Muhumure et al. 2024) . Although their modelling approaches and hydrogeological settings differ from the observational analysis at Tlogorejo, these studies provide a broader context for assessing how changing discharge may affect water-resource management. In this study, low availability is identified using an empirical reference derived from the lower tail of the historical discharge distribution, rather than a demand-based or regulatory threshold. The increasing recurrence of months below this reference therefore indicates a change in the frequency of relatively low-discharge conditions within the observed record, not proof that the spring has crossed a physical failure threshold. Hydrogeological processes may also

influence how climatic variability is translated into spring discharge, although the present results cannot resolve the internal flow mechanisms of Tlogorejo. Investigations of a major spring in a calcarenitic aquifer in Italy indicate that geological structure and the coexistence of rapid and diffuse flow components can affect discharge behaviour and resilience (Filippini et al. 2024). This provides a mechanistic comparison rather than a direct analogue, as the lithology and aquifer configuration differ from Tlogorejo.

The principal contribution of this study is to demonstrate why rainfall responsiveness alone is insufficient for evaluating the temporal reliability of spring-water resources. Monitoring frameworks that rely only on rainfall–discharge correlation may overlook a declining discharge regime and the increasing recurrence of low-availability conditions. The combined assessment of long-term discharge trends and the frequency of empirically defined low-availability months provides a complementary basis for identifying deterioration in water availability. This interpretation remains bounded by the observational evidence: the empirical reference is not a demand-based supply threshold, a regulatory limit, or proof of physical aquifer failure. Further measurements of groundwater levels, recharge, abstraction, and aquifer properties are needed to distinguish the processes responsible for the observed changes and to determine how they affect future water-resource reliability.

Increasing Recurrence of Low Spring-Water Availability

The analytical value of the Tlogorejo assessment lies in distinguishing a historical low-discharge indicator from a threshold designed to determine sustainable water abstraction. (Ferencz and Dawidek 2025), for example, applied a threshold-level approach based on the Q90 percentile of the flow-duration curve to evaluate the potential for sustainable spring-water extraction in southeastern Poland. That approach addresses the amount of water potentially available for use under specified constraints, whereas the empirical reference at Tlogorejo identifies months of relatively low discharge within the historical record. The two approaches therefore serve different purposes: one supports extraction assessment, while the other tracks the recurrence of low-availability conditions. The Tlogorejo reference should consequently be interpreted as a site-specific analytical indicator, not as a safe-abstraction limit or a regulatory compliance threshold.

The value of a long-term record becomes clearer when contrasted with assessments based on seasonal field observations. In the Kathmandu Valley, more than 90% of the surveyed springs exhibited lower discharge during the pre-monsoon survey than during the post-monsoon survey, and six springs were dry during the pre-monsoon

survey (Shah et al. 2026). Research on mountain springs in the Nepal Himalaya has also examined spring criticality and sustainability in relation to water quality and availability (Upreti et al. 2024). Such studies reveal important spatial and seasonal dimensions of spring-water availability. However, seasonal snapshots cannot establish whether the frequency or persistence of low-discharge conditions has changed across successive years. By comparison, the 2010–2025 monthly record at Tlogorejo provides this temporal perspective by allowing low-availability episodes to be identified as consecutive months below the empirical reference and characterized by their duration and cumulative discharge deficit. This distinction helps separate seasonal variability from the longer-term recurrence of constrained availability.

Model-based assessments address a different question: how spring discharge and groundwater availability might respond to specified future conditions. For the Medicine Lake Highlands/Fall River Springs aquifer system in California, climate scenarios projected decreases in groundwater recharge of 9–27% under three scenarios, whereas a fourth scenario projected a 32% increase in recharge associated with substantially greater precipitation (Mancewicz et al. 2021). In Indonesia, modelling of Ronggojalu Spring examined potential changes in discharge capacity under land-cover scenarios (Kuntjoro et al. 2025). These approaches evaluate possible future outcomes under specified conditions, while the Tlogorejo analysis characterizes the recurrence and severity of low-availability episodes already observed. The approaches are complementary: scenario modelling explores conditional future responses, whereas historical episode analysis describes when low availability occurred, how long it persisted, and the cumulative discharge deficit associated with each episode. This approach does not independently predict future discharge or identify the causal contribution of individual environmental drivers.

The methodological contribution of the Tlogorejo study is the integration of long-term discharge trends with low-availability frequency and episode-level characteristics. This combination addresses three related but distinct questions: whether discharge has changed over time, how often relatively low-discharge conditions occur, and how individual episodes differ in duration and cumulative deficit. Here, an episode is defined as a consecutive sequence of months with discharge below the empirical reference, while cumulative deficit represents the sum of the monthly differences between that reference and observed discharge during the episode. The resulting framework links the changing discharge regime to the temporal structure and magnitude of observed availability constraints. This framework goes beyond rainfall–discharge correlation or seasonal comparisons alone. The reference remains specific to Tlogorejo and should not be transferred directly to other springs without considering

their historical discharge distributions and water-resource requirements. The analytical approach, however, can be applied elsewhere to distinguish hydrological responsiveness from the recurrence and persistence of low-availability conditions.

Antecedent rainfall, ENSO, and temporal conditioning of low availability

The onset of low-availability conditions at Tlogorejo was more consistently associated with accumulated antecedent rainfall deficits than with a direct statistical relationship with ENSO. Here, onset is defined as the first month with discharge below the empirical reference, following at least one month at or above that reference. Among the antecedent windows examined, the 12-month rainfall anomaly retained a significant association with onset after Holm adjustment, whereas the shorter 1-, 3-, and 6-month windows did not meet the adjusted significance criterion. This pattern suggests that the onset of low availability was associated more clearly with rainfall deficits accumulated over an extended period than with rainfall anomalies immediately preceding onset. The result should not, however, be interpreted as evidence of a fixed 12-month hydrological response time. The analysis identifies a statistical association between antecedent rainfall conditions and onset, rather than directly measuring groundwater recharge pathways or aquifer storage dynamics.

The relevance of antecedent hydroclimatic conditions is consistent with research showing that groundwater systems can respond to precipitation variability over different temporal scales. In the Vietnamese Mekong Delta, groundwater-level variations were associated with annual precipitation variability at timescales of approximately one year, while relationships with ENSO differed between shallow and deep aquifers (Le et al. 2021) . A separate study in the humid tropics of Costa Rica linked El Niño-related rainfall reductions with restricted groundwater recharge and an earlier onset of minimum baseflow conditions (Sánchez-Murillo et al. 2023). These studies support the interpretation that rainfall deficits can influence groundwater-related availability beyond the timescale of individual rainfall events. Their findings do not establish an equivalent response mechanism at Tlogorejo, where the analysis uses monthly spring discharge and antecedent rainfall anomalies rather than groundwater levels, isotopic tracers, or direct recharge measurements.

ENSO provides a plausible large-scale context for hydroclimatic variability, but its influence on local water availability cannot be assumed to be uniform across regions or aquifer systems. An assessment of groundwater storage across the Kalahari Aquifer System found associations with both short-term drought indicators and climate

teleconnections, while the strength of groundwater–climate relationships varied spatially with hydrogeological conditions (Banda and Shilengwe 2025). Across the Indonesian archipelago, satellite-based analysis also identified regional differences in the climatic controls on groundwater storage, with the relative associations of ENSO and the Indian Ocean Dipole varying among islands (Sudradjat et al. 2026). These findings provide context for interpreting the Tlogorejo results: ENSO may contribute to the broader climatic conditions under which rainfall deficits develop, but its relationship with local spring availability depends on the local rainfall response to ENSO and the characteristics of the groundwater system.

At Tlogorejo, the direct ENSO term was not statistically significant when assessed using heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, whereas the 12-month antecedent rainfall anomaly remained significant in the joint model. This distinction does not demonstrate that ENSO has no hydrological influence. Rather, the available evidence does not support treating ENSO as an independently significant direct predictor of onset in this analysis. Nor does it establish a formal mediation pathway—that is, a statistically tested indirect effect of ENSO on spring discharge operating through rainfall. The more defensible interpretation is that accumulated antecedent rainfall provides a closer statistical indicator of the hydroclimatic conditions associated with onset than ENSO alone. The expanding-window AUC of 0.612 further indicates limited discrimination when the rainfall relationship is evaluated across successive prediction periods. Therefore, the association should not be presented as a validated operational forecasting model.

The practical implication is that monitoring of spring-water availability should consider antecedent rainfall accumulation alongside observed discharge, rather than relying exclusively on rainfall in the current month or ENSO phase. The 12-month rainfall anomaly may serve as a supplementary indicator for contextualizing observed low-discharge conditions, but its operational value requires independent validation using additional observations and future periods. The findings therefore support a monitoring approach that explicitly considers accumulated antecedent rainfall alongside measured discharge, while leaving the physical mechanisms linking rainfall deficits, subsurface storage, and spring discharge open for further investigation.

Episode Persistence and Implications for Spring-Water Management

The management significance of low spring discharge depends not only on how frequently it occurs but also on how long individual episodes persist and how large their cumulative discharge deficits become. At Tlogorejo, 14

low-availability episodes were identified, with a combined cumulative deficit of 77.86 L/s-month across the 2010–2025 observation period. The longest episode extended from April to December 2023, lasting nine consecutive months, and also recorded the largest cumulative deficit. These characteristics distinguish repeated short-duration reductions from prolonged episodes that accumulate larger deficits relative to the empirical reference. They do not, by themselves, establish whether demand was unmet or whether water-service interruptions occurred, because those outcomes were not directly measured.

The importance of episode duration is consistent with groundwater-drought research demonstrating that drought propagation and persistence vary with environmental and hydrological conditions. In the Sanjiang Plain, China, groundwater-drought propagation characteristics differed between irrigated and non-irrigated areas, indicating that groundwater-drought dynamics can vary with local conditions (Ling et al. 2024) . At the global scale, (Liu et al. 2026) examined the propagation of meteorological and hydrological droughts to groundwater drought using satellite-derived groundwater-storage information and drought indices. Their findings highlight differences in drought duration, severity, and propagation across hydrological systems. These studies provide a rationale for examining the duration and cumulative severity of low-availability episodes. However, groundwater-drought indices and regional groundwater observations are not directly equivalent to the discharge-based empirical reference used at Tlogorejo.

Research on low-flow hydrology demonstrates that the duration and timing of low-flow periods provide information relevant to water-resource management beyond the magnitude of individual low-flow observations. An analysis of 1,032 streamgages across the conterminous United States examined low-flow seasonality, temporal trends, and climate linkages, demonstrating the value of evaluating low-flow characteristics over extended periods (Simeone et al. 2024). In Hawai‘i, spring-discharge information was incorporated into a groundwater-management optimization framework to examine trade-offs between groundwater pumping and the protection of spring-dependent ecological, cultural, and human uses (Burnett et al. 2020). The Hawai‘i study illustrates how spring-discharge information can inform management decisions, although its optimization framework differs from the retrospective episode analysis applied at Tlogorejo. Taken together, these studies support the use of temporal discharge characteristics in water-resource assessment. They also underscore the need to interpret these characteristics in relation to the specific management question. At Tlogorejo, episode analysis characterizes the

persistence and cumulative magnitude of observed low-discharge conditions; it does not project future discharge or directly assess unmet demand.

For Tlogorejo, episode duration and cumulative deficit can complement long-term discharge trends and low-availability frequency in routine monitoring. A practical monitoring protocol could record the start and end of each episode, its duration, the minimum observed discharge, and the cumulative deficit relative to the empirical reference. These metrics would help distinguish an isolated low-discharge month from a prolonged episode requiring closer assessment. Any operational response, however, should be linked to independently established demand, storage, abstraction, and service-reliability information rather than treating the empirical reference as a supply-failure threshold. Future research could investigate the implications of these episodes for water-supply performance by combining discharge records with additional operational data, where available, and collecting information on water demand, abstraction, and service interruptions where these records are absent.

Implications for sustainable assessment of spring-water availability

Sustainable assessment of spring-water availability requires more than establishing whether spring discharge responds to rainfall variability. The Tlogorejo results demonstrate that a positive rainfall–discharge association can persist alongside a decline in mean discharge and an increase in the recurrence of low-availability conditions. This distinction is important because hydrological responsiveness describes the association between rainfall and discharge, whereas availability assessment must also account for changes in the discharge regime over time. Consequently, a persistent rainfall–discharge association should not be interpreted as evidence that the spring continues to provide a stable water resource.

A more comprehensive assessment can integrate three complementary dimensions: long-term discharge trends, the recurrence of low-availability conditions, and the persistence of individual episodes. Discharge trends characterize changes in the overall availability regime, while low-availability frequency indicates how often discharge falls below a defined empirical reference. Episode duration and cumulative deficit provide additional information on the temporal persistence and magnitude of these conditions. These dimensions address different aspects of hydrological availability and should therefore be interpreted jointly rather than treated as interchangeable indicators. The Tlogorejo assessment illustrates how their integration reveals changes in historical availability that are not captured by mean discharge or rainfall–discharge correlation alone. The findings provide

a basis for water-resource managers to distinguish between springs that remain responsive but are becoming less reliable and springs whose response to rainfall is genuinely weakening, supporting more targeted monitoring and allocation decisions.

Hydrological indicators, however, do not independently establish whether a spring-water supply system is sustainable in operational terms. Operational sustainability, in this context, refers to whether water demand can be met reliably. The empirical reference used at Tlogorejo identifies historically low-discharge conditions but does not define a safe abstraction limit, a demand-based supply threshold, or a point of supply failure. Assessing operational sustainability additionally requires information on water demand, abstraction, available storage, and service reliability. The distinction between hydrological availability and supply adequacy is therefore essential when translating historical discharge analysis into water-resource management decisions. The proposed assessment framework offers a basis for characterizing changes in spring-water availability, while its implications for actual supply sustainability must be evaluated using complementary operational evidence. The present analysis focuses on water quantity; future work could integrate water-quality monitoring to provide a more complete assessment of spring-water suitability for domestic and agricultural uses. Although the empirical reference is specific to Tlogorejo, the analytical approach can be tested in other spring systems, with reference values and interpretations established according to their respective hydrological and management contexts.

Conclusions

Rainfall and spring discharge both exhibited significant declining trends, and these trends remained significant after accounting for seasonal structure and serial dependence. The full-period rainfall–discharge association was positive ($r = 0.700$; $R^2 = 0.490$), but after removing the shared seasonal cycle, the association was substantially weaker while remaining positive ($r = 0.334$; $R^2 = 0.111$). After additionally removing the long-term trend, the residual association was weak and not statistically robust ($r = 0.129$; 95% block-bootstrap CI: −0.013 to 0.267). The results therefore do not indicate a detectable temporal change in the observed rainfall–spring discharge association, while the principal hydroclimatic change was a downward shift in the prevailing spring-discharge regime. This shift was accompanied by a marked increase in recurrent low-availability conditions, from 10.42% of months during 2010–2017 to 46.88% during 2018–2025. The statistically detected shift around 2018 should be interpreted as a change in the observed availability regime rather than as evidence of a physical tipping point.

Low-availability onset showed the strongest empirical association with the 12-month antecedent rainfall anomaly among the evaluated windows (OR = 0.807 per 100-mm increase; HAC-adjusted $p = 2.29 \times 10^{-5}$), although out-of-sample discrimination was limited (AUC = 0.612). Antecedent rainfall is therefore better interpreted as a hydroclimatic conditioning indicator than as a standalone predictor. ENSO was associated with antecedent rainfall conditions but showed no direct statistical association with low-availability onset, supporting its interpretation as an upstream hydroclimatic context rather than a direct predictor. Low-availability episodes further demonstrated that changing availability involved not only recurrence but also persistence and cumulative deficit, with 14 episodes lasting one to nine months during 2010–2025. Six qualifying recession segments described within-episode discharge decline, with recession coefficients of 0.101–0.134 $month^{-1}$; these coefficients describe observed recession behaviour rather than aquifer storage, residence time, or hydraulic memory. Overall, the findings indicate that assessment of spring-water reliability should consider the prevailing discharge regime together with low-availability recurrence, antecedent hydroclimatic conditions, and episode persistence rather than monthly rainfall–discharge association alone. Combining direct spring-discharge monitoring with rainfall-based hydroclimatic indicators can support closer monitoring and seasonal preparedness during prolonged low-availability periods. The empirical threshold and recession characteristics developed here are site-specific and should therefore be independently calibrated before application to other spring systems.

Acknowledgments

The authors express their gratitude to Perumda Air Minum Tirta Gemilang, Kabupaten Magelang, for providing the spring-discharge records used in this study, and to BBWS Serayu Opak (Balai Besar Wilayah Sungai Serayu Opak), a regional river-basin management agency under the Indonesian Ministry of Public Works and Housing, for providing the rainfall data from the Caturanom, Poncol Gelangan, and Badran stations. The Oceanic Niño Index data were obtained from the NOAA Climate Prediction Center.

References

Banda K, Shilengwe C (2025) Identifying potential hotspots of groundwater-climate interaction in the Kalahari Aquifer System, Upper Zambezi Basin, Southern Africa. J Hydrol Reg Stud 60:102484. https://doi.org/10.1016/j.ejrh.2025.102484

614 Burnett KM, Elshall AS, Wada CA, et al (2020) Incorporating historical spring discharge protection into
615 sustainable groundwater management: a case study from Pearl Harbor Aquifer, Hawai'i. Front Water 2:14.
616 https://doi.org/10.3389/frwa.2020.00014
617 Dass B, Abhishek, Sen S, et al (2021) Assessment of spring flows in Indian Himalayan micro-watersheds – A
618 hydro-geological approach. J Hydrol (Amst) 598:126354. https://doi.org/10.1016/j.jhydrol.2021.126354
619 Fan X, Goeppert N, Goldscheider N (2023) Quantifying the historic and future response of karst spring discharge
620 to climate variability and change at a snow-influenced temperate catchment in central Europe. Hydrogeol J
621 31:2213–2229. https://doi.org/10.1007/s10040-023-02703-9
622 Ferencz B, Dawidek J (2025) Sustainable spring water extraction—a remedy to water shortage? Sustainability
623 17:5798. https://doi.org/10.3390/su17135798
624 Filippini M, Segadelli S, Dinelli E, et al (2024) Hydrogeological assessment of a major spring discharging from
625 a calcarenitic aquifer with implications on resilience to climate change. Science of The Total Environment
626 913:169770. https://doi.org/10.1016/j.scitotenv.2023.169770
627 Giese M, Caballero Y, Hartmann A, Charlier J-B (2025) Trends in long-term hydrological data from European
628 karst areas: insights for groundwater recharge evaluation. Hydrol Earth Syst Sci 29:3037–3054.
629 https://doi.org/10.5194/hess-29-3037-2025
630 Gullacher A, Allen DM, Goetz JD (2023) Early warning indicators of groundwater drought in mountainous
631 regions. Water Resour Res 59:e2022WR033399. https://doi.org/10.1029/2022WR033399
632 Holm S (1979) A simple sequentially rejective multiple test procedure. Scand J Stat 6:65–70
633 Kendall MG (1975) Rank Correlation Methods, 4th edn. Charles Griffin, London
634 Klaas DKSY, Imteaz MA, Sudiayem I, et al (2020) Assessing climate changes impacts on tropical karst
635 catchment: Implications on groundwater resource sustainability and management strategies. J Hydrol
636 (Amst) 582:124426. https://doi.org/10.1016/j.jhydrol.2019.124426
637 Kumar M, Sen S, Kulkarni H, et al (2024) Ecohydrological and hydrogeological dynamics of groundwater springs
638 in Eastern Himalaya, India. Groundw Sustain Dev 27:101311. https://doi.org/10.1016/j.gsd.2024.101311
639 Kuntjoro K, Santoso IB, Tatas T, Robbi RAR (2025) Modelling the discharge capacity of Ronggojalu Spring
640 under land cover change scenarios. Discover Water 5:111. https://doi.org/10.1007/s43832-025-00288-w

Lamacova A, Ledvinka O, Bohdalkova L, et al (2024) Response of spring yield dynamics to climate change across altitude gradient and varied hydrogeological conditions. Science of The Total Environment 921:171082. https://doi.org/10.1016/j.scitotenv.2024.171082

Le PV V, Pham H V, Bui LK, et al (2021) Responses of groundwater to precipitation variability and ENSO in the Vietnamese Mekong Delta. Hydrology Research 52:1280–1293. https://doi.org/10.2166/nh.2021.024

Ling Z, Shu L, Wang D, et al (2024) Characteristics of groundwater drought and its propagation dynamics with meteorological drought in the Sanjiang Plain, China: Irrigated versus nonirrigated areas. J Hydrol Reg Stud 54:101911. https://doi.org/10.1016/j.ejrh.2024.101911

Liu L, Zhou Z, Li W, et al (2026) Global characteristics of drought propagation from surface water to groundwater. J Hydrol (Amst) 665:134734. https://doi.org/10.1016/j.jhydrol.2025.134734

Mancewicz LK, Davisson L, Wheelock SJ, et al (2021) Impacts of climate change on groundwater availability and spring flows: observations from the highly productive Medicine Lake Highlands/Fall River Springs Aquifer System. JAWRA J Am Water Resour Assoc 57:1021–1036. https://doi.org/10.1111/1752-1688.12976

Mann HB, Whitney DR (1947) On a test of whether one of two random variables is stochastically larger than the other. Ann Math Stat 18:50–60. https://doi.org/10.1214/aoms/1177730491

Muhumure J, Pohl E, Schulz S (2024) Assessing the impact of climate change on spring discharge using hydrological modelling in Musanze District, Rwanda. Hydrogeol J 32:1909–1923. https://doi.org/10.1007/s10040-024-02836-5

Nugroho AR, Tamagawa I, Harada M (2022) Spatiotemporal analysis on the teleconnection of ENSO and IOD to the stream flow regimes in Java, Indonesia. Water 14:168. https://doi.org/10.3390/w14020168

Pettitt AN (1979) A non-parametric approach to the change-point problem. J R Stat Soc Ser C Appl Stat 28:126–135. https://doi.org/10.2307/2346729

Qian J (2020) Multi-scale climate processes and rainfall variability in Sumatra and Malay Peninsula associated with ENSO in boreal fall and winter. International Journal of Climatology 40:4171–4188. https://doi.org/10.1002/joc.6450

Sánchez-Murillo R, Birkel C, Boll J, et al (2023) ENSO sentinels in the Americas' humid tropics: we need combined hydrometric and isotopic monitoring for improved El Niño and La Niña impact prediction. Hydrol Process 37:e15027. https://doi.org/10.1002/hyp.15027

Shah DN, Tachamo Shah RD, Mishra K, et al (2026) Seasonal dynamics of spring water quality and quantity in urban cities of Kathmandu Valley, Central Nepal. Environ Earth Sci 85:182. https://doi.org/10.1007/s12665-026-12915-3

Simeone C, McCabe G, Hecht J, et al (2024) Low-flow period seasonality, trends, and climate linkages across the United States. Hydrological Sciences Journal 69:1387–1398. https://doi.org/10.1080/02626667.2024.2369639

Sivelle V, Bittner D, Mazzilli N, Tramblay Y (2021) Assessment of the relative impacts of climate changes and anthropogenic forcing on spring discharge of a Mediterranean karst system. J Hydrol (Amst) 598:126396. https://doi.org/10.1016/j.jhydrol.2021.126396

Song X, Hao H, Liu W, et al (2022) Spatial-temporal behavior of precipitation driven karst spring discharge in a mountain terrain. J Hydrol (Amst) 612:128116. https://doi.org/10.1016/j.jhydrol.2022.128116

Sudradjat A, Brawijaya D, Fadiyah NN, et al (2026) Changes in groundwater storage dynamics in the tropical archipelago region. Environmental Challenges 23:101475. https://doi.org/10.1016/j.envc.2026.101475

Thaden RE, Sumadirdja H, P. W. Richards (1975) Geological map of Magelang and Semarang sheets, Java, scale 1:100,000. Geological Survey of Indonesia, Bandung

Upreti MR, Kayastha SP, Bhuiyan C (2024) Water quality, criticality, and sustainability of mountain springs—a case study from the Nepal Himalaya. Environ Monit Assess 196:57. https://doi.org/10.1007/s10661-023-12186-6

Yu Z-Q, Hosono T, Amano H, et al (2024) Groundwater resource assessment by applying long-term trend analysis of spring discharge, water level, and hydroclimatic parameters. Water Resour Manag 38:4161–4177. https://doi.org/10.1007/s11269-024-03857-1

Declarations

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of Data and Materials

The datasets generated and analyzed during the current study are not publicly available, as the discharge and rainfall data are owned by the regional water utility and river basin authority of Central Java, Indonesia, and are subject to institutional data-sharing policies. Data are available from the corresponding author (Rintis Hadiani) on reasonable request and subject to permission from the relevant data-owning institutions.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Author Contributions

All authors contributed to the study conception and design. Mahdika Putra Nanda collected, processed, and analyzed the data. Mahdika Putra Nanda wrote the first draft of the manuscript, and all authors commented on previous versions. Rintis Hadiani, Sobriyah, and Yusep Muslih provided supervision and critical review. All authors read and approved the final manuscript.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryNanda.docx