Annals of Arid Zone 65(1): 231-246, 2026

Investigating Rainfall Persistence in the Seybouse Watershed of Northeastern Algeria using the ARFIMA model

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Received: August 13, 2025 Accepted: December 17, 2025

Abstract: This research paper examines the persistence of precipitation forecast memory by estimating the fractional differentiation parameter (d) of the AutoRegressive Fractionally Integrated Moving Average (AutoRegressive Fractionally Integrated Moving Average (ARFIMA)) model and the corresponding Hurst exponent (H) using the maximum likelihood method (LM) and nonlinear least squares estimation method (NLS). The optimal method is selected based on criteria such as minimal AIC, portmanteau, and residue tests. The study focuses on monthly rainfall data from four representative stations in the Seybouse watershed area in the Algerian Northeast, covering the period from January 1, 1998, to December 31, 2007. To ensure data normality, the Cox-Box transformation is applied to model the studied process. The constructed Autoregressive Fractionally Integrated Moving Average (ARFIMA) models exhibit the following characteristics: Annaba station: (5; 0.13; 14) with a Hurst exponent (H) of 0.63, indicating long forecast memory; Oum El Bouaghi station: (0; 0.11; 0) with (H) of 0.61, indicating long forecast memory; Guelma station: (9; -0.16; 4) with (H) of 0.34, indicating long forecast memory; and Souk Ahras station: (2; -0.37; 2) with (H) of 0.13, indicating anti-persistence.

Key words: ARFIMA, Seybouse watershed, rainfall, hurst exponent, persistence.

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Citation
Belkacem, B. and Abdelatif, Z. 2026. Investigating rainfall persistence in the seybouse watershed of northeastern Algeria using the ARFIMA model. Annals of Arid Zone 65(1): 231-246

https://doi.org/10.56093/aaz.v65i1.170211

https://epubs.icar.org.in/index.php/AAZ/article/view/170211

Climate researchers heavily depend on historical rainfall data to project future precipitation trends, yet the application of standard statistical methods for short- and long-term forecasting remains a significant challenge. To address this, long-memory forecasting models have emerged as valuable tools in time series and hydrological forecasting, demonstrating their capability to capture the complex dynamics of hydrological processes. For instance, Serinaldi and Kilsby (2015) highlighted the effectiveness of these models in representing the non-stationary nature of extreme rainfall events, emphasizing the importance of long-range dependence. Furthermore, research in Sadaei *et al*. (2016) indicates that combining AutoRegressive Fractionally Integrated Moving Average (ARFIMA) models with fuzzy time series can enhance prediction accuracy across various fields. The value of long-memory models, particularly artificial neural networks, in improving hydrological and streamflow predictions has also been demonstrated in Tang *et al*. (1991). Similarly, Anctil and Coulibaly (2004) focused on optimizing recurrent neural network structures for streamflow forecasting, showcasing their ability to capture temporal dependencies and improve hydrological predictions. Collectively, these studies underscore the critical role of long-memory forecasting models in hydrological applications and their potential to advance rainfall pattern predictions.

The ARFIMA process has been extensively studied for modeling and forecasting, with foundational work on its development conducted in (Beran, 1995; Robinson, 1995), as discussed in (Doornik and Ooms, 2004); Retia and Gaidi, 2017). These contributions have advanced the long-memory ARFIMA (p,d,q) framework, which now sees broad applications across disciplines. As highlighted in (Olbermann *et al*., 2006; Guo *et al*., 2019), the ARFIMA process is utilized in fields such as economics, finance, hydrology, climatology, physics, biology, ecology, and urban environmental and population studies.

This study examines the characteristics and persistence of forecast memory in monthly rainfall data from four stations within the hydrologically significant Seybouse watershed in Northeastern Algeria, spanning the period 1998-2007. We utilize the ARFIMA (p,d,q) model to analyze rainfall patterns and forecast future trends. Parameter estimation is performed using maximum likelihood (ML) and nonlinear least squares (NLS) methods, while long-term correlation (forecast memory) is quantified via the Hurst exponent (H), a robust measure explored in (Valerie, 1998; Na *et al*., 2018). As part of the broader class of long-memory forecasting models, ARFIMA Serinaldiof research specifically focused on Northeastern Algeria, particularly within the Seybouse watershed. Furthermore, a prevailing focus on annual or seasonal rainfall data in existing studies overlooks the valuable insights offered by finer-grained monthly temporal variations. This study aims to bridge these gaps by conducting a detailed investigation into monthly rainfall persistence within the Seybouse watershed. Additionally, although ARFIMA models are widely applied, a thorough comparative analysis of different parameter estimation methodologies is lacking. Therefore, this research will contribute by comparing the efficacy of Maximum Likelihood and Nonlinear Least Squares estimation methods for ARFIMA model parameters. Finally, while preliminary research has explored the integration of ARFIMA models with other forecasting techniques, further investigation is needed to fully understand their synergistic potential. This study will address this by examining the integration of ARFIMA models with Hurst exponent analysis.

This article is structured as follows: Initially, we detail the data and study area. Subsequently, we review the concept of long memory and the ARFIMA model's properties. We then describe the maximum likelihood and nonlinear least squares estimation methods used to determine the differentiation coefficient (d) and Hurst exponent (H). Following this, we present and interpret our results. Finally, we conclude with a summary of the key findings.

Material and Methods

Data collection and study area

The study focuses on the Seybouse watershed in northeastern Algeria, which covers an area of 6400 km². The watershed covers approximately 0.288% of Algeria's land area and encompasses 68 communes (municipalities), 30 of which lie entirely within its boundaries. It originates on the Sellaoua and Haracta high plains and terminates on the Annaba coastal plain, flowing northward to discharge at Sidi Salem at 0 m (NGA vertical datum). The basin is elongated along a north-south axis, extending roughly 160 km and draining a set of highly heterogeneous physiographic regions (Ghachi, 1986; Kadi, 1997). Within the Seybouse basin, irrigated land totals 13976 ha, representing 2.18% of the basin's total surface area. The watershed is located between 35°53′ and 36°57′ N latitude and 6°48′ and 7°59′E longitude. It is bordered by the Tunisian borders to the east, the Mdjerda watershed to the west, the foothills of the Saharan Atlas to the south, and the southern coastline of the Mediterranean Sea to the north. The study area's precise location is shown in Figure 1.

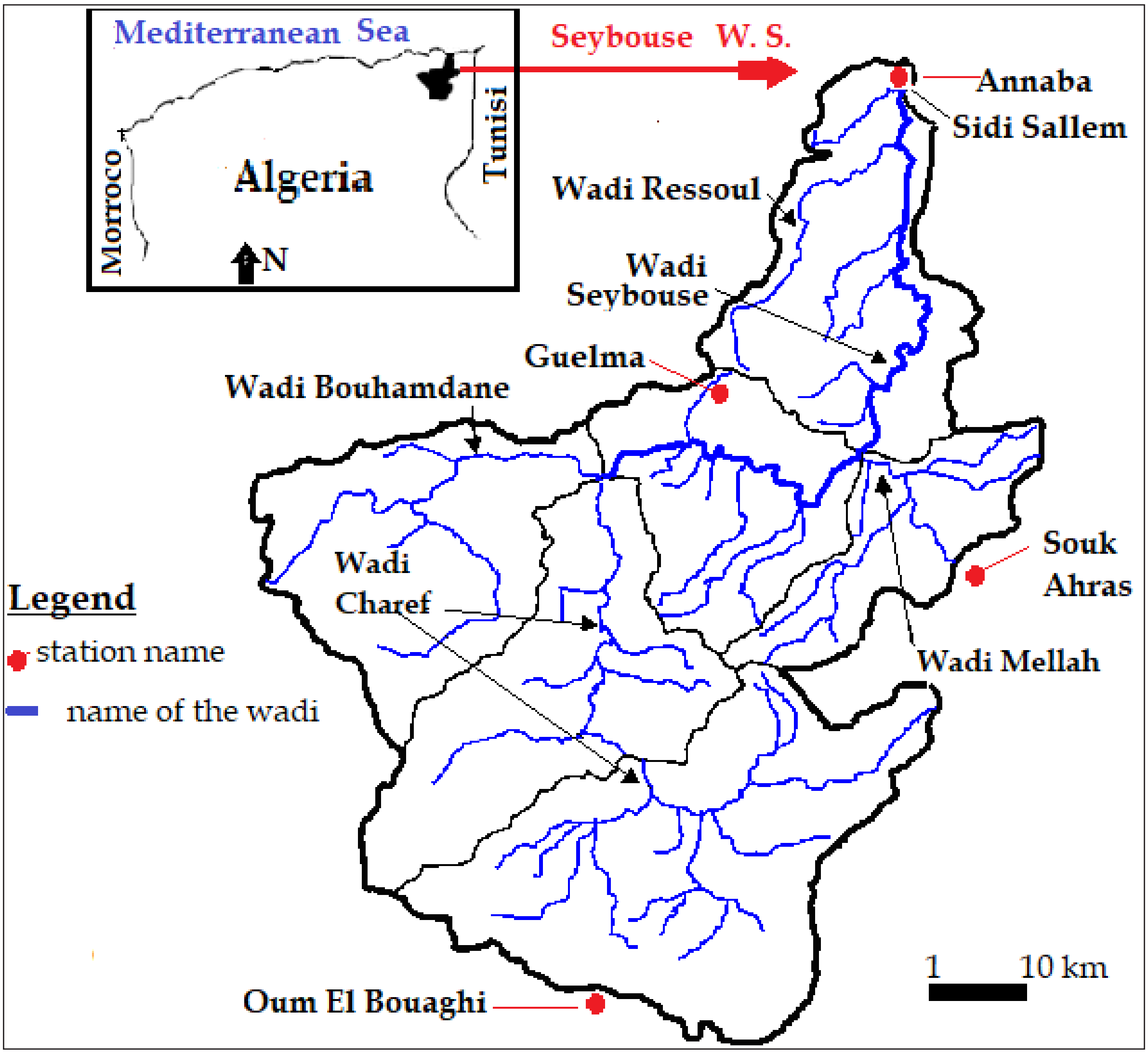

Fig. 1. Drainage network and locations of rainfall stations in the Seybouse Basin.

Monthly precipitation data for the study were obtained from the National Water Resources Agency (NWRA) of the Wilaya of Constantine and the Wilaya of Algiers. The research applies ARFIMA process modeling to four representative precipitation time series from four rainfall stations (Fig. 1). The data covers the period from 1998 to 2007, totaling 120 monthly cumulative records. The following is a list of the station names and their coordinates:

- Annaba station: altitude 3 m, latitude 36°50′N, longitude 7°48′E
- Guelma station: altitude 227 m, latitude 36°28′N, longitude 7°28′E
- Souk Ahras station: altitude 590 m, latitude 36°05′N, longitude 7°25′E
- Oum El Bouaghi station: altitude 889 m, latitude 35°52′N, longitude 7°07′E

Two rain gauges are located within a ≤15 km buffer outside the topographic divide but sample the same synoptic systems and elevation ranges as adjacent sub-basins. For basin aggregates, we compute spatial weights (Thiessen/IDW) clipped to the watershed polygon, so only the interior portion of each gauge's influence contributes to basin means.

Station representativeness and homogeneity checks

We assessed the representativeness and quality of each monthly rainfall series using a three-part workflow. First, data completeness and distributional adequacy were verified via the Jarque-Bera test, Box-Cox variance-

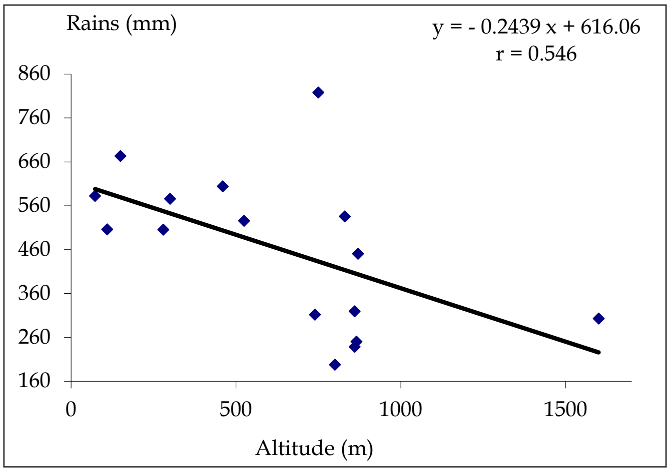

Fig. 2. Rainfall-altitude correlation diagram.

stabilizing transformation, and inspection of skewness/kurtosis; augmented Dickey-Fuller (ADF) testing rejected the unit-root null, confirming stationarity of transformed series. Second, homogeneity and trend were evaluated using Mann-Kendall, Buishand, Pettitt, and Von Neumann statistics at α = 0.05; results (Table 1) indicate homogeneous, trend-free series at monthly scale. Third, spatial representativeness was established by comparing station elevations with basin hypsometry and by computing Thiessen/IDW areas-of-influence clipped to the watershed polygon so that only the interior fraction of each gauge contributes to basin

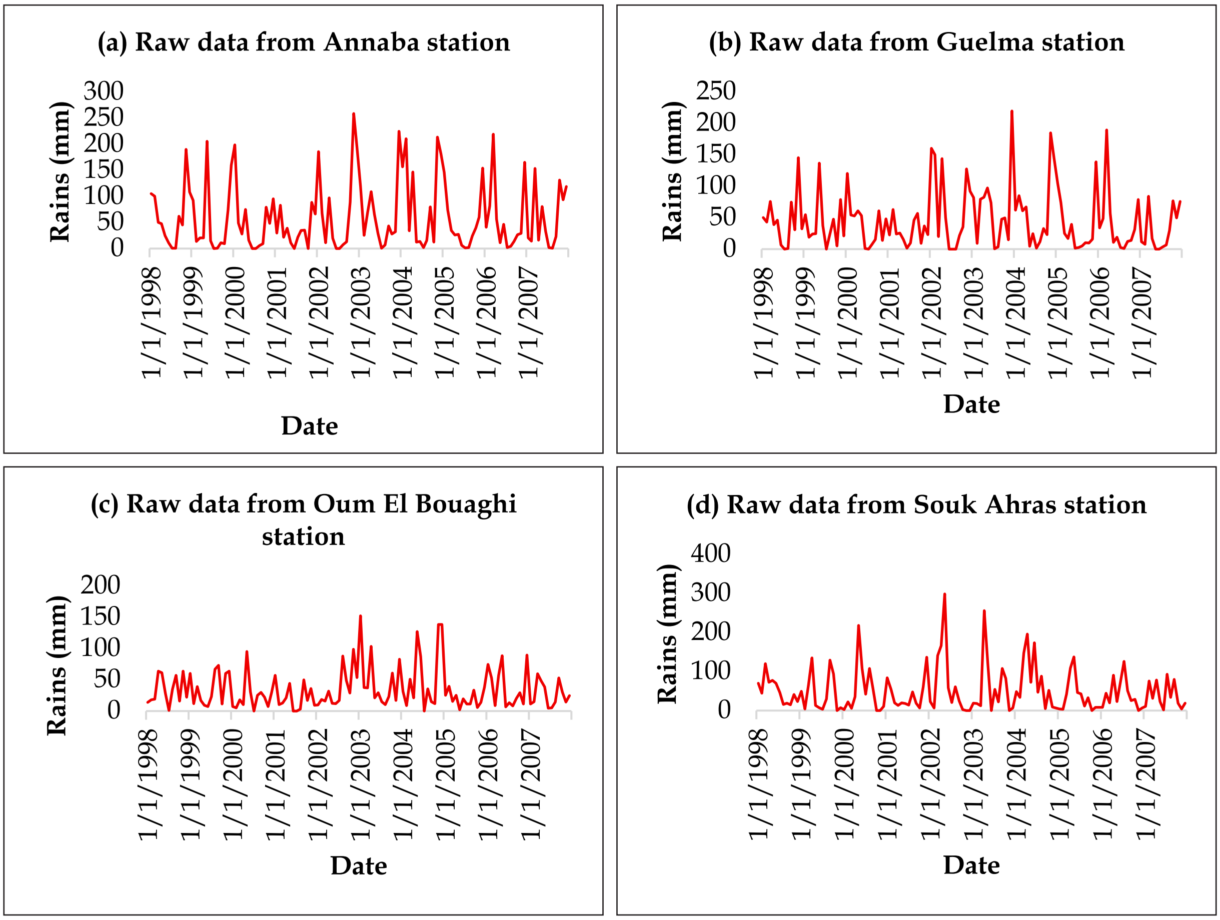

Fig. 3. Raw datasets collected from the meteorological stations of (a) Annaba, (b) Guelma, (c) Oum El Bouaghi and (d) Souk Ahras.

aggregates. A sensitivity check using only interior gauges reproduced the same qualitative persistence classes.

Climatic setting and hydroclimatic variability of the Seybouse basin (1970-2007)

Algeria has experienced pronounced multi-year droughts, alongside increases in mean annual air temperature of approximately 0.65-1.45°C between 1970 and 2004, a magnitude comparable to the global warming observed over 1906-2005 (Meddi *et al*., 2010). Consistent with these trends, a persistent hydrological deficit over the past three decades was attributable to an estimated 30% decline in precipitation (Balah, 2016). Within this national context, prior climatological studies of the Seybouse River Basin underscore its Mediterranean regime. Bouanani (2004) describes marked spatial and seasonal variability in rainfall and temperature across northern Algeria, with a rainy season spanning roughly September-May and a dry, sunny summer. Building on this, Balah (2016) applied Nicholson's standardized rainfall index (SRI) to regionalize and classify rainfall regimes across the basin. The analysis indicates a notable rainfall deficit and intense drought prior to 1972, followed by an alternation of dry and wet periods from 1972 to 2007. Two years are particularly diagnostic: 2001, characterized by extreme drought basin-wide, and 2003, marked by a basin-wide precipitation surplus. Balah (2016) also reports a negative rainfall-altitude gradient of approximately −0.244 (Fig. 2) along a south-north transect terminating at Sidi Salem (0 m, NGA datum), implying that lower-elevation gauges receive higher rainfall totals. This pattern is consistent with the maritime influence of the Mediterranean, including cyclogenesis centers and mobile depressions, which modulate precipitation over the basin as part of the broader regional climate system.

All four stations show the expected Mediterranean seasonality (wet winters-springs, dry summers) with strong interannual variability (Fig. 3). Annaba exhibits frequent winter-spring surges; Oum El Bouaghi is lower-amplitude; Guelma is intermediate; and Souk Ahras shows the most episodic extremes. The absence of obvious trends and the presence of multi-month wet/dry sequences are consistent with the persistence/anti-persistence patterns analysed later, justifying the ARFIMA approach.

Data transformation and model building

In time series analysis for modeling and forecasting, data transformations are commonly used to ensure that the experimental values conform to a normal distribution and exhibit a Gaussian and homoscedastic process, as proposed by Box and Cox (1964). However, it is important to note that such transformations to a nonlinear scale introduce modifications to both the model and the autocorrelation function of the transformed data, as discussed by Corduas (2000).

The analysis follows a basic procedure outlined as follows:

First, the normality of the monthly rainfall series from four representative stations in the Seybouse watershed is examined using the Jarque-Bera test, which calculates the statistical parameters of kurtosis and skewness. To ensure that the experimental distribution aligns with a theoretical law such as the normal distribution, a recommended transformation defined by equation (1) is applied (Box and Cox, 1964; Melard, 1979; D'Elia and Piccolo, 2004; Kharbbouch and Daoui, 2018).

$$Y_t \rightarrow \begin{cases} \dfrac{X_t^{\lambda}-1}{\lambda} & With \;\; X_t \geq 0 \;\; and \;\; \lambda > 0 \\ Ln(X) & With \;\; X_t > 0 \;\; and \;\; \lambda = 0 \end{cases} \quad ...(1)$$

Equation (1) introduces a constant λ that optimizes the normal distribution curve for maximum likelihood. The transformation is further evaluated by estimating ARFIMA models and forecast memory type through validation, using the actual values.

Second, to assess the consistency, trend, and homogeneity of the rainfall data, four tests are employed: Man-Kendall (MK), Buishand, Pettitt, and Von Neumann tests. For instance, the MK test detects trends in a time series without specifying their linearity. These tests have proven effective in trend detection and evaluation (Ludwig *et al*., 2004).

Third, the augmented Dickey-Fuller test (ADF) is used in statistical hydrology to examine the null hypothesis (H_0) of stationarity and trend. It efficiently determines the presence of a unit root in a rainfall series sample, contrasting it against the alternative hypothesis (H_a). Stationarity analysis aims to standardize asymptotic properties without influencing the model.

Fourth, after constructing the ARFIMA models, their quality is validated by testing the residuals.

Fifth, various methods for estimating the parameter (d) in univariate time series ARFIMA modeling are discussed and categorized as semi-parametric and parametric methods. The ML and NLS methods are implemented to estimate the ARFIMA model for monthly rainfall in the Seybouse watershed, utilizing the Ox metrics 6.0 program. This software effectively identifies and estimates the parameter (d) and resolves temporal data-related issues (Aouad *et al.*, 2012). The selected models were constructed without employing Robinson's method to enhance the estimation of the fractional differentiation parameter (d) (Retia and Gaidi, 2017).

ARFIMA Model

The ARFIMA model, developed by Granger and Joyeux (1980) and Hosking (1981), extends traditional ARIMA frameworks by allowing fractional differentiation (d), enabling flexible modeling of long-memory processes in fields like hydrology. Unlike ARIMA's integer-based differentiation, ARFIMA accommodates real-valued d, enhancing adaptability to complex datasets (Cao *et al.*, 2018; Retia and Gaidi, 2017). Key to its application is the Hurst exponent (H), which quantifies long-term memory and relates to d via $H = d + 0.5$ (Valerie, 1998).

Data classification by H:

- H = 0.5: Standard Brownian motion (no memory)
- H > 0.5: Persistent long-memory (positive autocorrelations)
- H < 0.5: Anti-persistent (alternating trends)
- 0.5 < H < 1: Hyperbolic decay in autocorrelations, non-periodic cycles
- 0 < H < 0.5: High-frequency dominance, anti-persistence (Mandelbrot-Joseph effect)

The ARFIMA(p,d,q) model (Equation 3) prioritizes estimating d to capture memory dynamics, making it vital for analyzing hydrological and economic time series :

$$\Phi(B)(1-B)^d X_t = \Theta(B)\varepsilon_t \quad For\ d \in (-0.5; 0.5) \qquad ...(3)$$

Here, d takes values within the range (-0.5, 0.5), ε_t represents a white noise process with

$E(\varepsilon_t) = 0$ and variance σ^2_ε, and B denotes the backshift operator such that $BX_t = X_{t-1}$.

The polynomials in Equation (4):

$$(B) = 1 - \Phi_1 B - \dots - \Phi_n B^P \ and \ \Theta(B) = 1 - \theta_1 B - \cdots \dots - \theta_q B_q \qquad ...(4)$$

have orders (p) and (q) respectively, with all their roots located outside the unit circle.

Maximum Likelihood (ML)

To estimate the fractional differentiation parameter (d) of the ARFIMA model and derive the Hurst exponent (H) from the rainfall time series in the Seybouse watershed, the maximum likelihood method is used. According to Lai [(Lai, 2004)], the ML method provides an asymptotically normally distributed estimate for the Hurst exponent in the case of fractional constant motion. McCoy and Walden (1996) proposed an approximate maximum likelihood estimation method (MLE) to estimate the fractional differentiation parameter of a fractional white noise process, which includes the regular long-memory parameter. The ARFIMA (p, d, q) model for y is represented by Equation (5):

$$\Phi(L)\ (1-L)^d\ (y-\mu) = \Theta(L)\ \varepsilon_t \quad ; t = 1, \dots, T \qquad ...(5)$$

where Φ (L) = (1 - 1 L − . . . - p L p) is the autoregressive polynomial and Θ (L) = (1 + θ_1 L_1 + . . . + θ q L q) is the moving average polynomial in the lag operator L. The parameters (p) and (q) are integers, and (d) is a real number. The term (1 - L) d represents the fractional difference operator, defined by the binomial expansion in Equation (6):

$$(1-L)^d = \sum_{j=0}^{\infty} \delta_j\ L^j = \sum_{j=0}^{\infty} \binom{d}{j}\ (-L)^j \qquad ...(6)$$

We assume ε ~ *NID* (0, σ^2) and denote μ_t as the mean of y_t, where ε_i represents a random error term. *NID(0, σ)* indicates a normally and independently distributed variable with mean 0 and variance σ^2.

The advantage of the ML method is that it considers both short-term and long-term information about the behavior of the time series because it simultaneously estimates the moving autoregressive average and the fractional differentiation parameter (d) (Aouad *et al.*, 2012).

Non-linear Least Squares estimation method (NLS)

Regression analysis typically employs the non-linear least squares method. An approximate maximum likelihood (ML) estimator, which minimizes the sum of squared residuals, was introduced in (Beran, 1995). This estimator is applicable to stationary ARFIMA processes with a fractional differentiation parameter d>0.5. The corresponding approximate log-likelihood is defined by Equation (7) (Cekim *et al.*, 2021).

$$Log\, L_A\,(d,\Phi,\theta,\beta) = c - \frac{1}{2} log \frac{1}{T-K}\sum_{t=2}^{T} \tilde{e}_t^2 \quad ...(7)$$

With is the residu. This equation can be further simplified as shown in Equation (8).

$$\sigma_e^2 = \frac{1}{T-K}\sum_{t=2}^{T} \tilde{e}_t^2 \quad ...(8)$$

The residual variance (Equation 8) estimator now uses T-k, ensuring unbiasedness when p = q = d = 0.

The asymptotic efficiency and normality of the estimators for (d, φ, θ) were demonstrated in Beran (1995). Monte Carlo evidence supporting its effectiveness for ARFIMA(0, d, 0) models with unknown means has been presented in (Doornik and Ooms, 2004; Beveridge and Oickle, 1993; Chung and Baillie, 1993). This estimator is referred to as the conditional sum-of-squares estimator in (Chung and Baillie, 1993).

Results and Discussion

Statistical analysis of monthly rainfall data

The estimation of ARFIMA model parameters for the examined monthly rainfall series (in mm), rainfall prediction, and determination of memory type using the Hurst exponent calculation involves a purely statistical investigation. This investigation includes assessing stationarity, testing homogeneity, and checking normality at a significance level of 5%.

The application of the ADF test reveals the presence of a unit root in all the considered rainfall data. These results provide evidence for the stationarity of the data, as the alternative hypothesis (Ha) is accepted, and the risk of incorrectly rejecting the null hypothesis (H_0) is extremely low. Specifically, the probability of rejecting H_0 when it is true is less than 0.001% for the Souk Ahras station, 0.004% for the Oum El Bouaghi station, 0.009% for the Guelma stations, and less than 0.0001% for the Annaba station.

Table 1 presents the descriptive statistics of the collected data and the optimal λ constants of the Cox-Box transformation. These constants are selected to align the experimental distribution curve of the precipitation series with the theoretical distributions, maximizing the likelihood and verifying the normality of the data. The λ values for each station are as follows: 0.274 for the Annaba station, 0.299 for the Guelma station, 0.147 for the Oum El Bouaghi station, and 0.174 for the Souk Ahras station.

The results obtained from the Jarque Bera (JB) test, which examines normality, indicate probabilities above the significance level of α = 5%. This confirms the stationarity and normality of the data, which is crucial for the feasibility of constructing ARFIMA models. In this context, the estimation of the transformation parameter λ is conducted separately to estimate the integration parameter (d) later. The significance of the latter effect is particularly noteworthy, as it suggests that an optimal data transformation using the constant λ could lead to an accurate estimation of the fractional differentiation parameter (d) in the ARFIMA model.

Descriptive statistical analysis reveals that the monthly rainfall data exhibit positive skewness, with a spread towards higher values than their mean. Additionally, the data display positive kurtosis, indicative of a relatively sharp distribution and the possibility of a leptokurtic distribution. These findings confirm that the process of generating the four rainfall datasets is non-Gaussian.

The results of the homogeneity and trend tests indicate that the monthly rainfall data are both homogeneous and stationary. The null hypothesis (H_0) of the Buishand and Pettitt tests is not rejected at the significance level of α = 5%, supporting the stationarity of the data. The MK test accepts the alternative hypothesis (Ha), further confirming that the data used are

Table 1. Statistical parameters and tests applied for the representative rainfall stations of the watershed

Parameters[1]	Station name			
	Annaba	Guelma	Oum El Bouaghi	Souk Ahras
λ	0.274	0.299	0.147	0.176
Average [mm]	59.794	45.2	34.1	50.6
Stand deviation [mm]	63.55	46.19	31.54	55.62
Cv	1.063	1.021	0.926	1.099
Maximum (P max) [mm]	258.9	219.5	152.2	298.6
Minimum (P min) [mm]	0	0	0	0
Skewness (β1)	1.277	1.488	1.574	1.845
Kurtosis (β2)	0.661	1.999	2.407	3.980
Test of normality (JB)	0.3579	0.7538	0.8675	0.399
MK test	0.645	0.836	0.938	0.524
Buishand test	0.382	0.457	0.144	0.357
Pettitt test	0.388	0.289	0.443	0.78
Von Neumann ratio test	0.004	0.09	0.058	0.001

(1): λ = optimal coefficients, C_V = coefficient of variation.

stationary. The results of the Von Neumann nullity hypothesis reveal that the data series from the Souk Ahras and Annaba stations are rejected (rate lower than 5%), while the data from the other two stations are accepted (rate higher than 5%). Based on the results of these three tests, we conclude that all the data used, covering the entire Seybouse watershed, are suitable for constructing ARFIMA models and examining the type of forecast memory.

Table 1 summarizes distributional (λ, C_V, skewness, kurtosis) and homogeneity tests (ADF, JB, MK, Buishand, Pettitt); the transformed monthly series are stationary and homogeneous at α = 0.05, with serial dependence treated in the ARFIMA/Hurst modeling.

Selection of Forecasting Technique: The selection of the best forecasting technique from the modelling results with the ARFIMA process indicated in Tables 2, 3, 4, and 5, suggests that the most suitable technique is that of ML to model the rain series of the stations studied. This choice is based on the following criteria:

- The test of the adequacy of the model gives a minimum information criterion of Akaike (AIC)
- The residue examination with the Ljung Box test (Portmanteau) defined in Equation (9) is acceptable and their value is greater than the alpha (α) significance level equal to 5%
- The values of the standard deviations of the ARFIMA models constructed are minimal
- The results of the normality test of residues by the ML method are greater than the α significance level equal to 5%.

$$Q = n.(n+2).\sum_{k=1}^{h}\frac{\rho_k^2}{n-k} \quad ...(9)$$

The auto-correlation function (ρ) measures the correlation between a time series and its lagged values, where k represents the lag, n is the data size, and h denotes the degrees of freedom.

The results of the residuals for the ARFIMA models built with the two methods NLS and ML, recorded in the tables (2-5) have negative kurtosis (ARFIMA models of the four stations) and skewness (models of the two rainfall stations of Oum El Bouaghi and Guelma). While the values of skewness of the ARFIMA model built for the station of Annaba, have a positive value with the method of ML and a negative value with the method NLS, and the value of skewness of residue for the ARFIMA model of the rainfall station of Souk Ahras is positive by the two methods ML and NLS.

Hurst exponent analysis

The results of Hurst exponents (H) are deduced from the values of the differentiation parameter (d) of the ARFIMA model according to the equation. (1), are different from zero,

Table 2. ARFIMA Model Results for Annaba Station Rainfall Data, with Hurst Exponents

Param.	ARFIMA (5,d,14) model estimated by the ML method				ARFIMA (5,d,14) model estimated by the Non-linear least squares estimation method NLS			
	Coeff AR (ϕ_i) MA (θ_i)	Std.Error	t-value	t-prob	Coeff AR (ϕ_i) MA (θ_i)	Std.Error	t-value	t-prob
d	0.13	0.3483	-0.382	0.73	**-0.59**	0.2501	2.35	0.021
H	0.63				-0.09			
AR-1	0.626772	0.0458	13.7	0	1.34306	0.155	8.67	0
AR-2	-0.244068	0.07197	-3.39	0.001	0.567901	0.2538	2.24	0.027
AR-3	0.703206	0.0659	10.7	0	-0.126619	0.3355	-0.377	0.707
AR-4	-0.803032	0.05327	-15.1	0	-2.14429	0.272	-7.88	0
AR-5	-0.207712	0.03261	-6.37	0	1.64123	0.2142	7.66	0
MA-1	-0.412519	0.3627	-1.14	0.258	-0.354405	0.2306	-1.54	0.128
MA-2	0.270703	0.1349	2.01	0.047	-0.418567	0.1491	-2.81	0.006
MA-3	-0.927349	0.1992	-4.66	0	-0.27097	0.22	-1.23	0.221
MA-4	0.694882	0.2635	2.64	0.01	0.498685	0.2689	1.85	0.067
MA-5	0.322676	0.2033	1.59	0.116	0.010788	0.1749	0.0617	0.951
MA-6	0.368237	0.2164	1.7	0.092	0.330378	0.1361	2.43	0.017
MA-7	-0.083817	0.2597	-0.323	0.748	-0.116907	0.18	-0.649	0.518
MA-8	-0.117847	0.1581	-0.745	0.458	-0.0731179	0.1658	-0.441	0.66
MA-9	-0.157533	0.177	-0.89	0.376	-0.0585876	0.1258	-0.466	0.642
MA-10	-0.002993	0.2093	-0.0143	0.989	-0.0142099	0.1523	-0.0933	0.926
MA-11	0.135514	0.199	0.681	0.498	0.0689121	0.1498	0.46	0.647
MA-12	0.068671	0.1639	0.419	0.676	0.0762915	0.1588	0.481	0.632
MA-13	-0.0272447	0.1709	-0.159	0.874	0.0052454	0.1435	0.0366	0.971
MA-14	-0.0862969	0.1363	-0.633	0.528	-0.0661308	0.1383	-0.478	0.634
Const.	6.52922	0.08996	72.6	0.00	6.51134	0.1220	53.4	0.00

ML method	NLS method
log-likelihood: -278.067494	log-likelihood: -1.54942263
no. of observations 120 no. of parameters 22	no. of observations 120 no. of parameters 22
AIC: 5.00112	AIC: 0.39249
mean: 6.51134 var: 10.7566	Mean: 6.51134 var: 10.7566
sigma: 1.51662 sigma^2: 2.30013	sigma: 4.72849 sigma^2: 22.36
Portmanteau (25): Chi-2(5) = 7.6019 [0.1796]	Portmanteau (25): Chi-2(5) = 25.919 [0.0001] **
Normality test for residuals	Normality test for residuals
Mean -0.0044	Mean -0.1285
Std. Devn. 2.3364	Std. Devn. 4.7070
Skewness 0.2819	Skewness -0.1079
Excess Kurtosis -0.5328	Excess Kurtosis -0.1887
Minimum -5.3177	Minimum -12.266
Maximum 5.9647	Maximum 11.789
Asymptotic test: Chi-2(2) = 3.0093 [0.2221]	Asymptotic test: Chi-2(2) = 0.41109 [0.8142]
Normality test: Chi-2(2) = 4.1310 [0.1268]	Normality test: Chi-2(2) = 0.26260 [0.8770]

certify the presence of a positive self-correlation and the process presents a form of persistence of long-memory namely: the station of Annaba and Oum El Bouaghi. These results mean that the predicted future rainfall is consistent with the observed rainfall over the entire study period (1997 to 2008). Unlike the rainfall data recorded at two stations in Souk Ahras and Guelma, which are inconsistent and present an anti-persistence (Joseph effect), hence, past rains are more likely to conflict with future rains.

Throughout our article, we use the notation AIC to contextually refer Akaike information criterion. An important finding is that the values of the Hurst exponent H estimated by the two

Table 3. ARFIMA Model Results for Guelma Station Rainfall Data, with Hurst Exponents

Param.	ARFIMA (9,d,4) model estimated by the ML method				ARFIMA (9,d,4) model estimated by the Non-linear least squares estimation method NLS			
	Coeff AR (ϕ_i) MA (θ_i)	Std.Error	t-value	t-prob	Coeff AR (ϕ_i) MA (θ_i)	Std.Error	t-value	t-prob
d	0.59	0.3144	-1.89	0.061	-0.16	0.084	-1.85	0.067
H	1.09				0.34			
AR-1	0.98964	0.4098	2.41	0.017	0.710281	0.1595	4.45	0
AR-2	0.560527	0.5947	0.943	0.348	0.677408	0.314	2.16	0.033
AR-3	-0.664742	0.4168	-1.59	0.114	-0.966752	0.4799	-2.01	0.047
AR-4	-0.594583	0.4184	-1.42	0.158	-0.231506	0.4713	-0.491	0.62
AR-5	0.385072	0.3068	1.26	0.212	0.156898	0.3442	0.456	0.65
AR-6	0.371424	0.143	2.6	0.011	0.312432	0.3742	0.835	0.406
AR-7	-0.256082	0.1864	-1.37	0.172	-0.232501	0.2348	-0.99	0.324
AR-8	-0.076419	0.2075	-0.368	0.713	-0.21539	0.211	-1.02	0.31
AR-9	0.181886	0.1401	1.3	0.197	0.258608	0.175	1.48	0.142
MA-1	-0.34095	0.3396	-1	0.318	-0.573256	0.2724	-2.1	0.038
MA-2	-0.584273	0.3802	-1.54	0.127	-0.554022	0.5311	-1.04	0.299
MA-3	0.159384	0.2959	0.539	0.591	0.195448	0.5763	0.339	0.735
MA-4	0.598214	0.2751	2.17	0.032	0.0897023	0.3927	0.228	0.82
Const.	6.32951	0.162	39	0.0	6.30653	0.071	88	0.0

log-likelihood: -286.065125	Log-likelihood -1.50253291
no. of observations 120 no. of parameters 16	no. of observations 120 no. of parameters 16
AIC: 5.03442	AIC: 0.29171
Mean: 6.30652 var: 9 .3577	Mean: 6.30652 var: 9.3577
sigma: 2.589 sigma^2: 6.70696	sigma: 4.5119 sigma^2: 20.357
Portmanteau (21): Chi-2(7) = 6.7444 [0.456]	Portmanteau (21): Chi-2(7) = 344.91 [0.0000]**
Normality test for residuals	Normality test for residuals
Mean 0.0564	Mean 0.2200
Std. Devn. 2.5892	Std. Devn. 4.4877
Skewness -0.0637	Skewness -0.107
Excess Kurtosis -0.2110	Excess Kurtosis -0.2344
Minimum -6.4817	Minimum -10.348
Maximum 6.3055	Maximum 11.078
Asymptotic test: Chi-2(2) = 0.30417 [0.8589]	Asymptotic test: Chi-2(2) = 0.50362 [0.7774]
Normality test: Chi-2(2) = 0.09652 [0.9529]	Normality test: Chi-2(2) = 0.29001 [0.8650]

methods are very different and show a spatial distribution. The values of H are limited from 0.05 to 0.13 for the Souk Ahras station, from 0.54 to 0.61 for the Oum El Bouaghi station, from -0.09 to 0.63 for the Annaba station and from 0.34 to 1.09 for the Guelma station.

Optimal ARFIMA Models

To accept an optimal ARFIMA model for our study area, among the two methods used in Tables 2, 3, 4 and 5, some conditions are taken into consideration: 1) the residuals follow a normal distribution, are asymptotic and homoscedastic for a significance level α greater than 5%, 2) the variance is minimal, 3) a value of the Akaike criterion is minimal. With all these conditions, we find the following:

We retain that the ML method seems optimal for the modelling with the ARFIMA process of the Annaba station data and the NLS method for the rest of the data.

The findings presented in this article align with the context, results, and observations of the study conducted by Rana [(Rana *et al.*, 2013)]. The study established that the NLS method is simple, more stable, and provides a better fit, which is consistent with field data. However,

Table 4. ARFIMA Model Results for Oum El Bouaghi Station Rainfall Data, with Hurst Exponents

Param.	ARFIMA (0,d,0) model estimated by the ML method				ARFIMA (0,d,0) model estimated by the Non-linear least squares estimation method NLS			
	Coeff AR (ϕ_i) MA (θ_i)	Std.Error	t-value	t-prob	Coeff AR (ϕ_i) MA (θ_i)	Std.Error	t-value	t-prob
d	0.04	0.08182	0.510	0.611	0.11	0.09095	1.21	0.231
H	0.54				0.61			
AR-0	-	-	-	-	-	-	-	-
MA-0	-	-	-	-	-	-	-	-
Const.	0.16128	0.16	26.3	0.0	4.16622	0.21	19.5	0.00
log-likelihood -214.042381					log-likelihood -0.365409444			
no. of observations 120 no. of parameters 3					no. of observations 120 no. of parameters 3			
AIC : 3.617372					AIC : 0.05609			
mean : 4.16622 var : 2.07869					mean : 4.16622 var : 2.07869			
sigma : 1.44008 sigma^ : 2.0738					sigma : 1.44715 sigma^2 : 2.0943			
Portmanteau (25): Chi-2(24) = 11.253 [0.9871]					Portmanteau (25): Chi-2(24) = 12.840 [0.9687]			
Normality test for residuals					Normality test for residuals			
Mean	0.0018				Mean 0.00231			
Std. Devn.	1.4401				Std. Devn. 1.4411			
Skewness	-0.031				Skewness -0.07634			
Excess Kurtosis	-0.2354				Excess Kurtosis -0.20749			
Minimum	-42018				Minimum -4.2675			
Maximum	3.1804				Maximum 3.1137			
Asymptotic test: Chi-2(2) = 0.29629 [0.8623]					Asymptotic test: Chi-2(2) = 0.3318 [0.8471]			
Normality test: Chi-2(2) = 0.03672 [.9818]					Normality test: Chi-2(2) = 0.1358 [0.9344]			

the results obtained from the ML method are considered more reasonable and statistically superior in predicting the parameters of the ARFIMA model.

Residual analysis

Examination of the residues with the Ljung-Box test, presents values greater than the level of significance $\alpha = 5\%$, which accepts the nullity hypothesis (H_0).

The value of the test is equal to 7.6 with a level of significance equal to 17.96% for the ARFIMA model representative of the station of Annaba, 6.744 with a level of significance equal to 45.6% for the rainfall of the station of Guelma, 11.253 with a level of significance equal to 98.71% for the rainfall of the station of Oum El Bouaghi and 21.211 with a level of significance equal to 38.48% for the ARFIMA model representing the rainfall of the station of Souk Ahras.

Concerning the ARFIMA models constructed and the values of the Hurst exponent estimated from the methods used in bold in tables 2,3,4 and 5 are the following: 1) for the Annaba station (5; 0.13; 14) corresponds to the Hurst exponent H equal to 0.63, the normally and independently distributed error NID (-0.0044, 2.3364), 2). For the station Guelma (9; 0.59; 4) corresponds to the Hurst exponent (H) equal to 1.09, the mean and standard deviation of residual is NID (0.00564, 2.5892), 3). For the station of Oum El Bouaghi (0; 0.04; 0) corresponds to the (H) equal to 0.54, the mean and standard deviation of residual are NID (0.0018, 1.4401) and 4) the station of Souk Ahras (2; -0.55; 2) corresponds to the H equal to 0.05 and the mean and standard deviation of residual are NID (-0.0138, 1.8698).

The results of the simple (ACF) and partial (partial ACF) autocorrelation functions are shown in Figures 4 (a-d). The bounds of the confidence interval are stylized by horizontal lines; each term that falls outside this interval is therefore significantly different from 0 at the 5% level.

Linking rainfall memory to watershed activities

We operationalise the persistence diagnostics for the Seybouse Basin by mapping

Table 5. ARFIMA Model Results for Souk Ahras Station Rainfall Data, with Hurst Exponents

	ARFIMA (2,d,2) model estimated by the ML method				ARFIMA (2,d,2) model estimated by the Non-linear least squares estimation method NLS			
Param.	Coeff AR (ϕ_i) MA (θ_i)	Std.Error	t-value	t-prob	Coeff AR (ϕ_i) MA (θ_i)	Std.Error	t-value	t-prob
d	-0.55	0.779	0.711	0.479	-0.37	0.7402	-0.498	0.62
H	0.05				0.13			
AR-1	0.608042	0.9175	0.663	0.509	0.493201	1.17	0.422	0.674
AR-2	0.00631181	0.5602	0.0113	0.991	-0.0555721	0.3592	-0.155	0.877
MA-1	0.218782	0.8192	0.267	0.79	0.156637	0.666	0.235	0.814
MA-2	0.0733935	0.2119	0.346	0.73	0.0743876	0.4157	0.179	0.858
Const.	5.05130	0.067	75.7	0.0	5.01361	0.204	24.6	0.00

ML method	NLS method
log-likelihood -245.926392	log-likelihood -0.628404532
no. of observations 120 no. of parameters 7	no. of observations 120 no. of parameters 7
AIC : 4.21544	AIC : 0.12714
Mean : 5.01361 var : 4.01553	Mean : 5.01361 var : 4.01553
sigma : 1.86985 sigma^2 : 3.496	sigma : 1.88248 sigma^2 : 3.544
Portmanteau(25): Chi-2(20) = 21.211 [0.3848]	Portmanteau(25): Chi-2(20) = 22.726 [0.3024]
Normality test for residuals	Normality test for residuals
Mean 0.0138	Mean 0.0952
Std. Devn. 1.8698	Std. Devn. 1.8722
Skewness 0.0376	Skewness 0.0492
Excess Kurtosis -0.6778	Excess Kurtosis -0.6785
Minimum -4.0733	Minimum -3.8949
Maximum 4.6806	Maximum 4.7542
Asymptotic test: Chi-2(2) = 2.3256 [0.3126]	Asymptotic test: Chi-2(2) = 2.3503 [0.3088]
Normality test: Chi-2(2) = 2.1543 [0.3406]	Normality test: Chi-2(2) = 2.2051 [0.3320]

station-specific Hurst exponents to concrete management levers. Persistent behavior ($H > 0.5$) at Annaba ($H \approx 0.63$) and Oum El Bouaghi ($H \approx 0.61$) indicates an elevated propensity for multi-month temporal clustering of wet or dry conditions, whereas anti-persistent behaviour ($H < 0.5$) at Guelma ($H \approx 0.34$) and Souk Ahras ($H \approx 0.13$) implies wet-dry alternation at the monthly scale. The guidance that follows is conditioned on these station-level diagnostics and synthesised to the basin scale using area weights from Thiessen/IDW polygons clipped to the watershed boundary, ensuring that near-boundary gauges contribute only their in-basin influence (Fig. 1; Table 2: ARFIMA-Annaba; Table 3: ARFIMA-Guelma; Table 4: ARFIMA-Oum El Bouaghi; Table 5: ARFIMA-Souk Ahras).

- Managed aquifer recharge (MAR): For persistent wet clusters and elevated spill risk, schedule MAR pulses downstream of reservoirs; under anti-persistence, favour smaller, more frequent injections to track alternation (Fig. 1; Table 2-5).
- Ecological flows: Use persistence signals to stage ecologically beneficial high-flow windows after multi-month wet clusters, while avoiding deleterious drawdown during developing dry clusters.
- Event sequencing: Anti-persistence increases wet-dry „whiplash“ that enhances erosivity; time hillside mulching, check-dam maintenance, and gully protection accordingly, especially in Guelma/Souk Ahras sub-basins (Fig. 1; Table 3; Table 5).
- Sediment management: At Annaba/Oum El Bouaghi, align desilting/sluicing windows with wet clusters rather than fixed calendar dates (Fig. 1; Table 2; Table 4)
- Allocation smoothing: Under anti-persistence, shorten allocation intervals (monthly rather than seasonal) and cap carry-over to avoid over-commitment after a single wet month (Fig. 1; Table 3; Table 5).

- Early warning: Use a 2-month cluster indicator (rolling 2-month sum standardised on the Box-Cox scale) as an operational signal for irrigation boards (Fig. 1; Table 2-5).
- Rule-curve buffer: For persistent upstream stations, apply an H-conditioned storage buffer (+5-8% of active storage during developing wet clusters; −3-5% during developing dry clusters) (Fig. 1; Table 2; Table 4).
- Flood preparedness: When 2-3 consecutive wet months occur at a persistent station (H > 0.55), initiate earlier pre-releases to create flood space while respecting environmental flows. (see Fig. 1; Table 2; Table 4).

Practical implications

The persistence/anti-persistence results translate directly into operational guidance for water management. At persistent stations (H > 0.5; Annaba H≈0.63, Oum El Bouaghi H≈0.61), there is an elevated likelihood of multi-month clusters of wet (or dry) conditions. This "memory" supports proactive adjustments to reservoir rule curves: increase the active-storage buffer by +5-8% when a wet cluster is developing to capture inflows, and reduce it by -3-5% when a dry cluster emerges to preserve environmental flows and limit evaporation. When 2-3 consecutive wet months are observed at a persistent station (H > 0.55), early pre-releases can be scheduled to create flood-control space while safeguarding downstream constraints (Fig. 1; Table 2: ARFIMA-Annaba; Table 4. ARFIMA-Oum El Bouaghi).

By contrast, anti-persistent stations (H < 0.5; Guelma H≈0.34, Souk Ahras H≈0.13) feature wet-dry alternation, which heightens operational volatility. In these catchments it is advisable to shorten allocation horizons (monthly rather than seasonal), implement carry-over caps to avoid over-commitment after a single wet month, and tighten reservoir hedging (avoid structural releases on the basis of one-month signals). The alternation also increases erosive "whiplash": plan hillslope mulching, check-dam maintenance, and gully protection immediately after wet spikes that are followed by dry months, when bare soils

Fig. 4. Autocorrelation and partial autocorrelation plots of the four rainfall stations :a-Annaba; b- Souk-Ahras; c- Oum El Bouaghi; d- Guelma.

are prone to crusting (Fig. 1; Table 3: ARFIMA-Guelma; Table 5: ARFIMA-Souk Ahras).

For sediment management and environmental flows, the persistence observed at Annaba/Oum El Bouaghi argues for timing desilting/sluicing windows to coincide with wet clusters rather than fixed calendar dates, leveraging higher transport capacity and reducing ecological impact. Regarding managed aquifer recharge (MAR), persistence supports batched recharge pulses during periods of elevated spill risk, whereas anti-persistence favours smaller, more frequent injections that track wet-dry alternation (Fig. 1; Tables 2-5).

To operationalise these signals, we propose (i) a two-month cluster indicator (two-month rolling sum standardised on the Box-Cox scale) as an early-warning trigger for irrigation boards and reservoir operators, and (ii) systematic use of Thiessen/IDW spatial weights clipped to the watershed boundary for basin aggregation, ensuring that near-boundary gauges contribute only their in-basin area of influence (Fig. 1; Tables 2-5). Together, these rules-indexed to the sign and magnitude of H, provide a reproducible framework to coordinate pre-allocation, flood-space management, erosion control, and MAR at the basin scale.

Limitations

A key limitation of this study is the record length and sampling frequency. Persistence in rainfall was quantified using ARFIMA through the fractional differencing parameter (d) and the implied Hurst exponent ($H = d + 0.5$) based on monthly observations for 1998-2007 (120 values per station). While this length is adequate for fitting parsimonious ARFIMA structures and performing standard residual diagnostics, shorter time series generally yield larger uncertainty in long-memory estimates and may reduce the statistical power to distinguish genuine long-range dependence from short-memory autocorrelation, regime shifts, or low-frequency non-stationarity (e.g., structural breaks, multi-year circulation anomalies). Accordingly, the reported d/H values should be interpreted as monthly-scale persistence within the available record, not as immutable long-term climatic parameters.

This limitation is not unique to the present study: in many semi-arid and data-sparse settings, long, homogeneous archives (especially at finer temporal resolution) are difficult to obtain. Recent research demonstrates that scientifically useful rainfall characterizations are often derived from short windows that capture intense episodes when longer records are unavailable. For instance, Machiwal *et al.*, 2025 used 1-min rainfall data from only two years (2020 and 2024) and explicitly noted that such high-resolution records were historically unavailable in that arid region; nevertheless, the study successfully quantified event metrics and identified storms reaching very high intensities.

To reduce sensitivity to record length, we relied on multiple estimators and selected the final specification using information criteria and diagnostic testing, but some uncertainty remains, particularly for borderline cases where d is near zero or where competing ARMA structures provide similar fits. Future work should therefore (i) extend the rainfall record where possible, (ii) evaluate the stability of d/H via rolling or split-sample estimation, and (iii) compare ARFIMA-based persistence with complementary estimators (e.g., DFA or wavelet-based scaling) while incorporating potential covariates (topography, LULC, and climate indices) to separate persistence from externally forced low-frequency variability.

Conclusions

This study assessed the memory properties of monthly rainfall in the Seybouse watershed (northeastern Algeria) using ARFIMA models and rigorous inference at α=0.05. Among the alternative estimators considered, nonlinear least squares (NLS) provided the best fit. The resulting classifications indicate anti-persistence ($H<0.5$) at Souk Ahras and Guelma, and persistence ($H>0.5$) at Annaba and Oum El Bouaghi, implying lower versus higher month-ahead predictability, respectively. Spatial variability in the estimated Hurst exponents underscores the role of local controls.

The H differences are consistent with Mediterranean coastal forcing at Annaba (multi-day frontal clustering), orographic setting and elevation over the Sellaoua-Haracta high plains (supporting stratiform sequences at Oum El Bouaghi), and lee/valley circulations that favor wet-dry alternation at Guelma and Souk Ahras. Additional modulation by land-surface heterogeneity (irrigated mosaics; urban coastal plain) may further condition month-to-month memory. These factors align with the persistence/anti-persistence partition reported here.

Overall, ARFIMA provides a suitable framework for diagnosing rainfall memory and informing risk-aware operations at monthly scale. Future work will integrate topography, land-use/land-cover (LULC), and climate-variability indices as covariates and refine the ARFIMA specification; an attribution analysis regressing H on distance-to-coast, elevation/slope/aspect, and LULC, conditioned on regional circulation indices, is a natural next step.

From a present-day perspective, the 1998-2007 record is best interpreted as a homogeneous baseline window that enables consistent inter-station comparison of monthly rainfall memory in the Seybouse watershed using a single ARFIMA framework. Because the sample comprises 120 monthly observations per station, uncertainty in the fractional differencing parameter and the implied Hurst exponent may be non-negligible; therefore, persistence classifications should be viewed as record-conditional indicators for this decade rather than fixed long-term climatic constants. Extending the analysis to longer archives and assessing parameter stability across sub-periods will further strengthen the generality of these findings.

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Printed in March 2026