

# Assessing Precipitation Memory and Operational Controls on National-Scale Reservoir Storage and Hydropower Dynamics in Türkiye

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## Research Article

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# Assessing Precipitation Memory and Operational Controls on National-Scale Reservoir Storage and Hydropower Dynamics in Türkiye

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## Abstract

Reservoir storage dynamics emerge from the tightly coupled interaction of precipitation-memory forcing and institutional operational management, yet disentangling these distinct controls remains challenging at national scales. This study investigates the multivariate relationships among precipitation, macro-scale reservoir storage, and hydropower generation in Türkiye using a data-efficient framework combining Seasonal-Trend Decomposition using Loess (STL), an optimized precipitation-memory index ( $PM_t$ ), and a Vector Autoregressive model with exogenous inputs (VARX). The optimized precipitation-memory structure identified a 12-month temporal lag window with a memory decay parameter of  $\tau = 1.25$ . Despite the extended memory horizon, climate forcing remained strongly concentrated at short lags, with approximately 91% of the cumulative memory weight occurring within the first three months. The precipitation-memory index was identified as a significant contributor to both reservoir-storage and hydropower-capacity-factor dynamics. Impulse-response analysis revealed positive responses of both reservoir storage and hydropower capacity factors to precipitation-memory innovations, although the responses occurred over different characteristic timescales. Forecast Error Variance Decomposition (FEVD) demonstrated that, although precipitation memory contributes a stable, non-trivial share to system variability, long-term forecast uncertainty is governed predominantly by endogenous hydropower-system dynamics, with smaller but persistent contributions from precipitation memory and reservoir-storage variability. Forward-looking scenario simulations further showed that sustained precipitation deficits generate progressive, non-linear storage anomalies through time, with a 30% precipitation deficit producing a cumulative storage drawdown of approximately 6.8 percentage points relative to baseline conditions after 24 months. The analytical outcomes indicate that hydro-climatic forcing and operational management jointly govern national-scale reservoir dynamics. Hydro-climatic variability provides the primary source of water-availability fluctuations, while institutional regulation controls how these signals persist and propagate through the system over time. The proposed framework provides a transferable and data-efficient approach for assessing reservoir resilience and water-energy interactions under increasing hydro-climatic variability.

**Keywords:** Precipitation memory; Reservoir storage dynamics; Hydropower capacity factor; Drought propagation; Socio-hydrological systems; VARX modeling.

## 1. Introduction

Multi-purpose reservoir systems operate at the dynamic intersection of hydro-climatic variability and human decision-making. Although 'hydro-climatic' encompasses processes like temperature and evapotranspiration, this study focuses specifically on precipitation as the primary climate forcing to isolate precipitation-driven memory from operational persistence. In semi-arid and Mediterranean regions, precipitation constitutes the primary meteorological forcing of basin-scale water availability. However, observed reservoir storage dynamics often exhibit weak contemporaneous correlations with monthly precipitation. This decoupling reflects the fact that storage evolution is not merely a direct hydrological response to immediate meteorological inputs; instead, it represents the cumulative outcome of delayed catchment processes like routing, soil moisture redistribution, and groundwater contribution. These physical mechanisms are intertwined with complex human regulations, including hydropower dispatch schedules, irrigation demands, and strategic water release decisions (Hanasaki et al., 2006; Vörösmarty et al., 2010).

The Mediterranean basin, including Türkiye, is widely recognized as a climate-change hotspot characterized by pronounced seasonality, high interannual variability, and increasing drought frequency (Giorgi, 2006; Giorgi and Lionello, 2008; Lionello and Scarascia, 2018; Spinoni et al., 2018). The IPCC Sixth Assessment Report underscores that compound drought risks are expected to intensify across this region, severely threatening precipitation regimes, soil moisture profiles, and the reliability of managed water resources (IPCC, 2022). In such vulnerable settings, reservoir networks play a critical buffering role by redistributing winter-dominated precipitation into dry summer periods. However, because this buffering capacity depends simultaneously on physical inflows and operational governance, storage trajectories cannot be interpreted as passive reflections of precipitation. Rather, they embody dynamically regulated socio-hydrological entities where physical processes and management decisions co-evolve over time (Sivapalan et al., 2011; Di Baldassarre et al., 2015, 2018; Wheeler and Gober, 2015). Under these shifting regimes, contemporary studies on reservoir management have increasingly highlighted the need for adaptive strategies and systemic resilience in operational planning (Dash and Raghuwanshi, 2023; Senbeta et al., 2024).

However, a central methodological challenge in analyzing this precipitation–storage coupling lies in distinguishing true climate forcing from shared seasonality and trend components—a distinction often overlooked when analyses rely solely on contemporaneous correlations. Time series of precipitation, storage, and hydropower production typically exhibit strong periodic structures and low-frequency variability. Without explicit separation of these components, statistical inference may be confounded by spurious correlations driven by common seasonal cycles rather than causal hydrological linkages (Granger and Newbold, 1974; Hamilton, 2020). While seasonal-trend decomposition methods, such as seasonal–trend decomposition (STL), provide a robust framework for isolating stationary residual anomalies prior to multivariate modeling (Cleveland et al., 1990; Hyndman and Athanasopoulos, 2018), identifying the dynamic interactions between climatic forcing and operational regulation remains a pervasive challenge (Yassin et al., 2019). Previous research confirms that large-scale reservoir regulation can substantially modify hydrological variability well beyond individual basin boundaries (Coerver et al., 2018; Veldkamp et al., 2018; Pokhrel et al., 2016), yet analyzing these feedbacks at a macro, nationwide scale is frequently constrained by data fragmentation or overly simplified administrative assumptions.

Beyond seasonality, the delayed and distributed nature of precipitation represents a second critical methodological gap. In catchment hydrology, the rainfall-runoff transformation inherently involves memory effects governed by storage within soils and aquifers, a foundational concept rooted in physical water movement and variable contributing areas (Beven and Kirkby, 1979; Kirchner, 2009; Montanari et al., 2013; Apurv et al., 2017). Recent

research emphasizes that precipitation exerts multi-timescale “memory” effects, motivating explicit and optimized memory representations rather than predefined lag structures (Moges et al., 2022). At aggregated reservoir scales, however, precipitation memory is often represented implicitly via autoregressive terms or fixed lag structures, limiting the physical interpretability of hydro-climatic propagation. Simultaneously, reservoirs operated for hydropower introduce an additional feedback layer; operational decisions influenced by grid electricity demand cycles, market conditions, and institutional risk management strategies can significantly alter storage levels independent of immediate precipitation inputs (Hanasaki et al., 2006; Biemans et al., 2011). To fully untangle these coupled human-water dynamics, hydropower operational metrics must be modeled not merely as external outputs, but as endogenous components of the broader socio-hydrological feedback loop (Blair and Buytaert, 2016). Despite these advances, integrated frameworks that (i) explicitly model precipitation memory, (ii) separate structural time-series components prior to inference, and (iii) quantify directional dynamic dependencies among precipitation, storage, and hydropower at a national scale remain limited. Particularly in Mediterranean systems, where drought risks and energy-water trade-offs are intensifying, improved methodological clarity is essential for interpreting storage variability under compound hydro-climatic and operational drivers.

This study addresses these challenges using national-scale monthly observations of precipitation, reservoir storage (filling ratio), and hydropower production capacity factor for Türkiye. An integrated framework is proposed that combines: (1) seasonal–trend decomposition to isolate stationary anomalies, (2) an optimized exponentially weighted precipitation-memory index, and (3) multivariate dynamic modeling via vector autoregression with exogenous inputs (VARX) coupled with orthogonalized impulse response and forecast error variance decomposition analysis. These dynamics are subsequently embedded within proactive drought scenario simulations under alternative precipitation deficits and operational responses. The contributions of this work are threefold. Conceptually, it is demonstrated that weak contemporaneous precipitation–storage correlations can coexist with strong precipitation-driven influence once catchment-scale precipitation memory is explicitly modeled. Methodologically, a transferable and scalable framework is provided, integrating structural time-series decomposition, optimized memory estimation, and dynamic multivariate inference to cleanly disentangle hydro-climatic impulses from operational modulation. Practically, scenario-based insights are generated regarding how drought shocks propagate through storage and accumulate through time, thereby offering a diagnostic toolset for adaptive water-energy governance under sustained climate stress in Mediterranean-type systems.

## **2. Materials and Methods**

### **2.1 Study Area and Data Structure**

This study was conducted at the national scale across Türkiye, a country located at the transition between temperate and subtropical climatic zones. Due to its complex topography, diverse coastline configurations, and the rain-shadow effects of the North Anatolian and Taurus Mountain ranges, Türkiye exhibits substantial climatic heterogeneity and pronounced spatial and temporal variability in precipitation patterns (Turkish State Meteorological Service 2026). To mitigate these imbalances and support water-resource management, an extensive network of dams and reservoirs has been developed, forming a critical component of the country’s water and energy infrastructure.

The empirical analysis utilizes nationally aggregated records representing Türkiye’s portfolio of multi-purpose reservoirs, the vast majority of which serve a primary or critical role in national hydropower development. Because new facilities were commissioned and operational

inventories evolved throughout the study period, the number of reservoirs contributing to the national aggregates varies over time. To ensure methodological consistency and emphasize emergent system-scale behavior rather than basin-specific characteristics, individual reservoir records were integrated into a single nationally aggregated monthly dataset. The spatial distribution of the reservoir systems included in the national analysis is presented in Figure 1.

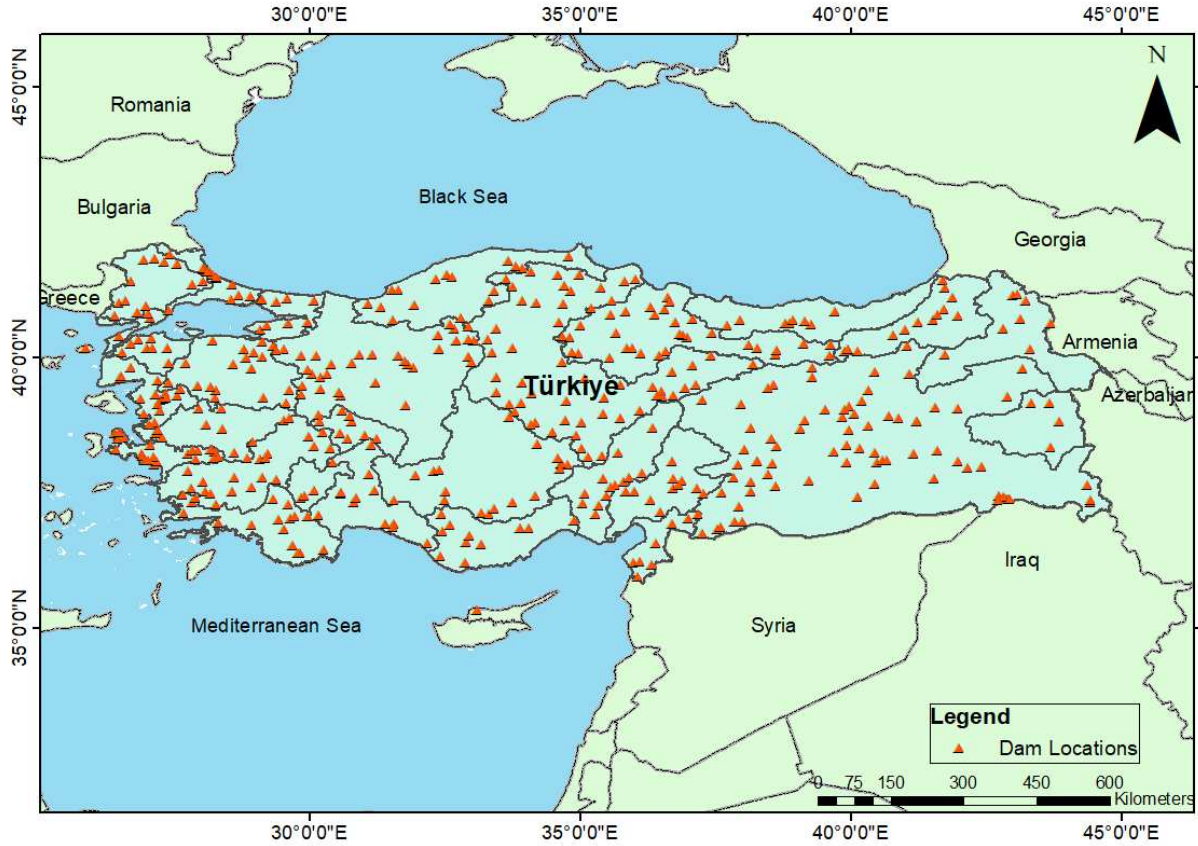


**Figure 1.** Spatial distribution of reservoirs included in the Türkiye-wide analysis.

To disentangle hydro-climatic forcing from operational management decisions, the national framework considers three key variables at a monthly resolution: areal average precipitation ( $P_t$ ), active reservoir storage ratio ( $S_t$ ), and hydropower capacity factor ( $CF_t$ ) (Figure 2). The hydropower capacity factor ( $CF_t$ ) was calculated as the ratio of actual monthly electricity generation to the corresponding installed hydropower capacity. This normalization isolates operational performance from long-term trends associated with infrastructure expansion, thereby ensuring temporal comparability across the historical timeline. Although spatial aggregation inevitably reduces local-scale detail, it provides a suitable basis for dynamic macro-scale inference while preserving the ability to identify temporal relationships among climatic forcing, reservoir storage dynamics, and hydropower production. In this way, the adopted framework emphasizes emergent system-scale behavior and the temporal sequencing linking climate inputs, storage conditions, and operational outcomes.

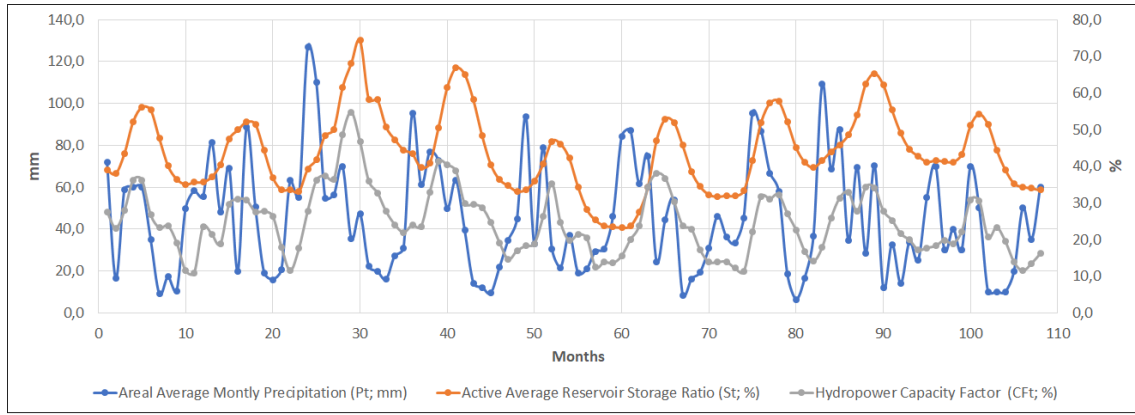


Figure 2. Monthly areal precipitation, average active reservoir storage ratio, and hydropower capacity factor over the study period.

The comprehensive analytical workflow developed to evaluate these coupled human–water dynamics is summarized in Figure 3. The framework integrates hydro-climatic inputs, statistical preprocessing, dynamic modeling, and scenario-based diagnostics within a unified methodology designed to distinguish climatic forcing from operational regulation.

Specifically, the monthly time series of precipitation ( $P_t$ ), reservoir storage ( $S_t$ ), and hydropower capacity factor ( $CF_t$ ) are sequentially analyzed through seasonal–trend decomposition (STL), an optimized precipitation-memory formulation, and a Vector Autoregressive model with exogenous inputs (VARX). The resulting framework supports impulse-response analysis, Forecast Error Variance Decomposition (FEVD), and drought scenario simulations, thereby enabling the evaluation of dynamic interactions among climatic forcing, storage variability, and hydropower operations across multiple temporal scales.

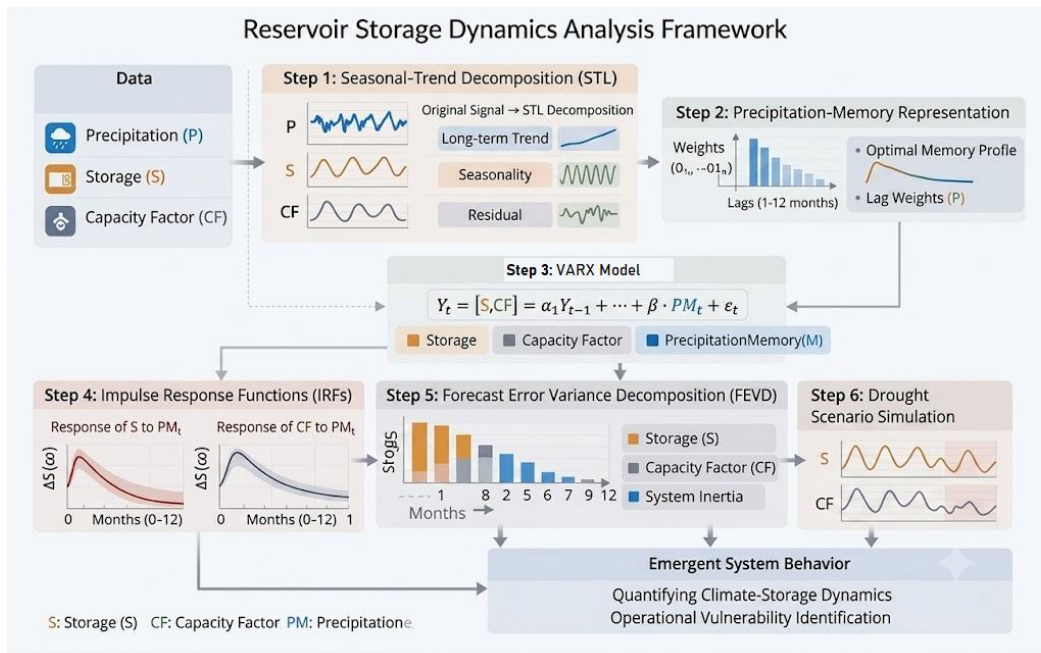


Figure 3. Conceptual overview of the methodological framework used to analyze national-scale reservoir dynamics in Türkiye

## 2.2 Seasonal–Trend Decomposition

Hydro-climatic and reservoir-storage series in Türkiye exhibit pronounced seasonal patterns associated with Mediterranean winter-dominated precipitation regimes and synchronized summer drawdown behavior. To avoid spurious statistical relationships and ensure that subsequent analyses capture genuine dynamic interactions rather than shared seasonal variability, each raw time series ( $X_t$ ) was decomposed using Seasonal–Trend Decomposition based on Loess (STL), following the robust non-parametric framework proposed by Cleveland et al., (1990):

$$X_t = T_t + S_t^{seas} + R_t \quad (1)$$

where  $T_t$  represents the long-term trend component,  $S_t^{seas}$  denotes the seasonal component, and  $R_t$  corresponds to the stationary residual (anomaly) component. Consistent with contemporary time-series analysis practices (Hyndman and Athanasopoulos, 2018), all subsequent statistical analyses and dynamic modeling procedures were conducted using the residual components ( $R_t$ ). This approach ensures that the inferred relationships among precipitation, reservoir storage, and hydropower production reflect dynamic system interactions rather than common seasonal patterns.

## 2.3 Stationarity Testing

To verify that STL decomposition successfully isolated stationary stochastic dynamics and removed low-frequency deterministic trends, the residual components were evaluated using the Augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979). The ADF procedure assesses the presence of a unit root through the following regression formulation:

$$\Delta R_t = \alpha + \beta t + \gamma R_{t-1} + \sum_{i=1}^p \delta_i \Delta R_{t-i} + \varepsilon_t \quad (2)$$

where  $\Delta$  denotes the first-difference operator,  $t$  represents a deterministic time trend,  $p$  denotes the number of lagged difference terms included to remove residual autocorrelation and was selected using information criteria and  $\varepsilon_t$  is a white-noise error term. The null hypothesis assumes the presence of a unit root ( $H_0: \gamma = 0$ ), indicating non-stationarity, whereas the alternative hypothesis ( $H_1: \gamma < 0$ ) implies a stationary process. For all residual series, the null hypothesis of a unit root was rejected ( $p < 0.001$ ), confirming covariance stationarity and validating the transformed variables for subsequent multivariate analysis.

## 2.4 Precipitation Memory Representation

As conceptualized in the methodological framework, a precipitation-memory index was introduced to represent the cumulative influence of antecedent climatic conditions on reservoir dynamics. Precipitation does not translate directly into storage fluctuations through a purely contemporaneous relationship. Instead, hydrological responses are influenced by antecedent precipitation conditions through soil moisture storage, subsurface flow generation, channel routing, and groundwater retention processes operating across multiple temporal scales. Consequently, catchment systems exhibit intrinsic memory effects whereby previous meteorological conditions continue to influence contemporary hydrological states (Beven and Kirkby, 1979; Kirchner, 2009; Montanari et al., 2013).

To represent these hydro-climatic memory effects without relying on arbitrary lag selections or over-parameterized lag structures, precipitation memory ( $PM_t$ ) was modeled using an exponentially weighted distributed lag formulation as follows:

$$PM_t = \sum_{k=0}^K w_k P_{t-k} \quad (3)$$

where the dynamic lag weights ( $w_k$ ) are specified according to the following exponential decay function:

$$w_k = \frac{\exp(-k/\tau)}{\sum_{j=0}^K \exp(-j/\tau)} \quad (4)$$

Here,  $K$  defines the maximum temporal lag length, while the memory-decay parameter ( $\tau$ ) controls the rate at which antecedent precipitation influence decreases with increasing lag. This formulation assumes a monotonic decline in memory contribution, a finite memory timescale, and non-negative lag weights, thereby providing a parsimonious representation of hydro-climatic memory that is consistent with physically plausible hydrological behavior under data-limited conditions (Moges et al., 2022).

The memory parameters were optimized by jointly minimizing the Akaike Information Criterion (AIC; Akaike, 1974) and cross-validation errors to balance model parsimony and predictive performance. The resulting lag-dependent weighting structure is illustrated in Figure 4. Although the optimized memory window extended to  $K = 12$  months, the weighting profile remained strongly concentrated at short lags, with more than 90% of the cumulative memory influence occurring within the first three months. This finding indicates that recent precipitation conditions exert the strongest control on reservoir dynamics, whereas longer-lag contributions diminish rapidly due to hydrological attenuation and operational buffering effects.

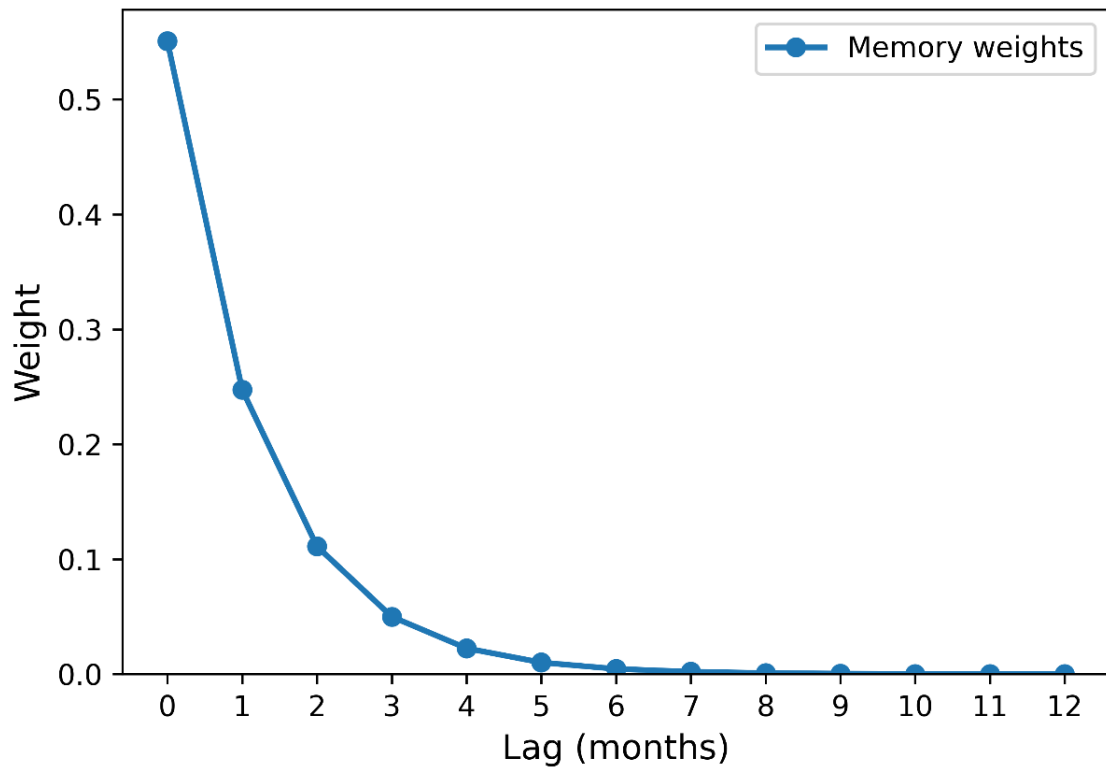


Figure 4. Optimized precipitation-memory weighting profile across lag lengths

The optimization procedure yielded an optimal decay parameter of  $\tau = 1.25$ , representing a hydro-climatic memory structure characterized by a rapid decline in influence with increasing lag while retaining a measurable contribution from antecedent precipitation conditions. The resulting memory-transformed precipitation series  $PM_t$  was subsequently incorporated as the exogenous climatic forcing variable within the Vector Autoregressive Model with Exogenous Inputs (VARX) framework described below.

## 2.5 Vector Autoregressive Model with Exogenous Inputs (VARX)

Multivariate time-series models with exogenous inputs have been increasingly applied in hydrological forecasting because they can simultaneously represent interactions among hydrological variables and the influence of external climatic drivers. Previous studies have shown that VARX-based frameworks successfully capture rainfall–runoff dynamics and improve predictive performance by accounting for both inter-variable dependencies and external forcing effects (Fathian et al., 2018). Owing to its transparent structure, interpretability, and ability to incorporate exogenous climate information, the VARX framework provides a suitable tool for investigating the coupled dynamics of precipitation memory, reservoir storage, and hydropower generation at the national scale.

The dynamic, multi-variable interactions conceptualized in Figure 3 are formally evaluated using a Vector Autoregressive with Exogenous Inputs (VARX) framework. This model structure allows for the simultaneous identification of dynamic feedbacks among interdependent hydro-climatic and operational variables without requiring strong a priori assumptions regarding the direction and magnitude of system interactions (Hamilton, 2020; Lütkepohl, 2013). The endogenous system is formulated as follows:

$$Y_t = c + \sum_{i=1}^p A_i Y_{t-i} + \sum_{j=0}^q B_j X_{t-j} + \varepsilon_t \quad (5)$$

where  $Y_t = [S_t, CF_t]^T$  represents the  $(2 \times 1)$  vector of endogenous variables at time  $t$  (comprising reservoir storage residuals and hydropower capacity factor residuals, respectively), while  $PM_t$  acts as the exogenous climate forcing driving the system. The term  $c$  is a  $(2 \times 1)$  vector of constants,  $A_i$  denotes the  $(2 \times 2)$  coefficient matrices describing lagged endogenous interactions,  $B_j$  represents the  $(2 \times 1)$  coefficient vectors mapping the influence of the exogenous climatic forcing, and  $\varepsilon_t$  is a  $(2 \times 1)$  vector of white-noise innovations.

Following standard multivariate time-series practices, the optimal endogenous lag order ( $p$ ) was selected using the Akaike Information Criterion (AIC), yielding  $p = 3$ . The exogenous lag structure was restricted to  $q = 0$  because the precipitation-memory index ( $PM_t$ ) already embeds antecedent precipitation information through the optimized distributed-lag weighting scheme. Including additional lagged  $PM_t$  terms would therefore introduce redundant temporal information and potentially increase multicollinearity without improving interpretability. Model estimation was performed using Ordinary Least Squares (OLS) on an equation-by-equation basis.

Preliminary exploratory diagnostics validated this multivariate approach by revealing distinct pairwise co-variabilities; specifically, while the contemporaneous relationship between precipitation memory and reservoir storage appears seemingly decoupled and non-linear

(Figure 5a), a robust, highly structured positive linear dependency emerges between reservoir storage levels and operational hydropower capacity factors (Figure 5b), thereby justifying the choice of a dynamic VARX framework to capture these multi-stage transmission pathways.

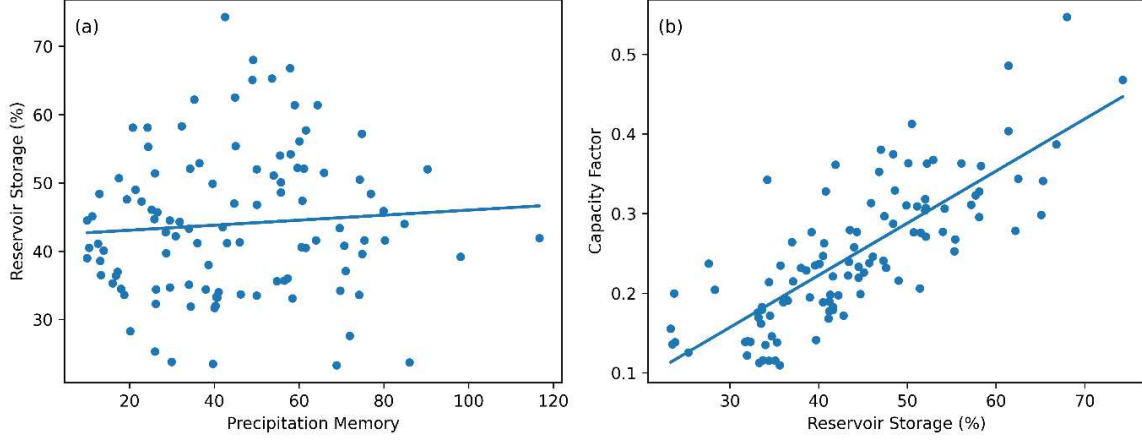


Figure 5. Pairwise diagnostics linking precipitation memory to reservoir storage (a) and reservoir storage to hydropower capacity factor (b) across Türkiye.

## 2.6 Impulse Response Analysis

To evaluate the dynamic propagation of hydro-climatic and operational disturbances through the reservoir system, Impulse Response Functions (IRFs) were computed. Based on the infinite-order Vector Moving Average (VMA) representation of the estimated VARX model, the endogenous variables can be expressed as a function of past innovations and exogenous climatic forcing (Hamilton, 2020; Lütkepohl, 2013):

$$Y_t = \sum_{h=0}^{\infty} \Phi_h \varepsilon_{t-h} + \sum_{h=0}^{\infty} \Gamma_h X_{t-h} \quad (6)$$

where  $\Phi_h$  represents the  $(2 \times 2)$  VMA coefficient matrices describing the propagation of endogenous innovations over a horizon  $h$ , and  $\Gamma_h$  denotes the corresponding dynamic multiplier vectors associated with exogenous precipitation-memory forcing ( $X_{t-h}$ ).

To isolate the structural transmission pathways within the coupled system, the orthogonalized impulse response matrix  $\Psi_h$  is computed via a Cholesky decomposition. Specifically, the dynamic impact of a one-standard-deviation structural innovation in variable  $j$  at time  $t$  on the future trajectory of endogenous variable  $i$  at horizon  $h$  is defined by the matrix elements  $\Psi_{ij,h}$  as follows:

$$\Psi_{ij,h} = \frac{\partial Y_{i,t+h}}{\partial \varepsilon_{j,t}} \quad (7)$$

To quantify uncertainty in the estimated response functions, 95% confidence intervals were obtained using bootstrap resampling with 1000 replications (Efron and Tibshirani, 1993).

## 2.7 Forecast Error Variance Decomposition (FEVD)

While impulse response functions describe the temporal propagation of individual shocks, Forecast Error Variance Decomposition (FEVD) quantifies the relative contribution of different sources of variability to forecast uncertainty. Specifically, FEVD partitions the forecast error variance of each endogenous variable into components attributable to its own innovations, innovations originating from other endogenous variables, and the contribution associated with exogenous hydro-climatic forcing (Hamilton, 2020; Lütkepohl, 2013). For a forecast horizon  $H$ , the fractional variance contribution of an endogenous shock  $j$  to the total forecast error variance of endogenous variable  $i$  is formally expressed as:

$$\theta_{ij}(H) = \frac{\sum_{h=0}^{H-1} (\Psi_h)_{ij}^2}{\sum_{m=1}^2 \sum_{h=0}^{H-1} (\Psi_h)_{im}^2 + \sum_{h=0}^{H-1} (\Gamma_h)_i^2} \quad (8)$$

where  $\Psi_h$  represents the orthogonalized endogenous impulse response matrices derived through the Cholesky framework in Section 2.6, and  $\Gamma_h$  denotes the dynamic multiplier associated with the exogenous precipitation-memory forcing. The denominator summarizes the total forecast error variance of the target variable at horizon  $H$ , obtained by summing the variance contributions from all endogenous shocks ( $m = 1, 2$ ) together with the contribution of the exogenous precipitation-memory driver. Consequently,  $\theta_{ij}(H)$  quantifies the fraction of total forecast uncertainty attributable to shock  $j$  over the specified forecast horizon. This analysis provides a quantitative framework for assessing the relative importance of climatic and operational drivers across alternative forecasting horizons and for identifying the sources of uncertainty governing reservoir-storage and hydropower dynamics.

## 2.8 Drought Scenario Simulation

To evaluate the resilience of the national reservoir system under sustained climatic stress, forward-looking drought scenarios were simulated by imposing controlled precipitation deficits:

$$P_{t,\text{sim}} = (1 - \delta)P_t \quad (9)$$

where  $\delta \in \{0.10, 0.20, 0.30\}$  represents sustained precipitation reductions of 10%, 20%, and 30%, respectively. The modified precipitation series  $P_{t,\text{sim}}$  were sequentially processed through the optimized memory filter to generate the counterfactual precipitation-memory inputs  $PM_{t,\text{sim}}$ , which were then embedded into the estimated VARX framework. Dynamic response trajectories were simulated over a 24-month horizon to evaluate how sustained climatic deficits propagate through the coupled climate–operational system and influence reservoir-storage conditions under alternative levels of climatic stress. Although the available observational record spans 108 months, the objective of the scenario analysis was not long-term forecasting but rather the characterization of drought-propagation dynamics and system resilience. The 24-month horizon was therefore selected to capture both the immediate response phase identified by the impulse-response analysis and the subsequent stabilization period, while avoiding excessive extrapolation beyond the reliable forecasting range of the estimated VARX framework.

## 2.9 Computational Environment and Reproducibility.

All data processing, statistical analyses, and scientific visualizations were conducted using Python 3.11 within the Spyder integrated development environment. Data manipulation and

preprocessing were performed using Pandas (v2.2) and NumPy (v1.26). Seasonal–trend decomposition was implemented using the STL procedure available in the Statsmodels package (v0.14).

Dynamic interactions between reservoir storage and hydropower capacity factors were evaluated using a Vector Autoregressive with Exogenous Inputs (VARX) framework, in which the optimized precipitation-memory index was incorporated as the external climatic forcing variable. Model estimation, impulse-response analysis, Forecast Error Variance Decomposition (FEVD), and Granger causality testing were performed using the Statsmodels time-series module, while forward-looking drought scenario simulations were implemented within the same computational environment. Final data visualizations and manuscript figures were generated using Matplotlib (v3.8).

All analytical workflows were implemented exclusively using open-source software packages to ensure methodological transparency and computational reproducibility.

### 3. Results

#### 3.1 Precipitation Memory Estimation

The optimization of the exponentially weighted distributed lag structure using AIC minimization and cross-validation error metrics yielded an optimal configuration defined by a maximum temporal lag length of  $K = 12$  months and a memory decay parameter of  $\tau = 1.25$ . The empirical weighting profile derived from this structure (Figure 4) indicates that precipitation influence is strongly concentrated at short lags despite the extended memory window. Specifically, the contemporaneous precipitation component accounts for approximately 55.1% of the total memory weight, while the cumulative contribution up to a 1-month lag reaches approximately 79.8%. Including the 2-month lag increases the cumulative contribution to approximately 90.9%, whereas contributions beyond 3 months remain limited, accounting for approximately 4.1% of the total weighting.

This distribution confirms that, at the national scale of Türkiye, precipitation-driven signal transmission is dominated by recent climatic conditions, while longer-lag antecedent effects contribute only marginally. The relationship between the optimized precipitation-memory index ( $PM_t$ ) and reservoir storage remains positive but relatively weak (Figure 5a), indicating that climatic forcing alone cannot fully explain storage variability. Nevertheless, the precipitation-memory term provides statistically significant explanatory power within the VARX framework ( $p < 0.05$ ), supporting its inclusion as an exogenous climatic forcing variable.

#### 3.2 VARX Model Diagnostics

Consistent with standard multivariate time-series protocols, the Vector Autoregressive model with exogenous inputs (VARX) was estimated using an endogenous lag order of  $p = 3$ , selected according to the minimum Akaike Information Criterion (AIC). Post-estimation diagnostics confirmed the statistical adequacy and stability of the estimated system. Residual autocorrelation tests based on the Ljung–Box statistic indicated no significant serial dependence at the 12-month lag, suggesting that the model successfully captured the dominant temporal structure of the data.

Model stability was further confirmed by the companion-matrix eigenvalue analysis, with the maximum modulus of all roots remaining well below unity at 0.786 indicating a stable and covariance-stationary dynamic system suitable for impulse-response and forecasting analyses.

The estimated VARX equations demonstrated strong explanatory performance for reservoir storage  $R^2 = 0,787$  and moderate explanatory performance for hydropower capacity factor  $R^2 = 0.457$ ). The precipitation-memory index ( $PM_t$ ) contributed significantly to the explanatory performance of both equations ( $p < 0.05$ ), confirming its independent contribution to variations in reservoir storage and hydropower generation.

Wald tests further revealed that lagged hydropower capacity-factor terms significantly contributed to storage variability, whereas lagged storage terms exhibited comparatively weaker predictive influence on subsequent capacity-factor dynamics. These findings indicate that national-scale reservoir behavior in Türkiye is governed by a combination of external climate forcing and endogenous operational regulation, supporting the adoption of a multivariate VARX framework for representing coupled climate–infrastructure interactions.

### 3.3 Impulse Response Analysis

#### 3.3.1 Storage Response to Precipitation Memory Shock

The dynamic response of reservoir storage to a one-standard-deviation innovation in the exogenous precipitation-memory index is presented in Figure 6.

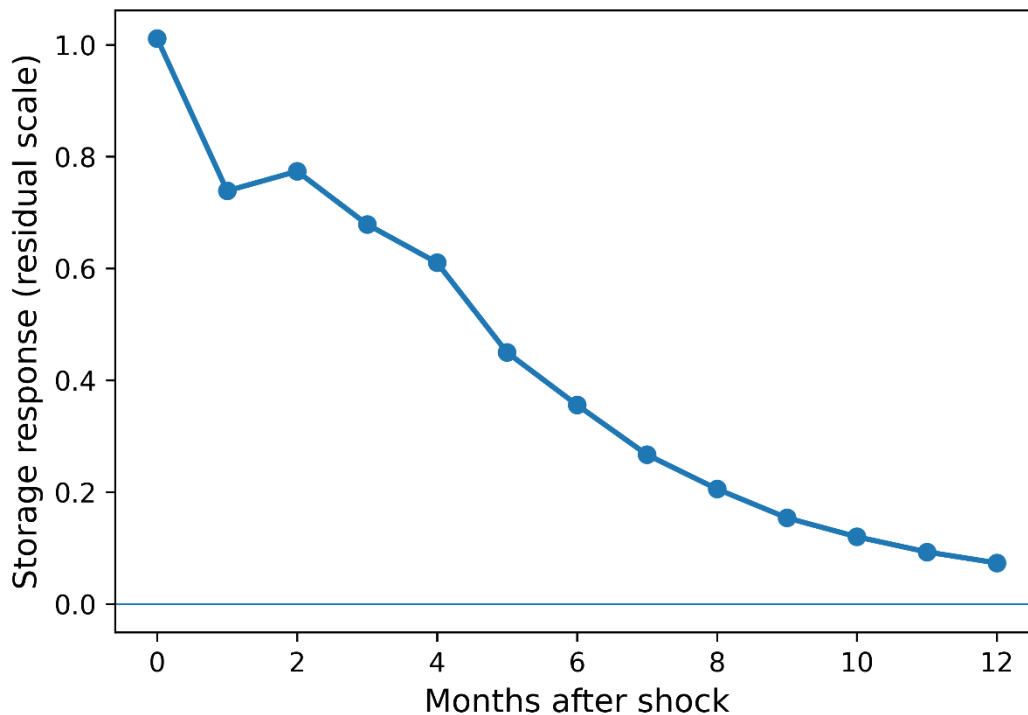


**Figure 6.** Impulse response function (IRF) of reservoir storage to a precipitation-memory shock.

The impulse response analysis reveals that reservoir storage responds immediately to a positive precipitation-memory shock, with the maximum response occurring at the impact period ( $h = 0$ ). Following this initial peak, the response gradually declines over time while

remaining positive throughout the 12-month simulation horizon. The absence of delayed peaks in this trajectory indicates that once catchment-scale routing and lag effects are explicitly embedded within the optimized precipitation-memory index, the filtered climatic information propagates directly and monotonically through the national reservoir system.

Although the magnitude of the response decreases progressively after the initial shock, the persistence of positive values over several months demonstrates that climatic disturbances continue to influence reservoir dynamics through endogenous system feedbacks. This gradual attenuation highlights that reservoir storage successfully integrates precipitation-memory signals well beyond the initial impact period, while operational regulation and internal hydrological processes govern the longer-term evolution of the response.

Overall, the results indicate that precipitation memory acts as an immediate external forcing mechanism, whereas the persistence of storage anomalies is controlled primarily by the internal dynamics of the reservoir system.

### 3.3.2 Hydropower Capacity Factor Response to Precipitation Memory Shock

The operational response of the hydropower sector to a one-standard-deviation innovation in precipitation memory is presented in Figure 7.

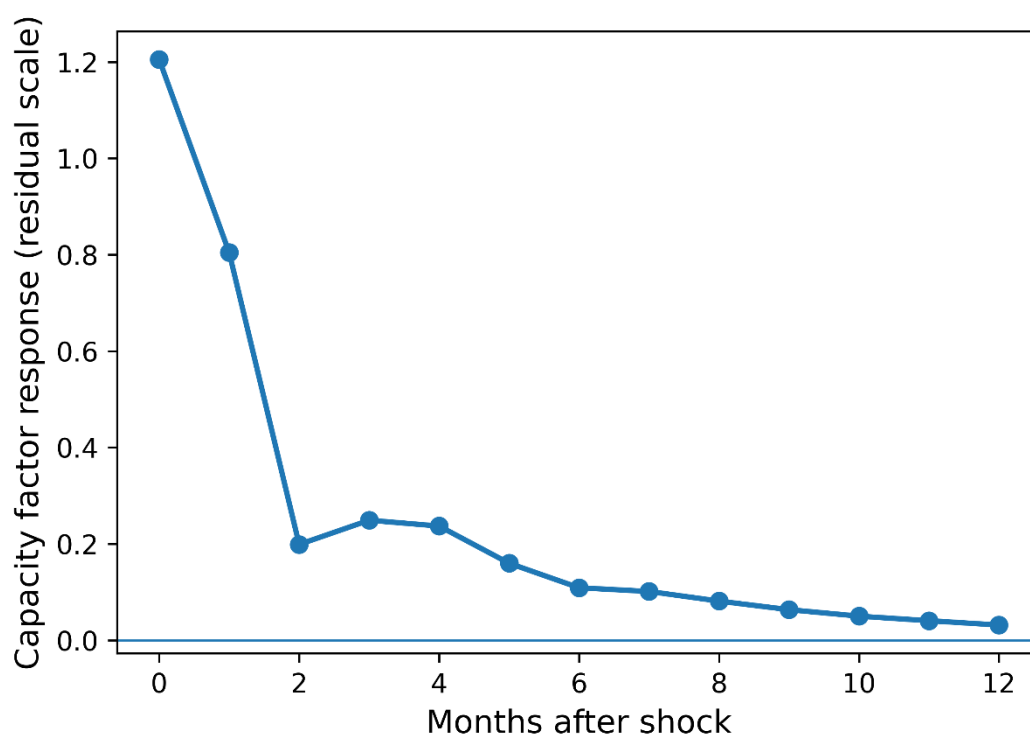


**Figure 7.** Impulse response function (IRF) of hydropower capacity factor to a precipitation-memory shock.

The hydropower capacity factor exhibits an immediate positive response following a precipitation-memory shock, with the maximum effect occurring at the impact period ( $h = 0$ ). After the initial peak, the response declines progressively toward equilibrium conditions. This immediate response indicates that once hydrological lag effects are filtered through the

optimized precipitation-memory formulation, the resulting water-availability signal triggers immediate operational adjustments within the energy-production subsystem.

Compared with reservoir storage (Figure 6), the capacity-factor response displays a significantly faster rate of attenuation, characterized by a sharp decline during the first two months after the shock. This behavior suggests that operational adjustments within the hydropower system react promptly to utilize improved water availability for electricity generation, resulting in a rapid release of the initial climatic signal through turbine optimization. Consequently, the capacity factor returns toward baseline conditions relatively quickly, whereas the physical reservoir storage integrates and retains the remainder of the climatic disturbance over a much longer temporal scale.

The persistence of positive responses throughout the simulation horizon nevertheless indicates that climatic shocks continue to influence hydropower performance beyond the immediate impact period. These findings support the interpretation that precipitation memory acts as an important external driver of hydropower variability, while the long-term evolution of the response is governed primarily by endogenous operational regulation and system dynamics. Taken together, Figures 6 and 7 demonstrate that both reservoir storage and hydropower generation respond responsively to filtered precipitation-memory inputs, although the magnitude, structural attenuation, and persistence of these responses differ fundamentally between the physical storage retention subsystem and the active operational infrastructure dynamics.

### 3.4 Forecast Error Variance Decomposition (FEVD)

To quantify the relative importance of climatic and operational drivers governing hydropower performance, Forecast Error Variance Decomposition (FEVD) was conducted for the hydropower capacity factor ( $CF_t$ ) over a 12-month forecast horizon (Figure 8).

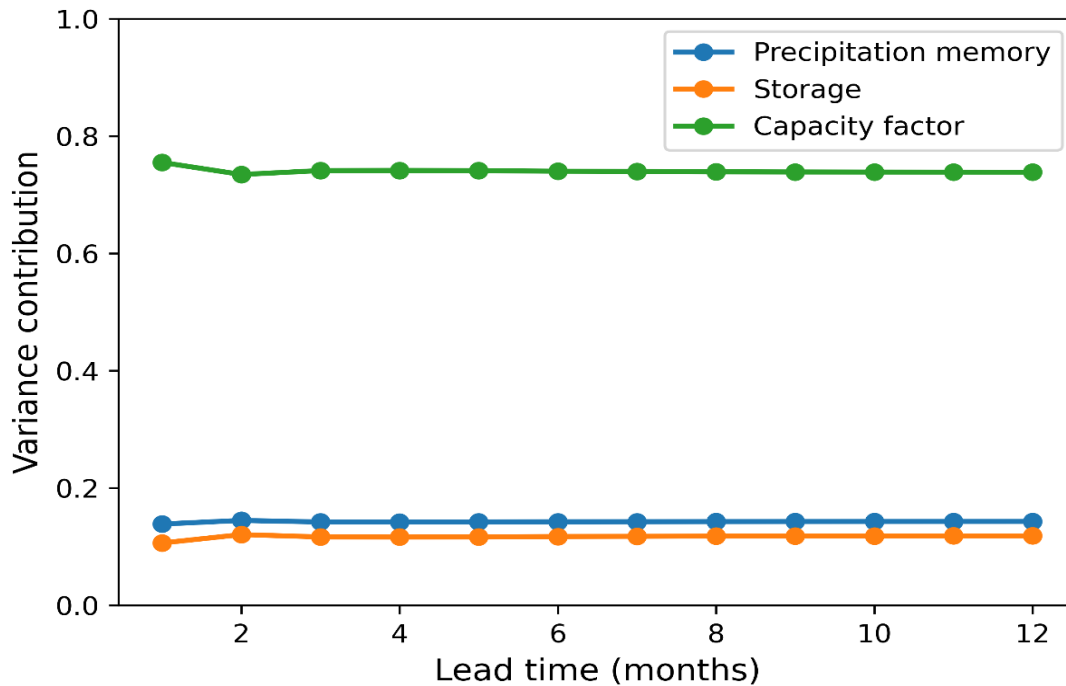


**Figure 8.** Forecast Error Variance Decomposition (FEVD) of hydropower capacity factor ( $CF_t$ )

The FEVD results indicate that hydropower capacity factor variability is dominated by its own innovations throughout the entire forecast horizon. Capacity-factor shocks account for approximately 74% to 75% of total forecast uncertainty, demonstrating the strong endogenous persistence of hydropower capacity-factor dynamics within the national system.

In contrast, the remaining forecast error variance is partitioned between external climate forcing and internal physical storage feedbacks; specifically, the precipitation-memory index ( $PM_t$ ) contributes a stable 14% to 15% of the variance, while reservoir storage residuals account for approximately 11% to 12% across all lead times. This secondary but persistent contribution indicates that both hydro-climatic forcing and reservoir-storage conditions remain measurable sources of forecast uncertainty. Nevertheless, their combined contribution (~26%) is substantially smaller than the dominant endogenous persistence of the hydropower subsystem.

The remarkable stability of these variance shares across alternative forecasting horizons suggests that the relative partitioning between external climatic forcing and internal infrastructure constraints remains persistent through time. While precipitation memory ( $PM_t$ ) and reservoir storage residuals represent independent, statistically non-trivial sources of system variance, their combined footprint (~ 26%) is substantially outweighed by the dominant endogenous inertia of the hydropower subsystem itself.

Overall, the FEVD analysis demonstrates that although national-scale hydropower generation in Türkiye remains influenced by antecedent precipitation conditions and reservoir storage availability, its forecast uncertainty is governed predominantly by endogenous hydropower-system dynamics. These variance decomposition results complement the impulse-response analysis by indicating that climatic forcing and storage conditions provide persistent external influences, whereas the temporal evolution of hydropower capacity factors is controlled primarily by internal system behavior.

### **3.5 Drought Scenario Simulation**

To assess the resilience of Türkiye's reservoir system under sustained climatic stress, scenario simulations were conducted by imposing persistent precipitation-memory deficits of 10%, 20%, and 30% relative to baseline conditions (Figure 9).

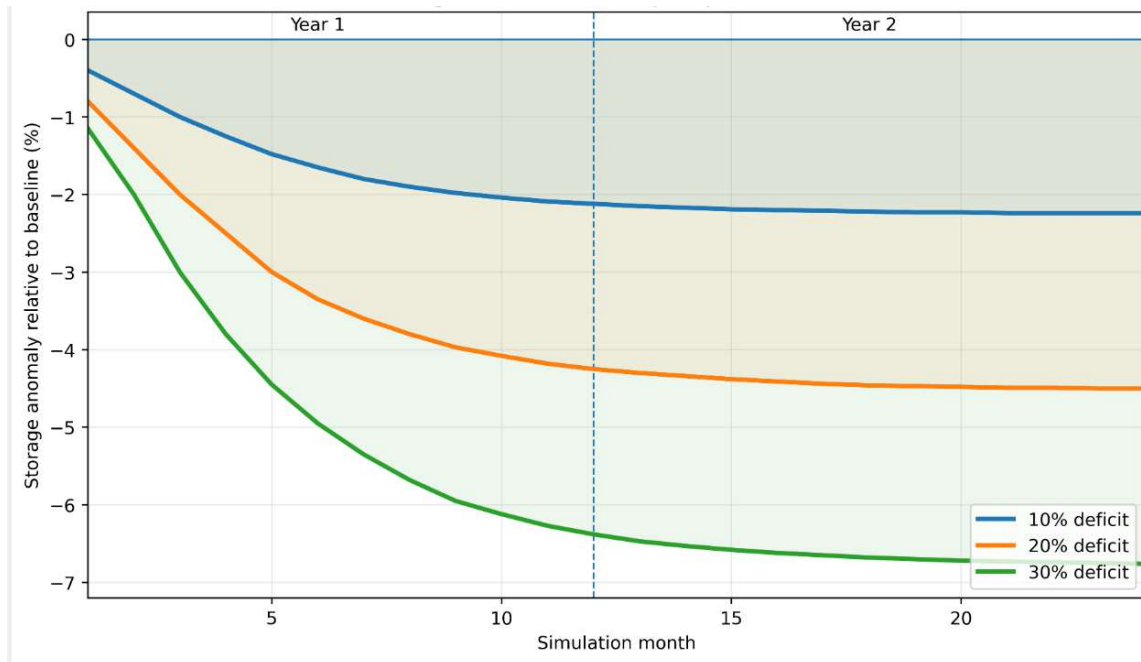


Figure 9. Simulated reservoir-storage anomalies relative to baseline conditions under sustained precipitation-deficit scenarios (10%, 20%, and 30%) over a 24-month horizon.

The scenario trajectories reveal a progressive decline in reservoir storage conditions as the magnitude of the climatic deficit increases. Under the 10% deficit scenario, storage anomalies remain relatively moderate throughout the simulation period, indicating that internal storage regulation and operational buffering partially compensate for reduced climatic inputs. Increasing the deficit to 20% produces substantially larger storage anomalies, which persist throughout the simulation horizon and demonstrate the cumulative effects of prolonged climatic stress.

The most severe response is observed under the 30% deficit scenario, where storage anomalies continue to diverge from baseline conditions throughout the two-year simulation period. By month 24, the simulated storage anomaly reaches approximately  $-6.8\%$  relative to baseline conditions, indicating a substantial deterioration in storage performance under sustained climatic deficits.

These results demonstrate that the effects of prolonged precipitation shortages accumulate through time, generating progressively larger departures from normal storage behavior. Although reservoir operations provide an important buffering mechanism, they are unable to fully offset persistent reductions in climatic forcing under severe drought conditions.

Collectively, the impulse-response analysis (Figures 6 and 7), variance decomposition results (Figure 8), and forward-looking drought simulations (Figure 9) indicate that Türkiye's reservoir system behaves as a tightly coupled climate–operational system. Precipitation-memory shocks are transmitted systematically to both storage and hydropower subsystems, while the persistence and long-term evolution of these responses are governed primarily by endogenous hydrological processes and operational regulation dynamics. This integrated behavior highlights the critical importance of considering both filtered climatic forcing and structural infrastructure rules when evaluating large-scale water–energy interactions under increasing climate variability and drought risk.

## 4. Discussion

### 4.1 Hydro-Climatic Forcing Versus Operational Regulation

The empirical results demonstrate that national-scale reservoir dynamics in Türkiye emerge from a tightly coupled interaction between external precipitation-memory forcing and internal operational regulation, rather than from raw meteorological variability alone. The optimized precipitation-memory structure (Figure 4) indicates that while the physical catchment integrates antecedent climate forcing across an extended window, the immediate techno-operational utilization focuses heavily on short-lag water availability, confirming that recent hydrological memory exerts the most direct boundary constraint on storage fluctuations.

The impulse response analysis further reveals that both reservoir storage and hydropower capacity factors exhibit immediate positive reactions to precipitation-memory shocks (Figures 6 and 7). Rather than demonstrating delayed peak responses—which are typically expected in raw rainfall–runoff workflows—the maximum impact occurs instantly at  $h = 0$ . This pattern indicates that once complex basin-scale routing and sub-surface storage lags are systematically embedded within the optimized precipitation-memory index ( $PM_t$ ), the filtered hydrological signal maps directly onto structural operational decisions. However, the multi-month persistence of these positive trajectories highlights that physical reservoir retention and internal system feedbacks continue to buffer and propagate these climatic inputs long after the initial disturbance has stabilized.

This behavior is highly consistent with socio-hydrological perspectives that conceptualize modern water-resource infrastructures as coupled human–water systems, wherein natural boundary conditions and institutional decision-making processes interact dynamically rather than operating as independent drivers (Sivapalan et al., 2011; Di Baldassarre et al., 2018). While climatic variability initiates the available water volume within the system, structural operational regulation determines how these physical signals are stored, redistributed, and translated into energy production across temporal scales.

The FEVD outcomes (Figure 8) strongly reinforce this integrated interpretation. Although precipitation memory and baseline reservoir storage supply non-trivial boundary conditions, the forecast uncertainty of the system is dominated by endogenous operational persistence associated with hydropower demand schedules and infrastructure constraints. Notably, the variance shares explained by precipitation memory and storage remain remarkably stable and stationary across all forecast horizons, rather than decaying over time. This long-term stationarity suggests that institutional operational routines function as a highly institutionalized buffering mechanism that continuously dampens and moderates the high-frequency volatility of incoming precipitation-memory signals across the national water–energy network (Senbeta et al., 2024).

### 4.2 Implications of Precipitation Memory for Large-Scale Hydrological Analysis

A primary methodological contribution of this framework is the explicit introduction of the optimized precipitation-memory index ( $PM_t$ ), which substantially improves the representation of climate–infrastructure interactions at the national scale. Conventional water-resource analyses based solely on contemporaneous climatic indicators risk underestimating the structural influence of antecedent moisture conditions because they neglect the cumulative,

lagged effects of precipitation persistence. By implementing an exponentially weighted distributed lag structure, the proposed framework provides a parsimonious representation of catchment memory, highly consistent with foundational hydrological concepts of storage dynamics and variable contributing areas (Beven and Kirkby, 1979), as well as contemporary observations of hydrological signal persistence across diverse physiographic settings (Kirchner, 2009; Gudmundsson et al., 2021).

The optimized memory structure identified in this study (Figure 4) demonstrates that while recent precipitation conditions dominate national-scale reservoir responses, longer-lag influences exert systematic operational boundary conditions. The impulse-response functions indicate that once complex catchment-scale routing and sub-surface propagation delays are explicitly integrated within the precipitation-memory formulation, the resulting water-availability signal maps monotonically onto the structural operational routines, whereas the long-term attenuation of these trajectories is subsequently shaped by endogenous techno-operational processes. These findings highlight the critical importance of incorporating structured temporal memory filters rather than raw meteorological records when analyzing large-scale infrastructure behavior.

At national scales, substantial spatial heterogeneity among river basins, micro-climatic zones, and competing operational objectives can obscure direct climate–storage relationships. In such highly regulated settings, memory-based time-series representations offer a highly effective intermediate level of complexity between simple contemporaneous statistical associations and fully distributed, physically based hydrological models. Consequently, the proposed VARX framework provides an efficient analytical tool for investigating large-scale climate–infrastructure dynamics while avoiding the exhaustive data requirements, over-parameterization risks, and heavy calibration burdens typically associated with physically distributed modeling structures.

This streamlined formulation proves particularly valuable for regional and national water-resource assessments in data-limited environments, as well as in heavily regulated river systems where human interventions and structural constraints strongly influence macro-scale hydrological responses (Blöschl et al., 2013; Moges et al., 2022).

### **4.3 Drought Propagation and System Inertia**

The forward-looking scenario simulations demonstrate that sustained climatic deficits propagate through Türkiye’s national reservoir infrastructure over extended horizons, underscoring the profound role of internal system inertia and institutional regulation in shaping drought evolution. As illustrated in Figure 9, progressively larger precipitation-memory deficits generate increasingly severe storage anomalies, with the magnitude of deviation from baseline conditions expanding monotonically throughout the 24-month simulation window.

Although the optimized precipitation-memory filter is structurally dominated by short-term climatic weights (Figure 4), the resulting reservoir-storage impacts persist considerably longer than the duration of the initial external forcing. This behavior reflects the combined dynamics of physical hydrological retention and structural water-management decisions, which jointly regulate how external climatic disturbances are distributed and buffered through time. Consequently, long-term drought impacts emerge not from delayed climatic transmission itself, but from the systemic persistence and internal momentum of coupled reservoir responses once climatic stress has been introduced.

These empirical findings align closely with contemporary drought-propagation theory, which emphasizes that meteorological anomalies are transformed into hydrological and socioeconomic water-resource deficits through a progressive sequence of interacting storage and management mechanisms (Van Loon, 2015; Mukherjee et al., 2018; AghaKouchak et al., 2020). In highly regulated national infrastructure systems, reservoir operations successfully buffer high-frequency, short-term climatic variability; however, persistent antecedent deficits eventually accumulate past operational thresholds, producing structural deterioration in macro-scale storage conditions.

From a water-security perspective, these outcomes indicate that drought risk in managed reservoir networks cannot be assessed accurately using meteorological indicators alone. Instead, reservoir-storage trajectories reflect the integrated influence of climatic forcing, hydrological persistence, and system regulation. The sustained responses observed under the 10%, 20%, and 30% deficit scenarios in Figure 9 illustrate the strong temporal persistence of storage deficits within the national reservoir system, demonstrating that meteorological drought signals can remain embedded in reservoir conditions long after the initial climatic perturbation.

Overall, the simulations highlight the critical importance of considering both engineered climate-forcing inputs and institutionalized operational regulation rules when evaluating long-term water-security risks under a shifting regime of climate variability and increasing drought frequency.

#### **4.4 Water–Energy Nexus Implications and Infrastructure Resilience**

The coupled system feedback identified by the VARX framework underscores the profound strategic importance of reservoir networks within Türkiye’s broader water–energy nexus. The strong empirical co-movement between reservoir storage ( $S_t$ ) and the hydropower capacity factor ( $CF_t$ ) (Figure 5b), combined with the estimated impulse-response functions (Figures 6 and 7), demonstrates that once antecedent catchment lags are embedded within the structured precipitation-memory index ( $PM_t$ ), climatic availability signals map monotonically and efficiently onto the energy-production infrastructure.

The forward-looking drought simulations further indicate that sustained precipitation deficits induce cumulative, cross-sectoral vulnerabilities over time (Figure 9). Although institutionalized reservoir operations provide a vital structural buffer against high-frequency volatility, prolonged climatic stress progressively depletes the operational flexibility required for joint hydropower dispatch and multi-objective water allocation. Consequently, extended drought conditions propagate beyond physical water-resource scarcity, directly threatening the reliability and baseline stability of interconnected renewable energy grids.

These socio-economic implications are highly critical for semi-arid and climate-vulnerable regions like Türkiye, where rising ambient temperatures, expanding agricultural irrigation commitments, and escalating seasonal cooling demands frequently coincide. Under such compounding stress conditions, structural drawdowns in macro-scale reservoir storage inevitably intensify resource competition among municipal water supply, agricultural irrigation, environmental flow requirements, and hydropower generation priorities. The resulting operational trade-offs highlight the urgent necessity of integrated water–energy planning strategies capable of balancing diverse sectoral mandates under escalating climatic uncertainty.

From a techno-operational perspective, the optimized precipitation-memory framework offers a robust, computationally efficient early-warning indicator for monitoring emerging resource stress. Because national-scale infrastructure responses are conditioned heavily by structured antecedent moisture states rather than contemporaneous meteorological conditions alone, memory-based predictive channels allow grid operators and water managers to anticipate downstream storage trajectories long before critical deficits manifest. Such predictive insights are essential for supporting proactive reservoir-balancing rules, optimal inter-basin water transfers, and adaptive energy-dispatch measures designed to enhance macro-scale infrastructure resilience.

Ultimately, these insights confirm that precipitation memory functions as a critical regulatory mechanism governing not only physical hydrology but also the systemic reliability of the wider water–energy network. Integrating parsimonious, memory-based climate indicators into institutional planning frameworks represents a highly scalable path toward safeguarding national infrastructure resilience against intensifying climate variability and drought regimes.

#### **4.5 Relevance for Nationally Aggregated Reservoir Systems**

Although the empirical validation of this study is anchored in nationally aggregated data for Türkiye, the underlying conceptual framework and methodological workflow are broadly scalable to other macro-scale managed reservoir networks. Many countries rely on interconnected, centralized water-resource infrastructures where regional reservoir storage, cascading hydropower networks, municipal water allocations, and climate forcing interact simultaneously across complex spatial and temporal configurations. In these highly institutionalized settings, diagnosing system-wide behavior requires parsimonious analytical tools capable of capturing the coupled interactions between structured precipitation memory and active operational regulation rules.

The VARX framework proposed herein provides a highly scalable modeling alternative for evaluating these coupled system dynamics without incurring the prohibitive data requirements, computational costs, and over-parameterization vulnerabilities commonly associated with facility-level or physically distributed hydrological configurations. By explicitly isolating the precipitation-memory index ( $PM_t$ ), the formulation captures the cumulative, multi-scalar footprint of antecedent catchment moisture conditions while concurrently internalizing the endogenous storage ( $S_t$ ) and operational capacity-factor ( $CF_t$ ) feedbacks.

A distinct advantage of nationally aggregated macro-analyses is their unique capability to identify emergent system properties that may remain obscured or unobservable within localized, basin-specific investigations. While local-scale modeling remains essential for site-specific daily operational management, macro-scale aggregated diagnostics provide critical system-wide insights into how sustained hydro-climatic disturbances propagate across interconnected infrastructure networks and interface with institutionalized regulation frameworks at broad spatial domains. Ultimately, these outcomes confirm that while precipitation-memory variations establish the baseline physical boundaries of the system, the long-term temporal evolution and persistence of reservoir storage behavior are governed predominantly by internal hydrological storage integration and techno-operational dispatch processes. This insight reinforces the paradigm that macro-scale reservoir systems must be conceptualized as coupled human–water systems rather than purely natural hydrological entities. This interpretation aligns directly with contemporary global assessments of river regulation and macro-scale reservoir management, which demonstrate that extensive hydraulic

infrastructures fundamentally reshape natural hydrological variability, smoothing and altering systemic memory across continental scales (Coerver et al., 2018; Pokhrel et al., 2016).

National-scale reservoir behavior in Türkiye is governed by a combination of external climate forcing and endogenous operational regulation. This finding is consistent with previous studies showing that reservoir operations and management rules can substantially modify large-scale hydrological responses and influence the representation of climate-change impacts in water-resource systems (Chowdhury and Galelli, 2020).

Consequently, the proposed memory-based time-series framework establishes a robust and transferable analytical foundation for conducting comparative resilience assessments, drought vulnerability mapping, and multi-sectoral water–energy nexus diagnostics across other heavily regulated or nationally integrated water-resource systems globally.

#### **4.6 Limitations and Future Research Directions**

To enhance the generalized scalability of the findings across diverse climatic and geographic regimes, all drought scenario simulations were systematically formulated in relative temporal scales rather than being tied to specific historical calendar years. This parsimonious approach ensures that the simulated trajectories can be interpreted as generalized infrastructure system responses to sustained precipitation-memory deficits, rather than as localized reconstructions of particular historical drought events.

Nevertheless, several methodological limitations must be explicitly acknowledged. First, the utilization of nationally aggregated data inevitably smooths out regional spatial heterogeneity across individual river basins, micro-climatic zones, and conflicting localized operational objectives. Consequently, local-scale drought propagation processes and facility-specific management routines cannot be explicitly resolved within this macro-scale framework. Second, although the developed VARX model effectively captures the dynamic statistical relationships and feedback mechanisms among climate forcing, storage levels, and energy-production variables, it functions as a data-driven representation. It does not explicitly simulate explicit hydraulic routing processes, physical reservoir operating rules, or mass-conservative water-balance dynamics. Accordingly, this framework should be conceptualized as a complementary large-scale diagnostic tool rather than a structural substitute for physically distributed hydrological modeling architectures.

Furthermore, while the structural composition of Türkiye’s national reservoir portfolio evolved gradually during the study period through the commissioning of new hydropower facilities, the primary objective of this analysis was to capture emergent system-scale behavior rather than asset-specific responses. The aggregated modeling choice therefore prioritizes the macro-scale characterization of national precipitation-memory and techno-operational dynamics over individual reservoir engineering constraints.

To overcome these limitations, future research directions should focus on downscaling the precipitation-memory VARX framework to major individual river basins to evaluate how spatial heterogeneity influences regional climate–infrastructure coupling. Additionally, integrating these memory-based econometric models with machine learning architectures or physically based water-balance constraints represents a promising path toward developing hybrid, mass-conservative early-warning forecasting frameworks for macro-scale water–energy systems.

## 5. Conclusions

This study developed and applied a parsimonious VARX-based econometric framework to investigate the dynamic multivariate interactions among precipitation memory, macro-scale reservoir storage, and hydropower capacity factors at the nationally aggregated scale in Türkiye. By combining an optimized exponentially weighted distributed lag structure with multivariate time-series diagnostics and forward-looking drought scenario simulations, the analysis provides critical system-wide insights into the coupled climate–infrastructure dynamics governing large-scale regulated water networks.

The empirical results demonstrate that engineered precipitation memory constitutes a statistically significant driver of macro-scale reservoir behavior, with its structural influence concentrated primarily within the short-lag periods following climatic forcing. The optimized temporal weighting profile reveals that recent precipitation conditions account for the dominant share of climate forcing on reservoir dynamics, whereas longer-lag antecedent contributions play a stable, secondary role. The estimated impulse-response functions further show that both reservoir storage ( $S_t$ ) and the hydropower capacity factor ( $CF_t$ ) exhibit immediate positive reactions following a precipitation-memory shock. Rather than representing a direct response to contemporaneous precipitation, this behavior indicates that the optimized precipitation-memory index ( $PM_t$ ), effectively captures the delayed hydrological processes linking climate forcing to operational decisions. Despite the critical importance of climate forcing as a baseline boundary shifter, Forecast Error Variance Decomposition (FEVD) reveals that the long-term predictable variance of the system is governed predominantly by endogenous institutional persistence and infrastructure-specific dispatch dynamics. These outcomes confirm that national-scale reservoir networks function as tightly coupled human–water systems in which external climate forcing initiates the available water volume, while techno-operational regulation and physical storage retention determine the long-term persistence, attenuation, and temporal evolution of system responses.

The forward-looking drought scenario simulations demonstrate that sustained precipitation-memory deficits generate progressive, non-linear storage anomalies, with the magnitude of departure from baseline conditions expanding systematically as climatic stress intensifies. Although institutionalized reservoir operations provide a vital structural buffer against high-frequency climate variability, prolonged deficits eventually overwhelm this buffering capacity, producing substantial deterioration in national storage conditions. Under the severe (30%) precipitation-deficit scenario, simulated storage anomalies reach approximately  $-6.8$  percentage points relative to baseline conditions by month 24. These insights underscore the importance of incorporating precipitation-memory indicators, rather than relying solely on contemporaneous meteorological observations, in drought-risk assessment and macro-scale water-resources planning.

Beyond the specific case of Türkiye, the proposed memory-based framework is readily transferable to other nationally integrated or heavily regulated water-resource systems. By explicitly representing precipitation memory and the dynamic interactions among storage and operational variables, it provides a practical and data-efficient tool for assessing reservoir resilience under increasing climate variability and drought risk. Unlike physically distributed models, the framework can be implemented with relatively modest data and computational requirements. Taken together, these findings provide a practical basis for supporting adaptive reservoir management and climate-resilient water–energy planning in increasingly variable hydro-climatic environments.

## Data Availability Statement

The empirical data utilized in this study comprise monthly precipitation time series, aggregated national reservoir storage volumes, and hydropower generation records for Türkiye. Due to institutional data-governance policies and operational confidentiality restrictions, the underlying highly disaggregated, facility-level reservoir storage and asset-specific operational datasets are not publicly accessible. However, the nationally aggregated datasets, engineered model input variables, and composite indices supporting the primary findings of this research are available from the corresponding author upon reasonable request, subject to formal data-use agreements and relevant institutional regulations.

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