



Markov Chain–Based Analysis of Hydrological Drought Transitions in the Nestos River Basin [†]

Konstantinos Spiliotis ^{1,*}, Mike Spiliotis ^{1,*} , Charalampos Skoulidakis ² , Stamatios Petkopoulos ¹,
Dimitris Bourdis ¹ and George Kampas ³

¹ Department of Civil Engineering, Democritus University of Thrace, Building A', University Campus, Kimmeria, 67100 Xanthi, Greece; kspiliot@civil.duth.gr (K.S.); stampetko@outlook.com (S.P.); dimitrismpourdis@gmail.com (D.B.)

² Department of Civil Engineering, Aristotle University of Thessaloniki, Building E10, University Campus, 54124 Thessaloniki, Greece; hskoulid@civil.auth.gr

³ Decentralized Administration of Macedonia-Thrace, Kath. Rossidi 11, 54655 Thessaloniki, Greece; geokampas@yahoo.gr

* Correspondence: mspiliot@civil.duth.gr or m.spiliotis@gmail.com; Tel.: +30-695-112-5783 or +30-254-107-9613

[†] Presented at the 6th International Conference on Efficient Water Systems (EWaS6), Thessaloniki, Greece, 11–14 May 2026.

Abstract

In this study Markov chains process in combination with chi-squared test were applied to hydrological drought dataset of Nestos hydrosystem to highlight the drought transition attitude from one drought state to another. This examined hydrosystem is of great importance to the region due to it is exploited for hydrodynamic generation and irrigation purposes. Hence, it is important to identify the transitions from one drought situation to another so that operational water management can be carried out throughout the year.

Keywords: Markov chains; chi-squared test; Streamflow Drought Index (SDI); hydrological drought; Nestos river hydrosystem

1. Introduction

Hydrosystems incorporating hydropower plants (HPPs) constitute critical regulation components in river basin management, as their operation affects not only energy production but also downstream water allocation, irrigation reliability, and the maintenance of environmental flows. Reservoir operation in such systems should be addressed as a multi-objective problem, in which hydropower production, agricultural water supply, and ecological requirements are evaluated simultaneously. In this context, drought conditions introduce significant pressure on system performance, reducing inflow availability and increasing competition among water uses, thereby requiring adaptive and flexible operating rules.

The Thissavros–Platanovryssi reservoir cascade, located in northeastern Greece, forms the principal regulation infrastructure of the transboundary Mesta/Nestos River system. The two reservoirs were originally developed primarily for hydropower generation, while they also support downstream irrigation demands and influence the hydrological regime of the river. Due to their location close to the Greek–Bulgarian border, the reservoirs receive substantial transboundary inflows from the upstream Bulgarian part of the basin, which accounts for approximately 54% of the total catchment area. These inflows, combined with runoff generated within the Greek territory, contribute to the coverage of agricultural water



Academic Editors: Vasilis Kanakoudis,
Evangelos Keramaris, Francesco
De Paola, Habib Muhammetoglu and
Theodora Papamitsou

Published: 29 June 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

requirements over an irrigated area of about 190,000 ha through an extended open-channel conveyance network [1,2], as well as hydropower generation during all years and the ecological recharge.

Hence, it is important to identify the transitions from one drought situation to another so that operational water management can be carried out throughout the year. Initially, a hydrological drought analysis was performed using the Streamflow Drought Index (SDI) on a three-month, six-month, nine-month, and twelve-month scale and the extracted data were submitted to the Markov process.

2. The Streamflow Drought Index (SDI)

Hydrological drought refers to periods of reduced water availability in rivers, reservoirs, and groundwater systems, usually occurring as a delayed response to prolonged deficits in precipitation and basin recharge. In contrast to meteorological or agricultural drought, hydrological drought reflects the cumulative effects of reduced inflows and storage within the hydrological system. To quantify hydrological drought conditions based on streamflow records, Tsakiris and Nalbantis (2009) [3] introduced the Streamflow Drought Index (SDI). The SDI is computed from cumulative streamflow volumes over selected reference periods (e.g., 3, 6, or 12 months) within each hydrological year. These cumulative volumes are standardized using their long-term mean and standard deviation, allowing the transformation of streamflow anomalies into a dimensionless index comparable across basins and time periods. Negative SDI values indicate drought conditions, with increasingly negative values corresponding to more severe hydrological drought events. The SDI has been widely applied in hydrological studies because it provides a simple and consistent framework for detecting, monitoring, and comparing drought conditions using observed river discharge data.

It is assumed that a time series of monthly streamflow volumes $Q_{i,j}$ is available where i denotes the hydrological year and j the month within that hydrological year ($j = 1$ for October and $j = 12$ for September). Hence, it holds [3]:

$$V_{i,k} = \sum_{j=1}^{3k} Q_{i,j} \quad i = 1, 2, \dots \quad j = 1, 2, \dots, 12 \quad k = 1, 2, 3, 4 \quad (1)$$

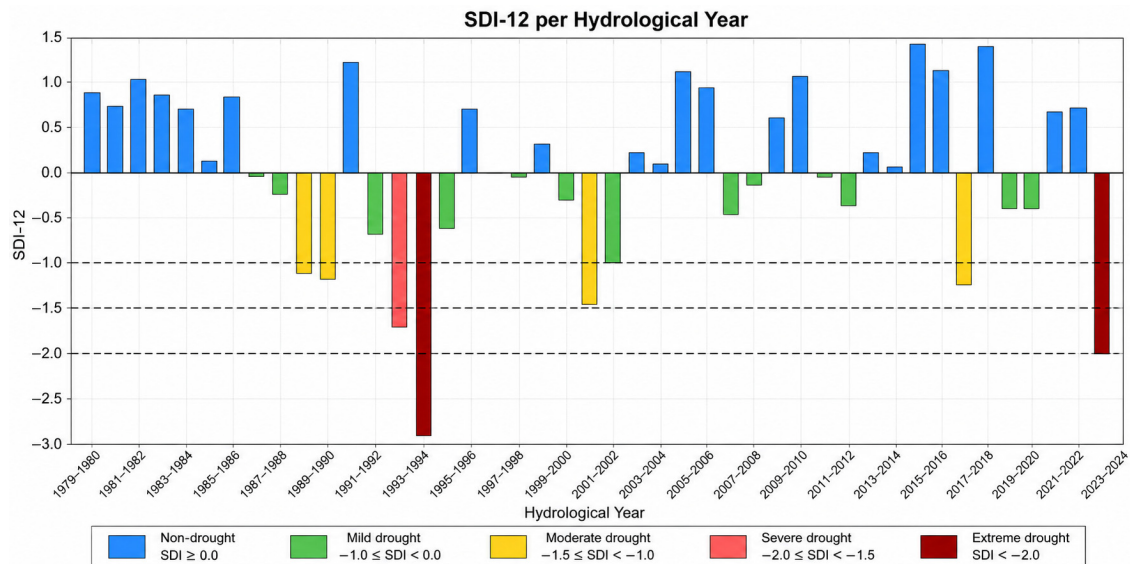
In which i refers to the hydrological year, j corresponds to the month of that year, k is the time duration of the period, and finally $V_{i,k}$ represents the cumulative streamflow volume for the i -th hydrological year with a period duration of k . Consequently, the SDI for the i -th hydrological year with period duration k is defined using the cumulative streamflow volumes $V_{i,k}$ as follows:

$$SDI_{i,k} = \frac{y_{i,k} - \bar{y}_k}{\sigma_{yk}} \quad i = 1, 2, \dots \quad k = 1, 2, 3, 4 \quad \text{where } y_{i,k} = \ln V_{i,k} \quad (2)$$

Based on the SDI values, hydrological drought conditions are classified into states consistent with those adopted for the meteorological drought indices SPI and RDI. Five drought states are considered, represented by integer values from 0 (non-drought) to 4 (extreme drought), according to the criteria presented in Table 1. For illustration purposes the annual hydrological drought is presented in Figure 1.

Table 1. Definition of the classes of drought.

State	Class of Drought	Numerical Criterion
0	Non-drought	$SDI \geq 0.0$
1	Mild drought	$-1.0 \leq SDI < 0.0$
2	Moderate drought	$-1.5 \leq SDI < -1.0$
3	Severe drought	$-1.5 \leq SDI < -1.0$
4	Extreme drought	$SDI < -2.0$

**Figure 1.** Values of the annual hydrological drought based on the SDI index.

3. Methodology

3.1. Markov Chain on Drought Events

By studying drought, it is found that it constitutes a random (stochastic) system; therefore, it is generally impossible to predict the future state with certainty. For this reason. In a Markov process of order q the future state is depended only on the q previous states. Specifically, let $X_1, X_2, \dots, X_n$ be a random states then the probability of the future X_{n+1} state is given [4]:

$$P(X_{n+1} = x | X_n = x_n, X_{n-1} = x_{n-1}, \dots, X_1 = x_1) = P(X_{n+1} = x | X_n = x_n, \dots, X_{n-q+1} = x_{n-q+1}).$$

In case of $q = 1$ we obtain

$$P(X_{n+1} = x | X_n = x_n, X_{n-1} = x_{n-1}, \dots, X_1 = x_1) = P(X_{n+1} = x | X_n = x_n) \quad (3)$$

i.e., the probability of a future depends only on the previous ones. Additionally, the zero order Markov process has no dependence on any previous states. The current state is completely independent, making the process entirely random and referred to as a renewal process [3].

A Markov process is fully characterized by the State Transition Matrix (STM), denoted P , For a first-order process ($q = 1$) with N states, $P = [p_{ij}]$ and p_{ij} denote the probability of transition from state $X_i \rightarrow X_j$ i.e.,

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{pmatrix} \quad (4)$$

The estimation of the probabilities p_{ij} is based on the maximum likelihood probability estimators [4]:

$$p_{ij} = \frac{n_{ij}}{n_i}, \quad (5)$$

where n_{ij} is the number of transitions from state $X_i \rightarrow X_j$ in the time series and n_i is the probability of being at state X_i i.e.,

$$n_i = \sum_{j=1}^k n_{ij} \quad (6)$$

In case of zero-order Markov process, the matrix P^0 has its i -column constant and equal with

$$p_i = \frac{n_i}{n} \quad (7)$$

and describes the probability of being at state i independently of any previous state.

Finally, for the application of Markov chains, the findings of the Hydrological Drought analysis were used (Table 1), in which five different drought states are discretized (Table 1). Therefore, in the present case, the transition matrix is as follows:

$$P = \begin{pmatrix} P_{01} & \cdots & P_{04} \\ \vdots & \ddots & \vdots \\ P_{40} & \cdots & P_{44} \end{pmatrix} \quad (8)$$

3.2. Statistical Analysis of Markov Chains: Comparing Zero and First Order Markov Process

We test how different is the zero and first order Markov process. Thus, we examine the statistical difference of P^0 and P^1 matrices using X^2 test of good fitness [Ktonas Anderson]:

$$X^2 = \sum_{i=1}^k \sum_{j=1}^k n_i \frac{(P_{ij} - P_{ij}^0)^2}{P_{ij}^0}$$

We examine the statistical Hypothesis $H_0 : P = P_0$ with $n(n - 1)$ degrees of freedom with $\alpha = 0.05$ of significance level.

4. Results and Discussion

From the SDI values we derive the discrete drought states (Figure 2), and then we apply the Markov process to the Nestos data in order to compute the 5-state transition matrix ($n = 5$):

$$P = \begin{pmatrix} P_{01} & \cdots & P_{04} \\ \vdots & \ddots & \vdots \\ P_{40} & \cdots & P_{44} \end{pmatrix} \quad (9)$$

Indicatively, the results of drought-state transition (using Equations (5) and (6)) from the six-month to the twelve-month time scale are presented below.

$$P = \begin{bmatrix} 0.8148 & 0.1852 & 0 & 0 & 0 \\ 0.1 & 0.5 & 0.2 & 0.1 & 0.1 \\ 0.2 & 0.4 & 0.4 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0.5 & 0 & 0 & 0.5 \end{bmatrix}$$

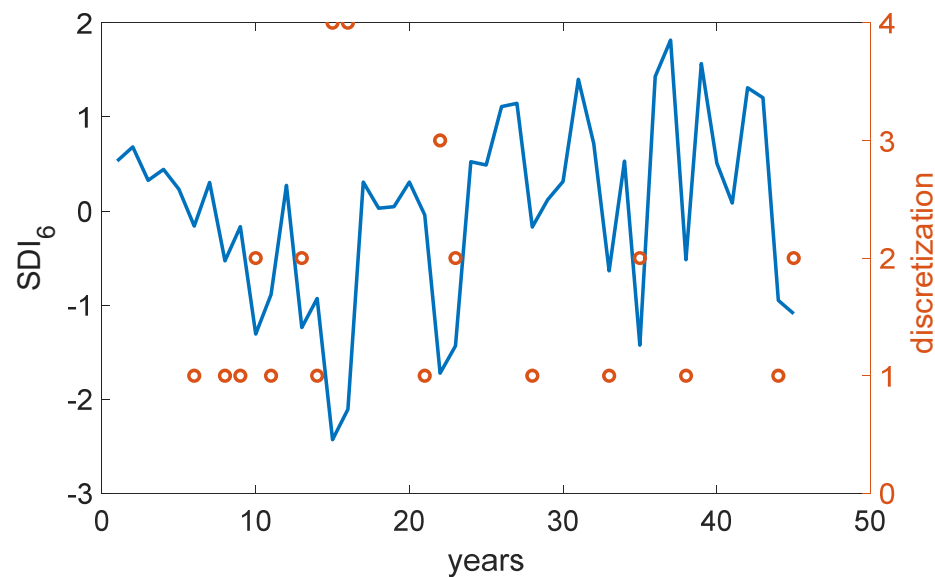


Figure 2. From SDI values to discrete states of drought from 0 to 4 (5 states according to Table 1).

Conclusions based on Markov chains: $p_{00} = 0.8148$, $p_{01} = 0.1852$, $p_{02} = p_{03} = p_{04} = 0$. Interpretation: If the first quarter begins under non-drought or mild drought conditions, then it will remain in the same states. Similarly, $p_{10} = 0.1$, $p_{11} = 0.5$, $p_{12} = 0.2$, $p_{13} = p_{14} = 0.1$. Interpretation: If the first quarter is characterized by mild drought, then with a probability of 10% the six-month period will be non-drought, 50% mild, 20% moderate, and 10% severe or extreme. The same reasoning applies accordingly to the remaining cases.

The X^2 statistical function was computed $X^2 = 44.99$ and $n(n - 1) = 20$ degrees of freedom the p -value is $p = 0.001$, thus we can reject the null Hypothesis $H_0 : P = P_0$ and hence the proposed analysis was accepted.

However, an interesting finding is that when the system starts from a state of extreme drought, after six months the annual transition probabilities indicate a 0.5 probability of remaining in extreme drought and a 0.5 probability of moving to mild drought. This behavior may reflect the influence of a specific historical event, which could be attributed either to a rare meteorological occurrence or to upstream flow regulation imposed from the Bulgarian side either the regulation of the upstream dams. Therefore, the use of Markov chain methodology for hydrological drought analysis in highly regulated systems may produce results that are of limited interpretative and practical value.

Author Contributions: K.S., M.S., C.S., S.P., D.B. and G.K. contributed equally to the conception, methodology, analysis, writing, and revision of this manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: Participation in the research project “Multi-criteria Management of the Nestos Hydrosystem with Emphasis on Drought Resilience,” serving as Principal Investigator (budget: €36,700 plus VAT; duration: 13 months), commissioned by the Regional Union of Municipalities of Eastern Macedonia and Thrace and implemented through the Democritus University of Thrace (2025–2026).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available upon personal communication with the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Bourdis, D.; Petkopoulos, S.; Skoulikaris, C.; Kampas, G.; Spiliotis, M. Climate-Driven Inflow Variability and Operational Management Conflicts in a Hydropower–Irrigation Hydrosystem. In Proceedings of the 9th IAHR Europe Congress: Innovating Hydro-Environment Engineering for a Sustainable Future. Arctic Waters and Beyond, Luleå, Sweden, 9–12 June 2026.
2. Skoulikaris, C.; Venetsanou, P.; Lazoglou, G.; Anagnostopoulou, C.; Voudouris, K. Spatio-Temporal Interpolation and Bias Correction Ordering Analysis for Hydrological Simulations: An Assessment on a Mountainous River Basin. *Water* **2022**, *14*, 660. [\[CrossRef\]](#)
3. Nalbantis, I.; Tsakiris, G. Assessment of Hydrological Drought Revisited. *Water Resour. Manag.* **2009**, *23*, 881–897. [\[CrossRef\]](#)
4. Korda, A.I.; Koliarakis, M.; Asvestas, P.A.; Matsopoulos, G.K.; Ventouras, E.M.; Ktonas, P.Y.; Smyrnis, N. Discrete states of attention during active visual fixation revealed by Markovian analysis of the time series of intrusive saccades. *Neuroscience* **2016**, *339*, 385–395. [\[CrossRef\]](#) [\[PubMed\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.