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A Novel Hybrid ANN-CCO Framework for Monthly Water Consumption Forecasting Driven by Temporal Dynamics

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Abstract

Accurate urban water consumption forecasting is vital for resilient resource management in metropolitan areas facing climate and anthropogenic pressures. This study introduces a novel hybrid intelligent framework that couples an Artificial Neural Network with the newly developed Cuckoo Catfish Optimizer (ANN-CCO) to predict monthly water consumption in Izmir, Turkey, based on a 120-month historical dataset (2015–2024). Prior to predictive modeling, the underlying time-series dynamics—encompassing long-term trends, Sen's slopes, and structural changepoints detected via the BEAST algorithm—were analyzed to establish a baseline for the hydro-climatic and socioeconomic drivers. The core innovation lies in leveraging the unique exploration, transition, and chaotic predation mechanisms of the CCO metaheuristic to optimize the architectural hyperparameters and weights of the neural network. Empirical results demonstrate that the proposed hybrid ANN-CCO model achieves exceptional predictive precision, yielding an outstanding correlation coefficient (R) of 0.9853, a Root Mean Square Error (RMSE) of 1.87 million m³, and a Mean Absolute Error (MAE) of 1.71 million m³. Crucially, the hybrid framework provides a substantial performance improvement; it enhances the correlation coefficient by 17.8% and reduces the RMSE by 46.8% compared to the standalone ANN benchmark. Furthermore, the proposed model outperforms XGBoost, achieving a 1.9% higher R and a 34.4% lower RMSE. Diagnostic distribution analysis confirms that this novel model successfully reproduces the statistical distribution of water consumption without systematic bias, offering a highly dependable decision-support tool for forward-looking urban water utility planning.

Keywords: Artificial Neural Network (ANN); Beast, Cucko Catfish Optimizer(CCO); forecasting; Izmir; time series; water consumption

1. Introduction

Water stands as a paramount resource safeguarding human survival, socio-economic prosperity, global food security, and ecological equilibrium. Accelerated demographic growth, hyper-urbanization, climate change, and unsustainable consumption have exerted unprecedented stress on global freshwater reserves (UNESCO, 2023). Over two billion individuals currently inhabit highly water-stressed territories, a metric projected to worsen significantly by mid-century (Fang et al., 2024). In arid and semi-arid geographies, this vulnerability is further exacerbated by deficient precipitation, high evapotranspiration rates, and systematic overexploitation of groundwater aquifers. The Eastern Mediterranean basin, where Turkey occupies a central position, is a recognized climate change hotspot with significant warming trends and highly erratic precipitation patterns (Sakalis, 2023). Consequently, municipal authorities and water utility operators face mounting pressure to maintain equitable, resilient, and efficient water distribution while reducing environmental footprints and operational costs (Donkor et al., 2014; House-Peters & Chang, 2011).

High-precision urban water consumption forecasting has emerged as a cornerstone of sustainable water management (Ghalekhondabi et al., 2017; Niknam et al., 2023). Reliable demand projections help utilities optimize pumping schedules, minimize energy consumption, detect network anomalies or leakages, streamline asset maintenance, and implement demand-side conservation strategies (Cembrano et al., 2000; Salomons et al., 2007). Medium-term monthly forecasts support infrastructure expansion planning, tariff adjustments, and climate adaptation initiatives (Billings & Jones, 2008; Donkor et al., 2014). However, historical water consumption series are notoriously intricate, exhibiting nonlinearity, non-stationarity, volatility, and multi-scale seasonality driven by climate, socio-economics, and human behavior (Herrera et al., 2010; Duerr et al., 2018). Capturing these dynamics with conventional predictive frameworks remains challenging.

Historically, urban water demand modeling has been dominated by classical parametric and statistical techniques, including AR, MA, ARIMA, SARIMA, and multivariate linear regression (Box et al., 2015; Hyndman and Athanasopoulos 2018). These models are favored for their theoretical foundations, computational simplicity, and interpretability. For instance, Sakalis (2023) used ARIMA and SARIMA to project monthly temperature and precipitation across the Eastern Mediterranean. Despite these merits, classical methods assume linearity, stationarity, and normally distributed homoscedastic errors—conditions that real-world water data routinely violate due to extreme fluctuations and complex human behaviors (Adamowski et al., 2012; Anele et al., 2017). Moreover, they struggle to ingest dynamic exogenous covariates like sudden meteorological shifts or tourism-induced demographic influxes without manual feature engineering (Shan et al., 2023), leading to performance degradation under structural breaks (Makridakis et al., 2018).

To overcome these limitations, the past two decades have seen a paradigm shift toward data-driven machine learning (ML) and deep learning (DL) paradigms. These algorithms can map complex, nonlinear relationships directly from

historical data without a priori assumptions (Solomatine et al., 2009). Shallow architectures such as ANNs, SVR, Random Forests (RF), and Gradient Boosting Machines (GBM) have consistently outperformed classical benchmarks across diverse urban areas (Herrera et al., 2010; Lee & Derrible 2020; Xenochristou et al., 2020). More recently, advanced DL models like LSTM, CNNs, and hybrid variations have demonstrated state-of-the-art proficiency in capturing long-range temporal dependencies, pushing the frontiers of short- and medium-term forecasting (Guo et al., 2018; Zanfei et al., 2022; Pu et al., 2023).

The systematic execution of stochastic time-series algorithms for municipal water systems traces back to pioneering works like Maidment and Miaou (1986), who constructed univariate ARIMA structures to track daily water utilization across nine distinct metropolitan areas in the United States. Smith (1988) subsequently enhanced the adaptability of daily water demand models by embedding an adaptive state-updating procedure to dynamically recalculate the moving mean. Recognizing the early limitations of purely linear approaches, Jain et al. (2001) executed a comparative assessment between conventional regression techniques, time-series benchmarks, and feed-forward ANNs for weekly water demand mapping at IIT Kanpur, India, providing early evidence of neural network superiority over classical alternatives. As data availability improved, researchers increasingly incorporated hydro-climatic inputs to refine predictive fidelity. Al-Zahrani and Abo-Monasar (2015) established a hybrid framework combining conventional ARMA formulations with General Regression Neural Networks (GRNN) to forecast daily residential consumption in Al-Khobar, Saudi Arabia. Adamowski et al. (2012) conducted a rigorous comparative evaluation of multiple linear regression, nonlinear formulations, ARIMA, standalone ANNs, and coupled Wavelet-ANN architectures for urban water forecasting in Montreal, Canada, concluding that wavelet decomposition prior to neural training yields the highest predictive precision. Focusing on the macro-climatic landscape of the Eastern Mediterranean, Sakalis (2023) executed non-parametric Mann-Kendall trend tests and Sen's slope estimations across multiple nations, documenting intense, statistically significant warming trends alongside highly localized precipitation anomalies, such as a significant positive precipitation slope of 4.36 mm/year in Greece during the 1990–2021 window. Da Silva et al. (2021) established monthly water consumption models using multivariate regression and cross-validation techniques for multifamily buildings in Southern Brazil, proving that structural and sociodemographic indicators—such as building age and alternative supply configurations—exert systematic control over regional demand profiles.

The decade spanning 2010 to 2020 marked a widespread transition toward machine learning for municipal demand forecasting. Herrera et al. (2010) evaluated a broad selection of ML configurations—encompassing ANNs, projection pursuit regression, multivariate adaptive regression splines, RF, and SVR—for hourly urban consumption tracking in southeastern Spain, identifying SVR as the top-performing framework. Chen et al. (2017) applied multiple Random Forest models to capture spatial-temporal interactions in southwestern China by integrating satellite-derived vegetation indices, land cover matrices, and localized evapotranspiration rates. Villarín and Rodríguez-Galiano (2019) contrasted Classification and Regression Trees (CART) against RF for municipal forecasting in Seville, Spain, determining that the ensemble aggregation of RF drastically minimizes overfitting risks. Xenochristou et al. (2020) later applied Gradient Boosting Machines across multiple spatial hierarchies, demonstrating that prediction accuracy is highly sensitive to the granularity of data aggregation and feature engineering. In residential sectors, Bennett et al.

(2013) designed an ANN-based framework to disaggregate high-resolution smart-meter data into appliance-level end-use profiles. Lee and Derrible (2020) utilized advanced machine learning models, including Lasso, Bayesian regression, and Gradient Boosting, to assess the impact of demographic and housing features on daily water demand across the United States, concluding that tree-based gradient boosting excels when dealing with high-dimensional exogenous predictors. Bata et al. (2020) proposed a hybrid configuration utilizing unsupervised Self-Organizing Maps (SOM) to cluster data profiles before feeding them into Regression Trees (RT), achieving vastly superior accuracy compared to unclustered RT and standalone SARIMA alternatives. Smolak et al. (2020) demonstrated that integrating highly dynamic exogenous data—specifically human mobility records—into shallow machine learning architectures like Random Forests and Support Vector Regression yields a marginal yet statistically visible accuracy enhancement over classical ARIMA configurations for short-term daily forecasting horizons. G and K (2026) developed a hyperparameter-optimized XGBoost framework incorporating temporal and contextual features such as festivals, weather variations, and public holidays, achieving an R^2 of 0.9399 and reducing RMSE by 11.29% compared to baseline models. Estrada et al. (2025) applied Multilayer Perceptron (MLP) neural networks with Backpropagation and Resilient Backpropagation training methods to forecast monthly water demand in Joinville, Brazil, achieving a MAPE of 1.59% for total water demand, with two-hidden-layer networks trained by RP outperforming single-layer networks. Seyid Abdellahi et al. (2025) employed Random Forest and Generalized Additive Models to forecast household water demand in Ben Guerir, Morocco, identifying household size and socio-economic profile as the dominant predictors ($R^2 \geq 0.91$), with scenario analysis showing that demographic and social shifts affect demand more than income or pricing alone.

The introduction of deep learning architectures has provided powerful new capabilities for temporal feature extraction. Guo et al. (2018) deployed Gated Recurrent Unit (GRU) networks for high-resolution short-term demand forecasting, establishing their superiority over shallow neural network configurations. Kühnert et al. (2021) utilized Long Short-Term Memory (LSTM) recurrent networks to capture complex multi-scale temporal dependencies, integrating day-of-the-week indicators and national holiday schedules to optimize municipal pump scheduling. Mu et al. (2020) constructed multivariate LSTM networks for urban water demand prediction in Hefei, China, documenting that the inclusion of dynamic temperature and relative humidity features significantly enhances deep learning forecasting precision. To exploit both localized spatial-temporal features and long-range dependencies, researchers turned toward hybridized deep frameworks. Mousavi-Mirkalaei and Banihabib (2019) introduced an ARIMA-NARX hybrid framework to model daily urban consumption in the Tehran metropolis, combining linear time-series formulations with exogenous climatic parameters like relative humidity, precipitation, and sunshine hours. Chen et al. (2022) developed a coupled Conv1D-GRU network that automates spatial feature extraction prior to recurrent temporal processing. Pu et al. (2023) validated a hybrid Wavelet-CNN-LSTM deep architecture for multi-step municipal forecasting, demonstrating that it systematically outperformed standard GRU, LSTM, and shallow ANN configurations. Du et al. (2021) integrated Discrete Wavelet Transforms (DWT) and Principal Component Analysis (PCA) with LSTM networks, reporting that multi-scale data decomposition prior to deep training greatly improves the model's capacity to isolate sudden peak demand anomalies. Recent studies have incorporated attention-driven mechanics to further isolate critical temporal points. Shan et al. (2023) engineered a comprehensive predictive

framework utilizing the Maximal Information Coefficient (MIC) for advanced feature isolation, an Attention-BiLSTM network for temporal forecasting, and an XGBoost model for residual error correction. Gil-Gamboa et al. (2024) developed a deep feed-forward neural network (DFFNN) leveraging automated hyperparameter tuning via Keras Tuner, achieving high precision across thousands of individual consumers in Seville, Spain. Conversely, Michalopoulos et al. (2024) executed a large-scale evaluation of machine learning paradigms across 2.1 million consumers in Athens, Greece, noting that under specific regional conditions, traditional ARIMA structures can still outperform complex recurrent neural architectures. Ghalekhondabi et al. (2017) reviewed soft computing methods for water demand forecasting and concluded that these methods are mainly used for short-term predictions, while medium- and long-term forecasting remains underexplored.

To eliminate the vulnerabilities of manual trial-and-error hyperparameter selection, metaheuristic and stochastic optimization algorithms have been widely adopted to automate neural network configuration. Zubaidi et al. (2024) introduced a hybrid approach coupling wavelet denoising with a hybrid PSOGA metaheuristic (integrating Particle Swarm Optimization and Genetic Algorithms) to optimize ANN configurations for monthly forecasting in College Station, USA, achieving superior predictive metrics over standalone PSO-ANN and GWO-ANN frameworks. Alsumaiei (2025) presented a multi-objective LSTM architecture optimized via the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to balance predictive accuracy against recurrent network complexity. Yang et al. (2024) developed a coupled Harris Hawks Optimization and Backpropagation Neural Network (HHO-BPNN) for regional forecasting across northern Jiangsu, China, reporting exceptional generalization ($R^2 > 0.95$) across distinct agricultural and domestic sectors. Dong et al. (2025) proposed an advanced Inception-V4 network optimized by Enhanced Single Candidate Optimization (ESCO) for water demand forecasting in Shanghai, demonstrating that metaheuristic-driven deep networks drastically reduce root-mean-square errors compared to standard optimization benchmarks.

A review of the literature reveals several notable research trajectories. First, there has been a steady progression from classical parametric approaches (ARIMA, SARIMA) to advanced shallow machine learning (ANN, SVR, RF) and deep hybrid networks (CNN-LSTM, attention mechanisms). Second, the integration of swarm intelligence and evolutionary metaheuristic optimizers (GA, PSO, GWO, HHO, ESCO) has consistently proven essential for maximizing data-driven model performance. Third, although the Eastern Mediterranean basin, including Turkey, has been identified as an acute climate change hotspot with significant historical warming trends (Sakalis, 2023), there remains a pronounced lack of research executing optimized hybrid architectures for urban water forecasting within this specific geographic territory. Fourth, the vast majority of existing literature addresses high-resolution short-term horizons (hourly/daily), whereas medium-term monthly forecasting—which is far more critical for municipal budgeting, monthly billing cycles, and reservoir allocation management—remains comparatively underrepresented (Michalopoulos et al., 2024). The application of the recently developed Cuckoo Catfish Optimizer (CCO) to urban water resource systems remains completely unexplored. Furthermore, while most metaheuristic-driven forecasting models focus on optimizing complex recurrent networks, there is limited research on feed-forward networks optimized by highly competitive, multi-phase swarm intelligence algorithms. Finally, comprehensive evaluations comparing new metaheuristic-driven hybrid neural networks against both standalone architectures and advanced tree-based

ensembles like XGBoost are noticeably scarce, particularly in semi-arid Mediterranean metropolitan areas like İzmir, Turkey, which face severe seasonal fluctuations. The present study directly addresses these interconnected research gaps.

The core novelty of this study centers on addressing regional temporal dynamics through a novel hybrid intelligence design. This study introduces the first-time deployment of the Cuckoo Catfish Optimizer (CCO) (Wang et al., 2025) within the domain of water resource engineering to eliminate global optimization stagnation. Instead of relying on standard manual tuning, a novel hybrid ANN-CCO framework is engineered, where the multi-phase competitive mechanics of CCO are strictly integrated to automate hyperparameter extraction and weight configuration in a feed-forward neural structure. The hybrid design is specifically optimized to adapt to aggressive multi-scale seasonality, capturing abrupt structural changepoints, Sen's slopes, and seasonal peak anomalies without systematic bias. The predictive fidelity of this newly formulated hybrid model is validated through a direct comparative execution against advanced tree-based ensembles (XGBoost) and standalone networks.

2. Materials and Methods

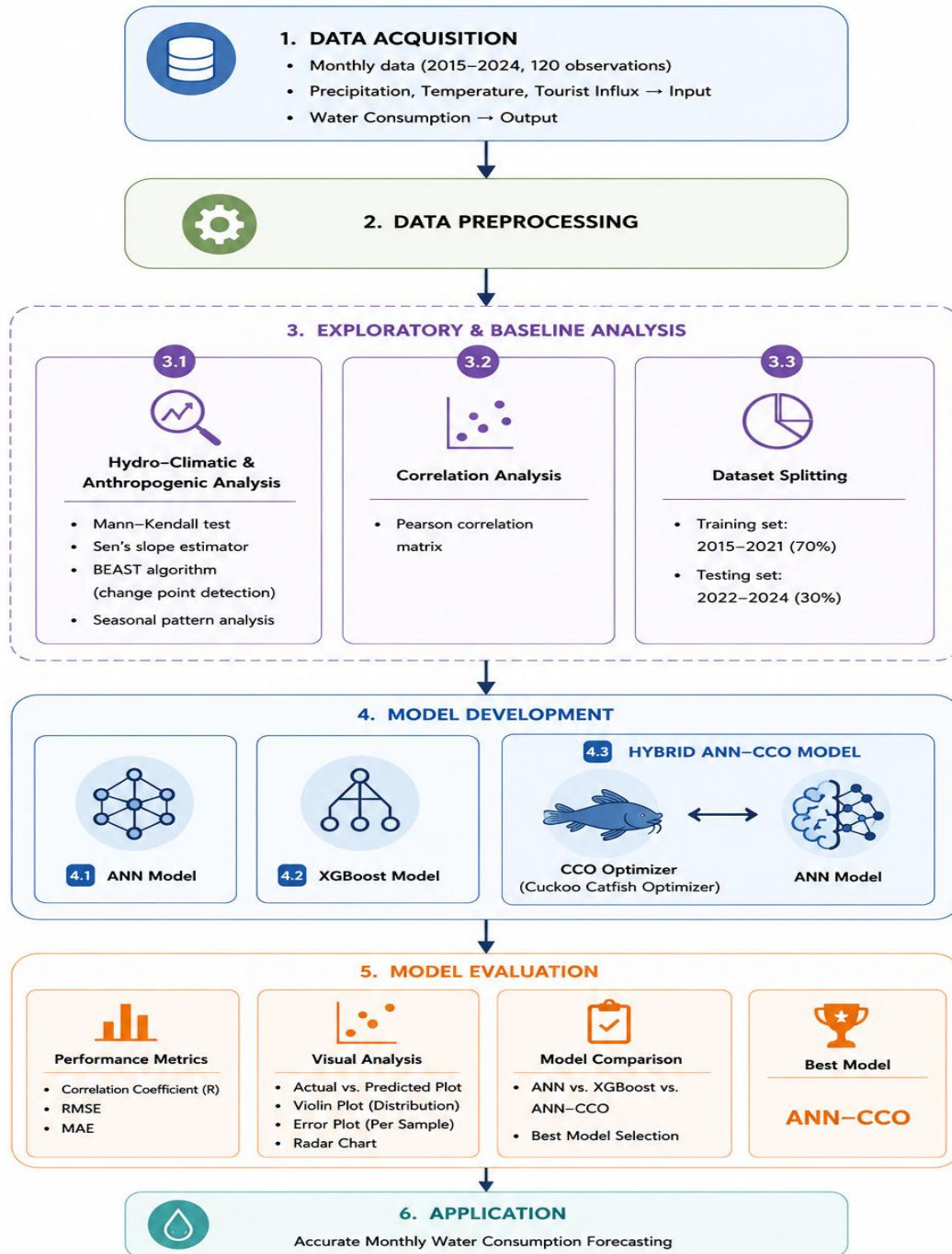


Figure 1. Overall framework of the proposed methodology.

2.1. Study Area and data

This study focuses on Izmir, the third-largest metropolitan city in Turkey, located on the Aegean coast. The city has a Mediterranean climate with hot, dry summers and mild, rainy winters. İzmir is one of the most populous and urbanized metropolitan cities in Turkey, experiencing significant land use and land cover changes (Kesgin & Ersoy,

2020). The southern region of İzmir faces risks from earthquakes, floods, and landslides, with a 6.9 magnitude earthquake occurring on 30 October 2020 (Ecemis Kılıç et al., 2025). İzmir faces water management challenges due to population growth (over 4.5 million), seasonal tourism, climate change, and urbanization. Water supply is managed by İZSU (İzmir Water and Sewerage Administration). Figure 2 illustrates the geographical location of İzmir, a metropolitan city in western Turkey on the Aegean coast.

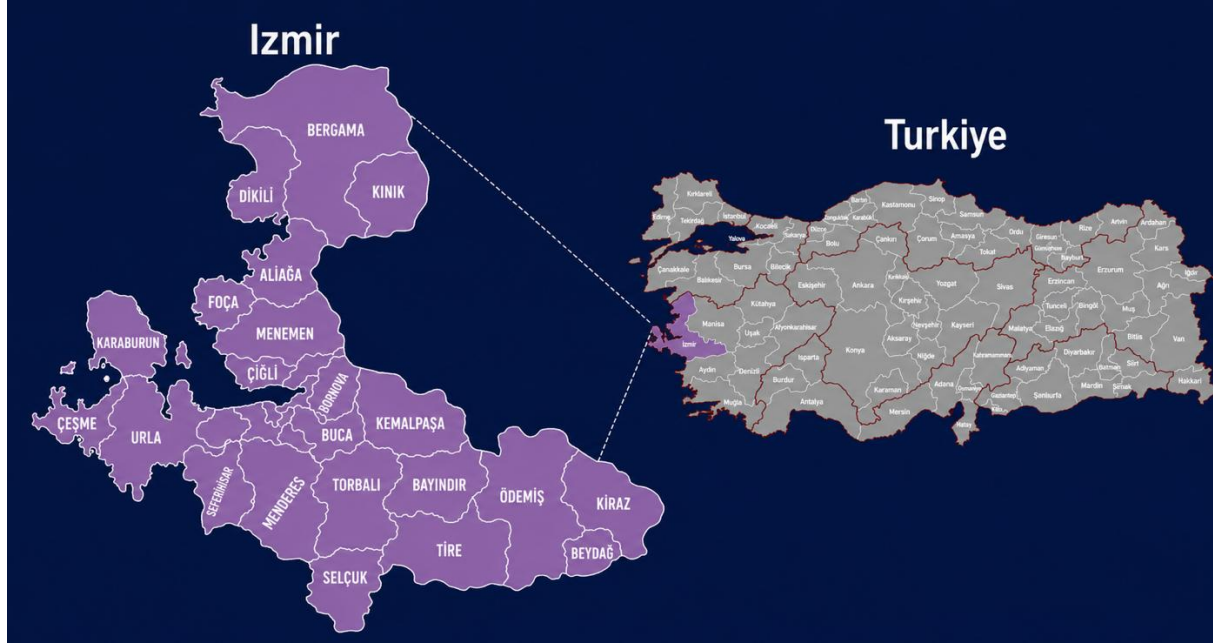


Figure 2. Location map of the study area

The dataset used in this study was compiled from two primary sources: İZSU (İzmir Water and Sewerage Administration) and TÜİK (Turkish Statistical Institute). The data is publicly available on the Kaggle platform under the title "Izmir_Water_Amount". The dataset comprises 120 monthly samples spanning a 10-year period from January 2015 to December 2024. Three input variables and one output (target) variable were extracted. The input variables include tourist count representing the monthly number of tourists visiting İzmir (persons), mean monthly temperature in degrees Celsius (°C) and monthly precipitation in millimeters (mm). The output variable is the total monthly water consumption in cubic meters (m³). Prior to model development, all variables were normalized using the Standard Scaler method. The dataset was divided into training (70%, 84 samples) and testing (30%, 36 samples) sets while preserving chronological order. Table 1 presents the statistical summary of the dataset, including the minimum, maximum, mean, and standard deviation (SD) for each variable.

Table 1. Statistical summary of the dataset

Variable	Min	Max	Mean	SD
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Tourist count	27,200	315,000	117,400	64,145
Average Temperature	5.1	33.7	20.04	8.27
Rainfall	4.0	188.1	65.12	50.58
Water Consumption	16,575,000	32,876,318	23,539,706	4,012,794

Prior to model development, all variables were normalized using the Standard Scaler method. The dataset was divided into training (70%, 84 samples) and testing (30%, 36 samples) sets while preserving chronological order.

2.2. Trend and Changepoint Detection

To identify structural breaks in the time series, the Bayesian ensemble changepoint detection algorithm BEAST was employed (Zhao et al., 2019). The non-parametric Mann-Kendall test was used to detect significant monotonic trends (Mann, 1945; Kendall, 1955), and Sen's slope estimator was applied to quantify the magnitude of the trends (Sen, 1968).

2.2.1. BEAST: A Bayesian ensemble change-detection algorithm

BEAST is a Bayesian ensemble algorithm introduced by Zhao et al. (2019) that decomposes time series into abrupt changes, seasonal patterns, and nonlinear trends (Zhao et al., 2019). Mathematically, BEAST models a time series $Y(t)$ as follows (Hu et al., 2021):

$$Y(t) = T(\theta_t) + S(\theta_s) + \varepsilon \quad (1)$$

where T and SS represent the trend and seasonal components, respectively, with abrupt changes encoded in the parameters θ_t (for trend changepoints) and θ_s (for seasonal changepoints), and ε is the Gaussian random error term following a normal distribution $N(0, \delta^2)$ with unknown variance δ^2 (Hu et al., 2021).

The unknown parameters are formulated as a posterior probability distribution according to Bayes' theorem (Zhao et al. 2019; Hu et al. 2021):

$$f(M | Y) \propto f(Y | M) \times f(M) \quad (2)$$

where $M = \{\theta_t, \theta_s, \delta^2\}$ represents the set of unknown parameters. The posterior probability $f(M|Y)$ encodes all information about the time series decomposition, including the number and locations of changepoints in both trend and seasonal components. Since this posterior distribution is analytically intractable, it is estimated using a reversible-jump Markov Chain Monte Carlo (MCMC) sampling scheme (Zhao et al., 2019; Hu et al., 2021).

Unlike conventional methods that rely on a single optimal model, BEAST employs Bayesian model averaging to combine multiple competing models, thereby estimating the probability of a change point at each time step and providing robust uncertainty measures (Zhao et al., 2019). The algorithm treats both the number and positions of change points as unknown parameters, which are inferred using the MCMC sampling scheme. This approach enables BEAST to

o automatically determine the optimal number of change points without requiring a predefined value, offering a significant advantage over traditional methods such as the Pettitt test or CUSUM.

A key feature of BEAST is its capability to produce probabilistic outputs, including the probability of a change point at any given time point, the posterior distribution of the total number of change points, and credible intervals for the estimated trend and seasonal components (Zhao et al., 2019). As noted by Hu et al. (2021), BEAST is a "fuzzy detector" that estimates the probability that a disturbance occurs for any given point in time, rather than simply reporting a binary result of whether a change has occurred. This uncertainty quantification is particularly valuable when analyzing real-world data with noise or complexity, as it helps differentiate true structural breaks from random fluctuations.

2.2.2 Mann-Kendall Test

To detect the presence of a significant trend in climatic and hydrological time series, the non-parametric Mann-Kendall test was employed (Mann, 1945; Kendall, 1955). This test does not assume a normal distribution of the data and is robust against outliers (Sakalis, 2023). The null hypothesis (H_0) of the Mann-Kendall test states that there is no trend in the time series, while the alternative hypothesis (H_a) indicates the existence of a monotonic upward or downward trend (Sakalis, 2023).

The test statistic S is calculated as follows:

$$s = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad (3)$$

where n is the number of data points, x_i and x_j are the data values at steps i and j , and the sign function returns +1, 0 or -1 for positive, zero, or negative differences, respectively (Sakalis 2023). Subsequently, the variance $V(S)$ and the standardized test statistic Z are computed and compared with the critical values of the standard normal distribution. A positive Z value indicates an increasing trend, while a negative value indicates a decreasing trend (Sakalis 2023). Furthermore, to eliminate the effect of serial correlation in the data, the modified Mann-Kendall test with the variance correction factor proposed by Hamed and Ramachandra (1998) was applied. In this approach, only significant correlation coefficients are included in the calculation of the correction factor CF (Sakalis 2023).

2.2.3 Sen's Slope Estimator

To estimate the magnitude of the trend, the non-parametric Sen's slope estimator (Sen, 1968) was utilized (Sakalis, 2023). This method is robust against outliers and provides a more realistic estimate than classical linear regression.

For a given time series with n data points, the slopes between all possible pairs (x_j, x_k) under the condition $j > k$ are calculated as follows (Sakalis, 2023):

$$\beta_i = \frac{x_j - x_k}{j - k}, \quad \forall \quad k \leq i \text{ and } i = 1, 2, \dots, N \quad (4)$$

The final slope (β) is then defined as the median of all β_i values. If the number of pairs (N) is odd, the final slope equals the $\beta_{(N+1)/2}$ value; if even, it equals the average of the two middle values $\beta_{N/2}$ and $\beta_{(N+2)/2}$ (Sakalis, 2023).

2.3. Predictive Models

Three models were implemented for monthly water consumption forecasting: ANN, XGBoost, and the proposed hybrid ANN-CCO. The hybrid integrates the Cuckoo Catfish Optimizer (Wang et al. 2025) with a standard ANN to automate hyperparameter and weight optimization.

2.3.1. Cuckoo Catfish Optimizer (CCO)

The Cuckoo Catfish Optimizer (CCO) is a novel swarm intelligence-based metaheuristic algorithm introduced by Wang et al. (2025). The algorithm is fundamentally inspired by the unique, aggressive, and highly adaptive biological and evolutionary warfare waged by the cuckoo catfish (*Synodontis multipunctatus*) against cichlid fish (*Cichlids*) in Lake Tanganyika, East Africa.

Unlike conventional cooperative swarm models, CCO models a highly competitive, dynamic, and multi-phased survival mechanism. The optimization process mimics five core evolutionary and behavioral milestones:

- Population Initialization: Distributing potential solutions uniformly across the search space.
- Exploration Phase: Simulating the widespread, multi-directional search for cichlid spawning grounds using wraparound and tight space search strategies.
- Transition Strategy: Maintaining a fluid, balanced socio-structural split in the swarm to seamlessly bridge global exploration and local exploitation.
- Chaotic Predation (Exploitation Phase): Modeling the chaotic, high-energy invasion of cichlid nests to consume host eggs.
- Death and Parasitic Strategy: Mimicking brood parasitism (forcing cichlids to mouth-brood catfish eggs) and the linear risk of mortality due to starvation, which triggers random re-birthing mechanics to escape local optima.

2.3.1.1. Biological Inspiration of CCO

To fully understand the mathematical design of CCO, it is essential to map the sophisticated biological arms race between the cuckoo catfish and its host. *Synodontis multipunctatus* is one of the few known obligate social brood parasites among fish. Its survival depends entirely on interrupting the spawning cycle of mouth-brooding cichlids. When cichlids lay their eggs, they quickly turn around to collect them in their mouths for safety (mouth-brooding). The cuckoo catfish must time its approach with absolute precision. Catfish swarms patrol the lake bed, hunting for mating cichlids (Exploration). Once a spawning pair is located, the catfish launch a rapid, chaotic strike (Exploitation/Predation). They dart into the nest, swiftly devour the host's eggs, and simultaneously deposit their own eggs before the cichlid can close its mouth. The deception relies on speed and physiological adaptation: (1) cuckoo catfish eggs hatch significantly faster than cichlid eggs inside the host's mouth (Parasitic Leverage); (2) once hatched,

the larval catfish consume the remaining unhatched cichlid eggs from the inside out (Internal Predation); and 3) if the swarm fails to locate active nests, individuals face starvation (Mortality Risk), forcing them to migrate to establish new colonies (Global Re-birth). CCO converts these precise biological thresholds into mathematical boundary conditions.

2.3.1.2. Population Initialization

The optimization routine begins by uniformly distributing a population of N individuals across a D -dimensional search space. The mathematical model for initializing the position of each individual is formulated as follows:

$$X_i^d = rand \times (Ub^d - Lb^d) + Lb^d, \begin{cases} i = 1, 2, \dots, N \\ d = 1, 2, \dots, D \end{cases} \quad (5)$$

where D represents the dimensionality of the problem, X_i^d is the d -th component of the i -th individual's position vector, and Ub^d and Lb^d denote the upper and lower bounds of the d -th decision variable, respectively.

2.3.1.3. Exploration Phase

During early iterations, the swarm focuses on a multi-dimensional wraparound search and a tight-space strategy to broadly chart the global terrain.

Space Escape and Dispersal Strategy. When a localized search strategy yields no further improvements over a set counter, the individual executes a spatial escape to prevent stagnation in local optima. The position is updated using two randomly selected swarm members via Eq. (6):

$$X_{new,i} = round(l_{esp}) + F \times \frac{r_1 \times R_1}{It^4} \times X_i^{new} \quad (6)$$

Where the Levy Escape relation l_{esp} is derived using Eq. (7):

$$l_{esp} = r_1 \times X_{r1} + (1 - r_1) \times X_{r2} \quad (7)$$

Here, $round(0)$ represents the rounding operator, while X_{r1} and X_{r2} represent the spatial positions of two distinct, randomly chosen individuals from the current population.

Superior Information Optimization Strategy. To enhance intra-swarm communication and intensify structural attraction toward promising regions midway through the runtime, Eq. (8) is utilized:

$$X_i^{new} = X_{best} \times (1 - (1 - \frac{1}{X_r}) \times R_1) \quad (8)$$

where X_{best} tracks the best-performing global solution discovered by the swarm up to the current iteration.

2.3.1.4. Transition Strategy

To establish a stable equilibrium and guarantee a smooth, adaptive transition between global exploration and local exploitation, a mathematically bifurcated transition strategy is utilized. The population is divided equally based on index parity. Even-indexed individuals focus on converging toward X_{best} to drive exploitation, while odd-indexed individuals move in parallel or opposite vectors to safeguard exploration diversity. This dual-motion mechanism is governed by Eq. (9):

$$X_i^{new} = \begin{cases} \frac{c}{It} \times (r_1 \times X_{best} - r_3 \times X_i) + T^2 \times lev(D) \times |Step_2| & \text{if } = mod(i, 2) = 0 \\ \frac{X_{best} + X_r}{2} + De \times \left(2 \times R_1 \times Step_2 - \frac{R_2}{2} \times (De \times R_3 - 1) \right) & \text{otherwise} \end{cases} \quad (9)$$

Levy Flight Simulation: Random wildlife trajectories characterized by frequent short steps punctuated by sudden, long-distance jumps are modeled via the D-dimensional Levy flight function $lev(D)$, preventing premature convergence:

$$lev = 0.05 \times \frac{u}{|v|^{-\beta}} \quad (10)$$

where u and v are drawn from standard normal distributions, and the power-law exponent is fixed at $\beta = 1.5$.

2.3.1.5. Chaotic Predation Strategy (Exploitation)

To mimic the high-energy disruption caused when catfish raid cichlid nests, the algorithm switches to a chaotic predation strategy. This phase factors in host alert thresholds and predator-host crowding density according to Eq. (11):

$$X_i^{new} = \begin{cases} X_{best} + F \times S \times (X_{best} - X_i) & \text{if } J_i > J_{in} \\ X_{best} \times (1 + T^5 \times Cy \times E) + F \times S \times (X_{best} - X_i) & \text{elsei } J_i > J_{in} \times Lx \\ X_{best} \times (1 + T^5 \times Gs) + F \times S \times (X_{best} - X_i) & \text{otherwise} \end{cases} \quad (11)$$

where L_x denotes the host cichlid's alert factor, derived via Eq. (12)

$$Lx = |rd| \times r_1 \quad (12)$$

The parameter C_y represents a small-scale chaotic perturbation coefficient simulating minor, defensive cichlid movements when danger is detected:

$$C_y = \frac{1}{\pi \times (1 + C^2)} \quad (13)$$

Conversely, G_s serves as a large-scale chaotic factor modeling major nest disruptions under confirmed predation. It is drawn from a Gaussian distribution with a mean of 0 and a variance of C^2 .

2.3.1.6. Death and Parasitic Strategy

In nature, failure to secure host nests introduces a linear risk of mortality (die). In early iterations, if a catfish agent is far from host clusters, it aggressively maneuvers toward the nearest nest to achieve brood parasitism using Eqs. (14)–(17):

$$best = X_{best} \times (lev(1) \times A + |rd_1| \times (1 - A)) \quad (14)$$

$$Up_c = \max(best) \quad (15)$$

$$Low_c = \min(best) \quad (16)$$

$$X_i^{new} = r_1 \times (Up_c - Low_c) + Low_c \quad (17)$$

where A is a random binary switcher selected from the set $\{0, 1\}$.

In late-stage iterations, depleted local food sources cause individual mortality. Starved agents are eliminated and randomly re-birthing across the global search space to find unexploited food reserves:

$$X_{new,i} = r_1 \times (Up - Low) + Low \quad (18)$$

The structural switch between these two survival/re-birth behaviors is governed by the boundary selection rule in Eq. (19):

$$\begin{cases} Eq. (17) & \text{if } rand > C \\ Eq. (18) & \text{else} \end{cases} \quad (19)$$

2.3.1.7. Final Position Updating

Following candidate position generation across the respective phases, a greedy selection mechanism determines population replacement according to Eq. (20):

$$X_i = \begin{cases} \begin{cases} X_i^{new} & \text{if } F_i^{new} < F_i \\ X_i & \text{else} \end{cases} & \text{if } F_i^{new} < F_i \\ X_i & \text{else} \end{cases} \quad (16)$$

where F_i^{new} and F_i denote the objective fitness values of the newly generated candidate position and the current position of the i -th individual, respectively. In minimization frameworks, a new position is accepted only if it yields a lower fitness value. The stall counter variable t tracks the consecutive number of iterations an individual has failed to improve its fitness. If t exceeds a critical threshold, the mortality risk reaches its maximum, forcing the agent to execute exploratory re-birth maneuvers to effectively escape local stagnation points.

2.3.2 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are efficient in modelling complex linear and non-linear relationships without the need for implicit assumptions (Somers & Casal, 2009). ANNs are computational models inspired by the structure and functioning of the human brain. They consist of interconnected layers of neurons that process input data and produce output predictions. Artificial Neural Networks are capable of approximating complex nonlinear relationships without requiring explicit mathematical formulations (Pai et al., 2008). A typical ANN consists of three main layers: an input layer, one or more hidden layers, and an output layer. The input layer receives raw data and transmits it to the hidden layers, where the actual processing occurs through weighted connections. The output layer then produces the final prediction or classification result. Information flows through the network in a forward direction, from the input layer to the output layer, with each connection between neurons having an associated weight that adjusts as learning progresses (Qamar & Zardari, 2023).

One of the key advantages of ANNs is their ability to learn adaptively. Through a training process, ANNs can adjust their internal parameters based on the data provided, without requiring explicit programming for each specific task. Once trained, an ANN can be considered an "expert" in the specific domain it has learned, capable of providing accurate predictions when presented with new, unseen data. Other notable features of ANNs include fault tolerance, meaning that partial damage to the network results only in gradual performance degradation rather than complete failure, and the ability to perform real-time operations through parallel processing (Qamar & Zardari, 2023).

2.3.3. Hybrid ANN-CCO

To enhance the predictive accuracy and training efficiency of Artificial Neural Networks (ANN), this study proposes a hybrid model integrating the Cuckoo Catfish Optimizer (CCO) with ANN, referred to as ANN-CCO. In conventional ANN training, back-propagation algorithms often suffer from slow convergence, sensitivity to initial weights, and entrapment in local minima. To address these limitations, the CCO algorithm is employed as a metaheuristic trainer to optimize the connection weights and biases of the ANN. In the proposed ANN-CCO framework, each individual (cuckoo catfish agent) represents a candidate solution encoding the set of weights and biases of the neural network. The fitness function is defined as the Root Mean Square Error (RMSE) or Mean Squared Error (MSE) between the network's predicted outputs and the actual target values. The CCO algorithm iteratively updates the population through its exploration (compressed space and surround search), transition, chaotic predation, and death-parasitic strategies to minimize the fitness function. The optimal solution found by CCO corresponds to the optimal weight and bias configuration of the ANN. The hybrid ANN-CCO model combines the global search capability of CCO with the local approximation power of ANN, effectively preventing premature convergence and improving generalization

performance. This approach is particularly suitable for complex, high-dimensional, and nonlinear problems where traditional gradient-based methods fail to produce satisfactory results. Figure 3 presents the flowchart of the proposed hybrid ANN-CCO model, which integrates the Cuckoo Catfish Optimizer (CCO) with an Artificial Neural Network (ANN) for optimizing the network's weights and biases.

The Cuckoo Catfish Optimizer (CCO) was configured with the parameters listed in Table 2, searching for optimal ANN hyperparameters within predefined bounds. The optimal configuration obtained from the best run is also presented in Table 2. As shown, the optimal ANN architecture consists of 37 neurons in the first hidden layer and 5 neurons in the second hidden layer, with a learning rate of 0.07143. The ReLU activation function and Adam solver were employed, and early stopping was applied to prevent overfitting.

Table 2. Parameter settings of the Cuckoo Catfish Optimizer (CCO) and optimized hyperparameters of the ANN-CCO model.

category	Parameter	Value
CCO setting	Population size	10
	Dimensions	3
	Lower bound	[5, 5, 0.001]
	Upper bound	[50, 50, 0.1]
	Max iterations	80
	Parameter a	1.34
	Parameter b	0.30
ANN-CCO Optimized	First hidden layer (N1)	37
	Second hidden layer (N2)	5
	Learnin rate (Lr)	0.071432
	Activation function	ReLU
	Solver	Adam
	Training iterations	500
	Early stopping	True

$$\hat{y}_i = (x_i) = \emptyset \sum_{k=1}^K f_k(x_i), \quad f_k \in \mathcal{F} \quad (21)$$

where K is the number of trees and f_k is the k-th tree. To find the best set of functions, the following objective function is minimized (Chen & Guestrin, 2016; Osman et al., 2021):

$$\mathcal{L}(\emptyset) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \quad (22)$$

Here, l is the loss function measuring the difference between predicted and actual values, while Ω is a regularization term that prevents overfitting. The regularization term is calculated as $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|w\|^2$, where T is the number of leaves and w is the weight of each leaf (Chen & Guestrin, 2016). In the t-th iteration, a new tree is added as follows (Osman et al., 2021):

$$\mathcal{L}^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (23)$$

A key difference between XGBoost and random forest is that random forest gives equal importance to all trees in the ensemble, whereas XGBoost builds each subsequent tree to address the shortcomings of the previous ones (Palanga et al., 2025). Moreover, XGBoost, like other decision tree-based methods, can directly work with categorical features by splitting on category values, thus removing the need for one-hot encoding (Achterberg et al., 2026; Anwas et al., 2026).

2.4 Model accuracy validation

To evaluate the predictive performance of the ANN, ANN-CCO, and XGBoost models, three statistical metrics were adopted: Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and the correlation coefficient (r). The mathematical formulations of these metrics are presented in Equations (24)–(26).

The MAE calculation formula is as follows:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - ty_i| \quad (24)$$

Where $\hat{y}_i$ is the predictive value and y_i is the true value. MAE values closer to zero reflect higher prediction accuracy.

The RMSE calculation formula is as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{n}} \quad (25)$$

The r calculation formula is as follows:

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (26)$$

In these expressions, x_i denotes the actual (observed) values and y_i corresponds to the model-predicted values, with n representing the sample size. The RMSE reflects the mean size of the prediction error, where smaller values approaching zero indicate superior predictive accuracy. The correlation coefficient (r) spans from -1 to +1; an r value of +1 reflects a perfect positive linear association, -1 indicates a perfect negative linear association, and 0 implies no linear relationship between the measured and forecasted values (Mahaki et al., 2024).

3. Results and Discussion

3.1. Hydro-Climatic Baseline and Anthropogenic Dynamics Analysis

As illustrated in Figure 4, which comprehensively displays the long-term trends, structural changepoints, and seasonal patterns for all four analyzed variables, the long-term monthly trajectories of the hydro-climatic parameters, socioeconomic vectors, and regional resource demand were evaluated over a 120-month temporal horizon spanning from 2015 to 2024. The empirical results demonstrate a highly decoupled behavioral framework between the stationary environmental baseline and the non-stationary, trend-driven anthropogenic components.

3.1.1. Precipitation Time Series

The non-parametric Mann-Kendall test applied to the precipitation series yields a test statistic of $Z = -0.442$ with a corresponding p -value = 0.658. This confirms the absence of a monotonic trend at the 0.95% confidence level ($p > 0.05$). Sen's slope estimator indicates a negligible net change rate of -0.0333 mm/month. This metric mathematically establishes long-term baseline stability over the studied horizon. The Bayesian Estimator of Abrupt Change, Seasonal, and Trend (BEAST) algorithm detected no structural changepoints within either the trend or the seasonal sub-components of the precipitation data over the study period.

3.1.2. Temperature Profiles

The thermal regime displays stable periodic oscillations across the analyzed decade. The Mann-Kendall test evaluates to $Z = -0.045$ with a p -value = 0.963, indicating a statistically non-significant trend line (ns). The calculated Sen's slope is exactly 0.000000.°C/month. This absolute zero change rate establishes that the regional temperature baseline has remained structurally constant.

The seasonal sub-component displays a symmetrical, sinusoidal configuration. The highest temperatures are recorded during July and August, exceeding 30°C. Symmetrically, the lowest values occur during January and February,

dropping to a minimum range of $8 - 10^{\circ}\text{C}$. The BEAST algorithm identified no structural change points or sudden discontinuities in the temperature trend line.

3.1.3. Tourist Influx and Exogenous Shocks

The longitudinal trajectory of tourist arrivals reveals a powerful upward expansion over time. The Mann-Kendall test validates this monotonic growth with a test statistic of $Z = 3.72$ and an extreme level of statistical significance ($p\text{-value} = 0.000194$, $p < 0.001$). According to the Sen's slope estimator, the tourist influx expanded at a substantial baseline rate of 0.562580 Thousands/month. The series displays high overall dispersion, with a sample standard deviation (SD) precisely calculated at 62.88 Thousands total visitors, which corresponds to 64,145.36 in raw absolute values. The application of the BEAST framework isolates two distinct structural change points (CP) within the trend component, both heavily driven by exogenous macroeconomic shocks:

- **First Change point (January 2020):** Identified with a 87% posterior probability, this structural break marks the abrupt cessation of the historic upward trajectory. This shift corresponds to an abrupt macroeconomic contraction and severe border-level travel constraints, forcing a sharp drop in tourist volumes.
- **Second Change point (January 2022):** Detected with a 55% probability, this turning point signifies the official transition into a structural recovery phase. Following the systematic relaxation of travel restrictions and international market resummptions, the series undergoes a sharp structural rebound, establishing an accelerated growth vector.

Seasonally, tourism exhibits a severe, climate-dependent polarization. The peak tourist concentration is localized in June and July (summer), with monthly arrivals climbing toward 200 thousand visitors. In contrast, the winter months (December and January) contract down to minimum baseline levels.

3.1.4. Water Consumption Trajectories

The regional water consumption profile exhibits a powerful behavioral parallel to the tourist growth vector. It maintains a highly linear and continuous upward trajectory from 2015 to 2024. The Mann-Kendall test yields a robust statistic of $Z = 4.906$ with an explicit significance level of $p\text{-value} = 0.000001$, ($p < 0.001$), decisively validating a persistent long-term expansion. Sen's slope estimator indicates that volumetric water demand grew at a highly stable, uninterrupted rate of 0.047527 Million m^3 /month. The sample standard deviation (SD) for water consumption evaluates to 4.00 Million m^3 , representing an absolute volumetric variation of 4,012,793.57 m^3 . The seasonal distribution of water demand is tightly coupled with the phase synchronization of environmental temperature peaks and maximum tourist concentrations. Due to the compound effects of peak domestic cooling and tourist occupancy, July and August mark the maximum volumetric demand (28 Million m^3 /month). Winter demand falls to a baseline of 18 Million m^3 /month. Significantly, despite the severe structural shocks observed in the tourism sector during the 2020–2022 window, the BEAST algorithm detected no matching structural change points in the water consumption trend. This systemic divergence indicates that regional water consumption is fundamentally driven by non-transient

factors. These drivers include expanding urban domestic networks, structural infrastructure development, and baseline population growth. These permanent components effectively cushioned and insulated the resource sector from temporary shocks in the hospitality industry.





Figure 4. Long-term trends, structural changepoints, and seasonal distributions of the four evaluated variables (2015–2024).

3.1 Correlation Analysis

Prior to model development, the linear relationships between the input variables (tourist count, temperature, precipitation) and the target variable (water consumption) were investigated using Pearson's correlation coefficient. This analysis helps to understand the data structure and provides a baseline for interpreting the subsequent model results. Figure 5 presents the correlation matrix of all four variables, along with the ranking of input variables according to their correlation strength with water consumption.

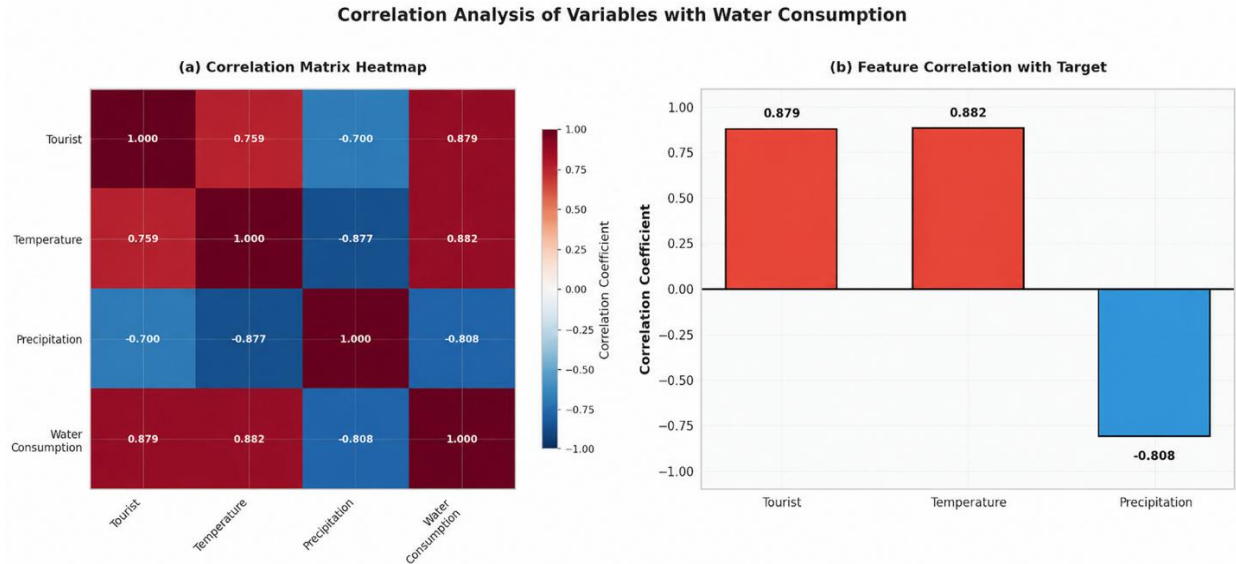


Figure 5. Correlation analysis of variables with water consumption: (a) Correlation matrix heatmap showing pairwise Pearson correlation coefficients among all variables; (b) Feature correlation with target variable (water consumption).

As shown in Figure 5(a), all three input variables exhibited strong correlations with water consumption. Temperature demonstrated the strongest positive linear correlation with water consumption ($r = 0.882$), followed closely by tourist count ($r = 0.879$). These high correlation coefficients indicate that increases in temperature and tourist numbers are strongly associated with higher water demand in the study area. This finding is intuitive, as warmer temperatures typically lead to increased water use for irrigation, cooling, and outdoor activities, while a higher influx of tourists directly contributes to greater water consumption in hotels, restaurants, and recreational facilities.

Precipitation exhibited a strong negative correlation with water consumption ($r = -0.808$). This inverse relationship indicates that periods of higher precipitation are associated with lower water demand. This pattern can be explained by reduced irrigation needs during wet periods and potential changes in outdoor water use behavior.

The correlation matrix also reveals substantial intercorrelations among the input variables. Temperature and precipitation showed a strong negative correlation ($r = -0.877$), which is consistent with the Mediterranean climate of the region, where hot summers coincide with dry conditions and mild winters bring higher precipitation. Tourist count also demonstrated a strong positive correlation with temperature ($r = 0.759$) and a strong negative correlation with precipitation ($r = -0.700$), reflecting the seasonal nature of tourism, which peaks during the warm, dry summer months.

As illustrated in Figure 5(b), temperature emerges as the most influential factor ($r = 0.882$), followed by tourist count ($r = 0.879$) and precipitation ($r = -0.808$). All three variables demonstrate strong correlations ($|r| > 0.8$), confirming that each plays a significant role in determining water consumption patterns.

These correlation results provide valuable insights for model development. The strong linear relationships observed between the input variables and water consumption justify the use of regression-based approaches. However, the presence of substantial multicollinearity among the input variables (e.g., temperature-precipitation: $r = -0.877$; temperature-tourist: $r = 0.759$) highlights the need for careful model selection. While simple linear regression might

suffer from unstable coefficient estimates due to these intercorrelations, the proposed ANN-CCO hybrid model, with its ability to capture nonlinear interactions and its optimization framework, is well-suited to handle such complexities. Overall, the correlation analysis confirms that tourist count, temperature, and precipitation are all strong predictors of water consumption in the study area, with temperature having the most dominant influence. These findings align with expectations for a Mediterranean tourist destination and provide a solid foundation for the predictive modeling undertaken in this study.

3.2 Prediction Performance

Following the change point detection analysis, three predictive models were developed and evaluated for water consumption forecasting: standalone Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost), and the proposed hybrid ANN-CCO model. Table 3 presents the performance comparison of these three models based on three evaluation metrics: correlation coefficient (R), root mean square error (RMSE), and mean absolute error (MAE).

Table 3. Performance comparison of ANN, XGBoost and ANN-CCO models for water consumption prediction

	Model	R	RMSE (m^3)	MAE (m^3)
Water consumption	ANN	0.8361	3,510,108	2,857,185
	XGBoost	0.9673	2,845,446	2,626,461
	ANN-CCO	0.9853	1,867,517	1,709,394

The results indicate that the proposed ANN-CCO hybrid model achieved superior performance with a correlation coefficient of 0.9853, root mean square error of 1,867,517 m^3 , and mean absolute error of 1,709,394 m^3 , outperforming both benchmark models.

The XGBoost model ranked second with a correlation coefficient of 0.9673, RMSE of 2,845,446 m^3 , and MAE of 2,626,461 m^3 . The standalone ANN model exhibited the weakest performance with a correlation coefficient of 0.8361, RMSE of 3,510,108 m^3 , and MAE of 2,857,185 m^3 .

Compared to the standalone ANN model, the proposed ANN-CCO hybrid model improved the correlation coefficient by 17.8%, reduced RMSE by 46.8%, and reduced MAE by 40.2%. Compared to the XGBoost model, the ANN-CCO model improved the correlation coefficient by 1.9%, reduced RMSE by 34.4%, and reduced MAE by 52.2%.

The superior performance of the ANN-CCO hybrid model can be attributed to the effective optimization of the ANN's hyperparameters by the Cuckoo Catfish Optimizer algorithm. The CCO algorithm successfully identified the optimal network architecture with 37 neurons in the first hidden layer, 5 neurons in the second hidden layer, and an optimal learning rate of 0.07143. This optimal configuration enabled the neural network to capture the complex nonlinear

relationships between the input variables (tourist count, temperature, rainfall) and the output variable (water consumption) more effectively than both the standalone ANN and XGBoost models.

Although the XGBoost model demonstrated reasonable performance, its higher prediction errors compared to the hybrid model may be attributed to the limited sample size (120 monthly observations), as tree-based methods generally require larger datasets to achieve optimal performance. The standalone ANN model, without any optimization, showed the weakest performance, highlighting the critical importance of hyperparameter optimization in neural network modeling.

Figure 6 presents a visual comparison of the three models across all evaluation metrics. As illustrated in Figure 6, the ANN-CCO model consistently achieves the highest correlation coefficient ($R = 0.9853$) and the lowest error values ($RMSE = 1.87$ million m^3 , $MAE = 1.71$ million m^3), while the XGBoost model shows moderate performance ($R = 0.9673$, $RMSE = 2.85$ million m^3 , $MAE = 2.63$ million m^3), and the standalone ANN model exhibits the weakest performance ($R = 0.8361$, $RMSE = 3.51$ million m^3 , $MAE = 2.86$ million m^3). This visual representation further confirms the superiority of the proposed hybrid model.

In summary, the proposed ANN-CCO hybrid model, with its superior accuracy and reliability, is introduced as a novel and effective approach for monthly water consumption prediction in the study area. The integration of the Cuckoo Catfish Optimizer with artificial neural networks provides a robust and efficient methodology that significantly outperforms conventional models, making it a valuable tool for water resource management and sustainable urban planning.

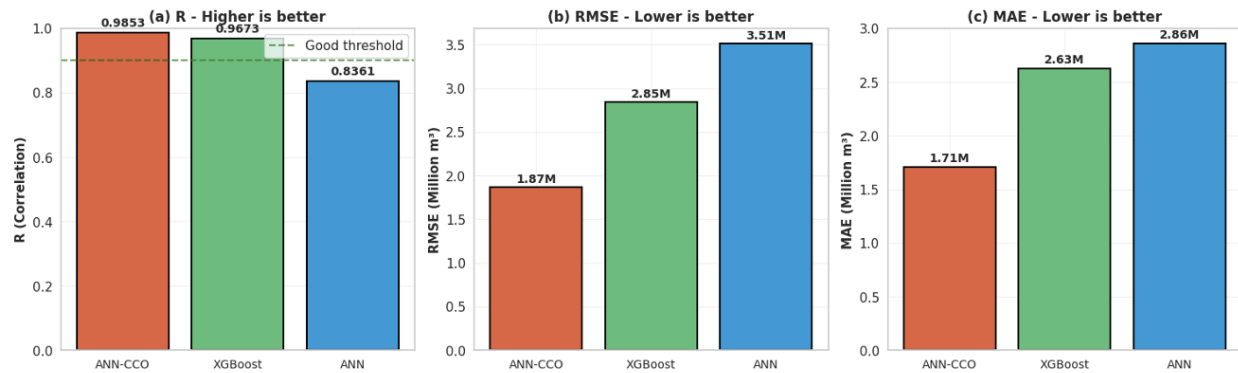


Figure 6. Bar charts of (a) correlation coefficient, (b) Root Mean Square Error, and (c) Mean Absolute Error for the three predictive models.

Figure 7 presents scatter plots comparing actual water consumption values against predictions generated by three models: ANN-CCO (Hybrid), XGBoost, and ANN. Panel (a) displays color-coded scatter plots where the color spectrum ranges from blue (low prediction error) to red (high prediction error). Panel (b) displays the same scatter plots with the dashed 1:1 line (perfect prediction) and the regression line.

In Panel (a), the ANN-CCO plot is dominated by blue and green colors, indicating very low prediction errors with tightly concentrated points. The XGBoost plot shows a noticeable increase in yellow, orange, and red points, indicating higher prediction errors and greater dispersion. The ANN plot is dominated by orange and red colors, clearly demonstrating the highest prediction errors and widest dispersion among all three models.

In Panel (b), the ANN-CCO plot shows data points clustered closely around the dashed 1:1 line, with the regression line nearly coinciding with it, demonstrating no systematic bias and confirming successful hyperparameter optimization by the Cuckoo Catfish Optimizer. The XGBoost plot exhibits greater dispersion around the 1:1 line, with the regression line deviating more noticeably, reflecting moderate systematic errors. The ANN plot shows the widest dispersion around the 1:1 line, with the regression line deviating substantially, particularly at higher consumption values, indicating that the unoptimized network fails to capture the underlying relationships between input variables and water consumption.

In summary, the ANN-CCO hybrid model dramatically outperforms the standalone ANN. The progressive improvement from ANN to XGBoost to ANN-CCO visually demonstrates how the Cuckoo Catfish Optimizer successfully transforms a poorly performing neural network into a highly accurate predictive model, significantly surpassing both benchmarks.

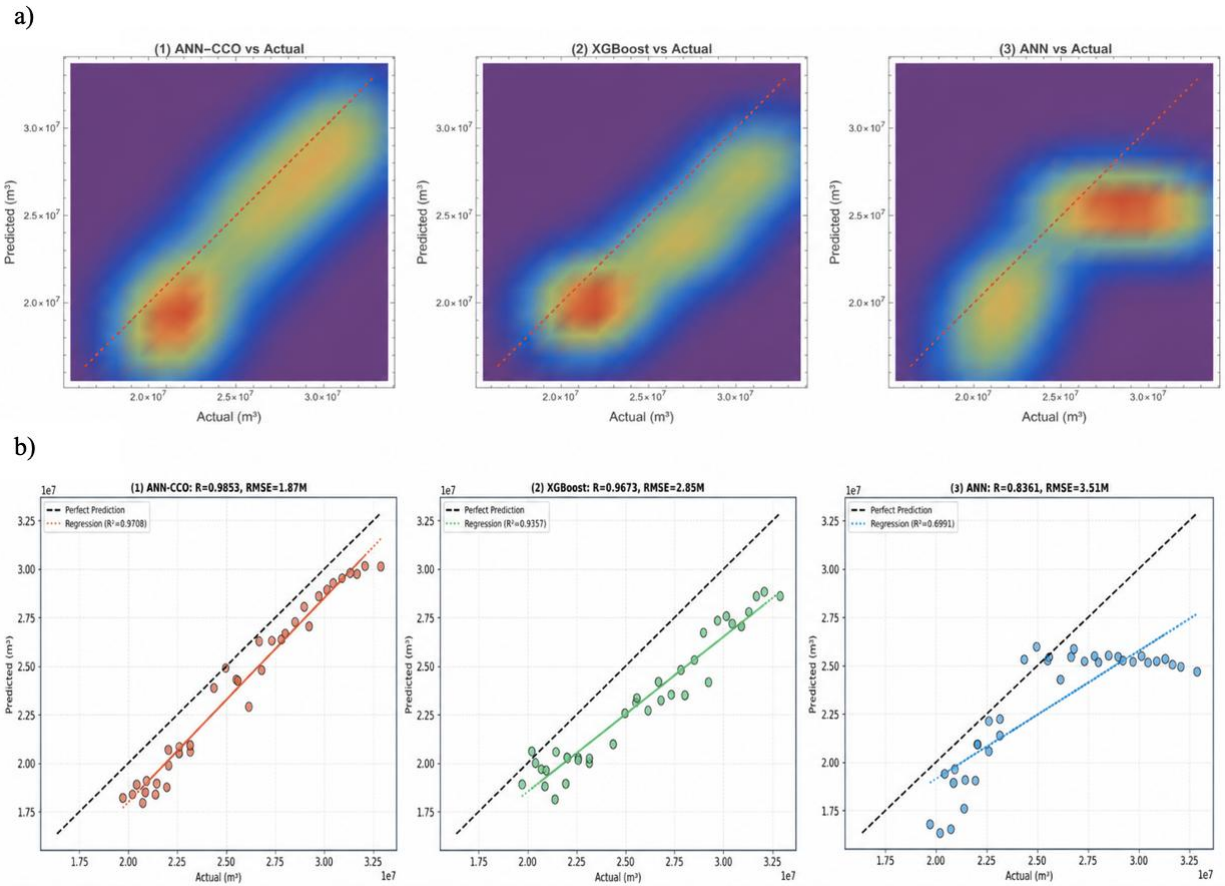


Figure 7. Scatter plots of actual vs. predicted water consumption: (a) Color-coded plots; (b) Plots with 1:1 line and regression line.

To evaluate the accuracy of the developed models in capturing the data distribution, a comparative analysis was conducted using the violin plots presented in Figure 8. Unlike standard error metrics that only show average performance, a violin plot serves as a clear diagnostic tool by simultaneously displaying the data density, probability distribution, and the spread of individual predictions across the entire dataset.

As shown in Figure 8, the actual observed data (Actual) exhibits a multi-modal distribution ranging from approximately 15 to 37. The highest density of data points is concentrated in the lower-mid range between 20 and 23, followed by an elongated upper tail representing higher values. A direct comparison reveals that the proposed Hybrid (ANN–CCO) model outperforms the other approaches by replicating this empirical distribution with exceptional accuracy. The overall shape of the Hybrid (ANN–CCO) violin plot, along with its internal data points, closely mirrors the actual baseline, successfully capturing both the lower limits (≈ 14) and the highest peak values (≈ 35) without underestimation.

In contrast, the alternative standalone models show noticeable structural distortions (Figure 8):

- XGBoost covers a realistic overall data range, but it fails to align with the core density pockets of the actual data, showing a narrower distribution in the mid-to-upper quantiles.
- ANN delivers the least reliable performance, characterized by a severe contraction of the prediction profile. It is completely unable to simulate values above 30 and incorrectly clusters its primary data density (the widest part of the violin) in a narrow zone around 25.

Consequently, the evidence in Figure 8 confirms that integrating the Artificial Neural Network with the CCO optimization algorithm effectively solves the underestimation problems inherent in standalone models. The Hybrid (ANN–CCO) model stands out as the most reliable framework, ensuring both low residual errors and a perfect match with the natural statistical distribution of the target dataset.

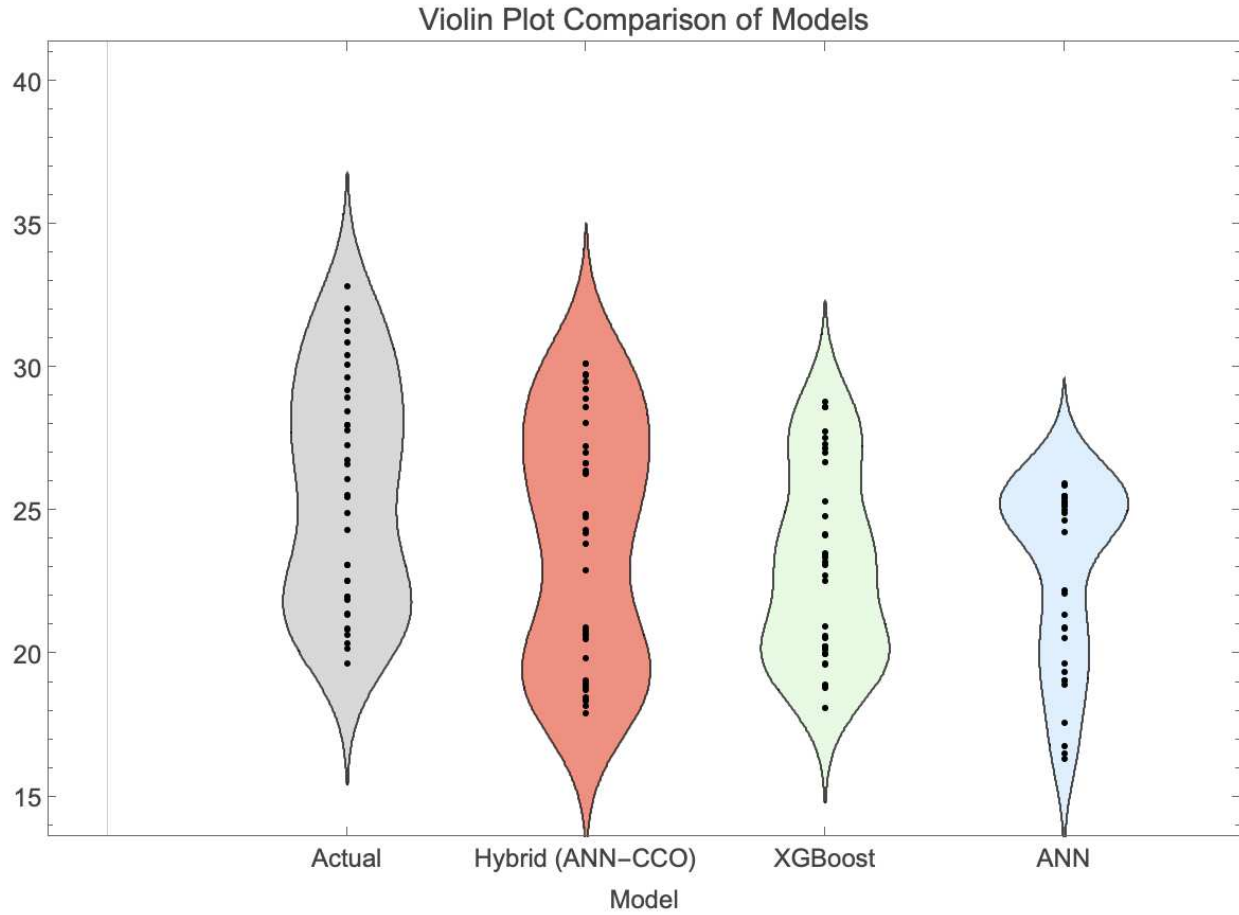


Figure 8. Violin plot comparison of the observed data against the predictive distributions of the (ANN-CCO), XGBoost and ANN models.

To further evaluate the reliability of the predictive frameworks, a sample-by-sample analysis of prediction errors was performed across the 36 test instances, as illustrated in Figure 9. Evaluating the individual error distributions provides crucial insights into the stability of each model and highlights their tendency toward extreme overestimation or underestimation under test conditions. As demonstrated in Figure 9, the standalone ANN model exhibits severe prediction instability. It suffers from massive localized errors, with peak prediction errors exceeding $6 \times 10^6 m^3$ at index 18 and surging past $8 \times 10^6 m^3$ at index 30. Furthermore, the ANN model displays highly volatile fluctuations, showing sharp negative errors (overestimation) at sample indices 3 and 15. This erratic behavior underscores the vulnerability of unoptimized neural networks when handling complex variations in water consumption data. Similarly, the XGBoost model demonstrates a highly fluctuating error profile. While it avoids the extreme error peaks observed in the standalone ANN, it still introduces substantial residual errors across numerous test samples. Notably, at indices 28, 30, and 32, the prediction errors for XGBoost escalate significantly, approaching and exceeding the $4 \times 10^6 m^3$ to $5 \times 10^6 m^3$ threshold. This indicates a limitation in the tree-based model's ability to maintain uniform accuracy

across all test patterns. In sharp contrast, the proposed Hybrid (ANN–CCO) framework displays exceptional error containment and structural stability across the entire testing horizon. The prediction errors for the ANN–CCO model remain tightly bounded, consistently hovering below the $3 \times 10^6 \text{ m}^3$ line with minimal sample-to-sample variance. The absence of dramatic error spikes or negative anomalies confirms that integrating the Artificial Neural Network with the CCO optimization algorithm significantly dampens residual variance. Consequently, Figure 9 delivers definitive visual and statistical proof that the Hybrid (ANN–CCO) model ensures the highest prediction precision and operational dependability for regional resource management.

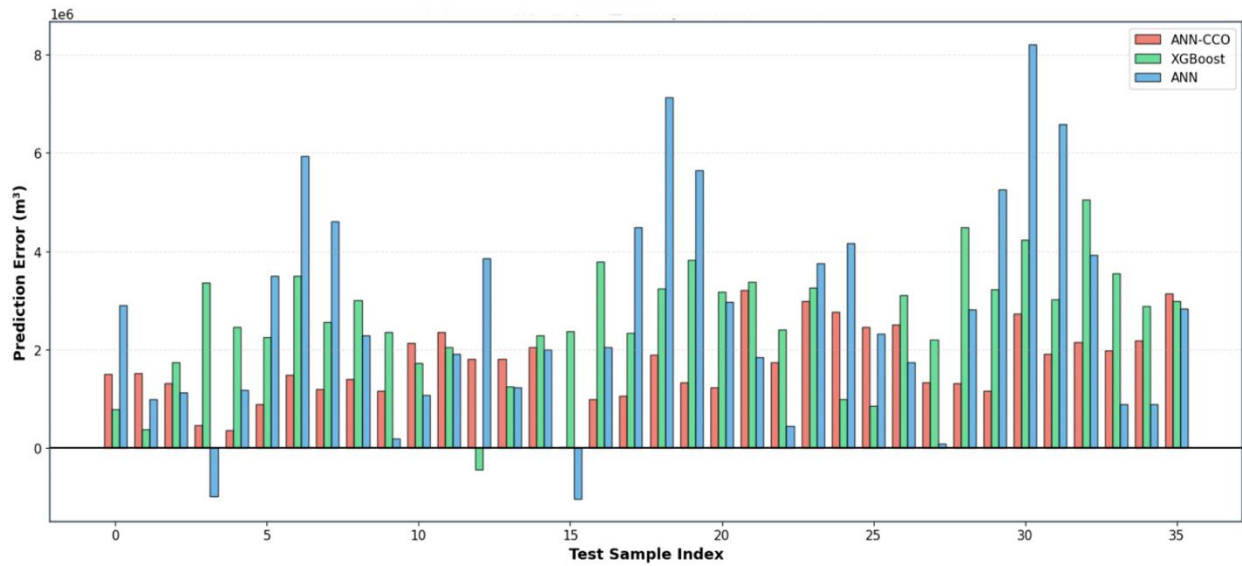


Figure 9. Prediction error comparison among the proposed Hybrid (ANN–CCO), XGBoost, and standalone ANN models across the 36 test samples.

Figure 10 presents a radar chart comparing the performance of three predictive models—ANN-CCO (Hybrid), XGBoost, and ANN (Baseline)—across three evaluation metrics: correlation coefficient (R), inverse root mean square error (1/RMSE), and inverse mean absolute error (1/MAE). All metrics have been normalized to a 0–1 scale, where values closer to 1 indicate superior performance. As illustrated in Figure 10, the proposed ANN-CCO hybrid model (red polygon) achieves the highest normalized scores across all three metrics, resulting in the largest coverage area. This model attains the maximum value on the R axis, reflecting a strong linear relationship between predicted and actual water consumption. Simultaneously, it reaches the outermost points on both the 1/RMSE and 1/MAE axes, demonstrating its capability to minimize prediction errors. The XGBoost model (green polygon) exhibits moderate performance, with its scores positioned between the ANN-CCO and the standalone ANN. Although it outperforms the baseline ANN across all metrics, it consistently falls short of the hybrid model, particularly on the error-based metrics (1/RMSE and 1/MAE). The standalone ANN model (blue polygon) shows the weakest performance, occupying the smallest area within the radar chart. Its scores on the R axis are considerably lower than both competing models, and its positions on the error-based axes indicate the highest prediction errors among all three models. Overall,

the radar chart findings confirm that the Cuckoo Catfish Optimizer algorithm, by identifying an optimal neural network architecture, has successfully produced a model capable of effectively learning the nonlinear relationships between input and output variables. The significant gap between the red and blue polygons across all three axes highlights the critical role of hyperparameter optimization in enhancing prediction accuracy. These results clearly demonstrate that the proposed ANN-CCO hybrid approach outperforms the benchmark models, particularly when dealing with data characterized by nonlinear complexities.

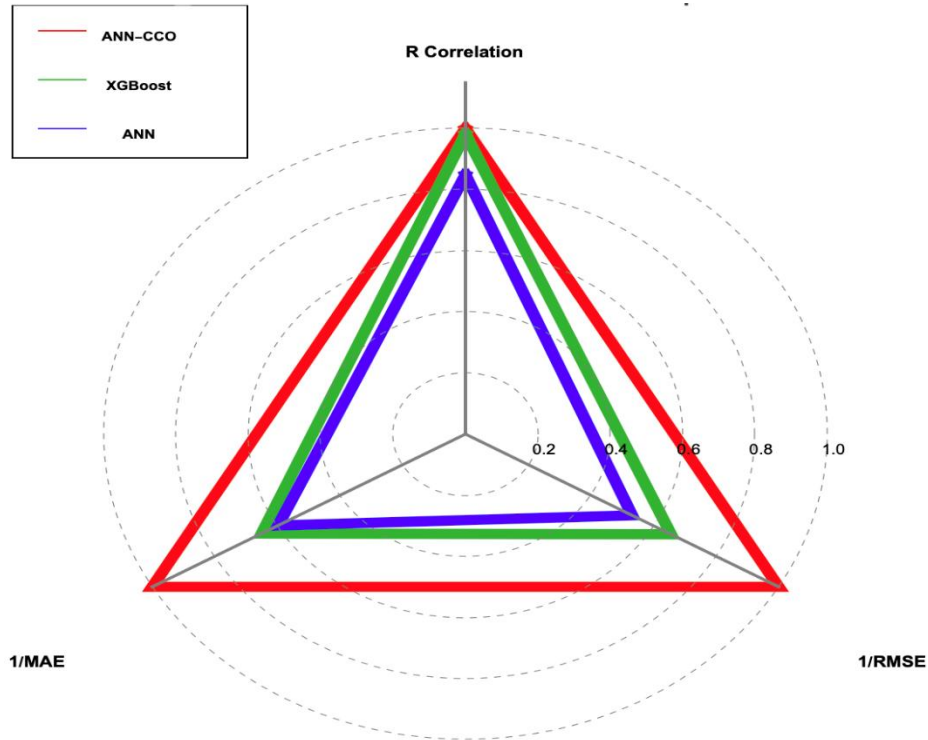


Figure 10. Radar chart of model performance comparison based on three evaluation metrics.

Conclusion

Accurate monthly water consumption forecasting is critical for sustainable urban water management in semi-arid Mediterranean metropolitan areas such as İzmir, Turkey. This study introduced a novel hybrid intelligence framework, ANN-CCO, integrating the Cuckoo Catfish Optimizer with a standard Artificial Neural Network to automate hyperparameter extraction and weight configuration. The proposed model was benchmarked against standalone ANN and XGBoost using 120 monthly samples (2015–2024) comprising tourist count, temperature, rainfall, and water consumption data. The ANN-CCO hybrid model significantly outperformed both benchmarks, achieving the highest correlation coefficient ($R = 0.9853$), the lowest RMSE (1.87 million m^3), and the lowest MAE (1.71 million m^3). Compared to standalone ANN, it improved R by 17.8%, reduced RMSE by 46.8%, and reduced MAE by 40.2%. Compared to XGBoost, it improved R by 1.9%, reduced RMSE by 34.4%, and reduced MAE by 34.9%. Changepoint

detection using BEAST revealed that water consumption maintained a stable upward trend (Sen's slope = 0.0475 million m³/month) despite severe shocks in the tourism sector during 2020–2022, indicating that urban water demand is fundamentally driven by permanent structural factors rather than transient fluctuations. The ANN-CCO model provides a reliable tool for monthly water consumption forecasting, supporting infrastructure planning, tariff adjustments, and reservoir management.

This study is limited to monthly data from a single city (İzmir) over a 10-year period and does not consider other potential influencing factors such as humidity, wind speed, water pricing, or public awareness campaigns. Future research should address these limitations by validating the proposed model in other semi-arid Mediterranean cities, incorporating higher-resolution data (daily or hourly), adding new exogenous variables, comparing the CCO algorithm with other metaheuristic methods, and investigating the long-term impact of climate change on water consumption patterns.

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Ethical approval

The research did not involve any direct human or animal participation.

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Declaration of competing interest

I declare that we have no competing interest in publishing this article on behalf of all the authors.

Data Availability

The dataset "Izmir_Water_Amount" is publicly available on Kaggle.

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