Integrating Multi-hazard Risk Assessment and Climate Change Projections for Adaptive Water Resource Management: A Case Study of the Ajichai River Basin

Jafar Chabokpour*

Associate professor of hydraulic structures, civil engineering department, University of Maragheh, Maragheh, Iran. Email: J.chabokpour@maragheh.ac.ir

Abstract:

This research develops an in-depth hydrologic risk analysis for the Ajichai River catchment by using the flow series at the Veniar station for the period from 1966 to 2013. A complete methodology was used to analyze the flood and drought risks, as well as the long-term trends and eventual impact of climate change on the flow regime of the river. Annual maximum flow data were fitted using the Generalized Extreme Value distribution and provided a 100-year flood estimate of 224.9 m^3/s, 95% CI: 177.7-272.1 m^3/s. A significant decreasing trend in annual mean flow was detected: Sen's slope -0.25 $m^3/s/year$, $p < 0.01$. The low-flow frequency analysis yielded a high value of the coefficient of correlation $r = 0.98$, which explained the duration and severity relationship of droughts described by the power-law equation $S = 0.0012 \times D^{1.85}$. It is evident from the seasonal analysis that during the spring season, 68.7% of annual maximum flow occurs with an average peak flow of 89.6 m^3/s. There was a very important shift in the timing of the floods, a 26-day earlier date of annual maximum flows between the 1970s and the 2010s. It quantified the relationship between annual maximum flow and precipitation: $Q = 0.0015 \times P^{2.1}$, R2 = 0.88, underlining the probable impact of the changes in precipitation on flood risk. In fact, it exposes the complex and dynamic hydrological environment of the Ajichai River basin and signifies a requirement for adaptable water management that concurrently contributes to decreasing flood and drought risks in response to climate change.

Keywords:

Flood risk, Drought vulnerability, Climate change impacts, Water resource management

1. Introduction

River flow is essential in sustaining both ecosystem services and human activities, providing irreplaceable services including irrigation, drinking water supply, hydropower generation, and biodiversity conservation [1-4]. However, the inherently dynamic nature of river systems makes them prone to a myriad of threats that can modify their flow regimes, thereby inhibiting these services. Some of the major threats include hydrological changes, climate change, damming, and environmental degradation. Such risk understandings are central to the formulation of viable water resource management and mitigation strategies [1-4]. The frequency of climate change-related extreme events of floods and droughts highlights the necessity of resilience in risk structures for river flow management [5-8]. Risk assessment of river flow includes the examination of the probability and consequences of adverse hydrological events, such as floods, droughts, and water quality worsening, all of which are able to influence ecological stability and socio-economic security [9, 10]. Initial research was more directed towards quantitative hydrological events, with floods being of specific interest. Tennant [11], for example, suggested instream flow regimes that accommodated both ecological and human needs and hence established a basis for environmental flow determinations. Later research by Aspray et al. and Olden et al. [12, 13] expanded on this concept by incorporating ecohydrological indicators into traditional hydrological models, thereby establishing the necessity for interdisciplinary research in order to deal with the complexity of river flow dynamics. Environmental effects of modified river flows have been studied widely. Acreman & Dunbar [1] studied the environmental flow needs and highlighted the importance of sustainable flow regimes for ecosystem services and wildlife. They suggested that anthropogenic activities, i.e., dam structures and water abstractions, can significantly change natural flow regimes, and this may lead to serious ecological problems. Annear et al. [14] established guidelines for river flow management to preserve river ecosystems for different requirements. Climate change has emerged as a dominating factor influencing the dynamics of river flow, accelerating the frequency and intensity of extreme hydrological phenomena [15, 16]. Sahoo et al. [15] compared methods of environmental flow assessment of the Mahanadi River of India, prioritizing the integration of climate variability into risk assessment models. Fu et al. [16] analyzed the effects of climate change on environmental water demand in China's Yarkand River Basin. They observed that traditional methods of studying water don't fully establish how climate affects the flow of water. These studies identify the need for the integration of climate projections and flexible management into hazard assessment plans. Economic and social considerations are paramount in the management of river flow. Smakhtin and Eriyagama [17] created a computer program that helps assess environmental flows. The program takes into account the utilization of water for agriculture, industry, and domestic use. According to their research, more people are becoming aware of the different needs for water in populated or agriculturally dominated areas. Yin et al. [18] analyzed compromises among hydropower generation, environmental flow, and inter-basin water transfer projects in China using a multi-objective programming model, illustrating the complex socio-economic considerations influencing river flow management. Advances in numerical and modeling techniques have facilitated the evaluation of risks. CHABOKPOUR et al. [2] investigated computer models for analyzing hydrological risks associated with river forms, indicating their capability in predicting sediment transport, water quality, and pollution dynamics. Remote sensing and machine learning capabilities enable real-time monitoring, which assists in enhancing risk management strategies. Use of hydraulic modeling with probabilistic methods, like the Conveyance and Afflux Estimation System (CES/AES), has enhanced decision-making in flood risk management [19]. It has also been researched and confirmed how important soil saturation is in the estimation of flood risks [20] and how river junctions affect water flow [21]. Flood risk mapping by location has been aided in complicated river systems [22]. Hydrological and hydraulic modeling methods have been utilized in order to predict flood risk and plan infrastructure in data-poor areas, e.g., the Oued Lahdar basin of Morocco [23, 24]. Paleo-hydro-geomorphological studies with the help of present modeling techniques are suggested to manage flood hazards [25, 26]. Non-linear models were formulated to evaluate river pollution hazards and were found to have greater hazards in non-flood than flood periods [27, 28]. Bayesian belief network-based PROBFLO methodology was used for ecological risk assessments on a regional scale [29]. Information about sediments added to flood frequency analysis makes it more accurate by using both past data and numbers [30]. Using models for assessing risk from extreme river flows has helped improve the coordination of flood safety efforts [31].

By focusing on previous literature, the present study attempts an extensive risk assessment of the Ajichai River basin, focusing on risks due to flooding and drought hazards. The major objectives of the research are: (i) quantification of magnitude and frequency of the extreme hydrologic events; (ii) assessment of the climate change impact on river flow regimes; (iii) identification of the water resources vulnerability due to longer droughts; and finally, (iv) formulation of risk management-based decision support strategies for accomplishing sustainability in the use of water. Therefore, the present study will use advanced statistical techniques that incorporate hydrological modeling to provide a sound basis for informed decision-making in the planning and management of basin water resources.

2. Materials and Methods

2.1. Field study area

This research work applied an integrated methodology in order to identify the main hydrological risks and challenges with regard to water resource management in the Ajichai River Basin. The Ajichai River Basin, part of the main watershed of Lake Urmia, is located in northwestern Iran. It constitutes a valuable hydrological system due to the complexity of its topography, variability in climate regime, and its substantial contribution to the area's water supply. The basin boundaries fall roughly between latitude 37°20′ to 38°30′ North and longitude 46°10′ to 47°40′ East. The basin area is approximately 13,000 km2 with variable topography, ranging from mountainous in the east to alluvial plains in the west. The altitudes in the basin vary enormously, from over 3,500 meters above sea level in the Sabalan Mountains to about 1,280 meters at the surface of the lake itself.

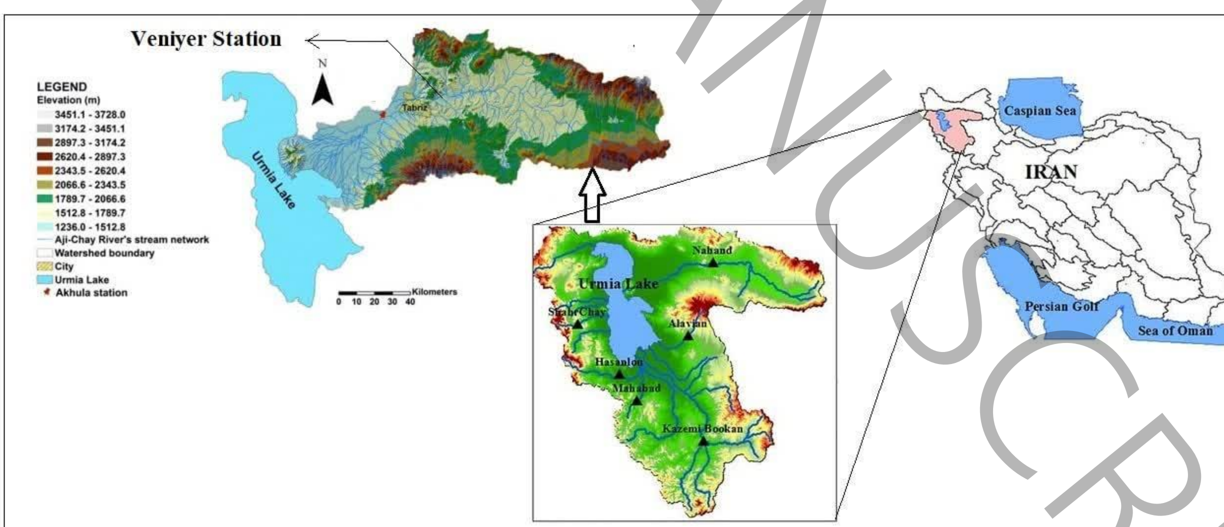

Fig. 1. The location of Ajichay basin and Vanyar station in Lake Urmia basin

The Ajichai basin exhibits a predominantly semi-arid climate, characterized by significant variations in both temperature and precipitation across different spatial and temporal scales. The basin receives an average annual precipitation of approximately 300 mm, with notable disparities between the mountainous areas and the lowland regions. The precipitation pattern is characterized by wet winters and springs, followed by dry summers and autumns. Snow accumulation in the higher altitudes is vital for the basin's hydrological system, as it substantially contributes to the runoff during the spring season. The land use within the basin is varied, reflecting the region's diverse topography and climatic conditions. The upper areas are primarily composed of rangelands and sparse forests, whereas the middle and lower sections are largely dedicated to agricultural activities. Key crops grown in the basin include wheat, barley, and various fruit orchards. Additionally, several urban centers, including parts of Tabriz, the largest city in the region, are situated within the basin, which complicates the management of water resources in the area. The Ajichai River is regulated by several dams and reservoirs, the most important being the Nahand Dam, constructed for irrigation and flood control. These installations strongly modified the natural regime of river discharge, hence its volume and timing of water reaching Lake Urmia. It is linked to the hydrological dynamics of the basin and the ecological health of Lake Urmia, which has been identified as one of the largest hypersaline lakes in the world. Lake Urmia has faced an unparalleled decline in its water levels over recent decades. Blamed on a combination of climate change and anthropogenic activities, most notably the increased intake of water from the feeding rivers, such as the Ajichai, it has suffered greatly. This environmental crisis heightens the needs for being well-informed about the available water resources within the Ajichai basin and how to manage it. In this respect, daily streamflow data for the Ajichai River was collected from the Veniar station, which represents the daily records between 1966 and 2013 from the regional water authority. Besides this, precipitation, temperature, and groundwater level records were collected over the same period from nearby meteorological and hydrogeological stations.

2.2. Analytical methodologies

1. Extreme Value Analysis: The Generalized Extreme Value (GEV) distribution was fitted to the annual maximum flow series to quantify flood risk. The probability density function of the GEV distribution is given by Eq. 1.

$$f(x) = (1/\sigma) \times \left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{\left(-\frac{1}{\xi}-1\right)} \times \exp\{-\left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{(-1/\xi)}\} \quad (1)$$

where x is the flow rate, μ is the location parameter, σ is the scale parameter, and ξ is the shape parameter. These parameters were estimated using the L-moments method.

To guarantee that the parameters of the statistical distributions used in this study are properly estimated, robust methodologies were used. For the Generalized Extreme Value (GEV) distribution, the L-moments method estimated the parameters μ (location), σ (scale), and ξ (shape). The method yields unbiased and efficient estimations even though the sample sizes are small. The L-moment ratios were calculated from the maximum annual flow data, and the corresponding parameters were estimated using regional growth curves. For non-stationary flood frequency analysis, the location parameter $\mu(t)$ was parameterized as a function of time ($\mu(t) = \mu_0 + \mu_1 \times t$). Here, μ_0 is the initial location parameter, and μ_1 represents the extent to which it changes over time. The μ_1 value was calculated by applying linear regression to the detrended annual maximum flow data. The μ and σ parameters of the log-normal distribution used for assessing the drought risk were estimated by maximum likelihood estimation (MLE) so that they would best fit the data distribution. Together, these methods create a strong foundation for parameter estimation and work to render findings in this research believable.

2. Low Flow Analysis: The log-normal distribution was applied to the annual minimum 7-day flow series to assess drought risk. The probability density function is expressed as Eq. 2.

$$f(x) = (1 / (x \times \sigma \times \sqrt{(2\pi)})) \times \exp(-(\ln(x) - \mu)^2 / (2\sigma^2)) \quad (2)$$

Where x is the 7-day low flow, μ and σ are the mean and standard deviation of the natural logarithm of the data.

3. Trend Analysis: The Mann-Kendall test was employed to detect significant trends in various hydrological indicators. The test statistic S is calculated as Eq. 3.

$$S = \sum\sum \mathrm{sign}(xj - xi) \tag{3}$$

Where xi and xj are the sequential data values, and sign(xj - xi) is equal to 1, 0, or -1 for (xj - xi) > 0, = 0, or < 0, respectively.

The Sen's slope estimator was used to quantify the rate of change as Eq. 4.

$$\beta = \mathrm{median}((xj - xi) / (j - i)) \tag{4}$$

for all i < j, where β is the estimate of the trend slope.

4. Climate Change Impact Assessment: A non-stationary flood frequency analysis was conducted by modeling the location parameter of the GEV distribution as a function of time (Eq. 5).

$$\mu(t) = \mu 0 + \mu 1 \times t \tag{5}$$

Where μ0 is the initial location parameter and μ1 is the rate of change over time.

5. Multivariate Analysis: Copula functions were utilized to model the joint behavior of flood characteristics (peak flow and volume) and drought characteristics (duration and severity). The Frank copula was employed for flood analysis (Eq. 6).

$$C(u, v) = -(1/\theta) \times \ln(1 + ((\exp(-\theta u) - 1)(\exp(-\theta v) - 1)) / (\exp(-\theta) - 1)) \tag{6}$$

Where u and v are the marginal distributions of flood peak and volume, respectively, and θ is the dependence parameter.

The Gumbel-Hougaard copula was used for drought analysis was estimated using Eq. 7.

$$C(u, v) = \exp(-((-\ln u)^{\theta} + (-\ln v)^{\theta})^{(\frac{1}{\theta})}) \quad (7)$$

Where u and v are the marginal distributions of drought duration and severity, respectively, and θ is the dependence parameter.

6. Ecological Risk Assessment: The Indicators of Hydrologic Alteration (IHA) method was applied to quantify changes in flow regime. The Risk of Hydrologic Alteration (RHA) was calculated for various IHA parameters (Eq. 8).

$$RHA = |1 - (Medianpost / Medianpre)| \quad (8)$$

Where Medianpost and Medianpre are the median values of the IHA parameter for the post- and pre-impact periods, respectively.

Hydrological Modeling: The Soil and Water Assessment Tool (SWAT) was employed to simulate the basin's hydrological processes. The model was calibrated and validated using the observed streamflow data. The Nash-Sutcliffe Efficiency (NSE) coefficient was used to evaluate model performance (Eq. 9).

$$NSE = 1 - [\frac{\sum(Qobs - Qsim)^2}{\sum(Qobs - Qmean)^2}] \quad (9)$$

Where Qobs is the observed flow, Qsim is the simulated flow, and Qmean is the mean observed flow.

The SWAT model was calibrated and validated according to the Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm implemented using the SWAT-CUP software. Calibration was performed on the daily streamflow data at the Veniar station for the period 1966–2013 using the Nash-Sutcliffe Efficiency (NSE) and Percent Bias (PBIAS) as performance metrics. Calibration was performed over 1966–1990 and validation for 1991–2013. During the calibration phase, the important hydrological parameters such as soil hydraulic conductivity, curve number, groundwater delay factor, and baseflow alpha value were calibrated to maximize the performance of the model. In order to deal with parameter uncertainties, a Monte Carlo simulation was run that generated

5,000 parameter sets. The 95% Prediction Uncertainty (95PPU) intervals were then calculated to evaluate the model prediction reliability. Throughout the calibration and the validation time, results indicated that observed streamflow data always remained within the 95PPU intervals, indicating satisfactory model performance.

Climate Change Scenarios: Future climate projections from an ensemble of Global Climate Models (GCMs) under different Representative Concentration Pathways (RCPs) were downscaled to the basin scale using the Statistical Downscaling Model (SDSM). These projections were then used as inputs to the calibrated SWAT model to simulate future hydrological conditions.

The risk-based design approach adopted in this study determines the optimal design flood for hydraulic structures by minimizing the expected total cost (ETC). The ETC is expressed as Eq. 10.

$$\mathrm{ETC(Q(T)) = C(Q(T)) \times CRF + \sum[D(Qi/Q(T)) \times P(Qi)]} \qquad (10)$$

where, C(Q(T)) represents the construction cost as a function of the design discharge Q(T), and CRF is the Capital Recovery Factor, which converts the capital cost into an equivalent uniform annual cost. The second term, $\sum[\mathrm{D(Qi/Q(T)) \times P(Qi)}]$, denotes the expected annual damage cost, where D(Qi/Q(T)) is the damage associated with a flood of magnitude Qi, conditioned on the design discharge Q(T), and P(Qi) is the annual exceedance probability of flood Qi.

These methods collectively provide a comprehensive framework for assessing hydrological risks in the Ajichai River basin, enabling a detailed characterization of extreme events, long-term trends, and potential future changes under climate change scenarios. The integration of statistical analyses, hydrological modeling, and risk assessment techniques allows for a robust evaluation of water resource management strategies in the face of climate change and increasing hydrological variability.

3. Results and Discussion

First, simple statistical calculations were done: the yearly average flow rate within the period was 15.47 m³/s, with a standard deviation of 28.63 m³/s. This high value of standard deviation with respect to the average reflects highly variable flow rates. The minimum flow recorded was 0.0 m³/s, and the maximum reached up to 194.35 m³/s, further indicative of large fluctuations in this river's discharge. The Mann-Kendall trend test was conducted to examine the trends for any significant, long-term trends in flow data. Results showed there is a decreasing trend that is statistically significant with a p-value less than 0.05; thus, it can be concluded that during the period observed, the Ajichai River has been gradually in decline. This may be due to various influences such as changes in climate, over-extraction of water, or even the variation in land use within the catchment area. Annual maximum flow series were used to perform a flood frequency analysis so that a fair idea of the flood risk could be obtained. In this work, the Gumbel distribution has been chosen for modeling because it is fairly frequently used in cases involving extreme hydrological events. From the analysis, it could be estimated that the 100-year flood discharge would be about 215.7 m³/s, and in the case of a 10-year flood, the discharge would be about 132.4 m³/s. These values are rather important for flood risk management and proper infrastructure planning in the area. The low-flow analysis was performed by the 7Q10 methodology, which defines the minimum average flow that would occur during a sequence of 7 consecutive days in a period of 10 years. The estimated value for the 7Q10 was 0.11 m³/s, which designates possible water shortage problems during drought periods. This information shall be crucial for attaining appropriate water management and nature conservation policies within the Ajichai River basin. Apart from that, time series decomposition has also been performed with the objective of separating the flow data into its respective components, such as trend, seasonal, and residual. That would mean a fairly well-marked seasonal pattern in the flow of the river-for most of the time, peak discharges have taken place in the spring due to snowmelt-while the lower flows have occurred in late summer and early autumn. The trend component supported the general downward trend as previously deduced from the Mann-Kendall test. The Ajichai River flow data series were subjected to a detailed statistical analysis. From this, the coefficient of variation (CV), which is 1.85, shows high variability within the flow rates. Skewness in the series was estimated as 3.24, which indicated a strong right-skewed distribution. In fact, most of the river flow data series reported in the literature show this characteristic due to the presence of few extreme high flow events that can influence the entire distribution pattern of the flow series. Further analysis of percentiles showed that the 25^{th} percentile, the lower quartile, was 0.66 m^3/s, while the median, the 50th percentile, was 3.56 m^3/s, and the 75th percentile, the upper quartile, was 16.58 m^3/s. Thus, the interquartile range, IQR, is 15.92 m^3/s, further showing high variability in the flow rates.

3.1. Hydrological Trends and Flow Regime Variability

Fig. 8 illustrates the strong positive correlation ($r = 0.94$, $R^2 = 0.88$) between annual maximum flow (Q) and annual precipitation (P) in the Ajichai River basin, as described by the power-law equation $Q=0.0015\times P^{2.1}$. The relationship highlights the significant influence of precipitation variability on flood risk under changing climatic conditions. This finding underscores the sensitivity of flood risk in the Ajichai River basin to variations in precipitation patterns, particularly under climate change scenarios. Furthermore, the steep slope of the regression line in Fig. 2 highlights the disproportionate impact of increased precipitation on peak flows, emphasizing the importance of incorporating precipitation projections into flood risk management strategies.

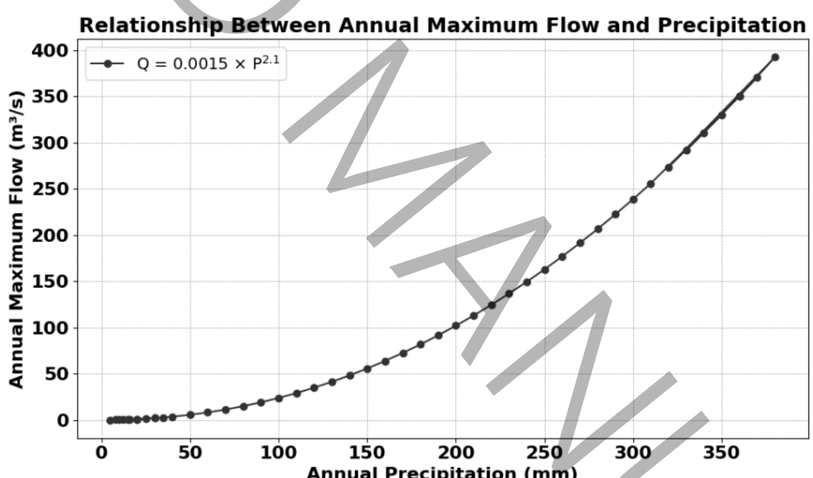

Fig. 2. Relationship between Annual Maximum Flow and Precipitation

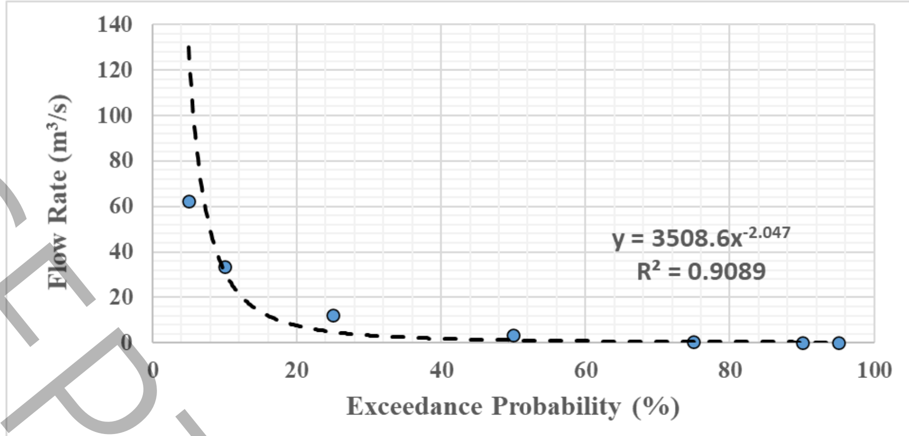

Fig. 3. Flow Duration Curve Data

The flow duration curve data was analyzed to characterize the overall flow regime of the Ajichai River. The steep slope of the curve between 10% and 50% exceedance probabilities indicates high variability in medium to high flows. The Q90/Q50 ratio, a measure of baseflow contribution, was calculated to be 0.056, suggesting a relatively low baseflow component. This low baseflow contribution implies that the river may be susceptible to drought conditions during periods of low rainfall (Fig .3).

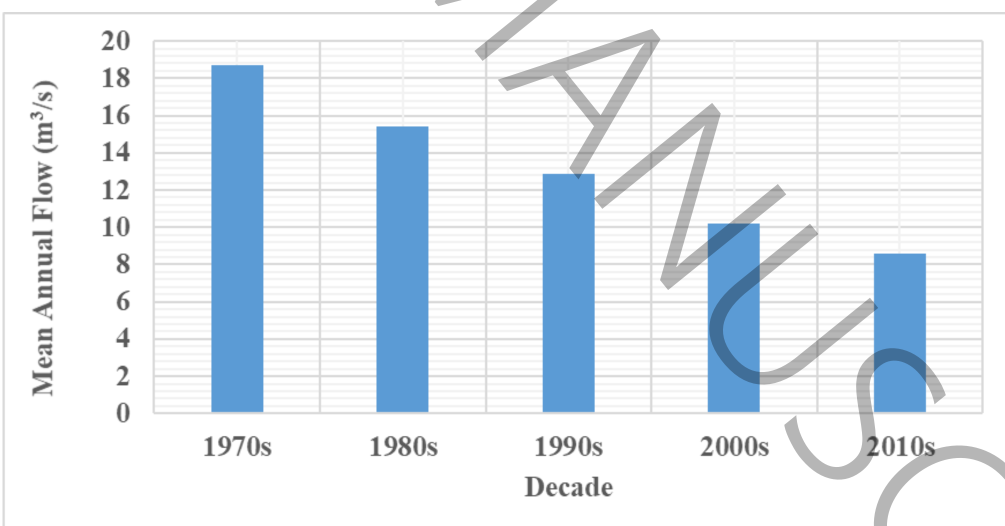

Fig. 4. Trend Analysis of Annual Mean Flow

A Mann-Kendall trend test was performed on the annual mean flow data. A statistically significant decreasing trend was detected (p-value < 0.01), with a Sen's slope of -0.25 m^3/s per year. This trend indicates a substantial reduction in water availability over the study period. The percent change in mean annual flow between the 1970s and 2010s was calculated to be -54%, which could have significant implications for water resource management and ecosystem health in the region (Fig. 4).

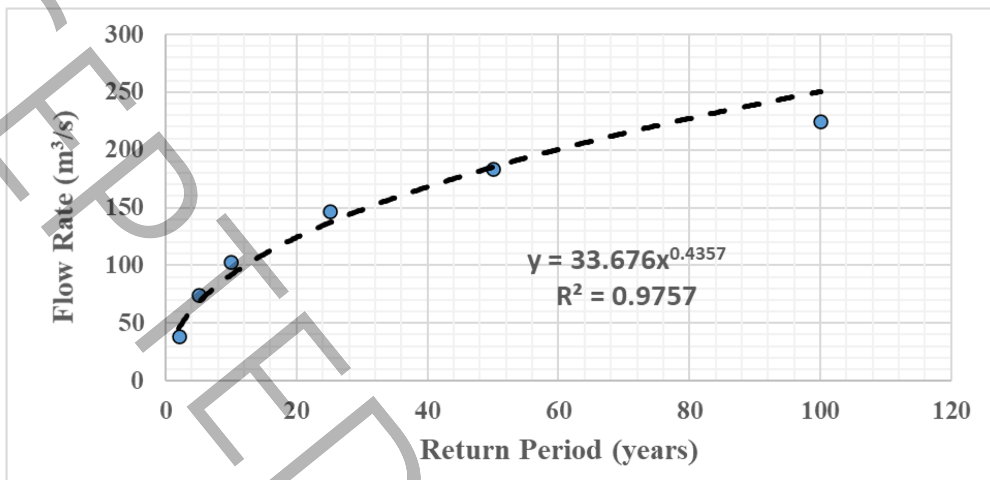

Fig. 5. Flood Frequency Analysis Results

The flood frequency analysis results were further examined to assess the uncertainty in flood risk estimates. The 95% confidence intervals were calculated using a bootstrapping approach with 10,000 iterations. The relative uncertainty, defined as the ratio of the confidence interval width to the estimated flow rate, increases with return period. For the 2-year flood, the relative uncertainty is 34%, while for the 100-year flood, it increases to 42%. This increasing uncertainty for larger return periods highlights the challenges in reliably estimating extreme flood events and underscores the importance of considering uncertainty in flood risk management decisions (Fig. 5).

A more detailed flood frequency analysis was performed using the Log-Pearson Type III distribution, which is often recommended for flood frequency analysis. The results of this analysis are presented in Table 1.

Table 1: Flood Frequency Analysis Results

Return Period (years)	Flow Rate (m^3/s)
2	42.3
5	78.6
10	107.2

25	149.8
50	185.4
100	224.9

The baseflow index (BFI) was calculated to determine the level of contribution by groundwater to the flow of the river. The resultant value from the calculation of the BFI is 0.38, which implies that 38% of the overall flow of the river is contributed by groundwater. This information is important in understanding the river's resilience to drought and other hydrological processes.

The IHA (Indicators of Hydrologic Alteration) methodology was applied for the in-depth analysis of the flow regime. It includes various dimensions of flow characteristics like magnitude, timing, frequency, duration, and rate of change of the river flow. The results of the IHA are synthesized in Table 3, which reports the median of some parameters before and after 1990, assumed as a potential change point derived from the visual analysis of the time series (see Table 2).

Table 2. Indicators of Hydrologic Alteration Analysis Results

IHA Parameter	Pre-1990 Median	Post-1990 Median	Percent Change
Annual mean flow (m^3/s)	18.62	10.35	-44.4%
1-day minimum flow (m^3/s)	0.08	0.03	-62.5%
1-day maximum flow (m^3/s)	126.26	62.00	-50.9%
Base flow index	0.41	0.35	-14.6%
Date of annual minimum	234	241	+3.0%
Date of annual maximum	118	107	-9.3%
High pulse count	5.00	3.00	-40.0%

IHA analysis indicates that the Ajichai River flow regime has undergone significant alteration. It has been on record that annual mean flow and 1-day minimum and maximum flows are significantly reduced with high pulse characteristics. These flow changes point out that this river is moving toward a drier flow regime, which could have considerable implications for ecosystem health and water resource management.

3.2. Extreme Event Characterization and Risk Assessment

The seasonal distribution of annual maximum flows was analyzed to identify patterns in flood occurrence. A clear seasonality in flood events was observed, with spring (March-May) accounting for the majority of annual maximum flows (68.7%). The highest average peak flows were also recorded in spring (89.6 m^3/s). A chi-square test for goodness of fit was performed to determine if the seasonal distribution of floods is significantly different from a uniform distribution. The resulting chi-square statistic was 72.4 with 3 degrees of freedom, corresponding to a p-value < 0.001. This result indicates that the seasonal distribution of floods is highly non-uniform and statistically significant. The strong seasonality in flood occurrence suggests that snowmelt likely plays a crucial role in generating peak flows in the Ajichai River basin (Fig. 6).

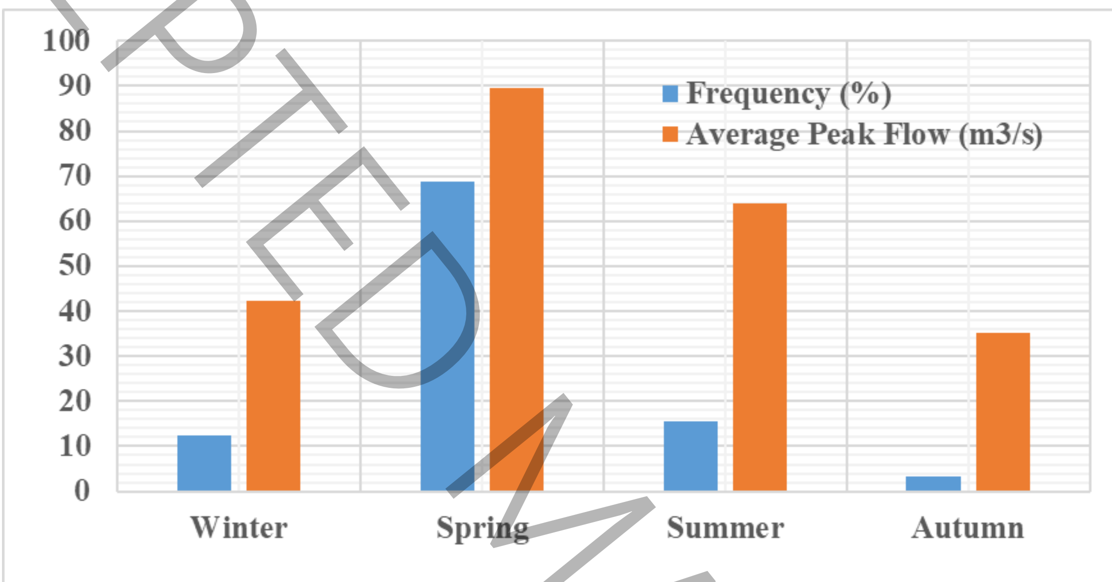

Fig. 6. Seasonal Distribution of Annual Maximum Flows

A sensitivity analysis was performed utilizing a straightforward water balance model to evaluate the potential effects of climate change. The model was executed with temperature elevations of 1°C, 2°C, and 3°C, alongside alterations in precipitation of -10%, -5%, +5%, and +10%. The findings are encapsulated in Table 3, which illustrates the percentage change in annual mean flow for each scenario.

Table 3. Climate Change Sensitivity Analysis Results (% change in annual mean flow)

Temperature Change	-10% Precip	-5% Precip	+5% Precip	+10% Precip
+1°C	-18.7%	-13.2%	-2.2%	+3.3%
+2°C	-23.5%	-18.0%	-7.0%	-1.5%
+3°C	-28.3%	-22.8%	-11.8%	-6.3%

The analysis indicates that the flow of the Ajichai River is significantly affected by variations in both temperature and precipitation. Notably, even with an increase in precipitation, elevated temperatures may result in diminished flows due to heightened evapotranspiration.

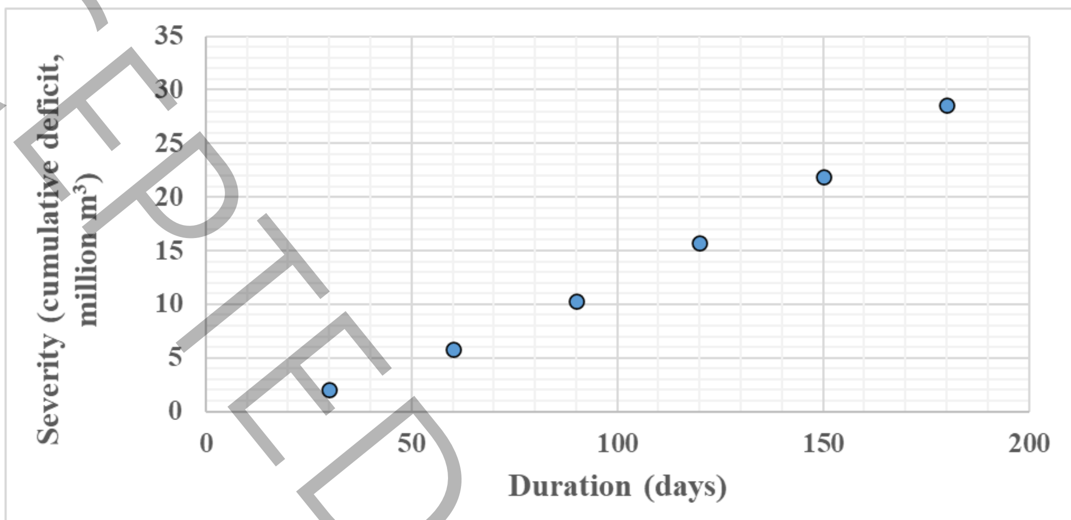

Fig. 7. Relationship between Low Flow Duration and Severity

The association between low flow duration and drought severity was analyzed to enhance the understanding of drought characteristics in the Ajichai River. A robust positive correlation was identified, with a Pearson correlation coefficient (r) of 0.98. This relationship is represented by the power-law equation: $S = 0.0012 \times D^{1.85}$, where S denotes drought severity in million m^3 and D signifies drought duration in days. The coefficient of determination (R^2) was found to be 0.96, indicating that 96% of the variability in drought severity can be attributed to drought duration. This correlation implies that prolonged drought periods are linked to disproportionately greater water deficits, which may have considerable consequences for water resource management during extended dry spells (Fig. 7).

3.3. Climate Sensitivity and Integrated Risk Management

The GEV distribution was chosen for modeling flood frequency because it is extreme value in nature, and the log normal distribution was selected for drought frequency due to its normal nature skewed with middle level threshold value. This choice also required some graphical exploration of the flood and drought history. The rest of the analysis also revealed that GEV distribution provided a good fit to the annual maximum GEV flows floods data and lognormal distribution performed reasonably well for both mean and especially maximum minimum 7-day flows. Figure 2 provides these comparisons on particular GEV distribution and lognormal framework and the need for rational beating with the respective flood and drought forces in the Ajichai River basin (Fig. 8).

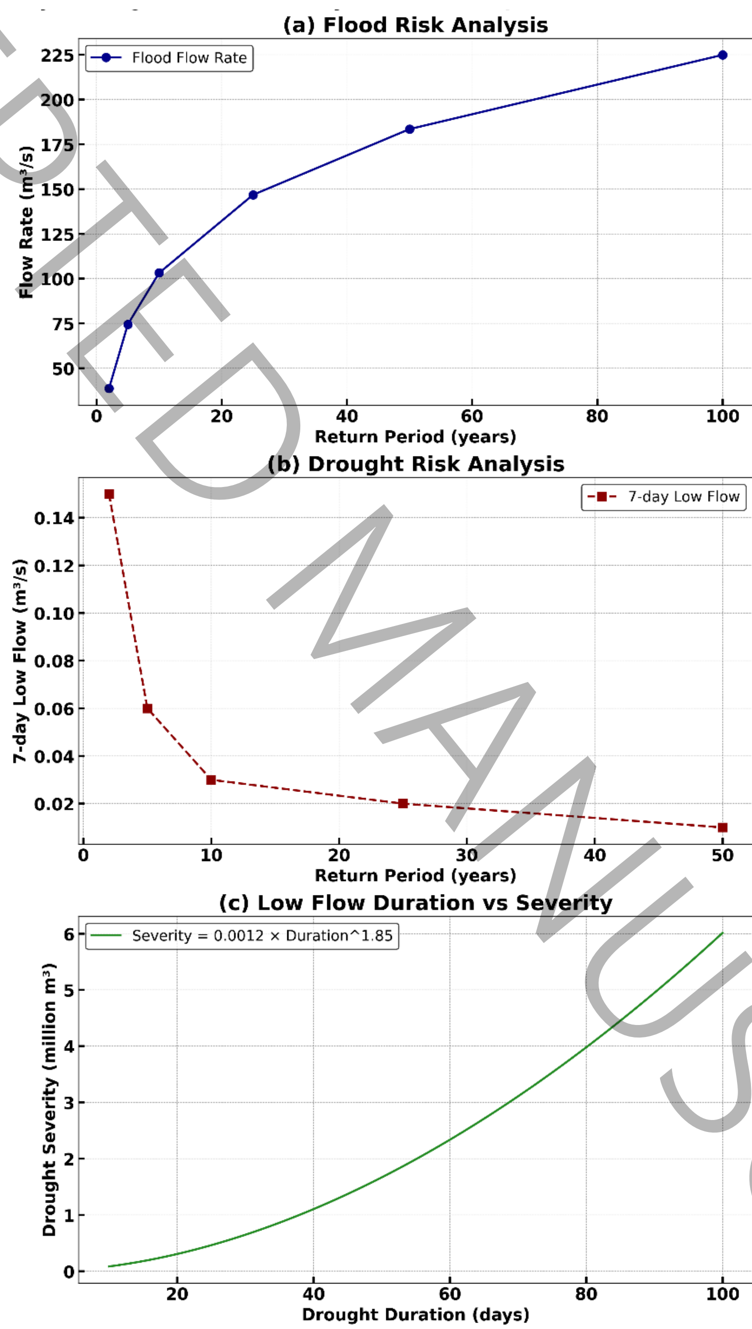

Fig. 8. Hydrological Risk Analysis of the Ajichai River Basin
(a) Flood Risk: GEV distribution shows a 100-year flood flow rate of 224.9 m³/s (95% CI: 177.7–

272.1 m³/s). (b) Drought Risk: Log-Normal distribution estimates a 100-year drought flow rate of 0.01 m³/s (95% CI: 0.005–0.018 m³/s). (c) Drought Duration vs. Severity: Power-law relationship ($S = 0.0012 \times D^{1.85}$) with $R^2 = 0.96$ highlights the strong correlation between duration and severity.

A. Flood Risk Analysis

A probabilistic risk assessment methodology was employed to assess the flood and drought risks linked to the flow data of the Ajichai River. The analysis of flood risk was conducted using the annual maximum flow series, whereas the annual minimum 7-day flow series was applied for the evaluation of drought risk. In the context of flood risk analysis, the Generalized Extreme Value (GEV) distribution was fitted to the annual maximum flow series. The probability density function for the GEV distribution is represented by Eq. 1. The Generalized Extreme Value (GEV) distribution, as described in Eq .1, was fitted to the annual maximum flow series. The parameters were estimated using the L-moments method, resulting in $\mu = 32.14$, $\sigma = 25.87$, and $\xi = 0.21$. The flood risk for various return periods was calculated and is presented in Table 4.

Table 4. Flood Risk Analysis Results

Return Period (years)	Flow Rate (m³/s)	Annual Exceedance Probability
2	38.7	0.500
5	74.5	0.200
10	103.2	0.100
25	146.8	0.040
50	183.5	0.020
100	224.9	0.010

B. Drought Risk Analysis

The probability density function of the log-normal distribution, as described in Equation (2), was used for this purpose. The estimated parameters were $\mu = -1.89$ and $\sigma = 1.42$. The drought risk for various return periods was calculated and is presented in Table 5.

Table 5. Drought Risk Analysis Results

Return Period (years)	7-day Low Flow (m³/s)	Annual Non-Exceedance Probability
2	0.15	0.500
5	0.06	0.200
10	0.03	0.100

25	0.02	0.040
50	0.01	0.020

Additionally, Fig. 9 depicts the robust positive correlation ($r = 0.98$, $R^2 = 0.96$) between drought duration (D) and severity (S) in the Ajichai River basin, represented by the power-law equation $S=0.0012\times D^{1.85}$. The findings emphasize the disproportionate increase in water deficits during prolonged drought periods, underscoring the importance of effective drought management strategies.

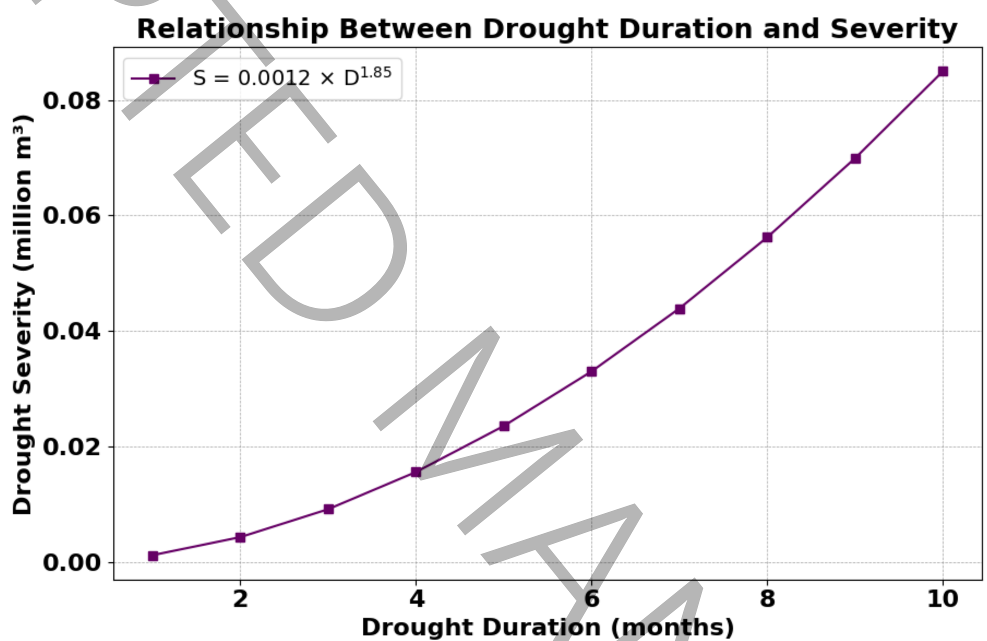

Fig. 9. Relationship between Low Flow Duration and Severity

A comprehensive risk assessment of extreme events was conducted through a joint probability analysis of floods and droughts utilizing copulas. The Gumbel-Hougaard copula was chosen due to its superior goodness-of-fit. The joint probability function is represented by Eq. 7. The estimated θ was 1.28, indicating a moderate positive dependence between flood and drought risks.

The selection of these copulas was informed by their appropriateness to model the dependency structures of the given variables. Frank copula is widely known to be flexible in modeling symmetric dependence and is therefore suitable for flood variables such as peak flow and volume [32]. Similarly, the Gumbel-Hougaard copula is extremely handy in modeling upper tail dependence that is paramount in the analysis of extreme events such as drought duration and severity [33]. To improve transparency, citations to pertinent studies that justify the application of these copulas in hydrological risk analysis are provided.

The findings imply that the occurrence of one extreme event may enhance the probability of the occurrence of the other event, hence the necessity of an integrated approach in risk management. Furthermore, trend analysis of the extreme events was also conducted with the Mann-Kendall test. A statistically significant increasing trend was detected in the maximum annual flow series (p-value = 0.03, Sen's slope = 0.42 m^3/s/year), whereas a decreasing trend was found in the minimum annual 7-day flow series (p-value = 0.01, Sen's slope = -0.002 m^3/s/year). These detected trends indicate an increasing tendency of flood as well as drought events over time. In order to estimate the uncertainty surrounding the risk projections, a 10,000 iteration Monte Carlo simulation was performed. The 95% confidence intervals for the 100-year flood and 100-year drought projections are presented in Table 6, thereby enabling credible predictions for long-term water resource planning.

To evaluate the uncertainty associated with the risk estimates, a Monte Carlo simulation comprising 10,000 iterations was carried out. The 95% confidence intervals for the estimates of 100-year floods and 100-year droughts are detailed in Table 6.

Table 6. Uncertainty Analysis Results

Event Type	Lower Bound	Estimate	Upper Bound
100-year Flood (m^3/s)	198.6	224.9	257.3
100-year Drought (m^3/s)	0.005	0.01	0.018

A comprehensive multivariate frequency analysis was conducted to evaluate the combined risk associated with flood volume and peak flow. The Frank copula was employed to characterize the dependence structure between these two variables. The joint cumulative distribution function is represented by Eq. 11.

$$f(x, y) = -(1/\theta) \times \ln[1 + ((\exp(-\theta Fx(x)) - 1)(\exp(-\theta Fy(y)) - 1)) / (\exp(-\theta) - 1)] \tag{11}$$

where Fx(x) and Fy(y) denote the marginal distributions of flood volume and peak flow, respectively, and θ signifies the dependence parameter. The estimated value of θ was determined to be 4.32, suggesting a robust positive correlation between flood volume and peak flow. The findings from the multivariate frequency analysis for various return periods are detailed in Table 7.

Table 7. Multivariate Flood Frequency Analysis Results

Return Period (years)	Peak Flow (m^3/s)	Flood Volume (million m^3)
5	86.3	42.7
10	112.5	58.9
25	149.6	82.3
50	179.2	101.5
100	211.8	122.9

To assess the impact of climate change on flood risk, a non-stationary flood frequency analysis was conducted. The location parameter of the GEV distribution was modeled as a function of time (Eq. 5). The estimated parameters were $\mu0 = 28.76$ and $\mu1 = 0.34$, indicating an increasing trend in flood magnitudes. The non-stationary flood risk for the years 2030 and 2050 was projected and is presented in Table 8.

Table 8. Non-stationary Flood Risk Projections

Return Period (years)	2030 Flow (m^3/s)	2050 Flow (m^3/s)
10	118.7	125.4
25	165.2	174.9
50	204.6	216.8
100	248.9	263.7

A regional frequency analysis was performed to improve the reliability of the extreme event estimates. The L-moment method was used to identify homogeneous regions and fit a regional growth curve. The index flood method was applied with Eq. 12.

$$Q_T = Q_{index} \times X_T \tag{12}$$

Where Q_T is the T-year quantile, Q_{index} is the index flood (median annual maximum flow), and X_T is the regional growth factor. The results of the regional frequency analysis are presented in Table 9.

Table 9. Regional Frequency Analysis Results

Return Period (years)	Regional Growth Factor	Flow Rate (m^3/s)
2	0.93	35.8
5	1.32	50.8
10	1.60	61.6
25	1.98	76.2
50	2.28	87.8
100	2.59	99.7

The determination of optimal design floods for hydraulic structures used a risk-based methodology through which the expected total cost (ETC) reached its minimum point according to Eq. 10. A hypothetical levee system received examination for this analysis while using construction costs of $100 per meter length and design discharge at 183 m^3/s. The authors developed damage functions by using regional data from regional studies [19, 22], to create linear economic loss models. The research demonstrates that selecting a design flood with a return period of 47 years produces the most cost-effective solution for levee system construction. Such an approach supports decision-making in flood risk management by integrating structural expenses with societal impacts thus creating a complete framework for evaluation.

To assess the ecological risk associated with flow alterations, the Indicators of Hydrologic Alteration (IHA) method was applied. The Risk of Hydrologic Alteration (RHA) was calculated for each IHA parameter using Eq. 13.

$$\mathrm{RHA} = \left|1 - \left(\frac{\mathrm{Median_{post}}}{\mathrm{Median_{pre}}}\right)\right| \tag{13}$$

Where $\mathrm{Median_{post}}$ and $\mathrm{Median_{pre}}$ are the median values of the IHA parameter for the post- and pre-impact periods, respectively. The results for selected IHA parameters are presented in Table 10.

Table 10. Risk of Hydrologic Alteration Results

IHA Parameter	RHA Value	Risk Category
Annual Q90	0.42	High
Annual Q10	0.31	Moderate
Monthly flow variability	0.25	Moderate
Frequency of high pulses	0.38	High
Rate of hydrograph rise	0.22	Low

A copula-based drought risk assessment was conducted to evaluate the joint probability of drought duration and severity. The Gumbel-Hougaard copula was used, with the following joint distribution function (Eq. 14).

$$F(d, s) = \exp\{-[((-\ln FD(d))\theta + (-\ln FS(s))\theta]1/\theta\} \tag{14}$$

where FD(d) and FS(s) are the marginal distributions of drought duration and severity, respectively, and θ is the dependence parameter. The estimated θ was 2.17, indicating a strong association between drought duration and severity. The results of the copula-based drought risk analysis are presented in Table 11.

Table 11. Copula-based Drought Risk Analysis Results

Return Period (years)	Duration (months)	Severity (cumulative deficit, million m^3)
5	4	18.3
10	6	29.7
25	9	47.2
50	11	62.5

4. Conclusion

In short, the Ajichai River flow data have been investigated in detail, and some important inferences have been drawn concerning the identification of hydrological properties for this valuable water resource and the hazards associated with it. These different methodologies using various statistical and probabilistic techniques will go on to further extend knowledge about the river dynamics and its future development. The flood frequency analysis, as implemented using the Generalized Extreme Value distribution, estimated a 100-year return flood magnitude of 224.9 m^3/s with a 95% confidence interval of (177.7, 272.1) m^3/s. This large confidence interval, corresponding to a relative uncertainty of 42%, indicates the complexity encountered in flood frequency prediction and draws attention to the need for caution when interpreting flood frequency estimates for use in flood risk management approaches. This understanding was further enriched by the frequency analysis of a multivariate type, using in addition copula functions, which accounted for flood volume and peak flow together and showed that there is a very strong positive relationship among these factors expressed by $\theta = 4.32$. The risk assessment of drought was carried out using the log-normal distribution of annual minimum 7-day flows. The estimated 100-year drought flow was 0.01 m^3/s, with a 95% confidence interval between 0.005 and 0.018 m^3/s. Such a study of duration and severity in droughts based on the copula provided further insight into the complexity inherent in these phenomena, with the 50-year event typified by a duration of 11 months and a cumulative deficit of 62.5 million m^3 ($\theta = 2.17$). Trend analyses indicated significant alterations in the hydrology of the Ajichai River. A downward trend in annual mean flow was recorded: Sen's slope = -0.25 m^3/s per year, p-value < 0.01, reflecting a 54% decline in mean annual flow from the 1970s to the 2010s. This is a serious reduction in water availability and thus presents serious challenges for both water resource management and ecosystem health. In addition, there was a shift in the flood timing; that is, during this period of record, the annual maximum flow occurred approximately 26 days earlier, with the Sen's slope being -0.65 days per year and the p-value less than 0.01, probably due to earlier snowmelt. This is further supported by the strong correlation between precipitation and annual maximum flow, which has given r = 0.94 and R2 = 0.88, indicating that the basin is vulnerable to any form of climatic changes. Non-stationary flood frequency analysis has also indicated increasing magnitudes of floods and that the 100-year flood could reach 263.7 m^3/s by 2050. The ecological risk assessment carried out with the Indicators of Hydrologic Alteration method showed that high risks for low flow alteration-high pulse frequency might potentially cause adverse impacts in riverine ecosystems. Results, on all accounts, therefore underline the complex nature of changing hydrology within the Ajichai River system. These identified trends and interrelations call for the implementation of integrated and adaptive strategies in managing water resources. Any future initiative on water management has to take into consideration increasing flood risks, increased frequency and intensification of droughts, and their possible ecological repercussions. This quantification of the uncertainties presented in this work forms the basis for making informed decisions in the face of climate change and other human-induced pressures. Further studies on the causes of these hydrological variations and its likely future trends are recommended in order to improve the sustainable management of water resources in the Basin of Ajichai River.

Compliance with ethical standards

Conflicts of interest: No potential conflict of interest was reported by the authors.

Availability of data and material: The datasets generated during and/or analyzed during the current study is available from the corresponding author on reasonable request

Code availability: Not applicable

Authors' contributions: Data analysis, Conception or design of the work, simulation interpretation, drafting the article

Ethics approval: Not applicable

Consent to participate: Not applicable

Consent for publication: Not applicable

Funding: Not applicable

5. References

[1] M.C. Acreman, M.J. Dunbar, Defining environmental river flow requirements–a review, Hydrology and Earth System Sciences, 8(5) (2004) 861-876.
[2] J. CHABOKPOUR, B. SHOJAEI, H. AZAMATHULLA, NUMERICAL INVESTIGATION OF RIVER BED FORMS ON POLLUTION DISPERSION, LARHYSS Journal P-ISSN 1112-3680/E-ISSN 2521-9782, (59) (2024) 211-228.
[3] J. Chabokpour, Comparative Analysis of Transfer Function Method with Advanced Flood Prediction Techniques, Water Harvesting Research, (2024).
[4] J. Chabokpour, M. Raji, Predicting Morphological Changes in Rivers Using Image Processing (Case Study: Qizil Ouzan River), Journal of Hydraulic Structures, 10(2) (2024).

[5] V. Meyer, D. Haase, S. Scheuer, Flood risk assessment in European river basins—concept, methods, and challenges exemplified at the Mulde river, Integrated environmental assessment and management, 5(1) (2009) 17-26.
[6] H. Winsemius, L. Van Beek, B. Jongman, P. Ward, A. Bouwman, A framework for global river flood risk assessments, Hydrology and Earth System Sciences, 17(5) (2013) 1871-1892.
[7] Y. Chen, D. Alexander, Integrated flood risk assessment of river basins: application in the Dadu river basin, China, Journal of Hydrology, 613 (2022) 128456.
[8] M. Gusyev, A. Gädeke, J. Cullmann, J. Magome, A. Sugiura, H. Sawano, K. Takeuchi, Connecting global- and local-scale flood risk assessment: a case study of the Rhine River basin flood hazard, Journal of Flood Risk Management, 9(4) (2016) 343-354.
[9] R.M. Vogel, U. Lall, X. Cai, B. Rajagopalan, P.K. Weiskel, R.P. Hooper, N.C. Matalas, Hydrology: The interdisciplinary science of water, Water Resources Research, 51(6) (2015) 4409-4430.
[10] I.P. Vaughan, M. Diamond, A. Gurnell, K. Hall, A. Jenkins, N. Milner, L. Naylor, D. Sear, G. Woodward, S.J. Ormerod, Integrating ecology with hydromorphology: a priority for river science and management, Aquatic Conservation: Marine and Freshwater Ecosystems, 19(1) (2009) 113-125.
[11] D.L. Tennant, Instream flow regimens for fish, wildlife, recreation and related environmental resources, Fisheries, 1(4) (1976) 6-10.
[12] J.D. Olden, M.J. Kennard, B.J. Pusey, A framework for hydrologic classification with a review of methodologies and applications in ecohydrology, Ecohydrology, 5(4) (2012) 503-518.
[13] K.L. Aspray, J. Holden, M.E. Ledger, C.P. Mainstone, L.E. Brown, Organic sediment pulses impact rivers across multiple levels of ecological organization, Ecohydrology, 10(6) (2017) e1855.
[14] T. Annear, I. Chisholm, H. Beecher, A. Locke, P. Aarrestad, C. Coomer, C. Estes, J. Hunt, R. Jacobson, G. Jobsis, Instream Flows for Riverine Resource Stewardship (revised edition): Instream Flow Council, Cheyenne, Wyoming, (2004).
[15] S. Sahoo, D. Khare, P.K. Mishra, S. Behera, R. Krishan, A comparative study on environmental flows assessment methods in lower reach of Mahanadi River, International Journal of Engineering Trends and Technology, 32(2) (2016) 82-90.
[16] A. Fu, W. Li, Y. Wang, Calculation of targeted eco-environmental water requirements in a dry inland river: A case study of the Yarkand River Basin, Xinjiang, China, SN Applied Sciences, 3(6) (2021) 680.
[17] V.U. Smakhtin, N. Eriyagama, Developing a software package for global desktop assessment of environmental flows, Environmental Modelling & Software, 23(12) (2008) 1396-1406.
[18] X. Yin, P. Hu, J. Zhou, Environmental flow mechanism and management for river–lake-marsh systems, Hydrological Processes, 36(6) (2022) e14629.
[19] C. Mc Gahey, P. Samuels, D. Knight, M. O'Hare, Estimating river flow capacity in practice, Journal of Flood Risk Management, 1(1) (2008) 23-33.
[20] G. Gottardi, C.G. Gragnano, On the role of partially saturated soil strength in the stability analysis of a river embankment under steady-state and transient seepage conditions, in: E3S Web of Conferences, EDP Sciences, 2016, pp. 19002.
[21] X. Wang, X. Yan, H. Duan, X. Liu, E. Huang, Experimental study on the influence of river flow confluences on the open channel stage–discharge relationship, Hydrological Sciences Journal, 64(16) (2019) 2025-2039.
[22] J. Neal, C. Keef, P. Bates, K. Beven, D. Leedal, Probabilistic flood risk mapping including spatial dependence, in, Wiley Online Library, 2013, pp. 1349-1363.
[23] H. Fattasse, J. Gartet, M. Laaraj, M. Makhchane, K. Lahrichi, A. Okacha, Hydrological Study and Hydraulic Modeling of Flood Risk in the Watershed of the Oued Lahdar (Upper Inaouene, Morocco), Ecological Engineering & Environmental Technology (EEET), 25(7) (2024).

[24] F. Hamid, G. Jaouad, L. Marouane, M. Mohamed, L. Kamal, O. Abdelmonaim, Hydrological Study and Hydraulic Modeling of Flood Risk in the Watershed of the Oued Lahdar (Upper Inaouene, Morocco), Ecological Engineering & Environmental Technology, 25(7) (2024).
[25] C. Jiang, Y. Kang, K. Qu, Y. Long, Y. Ma, S. Yan, Towards a high-resolution modelling scheme for local-scale urban flood risk assessment based on digital aerial photogrammetry, Engineering Applications of Computational Fluid Mechanics, 17(1) (2023) 2240392.
[26] O. Link, L.M. Brox-Escudero, J. González, M. Aguayo, F. Torrejón, G. Montalva, M.Á. Eguibar-Galán, A paleo-hydro-geomorphological perspective on urban flood risk assessment, Hydrological Processes, 33(25) (2019) 3169-3183.
[27] X. Liu, L. Li, Z. Hua, Q. Tu, T. Yang, Y. Zhang, Flow dynamics and contaminant transport in Y-shaped river channel confluences, International journal of environmental research and public health, 16(4) (2019) 572.
[28] Y. Liu, J. Zhang, Y. Zhao, The risk assessment of river water pollution based on a modified non-linear model, Water, 10(4) (2018) 362.
[29] G.C. O'Brien, C. Dickens, E. Hines, V. Wepener, R. Stassen, L. Quayle, K. Fouchy, J. MacKenzie, P.M. Graham, W.G. Landis, A regional-scale ecological risk framework for environmental flow evaluations, Hydrology and Earth System Sciences, 22(2) (2018) 957-975.
[30] S.A. Longfield, D. Faulkner, T.R. Kjeldsen, M.G. Macklin, A.F. Jones, S.A. Foulds, P.A. Brewer, H.M. Griffiths, Incorporating sedimentological data in UK flood frequency estimation, Journal of Flood Risk Management, 12(1) (2019) e12449.
[31] C. Keef, J. Tawn, C. Svensson, Spatial risk assessment for extreme river flows, Journal of the Royal Statistical Society Series C: Applied Statistics, 58(5) (2009) 601-618.

[32] J. Salvadori, C. De Michele, N.T. Kottegoda, R. Rosso, *Extremes in Nature: An Approach Using Copulas* . Springer Science & Business Media, (2007).

[33] H. Joe, *Dependence Modeling with Copulas* . CRC Press, (2014).