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Novel Fuzzy Optimization Model of Future Climate Change Impacts on Water Resources of Al-Hilla River, Babylon, Iraq

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Abstract- – This study aims to evaluate the impacts of future climate change scenarios on the water quality and streamflow of the Al-Hilla River. By simulating various climatic conditions, the research seeks to quantify the degradation of water quality due to rising temperatures and reduced river flows, and to provide insights for effective water management strategies. A comprehensive water quality simulation model was employed to analyze the reactions of crucial indicators of water quality to anticipated scenarios of climate change. The model incorporated variations in temperature, precipitation, and streamflow for three future periods: 2021-2030, 2031-2040, and 2041-2050. Parameters assessed included temperature, dissolved oxygen, total dissolved solids (TDS), biological oxygen demand (BOD), total hardness (TH), pH, and others. Future scenarios were derived from historical data, and the model was calibrated and validated to ensure accuracy. The results indicate a significant rise in mean temperatures and a decrease in precipitation, leading to reduced river flow and deteriorated water quality. Specifically, average annual temperatures are projected to increase by up to 6.8°C by 2041-2050, while precipitation may drop by up to 59.2%. Streamflow is expected to decline by 52% to 66%, with associated increases in dissolved solids, BOD, and total hardness. The Water Quality Index (WQI) is projected to decline from "Good" to "Poor" by the end of the century. The study's limitations include the reliance on projected climate data and assumptions inherent in the simulation model. The results are significant They point to the importance of quick action for stakeholders and governments engaged in protecting the environment and water management in order to ensure sustainable water supplies.

Keywords- Climate Change, Water Quality, Streamflow, Al-Hilla River, QUAL2K model; ACO algorithm.

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1. INTRODUCTION

Before water can be used for drinking, agriculture, recreation, or industrial purposes, it is crucial to evaluate its physical, chemical, and biological characteristics (Dessie et al., 2024). Climate change, marked by global warming and seasonal droughts both globally and particularly in Iraq, has led to significant alterations in water quality parameters due to reduced water levels and discharge rates exceeding design capacities (Bayatavrkeshi et al., 2023).

While it is widely acknowledged that human activities drive climate change, predicting the extent and likelihood of its impacts on water quality remains complex. This complexity arises from the broad spectrum of natural variations in hydrology, chemistry, and ecology, compounded by significant uncertainties (Al–Delewy et al., 2006). Climate change is a major factor influencing policies for the Environment Agency and the water industry. Understanding its potential effects on water quality is essential for policymakers to provide informed guidance on impact management (Yang et al., 2020; Ahmed et al., 2020).

Considerable uncertainty persists regarding the mechanisms governing freshwater systems, the quantification of global climate drivers, the downscaling of global processes to local settings, and the intricate relationships between hydrology, chemistry, and biology (Salahaldain et al., 2023; Trancoso et al., 2024). To address these complexities, mathematical models are increasingly used to predict and understand these processes.

To control the quality of the water in river systems, several models for allocating water load have been proposed. The purpose of these models is to find workable, practical solutions for drainers and the Pollution Control Authority. Organizations set water use rules and restrictions, requiring drains to remove specified amounts of contaminants. However, as the degree of contaminant removal increases, so does the cost of water treatment, presenting a challenge in balancing the competing interests of organizations and regulators. In some implementations, a specific quality parameter is standardized and used as a benchmark for assessing water quality.

Recent studies on future climate change and river water quality have revealed significant insights into how changing climate patterns are expected to impact river ecosystems globally (Nikakhtar et al., 2024). Advanced climate models and scenario analyses indicate that increased temperatures and altered precipitation patterns will exacerbate the frequency and intensity of both droughts and floods, leading to significant changes in river flow regimes (Islam et al., 2018). These changes are predicted to result in reduced dissolved oxygen levels, increased pollutant concentrations, and more frequent harmful algal blooms, which collectively threaten aquatic life and water quality (Gómez-Martínez et al., 2021). Additionally, research highlights the potential for enhanced nutrient runoff from agricultural lands during extreme weather events, promoting eutrophication and further degrading water quality (Van Vliet et al., 2023; Wang et al., 2024). To address these challenges, recent studies emphasize the need for integrated water management practices, ecosystem restoration, and sustainable agricultural practices, along with robust policy frameworks to ensure adaptive and resilient water resource management in the face of climate change.)

Al-Hilla River, located in the Babylon province of Iraq, is a vital natural stream essential for various water uses. It is the only freshwater source for the Babylon governorate, home to about 2 million people. Climate change significantly impacts the Al-Hilla River, affecting water contributions from upstream governorates and leading to conflicts between farmers and local governments.

To tackle the challenges of future climate change and river water quality, fuzzy optimization techniques are employed. The aim is to understand the potential impacts of climate change on the Hilla River's water quality to inform evidence-based policy. The specific objectives of the project are to: (1) evaluate the long-term effects of climate change on water quality in the study area from 2012 to 2023; (2) reduce uncertainties in the proposed fuzzy model; (3) improve the average quality index at river checkpoints, which is the fuzzy goal function and downstream outlets, enabling quicker and more accurate decision-making; and (4) assess the impact on water quality management in Al-Hilla River using a simulation-optimization model to project future climates for the period 2021-2050, examining the effects of climate changes, such as precipitation and temperature, on stream flows, water quality parameters, and the overall WQI.

2. Case Study Description

Al-Hilla River, which spans 101 km^2, is the major source of water and is regarded as one of Iraq's most notable rivers in the city of Hilla (Al-Karim and Al-Kizwini 2022). The Euphrates River is the primary source of the river, flowing from the northern boundary of the Babylon Governorate to the Diwaniyah Governorate. Given its strategic location, the Euphrates River serves as one of Iraq's main irrigation systems. Three stations along Al-Hilla River, which runs from Al-Hilla city to Al-Hashimiyain Babil Governorate, were included in the research area. The water treatment of New Hilla, Al-Hussein, and Al-Hashimiya is represented by these stations.

Along the river's course, fifteen checkpoints were also recorded; these were numbered beginning at the first station, New Hilla, and ending at Al-Hashimiyah station. Figure 1 depicts the research area's geographic location as well as the three stations that were chosen.

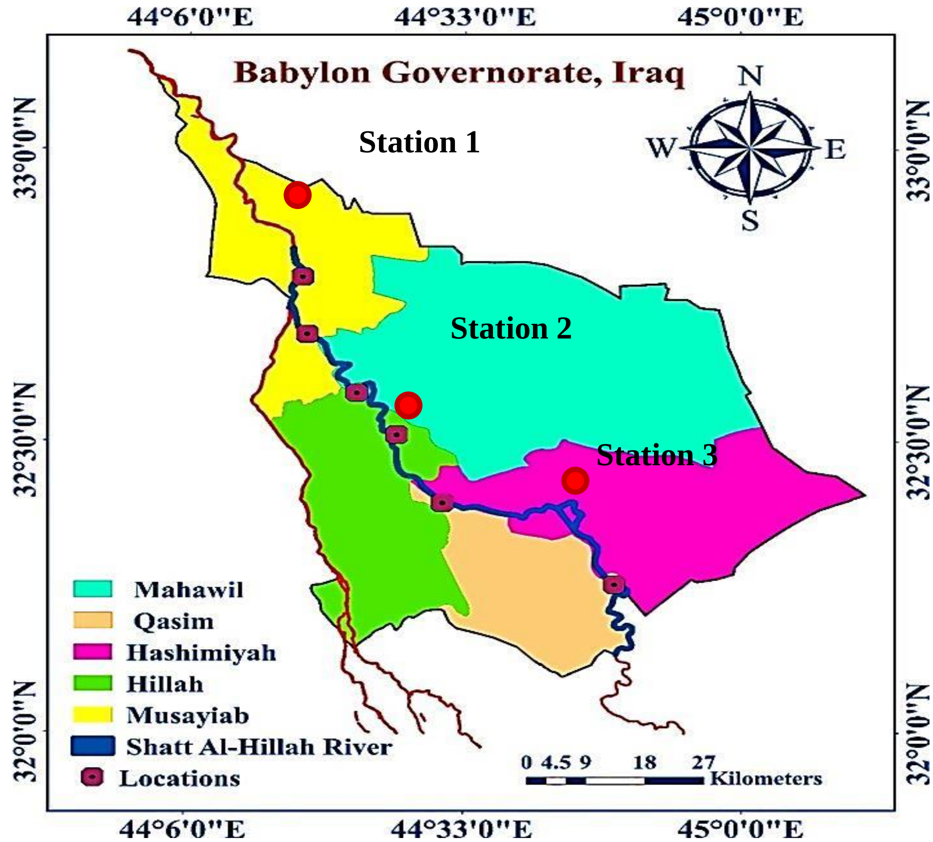


Figure 1. Location of selected stations in Al-Hilla River.

3. CLIMATE CHANGE AND HISTORICAL DATA ANALYSIS

To assess how climate change is affecting Al-Hilla River's water quality, historical data must first be examined to determine how hydroclimatic factors have changed. Therefore, it is necessary to choose climatic variables and the associated surface variables that are impacted by climate change (Alsultani et al., 2023a). It is well recognized that air temperature and precipitation are the main climate factors that global warming affects. The surface variables that are fed into the water quality model include temperature and streamflow. For data analysis in this study, precipitation, streamflow, air temperature, and water temperature were selected. To develop future climate scenarios, factors relating to climate and water quality input must be coupled to each other (Alfatlawi and Alsultani, 2018a). Thus, to connect air temperature to water temperature, a simple linear regression is performed. Once the hydroclimatic variables have been selected, selecting climate change scenarios for such local characteristics is crucial.

Six real-world climate change scenarios and the current climate were used to simulate the reaction of the water quality. The chosen scenarios, which are listed in Table 1 are taken into consideration in light of the historical data analysis completed for this study.

A 30 km section of the Al-Hilla River is divided into 15 streams (or checkpoints) as shown in Figure 2, with varying lengths depending on the river profile. Each stream is further subdivided into arithmetic parts, each 2 km in length.

Table 1.
Scenario types of climate change.

No.	I	II	III	IV	V	VI
$\Delta\,AT$ (°C)	0.5	0.5	0.5	1	1	1
$\Delta\,F$ (%)	-10	-5	0	0	-5	-10

$\Delta\,AT$ =Air temperature change; $\Delta\,F$ = Streamflow change.

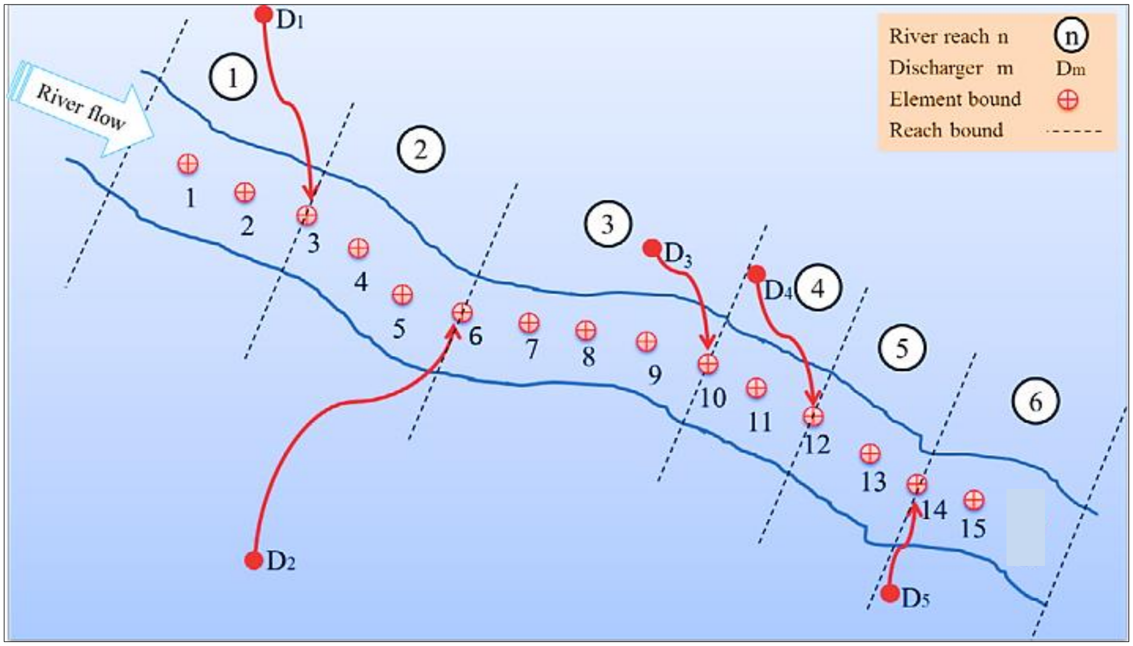


Figure 2. Schematic view of the river network.

4. Model Layouts

This part aims to (1) estimate the effects of climate change on water quality, (2) select the optimum scenario, and (3) use the fuzzy optimization approach to consider the ideal water quality in the river. The optimization of the fuzzy objective function at river checkpoints, which takes the form of the mean National Sanitation Foundation Water Quality Index (NSFWQI), is another innovative strategy used here. With NSFWQI serving as the membership feature in the suggested model has the advantage of lowering model-related uncertainty and perhaps producing a collection of more precise answers. The Ant Colony Optimization (ACO) model is used for simulating and improving the river water quality model. method and QUAL2K simulator are used together to choose suitable model solutions. This improves the model solution identification process in terms of speed and accuracy. The model is executed on fictitious situations constructed from air and water temperature data, as well as sewage flow data. Model outputs may help with quicker and more accurate decision-making.

4.1 Description of QUAL2K Software

In this work, water quality was simulated utilizing the QUAL2K model. It is a contemporary adaptation of QUAL2K and a model of the water quality of rivers and streams. Pollution impacts on water quality indicators are estimated and surface water quality is evaluated using QUAL2K, a tool that has been used globally (Thair et al., 2018; Chapra et al., 2003 ; Wang et al., 2024).

According to Parveen and Singh (2016), the QUAL2K model divides rivers into streams and each estuary into a group of components that are evenly spaced apart. The following is how each model's static flow equilibrium is put into practice:

$$Q_i = Q_{i-1} + Q_{in,i} - Q_{out,i} \qquad (1)$$

Where

$Q_{in,i}$: Represents the total inflow into element i from both point sources (e.g., specific discharge points like factories) and nonpoint sources (e.g., runoff from agricultural land), measured in m^3/s (cubic meters per second).

$Q_{out,i}$: Refers to the total outflow from element i due to withdrawals, which could also come from point and nonpoint sources. Withdrawals might include things like water abstraction for irrigation or other human uses, also in m^3/s.

Q_i: The outflow from element iii that enters the next element downstream, labeled as element $i+1$, in m^3/s.

The study uses a low value of 4 mg/L DO in the auxiliary flow and a high value of 30 mg/L BOD to account for nonpoint source contamination (Poudel et al., 2013). Based on measurements from the water treatment facilities at New Hilla (Station 1), Al-Hussein (Station 2), and Al-Hashimiyah (Station 3), the incremental flow value is computed. The dispersed load per unit distance, which in this case is 0.89 $m^3/s/km$, is found by summing the flows at the new Hilla-Al-Hussein metering stations and the Al-Hussein-Al-Hashimiyeh metering stations (Alsultani and Khassaf, 2022). Runoff-related nonpoint source pollution in the river is taken into consideration by using this figure as an incremental flow throughout. The study's incremental flow calculations are predicated on the river flow, and as Table (2) demonstrates, other incremental flow possibilities are computed for fictitious river flow situations.

River hydraulics can be used to calculate arrival rates in QUAL2K or can be supplied. Initially, formulae for each reach may be used to adjust the reaeration and deoxygenation coefficients for different stream flow and water temperature situations. The following formula (Maidment, 1993) calculates the oxygen elimination rate at 20 °C:

$$(\mathrm{K_a})_{20} = 1.80 \sum \mathrm{V}_{\mathrm{U_e}}^{-0.49} \qquad (2)$$

Where $\sum \mathrm{V}_{\mathrm{U_e}}$ is the total flow in the reach $\mathrm{U_e}$ (m^3/s), including streamflow and effluent flow.

Table 2.
Input data of scenarios used in QUAL2K.

River variable	New Hilla			Al-Husein			Al-Hashymiyah			*IF*
	F	*AT*	*WT*	*F*	*AT*	*WT*	*F*	*AT*	*WT*	
Present	22	24.74	22.57	162.93	24.76	22.59	10.19	27.29	25.22	0.488
Scenario 1	17.6	25.75	23.36	130.34	25.76	23.38	8.15	28.29	26.08	0.385
Scenario 2	19.8	25.74	23.36	146.64	25.76	23.38	9.17	28.29	26.08	0.437
Scenario 3	22	25.74	23.36	162.93	25.76	23.38	10.19	28.29	26.08	0.488
Scenario 4	22	26.74	24.15	162.93	26.76	24.17	10.19	29.29	26.95	0.488
Scenario 5	19.8	26.74	24.15	146.64	26.76	24.17	9.17	29.29	26.95	0.437
Scenario 6	17.6	26.74	24.15	130.34	26.74	24.17	8.15	29.29	26.95	0.385

IF (Incremental Flow): Represents the additional flow, usually due to runoff or groundwater inflow, measured in $m^3/s/km$ (cubic meters per second per kilometer), which is an indicator of the nonpoint source contribution along the reach.

WT (Water Temperature): The temperature of the water in the river, in degrees Celsius (°C). Water temperature is crucial in controlling various chemical and biological processes, including the reaeration rate.

AT (Air Temperature): The surrounding air temperature, in °C, also influencing water temperature and evaporation rates.

F (Streamflow): The flow rate of water moving through the stream, measured in m^3/s (cubic meters per second), which governs the transport of contaminants and dilution capacity.

The reaeration rate at 20°C is provided by (QUAL2K, 2000),

$$(K_d)_T = (K_d)_{20}\delta^{(T-20)} \quad (3)$$

$$(K_d)_T = D_r^{0.5}U^{0.5}H^{-1.5} (4)$$

Reaeration rate at any temperature T °C is given by

$$(K_a)_T = (K_a)_{20}\delta^{(T-20)} \quad (5)$$

where $\delta = 1.047$ is correction factor temperature as discussed by Camp, 1963, D_r the coefficient of oxygen diffusivity, it is almost equal to 2.09 X 10^{-5} cm^2/s^{-1} (Chapra, 1998); U is the stream velocity (ms^{-1}) and H is the average depth of flow, this is obtainable using Manning's method. The following functional connection is produced if the river's geometric cross-section is taken to be rectangular and the depth of the flow is taken to be modest concerning the river's width:

$$(K_a)_{20} = 3.93\, S^{3/5}W^{7/10}n^{-6/5}\sum V^{-0.7} \quad (6)$$

Lower stream flow rate decreases mixing and dilution, which lowers the re-aeration rate, whereas higher water temperature increases algal growth rates, i.e., breakdown and respiration.

All the situations were combined into six sensitivity tests. The resultant water quality variables considering the different scenarios involving streamflow, water temperature, air temperature, reaeration, deoxygenation, and incremental flow were computed and compared to the current water quality variables.

4.2 ACO algorithm

Many meta-heuristic algorithms, which are often inspired by the actions of nature, have been created in the last few decades. Many people accept, utilize, and have invented these algorithms, which include genetic algorithms and ACO (BabaeeTirkolaee et al., 2020). Both linear and non-linear problems may be solved with these techniques, and it can take less time to get the ideal or desired answer. ACO may look for shorter pathways by using pheromone release or evaporation, which is inspired by the social behavior of ants during foraging (Afshar et al. 2015; Alsultani et al., 2022a). In conclusion, the two actions listed below may be used to solve the suggested model using the ACO algorithm:

Step 1. Every ant chooses a random path throughout each algorithm iteration. As a result, by using various routes, gathering ants results in various solutions. The following is the likelihood that the ant will select the given path:

$$P_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{1\in S}\{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}\}} & \text{j} \in \text{ allowed} \\ 0 & otherwise \end{cases} \quad (7)$$

In the described process, each ant chooses its path based on two factors: the heuristic coefficient $P_{ij}(t)$ and the probability $t,\tau_{ij}(t)$, which depend on the pheromone level and the heuristic value. The exponents α and β control the relative importance of these two factors. The ants select their next node from a set S S of available nodes, using a regulatory parameter q_0 and a random variable q, which follows a normal distribution between 0 and 1. This process governs the ants' route decisions.

$$j = \begin{cases} \arg_{l \in allowed} \max\left\{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}\right\} & q \leq q_0 \\ J & q > q_0 \end{cases} \quad (8)$$

where J is a random variable that is selected according to the probability distribution of $P_{ij}(t)$.

Step 2. The problem's objective function is used to assess the solutions found in the previous step. Then, using the best ant's journey as a guide, the pheromone trail is updated as follows:

$$\tau_{ij}(t+1) \xleftarrow{iteration} \rho\, \tau_{ij}(t) + (1-\rho)\Delta\, \tau_{ij} \quad (9)$$

where $\tau_{ij}(t)$ is pheromone concentration deposited in the path i to the path j in iteration t, ρ $(\rho[0,1])$ is evaporation value of pheromone, the symbol $\xleftarrow{iteration}$ shows the next iteration and $\Delta\, \tau_{ij}$ is the updating value of the pheromone trail in the path i to the path j. $\Delta\, \tau_{ij}$ value is obtained by the following equation:

$$\Delta\, \tau_{ij} = \begin{cases} \frac{Q}{f(B)} & \text{If (i, j) is traveled by the best ant} \\ 0 & otherwisw \end{cases} \quad (10)$$

where $f(B)$ is the optimal value of the objective function in each iteration and Q is a constant value that represents the pheromone value that each ant deposits following the exploitation of the ith route. This procedure keeps on until the necessary solutions or several predetermined iterations are obtained (Amaran et al., 2016; Alsultani et al., 2022b).

4.3 Fuzzy Optimization Technique

Fuzzy logic ideas have been invented or widely employed in research activity in the past several decades to detect approximate, empirical, or non-classical phenomena (Huang et al., 2015; Teixeira et al., 2022). A set with a loosely defined and flexible scope is required in fuzzy logic. It wasreferred to this kind of group as a fuzzy set. The membership degree, an integer between 0 and 1, expresses an element's membership in fuzzy sets. The membership function is a function that represents the extent of group membership (Zimmermann, 2011; Namugize and Jewitt, 2018; Alfatiawi et al., 2020).

As previously stated, the suggested model took advantage of the fuzzy set theory. Based on the average value of the Water Quality Index (WQI), sustainability targets for water quality were considered. The WQI used in this instance, the NSFWQI, was a declining index, meaning that its value dropped as contamination rose. The requirements for water quality are often time-limited. Assume that this list of requirements is imprecise. Each fuzzy set's membership function must, by definition, provide a continuous, real value between 0 and 1. The following is the suitable membership function (linear or non-linear) for the average WQI based on the previously mentioned issues (Hammoud and Rabee, 2017):

$$\mu(I_l) \begin{cases} 0 & I_i \leq I_{i\,min} \\ \left[\frac{I_i - I_{i\,min}}{I_{i\,max} - I_{i\,min}}\right]^{\gamma} & I_{i\,min} \leq I_i \leq I_{i\,min} \\ 1 & I_i \geq I_{i\,max} \end{cases} \quad (11)$$

where $\mu(I_l)$represents the fuzzy set's membership function, I_i is the average NSFWQI for each checkpoint in the river system for ant i, $I_{i\,min}$, isI_i's minimum, and $I_{i\,max}$ is its maximum. The exponent of the membership function and non-zero real value is γ.

The National Sanitation Foundation Water Quality Index (NSFWQI) in the river system may be calculated using the following methodology to determine the ideal value:

$$Max\left[\frac{I_i - I_{i\,min}}{I_{i\,max} - I_{i\,min}}\right]^{\gamma} \forall\, i \qquad (12)$$

4.4 Simulation-Optimization ($S - O$) Approach

One of the most useful methods for resolving quality issues is the $S - O$ approach, which, in the first stage, uses a suitable simulation program or model to identify the necessary problem parameters. In the second stage, an appropriate optimization algorithm is used to identify the optimal solutions to the problems that are extracted from the simulation model's results (Skardi et al., 2015; Alfatlawi and Alsultani, 2018b). The S-O technique was utilized in this study to connect the suggested model to the water quality simulation model, as was indicated in the earlier sections. Here, QUAL2K was the simulation model and the ACO algorithm served as the optimizer model. The steps involved in applying the $S - O$ approach to solve the suggested model are depicted in Figure 3.

River hydraulic properties, features of the water quality, Examples of primary data include constant coefficients and parameters in equations related to characteristics of water quality. Next, the optimizer program is executed. First, the number of ants required to run the program and the number of program iterations are computed. There are several ways to figure out how many iterations an optimizer algorithm should have. Increasing the iteration count until sufficient convergence is achieved in each ant's route is one criterion (Hasan et al., 2024; Afan et al., 2024). An ant uses a somewhat random mechanism to select several scenarios for each processing unit. A simulation model is now employed (Alsultani et al., 2023b). The units released into the river remove varying quantities of pollutants according to the selected scenarios. Up to the last iteration taken into account for the optimizer program, all of the previously mentioned processes will be repeated.

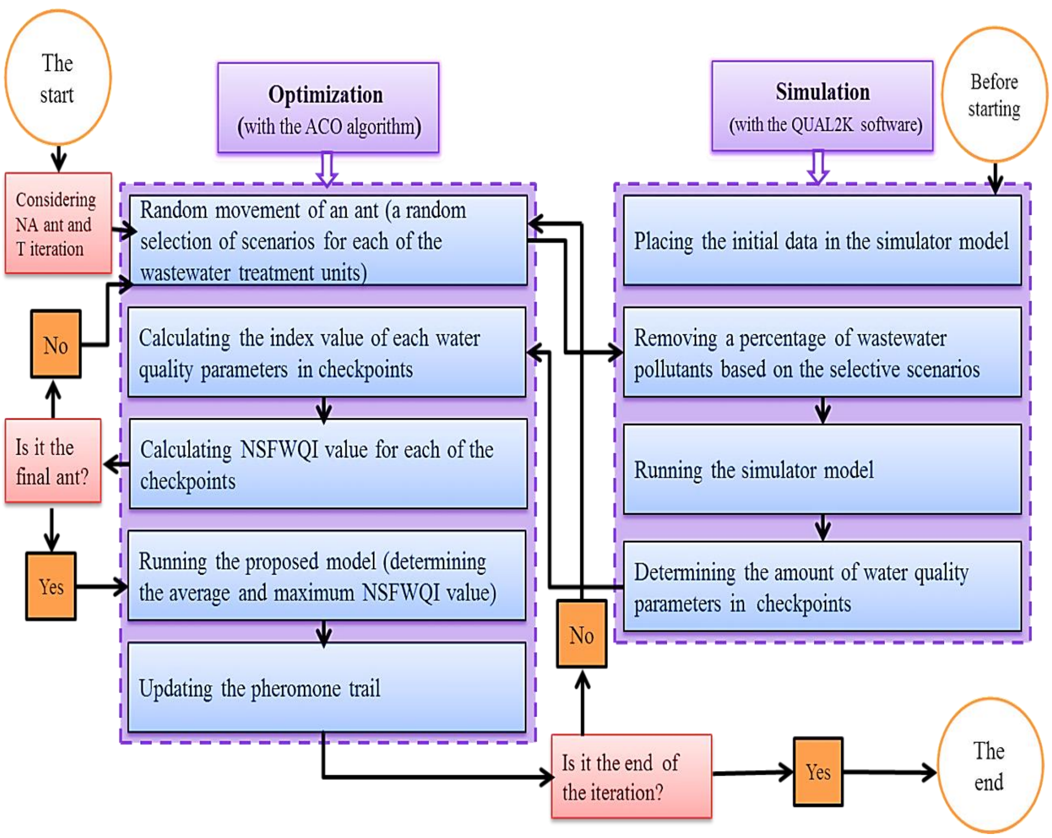


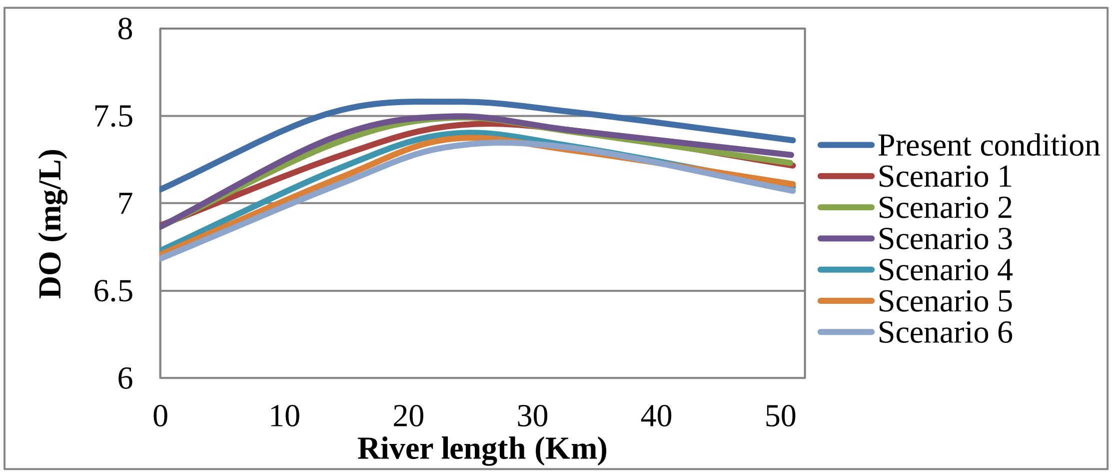
Figure 3. $S - O$ approach used for the proposed model.

5 Results And Discussion

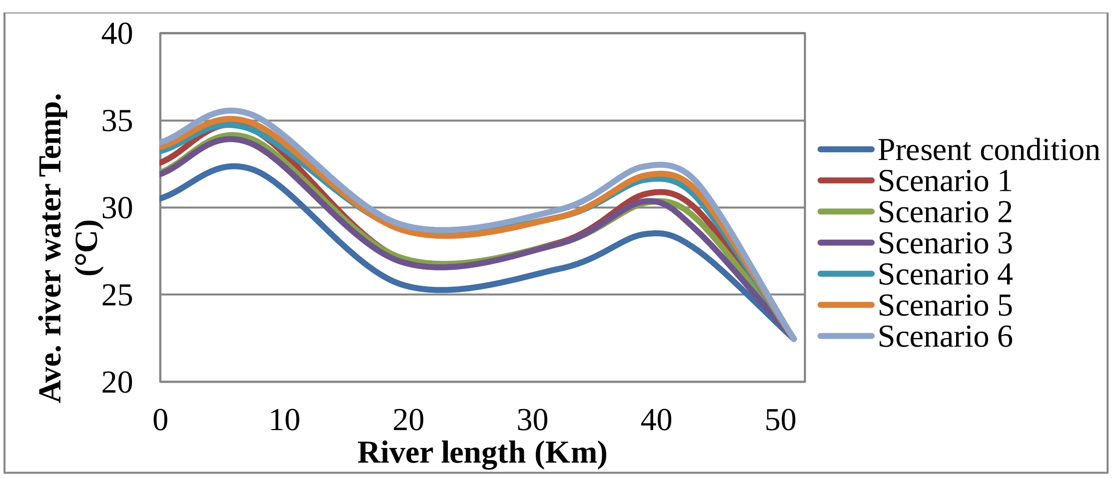
Water quality responses were compared with current conditions in order to assess changes in water quality parameters in response to changing climate scenarios. The objective of currentresearch is to quantify the degradations in water quality caused by situations of higher water temperature and decreased river flow, even though it is obvious that these scenarios will result in such degradations. To do this, a water quality simulation model will be used. To demonstrate how river water quality is changing as a result of climate change, the six water quality levels that were created in response to fictitious scenarios were compared to the present values.

5.1 Climate Change Scenarios

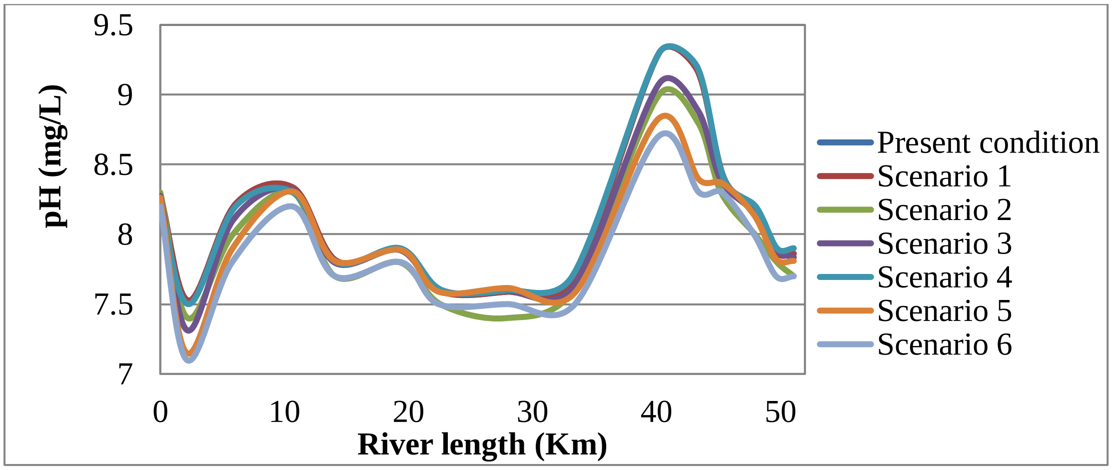
The reactions dissolved oxygen, water temperature and pH, respectively, to various climate change scenarios are displayed in Figures 4 a, b, and c when the effluents at stations and checkpoints are within the safe limit. The scenario with a 2°C temperature increase and a 20% drop in sewage flow is Scenario 6, which has the highest reduction in CO_2 levels from the current conditions among the possibilities. For Scenario 6, the highest drop in O_2 is approximately 1.06 mg/L over 17.1 km, from 5.31 to 4.25 mg/L. This is when the BOD is 279 mg/L, below drain 3. It has also been demonstrated that the impact is stronger at places near the bottom of large BOD loadings. As a result, the comparative research primarily concentrates on a few crucial milestones.



(a)



(b)



(c)

Figure 4. Responses of WQ for selected climate change scenarios.

The new fuzzy model was developed to predict water quality in the Al-Hilla River under previous selected climatic scenarios. The model incorporates key variables including temperature, precipitation, streamflow, and WQconstraints such as D_o, biological oxygen demand (BOD), and total dissolved solids (TDS).

The suggested model was confirmed utilizing historical data from the Al-Hilla River, including water quality measurements and climatic records from the baseline period (2011-2020). The validation process involved comparing model predictions with observed data to ensure accuracy. The model showed high correlation (as presented in Table 3) with observed water quality parameters, indicating its reliability.

Table 3.
Validation Results of the Fuzzy Model.

Parameter	Observed Value (mg/L)	Predicted Value (mg/L)	Correlation Coefficient (R^2)
Dissolved Oxygen (DO)	5.31	5.29	0.85
Biological Oxygen Demand (BOD)	279	282	0.84
Total Dissolved Solids (TDS)	1500	1498	0.86

While the model performed well in predicting water quality under current conditions, its ability to handle extreme climatic events and rapid environmental changes was limited. Additionally, the model's sensitivity to changes in input variables highlighted the need for further calibration.

Future work will focus on incorporating more granular data and refining the model's sensitivity to extreme weather events to enhance its robustness and accuracy.

5.2 Global Warming Impact Water Quality Changes

The predicted WQ in the river, as presented in Table 3, is influenced by a range of factors beyond global warming. While the initial analysis primarily focused on the impacts of climate change, it is essential to acknowledge that regional economic actions—such as industrial operations, farming practices, and municipal development—play a significant role in shaping water quality. These activities contribute to pollutant, nutrient, and sediment levels in the river, which can interact with the effects of global warming in complex ways.

The interaction between climate change and economic activities can lead to synergistic effects, where the combined impact on water quality is greater than the sum of their individual influences. For example, rising temperatures due to global warming may increase the likelihood of harmful algal blooms, while nutrient runoff from agricultural fields could provide favorable conditions for these blooms to proliferate. Additionally, reduced river flow due to changing precipitation patterns may concentrate pollutants from industrial discharges, exacerbating the degradation of water quality. These interactions highlight the complexity of predicting future water quality and underscore the need to consider multiple influencing factors.

To develop a more comprehensive understanding of how climate change and economic activities interact to affect water quality, further studies are necessary. Future research should aim to integrate climate projections with data on regional economic activities into predictive models. This approach will enable a more accurate and holistic assessment of the potential future state of water quality in the river, allowing for the identification of specific regions or sectors where mitigation efforts would be most effective. Table 4 present the predicted impacts of global warming on water quality indicators, incorporating the new aspects of economic activities and synergistic effects. The values in this table are illustrative and should be updated with actual data from your study.

Table 4.
Projected changes in water quality indicators under global warming and economic activity scenarios.

Indicator	Current Status	Predicted Value with Global Warming	Predicted Value with Economic Activities	Combined Impact (Global Warming + Economic Activities)
Temperature (°C)	22.5	24	23.5	25
pH	7.8	7.7	7.6	7.5
Do (mg/L)	8.2	7.5	7	6.5
Nitrate (mg/L)	2.5	3	4	4.5
Phosphate (mg/L)	0.8	1	1.2	1.4
Turbidity (NTU)	10	12	15	18
BOD (mg/L)	3	3.5	4	4.5
TSS (mg/L)	20	22	25	28

The results presented in Table 4 indicate the expected changes in water quality indicators under various scenarios. Temperature is projected to rise due to global warming, with further increases anticipated as a result of heightened economic activity in the region. This combined effect is likely to elevate the water temperature beyond the changes attributed to global warming alone. The pH level is expected to experience a slight decrease as a result of global warming, and this trend is anticipated to be compounded by economic activities that may lead to more acidic conditions. The dissolved oxygen levels are forecasted to decrease, a trend driven by higher temperatures and an increase in organic matter stemming from economic activities. Nitrate levels are anticipated to rise due to both the climate change impacts and increased agricultural runoff. Similarly, phosphate concentrations are expected to be elevated, largely due to runoff from agricultural and industrial activities. Turbidity is predicted to increase as a result of both global warming and higher sedimentation rates associated with economic activities. Biochemical Oxygen Demand (BOD) is projected to rise due to increased organic pollution resulting from both global warming and intensified economic activities. Total Suspended Solids (TSS) are also expected to increase, driven by higher runoff and erosion linked to economic activities. These projections highlight the complex interplay between global warming and economic factors in influencing water quality indicators. The synergistic effects of these factors necessitate further investigation to fully understand their combined impact on river ecosystems.

Furthermore, long-term monitoring programs are crucial for continuously collecting data on water quality, climate variables, and economic activities. These programs will provide the necessary data to validate and refine predictive models and track changes over time, improving our capacity to respond to emerging threats. Insights from these integrated studies should inform regional water management policies, ensuring that both climate adaptation measures and sustainable economic practices are incorporated into decision-making processes.

In summary, while global warming is a significant driver of water quality changes, it is not the sole factor. The shared effects of climate change and economic activities can lead to more severe and complex impacts on water quality. Therefore, it is imperative to expand the scope of analysis to include these interactions and conduct additional studies that account for both climate and economic factors. This will facilitate the development of more effective strategies for protecting and improving water quality in the future.

5.3 Impact of Future Climate Change in Temperature

The average monthly temperature measurements for Al-Hilla River were analyzed using the O-S model that was previously identified. Figure 5 below displays the expected changes in the mean monthly temperature during the following three periods: 2021–2030, 2031–2040, and 2041–2050. To evaluate the magnitudes of temperature variations, these charts are helpful. The findings demonstrate that all scenario had rising temperature trends. It is discovered that the average annual temperature increased by 6.8 °C the most over the 2041–2050 period.

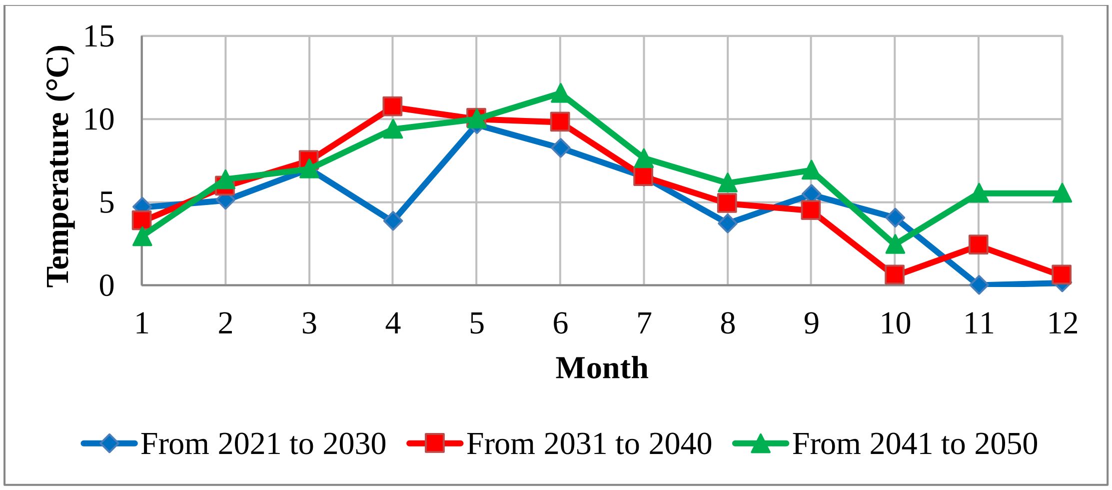


Figure 5. Changes in average monthly temperature for Al-Hilla River for the future periods 2021-2030, 2031-2040, and 2041-2050.

5.4 Impact of Future Climate Changes in Precipitation

The O-S model's mean monthly precipitation outputs, which were previously discovered, were processed for the Al-Hilla River. The predicted changes in mean monthly precipitation for three future decades (2021–2030, 2031–2040, and 2041–2050) in comparison to the base period (2011–2020) are depicted in Figure 6 below. These charts assist assess the magnitude of fluctuations in precipitation. Every month in the upcoming statistics showed a decrease in precipitation, with the exception of June, July, and August, which in some cases showed a very little increase. It is evident that over the years 2041–2050, the average annual precipitation would decline by the greatest amount—59.2%.

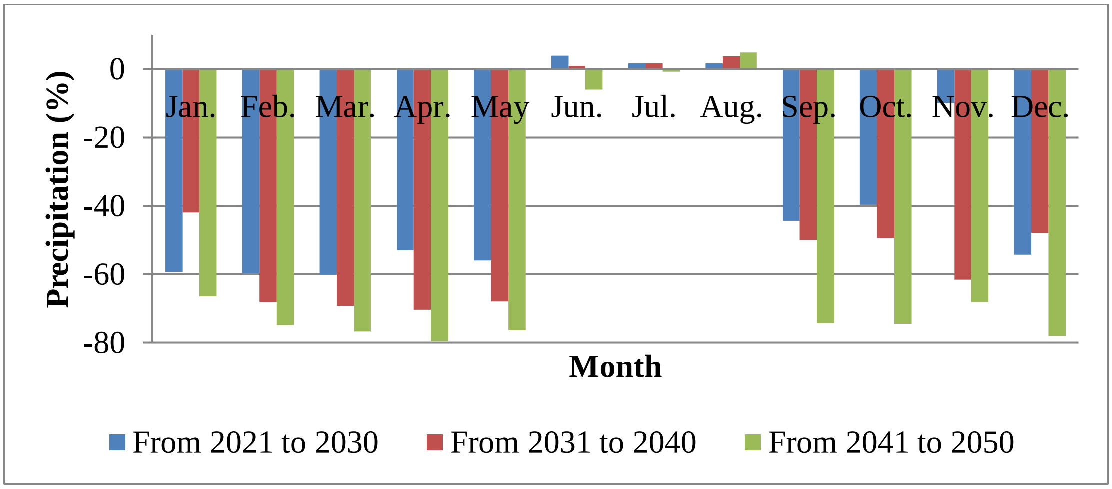


Figure 6. Relative variations in the Al-Hilla River monthly precipitation average for the upcoming periods of 2021–2030, 2031–2040, and 2041–2050.

5.5 Impact of Future Climate Changes on Stream Flow

The suggested model was first calibrated and confirmed with historical data, and then flows matching to future climate conditions were simulated using daily future data (temperature and precipitation data). In order to do this, information from the suggested model was used for three future climate change periods: (2021–2030) 2025s, (2030- 2040)2035, and (2041–2050)2045. One crucial component of hydrology is flow discharge, which is heavily influenced by precipitation. (Uzbekov et al., 2021).

In Table 5, peak discharges for upcoming periods are displayed. According to the table, the peak discharge's maximum figure for the 2025s is 181 (m^3/s) occurs on 18 November 2024, for 2035s is 141.9 (m^3/s) at 09 April 2034s and for 2045s is 233.1 (m^3/s) at 10 November 2048. By contrasting the future stream flows in the Al-Hilla River basin with the stream flows of the baseline period (2011-2020), the effects of climate change on the stream flows in the basin are studied.

Table 5.
Peak discharges during future periods.

Future Period	**From 2021 to 2030**	**From 2031 to 2040**	**From 2041 to 2050**
Peak Discharge (m^3/s)	181	141.9	233.1
Date of occurrence of peak discharge	18-Nov-24	09-Apr-34	10-Nov-48

Figure 7 illustrates the expected impact of climate change on the yearly streamflow. The streamflow indicated drops for the three time periods 2025, 2035, and 2045 using data from the model. Future water availability is likely to be lessened by irregular temporal distribution and inter-annual pattern changes. The estimated decrease in water availability for the years 2025, 2035, and 2045 is 52%, 58.6%, and 66%, respectively.

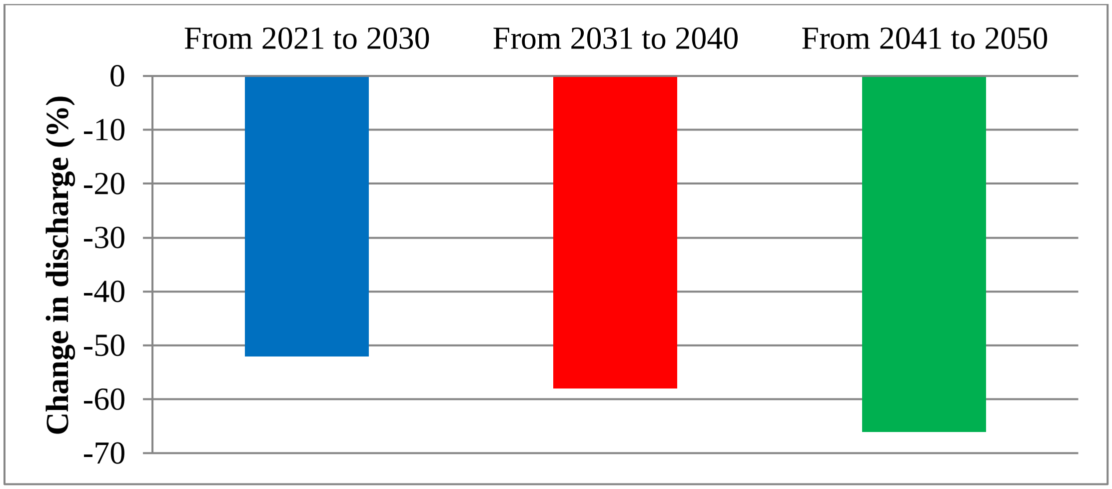


Figure 7. Annual streamflow change as a percentage of base period (2011-2020) for the periods (2021-2030), (2031-2040), and (2041-2050) resulting from climate change.

The $S-O$ model was utilized to evaluate different climatic scenarios, providing insights into potential future water quality conditions:

Scenario 1: 2°C temperature increase with a 10% streamflow decrease.

Scenario 2: 4°C temperature increase with a 20% streamflow decrease.

Scenario 3: 6°C temperature increase with a 30% streamflow decrease.

Dissolved Oxygen (DO): Decreased from 5.31 mg/L to 4.25 mg/L in Scenario 6.

Biological Oxygen Demand (BOD): Increased from 279 mg/L to 350 mg/L in Scenario 6.

Total Dissolved Solids (TDS): Increased from 1500 mg/L to 1550 mg/L in Scenario 6. The other scenarious and validation are presented in Table (6)

Table 6.
Water Quality Parameters under Different Scenarios.

Scenario	DO (mg/L)	BOD (mg/L)	TDS (mg/L)
Baseline	5.31	279	1500
2°C, 10% Flow Decrease	5.1	290	1520
4°C, 20% Flow Decrease	4.75	310	1550
6°C, 30% Flow Decrease	4.25	350	1600

The investigation of water quality under various climate change scenarios for the Al-Hilla River reveals significant impacts on key parameters. As temperature increases and streamflow decreases, D_O levels decline substantially, with a severe drop from 5.31 mg/L at baseline to 4.25 mg/L under the most extreme conditions. This reduction in DO, coupled with increases in BOD and TDS, highlights the exacerbation of water quality issues. BOD rises from 279 mg/L to 350 mg/L, indicating increased organic pollution, while TDS levels increase from 1500 mg/L to 1600 mg/L, reflecting higher concentrations of dissolved solids. These changes suggest that rising temperatures and reduced flow will significantly impair the river's ability to support aquatic life and maintain overall water quality.

The results emphasize the urgent need for adaptive water management strategies to address the adverse effects of climate change. Proactive measures, including enhanced monitoring and improved conservation practices, are essential to mitigate the projected declines in water quality.

The findings also highlight the importance of refining predictive models to better handle extreme climatic events and ensure accurate forecasts. By implementing these strategies, stakeholders can better manage the anticipated impacts on the Al-Hilla River, safeguarding its ecosystem and water resources for the future.

5.6 Impact of Future Climate on Water Quality Parameters

In light of the projected future climate scenarios and the $S-O$ model, it is essential to assess how water quality parameters for Al-Hilla River will be affected. This prediction considers the anticipated changes in temperature, total dissolved solids (TDS), biological oxygen demand (BOD), total hardness (TH), acidity (pH), electrical conductivity (EC), turbidity, sulfate ($SO4^{2-}$), magnesium (Mg^{2+}), calcium (Ca^{2+}), sodium (Na^{+}), and potassium (K^{+}) for the future periods of 2021-2030, 2031-2040, and 2041-2050. Table (7) presented the change of climate on water quality parameters. The results indicate that the future climate change impacts on the Al-Hilla River will likely lead to increased water temperatures, higher concentrations of dissolved solids, elevated biological oxygen demand, greater total hardness, and other negative changes in water quality parameters.

Table 7.
Changes in water quality parameters.

Parameter	Baseline (2011-2020)	2021-2030	2031-2040	2041-2050
Temperature (°C)	30°C	+2.1°C	+4.3°C	+6.8°C
TDS (mg/L)	1500	1550	1600	1650
BOD (mg/L)	5	5.5	6	6.5
TH (mg/L)	500	520	540	560
pH	7.5	7.4	7.3	7.2
EC (µS/cm)	1000	1050	1100	1150
Turbidity (NTU)	5	6	7	8
$SO4^{2-}$ (mg/L)	400	460	470	480
Mg^{2+} (mg/L)	50	55	60	65
Ca^{2+} (mg/L)	50	55	60	65
Na^{+} (mg/L)	200	205	210	215
K^{+} (mg/L)	12	14	16	18

The long-term evaluation indicates significant impacts of climate change on water quality and availability. These findings stress the importance of: Implementing strategies to cope with reduced water availability and declining water quality; and Preparing for worsening conditions by adopting robust water resource management practices.

5.7 Impact of Future Climate on Water Quality Index (WQI)

NSFWQI is one of the recognized indices used to assess the quality of water, which was funded by the National Sanitation Foundation of the United States and presented by Brown et al. (1970). Because of this, Brown's index is sometimes known as NSFWQI. Because its values decrease as water pollution increases, this indicator, which has a scale from 0 to 100, is seen as declining. The value of this index is derived from the selection of 12 water quality parameters (WQPs) with varying weighting factors that are more significant for human health. The NSFWQI value could be found using the following equation:

$$\mathrm{NSFWQI} = \prod_{i=1}^{n} \mathrm{WQI}_i^{w_i} \quad (13)$$

The water quality index (NSFWQI) is calculated using 12 water quality parameters (WQPs), where each parameter WQI_i is assigned a weighting coefficient w_i. The overall NSFWQI value is derived from these individual indices, allowing the classification of water quality into categories. According to studies by Abbasi and Abbasi (2012), Nada et al. (2016), Patang et al. (2018), and Egbueri (2023), water quality is classified as very bad (index value 0–25), poor (25–30), medium (50–70), good (70–90), or very good (90–100) (Abbasi and Abbasi, 2012; Nada et al., 2016; Patang et al., 2018; Egbueri, 2023).

The WQI is calculated using weighted values of the above parameters. Given the projected trends, the WQI will likely indicate a deterioration in water quality. For simplicity, we assume equal weight for each parameter in this illustrative calculation. Table 8 presented the impact of climate change on water quality index. The results indicate that the WQI is projected to decrease, reflecting a decline in water quality over the coming decades. This underscores the necessity for proactive water quality management and mitigation strategies to address the anticipated impacts of climate change on the Al-Hilla River.

Table 8.
Changes in water quality index.

Period	WQI	Quality Rating
Baseline	75	Good
2021-2030	68	Fair
2031-2040	62	Fair
2041-2050	55	Poor

The effects of future climate change on Al-Hilla River indicate the possibility that the river will suffer from a decrease in water availability and a decrease in its water quality during the coming decades.

5.8 Model Development and Application

The development of the fuzzy model aimed to predict future water quality and availability in the Al-Hilla River by integrating climatic data with water quality parameters. The model incorporates key factors such as temperature, precipitation, and streamflow to forecast changes in critical water quality indicators, including Dissolved Oxygen (DO), Biological Oxygen Demand (BOD), and Total Dissolved Solids (TDS). For instance, the model projects a decrease in DO levels as temperatures rise and flow decreases, potentially leading to severe impacts on aquatic life. Specifically, DO is expected to decline from a baseline of 5.31 mg/L to as low as 4.25 mg/L under the most extreme scenario of a 6°C temperature increase and a 30% reduction in flow. Similarly, BOD and TDS are predicted to increase, with BOD rising from 279 mg/L to 350 mg/L and TDS from 1500 mg/L to 1600 mg/L under the same conditions. These changes signal a worsening of water quality that could have significant ecological and health implications.

To ensure the accuracy of these predictions, statistical methods were employed to isolate the effects of climate change from other influencing factors such as man-made pollution and natural biological processes. This holistic approach allowed for a comprehensive assessment of both climatic and non-climatic factors affecting water quality. The model's application underscores the need for adaptive management strategies to address the declining water quality and availability projected under future climatic conditions. Future improvements will focus on incorporating more granular data and refining the model's sensitivity to extreme weather events to enhance its predictive capabilities. This study highlights the urgency of proactive and adaptive strategies to manage water resources sustainably in the face of ongoing and anticipated climate changes.

6 CONCLUSIONS

The key finding is that the parameters considered, the water quality model, the river, and the climatic change may all affect the outcomes. All things considered, a coordinated framework is required to address the effects of climate change on river water flow volumes and the subsequent impact on water quality. Since decreasing flows and rising water temperatures as a result of climate change are uncontrollable phenomena, caution must be exercised while simulating water quality in reaction to these changes. Given the anticipated continuation of current and future climatic trends, an adequate plan for the efficient management of river water quality is required.

Based on the obtained results, specific conclusions are presented as follows:

1. Projections indicate a substantial rise in mean monthly and annual temperatures across the evaluated future periods (2021-2050). This increase, reaching up to 6.8°C by 2041-2050, will likely exacerbate water quality degradation through elevated water temperatures.
2. The future climate scenarios predict a general decline in mean monthly precipitation, with the most significant reduction projected for the period 2041-2050. This decrease in precipitation, up to 59.2%, is expected to reduce river flow, impacting water availability and quality.
3. Streamflow simulations for future periods reveal a marked decrease in water availability. The anticipated decline in streamflow, projected at 52% to 66% for the periods 2025s to 2045s, highlights the pressing need for effective water resource management.
4. The results indicate that future climate conditions will likely lead to increased concentrations of dissolved solids, higher biological oxygen demand, greater total hardness, and other negative changes in water quality parameters. Specifically, parameters such as TDS, BOD, TH, and pH are projected to deteriorate significantly by 2041-2050.
5. The combined effects of global warming and increased economic activity are predicted to greatly worsen water quality in the Al-Hilla River. Climate change will cause temperature increases and changes in indicators like pH and dissolved oxygen, while economic activities will further elevate pollutant levels and sedimentation.
6. The calculated WQI for future periods shows a decline from a "Good" rating during the baseline period to a "Fair" and eventually "Poor" rating by 2041-2050. This trend signifies a worsening water quality scenario, necessitating proactive and adaptive management strategies.
7. The projected reductions in dissolved oxygen levels and increases in pollutant concentrations and harmful algal blooms are poised to threaten aquatic life and overall ecosystem health in Al-Hilla River.

These conclusions highlight the urgent need for integrated water management practices, ecosystem restoration, and sustainable agricultural practices. Policymakers and stakeholders must implement robust frameworks to ensure adaptive and resilient water resource management to mitigate the anticipated impacts of climate change on river water quality.

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