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RESEARCH ARTICLE

Optimization Model for Climatic Change Impact on the Water Quality of Al-Hilla River, Iraq

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ABSTRACT

This study presents an advanced optimization model to assess the impacts of climate change on water quality in the Al-Hilla River. To reduce uncertainties associated with climate change projections and quantify the river's water quality response, a novel model of the river system is developed, with the objective function integrated into optimization theory. Water quality simulations for different regions of the river system are performed using the QUAL2K model, while the Ant Colony Optimization (ACO) method is applied to optimize the model. Additionally, the study investigates the effects of temperature and DO variations on microbial populations and the self-purification capacity of the water body. The results indicate that all climate change scenarios lead to a decline in water quality, with significant reductions in dissolved oxygen (DO) levels, even under safe discharge conditions. The study demonstrates that the proposed technique can identify optimal solutions more efficiently, contributing to faster and more reliable decision-making in water quality management. Also, the findings reveal that both temperature and DO significantly influence microbial composition and self-purification processes, with higher temperatures and DO levels improving self-purification efficiency. These insights enhance our understanding of the complex interactions between environmental factors and water quality, offering a valuable foundation for future water management strategies aimed at mitigating the effects of climate change.

Keywords: Water quality; Al-Hilla river; optimization; climate change; QUAL2K model; ACO algorithm, microbial populations

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1. Introduction

Before utilizing water for any intended purpose, such as drinkable, agricultural, recreational, or industrial water usage, etc., it is vital to evaluate its physical, chemical, and biological properties[1, 2]. On the other hand, the climatic change impact represented by global warming and drought cycles during the seasons in the world in general and in Iraq, in particular, contributed to causing changes in the water quality parameters of these streams due to the decrease in water levels and the required discharges beyond the design[3].

Although it is now widely acknowledged that climate change is caused by humans, predicting the degree and likelihood of climate change impacts on water quality is challenging due to the wide range of natural fluctuations in hydrology, chemistry, and ecology. There is also a great deal of uncertainty associated with some issues. One major driver of policy for the Environment Agency and the water industry is climate change. Understanding the potential impacts of climate change on water quality is important so that policymakers can provide good advice on potential impacts and their use[4-6]. For instance, there is uncertainty regarding the processes that govern behavior in freshwater systems, the quantification of global driving climate processes, the processes that downscale processes from global to local riverine settings, and the intricate relationships between hydrology, chemistry, and biology[7-9]. Since it is hard for humans to comprehend all of these intricacies, mathematical models are being utilized more and more to forecast and comprehend these processes[10].

For the management of water quality in a river system, several water load allocation models have been presented to date. These models are generally used to find technically and financially viable solutions for drainers and the Pollution Control Authority[11]. Water use rules and restrictions are defined by organizations, and drains must remove a certain amount of different types of water contaminants. However, the cost of treating water goes up as the degree of partial removal of contaminants becomes up[11-13]. Thus, it has always been difficult to strike a balance between organizations' and directors' competing interests. Additionally, in certain implementations, a particular effective quality parameter is stated as a distinct, standardized quality indicator and is used as a standard for assessing the quality of water[14, 15].

This study employs Shaik 's FWLAM model to evaluate water quality indicators, conducting sensitivity tests under varying scenarios of air temperature, streamflow, water temperature, deoxygenation, and re-aeration rates[16]. Fractional removal levels and pollution control strategies are analyzed to predict future climate impacts. Similar studies in Iraq have utilized various methods, including statistical analysis, GIS-based modeling, and computational tools like Flow-3D and QUAL2K, to address water quality, sediment transport, and hydraulic processes. These approaches collectively aim to enhance the understanding of environmental systems and support sustainable water resource management in the region.

Al-Hilla River is one of the natural streams, which is located in the Babylon province of Iraq and has great importance in distributing its water for different uses. This river is considered the only source of freshwater in Babylon governorate, which is home to about 2 million people[17]. This river faces the problems of climate change and initially affects the water contribution of the other governorates located the downstream of Al-Hilla River, which led to the outbreak of conflicts between farmers and local governments[18-20].

Fuzzy optimization is utilized to handle the problem of climate change and river water quality. The goal is to comprehend the possible effects of climate change on the Hilla River's water quality to help the establishment of evidence-based policy. The following are the project's specific tasks: To improve the ideal scenario and take into account the optimal water quality in the river, (1) evaluate the long-term effects of climate change on water quality in the chosen study area for the period of 2012 to 2023; (2) lower the uncertainties in the proposed fuzzy model; (3) enhance the fuzzy objective function in the form of the average quality index at river checkpoints and downstream outlets, which helps to quicker and more accurate decisions, (4) assess the degree of change in biogenic element concentrations under varying environmental and operational conditions, (5) investigate the correlation between temperature fluctuations, dissolved oxygen levels, and the micro-biopopulation dynamics, and (6) determine the class of water in a given water source and the degree of change in the self-purification process of the source.

2. Materials and methods

2.1. Description of the study area

The 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[21]. 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. The Euphrates River feeds into the Hilla

River, which flows from it after the Indian bombs pass[22]. The Hilla River is utilized for farming and drinking. Though it has been overlooked recently, it is still regarded as a key attraction. The problem was being made worse by the river's gradually increasing salinity[23]. Three stations along the Al-Hilla River, which runs from the village of Al-Hashimiya in the Babil Governorate to the city of Al-Hilla, 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-Hashimiya station. **Figure 1** depicts the research area's geographic location as well as the three stations that were chosen.

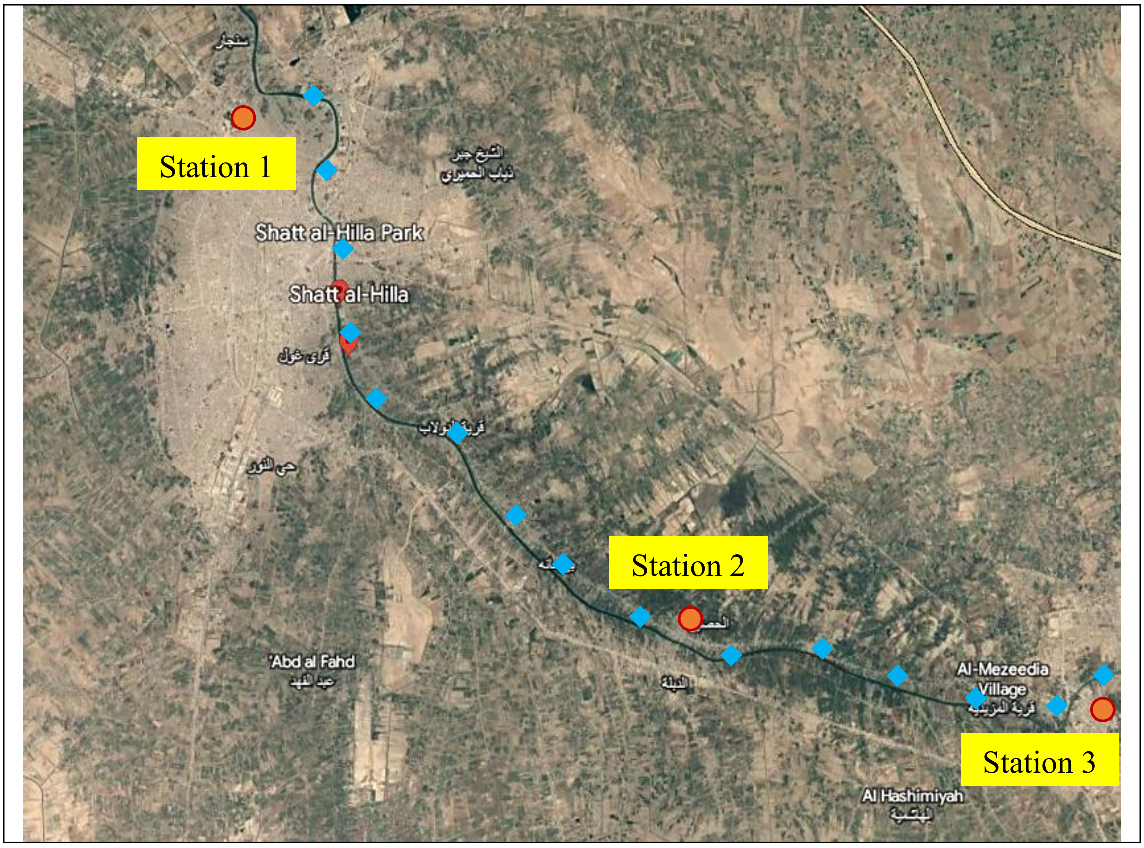


Figure 1. Location of selected stations in Al-Hilla River.

2.2. Climate change and historical data analysis

To assess how climate change is affecting the 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. Streamflow and water temperature are the surface variables that the water quality model uses as input[24-26]. Precipitation, streamflow, air temperature, and water temperature were therefore chosen for data analysis in this study. To develop future climate scenarios, factors relating to climate and water quality input must be coupled to each other. 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.

The Water Resources Directorate/Babylon frequently provides long-term observations or historical data that are used to create reality scenarios for the research region. Historical data is examined to establish a plausible range of streamflow possibilities. Historical data were studied to obtain an overview of variations in vapor flow. The results showed that the Hilla River's annual mean values for the last few years (2012 to 2023) had significantly decreased, as **Table 1** illustrates.

Table 1. Decline in average yearly flows.

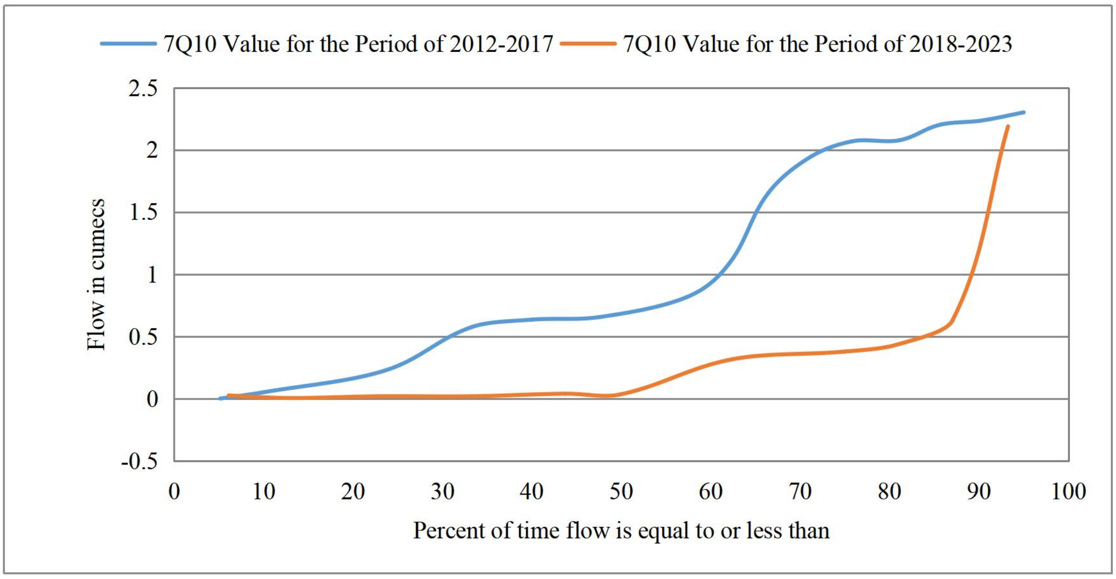
Station	Period	Percentage reduction in annual mean flow
New Hilla	2012-2017 2018-2023	3.12%
Al-Husein		12.28%
Al-Hashimyah		16.88%

Over the previous 12 years, the average sewage flow along the Hilla River has dropped from 3.12% (reduction in New Hilla) to 16.88% (down in Al-Hashimiya). As seen in **Figure 2**, which compares the 2010-Q7 values (as a 7-day average of low flows with a 10-year return period) throughout the two years, 2012-2017 and 2012-2017, to the period 2018-2023, the drop in average annual flows causes correspondingly huge declines in low flows[27,28].

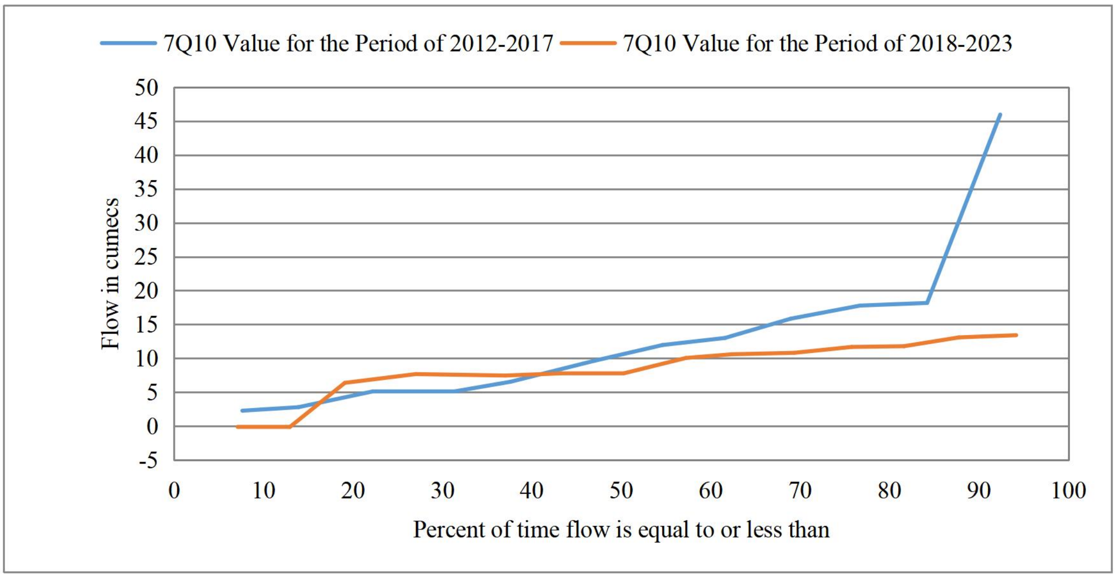
It was discovered that for the years 2012–2017 to 2018–2022, the computed 7Q10 values at the New Hilla station decreased from 0.052 to 0.002 cumec. Similarly, throughout the period from 2012–2017 to 2018–2022, the low flow value at Al Hussein station decreased from 2.65 to 0.009 COMIC during the seventh quarter. The value of the seventh quarter of 2010 at Al-Hashimiya station decreased by 0.027 to 0.00 COMIC when compared to historical years. Additionally, as

Table 2 illustrates, the variations in air and water temperatures in the past several years were contrasted with historical data for the two periods: 2012–2017 and 2018–2023.

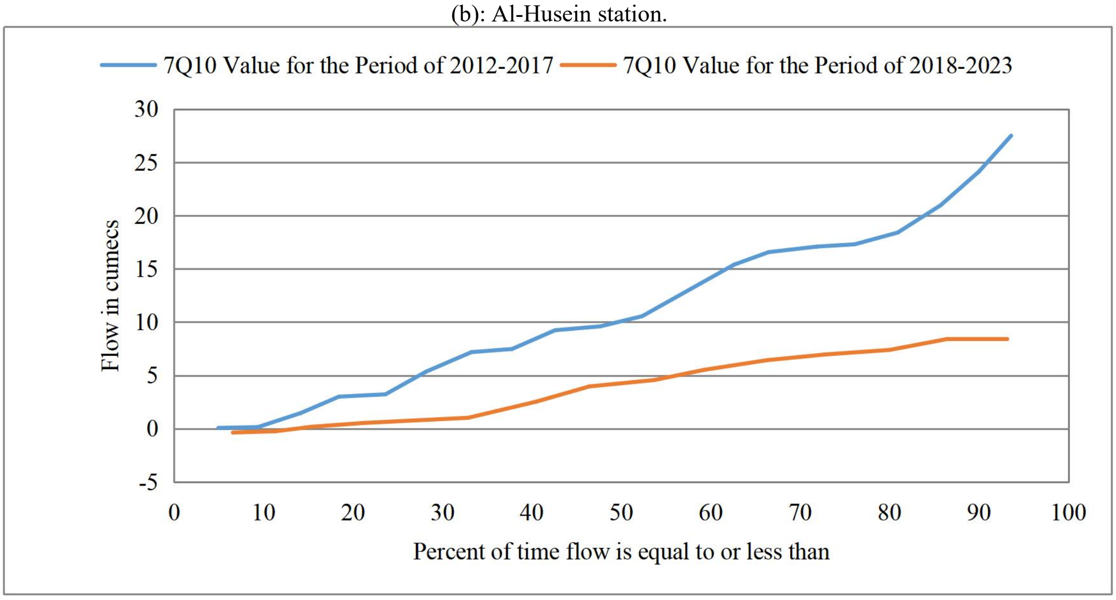
It has been noted in recent years that there has been a notable rise in both air and water temperatures. Along the boundary of the Hilla River, the air temperature rises from about 0.215 degrees Celsius (New Hilla) to 1.39 degrees Celsius (Al-Hashimiya), while the water temperature climbs from approximately 0.6 degrees Celsius (New Hilla) to 3.34 degrees Celsius (Al-Hussein). The water quality decrease was calculated and compared for the years 2012–2017 and 2018–2023, with lower flows as indicated in **Table 1**, and higher temperatures as indicated in **Table 2**. It is important to note that data on pollutants and their effluents are taken to be the same for both periods (2012–2017 and 2018–2023). The US Environmental Protection Agency's QUAL2K water quality modeling model is used to compute the drop in water temperature between 2012–2017 and 2018–2023.



(a): New Hilla station.



(b): Al-Husein station.



(c): Al- Hashimyah station

Figure 2. Low-flow analysis (7Q10) values of Al-Hilla River stations.

Table 2. Change in hydroclimatic variables in recent years.

Station	Variable	Period	Annual Mean Change
New Hilla	Air Temperature	2012-2017	Increase by 0.215 °C
	Water Temperature	2018-2023	Increase by 0.599 °C
Al-Husein	Air Temperature	2012-2017	Increase by 0.315 °C
	Water Temperature	2018-2023	Increase by 3.34 °C
Al-Hashimyah	Air Temperature	2012-2017	Increase by 1.39 °C
	Water Temperature	2018-2023	Increase by 1.79 °C

As seen in **Figure 3**, the resulting water temperature was compared along 15 chosen checkpoints for the years 2012–2017 and 2018–2023. At the chosen checkpoints, the rise in water temperature is observed to

Figure 2.

range (from 0.55 °C to 3.37 °C). Data analysis makes it evident that as air temperature rises, flows are declining and water temperature is rising.

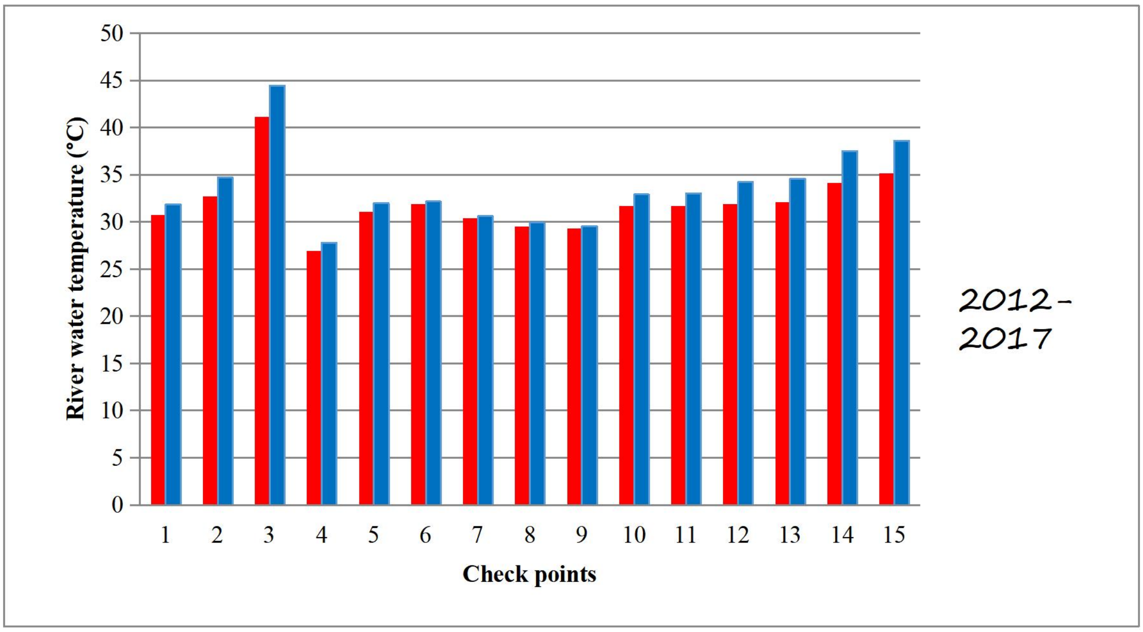


Figure 3. Annual average water temperature indicators.

2.3. Relating climate variables to water quality variables

This section attempts to establish connections between surface variables and climatic factors to ascertain their links. By determining their correlation coefficients, the hydroclimatic variables of the river were evaluated in connection to one another. Precipitation, air temperature, streamflow, and water temperature are the meteorological and hydrological factors taken into account[29,30].

The correlations between the hydroclimatic variables for the Hilla River are displayed in **Table 3** and are significant at the 90% confidence level. According to the correlation data, precipitation and streamflow have a positive association whereas air temperature and precipitation have a substantial negative link. Given that air temperature and water temperature are directly correlated, it is obvious that rising air temperatures will have an increasing effect on river water temperatures.

Table 3. Correlations of hydroclimatic variables.

Parameter	New Hilla			Al-Husein			Al-Hashimyah		
	Air Temp.	Rainfall	Streamflow	Air Temp.	Rainfall	Streamflow	Air Temp.	Rainfall	Streamflow
Air Temp.	1.0	-0.97	-0.36	1.0	-0.11	-0.33	1.0	-0.13	-0.5
Rainfall	-0.97	1.0	0.33	-0.11	1.0	0.14	-0.13	1.0	0.32
Streamflow	-0.36	0.33	1.0	-0.33	0.14	-0.5	-0.5	0.32	1.0
Water Temp	0.54	0.04	-0.389	*	*	*	0.66	-0.038	-0.318

* *Data not available.*

There is a strong negative link between water temperature and streamflow, but only a weak negative correlation with rainfall. Additionally, utilizing daily timeframe data from New Hilla and Al-Hashimyiah, a linear regression connection is fitted to determine a link between air temperature and water temperature. The regression equations are as follows:

$$WT = 3.03 + 0.79\,AT \text{ with } R^2 = 0.53 \text{ for New Hilla} \quad (1)$$

$$WT = 1.75 + 0.86\,AT \text{ with } R^2 = 0.57 \text{ for AlHashimyiah} \quad (2)$$

where WT is the water temperature and AT the air temperature.

A 30 km section of the Hilla River is separated into 15 streams (or checkpoints) of varying lengths based on the river profile; each stream is further broken into arithmetic parts of 2 km length (Figure 1). Waste quantities are discharged into the river from four primary effluent stations. The first station, known as Al-Zuwayr Al-Gharbi, is situated in the city's north; the second, known as the Health District, is situated in the city's center; the third, known as Al-Farsi, is situated in the city's center; and the fourth, known as the bottom of the city street. a place known as Al-Mimira. Municipal and industrial wastewater are included in these stations. **Table 4** provides specifics on the properties and composition of the river.

Table 4. Hydraulic variable values used in water quality simulations[31,32].

Checkpoints No.	Bed width (m)	Manning's coefficient	Longitudinal slope × 10^{-3} m/m
1	61.85	0.0246	1.66
2	62.88	0.0246	1.66
3	62.88	0.0246	1.66
4	75.44	0.0245	0.27
5	76.84	0.0455	0.062
6	77.46	0.0454	0.062
7	77.22	0.0453	0.062
8	77.14	0.0452	0.062
9	65.78	0.0452	0.062
10	68.74	0.0517	0.124
11	74.75	0.0455	0.062
12	76.36	0.0455	0.062
13	77.54	0.0453	0.062
14	76.45	0.0452	0.062
15	78.72	0.0452	0.062

2.4. Correlation between temperature fluctuations DO levels

To track the effect of changes in temperature and the amount of dissolved oxygen on the micro-biopopulation of the source and the degree of change in the self-purification process of the source based on microbiological indicators, the study investigates the correlation between temperature fluctuations, dissolved oxygen levels, and the micro-biopopulation dynamics, specifically focusing on the ratio of allochthonous (externally introduced) to autochthonous (native) microorganisms in the water source[33]. The analysis involves calculating the degree of change in the self-purification capacity of the source using microbiological indicators, such as the abundance and diversity of these microbial populations.

Temperature and dissolved oxygen levels are monitored over a specified period using standard field equipment. Water samples are collected at regular intervals and analyzed in the laboratory to quantify microbial populations[34]. Differentiation between allochthonous and autochthonous microorganisms is achieved through DNA sequencing or biochemical assays. Population ratios are calculated and compared under varying temperature and oxygen conditions.

2.5. Tracking changes in water class

Integral indicators are commonly used to classify the quality of water, taking into account multiple water quality parameters. These parameters can include:

Physical indicators: Temperature, turbidity, color

Chemical indicators: pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), nutrient concentration (e.g., nitrogen and phosphorus)

Microbiological indicators: Total coliforms, E. coli, other pathogen counts

To determine the class of water, we apply a weighted index approach, where each indicator is given a weight based on its significance in assessing water quality. These individual values are then aggregated into an overall water quality index (WQI) that classifies the water into one of the following classes, as presented in **Table 5**.

Table 5. Water quality classes[35].

Class	Rank	Description
Class I	Very Good	Suitable for drinking without treatment
Class II	Good	Suitable for drinking after treatment
Class III	Moderate	Suitable for recreational and industrial uses
Class IV	Poor	Suitable only for irrigation or industrial purposes
Class V	Very Poor	Unsuitable for most uses

The formula for calculating the WQI might look like this:

$$\boldsymbol{WQI} = \sum_{i=1}^{n} (w_i\,, Q_i\ ) \tag{3}$$

Where: w_i is the weight of indicator iii, Q_i is the normalized value of indicator iii, and n is the total number of indicators used.

To track changes in the class of water, we monitor the above-mentioned indicators over a defined period and calculate the WQI at regular intervals. This allows us to detect trends in water quality and identify factors influencing any observed changes (e.g., temperature, oxygen levels, microbial contamination). The self-purification capacity of the water source can be quantified by observing the recovery of water quality over time after an initial contamination event, such as the release of pollutants or organic matter. This is typically assessed by:

- Monitoring changes in BOD, COD, and nutrient levels.

- Tracking the abundance and diversity of microbial populations, including their rates of organic matter decomposition.

- Observing fluctuations in dissolved oxygen (DO) levels, which are an indicator of the oxygen consumed by microorganisms during the decomposition process.

The degree of change in the self-purification process can be modeled as the difference in water quality parameters (such as BOD, COD, or dissolved oxygen) before and after the contamination event. To predict the impact of climate change on water quality in the medium term, we develop a formula that incorporates key environmental variables influenced by climate change.

This can be represented as:

$$\Delta \mathrm{WQI} = \ \mathrm{WQI}_{\mathrm{post-contamination}} \ - \mathrm{WQI}_{\ \mathrm{pre-contamination}} \tag{4}$$

This difference gives us an estimate of the self-purification process and indicates the capacity of the water source to recover from pollution. By applying climate models and projections for temperature, precipitation, and other relevant factors, it can estimate the future values for these variables and calculate the predicted WQI under future climate conditions. This model can help assess the medium-term impacts of climate change on water quality and guide decision-making for water management.

3. Models

To simulate and optimize the river water quality model, the Ant Colony Optimization (ACO) method and the QUAL2K simulator are utilized together to identify the most suitable model solutions. This integration enhances the model solution identification process, significantly improving both the speed and accuracy of the results. The QUAL2K model, a widely recognized water quality simulation tool, is used to model the dynamics of river systems, including key parameters such as dissolved oxygen, nutrient concentrations, and water temperature. The ACO method, inspired by the foraging behavior of ants, is employed to search for optimal solutions by mimicking natural optimization processes, effectively addressing complex and non-linear water quality problems[36-38].

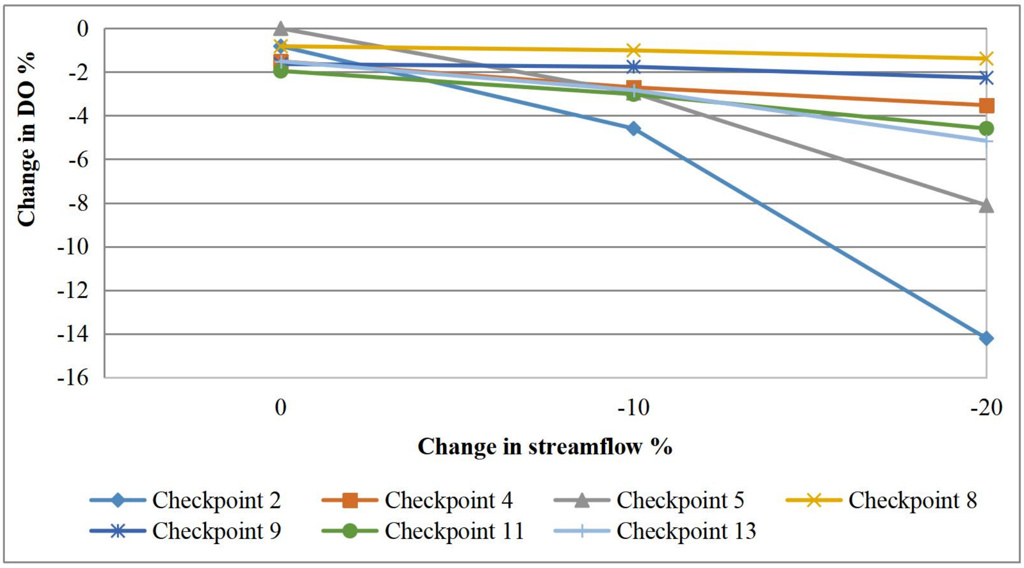
In this study, the model is tested under hypothetical scenarios based on historical air and water temperature data, as well as sewage flow data from the Al-Hilla River. These fictitious scenarios simulate potential future conditions influenced by climate change and varying discharge patterns. By applying ACO to these scenarios, the model quickly converges on optimal parameters that accurately predict the water quality outcomes for each situation, allowing for more efficient decision-making. The results from these simulations provide critical insights into potential water quality changes and can assist in the development of effective management strategies. The combined use of ACO and QUAL2K in this context offers a powerful approach for optimizing water quality management in rivers, contributing to faster, more accurate decision-making in the face of changing environmental conditions.

4. Results and Discussion

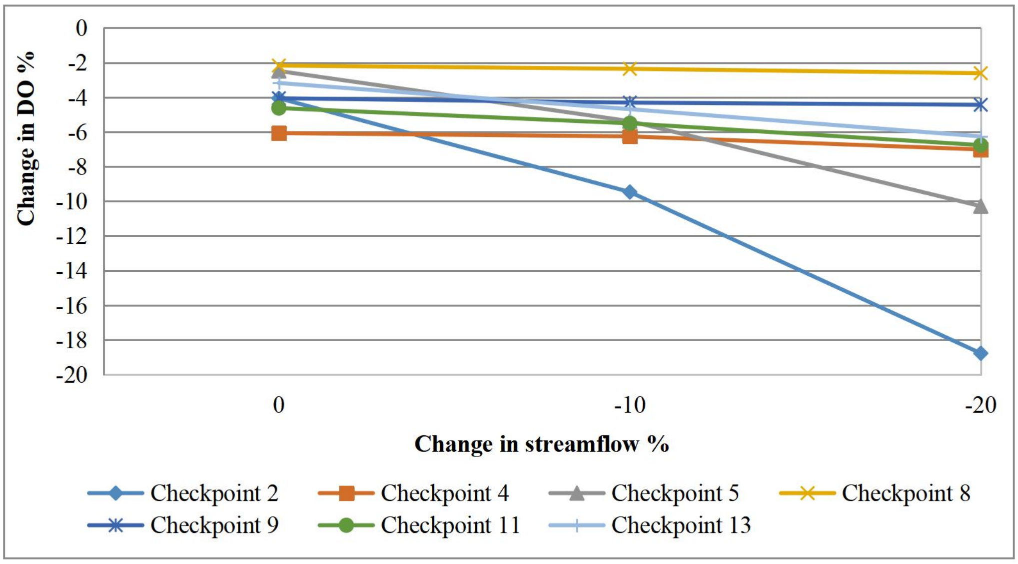
The objective of this study is to quantify the degradations in water quality caused by higher water temperature and decreased river flow, even though it is obvious that these scenarios will result in such degradations. To do this, a water quality Simulation-Optimization $(\mathrm{S}-\mathrm{O})$ proposed model will be used. To demonstrate how river water quality is changing as a result of climate change, the water quality levels that were created in response to fictitious scenarios were compared to the present values.

The positions of these crucial checkpoints (2, 4, 9, 11, and 13) are right downstream of the effluent when quality levels might drop noticeably. The research also considers two more crucial checkpoints: checkpoint 5 (the confluence with New Hilla station) and checkpoint 8 (the halfway point of the river). Because the contaminants being discharged are diluted, the remaining checkpoints are not particularly sensitive[39].

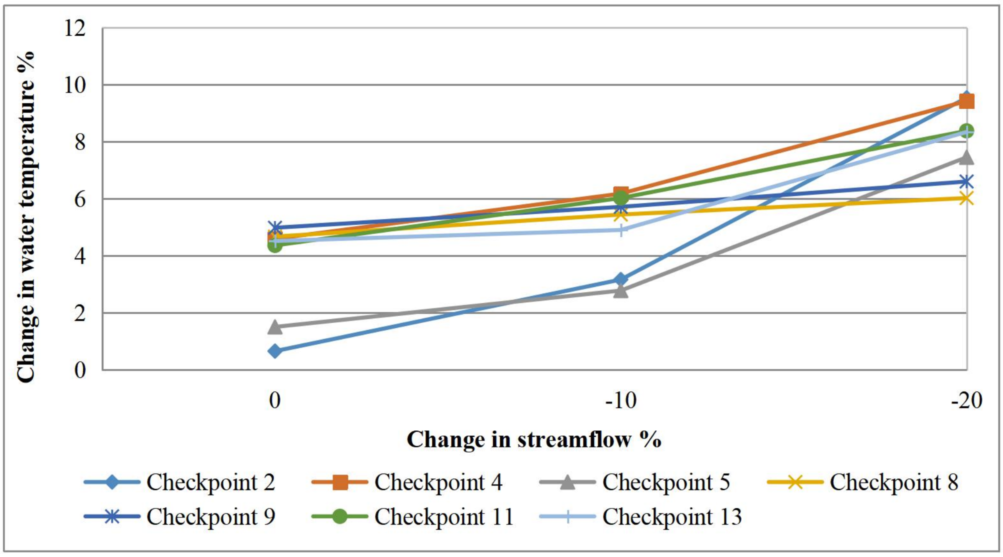
With a particular change in the flow rate along the various checkpoints as illustrated in **Figure 4(a)**, a negative percentage change in DO levels is seen, with a 2°C rise in temperature than a 1°C increase. The temperature rise for the remaining water quality indicators show a rather small variation between 1 and 2°C, similar to what was shown in DO. **Figure 4(b)** shows positive percentage changes in the water's temperature, showing the largest rise in temperature at almost 4.8 °C. Although there is no change in streamflow which showed a notable rise in water temperature (1.44 °C) in comparison to that seen in DO. At checkpoint 2, significant negative percentage changes in dissolved oxygen saturation of 5.54 and 7.17 were noted for water temperatures increased by 1 and 2°C, respectively. The water quality metrics are more susceptible to heat from the stream, as seen in **Figures 4(c and d)**. DO saturation, and water temperature are the aspects of water quality that are most susceptible to scenarios of climate change.



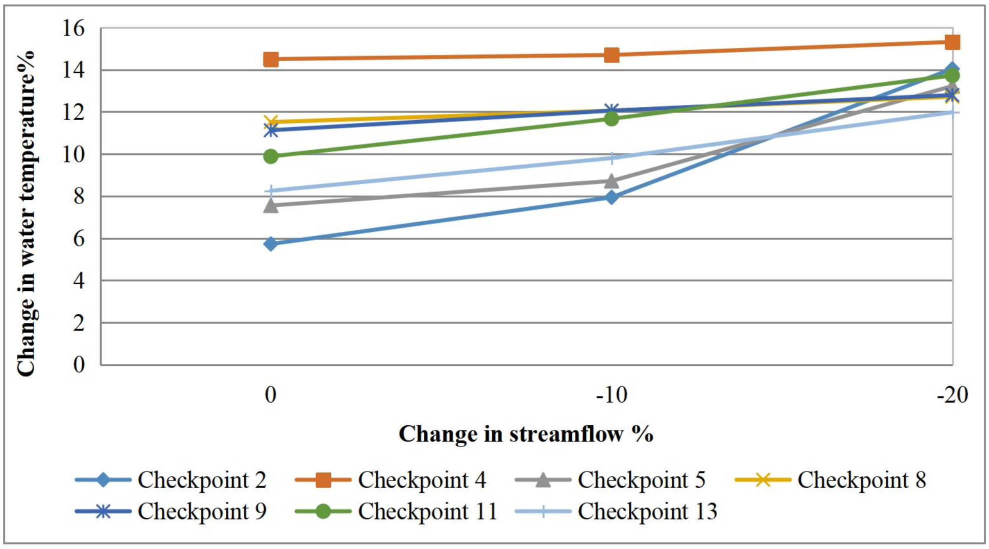
(a) Change in DO level at $\Delta T = 1$ ℃.



(b) Change in DO level at $\Delta T = 2$ ℃.



(c) Change in water temperature at $\Delta T = 1$ °C.



(d) Change in water temperature at $\Delta T = 2$ °C.

Figure 4. Comparison of changes in DO level and water temperature at some critical checkpoints in response to change in streamflow for a given temperature change.

The research analyzed the influence of biogenic elements such as nitrogen, phosphorus, and organic carbon in the water source, which are critical indicators of eutrophication and water quality degradation. The degree of change in these elements was modeled under varying environmental and operational scenarios, including changes in temperature, flow rates, and pollutant removal efficiencies. The results showed that biogenic element concentrations were significantly influenced by seasonal variations and management practices. For instance, higher temperatures increased the release of nutrients from sediments, exacerbating eutrophication risks. Conversely, improved pollutant removal strategies in treatment plants effectively reduced nutrient loads, mitigating their environmental impact. These findings underscore the need for targeted interventions to control biogenic element levels, particularly under future climate scenarios. **Table 6** showcasing the degree of change in biogenic elements under different scenario results. This illustrates how each scenario influences the concentration of biogenic elements, highlighting critical areas for intervention.

Table 6. Impact of environmental and operational scenarios on biogenic element concentrations.

Scenario	Temperature (°C)	Flow Rate (m^3/s)	Nitrogen Change (%)	Phosphorus Change (%)	Carbon Change (%)
Baseline (Current conditions)	20	50	-	-	-
Increased Temperature	30	50	15%	20%	12%
Reduced Flow Rate	20	30	10%	15%	8%
Improved Treatment Efficiency	20	50	-25%	-30%	-20%
Combined Scenario (High Temp + Low Flow)	30	30	30%	40%	25%

Using common field equipment, temperature and dissolved oxygen levels are tracked over a predetermined time period. To measure microbial populations, water samples are taken on a regular basis and examined in a lab[40]. DNA sequencing or biochemical tests are used to distinguish between allochthonous and autochthonous microorganisms. Under various oxygen and temperature circumstances, population ratios are computed and compared.

The degree of self-purification is assessed by evaluating changes in microbial activity, nutrient cycling,

Figure 4.

and organic matter decomposition. Key microbiological indicators, such as oxygen consumption rates and bacterial growth efficiency, are used to quantify the process. The results, summarized in the **Table 7**, highlight the impact of temperature and dissolved oxygen variations on microbial populations and self-purification efficiency.

Table 7. Effect of parameter variations on microbial populations and self-purification efficiency.

Parameter	Low Temp.	High Temp.	Low DO	High DO
Allochthonous Microorganisms (%)	60%	40%	70%	30%
Autochthonous Microorganisms (%)	40%	60%	30%	70%
Self-Purification Efficiency (%)	55%	75%	45%	80%

The findings demonstrate that higher temperatures and elevated dissolved oxygen levels favor the dominance of autochthonous microorganisms, which play a crucial role in the self-purification process. Conversely, low dissolved oxygen and lower temperatures result in a higher proportion of allochthonous microorganisms, leading to reduced self-purification efficiency. These results highlight the need for managing temperature and oxygen levels to optimize the natural cleansing capacity of aquatic ecosystems.

The analysis of water quality, tracking changes in the water class, and the self-purification process, can be presented as in **Table 8**. This table includes integral indicators (e.g., temperature, dissolved oxygen, nutrient levels, and microbial populations) and the resulting WQI for different time points.

Table 8. Results of water quality assessment and self-purification process.

Indicator	Initial Value (Pre-Contamination)	Post-Contamination Value	Self-Purification Degree (ΔWQI)*	Class of Water (Pre-Contamination)**	Class of Water (Post-Contamination)**	Comments
Temperature (°C)	20	22	-	Class II (Good)	Class III (Moderate)	Slight increase in temperature
Dissolved Oxygen (mg/L)	8	5	-3	Class II (Good)	Class III (Moderate)	Significant decrease in DO
Biochemical Oxygen Demand (BOD)	4	12	8	Class II (Good)	Class IV (Poor)	Increased demand for oxygen
Chemical Oxygen Demand (COD)	20	45	25	Class II (Good)	Class IV (Poor)	Increased COD after contamination
Nitrogen Concentration (mg/L)	2	10	8	Class II (Good)	Class III (Moderate)	Elevated nitrogen levels
Phosphorus Concentration (mg/L)	0.5	2	1.5	Class II (Good)	Class III (Moderate)	Increased phosphorus levels
Total Coliforms (CFU/100mL)	50	1000	950	Class II (Good)	Class IV (Poor)	Increased microbial contamination
E. coli (CFU/100mL)	20	150	130	Class II (Good)	Class IV (Poor)	Major increase in pathogens
Water Quality Index (WQI)	60	35	-25	Class II (Good)	Class IV (Poor)	Significant degradation in water quality

**Self-Purification Degree (ΔWQI): This column represents the change in the Water Quality Index (WQI) from the pre-contamination to the post-contamination state. A negative value indicates a deterioration in water quality.*

***Class of Water: The water class is based on the WQI calculated for each time point. The pre-contamination state is generally better, while post-contamination shows a decline in quality.*

The significant increase in BOD, COD, and nutrient concentrations (nitrogen and phosphorus) indicates a substantial increase in organic pollution after contamination, leading to a decline in dissolved oxygen and an increase in microbial contamination. The change in microbial populations, particularly the rise in coliforms and E. coli, highlights the severe contamination event that worsens water quality and moves it from Class II (Good) to Class IV (Poor). The degree of self-purification (ΔWQI) is calculated to show the overall impact on the water quality, and the results suggest that significant recovery or improvement in water quality would take a longer period and could be influenced by the water's natural self-purification capacity, which depends on various factors such as microbial activity, temperature, and dissolved oxygen.

The applied models, while effective in simulating water quality under varying scenarios, face limitations such as uncertainties in assumptions, simplified processes, data gaps, and reliance on specific stations, which may restrict their generalizability and precision. To enhance accuracy, future efforts should integrate more advanced models, improve data collection systems, validate predictions with extensive field data, and explore diverse climate scenarios, including extreme events. Additionally, adaptive management strategies and evidence-based policymaking should be prioritized to address the dynamic challenges of water quality and climate impacts on the Al-Hilla River.

5. Conclusions

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

1. A quantitative evaluation of the factors of water quality in response to rising temperatures and falling flows was carried out.
2. A notable drop in carbon dioxide levels and a rise in BOD and river water temperature might result from the changes in air temperature, water temperature, and streamflow.
3. Compared to the existing situation, which entails a 20% decrease in sewage flow and a 2°C rise in temperature, reveal a 1.02 mg/L drop in dissolved oxygen levels.
4. Because there will be more oxygen-demanding discharge sources, decreased dissolved oxygen would probably cause the conditions of the water quality to significantly worsen.
5. The key finding is that the parameters considered, the water quality model, the river, and the climatic change may all affect the outcomes.
6. 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.
7. It is important to implement adaptive management strategies to ensure consistent water quality standards, especially in response to dynamic environmental and operational conditions.
8. Temperature and dissolved oxygen significantly influence the balance of microbial populations and the self-purification capacity of water sources.
9. Effective environmental management strategies should aim to maintain optimal oxygen levels and mitigate temperature fluctuations to enhance water quality and ecosystem resilience.
10. By incorporating temperature, dissolved oxygen, and microbial dynamics into the model, it is possible to predict how future climate scenarios will influence the water source's quality, providing valuable insights for water management and policy decisions.

Author contributions

Conceptualization, Haibet Dinar and Atheer Al-Qaisi; methodology, Haibet Dinar; software, Atheer Al-Qaisi; validation, Haibet Dinar, Atheer Al-Qaisi, and Hadeel Kareem; formal analysis, Atheer Al-Qaisi; investigation, Hadeel Kareem; resources, Haibet Dinar; data curation, Atheer Al-Qaisi; writing original draft preparation, Haibet Dinar; writing review and editing, Atheer Al-Qaisi and Hadeel Kareem; visualization, Hadeel Kareem; supervision, Haibet Dinar; project administration, Atheer Al-Qaisi; funding acquisition, Hadeel Kareem. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare no conflict of interest.

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