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Implications of Dynamic Interactions between Meteorological Patterns and Surface Water Quality on Environmental Health—A Case Study of the Nairobi River

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Abstract

Urban areas face significant challenges in maintaining water quality amidst increasing urbanization and changing climatic patterns. This study investigates the complex interplay between meteorological variables and water quality parameters in Nairobi City, focusing on the impacts of rainfall and temperature on surface water quality. Data from multiple sources, including the Water Resources Authority, Nairobi Water and Sewerage Company, and the World Bank's Climate Change Knowledge Portal, were analyzed to assess the relationships between meteorological variables (rainfall and temperature) and water quality parameters (such as electroconductivity, biochemical oxygen demand, chloride, and pH). The analysis reveals varying impacts of rainfall and temperature on different water quality parameters. While parameters like iron and pH show strong relationships with both rainfall and temperature, others such as ammonia and nitrate exhibit moderate relationships. Additionally, the study highlights the influence of runoff, urbanization, and industrial activities on water quality, emphasizing the need for holistic management approaches. Recommendations encompass the establishment of annual publications on Nairobi River water quality, online accessibility of water quality data, development of hydrological models, spatial analysis, and fostering cross-disciplinary research collaborations. Implementing these recommendations can enhance water quality management practices, mitigate risks, and safeguard environmental integrity in Nairobi City.

Keywords

Water Quality, Meteorological Conditions, Urban Environment, Environmental

Health, Nairobi, Water Quality Parameters

1. Introduction

Water quality assessment involves the measurement of various parameters that help in evaluating the suitability of water for different purposes, ranging from drinking to aquatic ecosystems. These parameters can be categorized into physical, chemical, and biological aspects, each providing essential insights into the condition of water. Water quality assessment parameters encompass a wide array of physical, chemical, and biological factors. Their usefulness depends on the specific objectives of the assessment, the context in which they are applied, and the environmental conditions under consideration. Researchers and water quality managers must carefully select the parameters most relevant to their goals and locations to ensure accurate and effective assessments.

Omer (2019) classifies water quality parameters into three major categories: physical, chemical, and biological parameters Omer (2019). Physical Parameters include Turbidity, Temperature, Colour, Taste and odour, Solids, and Electrical conductivity (EC) Omer (2019). These parameters describe the sensory properties and visual aspects of water. Chemical parameters encompass a wide range of characteristics such as pH, Acidity, Alkalinity, Chloride, Chlorine residual, Sulphate, Nitrogen, Fluoride, Iron and manganese, Copper and zinc, Hardness, Dissolved oxygen (DO), Biochemical oxygen demand (BOD), Chemical oxygen demand (COD), Toxic inorganic and organic substances, and Radioactive substances. They provide information about the chemical composition of water and its potential for contamination. Biological parameters involve the presence and abundance of microorganisms in water, including Bacteria, Algae, Viruses, and Protozoa. They are critical for assessing the potential health risks associated with waterborne pathogens (Abu Shmeis, 2018).

The usefulness of these water quality parameters depends on the context and the specific objectives of the assessment. Microbial indicators such as *E. coli*, fecal coliforms, and total coliforms are crucial in monitoring water for microbial pathogens. These indicators are especially valuable when pathogens are present in low numbers, as they serve as proxies for potential health risks (Abu Shmeis, 2018). Emerging chemical and microbiological parameters, as highlighted by Brandt et al. (2017) include disinfection by-products, household and industrial by-products, pesticides, enteroviruses, and potential future contaminants related to waste and rainwater recycling (Brandt et al., 2017). These parameters reflect evolving concerns in water quality assessment. In cases like the Kitwe Stream in Zambia, as studied by Brandt et al. (2017), water quality analysis is crucial to understand the impact of engineering and human activities on local water bodies, thereby enabling the proposal of remedial actions (Brandt et al., 2017). Gule et al. (2023) emphasize the importance of assessing water quality both at the source and within supply networks (Gule et al., 2023). Effective sewage disposal, drainage, water treatment, and improved technologies are critical for ensuring water quality. Additionally, public health officials should monitor distribution taps to educate the public about water safety. Osińska et al. (2021) discuss the importance of water quality parameters in the context of glacial meltwater, with a focus on physical and chemical variables (e.g., salinity, pH, dissolved oxygen) and biological parameters (Osińska et al., 2021). These parameters help assess the impact of glacial meltwater on water quality in subglacial coves. Baloïtcha et al. (2022) stress the use of tools like the Water Quality Index (WQI) and Water Stability Index (WSI) for the easy assessment of water quality and aggressiveness. These indices provide a comprehensive overview of water quality and its suitability for various uses (Baloïtcha et al., 2022). Vyas and Jethoo (2015) highlight the significance of meteorological parameters in water quality assessment, as meteorological conditions can influence water quality, particularly in the case of weather-related events (Vyas & Jethoo, 2015). Temporal Scales: Rodrigues et al. (2012) emphasize the importance of assessing water quality at various temporal scales, including diurnal and seasonal, to understand the effects of both short-term and long-term climatic changes. Mayjor et al. (2023) note that high rainfall events can impact water quality by increasing dissolved oxygen and altering water height and volume, which are important considerations in water quality assessment (Mayjor et al., 2023). Regier et al. (2020) highlight the effects of precipitation events on water quality, particularly in the context of stormwater runoff (Regier et al., 2020). Such events can introduce distinct physical, chemical, and biological characteristics into receiving waters, affecting their overall quality.

The interactions between weather patterns and water quality parameters play a crucial role in assessing the environmental health of a city. Extreme weather events can have complex and multifaceted effects on water resources and contaminant mobilization, necessitating integrated approaches to water management and the consideration of both quantity and quality in urban water resource planning. These insights are fundamental to ensuring the sustainability and health of urban ecosystems.

Extreme weather events, such as heavy rainfall and temperature fluctuations, have garnered increasing attention due to their significant impact on global water supplies and surface water quality (SWQ). Kyei et al. (2023) have observed correlations between climate variables, particularly rainfall and temperature, and various water quality parameters, including dissolved oxygen, turbidity, total dissolved solids (TDS), nitrate (NO_3), phosphate (PO_4^3), and manganese (Mn) (Kyei et al., 2023). These correlations underline the dynamic interplay between climatic factors and water quality, offering valuable insights into the environmental health of cities. Geris et al., 2022 conducted a study in the Gaborone Reservoir catchment area, where they noted the effects of extreme rainfall and floods on water resources and contaminant mobilization (Geris et al., 2022).

While contaminants were mobilized and diluted during flooding, their concentration in surface water increased post-floods, primarily due to evapoconcentration. This observation highlights the complex consequences of extreme weather events on water quality and the need to address both the quantity and quality of water resources to ensure the environmental health of a city. Rahman et al. (2023) underscore the implications of declining precipitation and rising temperatures on agricultural practices, water availability, and overall ecosystem health (Rahman et al., 2023). Their findings emphasize the necessity for effective water management strategies that consider the interrelationship between rainfall and reference evapotranspiration (ET_0). These interrelated trends can inform decision-making processes and support equitable water resource distribution among various sectors within a city. Zhou et al. (2021) investigated the impact of spatial and temporal variability in rainfall on runoff quality and quantity in small watershed scales (Zhou et al., 2021). Their research demonstrated that the sensitivity of hydrological and water quality models to rainfall data variability highlights the importance of accounting for both spatial and temporal aspects when analysing variations in runoff quality and quantity. This underscores the need for accurate data to develop effective water quality management strategies in urban environments. Bertone et al. (2023) examined the influence of spatial distribution of rainfall during wet weather events on raw water quality (Bertone et al., 2023). They found that runoff from specific sub-catchments significantly affected turbidity and conductivity, contrasting with larger dam outflows that typically exhibited better water quality. This emphasizes the importance of understanding local rainfall patterns to manage urban water resources effectively. Yan et al. (2023) identified the impact of hydrologic extremities and erosion on mercury (Hg) emissions in watersheds (Yan et al., 2023). They highlighted the potential environmental risks posed to aquatic ecosystems by Hg emissions during rainfall-runoff events. Understanding the dynamics of pollutant transport during extreme weather events is crucial for safeguarding the environmental health of a city.

For decades, water quality assessment has been of paramount importance in environmental management and public health. Analysis of wastewater parameters has served as a cornerstone for decision-making in various aspects, including the design of treatment plants and the evaluation of treatment method effectiveness (Weerakoon et al., 2023). Traditional water quality assessment methods have been rooted in the analysis of physical and chemical parameters, providing valuable insights into the quality of water bodies (Chrea et al., 2023). Water quality assessment has evolved to address issues such as eutrophication caused by pollutants from different sources, including industrial effluence, domestic sewage, and human activities (Zhao et al., 2020). This highlights the importance of understanding the sources and impacts of water contaminants. In addition, the assessment of biota as indicators of aquatic ecosystem health has been a long-standing practice, dating back to the late 1800s, and has gained substantial momentum since the 1980s (Norris & Barbour, 2009). This approach encompasses the evaluation of various biotic components such as fish, algae, plants, and invertebrates, making it an integral part of water quality assessment. In conjunction with these methods, the Chemical Oxygen Demand (COD) test has played a significant role in evaluating the oxygen required for oxidizing organic and inorganic matter in water, particularly in rivers that receive wastewater (Thakkar et al., 2023). Historical trends have highlighted that many rivers serve as wastewater-receiving waterways, with downstream users participating in unintentional wastewater reuse (Wang et al., 2023).

While traditional water quality assessment methods have served well, there is a growing shift towards embracing emerging trends to address the evolving challenges of water quality management. Recent years have witnessed a significant integration of artificial intelligence (AI) models, including artificial neural networks (ANNs) and neuro-fuzzy systems, into water quality assessment (Nadiri et al., 2018). These AI models provide a data-driven alternative to traditional physics-based modeling, allowing for more accurate predictions of effluent water quality parameters. Water quality models have evolved to offer a more profound understanding of the factors that influence water quality changes in distribution systems, with the potential to revolutionize distribution system management decisions (Vasconcelos, 1995). This technological advancement can aid in addressing water quality issues within complex distribution networks. The assessment of water quality has progressed to include considerations of data uncertainty, emphasizing real-time monitoring and data-driven decision-making (Yan et al., 2022). This paradigm shift holds particular significance for regional sustainable development. Furthermore, statistical techniques and interdisciplinary approaches have contributed to the development of various assessment methods, such as single-factor assessment, fuzzy comprehensive evaluation, cluster analysis, and principal component analysis (Ding et al., 2022). These multifaceted approaches provide a more holistic understanding of water quality. Novel approaches, such as the combination of water quality index with self-organizing maps, have become prevalent, offering more detailed insights into surface water quality (Yotova et al., 2021). This synergy enhances the precision of water quality assessment and decision-making. Emerging research now encompasses the spatial-temporal distribution of trace elements in water bodies and their associated risk assessments (He et al., 2023). This innovative approach helps pinpoint the sources of contaminants and assess their potential impact on ecosystems and human health. Water data management is increasingly recognized as a pivotal component of successful water quality monitoring programs (Klima et al., 2003). Efficient data management is vital in facilitating water quality assessment and informed decision-making. The implications of unsafe water on both public health and the economy underscore the need for continuous monitoring, well-established water management systems, improved water treatment, and enhanced public awareness (Perveen & Ul Haque, 2023). Collaborative efforts are essential to ensure access to safe drinking water. Water quality assessment continues to rely on the analysis of essential parameters such as pH, total dissolved solids, electrical conductivity, and various anions and cations (Gosh & Biswajit, 2023). These foundational methods remain integral to assessing water quality. Incorporating these elements, the assessment of water quality has a rich history, with emerging trends focused on innovative technologies, data-driven approaches, and interdisciplinary methods to address contemporary water quality challenges, while preserving a strong foundation in traditional techniques. These advancements hold the promise of more effective water quality management and sustainable resource conservation.

By focusing specifically on Nairobi, the study addresses the unique challenges faced by the urban area, providing insights directly relevant to local policymakers and environmental agencies. The integration of data from multiple sources, including the Water Resources Authority, the Nairobi Water and Sewerage Company, and the World Bank's Climate Change Knowledge Portal, enhances the robustness of the analysis and ensures a comprehensive overview of both water quality parameters and meteorological variables. Through rigorous statistical analysis techniques such as regression and correlation analysis, the research quantifies these relationships and interprets the findings within the context of environmental factors and local conditions, offering meaningful insights into the implications of meteorological factors on water quality in Nairobi City.

Furthermore, the study explores the implications of changing climate patterns on water quality by analyzing trends in observed annual precipitation and mean surface temperature, contributing to the broader discourse on climate change adaptation and resilience in urban areas. Overall, the novelty of this research lies in its comprehensive approach, local relevance, integration of diverse data sources, rigorous statistical methods, and implications for climate change adaptation, ultimately advancing our understanding of the complex interactions between meteorological variables and water quality in Nairobi City.

2. Study Area

2.1. Nairobi City's Environmental Health

The city of Nairobi, Kenya, has been facing a myriad of environmental challenges, with water pollution being a significant concern. A complex interplay of urbanization, natural factors, and policy decisions that have led to the degradation of water sources in the city.

Nairobi's settlements are vulnerable to urban flooding exacerbated by anthropogenic factors, and the impacts of flooding on the city's settlements have been a subject of concern (Owuor & Mwiturubani, 2021). The lack of scientific evidence regarding the relationship between flooding impacts and coping strategies in Nairobi's settlements underscores the need for a comprehensive understanding of how urbanization and flooding interact to affect water quality and availability in the city.

Flooding in urban areas like Nairobi has a unique nature due to the built environment and the growing population, in addition to natural variations in rainfall (Tom et al., 2022). The effects of flooding are particularly felt in densely populated areas, such as informal settlements. The degradation of water sources can be attributed to the negative impacts of flooding in these areas, highlighting the necessity of addressing this issue comprehensively.

Nairobi's commitment to sustainability is reflected in policies such as dedicating a fifth of the road budget to non-motorized transport (Rajé, Tight, & Pope, 2018). While this policy is a step towards reducing pollution from vehicular emissions, other sources of pollution, such as industrial activities and solid waste, continue to impact water sources in Nairobi.

Emissions from heat sources, changes in land cover, and urban development have led to higher land surface temperatures (LSTs) in built-up areas, including industrial zones (Ochola et al., 2020). These increased temperatures, exacerbated by factors like the removal of vegetation and dark surfaces, can contribute to heatwaves and influence the quality of water in urban areas. The concentration of heat-generating activities in urban areas, like motor vehicles, factories, and homes, further compounds this issue.

Improper solid waste management in Nairobi has resulted in the city being labeled as "The Stinking City in the Sun" (Mwanthi, Nyabola, & Tenambergen, 1997). Improperly managed solid waste not only affects the aesthetics of the city but also pollutes water sources, as contaminants can leach into water courses, affecting both surface and groundwater quality. This mismanagement also provides breeding grounds for disease vectors.

Furthermore, the presence of antiretrovirals, such as nevirapine, in groundwater near pit latrines and septic tanks highlights the contamination of major drinking water sources in developing countries (K'oreje et al., 2016). The persistence of pharmaceuticals in the environment poses a threat to water quality, and this issue is further exacerbated by inadequate sanitation and wastewater management.

The challenges that Nairobi faces in terms of water pollution are multifaceted. These issues are driven by urbanization, flooding, industrial activities, solid waste mismanagement, and pharmaceutical contamination. Addressing these challenges requires a holistic and coordinated effort involving urban planning, environmental policy, and sustainable resource management to restore the once "Green City in the Sun" to its former glory and ensure access to clean and safe water sources for its residents.

2.2. State of the Water Quality of the Nairobi River

The state of water quality in the Nairobi River shown here in **Figure 1** is impacted by pollution sources, including stormwater runoff, sewage, domestic refuse, industrial discharges, agricultural runoff, and pharmaceutical pollution. Understanding the diverse origins of pollution is essential for developing effective strategies to improve water quality in this critical waterway.

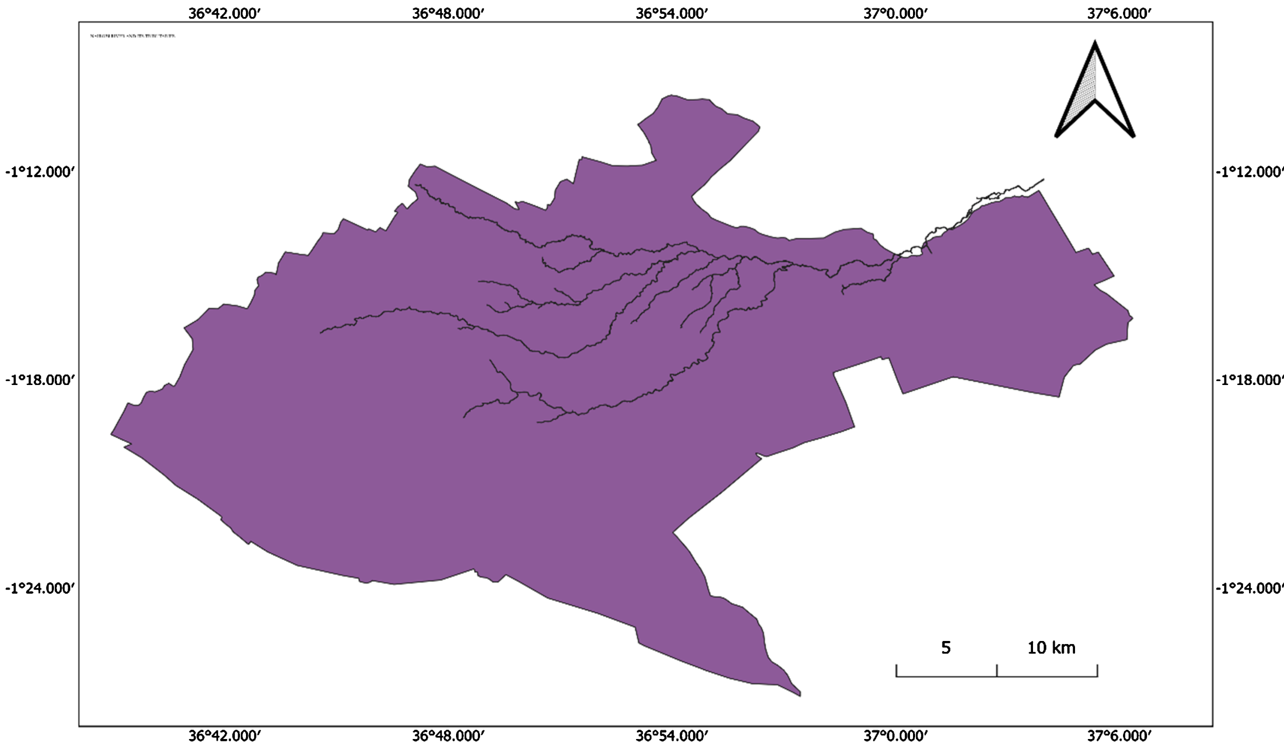

Figure 1. The Nairobi River and its tributaries.

The pollution of surface water, particularly the Nairobi River, with toxic chemicals and excess nutrients is a global environmental concern (Ouyang, 2005). This issue stems from various sources, including stormwater runoff, vadose zone leaching, and groundwater discharges. The Nairobi River's water quality is no exception to these concerns, as it faces similar challenges.

Recent research by Vane et al. (2022) has shed light on the composition of sediments in and around the Nairobi River (Vane et al., 2022). The study revealed that slum sediments exhibited a bimodal bound hydrocarbon composition, primarily attributed to sewage and domestic refuse. In contrast, river sediments in areas with different land uses, such as higher income residential, university, park, and quarry areas, were found to contain natural biopolymers. This stark contrast in sediment composition emphasizes the diversity of pollution sources affecting the Nairobi River and the need for targeted remediation efforts.

The presence of active pharmaceutical ingredients (APIs) and chemicals in the Nairobi River and its catchment area is a significant concern. Bagnis et al. (2020) identified the most frequently detected APIs, including caffeine, carbamazepine, trimethoprim, nicotine, and sulfamethoxazole (Bagnis et al., 2020). Notably, the informal settlements, industrial areas in Nairobi City, and the Dandora landfill were identified as primary sources of these APIs. Additionally, upstream agricultural sites were likely sources of veterinary APIs. This research highlights the complex interplay of pollution sources affecting water quality in the Nairobi River, including both urban and agricultural contributions.

Wilson et al. (2021) documented the impact of various sources of pollution on the Nairobi River. The study identified an area where wastewater from car wash operations joined the downstream, contributing to an increasing trend in water pollution along the stream course (Wilson, Michieka, & Mwendwa, 2021). The increasing turbidity downstream was indicative of rising concentrations of metallic elements, anions, and alluviation due to siltation from cultivated land. The destruction of the riparian environment played a role in exacerbating this problem. These findings underscore the importance of considering both point and non-point sources of pollution when addressing water quality in the Nairobi River.

Furthermore, Ngumba et al. (2016) provided insights into the presence of specific pharmaceuticals and drugs in the Nairobi River and its catchment (Ngumba, Gachanja, & Tuhkanen, 2016). Among the drugs studied, nevirapine (NVP), zidovudine (ZDV), lamivudine (3TC), trimethoprim (TMP), sulfamethoxazole (SMX), and ciprofloxacin (CIP) were identified. The presence of these drugs in the river is a clear indication of pharmaceutical pollution, likely originating from various sources, including healthcare facilities and residential areas. These findings underscore the need for targeted interventions to manage pharmaceutical pollution in the Nairobi River.

3. Methodology

3.1. Data Sources

The water quality data used in this study was obtained from multiple sources, including the Water Resources Authority in Nairobi and the Nairobi Water and Sewerage Company. This dataset comprises various water quality parameters, such as Electroconductivity (EC), Biological Oxygen Demand (BOD), Chloride (Cl), Chemical Oxygen Demand (COD), Color, Iron (Fe), Ammonia (NH_4), Nitrate (NO_4), pH, Sulphate (SO_4), Total Dissolved Solids (TDS), Water Temperature (T), and Total Suspended Solids (TSS). The data represents annual averages and covers a specified time period. Simultaneously, meteorological data, specifically annual average rainfall (Rain) and observed annual average mean surface temperature, was sourced from the World Bank's Climate Change Knowledge Portal. This meteorological dataset provides comprehensive information for Nairobi and aligns temporally with the water quality dataset.

3.2. Data Preprocessing

The collected data underwent a meticulous data cleaning process to ensure data quality and reliability. This preprocessing involved the following steps: a. Outlier Handling: Statistical methods were applied to detect and remove outliers from the datasets, ensuring that extreme values did not unduly influence the analysis, b. Missing Data Imputation: Missing values in the datasets were addressed through data imputation techniques such as linear interpolation or by considering nearby observations. This process aimed to fill gaps in the data while maintaining data integrity, and c. Data Integration: The water quality and meteorological datasets were integrated into a unified dataset, ensuring a common time stamp (e.g., date and time) for synchronization in subsequent analyses. This step was crucial for exploring temporal relationships.

3.3. Statistical Analysis

The statistical analysis was conducted to gain valuable insights into the relationships between meteorological variables, particularly rainfall and temperature, and water quality parameters. The following analytical procedures were employed:

1) Descriptive Statistics: Descriptive statistics, including mean, standard deviation, and range, were computed for each water quality parameter and meteorological variable. These statistics provided an initial overview of the dataset and highlighted key characteristics.

2) Correlation Analysis: Pearson's correlation coefficients were calculated to assess the linear relationships between rainfall, temperature, and each water quality parameter. These coefficients measured the strength and direction of associations, aiding in the identification of potential relationships.

3) Multiple Linear Regression: Multiple linear regression models were developed to quantify the relationship between meteorological variables (Rain and Temperature) and water quality parameters. These models allowed for a more in-depth exploration of how rainfall and temperature influence various water quality indicators. Significance testing was conducted using a significance level of 0.05 to assess the statistical importance of the regression coefficients.

4. Results and Analysis

4.1. Water Quality Parameters

In Table 1 below, we delve into the intricate relationship between various water quality parameters, rainfall, and temperature through regression analysis. Each row represents a distinct water quality parameter. Alongside each parameter, we provide insights into how it responds to changes in rainfall and temperature, crucial environmental variables that significantly impact urban water systems.

The multiple correlation coefficient (Multiple R) unveils the collective strength and direction of the linear relationship between the dependent variables (water quality parameters) and the independent variables (rainfall and temperature). With R values ranging from 0.73 to 1.00 across the parameters, it underscores a robust association between the environmental factors and the water quality parameters under examination.

Meanwhile, ***the coefficient of determination (R2)*** elucidates the proportion of variance in each water quality parameter that can be explained by variations in rainfall and temperature. Ranging from 0.53 to 1.00 across the parameters, R^2 indicates the percentage of variability in water quality parameters that can be attributed to changes in the environmental variables.

Adjusted R2: by factoring in the number of predictors in the model, refines the evaluation of model fit. With values ranging from 0.17 to 0.89, adjusted R^2 provides a more accurate gauge of how well the regression model captures the relationships between rainfall, temperature, and water quality parameters while mitigating the risk of overfitting.

Rain C and Temp C: These sections delineate the coefficients associated with rainfall and temperature, encompassing statistical measures such as t Stat (t-value) and P-value, providing a nuanced understanding of their individual contributions to the model.

The t Stat (t-value): The t-statistic (t-value) measures the strength of the relationship between each independent variable (rainfall and temperature) and the dependent variable (water quality parameters), while considering the variability of the data and the sample size. Higher absolute t-values indicate stronger relationships between the independent variable and the dependent variable. The sign of the t-value (+ or −) indicates the direction of the relationship (positive or negative).

P-value: The p-value indicates the probability of observing the calculated t-value (or one more extreme) under the null hypothesis that there is no relationship between the independent variable and the dependent variable. A lower p-value suggests stronger evidence against the null hypothesis and indicates that the relationship between the variables is statistically significant. Typically, if the p-value is below a certain threshold (commonly 0.05), the relationship is considered statistically significant, implying that the independent variable contributes significantly to explaining the variation in the dependent variable.

Table 1. Regression analysis (*C stands for Coefficient *T stands for water temperature).

Parameter	units	Multiple R	R^2	Adjusted R^2	Rain C	Rain t Stat	Rain P-value	Temp C	Temp t Stat	Temp P-value
EC	µS/cm	0.96	0.92	0.81	0.30	1.13	0.28	17.19	1.16	0.27
BOD	mg/L	0.80	0.65	0.19	0.07	0.44	0.69	−1.31	−0.12	0.91
Cl	mg/L	0.89	0.80	0.50	0.07	0.90	0.42	−0.62	−0.17	0.87
COD	mg/L	0.79	0.63	0.40	0.12	0.85	0.43	−0.91	−0.11	0.91
Colour		0.88	0.78	0.58	−0.10	−1.25	0.26	9.61	2.24	0.07
Fe	mg/L	0.99	0.98	0.73	0.01	8.31	0.00	−0.17	−5.63	0.00
NH_4	mg/L	0.76	0.57	−0.14	0.05	0.93	0.45	−2.86	−0.72	0.54
NO_3	mg/L	0.89	0.79	0.59	0.01	1.89	0.11	−0.22	−0.85	0.43
pH		1.00	1.00	0.89	0.00	−0.38	0.71	0.42	10.35	0.00
SO_4	mg/L	0.73	0.53	0.17	−0.03	−0.73	0.51	1.95	1.09	0.34
TDS	mg/L	0.97	0.94	0.84	0.17	1.41	0.19	9.56	1.38	0.20
T	˚C	1.00	0.99	0.83	0.00	0.89	0.41	0.89	3.67	0.01
TSS	mg/L	0.79	0.63	0.44	0.01	0.08	0.94	4.18	0.68	0.52

Table 2 below illustrates Pearson's correlation coefficients between each water quality parameter and the environmental factors of rainfall and temperature. Let's interpret the correlations:

Rain: The correlation coefficients between rainfall and each water quality parameter indicate the strength and direction of the linear relationship between rainfall and water quality. For instance: Positive coefficients (e.g., EC: 0.35, Fe: 0.97, NH4: 0.58) suggest a positive relationship, meaning that as rainfall increases, these parameters tend to increase as well. Negative coefficients (e.g., Color: −0.44, SO4: −0.36, pH: −0.1) indicate a negative relationship, implying that as rainfall increases, these parameters tend to decrease. Coefficients closer to 0 (e.g., TDS: 0.43, TSS: 0.02) suggest a weak or no linear relationship between rainfall and these parameters.

Temperature: Similarly, the correlation coefficients between temperature and each water quality parameter signify the strength and direction of the linear relationship between temperature and water quality. For instance: Positive coefficients (e.g., NH4: 0.83, TDS: 0.46, Cl: 0.32) indicate a positive relationship, meaning that as temperature increases, these parameters tend to increase as well. Negative coefficients (e.g., pH: −0.63, TSS: −0.26) suggest a negative relationship, implying that as temperature increases, these parameters tend to decrease. Coefficients closer to 0 (e.g., Color: 0.13, COD: −0.15) suggest a weak or no linear relationship between temperature and these parameters.

Table 2. Pearson's correlation coefficients.

Parameter	BOD	Cl	COD	Color	EC	Fe	NH_4	NO_4	pH	SO_4	TDS	T	TSS
Rain	0.26	0.42	0.32	−0.44	0.35	0.97	0.58	0.62	−0.1	−0.36	0.43	0.36	0.02
Temperature	0.21	0.32	−0.15	0.13	0.19	−0.23	0.83	0.49	−0.63	−0.21	0.46	0.1	−0.26

The following section delves into a comprehensive analysis of various key water quality parameters within the context of the Nairobi River. With the aim of understanding the intricate interplay between environmental factors and water quality dynamics, this investigation scrutinizes the influences of rainfall and temperature on the various water quality parameters. Each parameter undergoes meticulous examination, beginning with a scrutiny of its relationship with rainfall and temperature through regression analysis. Subsequently, Pearson's correlation coefficients provide additional insights into the strength and significance of these relationships. Moreover, the section delves into the implications of the observed variations in each parameter, offering critical assessments of potential pollution sources, environmental impacts, and implications for ecosystem health.

4.1.1. Electroconductivity (EC)

The regression analysis for electroconductivity (EC) yielded a high multiple R^2 value of 0.92, indicating a strong relationship with the explanatory variables. However, the Rain coefficient was found to be 0.30 with a p-value of 0.28, and the

Temp coefficient was 17.19 with a p-value of 0.27, suggesting that neither rainfall nor temperature had a significant impact on EC. In the Pearson's correlation analysis, EC showed a positive correlation of 0.35 with Rain and 0.19 with Temp, although neither correlation was statistically significant.

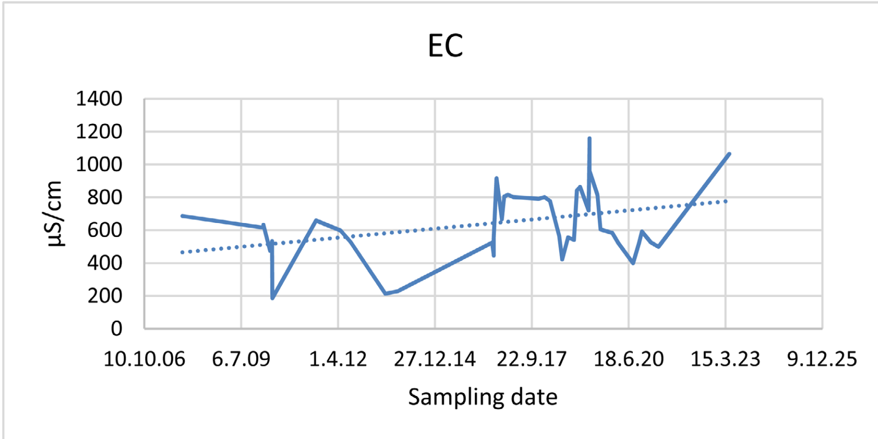

Figure 2. Electroconductivity trendline analysis.

As seen in Figure 2 above, EC values for the Nairobi River range from 187.2 to 1065 µS/cm (microsiemens per centimeter). While there are no specific standard limits provided for EC in the context of supporting aquatic life, elevated EC levels can indicate the presence of dissolved salts, nutrients, and other pollutants in the water. The provided EC values suggest that there is significant variation in the conductivity of the Nairobi River over time. Higher EC values may be indicative of increased pollution levels, including inputs from urban runoff, industrial discharges, and agricultural activities. These elevated EC levels can potentially impact aquatic organisms and overall ecosystem health.

4.1.2. Biochemical Oxygen Demand (BOD)

For BOD, the multiple R^2 value was 0.65, indicating a moderate relationship with the environmental factors. Rain showed a coefficient of 0.07 with a p-value of 0.69, while Temp had a coefficient of -1.31 with a p-value of 0.91, implying that neither rainfall nor temperature had a significant influence on BOD levels. BOD had a weak positive correlation with Rain (0.26) and a weak negative correlation with Temp (−0.21). However, none of these correlations were statistically significant.

The BOD values for the Nairobi River range from 11 to 400 mg/L as shown in Figure 3 below. Almost all of these values exceed the typical standard limit of below 5 mg/L, indicating that BOD levels are consistently above the standard. This points to severe pollution in the Nairobi River, likely due to the discharge of untreated sewage, industrial effluents, and other contaminants. High BOD levels lead to quick depletion of oxygen in the water, endangering aquatic life and compromising the river's ecosystem health.

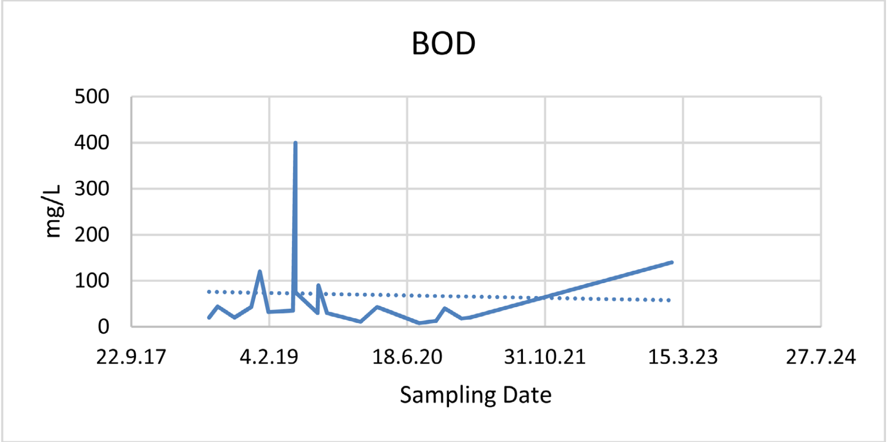

Figure 3. ln BOD trendline analysis.

4.1.3. Chloride (Cl)

The regression analysis for chloride showed a multiple R^2 value of 0.80, suggesting a substantial relationship with the explanatory variables. However, the Rain coefficient was 0.07 with a p-value of 0.42, and the Temp coefficient was −0.62 with a p-value of 0.87, indicating that neither rainfall nor temperature significantly affected chloride levels. Chloride had a moderate positive correlation with Rain (0.42) and a weak negative correlation with Temp (−0.15). However, these correlations were not statistically significant.

As we can see from Figure 4 below, Cl values for the Nairobi River range from 6 to 80 mg/L. These values generally fall within the typical standard limit for chloride in freshwater bodies, which is often below 250 mg/L. Thus, the chloride levels in the Nairobi River appear to be within acceptable limits. However, chloride concentrations can vary based on natural geological factors, industrial discharges, and urban runoff.

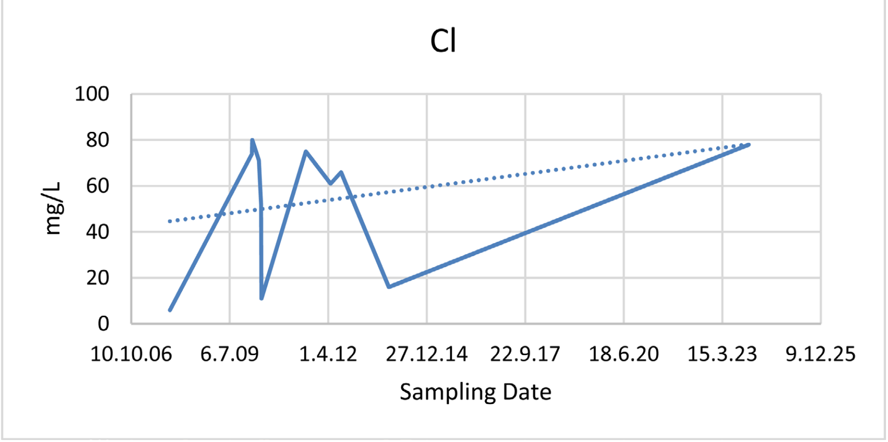

Figure 4. Chloride trendline analysis.

4.1.4. Chemical Oxygen Demand (COD)

The analysis for COD revealed a multiple R^2 value of 0.63, signifying a moderate relationship with the environmental factors. Rain displayed a coefficient of 0.12

with a p-value of 0.43, while Temp had a coefficient of −0.91 with a p-value of 0.91, suggesting that neither rainfall nor temperature significantly impacted COD. COD had a weak positive correlation with Rain (0.32) and a weak negative correlation with Temp (−0.15). However, these correlations were not statistically significant.

The COD values in **Figure 5** below for the Nairobi River range from 25 to 2800 mg/L Most of these values exceed the typical standard limit for COD in freshwater bodies, which is often below 10 - 20 mg/L. The elevated COD levels indicate significant organic pollution in the Nairobi River, likely due to the discharge of untreated sewage, industrial effluents, and other contaminants. High COD levels can lead to oxygen depletion in the water, negatively impacting aquatic life and overall ecosystem health.

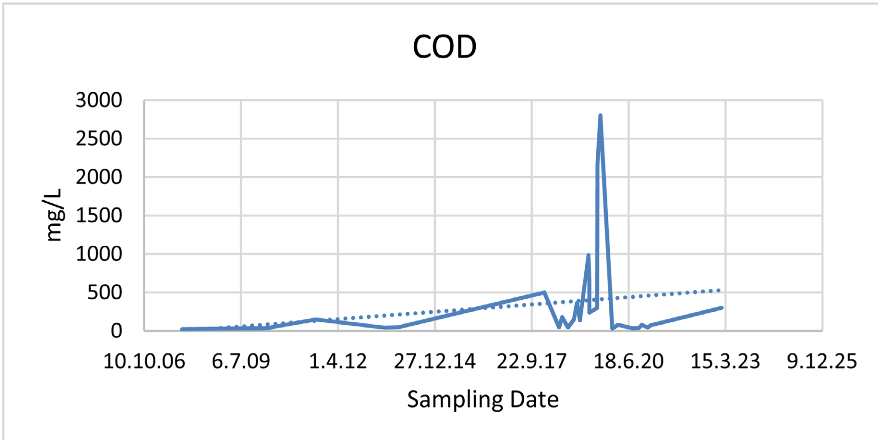

Figure 5. COD trendline analysis.

4.1.5. Color

For color, the multiple R^2 value was 0.78, indicating a strong relationship with the explanatory variables. Rain showed a coefficient of −0.10 with a p-value of 0.26, while Temp had a coefficient of 9.61 with a p-value of 0.07. While Rain had no significant impact, Temp showed a moderately significant influence on color. Color had a weak negative correlation with Rain (−0.44) and a weak positive correlation with Temp (0.13). The correlation with Temp was statistically significant.

The Color values for the Nairobi River in **Figure 6** below translate to values that range from 15 to 350. Color in water is often indicative of dissolved organic matter and suspended particles. While there are no specific standard limits provided for color, excessively high color levels can indicate the presence of pollutants such as organic compounds, sediment, and industrial discharges. Higher Color values may be indicative of increased levels of organic matter and suspended particles, which can negatively impact water clarity and aesthetics.

4.1.6. Iron (Fe)

The analysis for iron levels displayed a high multiple R^2 value of 0.98, suggesting a robust relationship with Rain and Temp. Rain exhibited a coefficient of 0.01 with a low p-value of 0.00, while Temp had a coefficient of −0.17 with a p-value of 0.00. Both Rain and Temp significantly influenced iron levels. Iron showed a very strong positive correlation with Rain (0.97) and a weak negative correlation with Temp (−0.23). Both correlations were statistically significant.

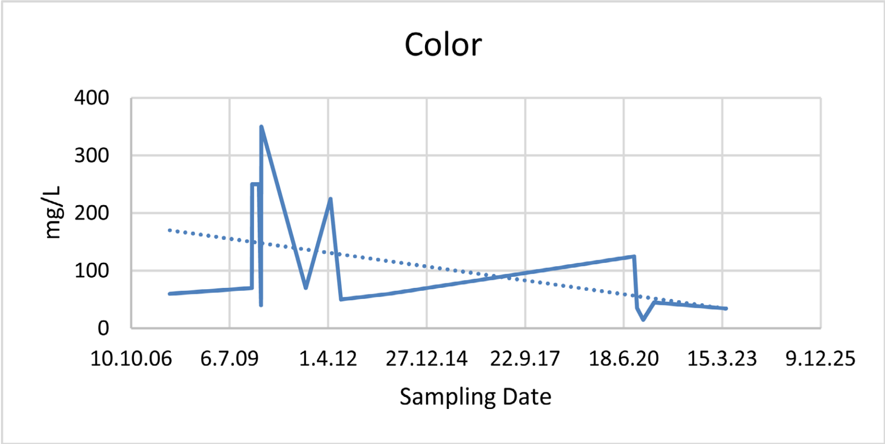

Figure 6. Trendline analysis of color.

Iron is a naturally occurring element that can be present in water sources. While there are no specific standards provided for iron in the context of the Nairobi River, elevated iron levels can have various implications for water quality and ecosystem health. The iron values provided range from 0.3 to 4.04 mg/L, with a notable outlier of 2.99 mg/L on 07/12/2023 as can be seen in Figure 7 below. Elevated iron concentrations can result from natural weathering of rocks and soil or anthropogenic activities such as industrial discharges or agricultural runoff.

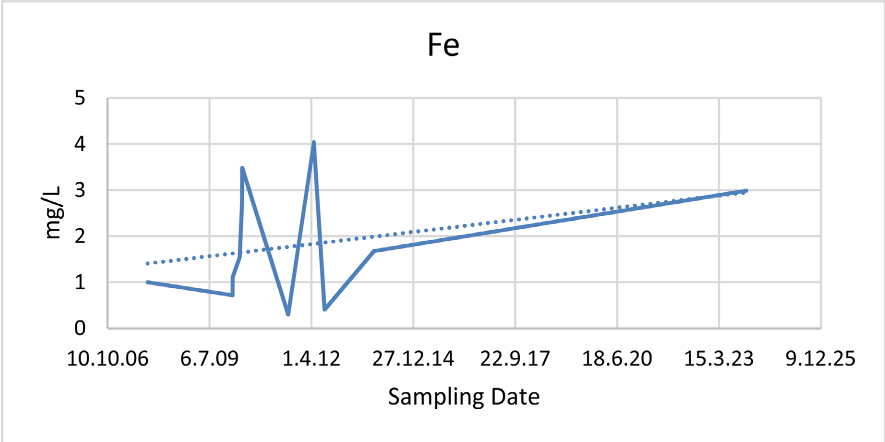

Figure 7. Trendline analysis of Iron (Fe).

4.1.7. Ammonia (NH_3)

The regression analysis for ammonia revealed a multiple R^2 value of 0.57, indicating a moderate relationship with the environmental factors. Rain displayed a coefficient of 0.05 with a p-value of 0.45, and Temp had a coefficient of −2.86 with a p-value of 0.54, suggesting that neither rainfall nor temperature had a significant impact on ammonia levels. Ammonia had a moderate positive correlation with Rain (0.58) and a strong positive correlation with Temp (0.83), but only the correlation with Temp was statistically significant.

Ammonia is a common pollutant in water bodies and can originate from various sources such as agricultural runoff, wastewater discharges, and industrial effluents. Elevated levels of ammonia can have harmful effects on aquatic organisms and overall water quality. The ammonia values provided range from 0.7 to 59.3 mg/L as shown in Figure 8 below. These concentrations vary over time and may indicate fluctuations in pollution sources or environmental conditions affecting ammonia levels.

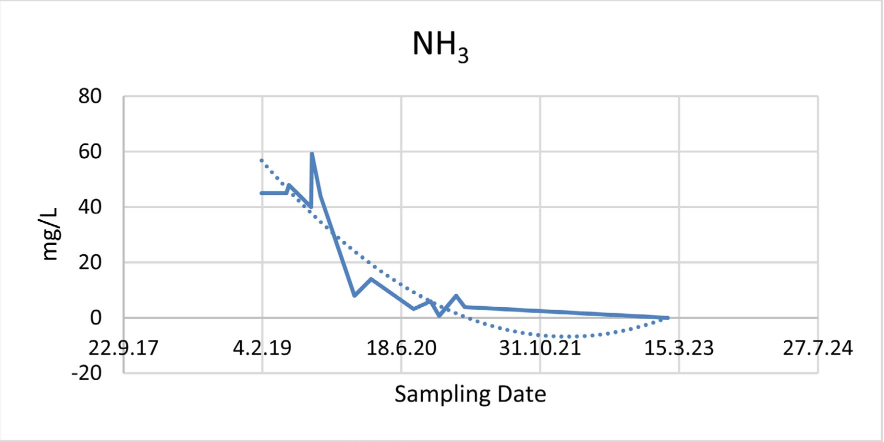

Figure 8. Trendline analysis of Ammonia.

4.1.8. Nitrate (NO_3)

For nitrate levels, the multiple R^2 value was 0.79, suggesting a substantial relationship with the explanatory variables. Rain showed a coefficient of 0.01 with a p-value of 0.11, and Temp had a coefficient of −0.22 with a p-value of 0.43, indicating that neither rainfall nor temperature significantly affected nitrate levels. Nitrate had a moderate positive correlation with Rain (0.62) and a weak negative correlation with Temp (−0.15). However, none of these correlations were statistically significant.

The NO_3 values range from 0.01 to 21 mg/L. Kenya's water quality standards for nitrate concentration depend on the designated use of the water body. Generally, nitrate levels should be kept within acceptable limits to prevent adverse effects on human health, aquatic life, and ecosystem balance. In Figure 9 below, nitrate concentrations vary over time, with some values exceeding typical standards for drinking water and aquatic life support. Elevated nitrate levels can indicate contamination from various sources such as agricultural runoff, sewage effluent, and industrial discharge.

4.1.9. pH

The regression analysis for pH yielded a remarkably high multiple R^2 value of 1.00, indicating a very strong relationship with Rain and Temperature. Rain showed a coefficient of −0.0003 with a p-value of 0.71, while Temperature had a coefficient of 0.42 with a very low p-value of 0.00. Both Rain and Temperature significantly influenced pH levels. pH exhibited a weak positive correlation with Rain (0.02) and a moderate positive correlation with Temperature (0.49). Both correlations were statistically significant.

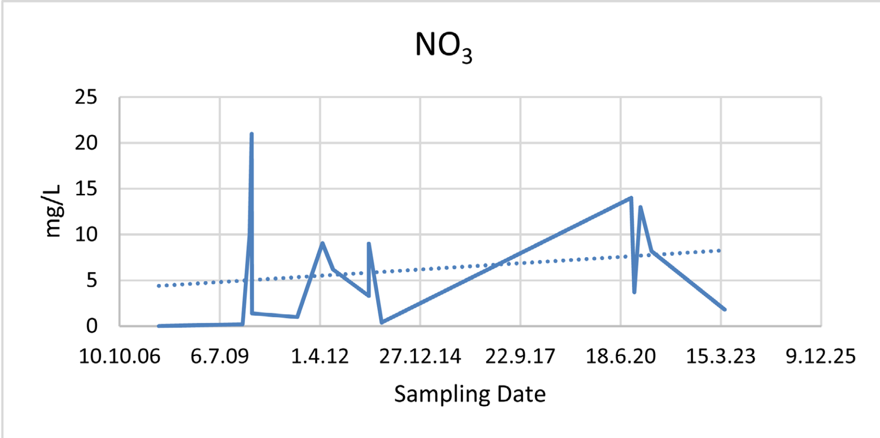

Figure 9. Trendline analysis of nitrate levels.

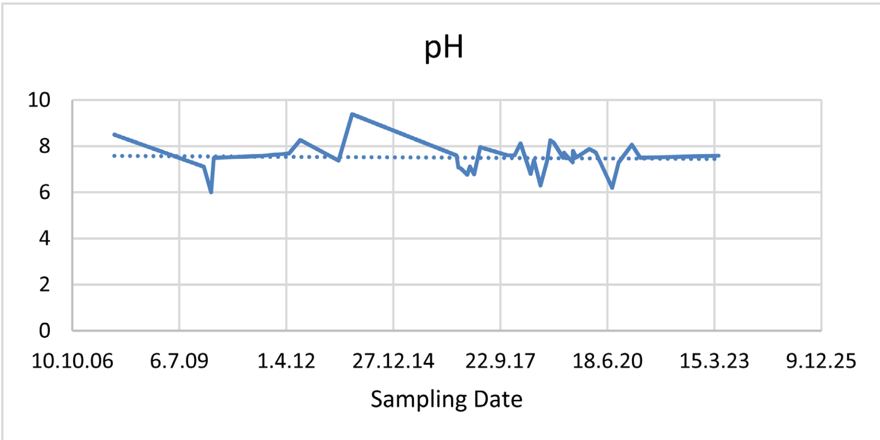

Figure 10. Trendline analysis of pH levels.

The provided pH values range from 6.2 to 9.39. Kenya's water quality standards typically recommend a pH range between 6.5 and 8.5, with variations allowed based on the specific requirements of the water body. pH levels outside of this range can indicate potential issues with water quality and ecosystem health.

As seen in Figure 10 above, pH levels fluctuate over time, with some values falling outside the recommended range. Extreme pH levels can have adverse effects on aquatic organisms, altering their behavior, growth, and reproduction. Low pH levels (acidic conditions) can be harmful to fish and other aquatic life, while high pH levels (alkaline conditions) can indicate excessive nutrient inputs or pollution.

4.1.10. Sulphate (SO_4)

The analysis for sulphate levels displayed a moderate multiple R^2 value of 0.53, indicating a moderate relationship with Rain and Temperature. Rain exhibited a coefficient of −0.03 with a p-value of 0.51, while Temperature had a coefficient of 1.95 with a p-value of 0.34, suggesting that neither rainfall nor temperature significantly affected sulphate levels. Sulphate had a weak negative correlation with Rain (−0.36) and a moderate positive correlation with Temperature (0.43). The correlation with Temperature was statistically significant.

The provided SO_4 values range from 0.2 to 40.3 mg/L. Kenya's water quality standards typically do not specify a maximum limit for sulfate concentration, as sulfate is generally considered less harmful at typical concentrations found in natural waters. However, extremely high sulfate levels can indicate contamination from industrial or agricultural sources, which may warrant further investigation and management.

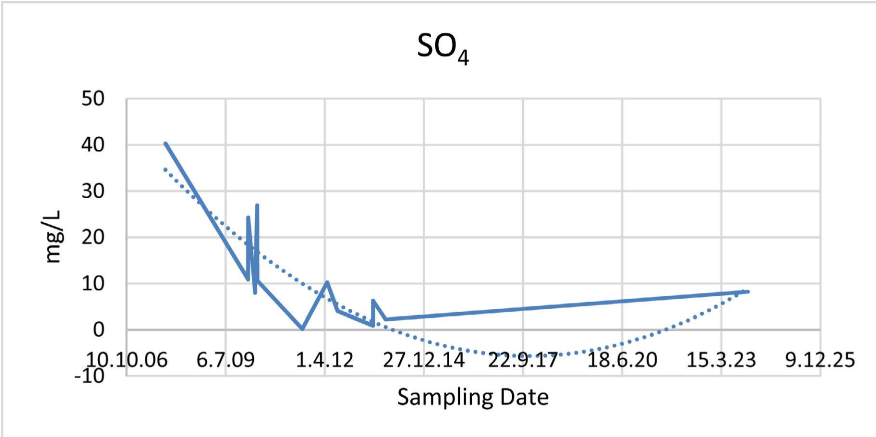

Figure 11. Trendline analysis of sulphate levels.

As we can see in **Figure 11** above, Sulfate levels vary over time, with some values being relatively low and others reaching higher concentrations. While occasional fluctuations in sulfate levels are expected, consistent or significant increases may indicate human activities contributing to sulfate pollution.

4.1.11. Total Dissolved Solids (TDS)

The regression analysis for TDS showed a high multiple R-squared value of 0.94, indicating a strong relationship with Rain and Temperature. Rain displayed a coefficient of 0.17 with a p-value of 0.19, while Temperature had a coefficient of 9.56 with a p-value of 0.20, suggesting that both Rain and Temperature significantly influenced TDS.

Pearson's Correlation Coefficients: TDS exhibited a moderate positive correlation with Rain (0.43) and a stronger positive correlation with Temperature (0.46). Both correlations were statistically significant.

The TDS values range from 116.1 to 719 mg/L as shown in **Figure 12** below. Kenya's water quality standards typically do not specify a maximum limit for TDS concentration, as TDS encompasses a wide range of dissolved ions and compounds, and the acceptable level can vary depending on the specific characteristics of the water body. However, extremely high TDS levels may indicate contamination from various sources, including industrial discharges, agricultural runoff, or natural geological processes.

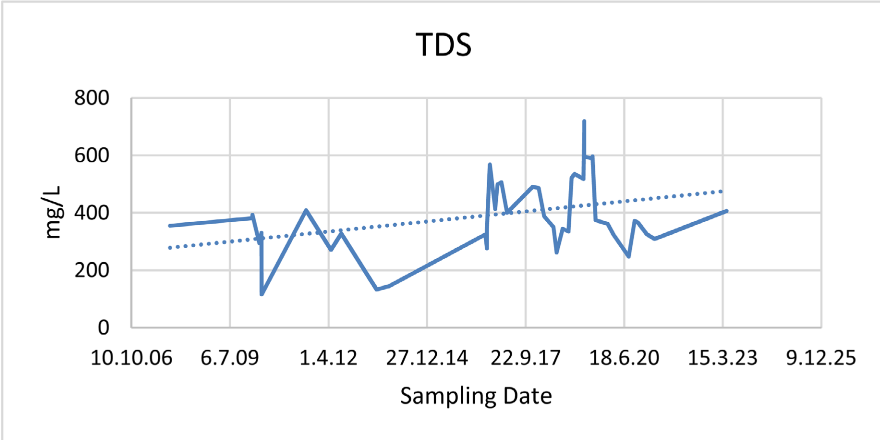

Figure 12. Trendline analysis of TDS levels.

4.1.12. Water Temperature

For water temperature, the multiple R^2 value was 0.99, suggesting an exceptionally strong relationship with Rain and Temperature. Rain exhibited a coefficient of 0.00 with a p-value of 0.41, while Temperature had a coefficient of 0.89 with a p-value of 0.01, indicating that both Rain and Temperature significantly influenced water temperature. Water temperature had a weak positive correlation with Rain (0.36) and a moderate positive correlation with Temperature (0.10), with both correlations being statistically significant. The provided temperature values range from 17.5˚C to 24.9˚C. Kenya's water quality standards typically specify that water temperatures should generally be kept below 30˚C, but specific limits may vary depending on the designated use of the water body.

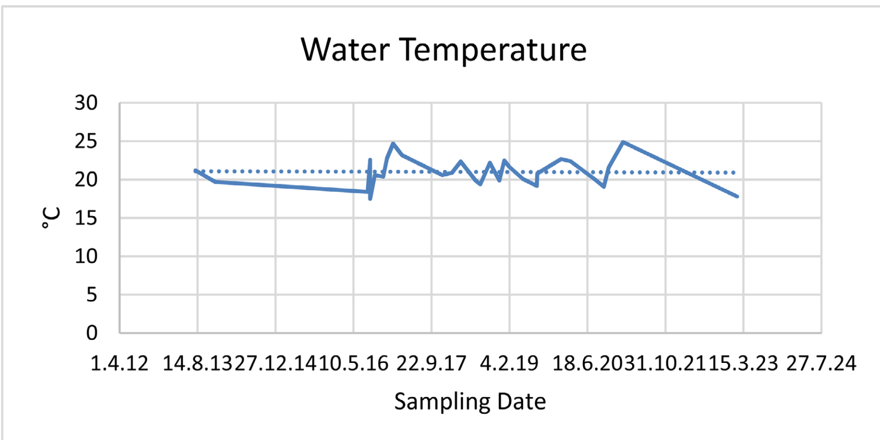

Figure 13. Trendline analysis of water temperature.

As we can see in **Figure 13** above, most of the temperature values fall within the acceptable range for supporting aquatic life and other water uses. However, it's essential to monitor temperature fluctuations over time, as significant deviations from the typical range can impact aquatic ecosystems. High temperatures can decrease the amount of dissolved oxygen in water, affecting aquatic organisms' survival and overall ecosystem health.

4.1.13. Total Suspended Solids (TSS)

The analysis for TSS revealed a moderate multiple R^2 value of 0.63, indicating a moderate relationship with Rain and Temperature. Rain displayed a coefficient of 0.08 with a p-value of 0.94, while Temperature had a coefficient of 4.18 with a p-value of 0.52, suggesting that neither rainfall nor temperature significantly affected TSS levels. TSS showed a weak positive correlation with Rain (0.02) and a weak negative correlation with Temperature (−0.26). However, none of these correlations were statistically significant.

The provided TSS values range from 10 to 250 mg/L. Kenya's water quality standards typically vary depending on the water body class, with stricter limits for higher-quality water bodies. In many cases, TSS levels are expected to be below 50 mg/L for water bodies supporting aquatic life.

As seen in Figure 14 below, most of the TSS values are within acceptable ranges, although some exceed typical standards. For instance, on 25/04/2012, the TSS value is 250 mg/L, which is higher than what is typically considered acceptable. Elevated TSS levels can cloud the water, block sunlight from reaching aquatic plants, and smother habitat for fish and other organisms. While the majority of the provided TSS values appear to meet typical standards, the instances of elevated TSS levels suggest potential sources of sediment pollution in the Nairobi River.

4.1.14. Summary

The analysis presented in Chapter 4 highlights untreated sewage as a primary contributor to water pollution in the Nairobi River.

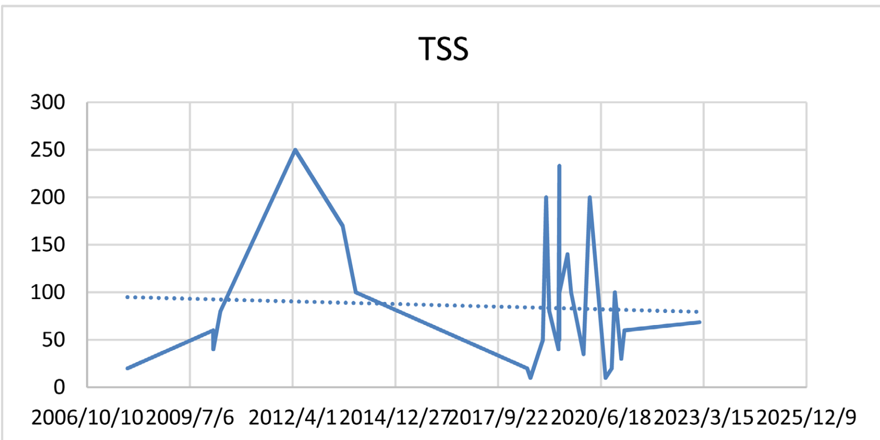

Figure 14. Trendline analysis of TSS levels.

Elevated BOD Levels: Biochemical Oxygen Demand (BOD) levels in the Nairobi River consistently exceed standard limits, indicating high organic pollution. BOD is a key indicator of organic matter decomposition, often originating from untreated sewage discharge into water bodies.

High COD Levels: Chemical Oxygen Demand (COD) values also surpass typical standards, indicating significant organic pollution. COD measures the amount of oxygen required to chemically oxidize organic compounds, commonly found in untreated sewage effluents.

Impact on Ecosystem Health: High BOD and COD levels lead to oxygen depletion in water, endangering aquatic life and compromising ecosystem health. Aquatic organisms require dissolved oxygen to survive, and excessive organic pollution from untreated sewage can lead to hypoxic or anoxic conditions, harming biodiversity.

Evidence of Pollution from other Water Quality Parameters: Other water quality parameters such as ammonia (NH4) and total suspended solids (TSS) also indicate pollution sources consistent with untreated sewage. Elevated NH4 levels are commonly associated with sewage discharge, while high TSS levels suggest the presence of suspended solids like sewage particulates.

Continuous Pollution Patterns: The chapter's analysis unveils a recurring pattern of water pollution in the Nairobi River, indicative of inadequate sewerline connectivity. Water quality parameters consistently exceeding acceptable limits suggest a persistent influx of contaminants, primarily from untreated sewage, into the river. Such continuous pollution patterns strongly imply insufficient sewerline connectivity, allowing untreated sewage to enter water bodies unchecked. The lack of proper infrastructure to channel sewage appropriately leads to direct contamination of the Nairobi River, jeopardizing ecosystem health and public well-being. Addressing this issue necessitates urgent action to enhance sewerline connectivity, ensuring effective sewage management and safeguarding water quality in the Nairobi River and its surrounding areas.

4.2. Meteorological Data

4.2.1. Observed Annual Average Precipitation

The positive trend in rainfall shown in **Figure 15** below aligns with projections of climate change, which anticipate an increase in precipitation in certain regions due to factors such as increased evaporation rates, changes in atmospheric circulation patterns, and more frequent extreme weather events. However, the variability in the model and the limited *R^2 value* suggest that while there may be a trend, other factors beyond climate change could also be influencing rainfall patterns.

4.2.2. Observed Annual Average Mean Surface Temperature

The slight positive trend seen in **Figure 15** below in temperature is also consistent with the broader expectation of global warming associated with climate change. While the trend is not as pronounced as that for rainfall, the overall increase in temperature is in line with predictions of rising global temperatures due to the accumulation of greenhouse gases in the atmosphere.

4.2.3. Summary

The combined impact of temperature and rainfall as demonstrated by the R^2

values shows the degree to which meteorological patterns influence the water quality of the Nairobi River. As we can observe from Figure 16 below, over 90% of changes in EC, Fe, TDS and water temperature can be explained by changing weather patterns. For BOD, Chloride, Color and Nitrate levels, that's over 80%. It is therefore easy to see that changing weather patterns do have a direct impact.

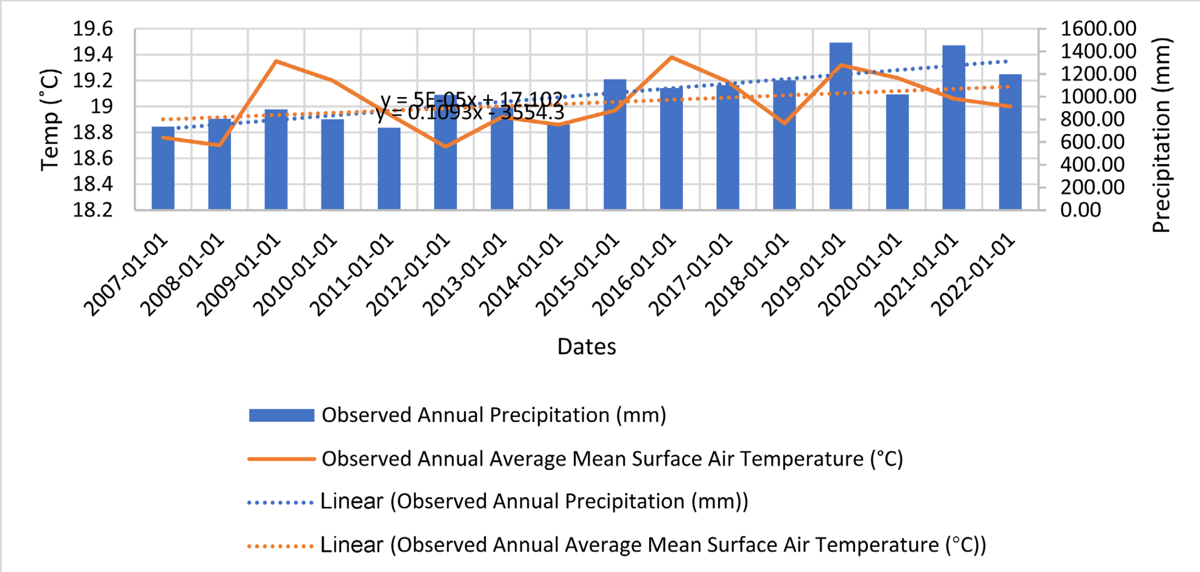

Figure 15. Climate data for Nairobi ("World Bank Climate Change Knowledge Portal," n.d.)

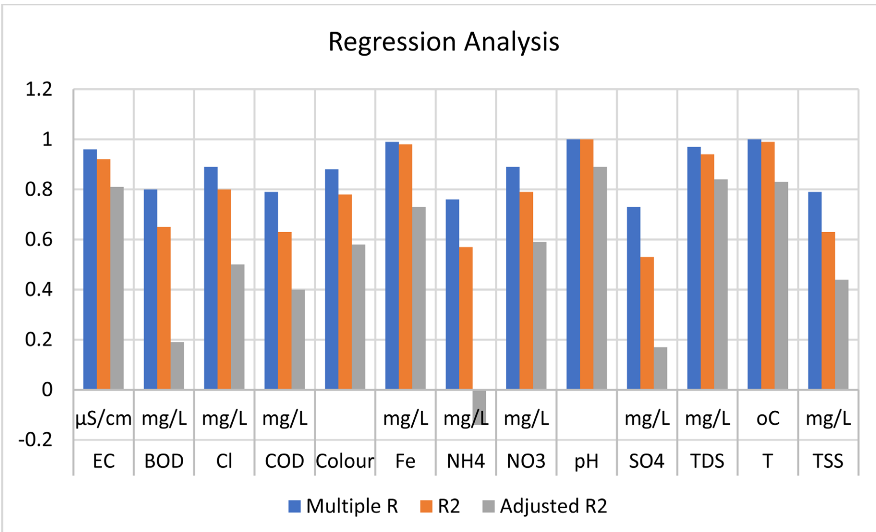

Figure 16. The collective ımpact of temperature and rainfall on water quality parameters.

Increase in Precipitation: Observed trends indicate a positive trend in annual average precipitation, aligning with projections of climate change. Increased precipitation can lead to more frequent and intense rainfall events, which, in turn, can contribute to higher levels of pollution in the Nairobi River through stormwater runoff and sewage overflow.

Rising Temperatures: There is also a slight positive trend in observed annual average mean surface temperature, consistent with global warming associated with climate change. Elevated temperatures can influence the hydrological cycle, potentially intensifying rainfall patterns and altering water quality dynamics in the Nairobi River.

5. Discussion

Water quality is influenced by a multitude of factors, including rainfall, temperature, runoff, and various environmental parameters. Understanding the interactions between these factors is crucial for effective water resource management and mitigating potential risks such as floods and degradation of water quality. In this comprehensive discussion, we will explore the intricate relationships between these parameters based on the provided data. Figure 17 below provides a quick view of the varying degrees of interaction based on Pearson's Correlation Analysis.

5.1. Impact of Rainfall on Water Quality

Rainfall plays a significant role in shaping water quality parameters. The data analysis reveals varying impacts of rainfall on different water quality indicators. For instance, while electroconductivity (EC) showed a strong relationship with explanatory variables, neither rainfall nor temperature significantly impacted it. Conversely, parameters like chloride (Cl) and iron (Fe) exhibited substantial relationships with rainfall, with both showing statistically significant positive correlations. This suggests that certain ions and metals may be mobilized and transported by rainfall, influencing water quality.

Recent research highlights the critical impact of heavy rainfall events on water quality, underscoring the need for comprehensive analysis and mitigation strategies. Heavy rainfall can trigger the runoff of significant quantities of dissolved

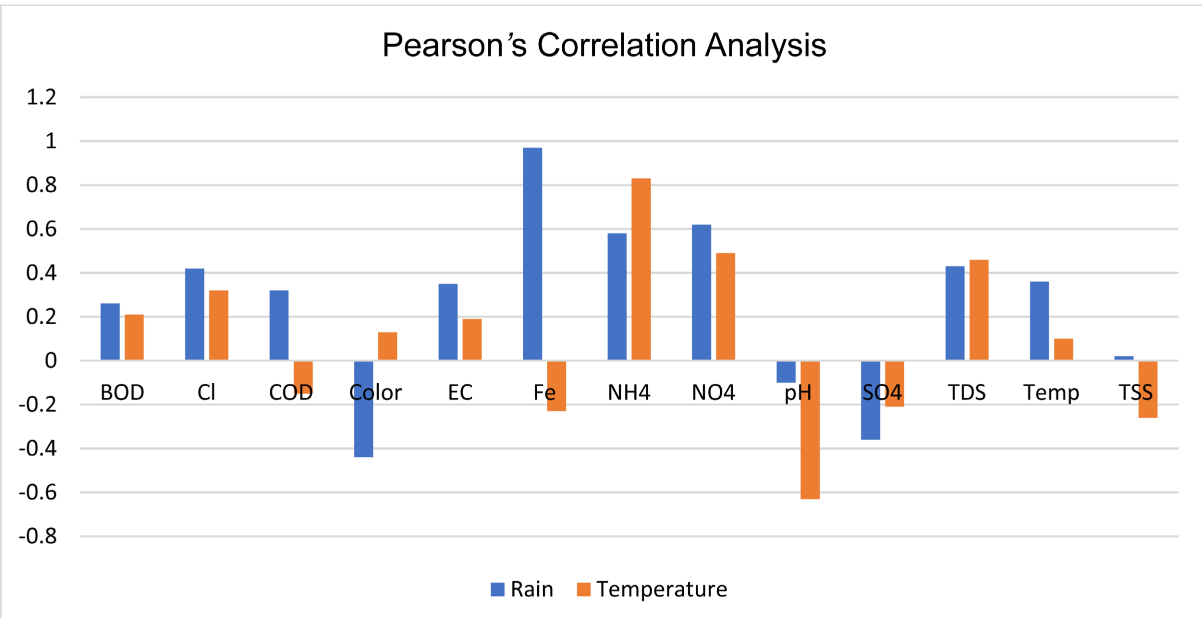

Figure 17. The Correlation between temperature, rainfall and the different water quality parameters.

and particulate matter into surface water sources, posing challenges for drinking water treatment processes. This runoff can lead to membrane fouling, increased chemical demands, and the formation of disinfection by-products (DBPs), including trihalomethanes (THM) and haloacetic acids (HAA), after disinfection (Delpla et al., 2023).

Furthermore, changes in precipitation patterns, including variations in timing, intensity, and duration, can detrimentally affect water quality. Intense rainstorms and increased precipitation contribute to flooding, which transports large volumes of water and contaminants into water bodies. Such flooding events can overwhelm stormwater, combined sewer, and wastewater systems, resulting in the direct discharge of untreated pollutants into waterways (Delpla et al., 2023).

The projected impact of climate change on precipitation patterns further exacerbates concerns regarding water quality. Studies warn that intensified precipitation cycles could lead to increased nitrogen runoff into waterways, potentially nearing 20 percent by 2100. This excess nutrient loading can induce eutrophication, characterized by toxic algal blooms and hypoxic dead zones, posing significant risks to human health, aquatic ecosystems, and the economy (Smith, 2017).

Empirical studies examining seasonal variations in water quality reveal distinct patterns associated with rainfall dynamics. Research indicates that water quality tends to deteriorate during the rainy season compared to the dry season, with significant fluctuations observed in key parameters such as dissolved oxygen (DO), nitrate nitrogen (NO_3^--N), ammonia nitrogen (NH_4^+-N), total suspended solids (TSS), and total phosphorus (TP). While DO concentrations may decline during heavy rainfall, NO_3^--N concentrations often decrease, albeit to a lesser extent in commercial lakes compared to park lakes. Conversely, NH_4^+-N, TSS, and TP concentrations typically increase following rainfall events (Jia et al., 2021).

Moreover, flash flooding events can result in notable changes in water quality parameters, including dissolved organic carbon (DOC) and various forms of phosphorus. Higher concentrations of certain ions and nutrients, such as electrical conductivity (EC), magnesium (Mg^{2+}), bicarbonate (HCO_3^-), chloride (Cl-), nitrate nitrogen (NO_3^--N), and total nitrogen (TN), are often observed during drought periods compared to average values. However, increased water retention in areas with a high degree of naturalness can mitigate the concentration of certain pollutants, such as ammonia nitrogen (NH_4^+-N), DOC, and phosphorus forms (Puczko & Jekatierynczuk-Rudczyk, 2020).

Furthermore, research underscores the strong correlation between antecedent rainfall and microbiological contamination of water supplies, particularly in untreated shallow groundwater sources. Intense precipitation events and flooding can transport pathogens, increasing the risk of gastrointestinal illnesses among communities reliant on untreated groundwater, such as wells (Nijhawan & Howard, 2022).

The multifaceted impacts of rainfall on water quality have therefore been noted multiple times, emphasizing the importance of proactive measures to mitigate adverse effects. Understanding the complex interactions between rainfall dynamics and water quality parameters is essential for effective water resource management and the development of resilient infrastructure and policies to safeguard public health and environmental integrity (Tian et al., 2022).

5.2. Impact of Temperature on Water Quality Compared to Rainfall

Temperature also exerts a notable influence on water quality parameters. The data indicates that temperature has a more significant impact on certain parameters compared to rainfall. For example, pH levels exhibited a remarkably strong relationship with both rainfall and temperature, with statistically significant correlations. This suggests that temperature variations can directly influence the acidity or alkalinity of water bodies, impacting aquatic ecosystems and overall water quality. Additionally, parameters like ammonia (NH_4) showed a strong positive correlation with temperature, indicating potential temperature-driven changes in nutrient dynamics and microbial activity, which can affect water quality.

Temperature plays a critical role in shaping water quality parameters, exerting a significant influence on aquatic ecosystems and human health. Several studies have emphasized the intricate relationship between temperature and water quality indicators, highlighting the importance of understanding these dynamics in the context of climate change (Osman et al., 2024; Powers et al., 2023; Surface Water: The Importance of the Water Temperature, 2024; Water Science School, 2024).

The relationship between temperature and rainfall and their impact on water usage patterns have been extensively studied across various regions. Research conducted in The Gambia, Mozambique, Pakistan, and Kenya revealed that higher temperatures were associated with decreased utilization of basic drinking water (BDW) (Buchwald et al., 2022). Additionally, measurements collected in rural Kenya demonstrated that heavy precipitation did not necessarily increase E. coli levels among respondents who treated their water, suggesting the efficacy of water treatment in mitigating the effects of rainfall on water quality (Powers et al., 2023).

Temperature influences a myriad of biological and chemical processes in water bodies, including the maximum dissolved oxygen concentration, photosynthesis of aquatic plants, metabolic rates of organisms, and sensitivity to pollution and disease (Water Science School, 2024; "Water Temperature", 2016). As water temperature increases, conductivity also tends to rise, affecting the solubility of gases like oxygen and influencing chemical reactions (O'Donnell, 2022). Moreover, increasing water temperatures have been linked to changes in nutrient concentrations, with studies showing a decrease in dissolved oxygen concentration and an increase in ammonia, nitrate, total nitrogen, chemical oxygen demand (COD), and phosphate levels (Wilson, Michieka, & Mwendwa, 2021).

The implications of rising temperatures on water quality extend beyond local ecosystems. Climate change projections indicate that future increases in air temperature and variations in precipitation patterns will have cascading effects on water quality in the United States and other regions (Paul et al., 2019; Rajesh & Rehana, 2022). Therefore, understanding the complex interplay between temperature, rainfall, and water quality is crucial for developing effective management strategies to mitigate the adverse impacts of climate change on aquatic environments and safeguard human health.

5.3. Impact of Runoff on Water Quality Based on Rainfall Patterns

Runoff, influenced by rainfall intensity and duration, is a critical pathway for transporting pollutants and contaminants into water bodies. The data analysis highlights the complex relationship between runoff and water quality. Parameters like total dissolved solids (TDS) and total suspended solids (TSS) showed moderate relationships with runoff, albeit without statistically significant correlations. However, the impact of runoff on specific water quality indicators may vary depending on local hydrological conditions, land use patterns, and the presence of pollutant sources. Further research and localized studies are warranted to comprehensively understand the implications of runoff on water quality.

Runoff, influenced by rainfall intensity and duration, serves as a critical pathway for transporting pollutants and contaminants into water bodies, posing significant threats to water quality and ecosystem health (US EPA, 2015; Yang et al., 2021). As rainfall events occur, runoff picks up a myriad of pollutants including fertilizers, oil, pesticides, dirt, and bacteria, among others, before discharging them untreated into streams, rivers, lakes, and oceans (Peacock, 2019).

Urbanization exacerbates the problem by altering natural drainage patterns, leading to increased volumes of runoff laden with pollutants (How Stormwater Affects Your Rivers, 2024). Polluted storm runoff not only deteriorates the water quality of receiving water bodies but also poses risks of flooding and damages to infrastructure and properties (How Stormwater Affects Your Rivers, 2024). Moreover, urban runoff can overwhelm local infrastructure, leading to sewage overflows and further contamination of waterways (How Stormwater Affects Your Rivers, 2024).

The relationship between rainfall characteristics and runoff-induced pollution is complex and multifaceted. Studies have shown that total rainfall preceding sampling is positively correlated with various water quality parameters such as turbidity, total suspended solids (TSS), biochemical oxygen demand (BOD), total phosphorus, and fecal coliform bacteria concentrations (Mallin, Johnson, & Ensign, 2009). Additionally, the effects of natural variables, including precipitation and flow rate, on water quality parameters have been investigated, revealing trends where concentrations of certain constituents decrease with increasing precipitation and flow rate (Pourfallah Koushali, Mastouri, & Khaledian, 2021).

Understanding the dynamics of runoff-induced pollution requires a comprehensive assessment of local hydrological conditions, land use patterns, and pollutant sources. This necessitates the implementation of targeted management strategies, including better sedimentation controls and stormwater management practices, to mitigate the adverse impacts of polluted runoff on water quality and aquatic ecosystems (Mallin, Johnson, & Ensign, 2009). Moreover, proactive measures such as green infrastructure solutions and improved land use planning are essential for minimizing runoff and preserving water quality in urban areas (Puczko & Jekatierynczuk-Rudczyk, 2020).

6. Conclusion and Recommendations

Water quality assessment parameters encompass a wide array of physical, chemical, and biological factors, with each category providing essential insights into the condition of water. Their importance is underscored by the multifaceted interplay between meteorological data and these parameters, which plays a crucial role in assessing the environmental health of a city. As we have explored in this study, the interaction between weather patterns and water quality parameters offers valuable insights into the environmental health of cities. The influence of climate variables such as rainfall and temperature on water quality parameters highlights the dynamic nature of this interplay.

In the context of a case study on Nairobi City's environmental health, it becomes evident that urbanization, flooding, industrial activities, solid waste mismanagement, and pharmaceutical contamination contribute to the multifaceted challenges faced by the city. These challenges are not unique to Nairobi but are part of a global concern regarding water pollution and its diverse origins. Addressing these challenges requires a holistic and coordinated effort involving urban planning, environmental policy, sustainable resource management, and targeted interventions to improve water quality and restore the city to its former glory. Nairobi's commitment to sustainability, as reflected in policies to reduce pollution from vehicular emissions and promote non-motorized transport, is a positive step. However, these efforts should be complemented with measures to mitigate the impact of flooding, improve solid waste management, and address pharmaceutical contamination.

Recommendations

Annual Publications on Nairobi River Water Quality. The establishment of a structured framework for the regular publication of annual reports on the water quality of the Nairobi River. These reports should encompass comprehensive analyses of water quality parameters, trends over time, and their implications for environmental health and human well-being. Relevant stakeholders, including government agencies, environmental organizations, research institutions, and community groups, can be engaged in the development and dissemination of these publication. It is also important to ensure that the reports are accessible to the public through various channels, such as government websites, libraries, and community centers, to raise awareness and promote transparency regarding the state of Nairobi River's water quality.

Online Accessibility of Water Quality Data. The implementation of an online platform or database to host and disseminate water quality data related to the Nairobi River. This is to help streamline the process for accessing this data to minimize any preexistent bureaucratic hurdles and facilitate ease of use for researchers, policymakers, and the general public. The online platform should provide comprehensive access to historical and real-time water quality data, along with relevant metadata and documentation to support data interpretation. It may also be necessary to foster collaboration with academic institutions, technology partners, and government agencies to develop and maintain the online platform, ensuring its reliability, security, and user-friendliness. Awareness and utilization of the online platform can be promoted through targeted outreach efforts, training workshops, and capacity-building initiatives for stakeholders interested in water quality research and management.

Hydrological Modeling. Develop hydrological models to forecast future scenarios and assess the impacts of climate change on water quality in the Nairobi River. Utilize these models to simulate various climate scenarios, including changes in rainfall patterns, temperature variations, and land use dynamics. Empower policymakers with actionable insights to make informed decisions and implement adaptive management strategies to mitigate potential risks to water quality. Optimize resource allocation by identifying vulnerable areas and prioritizing interventions to safeguard water resources and enhance resilience to climate change.

Spatial Analysis and GIS Mapping. Utilize spatial analysis and GIS mapping techniques to identify pollution hotspots and assess spatial patterns of water quality parameters in the Nairobi River basin. Integrate data from various sources, including remote sensing, field surveys, and water quality monitoring stations, to generate comprehensive spatial datasets. Prioritize conservation efforts and target management interventions effectively by identifying areas of high pollution risk and environmental degradation. Enhance stakeholder engagement and collaboration by visualizing spatial patterns of pollution and sharing geospatial information through interactive mapping platforms. Foster interdisciplinary research and decision-making processes by integrating spatial analysis tools into water quality management strategies and urban planning initiatives.

Cross-disciplinary research collaborations, particularly between meteorological and environmental protection agencies, are essential for addressing the multifaceted challenges of water quality management in Nairobi City. By fostering collaboration between scientists, policymakers, community members, and other stakeholders, interdisciplinary research teams can develop comprehensive solutions that tackle complex environmental issues holistically.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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