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Influence of climate change on water quality in Terra Nova River basin, Pernambuco, Brazil

Influência das mudanças climáticas na qualidade da água na bacia hidrográfica do Terra Nova, Pernambuco

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Climate changes tend to intensify water scarcity in arid and semi-arid regions, making water management in these areas more challenging, directly influencing hydrological dynamics, causing impacts on ecosystems and society. The Terra Nova River basin is crucial for the water security of the semi-arid region of Pernambuco, especially after the construction of the São Francisco River Integration Project (PISF), which saw the construction of six reservoirs to supply water for human consumption, agricultural, and industrial activities. Therefore, this study aims to analyzes the impacts of climate changes on water quality in the Terra Nova River basin in Pernambuco, using long-term data from the Hydrological Response Unit System for Pernambuco (SUPer). The ARIMA (Autoregressive Integrated Moving Averages) model is employed to predict water quality parameters in climate change scenarios, using data from the Intergovernmental Panel on Climate Change (IPCC) and the Oswaldo Cruz Foundation (Fiocruz). The variables include air temperature, precipitation, dissolved oxygen, nitrogen, and phosphorus. Simulated scenarios were compared with CONAMA No. 357/2005 limits, revealing potential decreases in dissolved oxygen and phosphorus concentrations, alongside an increase in nitrogen concentrations. Irregular rainfall rates, high air temperatures, and evapotranspiration, combined with conflicts by water resources, may exacerbate water access issues in the semi-arid region, worsening the water crisis and threatening water security.
Keywords: hydrological modeling, environmental monitoring, semi-arid climate.

As mudanças climáticas tendem a intensificar a escassez de água em regiões áridas e semiáridas, tornando a gestão da água nessas áreas mais desafiadora, influenciando diretamente a dinâmica hidrológica, causando impactos nos ecossistemas e na sociedade. A bacia hidrográfica do rio Terra Nova possui importância para a segurança hídrica do semiárido pernambucano, visto que após a construção do Projeto de Integração do Rio São Francisco (PISF), seis reservatórios foram construídos para oferta de água para consumo humano, atividades agrícolas e industriais. Logo, o presente estudo visa analisar o impacto das mudanças climáticas na qualidade da água na bacia do rio Terra Nova, em Pernambuco, utilizando dados históricos do Sistema de Unidade de Resposta Hidrológica de Pernambuco (SUPer). O modelo ARIMA (Autoregressive Integrated Moving Averages) é empregado para prever parâmetros de qualidade da água em cenários de mudanças climáticas, utilizando dados do Painel Intergovernamental sobre Mudanças Climáticas (IPCC) e da Fundação Oswaldo Cruz (Fiocruz). As variáveis consideradas incluem temperatura, precipitação, oxigênio dissolvido, nitrogênio e fósforo. Os cenários simulados foram comparados com os limites do CONAMA nº 357/2005, revelando potenciais reduções nas concentrações de oxigênio dissolvido e fósforo, juntamente com um aumento nas concentrações de nitrogênio. Chuvas irregulares, altas temperaturas e evapotranspiração, combinadas com conflitos por recursos hídricos, podem agravar os problemas de acesso à água no semiárido, agravando a crise hídrica e ameaçando a segurança hídrica.
Palavras-chave: modelagem hidrológica, monitoramento ambiental, clima semiárido.

1. INTRODUCTION

The latest report from the Intergovernmental Panel on Climate Change (IPCC) [1] highlights that the last four decades have been warmer than all previous decades since 1850. The IPCC defines climate changes as "changes in the climate over time due to natural variability and/or resulting from human actions." Projected impacts of climate changes are expected to get worse water scarcity in arid and semi-arid regions.

According to the National Water and Basic Sanitation Agency (ANA) [2], climate change is a complex and global challenge. Recent climate changes have influenced temperature and rainfall patterns, impacted hydrological processes and compromised water resources' availability and quality. This is because the effect of climate change exacerbate the vulnerability of ecosystems and, consequently, the population, given that the production and supply of food and energy contribute to the increased in greenhouse gas emissions. [3, 4].

The Northeast region of Brazil is particularly vulnerable to climate changes and requires more studies on natural and anthropogenic climate changes [4]. Projections from the Brazilian Panel on Climate Change (PBMC) [5] indicate that Brazil is expected to become at least 3ºC warmer. For the Northeast region, an increase of 0.5 to 1°C in air temperature by 2040 and 1.5 to 2.5°C for the period 2041-2070 is anticipated.

Projections for the Brazilian Northeast suggest a decrease of 10% to 20% in precipitation until 2040 and a further decrease of 25% to 35% in the period 2041-2070 [5]. In regions like the Northeast, especially the semi-arid region, precipitation is a crucial variable influencing local climate conditions and the hydrological system. Changes in precipitation significantly impact ecosystems, human activities, and may cause more intense and frequent extreme events. The State of Pernambuco has around 70% of the total area with semi-arid climates and has a history of natural disasters linked to prolonged droughts. Between 1991 and 2010, 5,227,293 people in Pernambuco were affected by droughts [6].

At the state level, the Pernambuco Water and Climate Agency (APAC) plays a pivotal role in implementing the State Water Resources Policy (PERH) for Pernambuco. APAC has spearheaded initiatives and research, leveraging technological innovations to enhance water resource management, exemplified using hydrological models. Furthermore, the state harnesses hydrological models as a crucial tool for environmental analysis, offering advantages in predicting and validating scenarios—whether realistic or hypothetical. This approach brings about cost-efficiency and time savings, particularly in regions where observations are scant or inaccessible, allowing for a comprehensive understanding of both physical and anthropogenic changes in river basins [7].

In the state of Pernambuco, a significant development is the implementation and operation of the Hydrological Response Unit System for Pernambuco (SUPer), functioning as a vital tool for assessing river basins. Originating from the SWAT (Soil Water Assessment Tool) hydrological model, SUPer stands out as an advanced system for modeling both water quantity and quality. Its capabilities encompass the comprehensive evaluation of the effects of soil management, water pollution, and climate change on the quantity and quality of water in the state's rivers and reservoirs [8]. In this context, the use of modeling systems, whether static or not, positively influences water analyzes in the region, as well as in different river basins.

The Terra Nova River basin, located in the semi-arid region of Pernambuco, is part of the main tributaries of the São Francisco River. It uses the waters of the North Axis of the São Francisco Integration Project (PISF), which has 7 delivery portals, 6 of which belong to the Terra Nova basin and are crucial for farmers and riverside families in the region. The PISF brings expectations of improved water security to the region, and environmental impact assessment and monitoring are essential [9].

Given the integrative role of the PISF, research on environmental monitoring and analysis becomes critical, especially considering the projected impacts of climate change. Developing studies on the effects of climate change on water quality contributes to building a solid information base focused on mitigating the effects of climate change on water resources, as well as protecting public health and fostering the socioeconomic development of the population. Understanding how climate projections affect the supply-demand balance for quality water is fundamental for planning and managing water resources to implement more effective strategies, thereby minimizing potential crises. Therefore, this study aims to analyze how climate change scenarios may impact water quality in the Terra Nova River Basin.

2. MATERIALS AND METHODS

2.1 Characterization of the study area

The Terra Nova River Basin is situated in the Sertão of Pernambuco, with an area of 4,887.71 km², corresponding to 4.97% of the state's area (Figure 1). The drainage area of the basin encompasses 12 municipalities of which 3 are fully inserted in the basin (Salgueiro, Cedro and Terra Nova), 2 are based in the basin (Verdejante and Serrita) and 7 are partially inserted (Belém do São Francisco, Parnamirim, Cabrobó, Mirandiba Carnaubeira da Penha, Orocó, São José do Belmonte).

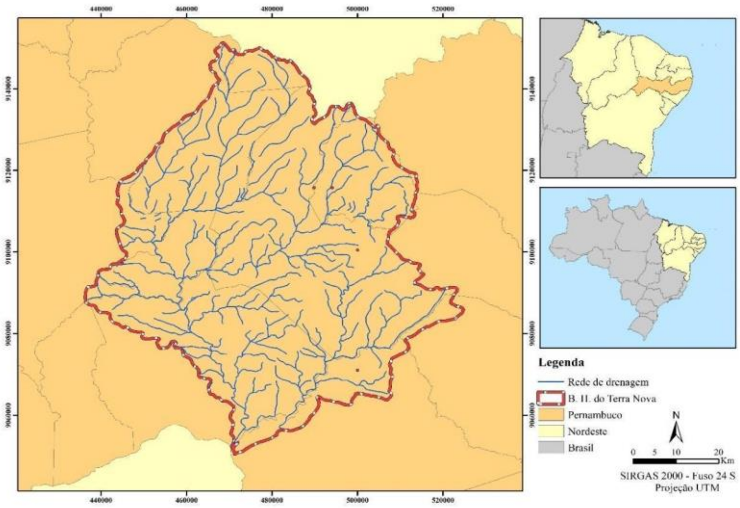

Figure 1. Location of the Terra Nova River Basin, Pernambuco.

Located in the northeastern semi-arid region, the watershed area presents a negative water balance due to average annual precipitation between 400 and 600 mm, average annual temperatures between 23°C and 29°C, and evaporation of 2000 mm/year. The rainy season is concentrated between January and April, while the dry season experiences minimal or no rainfall recorded from May to December [10].

The Intertropical Convergence Zone (ITCZ) is one of the main atmospheric systems influencing the semi-arid region of Pernambuco. The ITCZ is a belt of low pressure encircling the Earth near the equator, where the trade winds from the northern and southern hemispheres converge, causing intense convection and precipitation [10].

In the semi-arid region of Pernambuco, the ITCZ is active from December to May, bringing the highest rainfall rates and torrential rains, with peak precipitation occurring in March and April. These rains are essential for the region's water recharge, significantly contributing to water availability throughout the rest of the year [10].

The predominant soils in the Terra Nova basin are neosols, luvisols, and planosols [11]. The vegetation in the area consists of hyperxerophilous caatinga, featuring low trees, shrubs, and cacti. Concerning land use and occupation, the municipalities surrounding the basin predominantly engage in agriculture, with diverse crops associated with native vegetation, as well as livestock activities, emphasizing cattle farming, goat farming, and poultry farming [10].

2.2 Climate change scenarios

2.1.1 Data collected

Data was sourced from the National Oceanic and Atmospheric Administration (NOAA), covering the period from 1963 to December 2022. The entire historical series available in SUPer was utilized for predicting water quality variables in this study, spanning from 1963 to March 2021, resulting in a 58-year series.

The selected variables included temperature (Equation 1) and precipitation (Equation 2), along with the parameters of dissolved oxygen (Equation 3), nitrogen (Equation 4), and phosphorus (Equation 5). The equations used for estimation are as follows:

$$T_{hr} = T_{av} + \frac{(T_{mx} - T_{mn})}{2} . cos\ cos\ (0.2618.(hr - 15)) \quad (1)$$

Where, T_{hr}it is the air temperature during the hrday (°C), T_{av}it is the average temperature during the day (°C), T_{mx}it is the maximum daily temperature (°C) and T_{mn}It is the minimum daily temperature (°C).

$$R_{day} = \mu_{mon} + 2.\sigma_{mon}.(\frac{\left[\left(SND_{day} - \frac{g_{mon}}{6}\right).\left(\frac{g_{mon}}{6}\right) + 1\right]^3 - 1}{g_{mon}}) \quad (2)$$

In which R_{day}consists of the amount of rain on a given day (mm), $\mu_{mon}$is the average daily precipitation (mm) for the month, $\sigma_{mon}$is the standard deviation of daily precipitation (mm) for the month, $SND_{day}$is the normal standard deviation calculated for the day and $g_{mon}$is the asymmetric coefficient for daily precipitation in the month.

$$Ox_{surf} = Ox_{sat} - K_1.cbod_{surq}.\frac{t_{ov}}{24} \quad (3)$$

Where, $Ox_{surf}$is the concentration of dissolved oxygen in the surface flow (mg L^{-1}), $Ox_{sat}$is the saturation oxygen concentration (mg L^{-1}), $K_1$is the CBOD deoxygenation rate (day^1), $cbod_{surq}$is the concentration of CBOD in the flow surface (mg L^{-1}) and $t_{ov}$is the surface runoff concentration time (hr).

$$\Delta orgNstr = (\alpha 1 . \rho a . algae - \beta N, 3 . orgNstr - \sigma 4 . orgNstr).TT \quad (4)$$

Where, $\Delta orgNstr$ is the nitrogen concentration (mg L^{-1}), $\alpha 1$ is the fraction of algal biomass that is nitrogen (mg N mg algal biomass), ρa is the death or local algae respiration rate (day or hr), $algae$ is the concentration of algal biomass at the beginning of the day (mg algal L^{-1}), βN,3 is the coefficient of the nitrogen hydrolysis rate for ammonia (day or hr), $orgNstr$ is the concentration of organic nitrogen at the beginning of the day (mg L^{-1}), $\sigma 4$ is the coefficient of the rate for nitrogen settling (day or hr), and TT is the flow residence time in water (day or hr).

$$\Delta orgPstr = (\alpha 2 . \rho a . algae - \beta P, 4 . orgPstr . \sigma 5 . orgPstr) . TT \quad (5)$$

In which, $\Delta orgPstr$ is the phosphorus concentration (mg L^{-1}), $\alpha 2$ is the fraction of algal biomass that is phosphorus (mg P mg algal biomass), ρa is the local respiration or death rate of algae (day or hr), $algae$ is the concentration of algal biomass at the beginning of the day (mg algal L^{-1}), βP,4 is the coefficient of the rate of organic phosphorus mineralization (day or hr), $orgPstr$ is the concentration of phosphorus at the beginning of the day (mg L^{-1}), $\sigma 5$ is the coefficient of the rate for settling of organic phosphorus (day or hr), and TT is the flow residence time in water (day or hr).

2.1.2 Simulation of Climate change scenarios

SUPer also facilitates the analysis of the historical series of the variables through the Climate Sensitivity/Variability Analysis tool. This section allows the adjustment of precipitation and/or temperature values for the selected river basin. Precipitation can be modified as a percentage, while temperature can be adjusted using values in degrees Celsius (°C). For this study, climate change scenarios from the literature were employed to assess their potential impacts on water quality parameters, specifically dissolved oxygen, nitrogen, and phosphorus. The utilized scenarios are presented in Table 1.

Table 1. Climate change scenarios used to analyze the interference of climate change in the historical series of parameters

SOURCE	Temperature increase	Precipitation Reduction
IPCC (Scenario 1 - C1)	+ 3°C	- 22%
FIOCRUZ (Scenario 2 - C2)	+ 3°C	- 39%

Source: IPCC (2022) [1], Fundação Oswaldo Cruz (2022) [12].

2.1.3 Proposal of future water quality scenarios

The prediction of water quality parameters serves as a vital tool for planning and decision-making in water resources [13]. In this study, to fulfill this objective, the ARIMA (Autoregressive Integrated Moving Averages) methodology was employed [14], recognized for its application in modeling and forecasting time series, particularly in the analysis of hydrological variables [15].

The ARIMA (p, d, q) model has the following form:

$$\emptyset(B)(1-B)^d Z_t = \theta(B)_{\varepsilon_t} \tag{6}$$

Where, $\emptyset$and $\theta$are, respectively, autoregressive and moving averages, $\varepsilon_t$is described as white noise and d is the order of integration, number of differences necessary to make the series stationary.

Following the Box-Jenkins approach, Seasonal Autoregressive Integrated Moving Averages (SARIMA) models were developed, considering seasonality, a common characteristic in hydrological parameters [13, 16].

The SARIMA (p, d, q) (P, D, Q) model is given by:

$$\emptyset(B)\Phi\,(B)(1-B)^d(1-B^S\,)^D Z_t = \theta(B)\Theta(B)_{\varepsilon_t} \tag{7}$$

Where, p, d, q are orders of the model referring to ordinal dynamics, while P, D, Q, are referring to the seasonal part of the model, and are autoregressive and ordinal moving averages, and and $\emptyset$are θautoregressive Φparameters $\Theta$and of seasonal moving averages.

Short-term forecasts aim to ensure the effective operation of water resources, considering their diverse uses [17]. Moreover, higher accuracy rates were observed for SARIMA modeling in short-term forecasts [18]. Therefore, in this study, data were predicted up to 2024.

Initially, CO_2 values were forecasted until the year 2024. Subsequently, a model was developed to predict the available SUPer time series until December 2022, utilizing the CO_2 data available up to that period. For the prediction, dependent and independent variables were established for the model, as presented in Table 2.

Table 2. Dependent and independent variables analyzed.

Independent variables	Dependent variables
CO_2	Dissolved Oxygen
Temperature	Nitrogen
Precipitation	Phosphorus

2.1.3 Model evaluation criteria

Primarily, a descriptive analysis of the analyzed data was conducted, yielding mean values, standard deviation, minimum and maximum values. To assess the created models, R^2 and RMSE statistics were employed. R^2, also known as the Coefficient of Determination, gauges how well the predicted value aligns with the observed value. The closer the value is to one, the better the model's fit.

RMSE (Root Mean Square Error) serves as a statistical metric for evaluating model performance in environmental studies. The calculation is based on the square root of the average of the squared errors between the observed and predicted values, as per equation 8.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (Ei - Oi)^2} \tag{8}$$

Where: E_i and O_i are the estimated and observed (measured) values, respectively, and n is the number of observations.

3. RESULTS AND DISCUSSION

3.1 Analysis of the behavior of the historical water quality series

To enhance comprehension of the variables under study, descriptive measurements of the historical series, spanning from January 1963 to March 2021 and available on SUPer, were undertaken for dissolved oxygen, nitrogen, and phosphorus, considering the applied climate change scenarios. Scenario 1 (C1) involved a 3°C temperature increase and a 22% precipitation reduction [1]. In Scenario 2 (C2), the temperature increased by 3°C, accompanied by a 39% reduction in precipitation [12]. Subsequently, the climate change scenarios were implemented, and corresponding graphs with trend lines were generated.

The National Environmental Council (CONAMA), in its resolution 357 [19], designates Class 2 for water bodies without classifications, as observed in the state of Pernambuco, where the dissolved oxygen (DO) must exceed 5 mg L^{-1}. A reduction in the global average and maximum values of Dissolved Oxygen (OD) can be observed, transitioning from 6.81 mg L^{-1} and 8.82 mg L^{-1}, respectively, in the reference scenario, to 6.67 mg L^{-1} and 6.65 mg L^{-1} (average), and 8.44 mg L^{-1} and 8.42 mg L^{-1} (maximum value) for scenarios with alterations in temperature and precipitation. However, despite climate change, it is evident that the historical series' average remains within the limits set by CONAMA.

In comparison to the reference scenario, devoid of climate variations, all scenarios exhibit a reduction in DO values. The scenario without climate change alterations manifests 518 months with values surpassing 5 mg L^{-1}. In scenario 1 (Appendix A), out of the 699 months analyzed, 499 data points recorded values exceeding 5 mg L^{-1}. Moving to scenario 2 (Appendix B), the DO values remained within the established limits for 478 months.

For the nitrogen variable, CONAMA Resolution 357 [19] stipulates that the permitted concentration should not exceed 1.27 mg L^{-1}. An increase in the average concentration of the series can be observed, escalating from 2.66 mg L^{-1} to 3.99 mg L^{-1} and 4.38 mg L^{-1}. A similar trend is observed for the maximum values, surging from 10.19 mg L^{-1} in the unchanged scenario to 12.80 mg $L^{-1}$and 13.47 mg L^{-1} in the climate change scenarios. Consequently, in both climate change scenarios, nitrogen concentrations exceeded the prescribed limit.

In the case of the nitrogen variable, an increase in concentration was observed across all scenarios, as depicted in Appendices C and D. In the reference scenario, out of the 699 months, 468 falls within the acceptable limits for freshwater Class 2. Scenario 1 (Appendice C) reveals that, within the entire historical series analyzed, 439 months align with the established limits. Similarly, in scenario 2 (Appendix D), 447 months exhibit values in accordance with the regulatory resolution.

In adherence to CONAMA (2005) [19], the concentration of total phosphorus must not exceed 0.10 mg L^{-1}. However, in this study, all averages surpassed the limit proposed by the resolution, registering values of 0.40 mg L^{-1} for the reference scenario, and 0.37 mg L^{-1} and 0.31 mg L^{-1} for the scenarios with climate change. Regarding the maximum values, an upward trend is evident, escalating from 5.78 mg L^{-1} in the unchanged scenario to 6.98 mg L^{-1} and 7.41 mg L^{-1} with increasing temperature and decreasing precipitation.

In the case of total phosphorus, a marginal reduction is observed for this variable in the applied scenarios, as depicted in Appendices E and F. In the scenario without climate change, out of the 699 months, 434 falls within the limits established by legislation. Shifting to scenario 1 (Appendix E), 485 months of the historical series analyzed remained within the prescribed limits. Meanwhile, in scenario 2 (Appendix F), 521 months in the series comply with the legislation.

Climate change can have profound effects on aquatic ecosystems, posing risks to both the environment and the human population. Elevated temperatures and alterations in precipitation patterns can contribute to the deterioration of water quality. Temperature, a critical factor, influences various physical, chemical, and biological processes in water bodies, affecting biological activity and oxygen absorption rates [20]. Increased temperatures often result in decreased dissolved oxygen (DO) levels, a phenomenon particularly notable in tropical lakes compared to temperate lakes [21]. Consequently, climate-induced temperature increases are likely to lead to reduced DO levels in ecosystems.

The concentration of organic matter, coupled with high temperatures, exacerbates water deoxygenation, especially in shallow lakes common in Brazil. Shallow lakes, affected by variations in water levels during the rainy season, experience periodic reductions in oxygen levels. This deoxygenation, combined with organic matter, contributes to elevated nitrogen and phosphorus concentrations in the water [21, 22].

Nitrogen and phosphorus act as limiting nutrients for primary productivity and the growth of algae and macrophytes. Concentrations as low as 0.01 mg L^{-1} are sufficient for phytoplankton maintenance, while levels between 0.03 and 0.10 mg L^{-1} can lead to unrestrained growth, contributing to ecosystem eutrophication [21]. There is a direct relationship between phosphorus distribution in the water column and dissolved oxygen concentrations [21]. Hence, periods of lower dissolved oxygen coincide with increased phosphorus and nitrogen concentrations.

Given these complexities, continuous monitoring of water bodies becomes crucial for obtaining information about water quality and quantity. This is essential for addressing the diverse needs of a region. Such monitoring not only enables the adoption of measures to control and manage water resources but is particularly vital in regions, like the Brazilian semi-arid area, where water security is integral to social and economic development. Effective water resource management requires institutional organization, robust legislation, and technological support for substantial advancements, ensuring reliable and consistent data on water resource quality [22].

3.2 Prediction of future water quality scenarios

Emissions of greenhouse gasses (GHGs) resulting from human activities have experienced a substantial increase since the Industrial Revolution, leading to alterations in climate systems, global average temperatures, and sea levels [23]. The sixth IPCC report [1] highlights that between 2010 and 2019, greenhouse gas emissions, predominantly CO2, reached unprecedented levels in human history, contributing significantly to the global rise in temperatures. Brazil, being among the top ten global emitters, has committed to reducing GHG emissions.

Global warming has the potential to alter precipitation patterns across various regions, characterized by reduced rainfall volumes and an increased frequency of drought events [4]. The well-being of populations is intricately linked to climate variability. Hence, the development of models for climatic and hydrological variables, enabling the prediction of future climate and water resource conditions [24], becomes imperative for crafting public policies aimed at mitigating the impacts of climate change. This is particularly crucial for water resource management in regions already grappling with water crises, such as the Brazilian Northeast.

During this study, the initial phase involved modeling CO2 values up to 2024 using NOAA data available until December 2022. The model achieved an R^2 of 1.00, with a RMSE of 0.31 ppm. The graphical representation (Figure 2) illustrates a discernible upward trend in CO2, peaking at

425.56 ppm in May 2024. A parallel study conducted across the state of Pernambuco developed a CO2 model projecting values exceeding 430 ppm by the year 2027 [8].

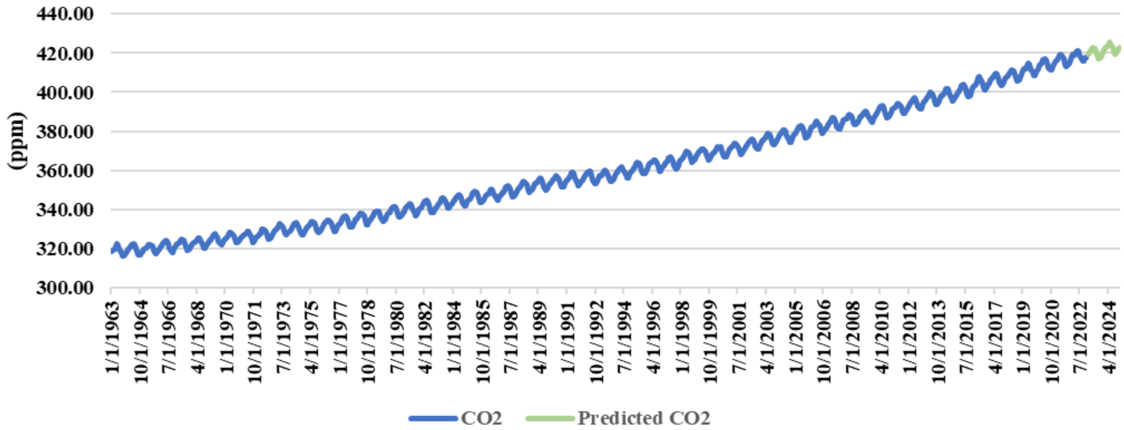

Figure 2. CO_2 modeling until the year 2024.

Subsequently, the CO2 model was used to simulate temperature and precipitation variables, correlating them with the analyzed water quality parameters, namely, dissolved oxygen, nitrogen, and phosphorus. For temperature and precipitation, numerous studies project an increase in the occurrence of extreme events, such as droughts or intense precipitation, along with an increase in drier and hotter days [24]. Future scenarios were simulated for the Brazilian Northeast until the year 2099 [25]. The authors observed a long-term temperature increase ranging from 2.1°C to 4°C, coupled with reduced precipitation and increased evapotranspiration, suggesting a trend toward increased aridity in the region.

For temperature, a historical average of 28.14°C was identified, with a predicted monthly average temperature reaching a maximum value of 28.80°C in November 2024, while the minimum predicted value was 25.03°C in June 2023. The SARIMA model (3,0,3) (0,1,1) proved to be the most accurate for temperature prediction, with an R^2 of 0.79 and RMSE of 0.64°C. Similar results were obtained in a time series analysis for monthly minimum and maximum temperatures in Rio Grande do Sul, using SARIMA [26]. The authors forecasted the variables for both three and six months, revealing lower RMSE values in the shorter-term predictions. They obtained values of 1.41 °C and 2.70 °C for minimum temperatures over three and six months, respectively. As for maximum temperatures, the corresponding values were 0.13 °C and 0.57 °C for three and six months, respectively.

In the current investigation, a trend towards higher average temperatures, ranging between 25°C and 28°C, has been discerned, as illustrated in Figure 3. This aligns with findings in a study developed through projection models covering the temperature of the Brazilian Northeast from 2016 to 2099, where a consistent temperature increase throughout the predicted series was found [27]. Additionally, another study issued warnings based on projections, indicating a potential increase of up to 2°C in northeastern Brazil's temperature by 2050 [28]. Such a temperature rise is anticipated to intensify evaporation and evapotranspiration, exerting negative impacts on water volumes in the region's reservoirs.

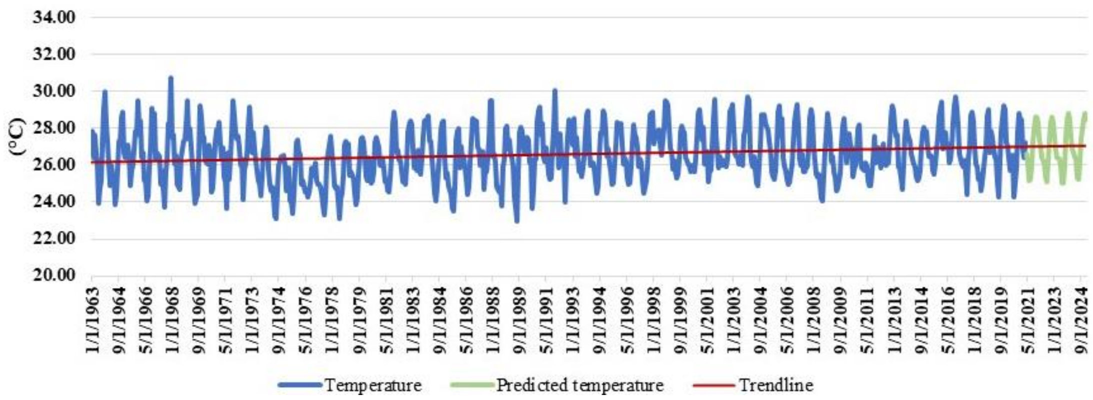

Figure 3. Temperature prediction until 2024. Source: Authors.

In terms of precipitation, the historical average was 30.09 mm, with the highest predicted monthly value of 84.46 mm, identified in March 2022, and the lowest value of 1.83 mm, for September 2024. The SARIMA model for precipitation was (1,0,0) (1,0,1), with an R^2 of 0.76 and an RMSE of 41.92 mm. The SARIMA (1,1,1) (0,1,1) model was utilized to predict average monthly temperatures for the northeastern semi-arid region, projecting future scenarios from March 2009 to March 2012 [29]. The historical series presented an average of 25.18 °C, while for the three years predicted, the average temperature was 25.71 °C. In a study conducted in the city of Rondonópolis (MT), the SARIMA (2,0,0) (0,1,2) model was applied to analyze precipitation series, identifying RMSE values for the model of 66.16 mm, indicating good adjustments to the data series [15].

As depicted in Figure 4, a trend towards a reduction in rainfall volumes for the region is evident, supporting studies in the state of Pernambuco [6, 27]. These studies demonstrated a downward trend in annual precipitation, with a higher likelihood of occurrences during periods of severe drought and drought [28]. In a study that analyzed trends in climate change in rainfall in the Pernambuco river basins, a decreasing in rainfall trends for the Terra Nova River Basin was observed [30].

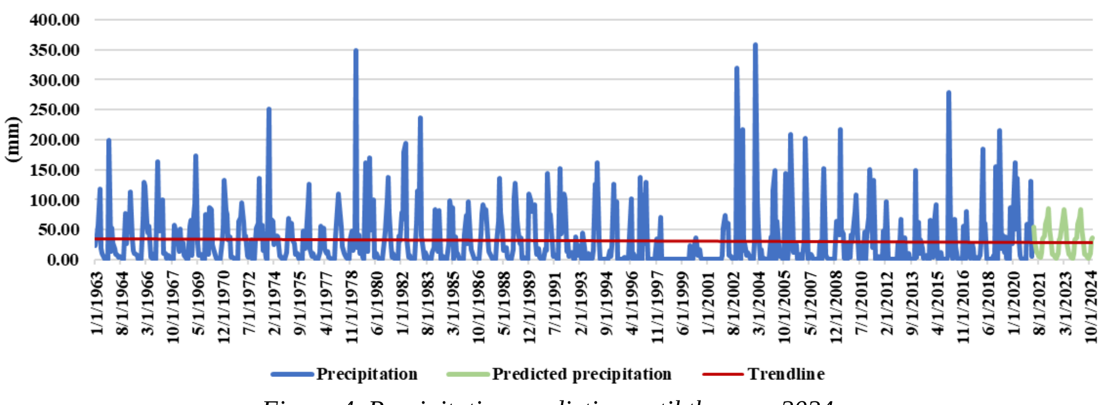

Figure 4. Precipitation prediction until the year 2024.

Predicting the behavior and conditions of water bodies is an important tool for proposing measures to combat pollution in these ecosystems, in addition to avoiding environmental problems, such as the eutrophication of reservoirs. Several studies have applied ARIMA modeling to analyze water bodies, such as for evaluating and predicting the volume of groundwater [31], in the volumetric analysis of reservoirs [32], to predict flows [16, 17], in predicting drinking water consumption in cities [33], in addition to the analysis of rainfall patterns [34], however, studies on ARIMA modeling applied to the prediction of water quality parameters are still scarce, especially for the Brazilian Northeast.

The prediction of water quality parameters was conducted by establishing correlations between temperature and precipitation variables. For dissolved oxygen, the historical average was 6.38 mg L^{-1}, with a predicted concentration range between 0.82 mg L^{-1} and 8.39 mg L^{-1}. Regarding nitrogen, the historical average value was 3.78 mg L -1, with values ranging from 0.09 mg L^{-1} to 3.71 mg L^{-1}. Phosphorus had a historical average of 0.96 mg L^{-1}, with a variation range between 0.20 mg L^{-1} and 1.10 mg L^{-1}. Figures 5, 6, and 7 illustrate graphs of the predicted time series for dissolved oxygen, nitrogen, and phosphorus.

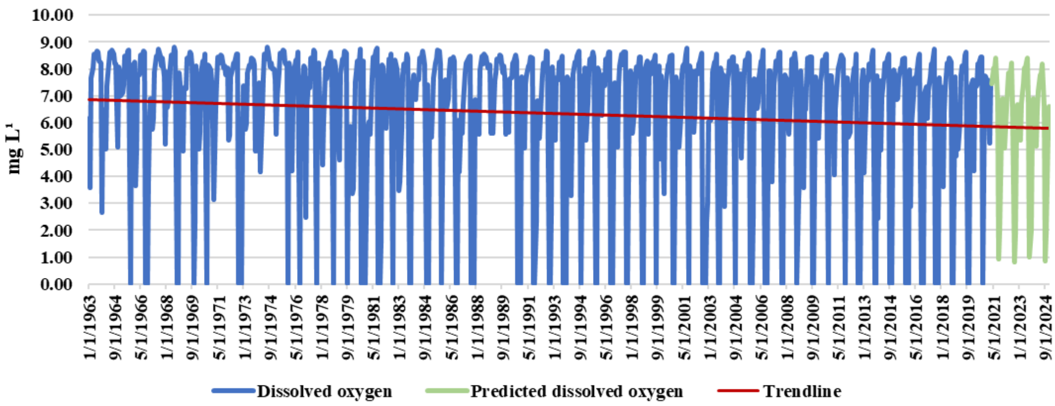

Figure 5. Prediction of dissolved oxygen until the year 2024.

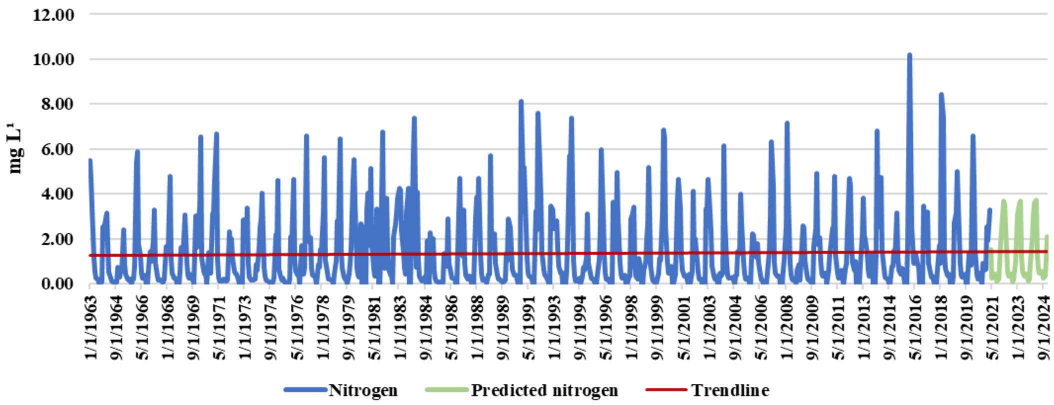

Figure 6. Nitrogen prediction until the year 2024.

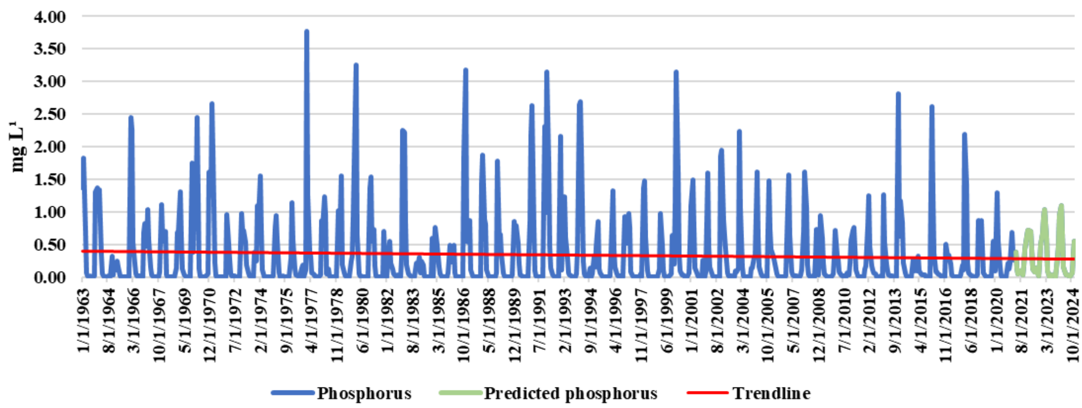

Figure 7. Phosphorus prediction until 2024.

In the state of Pernambuco, water bodies have not been officially classified, prompting the State Environmental Agency of Pernambuco (CPRH) to utilize the parameters of freshwater class

2 as outlined in Resolution 357 of CONAMA [19]. Examining the predicted water quality over the period from April 2021 to December 2024 (45 months), it was observed that, in just 8 months, dissolved oxygen values fell below 5 mg L^{-1}, aligning with the legislation but displaying a decreasing trend. Similar results were obtained in a current study in a 12-month prediction for dissolved oxygen, indicating that the predicted values remained within the limits while exhibiting a tendency towards reduced DO concentrations [35].

Concerning nitrogen, out of the 45 predicted months, this variable complied with the 1.27 mg L^{-1} limit in 29 months, showing an increasing trend in concentrations. For phosphorus, within the predicted 45 months, concentrations adhered to the proposed 0.10 mg L^{-1} limit in 19 months, with a tendency to decrease. However, it is noteworthy that the highest predicted concentrations of nitrogen and phosphorus occurred during the rainy season, spanning the months of January to April. The ARIMA methodology was utilized to predict nitrogen and phosphorus concentrations in northeast China, identifying an increase in nitrogen concentrations, while variations in phosphorus were not significant [36].

Table 3 outlines the SARIMA models for each water quality variable, along with the evaluation criteria for each model.

Table 3. SARIMA model and R^2 and RMSE values for each variable

Variable	SARIMA model	R^2	RMSE
Dissolved oxygen (mg L^{-1})	(2,0,0) (2,0,1)	0.59	1.94
Nitrogen (mg L^{-1})	(0,0,1) (0,1,1)	0.59	1.07
Total Phosphorus (mg L^{-1})	(0,0,1) (1,0,1)	0.56	0.31

A hybrid model utilizing the ARIMA model was devised to forecast water quality parameters, including dissolved oxygen, in the Beijing region for a one-month period [37]. The model achieved a quality level of approximately 97%, with an R^2 of 0.94 and an RMSE of 0.58 mg L^{-1} for dissolved oxygen (OD). In comparison, the present study yielded an R^2 of 0.59 and an RMSE of 1.94 mg L^{-1} for OD. The authors noted the applicability of the model to other reservoirs in the region but emphasized its stronger performance in short-term predictions, with less satisfactory outcomes over an extended period.

A hybrid model employing ARIMA and Neural Networks was developed to predict nitrogen and phosphorus concentrations in northeast China [36]. The RMSE values for nitrogen were 0.139 mg L^{-1} and 0.036 mg L^{-1} for phosphorus. In contrast, the current study obtained higher RMSE values, registering 1.07 mg L^{-1} for nitrogen and 0.31 mg L^{-1} for phosphorus. SARIMA modeling was applied to predict nitrogen, achieving more robust forecasts for the initial three months with confidence levels of 96%, declining to 82% for the six-month period, and no solid models were identified for 12-month forecasts [18]. The SARIMA model for nitrogen was (2,1,2) (1,0,1), with an R^2 of 0.51 and a concentration range between 0.8 mg L^{-1} and 4.1 mg L^{-1}, aligning with the current study where the R^2 for nitrogen was 0.59, with a series average of 3.78 mg L^{-1}.

Other studies have assessed the performance of time series models (ARIMA and SARIMA) for predicting water quality in water bodies, obtaining satisfactory results [38, 39]. Consequently, the modeling and prediction of water quality parameters emerge as vital tools for water resources management and control. These models can aid in planning, managing, and predicting the impacts of changes in aquatic ecosystems, contributing to the formulation of public policies to ensure water security [40].

4. CONCLUSION

The examination of historical series behavior in response to climate change, utilizing data from reputable sources such as the IPCC and Fiocruz to model water quality parameters, emerges as a viable strategy for water resource management in the Brazilian semi-arid region. The compounding factors of climate change, characterized by inadequate or minimal rainfall coupled with elevated temperatures and increased evapotranspiration rates, combined with ongoing conflicts over diverse water resource uses, can potentially lead to a severe crisis. This crisis poses heightened vulnerability to populations inhabiting the semi-arid region. The SUPer software, with its broad applicability, proves indispensable for public institutions dealing with water availability and quality analysis—a recurrent challenge in the state of Pernambuco.

The application of SARIMA modeling to predict water quality parameters demonstrated satisfactory outcomes, aligning favorably with findings from comparable studies. The results obtained from the SUPer historical series analysis scenarios support the trends modeled through the SARIMA methodology. Notably, concentrations of dissolved oxygen and phosphorus exhibit decreasing trends, while nitrogen concentrations show an upward trajectory.

It is imperative to acknowledge that simulating water quality variables presents significant challenges due to uncertainties linked to the considerable variability in precipitation and temperature, along with other parameters influencing dissolved oxygen, nitrogen, and phosphorus concentrations. Consequently, the ongoing on-site monitoring is essential for refining existing models and developing new ones. This collaborative effort contributes to the formulation of effective public policies, specifically addressing the equitable distribution of water in terms of both quantity and quality.

5. ACKNOWLEDGEMENTS

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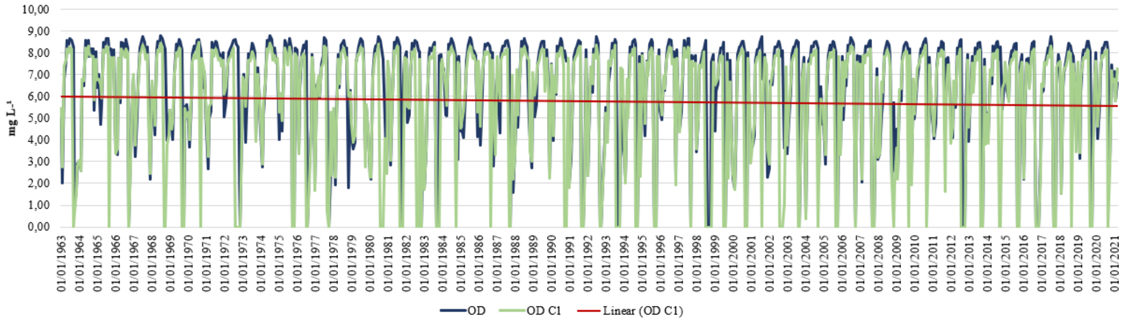
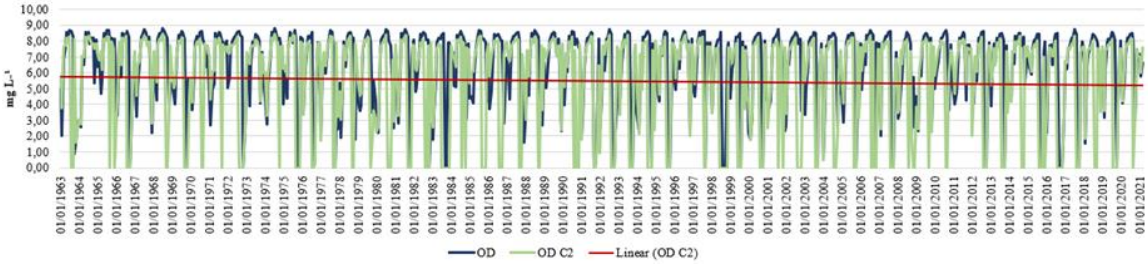
APPENDIX

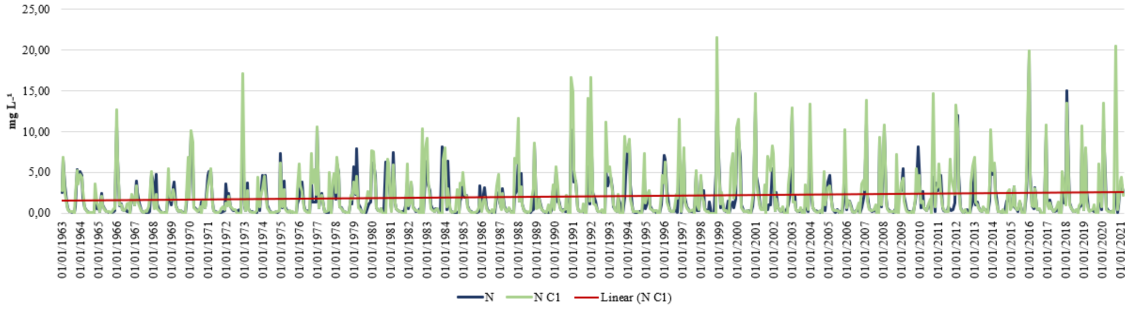
Appendix A - Comparison between the behavior of the historical series with the unchanged scenario, in blue, and C1, in green, for dissolved oxygen



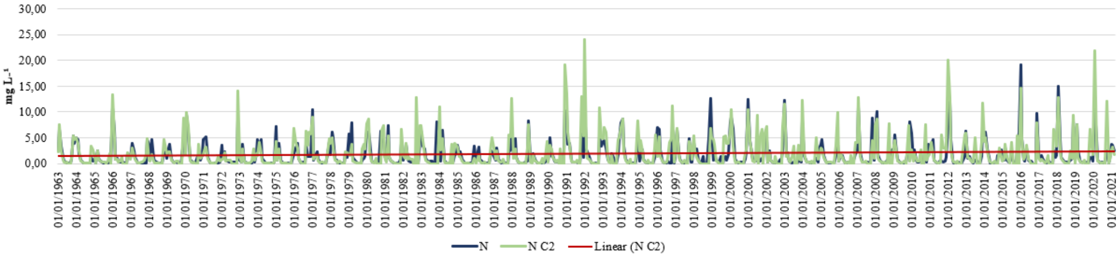
Appendix B - Comparison between the behavior of the historical series with the unchanged scenario, in blue, and C2, in green, for dissolved oxygen



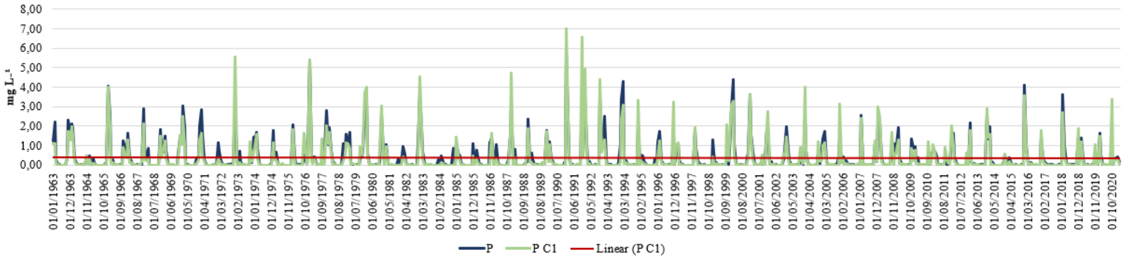
Appendix C - Comparison between the behavior of the historical series with no change scenario, in blue, and C1, in green, for nitrogen



Appendix D - Comparison between the behavior of the historical series with no change scenario, in blue, and C2, in green, for nitrogen



Appendix E - Comparison between the behavior of the historical series with a no-change scenario in blue, and C1, in green, for phosphorus



Appendix F - Comparison between the behavior of the historical series with the unchanged scenario, in blue, and C2, in green, for phosphorus