Climate change projections and impacts on raw water quality in the Paraíba do Sul River basin, Southeast Brazil

Projeções de mudanças climáticas e seus impactos na qualidade da água bruta na Bacia do Rio Paraíba do Sul Paulista

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ABSTRACT
This study aims to assess recent trends in water quality indicators in the Paraíba do Sul River Basin in the state of São Paulo and to analyse the influence of climate change on these parameters. A comparative analysis between future projections and a historical reference scenario reveals that climate variability plays a significant role in water quality. Additionally, the findings indicate a decline in water availability, particularly under high-emission scenarios, underscoring the urgency of mitigation and adaptation measures to ensure water security in the region.

Keywords: Regional climate models. Future scenarios. Water resources. Water security.

RESUMO

Este estudo tem como propósito avaliar a evolução dos indicadores de qualidade da água na Bacia do Rio Paraíba do Sul paulista ao longo dos últimos anos, bem como investigar os efeitos das mudanças climáticas sobre esses parâmetros. A análise comparativa entre projeções futuras e um cenário de referência revela que as variações climáticas estão associadas a alterações nos indicadores de potabilidade da água. Ademais, os resultados indicam uma tendência de redução da disponibilidade hídrica, sobretudo em cenários de maior emissão de gases de efeito estufa, o que evidencia a necessidade de ações voltadas à mitigação e à adaptação para garantir a segurança hídrica da região.

Palavras-chave: *Modelos climáticos regionais. Cenários futuros. Recursos hídricos. Segurança hídrica.*

1 INTRODUCTION

Climate change is likely to generate profound impacts on ecosystem health, the global economy, and the daily lives of populations. It is widely recognised as one of the main contemporary environmental challenges. Among the sectors most vulnerable to these transformations is the water resources sector, which faces direct consequences for both water quality and availability (IPCC, 2021; Prado, 2024). Previous studies have shown that changes in the physicochemical properties of water, influenced by climatic and hydrological factors, can compromise not only natural systems but also the water security of human societies (Amâncio; Cataldi, 2019; Cravinho *et al.*, 2004).

Extreme climate events, such as rising temperatures and variations in precipitation patterns, directly affect the quality and availability of water resources worldwide (Prado, 2024). According to the Intergovernmental Panel on Climate Change (IPCC, 2021), the frequency of these events has increased significantly, placing additional pressure on basic sanitation systems and water supply infrastructure. Recent examples include the 2014 water crisis in Brazil, which had major impacts on water, energy, and food security (Canamary *et al.*, 2023; Nobre *et al.*, 2016).

In the case of the Paraíba do Sul River Basin, several studies have indicated that the basin is highly vulnerable. Amâncio and Cataldi (2019) warn that, from the 2070s onward, there is a clear trend toward reduced streamflows in the basin, regardless of the climate scenario analysed. Therefore, understanding variations in water quality and the challenges associated with water treatment is essential for formulating effective management strategies to ensure access to safe drinking water for the population. To this end, climate models from the National Institute for Space Research (Inpe) were used, including EtaHadGEM2-ES, EtaMIROC5, and EtaCanESM2, to project future scenarios and assess potential impacts on water quality in the basin. Moreover, projected climate changes pose not only technical challenges but also financial impacts on treatment systems.

Previous studies support these projections (Delpla *et al.*, 2009; Whitehead *et al.*, 2009), indicating that climate change tends to degrade surface water quality, thereby increasing the challenges for conventional treatment. These changes may require investments in treatment technologies, monitoring, and operational control.

Climate change increases the operational costs of water treatment systems due to the greater demand for chemical inputs and the adoption of advanced technologies, such as membrane filtration. In addition, structural investments are required in modernisation, automated monitoring, and technical capacity building (Vörösmarty *et al.*, 2010). Incorporating climate risk into financial planning for sanitation systems becomes essential, given the direct and indirect impacts on public health, the environment, and the regional economy (Organisation for Economic Co-operation and Development – OECD, 2018).

Climate change is one of the most pressing contemporary environmental problems, with profound impacts on ecological health, the global economy, and people's lives. These changes have an impact.

Among the sectors most vulnerable to them are water resources, with direct consequences for both water quality and availability (IPCC, 2021; Prado, 2024). The physicochemical properties of water, which vary with climatic and hydrological factors, could jeopardise natural systems and human societies' water security (Amâncio; Cataldi, 2019; Cravinho *et al.*, 2004).

Certain extreme climate phenomena (temperature rise, changing precipitation patterns, etc.) affect water resources globally, directly impacting quality and access (Prado, 2024). Moreover, according to the Intergovernmental Panel on Climate Change (IPCC, 2021), these episodes are becoming increasingly frequent, placing greater strain on basic sanitation facilities and water supply systems. For example, a severe case that has been highlighted recently and is similarly important is the 2014 water crisis in Brazil, with dire implications for water, energy, and food security (Canamary *et al.*, 2023; Nobre *et al.*, 2016).

The Paraíba do Sul River Basin has a high hydrologic vulnerability. Amâncio and Cataldi (2019) caution that, from the 2070s onward, streamflows in the basin have fallen sharply, regardless of the climate scenario examined. Therefore, understanding variations in water quality and the challenges associated with its treatment is essential to designing effective, sustainable management strategies to ensure potable water is within reach for the populace. To this end, climate models from the National Institute for Space Research (Inpe) were used: EtaHadGEM2-ES, EtaMIROC5, and EtaCanESM2, to predict future scenarios and determine the probable impacts on water quality in the basin.

Some of the projected changes may be challenging. In the future, technological issues and financial hardship will arise with water supply and treatment systems. The simulations in this paper suggest that elevated climate variability—especially under more extreme warming scenarios such as the Representative Concentration Pathway 8.5 (RCP 8.5)—is directly linked to declines in water quality parameters, including turbidity, ammonia (NH_3–N), pH, and colour. These projections are consistent with prior investigations (Delpla *et al.*, 2009; Whitehead *et al.*, 2009), which show that climate change more commonly leads to decreased surface water quality and more difficult treatment for conventional solutions. The changes would likely require investment in treatment technologies, monitoring, and operational controls.

The operational costs of water treatment systems are increasing due to increased demand for chemical inputs and the adoption of innovative technologies, such as membrane filtration. Cost increases of up to 20% are based on climate-stress estimates (United Nations World Water Development Report, 2022; Water Environment Federation, 2023). Moreover, structural investments will be needed in modernisation, automated monitoring, and technological capacity development (Vörösmarty *et al.*, 2010). "Integrating climate risk into a financial planning framework for sanitation systems becomes crucial because it has direct and indirect influences on public health, the environment, and the regional economy" (Organisation for Economic Co-operation and Development – OECD, 2018).

2 STUDY AREA

This study focuses on the São Paulo portion of the Paraíba do Sul River Basin, located approximately between 22°00'S and 23°30'S latitude and 44°00'W and 45°52'W longitude, encompassing the Paraíba Valley in the State of São Paulo. The Mantiqueira Mountain Range bounds this region to the north, and the Serra do Mar to the south, extending from the headwaters of the Paraíba do Sul River—formed by the confluence of the Paraibuna and Paraitinga rivers—to the border with the State of Rio de Janeiro. The Paraíba do Sul River Basin has a drainage area of approximately 55,500 km², spanning the states of São Paulo (13,900 km²), Rio de Janeiro (20,900 km²), and Minas Gerais (20,700 km²). It is bounded to the north by the Grande and Doce river basins and by the Mantiqueira, Caparaó, and Santo Eduardo mountain ranges.

To the northeast, the basin is limited by the Itabapoana River; to the south, by the Serra dos Órgãos and Serra do Mar; and to the west, by the Tietê River basin, separated by branches of the Serra do Mar and Mantiqueira ranges. The Paraíba do Sul River is formed by the confluence of the Paraibuna and Paraitinga rivers and has a total length exceeding 1,100 km (National Water Agency, 2011).

Figure 1 below presents the spatial extent of the São Paulo portion of the Paraíba do Sul River Basin.

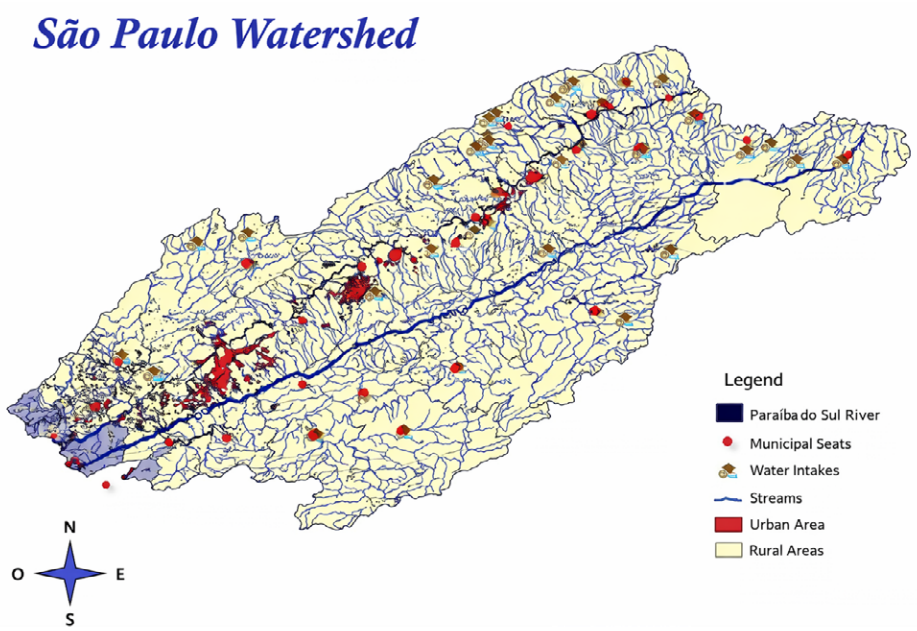

Figure 1 – São Paulo portion of the river basin considered in this study, indicating municipal centres, water intake points, the Paraíba do Sul River, and urban and rural areas.

Source: Prepared by the authors (2025).

3 METHODOLOGY

The integrated methods, combining climate models, hydrological modelling, and machine learning, used in the current work evaluated the effects of climate change on water-quality proxies in the São Paulo portion of the Paraíba do Sul River Basin.

Climate models are numerical approximations based on physical equations. They are employed to simulate, in a detailed (and computationally sound) way, the fundamental processes that regulate the Earth’s climate system, including interactions among the atmosphere, oceans, land surface, and biosphere. These models integrate basic physical principles, including conservation of mass, energy, and momentum, to represent climate dynamics at different spatial and temporal scales (IPCC, 2021). From each of these simulations, it is possible to project future changes in important meteorological variables, such as temperature, precipitation, and solar radiation, which can be used to calculate expected environmental and hydrological effects of climate change.

Climate models can be divided into two types: Global Climate Models (GCMs) and Regional Climate Models (RCMs). GCMs are large-scale models of the Earth’s atmosphere that simulate constant global atmospheric circulation, ocean dynamics, and interactions among different parts of the system. These models often provide only coarse spatial resolution for regional or local-scale analyses, and they still have limitations. Regional Climate Models provide valuable insights into regional variation and have been shown to address this limitation by leveraging climate downscaling to refine global projections spatially at finer spatial scales. Utilising this method allows for more representative, regionally reflective climate projections in regions where dynamic topography and hydrology intersect, such as river basins (Almagro *et al.*, 2020).

The regional climate model Eta is widely used in Brazil to downscale global climate scenarios. The regionalised climate projections from Eta offer higher spatial resolution, enabling more nuanced insights into the impacts of climate change on hydrological and environmental systems. Herein, projections were extracted from Global Climate Models (GCMs) of the Coupled Model Intercomparison Project Phase 5 (CMIP5) and then downscaled utilising the Eta model.

The selected models—HadGEM2-ES, MIROC5, and CanESM2—are recognised for representing climate variability and greenhouse gas emissions, known for their ability to capture diverging climate variability patterns. These models simulate climate trajectories under different greenhouse gas concentration scenarios, called Representative Concentration Pathways (RCPs).

The regionalised climate projections were used as inputs to the MHD-INPE hydrological model (e.g., precipitation, infiltration, evapotranspiration, surface runoff, groundwater flow). The MHD model is based on physical and mathematical concepts that enable the simulation of hydrological dynamics in the watershed system and provide a valuable reference for water resource availability and environmental conditions (Paiva *et al.*, 2023).

To study how climatic influences affect water quality systems of the Paraíba do Sul River, climate models and hydrological models, along with computer methods based on machine learning studies, could be integrated to conduct a combined investigation, along with an analysis of the downstream potential for a climate-variable impact of climate change on regional water resources. Indeed, although climate simulation methods are commonly used in environmental modelling, they are inherently limited because they must be overly simplified to represent the complex climate system. Climate projections are subject to different sources of uncertainty, arising from:

- Structural limitations of the models, related to the representation of atmospheric and oceanic processes.
- Differences among global climate models in simulating climate variability.
- Uncertainties associated with future greenhouse gas emission scenarios (IPCC, 2021).

Another important source of uncertainty is related to the climate downscaling process, which applies regional constraints to global estimates using boundary conditions derived from global models (e.g., the Eta climate model). In this context, any errors or biases in global models may be propagated and reflected in scale. In some cases, microscale spatial resolution may fail to capture important local processes, such as intense convective events and hydrological variability.

Due to these limitations, the use of multiple climate models—such as those adopted in this study (HadGEM2-ES, MIROC5, and CanESM2)—is widely regarded in the scientific literature as a common strategy to reduce overreliance on a single model and enhance the robustness of climate projections. This approach allows evaluating the sensitivity of results to different representations of climate processes, enabling a more comprehensive analysis of current and future scenarios (Almagro *et al.*, 2020; IPCC, 2021).

3.1 CLIMATE CHANGE SCENARIOS

HadGEM2-ES, MIROC5, and CanESM2 were selected as the climate models for this study. The selection of these models was based on their established reliability and high ability to simulate a broad spectrum of future climate scenarios (Almagro *et al.*, 2020). Among climate models, the HadGEM2-ES model from the Met Office Hadley Centre provides a particularly detailed and comprehensive representation of potential future climate changes. Conversely, MIROC5, developed by the Japan Agency for Marine-Earth Science and Technology, and CanESM2, developed by the Canadian Centre for Climate Modelling and Analysis, offer distinct approaches and perspectives for analysing climate phenomena. The integration of these three models made a comparison. It led to a better understanding of how climate change affects the water quality of the Paraíba do Sul River, as well as environmental factors and society (Rodrigues, 2022).

3.2 WATER TEMPERATURE SIMULATION

The calculation of water temperature is based on the principle of thermal equilibrium (Edinger *et al.*, 1968). This formulation has been widely used in several hydrological models, such as CE-QUAL-W2 (Cole; Wells, 2006) and MIKE SHE (Dhi, 2017), owing to its simplicity and numerical stability.

In the case of uniform temperature, where spatial gradients are equal to zero, the one-dimensional heat transport equation (Equation 1) can be expressed as:

$$\rho_w c_{pw} \frac{dTw}{dt} = \frac{q_{net}}{depth} \qquad (1)$$

Where ρ_w is the water density; c_{pw} is the specific heat of water; q_{net} is the net surface radiation; T_w is the water temperature; and $depth$ is the water depth.

Net radiation is composed of fluxes from several physical processes: net solar radiation; atmospheric longwave radiation; longwave radiation emitted by the water surface; evaporative heat flux; convective heat flux; and precipitation heat flux. Among these components, the most significant contribution corresponds to the net solar radiation term q_{atm}. Therefore, the previous equation can be simplified as:

$$\rho_w c_{pw} \frac{dTw}{dt} = \frac{q_{atm} + \varepsilon_q}{depth} \qquad (2)$$

Where ε_q is a parameter that incorporates the remaining radiation terms.

Edinger *et al.* (1968) defined the equilibrium temperature as the water temperature at which the net atmospheric heat flux () equals q_{atm}) is equal to zero. Under these conditions, the radiation balance can be expressed as:

$$q_{atm} = K(Te - Tw) \qquad (3)$$

Where T_e is the equilibrium temperature and K is the overall surface heat exchange coefficient. The total surface heat exchange coefficient, K, can be calculated using Edinger's empirical equations. K is a function of water temperature, dew point temperature T_{dew}, and wind speed , expressed as:

$$K = 4.48 + (\beta + 0.47)f_w + 0.05Tw$$

Where:

$$f_w = 9.2 + 0.46w^2$$

(4)

$$\beta = 0.35 + 0.015\left(\frac{Tdew + Tw}{2}\right) + 0.0012\left(\frac{Tdew + Tw}{2}\right)^2$$

$$Te = Tdew + \frac{S}{K} + \varepsilon_t \qquad (4)$$

Where S is the incident shortwave radiation, and ε_t is an adjustment parameter. By combining the two previous equations, the following expression is obtained:

$$\rho_w c_{pw}\frac{dTw}{dt} = \frac{K(Te - Tw) + \varepsilon_q}{depth} \qquad (5)$$

By integrating over the time interval, we obtain:

$$Tw_{t+\Delta t} = Te\left(1 - e^{-\frac{Kt_{res}}{\rho_w c_{pw} depth}}\right) + Tw_{in,t}e^{-\frac{Kt_{res}}{\rho_w c_{pw} depth}} + \frac{\varepsilon_q}{K}\left(1 - e^{-\frac{Kt_{res}}{\rho_w c_{pw} depth}}\right) \qquad (6)$$

Where T_w in represents the heat input from adjacent cells. This equation is very similar to that presented by Bogan *et al.* (2004).

3.3 PYTHON SIMULATION USING THE HISTGRADIENTBOOSTINGREGRESSOR MODEL

We employed the HistGradientBoostingRegressor algorithm from the scikit-learn library to estimate physicochemical parameters of water in the Paraíba do Sul River using Python for the analysis.

Predictor variables were climatic and hydrological indicators, including air temperature, precipitation, and streamflow, whereas response variables were key water quality indicators, namely pH, turbidity, apparent colour, and ammoniacal nitrogen (NH_3–N).

The datasets used to train the models were time series; these data were recorded and saved by official institutions such as the National Institute for Space Research (Inpe), the National Water and Sanitation Agency (ANA), and the National Institute of Meteorology (Inmet). This model provided quantitative insights into the climatic and hydrological impacts on water quality parameters, generating data applicable to predict future scenarios under climate change.

Recent work validates that model building using machine learning is effective when applied in the same field. Khan *et al.* (2021) used Principal Component Regression (PCR) combined with the Gradient Boosting algorithm to predict and classify water quality, achieving 95% and 100% accuracy in estimating the Water Quality Index (WQI) based on variables such as pH, turbidity, and dissolved oxygen (DO).

Similarly, Manikandan *et al.* (2024) showed that Gradient Boosting algorithms can achieve high accuracy in estimating the WQI using 20 physicochemical characteristics of water samples. The authors highlight a direct link between water quality degradation and associated risks to water security.

In this context, Wang *et al.* (2017) proposed a Support Vector Regression (SVR) method to predict the Water Quality Index (WQI), achieving over 90% accuracy using 22 input variables.

The prediction of water quality will be based on multidimensional data and complex relationships among environmental and chemical variables (as demonstrated by the HistGradientBoostingRegressor model).

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3.4 WATER QUALITY SCENARIOS

For the development of land use and land cover maps, the study by Rezende *et al.* (2018) was adopted, which outlined three future scenarios for land use and occupation changes between 2010 and 2050. This study emphasised transitions among forestry, forest, and pasture categories. These projections were later refined by Paiva *et al.* (2023), who incorporated urban expansion into the model.

Additionally, the scenarios proposed by Rezende *et al.* (2018) were further refined by incorporating assumptions about water demand behaviour for both human supply and industrial use, resulting in Optimistic, Pessimistic, and Current scenarios (Canamary *et al.*, 2023).

In the present study, water quality information was incorporated into these scenarios, considering the following parameters: water temperature (°C) and air temperature (°C) as physical variables; phosphorus (mg/L), biochemical oxygen demand – BOD_5 (mg/L O_2), pH (pH units), turbidity (NTU), and dissolved oxygen – DO (mg/L) as key physicochemical indicators. The scenarios were structured across three time horizons: Historical, Current, and Future. For the Current and future periods, three projected scenarios were considered: Optimistic, Pessimistic, and Current.

- Historical Period: 1976 to 2015.
- Current Period: 2016 to 2035.
- Future Period: 2036 to 2055.

a) Optimistic Scenario (O): A major rise in participation in the public water supply services, as well as a decrease in the per capita water use, considering a rise in public awareness in conserving water resources.

b) Pessimistic Scenario (P): Reflects enhanced access, even though per capita water demand is going up.

c) Current Scenario (A): As per the consumption and land use profiles found hitherto. The study by Martins *et al.* (2023) is extended to this model as well, with consideration of agricultural water consumption in the Paraíba do Sul River Basin in the São Paulo region. Also, both RCP 4.5 and RCP 8.5 models were developed to estimate greenhouse gas emissions, as they represent the two scenarios used to determine possible climate outcomes (Martins *et al.*, 2023).

4 RESULTS

The results of the executed modelling were presented graphically, supported by numerical tables and comparisons over the decades studied. The analysis enabled verification of the progressions, inclusions, and exclusions of each parameter in the treatment of raw water over the years analysed.

To confirm the model's accuracy, a comparative statistical analysis was performed between the data measured during raw water treatment processes (historical data, referred to as the Baseline) and the data simulated by the hydrological model.

4.1 AIR AND WATER TEMPERATURE

Projections from the CAM, MIROC, and HADGEM climate models indicate a progressive increase in air temperature across municipalities in the state of São Paulo between 2035 and 2055. The baseline scenario (Baseline) presents the lowest medians, with values concentrated between 21 °C and 22 °C for all three models. In 2035, temperatures show a slight increase compared to historical data, with minimal differences among the scenarios (current, optimistic, and pessimistic). By 2055, a more pronounced increase is observed, with pessimistic scenarios indicating the highest median values, suggesting a clear warming trend. Below is a graph, along with an analysis that includes descriptive statistics, variance, and Tukey's test.

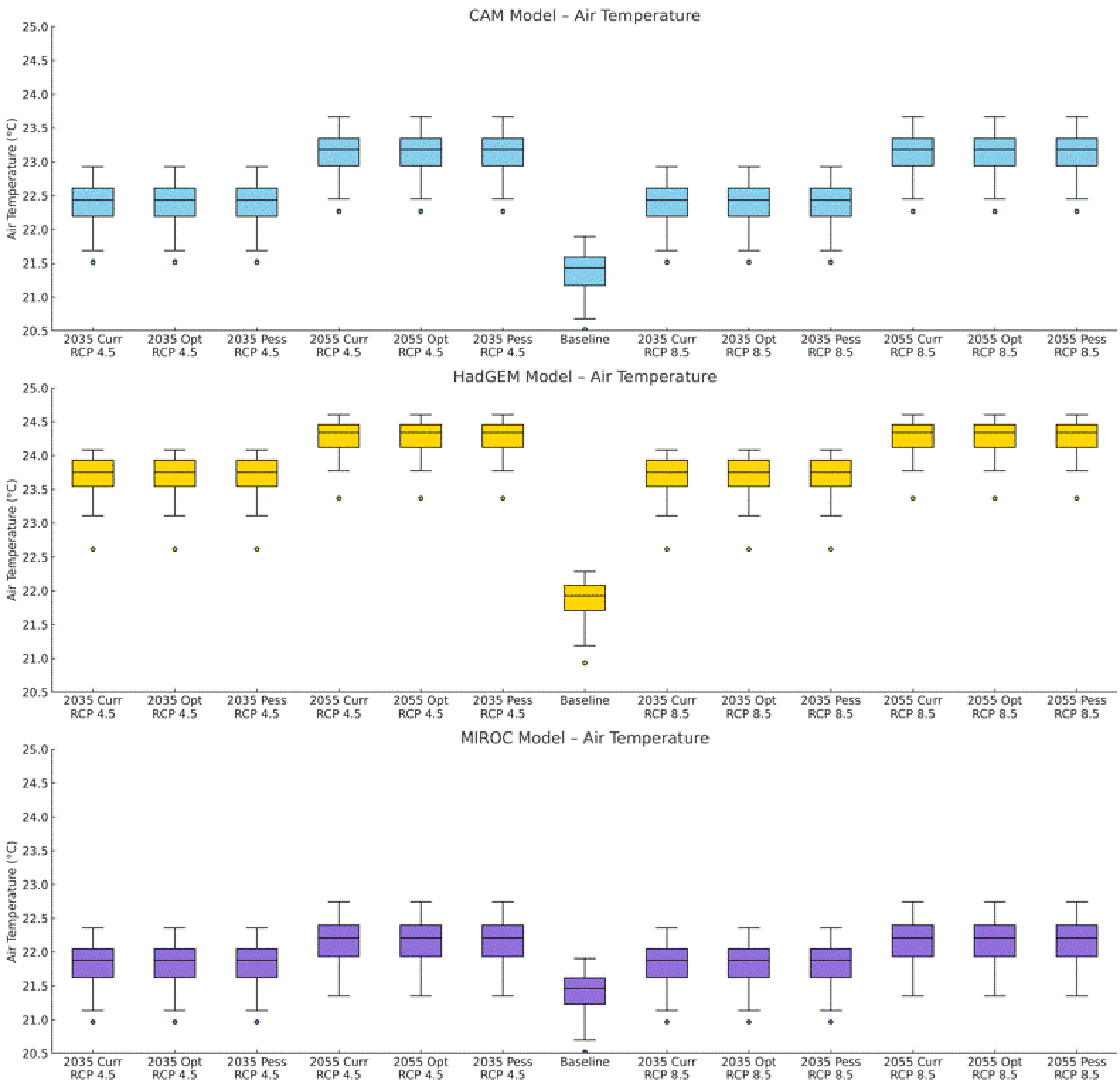

Figure 2 – Air temperature projections based on regional climate models (Eta–CMIP5).

Abbreviations: Curr= Current, Opt=Optimistic, Pess = Pessimistic

Source: Prepared by the authors (2025).

After conducting a post hoc analysis, we observed statistically significant differences across all climate models, underscoring the importance of multiple approaches to forecasting future climate scenarios. Projections for 2035 and 2055 indicate gradual increases in water temperature relative to the baseline scenario. Differences between scenarios in 2035 are small, but in 2055, there is a greater rise in temperature, most notably under the pessimistic scenario (RCP 8.5), which shows greater climate pressure and possibly other impacts on the water system.

Table 1 – Statistical analysis for the air temperature parameter

Descriptive statistics for the air temperature parameter				
Climate Model	***Mean Temperature (°C)***	***Mean Standard Deviation***	***Mean Range***	***Observations***
CAM	22,644	0,342	1,402	Moderate variability among scenarios.
HADGEM	23,809	0,3	1,352	Slightly lower variability compared to the CAM model.
MIROC	21,941	0,35	1,391	Variability comparable to the CAM model.
Air Temperature Among Scenarios Within Each Model				
Climate Model	***F-Statistic***	***p-Value***	***Statistical Significance***	***Interpretation***
CAM	83,52	< 0,0001	Yes	Statistically significant differences among the model scenarios.
HADGEM	161,21	< 0,0001	Yes	Marked statistical differences among the simulated scenarios.
MIROC	15,72	< 0,0001	Yes	All scenarios exhibited statistically significant variations.
Tukey's Test for Comparison of Mean Air Temperature Among Models				
Group 1	***Group 2***	***Mean Difference***	***p-Value***	***Statistical Significance***
CAM	HadGEM	+1,1649	< 0.001	Yes
CAM	MIROC	−0,7030	< 0.001	Yes
HadGEM	MIROC	−1,8679	< 0.001	Yes

Source: Prepared by the authors (2025).

The thermal behaviour of water follows, in an attenuated manner, the pattern observed for air temperature, reflecting the coupling between the atmosphere and the water surface. In future scenarios, the medians increase slightly, and the thermal amplitude expands under the pessimistic scenarios for 2055. These observations can be verified in Figure 3 below:

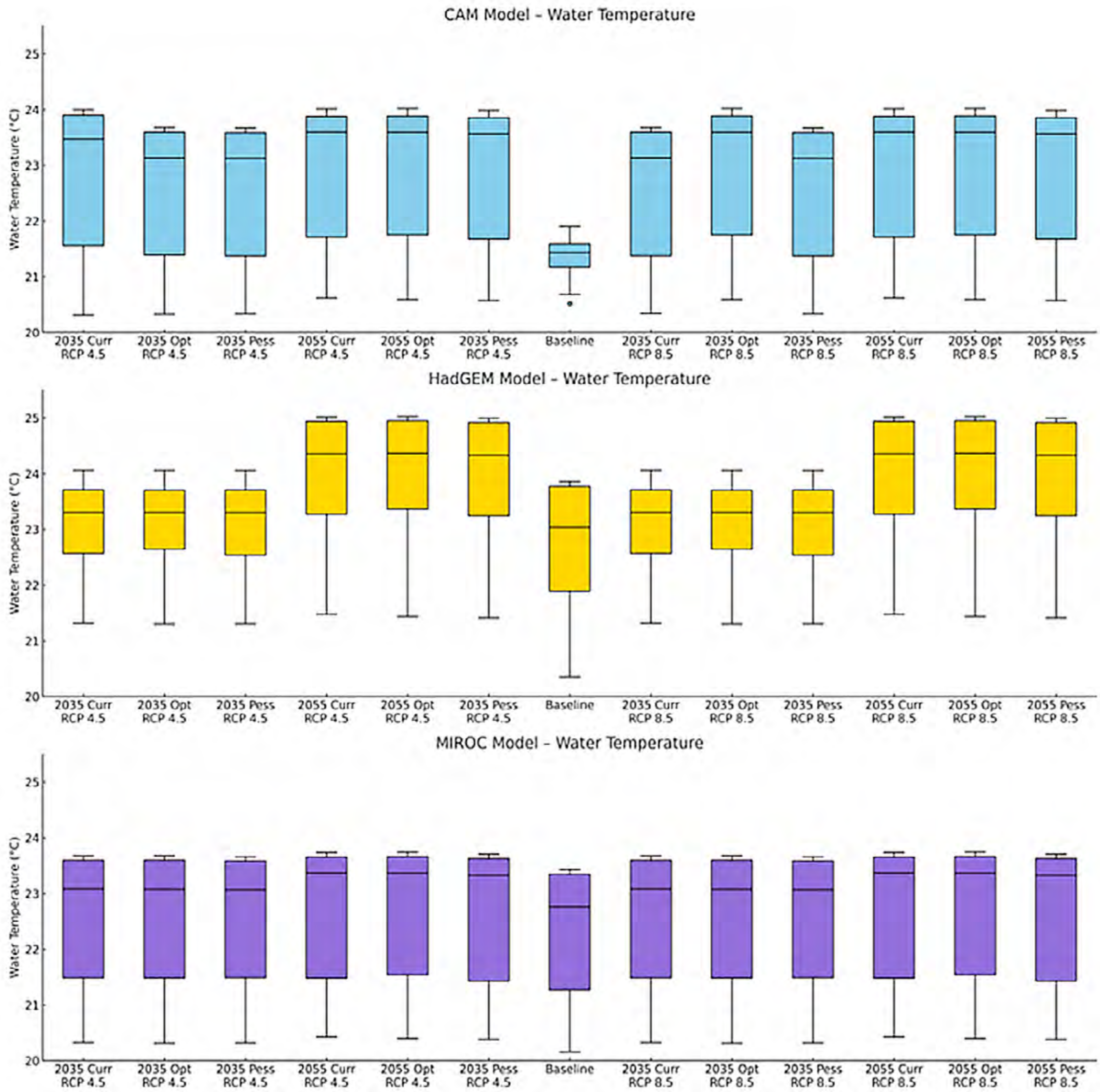

Figure 3 – Water temperature projections estimated by the MHD-INPE hydrological model.

Abbreviations: Curr= Current, Opt=Optimistic, Pess = Pessimistic

Source: Prepared by the authors (2025).

The statistical analysis of the Water Temperature parameter (Table 2) reveals distinct thermal patterns among the Eta-CamESM2, HadGEM, and MIROC climate models, reflecting structural differences in how these models represent energy exchange between the atmosphere and the water surface. The mean values ranged from 23.1 °C (MIROC) to 24.0 °C (HadGEM), with CAM presenting an intermediate value (23.5 °C). This difference of up to 0.9 °C between the extremes confirms the presence of a statistically significant inter-model thermal gradient.

Table 2 – Statistical analysis for the water temperature parameter

Descriptive statistics for the air temperature parameter				
Climate Model	***Mean Temperature (°C)***	***Mean Standard Deviation***	***Mean Range***	***Observations***
CAM	23,5	0,342	1,402	Moderate dispersion; considerable variability among scenarios.
HADGEM	24	0,3	1,352	Higher means than CAM; significant internal variability.
MIROC	23,1	0,35	1,391	Higher variability than HADGEM; homogeneous distribution.
Analysis of Variance (ANOVA) – Water Temperature Among Scenarios Within Each Model				
Climate Model	***F-Statistic***	***p-Value***	***Statistical Significance***	***Interpretation***
CAM	4,77	< 0,0001	Yes	Relevant statistical differences among model scenarios.
HADGEM	8,75	< 0,0001	Yes	big statistical differences among simulated scenarios.
MIROC	0,25	< 0,0001	No	No statistically significant differences.
Tukey's Test for Comparison of Mean Water Temperature Among Models				
Group 1	***Group 2***	***Mean Difference***	***p-Value***	***Statistical Significance***
CAM	HADGEM	+0,774	< 0.001	Yes
CAM	MIROC	- 0,084	>0.05	No
HADGEM	MIROC	-0,858	< 0.001	Yes

Source: Prepared by the authors (2025).

4.2 ESTIMATES OF WATER QUALITY PARAMETERS – PH, COLOR, TURBIDITY, AND NH_3

For the simulations presented, water and air temperature data were used as inputs, obtained from climate model simulations integrated with the hydrological model (MHD) and processed using Python. The graphs below present and analyse the four water quality parameters.

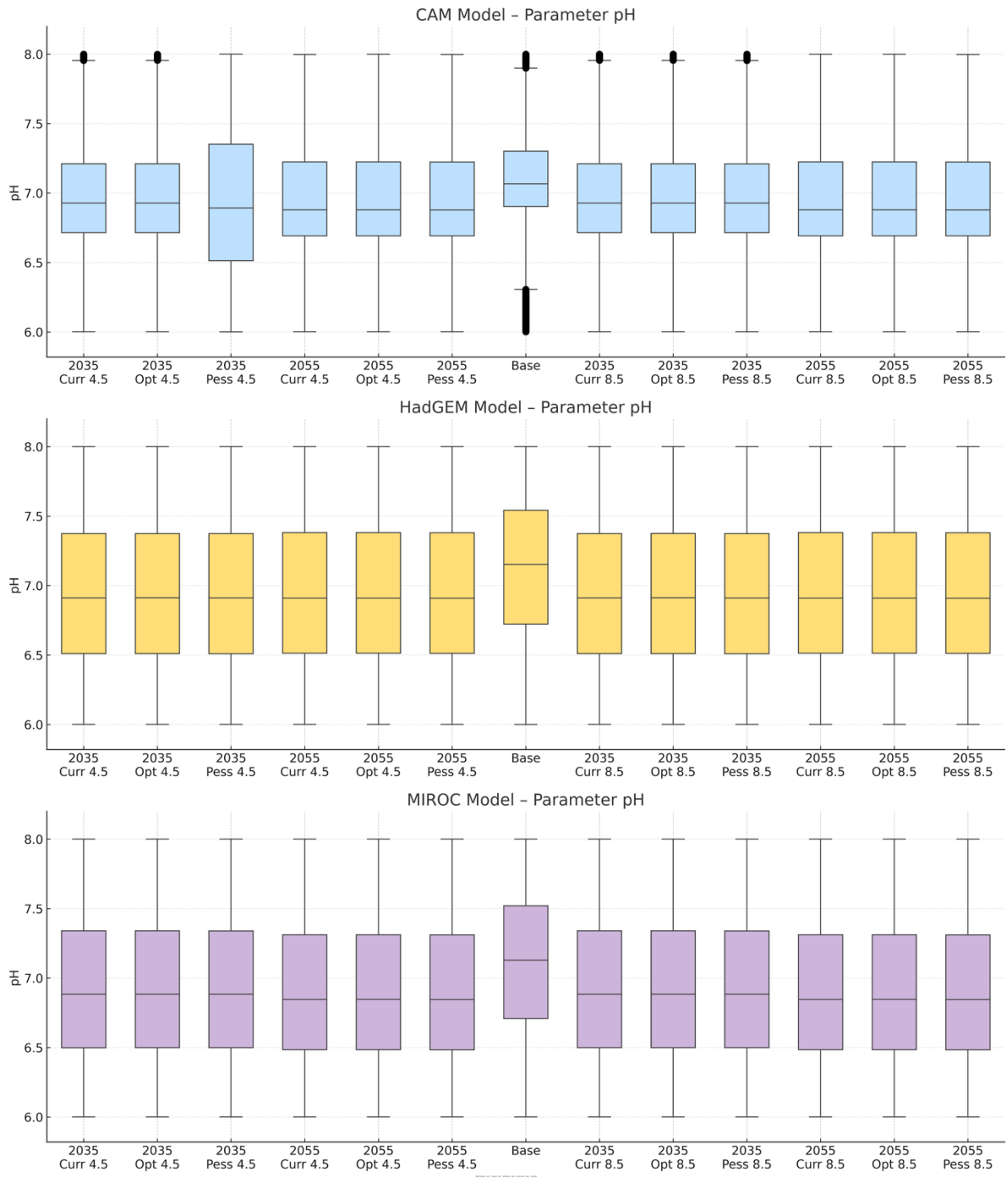

Figure 4 – Projections of water pH (Gradient Boosting) under climate variables (Eta–CMIP5) and hydrological variables (MH-D-Inpe) for 2035 and 2055.

Abbreviations: Curr= Current, Opt=Optimistic, Pess = Pessimistic

Source: Prepared by the authors (2025).

The graphics results for pH noted negligible differences. There remained near 7.0 as a means, indicating a neutral state in the absence of significant variation in any of the periods. Moderate variation was observed, as the CAM model generally had a pH between 6.7 and 7.7 across scenarios.

The pH observed in the 2055 scenarios is decreasing slightly, with a weaker trend toward outliers but no major outliers. The model indicates stable behaviour, though slightly more acidic in the future, at least as the model anticipates. Overall, according to the analyses, HADGEM had the most stable pH projections among the climate models in these studies, with median values near 7, low variability, and no outliers (the lowest value of a significant extreme-out variable), suggesting a stable model of climate projections. Regarding trends, MIROC showed greater variability and a negative trend in pH values in the 2055 scenarios, particularly under the pessimistic scenario, indicating wider dispersion of projections. The general trend indicates a modest decrease in pH in 2055 between the MIROC and CAM cases, whereas HADGEM shows little change. No significant acidification occurred, except in the CAM model for the high-emission scenario (RCP 8.5). Statistical findings revealed differences between the models and underscored the importance of using multiple modelling strategies in environmental evaluations.

Table 3 – Statistical analysis for the water pH parameter

Descriptive statistics for the pH parameter				
Climate Model	*Mean Temperature (°C)*	*Mean Range*	*Observations*	
CAM	0,365	1,999	Low dispersion, values concentrated near neutrality.	
HADGEM	0,543	6,931	Extreme values influence greater dispersion.	
MIROC	0,536	6,858	Variability similar to HADGEM; presence of extremes.	
Analysis of Variance (ANOVA) – pH Among Scenarios Within Each Model				
Climate Model	*F-Statistic*	*p-Value*	*Statistical Significance*	*Interpretation*
CAM	1387,44	< 0,0001	Yes	Statistically significant differences; however, with a small effect size.
HADGEM	697,85	< 0,0001	Yes	Significant; very small effect magnitude.
MIROC	905,09	< 0,0001	Yes	Significant; reduced effect size.
Tukey's Test for Comparison of Mean pH among models				
Group 1	*Group 2*	*Mean Difference*	*p-Value*	*Statistical Significance*
CAM	HADGEM	+ 0,01451	< 0,001	Yes
CAM	MIROC	+ 0,04487	< 0,001	Yes
HADGEM	MIROC	+ 0,03035	< 0,001	Yes

Source: Prepared by the authors (2025).

Turbidity analysis revealed many significant outliers (that is, measurements far from the mean) in the turbidity parameter. As in the baseline scenario, the median turbidity is near 20; however, some samples are in the 80 range due to intense rainfall and runoff events.

In the 2035 interval (C, O, P), the median is slightly higher while the outliers remain significant. In the 2055 projections (C, O, P), the median rises slightly, indicating a higher rate of turbidity events. The extensive outliers and peaks in turbidity across all periods indicate that turbidity control remains a continuing problem, which may necessitate operational adaptations in the future (Figure 5).

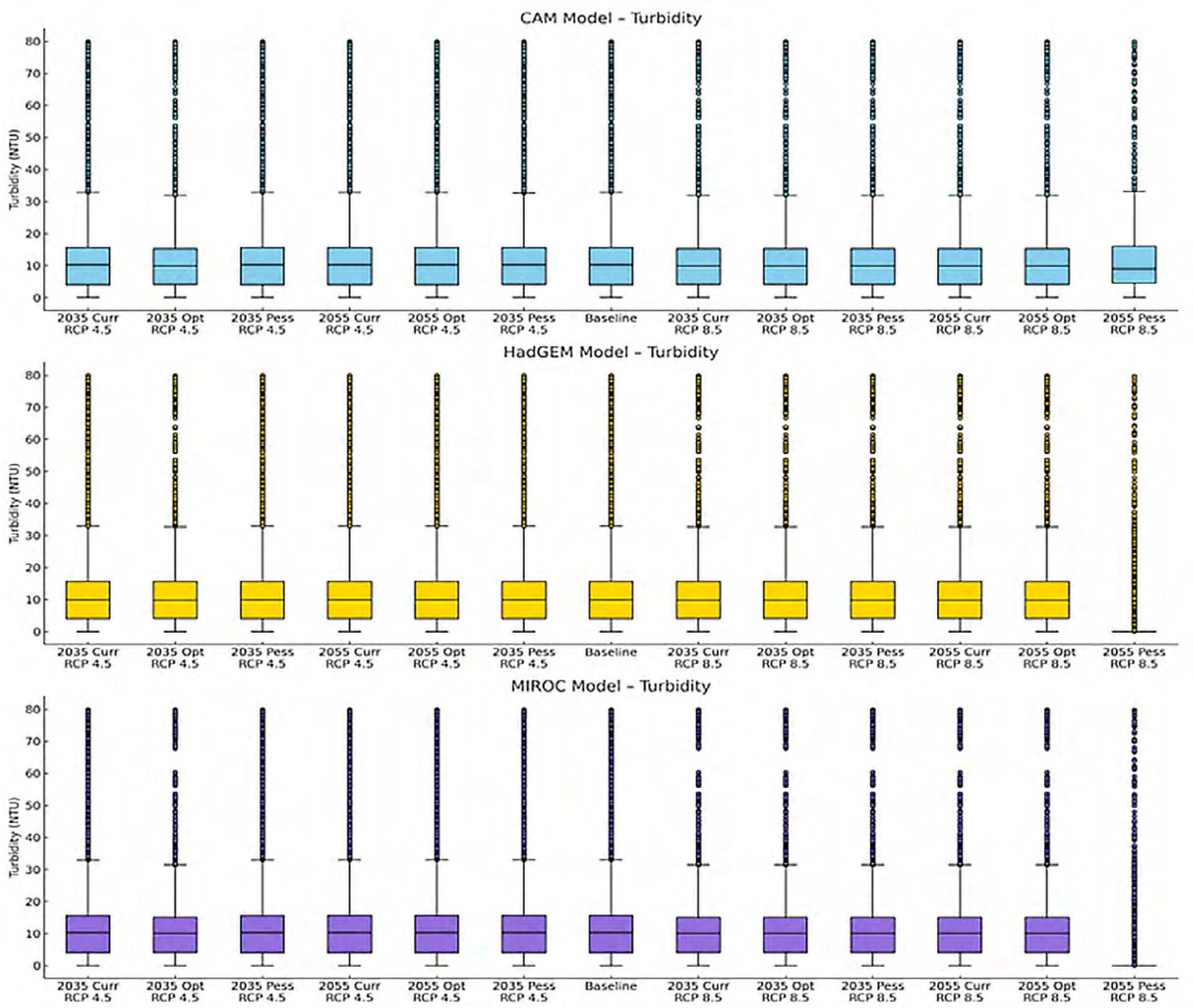

Figure 5 – Projections of water turbidity (Gradient Boosting) under climate variables (Eta–CMIP5) and hydrological variables (MHD-Inpe) for 2035 and 2055.

Abbreviations: Curr= Current, Opt=Optimistic, Pess = Pessimistic

Source: Prepared by the authors (2025).

In the descriptive statistics, heterogeneity among models is observed, with standard deviations ranging from 11.77 to 12.64 NTU and maximum ranges of approximately 80 NTU across all models, indicating the recurring presence of extreme values.

However, the overall means were very similar (≈12.5-12.8 NTU), suggesting little structural difference among the simulated average regimes.

Table 4 – Statistical analysis for the turbidity parameter

Descriptive statistics for the turbidity parameter			
Climate Model	***Mean Temperature (°C)***	***Mean Range***	***Observations***
CAM	12,188	79,999	Skewed distribution; presence of high extreme values.
HADGEM	12,636	79,997	Highest mean among the models; slightly greater dispersion.
MIROC	11,769	79,939	Lower mean; variability comparable to CAM.

ISSN-e 2179-9067

Analysis of Variance (ANOVA) – Turbidity Among Scenarios Within Each Model				
Climate Model	*F-Statistic*	*p-Value*	*Statistical Significance*	*Interpretation*
CAM	0,182	0,9991	No	No differences among scenarios.
HADGEM	5,933	< 0,0001	Yes	Statistical difference with an extremely small effect size.
MIROC	0,068	0,999	No	No differences among scenarios.
Tukey's Test for Comparison of Mean Turbidity Among Models				
Group 1	*Group 2*	*Mean Difference*	*p-Value*	*Statistical Significance*
CAM	HADGEM	+0,1225	< 0.001	Yes
CAM	MIROC	−0,1069	< 0.001	Yes
HADGEM	MIROC	−0,2294	< 0.001	Yes

Source: Prepared by the authors (2025).

The apparent colour parameter of water (Figure 6) illustrates the trend toward greater variance and dispersion predicted for the 2035 and 2055 phases of the study based on the CAM, HADGEM, and MIROC climate models. Such enhanced variability under worst-case scenarios implies a greater potential for instability in watercolour and could pose an ongoing operational challenge, given its direct correlation with turbidity. HADGEM is the most conservative for high-regulatory-precision applications, with low variability, smaller interquartile dispersion, and lower median values. Although CAM presented moderately stable projections with consistent medians across scenarios, MIROC suggested greater susceptibility to variability — particularly in the long run.

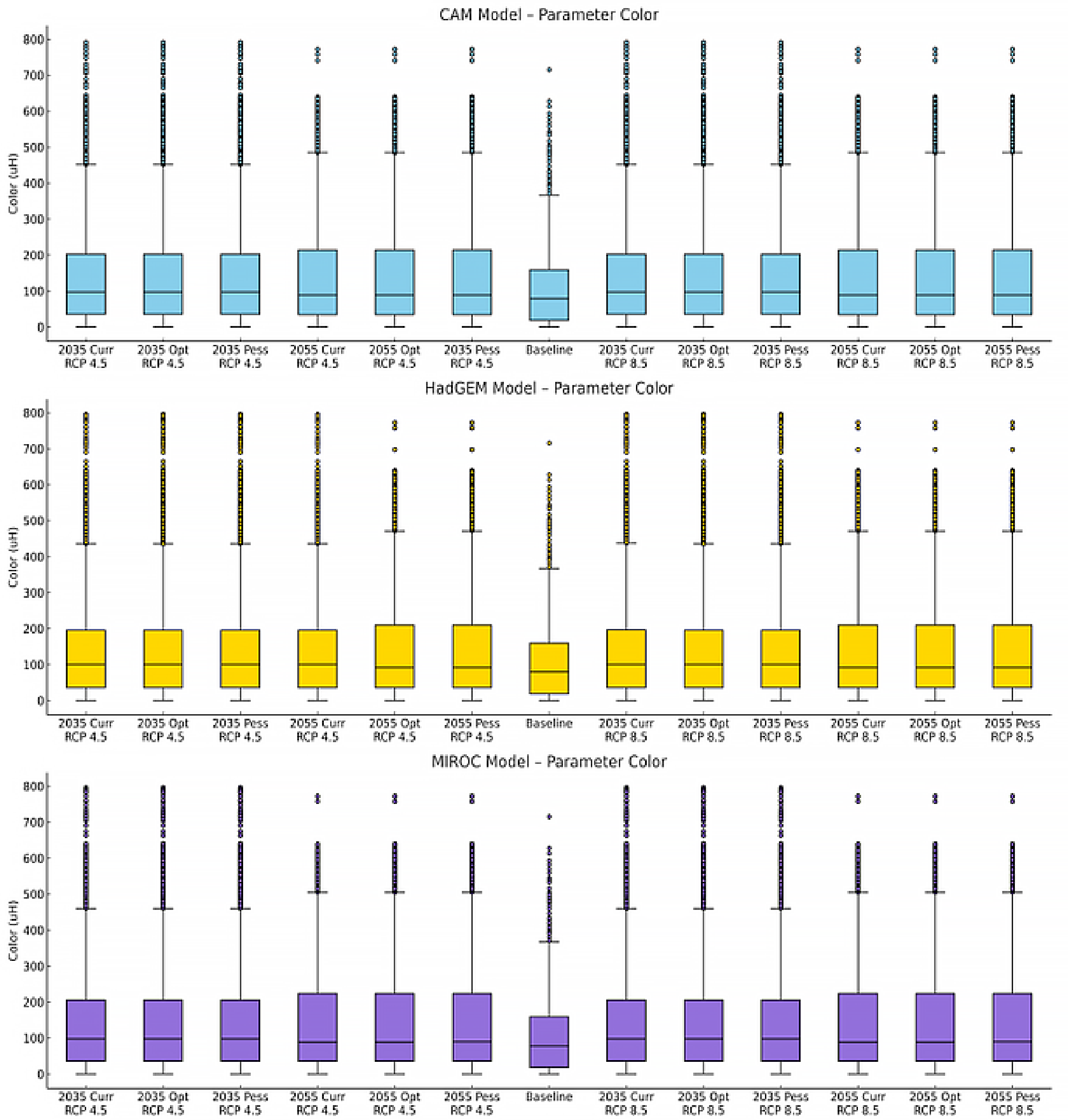

Figure 6 – Projections of apparent watercolour (Gradient Boosting) under climate variables (Eta–CMIP5) and hydrological variables (MHD-Inpe) for 2035 and 2055.

Abbreviations: Curr= Current, Opt=Optimistic, Pess = Pessimistic

Source: Prepared by the authors (2025).

The statistical analysis of the colour parameter (uH) provides quantitative support for interpreting the effects of climate on water quality. The Eta-CamESM2 model yielded a much wider interquartile range and many outliers, indicating greater internal variability. The ANOVA among scenarios within the CAM model yielded no significant differences ($F = 0.294$; $p = 0.995$), indicating no systematic shifts across alternative climate scenarios. The MIROC model, however, showed lower dispersion and median values close to the baseline, which indicates relative stability. The HadGEM model exhibited intermediate behaviour, with a median value slightly above the baseline and moderate variability.

Table 5 – Statistical analysis for the apparent colour parameter

Descriptive statistics for the turbidity parameter				
Climate Model	*Mean Temperature (°C)*	*Mean Range*	*Observations*	
CAM	32,418	199,998	Skewed distribution; recurring presence of high extreme values.	
HADGEM	33,104	199,997	Highest mean among the models; slightly greater dispersion.	
MIROC	31,884	199,995	Lower mean; variability comparable to CAM.	
Analysis of Variance (ANOVA) – Turbidity Among Scenarios Within Each Model				
Climate Model	*F-Statistic*	*p-Value*	*Statistical Significance*	*Interpretation*
CAM	0,294	0,995	No	No differences among scenarios.
HADGEM	7,814	< 0,0001	Yes	Statistical difference with an extremely small effect size.
MIROC	0,117	0,999	No	No differences among scenarios.
Tukey's Test for Comparison of Mean Turbidity Among Models				
Group 1	*Group 2*	*Mean Difference*	*p-Value*	*Statistical Significance*
CAM	HADGEM	+0,724	< 0,001	Yes
CAM	MIROC	-0,335	< 0,001	Yes
HADGEM	MIROC	-1,059	< 0,001	

Source: Prepared by the authors (2025).

Figure 7 shows NH_3–N parameter (ammoniacal nitrogen) behaviour under multiple climate scenarios based on the Eta-CamESM2, HADGEM, and MIROC models. In general, the projected future NH_3–N concentrations tend to increase under RCP 8.5 (pessimistic), suggesting that water quality is more susceptible to warming and hydrological variability.

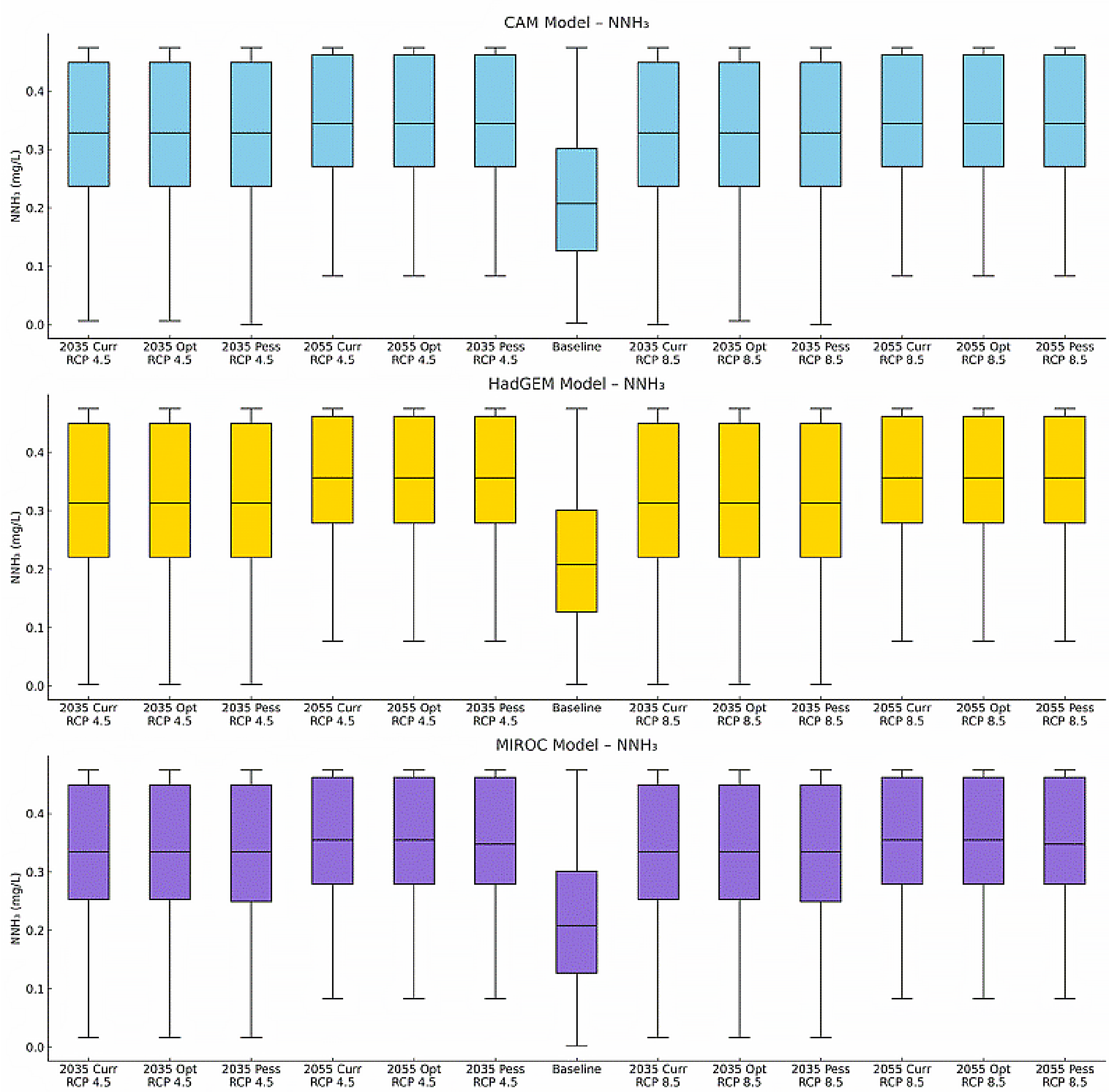

Figure 7 – Projections of NH_3–N in water (Gradient Boosting) under climate variables (Eta–CMIP5) and hydrological variables (MHD-Inpe) for 2035 and 2055.

Abbreviations: Curr= Current, Opt=Optimistic, Pess = Pessimistic

Source: Prepared by the authors (2025).

From an integrated perspective, the results indicate that Eta-CamESM2 shows greater sensitivity to internal variability, HADGEM exhibits more concentrated behaviour, and MIROC combines central stability with occasional extreme values.

However, the overall variability of NH_3–N is explained by the internal dynamics of the series and the occurrence of extreme events, rather than by robust structural differences among models or scenarios.

Table 6 – Statistical analysis for the NH_3–N parameter

Descriptive statistics for the turbidity parameter				
Climate Model	*Mean Temperature (°C)*	*Mean Range*	*Observations*	
CAM	0,1086	0,477	Moderate variability; presence of occasional outliers; relatively stable distribution across scenarios.	
HADGEM	0,1051	0,472	Dispersion similar to CAM; concentrated central behaviour.	
MIROC	0,104	0,472	Lower relative dispersion; occasional occurrence of extremes.	
Analysis of Variance (ANOVA) – Turbidity Among Scenarios Within Each Model				
Climate Model	*F-Statistic*	*p-Value*	*Statistical Significance*	*Interpretation*
CAM	2,873	< 0,0001	Yes	Detectable statistical difference; however, with a small effect size and low practical relevance.
HADGEM	4,912	< 0,0001	Yes	Detectable statistical difference; reduced effect magnitude.
MIROC	1,964	< 0,0001	Yes	Detectable statistical difference; variation explained by scenarios is small.
Tukey's Test for Comparison of Mean Turbidity Among Models				
Group 1	*Group 2*	*Mean Difference*	*p-Value*	*Statistical Significance*
CAM	HADGEM	+0,0037	< 0,001	Yes
CAM	MIROC	−0,0052	< 0,001	Yes
HADGEM	MIROC	−0,0089	< 0,001	Yes

Source: Prepared by the authors (2025).

The Python simulation of the NNH_3_predicted parameter shows a considerable increase over the baseline, around 0.2 mg/L. The results for the 2035 period (C, O, P) show a median of approximately 0.25 mg/L, an increase of about 25%.

In the 2055 period (C, O, P), the median remains stable, although variability persists.

The choice of climate model affects ammonia (NNH_3) projections, which in turn inform management objectives and acceptable risk levels.

5 DISCUSSION

The simulations suggest that climate change may exacerbate water-quality challenges in the Paraíba do Sul River basin. From the data review, we observed a direct correlation between air and water temperatures, and largely between the effects on pH, turbidity, colour, and ammonia (NNH_3).

It is predicted that more severe weather events, including prolonged droughts and heavy rainfall, will significantly impact the region's hydrological systems and pollutant and sediment concentrations, requiring modifications to treatment processes. Furthermore, rising temperatures promote algal growth and toxin production, exacerbating BOD and operational difficulties. Previous studies support these findings.

Andrade *et al.* (2016) showed that urbanisation, agriculture, and deforestation affect the water cycle (hydrological cycle) in the Paraíba do Sul River, thereby directly influencing water quality. Furthermore, Gonçalves *et al.* (2015) used the water quality index (WQI) to assess contamination in the domestic sewage (and other pollution sources), emphasising the importance of extra management strategies. Thermotolerant coliforms and total phosphorus had non-compliance rates of 54% and 12%, respectively, in the lower Paraíba do Sul region, between 2012 and 2019, indicating a need for improved governance (Nunes *et al.*, 2024).

Alvarenga *et al.* (2012) showed that conservation methods and environmental restoration within the Ribeirão dos Macacos watershed improved environmental quality, focusing on hydrological sustainability in general, whilst considering temperature as the most affected parameter with respect to flow seasonality.

Canamary *et al.* (2023), focusing on food and energy security under climate change in the Paraíba do Sul River basin, adopted the same deterministic hydrological model. Considering such a context, several ways can be made to reduce such impacts based on this context, potentially:

- Prepare water-stress scenarios to predict and plan actions in time-critical situations (e.g., severe drought or flooding).
- Build contingency reservoirs to ensure you have secure supplies during extreme climate events.
- Try alternative water sources (underground abstraction, desalination, or reuse) to reduce reliance on a single source.
- Modify operational protocols with climate-based forecast models, so that systems can adapt as hydrological variability increases.
- We can promote awareness of actions that minimise damage to water bodies.
- Reforest areas of aquifer recharge and environmental protection zones within the basin.
- Restore degraded and unused areas through reforestation.
- Reduce deforestation and advance environmentally sensitive conservation policies. Control 100% of domestic and industrial wastewater.
- Cut down on using fossil fuels.
- Strengthen monitoring of physical and chemical indicators of basin water quality.

Such measures help make water treatment systems more resilient, ensuring that treated water quality meets desired levels even under climate change. However, these will, of course, make the process costlier.

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6 CONCLUSIONS

The purpose of this study is to assess the effects of climate change on water quality in the Paraíba do Sul River Basin using climate models (CAM, HADGEM, and MIROC) and machine learning approaches. The results obtained support the proposed objectives by providing evidence of the potential connection between climate change and variation in water quality parameters, and by supporting mitigation and adaptation approaches. The difference between future scenarios and the Baseline (historical) scenario shows that its climate variability has a high impact on water potability and availability.

This trend of incremental changes in air and water temperatures, as well as long-term projections of pessimistic scenarios like 2055, is increasingly common. They may result in warming that alters the area's climate and hydrological conditions, raising raw water treatment costs and welfare. Rising temperatures lead to higher levels of algae and cyanobacteria, which can produce toxins harmful to human and animal health.

Warmer temperatures and more frequent extreme climate events, such as flooding and prolonged droughts, favour the spread of dangerous algae. These organisms degrade water quality by increasing biochemical oxygen demand (BOD) and decreasing dissolved oxygen (DO) levels. Previous studies have also confirmed their findings, indicating that they must be monitored and prevented from recurring. Climate change influences essential water quality parameters, including turbidity, colour, ammonia (NNH_3), and pH. Long-lasting droughts disrupt river flow, increasing pollutant concentrations, and extreme rainfall carries sediment and organic matter into water systems. The need for more sophisticated technologies is as high as 20%. As such, many mitigation measures were outlined in the previous section to address these challenges.

Taking these steps can increase the resilience of water treatment systems and ensure that, even under climate change scenarios, managed water meets applicable standards. Please note the financial implications of these steps, which will further increase treatment costs. While this study uses climate models (CAM, HADGEM, and MIROC), each with varying degrees of sensitivity and uncertainty, it is limited to these models. Further investigations should consider which treatment technologies are most suitable for extreme climate contexts and examine the influence of socio-environmental interventions on water quality.

The inclusion of high-resolution temporal and spatial data may also enhance projections.

The essence of the study is that water supply integration includes both technological ways and environmental management practices. Effective public policy for water security would benefit all concerned. It is therefore crucial to implement mitigation measures to ensure high-quality water for future generations.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

The authors used ChatGPT (OpenAI) only for language editing and stylistic polishing. All scientific content, analysis, and intellectual input were developed and verified by the authors, who take full responsibility for the accuracy and integrity of the manuscript.

ETHICAL CONSIDERATIONS

This study was based exclusively on secondary environmental data and computational modelling, without involving human subjects or animal experimentation. Therefore, submission to or approval by a research ethics committee was not required.

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