



# IMPACT OF CLIMATE CHANGE ON SURFACE WATER – ANALYSIS USING MACHINE LEARNING

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**Abstract:** This abstract highlights the significance of machine learning in analyzing surface water dynamics amidst climate change. It emphasizes how traditional methods struggle with the complexity of data generated by climate-induced alterations, while machine learning offers promising avenues for extracting meaningful insights. By leveraging techniques such as neural networks and decision trees, machine learning can identify intricate relationships between climatic variables and surface water dynamics, aiding in hydrological modeling, flood forecasting, water quality assessment, and ecological impact evaluation. The abstract stresses the importance of interdisciplinary collaboration to harness machine learning's full potential and develop robust strategies for adaptation and mitigation, promoting the resilience of water-dependent ecosystems and human communities.

**KEY WORDS:** Machine Learning, Model Selection and Training, Correlation Matrix, Interpretation and Visualization, Water Quality Monitoring, Decision Support Systems, Adaptation Strategies, Graphical User Interface

## I. INTRODUCTION

Climate change poses significant challenges to the management and sustainability of surface water resources worldwide. Alterations in precipitation patterns, temperature regimes, and land use practices are leading to profound shifts in surface water dynamics, impacting water availability, quality, and distribution. Addressing these challenges requires advanced analytical tools capable of comprehensively assessing the complex interactions between climate change and surface water systems. In recent years, machine learning has emerged as a promising approach for analysing and predicting the impacts of climate change on surface water resources.

Machine learning techniques offer the capability to process large, multidimensional datasets and uncover intricate relationships between climatic variables and surface water dynamics. By leveraging algorithms such as neural networks, decision trees, and ensemble methods, machine learning enables the extraction of valuable insights from vast amounts of observational and modelling data. These insights are essential for enhancing our understanding of the complex mechanisms driving changes in surface water systems under the influence of climate change.

This introduction sets the stage for exploring the intersection of climate change, surface water analysis, and machine learning. It highlights the pressing need to develop innovative approaches for assessing and managing surface water resources in a changing climate. By integrating machine learning techniques into surface water analysis, researchers and practitioners can unlock new opportunities for informed decision-making, adaptive management, and the sustainable stewardship of water resources in the face of ongoing environmental change.

## II. MACHINE LEARNING

Machine learning, a subfield of artificial intelligence (AI), has revolutionized the way we approach complex problems across various domains. At its core, machine learning is concerned with the development of algorithms and statistical models that enable computer systems to learn from and make predictions or decisions based on data, without being explicitly programmed to do so.

The essence of machine learning lies in its ability to recognize patterns and extract insights from vast amounts of data, allowing for the automation of tasks and the discovery of hidden relationships that may not be apparent to human observers. This capability has propelled machine learning to the forefront of numerous applications, ranging from image and speech recognition to medical diagnosis, financial forecasting, and autonomous driving.

Central to the success of machine learning is the iterative process of learning from data. Algorithms are trained on labelled datasets, where the input data and corresponding desired outputs are provided, enabling the algorithm to adjust its parameters and improve its performance over time. Through this process of training and validation, machine learning models can generalize from known examples to make predictions or decisions on new, unseen data.

Machine learning encompasses a wide range of techniques and algorithms, including supervised learning, where models learn from labelled data; unsupervised learning, where models identify patterns and structures in unlabelled data; and reinforcement learning, where models learn to make decisions through trial and error, guided by feedback from the environment.

The increasing availability of big data, coupled with advancements in computing power and algorithmic sophistication, has propelled the rapid evolution of machine learning in recent years. Today, machine learning algorithms are deployed in diverse applications across industries, driving innovation, efficiency, and insights that were previously unattainable.

As we develop deeper into the capabilities of machine learning and continue to push the boundaries of what is possible, the potential for transformative impact across society and industry is immense. From personalized healthcare and intelligent automation to predictive analytics and beyond, machine learning holds the promise of shaping a future where data-driven decision-making and intelligent systems are ubiquitous.

## III. OBJECTIVES

- To assess the influence of climate change on surface water on a study area by using machine learning.
- To examine the effects of climate change on surface water quality by using water quality parameters.

## IV. METHODOLOGY

### 1. Study Area

Bugudanahalli Lake, located in Tumkur District, Karnataka, is a significant water body known for its ecological importance and cultural significance to the local community. The lake serves as a vital source of water for irrigation, domestic use, and supporting biodiversity in the region.

### 2. Data Collection

Data collection in the analysis of the impact of climate change on surface water involves gathering comprehensive and diverse datasets that capture various aspects of the water system. The collected data serves as the foundation for machine learning models and other analytical tools to assess changes, identify patterns, and predict future scenarios through various sources. Here are key considerations for data collection:

- Hydrological Data
- Climate Data
- Water Quality Data
- Land Use and Land Cover Data
- Geospatial Data
- Ecological Data
- Historical Data
- Citizen Science Data

### 3. Data Analysis

Analysing the impact of climate change on surface water using machine learning involves processing and interpreting the collected data to uncover patterns, trends, and relationships. The goal is to gain insights into how climate change influences surface water systems and to develop predictive models for future scenarios. Here's an overview of the data analysis process.

1. Data Preprocessing
2. Exploratory Data Analysis (EDA)
3. Feature Selection
4. Model Selection
5. Training Model
6. Model Evaluation
7. Uncertainty Analysis
8. Graphical User Interface

## V. RESULTS AND DISCUSSIONS

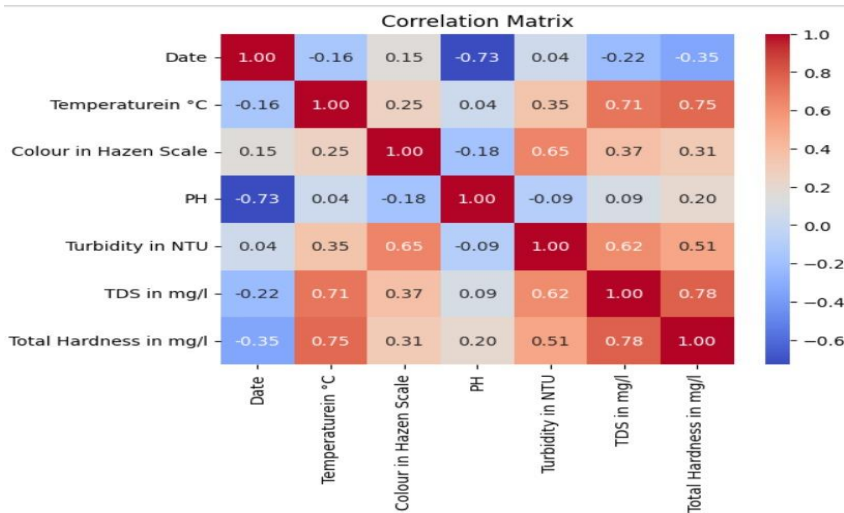
### 4.1 DATA DESCRIPTION

[4]:

	Date	Temperature in °C	Odour	Taste	Colour in Hazen Scale	PH	Turbidity in NTU	TDS in mg/l	Total Hardness in mg/l	Fluoride in mg/l
0	2023-01-02 00:00:00	28.5	Agreeable	Agreeable	10	8.18	13.8	110.8	62	Absent
1	2023-01-03 00:00:00	28	Agreeable	Agreeable	10	8.559	13.4	109.4	62	Absent
2	2023-01-04 00:00:00	28.3	Agreeable	Agreeable	10	8.661	12.1	111.8	62	Absent
3	2023-01-05 00:00:00	27.4	Agreeable	Agreeable	10	8.448	12.9	107.8	62	Absent
4	2023-01-06 00:00:00	27.4	Agreeable	Agreeable	10	8.541	13	106.9	62	Absent
...	...	...	...	...	...	...	...	...	...	...
248	2023-11-22 00:00:00	27.9	Agreeable	Agreeable	15	7.62	18.8	108.6	60	Absent
249	2023-11-23 00:00:00	27.6	Agreeable	Agreeable	15	7.48	20.5	108.8	62	Absent
250	2023-11-24 00:00:00	28.2	Agreeable	Agreeable	15	7.32	20.7	108.8	62	Absent
251	2023-11-25 00:00:00	27.5	Agreeable	Agreeable	15	7.48	20.1	108.6	60	Absent
252	2023-11-27 00:00:00	27.4	Agreeable	Agreeable	15	7.191	20.8	108.9	60	Absent

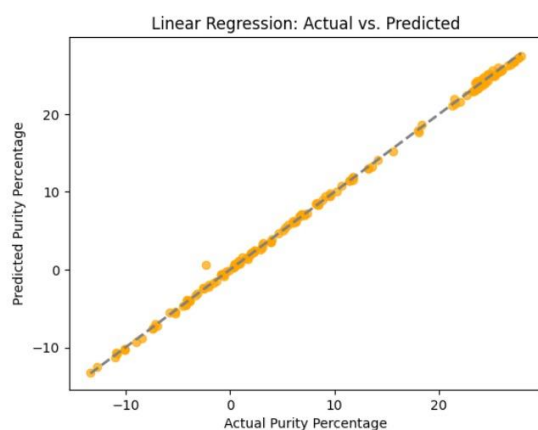
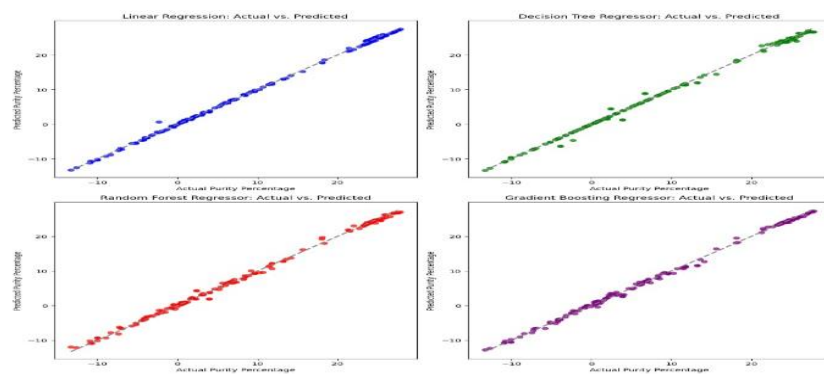
Water quality parameters including pH, temperature, turbidity, total dissolved solids (TDS), and hardness offer critical insights for predicting water chemistry changes, habitat fluctuations, and contamination risks. Analyzing these parameters enables proactive water resource management, pollution control, and ecosystem conservation efforts, ensuring sustainable freshwater use for present and future needs.

### 4.2 CORRELATION MATRIX BETWEEN VARIOUS PARAMETERS



In the correlation matrix, a strong positive correlation (0.78) exists between Total Hardness and TDS, indicating that as TDS concentration rises, Total Hardness tends to increase, both influenced by dissolved minerals. Conversely, a weak negative correlation (-0.18) between pH and Color suggests a slight tendency for higher pH to correspond with lighter coloration, though they are somewhat independent. These insights highlight interrelationships among parameters influencing water purity, guiding monitoring and management strategies for water quality.

### 4.3 MODEL EVALUATION AND SELECTION



The linear regression model outperforms other models, showing highest accuracy in predicting water purity percentages. Despite slight deviations, the graph demonstrates strong correlation between actual and predicted values, indicating effective pattern capture by the model. This alignment underscores the model's significance in water quality assessment, aiding informed decision-making for maintaining or enhancing water purity levels. Comparison with other models offers insights into diverse modelling approaches, guiding selection for specific datasets and applications.

#### 4.4 PURITY PERCENTAGE

Linear Regression R-squared: 99.92%

Decision Tree R-squared: 99.57%

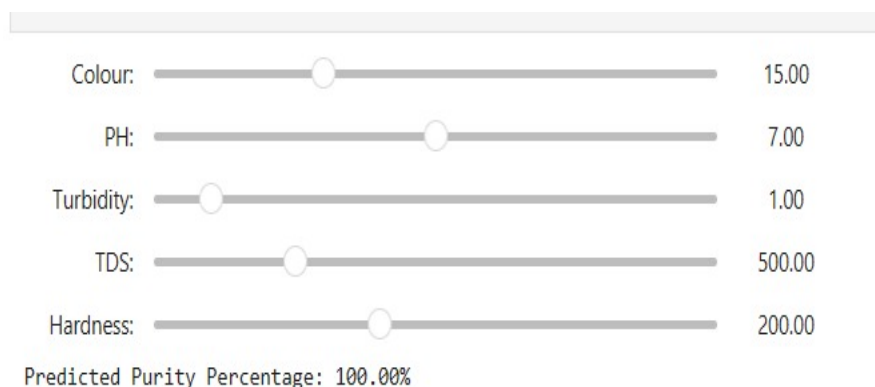
Random Forest R-squared: 99.82%

Gradient Boosting R-squared: 99.78%

	Colour in Hazen Scale	PH	Turbidity in NTU	TDS in mg/l	Total Hardness in mg/l	Purity_Percentage
count	253.0	253.000000	253.0	253.0	253.0	253.000000
unique	4.0	NaN	153.0	130.0	8.0	NaN
top	15.0	NaN	19.8	108.6	62.0	NaN
freq	165.0	NaN	8.0	12.0	105.0	NaN
mean	NaN	7.923246	NaN	NaN	NaN	23.154756
std	NaN	0.258253	NaN	NaN	NaN	4.391992
min	NaN	7.191000	NaN	NaN	NaN	-4.711679
25%	NaN	7.800000	NaN	NaN	NaN	22.806082
50%	NaN	7.920000	NaN	NaN	NaN	24.099378
75%	NaN	8.110000	NaN	NaN	NaN	25.053214
max	NaN	8.661000	NaN	NaN	NaN	29.102833

Limited data collection leads to linear regression model inaccuracies in predicting water purity percentages, as it heavily relies on available data to establish relationships between input parameters and the target variable. Insufficient data for specific parameter combinations can cause deviations from acceptable limits, highlighting reliability issues. Additionally, the model's assumption of a linear relationship may not capture the true complexity, leading to discrepancies in predictions.

#### 4.5 GRAPHICAL USER INTERFACE



The GUI enables easy prediction of water purity percentages by inputting parameters like color, Ph, turbidity, TDS, and hardness. Utilizing a linear regression model, it provides instant feedback on water purity predictions through visual indicators like color scales or progress bars. Additionally, it facilitates proactive decision-making by allowing "what-if" analyses for potential variations in water quality. The GUI further supports data logging for trend analysis, aiding in informed water quality management strategies. Ultimately, it offers a user-friendly interface for comprehensive water quality assessment and decision support.

## CONCLUSION

The study employed machine learning to assess climate change's impact on surface water quality, revealing insights into key parameters like pH, temperature, turbidity, TDS, and hardness. Notable trends included temperature fluctuations, increased turbidity in certain months, and a strong correlation between hardness and TDS. These findings are pivotal for formulating effective water management strategies, especially in the context of climate change. The study's contributions include novel methodologies and predictive models, highlighting machine learning's potential in environmental studies. Despite limitations like data constraints, the study recommends exploring complex models and incorporating diverse data sources for better accuracy. Practical application includes a GUI for real-time water purity predictions, aiding proactive management. Collaborative efforts are urged for comprehensive water security strategies. The research stresses the integration of predictive tools into water management to address climate change challenges effectively. Lastly, gratitude is extended to contributors and funding agencies for their support in advancing understanding and safeguarding surface water quality.

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