Precision Control Measures for Proactive Water Management to Improve Sustainability

MADHURI S. BHAGAT[1], ARADHANA SAHU[2], ANKUSH N. ASATI[3], AMELY R. KHEDIKAR[4], PRAVIN B. [5], SUDHA MISHRA[6], LAXMIKANT UMATE[7], RACHANA BAJAJ[8], ABDUL GHAFFAR NOOR MOHD[9]

[1]Yeshwantrao Chavan College of Engineering,
Nagpur- 441110,
INDIA

[2]Department of Computer Science and Engineering,
Rungta College of Engineering and Technology,
Chhattisgarh- 490024,
INDIA

[3]Department of Civil Engineering,
Yeshvantrao Chavan College of Engineering,
Nagpur 441110,
INDIA

[4]Tulsiramji Gaikwad-Patil College of Engineering and Technology,
Nagpur 441108,
INDIA

[5]Department of Civil Engineering,
Waghmare Acharya Shrimannarayan Polytechnic,
Maharashtra-442001,
INDIA

[6]Department of Computer Science and Engineering,
J. K. Institute of Engineering,
Chhattisgarh 495550,
INDIA

[7]Jawaharlal Nehru Medical College,
Maharashtra 442107,
INDIA

[8]Department of Civil Engineering,
Rabindranath Tagore University,
Bhopal- 464993,
INDIA

[9]Department of Civil Engineering,
Guru Nanak Institute of Technology,
Nagpur, Maharashtra 441501,
INDIA

Abstract: - Water resource management of sustainable development was an integral part of development, especially with regard to pollution, climatic fluctuation, and demands on water quality. This research will be aimed at prevention procedures, for the effective use of water, such as sophisticated mathematical models, monitoring, and the simulation systems. In this study, Linear Regression and Random Forest Regression models are used with the aim to estimate the various interactions between the pollutants, chemicals, thermal and groundwater, and water levels. Through the incorporation of real-time monitoring mechanisms, the approach allows the adaptation of water management approaches to new environmental conditions more efficiently. It is also revealed that specific approaches to pollutant control are useful for determining effective methods of protection of water bodies and aquatic organisms. The models of predictions and the simulations employed in this analysis assist the decision makers in future planning of dealing with essential pollutants such as carbon dioxide and thermal contaminants. The results show a possibility of using precision control measures toward a decrease in pollutant concentration and increased water sustainability. Therefore, this work advances the current knowledge of sustainable water management by postulating an approach to developing adaptable and data-driven solutions to current water resource issues. It also points to a level of technological solutions in enhancing responsive and sustainable management for water quality in a changing environmental system.

Key-Words: - Water Resource Management, Sustainable Development, Pollution Control, Climatic Fluctuation, Water Quality, Hydrological Modeling.

Received: June 18, 2024. Revised: November 26, 2024. Accepted: March 19, 2025. Published: May 9, 2025.

1 Introduction

Over the recent decades, water management has emerged as a critical and highly dynamic facet of sustainable development due to the expanding demand for safe, clean water and the expanding detrimental effects of industrialization, urbanization, as well as applications of modern agriculture, [1]. Pollution in water by chemicals, heat, and groundwater pollution poses a great challenge to environmental conservation and water supply [2], [3]. In many geographic areas, conventional techniques in managing water resources have encountered challenges in addressing the complex and cross-sectoral drivers that impact water systems – and therefore, pollution control and resource utilization have proven to be ineffective, [4]. The demand for better and explicit techniques of water resources management in real-time and, also in their predictability, has never been higher, [5]. This research examines an anticipatory approach to water management with the help of predictive analysis, control platforms, and modeling and simulation, [6], [7], [8]. These SRs make it easier to predict the conduct of the various pollutants with respect to the water levels thus enabling better control measures to be put in place, [9]. Linear Regression and Random Forest Regression models are used to forecast the relations between pollutants and water sources, while live monitoring systems allow for constant feedback and modification of the management strategies based on the incoming information, [10]. By using synthetic data generation and data visualization approaches, the study solves the problem of model interpretability and its applicability in decision-making under conditions of environmental variability, [11], [12], [13], [14].

In this context, the study puts much stress on accurate measurements aimed at water quality enhancements alongside a decrease in pollutant indicators, [15]. As a result, the collected research allows for the formulation of specific and responsive control measures to target the primary pollutants most damaging to water ecosystems, [16]. For instance, Pollutant-specific control measures like carbon dioxide emission control or thermal pollution control may be considered with reference to the knowledge obtained from real-time monitoring coupled with the anticipations from analytically modeled prognosis, [17]. The opportunity to trial these interventions before implementation also increases their efficiency and, by planning changes that will reduce the impact on the environment, boosting the benefits to water quality, [18]. In conclusion, this research benefits the still-emerging literature on sustainable water management with the holistic framework encompassing predictive analytics and monitoring techniques coupled with computational modeling, [19]. The combination of these techniques is a major advancement in the efficient and sustainable management of water resources that involves better, more resilient tools, [20]. According to the findings made in this study, the effectiveness of initiating timely and data-informed approaches toward tackling what constitutes one of the most emergent and demanding issues of the modern world – water pollution together with the necessity of developing adequate solutions to enhance the sustainable functioning of water systems in the context of increasing globalization and global changes, [21], [22]. The identified research gaps consist of handling multiple data sources, developing adaptive control mechanisms in real-time, uncertainty in environmental data, optimization for large scale systems, socio-economic effects, the long-term viability of the systems, multiple cross-disciplinary approaches, and public engagement in water management decision-making. Therefore, the aim of this research is to present a comprehensive approach to predictive water management, that sums up data from multiple sources, techniques of real-time monitoring, and adaptive control systems to improve overall reliability, efficiency, and flexibility of predictive models. It is designed to cope with data uncertainty, investigate socio-economic effects, estimate the extended-term potential for the environment, and include stakeholders in decision-making processes to contribute to better quality, use of resources, and environmental stability of the water resource.

2 Research Methodology

2.1 Data Collection and Preprocessing

The process of data collection is at the core of the attempt, and aims at gathering data sets of desirable quality in terms of representing various types of pollutants emerging in water basins. The relevant pollutants embrace chemical, thermal, and groundwater pollutants; water level data on pollutants of interest have been detected over certain intervals, [23], [24], [25]. These datasets were collected from environmental organizations and historical data so the coverage of the different water systems was comparatively better. The data was subsequently cleaned up to ensure standardization and reliability of the analysis conducted on the data collected. Normalizations of variables were also performed to adjust the scale of a set of variables, imputing missing data and feature extraction to consider only the pertinent or the most influential factors for water levels.

After data cleaning an exploratory feature engineering was done to create new informative features regarding the interactions among the pollutants and their effects on water levels. It produced the setting that enhanced the model accuracies as explained in this step. Moreover, other forms of data mishandling like data augmentation were used in instances where real data was unavailable, to warrant the models to perform optimally even in conditions or scenarios that were unfamiliar to them. Thus, the research adopts both real and synthetic data to provide a comprehensive as well as eligible range of samples for model training and testing.

2.2 Model Development and Training

Two types of predictive models: Linear regression and random forest regression algorithms are selected from the lists of regression techniques. Linear Regression was chosen because of the simplicity of its approach towards directly relating water levels to individual pollutants. This model also enables an easy understanding of how each of the pollutants impacts the water systems since it directly compares the changes in pollutant concentrations to the simulation results. But to include more detailed interactions and curved relationships, Random Forest Regression was also adopted. This kind of method makes a number of decision trees together to make the final prediction, this is able to deal with a large number of variables and multiple relationships in the data better than a straight-line model.

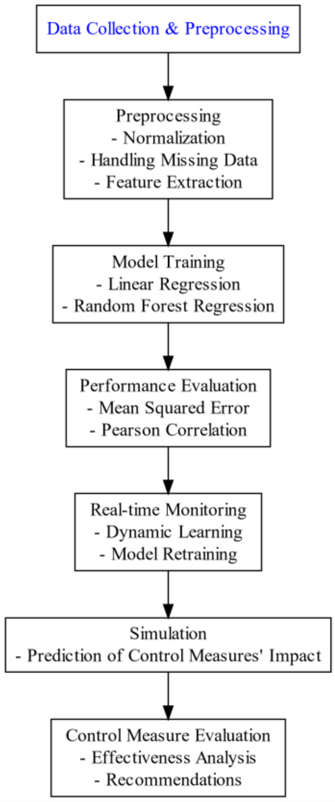

Fig. 1: Precision Control Measures for Proactive Water Management to Improve Sustainability

The above-mentioned models were trained with the-preprocessed-data, and model performances were rechecked at every cross-validation step. Figure 1 helps avoid very high variance models that are overly complex and tuned to the particular training data set. The integration of the synthetic data with the real-world observations also strengthened the models' reliability making them suitable for various conditions within the environment. This conceptual framework offers both a clear and complex structure to study the relationship between pollutants and water level and enhances prediction precision.

2.3 Performance Evaluation

The feasibility of both Linear Regression and Random Forest Regression models was evaluated by calculating the Mean Squared Error (MSE). MSE arrives at the mean of the square of the sum of the difference between the planned and the actual water levels providing a definite way to compare the accuracy of the prediction. MSE is generally preferred more than ME as it's an average of the squared residuals, and the lower the MSE, the closer the model predictions are to actual data. Besides that, the Pearson Correlation Coefficients tests were carried out to check the extent of pollutants and water level associations. These correlation coefficients gave a deeper understanding of which pollutants affected the water level most and where the enhancements in these models were required.

To this end, a conditional branching mechanism was incorporated with a view of enhancing model sufficiency. If the MSE of a particular model was high, i.e., above a predefined limit, then, different models were sought in order to obtain the best forecast outcomes. It was crucial in dynamic environmental systems because a number of times information changes and in order to improve the outcomes the process had to be iterative. To this end, the research includes steps to assess the validity of the existing models and initiate the search for other models in case the current models are not accurate enough or do not apply the best practices in making predictions to inform water management.

2.4 Real-Time Monitoring and Dynamic Learning

Real-time data analysis also forms part of this research as new environmental data was gathered to update the models on real real-time basis. The models are fully integrated with sensors and monitoring systems data to make adjustments based on the latest available data to make the predictions as precise as possible irrespective of fluctuations in environmental conditions. Another advantage of using real-time monitoring data for the model is that data is continuously provided to update the model so that the models are trained incrementally. This approach enables the predictions to be as close to actual real conditions as they evolve hence making the models sensitive to temporal changes in concentration and water level of pollutants.

This is because the learning process of the system involves actual updating of water management strategies in order to address changing circumstances. When models are fed fresh information they give better estimates of water levels depending on the status of pollutant concentrations. Of these, the most notable was the adaptive capability, which is critical in environmental monitoring and can dramatically improve water quality control with new information all other contingencies being equal. Thus the use of dynamic learning introduces another important development in the management of water as a transparent and adaptive approach that can easily adopt change in light of modern environmental factors.

2.5 Simulation and Control Measure Evaluation

Control measures were also modeled in order to determine the best approach to purifying water. Subsequently, the pollutant concentrations and water levels were modeled to explain the condition after performing interventions such as the reduction in emission of carbon dioxide or installation of filtration systems. Many complexities arose from the interactions of preemptive and protective controls of water quality as affected by pollutants in the environment and the simulations enabled close scrutiny of how specific pollutants affected water bodies at different control settings. Due to the changes in the levels of specific pollutants and what was reflected in the changes in water levels, the research came up with useful data to help in managing water pollution.

The simulations also provided the opportunity to compare the water quality from the state before the application of the control measures and after. For instance, the study showed that turnover and pollutant levels decreased, implying that targeted effort gained the desired effect. This paper aimed to compare various conditions before and after the intervention, making it easier to realize the efficacy of each control measure and come up with the best recommendations in water management. As a predictive tool, the use of simulations also enabled preparation and planning in the actual applications in order to apply control measures optimally.

3 Results and Discussion

In the conducted research and case-study on precision control measures for proactive water management, important correlates were established on water quality and pollution trends. By using highlighted models, which include Linear Regression and Random Forest Regression, insights regarding the interaction of pollutant concentrations were obtained from the data collected regarding water levels. Such outcomes have significant implications for enhancing the water management systems and the environmental health of these systems.

3.1 Pollutant-Impact Analysis

The analysis found that thermal, chemical, and ground water pollutants had dissimilar correlations with the water level. As for thermal pollutants, the obtained values were rather feeble and distributed in a limited interval, and were directly proportional to water levels, With evident evidence of acute temperature sensitivity in responders and low thermal tolerance of aquatic organisms. Chemical pollutants, which have a distribution in the wider concentration range, have a moderate influence on water quality while implying possible ecological effects. There was a weaker but more widespread correlation between state groundwater pollutants and levels, suggesting further specific measures are required in order to manage and fight sources of contaminants.

Pollutant categories and water levels were compared using a correlation heatmap. The relationship between water levels and chemical as well as groundwater pollutants was moderately positive, indicating that when the concentrations of the latter were high, slight rises in water levels were also experienced. However negative coefficients were noted for chemical and groundwater pollutants meaning that both types of pollutants are enemies and the degree of one hampers the other. This inverse interaction resonates the multi pollutant nature of many water bodies, asking for more refined actions.

3.2 Predictive Model Performance

The authors analyzed the results of modeling and found adequate results of predictive models in terms of water levels according to the concentration of pollutants. The performance of Linear Regression was good in locating routine patterns, but its efficiency in predicting specific levels of water was low. The Random Forest Regression model which has the advantage of capturing non-linear interactions was also prone to some of these problems in real-time water level prediction. The systematic deviation between the actual and the predicted values at the different time intervals provided an indication that the models were challenged by the richness of the data and the non-linear nature of the dependencies.

Still, the study revealed some predictive models regarding pollutant to water level relationships key to the understanding at that level of development of refining and developing further advanced models to capture the essence of these relationships correspondingly. The observed variations in model performance highlighted the need for continuous monitoring and recalibration of models as real-time data evolves.

3.3 Implementation Benefits of the Live Monitoring System

An alternative live monitoring system that was used in the study effectively captured the fluctuating pollutant concentrations and their effects on water levels in a real-life-like manner. The system used an adaptive learning approach in which the Linear Regression model was updated periodically from the most recently available data. This system was not fixed since the presence of pollutant concentrations enabled the provision of updated estimates on the water levels in real time. Another advantage of such an adaptive capability was important for the timely and appropriate decision-making processes of water treatment particularly where pollutant concentrations fluctuate within a short time as a result of biophysical conditions or human interventions.

The monitoring system provided full plots of pollutant concentration as well as water level over a period of time which provided effective visuals when making decisions. It led to better decisions about water management interventions and highlighted the value of real-time data in improving the accuracy of predictive structures and the monitoring of the physical environment.

3.4 Measures of Control

Pollutant identification was followed with control measures that brought about remarkable improvements in water quality. Intervention focused and based on the observed relationship between certain pollutants and water levels was particularly efficient in lowering the concentration of the pollutants. The analysis of simulation results of the study pointed to a dramatic decrease of pre-control pollutant concentrations ranging from 6 to 20 units, to the range of 2 to 7 units when control measures are applied. This amount suggests that many planning and control measures can help to minimize the impact of polluting agents on water systems.

Those that influence the AFR most significantly, that is, carbon dioxide and sulfur dioxide, were established as key control targets in the measures to be adopted. The dynamicity of the monitoring and control system required constant monitoring of the effectiveness of the processes and making the necessary changes to avoid interventions lapse. Such an approach was dynamic, and the management could only have served with considerable importance in handling the pollution variation as well as the water quality.

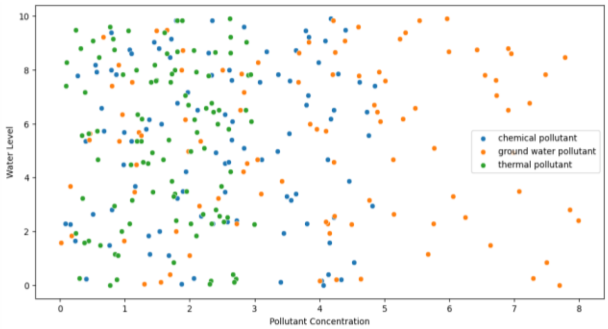

Fig. 2: Scatter plot of water levels vs Pollutants

Figure 2 provided illustrates the relationship between pollutant concentration and water levels, with three categories of pollutants: Chemical (blue), Groundwater (orange), and Thermal (green). This visualization is relevant to the research topic on proactive water management, and control precision measures for sustainable water management. The values of chemical pollutants are relatively skewed but the concentrations of the pollutants are between 1 and 5 while the water levels range between 0 and 10. In the case of groundwater pollutants, these are generalized as orange dots and spread out from 1 to 8 in concentration and have a mild increase in water levels. This suggests that the variability of water concentration in aquifers is strongly influenced by pollutants with greater effects on water level. Thermal pollutants are mostly found in smaller amounts (0 to 3) and are dispersed over different water levels, indicating that thermal pollutants' impact is felt more severely when the amount is low.

This pattern suggests non-proportionation and cognitively, non-linear relationship between density of pollutants and water levels thus the need for adequate approaches and control techniques. As established by the study, this visualization also affirms hypothesis III that shows the various pollutant types' effects on water levels as different, thus requiring specific precision control measures. Hence, chemical pollutants appear to have a smaller effect on the waters and therefore water levels than groundwater pollutants. The results suggest that management approaches must be pollutant type dependent; the priority should be given to the sources relevant to the most detrimental pollutants such as groundwater pollutants, although the thermal impact requirements must be evaluated continually.

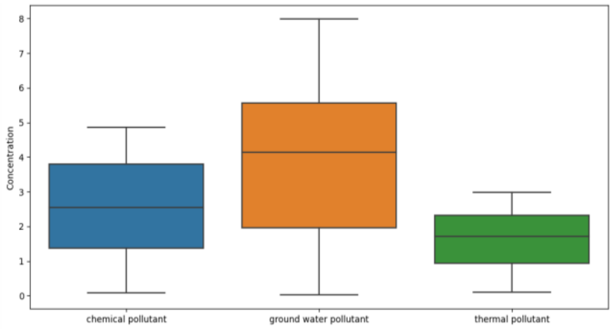

Fig. 3: Box plot of pollutant concentration

Figure 3 of chemical, groundwater, and thermal pollutants, we gained valuable information on their characteristics, including their relation to water levels needed for the precise control measures that are crucial for modern active water management. As seen from the graph, chemical pollutants (in blue) have a less spread distribution as compared to physical pollutants; the data points mostly lie between 1 and 5 units. The mid-50 % ranges of chemical pollutants estimated by the IQR mean that the values are closely grouped around 2–4 and there are very few outliers. This indicates that there is constant though moderate deposition of chemical pollutants which may affect water bodies.

In detail, contaminants of the second type present the maximal range of concentration variation from 0 to 8 units; the IQR is situated between 2.5 and 6 units, which corresponds to a more widespread and irregular distribution. This wider spread underline the prospects of variability and instability of the groundwater pollutants as compared to other water pollutants because the variations in their concentration can lead to increased fluctuations in water level and quality. With a median of approximately 4 standard units, the relative intensity of pollutants from the groundwater has been considered to be higher than other pollutants, which require more forceful measures to control effects on water bodies.

Thermal pollutants have the lowest variance with bulk of them occurring within a range of 1 and 3. This indicates that thermal pollutants are much more often present in concentrations below the median of 2, yet fluctuations in these concentrations could have significant effects on water bodies because water is rather sensitive to thermal differences.

In this view of proactive water management, this graph highlights the need for materials-specific control interventions. Thermal pollutants are lower in concentrations, yet they need specific control measures since they are dependent on temperature, while groundwater pollutants might need more active, possibly real-time response due to the broader range of their concentrations. Chemical pollutants, although more stable in concentration, still demand constant monitoring and mitigation efforts. Together, this analysis highlights the importance of adaptive, pollutant-focused management approaches in improving sustainability and protecting water resources.

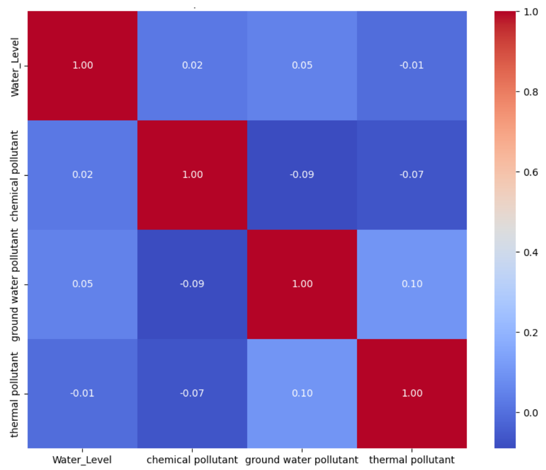

Fig. 4: Correlation heatmap between water level and pollutants

Figure 4 provided below depicts the syntactic relation of different features associated with this research theme namely Precision Control Measures for Proactive Water Management to Improve Sustainability. They include water level, chemical pollutants; groundwater pollutants, and thermal pollutants. A coefficient of + 1.0 can be interpreted as a perfect positive correlation, – 1.0 as a perfect negative correlation, and figures close to zero as no or little correlation.

On the basis of proactive water management, the heatmap shows a very low positive relationship between water level and chemical pollutants as well as groundwater pollutants 0.02 and 0.05 respectively; implicating that variation in water levels bear negligible effect on the chemical properties and presence of pollutants in the groundwater. On the other hand, the water level and thermal pollutants bear a very poor relationship at -0.01, suggesting that thermal pollutants in this system are nearly unresponsive to water level changes, a fact of paramount importance when considering the trend and influence of thermal pollution outside the parameters of water storage or flow.

Chemical pollutants show a very weak but negative relationship with both groundwater pollutants (-0.09) and thermal pollutants (-0.07), thereby also indicating that chemical pollutants have a small effect in reducing the level of groundwater and thermal pollution. While, interestingly, there is a weak but positive correlation with the thermal pollutants, which, like the groundwater pollutants, are 0.10.

In our water sustainability research, these correlations inform the precision control of the mechanisms. The conclusions indicate that reformation for multiple factor diverse strategies in pollution management is needed, especially the thermal and water pollution management strategies must be separated from each other while some scope of combined approaches may be considered in chemical and groundwater pollutants. This understanding aids the enhancement of the sensor placement and the manner in which the real-time interferences are calibrated for the enhancement of a comprehensive framework for sustainable water use.

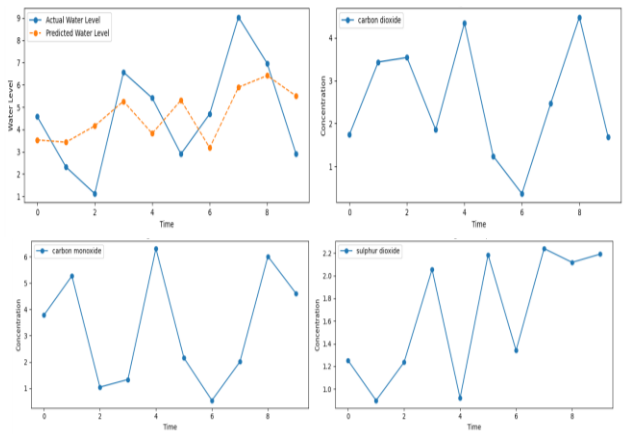

Fig. 5: Live monitoring of a) Water level predictions vs Actual water level b) Live changes in carbon dioxide c) Live changes in carbon monoxide d) Live changes in sulphur dioxide

Figure 5 afford important information on the trends in water levels and pollutants' concentrations to support the research area on Precision Control Measures for Proactive Water Management to Enhance Sustainability. In the first set of the graphs, for actual and predicted water levels, the reality track shows some great variations actually increasing to around 8 units at time point 6 while the predicted track mimics the actual variations to a fairly lower degree of variation. This can be interpreted as meaning that, though predictive models offer a good insight of the future, they still do not capture the wider oscillations, that are paramount to anticipation.

The remaining graphs represent fluctuations of particular pollutants and all of the depicted pollutants exhibit cyclic trends where carbon dioxide, carbon monoxide, and sulfur dioxide each have their own trends. For instance, the carbon dioxide levels range from 1 to 4 and the fluctuations may be as a result of industrialization and or contribution to pollution. Carbon monoxide is less stable and has many fluctuations up to around 6 units which are likely likely to car emissions and or activities such as industries. Sulfur dioxide trends towards 2.2 units which shows the buildup of pollutants over time.

In relation to sustainable water management, these time series patterns are useful in adopting the precision control approach by equating an increase in a particular pollutant with a possible contamination scenario. It is possible to prevent contamination risks with the help of effective measures such as using real-time sensors or changing the system of water flow if these pollutant behaviors are studied together with the variation in water levels. Thus, it is possible to harmonize control actions with pollutant and water level data to achieve the maximum results in drinking water management and decrease pollution levels.

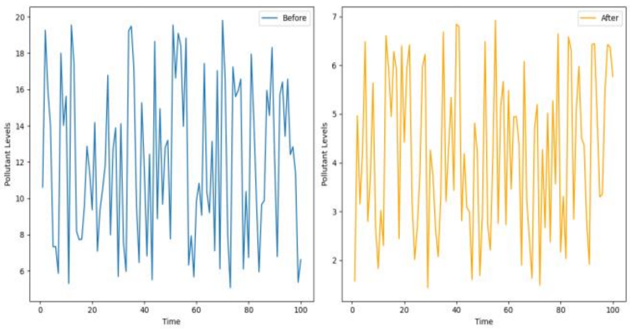

Fig. 6: Quality of water before and after control measures

Figure 6 which are used in this paper display how measures of precision control have helped in reducing water pollution levels in future periods. Before increasing pollutant concentrations appear as jagged and highly variable, also varying between 6 and 20 units at most. Therefore, it shows an uncontrolled or a system that has been controlled inexperienced where Pollutants tend to build up and hence display a high fluctuation in water pollution standards. These unpredictable trends of the pollutants are not suitable for the sustainable management of water resources and result in environmental and health hazards. However, the "After" graph on the right illustrates the situation if the client employs a set of preventive and accurate water leakage strategies. The pollutant level is much lower and slightly fluctuates between 1 to 7, unlike in other cases. This stabilization indicates better control of water quality through either new, improved monitoring systems, instantaneous or variable filters, and/or discharges. These precise measures help to contain water within specific standards of pollutants to help support its sustainability. In other words, displacement of peak pollutant concentrations as well as a reduction in fluctuations in overall water quality provides not only ecological benefits but is also consistent with other objectives for sustainable resource management, the attainment of improved environmental health for individuals and ecosystems.

4 Conclusion

From this study on precision control measures for proactive water management, it is deduced that proactive water management of today's challenges requires niche methodologies including sophisticated modeling, monitoring, and simulation. However, by using both Linear Regression and Random Forest Regression models, this study proves that it is possible to forecast pollutant influences on water level and, therefore, create specific strategies to enhance water quality. The impacts indicate that real-time data-driven pollutant-specific approaches hold vast promise in increasing water sustainability. The concentrations of chemical, thermal, and groundwater pollutants that the study targets cornerstones the value of dynamically controlling variables with feedback mechanisms resulting from the carrying out of continuous environmental monitoring. This specific approach to water management discussed in the course of this research should enable any organization to take proactive measures that will facilitate the optimization of the usage of water resources in ways that will least impact the ecological balance. Simulation has been adopted in assessing the efficiency of the control measures a suggestion that pre-deployment assessment is necessary in reducing the impacts of pollutants on aquatic life. The implementation of Real-Time monitoring in conjunction with Predictive Analysis does not only enhance the accuracy of Water Quality Management but also can also contribute to Sustainable Development since environmental sustainability is achieved through developing lasting solutions.

References:

[1] Cosgrove, W. J., & Loucks, D. P. (2015). Water management: Current and future challenges and research directions. *Water Resources Research, AGU Advances,* 51(6), 4823-4839. https://doi.org/10.1002/2014WR016869.

[2] Akhtar, N., Syakir Ishak, M. I., Bhawani, S. A., & Umar, K. (2021). Various natural and anthropogenic factors responsible for water quality degradation: A review. *Water, Advancing Open Science,* 13(19), 2660. https://doi.org/10.3390/w13192660.

[3] Saravanan, A., Kumar, P. S., Jeevanantham, S., Karishma, S., Tajsabreen, B., Yaashikaa, P. R., & Reshma, B. (2021). Effective water/wastewater treatment methodologies for toxic pollutants removal: Processes and applications towards sustainable development. *Chemosphere,* 280, 130595. https://doi.org/10.1016/j.chemosphere.2021.130595.

[4] Lenton, R., & Muller, M. (2012). Integrated water resources management in practice: Better water management for development. *Routledge,* 46 (4), 228. http://doi.org/10.1111/j.1752-1688.2010.00458.x.

[5] Lund, N. S. V., Falk, A. K. V., Borup, M., Madsen, H., & Steen Mikkelsen, P. (2018). Model predictive control of urban drainage systems: A review and perspective towards smart real-time water management. *Critical reviews in environmental science and technology,* 48(3), 279-339. https://doi.org/10.1080/10643389.2018.1455484.

[6] Berglund, E. Z., Pesantez, J. E., Rasekh, A., Shafiee, M. E., Sela, L., & Haxton, T. (2020). Review of modeling methodologies for managing water distribution security. *Journal of water resources planning and management,* 146(8), 03120001. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001265.

[7] Zhang, P., Cai, Y., & Wang, J. (2018). A simulation-based real-time control system for reducing urban runoff pollution through a stormwater storage tank. *Journal of Cleaner Production,* 183, 641-652. https://doi.org/10.1016/j.jclepro.2018.02.130.

[8] Liu, S., Guo, D., Webb, J. A., Wilson, P. J., & Western, A. W. (2020). A simulation-based approach to assess the power of trend detection in high-and low-frequency water quality records. *Environmental Monitoring and Assessment,* 192(10), 628. https://doi.org/10.1007/s10661-020-08592-9.

[9] Geissen, V., Mol, H., Klumpp, E., Umlauf, G., Nadal, M., van der Ploeg, M., & Ritsema, C. J. (2015). Emerging pollutants in the environment: a challenge for water resource management. *International soil and water conservation research,* 3(1), 57-65. https://doi.org/10.1016/j.iswcr.2015.03.002.

[10] Glasgow, H. B., Burkholder, J. M., Reed, R. E., Lewitus, A. J., & Kleinman, J. E. (2004). Real-time remote monitoring of water quality: a review of current applications, and advancements in sensor, telemetry, and computing technologies. *Journal of experimental marine biology and ecology,* 300(1-2), 409-448. https://doi.org/10.1016/j.jembe.2004.02.022.

[11] Gil, Y., Garijo, D., Khider, D., Knoblock, C. A., Ratnakar, V., Osorio, M., & Shu, L. (2021). Artificial intelligence for modeling complex systems: taming the complexity of expert models to improve decision making. *ACM Transactions on Interactive Intelligent Systems,* 11(2), 1-49. https://doi.org/10.1145/3453172.

[12] Akkem, Y., Biswas, S. K., & Varanasi, A. (2024). A comprehensive review of synthetic data generation in smart farming by using variational autoencoder and generative adversarial network. *Engineering Applications of Artificial Intelligence,* 131, 107881. https://doi.org/10.1016/j.engappai.2024.107881.

[13] Dong, W., Chen, X., & Yang, Q. (2022). Data-driven scenario generation of renewable energy production based on controllable generative adversarial networks with interpretability. *Applied Energy*, 308, 118387. https://doi.org/10.1016/j.apenergy.2021.118387.

[14] Murtaza, H., Ahmed, M., Khan, N. F., Murtaza, G., Zafar, S., & Bano, A. (2023). Synthetic data generation: State of the art in health care domain. *Computer Science Review,* 48, 100546. https://doi.org/10.1016/j.cosrev.2023.100546.

[15] National Research Council, Division on Earth, Life Studies, Water Science, Technology Board, & Committee to Assess the Scientific Basis of the Total Maximum Daily Load Approach to Water Pollution Reduction. (2001). Assessing the TMDL approach to water quality management. *National*

Academies Press, 121. https://doi.org/10.17226/10146.

[16] Altenburger, R., Ait-Aissa, S., Antczak, P., Backhaus, T., Barceló, D., Seiler, T. B., & Brack, W. (2015). Future water quality monitoring—Adapting tools to deal with mixtures of pollutants in water resource management. *Science of the total environment,* 512, 540-551. https://doi.org/10.1016/j.scitotenv.2014.12.057.

[17] Subramaniam, S., Raju, N., Ganesan, A., Rajavel, N., Chenniappan, M., Prakash, C., & Dixit, S. (2022). Artificial intelligence technologies for forecasting air pollution and human health: a narrative review. *Sustainability,* 14(16), 9951. https://doi.org/10.3390/su14169951.

[18] Schoumans, O. F., Chardon, W. J., Bechmann, M. E., Gascuel-Odoux, C., Hofman, G., Kronvang, B., & Dorioz, J. M. (2014). Mitigation options to reduce phosphorus losses from the agricultural sector and improve surface water quality: a review. *Science of the total environment,* 468, 1255-1266. https://doi.org/10.1016/j.scitotenv.2013.08.061.

[19] Fu, G., Jin, Y., Sun, S., Yuan, Z., & Butler, D. (2022). The role of deep learning in urban water management: A critical review. *Water Research,* 223, 118973. https://doi.org/10.1016/j.watres.2022.118973.

[20] Shen, C. (2018). A transdisciplinary review of deep learning research and its relevance for water resources scientists. *Water Resources Research,* 54(11), 8558-8593. https://doi.org/10.1029/2018WR022643.

[21] Rousso, B. Z., Do, N. C., Gao, L., Monks, I., Wu, W., Stewart, R. A., & Gong, J. (2024). Transitioning practices of water utilities from reactive to proactive: Leveraging Australian best practices in digital technologies and data analytics. *Journal of Hydrology,* 641, 131808. https://doi.org/10.1016/j.jhydrol.2024.131808.

[22] Kamyab, H., Khademi, T., Chelliapan, S., SaberiKamarposhti, M., Rezania, S., Yusuf, M., & Ahn, Y. (2023). The latest innovative avenues for the utilization of artificial Intelligence and big data analytics in water resource management. *Results in Engineering,* 101566. https://doi.org/10.1016/j.rineng.2023.101566.

[23] Rodgers, E. M., Opinion, A. G. R., Isaza, D. F. G., Rašković, B., Poleksić, V., & De Boeck, G. (2021). Double whammy: Nitrate pollution heightens susceptibility to both hypoxia and heat in a freshwater salmonid. *Science of The Total Environment,* 765, 142777. https://doi.org/10.1016/j.scitotenv.2020.142777.

[24] Molinari, A., Guadagnini, L., Marcaccio, M., & Guadagnini, A. (2012). Natural background levels and threshold values of chemical species in three large-scale groundwater bodies in Northern Italy. *Science of the Total Environment,* 425, 9-19. https://doi.org/10.1016/j.scitotenv.2012.03.015.

[25] Arora, B., Dwivedi, D., Faybishenko, B., Jana, R. B., & Wainwright, H. M. (2019). Understanding and predicting vadose zone processes. *Reviews in Mineralogy and Geochemistry,* 85(1), 303-328. https://doi.org/10.2138/rmg.2019.85.10.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.