

Groundwater quality analysis and water quality index prediction by means of machine learning methods

B. Vamsi ¹, B. Chandra Sekhar ^{2*}, V Vakdevi ³, M Rohit ³, Md Ibrahim ³, P Uday Kiran ³, Ch Srinivas ³, M Gopi Kiran ¹

¹ Department of Civil Engineering, Lingayas Institute of Management and Technology, Madalavarigudem, Vijayawada-521212, India

² Department of Chemical Engineering, RGUKT RK Valley, Iddupulapaya, Vempalli, YSR Kadapa-516330, India

³ Department of Computer Science and Engineering, Lingayas Institute of Management and Technology, Madalavarigudem, Vijayawada-521212, India

*Corresponding author E-mail: drbandi85@rguktrkv.ac.in

Abstract

The study of variations in the quality of groundwater due to subsequent changes in society is a matter of unease as groundwater is regarded as a vital water supply source among all the water sources available. Water quality assessment via monitoring paves the source for arbitrating the appropriateness of quality of water for various purposes including management of water quality. This study was mainly focused on monitoring and assessing the quality of groundwater collected from Madalavarigudem and Mudirajupalem, both from Krishna district, Andhra Pradesh, India. Standard methods were used for analyzing the collected samples for five parameters that include alkalinity, acidity, pH, total hardness (TH) and total dissolved solids (TDS). The groundwater quality parameter analysis indicate high values of pH and TDS, especially in the Mudirajupalem samples as it is located near to agricultural fields. Further, the water quality index (WQI) values supported that groundwater collected from Mudirajupalem is unfit for drinking purpose. This study employed random forest, decision tree and gradient boosted tree techniques for predicting the WQI values and, a hierarchical reconciliation algorithm proved favorable in foretelling water quality parameters. The predicted WQI values meticulously complemented with the obtained experimental results, further endorsing that Mudirajupalem groundwater is not apt for public consumption. Further, this study proposes implementing simple rainwater harvesting systems, which would eventually result in improving the groundwater recharge and maintain groundwater balance so as to making it as a viable source of life.

Keywords: Forecasting; Water Parameters; Algorithm; Groundwater Quality; Machine Learning.

1. Introduction

Water resources in the form of freshwater are considered as limited water resources that endures the entire environment. Groundwater is one among many sources, which is regarded as a key freshwater source that covers only 2.5% of water on the earth's surface [1-3]. In a study, it was reported that groundwater aids as potable water source for majority of the public and meets approximately 40% irrigation needs of the world [4]. The 21st century is witnessing water resources crisis, thus, making it as a universal concern owing to many developmental activities, change in the agricultural practices and waste disposal, eventually making the water unfit for human consumption [5]. Amongst the water resources available on the face of earth, groundwater is regarded as a fundamental water supply source available on the globe; however, the world is heading concerns in severe water deficiency owing to the depletion of groundwater faster than it is refilled naturally. Extensive application of agrochemicals, the current practices of industrial waste disposal, rapid urbanization, groundwater contamination by leachate from landfill sites and climate change induced intrusion of saltwater are regarded as solid reasons for the developing countries to encounter with groundwater quality challenges [6]. Therefore, it is an unprecedented fact that there is a necessity for periodic monitoring of groundwater resources for maintaining the quality of water for its safe and sustainable utilization.

Groundwater research has paved a way for progress and employment of numerous techniques for groundwater quality monitoring purpose. Water quality index (WQI) is viewed as the well-known applied tools for evaluating the quality of groundwater [7-10], which converts a vast data into a numerical value that discloses the water quality for its aptness for numerous applications. The current generation is witnessing an upsurge in the application of machine learning (ML) techniques in numerous fields, which also proved that ML techniques are effective in water management via groundwater prediction. The ML techniques cover dataset collection, datasets storing into databases and developing valuable outputs via processing the datasets, which eventually make the ML techniques feasible for innumerable applications [11]. Abu et al. [12] reported that decision tree regression (DTR), Random forest regression (RFR), artificial neural network (ANN) and multiple linear regression (MLR) were proved feasible in predicting the groundwater quality, whereas Apogba et al. [13] proved that RF was potential in predicting the groundwater quality.

The above cited literature highlights that it is an undisputed fact that groundwater acts as a focal part of global drinking water sources, thus making it very essential to continuously monitor and manage the quality of groundwater to meet sustainable development goals [14];

additionally, necessitates to make use of ML techniques for the prediction of groundwater quality. Thus, in view of the aforementioned literature, this study is focused on monitoring and variation in the groundwater quality parameters from two different sources i.e., Madalvarigudem and Mudirajupalem, Krishna district, Andhra Pradesh, India, as there is a significant lapse in the data in the study area. The groundwater samples collected were daily analyzed for a period of 35 days for alkalinity, acidity, total hardness (TH), pH and total dissolved solids (TDS) according to standard methods. Additionally, this study presents the results of few widely applied ML techniques in various fields, which include gradient boosted trees (GBT), decision tree (DT) and RF for the prediction of groundwater quality.

This study interprets the results of the groundwater analysis, which stands alone steered by an academic institution within the proximity of the selected study region essentially emphasizing the extent of groundwater quality via WQI and groundwater quality accuracy prediction. The results obtained in the present study substantiated the generation of basic information of the groundwater quality and its existing condition, which could eventually be beneficial to the public, as water is a naturally gifted inimitable resource. Furthermore, the present study throws a light of spark to perform research on prediction of the groundwater quality and put forward appropriate location specific systems for conserving water resources that would accommodate the future water needs.

2. Materials and methodology

2.1. Study area

Groundwater quality analysis was carried out by collecting samples from two different sources i.e., Madalvarigudem and Mudirajupalem, Krishna district, Andhra Pradesh, India, Maadalavarigudem is surrounded by Unguturu Mandal towards East, Penamaluru Mandal towards South, Kankipadu Mandal towards South, Agiripalli Mandal towards North. Mudirajupalem is a village located in Gannavaram mandal, Krishna district, Andhra Pradesh, India. The satellite images of the selected study area are shown in Figure 1.

Methodology

Groundwater samples were collected from two locations and monitored for 35 days continuously between March and April, 2024. The collected samples were analyzed for alkalinity, acidity, TH, pH and TDS according to the standard methods available in the American Public Health Association (APHA) [15] as these are few commonly used parameters for water quality analysis. A scientific pH paper was used to verify the pH in the samples (S. D. Fine-chem Ltd, Mumbai, India). A Generic Digital LCD TDS Meter was employed to determine the TDS in the samples (Generic, TDS-3, India). Alkalinity, total hardness and acidity in the samples were determined via titration described in the APHA standard methods. Bureau of Indian Standards (BIS) were applied for evaluating the groundwater quality [16], [17].



Fig. 1: The Satellite Images of the Selected Study Area, A.) Mudirajupalem, Krishna District and B.) Madalvarigudem, Krishna District.

The WQI of the selected groundwater samples is quantified according to Brown et al. [18] to examine the suitability of the groundwater quality for various purposes. Few widely employed ML techniques that are available in the literature were employed in this study, which include GBT, DT and RF for groundwater quality forecasting in the selected study region. The GBT makes use of decision trees for the purpose of prediction that commonly makes use of the weaker estimation method. It works efficiently in forecasting, which combines several smaller, inefficient models into one robust model, ultimately yielding reliable results. Rapidly classifying the datasets is the striking factor of this method, which makes it widely popular [19].

The DT is basically a supervised learning algorithm, which structures based on input, thus making it suitable for classification and regression tasks. It represents a tree-like structure, wherein each internal node tests on attribute, each branch resembles to attribute value and each leaf node signifies the final decision or prediction. A DT model is established through an automatic algorithm in which, a set of hierarchical decisions are used to partition the space of input variables into subspaces. A DT model represents as a hierarchical tree structure that involves nodes and branches [20]. In the RF technique, forecasts of multiple decision trees are conglomerated for performance enhancement. The RF stands out tall as it shows high accuracy in predictions, less susceptibility to overfitting and reduced variance, thus making these as few deciding factors of the RF technique apart from making it opt for larger datasets with numerous features [13]. The RF, GBT and DT are the ML techniques employed for predicting the groundwater quality, which are available in an open source simple ML for sheets developed by the TensorFlow Decision Forests team in Google Zurich. The future trend of the parameters was forecasted using a hierarchical reconciliation algorithm, which was ultimately used for quantifying the WQI values [21].

3. Results and discussion

Groundwater is a key water resource, which predominates half of the India's urban water use. Yet, owing to insufficient monitoring and assessment of the groundwater quality, enough information is not yet reported up to the mark. Therefore, it is essential to collect appropriate information on groundwater quality through monitoring, which aids in understanding the groundwater quality issues, its origin, reasons for it, and determining economical and durable solutions for water related problems. Figure 2 shows the pH range pertaining to the samples of two locations. The pH value reflects on the hydrogen ions concentration of the water, wherein the pH of any aquatic body shows impact on the chemical reaction in the water quality, therefore, considered as a driving factor of aquatic ecosystems [22], [23].

The results obtained in the study indicate that for the Mudirajupalem samples, the pH value was in the range of 8.5-10, whereas for the Madalavarigudem samples, the pH value was in the range of 6.5-9.0, which is outside the range of permissible limit as per the BIS standards (Fig. 2). It is apparent that high pH values were obtained in the Mudirajupalem samples, which could be ascribed to the existence of agricultural fields within the vicinity of the study area, which is also supported by the results obtained by Khatri et al. [24]. It can be deduced from the results that the pH value in the two groundwater sources show the groundwater to be in alkaline nature, which can be because of the different buffers normally exist in the groundwater [25].

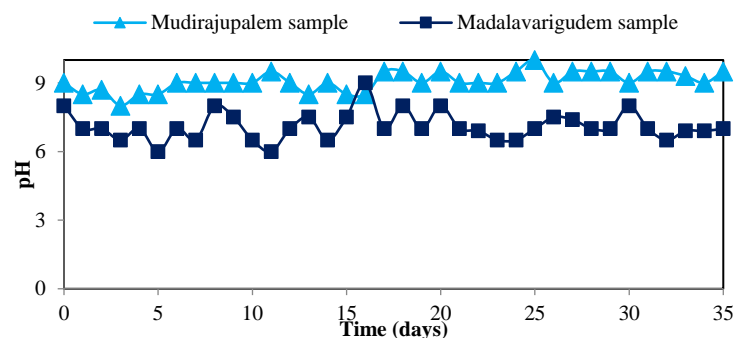


Fig. 2: The Ph Range of the Samples Collected from Two Locations of the Selected Study Area.

Geological formations, anthropogenic activities and climatic conditions are the few driving forces among many for the variation of groundwater quality in any area, which also may show impact on physical and chemical parameters [26], [27]. Besides, there is a scope for the variation of groundwater chemistry, which mainly depends on the contact time of groundwater with a specific rock environment, inferring that more is the contact time; more would be the susceptibility for the rock chemistry effect on the pH, subsequently formulation of the groundwater. The chemical changes that occur in the bedrock ambience incline to buffer the groundwater pH. The rock composition and sediments that mount the route of the water penetrating to the groundwater play a vital role on the variation of the pH of the groundwater [28].

The TDS indicate the dissolved material content existing in the water, which works as a factor to indicate the effluence level. Figure 3 shows the TDS range of the groundwater samples collected from the study area. Maximum TDS value was obtained in the Mudirajupalem samples with a range of 931-994 mg/L, whereas TDS values ranging between 117-280 mg/L was obtained in the Madalavarigudem samples. Normally, high TDS values in the groundwater can be due to the salts leaching from soil; moreover, increase in TDS values is maybe due to the percolation of domestic sewage into the groundwater [29]. Mudirajupalem samples showed high TDS values, which is maybe due to the occurrence of higher dissolved and suspended materials as a result of various anthropogenic undertakings taking place in the study area. The results obtained are supported by the results described by Lamare and Singh [30]. The TDS values of the two locations are beneath the maximum allowable limits in line with the BIS standards, which require treatment if it is destined for drinking, still, the groundwater can be straight away employed for daily needs. Reverse osmosis (RO), deionization (DI) and distillation are few methods, which could be employed to remove excess TDS present in the water.

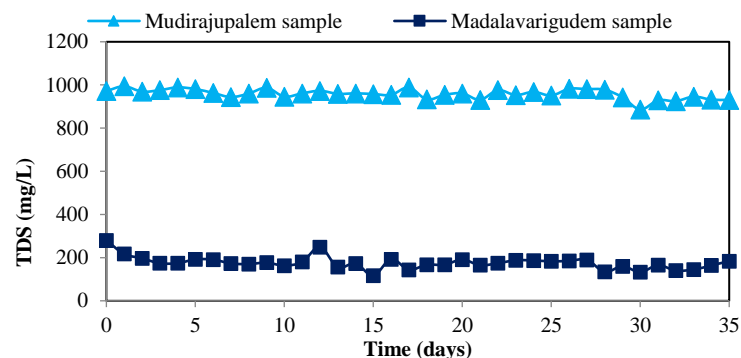


Fig. 3: Pattern of the TDS Values Obtained in the Samples from Two Sources.

Total hardness is characterized by the presence of dissolved minerals (mostly calcium and magnesium), which could be because of the presence of several metallic salts. It is determined for its suitability to domestic, industrial and drinking purpose [31]. Figure 4 shows the trend of TH values obtained in the samples from two sources. For the Mudirajupalem samples, TH was in the range of 20-246 mg/L, whereas the TH was in the range of 0-210 mg/L in the Madalavarigudem samples. Groundwater quality was classified in line with TH range, wherein, groundwater is tagged as soft if $TH < 75$, as moderately hard if TH is between 75–150, as hard with TH values in the range of 150–300 and $TH > 300$ mg/L as very hard [32]. In line with the results obtained in the study area, it is apparent that groundwater quality in the study area is hard to very hard. The TH values in two locations are outside the range of the maximum allowable limit according to the BIS standards, presuming that the groundwater is hard water, which need treatment if it is for drinking purpose, anyway, it can be as such used for daily needs. Water softening processes are widely popular for removing excess total hardness from water.

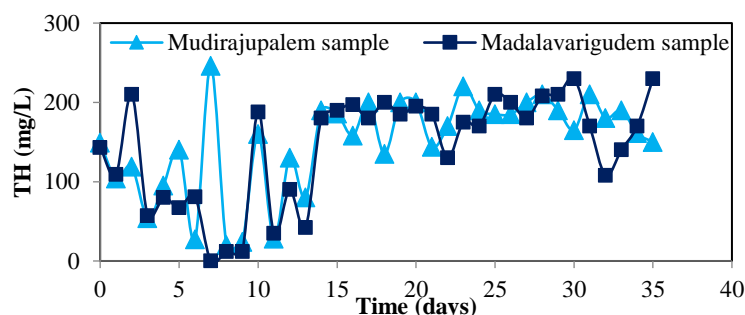


Fig. 4: The TH Values Trend Obtained in the Samples from Two Sources.

Murangan and Prabakaran [33] reported that acid neutralizing capability of water is measured by the alkalinity of aquatic systems. The alkalinity values obtained in the samples from two sources is shown in Figure 5. For the Mudirajupalem samples, a range of 460-850 mg/L of alkalinity was obtained, whereas alkalinity was in between 525-910 mg/L in the Madalavarigudem samples. Generally, naturally existing water comprise of Ca^{2+} , Mg^{2+} , alkaline metals and SO_4^{2-} , Cl^- , which contribute to alkalinity [29]. The results indicate that the alkalinity values in the two sources are outside the range of allowable limit according to the BIS standards, which may require treatment if it is intended for human consumption. Water softening processes are widely popular for removing excess alkalinity from water. Figure 6 shows the acidity in the samples obtained from two sources. A range of 45-480 mg/L of acidity was obtained in the Mudirajupalem samples, whereas a range between 105-460 mg/L of the acidity was obtained in the Madalavarigudem samples.

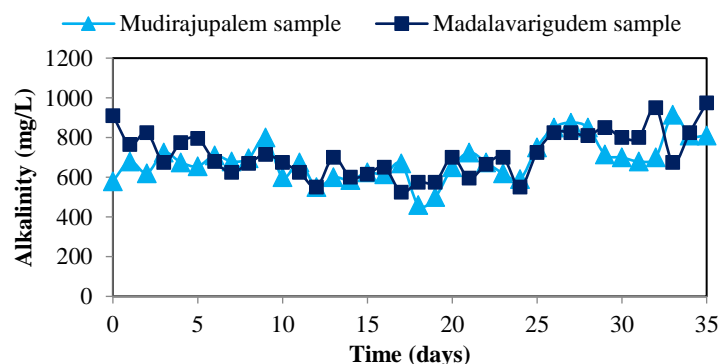


Fig. 5: The Trend of Alkalinity Values Obtained in the Groundwater Samples from Two Sources.

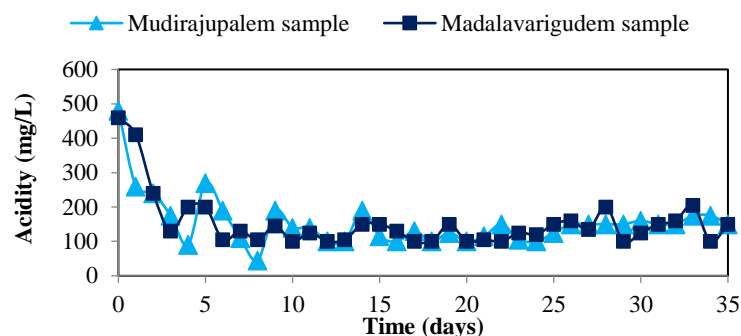


Fig. 6: The Trend of Acidity Values Obtained in the Samples from Two Sources.

The groundwater will tend to remain acidic if the geological conditions prevailing in the aquifer enclosing the groundwater is encompassed with carbonate rocks. In general, acidity by itself is not harmful to health, however, lead or copper existing in the plumbing pipes get dissolved in the presence of even mildly acid water. Based on this fact, almost all the standards devised to standardize the water quality govern that drinking water should be of a pH value in the range of 6.5 and 8.5 to limit the deposit of scales or dissolved contaminants concentration from acidic waters [28].

The WQI is regarded as a widely applied tool for measuring the water quality. The WQI can be employed to monitor the water quality changes in a certain water supply over a period of time; rather, it can be used for comparing any water supply quality with other water supplies in any region. The benefit of quantifying the WQI is that, it can be used to reduce the high volume of water quality data to a normal numerical number, which exhibits the quality of water irrespective of time and location taking several water quality parameters into view point. As per the WHO standards [17], the correlation between the WQI and water quality status indicate excellent water quality for WQI in the range 0-25, good water for WQI in the range 26-50, poor water quality for WQI in the range 51-75 and very poor water quality for WQI in the range 76-100, whereas water is unfit for drinking for WQI more than 100. The groundwater samples collected from Mudirajupalem and Madalavarigudem showed WQI values as 358.34 and 59.29, respectively, which confirmed that the Mudirajupalem groundwater is unfit for drinking as per the WHO [17]. In a study results reported by Prajapati and Bilas [34], similar results were obtained, i.e., for few samples, the WQI values ranged between from 28 to 65; whereas, the WQI values ranged between 182.48 and 535.32 in few samples, confirming that the water is unfit for drinking. Moreover, Madalavarigudem groundwater is tagged as poor water quality as per the WHO.

It is apparent from the groundwater sample analysis that very high values of alkalinity were obtained in the samples collected from two locations, whereas high values of pH and TDS were obtained especially in the Mudirajupalem samples as it is located near to agricultural fields. Khatri et al. [24] reported high hardness, alkalinity and TDS values in groundwater samples citing that it was caused due to the geological strata. The minerals surrounding the groundwater often tend to leach Calcium and Magnesium ions and accordingly, resulting in the increased hardness and alkalinity values, which are matching with the results obtained in the present study. Ramakrishna et al. [35] reported that in southern India, bedrock geology and climate play a vital role on the quality of groundwater; however, it was reported that agricultural and industrial sources lead to the pollution of groundwater in some parts.

A hierarchical reconciliation algorithm was employed to forecast the future trend of the selected water quality parameters for approximately two months, wherein, Figures 7 to 10 shows the forecasted pH, TDS, alkalinity and TH values of the samples collected from two sources along with the experimental results. A top-down reconciliation algorithm was used with forecast proportions for forecasting the data as most of the common top-down approaches identify disaggregation proportions on the grounds of historical proportions of the data. These approaches are widely popular as they are simple to use and produce consistent forecasts for the aggregate levels apart from being useful with low count data [21].

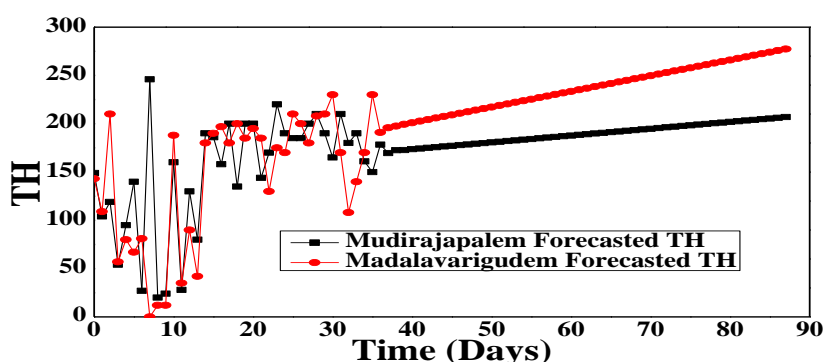


Fig. 7: The Forecasted TH Values Along with the Experimental Results in the Samples Collected from Different Sources.

The forecasted values of the WQI values of the groundwater from Mudirajupalem and Madalavarigudem followed the order of 362.96 and 63.81, which are meticulously identical with the attained experimental results, further confirming that Mudirajupalem groundwater doesn't fit for human consumption.

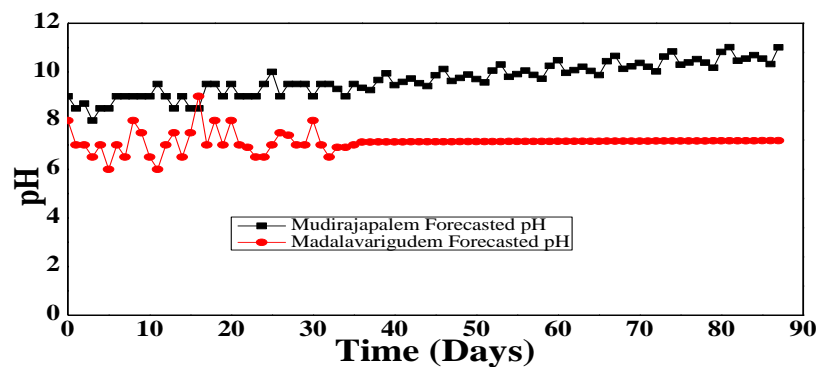


Fig. 8: The Forecasted pH Values Along with the Experimental Results in the Samples Collected from Different Sources.

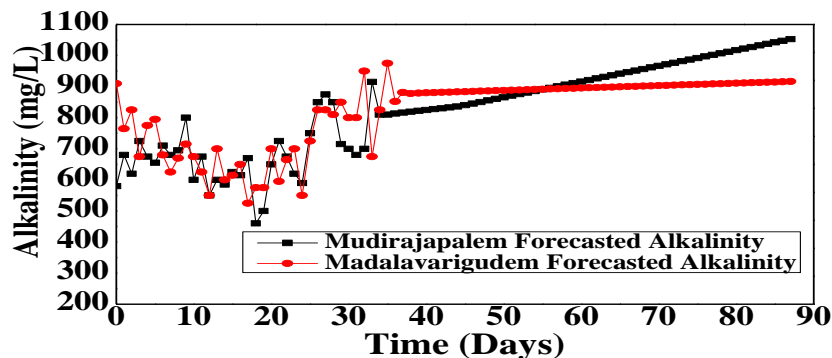


Fig. 9: The Forecasted Alkalinity Values Along with the Experimental Results in the Samples Collected from Different Sources.

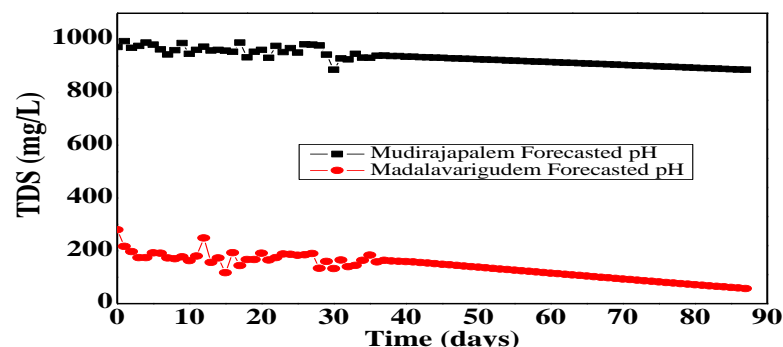


Fig. 10: The Forecasted TDS Values Along with the Experimental Results in the Samples Collected from Different Sources.

The GBT, RF and DT are the ML techniques, which were employed for the groundwater quality prediction, wherein, the RF resulted in R^2 values of 0.89 and 0.93 for Mudirajapalem and Madalavarigudem, respectively. The DT resulted in R^2 values of 0.87 and 0.84 for Mudirajapalem and Madalavarigudem, respectively, whereas the GBT resulted in R^2 values of 0.95 and 0.98 for Mudirajapalem and Madalavarigudem, respectively. The RF resulted in root mean squared error (RMSE) values of 17.55 and 48.86 for Mudirajapalem and Madalavarigudem, respectively. The DT resulted in RMSE values of 23.69 and 39.32 for Mudirajapalem and Madalavarigudem, respectively, whereas the GBT resulted in RMSE values of 17.55 and 20.66 for Mudirajapalem and Madalavarigudem, respectively.

In a study, RMSE of 23.03 and R^2 value of 0.82 were obtained using RF [13], which is matching with the present study results demonstrating that GBT and RF are capable to predict and yield favorable results. Abu et al. [12] yielded RMSE values of 6.8 and 6.0 with R^2 values of 0.89 and 0.91, respectively making use of DTR and RFR in a study carried out for groundwater characterization and quality forecasting using combination of multivariate statistics and ML techniques. Even though there is a slight deviation in the RMSE values, the present study results match with the literature in terms of R^2 values. Wang et al. [36], Sami et al. [37] and Ubah et al. [38] reported similar results of R^2 values of 0.92, 0.98 and 0.96, respectively in respective research works carrying out the WQI analysis. Different operating conditions, features and the range of values in the dataset are few driving forces which could be attributed to the variation in the RMSE and R^2 values. The GBT and RF yielded promising results that are matching with the experimental results among the three ML techniques employed. Further, the DT resulted in WQI values of 396.73 and 33.59 for Mudirajapalem, and Madalavarigudem, respectively, whereas the RF resulted in WQI values of 397.09 and 33.66 for Mudirajapalem and Madalavarigudem, respectively. The GBT resulted in WQI values of 396.74 and 33.62 for Mudirajapalem and Madalavarigudem, respectively. It can be inferred that the WQI values of Mudirajapalem samples are very high, once again closely identical with the experimental results, further confirming that Mudirajapalem groundwater is not fit for human intake. Abu et al. (12) reported similar WQI values ranging from 15 to 374 in a study carried out to characterize the groundwater quality and forecasting. Also, WQI values ranging from 9.51 to 69.99 were reported by Apogba et al. (13) with different features and conditions. The differences in WQI values could be attributed to the different hydrological conditions and features reported in the literature. This study perhaps proved that more such advanced ML techniques could be employed to predict more accurate groundwater quality. Also, this study emphasizes on implementation of locale specific rainwater harvesting systems to meet the future water scarcity issues, which may enhance groundwater recharge as this would also show impact on the groundwater quality.

4. Conclusion

In the current study, the monitoring and evaluation of the groundwater quality variation for a period of 35 days was carried out. Groundwater samples were collected from two sources and the groundwater quality parameters tested in this study include alkalinity, acidity, pH, TH and TDS. The results obtained in this study indicate very high alkalinity values in the samples collected from both the locations, whereas high values of pH and TDS were obtained especially in the Mudirajupalem samples as it is located near to agricultural fields. The groundwater samples collected from Mudirajupalem and Madalavarigudem showed WQI values as 358.34 and 59.29, respectively, which confirmed that the Mudirajupalem groundwater is unfit for drinking in line with WHO standards. Further, this study yielded favorable results in forecasting water quality parameters using hierarchical reconciliation algorithm and predicting the WQI values using GBT, RF and DT techniques. The experimental results obtained in this study matched with the predicted WQI values, further confirming that Mudirajupalem groundwater doesn't entail suitable for human intake. This study proved to yield productive results in groundwater quality prediction, which further opened up a scope to perform productive research on employing more advanced ML techniques for predicting accurate groundwater quality in the long-run.

Acknowledgments

All the individuals contributed to this study are acknowledged with due respect. Also thanks to various sources, which were used to carry out the machine learning part of the work.

References

- [1] S. Akter, A.S.M. Saifullah, N.T. Meghla, M.J. Uddin, and M.T.M Diganta, Seasonal variation of phytoplankton abundance and water quality parameters in Jamuna River, *J. Sci. Technol.* 8 (2018), 107–123.
- [2] A. Ghosh, P.P. Adhikary, B. Bera, and G.S. Bhunia, Assessment of groundwater potential zone using MCDA and AHP techniques: case study from a tropical river basin of India, *Appl. Water Sci.* 12 (3) (2022), 1–22. <https://doi.org/10.1007/s13201-021-01548-5>.
- [3] A.M. Sajib, M.T.M. Diganta, M. Moniruzzaman, A. Rahman, T. Dabrowski, M.G. Uddi, and A.I. Olbert, Assessing water quality of an ecologically critical urban canal incorporating machine learning approaches, *Ecol. Inform.* 102514 (2024). <https://doi.org/10.1016/j.ecoinf.2024.102514>.
- [4] T. Gleeson, M. Cuthbert, G. Ferguson, and D. Perrone, Global groundwater sustainability, resources, and systems in the anthropocene, *Annu. Rev. Earth Planet Sci.* 48 (2020), 431–463. <https://doi.org/10.1146/annurev-earth-071719-055251>.
- [5] H. Ibrahim, Z.M. Yaseen, M. Scholz, M. Ali, M. Gad, S. Elsayed, M. Khadr, H. Hussein, H.H. Ibrahim, M.H. Eid, A. Kovács, S. Péter, and M.M. Khalifa, Evaluation and Prediction of Groundwater Quality for Irrigation Using an Integrated Water Quality Indices, Machine Learning Models and GIS Approaches: A Representative Case Study. *Water (Switzerland)* 15 (2023), <https://doi.org/10.3390/w15040694>.
- [6] United Nations, Groundwater: Making the Invisible Visible. UN World Water Development Report 2022, (2022). <https://www.unwater.org/publications/un-world-water-development-report-2022/>.
- [7] M.G. Uddin, S. Nash, and A.I. Olbert, Application of water quality index models to an Irish estuary, in: *Civil and Environmental Research*, (2020), pp. 576–581.
- [8] H.S. Atta, M.A.S. Omar, and A.M. Tawfik, Water quality index for assessment of drinking groundwater purpose case study: area surrounding Ismailia Canal, Egypt, *J. Eng. Appl. Sci.* 69 (2022), 1–17. <https://doi.org/10.1186/s44147-022-00138-9>.
- [9] S. Madhavan, S.R. Kolanuvada, V. Sampath, P.D. Roy, P. Moorthy, L. Natarajan, and L. Chokkalingam, Assessment of groundwater vulnerability using water quality index and solute transport model in Poiney sub-basin of south India, *Environ. Monit. Assess.* 195 (2023), 1–15. <https://doi.org/10.1007/s10661-022-10883-2>.
- [10] M.G. Uddin, S. Nash, A. Rahman, and A.I. Olbert, A sophisticated model for rating water quality, *Sci. Total Environ.* 868 (2023), 161614. <https://doi.org/10.1016/j.scitotenv.2023.161614>.
- [11] E.A. Hussein, C. Thron, M. Ghaziasgar, A. Bagula, and M. Vaccari, Groundwater prediction using machine-learning tools. *Algorithms*, 13 (2020), 1–16. <https://doi.org/10.3390/a13110300>.
- [12] Mahamuda Abu, Rabi Musah, and Musah Saeed Zango, A combination of multivariate statistics and machine learning techniques in groundwater characterization and quality forecasting, *Geosystems and Geoenvironment*, 3 (2024), 100261. <https://doi.org/10.1016/j.geogeo.2024.100261>.
- [13] Joseph Nzotiyine Apogba, Geophrey Kwame Anornu, Arthur B. Koon, Benjamin Wullobayi Dekongmen, Emmanuel Daanoba Sunkari, Obed Fiifi Fynn, and Prosper Kpiebaya, Application of machine learning techniques to predict groundwater quality in the Nabogo Basin, Northern Ghana. *Heliyon* 10, (2024) e28527 <https://doi.org/10.1016/j.heliyon.2024.e28527>.
- [14] Sajib, Abdul Majed, Diganta, Mir Talas Mohammad, Rahman, Azizur, Dabrowski, Tomasz, Olbert, I. Agnieszka, and M. G. Uddin, Developing a novel tool for assessing the groundwater incorporating water quality index and machine learning approach, *Groundwater for Sustainable Development* 23 (2023) 101049. <https://doi.org/10.1016/j.gsd.2023.101049>.
- [15] American Public Health Association (APHA), American Water Works Association (AWWA) & Water Environment Federation (WEF): Standard Methods for the Examination of Water and Wastewater (2005) 21st Edition, (Washington D.C.).
- [16] Indian Standards (IS) for Drinking Water as per Bureau of Indian Standards (BIS) specifications (IS 10500-2012; Second Revision).
- [17] R.M. Brown, N.I. McClellan, R.A. Deininger, and R.G. Tozer, A water quality index—do we dare?—*Water Sew Works* 117 (1972), 339–343.
- [18] Kiran. Siripuri, Reddy, Ganta. Raghotham, S.P. Girija, S. Venkatramulu, Kumar Dorthi, V. Chandra Shekhar Rao, A Gradient Boosted Decision Tree with Binary Spotted Hyena Optimizer for cardiovascular disease detection and classification. *Healthcare Analytics*, 3 (2023), 100173 <https://doi.org/10.1016/j.health.2023.100173>.
- [19] G. Sarailidis, T. Wagener and F. Pianosi, Integrating scientific knowledge into machine learning using interactive decision trees, *Computers & Geosciences*, Volume 170 (2023), 105248. <https://doi.org/10.1016/j.cageo.2022.105248>.
- [20] R.J. Hyndman, and G. Athanasopoulos, *Forecasting: principles and practice*, 3rd edition (2021), OTexts: Melbourne, Australia. OTexts.com/fpp3. Accessed on 23-09-2024.
- [21] W. Wang, A. Chen, L. Wang, Y. Liu, and R. Sun, Effects of pH on survival, Phosphorous Concentration, Adenylate Energy Charge and Na⁺, K⁺ ATPase Activities of *Penaeus chinensis* Osbeck Juveniles, *Aquat. Toxicol.*, 60 (2002), 75–83. [https://doi.org/10.1016/S0166-445X\(01\)00271-5](https://doi.org/10.1016/S0166-445X(01)00271-5).
- [22] S.O. Fakayode, Impact assessment of industrial effluents on water quality of the receiving Alaro River in Ibadan, Nigeria. *Ajeam –Ragee*, 10 (2005), 1–13.
- [23] N. Khatri, S. Tyagi, D. Rawtani, M. Tharmavaram, and R.D. Kamboj, Analysis and assessment of ground water quality in Satlasana Taluka, Mehsana district, Gujarat, India through application of water quality indices. *Groundwater for Sustainable Development* 10 (2020), 100321 <https://doi.org/10.1016/j.gsd.2019.100321>.
- [24] W. J. Jr. Weber and W. Stun, Mechanism of hydrogen ion buffering in natural waters. *J. American Water Works Association*. 55 (1963), 1553–1555. <https://doi.org/10.1002/j.1551-8833.1963.tb01178.x>.
- [25] G. Matthes, John Wiley & Sons, New York, (1982) 406.
- [26] T. Subramani, L. Elango, and S.R. Damodarasamy, *Environmental Geology*, 47(8) (2005), 1099–1110. <https://doi.org/10.1007/s00254-005-1243-0>.

- [27] Acid Rain and Ground Water pH, (THE AMERICAN WELL OWNER, 2003, Number 3; © American Ground Water Trust)
- [28] S. Prasanth, S. V. Magesh, N. S. Jitheshlal, K. V. Chandrasekar, N, and K. Gangadhar, Evaluation of groundwater quality and its suitability for drinking and agricultural use in the coastal stretch of Alappuzha District, Kerala, India. *Appl Water Sci* 2 (2012), 165–175. <https://doi.org/10.1007/s13201-012-0042-5>.
- [29] R.E. Lamare., and O.P.Singh, Application of CCME Water Quality Index In Evaluating The Water Quality Status In Limestone Mining Area Of Meghalaya, India. *The Ecoscan*, 10(1&2) (2016), 149-154.
- [30] P. Deepa, R. Raveen, P. Venkatesan, S. Arivoli, and T. Samuel, Seasonal variations of physico-chemical parameters of Korattur Lake, Chennai, Tamil Nadu, India. *Int J Chem Stud*, 4 (3) (2016), 116—123.
- [31] C.N. Sawyer, and P.L McCarty, *Chemistry for Sanitary Engineers*, McGraw-Hill (1967), New York.
- [32] A.S. Murangan, and C. Prabakaran, Fish diversity in relation to physico-chemical characteristics of Kamala basin of Darbhanga District, India, *Int. J. Pharmaceut. Biol. Archi.*, 3(1) (2012), 211-217.
- [33] WHO, *Guidelines for Drinking Water Quality*, Third edition, (2004) Vol.1, Recommendation, world Health Organization, Geneva.
- [34] R. Prajapati., and Ram Bilas. Determination of water quality index of drinking water in Varanasi district, UP, India. *Journal of Scientific Research* Vol. 62 (2018), 1-13.
- [35] C. Ramakrishna, D. Mallikarjuna Rao, K. Subba Rao, and N. Srinivas, Studies on Ground Water Quality in slums of Visakhapatnam, *Asian Journal of chemistry*, 21(6) (2009), 4246-4250
- [36] X. Wang, F. Zhang, J. Ding, Evaluation of water quality based on a machine learning algorithm and water quality index for the Ebinur Lake Watershed, China. *Sci. Rep.* 7 (1) (2017), <https://doi.org/10.1038/s41598-017-12853-y>.
- [37] B.F. Sami, Ziyad, S.D. Latif, A.N. Ahmed, M.F. Chow, M.A. Murti, A. Suhendi, B.H. Ziyad Sami, J.K. Wong, A.H. Birima, and A. El-Shafie, Machine learning algorithm as a sustainable tool for dissolved oxygen prediction: a case study of Feitsui Reservoir. Taiwan. *Sci. Rep.* 12 (1) (2022), <https://doi.org/10.1038/s41598-022-06969-z>.
- [38] J.L. Ubah, L.C. Orakwe, K.N. Ogbu, J.L. Awu, I.E. Ahaneku, and E.C. Chukwuma, Forecasting water quality parameters using artificial neural network for irrigation purposes. *Scientific Reports*, 11(1) (2021), 24438. <https://doi.org/10.1038/s41598-021-04062-5>.