Paper ID: CE0301

Impacts of Climate Change on Groundwater Resources Through ML Models in Rajshahi District

A. Chowdhury[1], T. A. Asif[2], M. Z. Alam[3], H. M. Rasel[4], M. N. Bari[5]

[1]Department of Civil Engineering, RUET, Bangladesh
[2]Department of Civil Engineering, RUET, Bangladesh (tamimarasif@gmail.com)
[3, 4,5]Department of Civil Engineering, RUET, Bangladesh

Abstract

Groundwater is a crucial resource for many regions and communities due to its vulnerability to changes in climate. Climate change events such as droughts can also lead to increased demand for groundwater as surface water supplies become limited. Increased pumping can exacerbate the effects of drought on groundwater resources. Climate change poses a serious threat to the groundwater in Rajshahi, considering that it is a highland drought-prone area. The study focuses on the effect of climate change on the groundwater resources in this area for a better understanding of the present scenario necessary for the effective management of groundwater resources. The study applies machine learning algorithms to historical climate and groundwater level data to account for the impacts of climate variations on groundwater resources. The study integrates data from multiple sources, including water quality monitoring networks and satellite data sources, to develop machine learning models. The developed models are calibrated and validated based on historical data and used to simulate future scenarios under different climate change scenarios. The findings demonstrate that the groundwater level has a decreasing trend in the years 2015, 2016, 2019, and 2021. In those years, the groundwater averagely started to decrease in February–March and remained nearly 7 meters from the ground surface in April–May. Temperature emerged as the most effective factor in regression analysis, followed by precipitation, soil moisture, and evapotranspiration. These findings can help authorities develop sustainable plans to preserve this resource since groundwater is an important source of water for drinking, irrigation, and other daily purposes.

Keywords: *Climate change, Groundwater, Drought, Machine learning model, Rajshahi district.*

1 Introduction

Climate change is an alarming reality that affects that is profoundly impacting various aspects of our environment, including groundwater resources. Climate variables including rainfall, temperature, soil moisture, and evapotranspiration have recently had a negative impact on the valuable G.W. resource in a number of places throughout the world (Ahmed et al.,2022). Since 1861, there has been an observed increase in the global mean surface temperature by around (0.6±0.2 ºC) and the Intergovernmental Panel on Climate Change (IPCC) predicts that it will increase by 2 to 4 ºC over the next 100 years. The annual mean temperature has increasing trends in Rajshahi with increasing rates of +0.012 ºC/year during 1981-2016(Karmakar et al., 2019). Annual rainfall is also decreasing in the study area with decreasing rate of 8.946 mm/year (Karmakar et al., 2019). Warmer temperatures will have a considerable influence on the hydrologic cycle, resulting in changes in the rates of precipitation and evapotranspiration (Kumar et al.,2012). Simultaneously, groundwater, which refers to the water stored beneath the Earth's surface in underground aquifers, plays a critical role in sustaining ecosystems, agriculture, and human activities. These results not only significantly fluctuate groundwater levels but also influence on altering the availability, quality, and sustainability of groundwater resources worldwide.

The most widespread source of fresh water on earth is groundwater. Policymakers are now very concerned about the first increasing usage of groundwater, particularly in emerging nations with an agricultural economy like Bangladesh. Groundwater supplies are the major source of water for Bangladesh's agricultural and municipal sectors.. Irrigation is of the utmost importance to Bangladeshi agriculture throughout the eight dry months from mid-October to mid-June (Mohammad et al,2012). About 75% of the water used for irrigation originates from groundwater (GW). The condition of GW resources is getting worse because of rapid population increase and overexploitation. This is especially true for Bangladesh, where rising water consumption is a result of both growing industrialization and increasing population density. Groundwater is obviously essential for agricultural and municipal water supply in the Barind region of northwest Bangladesh (Mohammad et al,2012). For this reason, particularly in water-scarce areas like the Rajshahi District, groundwater level assessment and analysis are crucial for effective resource management.

Several data-driven models, including Artificial Neural Networks (ANN) (Di Nunno et al., 2020), Support Vector Machine (SVM) (Gong et al., 2016), Extreme Learning Machine (ELM) (Huang et al., 2006), and the M5 model (Kisi et al., 2015), have been created and tested for GW forecasting. Although the ANNs and ANFIS models have some advantages, such as the ability to assess unidentified variables using straightforward training tools and to detect complicated multidimensional associations between predicted values and target parameters, they also have some drawbacks, such as their over-fitting issues and "black box" nature (Dumitru et al., 2013). Furthermore, as SVM contains a variety of kernel functions, only one of them should be used for each performance metric (Sheikh et al., 2018). compared to these models, different tree-based models like Random Tree, Random Forest, and REP Tree only map data characteristics rather than requiring the processing of datasets (Gong M et al., 2020). There are a variety of combined group machine learning and genetic models available for use in various hydro-metrological solutions. Under particular scenarios, it has been seen that hybrid models occasionally outperformed solo models. For G.W. predictions, several hybrid ML models, including Wavelet-ANN, Wavelet-ANFIS (Mousavi et al., 2013), and Wavelet-MARS (Rezaie et al., 2017), have been examined.

In a number of fields, including hydrology, land use categorization, irrigation scheduling, evapotranspiration measurement, and temperature analysis, Breiman's Random Forest model is frequently utilized (Breiman et al., 2001). It is resilient to outliers and noises as a result, the impact of individual trees generating inaccurate predictions is minimized (V Rodriguez et al., 2015). Additionally, it successfully captures complex interactions and patterns in the data by handling non-linear correlations between input and destination variables. The feature importance provided by Random Forest quantifies the significance of each input variable in the prediction process. It has the potential to generalize, doing so successfully with previously unreported data and lowering the danger of overfitting.

Since the averaging effect of numerous trees makes it unlikely that missing data and outliers would significantly affect overall predictions, it can handle them using surrogate splits and outliers (Irving Gomez-Mendez, 2023). The model is easy to use and interpret, as it does not require extensive parameter tuning and features that help interpret the model and understand the factors influencing predictions

. The objectives are to

1. Predict groundwater levels using climatic and hydro-geological parameters.
2. Identify key climate variables that have the most significant influence on groundwater level fluctuations.
3. To provide insights and recommendations for policymakers, water managers, and stakeholders on utilizing machine learning models for effective decision-making and sustainable groundwater management strategies in the context of climate change.

The study intends to achieve these research objectives by utilizing machine learning algorithms to improve the understanding of the intricate relationships between climate change and groundwater supplies. It aims to provide useful insights for proactive planning, resource allocation, and adaptive management to maintain long-term groundwater sustainability in changing climate conditions.

2 Study site

For the study purpose, Bagha upazila of Rajshahi district was selected. Rajshahi is situated in the northern portion of Bangladesh. Bagha Upazila was established in 1983. It consists of 7 union parishad and 78 villages. The total area of this upazila is 184.25 square kilometers. It is located between 24.1917ºN latitude and 88.833ºE longitude. The area under consideration is geographically demarcated by the Charghat and Bagatipara upazilas to the north, the Daulatpur (kushtia) upazila to the south, and the Lalpur and Bagatipara upazilas to the east. To the west, it is surrounded by the West Bengal region of India and the Padma River.

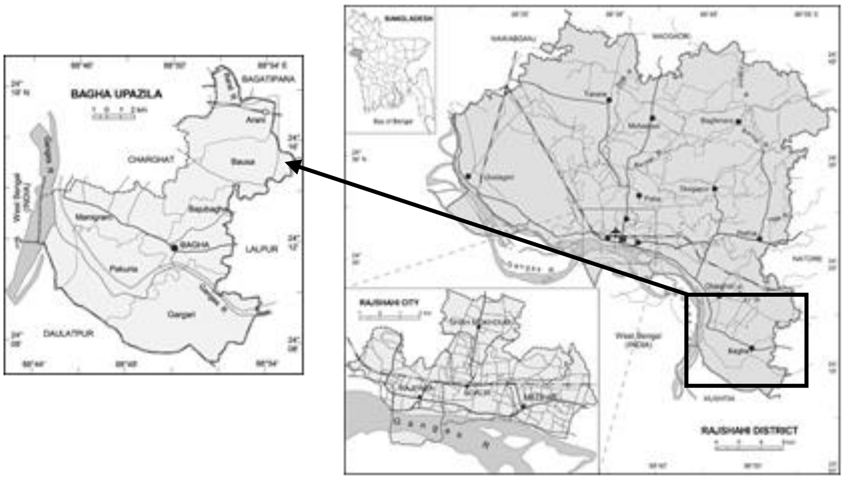

Figure 1. Map of the study area Bagha Upazila, Rajshahi district

3 Model development

3.1 Model parameters

For the development of the machine learning model, monthly average temperature, precipitation, groundwater level, evapotranspiration, and soil moisture data of the study area were collected.

The monthly precipitation, temperature, evapotranspiration, and soil moisture data of the Bagha upazila were collected from satellite sources (climateengine.org and power.larc.nasa.gov.). The groundwater level data of Bagha was collected from Barind Multipurpose Development Authority (BMDA). The entire dataset covers the years 2002-2011, beginning in January. According to Salam et al. (2020), the key hydro-geological and climatic factors that affect groundwater levels are the quantity of precipitation, temperature, evapotranspiration, and soil moisture. To better understand how groundwater levels fluctuate in the research region, this study has selected three variables, precipitation, temperature, and evapotranspiration, together with one hydro-geological variable, such as soil moisture.

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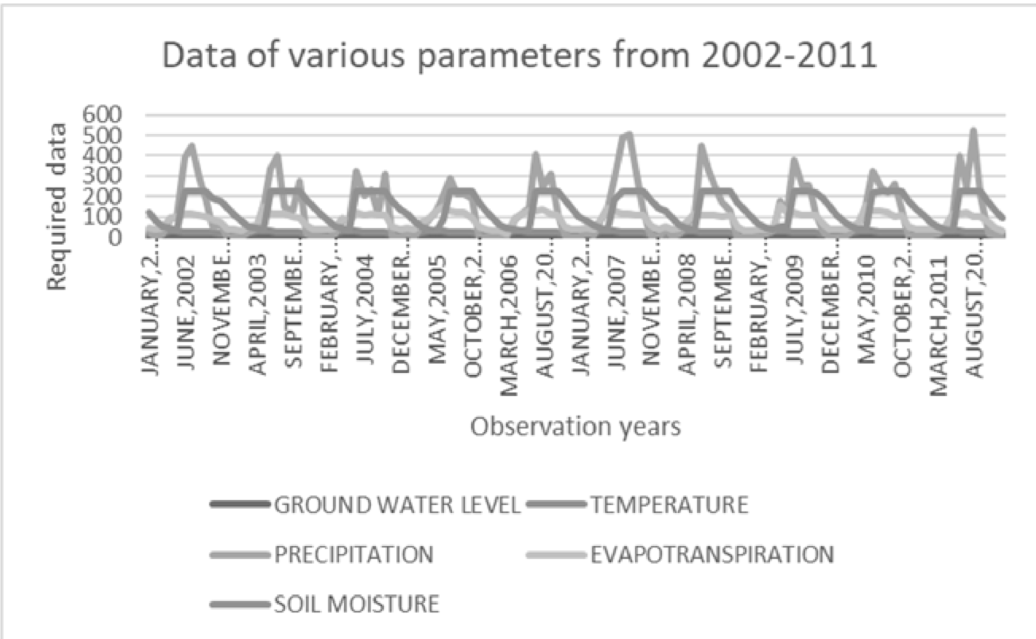


Figure 2. Data chart showing sample dataset

3.2 Modelling Processes

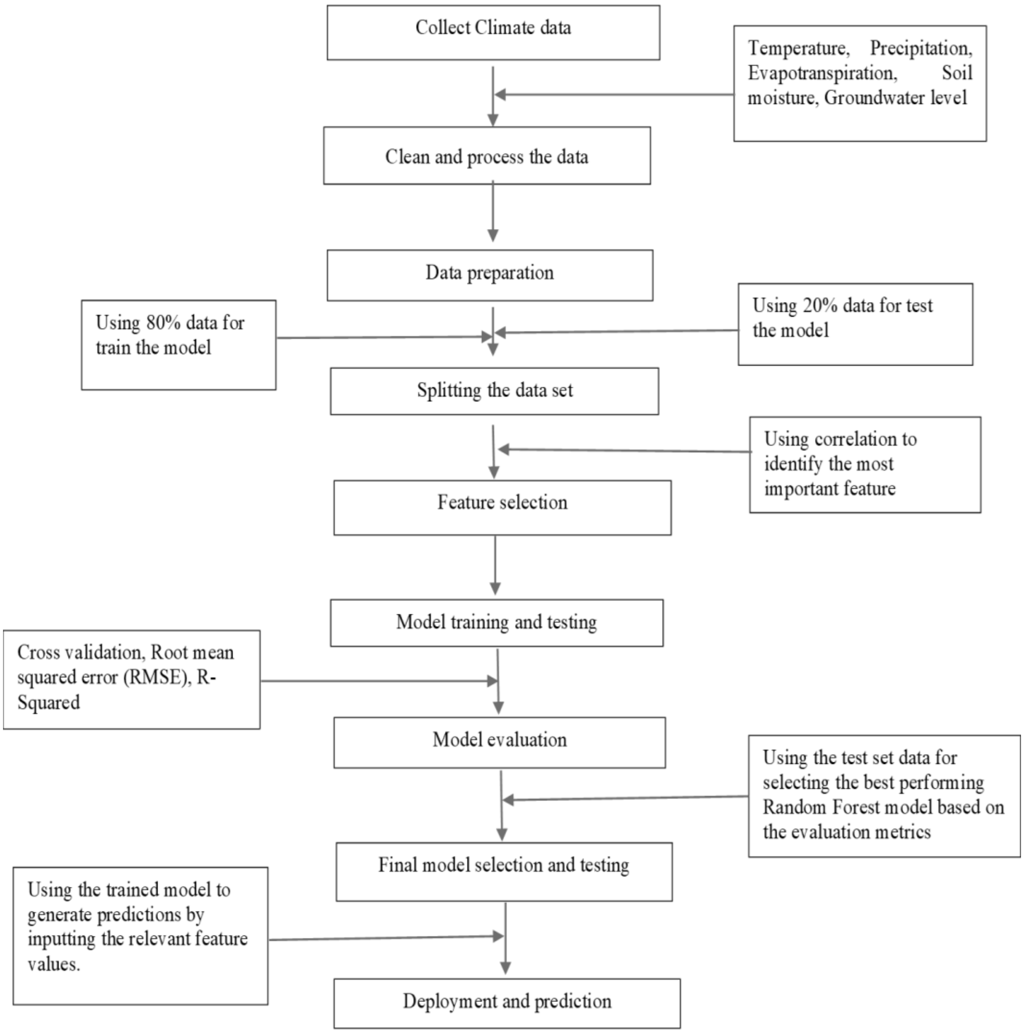
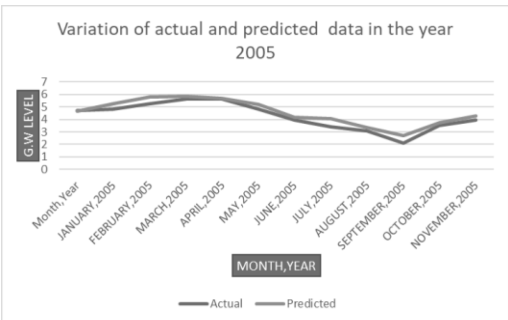


Figure 3. Flow chart showing the modeling process

4 Results & Discussions



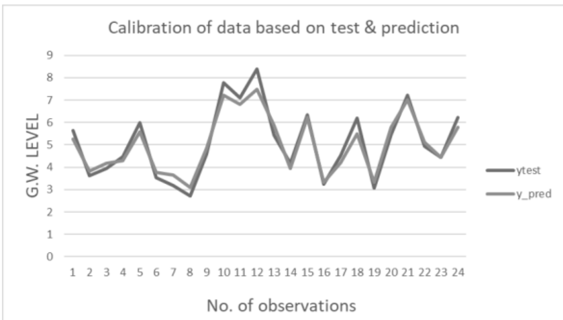


Figure 4. Data chart showing calibration

Figure 5. Data chart showing validation

The calibration technique used to compare the actual and anticipated values of the groundwater level for the research region is shown in Figure 4. The comparison is reported for the period January 2002 -December 2011. The performance metrics obtained for the calibration process were R-squared and RMSE and their corresponding values are 0.96 and 0.38m. Comparing the measured and anticipated values of the groundwater level for the research region is shown in Figure 5 as the validation procedure. The comparison is reported for the year 2005. The performance metrics obtained for the calibration process were R-squared and RMSE and their corresponding values are 0.97 and 0.38m.

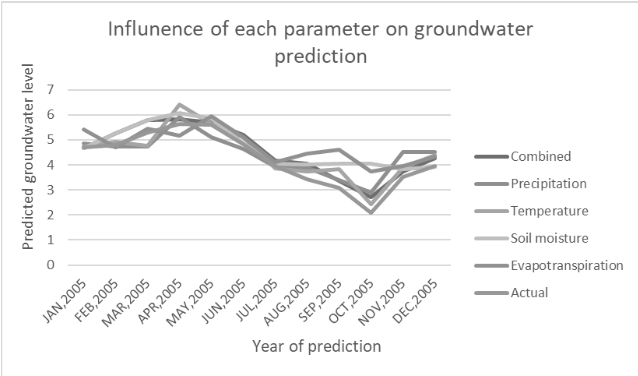


Figure 6. Impact of each component on groundwater level

Figure 6 shows the impact of each component on the groundwater level. In this analysis, G.W.L was predicted using separately each parameter. Temperature showed the effective component followed by precipitation, soil moisture, and evapotranspiration. A regression analysis was done using actual groundwater levels vs separately predicted groundwater levels to identify the most effective input parameter in this model. The R-squared values for temperature, precipitation, soil moisture, and evapotranspiration are accordingly 0.89,0.84,0.75 and 0.73.

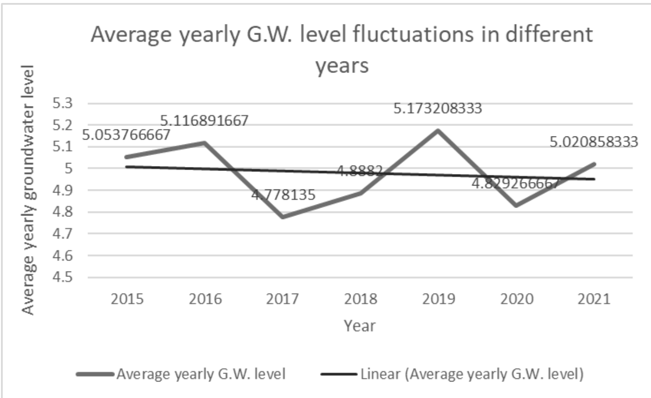


Figure 7. Average yearly fluctuations of groundwater level

From the analysis of the average yearly groundwater level in Figure 7, it has been observed that groundwater fluctuations have different trends. In the years 2015, 2016, 2019, and 2021, groundwater has shown a decreasing trend. In the above years, G.W.L. has decreased quite largely from its normal average position. In the year 2015, it was observed that groundwater started to decrease in February and continued up to May. From mid-June, groundwater started to increase, and in the months of July and September, groundwater remained approximately 3 m from the ground surface. In 2019, groundwater level fluctuations did not show much variation, although, in the month of April, they reached 7m from the ground surface and started to increase immediately in May. From August to November, groundwater remained within 3–4 m from the ground surface, then again started to decrease in December. For the years 2016 and 2021, observation shows that G.W.L. started to decrease in February and continued up to April. For both years, G.W. decreases to more than 7m in the months of April and May. In those years, G.W. started to increase in the month of June. It has been observed that after starting to increase in June, groundwater reached its minimum distance of nearly 3m from the ground surface in the months of October and August, consequently for the years 2016 and 2021.

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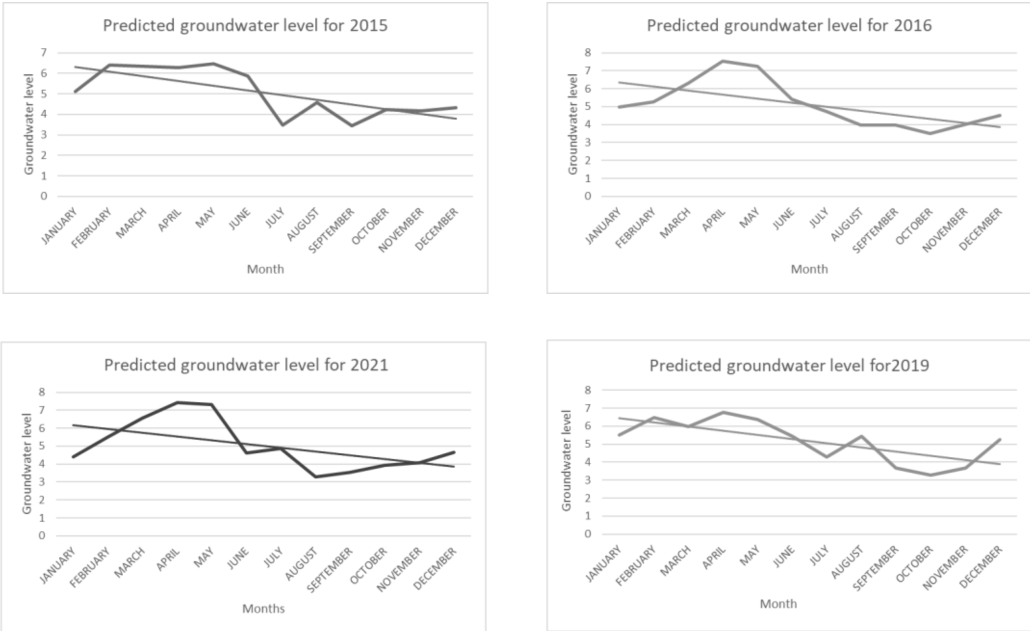

Figure 8. Groundwater level fluctuations in the years 2015,2016,2019 & 2021

5 Conclusions

Groundwater levels from various years were predicted for Bagha upazila using multiple climate parameters, as this study focuses on changing climate patterns and their impact on groundwater resources. From the study, it has been observed that in the years 2015, 2016, 2019, and 2021, groundwater levels have a decreasing trend. The changing climate pattern has enormous effects on groundwater levels. By comparing it with the combined prediction of groundwater level, it has been found that separate temperature is the most effective parameter for groundwater level variations. Groundwater levels showed variations mostly due to the effect of changing temperature patterns, followed by precipitation, soil moisture, and evapotranspiration.

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