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Delineation of fresh groundwater zone in the coastal aquifers of Bangladesh: a multi-modal approach by remote sensing and machine learning algorithm attribution

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DELINEATION OF FRESH GROUNDWATER ZONE IN THE COASTAL AQUIFERS OF BANGLADESH: A MULTI-MODAL APPROACH BY REMOTE SENSING AND MACHINE LEARNING ALGORITHM ATTRIBUTION

This thesis is submitted to
The Department of Environmental Science and Management
For the partial fulfillment of the award for the degree of
MASTER OF SCIENCE IN CLIMATE CHANGE AND DEVELOPMENT

By

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September 2026

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DECLARATION

I, Ragib Mahmood Shuvo, hereby declare that the work presented in this thesis has not been submitted for any other degree or professional qualification, and that it is the result of my own independent work.



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STATEMENT OF APPROVAL

This thesis has been approved in partial fulfillment of the requirements for the award of the degree of MASTER OF SCIENCE IN CLIMATE CHANGE AND DEVELOPMENT.

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Sincerely

Ragib Mahmood Shuvo

ABSTRACT

Groundwater Salinity Intrusion in the coastal belts of Bangladesh poses a severe threat to the livability and livelihood of more than 20 million population due to scarcity of freshwater. Climate change and anthropogenic activities is further exacerbating the salinity intrusion risks across these regions. This research aims to delineate the fresh groundwater potential zones in the six districts of the southwestern part of the coastal areas of Bangladesh with the help of remote sensing and machine learning approaches. 15 parameters were primarily selected to prepare the spatial layers which represent the topographic, meteorological, hydro-chemical and land use characteristics of the study area. Among these, 10 parameters were finally retained by multiple iterations of the Variable Inflation Factor (VIF) analysis at a threshold of 10 in order to exclude multicollinearity of the parameters. 117 groundwater samples for wet and dry season were collected from Bangladesh Water Development Board (BWDB) to classify the training and testing dataset. Synthetic Minority Oversampling Technique (SMOTE) was applied to the training dataset in order to address the imbalance of fresh and saline groundwater sample size. Five Machine Learning algorithms namely, Random Forest (RF), Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) were applied to delineate the fresh groundwater potential zones. The accuracy of the ML models was validated by using ROC/AUC, Precision-Recall, Sensitivity, Specificity, F-1 Score, Kappa accuracy. RF and XGBoost delineated the potential zones with the most accuracy, having an overall accuracy of 95.83%, AUC of 0.99, an average precision of 0.917, and zero false negatives on the testing dataset. The potential zones were divided into five classes and approximately 8-10% of the study area were delineated as very high potential zone for fresh groundwater with majority of the study area falling under very low potential areas. The inability to delineate similar outputs by other ML models highlighted the limitations in collecting, managing and storing spatially distributed groundwater quality data across the region and the severe heterogeneity of fresh and non-fresh groundwater quality within the sample dataset. The findings provide an emphasis on combining hydro-chemical data in groundwater potential zone mapping, especially in the coastal areas where further increase in climate change is going to shift the dynamics of freshwater resources. Therefore, similar research can drive anticipatory actions to conserve groundwater quality and establish a sustainable groundwater governance in similar vulnerable areas.

Keywords: Fresh Groundwater Potential Zone Mapping, Remote Sensing, Machine Learning, Groundwater Salinity, Coastal Areas.

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1 Introduction

Groundwater is one of the most important natural resources that is supporting communities since the beginning of the earth systems. It is the second most significant space for accessing freshwater in the whole world that supports almost one-third of the total freshwater supply (Hasan et al., 2025; Kalantar et al., 2019; Lee et al., 2020). Integrated with the hydrogeological formations, the availability of groundwater is underpinned by a number of climatic and geospatial factors like lithological & physiological patterns, draining networks, precipitation and infiltration rate, temperature and evapotranspiration trend and multiple complex hydrological factors(Ibrahim et al., 2026; Roy et al., 2024; Sarkar et al., 2024). The large share of dependency on groundwater has significantly contributed to the socio-economic dynamics of communities all around the world. For centuries, groundwater has been sufficiently supporting household, agricultural, and industrial demands, covering 22%, 69% and 9% respectively (Akbar et al., 2023). Alongside, the semi-arid and arid regions of the world where scarcity of surface water is substantially present, groundwater is the only source of their water supply. Therefore, groundwater is still a key resource to secure Sustainable Development Goals (SDGs) in many developing and underdeveloped nations (Bai et al., 2022; Lee et al., 2020; Sarkar et al., 2024).

However, with rapid population growth and increasing anthropogenic activities have significantly increased the demand of groundwater. Being a common pool resource, the overexploitation of groundwater has been severely affecting the renewability of the resource (Hasan et al., 2025; Howlader et al., 2023). Thereafter, groundwater is now being declared as a non-renewable resource in many parts of the world (Shuvo et al., 2024). On the contrary, climate change has been affecting the availability of groundwater in many places of the world, especially since the 1970s (Loáiciga, 2003). Erratic rainfall patterns, extreme temperature, disturbed water cycle, have caused major damage to groundwater recharging capabilities and availability. This divergence of increasing demand and degraded availability have caused significant deficiency in availing groundwater in a day-to-day basis. Currently, almost half of the world's population is living under heavily water-stressed regions (Yu et al., 2026).

In addition to the decay in groundwater quantity, increased human activities have severely damaged groundwater quality as well (Kumar et al., 2021a). In many parts of the world, groundwater has already been declared as unsafe to drink (Seifu et al., 2023). These outcomes are the results of unprecedented use of groundwater in industrial and agricultural activities that exceeded the natural recharge rate of groundwater (Roy et al., 2024; Sarkar et al., 2024). The

long-term result of such uncontrolled activities will affect public health, food and water security, ecosystems and finally, the livelihoods of communities (Tasneem et al., 2026). Along with the anthropogenic contributions, climate change is also directly affecting the groundwater quality. Global warming and subsequent glacier meltdown and sea level rise is affecting community spaces with salinity intrusion, droughts, desertification which are significantly degrading the groundwater quality (Madani & Niyazi, 2023; Roy et al., 2024; Tasneem et al., 2026).

Bangladesh, one of the largest deltas in the world, has been relying on groundwater for more than two decades. Almost 95 percent of domestic and 70 percent of agricultural water demand has been met by groundwater which has tremendously supported the communities in certain socio-economic growth (Hasan et al., 2025; Roy et al., 2024; Sarkar et al., 2025; Tasneem et al., 2026). However, Bangladesh is one of the top ten climate vulnerable countries in the world, with more than 14 hazards annually affecting 11 stress areas (MoEFCC, 2022). The coastal areas of Bangladesh, which also owns the largest mangrove forest in the world, is severely affected by sea level rise, coastal flooding and salinity intrusion (Tasneem et al., 2026). It was estimated that a rise of 10 cm to 60 cm in the sea level can inundate 15 to 75 percent of the mangrove forest and beyond the coastal communities of Bangladesh (Jabir et al., 2026). Hydro-chemical analyses of groundwater inundated with salinity in different places of Bangladesh have already found increased concentration of multiple indicators like electrical conductivity, pH, total dissolved solids, sodium, chloride, aggravated by additional chemical pollutants like magnesium, calcium, bicarbonate, sulphate and bromide (Tasneem et al., 2026). Increasing salinity in groundwater is not only affecting the agricultural productivity of these coastal areas, but also affecting communities with severe deficiency in drinking water, sanitation facilities, and public health issues like hypertension, maternal health complications (Howlader et al., 2023; Roy et al., 2024; Sarkar et al., 2025). Therefore, the undisputed damage of groundwater quantity and quality in the coastal areas is exposing more than 20 million residents under severe threat of water scarcity, livelihood and public health risks and migration enforcements. This will eventually disrupt the social fabric of the coastal communities in Bangladesh.

Despite of all the prescribed threats and vulnerabilities, there are still significant limitations in micro-spatial level database of groundwater potential areas (Adham et al., 2010; Howlader et al., 2023; Roy et al., 2024). A groundwater potential area is defined by the possibility of accessing groundwater within a given hydrogeological setting (Lee et al., 2020; Madani & Niyazi, 2023; Shandu & Atif, 2023). Therefore, Groundwater Potential Zone Mapping (GPZM)

is a globally renowned spatial approach to identify key areas for groundwater utilization. GPZM has the capability of identifying the spatial boundaries suitable for sectoral groundwater usage like agricultural, domestic and industrial abstraction, contributing to integrated water resource management at a large geospatial scale (Kalantar et al., 2019; Lee et al., 2020; Masroor et al., 2023). To identify these potential zones, traditional GPZM approaches rely on ground-based surveys of topographical, hydrological, geological, ecological and atmospheric factors which are significantly expensive and time-consuming in consideration to a larger spatial scale (Sarkar et al., 2025). GIS and Remote Sensing (RS) approaches have proven to be an effective toolset to replace such prolonged and complex ground-level study and identify the potential groundwater zones with a complementation of different approaches like the Analytical Hierarchical Process (AHP), Fuzzy logic model, Hybrid Multi-Criteria Decision Analysis (HMCDA). Alongside, the multi-parametric evaluation capability of GPZM enables it take multiple climate change and anthropogenic factors into account and delineate potential areas, ensuring conservation, economic growth and environmental sustainability (Bai et al., 2022). Therefore, there is a high potential of applying GPZM in the coastal areas of Bangladesh by tailoring the parameters that acknowledges salinity factors to delineate the fresh groundwater potential zones. However, modern methodologies have increasingly evolved to complement GIS and RS tools with Machine Learning (ML), Deep Learning (DL) algorithms, to create a GeoAI interface in dealing with multi-parametric spatial layers modelling and predicting (Oluwaleye et al., 2025). GeoAI overcomes the barriers of resolving non-linear interactions across variables of the traditional GIS and RS approaches and adapt to the changing hydrogeological scenarios (Janowicz et al., 2020; Li & Hsu, 2022). Therefore, a number of algorithms like Artificial Neural Network (ANN), Decision Tree Model, Random Forest (RF), Support Vector Machine (SVM), have been increasingly applied in a number of articles related to GPZM (Bai et al., 2022). However, in-depth literature review has exposed a research gap of exploring the capabilities of GeoAI approaches in delineating the non-saline groundwater potential zones that addresses all the factors of GPZM along with the salinity indicators which can enable the model to identify key areas with very low availability of groundwater salinity. The successful compilation of the methodological framework of the model along with a validated outcome can certainly highlight the importance of such approach in the climate vulnerable regions of the developing nations where ground-based database or survey is not available or affordable. Therefore, this research addresses the dire need of identifying the non-saline groundwater potential zones in the southwestern coastal areas of

Bangladesh. This research is expected to influence the policymakers and local leaders to support early intervention, irrigation planning, groundwater protection strategies, and climate-resilient adaptation. Therefore, this research addressed the dire need of identifying the non-saline groundwater potential zones in the southwestern coastal areas of Bangladesh with the help of remote sensing and machine learning algorithms. This research is expected to influence the policymakers and local leaders to support early intervention, irrigation planning, groundwater protection strategies, and climate-resilient adaptation.

2 Methods & Materials

The conventional approaches like hydrogeochemical ground surveys for delineating GPZM of larger areas are highly expensive and time consuming, which makes the large coastal belt of Bangladesh exposed to a major deficiency of database present to locate fresh groundwater regions (Sarkar et al., 2024, 2025; Tasneem et al., 2026). Recent studies applied geospatial tools like GIS and Remote Sensing to analyze spatiotemporal data of land surfaces and numerous climatic parameters that catalyzes the degradation of groundwater quality (Bai et al., 2022; Lee et al., 2020; Roy et al., 2024; Sarkar et al., 2025). To delineate GPZM based a series of parameters, approaches like MCDA, AHP/ANP, fuzzy-based AHP were identified as plausible tools to combine with GIS and RS approaches. In addition to these models, GPZM were identified with the help of numerous statistical approaches like Logistic Regression (LR), Evidential Belief Function (EBF), Probability-Frequency Ratio, Certainty Factors (CF), Weight of Evidence (WoF), and Principal Component Analysis (PCA) (Shandu & Atif, 2023). However, the multi-criteria decision models and statistical models failed to analyze and predict the dynamic and non-linear interaction between groundwater and conditioning factors. Aritificial Intelligence (AI), combined with GIS and RS, can play an important role is addressing this limitation and create a dynamic flow of generating more accurate and precise mapping procedures of the groundwater potential zones. Alongside, association of additional parameters to address the non-salinity of groundwater can add more non-linearity amongst the parameters which cannot be addressed through statistical or MCDA approaches. ML approaches has been identified as a feasible tool to analyze and predict such non-linearity amongst parameters and delineate potential zones with similar attributes of regions with groundwater availability. Several techniques such as XGboost, Random Forest (RF), Support Vector Machine (SVM) (Kalantar et al., 2019; Lee et al., 2020; S. A. Naghibi & Moradi, 2017; Sameen et al., 2019), Artificial Neural Networks (ANN) (Arabameri et al., 2021; Lee et al., 2020; Pal et al., 2020; Sameen et al., 2019), Boosted Regression Trees (BRT) (Chen et al.,

2020; Mosavi et al., 2021) and Convolutional Neural Networks (CNN), Neuro-fuzzy (Hakim et al., 2022; Hasanuzzaman et al., 2022; Panahi et al., 2020; Prasad et al., 2020) have been used to evaluate the potentiality of groundwater. These models have been applied to different regions including drylands of Botswana, Pakistan, China, Bangladesh, Tunisia, India and similar regions with groundwater research globally. Researchers employ RS, GIS and ML techniques for precise identification of the groundwater potential zones and to take informed decisions for its management (Lee et al., 2020; Sarkar et al., 2025). However, the research gap found in this rigor review was no other researchers experimented the additionality of non-salinity parameters with the help of remote sensing and machine learning approaches to delineate the fresh groundwater potential zones. Therefore, this research employed remote sensing and machine learning approaches with a more diverse range of surface and subsurface parameters, climatic attributes, and spatiotemporal patterns, enhancing the interpretability of the models and facilitating more informed decision-making for groundwater quality conservatory actions.

2.1 Study Area

The coastal areas of Bangladesh are located at the southern horizon of the country, spreading across 32 percent of the national land area. Situated along the Ganges-Brahmaputra-Meghna (GBM) basin, approximately 44.8 million people resides in these areas, representing more than 28 percent of the national population of Bangladesh (Sarkar et al., 2025; Tasneem et al., 2026). This large number of populations is surrounded by the Bay of Bengal and the Sundarbans at the south, and hilly areas of Myanmar at the east. The Sundarbans, the largest mangrove forest of the world, has been shielding the coastal areas from multiple cyclones, coastal floods and supporting livelihood opportunities for the communities (Tasneem et al., 2026). Alongside, the communities also render their livelihood services through accessing multiple resources from the estuarine systems, coral reefs, wetlands, salt marshes, seaweeds, croplands, majority of which rely on the groundwater availability and quality (Jabir et al., 2026). The concurrent climate change impacts have largely affected these low-lying deltaic regions through sea level rise and coastal flooding, making the surface waterbodies and aquifers highly susceptible to salinity intrusion. The combined effect of climate change impacts and groundwater-dependent livelihood activities have compromised groundwater quality at large scale, making the future of millions of residents unsustainable (Jabir et al., 2026).

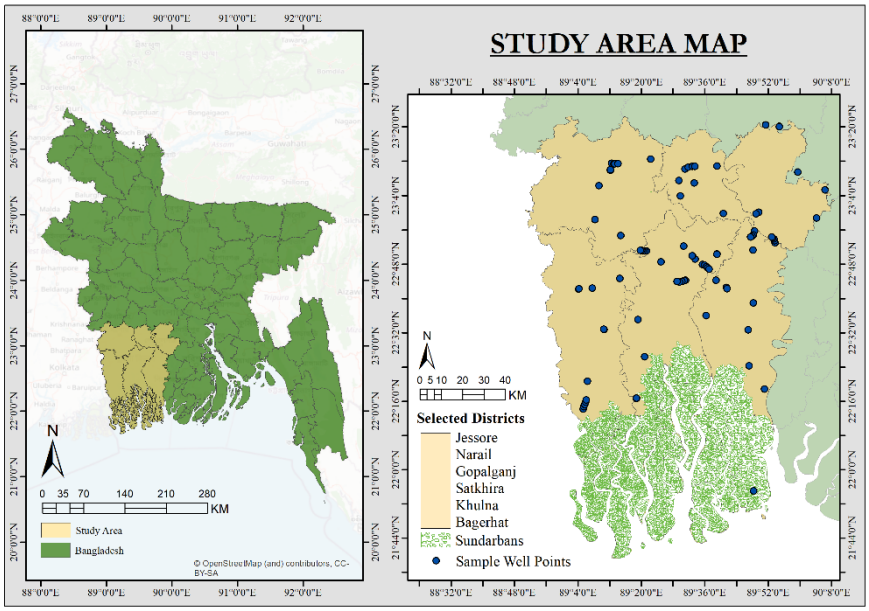


Figure 1. Study Area Map

The Ganges Tidal Floodplain regions of the coastal areas which is largely shielded by the mangrove forests, are extremely damaged by seawater inundation and subsequent salinity intrusion. A large share of the population who were dependent on agricultural activities, transitioned their livelihood approach into aquaculture that supports the presence of saline water. Shrimp farming has spread across 192,000 hectares of coastal lands, where researchers found more than 80 percent of the farmers abandoned rice cultivation to transit towards shrimp farming, especially in regions like Khulna, Satkhira, Bagerhat districts (Alam, 2024; Kabir et al., 2016; Rahman et al., 2025). On the contrary, the uncontrolled practices of land use transition have been affecting more land areas and aquifers with salinity intrusion. The lateral salinity intrusion pathway of groundwater shows radical changes of local hydrology in near future, risking more areas beyond the Bengal basin (Tasneem et al., 2026). Therefore, the study area for this research encompasses 41 sub-districts and 01 city corporation area of 06 districts of the southwestern coastal Bangladesh; 9 upazilas in Khulna District, 7 in Satkhira, 8 in Jashore, 9 in Bagerhat, 5 in Gopalganj, and 3 in Narail. The groundwater in these regions occurs in multilayered aquifer systems, transitioning from unconfined to semi-confined in the shallow alluvium and to fully confined at greated depths (Tasneem et al., 2026). The convergence of these environmental and anthropogenic pressures, along with the discrepancies of consistency in spatial data collection initiatives, highlight the critical need for groundwater salinity research and the development of non-saline groundwater potential models along the vertical direction of Khulna–Satkhira–Jashore region. As the Sundarbans is fully near The Bay of Bengal and kept as a national reserve forest, this area has been excluded from the spatial modelling of all

the parameters and fresh groundwater potential zoning, in order to avoid bias in salinity identification.

2.2 Groundwater Sample Data Collection

The groundwater samples were collected from the Bangladesh Water Development Board (BWDB) groundwater monitoring well stations located within the study area. Groundwater quality data of 117 well points were collected that comprised of the wet (2020) and dry (2021) seasonal groundwater quality data, helping the analytical approach with seasonal variation in hydrogeochemical properties across the study area. The well depths varied from approximately 19 m to 325 m across the study area. Alongside, a large metadata of groundwater quality, compromising of key physiochemical parameters like EC, TDS, bromide, sodium, potassium, calcium, magnesium, chloride, bicarbonate, sulfate, and carbonate, were collected for data training and validation of the non-saline groundwater potential zone map of the study area.

2.3 Selection of Parameters and Preparation of Parametric Spatial Layers

A total of 15 parameters were selected to analyze the surface, subsurface, hydrological and climatic attributes of the study area, namely, Distance from Major Streamlines (DS), Drainage Density (DD), Elevation (E), Terrain Ruggedness Index (TRI), Topographic Wetness Index (TWI), Topographic Position Index (TPI), Groundwater Level (GwL), Groundwater Salinity (GwS), Groundwater Electrical Conductivity (GwEC), Groundwater Chloride (GwCl), Dry Season rainfall (DR), Wet Season rainfall (DR), Land Use Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), Soil Permeability (SP), and Concentration of Soil Salinity (SS). All the datasets accessed to obtain the spatial data of the primary parameters are mentioned in the Table 01.

Table 1. Data Sources for Creating Spatial Layers of the Primary Parameters

Data	**Sources**	Year
DEM	SRTM Global 1 Arc-Second	2000
LULC	Landsat-8 Satellite Imagery (Cloud Cover: <5%)	2026
River Data	Bangladesh Agricultural Research Council (BARC)	2026
Soil Data	Bangladesh Agricultural Research Council (BARC)	2026
Groundwater Data	Bangladesh Water Development Board (BWDB)	2021
Rainfall	CRU TS Climate Dataset (Osborn et al., 2021)	1991-2025

2.3.1 *Rainfall (R)*

The rainfall maps were prepared using CRUTEM5 data, which underwent processing within the Google Earth Engine (GEE) platform (Osborn et al., 2021). The rainfall data were analyzed for a period of 34 years (1991-2025), addressing climate change impacts, rainfall pattern changes and infiltration pathways. The dry Season rainfall (March – May) exhibited higher rainfall in the eastern part, predominantly in the Gopalganj region, ranging from 318.17 to 346.17 mm (Figure 02a). The wet Season rainfall (June – Oct) exhibited higher rainfall in the south-eastern part, predominantly in the Bagerhat region, ranging from 1630.24 to 1865.2 mm (Figure 02b).

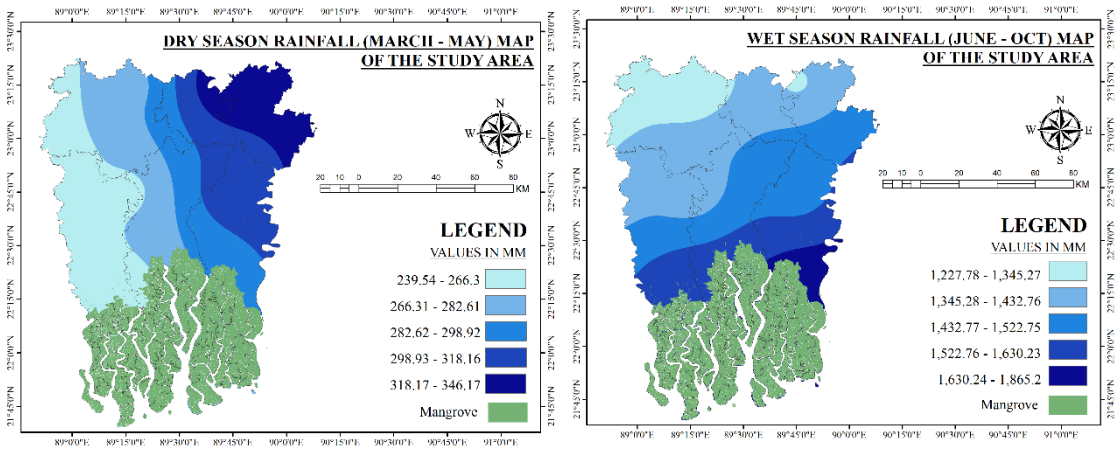


Figure 2. Dry Season (a) and Wet Season (b) Rainfall Map of the Study Area

2.3.2 *Drainage density (DD)*

The Drainage Density (DD) is mainly prepared from the Digital Elevation Models (DEM), which represent numerical explanation of the distance between channels of waterbodies within any geographic area. This analysis was compiled with the help of ArcGIS by using flow direction and accumulation of the centerlines of the watersheds, collected from DEM (Sarkar et al., 2025). DD has the capability of explaining the groundwater supply and possible direction of pollutants within any area. It highly assists researchers to assess and quantify the water permeability, runoff and infiltration ratio and relative relief. Since the study area is comparatively lower elevation region, there is comparatively lower drainage density than the mountainous regions. Therefore, higher drainage density has been identified as areas with higher risk of salinity intrusion within the aquifers and lower drainage density values are identified as regions safer in context of salinity intrusion and groundwater pollution (Lee et al., 2020; Sarkar et al., 2025). DD is calculated with the help of the following equation (Eq. 01):

$$DD = LS/BA \quad \ldots\ldots\ldots\

Here DD means drainage density while LS and BA stand for total length of stream area and basin area. Major depressions were found along the areas in Jessore other than the lower 3 districts which highlighted risk of saline water intrusion (Figure 03).

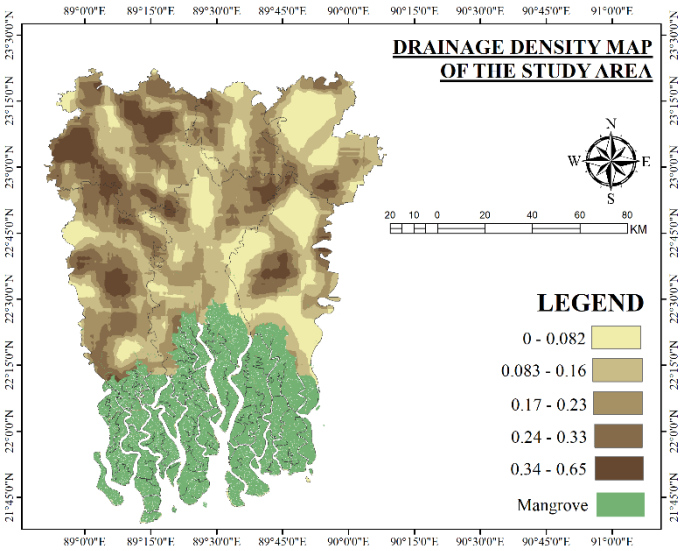


Figure 3. Drainage Density Map of the Study Area

2.3.3 Distance from Major Streamlines (DS)

Streamlines plays an important role in groundwater discharge (Tasneem et al., 2026). This relationship is largely influenced by the interaction between surface water and corresponded environment. Area locating near to rivers or streamlines may receive greater opportunity for infiltration, groundwater movement. The more the distance increase the influence may decline gradually which potentially reduce the contribution of river water in groundwater discharge (Howlader et al., 2023; Roy et al., 2024). On the contrary, regions located at a greater distance from major streamlines may see a reduced influx of water into the soil, rendering them less suitable for groundwater resources. This relationship makes proximity to streams particularly relevant when identifying fresh groundwater potential zones. Though, being close to a streamline does not mean that groundwater will be largely salinized, as infiltration also depends on other factors such as soil characteristics, topography, and land cover (Sarkar et al., 2024, 2025). The research employed the multiple ring buffer tool to generate a map of distance from major streamlines in the surrounding area using the GIS platform. Major streamlines were found in almost all the districts except Gopalganj. However, this exhibits the aquifer salinity intrusion pathway within the study area (Figure 04).

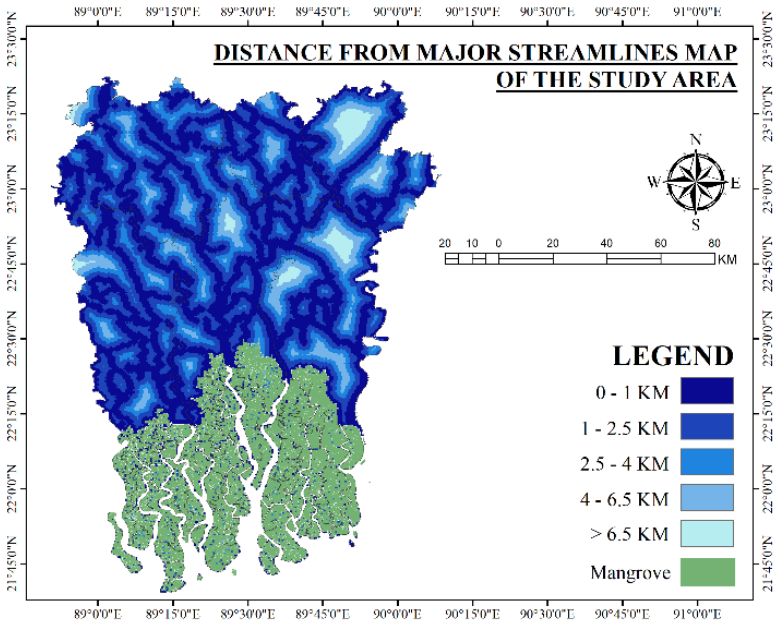


Figure 4. Distance from Major Streamlines Map of the Study Area

2.3.4 Elevation (E)

Elevation has a significant impact in predicting the groundwater flow, highlighting the potential of spatial salinity intrusion across certain region. This reflects on the terrain and shallow areas within any given region, indicating areas with groundwater flow, distribution, and storage (Lee et al., 2020; Roy et al., 2024). For this research, SRTM-2 data has been accessed to obtain the 30m resolution digital elevation model (DEM) image and the Elevation map of the study area has been prepared (Figure 05).

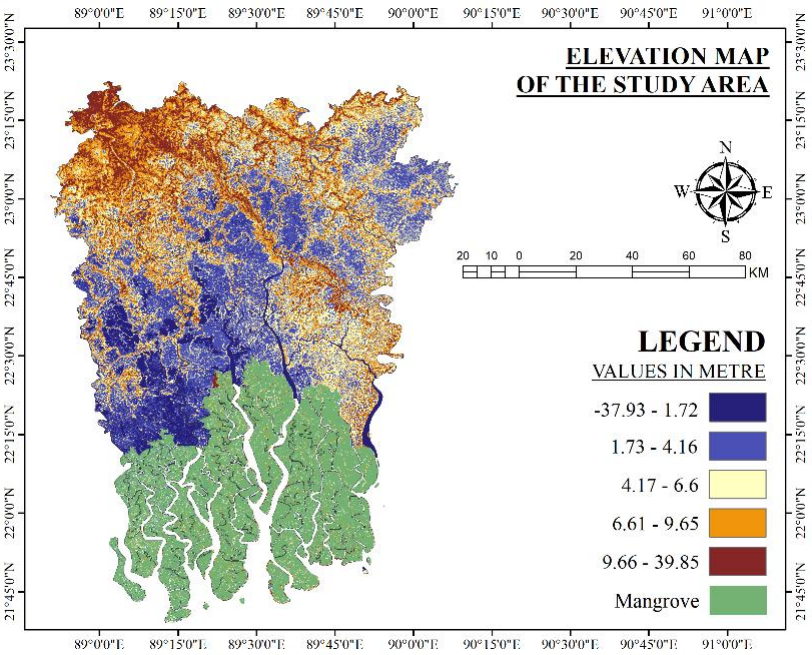


Figure 5. Elevation Map of the Study Area

2.3.5 Topographic Wetness Index (TWI)

The topographic wetness index (TWI) reliably indicates soil moisture and locates areas of water accumulation. TWI was calculated using digital elevation model (Roy et al., 2024). The topographic wetness index (TWI) is considered one of the important factors for assessing groundwater potential impact because the movement and accumulation of water is closely related to one another. This provides an indication of the tendency of an area to retain water by considering the slope and flow accumulation. According to Moore et al. (1991), TWI is a prominent parameter that is typically employed to compute for assessing the water accessibility in a location which is impacted by the influence of water accretion induced by topography. In short, places where water naturally covers and where the terrain is already gentle can hold moisture for a longer period of time. To understand the Topographic Wetness Index (TWI) the calculation begins with extracting the slope and flow accumulation raster from DEM. After that, the raster calculator was used to calculate TWI based on Eq. (02). Here, α is the flow accumulation raster, and β is the slope. Each class was assigned a weight based on their importance, where maximum weight was assigned for highest TWI and vice versa. Majority of the higher TWI in the lower regions of the study area where the higher regions like Jessore, Narail and Gopalganj were found with lower TWI values (Figure 06).

$$TWI = ln\left(^{\alpha}/_{Tan\beta}\right) \quad \ldots\ldots\ldots\

2.3.6 Topographic position index (TPI)

The topographic position index helps to understand how the relative position of a location within the surrounding landscape affects the groundwater conditions (Roy et al., 2024; Sarkar et al., 2025). It is a crucial factor for assessing groundwater resources since it provides valuable information on the topography, including the land's shape and elevation. It proved information about if a particular location is situated in relatively elevated position. This is important because the relative position of the land influences how water moves across the surface (Roy et al., 2024).

Areas with lower TPI values are particularly valleys and relatively flat locations. Those are most likely to receive and retain water from flowing from surrounding high areas. This creates higher opportunity for water accumulation (Roy et al., 2024). On the other hand, elevated locations may experience greater drainage and reduced water retention. Therefore, TPI helps to explain why two areas with similar elevations still have very different groundwater potential depending on their surrounding terrain. Majority of the TPI ranges in the study area were found within the range of -1.08 to 1.72 m exposed the drainage channels where higher possibility of groundwater salinity intrusion is present (Figure 07).

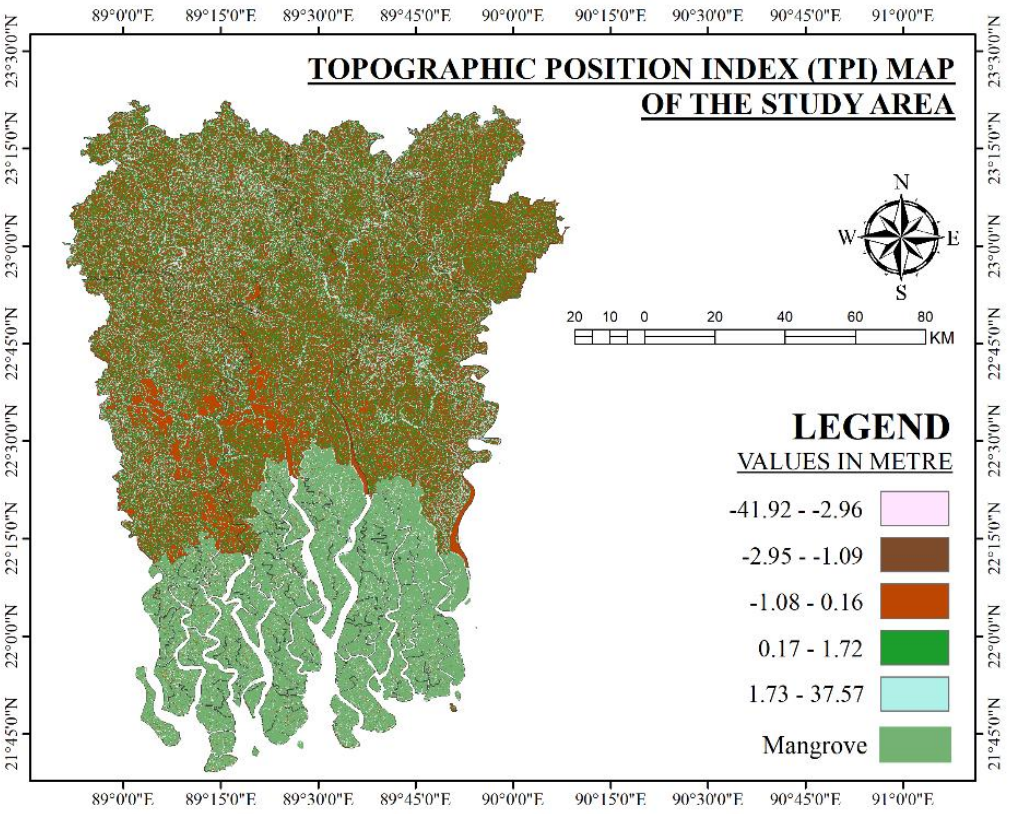


Figure 7. Topographic position index (TPI) Map of the Study Area

2.3.7 Terrain Roughness Index (TRI)

Terrain roughness index (TRI) is used to capture the degree of irregularity in the terrain and its influence on groundwater recharge. The physical roughness of the land affects how the rainfall moves across the surface. Comparatively smooth terrains provide favorable conditions for water to remain on or to move gradually across the surface, increasing its opportunity for water infiltration. On the contrary highly uneven terrain can increase runoff which means that a greater proportion of rainfall may not damage the area much as it has sufficient space to infiltrate into the grounds (Mogaji & Lim, 2018; Roy et al., 2024).

In research, Lower TRI values are considered more favorable for potential groundwater discharge, but higher TRI indicate rougher terrain and less effective groundwater recharge (Roy et al., 2024). The importance of TRI therefore does not lie merely in describing the shape of the land but in explaining how variations in terrain may influence the balance between surface runoff and sub surface infiltration. Lower ranges of TRI have been found mostly on Satkhira and Khulna, with minor presence in Narail and Gopalganj (Figure 08).

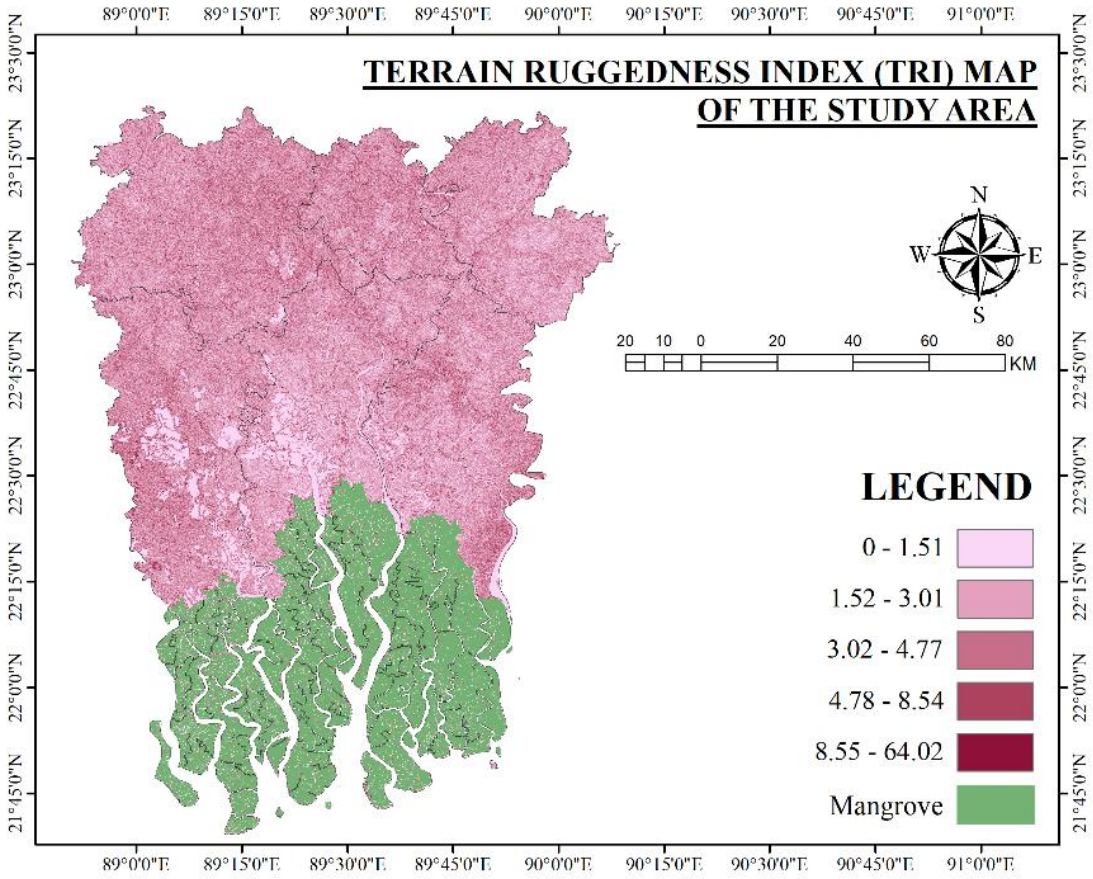


Figure 8. Terrain Roughness Index (TRI) Map of the Study Area

2.3.8 Land Use and Land Cover (LULC)

Land Use and Land Cover (LULC) is an important factor in groundwater potential assessment because it shows how the land is being used and what covers the land surface, such as vegetation, agricultural land, water bodies, or built-up areas. LULC provides an important connection between human activities and groundwater conditions. The land cover type shows that how rainfall interacts with the ground. For example, vegetated and agricultural areas generally allow more water to infiltrate into the soil, while built-up areas with roads and buildings increase surface runoff and reduce groundwater recharge.

To map the LULC in the region for 2025, the open-access GEE platform was used to process datasets acquired from Landsat-8 satellite imagery with a maximum cloud cover of 5%. The classification of the LULC was performed using a random forest (RF) classifier in google earth engine (GEE) using JavaScript (JS) programming language. The study area was classified into five classes. 200 training points per class and a total of 1000 points were used to train the RF classifier. The accuracy of the classification (89.57%) was assessed by generating a confusion matrix. The LULC highlighted a majority of the area as vegetation or agricultural (42.36%) and waterbodies (21.20%), with a decent portion of built areas (12.14%) and a large portion of the Sundarbans (24.17%) (Figure 09).

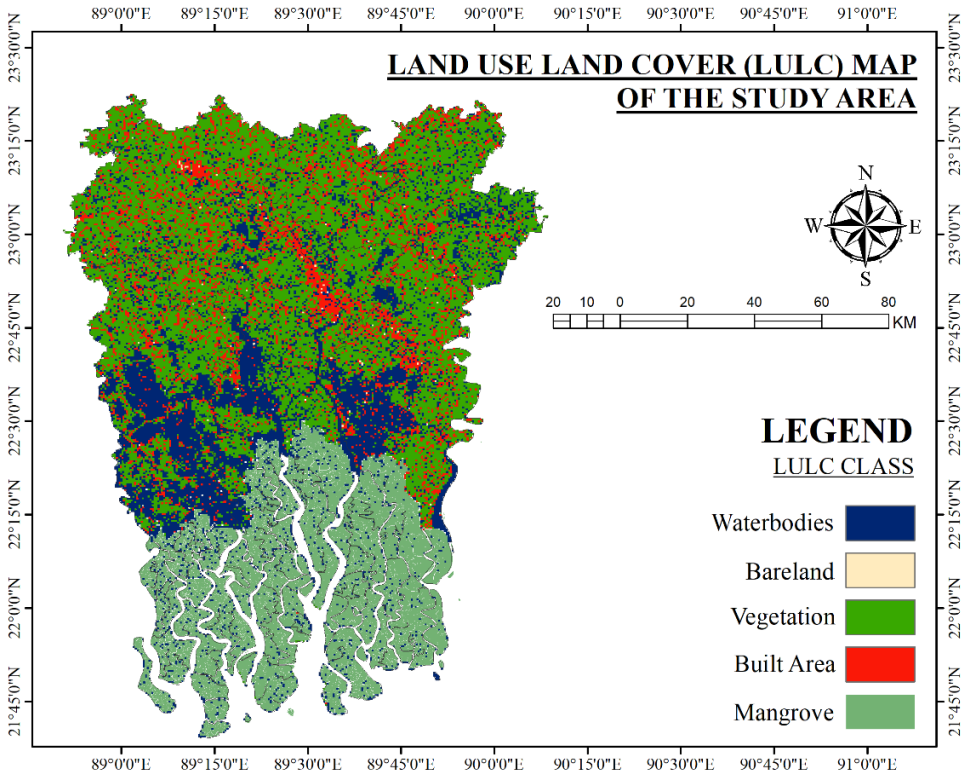


Figure 9. Land Use Land Cover (LULC) Map of the Study Area

2.3.9 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is use to capture the relationship between vegetation cover and groundwater availability (Uddin et al., 2026). It is needed for vegetation to have sufficient water to survive and maintain its growth. Areas with relatively dense and healthy vegetation indicates the presence of accessible moisture of ground water. Higher NDVI means an indication of favorable groundwater conditions, while lower values may represent those areas where vegetation is less are less capable of accessing sufficient water (Uddin et al., 2026). NDVI is calculated using the Band 4 and Band 5 of the Landsat-8 satellite image obtained for LULC analysis (Eq. 03). Higher NDVI values were observed in the northern regions whereas the southern regions had lower index values across the study area (Figure 10).

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{Red})/(\mathrm{NIR} + \mathrm{Red}) \quad \ldots\ldots\ldots\

infiltrate to groundwater rather than remaining on the surface. This creates more favorable condition for groundwater recharge.

The opposite situation occurs in soils with low permeability which means clay or compacted soils. These low permeable soils restrict downward movement of water increasing the percentage of surface runoff and reducing the amount of water that can reach the groundwater layer (Asfaw et al., 2018). On the other hand, areas with high soil permeability were considered more favorable for groundwater recharge, while areas with limited permeability were considered less favorable. This factor provides a direct physical explanation of how rainfall can become groundwater or vice versa. Higher permeability in the southern regions aligned with the groundwater quality data obtained from BWDB (Figure 11). Whereas, comparatively higher values were also found in the Narail and Gopalganj districts which is alarming.

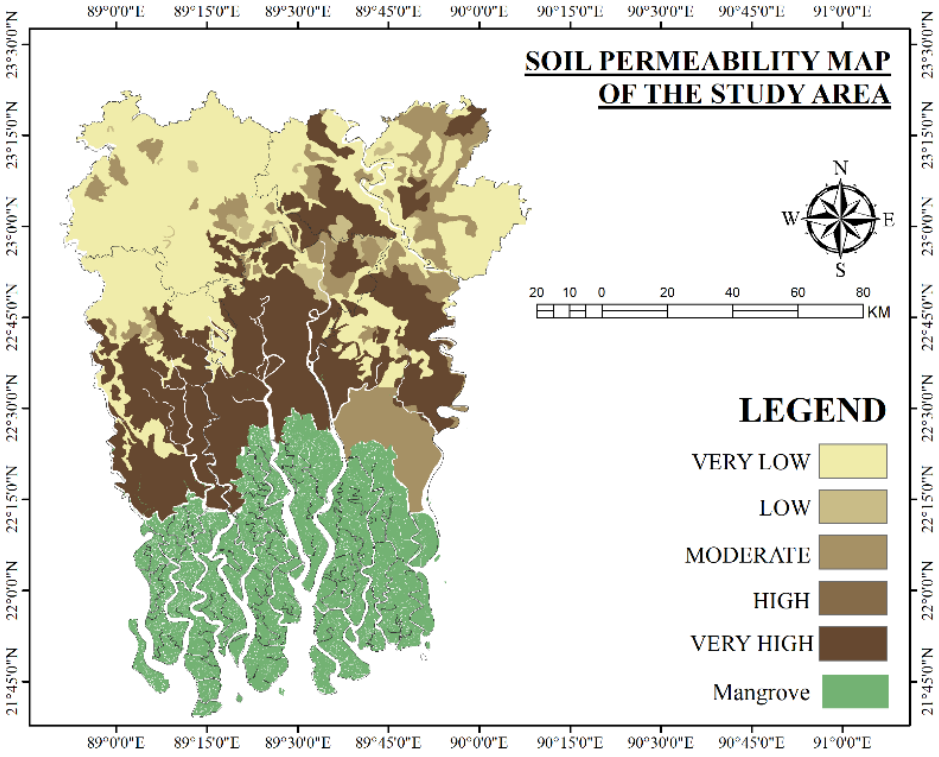


Figure 11. Soil Permeability Map of the Study Area

2.3.11 Soil Salinity (SS)

Groundwater salinity is significantly dependent on the quality of soil, the salinity content of soil and its permeability (Dasgupta et al., 2015). The soil salinity data has been collected from BARC, which is categorized into five classes of salinity. ArcGIS was used to prepare the SS map of the study area. Higher Salinity in the southern regions aligned with the groundwater

quality data obtained from BWDB. The northern districts were found to be low saline in respect to other regions (Figure 12).

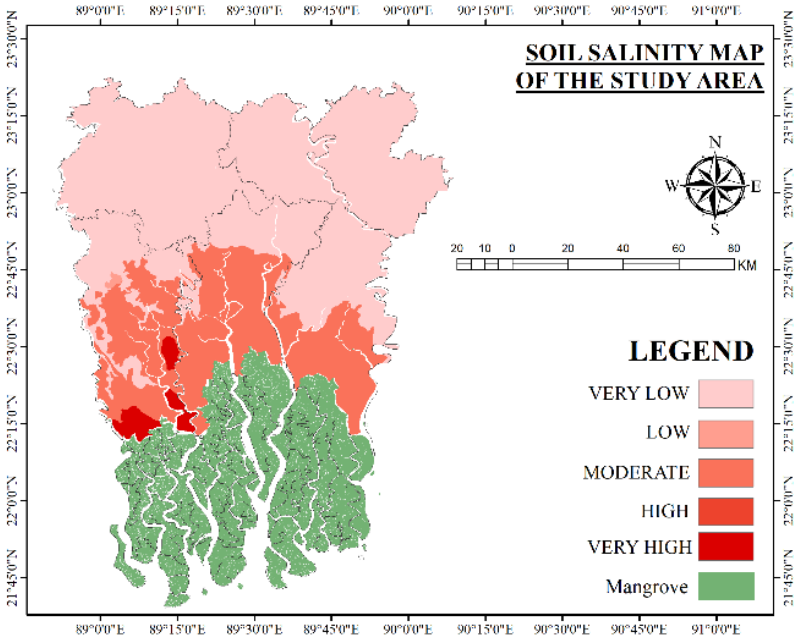


Figure 12. Soil Salinity Map of the Study Area

2.3.12 Groundwater Quality Parameters (GwL, GwS, GwEC, GwCl)

The groundwater quality within any certain region depends on multiple hydro-chemical and geophysical aspects (Tasneem et al., 2026). However, for delineating the fresh groundwater potential zones, GwS and GwEC are the most significant factors to determine groundwater salinity, while GwL plays a significant role in identifying the deep and shallow aquifers that regulates the groundwater infiltration. Additionally, as Tasneem et. al., (2026) stated that Groundwater chemistry shifts from Ca–Mg–HCO_3 facies(wet) to Na–Cl facies (dry), indicating widespread dry-season salinization, GwCl was also taken as a primary parameter. The spatial data of all the parameters were analyzed by ArcGIS with the help of Inverse Distance Weighting (IDW) method. The GW levels in the study area are predominantly lower than the other regions in Bangladesh, which highlights shallow aquifers all over the study area. The majority of the GwS and GwEC areas were located in the Satkhira and Khulna regions, with comparatively lower in the Jessore district. Higher GwCl values were observed in the southern regions whereas the northern regions had lower chloride contents in the dry season (Figure 13a, 13b, 13c, 13d).

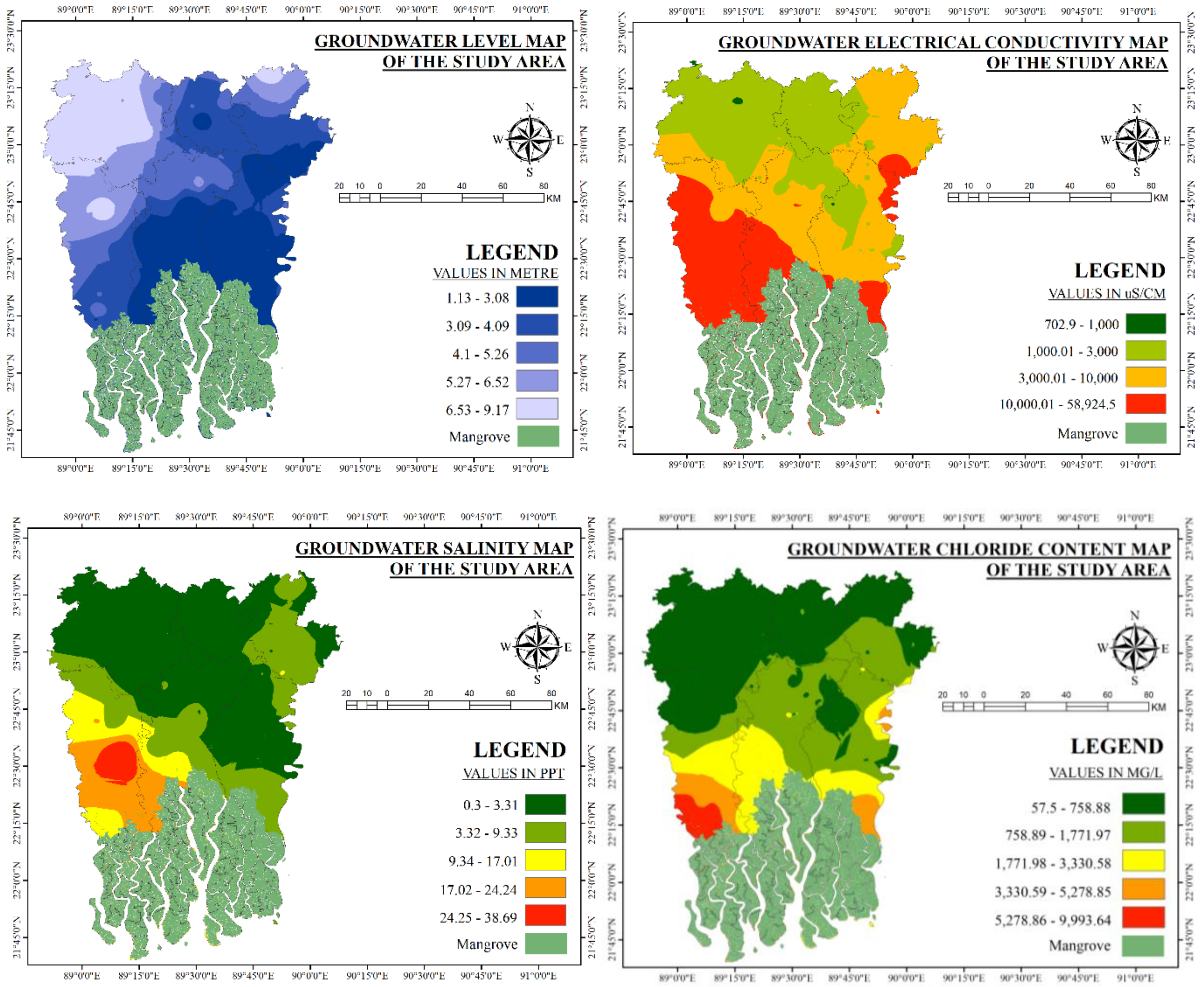


Figure 13(a, b, c, d). Groundwater Level, Groundwater Electrical Conductivity, Groundwater Salinity and Groundwater Chloride Content Map of the Study Area

2.4 Multicollinearity Assessment

The primarily selected parameters contained information about topographic, meteorological, hydro-chemical, and land use land cover. The spatial layers of all the parameters were prepared in order to obtain pixel-level information of the study area. Literatures have highlighted that during multiparametric modelling, multicollinearity among parameters can badly affect the output models ((Dey et al., 2023; Ibrahim et al., 2026; Tasneem et al., 2026). Therefore, Variable Inflation Factor (VIF) test was conducted amongst the parameters. Multiple iterations were run in order to finalize the parameters with a VIF score under 10. First two iteration marked Rainfall data of dry and wet seasons both, as the obtained data from CRU data had a broader 0.5° resolution of data, which produced nearly identical value within such smaller study area. The later iterations excluded Soil Salinity, Elevation and TWI which highlighted the importance of hydro-chemical data in similar modelling of fresh groundwater potential zone mapping (Figure 14).

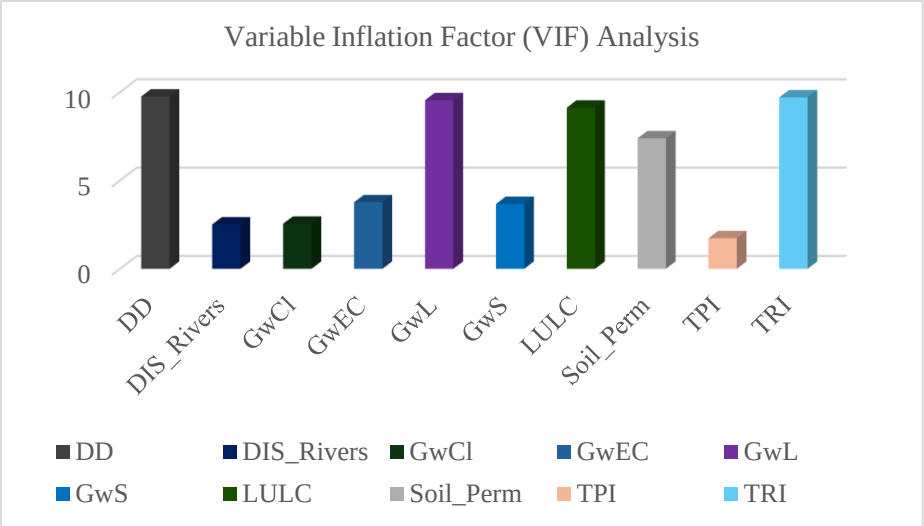


Figure 14. Multicollinearity Assessment by Variable Inflation Factor (VIF)

2.5 ML Approaches

2.5.1 SVM

Support Vector Machine (SVM) is another widely used supervised machine learning technique based on structural risk minimization and statistical learning theory (Naghibi & Pourghasemi, 2015; Rizeei et al., 2017). SVM is useful for groundwater potential zone mapping because it can identify complex relationships between groundwater occurrence and multiple environmental factors. The method determines an optimal hyperplane that separates different classes by maximizing the margin between them while minimizing classification errors (Naghibi & Pourghasemi, 2015). SVM can handle nonlinear relationships by transforming original data into higher-dimensional feature using kernel function. The kernel function used often include linear, polynomial, sigmoid, and radial basis function (RBF) kernels. In this study, the Radial Basis Function (RBF) kernel was used because of its ability to model complex and nonlinear relationships between the selected groundwater-influencing factors and groundwater potential classes (Roy et al., 2024).

The performance of the SVM model depends on several tuning parameters, especially the regularization parameter (C) and the kernel parameter (gamma (γ)). The regularization parameter controls the trade-off between maximizing the separation margin and minimizing classification errors. On the other hand, sigma parameters determine the influence or range of individual observations within the RBF kernel. Tuning parameters like regularization parameter (C) and gamma (γ) control the trade-off between margin and training errors, while the tolerance margin (ε) handles the SVR. SVM aims to find a function that maximizes the limits between hyperplanes while accounting for noisy class values (ε and ξ) (S. A. Naghibi et

al., 2015; Tehrany et al., 2015). In this research, SVM was modified by applying Radial Basis Function (RBF) kernel while regularization parameter C set to 10 and gamma set to scale and class weights were balances to account for the minority fresh class of groundwater.

2.5.2 K-Nearest Neighbor

KNN is an instance-based learning approach, which classifies each pixel based on the majority class of its k nearest training sample and the generalization of the training data is deferred until a prediction is made (Jari et al., 2023; Roy et al., 2024). KNN classifies an unclassified input vector by selecting the class of its closest example in the training set with the help of Euclidean distance. The key reason behind selecting KNN as a ML model for this research is the capability KNN not being affected by the multimodality or the size of the training set, which has a significant limitation in the context of this research. For this research, KNN was applied by using K = 7 with the help of distance based weighting and Euclidean distance approach.

2.5.3 Random forest (RF)

Random Forest (RF) is a machine learning technique that can be used for both classification and regression. It consists of multiple decision trees that work together to improve prediction accuracy and reduce the overfitting that commonly associated with individual decision trees (Breiman, 2001). In groundwater potential zone mapping, RF can effectively evaluate the relationships between multiple environmental factors and groundwater potential because it can accommodate both categorical and numerical variables and capture complex, nonlinear interactions among the predictors (Bai et al., 2022; Lee et al., 2020; Roy et al., 2024; Sarkar et al., 2024, 2025). During the training process, RF generates multiple bootstrap samples from the original dataset. Each decision tree is developed using a randomly selected sample of observations and a random subset of predictor variables at each split. The split increases the diversity among the trees. Approximately one-third of the observations are not included in the training of a particular tree and are therefore considered out-of-bag (OOB) observations. These OOB observations can be used to estimate the out-of-bag error, which provides an unbiased indication of the predictive performance of the RF model (Breiman, 2001).

Random forest can show classification problem. For this, the final prediction is determined through the majority voting of the individual decision trees. Although the regression predictions are generally obtained by averaging the outputs of the trees. The ensemble structure of RF improves the model stability and reduces the classification errors while avoiding the need for a separate pruning procedure. This makes Random Forest particularly suitable for

groundwater potential modelling, where environmental variables may have complex and nonlinear relationships (Madani & Niyazi, 2023). In this research, RF was applied by constructing 200 decision trees with a minimum of 2 samples per leaf node which class weights were balanced and the number of variables being sampled randomly at each split set to the square root of the total features.

2.5.4 Gradient Boosting Machine (GBM)

Gradient Boosting Machine (GBM) is a machine learning technique based on the gradient boosting framework, in which multiple decision trees are combined sequentially to develop a strong predictive model. Unlike bagging-based methods such as Random Forest, GBM creates the trees consecutively, with each new tree attempting to improve the errors produced by the existing ensemble (Zanotti et al., 2019). This sequential learning process allows GBM to capture complex and nonlinear relationships between environmental variables and groundwater potential (Roy et al., 2024). The steps of GBM begins with an initial prediction and subsequently calculating the residual errors between the observed and predicted values (Kumar et al., 2021b). Each subsequent decision tree is then fitted with these residuals, allowing the model to progressively reduce the prediction error. It is used to minimize the selected loss function by determining the direction in which the model should be improved. By giving greater attention to the observations that were poorly predicted by the previous trees, GBM technique can reduce the model biasness and improve predictability (Kumar et al., 2021b). In this study, the GBM model was developed using 200 sequential trees with a shrinkage factor of 0.05, maximum tree depth of 5 and a sub-sample ratio of 0.8 per tree, in order to assess its predictive performance and support model tuning.

2.5.5 Extreme gradient boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) is an advanced gradient boosting machine learning technique that can be applied to both classification and regression problems. It is designed to improve the computational efficiency and predictive accuracy of conventional gradient boosting methods. XGBoost develops a strong predictive model by sequentially combining a series of decision trees. In those decision trees each newly developed tree focuses on reducing the errors generated by the previous ones (Niazkar et al., 2024). This makes XGBoost particularly useful for analyzing complex relationships between multiple environmental factors and groundwater potential (Dey et al., 2023). During the modelling process, the decision trees are constructed sequentially with each subsequent tree learning from the residual errors. The

residuals represent the differences between the observed values and the predictions generated by the model at a particular stage. By continuously adding trees that improve these errors, XGBoost gradually increases the overall predictive performance of the ensemble. A learning-rate parameter controls the contribution of each individual tree which helps to regulate the learning process and reduce the risk of overfitting (Dey et al., 2023).

Mathematically, the prediction for the ith observation can be represented as the sum of the predictions generated by the individual decision trees (Eq. 04):

$$Y_i = \sum_{m=1}^{M} \lambda f_m (X_i) \quad \ldots\ldots\ldots\

outputs obtained from each model. Finally, Kappa coefficient is applied to obtain a statistically rigor calculation of the model capabilities under majority class imbalance of the fresh-saline groundwater samples, as in this research, almost 88.9% of the dataset contains non-fresh groundwater data (Avand et al., 2020; Talukdar et al., 2022).

3 Results

3.1 Training Groundwater Well Samples for ML Model Implementation

Within the given study area, 117 sample points were obtained which were spatially very undistributed. Alongside, for segregating the sample points into training and testing data, there were only 13 fresh groundwater data and 104 non-fresh data. The classification of fresh and non-fresh groundwater was conducted with the help of classification established by (Tasneem et al., 2026), as fresh (< 1000 μS/cm), slightly saline(1000–3000 μS/cm), moderately saline (3000–10,000 μS/cm), and highly saline (>10,000 μS/cm). Such imbalance in the sample points created a critical challenge for ML classifications, as these models are rather drawn towards skewed datasets and majority classes, which would result in poor delineation of fresh groundwater potential zones. To address this challenge, Synthetic Minority Oversampling Technique (SMOTE) was applied to the samples, exclusively to the training set before running the model codes (Bui et al., 2019; Chawla et al., 2002; Mallick et al., 2022). SMOTE creates synthetic sample points for the minority sample class by interpolating between the existing sample points and their k-nearest neighbors, which controlled the spatial diversity of the minority class without misinterpretation of the ground-truth values. In this research, k = 5 nearest neighbors were identified and SMOTE was applied after the division of the sample points into 80/20 train-test classes, to ensure that the testing dataset is kept completely out of SMOTE intervention.

3.2 ML Model Implementation and Validation

The five ML models, RF, SVM, KNN, GBM, XGBoost, were applied using the training and testing dataset to produce the fresh groundwater potential zone maps of the study area (Figure 15a-15e). Each of the models were evaluated with the help of training and testing dataset (Table 02). Evaluations with training dataset highlights how accurately the model explores the unseen spaces based on the training dataset. But the testing dataset exposes the possibility of model's overfitting on the training dataset, reflecting on the collection of more accurate, ground-based, and precise spatial modelling capabilities. The accuracy evaluations highlighted that RF, XGBoost and GBM obtained highest scores on testing accuracy respectively, indicating their

potential on predicting the fresh groundwater potential zones in the study area. SVM and KNN highlighted a comparatively lower scores in terms of accuracy assessment, scoring below 0.85.

The assessment of the five ML models with the help of the validation toolsets highlighted a clear differentiation in classification capabilities under the given conditions of this research, with RF, XGBoost, and GBM emerged as the most suitable algorithms with overall accuracy of 95.83% for RF and XGBoost, 70% for GBM. Alongside, RF and XGBoost obtained a sensitivity score of 1.0, highlighting every fresh groundwater sample in the testing dataset has been accurately identified by these models. The F1 score, Kappa Accuracy, and Specificity scores also highlighted the capability of the ML models in accurately differentiating the fresh and saline groundwater samples in this research. The results are consistent with the validation findings of multiple research conducted in similar sub-regions of the study area (Roy et al., 2024; Sarkar et al., 2025). However, lower accuracy scores of SVM and KNN reflected in the barriers these models faced during establishing the complex spatial relationships of the hydro-chemical, meteorological and topographic parameters with the groundwater samples drawn from the study area.

Table 2. Validation Scores of the ML Models

Model	Accuracy	Sensitivity	F1-Score	Kappa	AUC	Avg Prec
RF	0.9583	1	0.8571	0.8333	0.9921	0.9167
SVM	0.875	0.6667	0.5714	0.5	0.8968	0.5139
GBM	0.875	0.6667	0.5714	0.5	0.9444	0.7
KNN	0.8333	0.3333	0.3333	0.2381	0.8651	0.5778
XGB	0.9583	1	0.8571	0.8333	0.9921	0.9167

3.3 Mapping of the Fresh Groundwater Potential Zones

The fresh groundwater potential zone maps were developed with the help of the ML models to delineate the fresh groundwater zones across the study area. The Table 03 contains the area and the shared percentage of the potential zone classes from the total area, predicted by the ML models.

The fresh groundwater potential zones were divided into 05 classes, Very Low, Low, Moderate, High, and Very High, where very high reflects the highest probability of finding fresh sources of groundwater across the study area. RF model predicted almost 9.25% of the total area within a potential zone of finding fresh groundwater, with majority of the study area (>80%) falling

under low to very low potential of fresh groundwater sources. XGBoost also highlighted similar results in delineating the low and very low fresh groundwater zones but established a different scenario in highlighting the high (3.39%) and very high (8.68%) potential zones for finding fresh groundwater sources. While GBM also reflected on similar results as RF and XGBoost in delineating the high and very high potential zones for fresh groundwater, SVM and KNN predicted the zone classes as proportions different than the rest of the 3 ML models.

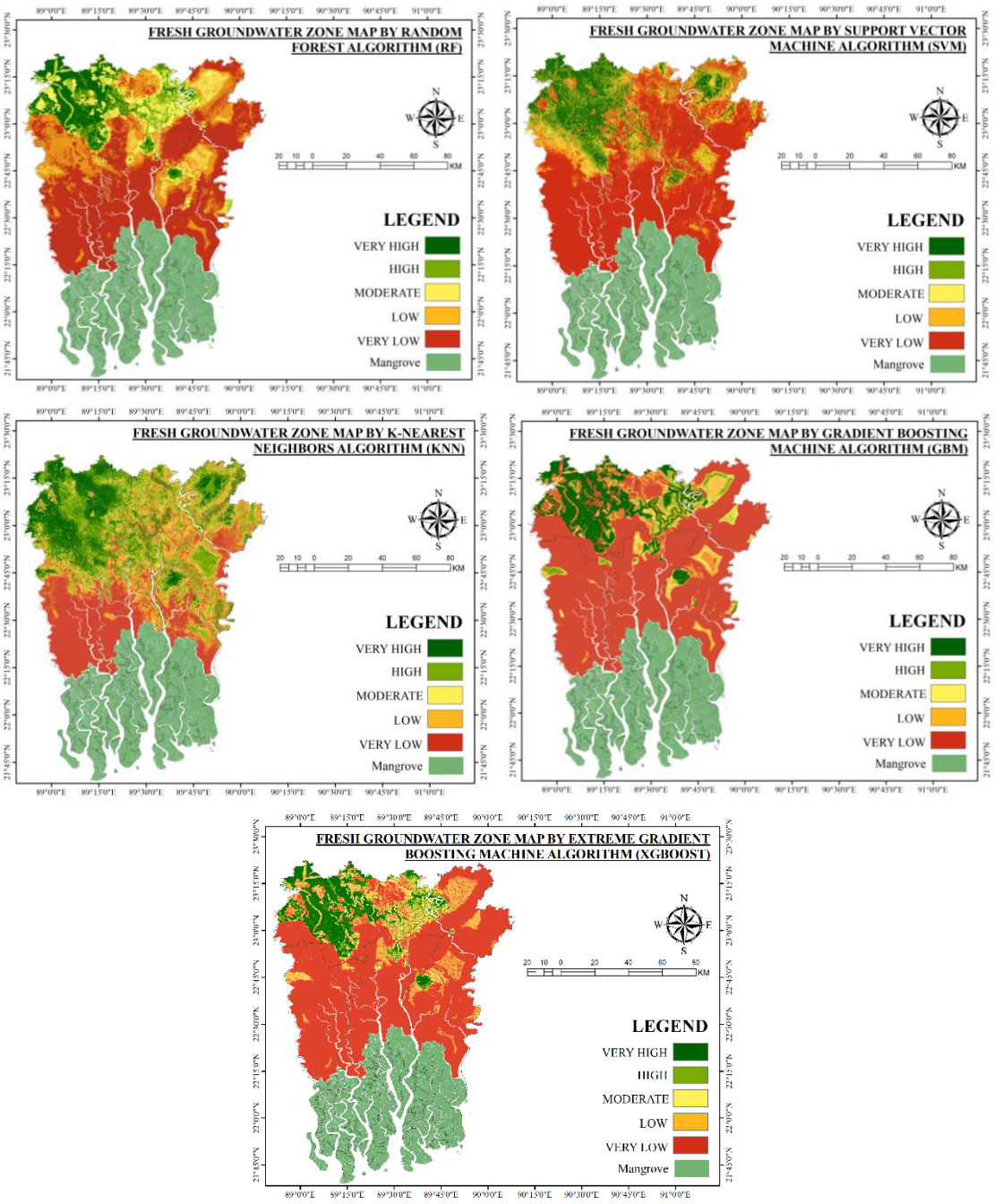


Figure 15 (a, b, c, d). Fresh Groundwater Potential Zone Maps by RF, SVM, KNN, GBM, and XGBoost

Table 3. ML model outputs of the Fresh Groundwater Potential Zone Classes

	RF		XGBoost		GBM		SVM		KNN	
	Area, Km^2	% Area	Area, Km^2	% Area	Area, Km^2	% Area	Area, Km^2	% Area	Area, Km^2	% Area
Very Low	7244	65.43	8507.92	76.85	8383.02	75.72	7609.04	68.73	4181.83	37.77
Low	2313	20.89	880.17	7.95	762.08	6.88	1261.1	11.39	2385.19	21.54
Moderate	1024	4.14	347.54	3.14	347.19	3.14	628.34	5.68	1662.05	15.01
High	458.5	0.29	375.22	3.39	218.71	1.98	583.96	5.27	1085.02	9.8
Very High	32.15	9.25	960.64	8.68	1360.48	12.29	989.05	8.93	1757.4	15.87
Grand Total	11071	100.00	11071.49	100.00	11071.48	100.00	11071.49	100.00	11071.49	100.00

Among all the maps generated by the ML models, Jessore was highlighted as an area with very high potential of fresh groundwater. This result also aligns with a similar research conducted by Roy et al. (2024) at Jessore area on groundwater potential zone mapping. However, the Satkhira district, along with the Khulna district have been delineated as areas with very low potential of accessing fresh groundwater, complementing multiple research articles on the hydro-geo-chemical assessment conducted on these regions (Shaibur et al., 2021; Tasneem et al., 2026).

The overall summary of the potential zone classes reflect that comparatively lower percentage of the study area has a potential of identifying fresh groundwater zones, indicating much higher risks for the northern districts of the study area where groundwater salinity has not been established as a direct threat to the communities (Dasgupta et al., 2015; Tasneem et al., 2026).

4 Discussion

ML based modelling has been globally accelerated to address environmental vulnerabilities due to their enhanced potential in working with geospatial data. Alongside, the spatiotemporal datasets are also analyzed accurately with the help of deep learning based models which have gained significant prospects in predicting the dynamic environmental problems, owing to the increased climate change impacts across the world (Panahi et al., 2020). The gaps in micro-spatial data collection of the hydro-geo-chemical and geophysical data have established more emphasis on the ML modelling to fill in the spatial data voids and work on such complex spatial relationships of the multi-parametric issues (Adham et al., 2010; Roy et al., 2024). Multiple ML models have been applied to delineate groundwater potential zone mapping in almost all

the research articles reviewed during the process of this research. Therefore, this research has also applied five ML models containing unique and differentiated analytical framework.

The primary parameters comprise of almost all the major influencing factors of groundwater quality as this research focuses on achieving its novelty on adding the fresh/non-fresh groundwater potential zoning instead of only delineating areas with the availability of groundwater across the study area. Therefore, the hydro-chemical parameters have been used in the primary parameters define the spatial heterogeneity of groundwater quality and the rest of the parameters define the availability, permeability, and chance of saline water infiltration into the aquifers based on topographic, meteorological and land use characteristics (Roy et al., 2024; Sarkar et al., 2025; Tasneem et al., 2026). Alongside, the exclusion of rainfall parameters from the research also identifies in the gap in collecting micro-spatiotemporal rainfall data in the study area. Despite of the importance of rainfall in identifying the potential areas for groundwater recharge, the 0.5° spatial resolution of the CRU TS rainfall data created minimal influence on delineating the fresh groundwater potential zones. The applied ML models explained the spatial distribution of potential zones of fresh groundwater using the ground-truth dataset and the spatial layers of the final parameters obtained from the multicollinearity tests. The VIF thresholds have been carefully selected based on similar research conducted on regions with similar characteristics of topography, hydrology and meteorology (Roy et al., 2024; Tasneem et al., 2026). The results from RF, XGBoost, and GBM highlighted their significant capabilities in delineating fresh groundwater potential zones whereas, SVM and KNN highlighted comparatively lower capabilities in explaining the parameters along with the collected groundwater datasets. The reason behind such inefficiency of these models lies in the limitations of this research; lack of unified spatial distribution of the sample points of groundwater wells and the lower share of fresh groundwater samples among the 117 well points. These hydro-chemical data collections are extremely expensive, in consideration to the economic condition of Bangladesh and the incompetencies in establishing the well points uniformly throughout the country have been consistently affecting the decision-makers of the country to take prompt actions in conserving groundwater quality (Tasneem et al., 2026).

Increasing climate change will subsequently affect the study area with sea level rise, tropical cyclones and salinity intrusion (Brammer, 2014; Dasgupta et al., 2015). Additionally, the increasing rate of LULC change by the communities, especially from agriculture to aquaculture has also significantly deteriorated groundwater quality over the years (Anisuzzaman et al., 2016). ML models have the potential to establish the relationship among these natural and

anthropogenic issues but the lack of collecting accurate and spatially uniform data have created barriers for the researchers to incorporate such critical parameters into such research. However, this research addressed a number of unexplored areas of interventions to advance such research endeavors in Bangladesh towards more comprehensive analysis of groundwater quality along with their availability. This research can certainly reflect on the areas extensively indicated by the National Adaptation Plan of Bangladesh as climate stressed areas, indicating the requirement of necessary actions for groundwater quality assurance (MoEFCC, 2022). Additionally, urgent actions are required to restrict human interventions that influence salinity intrusion in the study area. Since the LULC analysis highlighted a major portion of the study area as agricultural, efficient groundwater governance on irrigation and extraction should be established to conserve groundwater despite of the future climate change uncertainties. Similar research and efficient data collection approaches can certainly bring a holistic and evidence-based approach in conserving groundwater quality, preserving the livability and livelihoods of the coastal communities of Bangladesh.

5 Conclusion

This research has successfully established a holistic methodological approach to combine remote sensing and machine learning algorithms in order to delineate the fresh or non-saline groundwater potential zones in the southwestern coastal areas of Bangladesh. The study area was selected based on the rigorous literature review of similar articles that indicated the groundwater salinity intrusion pathway inbound the northern regions along The Sundarbans area. The finally selected parameters with the help of VIF indicated the increasing emphasis on the hydro-chemical database in delineating the potential zones of fresh groundwater. The final maps of fresh groundwater potential zones obtained with the ML models highlighted a mere 8-9% of very high potential zones for fresh groundwater, predominantly in the Jessore, Narail and Gopalganj districts, which reflects on the severe impacts imposed on the communities in accessing freshwater for their survival and livelihood. Among the applied ML models, RF and XGBoost achieved the highest overall accuracy of 95.83% and a sensitivity of 1, highlighting the complete identification of fresh groundwater samples without any false negatives. However, the severe imbalance of fresh and saline groundwater samples from the collected dataset and the dispersed spatial distribution of the sample points created barriers for ML models like SVM and KNN, which functions in a radial basis function and Euclidean distance function. The addition of salinity/non-salinity in the groundwater potential zone mapping domain and the exclusion of The Sundarbans from the analysis of the critical spatial

relationships advances the methodological framework from the existing studies in similar domains. Future research in these areas must emphasis on the collection, management and maintenance of spatially distributed database of groundwater well points and their hydro-geo-chemical heterogeneity in order to improve the quality of research that combines such diverse and complex spatial modelling. Alongside, the collection of temporal databases can further encourage researchers to combine similar methodology with the deep learning algorithms, improving predictions of fresh groundwater reserves in such complex coastal setting.

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