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An Exploration and Prediction of Rainfall and Groundwater Level for the District of Banaskantha, Gujrat, India

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Abstract: The groundwater level is declining all over the world, especially in India. Some states, such as Rajasthan and Gujarat, are experiencing very low levels of groundwater. In this study, we explored the rainfall pattern and groundwater level of the Banaskantha district of Gujarat and predicted a rise in the groundwater level using SARIMA, multi-variable regression, ridge regression, and KNN regression. The results indicated that the water table is declining for Banaskantha, but due to an increase in irrigated land and good rainfall in previous years, the decline in groundwater level is not alarming according to earlier studies. Ridge regression was found to be the most suitable method, given the constraint of low data availability, especially in this particular study where the remote area of Banaskantha, Gujarat was considered.

Keywords: Machine learning, SARIMA, Regression, Groundwater, Rainfall.

1. Introduction

Groundwater is water absorbed into the soil from rain or melting snow and ice. It is kept in the minuscule crevices (pores) between rocks and soil particles. The world's water resources include groundwater in their entirety. It is the main resource used for drinking, residential, agricultural, and industrial purposes in many different parts of the world. The groundwater level all over the world is rapidly declining [1] [2] which is a critical concern. In India, the number of tube wells are increasing day by day to extract groundwater. India uses groundwater highest in the world. India's 60% irrigation needs are met by groundwater. The groundwater levels in India are declining rapidly [3] [4] [5] due to overuse of groundwater resources and less water recharge.

The study [6] suggests that food crops could be reduced by up to 20% nationwide due to groundwater depletion in India, and by up to 68% in areas where groundwater supply is expected to be low by 2025.

In 2012, UNESCO [7] estimated 251 km3/yr of groundwater use by India. By the year 2050, India's water requirement for irrigation will increase by up to 56%, According to the Ministry of Water Resources [8].

Gujarat is a state on India's western coast with a total area of 196,024 square kilometres and a population of 60.4 million, Gujarat is the ninth-most populated state in India. Gujarat state is observing rapid decline in water level of approximately 20 meter per decade in Uttar Gujarat and Madhya Gujarat [9]. In some districts of Uttar Gujarat groundwater level in 1960 was at 1-2 mbgl (Meter Below Ground Level) in almost all places except (Charasan 46 mbgl and few other places). The recent reports of CGWB [11] suggest groundwater has now reached down to a depth of 54 to 160 meters in Banaskantha, 81 to 168 meters in Mehsana and 83 to 146 meters in Patan. Banaskantha [12] is situated in north part of Gujarat 24.3455°N, 71.7622°E. Palanpur is headquarter of district Banaskantha and it consists of 12 Talukas (District subdivision) Palanpur, Danta, Vadgam, Amirgadh, Dantiwada, Deesa, Dhanera, Kankrej, Diyodar, Bhabhar, Vav and Tharad. Total population of Banaskantha as per 2011 census, is 3,120,506. The Banaskantha case study [13], which highlights the value of ground water for village economies, calls for district-wide water management. The figure1 depicts current water level in India, Gujarat and Banaskantha. The Machine learning approaches widely used to predict ground water level and quality of ground water. The study [15] assesses suitability of Machine Learning Approaches to forecast ground water level prediction and demonstrates that the proposed Extreme Learning machine (ELM) model has better forecasting ability compared to the SVM model for monthly groundwater level forecasting. the comparative study of the models a monthly data collection including both meteorological and hydrological characteristics (temperature, evapotranspiration, rainfall, and groundwater level) for the sixth-year period from 2014 to 2020.

The various time series models like Auto Regressive Moving Average (ARMA) [17], [18] autoregressive integrated moving average (ARIMA), and Seasonal ARIMA (SARIMA) [19], [20], [21] to make future predictions, patterns between the recharge and extract of groundwater data. Fallah- Mehdipour et al. [22] concluded Adaptive Neuro-fuzzy Inference System (ANFIS) performs better than Genetic programming in predicting ground water of Iran. In [16] wavelet transforms (WA) and artificial neural networks (ANNs) models were found to provide more accurate for urban water demand forecasts than the Multivariate Linear Regression (MLR) [23],[24],[25],[26], Multivariate Non-Linear Regression (MNLR) and Auto Regressive Integrated Moving Average (ARIMA) models. The study [27] examined the efficacy of the Wavelet preprocessed Support Vector Machine (WSVM) model for monthly groundwater depth prediction in Mengcheng County from 1974 to 2010. The WSVM model is combination of the Support Vector Machine and DWT (Discrete Wavelet Transform) for prediction of groundwater level. In comparison to the ANN, SVM, and WSVM models, the WSVM model offered the most accurate and reliable groundwater depth prediction with least RMSE (Root Mean Square Error). Time series models and MLP are regarded as linear fitting models [28]. Time series models have the benefit of taking data point correlations into consideration [29]. However, in general, linear fitting is not the best method for describing groundwater's nonlinear behaviour. As a result, MLR models have been used more frequently in recent studies for comparison analysis [30]. The study [31] presents ML based downscaling algorithm uses Gravity Recovery and Climate Experiment (GRACE) data by utilizing the relationship between Terrestrial Water Storage Anomaly (TWSA) from GRACE and other information like vegetation coverage, land surface temperature, precipitation, streamflow, and in-situ groundwater level data. A variety of deep learning methods have also been used to predict rainfall and groundwater level, including SVR and LSTM [32],[33]. SVM [24], [34],[35],[36] has performed better than the Artificial Neural Network based approaches [37],[38]. Deep learning models are frequently viewed as "black boxes" which means that it is very difficult to unpack and understand the automated feature selection process that eventually takes place and the predictions that arise from any given deep-learning-based model [39]. They are highly dependent on a large quantity of high-quality data to produce an effective model; they are very expensive to train and use, in terms of time and resources [40].

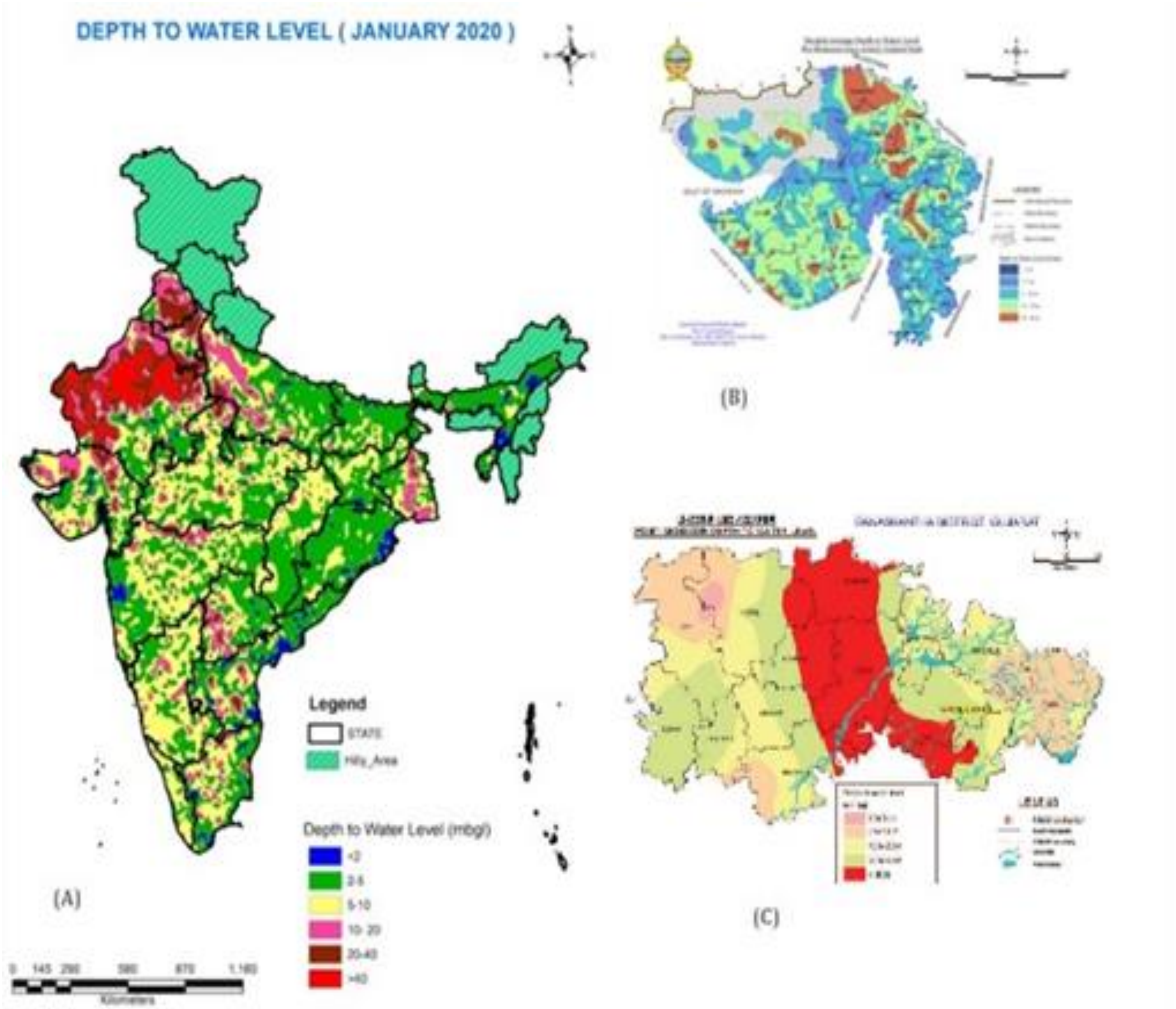

Figure 1:(A) Groundwater level India January 2020, (B) Decadal annual water level, Gujarat state May 2010-2020, (C) Banaskantha Depth to Water level Adapted from [14].

2. Materials and Methods

2.1. Study Area

Gujarat is an Indian state located on western coast. With a population of 60.4 million [41], Gujarat ranks tenth in terms of population in India. Gujarat, which covers 196,024 square kilometres, is the fifth-largest state by land area (75,685 square miles). Its neighbours include the Arabian Sea and Pakistan to the west, Rajasthan to the northeast, Dadra and Nagar Haveli and Daman and Diu to the south, Maharashtra to the southeast, Madhya Pradesh to the east, and Rajasthan to the southeast and east, respectively. Gujarat faced droughts many times in history. The Central Ground Water Board employed 1064 groundwater monitoring wells, including 290 piezometers [10]. Groundwater levels are checked quarterly, and in May, representative water samples are taken to check the quality. In the pre-monsoon of 2020, 62% of the wells have depths to water levels between 5 and 20 mbgl (metre below ground level). Some districts of Gujarat with greater water levels were Amreli, Banaskantha, Gandhinagar, Mahesana, Patan, and Sabarkantha. Currently, the Banaskantha and Patan districts are struggling with a significant groundwater problem.

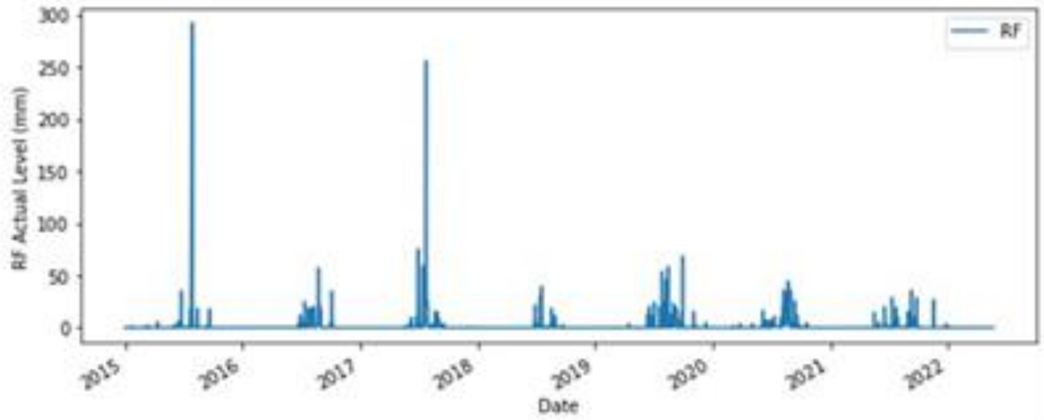

Figure 2: Rainfall Time Series (Banaskantha District)

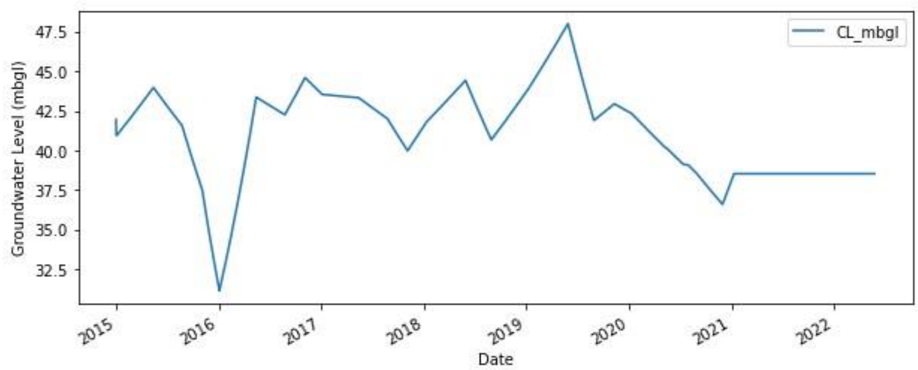

Figure 3: Groundwater level Time Series (Banaskantha District)

Banaskantha District includes the area around the Bank of Banas River. The district is situated between 23.33 to 24.45 north latitude and72.15 to 73.87 east longitude [42]. Banaskantha District lies on the north-east side of Gujarat State. The daily fall in underground water levels necessitates careful investigation of the aquifers in the region. The groundwater level of the unconfined aquifer has been reported to be below 160 metres at the majority of places. The groundwater table is losing 2 to 4 metres per year. The Figure 2 represents rainfall in Banaskantha district from 2015 to 2022 according to [43]. The Figure 3 depicts Ground water level of Banaskantha for the same duration. The overall flow for proposed architecture presented in the Figure 4.

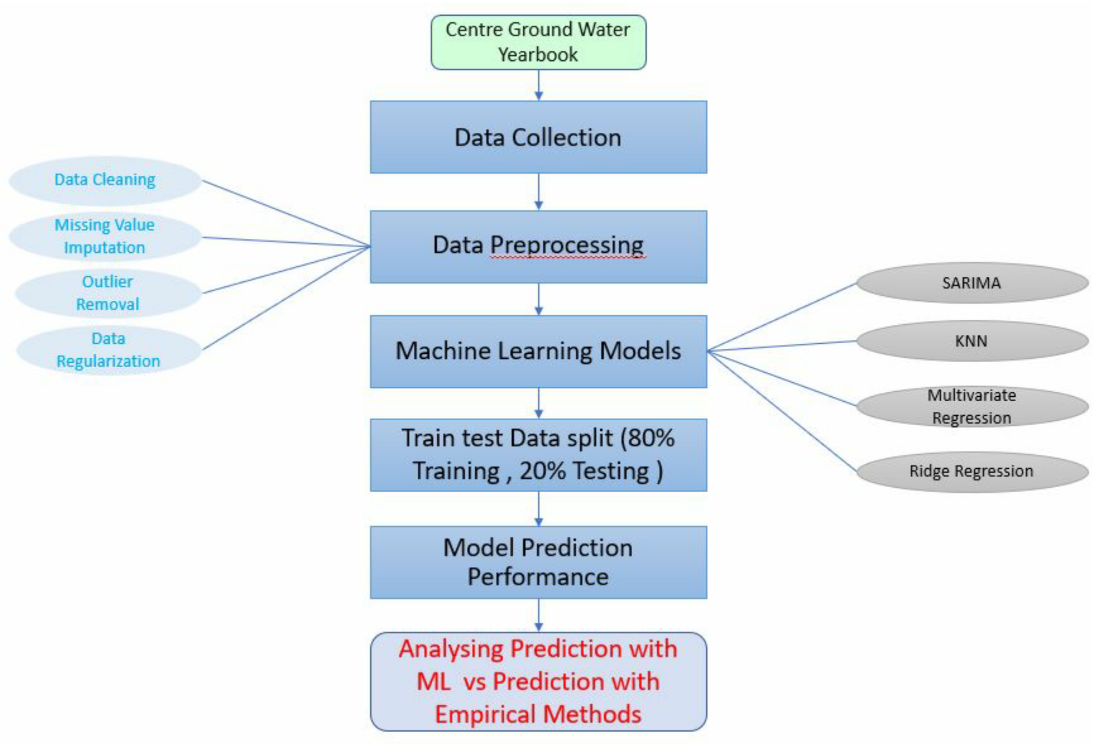

Figure 4: Proposed architecture for prediction of groundwater level

2.2 Machine Learning Techniques

2.2.1. SARIMA

The ARIMA (Auto Regressive Integrated Moving Average) [44], [45] refers to a class of models that uses a time series' previous values specifically, its own lags and lagged prediction errors to explain the time series to predict future values. The ARIMA equation has two components AR (Auto Regression) and MA (Moving Average). The predicted value is estimated based on linear combination lags of Y and Lagged forecast errors.

$$Yt = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + ... + \beta_p Y_{t-p} + \phi_1 \epsilon_{t-1} \phi_2 \epsilon_{t-2} + ... + \phi_q \epsilon_{t-q} \quad (1)$$

Where Yt is observed value of Y at time t, α, β are coefficients and ϵ is error, p is the order (number of time lags) of the AR model, d is the degree of differencing and q is the order of the MA model. The SARIMA (Seasonal ARIMA) [46] is useful in situations where a time series shows a seasonal variation.

The model of SARIMA can be represented by the notations (p, d, q) (P, D, Q)s of a autoregressive notation (P), seasonal moving average notation (Q) and order of difference (D) of seasonal part of the ARIMA model seasonal. The length of the seasonal period is indicated by the subscripted letter "s". The SARIMA can be represented as

$$\phi_p (B)\Phi_P (B^S)(1 - B)d\, (1 - B^S)^D Z_t = \theta_q (B)\Theta_Q (B^S) a_t \quad (2)$$

The ordinary autoregressive regressive component ϕ_p (B)

$$\phi_p (B) = 1 - \phi_1 B - \phi_2 B^2 - ....\phi_p B^p \quad (3)$$

The ordinary moving average component θq (B)

$$\theta q\,(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots\ldots.\theta q B^q \qquad (4)$$

The seasonal autoregressive components Φ_P (B^S)

$$\Phi_P\,(B) = 1 - \Phi_1 B - \Phi_2 B^S - \ldots\ldots.\phi_P B^{PS} \qquad (5)$$

The seasonal moving average components Θ_Q (B^S)

$$\Theta_Q\,(B) = 1 - \Theta_1 B - \Theta_2 B^{2S} - \ldots\ldots.\Theta_Q B^{QS} \qquad (6)$$

Where B is the backshift operator, d and D is the non-seasonal and seasonal order of differences. The ordinary autoregressive and moving average components are represented by polynomials ϕ_p(B) and θ_q(B) of orders p and q. The seasonal autoregressive and moving average components are Φ_P(B^S) and Θ_Q (B^S), where P and Q are their orders.

2.2.2. Multivariable Regression

Multivariable regression model [47] can be utilized to determine the relationship between a dependent variable and many independent variables.

It can be also used

(i) to determine patient characteristics associated with an outcome
(ii) ascertain the impact of a procedural technique on a specific result.
(iii) in order to compare various treatment modalities, correct for group differences
(iv) measure the size of an influence by using specifics.
(v) construct a propensity score
(vi) create models for predicting risk.

A statistical method known as multivariable regression, commonly referred to as multiple linear regression (MLR), makes use of a number of explanatory factors to forecast the results of a response variable. Modelling the linear connection between the explanatory (independent) factors and response (dependent) variables is the objective of multiple linear regression. Because multiple regression takes into account several explanatory variables, it may be thought of as an extension of ordinary least-squares (OLS) regression [48]. A simple multivariable model can be represented as

$$Y = c + a_1 x_1 + a_2 x_2 + a_3 x_3 \ldots\ldots\ldots a_n x_n \qquad (7)$$

Where Y is target feature, c is intercept of plane, ai is the weight or coefficient of feature i and x_i is the value of feature i. For optimization of coefficient, gradient descent algorithm and ridge regression algorithm is used.

2.2.3. Ridge Regression

In situations where the independent variables are highly correlated, ridge regression [1] is a technique used for estimating the coefficients of multiple-regression models. It has been applied to various disciplines, including engineering, chemistry, and econometrics. Ridge regression is a model tuning technique used to analyze any data that exhibits multicollinearity. This technique carries out L2 regularization. When the problem of multicollinearity arises, predicted values differ greatly from actual values, and the least-squares are unbiased while variances are large. The cost function of ridge regression is as follows:

$$cost(w) = \sum_{i=1}^{N}\{y_i - \sum_{j=0}^{M}\beta_j x_{ij}\}^2 + \lambda\sum_{j=0}^{M} w_j^2 \quad (8)$$

λ is a value given by user input (or by a grid search, or whatever),β is a vector of weights.

2.3. Evaluation Parameters

The SARIMA, multi variable regression, ridge regression and KNN regression models have been applied on dataset of groundwater level of Banaskantha from January 2015 to May 2021. The various evaluation performance, including MAE, MSE and MSLE (Mean Square Log Error) are used to evaluate the performance of each model. A lower error value indicates a better fitting.

2.3.1 MAE (Mean Absolute Error)

It is arithmetic average of absolute error. An error is difference between actual value x_i and predicted value y_i.

$$MAE = \frac{\sum_{i=1}^{n}(|y_i - x_i|)}{n}$$

2.3.2 RMSE (Root Mean Square Error)

The square root of Mean Squared Error is called Root Mean Squared Error. It calculates the residuals' standard deviation.

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}(|y_i - x_i|)^2}{n}}$$

3. Results

The SARIMA is applied on Banaskantha ground water level time series for identifying trends and seasonality. The Figure5 shows that annual seasonality exists in Banaskantha Ground water level.

The trend of average ground water level is declining with small extent. The Figure 6 depicts autocorrelation and Figure 7 represents partial correlation.

3.1. Groundwater level prediction with SARIMA

The primary characteristics of the time-series of groundwater fluctuations over a specific period are much better explained by the ACF and PACF approaches. The ACF and PACF plots helps in identifying Auto regressive and Moving Average order (0, 1, 1). The ADF test verifies p-value is .068 which confirms that the series is stationary series.

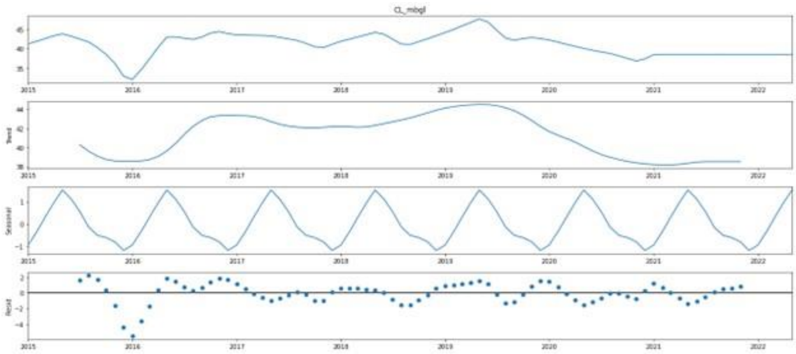

Figure 5: Trends and Seasonality in Banaskantha District Groundwater Level

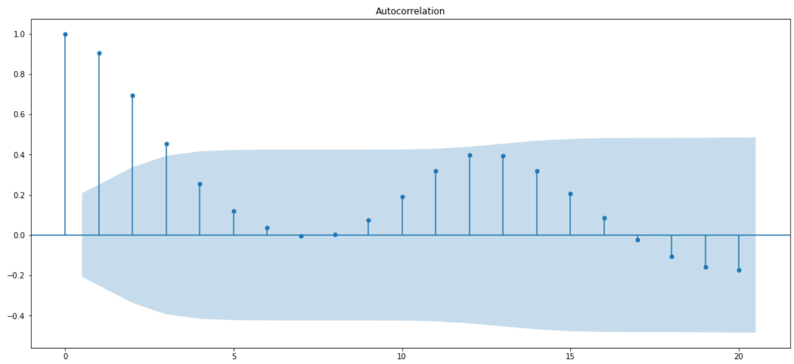

Figure 6: Autocorrelation for Banaskantha District Groundwater Level

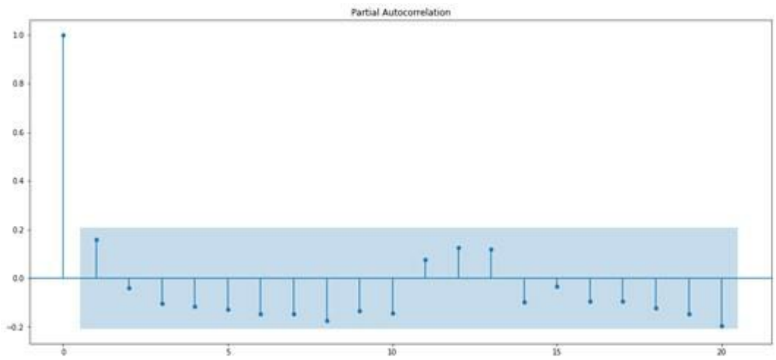

Figure 7: Partial Correlation for Banaskantha District Groundwater Level

One can observe from diagnostic plot given in Figure 8, the residuals are uncorrelated and have zero mean. The model offers a good fit to the data. The residuals are random.

The majority of the frequency counts are grouped in the center of the traditional bell-shaped, symmetric histogram. The actual and predicted values are compared in Figure 9. The ARIMA(0, 1, 1)x(0, 1, 3, 12)12 gives least AIC =434.03032282.

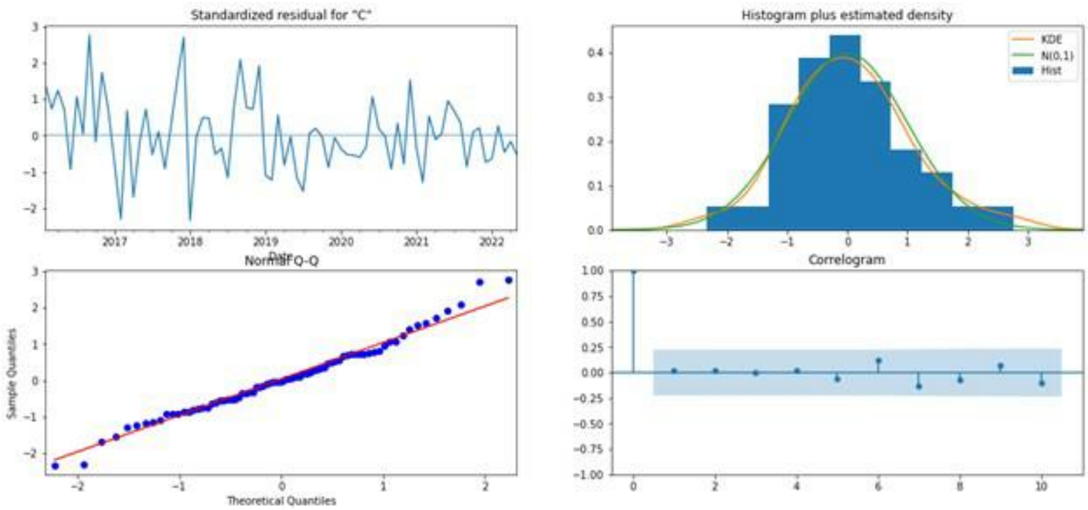

Figure 8: Diagnostic Plot for Banaskantha District Groundwater Level

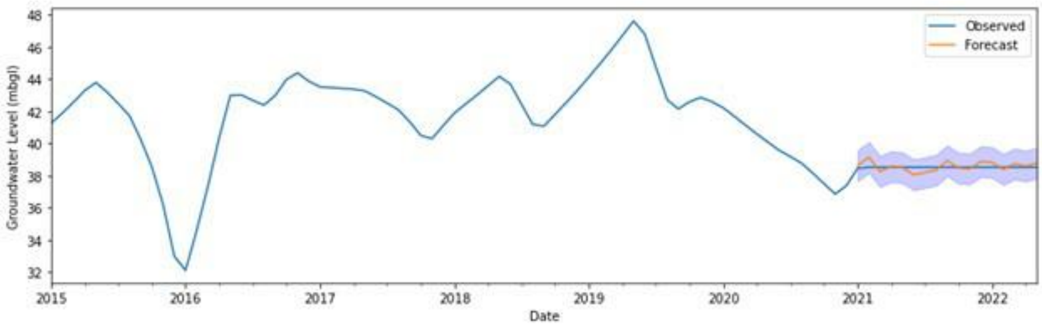

Figure 9: Actual vs Predicted values for Banaskantha District Groundwater Level using SARIMA

3.2. Groundwater level prediction with Multivariable Regression

The model is developed from dataset of ground water level of Banaskantha from Jan 2015 to May 2021. The data set contain average rainfall, current level of ground water and last year level of ground water and last ten-year level of ground water. The current level of ground water is used as target feature. For statistical similarity L2 normalization is applied on all feature. The data set id divided into training data set and test data set. The training data set used for identification of coefficient of feature and test data set is used for prediction of current water level. From the result we found that there is a strong relationship between water level and current rain fall value and previous year rain fall value. The MLR approach was used to derive the best model. R2 values were examined after developing a residual analysis.

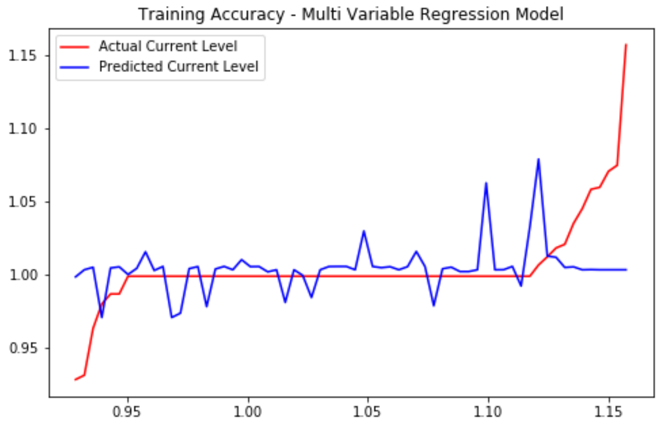

Figure 10: Training Accuracy Groundwater level prediction with Multivariable Regression

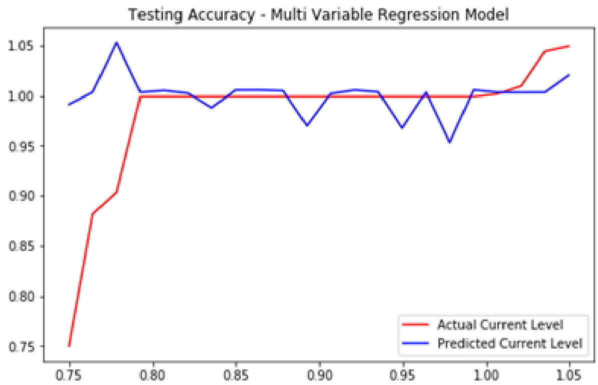

Figure 11: Testing Accuracy Groundwater level prediction with Multivariable Regression

3.3. Groundwater level prediction with Ridge Regression

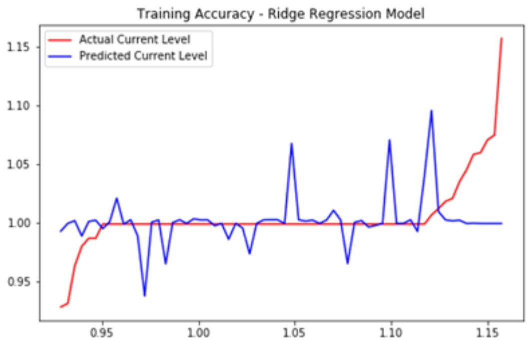

Figure 12: Training Accuracy Groundwater level prediction with Ridge Regression

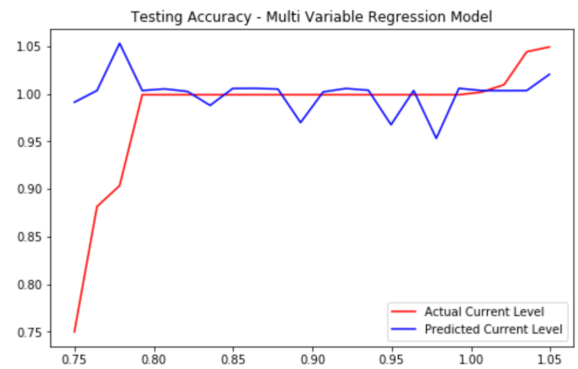

Figure 13: Testing Accuracy Groundwater level prediction with Ridge Regression

For comparative study of models, mean absolute error, mean squared error and mean squared log error is computed (Table 1) for multivariable regression, ridge regression and KNN regression.

Table 1: Regression Methods Results for groundwater prediction.

	Training Data Set			Testing Data Set		
Parameters	multi variable regression	ridge regression	KNN regression	multi variable regression	ridge regression	KNN regression
mean_absolute_error	0.016174	0.015348	0.015623	0.014869	0.012044	0.022834
mean_squared_error	0.00131	0.001563	0.001495	0.000946	0.000674	0.002161

3.4. Analysis of prediction with Empirical and ML Models

Some rainwater will evaporate, transpire, and discharge from the watershed, it might not fully infiltrate or contribute to the groundwater. Utilizing several empirical correlations between recharge and rainfall that were generated for various places with similar climatic conditions (rainfall and temperature data), the evaluation of rainfall recharge was carried out by various researchers (Figure14). The Dhanera Village of Banaskantha District is analyzed with empirical methods of groundwater prediction. The site DhaneraPz-I (Latitude:24.23055556, Longitude:71.91222222) of CGWB is having well depth of 193 meter.

The records of rainfall and groundwater level are available for last nine year (since 2021). The empirical methods use annual precipitation for calculation of water recharge Table 2.

No.	Formula Name	Equation (s)	Definition of parameter and coefficient value range
1	Chaturvedi Formula (in inch) (Chaturvedi, 1973)	$R = 2.0(P - 15)^{0.4}$	P = Yearly rainfall (inch)
2	Modified Chaturvedi Formula (in inch) (Kumar and Seethapathi, 2002)	$R = 1.35(P - 14)^{0.5}$	P = Yearly rainfall (inch)
3	Relationship of Krishna Rao (mm) (Krishna Rao, 1970)	$R = 0.30 (P - 500)$	P = Yearly rainfall (mm)
4	The Maxey-Eakin (1949) method (in mm)	$R = P^*a$	P = Yearly rainfall, a = 20 %
5	Bredenkamp et al. (1995) formula (in mm)	$R = 0.32 (MAP - 360)$	MAP = Mean Annual rainfall (mm)

Figure 14: Recharge computation from recorded waterfall

Table 2: Empirical Methods Results for groundwater prediction

Year	Annual Precipitation	Rise	Chaturvedi Formula	Modified Chaturvedi Formula	Fall	Max Discharge	Deficit
			2 (P-15)^.4	1.35(P – 14) ^0.5			
2015	862.36	6.3125	6.44368288	6.030000316	2.33	8.6425	2.19881712
2016	467	6.125	3.19002646	2.827207505	7	13.125	9.93497354
2017	1141.99	13.9	7.74783095	7.511648729	7.32	21.22	13.4721691
2018	230.87	3.3	4.09427183	5.888023973	11.98	15.28	11.1857282
2019	736.97	9.4	5.70489722	5.231055579	6.21	15.61	9.90510278
2020	712.05	8.2	5.53994782	5.057260819	6.83	15.03	9.49005218

Table 3: Comparison Result for different methods of groundwater prediction

Parameters	SARIMA	Multivariable Regression	Ridge Regression	KNN Regression
MAE	0.08	0.0148	0.012	0.0228
RMSE	0.29	0.03	0.025	0.046

The performance of the SARIMA, Multivariable, Ridge and KNN regression models is compared in Figure15 for forecasting rise in groundwater levels of different sites at Banaskanth district. All performance evaluation measures including RMSE, and MAE are showing Ridge regression is performing better. The groundwater level measured at this remote site is quarterly. In this particular situation sophisticated methods are not appropriate for forecasting. The SARIMA found to provides optimistic long-term forecasting as annual seasonality exists in data.

The empirical methods like Chaturvedi Formula for calculating rise in groundwater level are found to be pessimistic in this particular study. The Ridge regression found to be most appropriate in prediction of rise in groundwater level.

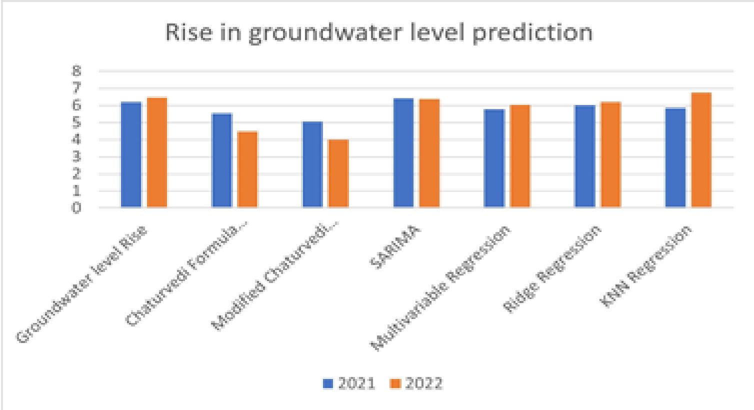

Figure 15: Rise in Groundwater level (in meter) by various methods

4. Conclusion and Future Work

Groundwater is a very important resource that fulfills the demands of drinking water, agriculture, and industries. In India, a rapid decline in groundwater is observed in many districts of Gujarat and Rajasthan states. The district of Banaskantha faces severe groundwater depletion. Groundwater modeling and prediction are very challenging in remote places of India where data availability is not sufficient. This study investigated the performance of various Machine Learning techniques in the case of data constraints. Ridge regression outperformed SARIMA, Multivariable regression, and KNN regression in terms of better MAE and RMSE. In subsequent research, we will use these techniques on different regions and climatic variables, such as humidity, air pressure, temperature, and rainfall. We are also trying to acquire more data with increased frequency (daily data) from Banaskantha. Deep learning methods could be applied when one has a large dataset. A dataset with all meteorological factors with hourly or daily frequencies can lead to better prediction. The more accurate prediction of groundwater levels gives the government more insight into groundwater management

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Data Availability Statement: The data used in this research is available publicly at:http://cgwb.gov.in/GW-data-access.html,https://indiawris.gov.in/wris/#/.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations: The following abbreviations are used in this manuscript:

ARMA SARIMA	AutoRegressive Moving Average
MNLR MLR	Seasonal AutoRegressive Integrated Moving
WA	Average
	Multivariate Non Linear
	Regression Multivariate Linear
	Regression Wavelet Transforms
ANFIS	Adaptive Neuro-fuzzy Inference System
TWSA GRACE	Terrestrial Water Storage Anomaly
ELM SVM	Gravity Recovery and Climate Experiment
WSVM LSTM	Extreme Learning Machine
MAE RMSE	Support Vector Machine
	Wavelet preprocessed Support Vector Machine
	Long Short Term Memory
	Mean Absolute Error
	Root Mean Sqaure Error

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