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Analysis of Groundwater Level Fluctuations using AI & ML - A Case Study on Arkavathi Watershed, Karnataka, India

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Abstract: The goal of this study is to forecast and assess groundwater levels in the Arkavathi Watershed by using cutting-edge Artificial Intelligent and Machine Learning approaches. Groundwater level and recharge is influenced by many factors like land use, soil properties, and climate, and recharge is essential for the sustainable management of water resources. To predict groundwater levels, statistical methods like Mann-Kendall (M-K) test and Sen's Slope Estimator and supervised learning systems like Random Forest, Gradient Boosting Machines, and Neural Networks use meteorological inputs and historical data. In the present work, the dataset acquired for the duration 2014 to 2023 from the Central Ground Water Board, Bangalore (CGWB) offers important information on interannual and seasonal trends in Arkavathi watershed. Out of 37 wells 76% of wells exhibited dropping trends, while 24% indicated growing trends. The significant declines in groundwater levels are seen in the northern and southwestern areas, with losses reaching up to 15 meters during the monsoon seasons probably because of inadequate infiltration, surface runoff, and over-extraction. With mean water levels varying between 10 and 15 meters below ground level, the center basin exhibits only slight changes, suggesting a more balanced recharge-extraction relationship. In the northwest and southeast, alluvial deposits and water-saving infrastructure enable the regular maintenance of stable groundwater levels below 12 meters. Further, the use of AI & ML techniques indicates that variations in rainfall patterns affects the groundwater levels. Also the use of ML algorithms helps to identify the most effective locations for artificial recharge structures, suggesting groundwater management decision-making can be made easier when artificial intelligence and machine learning are used to improve the accuracy of groundwater levels and recharge estimations.

Keywords: *Arkavathi Watershed, Groundwater, Machine Learning, Mann-Kendall Method, Random Forest*

1. Introduction

The hydrological cycle depends on groundwater recharge, which is crucial for preserving the sustainability of water supplies, especially in areas with little surface water. Rainfall interacts with elements like hydraulic conductivity and suction pressure to affect soil moisture and groundwater recharge [2]. Groundwater recharge is influenced by land use, soil properties and climate, and is essential for the sustainable management of water resources [3,4].

In hydrology and hydrogeology, estimating groundwater recharge from precipitation is essential. The pace at which groundwater recharges is critical to the sustainable extraction of water from an aquifer. Thus, for the best possible management of groundwater resources, it is essential to quantitatively assess the temporal and geographical distribution of groundwater recharge [5]. Many variables, including terrain, land use, plant cover, soil moisture levels, and the permeability of the recharge beds and aquifer materials, might affect this recharge rate [5].

To estimate recharge rates, the research uses a variety of techniques, such as soil moisture budgets, empirical infiltration coefficients, and the water table fluctuation (WTF) methodology [6]. This method was first used for groundwater recharge estimation and has been used in numerous studies for the same purpose [7,8] or groundwater storage changes estimation [9].

To anticipate groundwater levels, supervised learning systems like Random Forest, Gradient Boosting Machines, and Neural Networks use meteorological inputs and historical data. While time series analysis techniques like ARIMA, LSTM, and Prophet capture trends and seasonality, unsupervised learning approaches like DBSCAN and K-means clustering find patterns and anomalies. Inverse Distance Weightage (IDW) and statistical methods are used in geospatial trend analysis to show data [10]. Variations in groundwater levels are measured using the Mann-Kendall (M-K) test and Sen's Slope Estimator. The dataset from 2014 to 2023 from the Central Ground Water Board (CGWB) offers important information on interannual and seasonal trends. Groundwater management decision-making is made easier when artificial intelligence and machine learning are used to improve the accuracy of groundwater recharge estimations. This project tackles the issue of groundwater depletion in the face of rising water demands brought on by industry, urbanization, and agricultural growth. The emphasis is given to guarantee a sustainable water supply and alleviate problems such as soil salinity and waterlogging by

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highlighting the need of integrated surface and groundwater resource management [11,12]. The goal of this project is to forecast and assess groundwater levels in the Arkavathi Watershed by using cutting-edge AI and machine learning approaches.

2. Related Work

Hydrological research on groundwater recharge is essential for efficient water resource management, given the complexity of factors like terrain, plant cover, soil characteristics, and human activities. Traditional methods include soil moisture budgets, empirical infiltration coefficients, lysimeters, tracers, and the Water Table Fluctuation (WTF) method, which tracks groundwater level changes [13,14,15]. The WTF method is especially useful in semi-arid regions due to its simplicity and cost-effectiveness. Empirical formulas (e.g., Chaturvedi, UPIRI) provide region-specific estimates, while advancements in geospatial technology and remote sensing enhance the spatial analysis of recharge factors. Statistical tools like the Mann-Kendall test and Sen's Slope estimator are crucial for trend analysis. The integration of artificial intelligence (AI) and machine learning (ML), such as Support Vector Machine (SVM) and Random Forest, has significantly improved the prediction and evaluation of groundwater recharge [16,17,18]. These technologies handle large datasets and identify non-linear interactions, offering more accurate recharge estimates. Combining GIS, remote sensing, and AI/ML provides powerful tools for managing groundwater resources, identifying recharge zones, and predicting future trends. This project aims to apply these advanced technologies to improve groundwater recharge estimations in the Arkavathi watershed, aiding policymakers and stakeholders in sustainable groundwater management amid climate change and rising demand.

3. Methodology

3.1. Measurements of groundwater levels

Understanding the dynamics of groundwater in the research region, particularly in the Arkavathi Watershed, is critical to the project's use of groundwater level monitoring in piezometers and observation wells. In hydrogeology, piezometers and observation wells are crucial instruments for tracking variations in groundwater levels over time. A piezometer is a tool that is buried in the earth to measure groundwater pressure at a particular location. Usually, it is made of a perforated case with a screen at the bottom to let water in and keep dirt particles from clogging the apparatus. Piezometers give important information about the depth and flow of groundwater inside the aquifer by measuring the water pressure at various depths

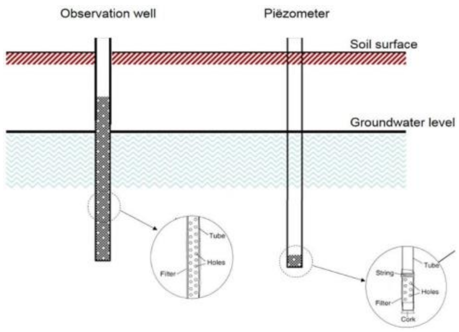

Fig 1. Groundwater level measurement in Piezometer and Observation well

Observation wells and piezometers, equipped with measurement tools, log groundwater levels continuously, providing data for trend analysis. Monitoring these wells helps evaluate factors affecting groundwater recharge, aiding sustainable management and conservation. In the Arkavathi Watershed, their strategic placement captures spatial fluctuations, identifying areas with varying recharge rates for targeted interventions. This data, combined with other hydrological information, allows researchers to develop comprehensive models for long-term groundwater sustainability.

3.2. Groundwater level location Arkavathi Watershed

The location of observation wells of Arkavathi Watershed is shown in Fig. 2.

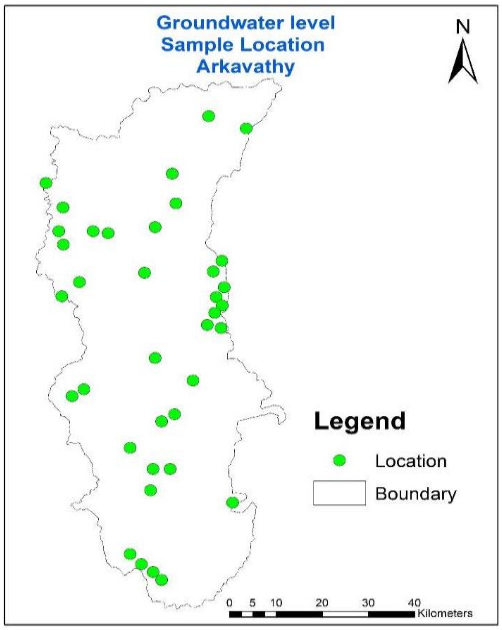

Fig 2. Observation Wells' location map of the study area

The Arkavathi Watershed research project strategically uses observation wells, as shown in figure, to monitor groundwater levels. These wells track seasonal fluctuations driven by climate and precipitation variations. Human activities such as industrial, agricultural, and drinking water extraction significantly impact groundwater levels, potentially causing aquifer depletion. Groundwater data from Bengaluru's Central Ground Water Board (CGWB) for 2014–2023 were analyzed to assess groundwater sustainability and health. This long-term data helps identify patterns, trends, and the factors influencing groundwater level variations in the Arkavathi Watershed.

3.3 Geo spatial Trend Analysis of Groundwater Level

Groundwater resource management has been made sustainable by the careful planning and implementation of geospatial variations in groundwater levels (GWL) [19]. A complete knowledge of the geographical and temporal dynamics of groundwater in the research region is achieved via a number of crucial processes in this extensive investigation.

3.3.1. Data Collection and Preparation

The gathering of groundwater level data from 37 observation wells dispersed across the Arkavathi Watershed is the first stage in this geospatial trend study. To guarantee that the data gathered offers a representative picture of the whole watershed, these wells cover a wide variety of sites. The data is gathered over a few years, with seasonal measurements being carefully documented. This large dataset provides a wealth of information on groundwater variations throughout time and serves as the foundation for the investigation that follows. The data has been acquired from Central Groundwater Board, Bangalore for the present study.

3.3.2. Data Processing

Data processing is an essential step that comes after the data collecting stage. To make sure the data is prepared for analysis, this entails cleaning and arranging it. It is necessary to handle any abnormalities or missing data points, which may include fixing incorrect data inputs or interpolating missing numbers. The data is cleaned up and then made ready for analysis utilizing a variety of statistical and geographic methods. The Inverse Distance Weightage (IDW) approach is one of the main techniques used in this research.

The Method of Inverse Distance Weightage (IDW) is a popular approach for geospatial interpolation, the IDW method calculates a variable's value at unsampled locations by using values at known places as a basis. IDW aids in establishing a continuous surface of groundwater levels across the research region when it comes to groundwater level analysis. The underlying idea of this approach is that points nearer the place of interest affect the estimated value more than those further away. Researchers may create intricate maps of groundwater levels using the IDW approach, which gives a visual depiction of the spatial differences across the watershed.

3.3.3. Methods of Statistics in Trend Analysis

Following processing and interpolation, a variety of statistical methods are used to find patterns and trends in the data [20]. The main techniques used in this study include moving averages, exponential smoothing, and linear regression.

- Linear Regression: This method aids in identifying the general pattern of groundwater levels over a period of time. Researchers can determine if groundwater levels are typically rising, falling, or staying steady by fitting a straight line across the data points. For long-term groundwater management, the slope of the regression line offers information on the rate of change.

-Moving Averages: This technique emphasizes longer-term trends while mitigating short-term swings. Moving averages reduce noise and highlight the underlying trend by averaging the data points over a predetermined time period.

-Exponential Smoothing: This method gives greater weight to newer observations by progressively lowering the weights of older data points. Understanding the most recent patterns in groundwater levels and creating short-term projections are two areas where exponential smoothing comes in handy.

Geographical Analysis

Applying several analytical techniques to the processed data in order to identify geographical patterns and trends is the basis of geospatial trend analysis. This investigation looks at how groundwater levels fluctuate at various points within the watershed in addition to their temporal aspect. Through the amalgamation of statistical findings and geographical data, scholars may pinpoint regions that are seeing notable fluctuations in groundwater levels and comprehend the fundamental reasons behind them.

3.3.4. Interpretation

Making the data understandable and useful requires first visualizing the geospatial trend analysis findings. Groundwater level fluctuations are shown visually in great detail using the IDW-generated maps, trend lines, and statistical results. These maps aid in pinpointing regions experiencing increasing water tables or hotspots of groundwater depletion. Furthermore, they provide a succinct and straightforward means of conveying results to interested parties, such as local community members, legislators, and managers of water resources.

3.3.5. Implications for Sustainable Management

Essential information for sustainable groundwater management is provided by this regional trend research, which enables targeted programs to lower over-extraction, enhance recharge, and guarantee long-term supplies. It maximizes resource distribution by identifying areas that need support. This project requires a methodical approach to data collection, processing, and analysis in order to provide a comprehensive knowledge of groundwater dynamics employing cutting-edge techniques. Effective resource preservation and use are made possible by exact outcomes that are guaranteed by methods such as IDW spatial interpolation when paired with strong statistical analysis.

The methodology followed has been presented in Fig 3.

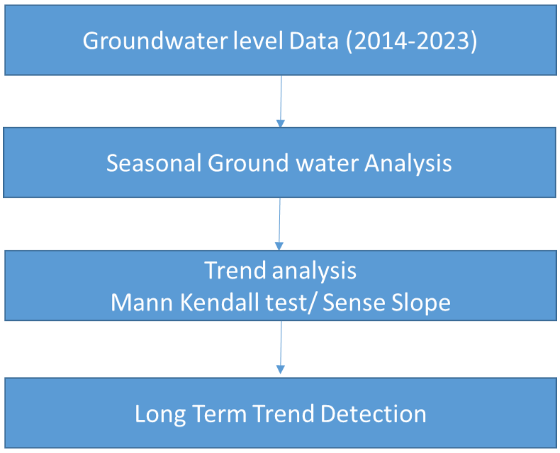

Fig 3. Steps followed for the present work

3.3.6. MANN–KENDALL (M-K) Test

The Mann-Kendall also termed, as M-K rank correlation test is a non-parametric statistical test used for trend analysis. The formula for Mann Kendall Statistic is:

$$S = \sum_{k=0}^{n-1} \sum_{j=k+1}^{n-1} sgn(xj - xk) \tag{1}$$

Where, n-number of data points

x_j- data points at time j

$$sgn(xj - xk) = \begin{pmatrix} +1 & if xj - xk & > 0 \\ 0 & if xj - xk & = 0 \\ -1 & if xj - xk & < 0 \end{pmatrix}$$

$$Var(S) = \frac{[n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)]}{18}$$

(2)

For n > 10, normal standard Z:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} if\ S > 0 \\ 0 \quad if\ S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} if\ S < 0 \end{cases} \tag{3}$$

3.3.7. SEN'S SLOPE (S-S) ESTIMATOR

Sen [1] gives a confidence interval for this slope and the formula for Sen's slope;

$$Q = \frac{x_i - x_j}{i - j} \tag{4}$$

Where x_i – data quantity at time i

x_j - data quantity at time j

4. Closure

Application of test statistics results is computed from groundwater level trends in the Arkavathi Watershed. M-K and S-S computed for the observed ground water level trend fluctuation detection is tabulated below

Table 1.: M-K and S-S Analysis for Sampling locations (2014 to 2023)

Sl No	Well Location	Northeast Monsoon		Pre Monsoon		Southwest Monsoon		Post Monsoon		Remarks
		Mann–Kendal l Z	Sen's slope	Mann–K endall Z	Sen's slope	Mann–Ke ndall Z	Sen's slope	Man Kandal	Sen's slope	
1	Basavanagudi	-0.045	-0.03	-0.0357	-0.222	0.222	0.25	-0.109	-0.102	Decreasing Trend
2	Chennamankere Achkattu	0.022	0.010	0.143	0.065	0.167	0.134	-0.143	-0.121	Decreasing Trend
3	Dasanapura	-0.270	-0.893	-0.143	-0.547	-0.611	-1.158	-0.571	-1.791	Decreasing Trend
4	Gollahalli	0.045	0.013	-0.214	-0.068	0.500	0.213	0.143	0.063	Increasing Trend
5	Hesaraghatta Pz	-0.597	-2.620	-0.500	-1.551	-0.556	-1.612	-0.429	-0.643	Decreasing Trend
6	Malleswaram	0.225	0.123	-0.143	-0.166	0.366	0.215	0.071	0.063	Increasing Trend
7	Rajajinagara	0.422	0.093	0.214	0.180	0.572	0.227	0.109	0.029	Increasing Trend
8	Bang Uni Ars Ls	-0.689	-1.775	-0.571	-2.029	-0.444	-1.299	-0.571	-1.654	Decreasing Trend
9	Chandasipalya	-0.111	-0.133	-0.500	-0.635	-0.197	-0.130	-0.357	-0.403	Decreasing Trend
10	Gsi Pz	0.270	1.078	0.571	0.650	0.278	0.860	0.500	0.525	Increasing Trend
11	Thalaghattapurapz	-0.045	-0.077	0.113	0.397	-0.085	-0.215	-0.286	-0.850	Decreasing Trend
12	Vasanthpura	0.022	0.050	-0.071	-0.036	0.278	0.166	0.000	0.005	Increasing Trend
13	Bairasandra	0.501	0.767	0.491	0.863	0.730	0.804	0.535	0.518	Increasing Trend
14	Dodballapur1	-0.644	-2.538	-0.357	-1.820	-0.556	-2.745	-0.691	-2.899	Decreasing Trend
15	Kanasvadi	-0.822	-3.065	-0.786	-2.141	-0.944	-2.391	-0.929	-2.819	Decreasing Trend
16	Aralalu	-0.270	-0.148	-0.357	-0.075	-0.111	-0.085	-0.286	-0.168	Decreasing Trend
17	Ganaldoddi	-0.022	-0.006	-0.071	-0.039	0.389	0.473	-0.357	-0.204	Decreasing Trend
18	Harohalli A	-0.225	-0.175	0.000	0.019	0.167	0.092	-0.357	-0.209	Decreasing Trend
19	Hegganur	-0.333	-0.265	-0.255	-0.059	-0.167	-0.111	-0.571	-0.189	Decreasing Trend
20	Helagalli	-0.244	-0.458	-0.714	-0.727	-0.500	-0.319	-0.500	-0.365	Decreasing Trend
21	Kadashivanahalli	-0.256	-0.286	0.048	0.025	-0.229	-0.299	-0.429	-0.509	Decreasing Trend
22	Kanakapura1	-0.225	-0.125	-0.214	-0.114	0.056	0.065	-0.182	-0.082	Decreasing Trend
23	Kottahalli	-0.460	-1.046	-0.540	-0.729	-0.057	-0.050	-0.857	-1.105	Decreasing Trend
24	Kylancha	-0.310	-0.348	-0.182	-0.406	-0.145	-0.134	0.296	0.158	Increasing Trend
25	Uyyamballi	0.024	0.000	0.081	0.000	0.386	1.008	0.038	0.000	Increasing Trend
26	Banavadi	-0.244	-0.075	-0.214	-0.195	-0.310	-0.340	-0.214	-0.162	Decreasing Trend
27	Panayan Palya	-0.556	-0.663	-0.571	-0.763	-0.429	-0.935	-0.214	-0.219	Decreasing Trend
28	Solur	-0.449	-1.323	-0.327	-1.248	-0.087	-0.368	-0.189	-0.414	Decreasing Trend

29	Talacha Kuppe	-0.244	-0.105	0.000	-0.016	0.056	0.046	-0.214	-0.094	Decreasing Trend
30	Ukkada	-0.135	-0.350	-0.143	-0.125	0.087	0.051	-0.071	-0.185	Decreasing Trend
31	Mahadevapura	-0.135	-0.043	0.000	0.011	0.254	0.168	0.143	0.066	Increasing Trend
32	Shivagange	-0.200	-0.193	-0.143	-0.248	0.111	0.114	0.714	0.353	Decreasing Trend
33	Yentiganahalli	-0.600	-0.875	-0.429	-0.582	0.000	-0.013	-0.214	-0.304	Decreasing Trend
34	Bidadi	-0.467	-1.148	-0.643	-1.626	-0.500	-0.714	-0.071	-0.280	Decreasing Trend
35	Nullahalli	-0.022	-0.135	0.238	0.638	-0.141	-0.047	-0.500	-0.900	Decreasing Trend
36	Ramanagara	-0.111	-0.208	-0.255	-0.188	-0.343	-0.802	-0.109	-0.287	Decreasing Trend
37	S.B.Doddi	-0.600	-0.413	-0.571	-0.325	-0.444	-0.176	-0.357	-0.454	Decreasing Trend

4.1 Key Observations

1. Basavanagudi: Declining groundwater levels, mainly in Post-Monsoon and Pre-Monsoon seasons.

2. Chennamankere Achkattu: Mixed trend, with small increases during Pre-Monsoon and Southwest Monsoon.

3. Dasanapura: Strong falling trend implies significant stress on aquifer.

4. Gollahalli: Possible recharging or reduced extraction, displaying growing trend.

5. Hesaraghatta Pz: High extraction rates reflected in considerable dips, notably Pre-Monsoon and Southwest Monsoon.

6. Malleswaram and Rajajinagara: Rising trends reflect natural recharge or effective management.

7. Bang Uni Ars Ls: Notable decreases, presenting concern to water resource sustainability.

8. Gsi Pz and Bairasandra: Steady increasing trend implies effective recharge or decreased aquifer stress.

9. Dodballapur1 and Kanasvadi: Strong declining trends imply serious over-extraction or decreased recharge.

10. Remaining Wells: Widespread groundwater depletion reported in Helagalli, Kadashivanahalli, Kanakapura1, and Harohalli A.

According to the study, most observation wells show a constant fall in groundwater levels throughout the Pre- and Post-monsoon seasons. This decline is probably caused by excessive extraction for home, commercial, and agricultural applications. Nonetheless, growing trends are seen in wells like Gollahalli and Gsi Pz, indicating effective groundwater management or recharge strategies in those regions. The complicated groundwater dynamics impacted by regional variables such land use changes, recharge rates, and extraction pressures are highlighted by the inconsistent patterns in some wells.

4.2. Spatiotemporal Study of Groundwater Levels in the Arkavathi Watersheds

4.2.1. Summary of the Study (2014–2023)

Data from 37 wells were used to do a spatiotemporal study of groundwater levels in the Arkavathi watershed. The significant declines in groundwater levels are seen in the northern and southwestern areas, with losses reaching up to 15 meters during the monsoon seasons as a result of inadequate infiltration, surface runoff, and over-extraction. With mean water levels varying between 10 and 15 meters below ground level, the center basin exhibits only slight changes, suggesting a more balanced recharge-extraction relationship. In the northwest and southeast, alluvial deposits and water-saving infrastructure enable the regular maintenance of stable groundwater levels below 12 meters.

4.2.2. Trend Evaluation

Overall, 76% of wells exhibited dropping trends, while 24% indicated growing trends.

-Growing Trends: Attributed to efficient water management and recharge structures, these trends have been seen at Bairasandra, Vasanthpura, Kylancha, Uyyamballi, Mahadevapura, Gsi Pz, Gollahalli, Malleswaram, and Rajajinagara.

4.2.3. Impact on Agriculture and Suggestions

Agriculture is under risk due to declining groundwater levels, especially in the north and southwest. To maintain water levels and improve groundwater supplies, artificial recharge techniques such as check dams, percolation tanks, and recharge wells are advised.

5. Implementation & Results

5.1. Enhanced Trend Analysis:

1. Non-Linear Pattern Recognition: AI and ML algorithms like decision trees, neural networks, and polynomial regression identify complex patterns in groundwater data, enhancing forecasting and trend analysis.

2. Dynamics of Time and Space: Sophisticated algorithms analyze changes in groundwater levels over time and space, providing insights into regional patterns, depletion hotspots, and the impact of factors like climate change and human activity.

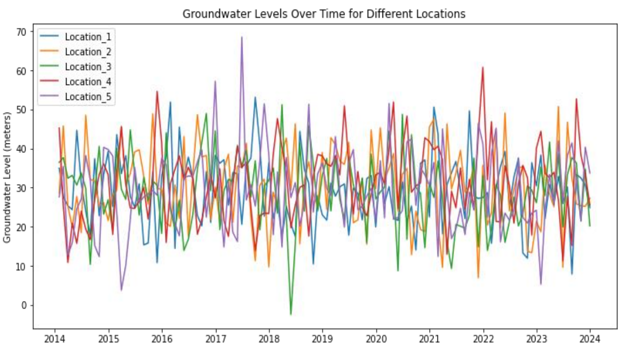

Fig 4.: Groundwater Levels Throughout Time at Various Locations

The temporal dynamics of groundwater levels at several places over a certain time period are shown in this line graph. The trend of the groundwater level for each line corresponds to a specific place. The graphic makes it easier to see how groundwater levels change over time and in various places, as well as if there are any recurring patterns or oscillations.

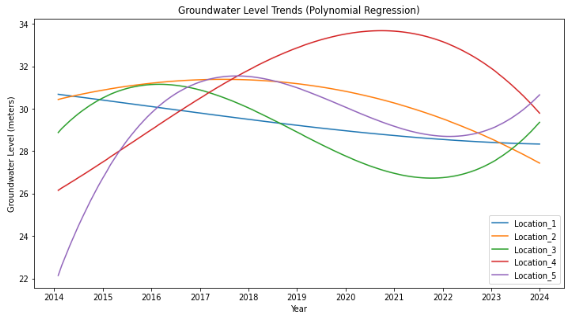

Fig 5.: Polynomial Regression Trends in Groundwater Levels

The trends in groundwater levels for each site, as determined via polynomial regression, are shown in this graphic. By fitting a polynomial function to the data, polynomial regression is able to capture non-linear correlations between time and groundwater levels. Plotting the underlying trend in groundwater levels, together with any non-linear patterns like exponential development or decline, helps understand the data.

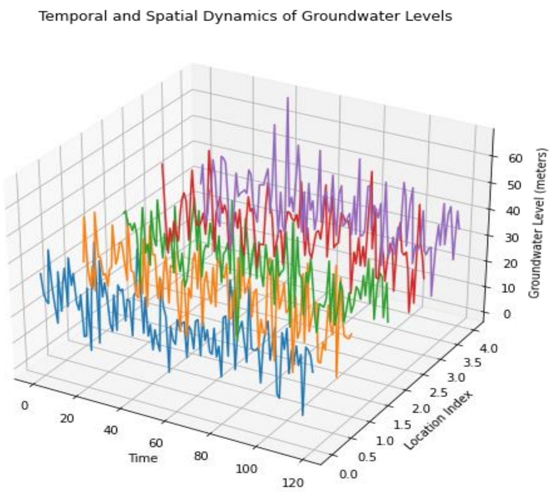

Fig 6.: Groundwater Level Dynamics: Temporal and Spatial Dynamics

The geographical and temporal dynamics of groundwater levels at several places throughout time are shown in this three-dimensional map. The x-axis represents time, each location's index by the y-axis, and the groundwater level by the z-axis. Plotting illustrates the temporal and geographical variability of groundwater levels; each line represents the trend of groundwater level for a particular site. An all-encompassing comprehension of the intricate relationships between groundwater dynamics, time, and place is offered by this graphic.

5.2. Predictive Groundwater Level Modeling

Predictive modeling forecasts future groundwater levels by using machine learning (ML) methods and historical data. This facilitates better understanding and administration of water resources.

	Well_ID	Year	Groundwater_Level (meters)	Rainfall (mm)	Temperature (°C)	\
0	1	2014	8.745401	975.357153	22.319939	
1	1	2015	6.660186	587.997260	15.580836	
2	1	2016	11.211150	874.036289	15.205845	
3	1	2017	13.624426	636.169555	16.818250	
4	1	2018	8.442422	802.378216	19.319450	
5	1	2019	11.618529	619.746930	17.921446	
6	1	2020	10.160700	952.587981	16.996738	
7	1	2021	11.624146	593.225206	21.075449	
8	1	2022	6.450516	1054.442769	24.656320	
9	1	2023	8.946138	638.836057	21.842330	

	Water_Usage (cubic meters)
0	219.731697
1	273.235229
2	293.981970
3	136.680902
4	158.245828
5	173.272369
6	202.846888
7	134.104825
8	261.679470
9	188.030499

Fig 7.: Data Generated

5.2.1. Predictive Modeling for short- and long-term forecasts

Proximate Future Forecasts: Short-term predictions aid in managing immediate water resource demands, utilizing daily or weekly data on temperature, precipitation, groundwater levels, and water consumption patterns.

Extended Forecasts: Long-term projections assist in strategic water resource planning over years or decades, incorporating annual data patterns, climatic forecasts, and shifts in water usage.

Analyzing Scenarios: Forecasting the impact of climate change on groundwater levels involves modeling altered rainfall patterns. Similarly, predicting changes in water consumption and their effects on groundwater levels can be simulated by adjusting water demand scenarios.

Root Mean Squared Error: 3.10

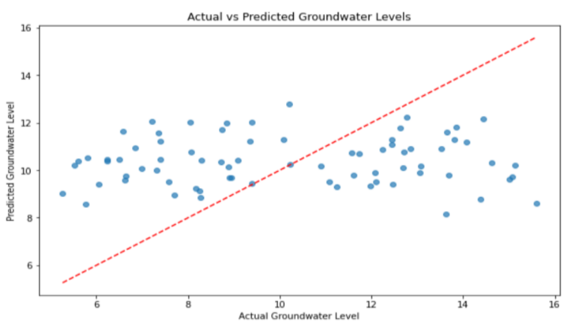

Fig 8.: Actual vs Predicted Groundwater Levels

In this figure, the groundwater levels as observed and those predicted by the machine learning model are contrasted. The ideal situation, in which estimates and actual values coincide exactly, is shown by the red dashed line. Accurate forecasts are shown by points around this line.

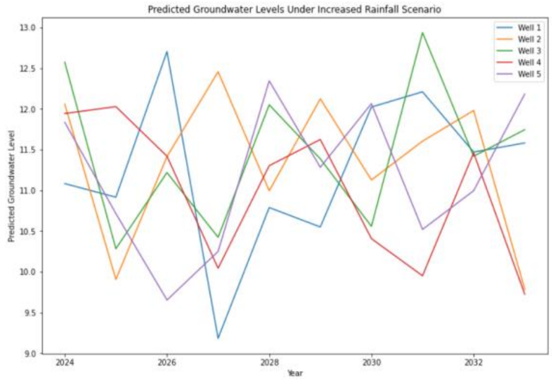

Fig 9.: Estimated Groundwater Levels in the Event of Higher Rainfall

The graph shows the expected groundwater levels under increasing rainfall caused by climate change over the next ten years. A distinct well is shown by each line, which illustrates how variations in rainfall patterns may affect groundwater levels. Understanding the possible long-term effects of climate change on groundwater supplies is made easier with the help of this depiction.

5.3. Anomaly Detection

<u>Identifying Abnormal Patterns:</u> AI can detect anomalies or sudden changes in groundwater levels, which could indicate issues like over-extraction, contamination, or equipment failure.

<u>Real-Time Monitoring:</u> Integrating real-time data with AI algorithms can provide immediate alerts for unusual groundwater level changes, allowing for timely intervention.

5.4. Optimization of Recharge Strategies

Optimal Location Identification Using spatial analysis and ML algorithms to identify the most effective locations for artificial recharge structures.

<u>Impact Assessment:</u> Evaluating the effectiveness of recharge strategies over time and optimizing them based on the results.

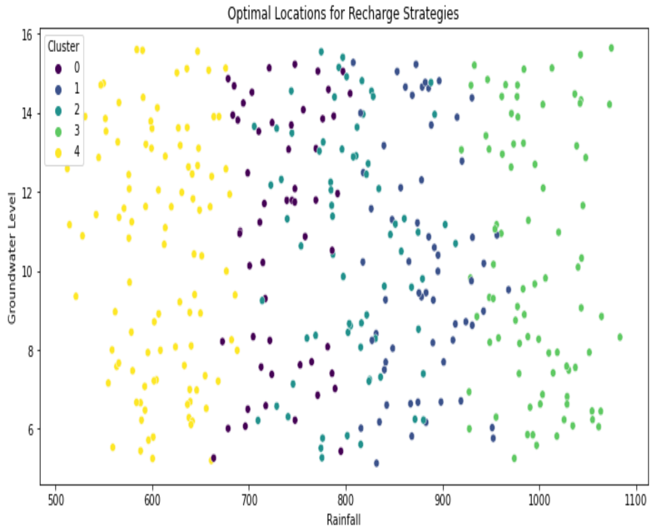

Fig 10: Optimal Conditions for Recharge Strategies

The scatter plot displays the link between rainfall and groundwater levels, with KMeans clustering applied to color data points. Clusters show regions with comparable features, helpful in selecting suitable places for recharging methods. Cluster analysis evaluates water demand patterns, temperature, rainfall, and groundwater levels to find ideal areas for artificial recharge structures.

5.5. Water Resource Management

<u>Integrated Management:</u> AI can integrate data from multiple sources (e.g., groundwater levels, surface water levels, climate data) to provide holistic water resource management solutions.

<u>Sustainability Planning:</u> Long-term sustainability planning can be supported by predictive models that account for various factors influencing groundwater levels.

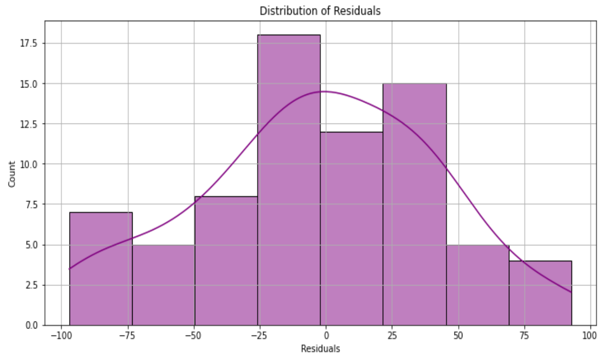

Fig 11: Distribution of Residuals

The residuals (errors) distribution is shown in this histogram, which aids in identifying any bias in the predictions.

6. Conclusion

Ten years of groundwater level variations in the Arkavathi watersheds was explored which depends on soil qualities, rainfall, and human activity and cause seasonal and regional fluctuations. Statistical tools like Sen's Slope Estimator and the Mann-Kendall (M-K) test, in conjunction with spatial interpolation approaches, were used to identify long-term trends. The trend analysis shows a constant fall in groundwater levels throughout the Pre and Post-monsoon seasons for most of the observation wells. The cause of decline can be due to excessive extraction for home, commercial, and agricultural applications. Widespread groundwater depletion reported in Helagalli, Kadashivanahalli, Kanakapura1 and Harohalli A. However, growing trends are seen in wells like Gollahalli and Gsi Pz, indicating effective groundwater management or recharge strategies in those regions.

Thanks to these advancements, stakeholders would be able to make informed decisions regarding groundwater management. These advancements included improved trend analysis, predictive modeling, anomaly detection, optimization of recharge strategies, and water resource management. This allows for sustainable use and can address the challenges of changing environmental conditions and increasing water demand. The use of AI and ML into groundwater research has been a significant advancement in our capacity to understand and manage groundwater resources, which are vital to the health of society and the environment.

7. Future Scope

Examining groundwater level fluctuations in the Arkavathi basins offers numerous study prospects. Enhancing prediction models with AI and ML, integrating diverse datasets, and implementing real-time monitoring systems can improve forecasting accuracy and anomaly detection. Including climate change predictions in models aids in forecasting groundwater level changes, while optimizing recharge procedures identifies optimal locations and techniques. Effective management requires user-friendly decision support tools and stakeholder engagement. Sustainable groundwater management necessitates long-term monitoring and interdisciplinary cooperation. Future work should focus on integrating GIS analysis, stakeholder engagement, and hydrological modeling with AI and ML.

Conflicts of interest

The authors declare no conflicts of interest.

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