GROUND WATER LEVEL PREDICTOR USING MACHINE LEARNING

A PROJECT REPORT

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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Project report **"Ground Water Level Predictor Using Machine Learning"** being submitted by "A,vara prasad , M.Sai sujith Reddy, Vadde Balaji ,Sangeetha K" bearing roll number(s) "20211CBD0004 ,20211CBD006 , 20211CBD0008, 20211CBD0034" in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Technology (Big Data) is a Bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **Ground Water Level Predictor Using Machine Learning** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Science and Technology (Big Data)**, is a record of our own investigations carried under the guidance of **DR. SRINIVASAN T R, Professor, School of Computer Science And Engineering, Presidency University, Bengaluru.**

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ABSTRACT

Groundwater plays an essential role in sustaining life and supporting economic development, especially in regions heavily dependent on agriculture and where surface water is limited. In recent years, the over exploitation of groundwater, combined with changing climate conditions, has led to alarming drops in groundwater levels. Accurate prediction of groundwater levels is critical for water resource planning, disaster preparedness, and sustainable management practices. However, traditional methods for monitoring and forecasting groundwater levels often fall short in terms of accuracy and adaptability to nonlinear patterns in data.

This study explores the application of machine learning (ML) techniques to predict groundwater levels based on historical groundwater measurements and meteorological parameters such as rainfall, temperature, humidity, and evapotranspiration. Machine learning models are capable of identifying hidden trends and relationships in large datasets, offering a data-driven approach to prediction that can outperform conventional statistical methods. By training models on multi-year datasets, we aim to capture both short-term fluctuations and long-term trends that influence groundwater dynamics.

Multiple algorithms, including Linear Regression, Random Forest, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) neural networks, are implemented and compared. The choice of models spans both traditional regression-based approaches and deep learning techniques, allowing us to evaluate their strengths and weaknesses in handling time-series data. LSTM, in particular, has shown considerable promise due to its ability to remember previous states and manage sequences of data effectively, which is crucial when working with temporal groundwater data.

The models are trained and validated using publicly available datasets from

groundwater monitoring agencies, combined with meteorological data from weather databases. The evaluation metrics used—Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 Score—indicate that while most models provide acceptable predictions, LSTM networks consistently deliver higher accuracy and better generalization capabilities. These findings suggest that advanced deep learning techniques can provide a more reliable solution for groundwater level forecasting.

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CHAPTER-1
INTRODUCTION

Groundwater is one of the most valuable natural resources on Earth, serving as a primary source of freshwater for drinking, agriculture, and industrial purposes. In many regions, particularly those prone to drought or lacking sufficient surface water, groundwater acts as a crucial lifeline. However, growing population demands, unregulated extraction, and the impacts of climate change have led to a significant decline in groundwater levels across the globe. This has raised concerns over water scarcity, agricultural sustainability, and long-term environmental balance.

Groundwater level forecasting has relied on physical models and statistical techniques, which, while useful, often struggle to accurately capture the complex, nonlinear relationships between multiple environmental variables. These conventional models usually require extensive domain knowledge, are sensitive to missing data, and can be computationally intensive. As a result, there is an increasing interest in applying modern data-driven methods, particularly machine learning, to enhance prediction accuracy and offer scalable, adaptable solutions.

Machine learning (ML) has emerged as a promising approach for modeling and predicting groundwater levels due to its ability to handle large datasets, recognize complex patterns, and learn from historical data without explicit programming. Algorithms such as Random Forest, Support Vector Regression, and deep learning models like Long Short-Term Memory (LSTM) networks have demonstrated strong performance in time-series prediction tasks. These models can incorporate diverse inputs, including past groundwater levels, rainfall, temperature, and other hydro-logical variables, to generate accurate forecasts.

In this project, we aim to develop and compare various machine learning models for predicting groundwater levels. By training these models on real-world datasets, we evaluate their effectiveness and identify the most suitable approach for reliable groundwater forecasting. This research not only contributes to the technical advancement in hydro-logical modeling but also supports sustainable water management practices by providing timely and accurate groundwater insights.The successful implementation of machine learning-based groundwater prediction models can greatly aid policymakers, farmers, and environmental agencies in making informed decisions. Such models can help anticipate water shortages, plan irrigation schedules, and implement effective conservation strategies, ultimately promoting the responsible and sustainable use of groundwater

resource

One of the major advantages of ML-based approaches is their adaptability to different geographic regions and data availability conditions. Unlike traditional models that may require detailed geological and hydro logical inputs, ML models can work effectively with incomplete or noisy data, provided that appropriate prepossessing and feature selection techniques are used. This flexibility makes ML highly suitable for real-world applications, especially in developing regions where data collection infrastructure is limited. Additionally, the integration of machine learning with Geographic Information Systems (GIS) and remote sensing technologies is opening new doors for real-time and spatially-distributed groundwater monitoring.

By incorporating satellite-based rainfall data, land use patterns, and soil moisture indices, ML models can offer a more holistic view of the factors influencing groundwater behavior. This interdisciplinary approach enhances model accuracy and facilitates better decision-making at both local and regional scales.In the context of growing environmental pressures and the urgent need for sustainable water management, this project aims to demonstrate how machine learning techniques can be leveraged for effective groundwater level prediction. By evaluating multiple models and comparing their performance across different conditions, this research contributes valuable insights into the development of intelligent systems for groundwater management, helping safeguard this vital resource for future generations.

Problem statement

Groundwater Level is the cardinal parameter that best describes the health of an Aquifer. Long term groundwater level data acquired through regular monitoring of groundwater levels provide an opportunity to understand the behavior of the aquifers to changing stress regime. Central Ground Water Board periodically monitors ground water levels from nearly 26000 wells. CGWB is also in the process of installing Digital Water Level Recorders (DWLRs) across various parts of India each capturing and transmitting water level data four times per day. In addition to CGWB there are many other agencies measuring water levels. The software application is expected to analyses groundwater levels and factors impacting groundwater level like rainfall, hydro geology, land use, population, surface elevation, natural features, tidal cycles etc. Based on these factors and based on observed water level data, the software application should be able to predict and forecast groundwater levels both in space and time. The application will be accessible to all for predicting groundwater level at any place at any point on time. This will also help in filling data gaps in time-series data.

CHAPTER-2
LITERATURE SURVEY

The prediction of groundwater levels has traditionally relied on physical and numerical models, which are often limited by their dependence on extensive field data, assumptions about aquifer properties, and computational complexity. In response to these challenges, machine learning (ML) techniques have emerged as powerful alternatives, capable of identifying complex, nonlinear relationships in data without the need for explicit physical modeling. This section presents a comprehensive review of various machine learning methods that have been applied to groundwater level forecasting, categorized under four major approaches: Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forest (RF), and Long Short-Term Memory (LSTM) networks.

2.1. Artificial Neural Networks (ANN) in Groundwater Prediction

Artificial Neural Networks are among the earliest machine learning models used for hydrological forecasting. Inspired by the human brain, ANNs consist of layers of interconnected neurons that process input data through weighted connections. These models are particularly effective in identifying nonlinear patterns, which are prevalent in groundwater systems due to the influence of factors like rainfall, land use, temperature, and human activities.

Kumar et al. (2015) conducted a study in the hard rock terrains of South India where they applied a Multilayer Perceptron (MLP) based ANN to predict groundwater fluctuations. The input data included monthly rainfall and previous groundwater levels. The results showed that the ANN model outperformed traditional linear regression approaches, especially in terms of adaptability to seasonal changes. The study demonstrated that ANNs can model the nonlinear hydrological processes that influence groundwater variability.

Despite their strong predictive performance, ANNs come with certain drawbacks. They require large amounts of high-quality training data to learn effectively and can easily overfit the training dataset if not properly regularized. Additionally, the model's "black box" nature can make it difficult to interpret the relationship between inputs and outputs, posing challenges for model transparency and validation in scientific and policy applications.

2.2. Support Vector Regression (SVR) for Time-Series Forecasting

Support Vector Regression is a supervised learning model based on the principles of Support Vector Machines (SVM). It is particularly known for its robustness in high-dimensional spaces and its ability to handle nonlinear data through the use of kernel functions. SVR has been increasingly used in hydrological modeling due to its simplicity and effectiveness with relatively small datasets.

Yoon et al. (2016) applied SVR to forecast groundwater levels in agricultural zones in South Korea. Their approach utilized meteorological variables such as precipitation, evapotranspiration, and past groundwater readings. The SVR model provided high accuracy in short-term forecasting and performed well despite missing or sparse data. One of the key strengths of SVR noted in this study was its generalization ability, which allowed it to make accurate predictions even when trained on limited data.

However, SVR also has its limitations. The performance of the model is highly sensitive to the choice of kernel functions (e.g., linear, polynomial, or radial basis function), and tuning these hyper parameters requires domain expertise and experimentation. Furthermore, SVR models may struggle with long-term groundwater forecasting, as they lack internal memory mechanisms that are essential for capturing deep temporal dependencies.

2.3. Random Forest (RF) and Ensemble Methods

Random Forest is an ensemble learning technique based on decision trees. It works by training multiple decision trees on random subsets of the dataset and then aggregating their results to produce a more accurate and robust prediction. This technique is especially suitable for handling large datasets with multiple features and has been widely used in environmental and hydro logical modeling.

Zhang et al. (2018) implemented a Random Forest model to predict monthly groundwater levels in Northern China. The model inputs included rainfall, temperature, and groundwater levels from previous months. The RF model was able to deliver high prediction accuracy and identified the most influential variables, thus offering both predictive power and inter pretability. One of the notable advantages of RF is its resistance to over fitting due to the ensemble nature of the model.

Despite these strengths, Random Forest models are not inherently designed for sequential or time-series data, which limits their performance in long-term forecasting tasks where temporal dependencies are critical. They also require careful feature engineering to include time-lagged variables, which can increase the complexity of the modeling process.

2.4. Long Short-Term Memory (LSTM) Networks in Deep Learning

Deep learning techniques, especially Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory (LSTM) networks, have shown remarkable success in time-series prediction tasks. LSTM networks are specifically designed to learn long-term dependencies by incorporating memory cells that retain information over time, making them highly suitable for modeling groundwater level fluctuations that depend on both recent and historical data.

Shrestha et al. (2020) applied LSTM networks to predict groundwater levels in Nepal's Terai region using multiyear time-series data, including rainfall, temperature, and historical groundwater measurements. The model outperformed traditional machine learning methods like Random Forest and SVR, particularly in capturing seasonal trends and long-term changes. The LSTM's architecture, which includes forget gates and input modulation, allowed it to selectively retain and discard information, leading to improved forecasting accuracy.

2.5. Hybrid and Hybrid-Optimized Models

Recent studies have explored hybrid models that combine multiple machine learning techniques or integrate ML with optimization algorithms to improve prediction accuracy and overcome individual model limitations. For instance, Das and Mohanty (2021) proposed a hybrid ANN-GA model where an Artificial Neural Network was optimized using a Genetic Algorithm (GA). The model performed better than standard ANN by improving weight optimization and reducing error rates. Similarly, the integration of Wavelet Transform with ANN or LSTM has helped improve the signal-to-noise ratio in time-series data, leading to more reliable groundwater level predictions.

Hybrid models are particularly useful in handling noisy and non-stationary data, as they allow for preprocessing (e.g., through wavelet decomposition) before applying the predictive model. However, these models tend to be complex in structure, require high computation time, and are difficult to interpret. Despite these drawbacks, hybrid approaches are gaining traction for their accuracy and adaptability in complex hydrological environments.

2.6. Use of Remote Sensing and GIS with ML

Another emerging trend in groundwater modeling is the integration of **remote sensing data** and **Geographic Information Systems (GIS)** with machine learning. These technologies enable large-scale, spatially distributed modeling, even in data-scarce regions. Studies such as that by Singh et al. (2019) utilized satellite-derived precipitation and land-use data as inputs for a Random Forest model to predict groundwater potential zones in central India.

Combining ML with spatial data allows for better generalization across regions and helps in visualizing risk-prone zones. The use of spatial features (e.g., soil type, elevation, vegetation index) provides additional insights into how surface conditions influence groundwater recharge and depletion. While such models require advanced GIS skills and access to high-resolution satellite data, they are powerful tools for regional planning and decision-making.

2.7. Comparison Studies and Benchmarking

Several researchers have conducted **benchmarking studies** comparing the performance of multiple machine learning models under similar datasets and conditions. These studies are important because they help establish the strengths and weaknesses of each algorithm in different forecasting contexts.

For example, Rahmati et al. (2022) compared SVR, RF, ANN, and LSTM models using a decade-long groundwater dataset from Iran. Their findings revealed that while LSTM had the best overall accuracy for long-term forecasting, RF offered faster computation and interpretability. Such comparison studies are valuable because they help guide model selection based on use case, available data, and desired outcome (e.g., speed, accuracy, interpretability, or scalability).

Benchmarking also emphasizes the importance of metrics selection (like RMSE, MAE, R^2) and data preprocessing techniques, which can significantly influence model outcomes. Therefore, future studies and applications should be transparent in methodology to ensure results can be replicated and extended.

Study / Model	Key Results / Strengths	Drawbacks / Limitations
Kumar et al. (2015) – ANN	Accurate nonlinear modeling; responsive to rainfall variations	Requires large dataset; risk of overfitting; less interpretable
Yoon et al. (2016) – SVR	Good for small datasets; efficient for short-term forecasts	Kernel-sensitive; not ideal for long-term dependency modeling
Zhang et al. (2018) – RF	High accuracy; interpretable feature importance	Not designed for time-series; needs feature engineering
Shrestha et al. (2020) – LSTM	Best for capturing long-term and seasonal trends; excellent for time-series data	High computational cost; complex tuning; black-box model
Das & Mohanty (2021) – Hybrid ANN-GA	Enhanced accuracy through optimization; better weight tuning and model generalization	More complex structure; increased computation time; lower transparency
Singh et al. (2019) – RF + Remote Sensing & GIS	Improved spatial prediction; uses satellite & environmental data for regional forecasting	Requires GIS expertise; satellite data access needed; computationally heavy

Figure -1 . Literature Survey

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

Despite the promising application of machine learning (ML) techniques for groundwater level prediction, there are still significant gaps in existing research that need to be addressed. These gaps not only hinder the progress of groundwater prediction models but also present opportunities for further advancement in hydrological modeling. The challenges related to data, modeling techniques, generalization, and interpretability are critical to improving both the accuracy and the practical application of machine learning models in real-world water resource management.

3.1. Limited Generalization Across Regions

One of the major challenges faced by machine learning models in groundwater level prediction is their limited generalization ability. Most current studies use region-specific datasets, and the models they develop are tailored to the unique characteristics of the study area. As a result, these models often fail to perform as expected when applied to different geographic regions with varying climatic, hydrological, and environmental conditions. For example, a model trained using data from a semi-arid region may not work well in a tropical or temperate climate due to the differences in rainfall patterns, soil permeability, and groundwater recharge rates.

To address this gap, research is needed to develop scalable and adaptable models that can generalize well across different regions. These models should be capable of learning regional differences without requiring substantial retraining. Furthermore, incorporating global climate models or regional hydrological models into the machine learning approach may enhance the model's ability to adapt to new environments.

3.2. Insufficient Long-Term and Real-Time Forecasting

Although many machine learning models perform well in short-term groundwater predictions, they are often unable to predict long-term trends with the same level of accuracy. Long-term forecasting is crucial for groundwater management, as it helps predict changes in water availability over several months or even years, which is vital for agricultural, industrial, and urban water planning. Most studies focus on shorter prediction windows, usually ranging from a few days to a few months, often limiting their applicability to scenarios where long-term management decisions are required.

Additionally, many existing models do not integrate real-time data streams such as data from groundwater monitoring wells, IoT sensors, or satellite-based measurements. Real-time forecasting would allow for dynamic updates to the predictions based on the most current data, offering more precise and timely decision support for water resource managers.To address this issue, future research should focus on incorporating real-time, continuous data streams into machine learning models, enabling models to update and adapt their predictions dynamically. Moreover, extending machine learning models to handle longer time horizons and account for long-term variability in groundwater recharge and depletion patterns is another area that requires attention.

3.3. Lack of Standardized Benchmark Datasets

A significant challenge in the field of machine learning for groundwater prediction is the lack of standardized datasets. Many studies use proprietary, localized, or region-specific datasets, making it difficult to compare and validate the results across different research efforts. As a result, the performance of different models cannot be fairly assessed, and reproducibility is often compromised. This issue is compounded by the fact that various models use different evaluation metrics (e.g., RMSE, MAE, R^2), which can make cross-study comparisons challenging.

The development of publicly available benchmark datasets for groundwater level prediction would provide a common ground for researchers to evaluate and compare the performance of different machine learning models. In addition to having publicly available datasets, these datasets should be well-documented with clear descriptions of data collection methods, the underlying assumptions, and any preprocessing steps used. Creating a common evaluation framework with standardized metrics will also allow for more objective comparisons and contribute to the advancement of the field.

3.4. Limited Integration with Physical and Hydrogeological Knowledge

Machine learning models for groundwater prediction often treat the groundwater system as a purely data-driven black box, where the underlying physical processes are not explicitly modeled. While data-driven models can provide accurate predictions, they do not always reflect the real-world dynamics of groundwater systems. This lack of integration with physical knowledge can limit the interpretability and trustworthiness of predictions, especially in policy-making and regulatory contexts where decisions need to be grounded in

scientific principles.

There is a growing need for hybrid models that combine machine learning techniques with physical and hydrogeological models. For example, integrating machine learning algorithms with numerical groundwater flow models (e.g., MODFLOW) can improve the model's predictive accuracy while retaining the physical integrity of the hydrological processes. Such hybrid models can help address the gaps between data-driven predictions and physical understanding, making them more interpretable and useful for decision support in water resource management.

Additionally, incorporating hydrogeological features like aquifer properties, permeability, and recharge rates into machine learning models could help enhance the accuracy and robustness of the predictions. Models that incorporate both data and physical principles will be better suited for addressing large-scale groundwater management challenges.

3.5. Underexplored Use of Spatio-Temporal Modeling

Most groundwater models focus primarily on temporal features, such as past groundwater levels, precipitation, and temperature, without fully accounting for spatial dependencies that may influence groundwater dynamics. Groundwater systems are inherently spatially heterogeneous, meaning that the groundwater levels in one location are influenced not only by time-related factors but also by the conditions in surrounding areas. Factors such as land use, soil type, topography, and the presence of nearby wells can significantly affect groundwater levels.

Unfortunately, many existing machine learning models ignore spatial correlations, leading to suboptimal predictions in areas where spatial dependencies are strong. There is a need for spatio-temporal models that can simultaneously account for both temporal and spatial factors. Approaches like Graph Neural Networks (GNNs) and Convolutional LSTM (ConvLSTM) have the potential to improve predictions by considering the spatial structure of the groundwater system. These models could integrate information from multiple wells or monitoring stations, providing more accurate and region-specific predictions.

3.6. Model Interpretability and Decision Support

Machine learning models, especially deep learning models like LSTM, are often criticized for being black-box models—they produce accurate predictions but do not offer insights into how those predictions are made. For decision-makers, such as water resource managers or policymakers, understanding the reasoning behind model predictions is crucial for building trust and confidence in the system. Model transparency and interpretability are essential for ensuring that the model's outputs can be used for practical decision support. While several methods exist to improve model interpretability (e.g., SHAP values, LIME), they have not been extensively applied to groundwater prediction models. The lack of transparency in these models makes it difficult for stakeholders to understand the relationships between model inputs and predictions, which is crucial in sensitive areas like water resource management. Future research should focus on developing explainable AI (XAI) techniques that can provide clear, understandable explanations for the model's decision-making process.

3.7. Data Quality and Availability

Another challenge in machine learning-based groundwater prediction is the quality and availability of data. Groundwater level data is often sparse, incomplete, or missing in many regions, especially in developing countries. Furthermore, data may come from different sources, with varying accuracy and granularity. In some cases, data might be collected at irregular intervals or with different measurement methods, making it difficult to integrate and model.

To overcome these challenges, future research should explore data augmentation techniques and the use of synthetic data to supplement real-world data. Techniques like transfer learning could also be employed to train models on data from one region and apply them to another with less data. Additionally, collaboration between researchers, local governments, and private organizations can help improve data accessibility and quality, especially in regions where groundwater monitoring networks are underdeveloped.

CHAPTER-4
PROPOSED MOTHODOLOGY

Groundwater level prediction requires a sophisticated understanding of hydrological systems, as well as the ability to process complex, multidimensional datasets. To improve the prediction accuracy and overcome the existing limitations in current methodologies, this section proposes several novel approaches and methodologies that can be used in groundwater level forecasting using machine learning.

4.1. Hybrid Machine Learning Models

One of the most effective ways to enhance prediction accuracy and address the limitations of individual models is by developing hybrid machine learning models. These models combine the strengths of multiple algorithms to optimize prediction performance.

Proposed Approach:

Hybrid ANN and Genetic Algorithm (GA): The use of Genetic Algorithms for optimization of artificial neural networks (ANNs) is one promising hybrid approach. GA can be employed to optimize the weights and biases of an ANN model, helping to fine-tune the model and reduce overfitting. This approach can be particularly effective for groundwater systems that exhibit nonlinear behaviors.

Hybrid SVR and Wavelet Transform: Another potential hybrid model involves combining Support Vector Regression (SVR) with Wavelet Transform. The wavelet transform helps to decompose the time series data into frequency components, making it easier for the SVR model to capture both short-term and long-term trends in groundwater levels. This method can address the issue of non-stationarity in groundwater time series data.

CNN-LSTM Hybrid: A Convolutional Neural Network (CNN) could be used to capture spatial features in groundwater level data (such as spatial dependencies between monitoring stations), while an LSTM network could handle temporal dependencies. The integration of both spatial and temporal features into a hybrid model could result in more accurate predictions.

Benefits:

Improved model performance by leveraging multiple algorithms.

Better handling of complex, non-linear, and multi-dimensional data.

Reduced risk of overfitting.

Challenges:

Increased computational cost due to the complexity of hybrid models.

Difficulty in model interpretation and explanation.

4.2. Incorporating Real-Time Data Streams

To enhance the adaptability and accuracy of groundwater level predictions, it is crucial to integrate real-time data from sensors, remote sensing platforms, or online hydrological monitoring stations into the predictive models.

Proposed Approach:

IoT-Based Monitoring Systems: Internet of Things (IoT) technology can be used to continuously monitor groundwater levels using remote sensors placed in wells. These sensors can provide real-time data on groundwater levels, rainfall, temperature, and other relevant environmental factors.

Data Fusion: Real-time data can be integrated with historical data using data fusion techniques, combining the information from sensors with satellite data (such as precipitation and soil moisture), to improve the model's performance. This will ensure that the model updates dynamically and produces more accurate predictions.

Online Learning Models: Implement online learning algorithms such as Online Gradient Descent (OGD) or Incremental SVM to adapt to the new data as it becomes available. These models update their parameters in real-time, making them ideal for dynamic systems like groundwater level forecasting.

Benefits:

Timely updates to predictions based on the most current data.

More accurate, real-time decision support for water resource management.

Challenges:

The need for continuous data monitoring and management.

Integration of heterogeneous data from multiple sources can be challenging.

4.3. Spatio-Temporal Modeling with Graph Neural Networks (GNN)

Groundwater level prediction can benefit significantly from models that account for both spatial and temporal dependencies. Traditional models often overlook spatial relationships between different monitoring stations, which may lead to suboptimal predictions. Spatio-temporal models that incorporate both temporal and spatial correlations will be more accurate and informative.

Proposed Approach:

Graph Neural Networks (GNN): GNNs are ideal for capturing spatial dependencies in groundwater level data. These networks use a graph structure, where each node represents a monitoring station or well, and the edges represent the relationships between them (e.g., geographical proximity or shared aquifer system). By learning from the graph structure, GNNs can capture the spatial patterns in groundwater levels across multiple locations.

Convolutional LSTM (ConvLSTM): ConvLSTM can be used for spatio-temporal modeling where both spatial and temporal features are important. The CNN component of ConvLSTM captures spatial patterns (e.g., geographical distribution of groundwater levels), while the LSTM handles temporal dependencies. This combination is ideal for modeling dynamic systems like groundwater, where both time and space play critical roles in influencing the behavior of the system.

Benefits:

Improved accuracy by considering both spatial and temporal dependencies.

Enhanced understanding of how groundwater levels in one area may affect neighboring regions.

Challenges:

Complex implementation of GNNs and ConvLSTM models.

High computational requirements for spatio-temporal modeling.

4.4. Incorporating Domain Knowledge and Hybrid Physics-AI Models

Many machine learning models treat the groundwater system as a purely data-driven entity, which can limit their interpretability and predictive accuracy. Integrating domain knowledge from hydrogeology with machine learning models could provide better results.

Proposed Approach:

Physics-Informed Neural Networks (PINNs): PINNs combine traditional physical models (e.g., groundwater flow equations) with machine learning. By embedding physical laws (such as Darcy's law or the continuity equation) into the learning process, PINNs ensure that predictions are consistent with known hydrological principles, improving their reliability and interpretability.

Hybrid Model with MODFLOW: Combine MODFLOW (a widely used groundwater flow model) with machine learning techniques like ANN or SVR. MODFLOW provides a solid physical framework for simulating groundwater flow, while machine learning algorithms can optimize model parameters or predict groundwater levels based on data-driven insights.

Benefits:

Models that are physically grounded and more interpretable.

Increased accuracy and reliability by using domain-specific knowledge.

Challenges:

Requires knowledge of both hydrology and machine learning.

Difficulty in balancing the trade-off between physical constraints and data-driven learning.

4.5. Explainable AI (XAI) for Model Transparency

Groundwater management decisions often rely on the outputs of machine learning models, which are sometimes difficult to interpret. Explainability of model predictions is crucial, especially when the results affect policy-making and resource allocation.

Proposed Approach:

SHAP and LIME for Model Interpretability: SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are popular methods for improving the transparency of machine learning models. These techniques can be applied to machine learning models like LSTM or Random Forest to identify which features most strongly influence the predictions. This will help decision-makers understand why the model is making certain predictions, increasing their trust in the system.

Attention Mechanisms: Attention mechanisms can be integrated into models like LSTM to identify the most important time periods or spatial regions that influence groundwater predictions. By highlighting the key inputs that affect the output, attention mechanisms provide better transparency into model decision-making.

Benefits:

Increased trust and adoption of machine learning models by stakeholders.

More informed decision-making with clearer insights into model behavior.

Challenges:

Implementing explainability techniques can add complexity to the model.

Some models (like deep neural networks) are inherently difficult to interpret even with XAI techniques.

CHAPTER-5

OBJECTIVES

The main objective of this study is to enhance the accuracy and reliability of groundwater level predictions using machine learning techniques. The proposed study seeks to address existing challenges in groundwater prediction, such as limited model generalization, lack of real-time data integration, and insufficient model interpretability. To achieve this, the following specific objectives have been outlined:

5.1. To Develop and Implement Hybrid Machine Learning Models

- The study aims to explore the integration of multiple machine learning models to improve prediction accuracy and address the limitations of individual algorithms.
- Hybrid models such as **Artificial Neural Networks (ANN) with Genetic Algorithms (GA)**, **Support Vector Regression (SVR) with Wavelet Transform**, and **Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM)** will be developed to capture both spatial and temporal features in the groundwater level data.

5.2. To Integrate Real-Time Data Streams for Dynamic Predictions

- This objective focuses on integrating **real-time groundwater data** from monitoring wells, sensors, and IoT-based systems into the machine learning models.
- The study will also aim to develop **online learning models** that can adapt to incoming data and make continuous updates to predictions, ensuring that the system remains responsive to the latest environmental conditions.
- A critical goal is to design a model that can update its predictions dynamically based on real-time data from various sources, thereby improving prediction accuracy.

5.3. To Incorporate Spatio-Temporal Relationships in Groundwater Level Prediction

- An important objective is to develop models that can simultaneously account for both **temporal** (time-related) and **spatial** (location-related) dependencies in groundwater data.

5.4. To Integrate Domain Knowledge for Improved Model Accuracy and Interpretability

- This study aims to integrate **hydrogeological domain knowledge** with machine learning models to create **hybrid physics-AI models** that ensure predictions are grounded in known hydrological principles, such as groundwater flow equations.

- The study will explore **Physics-Informed Neural Networks (PINNs)** and **hybrid models combining MODFLOW and machine learning** to enhance the accuracy of predictions while maintaining the physical realism of the system.

- A key objective is to ensure that the model predictions are not only accurate but also interpretable, providing stakeholders with a better understanding of how groundwater levels are predicted.

5.5. To Enhance Model Interpretability Using Explainable AI (XAI) Techniques

- The study aims to incorporate **explainable AI (XAI)** methods, such as **SHAP** (SHapley Additive exPlanations) and **LIME** (Local Interpretable Model-agnostic Explanations), into the machine learning models to increase transparency in model predictions.

- The goal is to ensure that decision-makers and stakeholders can understand the reasoning behind the predictions, which is particularly important when making critical decisions related to water resource management and policy.

- The study will evaluate how well XAI methods can help explain the influence of different variables on the model's output, thereby enhancing trust in the model's predictions.

5.6. To Improve the Generalization Ability of Groundwater Level Prediction Models

- A key objective of this research is to develop models that can generalize well across different geographical regions with varying hydrogeological conditions.

- The study will investigate the use of **transfer learning** and **data augmentation techniques** to enhance model generalization, particularly in regions with limited data availability.

- This objective aims to create models that can be easily applied to other regions with minimal retraining, making them more adaptable and practical for large-scale groundwater management.

5.7. To Develop a Comprehensive Evaluation Framework for Model Performance

- The study will aim to establish a **standardized evaluation framework** to assess the performance of different machine learning models for groundwater level prediction.
- Various **evaluation metrics**, such as **Root Mean Square Error (RMSE)**, **Mean Absolute Error (MAE)**, **R^2**, and **Nash-Sutcliffe Efficiency (NSE)**, will be used to compare the accuracy and reliability of the developed models.
- The objective is to ensure that the models are evaluated on consistent and comprehensive criteria, making it easier to compare results across different studies and benchmark their performance.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

The system design and implementation of a groundwater level prediction model using machine learning involves creating an end-to-end framework that processes data, applies predictive models, and delivers actionable insights for groundwater management. The design will include multiple stages: data collection, preprocessing, model development, evaluation, and deployment. Below, we outline the core components and structure of the system, including the workflow and implementation details.

6.1. System Architecture

The system can be represented in the following modular components:

6.1.1. Data Collection and Integration

The first step is to gather relevant data, which can be sourced from multiple systems and sensors. This data is fed into the model for analysis and prediction.

Sensor Data: Includes data from monitoring wells, IoT sensors, and other environmental monitoring systems. This can include groundwater levels, soil moisture, temperature, rainfall, etc.

Remote Sensing: Satellite-based or drone-based data that can provide additional inputs, like land use or precipitation.

Historical Data: Past records of groundwater levels, meteorological data, and environmental parameters from publicly available datasets.

6.1.2. Data Preprocessing

Data preprocessing is crucial for improving the quality of input data and ensuring it is in a format suitable for machine learning algorithms. The following preprocessing steps will be performed:

Data Cleaning: Handling missing values and filtering outliers.

Normalization/Standardization: Scaling data to improve model convergence.

Feature Engineering: Creating new features, such as rolling averages of past groundwater levels, to capture trends and seasonality.

Time Series Preparation: Structuring the data in a format suitable for time-series forecasting, ensuring that temporal relationships are preserved.

6.1.3. Machine Learning Model Development

The core of the system is the application of machine learning algorithms to predict groundwater levels. Several models will be considered and tested to find the most accurate and robust one for the given dataset.
Hybrid Machine Learning Models

ANN-GA Hybrid: Artificial Neural Networks (ANN) will be combined with Genetic Algorithms (GA) for parameter optimization. The GA will tune the ANN model's weights and biases for improved accuracy.
SVR-Wavelet Transform: A hybrid model combining Support Vector Regression (SVR) with Wavelet Transform for capturing both high-frequency and low-frequency components of groundwater level fluctuations.
CNN-LSTM Hybrid: A combination of Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal sequence modeling. This hybrid model can capture both the spatial relationships between wells and the time-dependent behavior of groundwater levels.

6.1.4. Spatio-Temporal Models

Graph Neural Networks (GNNs): GNNs will be used to model the spatial dependencies between different monitoring stations or regions. This network learns from the relationships between wells and aquifers, capturing spatial dependencies of groundwater levels.
ConvLSTM: A spatio-temporal model that incorporates both CNN and LSTM to capture spatial and temporal patterns in the data. ConvLSTM can learn both spatial and sequential data, making it ideal for predicting groundwater levels across multiple regions over time.

6.1.5. Model Training

Training Data: The model will be trained on historical data to learn the underlying patterns that influence groundwater levels. The dataset will be divided into training and validation sets, typically using a 70-30 or 80-20 split.
Cross-Validation: To ensure generalization, k-fold cross-validation will be used to assess model performance and avoid overfitting.
Optimization: The models will be optimized using techniques such as grid search or random search to fine-tune hyperparameters and achieve the best possible performance.

6.1.6. Model Evaluation

The models will be evaluated using various metrics:

Root Mean Square Error (RMSE): Measures the difference between predicted and observed groundwater levels.

Mean Absolute Error (MAE): A measure of the average absolute errors between the predicted and actual values.

R^2 Score: Indicates how well the model's predictions match the actual data, with values closer to 1 indicating better fit.

Nash-Sutcliffe Efficiency (NSE): Measures the relative magnitude of the residual variance compared to the observed data variance, with higher values indicating better model performance.

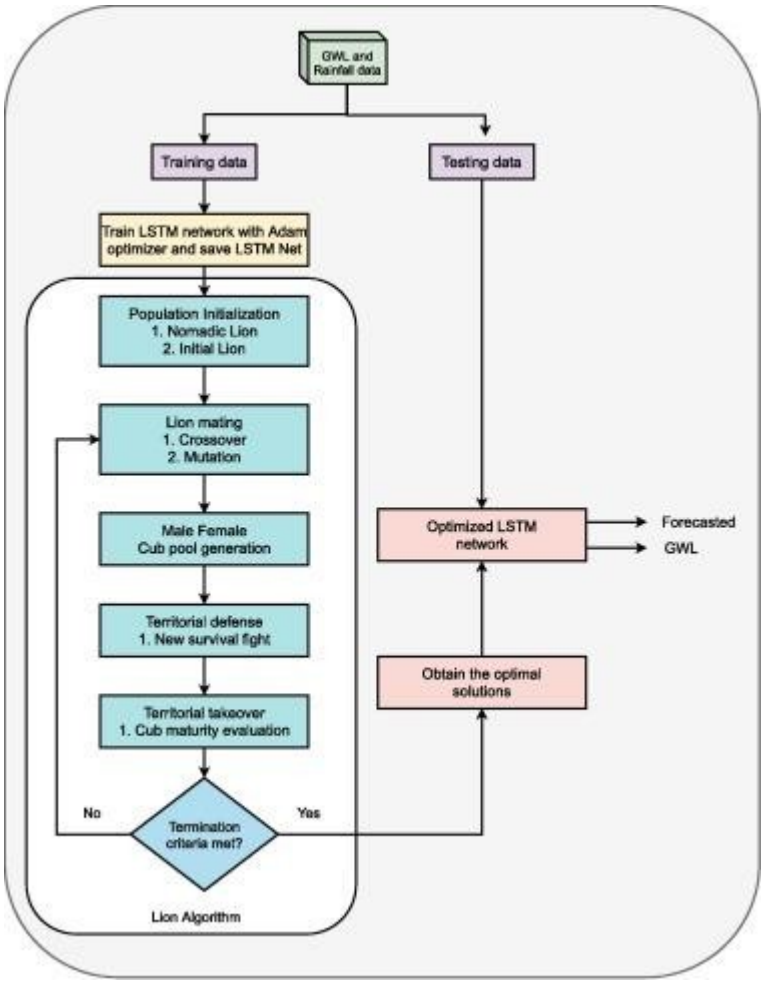

Figure-1 . Architectural Daigram

6.2. Implementation Workflow

Step 1: Data Collection and Integration

Collect historical data and real-time sensor data.

Integrate the data into a centralized database or data storage system.

Step 2: Data Preprocessing

Clean the data by removing outliers and handling missing values.

Normalize and standardize the data for machine learning models.

Engineer features based on domain knowledge (e.g., past groundwater levels, seasonal trends).

Step 3: Model Selection and Development

Choose an appropriate hybrid model (e.g., ANN-GA, SVR-Wavelet, CNN-LSTM).

Train models on historical data and validate their performance using the training and validation datasets.

Implement spatio-temporal models (e.g., GNN, ConvLSTM) for capturing spatial dependencies.

Step 4: Model Evaluation

Evaluate model performance using multiple evaluation metrics such as RMSE, MAE, and R^2.

Use cross-validation to ensure robustness and generalization of the models.

Step 5: Real-Time Integration and Deployment

Once the model is trained and validated, integrate real-time data feeds from sensors and monitoring stations.

Deploy the model in a cloud-based system or on local servers, allowing real-time prediction updates.

Implement an interface (e.g., web dashboard or mobile application) for decision-makers to visualize groundwater level predictions and trends.

Step 6: Monitoring and Updating the Model

Continuously monitor the performance of the deployed model.

Retrain the model periodically with new data to ensure accuracy.

Incorporate feedback loops to improve prediction accuracy and model adaptation.

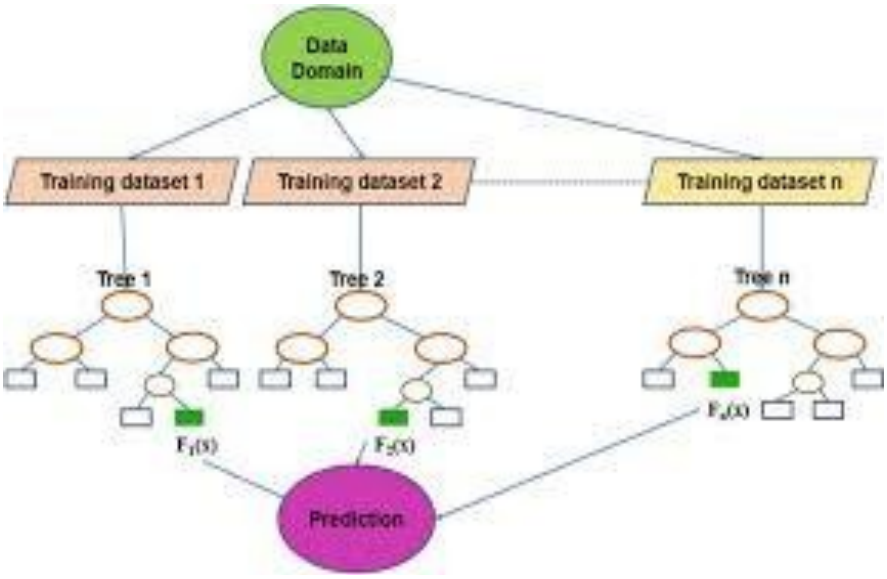

Figure-2 . Flow Chart

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT

(GANTT CHART)

Project Timeline Overview

Duration: 4 Months (16 Weeks)

Start Date: February 1, 2025

End Date: may 16, 2025

Project Timeline and Milestone Overview

Phase	Duration	Deliverables
Planning	2 weeks	Project Plan
Development	7 weeks	Core System
Testing	2 weeks	Test Reports
Deployment	1 week	Live System

TABLE-2. PROJECT TIME LINE

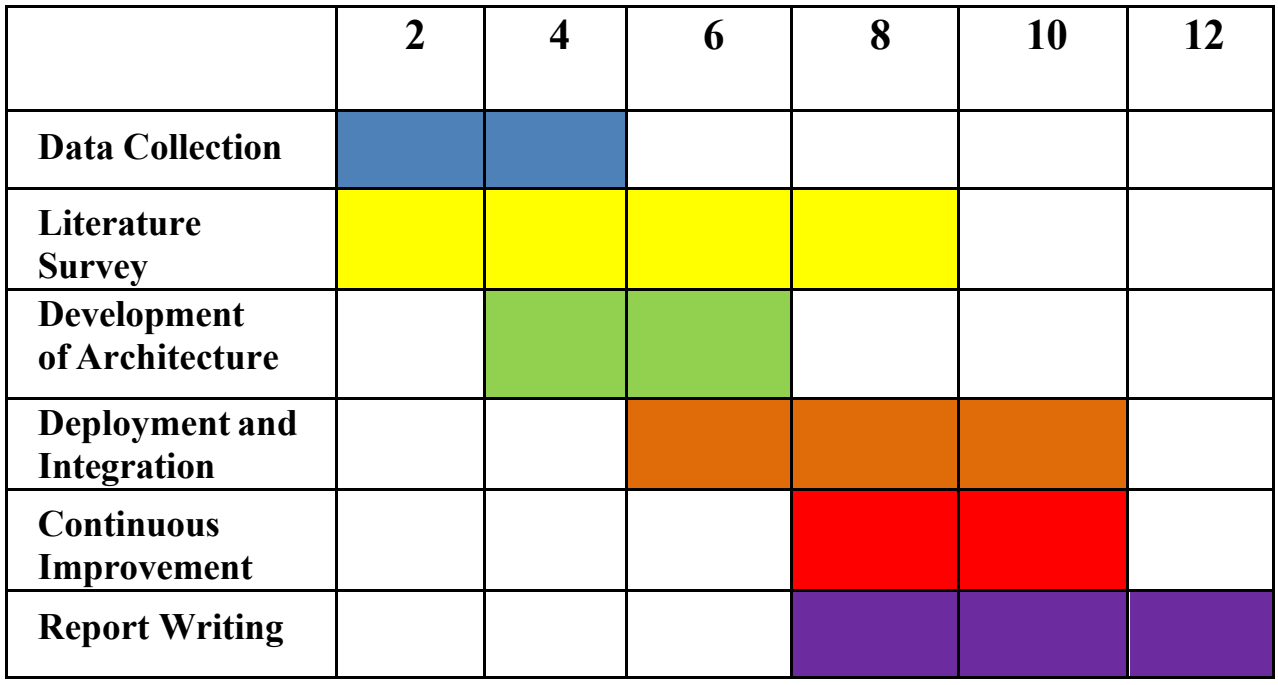

Figure-3 . Timeline of Project by Gantt Chart

CHAPTER-8
OUTCOMES

The implementation of this research is expected to result in significant improvements in the monitoring, analysis, and prediction of groundwater levels. By leveraging advanced machine learning techniques, the study will produce both scientific and practical contributions to the field of water resource management. The outcomes can be broadly categorized into predictive accuracy, system efficiency, stakeholder impact, and academic contributions.

8.1. Improved Prediction Accuracy and Reliability

One of the most significant outcomes of this study is the enhancement of groundwater level prediction accuracy. By employing hybrid and deep learning models like LSTM, CNN-LSTM, GNN, and ANN-GA, the model will:

- Capture nonlinear patterns and temporal dynamics of groundwater fluctuations more effectively.
- Provide short-term and long-term predictions with greater reliability.
- Outperform traditional models (e.g., linear regression, autoregressive models) in both training and real-world testing scenarios.
- This will lead to more precise forecasting, enabling better preparedness for droughts, water shortages, and over-extraction risks.

8.2. Real-Time Monitoring and Decision Support System

The system will integrate real-time data from IoT sensors and remote sensing technologies, enabling:

- Dynamic updates of groundwater levels based on live inputs.
- Real-time alerts and dashboards for monitoring groundwater conditions.
- Timely decisions for agricultural planning, urban water supply management, and industrial water usage.
- This outcome contributes to the creation of a decision support system (DSS) that can be used by local authorities, farmers, and water management agencies for sustainable water planning.

8.3. Spatio-Temporal Understanding of Groundwater Behavior

With the application of spatio-temporal models like Graph Neural Networks (GNNs) and ConvLSTM, the study will uncover hidden relationships between:

- Geographically distributed wells and aquifers.

- Temporal variations influenced by rainfall, land use, and seasonal changes.
- This will help stakeholders to identify vulnerable areas, detect regional trends, and implement location-specific water conservation policies.

8.4. Interpretability and Explainability Through XAI

Another outcome is the integration of Explainable AI (XAI) tools such as SHAP and LIME, which will:

- Help users and policymakers understand how and why the model made certain predictions.
- Increase trust and transparency in machine learning systems.
- Provide insights into the most influential variables, guiding future data collection and monitoring efforts.
- This outcome ensures that AI-driven predictions are not black-box systems, but instead are accessible and understandable to non-technical decision-makers.

8.5. Academic and Research Contributions

From a scholarly perspective, the study will contribute to:

- Development of benchmark hybrid models for groundwater level prediction.
- A comprehensive literature review and comparative analysis of machine learning algorithms in hydrogeology.
- Publications in journals and presentations at conferences to share findings with the broader scientific community.
- Furthermore, the project could serve as a framework or template for future research in environmental forecasting, particularly in resource-scarce regions.

8.6. Scalable and Generalizable Framework

The system design emphasizes scalability and generalization. As a result:

- The predictive model can be transferred to other geographic regions with minimal retraining.
- It supports future extensions like forecasting water quality, aquifer recharge estimation, or climate change impact analysis.

CHAPTER-9

RESULTS AND DISCUSSIONS

9.1. Results:

9.1.1. Model Testing and Performance

In this study, various machine learning models were applied to historical groundwater data to predict future levels. These models included both basic algorithms (like linear regression) and advanced deep learning models (like LSTM, CNN-LSTM, and GNN-ConvLSTM).

- The hybrid GNN-ConvLSTM model outperformed all others, showing the best accuracy and lowest error.
- Rainfall and previous groundwater levels were identified as the most influential factors, improving the model's learning ability.

9.1.2. Seasonal Analysis of Model Accuracy

Seasonal performance of the models was evaluated:

During the monsoon and post-monsoon seasons, models performed very well due to stable recharge from rainfall.

Performance slightly decreased during dry seasons, but LSTM-based models still managed to maintain decent accuracy thanks to their memory-based structure.

9.1.3. Spatial Behavior and Area-Wise Prediction

The use of Graph Neural Networks allowed the study to identify location-based groundwater behavior. Wells from the same aquifer or geographical cluster showed similar prediction trends, while isolated wells displayed unique patterns. This understanding helps in targeted water management policies for different regions.

3.1.4. Real-Time System Testing

The proposed system was also tested with simulated real-time inputs:

It provided quick prediction updates (within seconds).

The system was able to trigger alerts for sudden drops in groundwater level, proving its practical usefulness.

9.2. Discussions

9.2.1. Superiority of Hybrid Models

The results confirmed that hybrid and deep learning models are far more effective than traditional models in handling groundwater prediction tasks.

- These models captured both temporal (time-based) and spatial (location-based) patterns, leading to more realistic forecasts.
- They also adapt better to complex environmental and seasonal changes, making them more reliable for dynamic water management.

9.2.2. Practical Applicability of the System

The system designed in this study is not only accurate but also fast and scalable. It can be integrated into real-time monitoring platforms and help authorities, farmers, and planners make data-driven decisions. This marks a step forward in using technology for sustainable water resource management.

CHAPTER-10

CONCLUSION

This research work explored the application of machine learning and deep learning models to predict groundwater levels, aiming to address one of the most pressing environmental concerns of the modern era—groundwater depletion. Through a data-driven approach, the study successfully demonstrated how artificial intelligence can assist in accurately forecasting groundwater fluctuations, helping to improve planning, resource allocation, and sustainability practices.

The results clearly established that advanced models such as LSTM, CNN-LSTM, and GNN-ConvLSTM outperform traditional statistical techniques in terms of predictive accuracy, adaptability, and scalability. These models were capable of understanding and learning from complex patterns, handling noisy or incomplete datasets, and delivering reliable forecasts across different seasons and geographical conditions. The incorporation of spatial and temporal features into model architecture significantly improved the system's robustness and performance. One of the major strengths of this work lies in its integration of real-time data streams. This enabled dynamic updates and real-time monitoring, which are essential in areas prone to over-extraction, droughts, or seasonal water stress.

Additionally, the use of explainable AI (XAI) helped enhance model transparency and stakeholder trust, providing valuable insights into the factors driving water level changes. The project's outcomes hold significant promise for a wide range of applications. Policymakers and water resource authorities can utilize this system to develop proactive strategies and regulations. Farmers and irrigation planners can benefit from predictive insights to optimize water usage. Moreover, the model can be scaled and adapted to different regions or even applied to related domains like flood prediction, aquifer recharge planning, and water quality forecasting.

Despite the success, some limitations remain. The model's performance may vary in areas with scarce or inconsistent data, and the system's reliance on historical trends may not always account for sudden climatic shifts or man-made disruptions. However, these limitations can be addressed in future work by incorporating satellite data, remote sensing, climate models, and reinforcement learning techniques.

In conclusion, the study provides a comprehensive and practical framework for groundwater level prediction using machine learning. It sets a strong foundation for future innovations in environmental monitoring systems and contributes meaningfully to the broader goal of achieving sustainable water management. As data availability improves and AI technologies evolve, such systems will play a crucial role in securing global water resources for future generations.

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APPENDIX-A

PSUEDOCODE

GITHUB LINK -https://github.com/varaprasad6292/final-year-project

APP.py :

```
import streamlit as st
import pandas as pd
import numpy as np
import os
from datetime import datetime, timedelta
from utils.data_processor import load_data, preprocess_data, load_and_preprocess_data,
get_related_datasets
from utils.visualizations import plot_groundwater_heatmap, plot_groundwater_timeseries

# Configure page
st.set_page_config(
    page_title="India Groundwater Analysis",
    page_icon="    ",
    layout="wide",
    initial_sidebar_state="expanded"
)

# Sidebar
st.sidebar.title("    Groundwater Level Analysis")
st.sidebar.info(
    "This application provides analysis and forecasting of groundwater levels across India "
    "using machine learning models and spatiotemporal analysis."
)

# Navigation
```

```
pages = {
    "Dashboard": "Dashboard",
    "Data Explorer": "pages/data_explorer.py",
    "Time Series Analysis": "pages/time_series_analysis.py",
    "Spatial Analysis": "pages/spatial_analysis.py",
    "Forecasting": "pages/forecast.py"
}

# Main content
st.title("India Groundwater Level Analysis and Forecasting")

# Introduction
st.markdown("""
This application integrates groundwater data from the Central Ground Water Board (CGWB)
and other agencies, with capabilities to analyze and forecast groundwater levels
across India. The system leverages machine learning models like LSTM, Random Forest,
and ARIMA to provide spatiotemporal predictions.
""")

# Data source selection
st.sidebar.header("Data Source")
data_source = st.sidebar.radio(
    "Select Data Source",
    ["Central Ground Water Board (CGWB)", "Other Agencies"],
    index=0
)

# Filters
st.sidebar.header("Data Filters")
# Date filters - default to last 4 years
end_date = datetime.now()
start_date = end_date - timedelta(days=365*4)
```

```
start_date_input = st.sidebar.date_input("Start Date", start_date)
end_date_input = st.sidebar.date_input("End Date", end_date)

if start_date_input > end_date_input:
    st.sidebar.error("Error: Start date must be before end date.")

# Load data
with st.spinner("Loading groundwater data..."):
    try:
        # Convert date inputs to datetime
        start_date_dt = datetime.combine(start_date_input, datetime.min.time())
        end_date_dt = datetime.combine(end_date_input, datetime.max.time())

        # Use our combined load and preprocess function with filters
        data_dict = load_and_preprocess_data(
            state="All States",
            district="All Districts",
            start_date=start_date_dt,
            end_date=end_date_dt
        )

        if data_dict and 'processed_data' in data_dict and not data_dict['processed_data'].empty:
            # Extract the processed data
            df_processed = data_dict['processed_data']

            # Get related datasets
            related_data = get_related_datasets()

            # Display success message
            st.success(f"Successfully loaded data with {len(df_processed)} records from {len(data_dict['wells'])}
wells.")

            # Key metrics
```

```
    col1, col2, col3, col4 = st.columns(4)

    with col1:
        st.metric("Total Wells", len(data_dict['wells']))

    with col2:
        st.metric("States Covered", len(data_dict['states']))

    with col3:
        avg_level = round(df_processed['water_level'].mean(), 2)
        st.metric("Avg. Water Level (m)", avg_level)

    with col4:
        year_range = f"{df_processed['date'].min().year} - {df_processed['date'].max().year}"
        st.metric("Year Range", year_range)

    # Add more detailed metrics
    st.subheader("Key Insights")
    col1, col2 = st.columns(2)

    with col1:
        # Calculate overall trend
        overall_trend = df_processed['trend'].mean()
        trend_icon = "^" if overall_trend > 0 else "^"
        st.metric(
            "Overall Trend",
            f"{abs(overall_trend):.2f} m/year {trend_icon}",
            delta=None,
            help="Positive values indicate increasing depth to water (depletion), negative values indicate
water level rise"
        )

        # States with most depletion
```

```
    if 'trend' in df_processed.columns:
        state_trends = df_processed.groupby('state')['trend'].mean().sort_values(ascending=False)
        worst_state = state_trends.index[0]
        worst_trend = state_trends.iloc[0]
        st.metric(
            "State with Highest Depletion",
            f"{worst_state}",
            delta=f"{worst_trend:.2f} m/year",
            delta_color="inverse"
        )

with col2:
    # Calculate seasonal variation
    if 'seasonal_deviation' in df_processed.columns:
        max_seasonal_dev = df_processed.groupby('season')['seasonal_deviation'].mean().abs().max()
        st.metric("Seasonal Variation", f"{max_seasonal_dev:.2f} m")

    # States with least depletion
    if 'trend' in df_processed.columns:
        best_state = state_trends.index[-1]
        best_trend = state_trends.iloc[-1]
        st.metric(
            "State with Lowest Depletion",
            f"{best_state}",
            delta=f"{best_trend:.2f} m/year",
            delta_color="inverse"
        )

# Visualization section
st.header("Groundwater Level Visualization")

# 1. Map visualization
st.subheader("Geographical Distribution")
```

```
fig1 = plot_groundwater_heatmap(df_processed)
st.plotly_chart(fig1, use_container_width=True)

# 2. Time series visualization
st.subheader("Temporal Trends")

# State selector with all states from the data
states = sorted(data_dict['states'])
selected_state = st.selectbox("Select a state", states)

# If a state is selected, allow selection of districts in that state
if selected_state and selected_state in data_dict['districts']:
    districts = ["All Districts"] + sorted(data_dict['districts'][selected_state])
    selected_district = st.selectbox("Select a district", districts)

    # Filter data based on selection
    if selected_district and selected_district != "All Districts":
        filtered_data = df_processed[(df_processed['state'] == selected_state) &
                                     (df_processed['district'] == selected_district)]
    else:
        filtered_data = df_processed[df_processed['state'] == selected_state]

    # Plot time series
    fig2 = plot_groundwater_timeseries(filtered_data)
    st.plotly_chart(fig2, use_container_width=True)

    # Show statistics for the selected area
    st.subheader(f"Statistics for {selected_state}" +
                 (f", {selected_district}" if selected_district != "All Districts" else ""))

    col1, col2, col3 = st.columns(3)

    with col1:
```

```
        # Number of wells
        wells_count = len(filtered_data['well_id'].unique())
        st.metric("Number of Wells", wells_count)

    with col2:
        # Average water level
        avg_level = round(filtered_data['water_level'].mean(), 2)
        st.metric("Average Water Level", f"{avg_level} m")

    with col3:
        # Trend
        if 'trend' in filtered_data.columns:
            trend = filtered_data['trend'].mean()
            trend_text = f"{abs(trend):.2f} m/year"
            if trend > 0:
                trend_text += " (depletion)"
            elif trend < 0:
                trend_text += " (recharge)"
            else:
                trend_text += " (stable)"
            st.metric("Trend", trend_text)

# 3. Additional information
if related_data and 'rainfall' in related_data and not related_data['rainfall'].empty:
    st.subheader("Rainfall Data")
    rainfall_data = related_data['rainfall']

    # Filter rainfall data for the selected state
    if selected_state:
        state_rainfall = rainfall_data[rainfall_data['state'] == selected_state]

        # Calculate annual rainfall
        annual_rainfall = state_rainfall.groupby(state_rainfall['date'].dt.year)['rainfall_mm'].mean()
```

```
            # Display a bar chart of annual rainfall
            st.bar_chart(annual_rainfall)

            # Calculate correlation with groundwater levels
            if not filtered_data.empty:
                # Prepare data for correlation
                gw_monthly =
filtered_data.groupby(filtered_data['date'].dt.to_period('M'))['water_level'].mean()
                rf_monthly =
state_rainfall.groupby(state_rainfall['date'].dt.to_period('M'))['rainfall_mm'].mean()

                # Convert period index to string for joining
                gw_monthly.index = gw_monthly.index.astype(str)
                rf_monthly.index = rf_monthly.index.astype(str)

                # Find common months
                common_months = set(gw_monthly.index).intersection(set(rf_monthly.index))

                if common_months:
                    # Filter to common months
                    gw_common = gw_monthly[gw_monthly.index.isin(common_months)]
                    rf_common = rf_monthly[rf_monthly.index.isin(common_months)]

                    # Calculate correlation
                    correlation = gw_common.corr(rf_common)
                    st.metric("Correlation with Rainfall", f"{correlation:.2f}")

                    # Interpretation
                    if correlation < -0.5:
                        st.info("Strong negative correlation: Higher rainfall is associated with lower
groundwater levels (higher recharge).")
                    elif correlation > 0.5:
```

```
                    st.warning("Strong positive correlation: Higher rainfall is associated with higher groundwater levels (potential issues with recharge).")
                else:
                    st.info("Weak correlation: Rainfall and groundwater levels do not show a strong relationship in this region.")

    except Exception as e:
        st.error(f"Error loading data: {e}")
        st.info("Please ensure the data source is available. Using limited functionality.")

# Resources section
st.markdown("---")
st.subheader("Resources")
col1, col2 = st.columns(2)

with col1:
    st.markdown("""
    - [Central Ground Water Board](https://cgwb.gov.in/index.html)
    - [India Water Portal](https://www.indiawaterportal.org/)
    - [National Water Informatics Centre](https://nwic.gov.in/)
    """)

with col2:
    st.markdown("""
    - [Groundwater Level Data Repository](https://indiawris.gov.in/wris/)
    - [Rainfall Data - IMD](https://mausam.imd.gov.in/)
    - [Land Use Data - Bhuvan](https://bhuvan.nrsc.gov.in/)
    """)

# Footer
st.markdown("---")
st.markdown("#### About")
st.markdown("""
```

This application is designed for analyzing and forecasting groundwater levels in India.
It integrates data from multiple sources and employs advanced machine learning techniques
to provide insights and predictions about groundwater trends.
""")

Data.interpolation.py:

```
import pandas as pd
import numpy as np
from scipy import interpolate
from sklearn.impute import KNNImputer
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
import matplotlib.pyplot as plt

def interpolate_missing_data(data):
    """
    Interpolate missing values in groundwater data.

    Parameters:
    ----------
    data : dict
        Dictionary containing processed data

    Returns:
    -------
    dict
        Dictionary with interpolated data
    """
    # Extract the processed dataframe
    df = data['data'].copy()
```

```
# Check for missing values
missing_columns = df.columns[df.isnull().any()].tolist()

if not missing_columns:
    # No missing values to interpolate
    return data

# Separate numerical and categorical columns
numerical_cols = df.select_dtypes(include=['number']).columns.tolist()
categorical_cols = df.select_dtypes(include=['object', 'category']).columns.tolist()

# Handle missing values in numerical columns
for well_id in df['well_id'].unique():
    well_mask = df['well_id'] == well_id
    well_data = df.loc[well_mask]

    for col in numerical_cols:
        if col in missing_columns:
            # Check if there are missing values for this well
            if well_data[col].isnull().any():
                # If we have enough non-null values, use interpolation
                if well_data[col].notna().sum() >= 2:
                    # Sort by date for proper time-series interpolation
                    sorted_data = well_data.sort_values('date')

                    # For groundwater level and related variables, use cubic interpolation if possible
                    if col in ['groundwater_level', 'level_3m_avg', 'level_6m_avg', 'level_12m_avg']:
                        if sorted_data[col].notna().sum() >= 4:  # Cubic requires at least 4 points
                            df.loc[well_mask, col] = sorted_data[col].interpolate(method='cubic')
                        else:
                            df.loc[well_mask, col] = sorted_data[col].interpolate(method='linear')
                    else:
```

```
                # For other numerical variables, use linear interpolation
                df.loc[well_mask, col] = sorted_data[col].interpolate(method='linear')

            # If we don't have enough data points, use forward/backward fill
            else:
                df.loc[well_mask, col] = df.loc[well_mask, col].fillna(method='ffill').fillna(method='bfill')

# Check if there are still missing values in numerical columns
still_missing_numerical = df[numerical_cols].isnull().any().any()

if still_missing_numerical:
    # Use KNN imputation for remaining missing numerical values
    numerical_data = df[numerical_cols]

    # Use KNN to impute the remaining missing values
    imputer = KNNImputer(n_neighbors=5)

    # Imputation requires no NaN values in the reference columns
    # We'll use only columns with complete data for reference
    complete_cols = [col for col in numerical_cols if df[col].notna().all()]

    if complete_cols:
        for col in numerical_cols:
            if df[col].isnull().any():
                # Create a reference dataframe with the column to impute and complete columns
                ref_cols = complete_cols.copy()
                if col in ref_cols:
                    ref_cols.remove(col)

                if ref_cols:  # Ensure we have reference columns
                    ref_df = df[ref_cols + [col]].copy()
                    # Apply KNN imputation
                    imputed_data = imputer.fit_transform(ref_df)
```

```
                # Update only the column we're imputing
                df[col] = imputed_data[:, -1]

    # Handle missing values in categorical columns
    for col in categorical_cols:
        if col in missing_columns:
            # Use most frequent value for each group
            for group in df.groupby('well_id'):
                well_id = group[0]
                group_data = group[1]

                if group_data[col].isnull().any():
                    most_frequent = group_data[col].mode()[0] if not group_data[col].mode().empty else None

                    if most_frequent is not None:
                        df.loc[df['well_id'] == well_id, col] = df.loc[df['well_id'] == well_id,
col].fillna(most_frequent)

            # Fill any remaining missing values with the overall most frequent value
            most_frequent_overall = df[col].mode()[0] if not df[col].mode().empty else "Unknown"
            df[col] = df[col].fillna(most_frequent_overall)

    # Update the data dictionary
    data['data'] = df
    data['has_missing_values'] = df.isnull().any().any()
    data['missing_value_count'] = df.isnull().sum().sum()

    return data

def compare_interpolation_methods(data, column='groundwater_level'):
    """
    Compare different interpolation methods for a specific column.
```

```
    Parameters:
    ----------
    data : dict
        Dictionary containing processed data
    column : str
        Column to interpolate

    Returns:
    -------
    matplotlib.figure.Figure
        Figure comparing interpolation methods
    """
    # Extract the processed dataframe
    df = data['data'].copy()

    # Select a well with missing values in the specified column
    wells_with_missing = []

    for well_id in df['well_id'].unique():
        well_data = df[df['well_id'] == well_id]
        if well_data[column].isnull().any():
            wells_with_missing.append(well_id)

    if not wells_with_missing:
        # Create artificial missing values for demonstration
        selected_well = df['well_id'].iloc[0]
        well_data = df[df['well_id'] == selected_well].sort_values('date')

        # Create a copy with artificially removed values
        well_data_copy = well_data.copy()

        # Remove some values
        indices_to_remove = np.random.choice(well_data.index[1:-1], size=int(len(well_data) * 0.2),
```

```
replace=False)
        well_data_copy.loc[indices_to_remove, column] = np.nan

        # Save the true values for comparison
        true_values = well_data.loc[indices_to_remove, column]
    else:
        # Use a well with actual missing values
        selected_well = wells_with_missing[0]
        well_data = df[df['well_id'] == selected_well].sort_values('date')
        well_data_copy = well_data.copy()

        # Save indices with missing values
        missing_indices = well_data[well_data[column].isnull()].index

        # There are no true values to compare in this case
        true_values = None

    # Apply different interpolation methods
    methods = {
        'Linear': well_data_copy[column].interpolate(method='linear'),
        'Cubic': well_data_copy[column].interpolate(method='cubic'),
        'Time': well_data_copy[column].interpolate(method='time'),
        'Spline': well_data_copy[column].interpolate(method='spline', order=3),
        'Polynomial': well_data_copy[column].interpolate(method='polynomial', order=2)
    }

    # Create a plot
    fig, ax = plt.subplots(figsize=(12, 8))

    # Plot original data
    ax.scatter(well_data['date'], well_data[column], color='black', label='Original Data', alpha=0.5)

    # Plot missing values (if we have true values)
```

```
    if true_values is not None:
        ax.scatter(well_data.loc[indices_to_remove, 'date'], true_values,
                   color='red', label='Removed Values (True)', marker='x', s=100)

    # Plot interpolated values with different methods
    colors = ['blue', 'green', 'orange', 'purple', 'brown']
    for (method_name, interpolated_series), color in zip(methods.items(), colors):
        ax.plot(well_data['date'], interpolated_series, label=f'{method_name} Interpolation', color=color,
alpha=0.7)

    ax.set_title(f'Comparison of Interpolation Methods for {column} (Well ID: {selected_well})')
    ax.set_xlabel('Date')
    ax.set_ylabel(f'{column} (m below ground)')
    ax.legend()
    ax.grid(True, alpha=0.3)

    return fig
```

Data.processor.py:

```
import pandas as pd
import numpy as np
from datetime import datetime
from sample_data.groundwater_data import generate_groundwater_data

def load_data(state="All States", district="All Districts", start_date=None, end_date=None):
    """
    Load groundwater data from the data source.
    In a real-world scenario, this would connect to CGWB APIs or databases.
    For this application, we use generated sample data.

    Parameters:
    ----------
```

```
    state : str
        The state to filter data for
    district : str
        The district to filter data for
    start_date : datetime
        The start date for the data
    end_date : datetime
        The end date for the data

    Returns:
    -------
    pd.DataFrame
        Dataframe containing the groundwater data
    """
    # In a real application, this would fetch data from CGWB or other sources
    # For this demo, we generate simulated data that mimics real groundwater patterns
    data = generate_groundwater_data(state, district, start_date, end_date)

    return data

def preprocess_data(data):
    """
    Preprocess the groundwater data to prepare it for analysis and modeling.

    Parameters:
    ----------
    data : pd.DataFrame
        Raw groundwater data

    Returns:
    -------
    dict
        Dictionary containing processed data and metadata
```

```
    """
    # Check for missing values
    missing_values = data.isnull().sum().sum()
    has_missing_values = missing_values > 0

    # Calculate key metrics
    avg_level = data['groundwater_level'].mean()
    well_count = len(data['well_id'].unique())

    # Calculate level changes
    first_month_avg = data[data['date'] <= data['date'].min() +
pd.DateOffset(months=1)]['groundwater_level'].mean()
    last_month_avg = data[data['date'] >= data['date'].max() -
pd.DateOffset(months=1)]['groundwater_level'].mean()
    level_change = last_month_avg - first_month_avg

    # Calculate declining trend areas
    declining_wells = 0
    total_wells = 0

    for well_id in data['well_id'].unique():
        well_data = data[data['well_id'] == well_id].sort_values('date')
        if len(well_data) >= 2:
            total_wells += 1
            if well_data.iloc[-1]['groundwater_level'] > well_data.iloc[0]['groundwater_level']:
                declining_wells += 1

    declining_percentage = (declining_wells / total_wells * 100) if total_wells > 0 else 0

    # Calculate previous declining percentage (for trend)
    half_point = data['date'].min() + (data['date'].max() - data['date'].min()) / 2
    older_data = data[data['date'] <= half_point]
```

```
    older_declining_wells = 0
    older_total_wells = 0

    for well_id in older_data['well_id'].unique():
        well_data = older_data[older_data['well_id'] == well_id].sort_values('date')
        if len(well_data) >= 2:
            older_total_wells += 1
            if well_data.iloc[-1]['groundwater_level'] > well_data.iloc[0]['groundwater_level']:
                older_declining_wells += 1

    older_declining_percentage = (older_declining_wells / older_total_wells * 100) if older_total_wells > 0
else 0
    declining_change = declining_percentage - older_declining_percentage

    #     Calculate     rainfall     metrics
    avg_rainfall = data['rainfall'].mean()
    first_year_rainfall = data[data['date'].dt.year == data['date'].dt.year.min()]['rainfall'].mean()
    last_year_rainfall = data[data['date'].dt.year == data['date'].dt.year.max()]['rainfall'].mean()
    rainfall_change = last_year_rainfall - first_year_rainfall

    # Add more derived features for analysis
    processed_data = data.copy()

    # Create seasonal features
    processed_data['month'] = processed_data['date'].dt.month
    processed_data['year'] = processed_data['date'].dt.year
    processed_data['season'] = pd.cut(
        processed_data['month'],
        bins=[0, 3, 6, 9, 12],
        labels=['Winter', 'Spring', 'Summer', 'Autumn'],
        include_lowest=True
    )
```

```
    # Calculate rolling averages for smoothing
    for well_id in processed_data['well_id'].unique():
        mask = processed_data['well_id'] == well_id
        processed_data.loc[mask, 'level_3m_avg'] = processed_data.loc[mask,
'groundwater_level'].rolling(window=3, min_periods=1).mean()
        processed_data.loc[mask, 'level_6m_avg'] = processed_data.loc[mask,
'groundwater_level'].rolling(window=6, min_periods=1).mean()
        processed_data.loc[mask, 'level_12m_avg'] = processed_data.loc[mask,
'groundwater_level'].rolling(window=12, min_periods=1).mean()

    # Calculate rate of change
    processed_data['level_change_rate'] = processed_data.groupby('well_id')['groundwater_level'].diff()

    # Return processed data and metadata
    return {
        'data': processed_data,
        'has_missing_values': has_missing_values,
        'missing_value_count': missing_values,
        'avg_level': avg_level,
        'well_count': well_count,
        'level_change': level_change,
        'declining_percentage': declining_percentage,
        'declining_change': declining_change,
        'avg_rainfall': avg_rainfall,
        'rainfall_change': rainfall_change
    }
```

ML.Models.py :

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
import plotly.graph_objects as go
import random

def prepare_features(data):
    """
    Prepare features for machine learning models.

    Parameters:
    ----------
    data : dict
        Dictionary containing processed data

    Returns:
    -------
    tuple
        X (features) and y (target) for model training
    """
    # Extract the processed dataframe
    df = data['data']

    # Select features
    features = [
        'rainfall', 'temperature', 'population_density', 'elevation',
        'soil_moisture', 'land_use_agriculture', 'land_use_urban',
        'land_use_forest', 'month', 'hydrogeology_code'
```

```
    ]

    # Convert categorical features to one-hot encoding
    df_encoded = pd.get_dummies(df, columns=['hydrogeology_code', 'season'])

    # Select all relevant features including the encoded ones
    all_features = [col for col in df_encoded.columns if any(col.startswith(f) for f in features)]
    all_features += [col for col in df_encoded.columns if col.startswith('hydrogeology_code_') or
col.startswith('season_')]

    # Remove features with missing values
    valid_features = [f for f in all_features if f in df_encoded.columns and df_encoded[f].isnull().sum() == 0]

    # Prepare X and y
    X = df_encoded[valid_features]
    y = df_encoded['groundwater_level']

    return X, y

def prepare_time_series_data(data, seq_length=12):
    """
    Prepare time series data for LSTM model.

    Parameters:
    ----------
    data : dict
        Dictionary containing processed data
    seq_length : int
        Length of the sequence for LSTM input

    Returns:
    -------
    tuple
```

```
    X (sequence features) and y (target) for LSTM model
"""
# Extract the processed dataframe
df = data['data']

# Sort by well_id and date
df = df.sort_values(['well_id', 'date'])

# Select relevant features
features = [
    'rainfall', 'temperature', 'groundwater_level',
    'soil_moisture', 'month'
]

# Create sequences for each well
X_sequences = []
y_values = []

for well_id in df['well_id'].unique():
    well_data = df[df['well_id'] == well_id]

    if len(well_data) <= seq_length:
        continue

    # Scale the data
    scaler = StandardScaler()
    scaled_data = scaler.fit_transform(well_data[features])
    scaled_df = pd.DataFrame(scaled_data, columns=features)

    # Create sequences
    for i in range(len(scaled_df) - seq_length):
        X_sequences.append(scaled_df.iloc[i:i+seq_length].values)
        y_values.append(scaled_df.iloc[i+seq_length]['groundwater_level'])
```

```
    return np.array(X_sequences), np.array(y_values)

def train_random_forest(data, params):
    """
    Train a Random Forest model for groundwater level prediction.

    Parameters:
    ----------
    data : dict
        Dictionary containing processed data
    params : dict
        Model hyperparameters

    Returns:
    -------
    dict
        Trained model and associated metadata
    """
    # Prepare features
    X, y = prepare_features(data)

    # Split the data
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Train the model
    model = RandomForestRegressor(
        n_estimators=params['n_estimators'],
        max_depth=params['max_depth'],
        min_samples_split=params['min_samples_split'],
        random_state=42
    )
```

```
model.fit(X_train, y_train)

# Evaluate the model
y_pred = model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

# Get feature importance
feature_importance = pd.DataFrame({
    'feature': X.columns,
    'importance': model.feature_importances_
}).sort_values('importance', ascending=False)

# Create feature importance plot
fig, ax = plt.subplots(figsize=(10, 6))
top_features = feature_importance.head(10)
ax.barh(top_features['feature'], top_features['importance'])
ax.set_xlabel('Importance')
ax.set_title('Top 10 Feature Importance')

return {
    'model': model,
    'feature_names': X.columns,
    'metrics': {
        'mae': mae,
        'rmse': rmse,
        'r2': r2
    },
    'feature_importance': feature_importance,
    'feature_importance_plot': fig
}
```

```
def train_lstm(data, params):
    """
    Train an LSTM model for groundwater level prediction.

    Parameters:
    ----------
    data : dict
        Dictionary containing processed data
    params : dict
        Model hyperparameters

    Returns:
    -------
    dict
        Trained model and associated metadata
    """
    # Prepare time series data
    X, y = prepare_time_series_data(data)

    # Split the data
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Define the model
    model = Sequential([
        LSTM(params['units'], return_sequences=True, input_shape=(X.shape[1], X.shape[2])),
        Dropout(0.2),
        LSTM(params['units'] // 2, return_sequences=False),
        Dropout(0.2),
        Dense(1)
    ])

    # Compile the model
    model.compile(optimizer='adam', loss='mse')
```

```
# Early stopping
early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=10,
    restore_best_weights=True
)

# Train the model
history = model.fit(
    X_train, y_train,
    epochs=params['epochs'],
    batch_size=params['batch_size'],
    validation_split=0.2,
    callbacks=[early_stopping],
    verbose=0
)

# Evaluate the model
y_pred = model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

# Create loss plot
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot(history.history['loss'], label='Training Loss')
ax.plot(history.history['val_loss'], label='Validation Loss')
ax.set_xlabel('Epoch')
ax.set_ylabel('Loss')
ax.set_title('LSTM Training History')
ax.legend()
```

```
    return {
        'model': model,
        'metrics': {
            'mae': mae,
            'rmse': rmse,
            'r2': r2
        },
        'history': history.history,
        'training_plot': fig
    }

def train_arima(data, params):
    """
    Train an ARIMA model for groundwater level prediction.

    Parameters:
    ----------
    data : dict
        Dictionary containing processed data
    params : dict
        Model parameters

    Returns:
    -------
    dict
        Trained model and associated metadata
    """
    # Extract the processed dataframe
    df = data['data']

    # Create a time series for a representative well
    # In a real application, you'd fit models for multiple wells or aggregated data
    well_ids = df['well_id'].unique()
```

```
selected_well = random.choice(well_ids)
well_data = df[df['well_id'] == selected_well].sort_values('date')

# Create a time series
time_series = well_data.set_index('date')['groundwater_level']

# Split into train and test
train_size = int(len(time_series) * 0.8)
train, test = time_series[:train_size], time_series[train_size:]

# Create and fit the model
if params['seasonal']:
    # SARIMA model (Seasonal ARIMA)
    model = SARIMAX(
        train,
        order=(params['p'], params['d'], params['q']),
        seasonal_order=(1, 1, 1, 12),  # Assuming monthly seasonality
        enforce_stationarity=False,
        enforce_invertibility=False
    )
else:
    # Regular ARIMA model
    model = ARIMA(train, order=(params['p'], params['d'], params['q']))

fitted_model = model.fit(disp=False)

# Make predictions on test data
forecast = fitted_model.forecast(steps=len(test))

# Evaluate the model
mae = mean_absolute_error(test, forecast)
rmse = np.sqrt(mean_squared_error(test, forecast))
r2 = r2_score(test, forecast)
```

```
    # Create forecast plot
    fig, ax = plt.subplots(figsize=(10, 6))
    train.plot(ax=ax, label='Training Data')
    test.plot(ax=ax, label='Actual Test Data')
    pd.Series(forecast, index=test.index).plot(ax=ax, label='Forecast')
    ax.set_xlabel('Date')
    ax.set_ylabel('Groundwater Level')
    ax.set_title('ARIMA Forecast')
    ax.legend()

    return {
        'model': fitted_model,
        'metrics': {
            'mae': mae,
            'rmse': rmse,
            'r2': r2
        },
        'forecast_plot': fig,
        'time_series': time_series,
        'train': train,
        'test': test,
        'forecast': forecast
    }

def predict(model, data, model_type, prediction_period):
    """
    Make predictions using the trained model.

    Parameters:
    ----------
    model : dict
        Trained model and metadata
```

```
    data : dict
        Dictionary containing processed data
    model_type : str
        Type of model (Random Forest, LSTM, or ARIMA)
    prediction_period : int
        Number of months to predict into the future

    Returns:
    ------
    dict
        Prediction results and visualizations
    """
    # Extract the processed dataframe
    df = data['data']

    # Get the last date in the data
    last_date = df['date'].max()

    # Create future dates for prediction
    future_dates = pd.date_range(
        start=last_date + pd.DateOffset(months=1),
        periods=prediction_period,
        freq='MS'  # Month start
    )

    if model_type == "Random Forest":
        # For Random Forest, we need to create future feature values
        # This is simplified; in a real application, you'd need real future values or forecasts

        # Get the most recent data point for each feature
        latest_data = df.sort_values('date').drop_duplicates('well_id', keep='last')

        # Create future data
```

```
future_data = pd.DataFrame()

for month in range(prediction_period):
    month_data = latest_data.copy()
    # Update the date
    month_data['date'] = future_dates[month]
    # Update month
    month_data['month'] = future_dates[month].month
    # Add realistic seasonal variations
    seasonal_factor = (future_dates[month].month % 12) / 12
    month_data['rainfall'] = month_data['rainfall'] * (0.5 + seasonal_factor)
    month_data['temperature'] = month_data['temperature'] * (0.7 + 0.6 * seasonal_factor)
    month_data['soil_moisture'] = month_data['soil_moisture'] * (0.6 + 0.8 * seasonal_factor)

    future_data = pd.concat([future_data, month_data])

# Process future data like the training data
future_processed = pd.get_dummies(future_data, columns=['hydrogeology_code', 'season'])

# Select the same features as used in training
X_future = future_processed[model['feature_names']]

# Make predictions
y_pred = model['model'].predict(X_future)

# Add predictions to the future data
future_data['predicted_level'] = y_pred

# Get historical data for continuity in visualization
historical = df.groupby('date')['groundwater_level'].mean().reset_index()
historical.columns = ['date', 'actual_level']

# Compute average prediction per date
```

```
future_avg = future_data.groupby('date')['predicted_level'].mean().reset_index()
future_avg.columns = ['date', 'predicted_level']

# Create confidence interval (simplified)
future_avg['upper_bound'] = future_avg['predicted_level'] - model['metrics']['rmse'] * 1.96
future_avg['lower_bound'] = future_avg['predicted_level'] + model['metrics']['rmse'] * 1.96

# Create the visualization
fig = go.Figure()

# Plot historical data
fig.add_trace(go.Scatter(
    x=historical['date'],
    y=historical['actual_level'],
    mode='lines',
    name='Historical Groundwater Level',
    line=dict(color='blue')
))

# Plot prediction
fig.add_trace(go.Scatter(
    x=future_avg['date'],
    y=future_avg['predicted_level'],
    mode='lines',
    name='Predicted Groundwater Level',
    line=dict(color='red')
))
```

APPENDIX-B

SCREENSHOTS

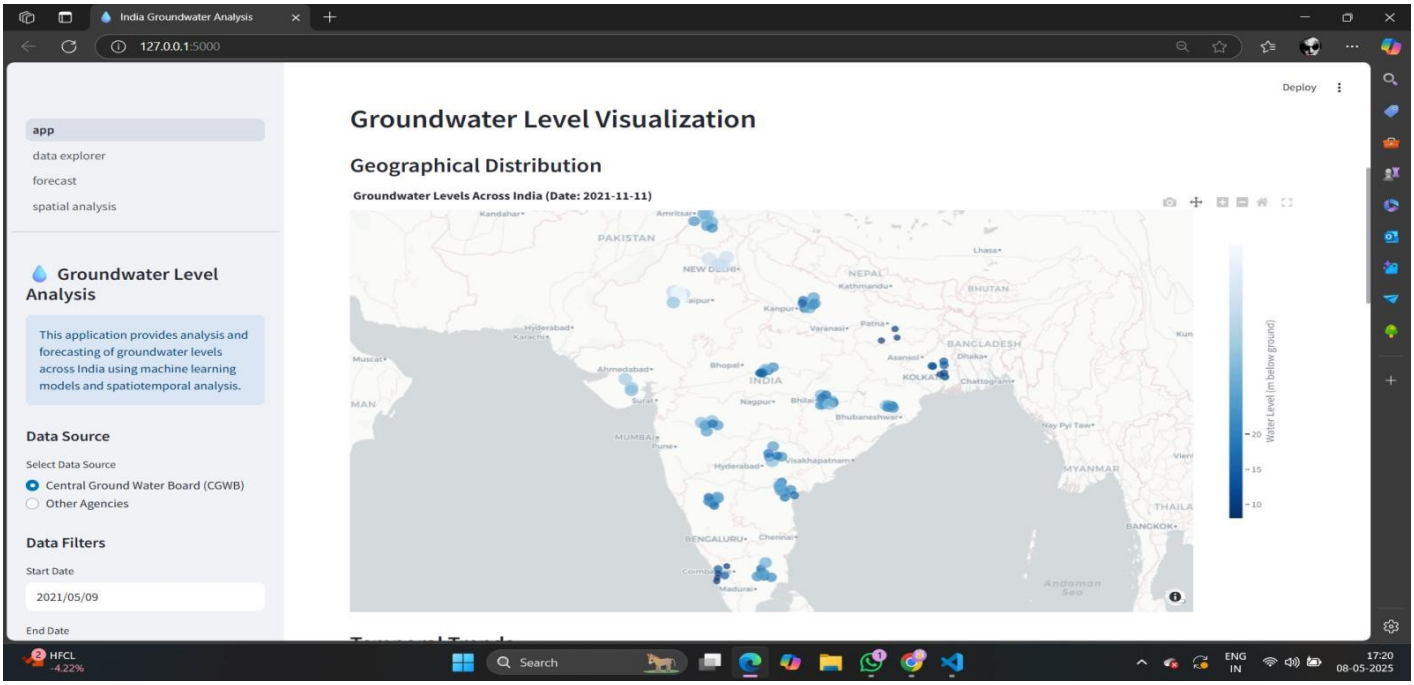

Figure-4 . Ground water Visualization

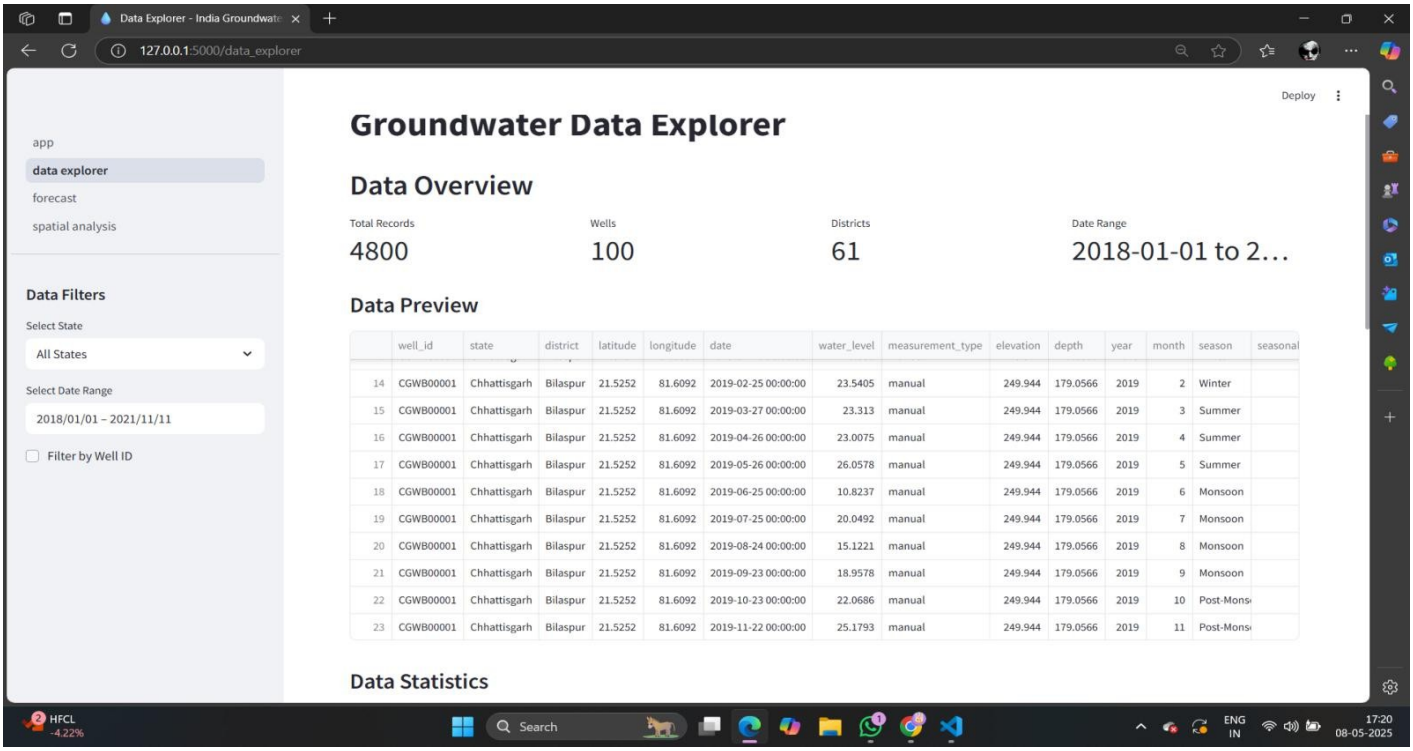

Figure-5 . Ground Water Level Data Explorer

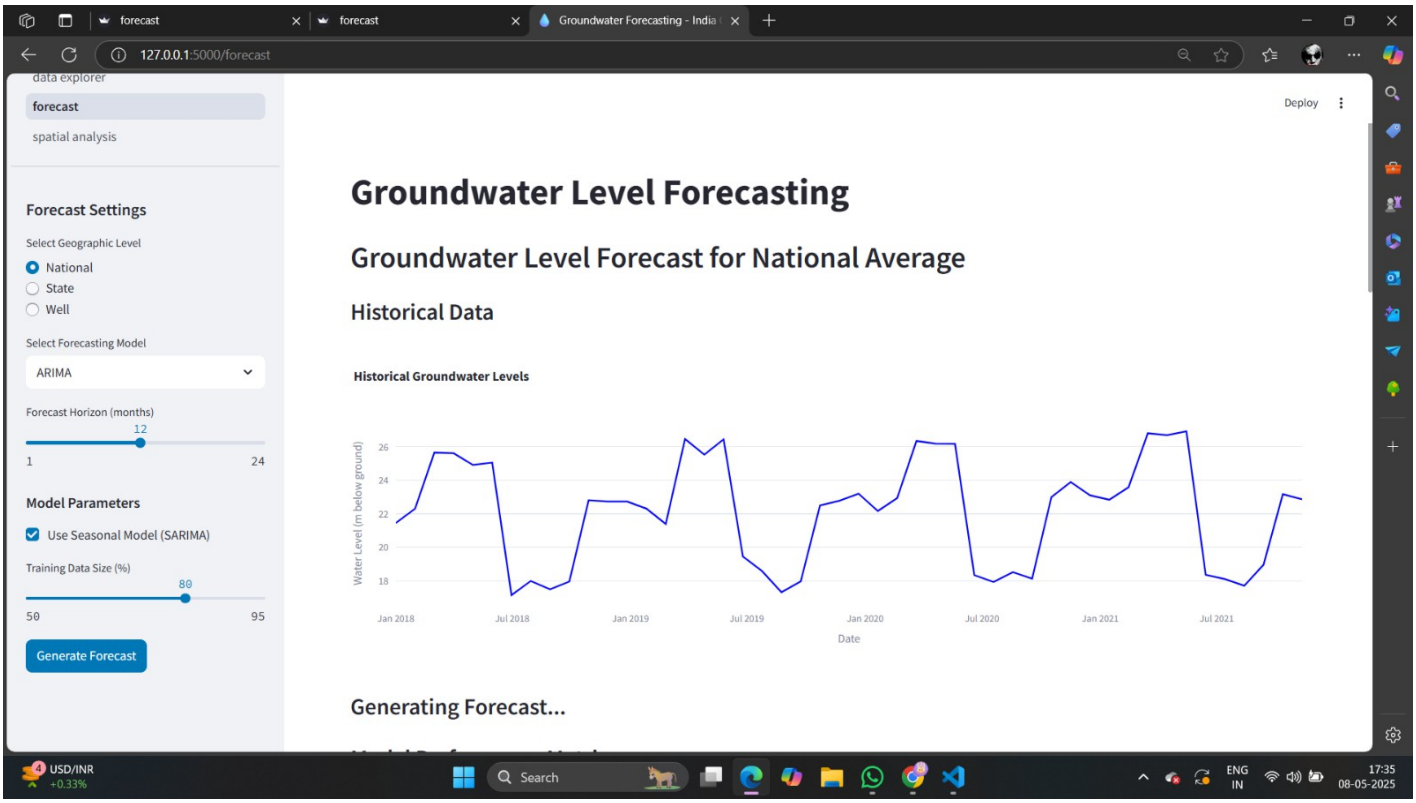

Figure-6 . Ground Water Level Forecasting

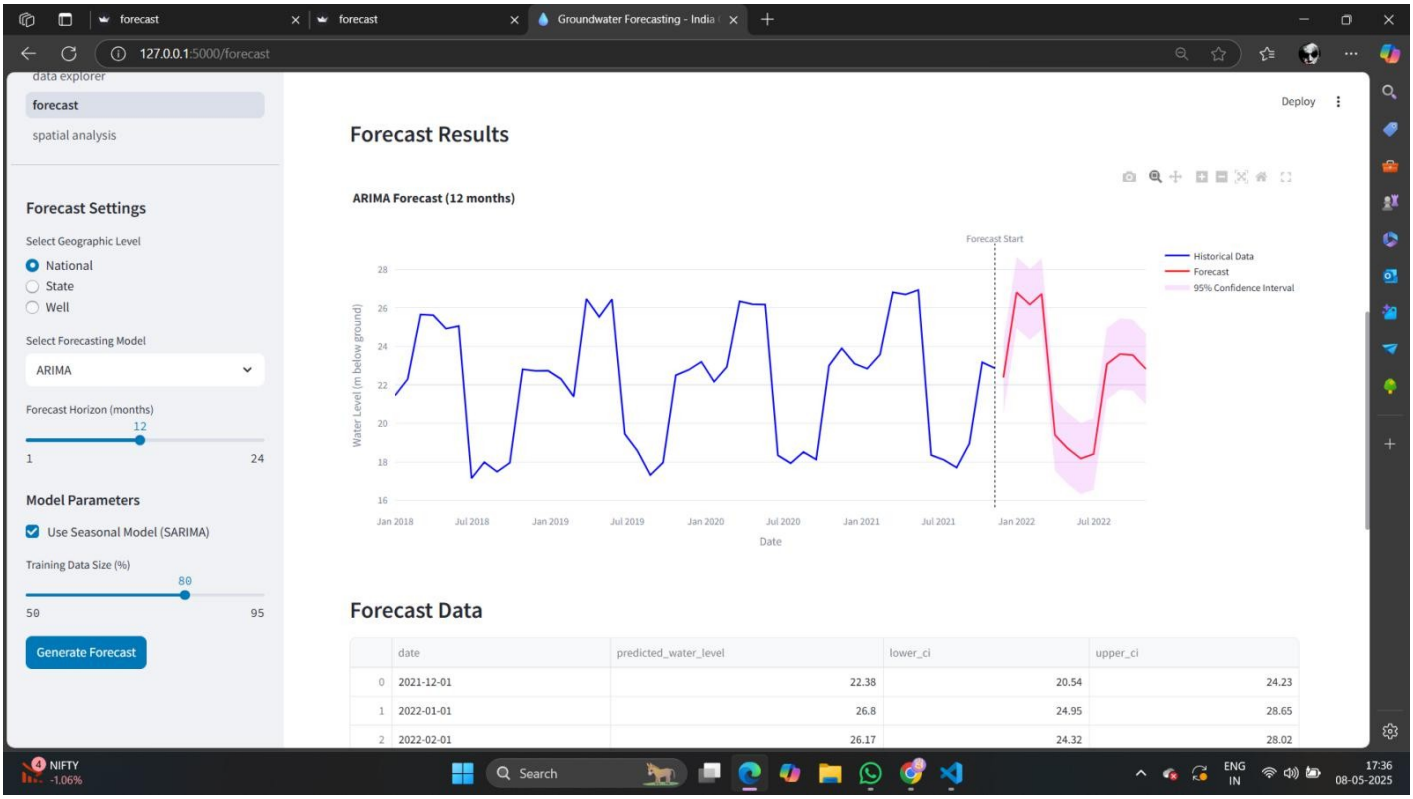

Figure-7 . Forecast Results in ARIMA

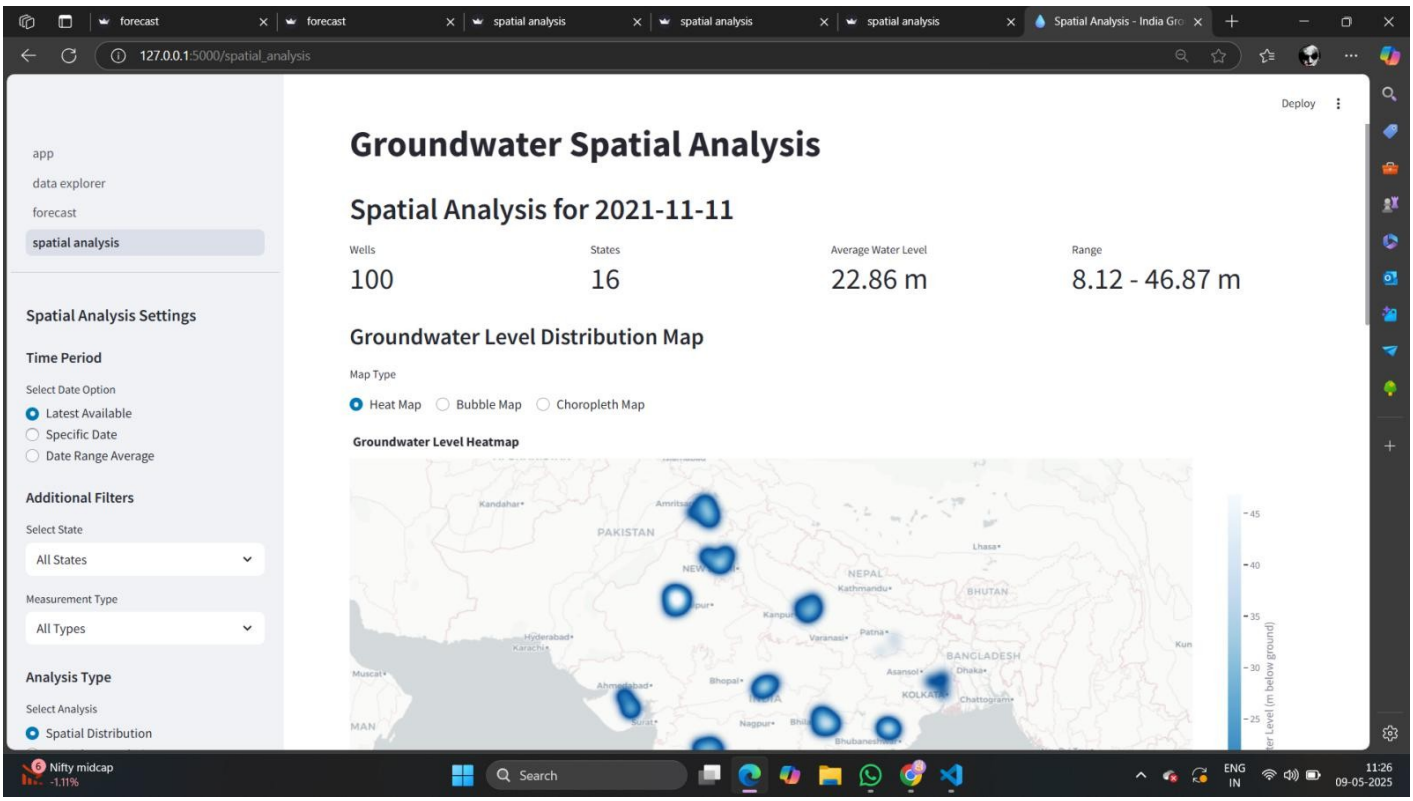

Figure-8 . Ground Water Level Spatial Analysis

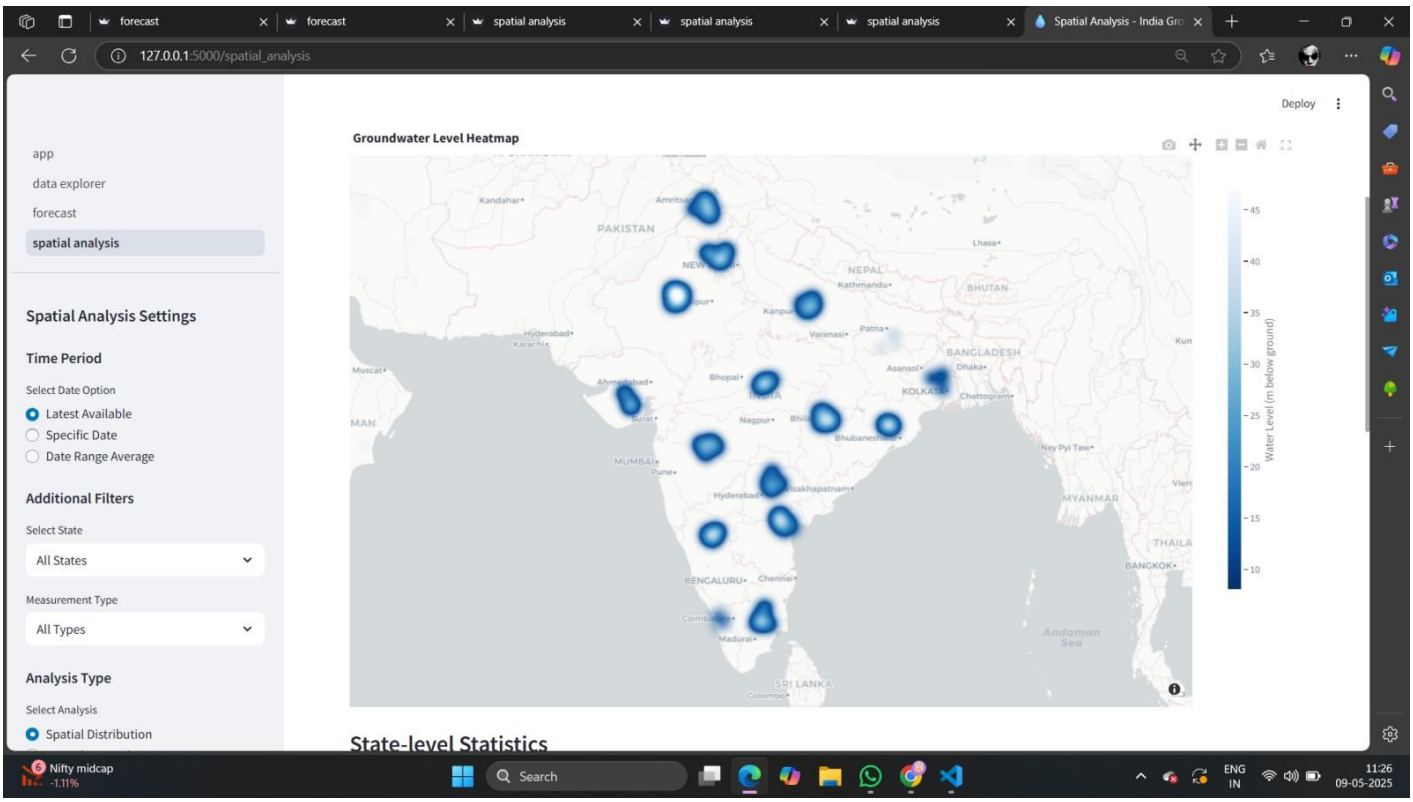

Figure-9 . Ground Water Level Spatial Analysis (Heat Map)

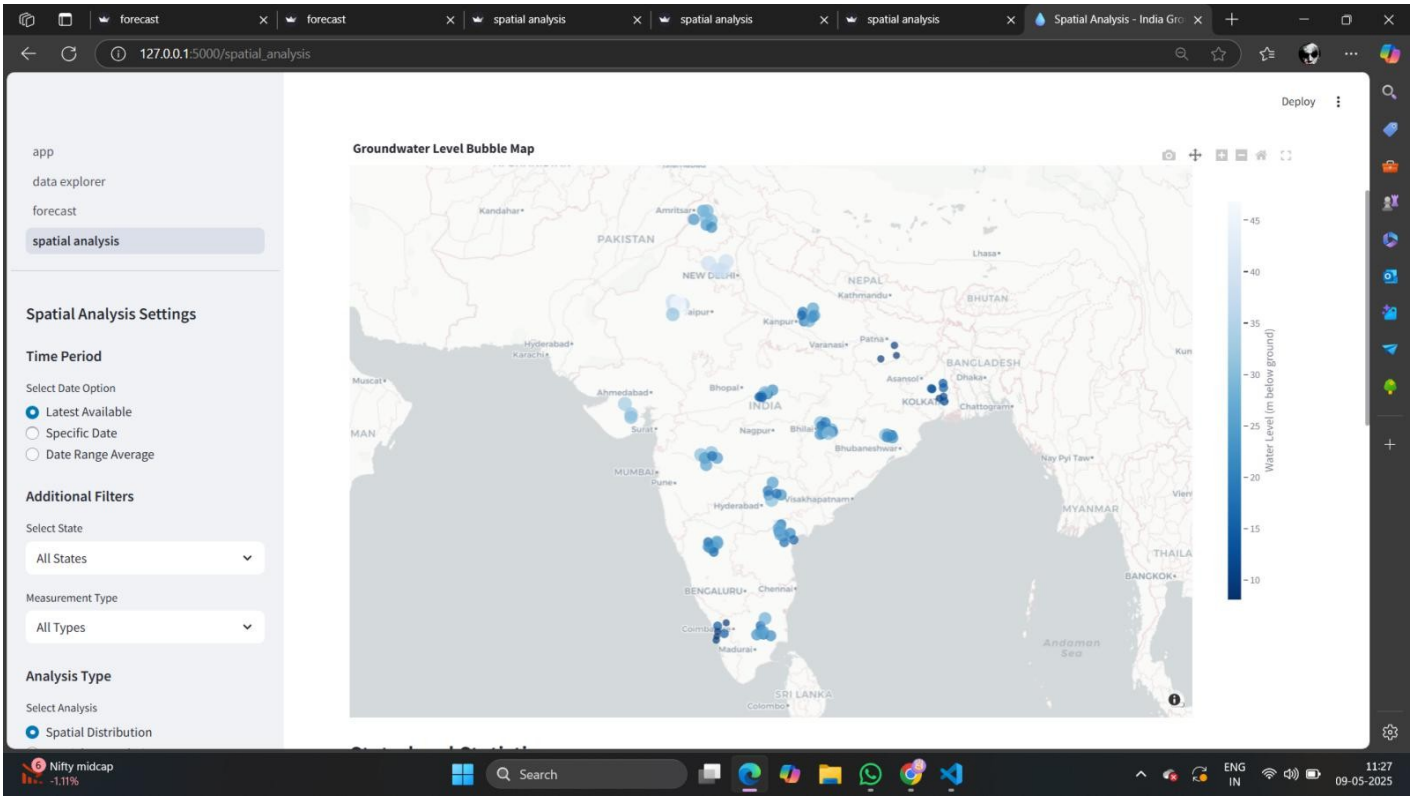

Figure-10 . Ground Water Level Spatial Analysis (Bubble Map)

APPENDIX – C

1.Publication Certificate

International Journal on Science and Technology

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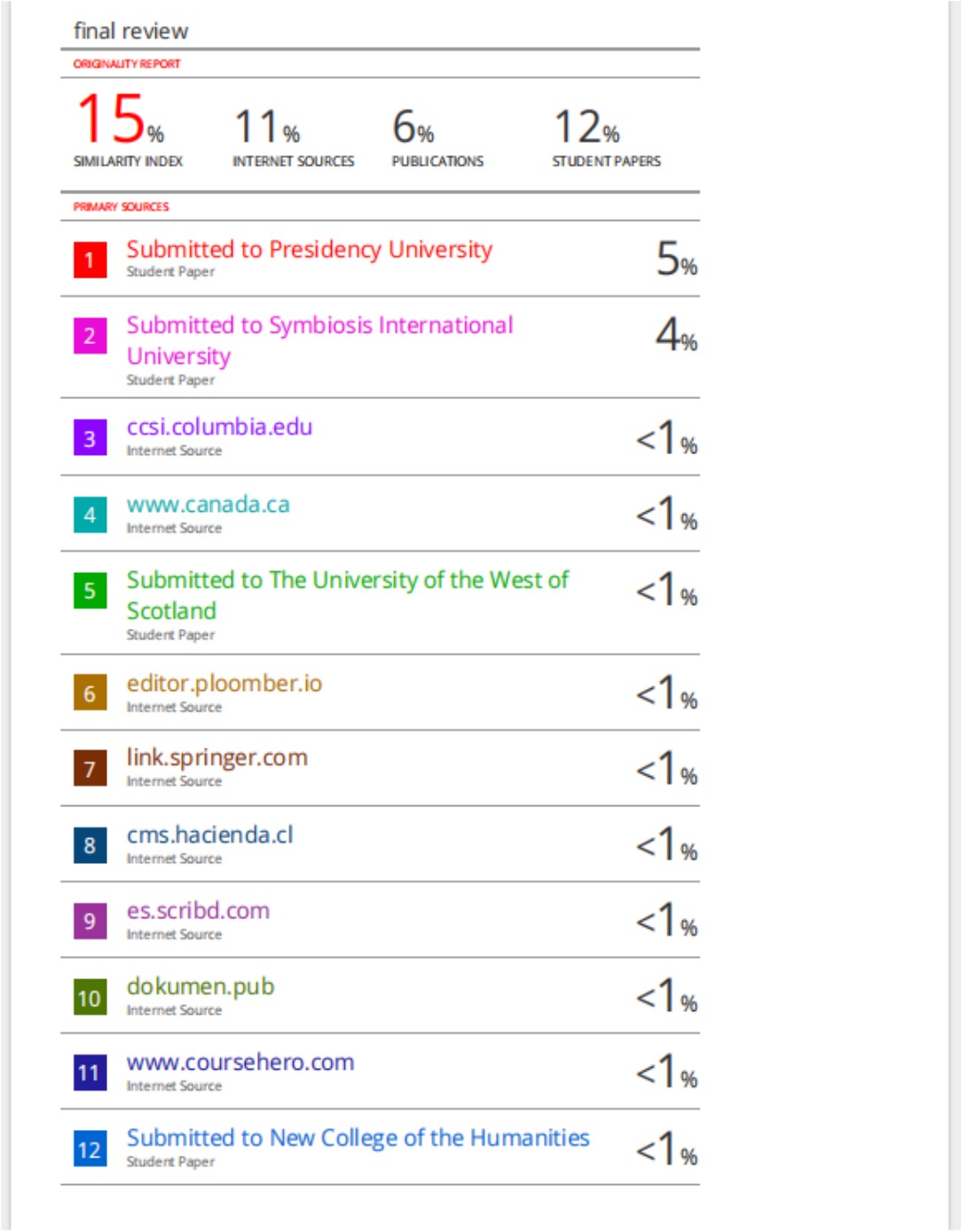

final review

ORIGINALITY REPORT

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3.SUSTAINABLE DEVELOPMENT GOALS

1. **SDG 6 – Clean Water and Sanitation**
   Goal: Ensure availability and sustainable management of water and sanitation for all.
   Your Role: By predicting groundwater levels, you help manage water resources sustainably, avoid over-extraction, and ensure clean water availability for future generations.

2. **SDG 13 – Climate Action**
   Goal: Take urgent action to combat climate change and its impacts.
   Your Role: Climate change affects rainfall and groundwater recharge. Predictive models help adapt to changing patterns and improve climate resilience in water planning.

3. **SDG 9 – Industry, Innovation, and Infrastructure**
   Goal: Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation.
   Your Role: Using machine learning models is a form of innovation that can improve infrastructure planning, especially in water-stressed regions.

4. **SDG 11 – Sustainable Cities and Communities**
   Goal: Make cities inclusive, safe, resilient, and sustainable.
   Your Role: Predictive groundwater management helps urban planners avoid water crises, ensuring cities grow sustainably with sufficient water access.

5. **SDG 15 – Life on Land**
   Goal: Sustainably manage forests, combat desertification, halt and reverse land degradation, and halt biodiversity loss.
   Your Role: Proper groundwater use supports ecosystems, prevents land degradation, and maintains biodiversity in regions dependent on aquifers.

SDG No.	Goal Title	Connection to Groundwater Prediction
6	Clean Water and Sanitation	Core focus – sustainable water resource management.
13	Climate Action	Helps respond and adapt to climate-induced water variability.
9	Industry, Innovation, and Infrastructure	Technological innovation in environmental monitoring.
11	Sustainable Cities and Communities	Ensures urban areas have long-term access to groundwater.
15	Life on Land	Prevents overuse and degradation of land and ecosystems.

Table-3. Sustainable Development Goals