



Ground Vision: A Review of Machine Learning-Based Groundwater Level Prediction and Risk Analysis

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ABSTRACT—

Groundwater is one of the most important sources of water for agriculture, domestic consumption, and industrial activities, yet its availability is strongly influenced by rainfall, recharge, temperature, evapotranspiration, hydrogeological characteristics, agricultural activity, irrigation demand, and human extraction. Conventional groundwater-prediction systems mainly forecast a future water-level value and give limited insight into the drivers behind that value or the effect of possible interventions. This paper reviews the application of Artificial Intelligence (AI), Machine Learning (ML), time-series forecasting, explainable AI, and decision-support techniques for groundwater-level prediction and management. The reviewed literature covers algorithms such as Random Forest, Support Vector Machine, XGBoost, Long Short-Term Memory networks, and hybrid ML–DL models, together with SHAP-based explainability, GIS-based risk mapping, drought early-warning systems, and IoT-based groundwater monitoring. Building on these approaches, GroundVision is proposed as a groundwater intelligence and policy-simulation platform that separates natural climate-driven groundwater behaviour from anthropogenic stress using a dual-layer prediction architecture, explains its predictions using SHAP, classifies locations into groundwater-risk categories, and allows administrators to test rainfall, irrigation, and drip-irrigation adoption scenarios through an interactive What-If Policy Sandbox. The review highlights that, while existing studies achieve strong prediction accuracy, they rarely combine forecasting, human-stress attribution, explainability, risk classification, and policy simulation within a single decision-support system, which is the gap that GroundVision aims to address.

Keywords—Deep Learning, Explainable AI, GIS, Groundwater Level Prediction, Groundwater Risk Assessment, IoT Monitoring, Machine Learning, Policy Simulation, Random Forest, SHAP, Time-Series Forecasting, Water Resource Management, XGBoostIntroduction

I. Introduction

Groundwater is a critical natural resource that supports agriculture, domestic water requirements, and industrial activities. Its availability varies with rainfall, recharge, temperature, evapotranspiration, soil and aquifer characteristics, agricultural intensity, irrigation demand, and groundwater extraction. Conventional groundwater-prediction approaches generally provide a future groundwater-level value based on historical observations and environmental variables. Although such forecasts are useful, a prediction alone rarely explains why groundwater levels are rising or falling, and it does not allow decision-makers to test how a proposed intervention — such as increased drip-irrigation adoption or reduced borewell growth — might change future groundwater conditions.

Machine Learning (ML) provides an opportunity to model the complex, nonlinear relationships between groundwater levels and multiple environmental and human variables. Algorithms such as Random Forest, Support Vector Machine, XGBoost, and deep-learning architectures including LSTM and CNN-LSTM have been used to learn patterns from historical groundwater and environmental data, and a growing number of studies report high prediction accuracy when adequate historical data is available [1]–[3], [7]–[12], [19]–[22]. However, groundwater management is not only a forecasting problem: administrators also need to understand the dominant drivers of groundwater stress, classify locations by risk level, and compare candidate interventions before implementing them.

This review therefore surveys ML- and AI-based approaches for groundwater-level prediction, explainable AI methods such as SHAP for interpreting those predictions, GIS- and ML-based groundwater risk and drought assessment, and IoT-based groundwater monitoring infrastructure. Building on this literature, the paper describes GroundVision, a groundwater intelligence and policy-simulation prototype that combines a climate-baseline model, a human-stress residual model, SHAP-based explainability, a groundwater-risk engine, and an interactive What-If Policy Sandbox within a single GIS-based dashboard.

II. Problem Statement

Groundwater monitoring produces valuable historical observations, but converting these observations into effective decision-support information remains difficult for several reasons.

A. Limited Explanation of Predictions

Many groundwater-forecasting systems predict future groundwater levels without clearly attributing a decline or rise to rainfall, temperature, recharge, agricultural demand, irrigation, or other factors [1], [2].

B. Complex, Delayed Groundwater Dynamics

Groundwater does not respond immediately to rainfall or recharge events. Delayed responses, seasonal cycles, and local hydrogeological conditions can significantly influence groundwater behaviour, which time-series and sequence models such as LSTM attempt to capture [19]–[22].

C. Incomplete Extraction Data

Direct groundwater-extraction measurements are often unavailable at fine spatial scales, particularly for agricultural use, so human-induced stress must frequently be estimated through observable proxy variables such as crop intensity, irrigated area, and irrigation demand [5], [8].

D. Climate-Only Prediction Limitations

A model based primarily on climate variables may fail to capture sudden increases in agricultural demand or irrigation-related stress, since human activity can create additional pressure even when climatic conditions are stable [3], [9].

E. Lack of Interactive Policy Simulation

Administrators often want to know how groundwater conditions would change if irrigation demand fell, drip-irrigation adoption rose, or rainfall patterns shifted, but most existing prediction studies stop at forecasting and do not provide an interactive scenario-testing environment [4], [14].

GroundVision addresses these gaps through dual-layer prediction, proxy-based anthropogenic-stress modelling, SHAP-based explainability, GIS-based risk assessment, and an interactive Policy Sandbox, as discussed in the following sections.

III. Literature Survey

Recent research shows increasing use of Machine Learning and Artificial Intelligence for groundwater-level prediction, explainability, risk assessment, and groundwater infrastructure monitoring. The reviewed literature is grouped below by theme.

A. Classical and Ensemble Machine Learning for Groundwater Prediction

Subhadarsini et al. analysed groundwater dynamics in the Kharun River Basin, Chhattisgarh, using data from 143 observation wells combined with GIS mapping and multi-feature correlation; Logistic Regression achieved high classification accuracy, supporting groundwater conservation planning [1]. Wang applied Random Forest Regression using rainfall, river flow, temperature, saturation deficit, and evaporation as inputs, reporting prediction errors below 5% and identifying rainfall as the most influential factor [3]. Tiwari and Verma compared several advanced ML techniques for groundwater-level prediction using regional climate-model data [4]. Sarkar et al. evaluated K-Nearest Neighbour, Random Forest, Support Vector Machine, XGBoost, and Polynomial Regression for spatially varying groundwater-level prediction, finding that XGBoost captured strong input–output relationships while KNN generalised well with limited site data [7]. Pham et al. compared seven ML models — including Random Tree, Random Forest, MSP, SVM, and REP Tree — for groundwater-level prediction in a drought-prone area of Bangladesh [8]. Li et al. used multiple linear regression, MARS, ANN, Random Forest, and Gradient Boosting Regression to predict depth-to-water-table in a data-scarce, water-scarcity region for guiding borehole drilling decisions [9]. Martínez-Santos et al. proposed a tree-regressor-based surrogate model for spatio-temporal groundwater-level prediction incorporating recharge and pumping covariates [10].

B. Deep Learning and Hybrid ML–DL Models

Tiwari and Himanshu compared Random Forest, SVM, LSTM, and hybrid ML–DL models for time-series groundwater-level forecasting, reporting that Random Forest achieved the strongest classical-ML performance while hybrid approaches improved accuracy further [2]. Feng et al. evaluated CNN, RNN, SVM, Decision Tree, Random Forest, and GAN architectures for groundwater-level prediction using extraction rate, rainfall, and river-flow inputs, finding that CNN performed best among the models tested [12]. Gezici et al. combined an Extreme Learning Machine with EEMD, VMD, and EWT signal-decomposition techniques for monthly groundwater-level prediction in a snow-dominated basin [19]. Hu et al. proposed a hybrid CNN–LSTM model that extracts multivariate hydro-meteorological features with a CNN component and models temporal dependencies with an LSTM component for groundwater-level forecasting in an arid, human-influenced basin [20]. Sun et al. combined LSTM networks with a physics-based model to improve daily-scale groundwater-level prediction in an intensively pumped alluvial fan [21]. Wunsch et al. compared LSTM, CNN, and NARX architectures for groundwater-level forecasting with artificial neural networks, providing a widely cited benchmark for deep-learning groundwater models [22]. Zowam and Milewski produced the first statewide groundwater-level-anomaly prediction for Arizona by combining machine learning with geostatistical interpolation across two distinct aquifer systems [11].

C. Explainable AI for Groundwater and Hydrological Models

Because ensemble and deep-learning groundwater models behave as black boxes, several recent studies incorporate SHAP (SHapley Additive exPlanations) to attribute predictions to individual input features. Habibi and Hassanpour combined Ridge Regression and Random Forest with XGBoost-guided feature re-weighting and SHAP-based interpretation to forecast lake/groundwater storage equivalent from satellite data, showing that SHAP made the dominant climatic drivers of the forecast transparent [13]. Related hydrological XAI studies show that SHAP is increasingly used to identify the contribution of rainfall, temperature, and human-demand proxies to groundwater and streamflow predictions, moving groundwater modelling from a pure forecasting exercise toward an interpretable decision-support tool.

D. GIS-Based Risk Assessment and Drought Early Warning

Arabameri et al. integrated meteorological, hydrological, agricultural, and socio-economic factors with ensemble machine-learning models and geospatial techniques to assess drought risk, producing spatial risk maps useful for early-warning planning [14]. Jibhakate and Katpatal applied machine-learning algorithms to predict rainfall and groundwater for the Nagpur Division specifically, which is directly relevant to the regional context of this project [5]. Such GIS-integrated risk-classification approaches inform the risk-engine component of GroundVision, which classifies groundwater conditions into stress categories analogous to established groundwater-resource-assessment terminology.

E. IoT-Based Groundwater Monitoring Infrastructure

Since ML-based groundwater prediction depends on the availability of reliable, timely groundwater observations, several studies have developed low-cost sensing infrastructure for groundwater monitoring. Kombo et al. designed a low-cost, low-power LoRa-GSM IoT system with energy-harvesting integration for groundwater monitoring in a resource-constrained setting [15]. Bo and Cheng combined image recognition with IoT communication to remotely monitor groundwater level and generate flood or low-water alerts [16]. Oppus et al. developed a remote, real-time sensor system for groundwater level and quality monitoring [17], while Kondapuram et al. presented an IoT-based real-time underground water-level sensor system evaluated under field conditions [18]. These works indicate a practical pathway for extending prototypes such as GroundVision — which currently uses synthetic and secondary data — toward real-time IoT-fed groundwater intelligence.

F. Summary of Findings and Positioning of GroundVision

The reviewed studies confirm that Machine Learning can effectively model the nonlinear relationships between groundwater levels and environmental variables, that ensemble methods such as Random Forest and XGBoost provide strong baseline performance, and that hybrid deep-learning models can capture delayed and seasonal groundwater dynamics. Explainable AI, GIS-based risk mapping, and IoT monitoring are each active but largely separate research threads. However, the surveyed literature seldom integrates prediction, human-stress attribution, explainability, risk classification, and interactive policy simulation within one platform. GroundVision is positioned to combine these threads into a single groundwater-intelligence and decision-support system.

IV. Proposed Methodology

A. Review Methodology

This review focuses on literature concerning: (i) machine-learning-based groundwater-level prediction; (ii) deep-learning and time-series forecasting; (iii) Random Forest, XGBoost, and other ensemble methods; (iv) explainable artificial intelligence, particularly SHAP; (v) GIS- and ML-based groundwater risk and drought assessment; and (vi) IoT-based groundwater monitoring infrastructure. The reviewed studies were used to identify common techniques, advantages, limitations, and opportunities for building GroundVision.

B. Data Collection

GroundVision combines multiple categories of data. Groundwater-level observations are sourced from the Central Ground Water Board (CGWB) framework [6] and aligned spatially and temporally with rainfall, temperature, recharge, and hydrogeological data. Agricultural variables include cropping pattern, irrigated area, crop intensity, and irrigation-demand indicators. Satellite-derived variables include NDVI, land-use, and soil-moisture information. For the current prototype, a synthetic dataset covering 14 tehsils of the Nagpur district across 2010–2024 and four seasons was constructed with realistic underlying structure so that the train/test split is genuinely learnable while real data sources (India-WRIS, IMD, data.gov.in, and the Minor Irrigation Census) are integrated.

C. Data Preprocessing and Feature Engineering

Preprocessing includes handling missing observations, removing duplicate records, detecting abnormal values, standardising spatial and temporal information, and integrating groundwater and climate observations. Lagged, seasonal, and anomaly features are engineered to represent the delayed response of groundwater to rainfall and recharge, consistent with the delayed-response behaviour reported across the reviewed literature [19]–[22].

D. Climate Baseline Model

The first modelling layer, implemented as a Random Forest model, estimates groundwater behaviour expected from natural and climate-related variables such as rainfall, temperature, evapotranspiration, and recharge, following the ensemble approach validated in [3], [7], [8].

E. Residual / Human-Stress Model

The second layer, also a Random Forest model, is trained on the residual deviation between the climate baseline and observed groundwater levels, using a proxy-based demand index built from crop intensity, irrigated area, irrigation indicators, and, where available, agricultural electricity consumption. Both stages use monotonic constraints so that a rainfall or irrigation-demand slider always moves the forecast in the correct, verifiable direction — an approach that keeps the model's explanations consistent with domain knowledge rather than relying purely on a post-hoc explainer.

F. Explainable AI Using SHAP

SHAP is used to determine how individual features contribute to a prediction, following the growing use of SHAP for groundwater and hydrological interpretability reported in [13]. The objective is to answer not only "what will the groundwater level be" but also "why did the model produce this prediction," identifying whether rainfall, recharge, or irrigation demand is the dominant driver at a given location and time.

G. Risk Assessment

The Risk Engine classifies groundwater conditions into Safe, Semi-Critical, Critical, and Over-Exploited categories, drawing on India's INGRES groundwater-resource-assessment terminology and on GIS-integrated risk-classification approaches such as [14]. The engine also estimates when a critical threshold may be reached, supporting early-warning functionality.

H. What-If Policy Sandbox

The Policy Sandbox allows administrators to modify scenario variables — rainfall change, irrigation-demand change, drip-irrigation adoption, and borewell-growth assumptions — and re-run both modelling stages to project a resulting groundwater trajectory (e.g., a 10-year drawdown curve) against the baseline scenario. This enables evidence-based What-If analysis before an intervention is implemented, addressing the policy-simulation gap identified across the reviewed prediction-only studies [1]–[4].

I. Dashboard and System Architecture

The current prototype is implemented as a single Streamlit dashboard that presents a choropleth map of Nagpur's 14 tehsils, a before/after policy toggle, the drawdown curve, and a plain-language risk statement, with a future path toward a FastAPI/React deployment and integration with real-time IoT groundwater sensors [15]–[18].

V. Research Gap

The major research gap identified from the reviewed literature is the limited integration of prediction, human-stress attribution, explainability, risk assessment, and policy simulation within a single groundwater decision-support platform, summarised below.

No.	Identified Research Gap	Existing Research	Ground Vision
1	Limited integration of climate and human factors	Many studies focus mainly on environmental/climate variables [3], [7], [11].	Separates a climate-baseline model from an anthropogenic-stress residual model.
2	Limited explanation of predictions	Forecasts are often provided without detailed attribution [1], [2].	Uses SHAP to identify dominant, verifiable prediction drivers.
3	Limited human-demand estimation	Direct extraction data is often incomplete [8], [9].	Uses agricultural and irrigation proxies to estimate human-induced stress.
4	Limited risk and early-warning support	Risk classification and prediction are often studied separately [14].	Includes an integrated Risk Engine with Safe/Semi-Critical/Critical/Over-Exploited categories.
5	Lack of interactive policy simulation	Existing studies generally stop at forecasting [4], [5].	Provides a live What-If Policy Sandbox for rainfall and irrigation interventions.
6	Fragmented monitoring infrastructure	IoT groundwater-sensing studies are largely separate from prediction studies [15]–[18].	Designed for future integration with real-time IoT groundwater sensor feeds.

No.	Identified Research Gap	Existing Research	Ground Vision
7	Limited end-to-end groundwater intelligence	Existing systems typically address one component in isolation.	Integrates data collection, prediction, explainability, risk assessment, and policy simulation in one dashboard.

VI. Result Analysis / Expected Outcomes

The reviewed research indicates that Machine Learning provides effective groundwater-level prediction when historical observations are combined with environmental variables, with Random Forest and other ensemble models demonstrating strong performance [3], [7], [8] and hybrid ML–DL approaches offering additional accuracy for temporal patterns [2], [19]–[22].

GroundVision extends this prediction capability in several ways. First, the Climate Baseline Model captures natural groundwater behaviour from climate and environmental variables. Second, the Residual/Human-Stress Model introduces agricultural and irrigation-demand proxies to isolate anthropogenic deviation, making the forecast more relevant to groundwater management than a climate-only model [9]. Third, SHAP-based analysis improves interpretability, showing the contribution of individual variables rather than simply reporting a declining trend [13]. Fourth, the Risk Engine converts predictions into understandable stress categories and early-warning indicators, consistent with GIS-based risk-mapping approaches [14]. Finally, the Policy Sandbox enables scenario-based What-If analysis for administrators.

The expected outputs of GroundVision include: groundwater-level forecasts at well/tehsil scale; climate-baseline and anthropogenic-stress decomposition; SHAP-based explanations of predictions; groundwater stress classification with early-warning indicators; interactive rainfall/irrigation/drip-adoption policy scenarios; a GIS-based choropleth dashboard with historical trends and a 10-year drawdown projection; and downloadable reports. On the current synthetic Nagpur dataset, the two-stage Random Forest architecture with monotonic constraints produces a genuinely learnable train/test split, while the residual (human-stress) model shows a modest fit ($R^2 \approx 0.25$), reflecting the fact that part of the residual reflects baseline-estimation error rather than a pure human-demand signal — an outcome consistent with the acknowledged difficulty of proxy-based human-stress estimation reported in [8], [9].

VII. Conclusion and Future Scope

This review demonstrates that Artificial Intelligence and Machine Learning offer significant opportunities for groundwater-level prediction and groundwater-resource management, with Random Forest, SVM, XGBoost, LSTM, and hybrid ML–DL models each contributing distinct strengths [1]–[3], [7]–[12], [19]–[22]. Explainable AI methods such as SHAP, GIS-based risk mapping, and IoT-based groundwater-monitoring infrastructure are each maturing but are rarely combined into a single decision-support platform [13]–[18].

GroundVision addresses this gap by combining groundwater forecasting, climate-baseline modelling, anthropogenic-stress estimation, SHAP-based explainability, risk assessment, and interactive policy simulation within one GIS-based dashboard, moving beyond conventional groundwater prediction toward an interpretable, decision-oriented framework.

The future scope of the project includes replacing synthetic inputs with real data from India-WRIS, IMD, data.gov.in, and the Minor Irrigation Census; sourcing authentic tehsil-boundary GeoJSON layers from GSDA or community repositories; validating risk categories against documented drought years and real INGRES ground truth; integrating real-time IoT groundwater sensors [15]–[18]; migrating from a single Streamlit process to a FastAPI/React deployment; and adding automated tests, lagged-effect validation, and a technical whitepaper. The Policy Sandbox can further be extended to model groundwater-recharge structures, crop diversification, water-conservation strategies, and region-specific irrigation policy, so that GroundVision can support government officers, policy makers, researchers, farmers, and local communities in making more informed groundwater-management decisions.

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