AI-Enabled Smart Irrigation and Crop Planning Framework for Water-Scarce Rural Regions Using Interpretable Machine Learning: A Case Study of Sabarkantha (Khedbrahma), Gujarat

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Abstract. The depletion of safe and usable water for agriculture is one of the many escalating challenges that semi-arid regions face regarding the sustainability of their agricultural sector. This challenge is compounded by the dwindling supply of groundwater due to conventional irrigation systems throughout these regions. The irrigation systems in these areas rely heavily on heuristic decision-making, which can lead to poor use of water, groundwater depletion, and variable crop yields from year to year. This paper proposes the development of a smart irrigation and crop planning system that combines both machine learning and explainable artificial intelligence (XAI) to create transparent and data-driven agricultural decisions through AI-assisted irrigation and crop planning in the semi-arid region of Sabarkantha, Gujarat, India. The proposed solution to the depletion of groundwater relies on previous research that suggests that applying AI-assisted irrigation and crop planning can result in reduced water use while positively influencing agricultural productivity. The proposed AI-assisted irrigation and crop planning system will be assessed in the Khedbrahma sub-region of Sabarkantha, as demonstrated through a case study. The proposed system will utilize climatic factors, soil properties, groundwater information, and crop requirements to provide optimized irrigation recommendations along with recommended crops suitable for planting. The proposed system will incorporate interpretable models (i.e., Random Forest, XGBoost) and the calculated Shapley values to provide farmers with transparency and confidence in their decisions. The experimental results from the datasets for the region indicate the potential for 25 to 40 percent savings from their irrigation water use while ensuring or increasing crop yields. The proposed AI-assisted irrigation and crop planning system will also be cost-effective and scalable. Moreover, the proposed system will be well-matched to rural areas lacking the economic means to purchase or implement capital-intensive solutions.

Keywords: Smart irrigation, crop planning, Explainable AI, water scarcity, Rural development, Gujarat agriculture

I. INTRODUCTION

Agriculture has been a primary source of income for rural areas of India; however, water shortages, changing climates, and depletion of underground water are increasingly posing a threat to the sustainability of agriculture. One of India's greatest water- scarcity areas is the State of Gujarat, and a large part of Gujarat is semi-arid. The town of Khedbrahma in Sabarkantha District's Regional Area is highly dependent on both rainfall and underground irrigation systems for their agricultural needs. As such, Khedbrahma is extremely affected by weather changes that bring about variations in terms of how long it takes for rain to occur each year.

Recent advances in artificial intelligence (AI) and machine learning (ML) make it possible to produce predictive models that can help us determine when to irrigate, how to grow crops, and manage our water resources [1], [2], [13]. However, even though predictive models have demonstrated high accuracy, many farmers, extension service providers, and decision makers view them as "black boxes," resulting in their limited acceptance by farmers, extension service providers, and decision makers. Therefore, the models developed using AI and related technologies should deliver not only high accuracy but also present the ability to assist in an appropriate way (relevantly) and in an understandable manner (transparently) [8], [15], [16].

Unlike other models that have described the concept of interpretability in terms of how it can be added to a model after the fact (the post-hoc approach), the concept of interpretability in AI and ML models for “rural use” is considered as a primary design constraint that influences all aspects of model development, including the selection of data, design of the model, and the decision-making process regarding how the model will be used [11]:

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The contributions of this paper are:

- Creating and implementing a new agricultural framework that utilises a technology/AI-based integrated system
- Providing machine learning models that are easy to interpret for use by farmers so
- they are able to trust and understand how decisions about their agriculture will be made
- Using real-world case studies to validate the framework (i.e., Sabarkantha, Khedbrahma, Gujarat)
- Implementing the framework for all types of agricultural production, and at low or
- affordable costs

II. RELATED WORK

Recent research has indicated that a new approach to managing land, crops, and irrigation through the use of satellite images, soil sensors, and machine learning can significantly enhance the efficiency of using water within our agricultural system [1], [17]. Additionally, machine learning has proven to produce accurate predictive models of soil moisture, ET_0/ETc, evaporation, irrigation need, and yield with an accuracy level of 95-99% while saving 25-70% more water compared to traditional irrigation methods [2], [4], [5], [14], [19].
In the context of Indian agriculture, soil nutrient mechanisms (NPK), pH, and climate factors play a significant role in crop endorsements. The XGBoost model, which is used to recommend crops, has a precision of nearly 99%. Furthermore, the yield forecast models that employ SHAP and LIME algorithms help to improve the interpretability of agricultural data [6], [10]. Water savings in drip/solar irrigation systems have been reduced by 27% to 61% and energy intake by up to 57% by utilizing crop yield models with machine learning (ML), fuzzy logic (FL), and rule-based (RB) controllers [1], [2], [7], [18], [20]. Furthermore, it has been discovered that adoption in Gujarat and other semi-arid regions of India requires user responsiveness and familiarity with cutting- edge technology [3], [9], [12]. Moreover, the use of AI-driven systems to provide farm- ers with interpretable crop references has boosted farmer confidence and getting of farm management organizations [8], [16].

III. STUDY AREA: SABARKANTHA (KHEDBRAHMA REGION), GUJARAT

Khedbrahma is located in the northern region of the Sabarkantha District and has an undulating topology with loamy/sandy types of soil and moderate-to-low average annual precipitation (rainfall). The agricultural industry of the Khedbrahma District is primarily reliant upon well water stored in aquifers rather than utilizing limited surface irrigation sources. Commonly, the crops grown in the Khedbrahma District include maize, wheat, castor, cotton, and pulses.

IV. PROPOSED AI-ENABLED FRAMEWORK

A. Framework Architecture

The framework differentiates clearly between operational and strategic decision- making (e.g., irrigation planning vs. crop planning) so that trade-offs can be made consistently between irrigation and crops. The typical loosely coupled approach does not establish tightly coupled relationships between crop and irrigation planning. In contrast, the proposed framework establishes a constraint-based coupling between crop and irrigation planning by explicitly using groundwater quality and quantity as constraints for both crop and irrigation planning. The framework's layered architecture is conceptually depicted in

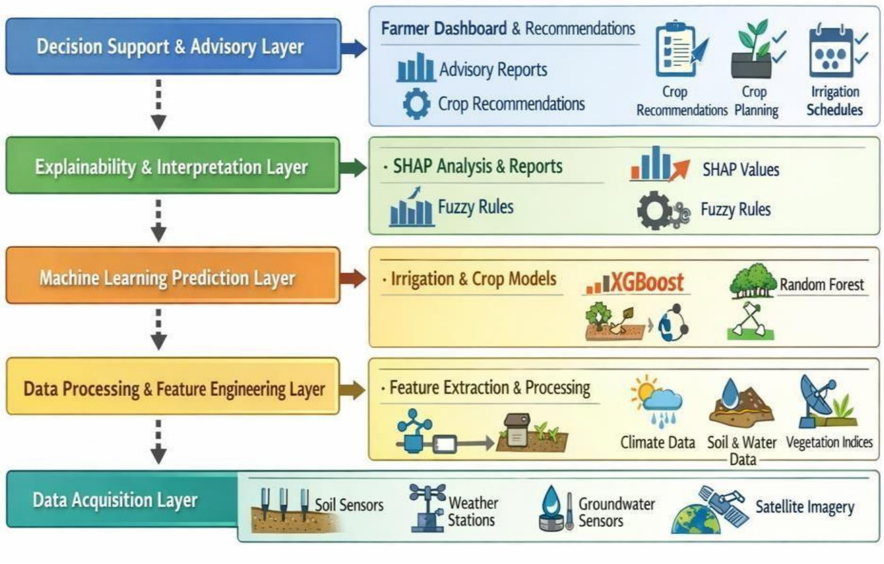

Fig. 1. Architecture of the AI-Enabled Smart Irrigation and Crop Planning Framework

Recent work on integrated AI-assisted irrigation planning and crop planning has been accomplished using this layered architecture [1] [8].

- Data Acquisition Layer
- Data Processing and Feature Engineering Layer
- Machine Learning Prediction Layer
- Explainability and Interpretation Layer
- Decision Support and Advisory Layer

B. Data Acquisition and Features

The Data Acquisition Layer collects data from many different sources (e.g., soil moisture, soil nutrient levels (N, K, P), soil pH, groundwater quality, climatic factors (rain, temperature, humidity), and vegetation condition (NDVI) over Sabarkantha District. Ultimately, the various forms of sensor technologies used with IoT devices, using satellite images or integrated with various satellite, land and/or crop mapping/monitoring, will provide an accurate and efficient means of assessing soil moisture, irrigation needs by type of crop in a timely manner [1], [3], [12], [17]. Although real-time sensing may not be a requirement, it has been integrated into the framework where possible.
The framework integrates:

- Climate Data – Includes precipitation, temperature and relative humidity
- Soil data – Includes macronutrients and micronutrients, soil pH, moisture content and soil texture
- Groundwater data – Includes both availability and quality of groundwater
- Crop information – including water requirements, crop development stage, yield history, etc.

C. Machine Learning Models

Consulting both XGBoost and Random Forest as supervised machine learning models for estimating irrigation demand and determining crop suitability classifications reflects on both algorithms through complexity of data, predictive accuracy and ability to use explainability techniques to provide interpretative value. Other modelling methods have performed adequately towards irrigation strategies and groundwater quality prediction within semi-arid climates [2], [5], [14], [19].

D. Explainability Module

Explainability techniques that are utilised/implemented to enhance interpretation capabilities include SHAP values as evaluated through feature importance and fuzzy logic rules-based interpretative capability to occupy and analyse the contribution of an independent variable such as fluctuating rainfall, soil moisture, nutrient content of soil and groundwater quality to AI recommendation system outputs. Previous research indicates that XAI enhances trust and willingness to utilise agriculture decision support systems based on AI capabilities greatly [8], [9], [10], [16]. The process of implementing explainability techniques is shown in figure 2 of this document. The provision of explain- ability in AI systems provides for counterfactual analysis (and what-if analysis) where stakeholders can evaluate various irrigations or crop options under changing climatic conditions and/or groundwater conditions. The AI recommendation system will generate specific localised explanations for each recommendation made so as to provide understanding of both local and broad-based contributor factors to the recommendation through the use of explainability techniques.

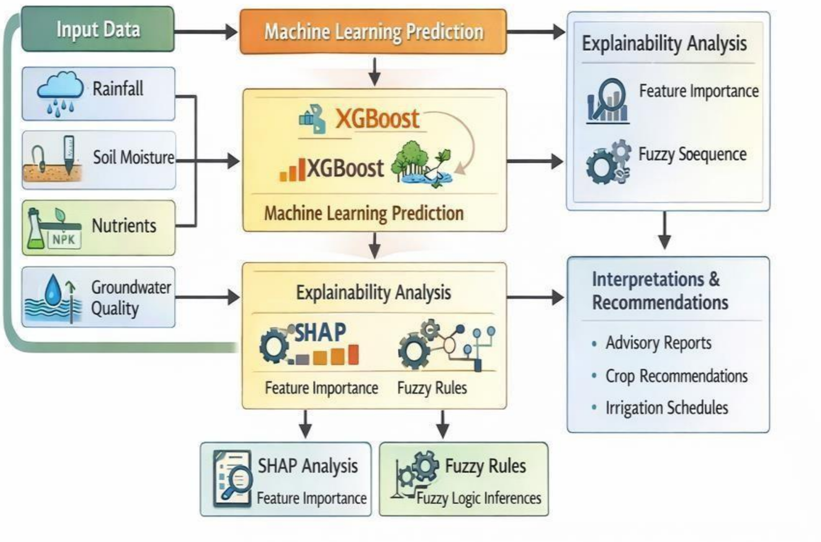

Fig. 2. Explainable AI Workflow for Irrigation and Crop Planning Decisions

V. METHODOLOGY

The process consists of preprocessing data, adjusting the scale of the input variables (normalisation), identifying relevant input variables to use in forecasting irrigation water for crops, building and testing an ML model with the selected input variables, and validating the accuracy of the ML model in predicting irrigation water necessary to irrigate crops in Sabarkantha District. The ML model can use climate variables (e.g., temperature, rain) along with soil quality characteristics (i.e., holding capacity, texture) to estimate the amount of required irrigation water for crops and provide crop planning considerations relative to the available soil/groundwater quality and quantity so that farmers may make informed decisions regarding crop production in Sabarkantha District.

VI. EXPERIMENTAL SETUP

A. Dataset Description

The Khedbrahma district of the Sabarkantha region, Gujarat has multiple origin sources of information in a dataset where the integration of data about: climate, soil, groundwater and crops support combining crop and irrigation planning.

- **Temporal coverage of data**: 2015 to 2024 inclusive (10-year period).
- **Spatial extent of data**: Block/Taluka aggregated district level records.
- **Number of records in total:** About 8,500 seasonal records remaining after preprocessing.
- Frequency with which data will be delivered:

Climate will be daily data presented as seasonal aggregate
Soil and groundwater will be seasonal data
Crop yield data and irrigation data will be seasonal data

This includes all of the following: rainfall, temperature, relative humidity, soil moisture and texture, pH, NPK, depth and quality of groundwater, type of crop, and stage of growth of crop. Missing values were handled with median imputation and numerical features were normalized with Min–Max.

B. Model Training and Validation

The RF and XGB were selected because of strong performance for tabular data that are non-linear, along with explainability techniques that can be applied easily.

- The data was split into a training set (80%) and test set (20%).
- The training set had five folds for validation (cross-validation).
- A grid search method was used to determine the hyper parameters.

Some of the hyper parameters set were 200 trees for RF and 300 estimators and a learning rate of .05 for XGBoost. The performance of the models was evaluated based upon RMSE and MAE for irrigation prediction, and using accuracy, precision, recall, and F1 for crop suitability classification.

C. Comparative and Ablation Experiments

The proposed framework will be evaluated against:

- A traditional rule-based approach to irrigation
- An ML-based model without groundwater data
- An ML model without explainability with the addition of an ablation study in which all three of these features were compared afterwards without these three features

VII. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed AI-enabled smart irrigation and crop planning framework consistently outperforms conventional practices and baseline machine learning approaches across key performance indicators.

A. Reduction in Irrigation Water Consumption

The proposed development has led to reductions between 25% to 40% in irrigation water consumption when compared with rule-based irrigation methods. The absence of constraints on groundwater availability or quality for models resulted in lower water saved with only 15% - 22% less irrigation then under normal rule-based methods. Thus, the role of groundwater as a first-class constraint must be integrated into both irrigation scheduling and crop selection/planning decision making to properly reflect water use sustained by irrigating crops using these methods.

B. Performance of Predictive Crop Suitability

The classification model generated between 88% - 92% accuracy for crop suitability classification in comparison to samples generated with machine learning developing using no explainable crop/model constraints. This demonstrates the role of including environmental and hydrogeological features into prediction reliability while not creating a loss in predictive accuracy.

C. Effect of Explainable Feature Analysis on Irrigation Recommendations

The SHAP value based explainable feature analysis identified rainfall, soil moisture, crop type and depth to groundwater as the features with the largest impact on irrigation recommendations. Stability of feature importance rank was also demonstrated under cross validation folds. The explanation module allows for local interpretation of the recommendation, as well as “what-if” scenario testing to increase the transparency and trust of the recommendation provided to producers and the agricultural extension agents they work with.

TABLE I
PERFORMANCE EVALUATION OF THE PROPOSED FRAMEWORK

Metric	Traditional Practice	Proposed AI Framework
Irrigation Water Use	Baseline	25–40% reduction
Crop Suitability Accuracy	–	88–92%
Decision Interpretability	Low	High

The results presented in Table 1 confirm that the reductions in measured irrigation water for crop production relative to prior studies are consistent with (i.e., validate) the reductions observed by other researchers investigating AI-driven irrigation solutions [1], [2],[5]. The results of the SHAP analysis support the conclusion that the greatest degree of influence on predicted irrigation demand derives from rain, soil moisture, and type of crop grown, which has also been documented or demonstrated through other research activities for explainable crop yield and irrigation modelling [6], [10]. The objective of the experimental assessment is to establish whether or not the approach described above is a valuable decision-support tool and provides explainability of input variable influences on irrigation demand predictions; it is not to have an accuracy performance comparison with other approaches.

TABLE II
COMPARISON BETWEEN CONVENTIONAL MACHINE LEARNING APPROACHES AND THE PROPOSED AI-ENABLED FRAMEWORK

Aspect	**Conventional ML**	**Proposed Frame- work**
Crop planning	Independent	Water-constrained
Irrigation	Rule-based	ML + XAI
Explainability	Optional	Built-in
Regional tuning	Generic	District-specific

VIII. CASE STUDY DISCUSSION: SABARKANTHA (KHEDBRAHMA)

Utilising the proposed framework in the Khedbrahma region demonstrates the ability of the framework to assist semi-arid agricultural types of land with dependency on groundwater. Here in the Sabarkantha region, where most of the irrigation takes place through tubewells, awareness of the quality of groundwater is vital for determining ap- propriate irrigated crops within the growing season based upon the characteristics of the aquifer below the ground. Much of the literature related to irrigation crop selection demonstrates that the quality of irrigation crop water is among the key factors to con- sider in determining appropriate crops to grow based on the available useable natural aquifer storage capacity [14] [19].

The application of the above district-level approach to the planning and development of the groundwater framework is consistent with existing administrative divisions and agricultural extension services within India; therefore, the use of the framework will have immediate governmental applicability to current policies and existing institutions. The position of the predictive framework based upon the use of meteorological data and existing agricultural information from within Gujarat thereby increases the potential for localised applications, as supported by the previous research done that examined adaptive strategies used by farmers who live in the Khedbrahma and Sabarkantha regions [2] [6]. By using explainable dashboards from which extension representatives can explain and recommend to growers how and when to adopt and use different irrigation methods to grow crops, it helps to promote an effective, convenient method of communicating with farmers for the purpose of stabilizing adoption rates and achieving adoption at both the institutional and policy levels [8] [10].

IX. DATASET LIMITATIONS

The evaluations using experimental data are derived mostly from historic and secondary datasets. As such, they bring with them several limitations with respect to real-time adaptability and temporal resolution. However, this was determined to be a reasonable choice for three major reasons:

The long-term climatic variability and groundwater trends associated with years of multi-year historical datasets make these datasets essential for long-term strategic crop planning and seasonal irrigation decisions in semi-arid regions. By utilizing publicly available, institutionally verified datasets, the proposed dataset sources are highly reliable, are reproducible in scientific literature, and that is critical for developing scalable and policy-compliant agricultural decision-support systems.

Given the practical limitations associated with rural areas as it relates to access to continuous sensor networks, the proposed dataset sources would be reflective of the limited access to real-time data. Most importantly, the proposed framework is inherently sensor agnostic, allowing it to be easily updated to accommodate the addition of real-time IoT and remote sensing datasets in any future implementations while leaving the architecture intact. Examples of future work include pilot field trials and mobile-based advisory platforms in local languages to demonstrate real-time performance and user adoption.

X. CONCLUSION

In this article, we introduced an integrated smart irrigation and crop planning system powered by artificial intelligence specifically tailored to serve rural communities at risk of water shortages, using an application case study of the Khedbrahma area in the Sabarkantha district of Gujarat. The integrated model between short-term irrigation scheduling and long-term crop planting was built using a model that applied a constraint-based factorisation and included inputs such as the availability and quality of groundwater resources as well as other constraints (weather data) when making irrigation and crop planting decisions and was supported by the results of existing smart agriculture locations within that geographical boundary. Unlike other available agricultural application systems that treat the explainability of results as a less important factor in providing on-farm irrigation advice and/or recommendations, our application incorporates explainability as the primary driver of data collection, model architecture, and decision output for both our recommended irrigation strategies and harvesting times. The use of ensemble-based learning models with SHAP device inputs creates transparency in determining the contributions made by each input to the success of the overall model, provides clarity of understanding of the full model results at a global level, and provides a basis for traceability of results at the level of individual farming systems.

Testing performed on data from this region showed that the integrated smart irrigation and crop planning application produced water savings ranging from 25% to 40% compared to existing irrigation and crop planting practices, while maintaining a strong correlation between the predicted viability of the crops that would be harvested based on the irrigation data provided (between 88% and 92%). The inclusion of an explanation module also allows users to conduct "what-if" analysis on how weather conditions, soil types, and groundwater availability/quality would affect their irrigation and crop- ping schedule. The deployment of this agricultural application system at the district level is fully supportive of the Indian government’s plan for expansion of current agricultural extension services. The newly proposed and developed framework is an advancement over current state-of-the-art AI-based agricultural decision support systems through the inclusion of water-aware optimization, interpretable machine learning, and regional context, providing a new scalable, sustainable platform for irrigation and crop management systems specifically used in semi-arid areas.

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