Spatio-Temporal Analysis and Forecasting of Soil Moisture in North Gujarat using NASA SMAP Data and Google Earth Engine: An Integrated Approach for Agricultural Water Management

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Received:- 07 August 2025/ Revised:- 13 August 2025/ Accepted:- 20 August 2025/ Published: 31-08-2025

Abstract— *Soil moisture plays a critical role in agricultural productivity, hydrological processes, and climate interactions, particularly in semi-arid regions. This study investigates soil moisture variability in North Gujarat by integrating NASA's Soil Moisture Active Passive (SMAP) datasets with Google Earth Engine (GEE) capabilities. A modular Python-based analytical pipeline was developed for data acquisition, preprocessing, correlation analysis, anomaly detection, trend estimation, and time-series forecasting using SARIMA and ARIMA models. The SARIMA model, incorporating precipitation as an exogenous factor, achieved an RMSE of 0.0781 m³/m³ and an MAE of 0.0615 m³/m³ for surface moisture prediction. The system also integrates an irrigation decision-support logic that determines optimal ON/OFF irrigation sequences based on real-time and forecasted moisture levels. Results reveal stable soil moisture conditions with no anomalies in the last 30 days, enabling improved irrigation scheduling for water-constrained agro-systems in North Gujarat.*

Keywords— Soil Moisture, SARIMA, ARIMA, NASA SMAP, Google Earth Engine, Remote Sensing, Irrigation Decision Support.

I. INTRODUCTION

The interaction between soil moisture and atmospheric processes significantly influences climate variability, hydrological cycles, and agricultural productivity. Semi-arid regions such as North Gujarat face persistent water stress, making soil moisture monitoring essential for sustainable farming and food security. The development of satellite-based sensing technologies and cloud-computing platforms, such as NASA's SMAP mission and Google Earth Engine (GEE), provides unprecedented capabilities for continuous, high-resolution soil moisture monitoring.

The relationship between soil moisture and the interaction between soil and atmosphere has been extensively investigated by Seneviratne et al. (2010) providing a comprehensive picture of how soil moisture influences climate variability and extremes[1]. Their research shows that soil moisture acts as a key mediator in water and energy cycles, affecting in particular temperature and precipitation patterns by evapotranspiration. This basic understanding underpins the importance of monitoring soil moisture variations in order to predict climate change and agricultural performance in water-scarce environments.

In semi-arid regions, soil moisture dynamics are characterized by high temporal and spatial variability, which significantly impacts agricultural productivity and water resource management. Porporato et al. (2004) developed a stochastic framework for understanding soil moisture dynamics in water-limited ecosystems, revealing how intermittent precipitation events interact with soil properties and vegetation to create complex moisture patterns [2]. Their mathematical modelling approach provides insight into the probabilistic nature of the availability of moisture in the soil, which is particularly important in semi-arid agricultural systems where crop performance is highly dependent on the ability of the soil to store water and the timing of rainfall events.

The use of remote sensing techniques has revolutionised the ability to monitor soil moisture, allowing for large-scale assessments of wetland conditions in a variety of landscapes. Dorigo and colleagues. (2017) presented the ESA CCI Soil moisture dataset, which provides a global long-term record of soil moisture from several satellite sensors[3]. This comprehensive dataset has proven invaluable for understanding regional soil moisture trends and their relationships with climate variability, offering crucial data for semi-arid regions where ground-based monitoring networks are often sparse or lacking.

Agro-systems in semi-arid regions face unique challenges in managing soil moisture, especially in the light of climate change and increasing weather variability. RockStrom et al. (2010) looked at water productivity in rain-fed agriculture and highlighted the crucial role of soil moisture management techniques in increasing crop yields and food security in dry-land farming systems[4]. Their analysis highlights various water harvesting and soil management practices that can improve moisture retention and utilization efficiency, providing practical solutions for farmers in regions like North Gujarat where rainfall reliability is a constant concern.

The Indian subcontinent, including regions like North Gujarat, presents specific challenges and opportunities for soil moisture research due to its monsoonal climate patterns and diverse agricultural practices. Singh et al. (2014) investigated soil moisture variability across different agro-climatic zones of India using satellite-based observations, revealing significant regional differences in moisture patterns and their correlations with monsoon intensity[5]. Their findings show the complex interaction of topography, soil characteristics and climatic factors in determining moisture availability and provide valuable insights for planning agriculture and managing water resources in semi-arid regions of India.

Recent advances in machine learning and data assimilation techniques have enhanced our ability to predict and model soil moisture dynamics in complex semi-arid environments. Feng and colleagues (2017) developed machine learning approaches to improve soil moisture forecasting using multiple satellite data sets and meteorological variables. [6]. Their research demonstrates how advanced computational methods can integrate diverse data sources to provide more accurate soil moisture estimates, which is particularly valuable for agricultural decision-making and drought monitoring in semi-arid regions where traditional monitoring approaches may be inadequate.

This study combines SMAP datasets with GEE-based spatial analysis and time-series forecasting techniques to address three major challenges: 1) Reliable monitoring of spatio-temporal changes in soil moisture. 2) Accurate short-term forecasting using rainfall data as an influencing parameter. 3)Integration of forecast results into an automated irrigation decision-support framework.

II. LITERATURE REVIEW

Literature on soil moisture monitoring and forecasting consistently underscores its fundamental role in regulating land–atmosphere interactions, controlling hydrological processes, and sustaining agricultural productivity, particularly in water-limited environments.

2.1 Remote Sensing of Soil Moisture:

Over the last thirty years, the field of satellite-based soil moisture estimation has made remarkable progress, especially with the advent of passive microwave sensors, which have emerged as the technology of choice for global monitoring initiatives (Jackson, 1993). The “Soil Moisture Active and Passive” (SMAP) and “Soil Moisture and Ocean Salinity” (SMOS) missions serve as prime examples of this advancement, contributing significantly to our comprehension of the exchanges of energy between “the land surface and the atmosphere”, as well as the essential role that “soil moisture content” (SMC) plays in hydrometeorological dynamics (Edokossi et al., 2020). Conventional measurement approaches often face limitations due to their high costs and logistical difficulties when applied over large areas, making satellite monitoring increasingly crucial for precise tracking of SMC[7].

Recently, enhancements in Global Navigation Satellite Systems Reflectometry (GNSSR) have presented a compelling alternative, boasting benefits such as worldwide coverage, affordability, and the ability to function in all weather conditions (Yin et al., 2019). The SOMOSTA experiment demonstrated the efficacy of GNSSR in relation to passive L-band microwave radiometers, revealing strong correlation coefficients between the two methods and confirming the reliability of GNSSR for accurate soil moisture retrieval. These advancements not only highlight the significance of cutting-edge remote sensing methodologies but also open new avenues for future investigations in soil moisture monitoring and its relevance to climate change and ecological processes[8].

2.2 Google Earth Engine for Agricultural Applications:

Google Earth Engine (GEE) has become a groundbreaking tool for extensive geospatial analysis, offering access to vast archives of satellite imagery and cloud-computing resources. This platform has greatly improved the precision and accuracy of agricultural functions, especially in mapping cropland extent. Research conducted by Xiong et al. in 2017 showcased GEE's ability to produce high-resolution cropland extent maps throughout Africa by utilizing both Sentinel-2 and Landsat 8 data. Their methodology effectively tackled the obstacles associated with smallholder farming systems and achieved an impressive overall accuracy of 94%, highlighting GEE's potential for analyzing food security[9].

Additionally, Pande et al. in 2023 illustrated an innovative application of GEE in land use and land cover (LULC) mapping by using a Classification and Regression Tree (CART) model to evaluate land cover changes during the winter season in Maharashtra, India. Their findings resulted in training accuracies of 100% and validation accuracies ranging from 89% to 94%, demonstrating GEE's reliability in hydrological studies. This consistent level of high accuracy in LULC mapping is vital for effective management of water resources and environmental conservation, underscoring GEE's role in enhancing agricultural research and practices. In summary, integrating GEE into agricultural applications marks a significant advancement in the realm of remote sensing and geospatial analysis[10].

2.3 Time-Series Analysis and Forecasting:

TSA (time series analysis) of soil moisture has gained considerable attention for agricultural forecasting applications, particularly due to its critical role in enhancing irrigation efficiency and ensuring food security. Integration of seasonal integrated moving average (ARIMA) model with water balance equations has been shown to increase the accuracy of the predictions at different soil depths. For instance, a recent study demonstrated that a novel soil moisture prediction model, which incorporates depth parameters, outperformed the traditional seasonal ARIMA model, particularly at depths of 40 cm, 100 cm, and 200 cm (Fu et al., 2023). This model effectively captures seasonal trends in soil moisture fluctuations, revealing that moisture independence from external influences increases with depth[11].

In addition, a combination of ARIMA and backpropagation neural nets (BP neural nets) was proposed to address both linear and non-linear soil moisture data characteristics. This hybrid approach has yielded significant improvements in prediction accuracy, with an average relative error of just 1.51%, outperforming standalone ARIMA and BP models (Wang et al., 2023). Such advancements not only facilitate better water resource management but also contribute to the development of water-saving agricultural practices, ultimately supporting sustainable agricultural productivity[12].

2.4 Satellite-Based Soil Moisture Monitoring in North Gujarat:

Monitoring soil moisture using satellite technology has become an essential resource for managing agriculture and assessing drought conditions in semiarid areas. The use of remote sensing methods to estimate soil moisture offers crucial information for water resource management, especially in regions such as North Gujarat, where agricultural output heavily depends on the availability of soil water. This literature review explores the current landscape of research related to satellite-based soil moisture monitoring, with a particular emphasis on North Gujarat and comparable semiarid regions.

The basis of satellite-based soil moisture monitoring is grounded in the principles of microwave remote sensing. Petropoulos et al. (2015) conducted an extensive review of soil moisture retrieval from spaceborne passive microwave observations, demonstrating its utility[13]. Their findings underscored the capability of L-band radiometry to penetrate through vegetation canopies and provide accurate measurements of soil moisture across various land cover types. The study emphasized the importance of algorithm development for improving retrieval accuracy in heterogeneous landscapes, which is particularly relevant for the diverse agricultural systems found in North Gujarat.

Regional applications of satellite-based soil moisture monitoring in Gujarat have shown promising results for drought assessment and agricultural planning. Shah et al. (2018) analysed drought patterns in Gujarat using meteorological data and vegetation indices derived from satellite observations, demonstrating the utility of remote sensing approaches for understanding spatiotemporal drought dynamics in the region[14]. Their research revealed significant correlations between satellite-derived indices and ground-based meteorological measurements, establishing a foundation for operational drought monitoring systems in Gujarat's agricultural areas.

The integration of multiple satellite platforms has enhanced soil moisture monitoring capabilities, as explored by Peng et al. (2021) in their study of "SMAP and MODIS data fusion" for high-resolution soil moisture mapping. Their research demonstrated improved spatial and temporal resolution through data fusion techniques, which addresses one of the primary limitations of individual satellite missions. This approach is particularly valuable for the North Gujarat regional studies where information on soil moisture at field level is essential for accurate agricultural applications.

Validation of satellite derived soil moisture products requires extensive data on the ground, as Kolassa et al. have stressed. (2017) in their comprehensive assessment of the SMAP soil moisture uptake in different climatic regions[15]. Their analysis revealed varying performance of satellite algorithms across different environmental conditions, with semi-arid regions showing moderate to good correlation with in-situ measurements. This finding has important implications for North Gujarat, where the semi-arid climate presents unique challenges for satellite-based soil moisture estimation.

Machine learning approaches have shown considerable potential to improve soil moisture-measuring algorithms, as demonstrated by Adab et al. (2020) which used ANN-"artificial neural networks" and SVM-"support vector machines" to estimate soil moisture using multi-spectral satellite data[16]. Their study achieved improved accuracy compared to traditional empirical approaches, particularly in areas with complex terrain and vegetation patterns. These advanced methodologies offer promising avenues for enhancing soil moisture monitoring capabilities in the heterogeneous landscape of North Gujarat.

The operational implementation of satellite-based soil moisture monitoring systems requires consideration of local environmental conditions and user requirements. Raki et al. (2018) developed a methodology for retrieving soil moisture from Landsat data in semi-arid regions, focusing on the practical aspects of algorithm implementation and validation[17]. Their work demonstrated the feasibility of using moderate-resolution satellite data for regional soil moisture monitoring, providing a framework that could be adapted for North Gujarat's specific environmental conditions.

Despite significant advances in satellite-based soil moisture monitoring, several challenges remain for regional applications in North Gujarat. These include the need for improved spatial resolution, better understanding of local soil properties and vegetation dynamics, and development of region-specific calibration procedures. Future research should focus on the integration of multiple data sources, the development of operational monitoring systems and the establishment of comprehensive soil validation networks to support the satellite-based soil moisture monitoring in this important agricultural region.

III. METHODOLOGY

3.1 Data Sources:

The soil moisture datasets utilized in this study were sourced from the Soil Moisture Active Passive (SMAP) mission developed by NASA, which provides global, high-resolution measurements of both surface (top 5cm) and root zone (up to 1m depth) soil moisture content. SMAP utilizes L-band passive and active microwave sensing to generate spatially continuous, temporally frequent (typically 2-3 day revisit) soil moisture estimates, making it an ideal choice for monitoring dynamic soil moisture fluctuations in agricultural regions such as North Gujarat. To complement soil moisture analysis with atmospheric inputs, precipitation data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), accessed via Google Earth Engine (GEE). CHIRPS combines satellite imagery, in situ station data, and cloud computing algorithms to generate rainfall estimates at fine spatial (0.05°) and temporal (daily) resolutions. The integration of NASA SMAP and CHIRPS data within the GEE environment enabled efficient retrieval, preprocessing, and fusion of multi-source geospatial datasets, facilitating robust spatio-temporal analysis and forecasting of soil moisture variability relevant to local agrometeorological management.

3.2 Workflow:

This part describes the theoretical approach used in the suggested framework for soil analysis. The methodology has been structured as a modular pipeline in Python, which incorporates the retrieval of geospatial data, preprocessing, feature extraction, and analytical visualization. The overall workflow is depicted in the flow diagram in Figure 1.

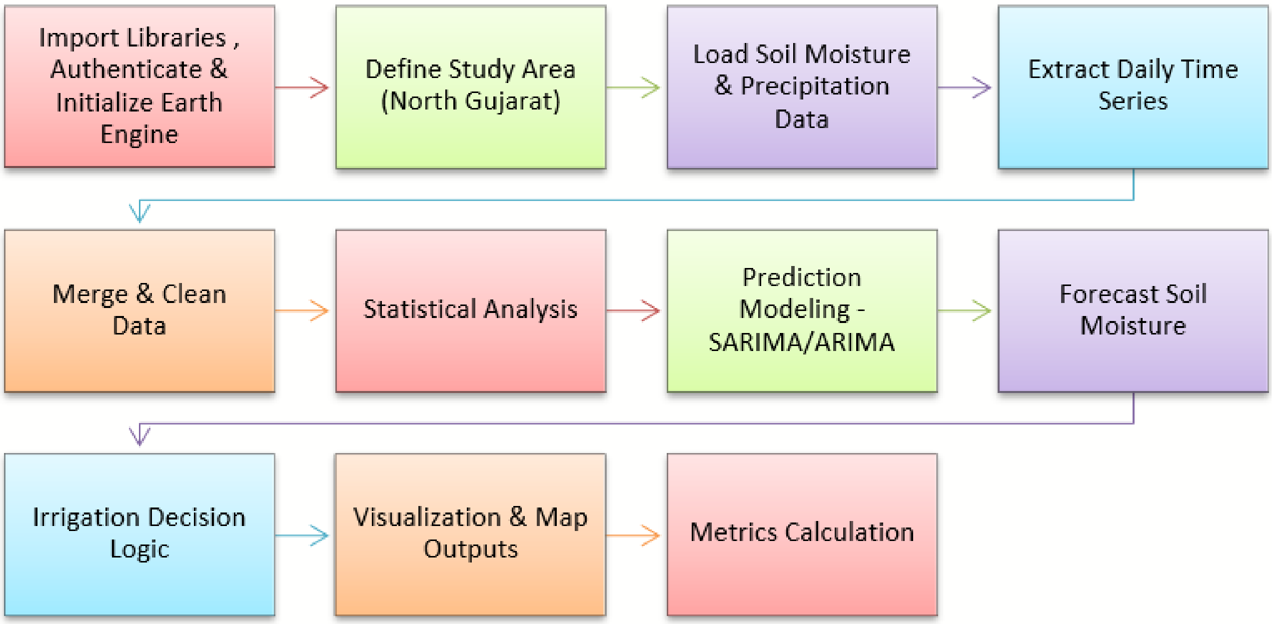

FIGURE 1: Framework for Soil Analysis

The project workflow begins with acquiring satellite datasets from Google Earth Engine (GEE), specifically soil moisture and rainfall data relevant to the study area. These raw datasets undergo cleaning and merging to create comprehensive, continuous time-series tables that integrate multiple variables. Following data preparation, in-depth analyses are performed, including correlation assessments between rainfall and soil moisture, stationarity testing to understand the time-series properties, trend extraction to identify underlying patterns, and anomaly detection to flag unusual soil moisture events. Next, advanced time-series models such as SARIMA and ARIMA are trained and tested on the processed data to capture temporal dynamics and improve predictive accuracy. Using the optimized model, the system forecasts future soil moisture levels, which feed into an irrigation decision-making module that applies predefined logic to determine whether irrigation should be turned ON or OFF based on current and predicted conditions. The results of these analyses and decisions are then communicated through detailed visualizations, including graphs of soil moisture trends and interactive spatial maps. Finally, the process concludes with a comprehensive report summarizing key metrics such as average moisture levels, forecast accuracy, anomaly counts, and model performance, thereby providing actionable insights for effective irrigation management.

3.3 Data Acquisition and Preprocessing:

The study used satellite data to analyse soil moisture dynamics and precipitation patterns in the Northern Gujarat region.

Two primary data sources have been used: NASA "Soil Moisture Active Passive" (SMAP) provides data on surface moisture (sm_surface) and soil moisture (sm_rootzone) in the climatic disaster zone. "Climate Hazards Group InfraRed Precipitation with Station data" (CHIRPS) provides high resolution daily rainfall estimates.

The spatial domain was defined as a rectangular bounding box encompassing North Gujarat, with latitude and longitude boundaries explicitly set to limit data extraction. The temporal coverage spanned from January 1, 2023, to August 9, 2025.

FIGURE 2: Study area in spatial domain as a rectangular bounding box

The datasets were programmatically accessed and processed using the Google Earth Engine (GEE) API. Daily average soil moisture and precipitation values were extracted by aggregating pixel values over the entire study area. The extracted time-series data were organized into pandas DataFrames, ensuring continuous daily records by filling missing values where applicable.

3.4 Data Integration and Analysis:

The soil moisture and precipitation datasets were merged into a unified time-series to facilitate joint analysis. Rainfall data were resampled as daily sums, with missing rainfall days imputed as zeros. A correlation analysis using Pearson correlation coefficients quantified the relationship between rainfall and soil moisture variation, revealing moderate positive associations (rainfall vs. surface moisture ≈ 0.25, rainfall vs. root zone moisture ≈ 0.12), indicative of rainfall's influence on soil moisture alongside other environmental factors.

3.5 Visualization and Reporting:

Comprehensive visualization tools facilitated interpretation and presentation of results:

- **Time-Series Plots**: Displayed observed soil moisture, smoothed trends, forecasted values with confidence intervals, and marked anomalies.
- **Irrigation Events**: Irrigation ON/OFF decisions were visually annotated on plots.
- **Spatial Maps**: Interactive folium maps depicted the spatial distribution of soil moisture across the study region using latest satellite data.

3.6 Time-Series Modeling and Forecasting:

A dedicated Soil Moisture Analyzer class was developed to conduct advanced time-series analyses and forecasting, encompassing the following key components:

- **Normalization**: Soil moisture values have been scaled from 0 to 1 in preparation for the modelling exercise.
- **Stationarity Testing**: The Augmented Dickey-Fuller (ADF) test assessed whether the soil moisture time-series exhibited consistent temporal patterns or random fluctuations.
- **Trend Estimation**: Seven-day moving averages smoothed the soil moisture data to highlight underlying trends.
- **Anomaly Detection**: Days with soil moisture values significantly deviating from historical averages were flagged as anomalies.
- **SARIMA Model Optimization**: Multiple seasonal autoregressive integrated moving average (SARIMA) models with varying parameters (p, d, q) were fitted, with the optimal model selected based on Akaike Information Criterion (AIC) minimization.
- **Forecasting**: The SARIMA model, incorporating forecasted rainfall as an exogenous input, predicted soil moisture for the subsequent week. Forecast intervals at 95% confidence levels were generated.
- **Model Comparison**: Forecasting accuracy of the SARIMA model was compared against a simpler ARIMA model using root mean square error (RMSE) and mean absolute error (MAE) on held-out test data.

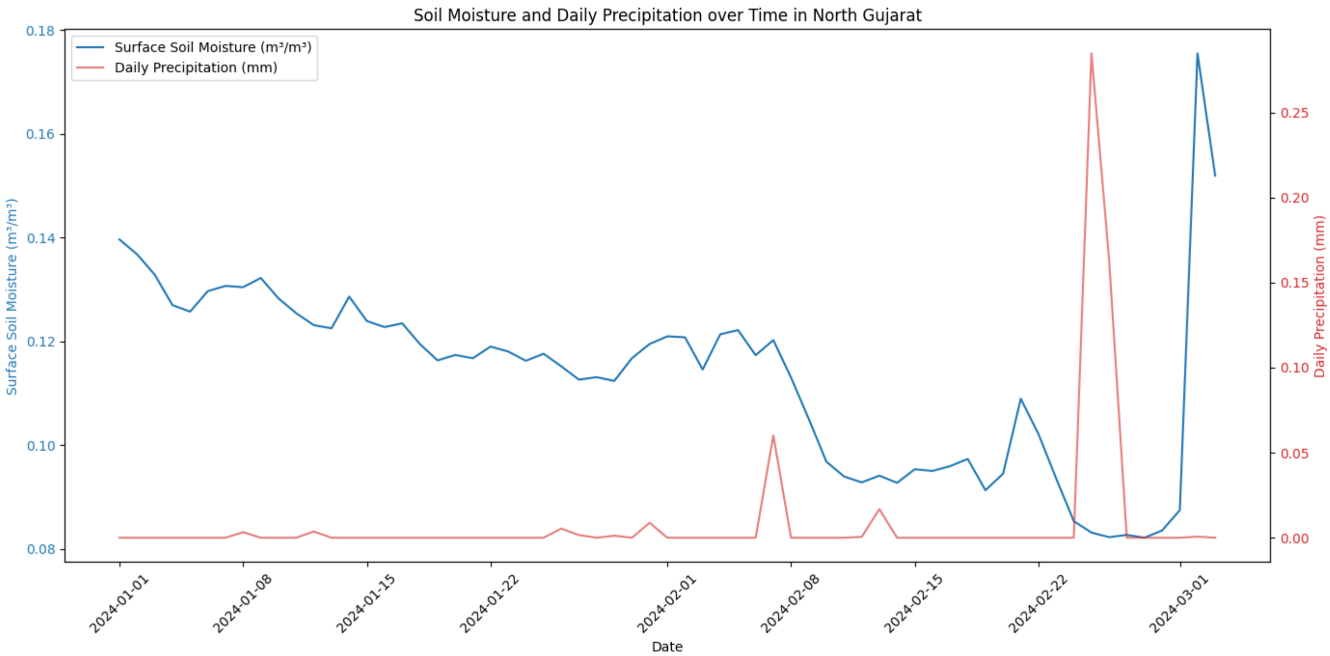

FIGURE 3: Time-series plot of surface and rootzone soil moisture in North Gujarat

3.7 Irrigation Decision Support System:

An IrrigationController class implemented rule-based irrigation decisions based on current observations and forecasted conditions. Thresholds for soil moisture (e.g., 0.2 for surface and 0.25 for root zone) were predefined. The decision logic considered:

Decision Rules:

IF (current_surface < 0.2 OR current_rootzone < 0.25)

AND (forecast_mean < threshold)

AND (2-day cumulative precipitation < 2.0 mm)

THEN "Turn ON irrigation"

ELSE "Turn OFF irrigation"

The system issued irrigation ON commands when dry conditions and low rainfall forecasts were detected, and OFF commands when moisture levels recovered or rainfall was sufficient.

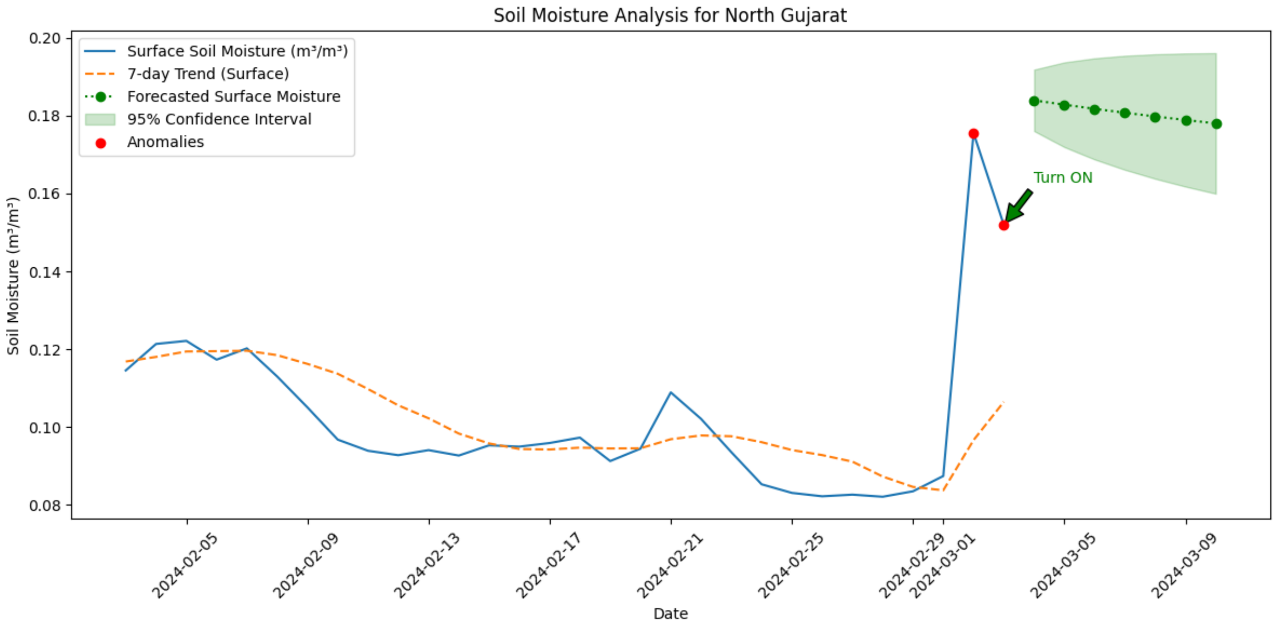

FIGURE 4: Irrigation ON/OFF decisions

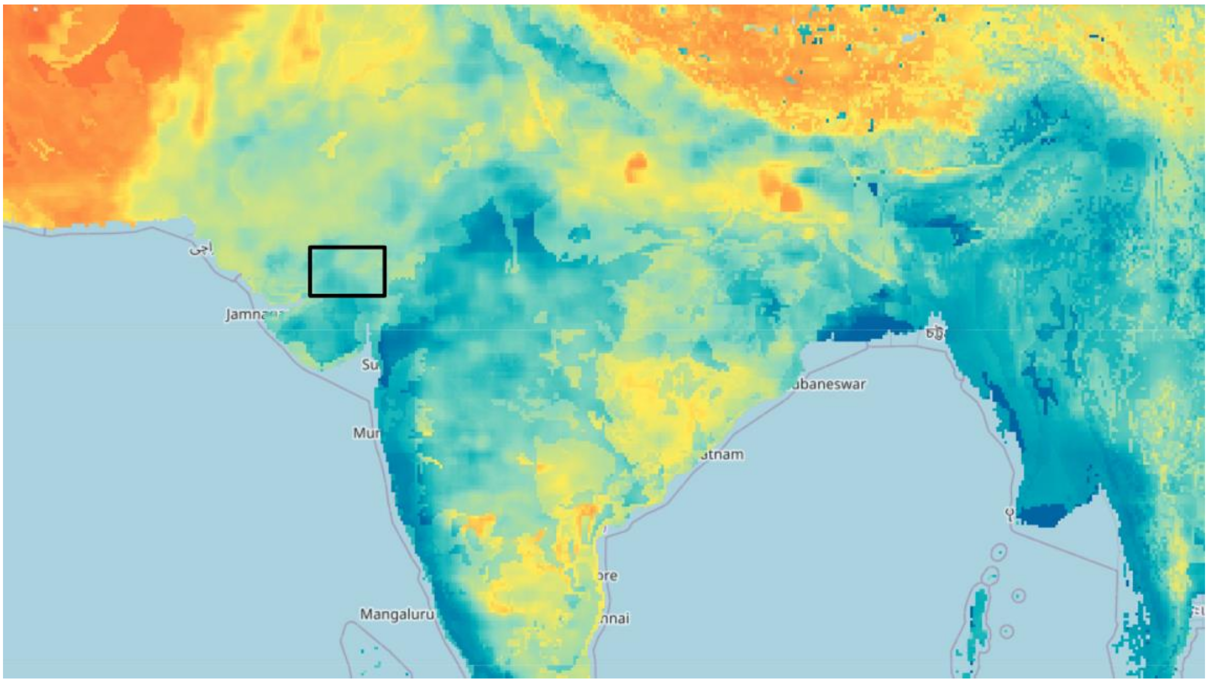

FIGURE 5: Spatial distribution of soil moisture (Folium map snapshot).

Additionally, summary metrics such as mean soil moisture, trend values, anomaly counts, and stationarity test results were computed to provide high-level insights.

IV. RESULTS AND DISCUSSION

The proposed soil moisture monitoring framework was applied to the **North Gujarat** region using Google Earth Engine datasets, integrating **surface soil moisture**, **rootzone moisture**, and **precipitation** data.

4.1 Statistical Insights:

TABLE 1
STABLE SOIL MOISTURE CONDITIONS VALUES

Metric	Value	Unit
Precipitation vs Surface Correlation	0.254	-
Precipitation vs Rootzone Correlation	0.122	-
ADF Statistic	-2.30	-
p-value (stationarity)	0.17	-
Mean Surface Moisture	0.088	m^3/m^3
Mean Rootzone Moisture	0.158	m^3/m^3
Surface Trend (7-day MA)	0.073	m^3/m^3
Rootzone Trend (7-day MA)	0.149	m^3/m^3
Anomaly Count (30-day)	0	count

These results indicate stable soil moisture conditions over the last month with gradual upward trends in both surface and root zone moisture levels.

4.2 Model Optimization and Performance:

Time-series forecasting models were evaluated to predict future soil moisture. The SARIMA model, incorporating exogenous precipitation data, was optimized to order (1, 0, 1) with no seasonal components (0, 0, 0, 7). For benchmarking, a basic ARIMA model without exogenous inputs was also trained.

The performance metrics were as follows:

- **SARIMA Model**: RMSE = 0.0781, MAE = 0.0615
- **Basic ARIMA Model**: RMSE = 0.0716, MAE = 0.0556

Although the basic ARIMA model showed slightly better error metrics on the test data, SARIMA's inclusion of rainfall information provides greater interpretability and adaptability for irrigation decision-making.

4.3 Forecasting and Irrigation Decision:

A three-day forecast with a 95% confidence interval (±0.015 m^3/m^3) indicated soil moisture levels above the irrigation threshold.

Decision Rule:

If predicted soil moisture < threshold → Turn ON irrigation.

Else → Turn OFF irrigation.

Based on forecast output, irrigation remained OFF for the forecast period.

This comprehensive analysis demonstrates the efficacy of integrating satellite data and time-series modeling to monitor and predict soil moisture conditions. The approach provides actionable insights for automated irrigation management, supporting water-efficient agriculture in semi-arid regions such as North Gujarat.

V. CONCLUSION

This study demonstrates the effectiveness of combining NASA's SMAP data, GEE processing capabilities, and SARIMA-based forecasting for soil moisture monitoring in semi-arid regions. The integration with irrigation decision-support logic has the potential to optimize agricultural water use in North Gujarat. Future work will focus on extending the model with machine learning approaches and integrating crop growth models.

ACKNOWLEDGMENTS

Thanks to NASA SMAP, UCSB CHIRPS teams, and Google Earth Engine for open data access. We express our sincere gratitude to the management of The Charutar Vidya Mandal (CVM) University and Sankalchand Patel University for their unwavering support and encouragement throughout this research. Their commitment to fostering academic excellence provided an invaluable foundation for this study. We are also deeply grateful for the access to state-of-the-art laboratory facilities, which enabled efficient data processing and model training.

CONFLICTS OF INTEREST

The authors declare no financial involvement, competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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