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A HYBRID CONVLSTM–HIERARCHICAL GNN FRAMEWORK FOR SOIL MOISTURE PREDICTION USING IOT AND SENTINEL-2

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Abstract

Machine Learning (ML) technology in Indian agriculture targets the improvement of crop supplies, reducing resource usage, and enhancing farmer efficiency through various applications such as Soil Moisture Prediction and crop health monitoring. Soil moisture prediction helps to reduce water usage and supports personalized advisory systems for farmers. Soil moisture prediction has a major impact on agricultural water resource management. In Traditional ML approaches based up on Convolutional Long Short-Term Memory (ConvLSTM) and Graph Neural Networks (GNN) to implement soil moisture prediction using Sentinel-2 images and in-situ soil moisture data. In-situ soil moisture observations were collected from networks such as the International Soil Moisture Network (ISMN). These point-based measurements are insufficient for building, training, and validating soil moisture prediction models over state- and district-level scales. Recent Advances in ML have enabled the integration of multisource data to enhance predictive accuracy. In this paper, we propose a model that combines multi-source data, that is Internet of Things (IoT), Sentinel-2, and Andhra Pradesh Water Resources Management (APWRMS), to make predictions across district-to-state scales. In this research, ConvLSTM was used to extract spatiotemporal features from Sentinel-2 images, and a Hierarchical GNN was used to capture multi-scale spatial dependencies. The main advantages are expanded spatial coverage and improved accuracy through multi-source integration. The model used six Sentinel-2 spectral bands (B2, B4, B6, B8, B10, and B12) for district level soil moisture estimation in Andhra Pradesh. Model performance was evaluated using the coefficient of determination (R^2) and the root mean square error (RMSE). Experimental results demonstrate that the proposed ConvLSTM–Hierarchical Graph Neural Network (CHGNN) model achieves $R^2 = 0.88$ and RMSE = 0.0403, significantly outperforming the traditional ConvLSTM–GNN approach ($R^2 = 0.692$, RMSE = 0.0645). This study highlights the potential of multi-source, deep, and multi-fusion learning frameworks for accurate and efficient soil moisture and soil health monitoring.

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Keywords: Convolutional LSTM (ConvLSTM), Graph Neural Networks (GNN), Spatiotemporal Deep Learning, Soil Moisture Prediction, Multi Source Data Fusion, Sentinel 2 imaginary.

1.Introduction

Machine learning (ML) enhances soil analysis in agriculture by accurately integrating diverse environmental data to predict soil properties and classify soil types, enabling precise mapping and informed decision-making. ML enables the integration of diverse environmental data to model complex, nonlinear relationships affecting soil moisture, producing accurate spatial and temporal predictions. It enhances prediction reliability across various soil types and climates, supporting real-time monitoring and decision-making in precision agriculture [1]. ML techniques can process large datasets from remote sensing, weather stations, and soil sensors to generate accurate, spatially and temporally resolved predictions. This leads to improved soil management practices and optimized agricultural productivity.

Soil is an essential foundation for plant growth and is an extremely important resource for our country. More than 54% of our workforce depends directly on agriculture or allied activities for their livelihood or through allied activities. Therefore, the health of the soil affects more than 54% of our workforce. Soil health is fundamental to the country’s food system. It forms the keystone of agriculture and serves as the crucial medium for plant growth. When soils are healthy, they produce higher productivity and yield more nourishment crops that provide nutrition for both humans and animals [2] .

Soil samples were collected at the agricultural field scale, and their variability was assessed using laboratory analyses and statistical methods. This analysis helps farmers tailor soil fertility management. In India, soil degradation, nutrient deficiencies, and unsustainable agricultural practices are major challenges to the effective implementation of soil management [3]. Many Research studies covers only satellite-based observations on certain regions and seasons, the main limitation is the lack of field scale measurements [4]. In the Indian region, soil moisture prediction has mainly been performed using global and regional datasets. Due to limited availability of local datasets, the model performance remains low [5].

The predicting features used in research studies only include meteorological parameters such as rainfall, temperature as well as and soil properties and indices extracted from remote sensors such as Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI) etc [6]. some research studies have used simulated NASA-ISRO Synthetic Aperture Radar (NISAR) data therefore the results do not fully reflect on real world conditions, and the findings are not focused on soil health [7].one study focus on soil moisture prediction using IoT-based irrigation data and applied machine learning techniques however, it lacked consideration of the spatial and temporal variability of soil properties [8]. some studies have focused on the assessment of soil organic carbon, covering five type of lands such as scrub land, mango plantation, groundnut, bajra, and paddy where soc measurements were taken at selected soil depths [9].

The proposed framework aims to overcome the limitations of existing soil moisture prediction approaches by integrating multi-source heterogeneous data including Internet of Things (IoT) sensor data, Sentinel-2 satellite imagery, and Andhra Pradesh Water Resources Management System (APWRMS) data to enable soil moisture prediction from the district to the state-level.

The proposed ConvLSTM–Hierarchical Graph Neural Network (CHGNN) model is designed to capture both spatiotemporal and multi-scale spatial dependencies. ConvLSTM layers extract temporal and spatial features from Sentinel-2 imagery, while Hierarchical GNN layers learn graph-based spatial relationships between regions. The integrated model effectively combines ground-based IoT sensor data with satellite-derived features, enhancing prediction accuracy and improving generalization across varying climatic and vegetation conditions.

The main contributions of this research are summarized as follows:

1. Multi-source Data Fusion: Integration of IoT-based district-level soil moisture data, Sentinel-2 imagery, and APWRMS datasets for state-wide soil moisture estimation.
2. Deep Multi-Fusion Framework (CHGNN): Development of a hybrid ConvLSTM–Hierarchical GNN model for capturing spatiotemporal and spatial relationships.
3. Improved Prediction Accuracy: Achieved higher accuracy ($R^2 = 0.88$, RMSE = 0.0403) compared to traditional ConvLSTM–GNN models ($R^2 = 0.692$, RMSE = 0.0646).
4. Scalable and Interpretable Model: Enables large-scale prediction from district to state level, supporting sustainable water resource management in agriculture.
5. Heterogeneous Feature Learning: Efficiently integrates remote sensing and IoT sensor data for holistic soil health monitoring.

2.Related Work

Research on soil health and soil moisture prediction assessment has evolved in four main areas of IoT-based monitoring, Machine Learning (ML), deep spatio-temporal modelling, and secure digital agriculture. While each of these approaches has made different strides, they generally fail to capturing multi-scale spatial dependencies.

2.1 Soil Monitoring via IoT and Edge-AI

IoT-based research enable real-time monitoring of Soil acidity, nutrients, and moisture prediction, providing important information on agricultural [10]. Integration of IoT with edge computing technology decreases latency and supports immediate responses [11]. However, most systems are only descriptive, with little predictive modelling for Soil Organic Carbon (SOC) assessment, and little integration of biochemical/satellite data [12].

2.2 ML for SOC estimation

Random Forests, SVM, and hybrid ensembles have been effective in SOC estimation and soil classification [13 - 16]. Vegetation indices (NDVI, NDMI, EVI) can increase predictive accuracy [17]. However, these approaches are unimodal and cloud-based, reducing their applicability to regional agricultural conditions [18], [19].

2.3 Deep learning and spatio-temporal models

CNN, LSTM, ConvLSTM models have been used in SOC mapping and precipitation forecasting [20]. Newer STGNNs capture soil–atmosphere parameters well [21], [22]. However, these are mostly black-box systems, and are less able to integrate physical soil processes.

Recent research underscores the necessity for hybrid models that integrate data-driven learning with domain-specific physical limitations to improve interpretability. In this context, the proposed CHGNN framework leverages multi-source data fusion and hierarchical graph modelling to improve both spatial scalability and prediction transparency in soil moisture estimation.

2.4 Security and Sustainability in Agricultural Systems

Block chain-based IoT solutions can enhance traceability and reliability and no-till farming, crop diversification, and sustain SOC and crop production [23]. Integrating sustainability insights with computational systems predictive SOC modelling is less common.

The above discussion on research carried out in this area are illustrated in Table 1. The current studies concentrate on conventional point-based or single-source models. In contrast, the proposed approach facilitates predictions from district to state level, hence improving the coverage and scalability of soil moisture prediction.

The proposed CHGNN model demonstrates superior predictive performance, offering a practical solution for precision irrigation and sustainable water resource management in Indian agriculture. The fusion of heterogeneous data sources ensures robustness against missing or noisy observations, which is a common limitation in conventional soil monitoring systems. The proposed framework integrates IoT-based soil sensors, Sentinel-2 imagery, and APWRMS datasets to achieve large-scale soil moisture prediction with improved spatial generalization.

Table 1: Comparison of Existing Soil related Prediction Frameworks with the Proposed Framework

Reference	Model/Framework	Application Domain	Limitations
[11] Padarian et al., 2019 (Soil Journal)	CNN-based deep learning	Digital soil mapping	Ignores temporal dynamics and physical relationships in soil processes
[12] Shi et al., 2015 (arXiv)	ConvLSTM	Precipitation nowcasting	Cannot effectively model spatial dependencies in graph-structured data
[19] Pan et al., 2024 (Journal of Hydrology)	Graph Neural Network + ConvLSTM	Soil moisture prediction	Lacks explicit integration of physics-based constraints
[22] Patil, 2022	Supervised ML (e.g., regression, decision	Soil health	Performance degrades for complex spatiotemporal

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Reference	Model/Framework	Application Domain	Limitations
(IJRASET)	trees)	classification	datasets
Proposed CHGNN Framework	Hierarchical GNN + ConvLSTM	Spatiotemporal prediction of soil moisture moisture	-

3.Data sources

3.1 Andhra Pradesh State Sentinel Images Collection

Ground truth soil moisture values are essential for constructing the soil moisture prediction model. The Andhra Pradesh Water Resources Management (APWRM) database provided the soil moisture values for each district [24].

The APWRM system integrates environmental, demand, and supply data across the state with a strong emphasis on sustainability. It offers stakeholders and policymakers real-time monitoring and decision support capabilities by leveraging cutting-edge technologies including satellites, sensors, and artificial intelligence. The primary objectives of the system are to enhance water use efficiency, improve agricultural productivity, and ensure water security for drinking, irrigation, and industrial purposes.

To construct the CHGNN model for predicting soil moisture values across the state of Andhra Pradesh, Sentinel-2 images were collected using Google Earth engine (GEE) [25]. GEE is a free cloud-based platform for accessing geospatial data. In this research the Copernicus (Sentinel-2) was used to satellite imagery. A Total, 26 districts in Andhra Pradesh, India, were selected, with each district considered as a single observation station. Based on the latitude and longitude coordinates, the soil moisture values for each district were mapped, and a shape file was generated. This shape file was then compressed into a ZIP file, and uploaded to the Google Earth Engine (GEE) Code Editor for further processing.

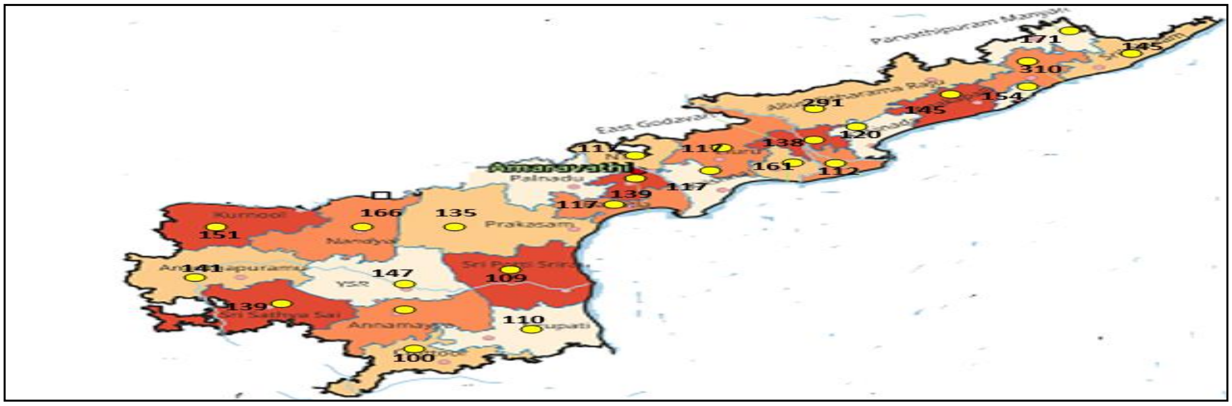

Figure 1. Map of Andhra Pradesh showing the study area and the number of Sentinel-2 images available for each station location.

Received: August 13, 2025

JavaScript code was developed and executed in GEE to extract Sentinel-2 imagery corresponding to the selected 26 districts. The dataset covers the period August 1, 2022, to December 31, 2024. A total of 3,801 Sentinel-2 image samples were collected across different districts of Andhra Pradesh. Each Sentinel-2 image has a spatial dimension of 32×32 pixels with six spectral, resulting in a consistent volume of 32×32×6.The six spectral bands are B2, B3, B4, B8, B11, and B12.Figure 1 shows the district-wise distribution of the collected Sentinel-2 images, illustrating the variation in sample counts across the 26 districts.

The images are then prepared for training and testing as follows:

- X-values: Sentinel-2 images
- Y-values: APWRM soil moisture values (ground truth)

3.2 Soil Sensor Node Creation

This system illustrates an Arduino-based smart irrigation setup. The soil moisture sensor measures the soil's water content and sends data to the Arduino for processing. A DHT11 sensor monitors temperature and humidity levels, while the NodeMCU module enables wireless data transmission via Wi-Fi. Power is supplied through a 12V transformer and regulated by an LDO module, and a relay module controls irrigation devices automatically. Figure 2. shows the soil sensor node, which retrieves real-time soil moisture values for intelligent irrigation management.

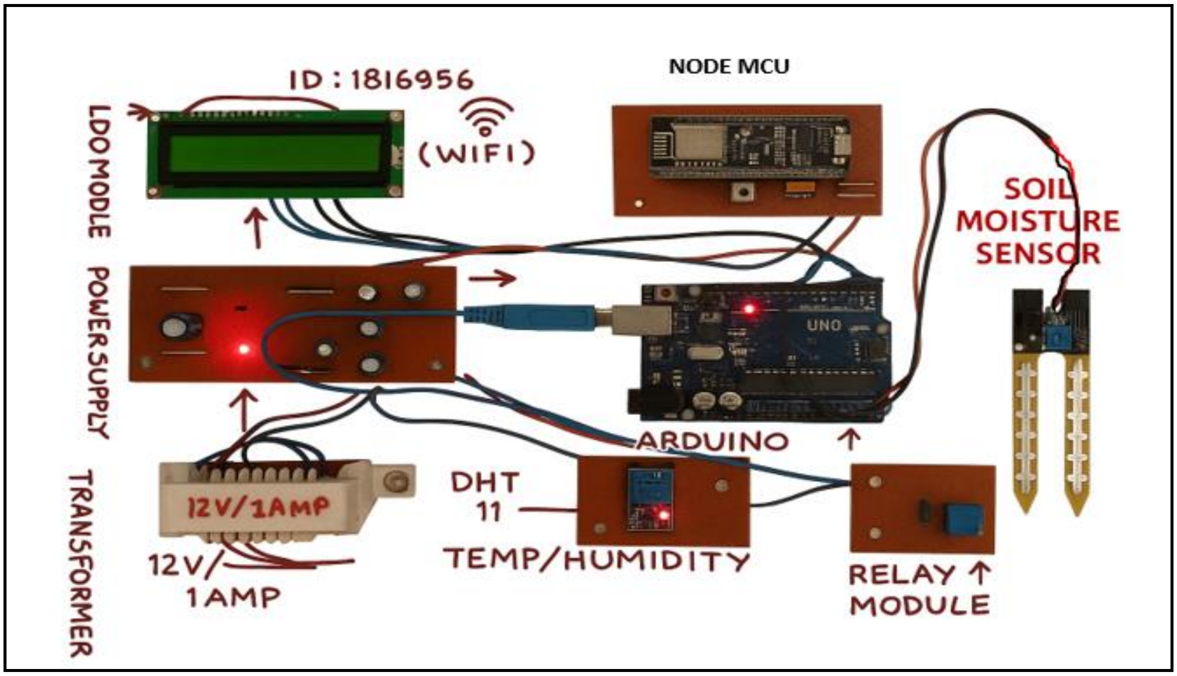

Figure 2. Soil Sensor Node

Using the soil sensor nodes, soil moisture, temperature, and humidity values were collected.

The main objectives of this research work are:

1. To generate the CHGNN model for predicting soil moisture using Sentinel-2 images and APWM soil moisture values as ground truth (state-level model).
2. To generate the CHGNN model for predicting soil moisture using Sentinel-2 images and IoT sensor-based soil moisture values as ground truth (district-level model).

The pin diagram of the sensor node is shown in Figure 3. The LCD display provides real-time visualization for farmers, while the Wi-Fi-enabled Node MCU enables remote monitoring and loud-based data storage. Figure 3 illustrates the wiring diagram showing the interconnections between the MCU, soil moisture sensor, DHT11, relay, and display unit.

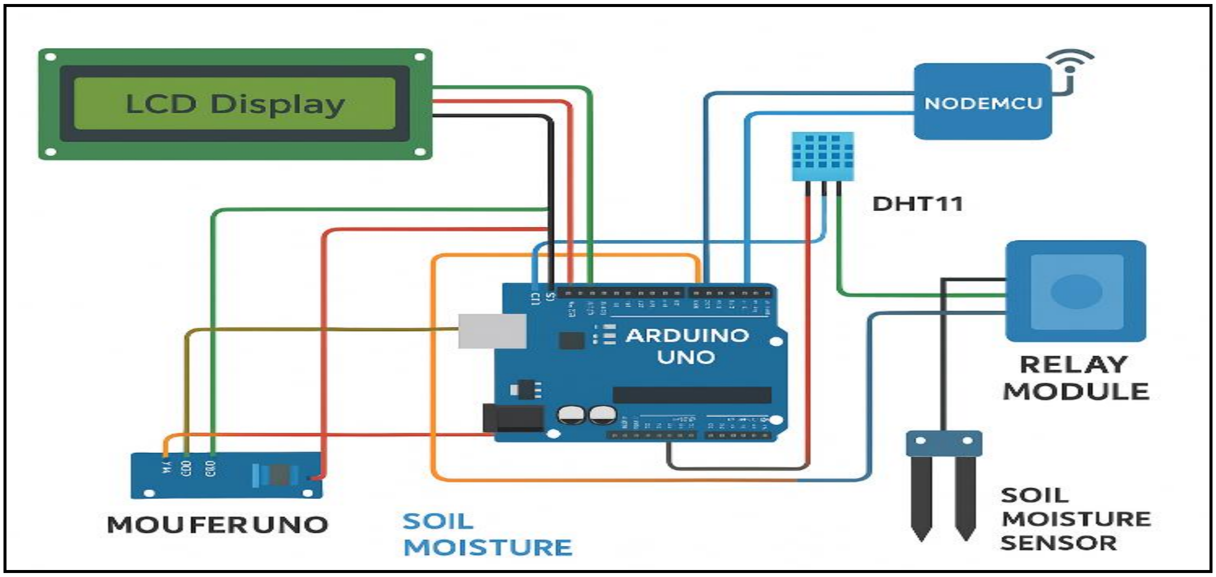

Figure 3. Pin diagram of the Soil Sensor Node

4.Proposed CHGNN Architecture

This section presents the methodological framework adopted for soil moisture prediction using Sentinel-2 satellite imagery and IoT-based soil sensor data. Two different architectures are designed and evaluated: an existing ConvLSTM–GNN hybrid model, and the proposed ConvLSTM–Hierarchical Graph Neural Network (CHGNN) model. Both models aim to exploit spatial and temporal dependencies within the data, but differ in their representation learning and graph-level aggregation strategies.

4.1 ConvLSTM–GNN Model

In Existing ConvLSTM–GNN model combines convolutional recurrent layers with graph-based feature propagation. First, a Convolutional Long Short-Term Memory (ConvLSTM) network processes sequential Sentinel-2 images to capture both spatial textures and temporal dynamics. The convolutional layers extract local spatial features, while the LSTM gates learn temporal dependencies between consecutive image frames.

The extracted temporal–spatial features are then flattened and used as node features in a Graph Neural Network (GNN) framework. Each district or observation region is represented as a node, and edges are defined based on geographical proximity or hydrological adjacency. The GNN, implemented using Graph SAGE convolution, aggregates neighbouring node features to capture regional spatial correlations.

Although this architecture effectively integrates temporal and spatial information, its representation learning remains shallow. The model performs aggregation only once across the graph, which limits its ability to capture hierarchical spatial relationships among multiple levels of neighbourhood connectivity. This limitation motivates the development of the proposed CHGNN model.

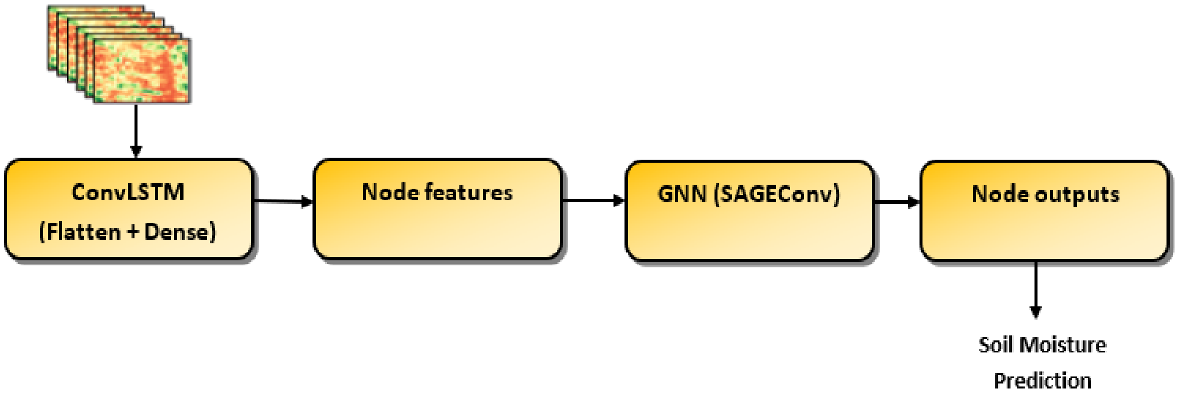

Figure 4. **Architecture of the ConvLSTM–GNN model**

4.2 Proposed ConvLSTM–Hierarchical Graph Neural Network (CHGNN) Model

The proposed ConvLSTM–Hierarchical Graph Neural Network (CHGNN) model is designed to predict soil moisture values by integrating both temporal–spatial features from Sentinel-2 imagery and inter-district spatial correlations through hierarchical graph reasoning. The model operates through six major stages, as illustrated in Figure 5.

In the first stage, Sentinel-2 satellite image sequences are input to a ConvLSTM2D network. Two ConvLSTM2D layers, each with 32 filters and 3×3 kernels, are applied sequentially to extract rich temporal and spatial features from the multi-date imagery. The ConvLSTM combines convolutional operations (for spatial feature extraction) and LSTM gates (for temporal memory), enabling the model to learn how reflectance patterns evolve over time. Batch Normalization layers are incorporated after each ConvLSTM2D layer to stabilize the learning process and prevent internal covariate shift.

In the stage 2, the feature maps obtained from ConvLSTM2D are flattened and passed through a Dense layer with 128 ReLU units, generating compact feature embedding for each observation region or district. These embedding represent node-level temporal–spatial features.

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A graph is then constructed where each node corresponds to a district, and edges define the spatial adjacency or hydrological connectivity among districts. The resulting graph dataset is represented as Data (x, edge_index, y), where:

- *x* denotes node feature vectors,
- *edge_index* defines connections between nodes, and
- *y* represents ground truth soil moisture values.

In stage 3, node embedding is processed through the first GraphSAGE convolution layer (SAGEConv) with 128 input and 64 hidden units. The ReLU activation introduces nonlinearity. After feature aggregation, Top-K pooling is applied with a pooling ratio of 0.5 to retain the most informative nodes while discarding redundant ones. A Global Mean Pooling operation (g_1) summarizes the first-level global representation, capturing coarse spatial dependencies across the graph.

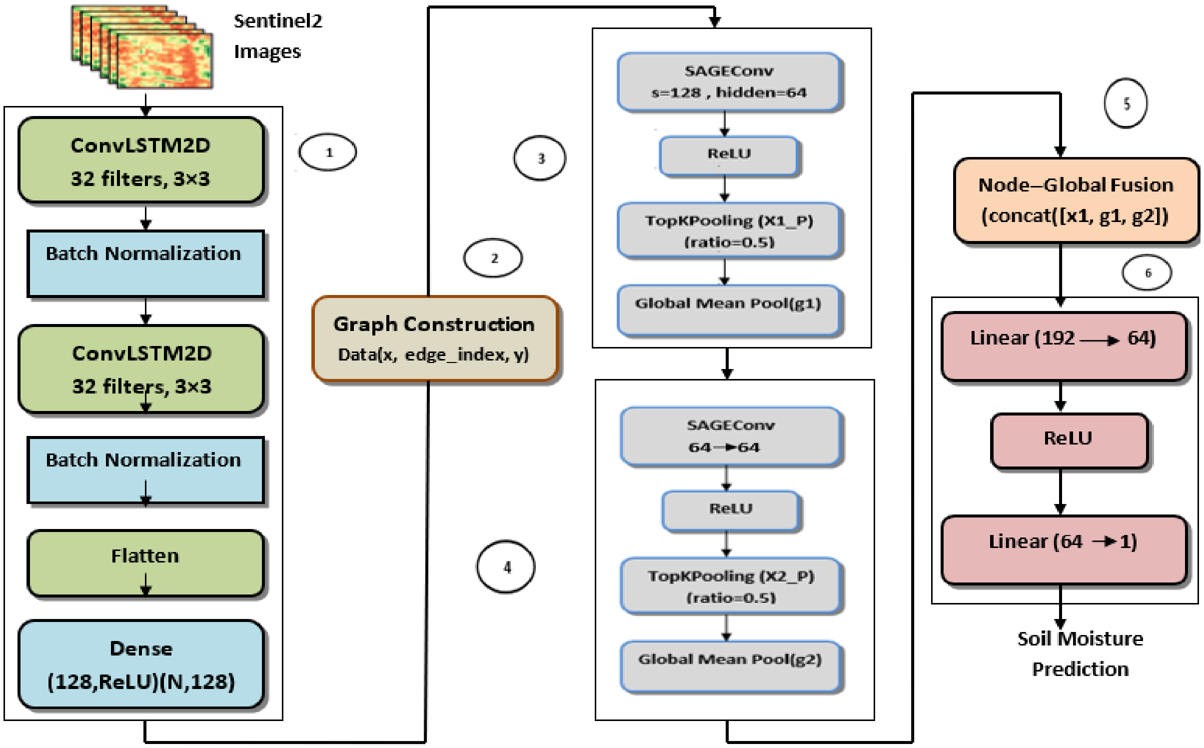

Figure 5. Architecture of the Proposed CHGNN Model

In stage 4 the pooled graph from Stage 3 is further processed using a second SAGEConv layer (64→64), followed by Top-K pooling (ratio = 0.5) and Global Mean Pooling (g_2). This stage refines the graph structure by learning deeper spatial dependencies among districts.

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The hierarchical pooling mechanism ensures that the model captures multi-scale spatial features, from local neighbourhood effects to state-level regional influences.

In Stage 5 the node features (x_1) from the ConvLSTM encoder are concatenated with the two global graph-level embedding (g_1 and g_2) obtained from the hierarchical GNN. This Node–Global Fusion stage creates a unified representation, combining local temporal–spatial features and global relational context. The fused vector [x_1, g_1, g_2] provides a comprehensive description of each district, incorporating both its intrinsic temporal behavior and its spatial correlations with other regions.

In Stage 6, the fused node representations are passed through a Multi-Layer Perceptron (MLP) that performs regression to predict soil moisture values.

The MLP consists of two fully connected linear layers:

- The first transforms the 192-dimensional input vector to 64 units, followed by a ReLU activation.
- The second maps the 64-dimensional feature vector to a single output neuron corresponding to the predicted soil moisture value.

5.Results

This section presents the performance evaluation of the proposed CHGNN (ConvLSTM–Hierarchical Graph Neural Network) model and compares it with the existing ConvLSTM–GNN (CGNN) architecture, which is widely applied for Sentinel-2 image analysis.

5.1 Soil Moisture Prediction Using Sentinel-2 Images and APWRMS Data

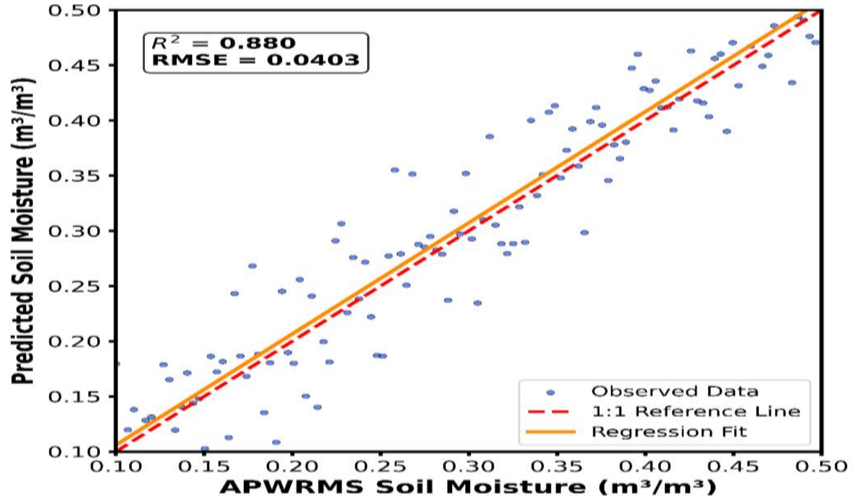

Figure 6. CHGNN Model Predicted vs. APWRMS Observed Soil Moisture

Figure 6 represents the results of the proposed CHGNN model using six Sentinel-2 spectral bands as input. The scatter plot illustrates the relationship between the observed APWRMS soil moisture and the predicted soil moisture obtained from the CHGNN model. A total of 3,801 Sentinel-2 image patches, covering all districts of Andhra Pradesh, were used for model training and validation.

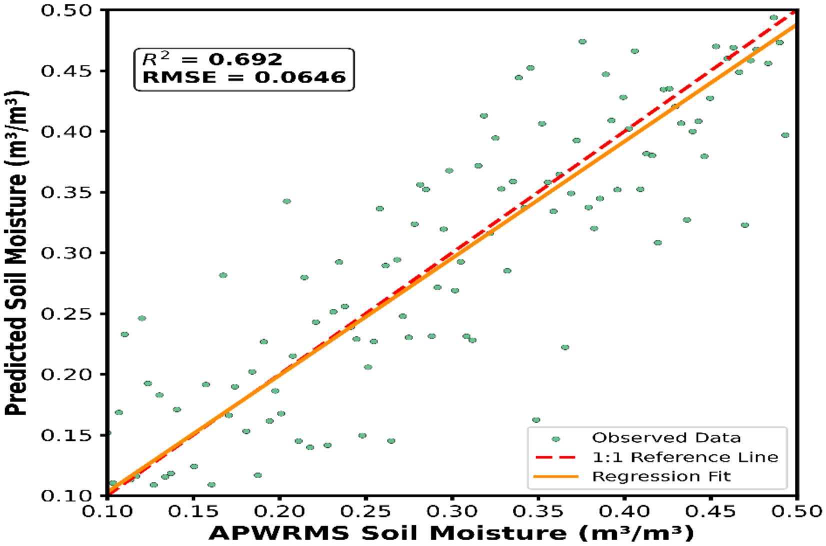

Figure 7. Existing CGNN Model Predicted vs. APWRMS Observed Soil Moisture

The model achieved a high coefficient of determination ($R^2 = 0.880$) and a low root mean square error (RMSE = 0.0403 m^3/m^3), indicating excellent agreement between observed and predicted soil moisture values.

Figure 7 shows the performance of the existing CGNN (ConvLSTM–GNN) model under the same experimental conditions. The obtained statistical metrics are $R^2 = 0.692$ and RMSE = 0.0646 m^3/m^3, suggesting a weaker correlation and higher prediction error compared to the CHGNN model. The visual comparison between Figures 6 and 7 highlights the superior predictive capability and robustness of the proposed CHGNN architecture.

5.2 Soil Moisture Prediction Using Sentinel-2 Images and IoT Sensor Data

This section presents the soil moisture prediction performance of the proposed CHGNN model using IoT-based in-situ sensor data collected from the Kadapa district as ground truth. A total of 1,810 Sentinel-2 image patches corresponding to the IoT sensor network locations were used for model training and validation. The scatter plot (Figure 8) shows the relationship between observed IoT-based soil moisture values and predicted soil moisture obtained from the CHGNN model. The proposed model achieved $R^2 = 0.841$andRMSE = 0.0464 m^3/m^3, demonstrating strong correlation and high prediction accuracy. These results indicate that the CHGNN model effectively captures spatial soil moisture variability even with localized IoT sensor measurements.

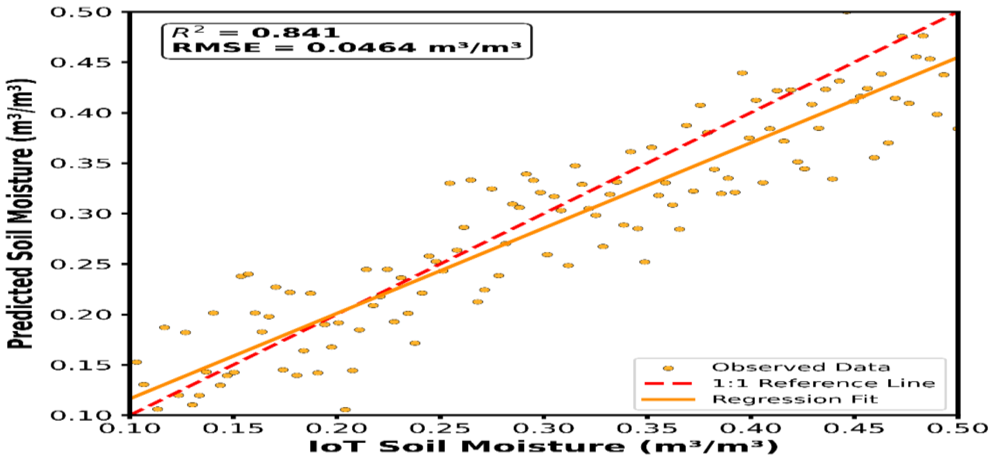

Figure 8. Proposed CHGNN Model Predicted vs. IoT Sensors Observed Soil Moisture

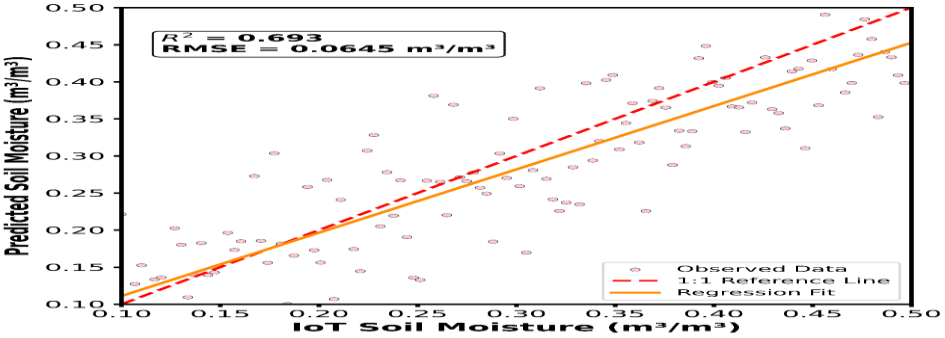

Figure 9. Existing CGNN Model Predicted vs. IoT Sensors Observed Soil Moisture

For comparison, Figure 9 shows the performance of the existing CGNN model under identical experimental settings using the same IoT sensor dataset. The obtained metrics $R^2 = 0.693$ and RMSE = 0.0645 m³/m³ reveal a weaker linear relationship and higher prediction error compared to CHGNN. The comparative visualization between Figures 8 and 9 clearly establishes that the CHGNN architecture outperforms the conventional CGNN, achieving improved consistency, robustness, and generalization when trained using IoT sensor data as reference. This confirms the effectiveness of the proposed CHGNN model in integrating spatiotemporal and contextual informationfor enhanced soil moisture estimation across agricultural landscapes.

5.3 Temporal Validation of Soil Moisture Predictions

Figure 10 illustrates the temporal variation of predicted and observed soil moisture at the Andhra Pradesh Site from2022 to 2024. The CHGNN model demonstrates a close alignment between the predicted and actual soil moisture trends, capturing both seasonal fluctuations and long-term variations. The obtained statistical indicators $R^2 = 0.88$andRMSE = 0.0403 m³/m³ confirm the high predictive accuracy and temporal consistency of the proposed model. This result highlights the capability of CHGNN to generalize well across time, effectively monitoring dynamic soil moisture conditions using Sentinel-2 data.

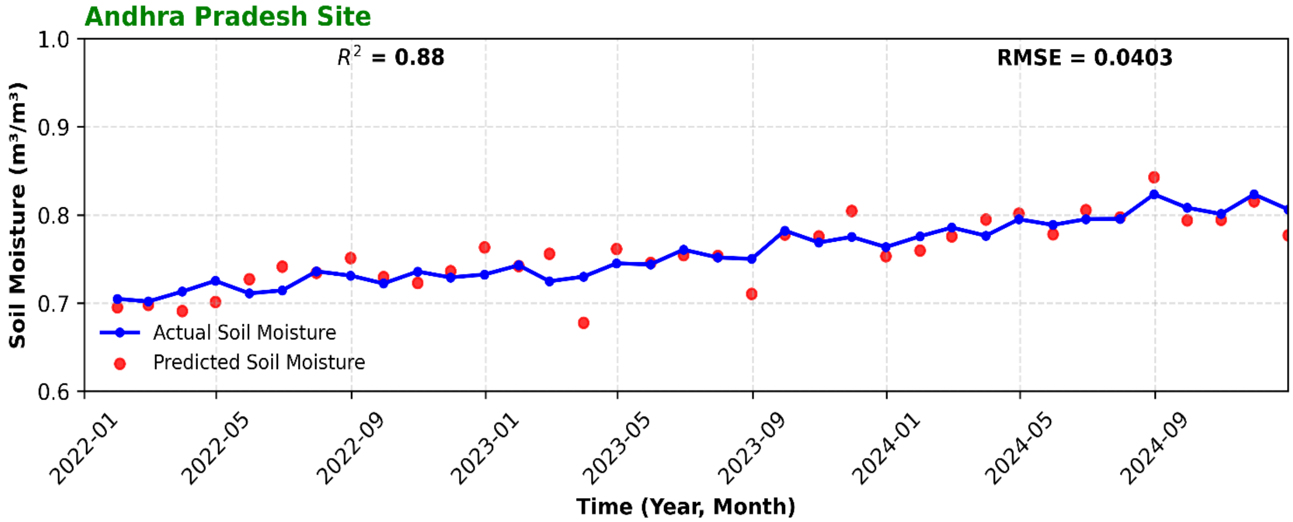

Figure 10. **Temporal Variation of Predicted and Observed Soil Moisture at Andhra Pradesh Sites**

5.3 Model Training and Evaluation Summary

The proposed CHGNN (ConvLSTM–Hierarchical Graph Neural Network) model was trained and evaluated using a total of 3,801 Sentinel-2 image samples collected from all districts of Andhra Pradesh. Out of these, 3,040 samples (80%) were used for training and 761 samples (20%) were reserved for testing.

To model spatial dependencies, a62 × 62 spatial grid was constructed, comprising 29,912 edges defined using a 4-nearest neighbour topology (up, down, left, and right adjacency). The graph edges were considered unweighted, and the model was trained using a temporal window of size1 to capture local spatiotemporal interactions in soil moisture dynamics.

The ConvLSTM2D module extracted spatial-temporal features with a feature dimension of 128, while the graph neural network component consisted of 64 hidden channels and a pooling ratioof 0.5**.** The model was trained for 300 epochs with a learning rate of 0.01**.**

Performance evaluation on the test set demonstrated strong predictive capability, achieving a Root Mean Square Error (RMSE) of 0.0403 and a coefficient of determination (R^2) of 0.88**,** indicating a high degree of correlation between predicted and observed soil moisture values.

6.Conclusion

The suggested method effectively captures spatiotemporal dependencies in Sentinel-2 soil images using ConvLSTM layers and multi-scale spatial linkages via the Hierarchical GNN component. By combining data from multiple diverse sources, the model provides improved spatial coverage and robustness compared to conventional soil moisture prediction methods.

Experimental results demonstrated that the CHGNN model achieved a strong predictive performance with $R^2 = 0.88$ and RMSE = 0.0403, significantly outperforming the traditional ConvLSTM–GNN architecture. This indicates the model's capacity to generalize well across different climatic zones and vegetation types, enhancing its potential for large-scale agricultural applications. The integration of IoT and remote sensing data offers a promising pathway for real-time soil moisture monitoring and precision irrigation management, supporting more sustainable water usage in agriculture. Future work may include incorporating climate forecasting data**,** additionalspectral indices (NDWI, SAVI)**,** and deep attention mechanismsto further refine spatial–temporal featureextraction. Expanding the model to includereal-time IoT edge computationandtransfer learning for cross-regional adaptabilitycan enhance its operational efficiency and scalability for broader agricultural decision-support systems.

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