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A novel AI framework for soil moisture estimation using sentinel-2 multispectral imagery and temporal convolutional networks

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ABSTRACT

Accurately assessing soil moisture is indispensable for agriculture, water resources management, and hydrology studies. The priority of these forecasts is even higher, especially in areas with different climatic conditions and terrain characteristics. Most satellite-based approaches currently in use are not able to effectively account for spectral information, spatial characteristics, and seasonal changes all at once. With this problem in mind, we have proposed a new deep learning approach that uses a combination of Sentinel-2 multi-spectral satellite images and ground-based soil moisture measurements. We have used the Spectral Fusion Enhancement approach to prioritize important spectral bands, Convolutional Neural Networks to identify terrain features, and Dynamic Dilated Temporal Convolutional Networks to analyze seasonal changes. The study used 3,801 Sentinel-2 satellite image patches collected from 26 districts of Andhra Pradesh state by Google Earth Engine and the actual soil moisture values obtained from APWRIMS. According to the results of the experiment, the proposed model achieved values of 4.52 RMSE, 1.67 MAE, and 0.94 R2, showing better performance than other ordinary models. The ablation study also demonstrated that the predictive accuracy is significantly improved when each component is worked together. Therefore, this approach is useful for reliably estimating soil moisture at the regional level and is crucial in precision agriculture and water management.

Contribution/Originality: This study contributes to existing literature through integrated spectral–spatial–temporal soil moisture modeling. It employs a novel spectral fusion, CNN, and dilated temporal convolution methodology. The study introduces a spectral prioritization formula and is among the few Sentinel-2 regional analyses with ground data. It provides the first logical prioritization analysis and documents validated multi-district accuracy gains.

1. INTRODUCTION

Soil moisture is an important physical parameter in land-climate interactions, agricultural productivity, water flow processes, and predictions of sunny conditions. Proper information on soil moisture on the surface of the earth is very useful for irrigation management, crop yield estimation, flood early warnings, and climate studies. However, soil moisture varies greatly from region to region due to changes in soil nature, vegetation, terrain features, and climatic conditions. Because of this, it has become difficult to effectively monitor soil moisture over wide areas. Satellite-based remote sensing technologies have been widely used to combat this problem. Early satellite missions such as Soil Moisture and Ocean Salinity (SMOS) and Soil Moisture Active Passive (SMAP) demonstrated that it is possible to estimate soil moisture on a global scale through microwave observations [1, 2]. Subsequent studies have clarified that satellite-based soil moisture products are useful for hydrological and agricultural applications [3]. In addition, long-term global soil moisture datasets, such as the ESA Climate Change Initiative (CCI) and Soil Grids, have further expanded soil-related information needed for Earth system studies [4, 5]. However, as microwave-based soil moisture products typically have low spatial resolution, their use for district-level agricultural monitoring is limited. Alternatively, optical satellite missions such as Sentinel-2 can provide high-resolution multispectral images that clearly capture spectral characteristics sensitive to vegetation conditions, soil brightness, and moisture. Therefore, remarkable research is being conducted recently on soil moisture estimation through data-driven methods using Sentinel-2 data.

In recent years, machine learning and deep learning technologies have achieved significant improvements in soil moisture predictions based on satellite data. In particular, convolutional neural networks (CNNs) are widely used to detect spatial features from multi-spectral satellite images. Several studies have shown that CNN-based models and data fusion methods using Sentinel satellite data have yielded good results in soil moisture prediction [6, 7]. Also, important studies suggest that deep learning models show better performance than traditional regression methods, due to their ability to better capture the complex non-linear relationships that exist between spectral properties and soil moisture [7, 8]. Since soil moisture is naturally a time-varying parameter, models that rely solely on topographical features cannot fully capture time-related effects such as rainfall, evaporation, and water movement in the soil.

To overcome this deficit, periodic deep learning models such as recurrent neural networks and temporal convolutional networks (TCNs) have been introduced into soil moisture modeling [9]. However, although these models reflect period information well, their performance is likely to be reduced when spectral significance is not clearly considered. Another important challenge is the effective use of Sentinel-2 multispectral bands. Not all spectral bands contribute equally to soil moisture under different terrain and vegetation conditions. If there is no proper spectral weight allocation, the important bands may not be fully utilized, resulting in reduced feature extraction quality. Recent research suggests that spectral fusion and attention-based approaches are key to increasing soil moisture sensitivity in multisensory and multispectral frameworks [10, 11].

Based on the above observations, it is clear that improving spectral information, learning spatial patterns, and correctly detecting changes over time all need to be implemented together in a single integrated modeling approach. Using Sentinel-2 satellite imagery and ground-based soil moisture observations, we propose a new deep learning architecture that combines spectral fusion. This approach helps to make soil moisture predictions more accurate. The Dilated Temporal Convolutional Networks framework not only achieves high predictive accuracy but is also computationally efficient, making it suitable for regional-level agricultural monitoring.

Although satellite-based soil moisture products are available and significant progress has been made recently in machine learning, accurate assessment of soil moisture at the regional and district levels remains a critical issue. Existing approaches are unable to simultaneously capture the spectral significance of multispectral bands, the spatial variability of terrain features, and the temporal changes caused by seasonal climate variations. Therefore, the key research problem addressed in this study is how to design an integrated modeling framework that can effectively combine spectral, spatial, and temporal information to improve soil moisture estimation accuracy using high-resolution Sentinel-2 imagery and ground-based observations.

The remainder of this paper is organized as follows. Section 2 describes related work on soil moisture estimation using remote sensing and deep learning techniques. Section 3 describes data sources and preprocessing steps. Section 4 presents the proposed SFE–CNN–DD-TCN methodology in detail. Section 5 discusses experimental results and performance evaluation. Finally, Section 6 concludes the paper and outlines future research directions.

2. RELATED WORK

Recent advances in remote sensing and deep learning have significantly improved soil moisture prediction at both global and regional levels. Early studies have shown that multi-sensor data fusion approaches using a combination of Sentinel-1 and Sentinel-2 satellite images are useful for soil moisture assessment. However, these approaches are mainly limited to combining radar and optical data and do not explicitly model spectral preferences or seasonal changes [11]. Recent research has attempted to effectively capture long-term soil moisture changes using deep temporal architectures such as TCN-Transformer. However, these models are computationally cumbersome and mainly suitable for global-scale reconstruction and are limited to regional monitoring [12].

Dilated convolution techniques have been widely used in remote sensing to expand the receptive field and obtain multi-scale features [13-15]. Although they improve the representation of topographical features, they are not specifically designed for soil moisture assessments and do not consider seasonal factors naturally present in soil moisture. Recent spatio-temporal-spectral fusion frameworks that attempt to integrate different information quantities have shown improved performance in soil moisture downscaling [16]. However, many of these approaches treat multispectral bands equally and do not give special preference to spectral bands important for soil moisture.

Some research has attempted to increase soil moisture sensitivity in deep learning models using spectral fusion and attention-based methods [17, 18]. Although attentional approaches have improved feature weighting, they often face problems such as high computational complexity and limited scalability over large regional datasets due to their reliance on recurrent architectures such as LSTM. Although recent deep learning models based on Sentinel-2 have shown higher spatial resolution and improved predictive accuracy at the regional level [19, 20] many approaches focus on only one aspect of spatial or temporal learning and are unable to model spectral preference, spatial variation, and temporal change in a comprehensive manner.

High accuracy in surface soil moisture estimation has been achieved through multi-source deep learning frameworks based on Sentinel satellite data. However, such approaches face high model complexity due to the combined use of multiple data sources [21]. Comprehensive evaluations conducted on various machine learning models for soil moisture predictions using satellite observations indicated that the performance of the model is highly dependent on feature selection and data properties [22, 23]. Also, recent studies have shown that high-resolution soil moisture predictions are possible using optical satellite images and deep learning technologies. However, these approaches focus primarily on spatial learning and do not explicitly consider seasonal changes or spectral preferences.

These limitations clearly show the need for a comprehensive and computationally efficient deep learning framework that can effectively model spatial and temporal features while also enhancing spectral information. The SFE-CNN-DD-TCN architecture proposed in this research directly addresses this research gap by prioritizing spectral bands important for soil moisture and implementing spatial-periodic learning. This approach will enable accurate and scalable soil moisture predictions at the regional level. To better illustrate the limitations of existing soil moisture assessment methods and to clearly establish the contribution of the proposed approach, a comparative summary of representative studies is shown in Table 1.

Table 1. Comparison of existing soil moisture estimation methods and the proposed approach.

Ref	Methodology	Data Source	Key Limitation
Hegazi, et al. [9] and Singh and Gaurav [10]	CNN based Models	Sentinel-2, Sentinel-1/2	Changes in time are not clearly modeled.
Liu, et al. [11]	Deep Learning Multi-Source Data Fusion	S1/S2+SMAP+GLDAS	High model complexity and computational load.
Wang, et al. [12]	TCN Transformer Parallel Architecture	FY-3B	Spectral significance is not considered.

Ref	Methodology	Data Source	Key Limitation
Hamaguchi, et al. [13] and Hamaguchi, et al. [14]	Dilated and Multi-scale CNN Models	Remote Sensing Imagery	Not designed directly for soil moisture assessment.
Li, et al. [15] and Jiang, et al. [16]	Spatial-Temporal/Spatio-Spectral Fusion Models	RS+ Ground Multi Source	High Computational Cost
Proposed work	SFE+CNN+DD-TCN	Sentinel-2+APWRIMS	-

As shown in Table 1, most current approaches focus primarily on spatial feature identification, temporal sampling, or multi-source data fusion. This results in limitations such as high computational complexity or spectral preference not being considered appropriately. While clearly considering spectral preference, approaches to comprehensively model spatial and temporal variations simultaneously are currently very limited. To address this shortcoming, the framework proposed in this research combines spectral enhancement, spatial feature learning, and periodic sampling into a single, computationally efficient architecture.

3. DATA SOURCES AND PRE-PROCESSING

3.1. Satellite Data

The multi-spectral satellite images used in this study were collected by the Google Earth Engine (GEE) platform from the Sentinel-2 mission. Surface reflectance data from the COPERNICUS/S2_SR collection were used, covering the period from January 1, 2020, to December 31, 2024 [20]. The high-resolution optical data provided by the Sentinel-2 satellite is highly suitable for terrain and agriculture-related observations. Six spectral bands have been selected, which are important for soil moisture and vegetation analysis: B2 (Blue), B3 (Green), B4 (Red), B8 (Near-infrared), B11 (Short-wave infrared-1), and B12 (Short-wave infrared-2). These bands can reflect changes in soil moisture levels, vegetation density, and surface reflectivity.

Each satellite image is divided into fixed-size patches based on the geographical areas corresponding to different districts of the state of Andhra Pradesh. Through this, we have been able to effectively derive spatial patterns that reflect soil moisture variations at the regional level. A total of 3,801 Sentinel-2 multispectral image patches were collected. Each patch has been resized to the same spatial resolution to ensure uniformity across all models. Min-max normalization method has been implemented on each spectral band to reduce radiometric differences and improve computational stability during model training. Figure 1 shows the geographical area of the state of Andhra Pradesh, the selected Sentinel-2 spectral bands, and the scientific evidence responsible for the band selection.

Since soil moisture estimation is designed as a regression problem, conventional class imbalance management approaches are not applicable to this study. To avoid distortion caused by the unequal spatial distribution of samples between districts, we used stratified sampling during data separation. Since the data used in this study was collected entirely from real-world satellite observations, no synthetic data augmentation was employed.

3.2. Land-Based Soil Moisture Data

The land-based soil moisture values were collected from Andhra Pradesh Water Resources Information and Management Systems (APWRIMS) [19]. It functions as an official state-level information system that continuously records hydrological and soil moisture observations. The APWRIMS network covers all 26 districts of Andhra Pradesh and provides reliable soil moisture measurements at specific locations. These ground-based measurements were used as ground truth labels for supervised learning. An accurate correlation between the satellite inputs and the actual soil moisture values was achieved by comparing each Sentinel-2 image patch with the APWRIMS soil moisture data of the same date in terms of time.

Soil moisture values are standardized by z-score normalization to effectively perform model training and minimize scale differences. Then, performance evaluation and analysis are undertaken by converting the model estimates back into actual physical units. Table 2 shows district-wise dataset abstraction, names of districts, number of Sentinel-2 patches collected, and corresponding APWRIMS soil moisture values.

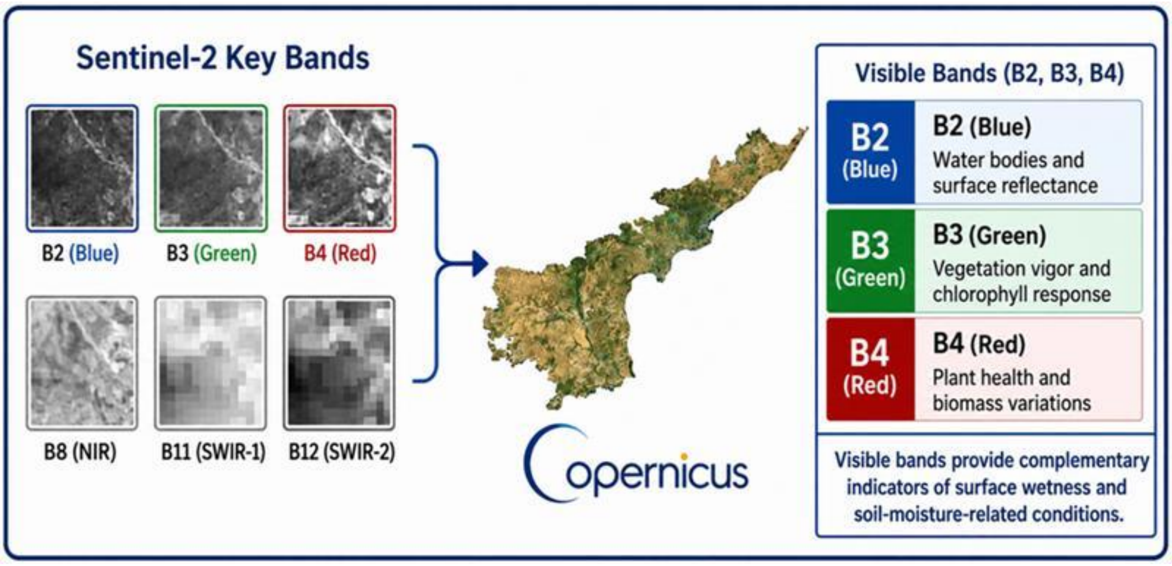

Figure 1. Geographical area of the state of Andhra Pradesh, the selected Sentinel-2 spectral bands.

Table 2. Dataset abstraction.

District name	Sentinel 2 images collected	APWRIMS soil moisture (Ground truth value)	District name	Sentinel 2 images collected	APWRIMS soil moisture (Ground truth value)
Srikakulam	145	94.52	Guntur	117	63.17
Vizianagaram	310	89.83	Bapatla	117	81.19
Parvathipuram Manyam	154	84.85	Palnadu	139	68.16
Alluri Sitharama Raju	291	86.84	Prakasam	117	61.96
Visakhapatnam	145	96.94	Sri Potti Sriramulu Nellore	109	45.48
Anakapalli	120	95.28	Kurnool	151	78.42
Kakinada	118	84.20	Nandyal	166	61.92
Konaseema	120	76.36	Ananthapuramu	141	35.41
East Godavari	138	48.26	Sri Satya Sai	139	62.29
West Godavari	117	74.44	YSR Kadapa	147	76.62
Eluru	112	50.78	Annamayya	200	59.45
Krishna	161	66.2	Chittoor	100	95.38
NTR	117	79.57	Tirupati	110	62.43

4. THE PROPOSED METHODOLOGY

The proposed approach is designed to accurately predict soil moisture by sampling spectral, spatial, and seasonal characteristics in a single integrated deep learning framework. This approach first applies Spectral Fusion Enhancement that prioritizes Sentinel-2 spectral bands sensitive to soil moisture. It then uses convolutional neural networks to learn spatial patterns from multispectral image patches. Next, it effectively learns seasonal and climatic effects using the Dynamic Dilated Temporal Convolutional Network to model seasonal changes in soil moisture. While many past studies have focused on only one aspect of spatial feature identification, temporal sampling, or multi-source data fusion, the proposed framework emphasizes spectral preference first and then implements spatial-temporal learning. This design improves forecast accuracy while reducing unnecessary model complexity, making this research stand out from current CNN, LSTM, or transformer-based soil moisture forecasting approaches. The soil moisture assessment method proposed in this research was developed by analyzing the strengths and limitations of two existing deep learning structures: the Plain Spectral Fusion Enhancement (SFE) model and the CNN-DD-TCN model, shown in Figure 2 and Figure 3, respectively. Although these structures offer useful properties, they are not sufficient individually to fully understand the spectral, spatial, and temporal properties of soil moisture. To address these limitations, we propose a comprehensive and improved structure, as shown in Figure 4, Motivation for the proposed policy.

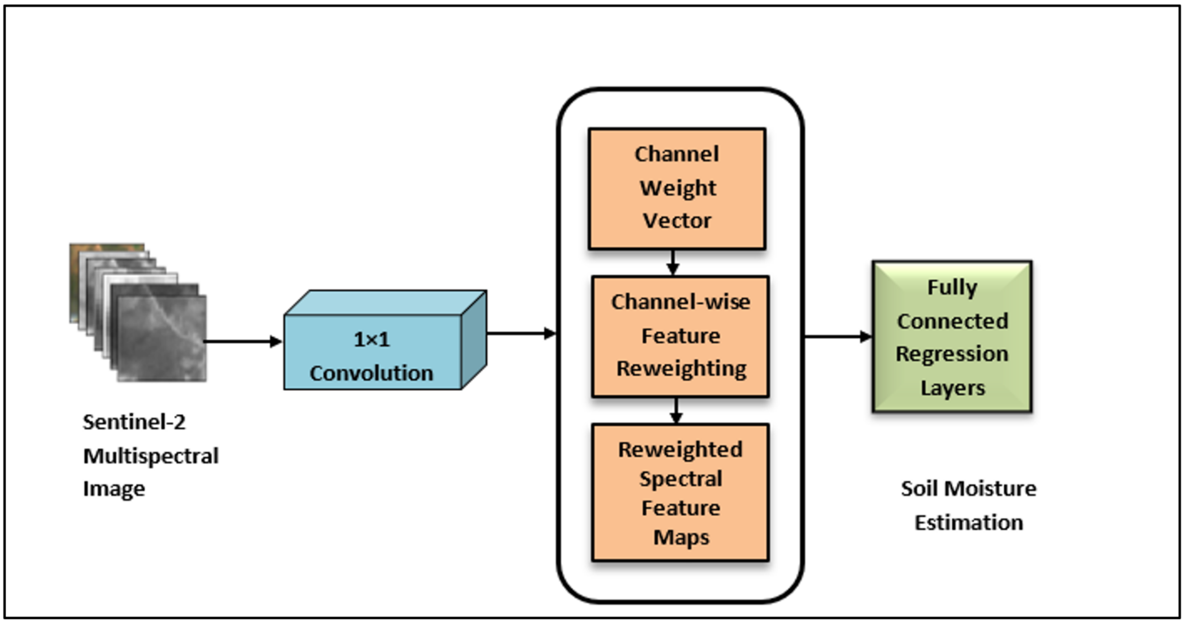

Figure 2. Plain SFE architecture.

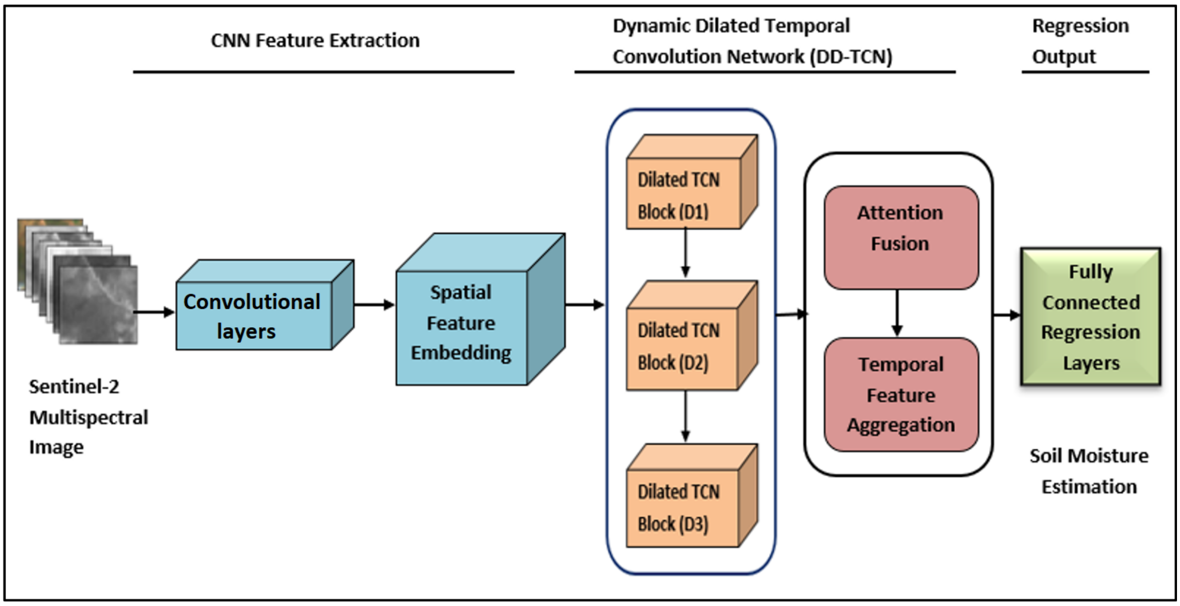

Figure 3. CNN-DD-TCN structure.

The Plain SFE structure (Figure 2) improves spectral information mainly by rearranging Sentinel-2 spectral bands through channel attention. While it highlights useful spectral information, it does not explicitly model spatial patterns or seasonal changes on Earth's surface. Consequently, its performance is limited in areas with different terrain conditions.

On the other hand, the CNN-DD-TCN structure (Figure 3) can effectively detect spatial features through convolutional layers and model temporal relationships through dynamically dilated temporal convolutional networks.

However, this structure treats all spectral bands equally, with direct use of raw spectral data. As a result, spectral information, which is important for soil moisture, may not be fully utilized at an early stage. For these reasons, it became clear that a new integrated approach was needed that first improved spectral information and then combined spatial and temporal features. As shown in Figure 4, the proposed architecture uses spectral fusion enhancement, CNN-based spatial feature extraction, and dynamically dilated temporal convolutional networks combined in a coordinated and interoperable manner.

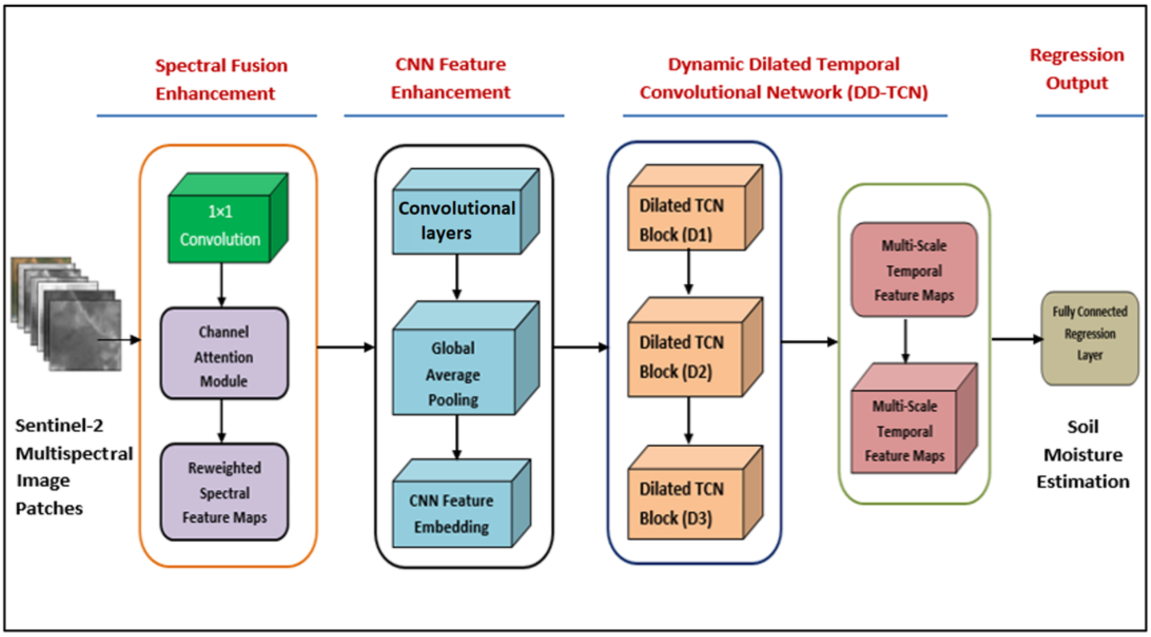

Figure 4. Proposed SFE-CNN-DD-TCN architecture.

4.1. Proposed SFE-CNN-DD-TCN Structure

First, we apply Spectral Fusion Enhancement (SFE) to Sentinel-2 multispectral image patches. In this step, the spectral bands are first converted into a common feature space using 1×1 convolution. The channel then learns the importance of each band through the attention mechanism. This makes the bands that are most useful for soil moisture assessment more preferable, and the effect of fewer desirable bands is minimized.

The enhanced spectral features are then forwarded to the CNN-based feature extraction module. In this step, several convolutional layers and global average pooling are used to identify spatial patterns related to soil nature, vegetation, and terrain characteristics, and to generate concise and useful feature representations. Finally, these spatial features are processed by a dynamically dilated temporal convolutional network (DD-TCN). Temporal convolutional blocks with different dilation rates capture changes that are present at different time magnitudes. An attention-based fusion mechanism effectively combines these multiple levels of temporal features to form a final feature. Then, the final soil moisture assessment is obtained through the fully connected regression layer.

4.2. Novelty and Advantages of the Proposed Policy

The important innovation in this proposed approach lies in integrating spectral enhancement with spatial and temporal learning. While the Plain SFE model (Figure 2) is limited to spectral rearrangement, the proposed approach additionally makes full use of spatial and temporal information. Compared to the existing CNN-DD-TCN model (Figure 3), the proposed architecture operates on improved input features by introducing spectral enhancement at an early stage.

The main benefits of this approach include improved detection of important spectral information from Sentinel-2 bands, stronger spatial feature learning through CNN layers applied to spectrally enhanced inputs, and effective modeling of multi-level temporal relationships using dynamically dilated convolutions. Additionally, this model shows improved generalizability across different agro-climatic zones and achieves lower error rates. By effectively combining the strengths of two existing frameworks and addressing their limitations, the proposed SFE-CNN-DD-TCN framework offers an overarching and effective solution for soil moisture assessment.

5. RESULTS

The experiments in this study were based on a dataset consisting of 3,801 Sentinel-2 multispectral image patches and their corresponding ground-based soil moisture values collected by APWRIMS. The data was divided in the ratio of 80:20, with 3,040 samples used for model training and 761 samples used for testing.

5.1. Experimental Step

Each input patch has a spatial size of 34 × 33 pixels, with a total of 6 spectral bands. Hence, the input data format is defined as (H, W, C) = (34, 33, 6). Since ground truth soil moisture data is available only for each observation date, the temporal window is determined as TIME_STEPS = 1.

The proposed model was trained for a maximum of 80 epochs using the Adam optimizer. In this process, the learning rate was set to 0.001, and the batch size was 32. Criteria such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Decision Coefficient (R^2) were used to evaluate the model's performance.

5.2. Performance of the Proposed Model

The accuracy of the proposed method was analyzed using three correlation graphs based on the test dataset.

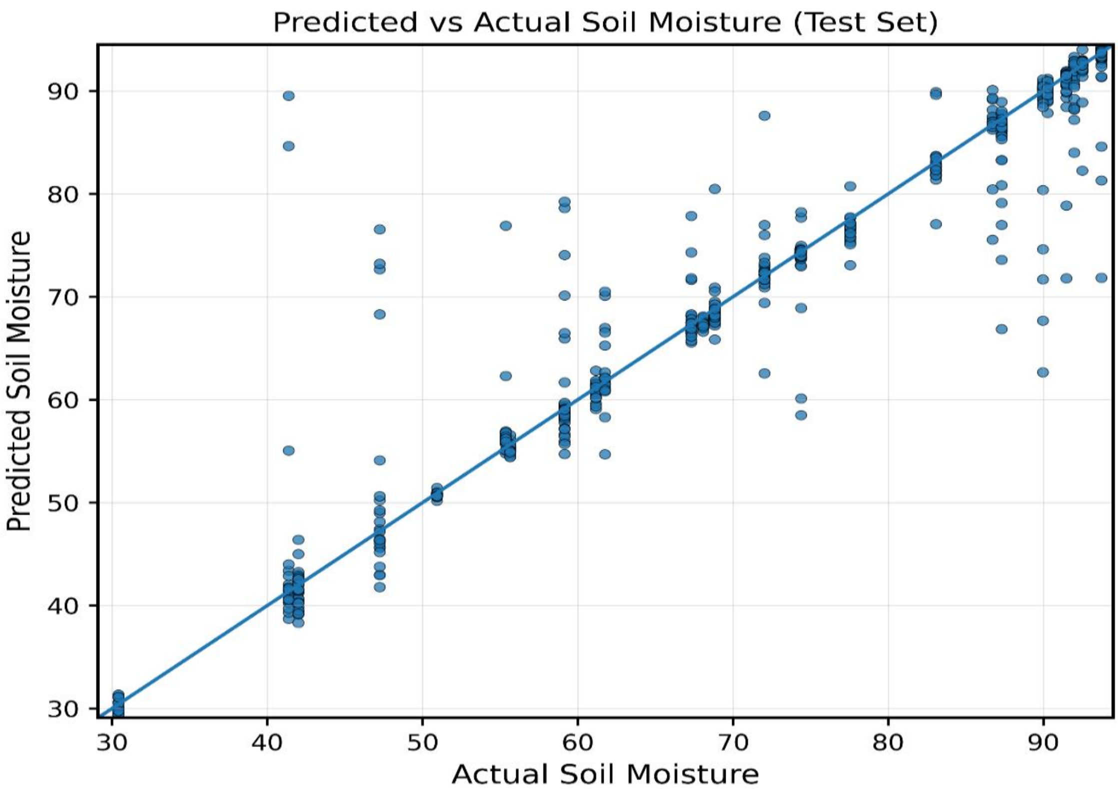

Figure 5. Predicted values vs actual soil moisture values.

The Figure 5 illustrates the relationship between soil moisture values predicted by the model and the corresponding ground truth measurements. Most data points lie close to the ideal diagonal line, indicating strong agreement between predicted and actual values and demonstrating the model's high accuracy in soil moisture estimation.

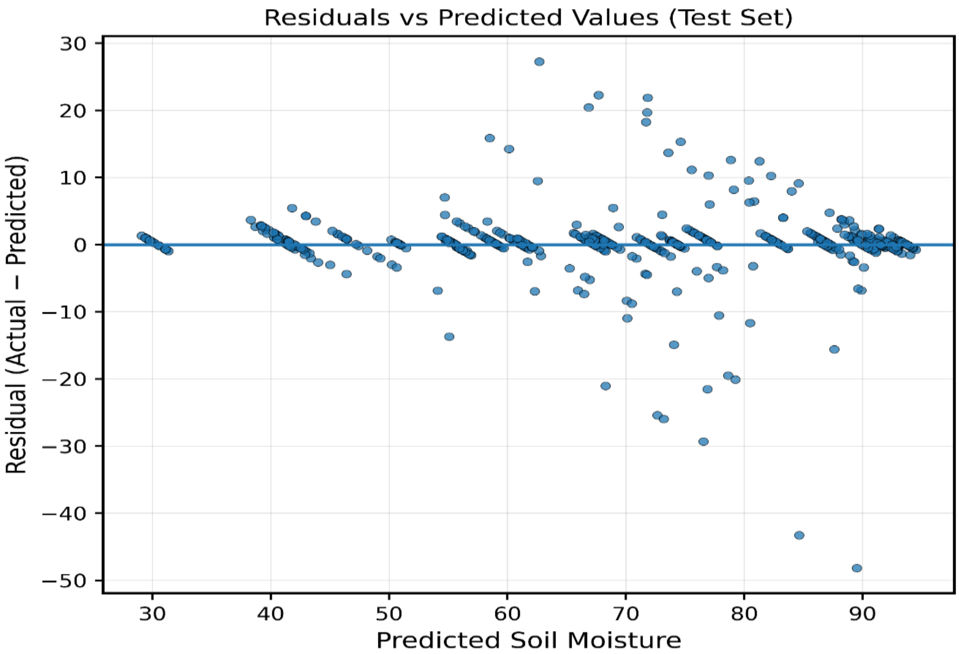

Figure 6. Residuals vs. predicted soil moisture values.

The Figure 6 shows how the errors in the model estimates are distributed. Since the remaining errors are mainly concentrated around zero, it is clear that there is no systematic bias in the model.

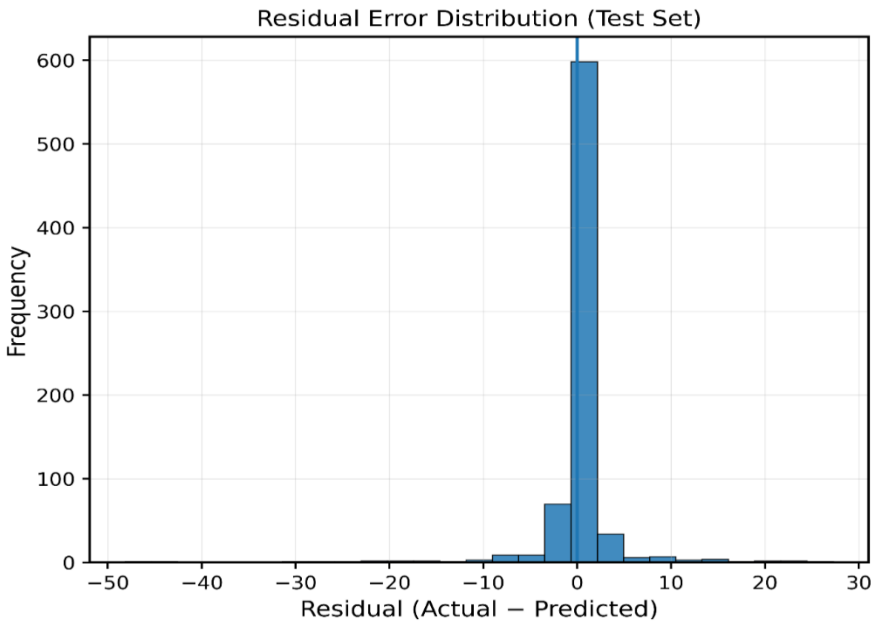

Figure 7. Residual error distribution histogram.

The Figure 7 shows the frequency distribution of the remaining errors. The distribution of errors is roughly symmetrical and concentrated near zero. This indicates that the model's predictions are consistent and reliable. Taking a comprehensive look at these three graphs, it is concluded that the proposed model provides reliable soil moisture predictions with low error spread and good generalizability.

5.3. Ablation Study

The ablation study was conducted to analyze the extent to which each component of the proposed architecture contributes to the overall performance. Table 3 shows the ablation study results along with the performance analysis of each model configuration.

Table 3. Ablation study results and model-wise performance analysis.

Model	RMSE	MAE	R^2	Model Analysis
Plain SFE	15.6769	12.4925	0.2330	Uses spectral fusion only. no spatial and temporal analyses
TCN	14.3107	11.2198	0.3609	Analyzes seasonal changes but does not consider spatial information
DD-TCN	14.0461	10.6961	0.3843	Identifies temporal patterns with dilated convolutions; no spatial and spectral features
CNN	5.5099	2.8251	0.9053	Effectively learns spatial features of the Earth's surface but lacks temporal information
CNN–TCN	5.4892	2.2909	0.9060	Identifies seasonal changes by combining spatial and temporal characteristics
CNN + DD-TCN	4.9916	2.1420	0.9222	Performs spatial and multispectral analysis but does not have spectral enhancement
SFE + CNN + DD-TCN (Proposed)	4.5206	1.6720	0.9362	A complete structure integrating spectral, spatial and temporal properties

5.4. Discussion

The proposed SFE–CNN–DD-TCN framework achieves high prediction accuracy, demonstrating that explicitly integrating spectral enhancement with spatial and temporal learning improves regional soil moisture estimation. Similar improvements using Sentinel-based deep learning approaches have been reported in recent studies; however, many such methods primarily focus on spatial learning and do not explicitly consider seasonal variability or spectral preferences [23].

Recent seasonal and fusion-based models have demonstrated good performance in soil moisture predictions, especially across diverse areas. However, these approaches often involve high computational complexity and appear to have limited applicability at the regional level [12, 21]. By prioritizing spectral bands sensitive to soil moisture before creating a spatio-temporal model, the proposed approach offers an effective, scalable alternative. It overcomes major limitations reported in existing studies [16, 22].

6. CONCLUSION AND FUTURE WORK

In this research, we propose an efficient soil moisture prediction framework using Sentinel-2 satellite imagery and ground-based soil moisture data collected from APWRIMS. The proposed SFE–CNN–DD-TCN model integrally analyzes spectral information, spatial characteristics, and seasonal variations. Spectral Fusion Enhancement prioritizes spectral bands important for soil moisture, while the CNN effectively captures geographical features.

Additionally, the Dynamic Dilated Temporal Convolutional Network effectively detects changes across different time dimensions. The experiment results showed that the proposed model achieved a high R2 value and low RMSE and MAE values. Through ablation studies, it was established that the model's performance is significantly improved when all components work together.

6.1. Practical Implications

This proposed framework offers a reliable solution for soil moisture monitoring at the regional level. It is useful in various climatic conditions, in precision agriculture, irrigation planning, and water resource management. The model's computational efficiency is suitable for large-scale agricultural applications.

6.2. Limitations

Although the model showed good performance, the current implementation used only single-period data. Additionally, due to reliance on Sentinel-2 satellite imagery, the study was unable to fully reflect the effects of extreme weather conditions or long-term climate change.

6.3. The Future Directions of Research

Long-term soil moisture changes can be more accurately analyzed using multi-period phase data, such as TIME_STEPS > 1 in future research. Additionally, the model's generalizability can be further improved by incorporating data from other satellite missions and weather-related parameters.

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Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

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