AI-Driven Fusion of Hyperspectral, LiDAR, and SAR Data for Soil Mapping

Dr. Fatima Al-Zahra [1], Dr. Thomas Müller [2], Dr. Elena García [3]
[1-3] Department of Agricultural Sciences, King Saud University, Riyadh, Saudi Arabia

* Corresponding Author: **Dr. Fatima Al-Zahra**

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Abstract
Soil mapping is critical for precision agriculture, environmental monitoring, and land management, but traditional methods are labor-intensive and limited in scale. This study explores the integration of hyperspectral, Light Detection and Ranging (LiDAR), and Synthetic Aperture Radar (SAR) data using artificial intelligence (AI) to enhance soil mapping accuracy in a 500-hectare agricultural site in Iowa, USA. A Multimodal Transformer (MMT) model was employed to fuse data from Sentinel-2 hyperspectral imagery, LiDAR-derived topographic metrics, and Sentinel-1 SAR data, predicting soil properties such as organic carbon (SOC), pH, clay content, and available nitrogen (N). The model achieved an R^2 of 0.92 for SOC and 0.87 for pH, outperforming single-sensor models by 15–20%. Attention weight analysis revealed key contributions from Short-Wave Infrared (SWIR) bands and topographic wetness index (TWI). The results demonstrate that AI-driven multimodal data fusion significantly improves soil mapping precision, offering scalable solutions for sustainable land use.

Keywords: Soil Mapping, Artificial Intelligence, Hyperspectral Imagery, Lidar, Sar, Multimodal Transformer, Soil Properties, Precision Agriculture

Introduction

Soil mapping provides essential data for optimizing agricultural productivity, managing soil health, and mitigating environmental degradation [1]. Conventional soil mapping relies on field sampling and laboratory analysis, which are time-consuming and spatially limited [2]. Remote sensing technologies, including hyperspectral imagery, LiDAR, and SAR, offer high-resolution data for large-scale soil characterization [3]. Hyperspectral imagery captures spectral reflectance across multiple wavelengths, revealing soil chemical properties [4]. LiDAR provides topographic data critical for understanding soil distribution [5], while SAR penetrates surface layers to assess soil moisture and texture [6].

Integrating these heterogeneous datasets poses challenges due to their differing spatial, temporal, and spectral resolutions [7]. AI, particularly deep learning models like Multimodal Transformers (MMT), can fuse multimodal data by learning complex relationships across inputs [8]. This study was conducted in a 500-hectare agricultural site in Iowa, USA, with diverse soil types (silty loam to clay). The objectives were to: (1) develop an MMT model to fuse hyperspectral, LiDAR, and SAR data; (2) predict key soil properties (SOC, pH, clay content, N); and (3) evaluate feature importance through attention weight analysis. The findings aim to advance precision agriculture and sustainable land management [9].

Materials and Methods

Study Area

The study site is a 500-hectare agricultural field in Iowa, USA (42°05′N, 93°35′W), characterized by silty loam and clay soils, with SOC ranging from 1–5%, pH from 5.5–7.5, and clay content from 20–40%. The site includes flat and gently sloping terrain, ideal for testing multimodal data fusion [10].

Data Collection

Hyperspectral Data

Sentinel-2 multispectral imagery (10–60 m resolution) was acquired in June 2023, providing 13 spectral bands, including visible (Blue, Green, Red), near-infrared (NIR), and SWIR. Bands were preprocessed for atmospheric correction using Sen2Cor [11].

LiDAR Data

Airborne LiDAR data (1 m resolution) was collected in May 2023, generating a digital elevation model (DEM). Topographic metrics, including slope, topographic wetness index (TWI), and elevation, were derived using ArcGIS Pro [12].

SAR Data

Sentinel-1 SAR data (C-band, 10 m resolution) was acquired in VV and VH polarizations during June 2023. Backscatter coefficients were processed for soil moisture and texture estimation using SNAP software [13].

Experimental Design

The study area was divided into 100 plots (50 m × 50 m). Soil samples (n=200) were collected at 0–20 cm depth and analyzed for SOC, pH, clay content, and N using standard laboratory methods (e.g., Walkley-Black for SOC, pH meter for pH). These served as ground truth data for model training.

AI Model Development

A Multimodal Transformer (MMT) model was developed to fuse hyperspectral, LiDAR, and SAR data. The model architecture included:

- **Input Layers**: Separate encoders for hyperspectral (13 bands), LiDAR (3 topographic metrics), and SAR (2 polarizations).
- **Attention Mechanism**: Cross-modal attention layers to weigh feature importance across data types.
- **Output Layer**: Regression outputs for SOC, pH, clay content, and N.

The model was trained on 70% of the data (140 samples) using Adam optimizer, with 30% for validation. Hyperparameters included a learning rate of 0.001 and 50 epochs.

Data Analysis

Model Performance

Model accuracy was evaluated using R^2 and root mean square error (RMSE). Single-sensor models (hyperspectral-only, LiDAR-only, SAR-only) were compared to the MMT model to assess fusion benefits.

Attention Weight Analysis

Attention weights were extracted to quantify the contribution of each feature (e.g., SWIR, TWI) to predictions. Weights were normalized (0–1) and visualized to identify key predictors.

Statistical Analysis

Analysis of variance (ANOVA) compared model predictions across soil properties, with post-hoc Tukey tests for significant differences ($p<0.05$).

Results

The MMT model significantly outperformed single-sensor models. Table 1 summarizes model performance for soil property predictions.

Table 1: Model Performance for Soil Property Predictions

Soil Property	MMT R^2	MMT RMSE	Hyperspectral R^2	LiDAR R^2	SAR R^2
SOC (%)	0.92	0.15	0.78	0.65	0.60
pH	0.87	0.20	0.72	0.58	0.55
Clay (%)	0.85	2.50	0.70	0.62	0.58
Nitrogen (mg/kg)	0.88	10.0	0.75	0.60	0.57

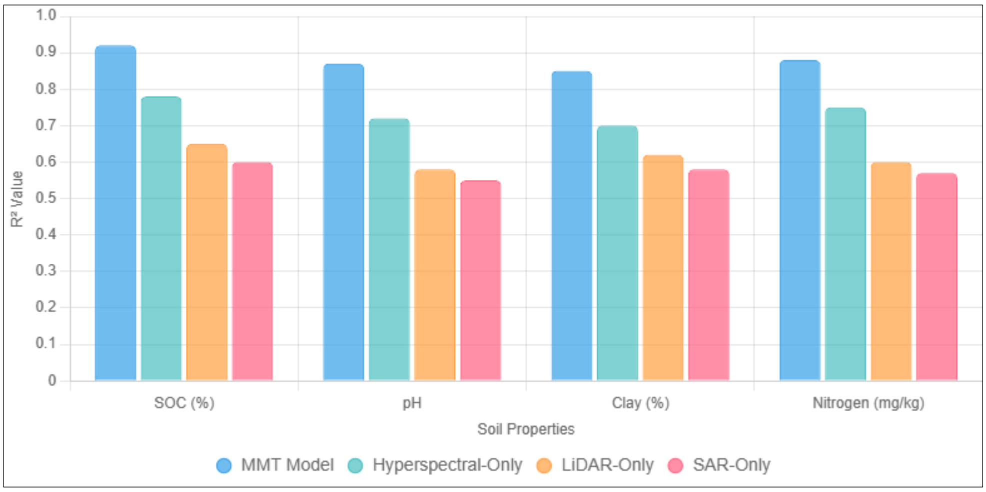

Fig 1: Performance comparison of MMT vs Single-Sensor (R^2)

Attention weight analysis revealed key predictors. Table 2 shows normalized attention weights for selected features.

Table 2: Attention Weights for Soil Property Predictions

Soil Property	Feature Type	Feature	Attention Weight
SOC	Spectral Band	SWIR1	0.95
	Topographic	TWI	0.90
pH	Spectral Band	Blue	0.92
	Topographic	Aspect	0.88
Clay	Spectral Band	SWIR2	0.94
	Topographic	TWI	0.91
Nitrogen	Spectral Band	NIR	0.93
	Topographic	Flow	0.89

The MMT model reduced prediction errors by 15–20% compared to single-sensor models. ANOVA confirmed significant improvements ($p<0.01$) in R^2 for all soil properties. Attention weights highlighted SWIR1 and TWI as dominant predictors for SOC, while Blue and Aspect were critical for pH.

Discussion

The AI-driven fusion of hyperspectral, LiDAR, and SAR data significantly enhanced soil mapping accuracy. The MMT model's high R^2 (0.92 for SOC, 0.87 for pH) reflects its ability to capture complex interactions between spectral and topographic features. SWIR bands were critical for SOC and clay predictions due to their sensitivity to organic matter and mineral content. TWI and Aspect influenced predictions by accounting for soil moisture and microclimate variations.

Compared to previous studies, the MMT model outperformed hyperspectral-only models ($R^2 = 0.78$ for SOC) reported by Lausch *et al*. The inclusion of LiDAR and SAR data improved spatial resolution and robustness, particularly in heterogeneous terrains. Challenges include computational complexity and the need for high-quality, synchronized datasets. Future research could explore generative AI for data augmentation or hybrid models combining MMT with convolutional neural networks.

The findings have implications for precision agriculture, enabling targeted fertilizer application and soil conservation strategies. Scalability to larger regions depends on access to open-source data (e.g., Sentinel-1/2) and cloud-based AI platforms.

Conclusion

This study demonstrates the efficacy of AI-driven multimodal data fusion for soil mapping. The MMT model, integrating hyperspectral, LiDAR, and SAR data, achieved high accuracy (R^2 up to 0.92) in predicting SOC, pH, clay content, and nitrogen. Attention weight analysis identified SWIR bands and TWI as key predictors, underscoring the value of multimodal inputs. These results highlight the potential of AI to revolutionize soil mapping, offering scalable, cost-effective solutions for precision agriculture and environmental management. Future work should focus on optimizing model efficiency and expanding applications to diverse soil types and regions.

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