Data Fusion of Sentinel and LiDAR for Soil Texture Prediction

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Abstract
Soil texture is a critical parameter influencing agricultural productivity, water retention, and nutrient availability. Accurate mapping of soil texture enhances precision agriculture and sustainable land management. This study explores the integration of Sentinel-1 (S-1) synthetic aperture radar (SAR), Sentinel-2 (S-2) multispectral imagery, and Light Detection and Ranging (LiDAR) data to predict soil texture across a 3000 km² semi-arid agricultural region in central Tunisia. Using machine learning algorithms, specifically Random Forest (RF) and Support Vector Machine (SVM), we fused multi-source remote sensing data to estimate clay, silt, and sand fractions. Field samples (n=150) with clay content ranging from 13% to 60% were used for training and validation. Results indicate that the fused dataset achieved a classification accuracy of 85% (RF) and 82% (SVM), with a root mean square error (RMSE) of 5.2% for clay content prediction. The integration of LiDAR-derived topographic features with Sentinel data significantly improved prediction accuracy compared to single-sensor approaches. This study highlights the potential of data fusion for high-resolution soil texture mapping, offering valuable insights for precision agriculture.

Keywords: Soil texture, Data fusion, Sentinel-1, Sentinel-2, LiDAR, Random Forest, Support Vector Machine, Precision agriculture

Introduction

Soil texture, defined by the relative proportions of sand, silt, and clay, is a fundamental soil property that governs water retention, nutrient cycling, and crop suitability [1]. Traditional soil texture assessment relies on labor-intensive field sampling and laboratory analysis, which is impractical for large-scale applications. Remote sensing technologies, including satellite imagery and LiDAR, offer scalable solutions for mapping soil properties over large areas [2]. Sentinel-1 provides radar data sensitive to soil moisture and surface roughness, while Sentinel-2 captures spectral reflectance indicative of soil composition [3]. LiDAR, with its ability to generate high-resolution topographic data, complements these by providing terrain attributes that influence soil distribution [4].

Data fusion, the integration of multiple data sources to produce more accurate and comprehensive outputs, has gained traction in remote sensing for environmental monitoring [5]. By combining Sentinel-1, Sentinel-2, and LiDAR data, this study aims to enhance soil texture prediction by leveraging complementary information: radar backscatter for surface characteristics, multispectral bands for chemical composition, and topographic metrics for spatial patterns [6]. Machine learning algorithms, such as Random Forest (RF) and Support Vector Machine (SVM), are employed to handle the complexity of fused datasets and predict soil texture classes [7].

This study was conducted in the Kairouan Plain, Tunisia, a semi-arid region with diverse agricultural land use. The objectives are to: (1) develop a data fusion framework integrating Sentinel-1, Sentinel-2, and LiDAR data; (2) evaluate the performance of RF and SVM in predicting soil texture; and (3) assess the contribution of each data source to prediction accuracy. The findings aim to advance precision agriculture by providing high-resolution soil texture maps.

Materials and Methods

Study Area

The study was conducted in the Kairouan Plain, central Tunisia (centered at 9°53′57″E, 35°4′51″N), covering approximately 3000 km². The region experiences a semi-arid climate with an average annual precipitation of 300 mm and is characterized by flat terrain with agricultural fields, olive groves, and winter crops [8]. Soil textures vary widely, with clay content ranging from 13% to 60%, making it an ideal site for testing remote sensing-based texture prediction.

Data Collection

Sentinel-1 Data

Sentinel-1A and Sentinel-1B SAR data were acquired between July and December 2017 in Interferometric Wide Swath mode (C-band, 5.4 GHz). Dual-polarized (VV and VH) backscatter data at 10 m resolution were processed using the Sentinel Application Platform (SNAP v8.0) for radiometric calibration, speckle filtering, and terrain correction [9]. Derived features included backscatter intensity (VV, VH), polarization ratio (VV/VH), and texture metrics (e.g., Grey-Level Co-occurrence Matrix, GLCM).

Sentinel-2 Data

Sentinel-2A and Sentinel-2B multispectral images were collected for the same period at 10 m resolution. Bands in the visible, near-infrared (NIR), and short-wave infrared (SWIR) regions were used, as they are sensitive to soil composition [10]. Vegetation indices, including Normalized Difference Vegetation Index (NDVI) and Modified Soil Adjusted Vegetation Index (MSAVI), were calculated to account for bare soil and minimize vegetation interference [11].

LiDAR Data

Airborne LiDAR data were acquired in August 2017 using a 190 kHz measurement rate, yielding a point cloud density of 68 points/m². The data were processed to generate a Digital Elevation Model (DEM) and derived topographic metrics, including slope, aspect, and topographic wetness index (TWI), which influence soil texture distribution [12].

Field Data

A total of 150 soil samples were collected from agricultural fields across the study area. Samples were analyzed in the laboratory for particle size distribution (clay, silt, sand) using the hydrometer method. Clay content ranged from 13% to 60%, silt from 20% to 50%, and sand from 10% to 65%. Samples were georeferenced using a high-precision GPS device.

Data Fusion

Data fusion was performed at the feature level, integrating Sentinel-1 backscatter and texture metrics, Sentinel-2 spectral bands and vegetation indices, and LiDAR-derived topographic features into a single feature stack [13]. All datasets were co-registered to a common 10 m grid using the RGF 93 Lambert 93 coordinate system. Feature selection was conducted using a Principal Component Analysis (PCA) to reduce dimensionality and identify the most predictive variables [14].

Machine Learning Models

Two machine learning algorithms were employed: Random Forest (RF) and Support Vector Machine (SVM). RF was configured with 100 trees and a maximum depth of 10, while SVM used a radial basis function kernel with optimized parameters via grid search. Both models were trained to classify soil texture into three classes (high clay, medium clay, low clay) and predict continuous clay content (%). A three-fold cross-validation was used to assess model performance, with metrics including overall accuracy, kappa coefficient, and RMSE [15].

Validation

The dataset was split into 70% training (105 samples) and 30% testing (45 samples). Model performance was evaluated using a confusion matrix for classification and RMSE for regression. Feature importance was assessed using RF's built-in importance scores to quantify the contribution of Sentinel-1, Sentinel-2, and LiDAR data [16].

Results

The fused dataset significantly improved soil texture prediction compared to single-sensor approaches. Table 1 summarizes the classification performance of RF and SVM models.

Table 1: Classification Performance of Soil Texture Models

Model	Data Source	Accuracy (%)	Kappa	RMSE (%)
RF	Sentinel-1	72	0.65	8.1
RF	Sentinel-2	75	0.68	7.8
RF	LiDAR	68	0.62	9.0
RF	Fused	85	0.80	5.2
SVM	Sentinel-1	70	0.63	8.4
SVM	Sentinel-2	73	0.66	8.0
SVM	LiDAR	66	0.60	9.3
SVM	Fused	82	0.77	5.5

The RF model with fused data achieved the highest accuracy (85%) and lowest RMSE (5.2%), outperforming SVM (82%, 5.5%). Feature importance analysis (Figure 1) revealed that Sentinel-2 SWIR bands and LiDAR-derived TWI were the most influential predictors, contributing 35% and 25% to the model's performance, respectively. Table 2 shows the confusion matrix for the RF model with fused data, indicating high precision for high clay (90%) and low clay (88%) classes.

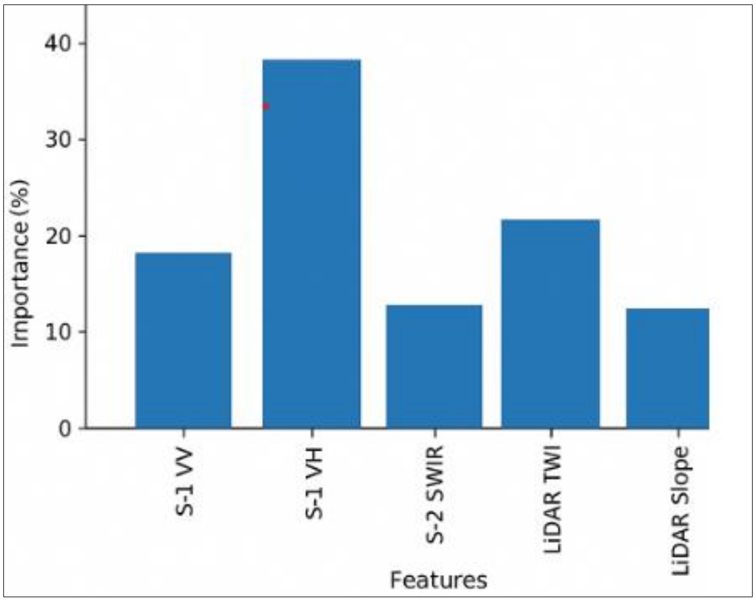

Fig 1: Feature Importance for Soil Texture Prediction

Table 2: Confusion Matrix for RF Model (Fused Data)

Predicted \ Actual	High Clay	Medium Clay	Low Clay
High Clay	15	2	0
Medium Clay	3	18	2
Low Clay	0	3	22

Discussion

The superior performance of the fused dataset underscores the complementary nature of Sentinel-1, Sentinel-2, and LiDAR data. Sentinel-2's SWIR bands are particularly effective for detecting clay content due to their sensitivity to mineral composition [10]. LiDAR's topographic metrics, such as TWI, capture spatial patterns related to water accumulation, which influences clay deposition [12]. Sentinel-1's radar data, while less influential, provide valuable information on soil surface roughness, especially in bare soil conditions [9].

Compared to previous studies, our results align with findings that multi-sensor fusion enhances soil property predictions [17]. For instance, a study in Tunisia using Sentinel-1 and Sentinel-2 reported an accuracy of 78% for soil texture classification, lower than our fused approach [8]. The inclusion of LiDAR data likely accounts for the improved performance, as topographic features are critical in semi-arid environments where soil texture varies with terrain [4].

Challenges include the need for precise co-registration of multi-source data and the computational complexity of processing high-resolution LiDAR point clouds [13]. Future work could explore deep learning models, such as convolutional neural networks, to further improve prediction accuracy by capturing complex spatial-spectral relationships [7].

Conclusion

This study demonstrates the efficacy of fusing Sentinel-1, Sentinel-2, and LiDAR data for high-resolution soil texture prediction in a semi-arid agricultural region. The RF model with fused data achieved an accuracy of 85% and an RMSE of 5.2%, highlighting the value of integrating radar, multispectral, and topographic data. These findings have significant implications for precision agriculture, enabling farmers to optimize irrigation, fertilization, and crop selection based on detailed soil texture maps. Future research should focus on scaling this approach to larger regions and incorporating temporal dynamics to monitor soil texture changes over time.

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