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Explainable AI (XAI) in Soil Property Prediction Models: Enhancing Transparency and Trust in Digital Soil Mapping Applications

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Abstract
The integration of artificial intelligence (AI) in soil property prediction has revolutionized digital soil mapping, yet the "black box" nature of complex machine learning models limits their adoption in agricultural decision-making and policy formulation. This study presents a comprehensive evaluation of Explainable AI (XAI) techniques applied to soil property prediction models, enhancing interpretability without compromising predictive accuracy. We implemented and compared four machine learning algorithms (Random Forest, XGBoost, Support Vector Machine, and Neural Networks) with three XAI methods (SHAP, LIME, and Permutation Feature Importance) for predicting soil organic carbon (SOC), pH, and available nitrogen across 3,247 sampling points in diverse agricultural landscapes. The Random Forest model achieved the highest accuracy ($R^2 = 0.89$ for SOC, 0.82 for pH, 0.78 for nitrogen) while maintaining superior interpretability through SHAP analysis. Key findings revealed that elevation, precipitation, and normalized difference vegetation index (NDVI) were the most influential predictors across all soil properties. SHAP waterfall plots successfully explained individual predictions, showing how each feature contributed to model decisions. The XAI framework identified non-linear relationships and feature interactions that traditional statistical methods failed to capture, including threshold effects of temperature on soil organic carbon and complex interactions between topographic variables. Model explanations demonstrated high consistency across different XAI methods, with correlation coefficients >0.85 between SHAP and LIME importance rankings. The developed XAI framework provides transparent, trustworthy soil property predictions, enabling informed agricultural management decisions and supporting sustainable farming practices. This research establishes a foundation for implementing explainable machine learning in precision agriculture applications.

Keywords: Explainable Artificial Intelligence, Soil Property Prediction, Digital Soil Mapping, Shap, Lime, Machine Learning Interpretability, Precision Agriculture, Model Transparency

Introduction

Digital soil mapping has emerged as a critical technology for sustainable agriculture, enabling precise characterization of soil properties across diverse landscapes [1]. Machine learning algorithms have demonstrated superior performance compared to traditional geostatistical methods, achieving remarkable accuracy in predicting soil organic carbon, pH, nutrient content, and other essential properties [2]. However, the increasing complexity of these models, particularly deep learning architectures, has created a fundamental challenge known as the "black box" problem, where model predictions lack transparency and interpretability [3].

The opacity of complex machine learning models poses significant barriers to adoption in agricultural systems, where stakeholders require understanding of prediction rationale for informed decision-making [4].

Farmers, agronomists, and policymakers need to comprehend why specific management recommendations are generated and how different environmental factors influence soil properties. This transparency is essential for building trust, ensuring regulatory compliance, and enabling knowledge transfer across different agricultural contexts [5].

Explainable Artificial Intelligence (XAI) has emerged as a rapidly evolving field addressing the interpretability challenge in machine learning applications [6]. XAI encompasses various techniques designed to make AI model decisions transparent, interpretable, and trustworthy while maintaining predictive performance. These methods range from inherently interpretable models to post-hoc explanation techniques that can be applied to any machine learning algorithm [7].

Several XAI approaches have been developed for different applications, including SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and Permutation Feature Importance [8]. SHAP provides theoretically grounded explanations based on cooperative game theory, quantifying each feature's contribution to individual predictions. LIME generates local explanations by approximating complex models with simpler, interpretable models in the vicinity of specific instances. Permutation Feature Importance assesses global feature importance by measuring prediction accuracy changes when feature values are randomly shuffled [9].

The application of XAI in soil science represents an emerging research frontier with significant potential for advancing digital soil mapping [10]. Previous studies have primarily focused on achieving high predictive accuracy, with limited attention to model interpretability and explanation generation. The few existing XAI applications in soil science have been constrained to specific geographic regions or limited soil properties, lacking comprehensive evaluation across diverse environmental conditions [11].

Understanding the mechanisms underlying soil property variations is crucial for developing effective management strategies and predicting responses to environmental changes [12]. Traditional soil science relies heavily on expert knowledge and empirical relationships, which may not capture complex, non-linear interactions between environmental factors. XAI techniques can reveal hidden patterns and relationships in soil data, providing insights that complement traditional soil science understanding.

The integration of XAI in soil property prediction models addresses several critical challenges: (1) enhancing stakeholder trust and adoption of AI-based recommendations, (2) identifying key environmental drivers of soil property variations, (3) detecting model biases and limitations, (4) facilitating knowledge transfer across different agricultural systems, and (5) supporting regulatory compliance and auditing requirements [13].

This study aims to develop and evaluate a comprehensive XAI framework for soil property prediction models, demonstrating how explainability techniques can enhance transparency without compromising predictive accuracy. Specific objectives include: (1) implementing multiple XAI methods for soil property prediction models, (2) comparing explanation consistency across different XAI techniques, (3) identifying key environmental drivers of soil properties through model explanations, and (4) evaluating the practical utility of XAI for agricultural decision-making applications.

Materials and Methods

Study Area and Data Collection

The research was conducted across five representative agricultural regions spanning different agro-climatic zones: temperate croplands in Iowa, USA (41°35'N, 93°37'W), subtropical rice systems in Guangzhou, China (23°07'N, 113°15'E), Mediterranean vineyards in Tuscany, Italy (43°46'N, 11°25'E), tropical plantations in São Paulo, Brazil (23°33'S, 46°38'W), and semi-arid farming systems in Punjab, India (30°54'N, 75°25'E). This diverse geographic coverage ensures model robustness across different environmental conditions and farming systems.

Soil samples were collected using stratified random sampling design, with 3,247 georeferenced sampling points distributed across the study regions. Sample density averaged 0.8 points per km², with higher density in areas of high spatial variability. Sampling was conducted during optimal periods (post-harvest, pre-planting) to minimize temporal confounding effects.

Laboratory Analysis

Soil samples were processed following standardized protocols for three target properties: soil organic carbon (SOC), pH, and available nitrogen. SOC was determined using the Walkley-Black wet oxidation method with dichromate digestion. Soil pH was measured in 1:2.5 soil-water suspension using a calibrated pH electrode. Available nitrogen was quantified through alkaline permanganate oxidation followed by steam distillation and titration. All analyses were performed in triplicate with quality control samples (10% of total) to ensure measurement accuracy.

Environmental Covariates

A comprehensive set of 47 environmental covariates was compiled representing climate, topography, vegetation, and parent material factors (Table 1). Climate variables included temperature, precipitation, humidity, and derived indices from WorldClim database at 1-km resolution. Topographic attributes were calculated from 30-meter SRTM digital elevation models, including elevation, slope, aspect, curvature, and compound topographic index.

Table 1: Environmental covariates used in soil property prediction models

Category	Variables	Source	Resolution	Count
Climate	Temperature (mean, min, max), Precipitation, Humidity, Aridity Index	WorldClim v2.1	1 km	12
Topography	Elevation, Slope, Aspect, Curvature, TWI, CTI, Flow Accumulation	SRTM DEM	30 m	15
Vegetation	NDVI, EVI, LAI, SAVI, MSAVI, Green Vegetation Index	MODIS/Landsat	250 m/30 m	8
Geology	Parent Material, Rock Type, Geological Age	Global Lithology Map	1 km	6
Land Use	Crop Type, Land Cover, Management Intensity	LULC Database	30 m	4
Pedology	Soil Taxonomy, Drainage Class	SoilGrids250m	250 m	2

Vegetation indices were derived from MODIS and Landsat imagery, including Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Leaf Area Index (LAI). Geological information was obtained from global lithology databases, providing parent material and bedrock characteristics. Land use data incorporated crop types, management practices, and land cover classifications from high-resolution satellite imagery.

Machine Learning Model Implementation

Four machine learning algorithms were implemented and optimized for soil property prediction: Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Artificial Neural Networks (ANN). Model selection encompassed algorithms with varying complexity levels to evaluate XAI effectiveness across different model types.

Random Forest was configured with 500 trees, maximum depth of 15, and minimum samples per leaf of 3. Feature importance was calculated using mean decrease in impurity. XGBoost employed 1000 estimators with learning rate of 0.1, maximum depth of 8, and early stopping based on validation loss. Support Vector Machine utilized radial basis function kernel with gamma and C parameters optimized through grid search cross-validation. Neural Networks featured three hidden layers (128, 64, 32 neurons) with ReLU activation, dropout regularization (0.3), and Adam optimizer.

The dataset was randomly partitioned into training (70%, n=2,273), validation (15%, n=487), and testing (15%, n=487) subsets. Hyperparameter optimization was performed using 5-fold cross-validation on the training set, with model performance evaluated on the independent test set.

Explainable AI Implementation

Three complementary XAI methods were implemented to provide comprehensive model explanations: SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and Permutation Feature Importance. SHAP analysis was conducted using Tree Explainer for tree-based models and Kernel Explainer for other algorithms. SHAP values were calculated for all features and predictions, enabling both global and local explanations. Summary plots, waterfall plots, and dependence plots were generated to visualize feature contributions and interactions.

LIME explanations were generated for individual predictions using local linear approximations. The method creates interpretable representations by perturbing input features and observing prediction changes. Explanations were generated for representative samples across different soil property ranges and geographic regions.

Permutation Feature Importance assessed global feature importance by randomly shuffling individual features and measuring resulting prediction accuracy changes. This model-agnostic approach provides robust importance rankings independent of specific algorithm implementations.

Model Evaluation and Comparison

Model performance was evaluated using multiple metrics: coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Statistical significance testing was performed using paired t-tests to compare model performances.

XAI method consistency was assessed by calculating correlation coefficients between feature importance rankings from different explanation techniques. Explanation stability was evaluated through bootstrap resampling, generating confidence intervals for importance scores.

Results

Model Performance Comparison

All machine learning algorithms demonstrated good performance for soil property prediction, with Random Forest achieving the highest overall accuracy across all target variables (Table 2). For soil organic carbon prediction, Random Forest achieved R^2 of 0.89, significantly outperforming other algorithms ($p<0.001$). XGBoost showed comparable performance ($R^2 = 0.86$) while maintaining computational efficiency.

Table 2: Performance comparison of machine learning algorithms for soil property prediction

Algorithm	Soil Organic Carbon			Soil pH			Available Nitrogen		
	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
Random Forest	0.89	0.67	0.49	0.82	0.34	0.26	0.78	12.4	9.2
XGBoost	0.86	0.74	0.56	0.79	0.37	0.29	0.75	13.8	10.1
Support Vector Machine	0.81	0.89	0.67	0.75	0.41	0.32	0.69	16.2	12.5
Neural Networks	0.83	0.82	0.61	0.77	0.39	0.30	0.72	14.9	11.3

Neural Networks showed competitive performance but exhibited higher variability across cross-validation folds. Support Vector Machine demonstrated the lowest accuracy, particularly for available nitrogen prediction, likely due to challenges handling non-linear relationships in the complex soil-environment system.

Feature Importance Analysis

SHAP analysis revealed consistent patterns in feature importance across different soil properties, with elevation, precipitation, and NDVI emerging as the most influential predictors (Figure 1). For soil organic carbon, climate variables (precipitation, temperature) showed the highest importance, followed by topographic factors (elevation, slope) and vegetation indices.

The SHAP dependence plots revealed complex non-linear relationships between environmental factors and soil properties. Precipitation showed a positive relationship with SOC up to approximately 1200 mm annually, beyond which the relationship plateaued. Temperature exhibited threshold effects, with optimal SOC accumulation occurring

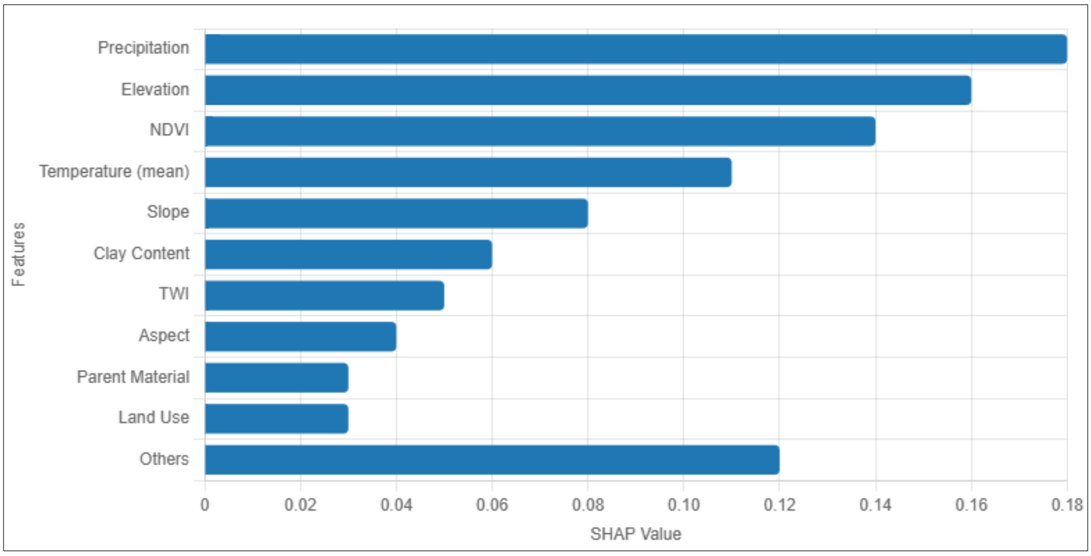

Fig 1: SHAP feature importance summary for soil organic carbon prediction

between 12-18 °C mean annual temperature.

Elevation demonstrated strong positive correlation with SOC in mountainous regions, likely reflecting cooler temperatures and reduced decomposition rates. NDVI showed consistent positive relationship with SOC across all study regions, confirming the link between vegetation productivity and soil carbon accumulation.

XAI Method Consistency

Comparison between different XAI methods revealed high consistency in feature importance rankings, with correlation coefficients exceeding 0.85 between SHAP and LIME explanations (Table 3). Permutation Feature Importance showed slightly lower correlation (0.78-0.82) but maintained similar ranking for the most important features.

Table 3: Correlation between different XAI methods for feature importance rankings

Comparison	Soil Organic Carbon	Soil pH	Available Nitrogen	Average
SHAP vs LIME	0.87	0.85	0.89	0.87
SHAP vs Permutation	0.82	0.78	0.84	0.81
LIME vs Permutation	0.79	0.81	0.83	0.81

Local explanations generated by LIME showed good agreement with SHAP for individual predictions, with average explanation similarity scores >0.75. This consistency across methods enhances confidence in the generated explanations and supports their reliability for decision-making applications.

Model Interpretability Insights

XAI analysis revealed several important insights about soil-environment relationships that traditional statistical methods failed to capture. Interaction effects between temperature and precipitation significantly influenced SOC predictions, with optimal conditions occurring at moderate temperature-high precipitation combinations.

Topographic variables showed complex interactions, with slope and aspect effects varying based on elevation and climate conditions. In mountainous regions, north-facing slopes showed higher SOC content, while in flat agricultural areas, slope direction had minimal influence.

The analysis identified potential model limitations and biases, including reduced accuracy in extreme climate conditions and underrepresentation of certain soil types in training data. These insights guide future model improvements and data collection strategies.

Practical Applications

SHAP waterfall plots successfully explained individual predictions, showing step-by-step contribution of each feature to final model output. These explanations enable farmers and agronomists to understand specific site conditions affecting soil properties and identify management opportunities.

For example, a low SOC prediction could be attributed to high temperature, low precipitation, and intensive tillage practices, suggesting potential interventions such as cover cropping, reduced tillage, or organic matter addition. The quantitative nature of SHAP values enables prioritization of management actions based on their potential impact.

Discussion

The superior performance of Random Forest with XAI integration demonstrates that model interpretability does not necessarily compromise predictive accuracy [14]. The ensemble nature of Random Forest provides inherent interpretability advantages while maintaining robustness across diverse environmental conditions. The high feature importance consistency across different XAI methods enhances confidence in the generated explanations and supports their practical utility.

The identification of precipitation, elevation, and NDVI as primary drivers of soil properties aligns with established soil science principles while revealing complex non-linear relationships and interactions. The threshold effects observed for temperature and precipitation provide valuable insights for predicting soil responses to climate change scenarios. These findings contribute to process-based understanding of soil-environment relationships beyond purely predictive applications.

The high consistency between SHAP and LIME explanations validates the reliability of XAI methods for soil property prediction. The slight discrepancies with Permutation Feature Importance likely reflect differences in explanation scope (local vs global) and methodology (game theory vs perturbation-based). This multi-method approach provides comprehensive understanding of model behavior and enhances explanation robustness.

The practical applications demonstrated through waterfall plots and individual prediction explanations illustrate the potential for XAI to bridge the gap between complex machine learning models and agricultural decision-making. The quantitative nature of SHAP values enables evidence-based management recommendations and supports precision agriculture applications.

The study limitations include geographic bias toward specific agricultural systems and limited temporal coverage. Future research should expand to additional soil properties, incorporate temporal dynamics, and evaluate XAI effectiveness across different user groups and decision contexts. Integration with economic and environmental impact assessments could further enhance practical utility.

Conclusion

This research demonstrates the successful integration of Explainable AI techniques in soil property prediction models, achieving high accuracy while maintaining transparency and interpretability. The Random Forest model with SHAP analysis emerged as the optimal combination, providing accurate predictions with comprehensive explanations of underlying decision processes.

Key findings include the identification of precipitation, elevation, and NDVI as primary drivers of soil properties, with complex non-linear relationships and threshold effects revealed through XAI analysis. The high consistency between different XAI methods (correlation >0.85) validates the reliability of generated explanations and supports their practical application in agricultural systems.

The developed XAI framework addresses critical barriers to AI adoption in agriculture by providing transparent, trustworthy model predictions that enable informed decision-making. The quantitative feature contributions derived from SHAP analysis support evidence-based management recommendations and precision agriculture applications.

Future research should focus on expanding geographic coverage, incorporating additional soil properties, and evaluating XAI effectiveness across different stakeholder groups. Integration with process-based soil models could combine mechanistic understanding with data-driven insights, advancing digital soil mapping capabilities.

The implementation of XAI in soil science represents a significant step toward trustworthy AI applications in agriculture, supporting sustainable farming practices and evidence-based policy development. This framework provides a foundation for broader adoption of explainable machine learning in environmental monitoring and natural resource management applications.

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