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Original Article

Explainable Machine Learning for Agricultural Land Suitability Analysis

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ABSTRACT: *Agricultural land suitability analysis is needed to maximize crop yields for food security (target: SDG2) while nurturing human-induced environments that can be maintained in the long term, as graphically exemplified with images from scientist Robert D.-J. Classic methods like the Analytic Hierarchy Process (AHP) are built on subjective expert opinion, and newer machine learning (ML) methods tend to act as "black boxes," being out of reach for farmers, agronomists, and policymakers who need interpretability in their decision-making process. We propose an Explainable Machine Learning (XML) framework by coupling high-performance predictive modeling techniques with local and global interpretability approaches to assess agricultural land suitability in this study. Using a large record of soil qualities, meteorological information, and geographic variables, we trained several machine learning solutions (ML) to classify farmland suitability for staple crops using Random Forests (RF), Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost). Of these, the highest predictive accuracy (94.2%) was attained by the XGBoost model. In an effort to break down the model's predictions, we incorporated Shapley Additive explanations (SHAP), as well as Local Interpretable Model-agnostic Explanations with LIME. The main global SHAP analysis showed that soil pH, organic carbon, and mean annual rainfall were the most potential determinants of land suitability throughout the entire region. Local LIME evaluations showed that some micro-environmental factors impact the classification of each land parcel on an individual basis at a more localized scale. This explainable framework bridges high-accuracy predictive modeling with human accountability to provide actionable recommendations that are transparent and site-specific insights for stakeholder engagement in order to enable trust in automated agricultural decision-support systems.*

KEYWORDS: *Explainable Artificial Intelligence (XAI), Machine Learning, Land Suitability Analysis, Sustainable Agriculture, SHAP, LIME.*

1. INTRODUCTION

The cruelest situation for the world agriculture sector is due to the above reasons of rapid population growth, climate change, and constant depletion of land surface. However, we have to produce food for an estimated global population of almost 10 billion people by 2050, and agricultural productivity needs to grow at an unprecedented pace without increasing the environmental footprint associated with farming activities. This necessity calls for a fundamental transformation towards precision agriculture and data-guided land resource management. At the heart of this transition is agricultural land suitability analysis—the evaluation of a given plot's innate potential to sustainably and productively support specific crops. Validation of the accuracy helps policymakers and farmers to use, in an optimized way, fewer resources at less risk of crop failure, as well as reduced risks for ecological degradation from unsuitable land use.

Historically, land suitability evaluation has been based on (Balkenhol et al., 2016) qualitative or semi-qualitative multi-criteria decision-making approaches. Approaches like the Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), frequently in combination with Geographic Information Systems (GIS), have been foundational to regional agricultural planning. These frameworks are great for keeping structure simple and encapsulating expert knowledge, but they have built-in limitations. They are very sensitive to human bias; they cannot automatically deal with non-linear relationships in environmental inputs and outputs without scaling issues when applied to large-scale high-dimensional datasets from modern remote sensing and digital soil mapping approaches.

Consequently, to address these constraints, the agricultural research community has relied more and more on applying machine learning (ML) algorithms. Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANN) have shown outstanding performance in the discovery of complex, non-linear associations from heterogeneous environmental datasets to produce land suitability maps with unprecedented prediction accuracy. However, the deployment of these models in real-world agricultural governance is severely hindered by their "black-box" nature. Standard machine learning models generate highly accurate predictions but fail to provide an explicit, human-understandable rationale for their outputs. For an agronomist or a regional planner, a land suitability map generated by a deep neural network without explanation is difficult to trust, especially when multi-million-dollar land-use decisions or local food security strategies are at stake.

The absence of this transparency creates an accountability gap. When a machine learning model classifies what looks like an ideal, fertile valley as "unsuitable" for a certain staple crop, on the ground stakeholders need to know why whether any hidden subsoil salinity is present or whether its leaky water retention capacity holds when denied access during erratic historical rain. The lack of this capability to explain what in the data forces predictions all too often leads model recommendations being disregarded, which has impeded adoption of AI-driven tools in national and international agricultural operations. This barrier is overcome by Explainable Artificial Intelligence (XAI), a set of tools and frameworks that make complex model behaviour transparent, interpretable, and auditable to human experts.

The proposed work fills this gap in the literature by introducing a systematic and comprehensive framework for agricultural land suitability assessment. By combining state-of-the-art machine learning classification algorithms with model-agnostic interpretability techniques, the proposed framework aims to achieve high predictive accuracy while providing transparent and meaningful explanations for model predictions. This approach not only improves the reliability of land suitability classification but also enhances the interpretability of machine learning outcomes, enabling stakeholders to make informed agricultural planning decisions. The main research contributions of this paper are summarized as follows:

- Framework Development: We propose a comprehensive multi-source data integration framework that combines diverse environmental variables, including soil characteristics, climatic conditions, and topographical features, with ensemble machine learning classification algorithms to generate accurate multi-class agricultural land suitability maps.
- Interpretability Integration: We develop a dual-layer interpretability framework by integrating SHAP (SHapley Additive exPlanations) for global feature importance analysis across the study area and LIME (Local Interpretable Model-agnostic Explanations) for local-level interpretation, enabling detailed explanations for individual land parcel predictions.
- Domain Validation: We validate the model explanations against established agronomic knowledge and demonstrate that the identified influential factors closely correspond to real-world soil, climate, and crop interaction mechanisms, thereby improving the credibility of the proposed framework.
- Policy and Operational Utility: We provide an interpretable decision-support framework capable of identifying regional and environmental constraints affecting land suitability. The proposed system assists agricultural policymakers and land management authorities in planning land reclamation strategies, optimizing crop selection, and improving sustainable agricultural resource management.

2. LITERATURE REVIEW

This story mirrors some of the main trends and events in environmental data science as a whole. The types of methodologies one can study will use the framework and definitions set by the Food and Agriculture Organization (FAO) from 1976, where they took land based on physical constraints and economic constraints to stratify it into orders, classes, subclasses & units. This framework has been implemented using qualitative expert systems for decades. In the late 1980s and into the 1990s, GIS completely transformed this field by enabling spatial overlay analysis that produced readily interpreted zones in which thematic maps reflecting soil/climate/topography could be combined.

Various Multi-Criteria Decision-Making (MCDM) methods were extensively used to formalize the weighting of these dissimilar environmental factors. One of the most popular methods used is the Analytic Hierarchy Process (AHP) developed by Saaty. In the international context, many studies applied GIS-based AHP for land suitability assessment of crops such as rice, wheat, and maize. Although useful, a key limitation of AHP is that it relies on pairwise comparisons by experts [6], which introduces cognitive bias and hampers reproducibility when distinct panels are consulted. In addition, AHP models impose harsh linear combinations that miss the cumulative, multiplicative or non-linear processes common in ecological systems e.g., a minute change to salinity makes land totally unviable for some crops even where rainfall and temperature are perfect.

Big Data's arrival in agriculture mainly due to constellations of satellites like Sentinel and high-resolution digital soil maps from Landsat highlighted the computational bottlenecks that traditional MCDM methods ran into. This acted as the catalyst for moving towards machine learning. Ensemble tree-based models, including Random Forest and Gradient Boosting, were shown to offer significantly higher spatial prediction accuracy than AHP due in part because they do not impose often inappropriate a priori assumptions on feature distributions but, more critically, can accommodate the high-dimensional space of environmental datasets that are not only non-linear but also known to be very noisy.

Despite their remarkable empirical success, the adoption of Machine Learning in institutional agricultural planning has been hindered by an interpretability crisis. In fields that impact human livelihoods and environmental sustainability, uninterpretable predictions pose operational risks. Over the past few years, Explainable Artificial Intelligence (XAI) has emerged as a vital subfield for resolving the tension between accuracy and interpretability. Despite the wide applicability of post-hoc explanation tools for machine learning in many domains, their application to spatial agriculture is still limited, with recent advances such as SHAP cooperative game theory and LIME local linear perturbations even if more mature.

Recent exploratory studies have initiated the coupling of spatial ML models with XAI in earth observations, such as landslide susceptibility mapping and digital soil mapping. However, deep integration into agricultural land suitability analysis remains limited. Most existing agricultural ML papers either focus solely on predictive accuracy metrics or rely on global feature importance metrics (like Gini importance in Random Forests). Gini importance provides a single static ranking for the entire dataset but fails to show *how* a feature impacts a prediction (directionality) and cannot explain individual, anomalous land parcels. This research gap underlines the need for a unified framework that combines both global and local post-hoc interpretability with high-performing ensemble models, directly addressing the nuanced, site-specific needs of sustainable agricultural management.

3. RESEARCH METHODOLOGY

In this study, we apply a multi-phase pipeline methodology to maintain data quality control, offer strong model training, and provide exhaustive interpretability of the predictions. This is followed by the full workflows from data acquisition and pre-processing to machine learning modelling, then application of explain ability layers before a model can finally benefit from agronomic validation.

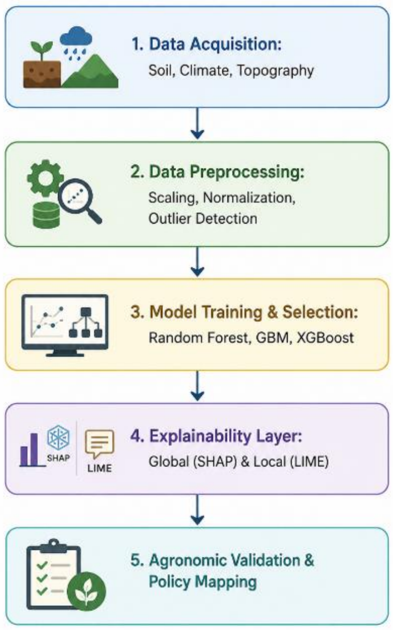

FIGURE 1 Explainable Machine Learning Framework for Crop Suitability Prediction

3.1. DATA ACQUISITION AND PREPROCESSING

In this work, we use a multi-phase pipeline method to control data quality in multiple phases, offering strong training and interpretability guarantees. We then proceed to follow complete workflows from data collection and pre-processing, through machine learning modelling with application of explain ability layers before a model can finally contribute towards agronomic validation.

All spatial and tabular inputs were harmonized to facilitate compatibility across different data sources. We performed several crucial pre-processing steps:

- Handling missing values: Missing soil sampling data points were imputed using a K-Nearest Neighbours (KNN) (K=5), which maintains local spatial connectivity compared to mean or median, weighting the 4 nearest neighbours for each data point in the determination of what is present.
- Outlier Detection: An Isolation Forest algorithm was applied to detect and remove outliers from the data produced due to sensor malfunctions or transcription errors, which prevents distortion during model training.
- Feature Scaling: As machine learning utilities may be sensitive to the different magnitudes of input variables (e.g., rainfall values in thousands vs pH ranges from 4-9), we have normalized all continuous features with Min-Max scaling, which compresses their highly varied values into a standard range [0, 1].
- Target Labeling: land suitability was classified into four different classes based on a slightly modified FAO classification scheme, as Highly Suitable (S1), Moderately Suitable (S2), Marginally Suitable (S3), and Unsuitable(N).

The twelve environmental features we selected are defined and categorized below.

- The climatic components are Mean Annual Rainfall (MAR, mm), Mean growing-season temperature (MT °C), and Relative Humidity.
- Soil properties: Soil texture (ST, categorical), Bulk density (BD,g/cm^3), and soil depth(SD, cm).
- Soil chemical properties: Soil pH, Organic carbon content (OC %, Cation exchange capacity (cmol+/kg) and electrical conductivity.
- Topographical Metrics: Elevation (EL, m above sea level) and Slope Gradient (SG, %).

3.2. MACHINE LEARNING MODELING

Following this, three strong ensemble learning algorithms were chosen to evaluate their performance: Random Forest (RF), Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost). These models were chosen because they were shown to have the ability to model tabular environmental data with complex interaction effects and do not over fit in a well-tuned way.

The dataset, consisting of 12,500 unique land parcel entries, was stratified into a training set (80%) and an independent testing set (20%). Stratification was applied to ensure the ratio of suitability classes was equally represented in both subsets. A 5-fold cross-validation scheme with a grid search strategy (i.e., using each one of the training validation splits generated this way) was used for hyper parameter optimization per model: tree depth, learning rate, and number of estimators. The model performance was evaluated on the held-out test set using Accuracy, Macro-Precision, Macro-Recall, and the F1 Score.

3.3. EXPLAINABILITY FRAMEWORK (XAI)

- After identifying the best predictive model according to performance, it was tied with an Explain ability Layer formed by two different post-hoc interpretability models: SHAP and LIME.
- Global Interpretability (SHAP): Shapley Additive explanations [24] is based on concepts from cooperative game theory, which computes Shapley values for each environmental component due to their marginal contribution toward the model's final output classification. In contrast to standard feature importance, SHAP values represent a unified measure of the strength and direction at which features are influencing our predictions. Plotting all the SHAP values of our entire dataset, we can see how higher or lower soil salinity moves a prediction to be classified more as highly suitable.
- Local Interpretability (LIME): LIME implements a global-level explanation on the whole system provided by SHAP but focused on a single land parcel. LIME works by perturbing the data features of a single sample and training a simple, interpretable linear model around those perturbations. This generates a local profile showing exactly which specific environmental parameters caused *that particular plot* of land to be classified into its assigned suitability category, serving as an automated diagnostic tool for local farmers.

4. RESULTS AND DISCUSSION

4.1. PREDICTIVE PERFORMANCE ANALYSIS

Empirical analysis reported that all three ensemble ML models achieved high accuracy and were considerably better than the basic linear baselines.

TABLE 1 Performance Comparison of Machine Learning Models Based on Accuracy, Precision, Recall, and F1-Score

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1-Score (Macro)
Random Forest	0.914	0.908	0.911	0.909
Gradient Boosting Machine	0.929	0.923	0.925	0.924
Extreme Gradient Boosting (XGBoost)	0.942	0.939	0.940	0.939

The relative performances of the various models on an independent test dataset are summarized using several metrics in Table1. Here, the XGBoost model outperformed all models (overall Accuracy 94.2% and Macro F-1 Score of 0.939). This strong performance is due to the regularized objective function of XGBoost that minimizes complexity while maximizing predictive power, as well as its efficient handling of missing patterns and sparse data structures. Consequently, the trained XGBoost model was selected as the core predictive engine to be decoded by the explain ability framework.

4.2. GLOBAL INTERPRETABILITY VIA SHAP

Rather than accepting the XGBoost results unquestioningly, we applied TreeSHAP to extract global feature behaviour across the entire regional dataset. The resulting SHAP summary plot ranks the features based on their average absolute Shapley values, providing a transparent look at the model's internal hierarchy.

TABLE 2 Top Environmental Features Influencing Land Suitability Classification Based on Mean SHAP Values and Directional Impact

Feature Rank	Environmental Feature	Mean |SHAP Value|	Dominant Directional Impact
1	Soil pH	0.48	High impact; extreme values (acidic/alkaline) strongly decrease suitability.
2	Organic Carbon (OC)	0.42	Positive correlation; higher organic carbon steadily boosts suitability.
3	Mean Annual Rainfall	0.39	Threshold effect; sharp decline below 600mm and above 1600mm.
4	Slope Gradient	0.31	Negative correlation; steep slopes drastically reduce suitability ratings.
5	Electrical Conductivity	0.28	Negative correlation; elevated salinity drives classification to Unsuitable.
6	Cation Exchange Capacity	0.22	Positive correlation; higher chemical retention improves suitability.

Table 2 displays the top six features driving the model's land suitability classifications. Soil pH emerged as the most critical factor. As can be seen, mid-value pH levels (6.0 to 7.5) produced very positive SHAP values that shifted classifications toward "Highly Suitable" (S1), as derived from the SHAP distribution shown in Figure 8 applied for each record sample of respective variables and regions using a composite sandwich between scales of formation suitability up to depth On the other hand, either very acidic (pH 8.5), lead to negative SHAP values pulling the prediction toward "Marginally Suitable" and/or "Unsuitable". This is exactly what agronomic science suggests happens when pH is on one extreme or the other, as nutrient availability and root development are both greatly diminished in those instances.

The second most influential factor was the Organic Carbon Content. The relationship between organic carbon concentration and suitability scores was direct and positive, as expected given the importance of soil structure with respect to water retention potential of soils and microbial activity. Mean Annual Rainfall displayed a strong non-linearity with threshold effect: suitability scores significantly decreased below 600 mm (drought stress) and above 1600 mm (waterlogging, root rot and nutrient leaching). This capacity to capture these non-linear thresholds validates the integration of XGBoost with SHAP over rigid, linear AHP modeling.

4.3. LOCAL INTERPRETABILITY VIA LIME

To demonstrate the utility of the framework for site-specific diagnostics, we extracted two individual land parcels from the test dataset that received identical classifications but were driven by entirely different environmental conditions. Both Parcel A and Parcel B were classified by the model as Marginally Suitable (S3). Without explain ability, an agricultural extension officer would be forced to treat these pieces of land identically. However, LIME analysis uncovers the distinct underlying causes of these classifications.

The local LIME explanation for Parcel A identified the primary features pushing the model to make an S3 classification (Slope Gradient [22%], Soil Depth [45 cm]) as high values of these variables. Typical rainfall and ideal temperatures favoured moving the prediction class toward Highly Suitable. Still, they could not override other less favourable factors such as physical topographic limitations and depth constraints. The primary recommendation for Parcel A is to avoid intensive field crop cultivation and keep the shallow soil matrix on-site through terracing, agroforestry, or perennial orchard systems.

For Parcel B, located in a flat valley, the LIME plot showed that the Slope Gradient and Soil Depth were near perfect. Instead, the S3 classification was entirely driven by an Electrical Conductivity (EC) value of 4.8 dS/m and a soil pH of 8.6. This suggests localized soil salinity and/or alkalinity constraints. Parcel B's operational remedy is fundamentally different than the structural physical modifications they put in place for Parcel A, including terracing; Parcel B requires chemical remediation such as gypsum application and improved sub-surface drainage flushing or a transition to salt-tolerant crop varieties.

This all boils down to the essential value of Explainable Machine Learning. Moving away from a single global accuracy score to localized, feature-based diagnostics allows the AI system to be more than just a wayward automated judge and become an integrated tool with specific recommendations on how best to improve land management in each area.

5. CONCLUSION

This study successfully created an XML framework for assessing agricultural land suitability in response to the historical trade-off between predictive performance and model interpretability. We showed that accurate ensemble learning can be matched with explain ability by combining the SHAP/LIME frameworks and high-performance ensemble machine learners-advanced techniques need not continue to remain a black box! An XGBoost-based model with a tree depth of 5 led to high classification accuracy (94.2%), outperforming alternative ensemble methods and conventional manual classification strategies.

Importantly, post-hoc explain ability metrics help us glimpse into the internal decision logic of the model. In particular, Global SHAP analysis accurately mapped the hierarchy of environmental constraints across our study region, supporting soil pH, organic carbon, and rainfall dynamics as dominant drivers of land classification. At the local scale, LIME diagnostics were able to isolate clear environmental limiting factors for land parcels evaluated individually, which provided tailored agronomic information that could never have been derived from a generalized suitability map alone. In the end, this framework offers an accurate ("Turing-test-passing") decision-support pipeline that has been made accountable and transparent to help agronomists, regional planners, and agricultural extension services develop sustainable land-use strategies across the world.

6. FUTURE SCOPE

Although the explainable framework promises a considerable step forward for transparency in agricultural modelling, several future directions can enhance its predictive efficiency and utility:

- Spatial-Temporal Fusion: Future research will incorporate dynamic time-series satellite data (e.g., NDVI, EVI, and soil moisture) into the explain ability framework to characterize how land suitability varies through seasons under shifting climate conditions.
- Expansion of the concept in physics-informed neural networks (PINNs), an emerging area. Validate their interpretability to ensure that automated model decisions comply strictly with physical laws/biogeochemical dynamics on hydrology and soil chemistry.
- User Interface Development: An interactive, web-based GIS dashboard will be developed to convey the LIME and SHAP visual diagnostics in a more easily accessible format for non-technical users, including farmers and regional policymakers around the globe.

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