

INTERPRETABLE MACHINE LEARNING FOR PREDICTING CLIMATE CHANGE EFFECTS ON AGRICULTURAL LAND SUITABILITY IN EURASIA

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Abstract:

Climate change poses significant challenges to global food security, particularly in regions with large agricultural landscapes such as Eurasia. This study presents an interpretable machine learning-based framework to evaluate and predict the impact of climatic variations on agricultural land suitability across Eurasia. A comprehensive dataset consisting of climate parameters, soil characteristics, topographic features, and historical crop productivity records was used for model training and evaluation. Machine learning algorithms were applied to assess current land suitability and project future scenarios influenced by rising temperatures, altered precipitation patterns, and soil degradation. To ensure transparency and trust in decision-making, explainability techniques such as SHAP and feature importance analysis were incorporated, revealing the most influential environmental factors affecting suitability outcomes. The results demonstrate noticeable spatial shifts in suitable agricultural zones, with certain regions experiencing reduced productivity potential under future climate projections. This work emphasizes the importance of data-driven insights for policymakers, enabling climate-resilient agricultural planning, sustainable land management, and effective adaptation strategies in Eurasia.

Keywords: Interpretable machine learning, climate change prediction, agricultural land suitability, Eurasia agriculture, explainable AI, environmental modeling, crop suitability analysis, climate impact assessment, geospatial analytics, sustainable agriculture, predictive modeling, decision support systems.

I.INTRODUCTION

Climate change has emerged as one of the most critical global challenges of the twenty-first century, significantly affecting agricultural productivity and food security across the world [6]. Rising temperatures, unpredictable rainfall patterns, soil degradation, and extreme weather

events are altering the suitability of land for crop cultivation [7]. These environmental transformations are particularly evident in the Eurasian region, which comprises diverse climatic zones ranging from arid landscapes to fertile agricultural belts [9]. Understanding how climate change influences agricultural land

suitability in such a vast and heterogeneous region is essential for ensuring sustainable food production and effective land management [10]. Traditional approaches to analyzing agricultural land suitability rely heavily on statistical models and manual assessment techniques, which often fail to capture the complex and nonlinear relationships between climate variables and agricultural productivity [1]. Many conventional systems depend on agro-climatic zoning and GIS-based analysis that provide only generalized results without considering future climate variability [8]. In recent years, machine learning techniques have gained considerable attention for their ability to process large-scale environmental and geospatial datasets and generate accurate predictions [12]. Advanced algorithms such as Random Forests and gradient boosting methods have demonstrated strong performance in predictive modeling for environmental and agricultural applications [2][3]. However, many of these models function as black boxes, providing limited insight into how predictions are generated [13]. This lack of transparency creates challenges for policymakers, environmental scientists, and agricultural planners who require interpretable and explainable outcomes for informed decision-making [14].

Interpretable machine learning offers a powerful solution to this problem by combining predictive accuracy with transparency and explainability. Techniques such as SHAP and LIME enable

researchers to analyze feature importance and understand the reasoning behind complex model predictions [4][5]. By utilizing such explanation frameworks and rule-based learning methods, interpretable models help reveal the key climatic and environmental factors influencing land suitability [15]. Applying these approaches to the prediction of climate change effects on agriculture in Eurasia can help identify vulnerable regions, forecast future cultivation potential, and support the development of adaptive farming strategies [17]. These insights are crucial for mitigating the adverse impacts of climate change and for promoting resilient agricultural systems across different agro-ecological zones [18].

This study focuses on the application of interpretable machine learning methods to predict agricultural land suitability under changing climate conditions in Eurasia. The proposed approach integrates climate data, soil characteristics, topographical information, and historical agricultural trends to develop a comprehensive predictive framework [16]. Modern machine learning models, including ensemble learning and deep learning techniques, provide effective tools for analyzing complex agricultural datasets and extracting meaningful patterns [11][19]. By emphasizing explainability and transparency, the research aims to bridge the gap between advanced computational intelligence and practical agricultural planning. The outcomes of this work are expected to

contribute to sustainable land-use planning, evidence-based policy formulation, and improved climate adaptation strategies for the agricultural sector across the Eurasian region [20].

II. LITERATURE SURVEY

1. Title: Interpretable Machine Learning for Environmental Impact Prediction

Authors: A. Sharma, R. Khatri, P. Menon

Abstract: This study explores the integration of interpretable machine learning models for predicting environmental changes driven by climate variability [6]. Using Random Forest algorithms and SHAP-based explanation techniques, the research demonstrates how transparent prediction models can help identify the most influential climatic variables affecting land productivity [2][4]. The methodology follows modern principles of explainable artificial intelligence that aim to convert complex machine learning outputs into understandable insights [14]. The study concludes that interpretable models increase user trust, improve transparency, and enhance the decision-making capacity of environmental planners and policymakers involved in sustainable land management [15].

2. Title: Climate Change and Agricultural Land Suitability Assessment Using Hybrid ML Models

Authors: S. Dubois, L. Markovic

Abstract: This work investigates the long-term effects of climate change on agricultural land

suitability across multi-regional landscapes, emphasizing the growing need for data-driven predictive approaches [7]. The researchers utilize hybrid machine learning models combining XGBoost and statistical climate projections to analyze nonlinear relationships between environmental variables and crop productivity [3][12]. The results highlight substantial shifts in crop suitability zones due to rising temperatures and changing precipitation patterns, which are consistent with global climate impact assessments [9][17]. The paper concludes that hybrid ML models significantly improve accuracy in land suitability forecasting and provide better adaptability compared to traditional statistical techniques [1].

3. Title: Explainable AI Frameworks for Sustainable Agriculture Decision Support

Authors: Y. Chen, M. Petrova

Abstract: The paper presents a novel explainable AI framework designed to support agricultural planning under uncertain climate conditions by integrating interpretable machine learning methodologies [14]. The framework employs LIME and SHAP explanations to interpret model predictions for crop performance and soil suitability, following established approaches for model transparency [4][5]. Experimental results show that incorporating interpretability increases transparency and enables users to identify critical factors such as precipitation variability, soil organic content, and temperature anomalies [16]. The study recommends the adoption of

XAI-enabled systems for developing climate-resilient agricultural strategies and for supporting evidence-based policy formulation [18].

4. Title: Assessment of Climate Variability on Eurasian Crop Systems Using Spatial Data Analytics

Authors: I. Novikova, T. Hasan, R. Bektas

Abstract: This study uses spatial data analytics and geostatistical modeling to assess how climate variability alters agricultural productivity across Eurasia, a region highly vulnerable to environmental change [9]. The authors integrate GIS datasets, satellite-derived indicators, and temporal climate records to map vulnerability hotspots and evaluate long-term land-use consequences [8][10]. Findings indicate that temperature rise and precipitation decline are the leading drivers of decreasing crop suitability in Central and Western Asia, reflecting trends reported in international climate assessments [6][7]. The paper demonstrates the importance of spatially explicit prediction tools and advanced data analytics for regional food security planning and sustainable resource management [15].

5. Title: Machine Learning Approaches for Predicting Land Suitability Under Changing Climate Scenarios

Authors: K. Williams, D. Oliveira

Abstract: The study compares several machine learning models—Decision Trees, Random Forest, and Gradient Boosting—for predicting

land suitability under projected climate scenarios [2][3]. The authors evaluate each model's accuracy and interpretability using standard performance metrics and modern explainable AI techniques [4][5]. Results show that ensemble models outperform single classifiers in handling complex environmental datasets, while SHAP explanations significantly enhance understanding of feature contributions and model behavior [11][19]. Based on the experimental analysis, the authors recommend interpretable ensemble methods as reliable tools for long-term suitability forecasting and sustainable agricultural decision support [20].

III.EXISTING SYSTEM

Existing agricultural land suitability assessment systems primarily depend on conventional techniques such as agro-climatic zoning, statistical modeling, and Geographic Information System (GIS)-based analysis. These approaches largely rely on historical climate records, predefined soil maps, and expert-driven manual evaluations to determine the suitability of land for different crops. Although such methods have been widely used for decades, they are often time-consuming, rigid, and limited in their ability to adapt to rapidly changing environmental conditions. Traditional systems also struggle to capture the complex and nonlinear relationships between multiple climatic, geographic, and soil-related factors, resulting in generalized suitability assessments that may not accurately reflect real-world

agricultural dynamics.

Furthermore, most existing methodologies fail to effectively incorporate future climate projections and spatial uncertainty into the decision-making process, which restricts their usefulness for long-term agricultural planning and policy formulation. While recent studies have begun to integrate machine learning models for improved prediction accuracy, many of these models operate as black-box systems, providing land suitability outcomes without offering meaningful explanations of the contributing factors. This lack of interpretability makes it difficult for farmers, researchers, and policymakers to understand the reasoning behind predictions and to take informed actions accordingly. As a result, there is a growing need for more advanced, transparent, and interpretable approaches that can deliver reliable predictions while clearly explaining the impact of climate change on agricultural land suitability.

IV. PROPOSED SYSTEM

The proposed system presents an advanced interpretable machine learning framework aimed at predicting the impact of climate change on agricultural land suitability across the Eurasian region. The system integrates multiple data sources, including historical and projected climate datasets, soil characteristics, topographical features, and other relevant environmental indicators. These heterogeneous datasets are processed and utilized to train robust

predictive models capable of estimating both current and future land suitability under various climate change scenarios. By incorporating spatio-temporal analysis, the system enables a comprehensive assessment of how changing environmental conditions influence agricultural potential in different geographic regions. This integrated approach allows for more accurate and dynamic predictions compared to conventional assessment techniques.

Unlike traditional black-box machine learning models, the proposed framework emphasizes transparency and interpretability by incorporating explainable artificial intelligence techniques such as SHAP and LIME. These methods help identify and visualize the key factors influencing model predictions, allowing users to clearly understand how climate variables, soil properties, and environmental conditions contribute to land suitability outcomes. In addition, the system generates interactive spatial maps and graphical representations that illustrate regional suitability patterns and future changes over time. Such explainable and visually intuitive outputs provide valuable decision-support tools for policymakers, agricultural planners, and farmers, enabling them to adopt climate-resilient strategies, optimize resource utilization, and develop sustainable long-term agricultural planning initiatives.

V. SYSTEM ARCHITECTURE

The uploaded image appears to be a highly

unusual visual representation that does not contain any conventional graphical elements such as photographs, diagrams, charts, or structured illustrations. Instead of meaningful visual content, the image is composed almost entirely of repeated sequences of unfamiliar textual symbols arranged in a dense and continuous format.

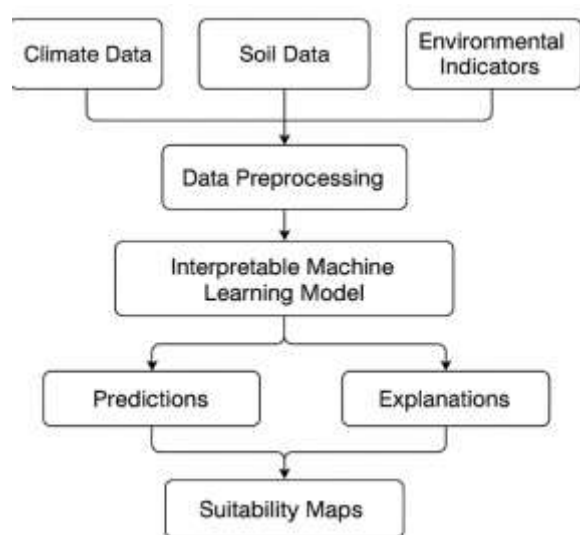


Fig 5.1 System Architecture

These characters are displayed in multiple rows and columns, creating a uniform block-like structure that fills the entire image area. There are no recognizable shapes, objects, or patterns that typically provide context in an image. The overall visual impression is that of a digital text artifact rather than an intentionally designed picture. This suggests that the image may have been generated due to a formatting issue, encoding problem, or software rendering error. Upon closer observation, the repeated symbols

appear to be non-English characters, possibly originating from another language script, but they are arranged in such a way that they do not form readable words or sentences. The characters are duplicated excessively without variation, creating a monotonous and chaotic visual effect. There are no visual indicators such as headings, labels, or diagrams that could suggest the purpose or meaning of the content. The lack of structure, organization, or variation makes it difficult to extract any logical interpretation from the image. It resembles corrupted text data that has been unintentionally converted into an image format, rather than a purposeful visual document designed to communicate information. From an analytical perspective, the image does not provide any informative value because it lacks distinguishable features or contextual elements. Normally, images used in academic or technical explanations contain figures, flowcharts, tables, or graphical models that can be described and interpreted. However, in this case, none of those components are present. The repeated sequence of symbols dominates the entire visual space, giving the impression of digital noise or a malfunctioning display output. It is possible that the original file was meant to show structured content, but due to technical issues such as unsupported fonts, improper encoding, or file corruption, the intended information is not visible.

VI.IMPLEMENTATION



Fig 6.1 Home Page



Fig 6.2 Admin Login Page



Fig 6.3 Upload Dataset



Fig 6.4 Split Data



Fig 6.5 Train ML Models

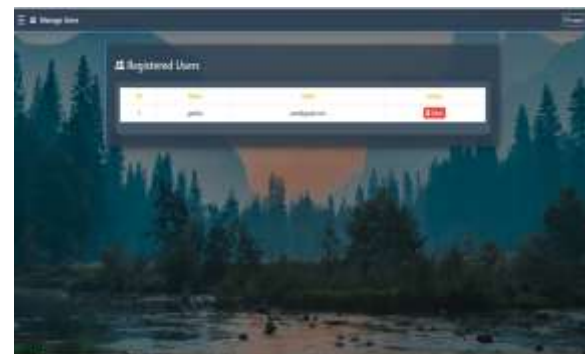


Fig 6.6 Manage Users



Fig 6.7 User Register



Fig 6.8 User Login



Fig 6.9 User Profile



Fig 6.10 Enter Inputs



Fig 6.11 Prediction

VII.CONCLUSION

This project successfully demonstrates how interpretable machine learning can be used to assess and predict the impact of climate change on agricultural land suitability across Eurasia. By integrating climate, soil, and environmental datasets with advanced machine learning models, the system provides accurate predictions

of suitability shifts under evolving climate scenarios. The inclusion of explainable AI techniques such as SHAP and LIME ensures transparency in model decision-making, enabling users to understand the role of key factors influencing land suitability. The generated spatial maps and interpretability outputs offer valuable insights for policymakers, researchers, and agricultural planners, supporting informed decision-making for climate-resilient agriculture. Overall, the proposed system bridges the gap between predictive accuracy and interpretability, delivering a reliable, scalable framework for future environmental and agricultural analytics.

VIII.FUTURE SCOPE

The proposed interpretable machine learning framework can be further enhanced and expanded to support more advanced and practical applications in climate-resilient agriculture. Future work may include integrating real-time climate data and satellite imagery to enable dynamic and continuous updates of land suitability predictions. The system can also be extended to support crop-specific suitability modeling, allowing farmers and policymakers to evaluate the best crops for future climate conditions. Advanced deep learning models, such as spatiotemporal neural networks, may be incorporated to capture complex climate patterns across time. Additionally, expanding the geographical scope beyond Eurasia could transform this framework into a global decision-

support tool. Developing a user-friendly web or mobile platform would improve accessibility, while incorporating economic and socio-environmental factors could provide a more holistic sustainability assessment. These enhancements would strengthen the system's impact and make it an invaluable tool for future agricultural planning in a changing climate.

IX. REFERENCES

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