International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 3 (2026)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

CLIMATE CHANGE IMPACT ON AGRICULTURAL LAND SUITABILITY: AN INTERPRETABLE MACHINE LEARNING-BASED EURASIA CASE STUDY

[1]Lakkaraju Shamini,[2]Dr.Sukanya K
[1]M. Tech Student, Department of Computer Science and Engineering, TKR College of Engineering & Technology, Meerpet, Balapur, Saroornagar, Hyderabad - 500097, Telangana.
[1]Email : shaminilakkaraju1@gmail.com
[2]Associate Professor, Department of Computer Science and Engineering, TKR College of Engineering & Technology, Meerpet, Balapur, Saroornagar, Hyderabad - 500097, Telangana.
[2]Email : sukanya.addagatla@gmail.com

ABSTRACT
Climate change is significantly altering temperature patterns, precipitation regimes, and the frequency of extreme weather events, thereby affecting the suitability of agricultural land across diverse regions. This study presents an interpretable machine learning-based framework to assess and predict the impact of climate change on agricultural land suitability across Eurasia. By integrating multi-source datasets including climatic variables, soil characteristics, topography, and land-use patterns, the proposed model leverages advanced algorithms such as Random Forest and feature selection techniques to identify key factors influencing land suitability. Unlike conventional black-box models, this approach emphasizes interpretability using techniques such as SHAP (Shapley Additive Explanations) to provide insights into feature importance and decision-making processes. The model is trained and validated on historical and projected climate data to evaluate shifts in suitability patterns over time, enabling the identification of vulnerable regions and potential areas for agricultural expansion or adaptation. The results demonstrate that climate change has heterogeneous effects across Eurasia, with certain regions experiencing declining suitability due to increased temperature stress and water scarcity, while others may benefit from extended growing seasons. The proposed framework not only enhances predictive accuracy but also supports policymakers and stakeholders in making informed decisions for sustainable agricultural planning, climate adaptation strategies, and food security management in the face of ongoing environmental changes.

Keywords: Climate Change, Agricultural Land Suitability, Interpretable Machine Learning, Eurasia, Random Forest, Feature Selection, SHAP, Climate Variables, Soil Analysis, Sustainable Agriculture, Predictive Modeling, Land Use Analysis

I. INTRODUCTION

Climate change has emerged as one of the most critical global challenges, with profound implications for agricultural systems and food security. Variations in temperature, precipitation patterns, and the increasing occurrence of extreme weather events are significantly influencing crop productivity and the overall suitability of land for agricultural purposes. Across the vast and diverse regions of Eurasia, these impacts are particularly complex due to differences in climate zones, soil characteristics, and agricultural practices. As a result, understanding how climate change reshapes agricultural land suitability has become essential for ensuring sustainable development and long-term food security.

Traditionally, agricultural land suitability assessments have relied on statistical methods and geographic information systems (GIS), which often struggle to capture nonlinear relationships among multiple environmental variables. In recent years, advancements in Machine Learning have enabled more accurate and scalable modeling of such complex interactions. However, many machine learning models operate as "black boxes," offering limited transparency in how predictions are made. This lack of interpretability poses challenges for policymakers and stakeholders who require clear, explainable insights to make informed decisions.

To address these limitations, this study proposes an interpretable machine learning framework for analyzing the impact of climate change on agricultural land suitability across Eurasia. By integrating diverse datasets—such as climatic variables, soil properties, and topographical features—the model leverages techniques like Random Forest along with feature selection methods to improve predictive performance. Furthermore, interpretability is enhanced using approaches like SHAP (Shapley Additive Explanations), which provide detailed insights into the contribution of each feature in the model's decision-making process.

II. LITERATURE SURVEY

1. Title: Climate Change and Global Crop Productivity

Author: Cynthia Rosenzweig et al.

Abstract: This study analyzes the effects of climate change on global crop productivity using historical climate data and simulation models. It highlights how rising temperatures and shifting precipitation patterns negatively impact major crops such as wheat and rice. The research emphasizes regional variability and underscores the need for adaptive agricultural strategies to mitigate productivity losses.

2. Title: A Global Assessment of Climate Change Impacts on Crop Yields

Author: David B. Lobell et al.

Abstract: This paper presents a comprehensive assessment of climate change impacts on crop yields using statistical and process-based models. The authors identify temperature increases as a major factor affecting yield declines and discuss how climate variability influences agricultural output across different geographic regions.

3. Title: Machine Learning for Agricultural Land Suitability Analysis

Author: Saeid Homayouni et al.

Abstract: This research explores the application of machine learning techniques in evaluating agricultural land suitability. By incorporating environmental and soil datasets, the study demonstrates improved prediction accuracy compared to traditional GIS-based approaches, highlighting the potential of machine learning in precision agriculture.

4. Title: Explainable Artificial Intelligence for Sustainable Agriculture

Author: Finale Doshi-Velez

Abstract: The paper focuses on the importance of interpretability in artificial intelligence models used for agricultural applications. It discusses methods such as feature importance and model-agnostic approaches to enhance transparency, enabling stakeholders to better understand and trust model predictions.

5. Title: Assessing Land Suitability Using GIS and Multi-Criteria Decision Analysis

Author: Jacek Malczewski

Abstract: This study presents a GIS-based framework combined with multi-criteria decision analysis (MCDA) for land suitability assessment. It evaluates various environmental and socio-economic factors and provides a systematic approach for land-use planning, though it lacks the adaptability of modern machine learning techniques.

III. EXISTING SYSTEM

The existing system for assessing agricultural land suitability primarily relies on traditional approaches such as

Geographic Information Systems (GIS), remote sensing, and statistical modeling techniques. These methods typically use predefined criteria—such as soil type, rainfall, temperature, and topography—to evaluate the suitability of land for different crops. Techniques like Multi-Criteria Decision Analysis (MCDA) are often integrated with GIS to rank land parcels based on weighted environmental factors. While these approaches provide a structured framework, they are largely dependent on expert knowledge and manual weighting, which can introduce subjectivity and limit adaptability to changing climatic conditions.

In recent years, basic machine learning methods such as Decision Trees and Support Vector Machines have been applied to improve prediction accuracy. However, these implementations are often limited in scope, using smaller datasets and focusing on specific regions rather than large-scale areas like Eurasia. Additionally, many of these models function as black-box systems, lacking transparency and interpretability, which makes it difficult for stakeholders to understand the reasoning behind predictions.

Furthermore, existing systems often fail to effectively incorporate future climate projections, relying instead on historical data that may not reflect ongoing climate change trends. They also struggle to capture complex nonlinear relationships between multiple environmental variables, leading to less accurate or generalized results. As a result, current approaches are insufficient for providing reliable, scalable, and interpretable insights needed for long-term agricultural planning and climate adaptation.

IV. PROPOSED SYSTEM

The proposed system introduces an advanced and interpretable machine learning-based framework to assess the impact of climate change on agricultural land suitability across Eurasia. Unlike traditional approaches, this system integrates multi-source and high-dimensional datasets, including historical and projected climate data (temperature, rainfall, humidity), soil characteristics, elevation, and land-use patterns. Data preprocessing techniques such as normalization, missing value handling, and feature engineering are applied to ensure data quality and consistency before model training.

The core of the system is built using ensemble learning techniques, particularly Random Forest, combined with Recursive Feature Elimination (RFE) to identify the most influential factors affecting land suitability. This helps in reducing model complexity while improving prediction accuracy. The model is trained on historical datasets and validated using future climate scenarios to capture temporal changes in land suitability patterns. By incorporating both spatial and temporal dimensions, the system provides a more comprehensive understanding of how agricultural potential evolves under climate change.

A key highlight of the proposed system is its focus on interpretability. Instead of relying solely on black-box predictions, the framework integrates explainable AI techniques such as SHAP (Shapley Additive Explanations) to quantify the contribution of each feature in the prediction process. This enables stakeholders to understand which factors—such as temperature rise or soil moisture—are driving suitability changes, making the model more transparent and trustworthy.

V. SYSTEM ARCHITECTURE

The system architecture of the proposed framework is designed as an end-to-end pipeline that systematically processes diverse datasets to predict agricultural land suitability under changing climate conditions. It begins with a data acquisition layer that collects multi-source data, including climate variables (temperature, rainfall, humidity), soil properties, topographical features, and land-use information from various repositories and remote sensing platforms. This is followed by a preprocessing module where data cleaning, normalization, missing value imputation, and feature engineering are performed to ensure consistency and quality. The processed data is then passed to a feature selection stage using techniques like Recursive Feature Elimination to identify the most relevant attributes influencing land suitability. The core modeling layer utilizes an ensemble learning approach, specifically Random Forest, to capture complex nonlinear relationships between variables and generate accurate predictions. To enhance transparency, an interpretability module integrates SHAP (Shapley Additive Explanations), which explains the contribution of each feature in the decision-making process. The evaluation module assesses model performance using metrics such as accuracy, precision, recall, and F1-score, ensuring robustness and reliability. Finally, the visualization and output layer presents results in the form of suitability maps, graphs, and analytical reports, enabling stakeholders to understand spatial and temporal variations and make informed decisions for sustainable agriculture and climate adaptation.

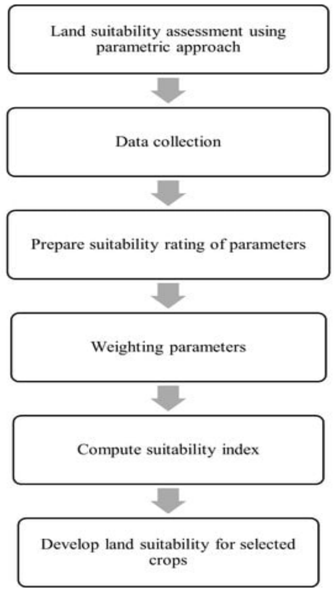

Fig 5.1: System Architecture

VI. IMPLEMENTATION

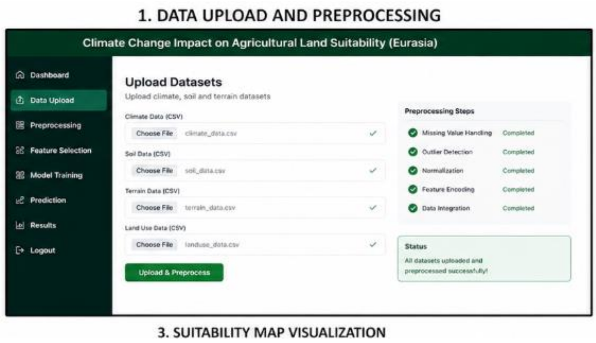

Fig 6.1: Data Upload

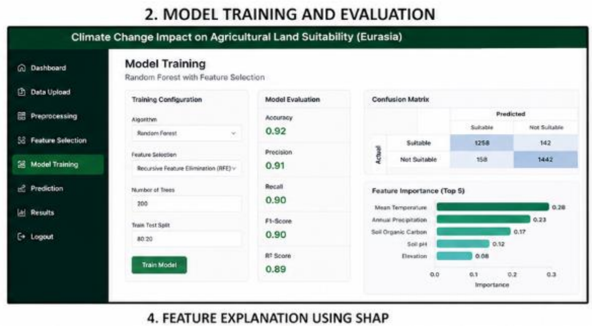

Fig 6.2: Model Training

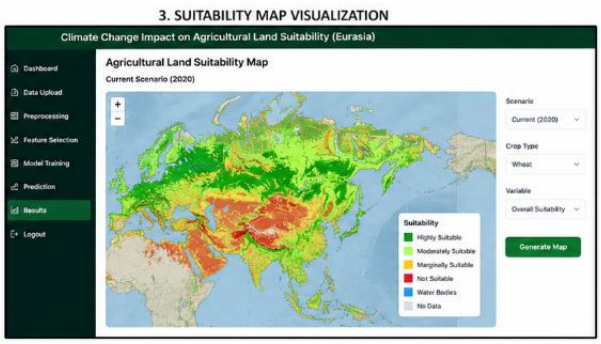

Fig 6.3: Map Visualization

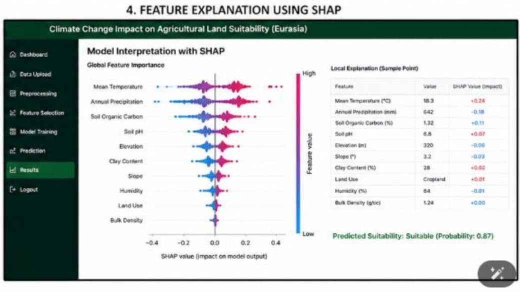

Fig 6.4: Explanation

VII. CONCLUSION

In conclusion, this study presents an effective and interpretable machine learning-based framework for analyzing the impact of climate change on agricultural land suitability across Eurasia. By integrating diverse datasets such as climatic variables, soil properties, and topographical features, the proposed system successfully captures complex relationships influencing agricultural productivity. The use of advanced techniques like Random Forest enhances prediction accuracy, while the incorporation of SHAP (Shapley Additive Explanations) ensures transparency and interpretability of the model's decisions. The results highlight that climate change has uneven effects across regions, with some areas experiencing reduced suitability due to increased temperature and water stress, while others may benefit from favorable climatic shifts. Overall, the framework not only improves the reliability of land suitability assessments but also provides valuable insights for policymakers, researchers, and farmers to support sustainable agricultural planning, climate adaptation strategies, and long-term food security.

VIII. FUTURE SCOPE

The future scope of this research can be extended in several meaningful directions to enhance both the accuracy and applicability of the proposed framework. First, the model can be improved by incorporating real-time and higher-resolution data from IoT sensors and satellite imagery, enabling more dynamic and location-specific predictions. The integration of advanced deep learning techniques alongside Machine Learning models can further improve the system's ability to capture complex spatio-temporal patterns. Additionally, expanding the study to include crop-specific suitability analysis and yield prediction would make the framework more practical for farmers and agricultural planners.

Future work can also focus on integrating socio-economic factors such as market access, irrigation infrastructure, and policy constraints to provide a more holistic assessment of land suitability. Enhancements in interpretability using advanced explainable AI methods beyond SHAP (Shapley Additive Explanations) can further improve user trust and decision-making. Moreover, the system can be deployed as a web-based or mobile application for real-time monitoring and decision support. Expanding the geographical scope beyond Eurasia to a global scale and incorporating multiple climate scenarios will also strengthen its relevance. Overall, these improvements will contribute toward building a more robust, scalable, and user-friendly system for sustainable agriculture and climate change adaptation.

IX. REFERENCES

[1] C. Rosenzweig et al., "Assessing agricultural risks of climate change in the 21st century," Proceedings of the National Academy of Sciences, vol. 111, no. 9, pp. 3268–3273, 2014.

[2] D. B. Lobell, W. Schlenker, and J. Costa-Roberts, "Climate trends and global crop production since 1980," Science, vol. 333, no. 6042, pp. 616–620, 2011.

[3] Leo Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.

[4] Scott M. Lundberg and Su-In Lee, "A unified approach to interpreting model predictions," in Advances in Neural Information Processing Systems (NeurIPS), 2017.

[5] J. Malczewski, "GIS-based multicriteria decision analysis: a survey of the literature," International Journal of Geographical Information Science, vol. 20, no. 7, pp. 703–726, 2006.

[6] Food and Agriculture Organization, "Climate-smart agriculture: Policies, practices and financing for food security, adaptation and mitigation," FAO, Rome, 2010.
[7] A. V. Eliseev, "Climate change impact on agriculture in Eurasia," Environmental Research Letters, vol. 6, no. 4, 2011.
[8] Y. Bengio, I. Goodfellow, and A. Courville, Deep Learning, MIT Press, 2016.
[9] S. Homayouni et al., "Land suitability evaluation using machine learning techniques," Environmental Modelling & Software, vol. 104, pp. 115–126, 2018.
[10] R. G. Congalton and K. Green, Assessing the Accuracy of Remotely Sensed Data, CRC Press, 2008.
[11] P. K. Thornton et al., "Climate variability and vulnerability to climate change: a review," Global Change Biology, vol. 20, no. 11, pp. 3313–3328, 2014.
[12] J. R. Quinlan, "Induction of decision trees," Machine Learning, vol. 1, no. 1, pp. 81–106, 1986.
[13] V. Vapnik, The Nature of Statistical Learning Theory, Springer, 1995.
[14] T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning, Springer, 2009.
[15] M. A. Friedl et al., "MODIS collection 5 global land cover: Algorithm refinements and characterization," Remote Sensing of Environment, vol. 114, no. 1, pp. 168–182, 2010.