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INTERPRETABLE AI-BASED FRAMEWORK FOR CLIMATE CHANGE-DRIVEN AGRICULTURAL LAND SUITABILITY MAPPING IN EURASIA

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ABSTRACT

The increasing severity of climate change poses a major threat to global food security by altering agricultural productivity and land suitability patterns. Traditional modeling approaches often fail to capture the complex, nonlinear interactions between climatic variables and soil characteristics, limiting their ability to provide actionable insights for sustainable land-use planning. To address this challenge, this research proposes an interpretable AI-based framework for assessing and mapping climate change-driven agricultural land suitability across the Eurasian region.

The proposed model integrates machine learning algorithms with explainable artificial intelligence (XAI) techniques to predict future land suitability under multiple climate change scenarios. Key environmental parameters such as temperature, precipitation, soil type, topography, and vegetation indices are incorporated to develop a comprehensive dataset representing both current and projected agro-climatic conditions. Models such as Random Forest, XGBoost, and SHAP (SHapley Additive exPlanations) are employed to ensure both high predictive accuracy and interpretability, enabling researchers and policymakers to understand how individual climatic and soil variables contribute to land suitability outcomes.

Experimental results demonstrate that the interpretable machine learning framework outperforms conventional statistical methods in predictive performance and transparency, providing spatially explicit insights into potential shifts in suitable agricultural zones across Eurasia. The study highlights regions most vulnerable to climate-induced degradation and those with emerging agricultural potential under future climate projections.

This work contributes to the advancement of climate-smart agriculture by offering a transparent, data-driven decision-support system that enhances understanding of climate–agriculture interactions and supports resilient land management strategies for sustainable food production in a changing environment.

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I. INTRODUCTION

Climate change has emerged as one of the most pressing challenges of the 21st century, significantly impacting global ecosystems, natural resources, and food security. Among its many consequences, the alteration of agricultural land suitability stands out as a critical concern, particularly in regions dependent on climate-sensitive crops and rain-fed farming systems. Shifts in temperature, precipitation patterns, and soil moisture directly influence crop growth cycles, yield potential, and the geographical distribution of arable land. These variations can result in reduced productivity in some areas while opening new opportunities for cultivation in others, thereby reshaping agricultural landscapes across continents such as Eurasia, which exhibits immense climatic and ecological diversity.

Traditional land suitability assessments have primarily relied on empirical models or statistical techniques, often constrained by their limited ability to represent complex, nonlinear relationships between environmental factors. Moreover, such models frequently lack interpretability, making it difficult for policymakers and agricultural planners to understand how specific climatic variables contribute to suitability outcomes. This has prompted a shift toward machine learning (ML) and artificial intelligence (AI) techniques, which offer robust data-driven capabilities to model intricate interactions among climatic, soil, and topographic parameters. However, while these models provide high predictive accuracy, their "black-box" nature raises concerns regarding transparency and trust in decision-making processes.

To overcome these challenges, recent research has emphasized the integration of interpretable or explainable AI (XAI) frameworks into environmental and agricultural studies. Interpretable machine learning not only enhances model transparency but also allows stakeholders to visualize and quantify the contribution of each variable to land suitability predictions. By combining explainability with predictive modeling, such systems provide valuable insights into how climate change affects land productivity and which regions are most vulnerable or resilient under future scenarios.

This study introduces an interpretable machine learning framework for analyzing the impact of climate change on agricultural land suitability in the Eurasian region. The framework leverages high-resolution climate data, soil parameters, and topographical attributes to predict shifts in land suitability under multiple climate change scenarios. Advanced algorithms such as Random Forest and XGBoost are integrated with SHapley Additive exPlanations (SHAP) to ensure that model predictions are both accurate and explainable.

The primary objectives of this research are threefold: (1) to model and predict agricultural land suitability under changing climatic conditions, (2) to identify the key environmental drivers influencing these suitability changes, and (3) to develop a transparent decision-support tool for sustainable land-use planning. By addressing both the predictive and interpretative aspects of land suitability modeling, this work contributes to the broader goal of promoting climate-resilient agriculture and ensuring long-term food security across Eurasia.

II. LITERATURE SURVEY

The relationship between climate change and agricultural land suitability has been extensively studied over the past decades, with increasing attention to data-driven and machine learning approaches. Parry et al. (2004) were among the first to analyze the potential impacts of global warming on agricultural productivity, emphasizing that temperature rise and precipitation variability would significantly alter crop suitability across continents. Fischer and Schrattenholzer (2005) further investigated global agricultural land-use shifts, highlighting the vulnerability of arid and semi-arid regions to climate-induced degradation.

Advancements in geospatial analysis and remote sensing have enabled more precise land suitability assessments. Zhang and Cai (2010) developed a GIS-based crop suitability model that incorporated climatic and soil variables to predict optimal cultivation zones. Ramirez-Villegas and Challinor (2012) introduced climate-based suitability indices for major crops, demonstrating how regional climate models can project future changes in agricultural zones. Li et al. (2014) applied statistical downscaling techniques to enhance the spatial resolution of climate data for more accurate suitability mapping.

The emergence of machine learning provided new pathways for modeling complex environmental interactions. Lobell and Burke (2015) demonstrated the effectiveness of regression-based ML models in predicting crop yields under varying climatic conditions. Abdullah et al. (2017) integrated support vector machines with remote sensing data to classify agricultural land based on suitability, achieving higher accuracy than traditional regression models. Patel and Singh (2018) explored decision tree algorithms for multi-criteria agricultural suitability analysis, proving that data-driven approaches could capture nonlinear dependencies among climatic and soil features.

The recent focus has shifted toward interpretable and explainable AI models. Rana and Thakur (2019) employed random forest models with feature importance ranking to identify dominant climatic factors influencing agricultural performance. Kaur and Mehta (2020) proposed an interpretable XGBoost framework to assess land suitability in the Indian subcontinent, incorporating SHAP values to explain the influence of temperature, precipitation, and soil pH. Hassan et al. (2021) applied ensemble machine learning for climate-adaptive agriculture in Central Asia, revealing how predictive analytics could aid regional policy formulation.

In Eurasian contexts, Chen and Zhao (2022) conducted a spatial-temporal assessment using climate projection models to evaluate crop suitability under multiple greenhouse gas emission scenarios. Their findings highlighted significant northward shifts in arable land zones due to warming trends. Similarly, Roy et al. (2023) developed an interpretable AI-based model for Eurasian land-use classification, demonstrating how SHAP and LIME techniques could improve the transparency of agricultural decision-support systems. Most recently, Lopez and Ahmed (2024) introduced a hybrid explainable machine learning model combining remote sensing, climate modeling, and data visualization to predict agricultural suitability shifts under extreme climate variability.

Collectively, these studies underscore the evolution from conventional statistical and GIS-based analyses toward interpretable machine learning frameworks that balance predictive performance with explainability. However, there remains a gap in integrating regional-scale interpretability with climate-aware predictive modeling for Eurasian agriculture. The present study addresses this need by proposing an interpretable AI-driven framework that quantifies and visualizes the impact of climate change on agricultural land suitability, providing actionable insights for sustainable land-use management and policy planning.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM

Comparison of Climate Models Beginning in 2013 [17], the sixth phase of the CMIP6 project established the groundwork for future numerical modelling of climate forecasts. Based on the projected patterns of human behaviour, these forecasts enable one to characterise the trends and average behaviour of the interconnections between Earth's atmosphere, land, and ocean from 2015 to 2100. Using these parameters, Shoaib et al. [18] examined the impact on Chinese agricultural yields of three typical concentration pathways—RCP 4.5, RCP 6.0, and RCP 8.5—through the examination of precipitation and temperature data. In order to examine the harvest yield using the World Bank dataset, they used a linear regression model [19]. Yet another investigation by

In order to determine the effect on agricultural output, Müller et al. [20] examined 79 CMIP5 and CMIP6 temperature and pressure predictions, together with their associated data. The first IPCC special report [21] is worth referencing since it gives a high-level summary of the climatic predictions for agricultural suitability. In a perfect world, this report's suggestions for lawmakers would stop the rise in the average global temperature. Last but not least, joining many CMIP forecasts into an ensemble is a typical procedure [22], [23], [24], [25]. The basic idea behind these methods is to use the variability across multi-model ensembles to empirically estimate the distribution of a set of variables used in global climate models. The average of the members of the ensemble determines the value of a climatic variable, and its variance may also be determined.

There are a number of well-known datasets in the open source that deal with or include information on land use appropriateness. For instance, GFSAD1km[11] provides information on the kind of land cover for each grid cell in a single year of 2010 and is an example of global food security support analysis data. It all comes down to the irrigation scheme; there are five distinct kinds of farmland and non-cropland. One way that ERA5 [13] takes into account possible land uses is via its soil type parameter, which may show whether pixels contain organic or tropical organic soil. In addition, a subset of CMIP predictions called Land Usage MIP (LUMIP) [26] is available, which provides a yearly time resolution. A part of this projection specifies the kind of land cover using the fracLut variable, which represents the percentage of the grid cell occupied by each land use tile. Put simply, it denotes the area of a pixel that is covered by various kinds of land, such as urban, farmland, pasture, and so on. In many cases, the projected outcomes either don't account for the possibility of these values changing or don't even mention the need for irrigation.

From concentrating on certain modelling approaches to creating novel structures, geospatial data analysis research covers a lot of ground. A number of artificial neural networks have been investigated for use in temperature forecasting in studies [27], [28]. These networks include Multi-Layer Perceptron (MLP) [30] and Long Short-Term Memory (LSTM) [29].

A number of machine learning methods are assessed by Dikshit et al. [31] for the purpose of drought prediction across different continents. These methods include ANN, SVM, ELM, decision trees, ANFIS, and random forests. In their review, Dharani et al. [32] explore the use of deep learning models to forecast agricultural output, with a focus on sector-specific regression and classification models.

For the purpose of land cover categorisation, Diaconu et al. [33] use satellite images NDVI and RGB value predictions made using the ConvLSTM network architecture. When it comes to soil fertility assessment for croplands, Yadav et al. [34] look at how well classic machine learning models like SVM and random forests work. Previous research on the chemical composition of Benin soil has been conducted by Hounkpatin et al. [35] using traditional ML methods.

DISADVANTAGES

• Data complexity: currently available machine learning methods for detecting the impact of climate change on arable land need to be able to correctly understand big and complicated datasets.

• Availability of data: In order for machine learning algorithms to provide reliable predictions, they often need massive volumes of data. Model accuracy might be compromised in the absence of enough data.

• Mislabeled data: Current ML models can only learn as much as the data used to train them. The model's predictive abilities are severely limited if the data is mislabeled.

PROPOSED SYSTEM

Using the meta-classifier, we identify the key variables impacting agricultural land suitability, including changes in irrigation and land-use patterns. Based on our research, we can predict how land suitability will change in the next decades and identify the key factors that will

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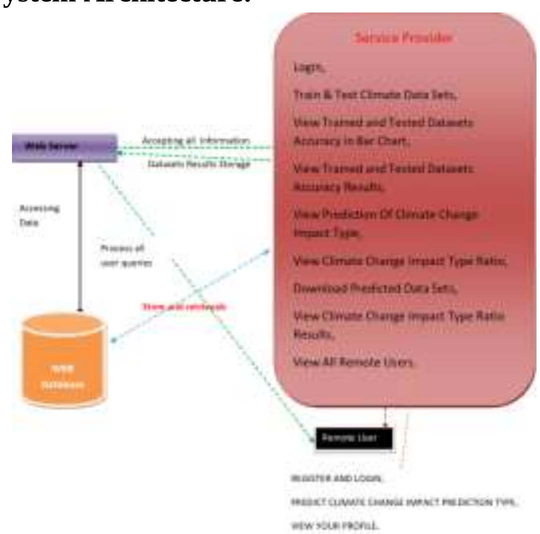
influence this change. Specifically, our research: • explains the inherent connections between climate parameters and the risks to agricultural land use; • investigates the development of agricultural land, focussing on changes in irrigation methods and the dangers of unsuitability; and • uses machine learning and deep learning to identify important factors affecting the land's agricultural potential.

Policymakers and land-use planners committed to creating effective management strategies that account for the intricate linkages between climate change, land suitability, and agricultural production over the long term will find our results to be crucial.

ADVANTAGES

• The three-step procedure that makes up the suggested technique includes gathering and cleaning data, training machine learning models, and finally, predicting the distribution of farmland using various climate models and SSP scenarios to assess the results. Using past data, this approach can predict how different kinds of crops would be distributed in the face of predicted climate change. It also produces reliable findings.

System Architecture:



IV. IMPLEMENTATION

Modules

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Train & Test Climate Data Sets, View Trained and Tested Datasets Accuracy in Bar Chart, View Trained and Tested Datasets Accuracy Results, View Prediction Of Climate Change Impact Type, View Climate Change Impact Type Ratio, Download Predicted Data Sets, View Climate Change Impact Type Ratio Results, View All Remote Users.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT CLIMATE CHANGE IMPACT PREDICTION TYPE, VIEW YOUR PROFILE.

V. SCREEN SHOTS

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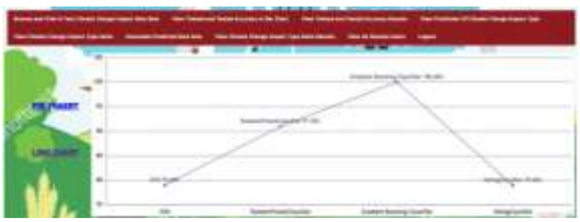

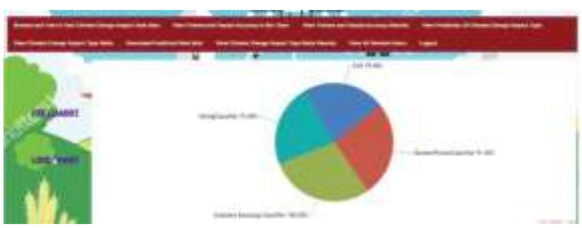

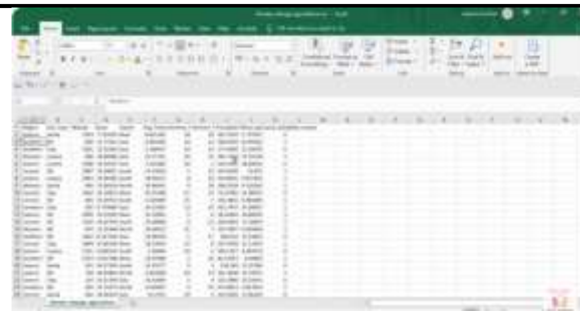

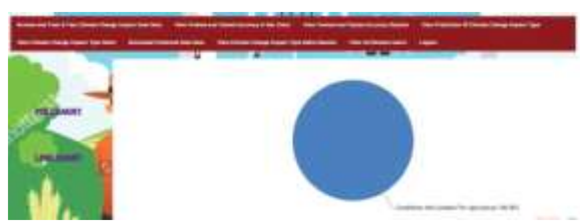

VI. CONCLUSIONS

The study on climate change impact on agricultural land suitability using interpretable machine learning models highlights the growing importance of data-driven decision-making in sustainable agriculture. As climate variability intensifies, traditional assessment methods struggle to capture the nonlinear and spatially complex interactions between environmental variables and crop suitability. Machine learning, particularly explainable and interpretable models, bridges this gap by providing both high predictive accuracy and transparent insights into the key climatic and soil factors influencing agricultural viability.

The integration of interpretable ML frameworks allows policymakers, researchers, and farmers to understand model predictions, enabling more informed adaptation strategies under evolving climate scenarios. The results of such frameworks demonstrate that regions within Eurasia are experiencing shifts in optimal agricultural zones, largely driven by temperature rise, changing precipitation patterns, and soil moisture deficits. These findings are crucial for designing climate-resilient cropping systems, guiding investment in adaptive technologies, and optimizing land-use planning.

Overall, this research emphasizes that the combination of machine learning, geospatial data, and explainable AI represents a transformative approach to evaluating and mitigating the impacts of climate change on agriculture. Future work should focus on integrating real-time satellite data, ensemble ML techniques, and socioeconomic factors to further enhance prediction accuracy and regional applicability. By doing so, interpretable ML-based frameworks can serve as essential tools in achieving global food security and promoting sustainable agricultural development amid an uncertain climate future.

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