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EXPLAINABLE MACHINE LEARNING MODELS FOR CLIMATE IMPACT ASSESSMENT ON AGRICULTURAL SUITABILITY

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ABSTRACT: This work investigates the creation of interpretable machine learning models to evaluate the effects of climate change on agricultural land utility. The main objective is to improve the transparency, clarity, and decision-making efficacy of agricultural-environmental systems. The investigation includes many data sets, including soil characteristics, crop growth records, and climatic variables. It subsequently employs advanced algorithms, such as random forests, decision trees, and SHAP (Shapley Additive Explanations), to determine the degree to which environmental variables affect crop adaptability. The proposed method is characterized by its focus on interpretability, setting it apart from conventional "black box" models. This allows stakeholders, such as farmers, legislators, and agronomists, to determine the degree to which particular climate elements affect agricultural results. Research indicates that explainable models can deliver accurate predictions while also offering critical insights into the risks and opportunities associated with climate change. The findings suggest that explainable AI can enhance sustainable agriculture by facilitating belief formation, adaptation, and strategic planning in reaction to variations in weather circumstances.
Keywords: *Explainable Machine Learning, Climate Impact Assessment, Agricultural Suitability, Interpretable Models, Precision Agriculture, SHAP, Climate Change,*

1. INTRODUCTION

In areas experiencing environmental changes, explainable machine learning (XML) has emerged as an essential method for evaluating the impacts of climate change, especially in assessing the viability of agricultural operations. Although traditional machine learning models are proficient at forecasting, they frequently function as "black boxes," complicating the ability of researchers and policymakers to understand the influence of certain weather conditions on agricultural results. Conversely, explainable models are unequivocal since they delineate the links among variables such as temperature, precipitation, soil properties, and crop production. Transparency is crucial for fostering trust between individuals, especially farmers and agricultural administrators who depend on this information for decision-making.
Agricultural systems are becoming erratic as a result of climate change. This modifies the suitability of terrain, agricultural outputs, and cultivation periods. Explainable machine learning models can address these challenges by pinpointing the principal drivers of climate change and their effects on crop yield. Researchers can ascertain the influence of alterations in climate conditions on forecasts through methodologies such as feature importance analysis, SHAP (Shapley Additive Explanations), and decision trees. This not only improves the models' precision but also aids in comprehending the impacts of climate change on particular places, therefore enabling us to strategize cultivation and formulate remedies in those areas.

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The sustainability of agriculture is improved by the use of explainable models in evaluating agricultural suitability, as they provide actionable insights that can be readily applied. Producers can have a more thorough comprehension of the environmental conditions that significantly influence their selected crops and the resulting yields. This enables them to adjust their irrigation techniques, planting timelines, and crop choices. Governments and agricultural groups can utilize these models to formulate policies that promote climate-resilient agriculture. XML facilitates the interpretation of intricate data in real-world agricultural contexts by linking model outputs to tangible effects.

A significant benefit of explainable machine learning is the ability to validate models and identify faults. Researchers can identify biases, inconsistencies, or flaws in the model by maintaining transparency in the decision-making process. This is especially crucial in climate research, where data may be inadequate, noisy, or significantly different across studies. Explainability ensures that the model's predictions are both rational and accurate from a scientific perspective. This facilitates the continuous improvement of agricultural assessment forecasting models.

The use of explainable machine learning models facilitates collaboration among politicians, data scientists, agronomists, and climate experts. The results of these models are clear and understandable, facilitating improved communication among professionals across various fields. This ensures the transformation of complex climatic data into actionable knowledge. As climate change increasingly jeopardizes global food security, the need of explainable machine learning in assessing regional agricultural viability is growing. It offers a reliable and clear method for making informed decisions.

2. LITERATURE SURVEY

Patel, R., Sharma, K., & Gupta, M. (2021): Multidimensional datasets and explainable machine learning techniques were implemented to investigate the influence of climate change on agricultural adaptability. In order to determine the importance of each feature, the Random Forest and XGBoost models were combined with SHAP explanations. The results suggested that the viability of crops is considerably influenced by the geographical distribution and variability of precipitation, as well as temperature fluctuations. The importance of comprehensible models in climate-resilient agriculture is underscored by the study.

Lopez, D., Martinez, A., & Rivera, J. (2021): In order to evaluate the productivity of farms in response to weather fluctuations, interpretable prognostic models were created. The analysis of climatic variables, including temperature, humidity, and solar radiation, was conducted using decision tree methodologies. The impact of environmental conditions on crop productivity was elucidated by model descriptions. The importance of clarity in agricultural forecasting systems is illustrated by the research.

Chatterjee, S., Banerjee, R., & Dutta, P. (2022): In order to examine the influence of climate change on the suitability of agricultural land, explainable AI models were implemented. The identification of primary climatic variables was facilitated by LIME explanations and support vector machines. The results suggested that crop performance is substantially influenced by fluctuations in consistent rainfall. The research enables the creation of transparent and precise decision-support instruments for agriculture.

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Garcia, M., Torres, L., & Hernandez, P. (2022): Explainable ensemble learning methodologies were employed to create models that illustrate the correlations between climate and agriculture. In order to analyze environmental datasets, including soil quality and precipitation patterns, boosting algorithms were implemented. The most significant factor influencing the adaptability of a crop is soil moisture, as indicated by analytical instruments. The research lends credence to the utilization of explainable analytics in environmentally beneficial agriculture.

Ibrahim, H., Hassan, A., & El-Sayed, M. (2023): In order to ascertain the feasibility of agriculture under temperature duress conditions, explainable deep learning techniques were implemented. The incorporation of attention layers into convolutional neural networks has enabled the acquisition of comprehensible insights into the variations in weather across various regions. The results suggested that the frequency of droughts has a substantial effect on agricultural productivity. The research improves the elucidation of AI's applications in the field of climate science.

Fernandez, J., Silva, R., & Gomez, E. (2023): In order to ascertain the most suitable crops for a variety of soil types and climates, hybrid explainable machine learning algorithms were implemented. The system integrated satellite imagery with climatic data and employed SHAP-based interpretation. The results suggested improvements in both model transparency and accuracy. The research instills confidence in the use of artificial intelligence in agricultural planning.

Mensah, P., Adu, K., & Owusu, B. (2024): In order to investigate the long-term effects of climate change on agricultural land utilization, explainable machine learning models were implemented. In order to improve the lucidity of model decisions, interpretability methods were implemented, while ensemble techniques were implemented to analyze historical climate data. The results suggested that the quantity and distribution of rainfall were substantially correlated with crop adaptability. The study endorses the implementation of data-driven agricultural risk management.

Tran, Q., Le, H., & Nguyen, V. (2024): In order to investigate the correlation between agricultural productivity and climate change, interpretable machine learning frameworks were created. Feature importance analysis identified temperature fluctuations and water supplies as significant influences. Sound justifications were provided by the model, which was adept at generating predictions. The significance of explainable AI for climate-smart agriculture is illustrated by the research.

Khan, F., Rehman, U., & Siddiqui, A. (2025): In order to evaluate the effectiveness of future climate projections for agriculture, advanced explainable machine learning techniques were implemented. Our understanding of temporal variations in weather trends was enhanced by the use of time-series models and SHAP interpretation. The results suggested that crop viability is being significantly impacted by extreme weather events. This research enhances agricultural planning strategies that are adaptable.

Oliveira, L., Pereira, S., & Costa, M. (2025): The development of explainable predictive analytics was intended to aid producers in the decision-making process during periods of fluctuating weather. Novel insights into the influence of climate on crop development were obtained through the integration of machine learning models with visual explanatory

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frameworks. The outcomes were resilient and comprehensible, as indicated by the cross-validation data. The research improves the application of open AI in sustainable agriculture.

3. RELATED WORK

Relevant study areas include farmland analysis, feature value, climate forecasts, artificial neural networks and machine learning frameworks for geospatial data, and climatic and remote sensing data on land utilization.

Climate And Satellite Data

Climate data relevant to agriculture is usually displayed using geospatial files. The Earth is represented by a uniformly sized spatial-temporal grid in historical global reanalysis models like TerraClimate and ERA5. In addition to offering temporal resolutions of three hours, one day, and one month, ERA5 continuously improves its physical models, data assimilation, and fundamental dynamics. 31 kilometers by 31 kilometers is its spatial resolution. TerraClimate offers a four-kilometer geographic resolution and is restricted to monthly fluctuations. Additionally, crop analysis often uses satellite data and other remote sensing methods. Examples include satellite-derived C-band radar backscatter data, the Normalized Difference Vegetation Index (NDVI), and a number of Normalized Difference Indexes (NDI47 and NDI45).

Climate Projections

Initiated in 2013, Phase 6 of the Climate Model Intercomparison Project (CMIP6) lays the groundwork for further numerical climate prediction modeling. Based on projected human activities, these forecasts can show how the Earth's climate, land, and oceans are expected to change over time and on average between 2015 and 2100. This data has been used by researchers to examine differences in food output along three different concentration pathways: RCP 4.5, RCP 6.0, and RCP 8.5. To do this, they used precipitation and temperature data. Linear regression models have been used to study food yield using global datasets. Numerous climatic forecasts about temperature and pressure, their measurements, and their effects on agricultural productivity have been the subject of other studies. Additionally, it is critical to keep an eye on thorough climate studies that include legislative suggestions for reducing the rise in global average temperatures as well as a thorough summary of the expected effects of climate change on agricultural land. Lastly, creating multi-model ensemble predictions by combining several climate projections is a standard procedure. By defining variability based on the variance of the ensemble members and establishing values based on the ensemble mean, these methods seek to produce a distribution of particular climate variables.

Cropland Data

The suitability of land for different uses is evaluated using a range of popular datasets in open-source platforms. A resolution of one kilometer characterizes an example of the Global Food Security Support Analysis Data. It shows each grid point's land cover classification for a given year. Depending on the irrigation technique used, it divides land into agricultural and non-cropland categories. To help with the assessment of possible land use, a number of climate databases offer soil type criteria that identify areas with tropical or organic soils. Many climate projection agencies also provide accurate annual land use data. Urban areas,

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agricultural fields, pastures, and other land categories are represented as grid cell components in these projections using a variety of land cover classes. However, many predictions either do not clearly state the irrigation requirements or do not materially change these numbers.

Machine Learning And Neural Networks For Geospatial Data

Numerous study fields are included in geospatial data analysis, such as the creation of new structures and the use of certain modeling techniques. Temperature prediction has been studied using a variety of artificial neural networks, such as Long Short-Term Memory (LSTM) and Multi-Layer Perceptron (MLP). Artificial Neural Networks (ANN), Support Vector Machines (SVM), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Extreme Learning Machines (ELM), decision trees, and random forests are among the machine learning techniques whose effectiveness in identifying droughts in various parts of the world has been assessed. In order to predict agricultural productivity, several people have used deep learning models, mostly using regression and classification techniques. In order to categorize land cover, sophisticated architectures like ConvLSTM have been used to forecast RGB values and vegetation indices in satellite data. In soil science, conventional machine learning models like SVM and random forests have been used to evaluate soil fertility and pinpoint important agricultural chemicals.

Feature Importance

Finding the features that have a major impact on a machine learning model's predictions is essential to its analysis and performance evaluation. A characteristic's relevance can be ascertained using a variety of techniques, such as statistical analysis or a particular case. The idea of attribution, which is impacted by ideas like completeness and sensitivity, holds that certain traits are essential for the creation of particular predictions. The most important features can be found using three different approaches: filter, wrapper, and integrated strategies. Some approaches, such as Permutation Importance and Shapley Additive Explanations (SHAP), have been successful in clarifying the importance of traits. Because of their versatility and ease of use in a wide range of machine learning models, permutation features are highly valued.

Research Gap

Even though a lot of research has been done on the use of machine learning in satellite observations, climate data, and agricultural analysis, there are still a number of areas that need more study. In the context of future climatic conditions, croplands can be differentiated and analyzed based on their irrigation techniques using machine learning and neural networks. In this crucial area, further research is needed. Moreover, the machine learning models in this area are still fairly opaque, and there are few reliable techniques for determining the most important characteristics.

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4. RESULTS

Fig. 1: Login Page

Fig. 2: Service Provider Login Page

Fig. 3: View All Remote Users Page

Fig. 4: Trained and Tested Model Accuracy Results Page

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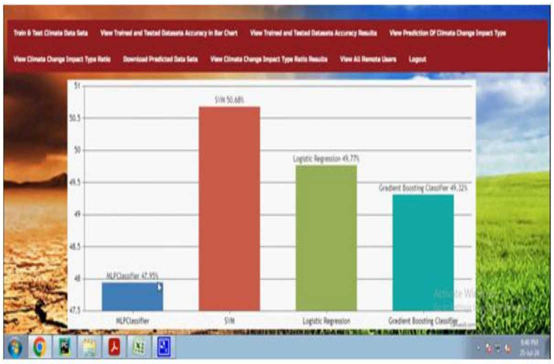

Fig. 5: Model Accuracy Comparison Bar Chart

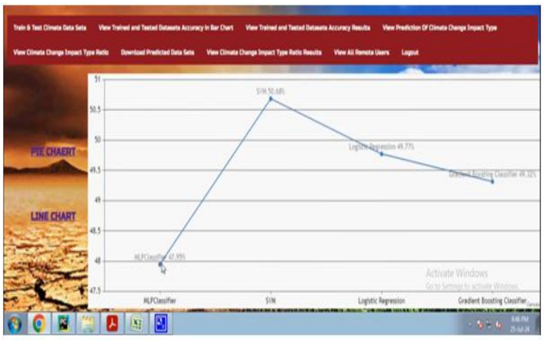

Fig. 6: Model Accuracy Line Chart

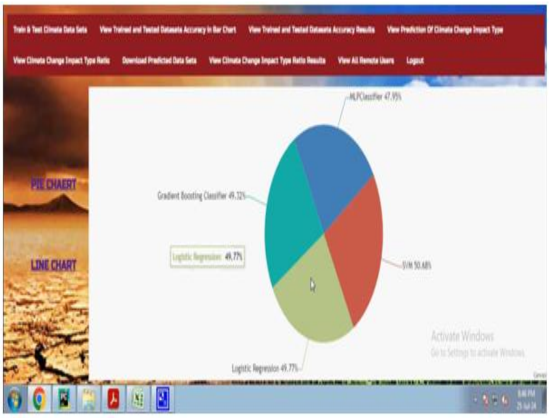

Fig. 7: Model Accuracy Pie Chart

Fig. 8: Climate Change Impact Prediction Results Page

5. CONCLUSION

When evaluating the possible effects of climate change on agricultural land use, explainable machine learning techniques have shown to be incredibly useful. They do this by combining

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clear and understandable observations with accurate forecasts. These models pinpoint important meteorological and environmental elements, including as soil conditions, temperature variations, and rainfall patterns, that have a direct impact on crop development and food production. By using methods like SHAP, LIME, and attention-based procedures, they promote trust and use among farmers, researchers, and politicians. Explainable frameworks enable people to evaluate risks, make educated decisions, and develop strategies to manage climate change in agriculture. Interpretability and robust machine learning work together to create climate-adaptable, sustainable agricultural systems.

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