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

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ABSTRACT

In light of climate change, this study examines the urgent worldwide issue of food security, with a focus on its impact on agricultural land suitability. The main objective is to predict the possible threats associated with the drops in land productivity and irrigation patterns, which irrevocable consequences on the world food resources. In line with the United Nations Sustainable Development Goals of eradicating hunger and malnutrition, the focus of this research is on Central Eurasiaa region that is characterised by certain socio-economic vulnerabilities. We use machine learning models which can be partially interpreted to explore the effect that various carbon emitting futures have on land viability as applied to agriculture. A multi-class land suitability prediction has a prediction accuracy that is 86 % and 72 % mean average precision rate in our predictive model. He reveals the relevance of geographical factor by listing out the weakest regions in the Eastern world. It therefore falls on to you the task of determing the time of the New order. Results that are used by policymakers are given in Europe and Northern Asia. The insights will aid in making data-driven decisions pertaining to efficient allocation of the necessary provision of resources like water and fertilizers in order to prevent future disaster of food crises. Altogether, the work proves the possibility of machine learning as the tool that will help to predict the negative outcomes of climate change on food producing systems and eliminate it.

Keywords: *Climate Change, Land Suitability to Agriculture, Machine Learning, Enviromental effects, Crop Land Panel, Sustainable Farning.*

INTRODUCTION

Agricultural sustainability is increasingly under threat posed by rate of environmental and climatic change, which is already increasing at a rapid rate. The role of climate change in relation to agricultural productivity and land usability has become a question of paramount concern that should be made accurate and precise. This is especially in the areas, which are significantly subjected to farming land as the source of economic prosperity and food security. By integrating climate data, soil characteristics, and historical land use patterns, land suitability evaluation systems fail to describe the dynamic and complex varying relations between land characteristics and climatic variables. In this regard, the use of accessibility is applicable. A feasible solution to investigate the environmental factors affecting land suitability to farming is related to explanatory and interpretable models of machine learning (ML). This study is a forward looking investigation into the utility of machine learning approaches to predict changes in agricultural land suitability under varying environmental scenarios. The authors unite the soil type and history of land use information with the climate data to find out how ML can be used not only to establish current suitability but also any future changes with possible farming outcomes. This task is related to the possibility to give early warnings of risk-prone areas and develop reasonable decisions in terms of agricultural planning and resource allocation. we would use a combination of data driven algorithms and interpretable machine learning explanatory power in identifying the most meaningful parameters of land degradation and transformation in the area of Central Eurasia as an empirical measurable region, since it is an area that is open to environmental pressure and coping with rapid climate changes. The advantage of this status is a cheat as it can reach the universal target of food security, the threat of the lands risks.

This is attributed to the mismanagement and promotion of more adaptivity measures to come up with sustainable farming. The above model not only enables accurate projection but also could be very explicable in satisfying the need of its applicability by the policy makers, environmentalists and the agronomists.

LITERATURE SURVEY

The issue to be addressed in the modern world is how to investigate the impacts of environmental and climatic change on the availability of the farm land. A number of modelling methods have been tested to identify the potential land of interest and the land possible to practise farming, that are primarily data-driven and climatic simulation. It is possible to present the basic estimations of the future of the climate which can be offered with the help of the Climate Model Intercomparison Project Phase 6 (CMIP6). This is however not the short term climate variations but has at its far end the long term climate forecasts such as RCP 4.5,2 rtcp6 and RCP8.5. scenarios.. Shoaib et al. used CMIP data to analyze crop yield changes in China by means of linear regression replicas based on rainfall and temperature trends. Similarly, Muller et al. compared several CMIP5 and CMIP6 models to test how pressure and temperature changes may influence crop productivity. Regarding data, such resources as Global Food Security Support Analysis Data (GFSAD1km) have provided a resolution-paper-thin level of cropland mapping and irrigation coverage. Critical measures that have been provided in ERA5 data and in projections made by the Land Use MIP (LUMIP) model are soil type and land fraction coverage. In this area, representations in the form of machines have been applied profusely. These analyses revealed such Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), to be applied in the drought prediction of various regions. Oracle actual crop yields are also fed to deep learning GPs, as examined by Dharani et al. In the area of land cover prediction, Diaconu et al. implemented Conv LSTM networks to predict vegetation indices from satellite imagery. Additionally, Yadav et al. utilized SVM and RF to assess soil fertility, while Hounkpatin et al. employed classical ML techniques to investigate soil chemical properties in West Africa. Despite the progress, current models face notable challenges:

This study overcomes these constraints by creating an interpretable and accessible ML framework to examine climate-driven land suitability changes, focusing on ease of use, scalability, and actionable insights.

EXISTING SYSTEM

The Climate Model Intercomparison Project Phase 6 (CMIP6), launched in 2013, serves as a comprehensive platform for simulating future climate scenarios through numerical modeling. These imitations deliver vision into long-term trends in Earth's atmospheric, terrestrial, and oceanic systems from 2015 to 2100, influenced by projected human activities. Shoaib et al. used the CMIP data to determine the difference between crop yields in China capacity under unlike climates. particular conditions- namely RCP 4.5, RCP 6.0, and RCP 8.5-this is calculated by carrying out linear regression analysis on the temperature and precipitation data obtained through the World Bank. Similarly, Mller et al. have completed an extensive evaluation of 79 climate projections sets per CMIP5 and CMIP6 and analysed trend pressure and temperature and its impact on agricultural productivity. To add to this, the Intergovernmental Panel on Climate Change (IPCC) produced a pivotal report that gave advance recommendations on what could be done to manage the increasing world temperatures and how worst of all crops could be used as arable land. In the region of the open-use data, the number of high-resolution yet useful datasets is quite big concerning the suitability in the land. One of its numerous examples, the Global Food Security Support Analysis Data (GFSAD1km) comes with land classification of the 2010 landscape on a 1-kilometer resolutions of irrigated and non-irrigated croplands. The ERA5 also brings forth further context with variables such as the types of soil; this may be valuable in determining areas with organic-rich soils. In addition, Land Use Model Intercomparison Project (LUMIP) is another extension to CMIP that facilitates annual projections on the type of land use, e.g., cropland, pasture and urban areas through the variable. The analysis of geospatial data is also among the top-priority instruments in these spheres to the advancement of machine learning and deep learning algorithms. The present educations utilize practical imitations and they involve Long Short Term Memory (LSTM) and Multi Layer. To make climate predictions such as prediction of temperature it uses Perceptron (MLP).Dikshit et al. evaluated several machine machine learning models including ANN, SVM, ANFIS, Extreme Learning Machines (ELM), decision trees, and random forests for their effectiveness in drought prediction across different continents.

potential in crop yield prediction through classification and regression frameworks. Diaconu et al. employed ConvLSTM networks to forecast vegetation indices (e.g., NDVI) and RGB imagery for land cover analysis. In the soil domain, Yadav et al. demonstrated how SVM and RF models could be used to evaluate soil fertility. Hounkpatin et al. further validated the application of traditional ML techniques to Analyze the chemical composition of soil in Benin.

PROPOSED SYSTEM

This study introduces a meta-classification framework aimed at identifying the key determinants that influence agricultural land suitability, including changes in irrigation practices and terrestrial use configurations. The proposed method delivers serious visions into how land suitability is expected to evolve over the coming decades by isolating the primary environmental and climatic factors driving these changes. Specifically, the research Analyze the relationship between climatic indicators and the associated risks to productive land use; Investigates the trends in agricultural land development, focusing on emerging irrigation methods and potential degradation in land viability; Applies both machine learning and deep learning techniques to uncover the variables most impactful in determining farming potential. The findings serve as a strategic resource for policymakers and land management for the professionals, offering evidence-based guidance to create adaptive plans that respond to the intertwined effects of climate change and agricultural productivity.

Advantages

The proposed system follows a structured three-phase methodology:

Data Collection and Preprocessing – Involves gathering and cleaning historical and projected climate and agricultural data.

Model Training – Employs accessible and interpretable ML algorithms to learn from the processed data.

Result Evaluation and Prediction – Uses the trained models to simulate future cropland distribution below numerous Shared Socioeconomic Pathways (SSP) and climate scenarios. This framework delivers accurate, data-driven forecasts, leverages existing datasets effectively, and facilitates reliable projections of agricultural land suitability for future planning.

System Architecture

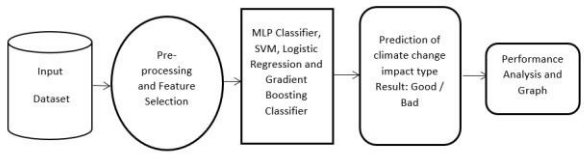


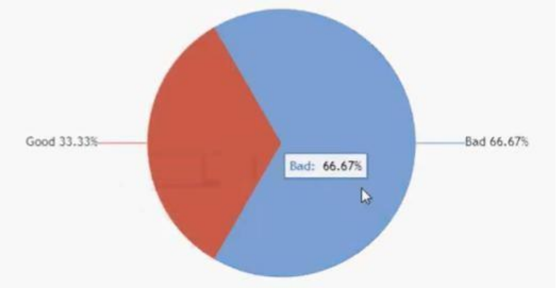
Fig 1. System Architecture

METHODOLOGY

The system is structured into two main modules: the Remote User Module and the Service Provider Module. The Remote User Module is designed for individuals such as farmers, researchers, and agricultural analysts who seek to measure the influence of climate change on agricultural land suitability. Users can register, manage their profiles, and input data related to their geographical region, soil characteristics, and climate variables. Based on this input, the system utilizes suitability of land in future climatic conditions. The result of the prediction is segmented into two pools, namely, Good or Bad, i.e., the land is fertile or not to farming. In addition, the system offers useful clues that reflect the significant factors of the environment that played into the prediction, and, By incorporating climate information with the soil type and a record of land use,,, enable the user to understand the rationale behind the given prediction. The Back-end user, which are system administrators including research analysts of the application, are presented with Administrator Panel displayed to them as the Back-end users of the application. This module gives a wide access to user management where all the registered users and their action can be monitored. It will also have a history of all the forecasts made, input data and the outcomes of the results achieved. The visualization dashboard can be discussed as one of the main capabilities of this module since the visual presentation of each graph, chart, and geospatial map enables one to see the trend in the information on the graph and demonstrate prediction outcome.The Pictorial representations thus made will enable one to determine an overall assessment of suitability of lands in the various localities and on various conditions. This also enables the service provider to download all the prediction data sets, and download the information, which can be used in further analysis or optimise the models.

EXPERIMENTAL RESULTS

The system in discussion will include two modules namely Remote User and the Service Provider that will have various features in the mentioned application. The Target audience of the User Remote should correspond to the farmers, researchers in the approaching of agriculture or ecologists to they have demand to define the influence of the climate change on the appropriateness of the lands. In this unit, operators are able to do what concerns the user profile such as the registration of the account, the log-in and the updating of the user profile. The primary feature would be the Prediction Page that requires users to feed in certain data that can be critical to the environment like temperature, rainfall, type of soil present, and vegetation index. The system processes this data through a trained machine learning model and outputs a prediction result, classified as either “Good” (indicating suitable conditions for farming) or “Bad” (indicating potential land degradation or unsuitability for agriculture).



The Service Provider module is created with administrators, policy-makers, or subject matter experts in mind who monitor system usage and data trends. The module gives access to all the user profiles and their correlated prediction actions. It has an enhanced dashboard showing all the dashboard prediction posts made by users The module is also graphically represented so that one can analyze detailed trends of prediction patterns, regional trends, climate impact statistics. Moreover, the service provider is capable of replicating the retraining the model. Collectively, these modules offer an integrated system that will facilitate climate-sensitive decision-making in agriculture via available machine learning technologies.

CONCLUSION

This project presents an effective and intelligent solution for enhancing crop quality and managing weed infestation using advanced computational techniques. By integrating Machine Learning and Deep Learning models, the system achieves high accuracy in classifying crop health and identifying invasive weeds. The use of feature extraction methods, pre-trained deep neural networks, and dataset balancing techniques like SMOTE significantly improved model performance. The system not only provides reliable prediction results but also supports decision-making in modern agriculture through a user-friendly platform for both farmers and service providers. With strong results on benchmark datasets, the solution proves to be practical, scalable, and environmentally sustainable. It holds great potential to advance precision farming, reduce chemical usage, and improve overall agricultural productivity.

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