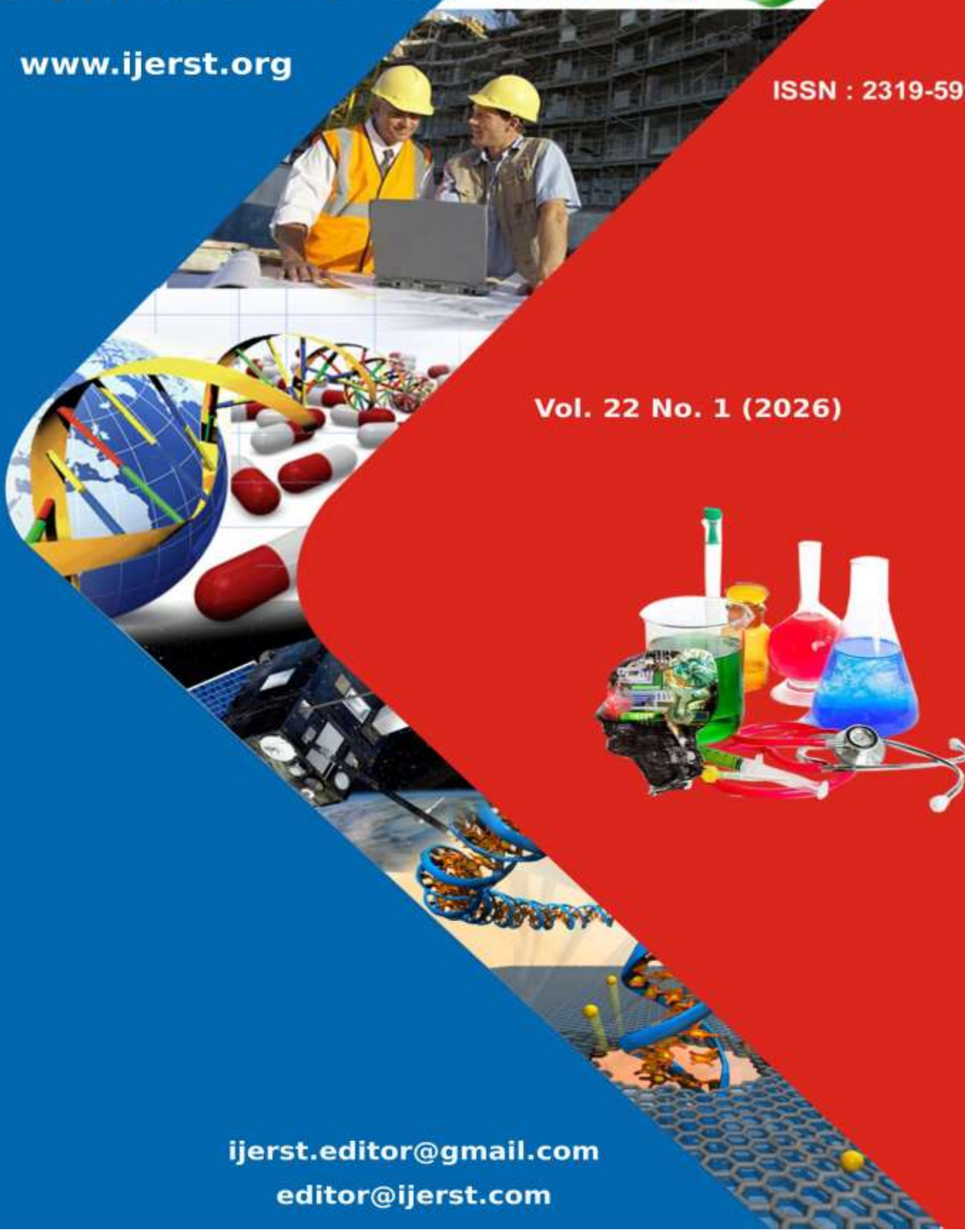
International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991



Vol. 22 No. 1 (2026)

ijerst.editor@gmail.com
editor@ijerst.com

Climate Change Impact on Agricultural Land Suitability: An Interpretable Machine Learning-Based Eurasia Case Study

Mr.P.V. KOTESWARA RAO, M.Tech., Assistant Professor, Department of MCA, Bapatla Engineering College, Bapatla, Andhra Pradesh
Ms.UPPALAPATI JAYASRI, Reg No: Y25MC23094, Ms.SHAIK ASMA SONU, Reg No: Y25MC23076
Ms.KOPPURAVURI BABYSREE, Reg No: Y25MC23036, Ms.BANDIREDDY DURGA TIRUMALA LAKSHMI, Reg No: Y25MC23007, Department of MCA, Bapatla Engineering College, Bapatla, Andhra Pradesh

***Abstract*—Climate change is an issue for the food we eat everywhere in the world.**

It is changing the land where we grow our food.

The way we get water to our crops is also being affected by climate change.

We need to know what is going on with climate change so we can keep growing food in a way that's good for the planet.

In some places people are already having a time with money and social problems.

Climate change is especially important for these places.

This study is, about how climate change's affecting the land where we grow our food in Central Eurasia.

We are talking about climate change. How it affects our food.

Climate change is a problem that we need to deal with so we can keep eating food. This region is really sensitive to weather changes so we want to know how it affects our food. This is a problem for the land where we grow food especially in Central Eurasia. We need to think about what this means for the food we eat. We are working to meet the United Nations goals to reduce hunger. People not getting enough nutrients. Our goal with this research is to figure out the risks of the land not being good, for farming and how we will get water to our crops when the weather is different.

We use machine learning methods to see how good the land is for farming under different carbon emission situations. The model we made can figure out what kind of land is suitable for what. It is right about 86 percent of the time. It also gets the details right 72 percent of the time which is really good.

The model is easy to understand so we can see how things like weather affect the land and what we can grow on it. When we looked at the results we found that some areas are in trouble like Eastern Europe and Northern Asia. In these places the changing climate is making the land less good for farming which's a big problem, for growing food.

The findings offer valuable guidance for policymakers and stakeholders by supporting informed decision-making on resource allocation, including water management and fertilizer distribution. Overall, this study demonstrates the effectiveness of interpretable machine learning as a decision-support tool for anticipating and mitigating the impacts of climate change on agricultural land suitability and long-term food security.

Keywords: 1. Climate Change, 2. Agricultural Land Suitability, 3. Food Security, 4. Interpretable Machine Learning, 5. Carbon Emission Scenarios, 6. Eurasia

I. INTRODUCTION

The Earth is getting really sick because of climate change. This is one of the problems we are facing today. Global climate change is affecting everything around us. It is not just the environment that is getting hurt. Also, our economy and society. We all know that global climate change is bad for animals and plants. It is also affecting the food we eat our health and even how countries get along with each other. The temperature of the Earth is getting higher the air is getting drier. The way it rains is changing. All of this is putting a lot of pressure on the systems that grow our food. Global climate change is a deal and it is affecting agricultural systems all, around the world. The Earths food crops are in trouble. 40 Percent of the Earths croplands and pastures are at risk right now. This is happening because of weather and that is a big problem. The Earths croplands and pastures are very important for food. If the Earths croplands and pastures are not healthy then the food that people need will be in supply. This is a threat, to the food supplies. The global food supplies are what keep people fed over the world. The Earths croplands are where food crops are grown. The Earths pastures are where animals are raised for food.

The problem of food demand is getting worse because people need food really fast. We think that the world will need a lot food, maybe even 110% more by the year 2050. This is because there are people people are eating differently and more people are moving to cities. At the time the Earth is getting hotter there is less snow and there are more bad things in the air which makes it hard for crops to grow well. Food demand and these changes in the weather are problems that happen at the same time so we really need to figure out if the land will still be good, for growing food in the future.

To really get how climate change affects the sustainability of agriculture we need models that can handle how complicated the environment is and how unsure we are about what will happen. The Shared Socioeconomic Pathways or SSPs give us scenarios that describe what the future might look like in terms of carbon emissions and how societies will develop. At the time the Coupled Model Intercomparison Project Phase6

or CMIP6 gives us a big set of models that simulate important things like temperature and humidity. Using these tools we can systematically look at how climate change will affect us if we have emissions, medium emissions or high emissions. Climate change will have an impact on agriculture and we need to understand this. The SSPs and CMIP6 are important for understanding climate change and its effects, on sustainability.

Eurasia is an important place when we talk about food. This region has different types of climates and soil that are good for growing different things. Eurasia is also a place where people can be really affected by problems.

Eurasia is very important for growing food for the world but it is also very sensitive to changes in the climate. This means that if the weather changes it can affect how food we can grow in Eurasia.

If we start growing food in areas of Eurasia or if we change the way we use water to grow food it can have big effects on how much food we have in this region and in the whole world. Eurasia and its food production are really important for food security in the world and, in Eurasia.

We have a lot of problems to solve. So we are using a machine learning framework that's easy to understand to look at how good the land is for farming under different carbon emission scenarios. We are putting together information about the weather from something called CMIP6 ensembles with data about irrigation on farms. This way we can see how the weather and water affect the farms. We are using a method called stacked ensemble to make our predictions better and still be able to understand what is going on. This helps us to see what is important when it comes to deciding if the land is good, for farming. Agricultural land suitability is what we are trying to figure out. Agricultural land suitability is very important.

The primary objectives of this research are threefold:

to evaluate the impact of climate change under different SSP scenarios on the spatial distribution of croplands;

to identify regions facing elevated food security risks; and to analyse the role of irrigation practices in determining agricultural land suitability.

By providing data-driven insights into future agricultural transitions, this study supports evidence-based decision- making for policymakers and stakeholders. The findings contribute to strategic planning for sustainable agriculture, resource allocation, and climate adaptation, aligning with global efforts to enhance food security under a changing climate.

II. LITERATURE SURVEY

Recent research on agricultural land suitability under climate change spans multiple interdisciplinary domains, including climate modeling, remote sensing, geospatial data analysis, and machine learning. Existing studies can be broadly categorized into four major areas: (A) climate and satellite data for land-use analysis, (B) climate projections, (C) cropland and irrigation datasets, and (D) machine learning and neural network approaches for geospatial applications.

A. Climate and Satellite Data for Land-Use Analysis: Climate data relevant to agriculture are commonly represented as large-scale geospatial datasets with spatio-temporal resolution. Widely used global reanalysis datasets such as ERA5 and TerraClimate provide historical climate indicators including temperature, precipitation, humidity, and soil moisture. ERA5 offers high temporal granularity with hourly, daily, and monthly resolutions at a spatial resolution of approximately 31 km, making it suitable for long-term climate trend analysis. TerraClimate provides finer spatial resolution (approximately 4 km) but is limited to monthly temporal data.

In addition to climate reanalysis data, remote sensing products play a crucial role in cropland monitoring and land-use analysis. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Indices (NDI), and satellite radar backscatter data have been extensively used to assess vegetation health, crop phenology, and land cover dynamics. These satellite-derived indicators provide valuable insights into agricultural productivity and land suitability at regional and global scales.

B. Climate Projections and Emission Scenarios: Future climate assessment is commonly conducted using projections from the Coupled Model Intercomparison Project (CMIP). CMIP Phase 6 (CMIP6) provides a standardized framework for simulating future climate conditions based on different emission and socioeconomic scenarios. These projections enable the analysis of long-term trends in temperature, pressure, precipitation, and atmospheric dynamics from the present to the end of the 21st century.

Several studies have utilized CMIP projections to assess climate impacts on agriculture. Shoaib et al. analyzed crop yield changes in China using temperature and rainfall projections under multiple emission scenarios, employing regression-based approaches. Mu¨ller et al. evaluated a large ensemble of CMIP5 and CMIP6 models to study temperature and pressure variability and their influence on crop yield uncertainty. Reports by the Intergovernmental Panel on Climate Change (IPCC) further provide high-level assessments of cropland suitability and climate risks, offering policy- oriented recommendations for limiting global temperature rise.

To reduce uncertainty, many studies adopt multi-model ensemble approaches, combining outputs from multiple climate models. Such ensembles estimate climate variables based on the mean behavior of different models while capturing uncertainty through variance analysis, leading to more robust climate impact assessments.

C. Cropland and Irrigation Datasets: Accurate assessment of agricultural land suitability also depends on reliable cropland and irrigation datasets. One prominent dataset is the Global Food Security Support Analysis Data (GFSAD1km), which provides high-resolution land cover information and categorizes cropland based on irrigation practices. This dataset enables differentiation between rainfed and irrigated agriculture, which is critical for food security analysis under climate stress.

Other datasets, such as soil classification layers within ERA5 and land-use projections from the Land-Use Model Intercomparison Project (LUMIP), offer additional information on soil properties and land-cover fractions. However, many climate projection datasets either assume static land use or lack detailed irrigation information, limiting their applicability for fine-grained agricultural suitability analysis.

D. Machine Learning and Neural Networks for Geospatial Data: Machine learning has emerged as a powerful tool for modeling complex, non-linear relationships in geospatial and climate data. Prior research has explored a wide range of algorithms, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, Extreme Learning Machines (ELM), and Neuro-Fuzzy systems, for applications such as drought prediction, crop yield estimation, and land classification.

Deep learning approaches have also gained attention in geospatial analysis. Long Short-Term Memory (LSTM) networks and Convolutional LSTM (ConvLSTM) architectures have been applied to time-series climate forecasting and satellite image prediction, particularly for NDVI and land cover classification tasks. Studies in soil science further demonstrate the effectiveness of classical machine learning models in evaluating soil fertility and chemical properties relevant to agriculture.

Despite these advances, many existing approaches emphasize predictive accuracy while offering limited interpretability. This restricts their usability in policy-driven decision-making contexts, where understanding the influence of climatic and environmental factors is essential.

E. Research Gap: While prior studies have independently examined climate projections, cropland datasets, and machine learning models, there remains a lack of integrated frameworks that combine multi-model climate projections, high-resolution cropland and irrigation data, and interpretable machine learning techniques for large-scale agricultural land suitability assessment. Addressing this gap is crucial for supporting transparent, data-driven decision-making related to food security under climate change.

III. METHODOLOGY

.

This part is about how we plan to figure out how climate change affects the land that is used for farming in Eurasia and how it impacts food security. We will use a kind of machine learning that is easy to understand and we will look at what happens when we have different amounts of carbon emissions. Our plan brings together what we know about the climate the land that is used for crops and the water that is used for irrigation. It uses a group of machine learning models to make predictions about which land is suitable for farming that are accurate and easy to see. We are using climate change and machine learning to understand what will happen to agricultural land suitability and food security, in Eurasia.

A. Study Area and Scope:

The Eurasian region is what this study is looking at. This region includes different types of areas with different climates and ways of growing crops across Eastern Europe and Northern Asia. The Eurasian region is very sensitive to changes in the climate. The Eurasian region is also very important for producing food for the world. This analysis is trying to figure out how the climate changing in the future will affect the land that's suitable, for growing crops and how people water their crops, which will then affect how safe our food supply is.

B. Climate Data and Emission Scenarios:

The future climate conditions are figured out using information from the Coupled Model Intercomparison Project Phase 6. We pick an Earth System Models to see how they are different from each other and how sure we can be about the results. We look at things, like the temperature how much it rains how humid it is and the air pressure. These climate variables, like mean temperature and precipitation are what we focus on. We also consider humidity and atmospheric pressure to get a picture of the future climate conditions.

The study looks at things, under three Shared Socioeconomic Pathways. These Shared Socioeconomic Pathways show ways that carbon emissions can go.

SSP1-2.6: Low-emission, sustainable development scenario SSP2-4.5: Intermediate, business-as-usual scenario

SSP5-8.5: High-emission, fossil-fuel-intensive scenario

These situations help us figure out if the land is good for farming when the weather changes in ways. We can see how the land will do with climate futures. The land we are talking

about is land. We want to know if it is suitable, for farming under these climate futures.

C. Cropland and Irrigation Data:

The Global Food Security-support Analysis Data, also known as the GFSAD1km dataset is used to find out how agricultural land is being used now. This Global Food Security- support Analysis Data dataset gives us detailed information about what is on the land and it groups cropland into types based on how the crops are watered. The agricultural land is divided into four groups: land that uses a lot of irrigation, land that uses an irrigation, land that relies on rain for water and land that is not used for crops. This way of grouping the land helps us understand how the land will be affected by changes, in the weather especially when it comes to irrigation and the Global Food Security-support Analysis Data.

D. Data Preprocessing and Feature Engineering:

The climate and cropland datasets are put together in a way that they all match up and have the level of detail. This is done so that the climate and cropland datasets are easy to compare. The climate information is looked at over periods of time to see what happens over the long term. The climate and cropland datasets are also checked to make sure they are correct and consistent. This is done so that the computer model can learn from the climate and cropland datasets in a way. The final set of information includes climate indicators, irrigation attributes and land-cover information, for each part of the grid. The climate indicators and land-cover information and irrigation attributes are all put together for each grid cell.

E. Interpretable Machine Learning Framework:

We use a way of combining models to make better predictions about land suitability. This method helps us understand the results too. We train simple models, like tree models and regression models on our data separately. Then we use a model to put together the results from these simple models to get our final answer about land suitability. We call this a stacked learning approach and it helps us make good predictions, about land suitability while still being able to understand how we got those predictions.

To help us understand things that can inform policy decisions we use machine learning techniques that're easy to understand. These techniques help us figure out how important things like climate and irrigation are. This makes it clear how different carbon emission scenarios and climate factors affect whether land is suitable, for farming. We can see how climate and irrigation features impact agricultural land suitability.

F. Model Training and Evaluation:

The model does a classification task for the four land-use categories. It looks at how it does this task by using things, like how accurate it is and the mean average precision. The model uses cross-validation to make sure it works well in climates and geographic locations. This helps the land-use categories model be more robust and work better in general.

G. Food Security Risk Assessment:

We need to look at the land and see where it is getting worse or where it is changing. This will help us find the places that are going to have problems with food. These places are the ones that will have a time growing food and that is why they are at risk. This information is very important for planning and making sure we have water and food. We can use it to make decisions about how to take care of the land and how to deal with the changing weather. Food security is a deal and we need to make sure we are ready, for what is going to happen to the land and the food.

H. Methodology Summary:

The proposed methodology integrates climate projections, cropland and irrigation data, and interpretable ensemble machine learning to assess agricultural land suitability under future climate scenarios. By combining predictive accuracy with model transparency, the framework supports informed decision-making for enhancing food security in climate- vulnerable regions of Eurasia.

IV. ALGORITHM

K-Nearest Neighbors (KNN)–Based Classification

The K-Nearest Neighbors algorithm is a way to teach machines. It is used for classification and regression tasks. In this study the K-Nearest Neighbors algorithm is used to compare with methods. The K-Nearest Neighbors algorithm works with the data it has already seen. It does not need a training session. This makes the K-Nearest Neighbors algorithm easy to use and understand. The K-Nearest Neighbors algorithm looks at the relationships, between the input features and the target classes.

When we get a set of data the KNN system calculates how far this new data is, from all the other data points we already have in our training set. It does this by using a way to measure distance like the Euclidean or Manhattan distance. Then it looks at the data and decides what group it belongs to based on what the majority of its closest neighbors are. The KNN system uses a number, the KNN parameter to figure out how many of these neighbors to consider when making this decision. The choice of this parameter is important because it affects how the KNN system works.

The value of k has an impact, on how the model behaves. When the values of k are small the model behaves in a way because of the small values of k.

The number k tends to result in bias and high variance while larger values of the number k result in the opposite. The thing with the number k is that when it is small you get bias and high variance. On the hand when the number k is large you get high bias and low variance. This means the number k has an effect, on the results.

When we have a small k it can lead to bias and reduced variance in the k nearest neighbors. The k nearest neighbors have an impact, on the outcome. So a small k will lead to bias in the k nearest neighbors. This means the k nearest neighbors will not be very accurate. On the hand a small k will also lead to reduced variance in the k nearest neighbors. This is because the k nearest neighbors are not taking into account other points. The k nearest neighbors are only looking at a points.

The KNN method is really simple. It can be very slow when it is used to make predictions. This is because it has to calculate the distance from the data to every single piece of data in the training set.. Even with this problem the KNN method is still a good way to test how well a classification system is working especially when you are dealing with data that has to do with the earth and the environment like geospatial and environmental datasets. The KNN method is a benchmark, for these types of datasets.

Distance Metric

To see how similar things are between samples, in the feature space we use the distance. Let us say we have two feature vectors.

p = (p1, p2, pn) and

q = (q1, q2, qn)

The Euclidean distance is defined as:

$$\sqrt{\textstyle\sum}$$

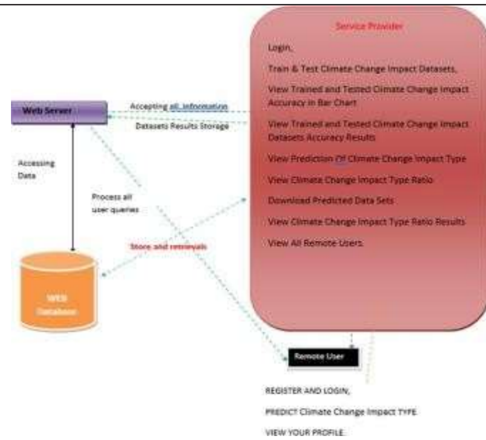


Fig. 1. Enter Caption

model needs the k folds to be trained. k 1

They use something called k1 folds. They check how it does on the remaining fold. They do this for all the folds. Then they tell you how it did on average. They keep doing this process for all the k1 folds and the remaining fold. Then they give you the average performance of the k1 folds and the remaining fold, which is the average performance of the k1 folds.

Comparative Classification Algorithms

To see how well KNN works we will look at some classi- fication algorithms that people use a lot:

Logistic Regression

Linear Discriminant Analysis K-Nearest Neighbors (KNN) Decision Tree Classifier Support Vector Classifier

$d(p, q) =$,

$i=1$

$(p_i - q_i)^2$ (1) Random Forest Classifier Logistic Regression

This metric is often used because it is simple and it works well in feature spaces. The metric is a choice for this reason. It is easy to understand. It is effective, in continuous feature spaces.

Classification and Model Evaluation Strategy

To see how well the classification models work we split the dataset into two parts. We use 80 percent of the data to train the classification models and 20 percent to test the classification models. This way we can make sure the classification models are good, at what they do. We also want to make sure the classification models do not get too good at the training data so we use something called -fold cross- validation when we train the classification models. This means we divide the training data into parts.

We use k folds for this. The model is trained on some of the k folds. We do this so the model can learn from the k folds. The k folds are very important, for the model. The

Logistic regression is a statistical classification method that models the probability of class membership using a logistic function. It estimates the relationship between input features and a binary or multi-class outcome by learning a linear decision boundary in the feature space. Unlike simple classifiers, logistic regression provides probabilistic outputs, which are useful for uncertainty analysis. Due to its efficiency and interpretability, logistic regression is commonly used as a baseline model in applied machine learning and discrete data analysis.

V. SYSTEM ANALYSIS

This section presents the system analysis of the proposed framework for assessing the impact of climate change on agricultural land suitability and food security in Eurasia using interpretable machine learning under multiple carbon emission scenarios. The analysis focuses on problem definition, system objectives, requirements, feasibility, assumptions, and limitations.

A. Problem Analysis:

Climate change introduces complex and long-term variations in temperature, precipitation, humidity, and atmospheric conditions, directly affecting agricultural land suitability and irrigation requirements. Traditional statistical approaches often fail to capture the nonlinear interactions between climatic variables and land-use patterns, particularly when future climate uncertainty is considered. Moreover, many machine learning-based approaches prioritize predictive accuracy while lacking interpretability, limiting their applicability for policy- driven decision-making related to food security.

The core problem addressed in this study is the lack of an integrated, interpretable framework that combines climate projections, cropland and irrigation data, and machine learning techniques to assess future agricultural land suitability under varying carbon emission scenarios at a regional scale.

B. System Objectives

The primary objectives of the proposed system are:

1. To analyze the impact of climate change on agricultural land suitability in Eurasia.

2. To evaluate land suitability under multiple carbon emission scenarios.

3. To identify regions facing elevated food security risks.

4. To incorporate interpretable machine learning for transparent decision support.

5. To support policymakers with data-driven insights for sustainable agricultural planning.

C. Functional Requirements

The system is designed to satisfy the following functional requirements:

1. Ingest climate projection data from multiple Earth system models.

2. Integrate high-resolution cropland and irrigation datasets.

3. Preprocess and harmonize heterogeneous geospatial data sources.

4. Perform multi-class classification of agricultural land suitability.

5. Evaluate land suitability under different emission scenarios.

6. Provide interpretable outputs highlighting key influencing factors.

7. Identify high-risk regions for food insecurity.

D. Non-Functional Requirements

The system must also meet the following non-functional requirements:

Scalability: Capable of handling large-scale geospatial datasets.

Reliability: Ensure consistent and reproducible predictions.

Efficiency: Minimize computational overhead during model inference.

Interpretability: Enable transparent understanding of model decisions.

Usability: Provide results that are understandable to non-technical stakeholders.

E. Assumptions and Constraints

The proposed system operates under the following assump- tions:

1. Climate projection models reasonably represent future climate trends.

2. Cropland and irrigation datasets accurately reflect current land-use patterns.

3. Climatic variables are the primary drivers of land suitability changes.

4. Socio-economic factors are implicitly represented through emission scenarios.

Key constraints include:
Uncertainty inherent in long-term climate projections.

Limited availability of dynamic irrigation data in future scenarios.

Spatial resolution differences among datasets.

F. Feasibility Analysis Technical Feasibility:
The system leverages well-established climate datasets and widely adopted machine learning algorithms, making it technically feasible.

Operational Feasibility:
The framework supports offline analysis and does not require real-time data, enabling easy adoption by research and policy institutions.

Economic Feasibility:
As the system relies on open-source datasets and software tools, it does not incur significant operational costs.

G. Limitations
While effective, the system has certain limitations:
1. It does not explicitly model socio-political or economic shocks affecting food security.

2. Predictions depend on the accuracy of climate models and emission scenarios.

3. Sudden extreme climate events may not be fully captured by long-term projections.

H. Summary
The system analysis demonstrates that the proposed framework is a feasible, scalable, and interpretable solution for evaluating climate change impacts on agricultural land suitability and food security in Eurasia. By integrating climate projections with interpretable machine learning, the system addresses key limitations of existing approaches and provides actionable insights for climate-resilient agricultural planning.

VI. RESULT ANALYSIS

This part is about what we found out from our new machine learning tool. We used it to see how climate change affects the land where we grow food in Eurasia. We looked at what happens when we release amounts of carbon into the air. Our tool helps us understand how well it works, how the land changes and what this means for food security in Eurasia under these carbon emission scenarios. We also compared the results from each scenario to see what happens to the land and food security. Climate change has an impact on agricultural land suitability and food security, in Eurasia.

A. Model Performance Evaluation:
The new model for classifying land is really good at predicting what type of land it is. It can tell if the land is used for irrigation, minor irrigation, rainfed cropland or non- cropland. The model is able to classify the land 86 percent of the time. It also does a job of finding the right category for each piece of land with an average precision of 72 percent. This shows that using models together makes the results more reliable and accurate, than using just one model. The agricultural land model is better because it combines different models.

The results from checking the model with sets of data show that it works well every time. This means the model is good and it does not just work well with the data it was trained on. The model works with different kinds of weather and places, in Eurasia. This is important because Eurasia has a lot of climates and geography. The model can handle all of these differences. Still give good results.

B. Impact of Carbon Emission Scenarios:

The results show us some patterns when it comes to how good the land is for farming under different Shared Socioeconomic Pathways. If we look at the SSP1-2.6 low-emission scenario, the land that is good for farming does not change much. In the areas we see a little more land being used for crops that rely on rain. This scenario is what happens when we do things in a way that's good for the earth and we do not put too many bad things into the air. Shared Socioeconomic Pathways like this one are important because they help us see what the future might be like. The Shared Socioeconomic Pathways are, like a guide for us to follow.

The SSP2-4.5 scenario is a little different. It has some things and some bad things. There are some places where the land is getting better, for growing crops.. In other places, where people have always grown a lot of food the land is getting worse.

The SSP5-8.5 scenario is the one that shows the changes. The land that people are already using to grow crops is getting worse. This means that people will have to use water to irrigate their crops. This is a problem because it means that there is a risk that people will not have enough food. The SSP5-8.5 scenario and the SSP2-4.5 scenario are both related to food security risks. The SSP5-8.5 scenario is particularly concerning when it comes to the SSP5-8.5 scenario and food security risks.

C. Spatial Shifts in Agricultural Land Suitability:

The analysis shows that agricultural land in Eurasia is becoming more suitable for farming in the north. Places in Northern Asia and some parts of Eastern Europe are getting better for growing crops with rain because it is getting warmer and the time to grow crops is getting longer. On the hand some southern areas that are really good for farming now are getting less suitable because it is getting too hot the soil is getting dry and the weather is getting more unpredictable. This is happening to land and it is a big change, for agricultural land.

These changes in the Earths climate are happening in ways in different places. This shows us that climate change is affecting some areas than others. Because of this we need to come up with plans that're specific to each region to deal with the effects of climate change. The thing, about climate change is that it is not the same so we need to think about what will work best for each place when we make our climate change plans.

D. Irrigation Dependency and Food Security Risks:

The results show that people are using irrigation more and more when there is a lot of carbon dioxide in the air. This is especially true in places where it does not rain much as it used to and the sun makes the water evaporate really fast. Some areas are changing from relying on rain to relying on irrigation to grow food. These areas are at a risk when it comes to having enough food because they will not have enough water and that will cause a lot of problems. Irrigation is a deal, in these areas because they really need it to grow food.

When we look at the irrigation data for crops we can get a better idea of how farming is affected by climate change. The thing is, people often do not think about this when they do studies on how climate change affects farming. Irrigation data, for crops helps us understand agricultural vulnerability in a more realistic way.

E. Interpretability and Feature Influence:

When we look at the results of machine learning analysis that we can understand we see that the temperature and precipitation and humidity and emission scenario indicators are the things that affect land suitability predictions the most. This means we can clearly see how temperature and precipitation and humidity and emission scenarios affect the land. The model is easy to understand so we can see how these climate things are changing the suitability of the land, which makes policymakers and stakeholders trust the results and want to use them.

F. Discussion:

The results show that climate change is going to change the way we use land for farming in Eurasia. This is a deal because it affects how much food we will have in the future. Some places might actually get conditions for farming but a lot of the areas that are already good for farming will not be as good anymore. We will also need to use water for irrigation, which is a problem.

The climate change results mean that we need to be prepared and take action now. We have to manage water in a way that's good for the earth and we have to reduce the bad things we put into the air. Climate change is an issue and we need to think about how it will affect farming, in Eurasia and what we can do to make sure we have enough food.

G. Summary of Results:

The experimental results show that the proposed framework is really good. It does what we thought it would do. The proposed framework works well. We can see this from the results. The proposed framework is a success.

Accurately predicts agricultural land suitability under varying climate scenarios, captures spatial and scenario- dependent variability across Eurasia, Identifies regions at heightened risk of food insecurity, and Provides interpretable insights to support policy-oriented decision-making.

OUTPUT SCREENS

Fig: 2 Main Page

Fig 3 Login Page

Fig. 4 Accuracy Graph

Fig: 5 prediction result

CONCLUSION

Climate change is a problem for the food we eat around the world. It is changing the land where we grow food and making it hard to know how food we will have. The Earth is getting warmer. The rain is not falling like it used to. This is changing where we can grow food in places like Eurasia where the weather is really important for farming. We need to understand what is happening so we can find ways to deal with it and make sure we have food. Climate change is making this hard so we have to be smart, about how we grow food and take care of the Earth.

This study is about how climate change affects the land that is used for farming in Eurasia. The people who did this study wanted to see what would happen to the land if we keep putting things into the air. They used computer programs to look at what might happen in the future. These programs took into account what the weather might be like and how that would affect the land.

They also used information about the land that is already being used for farming and how water is being used to help plants grow. The computer programs helped them figure out which land would be good for farming and which would not.

The good thing about the way they did this study is that they can tell us exactly what factors affect whether the land is good for farming or not. This means that the people who make decisions about how to use the land can trust the results of the study and make choices about food and farming in Eurasia. The study looks at climate change and agricultural land suitability and food security in Eurasia under carbon emission scenarios, like the ones, from CMIP6 climate projections.

The results of the experiments show that the suitability of land in Eurasia really depends on what happens with emissions in the future. If we have emission scenarios then some areas in the north will be okay or even a little better for farming.. If we have high emission scenarios then the land that is currently good for crops will get worse and we will have to use more irrigation. This means that the areas that are good for farming are moving north and we are going to need water, which is a problem for food security and it is not fair for all regions. Agricultural land suitability, in Eurasia is a deal and it is going to be affected by emissions.

This work shows that machine learning that we can understand is really useful for helping us make decisions about how climate change affects farming. The results give us information that people who make policies plan agriculture and have a stake in this can use to make plans that work use resources wisely and make food systems stronger against climate change. Machine learning that we can understand is helpful for this. Climate change impacts, on agriculture are a deal and machine learning that we can understand can help us deal with them.

Future work will focus on incorporating socio-economic factors, dynamic irrigation projections, and extreme climate events to further improve food security risk assessment. Expanding the framework to other vulnerable regions and integrating real-time monitoring data also represent promising directions for future research.

REFERENCES

[1] J. A. Foley, R. DeFries, G. P. Asner, C. Barford, G. Bonan, S. R. Carpenter,

a. S. Chapin, M. T. Coe, G. C. Daily, H. K. Gibbs, J. H. Helkowski, T. Holloway, E. A. Howard, C. J. Kucharik, C. Monfreda,

[2] A. Patz, I. C. Prentice, N. Ramankutty, and P. K. Snyder, "Global consequences of land use," Science, vol. 309, no. 5734, pp. 570–574, 2005.

[3] H. C. J. Godfray, J. R. Beddington, I. R. Crute, L. Haddad, D. Lawrence,

[4] F. Muir, J. Pretty, S. Robinson, S. M. Thomas, and C. Toulmin, "Food security: The challenge of feeding 9 billion people," Science, vol. 327, no. 5967, pp.

812–818, 2010.

[5] D. Tilman, C. Balzer, J. Hill, and B. L. Befort, "Global food demand and the sustainable intensification of agriculture," Proc. Nat. Acad. Sci. USA, vol. 108, no. 50, pp. 20260–20264, Dec. 2011.

[6] V. Gitz, A. Meybeck, L. Lipper, C. D. Young, and S. Braatz, "Climate change and food security: Risks and responses," Food Agricult. Org. United Nations (FAO), Rome, Italy, Tech. Rep. 110, 2016, pp. 2–4.

[7] L. S. Huning and A. AghaKouchak, "Global snow drought hot spots and characteristics," Proc. Nat. Acad. Sci. USA, vol. 117, no. 33, pp. 19753– 19759, Aug. 2020.

[8] J. R. Porter, L. Xie, A. J. Challinor, K. Cochrane, S. M. Howden, M.
   a. M. Iqbal, D. B. Lobell, and M. I. Travasso, Food Security and Food Production. Cambridge, U.K.: Cambridge Univ. Press, Jan. 2014, pp. 485–533.

[9] J. A. Foley, R. DeFries, G. P. Asner, C. Barford, G. Bonan, S. R. Carpenter,
   a. S. Chapin, M. T. Coe, G. C. Daily, H. K. Gibbs, J. H. Helkowski, T. Holloway, E. A. Howard, C. J. Kucharik, C. Monfreda,

[10] A. Patz, I. C. Prentice, N. Ramankutty, and P. K. Snyder, "Global consequences of land use," Science, vol. 309, no. 5734, pp. 570–574, 2005.

[11] H. C. J. Godfray, J. R. Beddington, I. R. Crute, L. Haddad, D. Lawrence,
   a. F. Muir, J. Pretty, S. Robinson, S. M. Thomas, and C. Toulmin, "Food security: The challenge of feeding 9 billion people," Science, vol. 327,
   b. no. 5967, pp. 812–818, 2010

[12] D. Tilman, C. Balzer, J. Hill, and B. L. Befort, "Global food demand and

[13] the sustainable intensification of agriculture," Proc. Nat. Acad. Sci. USA, vol. 108, no. 50, pp. 20260–20264, Dec. 2011.

[14]V. Gitz, A. Meybeck, L. Lipper, C. D. Young, and S. Braatz, "Climate change and food security: Risks and responses," Food Agricult. Org. United Nations (FAO), Rome, Italy, Tech. Rep. 110, 2016, pp. 2–4.

[15]Nandigama, N. C. (2019). Hybrid Facial Recognition System Using Histogram of Oriented Gradients and Deep Learning with Dimensionality Reduction. Research Journal of Nanoscience and Engineering, 3(4), 30–35. https://doi.org/10.22259/2637-5591.0304005

[16]L. S. Huning and A. AghaKouchak, "Global snow drought hot spots and characteristics," Proc. Nat. Acad. Sci. USA, vol. 117, no. 33, pp. 19753– 19759, Aug. 2020.

[17]J. R. Porter, L. Xie, A. J. Challinor, K. Cochrane, S. M. Howden, M.

[18] Iqbal, D. B. Lobell, and M. I. Travasso, Food Security and Food Production. Cambridge, U.K.: Cambridge Univ. Press, Jan. 2014, pp. 485– 533.

[19][13] Todupunuri, A. (2025). Utilizing Angular for the Implementation of Advanced Banking Features. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5283395.

[20]Nandigama, N. C. (2020). CATS-DRL-PFOA: A Cost-Aware Task Scheduling Framework using Deep Reinforcement Learning and Pufferfish Optimization in Secure Cloud Environments. Research Journal of Nanoscience and Engineering, 4(1), 36–44. https://doi.org/10.22259/2637-5591.0401005

[21]H. C. J. Godfray, J. R. Beddington, I. R. Crute, L. Haddad, D. Lawrence, J. F. Muir, J. Pretty, S. Robinson, S. M. Thomas, and C. Toulmin, "Food security: The challenge of feeding 9 billion people," Science, vol. 327, no. 5967, pp. 812–818, 2010.

[22]D. Tilman, C. Balzer, J. Hill, and B. L. Befort, "Global food demand and the sustainable intensification of agriculture," Proc. Nat. Acad. Sci. USA, vol. 108, no. 50, pp. 20260–20264, Dec. 2011.

[23]V. Gitz, A. Meybeck, L. Lipper, C. D. Young, and S. Braatz, "Climate change and food security: Risks and responses," Food Agricult. Org. United Nations (FAO), Rome, Italy, Tech. Rep. 110, 2016, pp. 2–4.

[24]Lakshmi Prasad Rongali. (2025). Integrating AI and Devops Practices to Develop Cybersecurity Frameworks That Enhance Resilience in Utility Infrastructure. Journal of Informatics Education and Research, 5(2). https://doi.org/10.52783/jier.v5i2.2838.

[25]J. R. Porter, L. Xie, A. J. Challinor, K. Cochrane, S. M. Howden, M.

[26] Iqbal, D. B. Lobell, and M. I. Travasso, Food Security and Food Production. Cambridge, U.K.: Cambridge Univ. Press, Jan. 2014, pp. 485– 533.

[27] K. Riahi et al., "The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview".