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## A EURASIAN CASE STUDY ON CLIMATE CHANGE AND AGRICULTURAL LAND SUITABILITY USING INTERPRETABLE MACHINE LEARNING

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### ABSTRACT

As a result of climate change's impact on the appropriateness of agricultural land, this research seeks to solve the pressing worldwide problem of food security. Predicting the risks of land suitability deterioration and changes in irrigation patterns, which directly effect food security, is the fundamental focus of our study. The fight against hunger and malnutrition is one of the United Nations' sustainable development objectives, and this study fits in with that. Our research focusses on Central Eurasia because it is a prime example of an area dealing with distinct social and economic issues; this makes it ideal for studying how climate change affects food security. We use interpretable machine learning methods to assess how various carbon emission scenarios would affect the usability of agricultural land in the face of climate change. The generated model performs well in a multi-class land suitability classification test, with an accuracy of 86% and a mean average precision of 72%. Our study gives policymakers important insights into the most susceptible locations in Northern Asia and Eastern Europe. Insights like these are crucial for humanitarian crisis prevention strategy, which includes allocating vital resources like water and fertilisers. The findings prove that machine learning is a potent instrument for foreseeing and controlling the effects of climate change on food security.

### I. INTRODUCTION

Worldwide pandemics, food shortages, and political and social unrest are all profoundly impacted by the effects of climate change, which permeate all areas of human endeavour. Nearly 40% of the world's arable land and pastures are in danger as a result of rising global temperatures and decreasing humidity levels [1]. By 2050, predictions suggest that the world's food consumption would increase by around 110% [2], [3]. To make matters worse, there are already significant obstacles to sustaining ideal circumstances for agricultural production due to rising average temperature, snow-water equivalent, and concentrations of greenhouse gases [4, 5, 6].

Using the Shared Socioeconomic Pathways (SSP) [7], which are representations of likely pathways for carbon emissions, this research investigates how climate change would affect the sustainability of agriculture. Key climate indicators including mean temperature, humidity, and atmospheric pressure are evaluated by a wide range of models made available by the Coupled Model Intercomparison Project (CMIP). Our research has made use of three CMIP6 ensembles: CMCC-ESM2 from the Italian Centre for Mediterranean Climate Change, CNRMCM6-1 from the French National Centre for Meteorological Research, and MRI-ESM2-0 from the Japanese Meteorological Research Institute Earth System Model [8, 9], [10]. The three separate SSP scenarios that were used to evaluate each ensemble were as follows: SSP1-2.6, which

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represents a future with sustainable, low-emission green energy; SSP2-4.5, which represents a "business-as-usual" trajectory with moderate emissions; and SSP5-8.5, which represents a scenario with high reliance on fossil fuels and considerably higher emissions of greenhouse gases. We have also included the Global Food Security-support Analysis Data at a 1 km x 1 km resolution (GFSAD1km) to examine the irrigation conditions for crops [11].

Our study aims to address three important questions raised by policymakers, academics, and industry stakeholders: (1) how different SSP scenarios could affect the distribution of croplands; (2) which regions pose the greatest threat to food security; and (3) what factors significantly impact the suitability of croplands, especially in regard to the type of irrigation used.

To accomplish these goals, we have used a stacked ensemble approach, which involves merging eight top-tier machine learning models into a single meta-classifier. In most cases, as shown by Mohandes et al. [12], the combined models outperform the individual ones. According to the weather, agricultural land may be precisely divided into four types using this method: major irrigation, minor irrigation, rainfed, and non-cropland. In order to alleviate concerns about food security in vulnerable areas, our analysis predicts a significant increase in arable land by 2050, with a preference for rainfed agriculture. We also foresee an increase in the danger to already farmed areas and a movement of agriculturally suitable zones northward.

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 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 suitability reduction; • uses machine learning and deep learning to identify important factors affecting the land's agricultural potential.

Our findings will be useful for land-use strategists and policymakers who are committed to creating effective management plans that account for the long-term interdependencies of climate change, land suitability, and agricultural production.

In Section II, we survey the literature that is pertinent to our investigation. Section III details the process, data used, and algorithms that were put into action. The evaluation of our models, as well as predictions and forecasts for future situations, are detailed in Section IV. In Section V, we address the study's weaknesses and suggest directions for further research. In Section VI, we summarise our key results and end the study.

## II. LITERATURE SURVEY "Global consequences of land use,"

**J. A. Foley, R. DeFries, G. P. Asner, C. Barford, G. Bonan, S. R. Carpenter, F. S. Chapin, M. T. Coe, G. C. Daily, H. K. Gibbs, J. H. Helkowski, T. Holloway, E. A. Howard, C. J. Kucharik, C. Monfreda, J. A. Patz, I. C. Prentice, N. Ramankutty, and P. K. Snyder,**

In this work, we use a set of sophisticated machine learning algorithms to assess the future farmland suitability under several climatic scenarios up to 2050. Our research provides solid evidence for future land suitability change predictions. Notably, this research supports and adds to the suggestions made by the Intergovernmental Panel on climatic Change (IPCC) [53], which highlight the need of thorough regional evaluations in preparing for

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climatic unpredictability and guaranteeing food supply. As highlighted in the IPCC report, our work provides practical insights for policymakers by outlining possible changes in cropland viability and irrigation needs. These insights are particularly important in the context of global efforts to combat hunger and malnutrition, as they are critical for effective risk management and adaptation strategies.

The most relevant parameters for categorisation were monthly precipitation and a set of characteristics linked to temperature. There was a robust correlation between temperature and morphological variation in croplands classified by irrigation method. Particularly for risky areas in China, our regional feature importance study highlights the weight of severe heat and cold as well as patterns of precipitation. This emphasises the need of addressing climate change via region-specific actions, such changing irrigation techniques or redistributing agricultural resources.

It is anticipated that the overall quantity of arable land would grow, with an expansion to the north. However, there may be hazards associated with the need to enhance irrigation in certain already-exploited agricultural areas. Significant area development potential and the ability to fulfil the increasing food demand are both hinted at by this expansion. Substantial investments and smart land management are necessary to tap on this potential. Huge agricultural loss, threatening food security, may result from ignoring the effects of climate change.

If you want to do the same study that was in the publication, you may find our code on GitHub1.

**“Food security: The challenge of feeding 9 billion people,”**

**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,**

The world's need for food will rise over the next 40 years or more if current trends in population and consumption are any indication. Overfishing, rising energy and water prices, and increasing competition for arable land are all factors that will have an effect on food production. Another pressing issue is the need to lessen the environmental impact of the food system. Another danger is the impact of global warming. But we can increase food production and make sure it's distributed fairly. Sustainable and equitable food security requires a global plan that is both complex and interconnected, and this article explores some of those components.

**“Global food demand and the sustainable intensification of agriculture,”**

**D. Tilman, C. Balzer, J. Hill, and B. L. Befort,**

Both the demand for food throughout the world and the negative effects of agriculture on the environment are on the rise. In this study, we assess the potential environmental consequences of several strategies for meeting the projected worldwide demand for agricultural output in the year 2050. Since 1960, we see that the demand for crops per capita, whether expressed as the total caloric or protein content of all crops, has also increased in direct proportion to the real GDP per capita. From 2005–2050, the worldwide demand for crops is expected to rise by 100–110% according to this connection. According to quantitative evaluations, the environmental consequences of satisfying this demand are conditional on the rate of world agricultural expansion. By 2050, the world would have cleared around 1 billion hectares of land, with CO<sub>2</sub>-C equivalent greenhouse gas emissions reaching around 3 Gt y<sup>-1</sup> and N use around 250 Mt y<sup>-1</sup> if the current trends of increased agricultural intensification in wealthier nations and increased land clearing

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(extensification) in poorer nations persist. Our analyses predict that land clearing would be minimal at around 0.2 billion ha, greenhouse gas emissions would be around 1 Gt y(-1), and global nitrogen use would be around 225 Mt y(-1) if the 2050 crop demand was met through moderate intensification targeting underyielding nations' existing croplands, adaptation and transfer of high-yielding technologies to these croplands, and overall technological improvements. Nitrogen usage might be significantly reduced with effective management techniques. In order to meet the worldwide demand for crops while minimising environmental consequences, it is crucial to achieve high yields on the croplands of countries that are not producing enough.

**“Climate change and food security: Risks and responses,”**

**V. Gitz, A. Meybeck, L. Lipper, C. D. Young, and S. Braatz,**

Climate change and food security: risks and responses compiles data on the effects of climate change on nutrition and food security from the Intergovernmental Panel on Climate Change (IPCC), which has been revised to include the most recent scientific findings and evidence in addition to data collected from real-world situations. It demonstrates how several vulnerabilities interact with a domino effect of affects on ecosystems and livelihoods, threatening the nutrition and food security of the most vulnerable people. Adaptation strategies, vulnerability reduction tactics, and resilience building strategies are all laid forth in the paper. It highlights the need to take immediate action to combat climate change, guarantee food security, and promote healthy nourishment for all people. No. 5188E.

**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

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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 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

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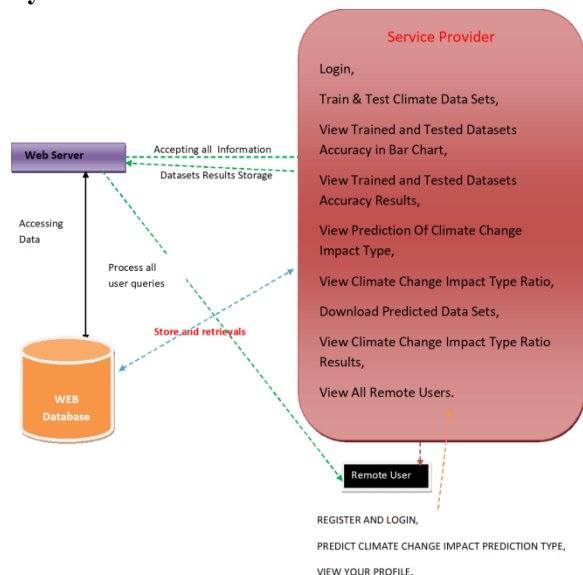
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climate change, land suitability, and agricultural production over the long term will find our results to be crucial.

**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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## REFERENCES

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

[2] 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.

[3] 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.

[4] 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.

[5] 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.

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

[7] K. Riahi et al., “The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview,” *Global Environ. change*, vol. 42, pp. 153–168, Jan. 2017.

[8] D. Peano, T. Lovato, and S. Materia, “CMCC-ESM2 model output prepared for

<https://doi.org/10.62643/ijerst.2025.v21.i2.pp1115-1124>

Vol. 21, Issue 2, 2025

CMIP6 LS3MIP,” Earth Syst. Grid Fed., Rome, Italy, Tech. Rep., 2020. [Online]. Available: <https://www.ipcc.ch/srccl/cite-report/>

[9] A. Voldoire et al., “Evaluation of CMIP6 deck experiments with CNRMCM6-1,” *J. Adv. Model. Earth Syst.*, vol. 11, no. 7, pp. 2177–2213, 2019.

[10] S. Yukimoto, H. Kawai, T. Koshiro, N. Oshima, K. Yoshida, S. Urakawa, H. Tsujino, M. Deushi, T. Tanaka, M. Hosaka, S. Yabu, H. Yoshimura, E. Shindo, R. Mizuta, A. Obata, Y. Adachi, and M. Ishii, “The meteorological research institute Earth system model version 2.0, MRIESM2.0: Description and basic evaluation of the physical component,” *J. Meteorol. Soc. Japan. Ser. II*, vol. 97, no. 5, pp. 931–965, 2019.

[11] P. Thenkabail, J. Knox, M. Ozdogan, M. Gumma, R. Congalton, Z. Wu, C. Milesi, A. Finkral, and M. Marshall, and I. Mariotto, “NASA making earth system data records for use in research environments (MEASUREs) global food security support analysis data (GFSAD) crop dominance 2010 global 1 km v001,” NASA, Washington, DC, USA, Rep. GFSAD1KCD v001, 2016.

[12] M. Mohandes, M. Deriche, and S. O. Aliyu, “Classifiers combination techniques: A comprehensive review,” *IEEE Access*, vol. 6, pp. 19626–19639, 2018.

[13] H. Hersbach, B. Bell, P. Berrisford, S. Hirahara, and J. Thépaut, “The ERA5 global reanalysis,” *Quart. J. Roy. Meteorolog. Soc.*, vol. 146, no. 730, pp. 1999–2049, 2020.

[14] J. T. Abatzoglou, S. Z. Dobrowski, S. A. Parks, and K. C. Hegewisch, “TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015,” *Sci. Data*, vol. 5, no. 1, Jan. 2018, Art. no. 170191.

[15] A. M. de Oca, L. Arreola, A. Flores, J. Sanchez, and G. Flores, “Lowcost multispectral imaging system for crop monitoring,” in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Jun. 2018, pp. 443–451.

[16] B. I. Evstatiev and K. G. Gabrovska-Evstatieva, “A review on the methods for big data analysis in agriculture,” *IOP Conf. Ser., Mater. Sci. Eng.*, vol. 1032, no. 1, Jan. 2021, Art. no. 012053.

[17] V. Eyring, S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, “Overview of the coupled model intercomparison project phase 6 (CMIP6) experimental design and organization,” *Geosci. Model Develop.*, vol. 9, no. 5, pp. 1937–1958, May 2016.

[18] S. A. Shoaib, M. Z. K. Khan, N. Sultana, and T. H. Mahmood, “Quantifying uncertainty in food security modeling,” *Agriculture*, vol. 11, no. 1, p. 33, Jan. 2021.

[19] WorldBank. (2023). World Bank Group, Climate Change Knowledge Portal. World Bank Group. Accessed: Feb. 27, 2023. [Online].

Available: <https://climateknowledgeportal.worldbank.org/download-data>

[20] C. Müller, J. Franke, J. Jägermeyr, A. C. Ruane, J. Elliott, E. Moyer, J. Heinke, P. D. Falloon, C. Folberth, L. Francois, T. Hank, R. C. Izaurralde, I. Jacquemin, W. Liu, S. Olin, T. A. M. Pugh, K. Williams,



<https://doi.org/10.62643/ijerst.2025.v21.i2.pp1115-1124>

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and F. Zabel, “Exploring uncertainties in global crop yield projections in a large ensemble of crop models and CMIP5 and CMIP6 climate scenarios,” *Environ. Res. Lett.*, vol. 16, no. 3, Mar. 2021, Art. no. 034040.