Impacts of climate change on food security

Group Members Names:

1. Mohamed Fadlelseed
2. Fulchany Arvelin NANİTELAMİO
3. Bacoro dit Elhafji lansar
4. Madalena Makiesse
5. Zeinab Mohmmed
6. Israa Abdulrahman Mohammed kheir

1 Literature Review

1.1 Introduction

Climate change poses a significant threat to food security by affecting crop yields, water availability, and livestock productivity. Addressing climate change is essential for ensuring food security and combating hunger. Conversely, improving food security can also mitigate the impacts of climate change by reducing greenhouse gas emissions associated with agriculture and food production. projects that address both SDG 13 and SDG 2 are critical for creating a more sustainable and equitable world.

Machine learning can significantly contribute to addressing and achieving SDGs 13 and 2 by enhancing predictive analytics, optimizing agricultural practices, and improving system efficiencies. However, the successful implementation of ML solutions requires careful consideration of data quality, ethical implications, and the integration of these technologies into existing agricultural and food systems.

Literature reviews can provide insights into the types of data that have been successfully used in similar predictive modeling efforts and determine the current state-of-the-art. Understanding what data features have been found to be significant for predicting climate change indicators can inform the data collection and preprocessing strategies for this project. This includes knowing which environmental, socio-economic, and demographic factors have been correlated with the indicators of interest.

1.2 Summary and synthesis

Paper 1: Effects of climate change on global food production under SRES emissions and socio-economic scenarios:

- **Key findings of the paper:**

1. The study indicates that climate change is likely to exert a slight to moderate negative impact on global crop yields under most SRES scenarios, even when accounting for beneficial direct effects of CO2 and farm-level adaptations (1).
2. The effects of climate change on agriculture are not uniform; they vary significantly by region. Low-latitude regions are expected to experience major vulnerabilities, while high and mid-latitude areas may see different impacts.
3. The research emphasizes the importance of adaptation strategies, such as changes in planting dates and increased use of fertilizers and irrigation, which can mitigate some negative impacts of climate change on crop yields.
4. The study highlights that socio-economic factors, including price changes and shifts in comparative advantage, play a crucial role in determining agricultural responses to climate change.

- **Contribution to the Field**

1. **Comprehensive Analysis**: The paper contributes to the understanding of how climate change affects global food production by integrating biophysical and socio-economic factors, which is often overlooked in previous studies.

2. **Policy Implications**: The findings provide valuable insights for policymakers regarding the potential impacts of climate change on food security and the importance of adaptation strategies in mitigating these effects.

3. **Foundation for Future Research**: By employing robust methodologies and presenting detailed regional analyses, the study lays the groundwork for future research on climate change impacts on agriculture, encouraging further exploration of adaptation strategies and socio-economic responses

Paper 2: "Assessing the impacts of temperature extremes on agriculture yield and projecting future extremes using machine learning and deep learning approaches with CMIP6 data"

- **Key findings of the paper:**

1. The study found that temperature extremes, particularly cold and warm nights, have significant impacts on wheat and rice yields in the Punjab region of Pakistan (2).
2. Using machine learning (ML) and deep learning (DL) models, the study projected that future temperature extremes, such as increased warm nights (TN90p) and decreased cold spell durations (CSDI), will pose challenges for agricultural productivity.

3. The study highlighted regional variations in temperature extremes, indicating specific areas like Muree might experience different trends compared to others.

- **Methodology:**
  The study employs machine learning (ML) and deep learning (DL) models using CMIP6 data to analyze historical temperature trends and predict future extremes.

- **The major contribution of this study**

1. The study is one of the first to explore the association between temperature extremes (quantified using ETCCDI indices) and crop yields in Punjab, Pakistan, offering new insights into how thermal extremes impact agricultural production in the region.
2. Projecting temperature extremes using state-of-the-art ML and DL models with the data from the CMIP6 archive under two SSPs. This will help relevant stakeholders in taking adaptation and mitigation measures in the light of insights explored in the first contribution of this study

Paper 3: Machine learning-enhanced evaluation of food security across 169 economies:

- **Key Findings:**

1. The assessment revealed significant disparities in food security across 169 countries, with regions like Europe, Oceania, and North America exhibiting higher food security levels, while Africa and South Asia faced more severe challenges (3).
2. Countries such as Yemen, Afghanistan, Congo, Nigeria, and Somalia are experiencing food insecurity crises due to ongoing conflicts, extreme weather events, and economic shocks.
3. The study identified pronounced polarization in food utilization among countries, with some underutilizing and others over utilizing their food resources.
4. The research proposes actionable policy recommendations, including humanitarian relief efforts, the expansion of social safety nets, and the development of efficient transportation networks to enhance food security.

- **Methodology:**

1. Machine Learning Models: The study employed four machine learning models to impute missing data for food security performance indicators, addressing significant gaps, particularly in Africa and South Asia.
2. Comprehensive Indicator Analysis: A total of 44 indicators across five dimensions of food security were analyzed, providing a rich dataset for evaluation.

3. Dimensional and Comprehensive Values Calculation: The research calculated both dimensional and comprehensive values of food security performance for the 169 countries, allowing for a detailed assessment of food security across different regions

➢ **Contribution to the field:**

By utilizing machine learning to improve data quality and fill gaps, the study contributes to more accurate assessments of food security, which is crucial for effective policy making. In addition, this study significantly advances the understanding of global food security dynamics and offers a robust framework for future research and policy development.

1.3 Compare and contrast the papers to highlight commonalities and differences

1.3.1 Commonalities Across the Papers

1. Focus on Agriculture and Food Security:

   All three papers investigate aspects of agriculture and food security, highlighting the critical role of environmental and socio-economic factors in shaping outcomes. The first paper (1) examines the impact of climate change on global food production, the second focuses on temperature extremes' effects on crop yields (2), and the third assesses global food security across various economies (3).

2. Emphasis on Climate Change:

   Climate change is a central theme in all three studies. The first paper explores the broader impact of climate change on global crop yields, the second analyzes temperature extremes driven by climate change, and the third indirectly addresses climate-related challenges as they contribute to food insecurity in vulnerable regions.

3. Importance of Adaptation Strategies:

   Each paper discusses the need for adaptation to mitigate the negative impacts of environmental changes on agriculture. The first paper emphasizes farm-level adaptations, the second highlights the potential of ML and DL models to project temperature extremes, which could inform adaptation efforts, and the third suggests policy interventions to enhance food security in response to climate challenges.

4. Use of Advanced Methodologies:

   The papers employ sophisticated methodologies to analyze their respective topics. The first paper uses biophysical and socio-economic models to assess climate change impacts, the second applies ML and DL models to project temperature extremes, and the third utilizes ML to improve the accuracy of food security assessments.

1.3.2 Differences Among the Papers

1. Scope and Scale:

   The first paper has a global focus, examining the impacts of climate change on agriculture worldwide. The second paper is region-specific, concentrating on temperature extremes in Punjab, Pakistan. The third paper, while also global in scope, provides a more comprehensive analysis of food security across 169 countries.

2. Methodological Approaches:

   The first paper integrates biophysical and socio-economic models, while the second and third papers rely heavily on machine learning techniques. The second paper uses ML and DL to predict temperature extremes, while the third employs ML to impute missing data and assess food security indicators.

3. Research Focus:

   The primary focus of the first paper is on the direct and indirect effects of climate change on crop yields, emphasizing the regional disparities in impact. The second paper is more specialized, concentrating on the effects of temperature extremes on specific crops (wheat and rice) in a particular region. The third paper takes a broader approach, evaluating food security across multiple dimensions and regions.

4. Contributions to the Field:

   The first paper contributes by offering a comprehensive analysis that combines biophysical and socio-economic factors, providing insights for policymakers. The second paper's contribution lies in its novel application of ML and DL to predict temperature extremes and their impact on agriculture in Punjab. The third paper advances the understanding of global food security by utilizing ML to improve data quality and fill gaps in food security assessments.

1.4 Conclusion

The project directly aligns with the United Nations' Sustainable Development Goals (SDGs), specifically SDG 13 (Climate Action) and SDG 2 (Zero Hunger). By predicting the impacts of climate change on various indicators, it offers actionable insights that can inform policies and interventions to mitigate climate change and enhance food security.

2 Data Research

2.1 Introduction

FAOSTAT provides data in domains, such as Food security and Nutrition, Food balances, SDG indicators and so on (3). Following the recommendation of experts gathered at the Committee on World Food Security (CFS) Round Table on hunger measurement hosted at FAO in September 2011, a set of indicators aiming to capture the four dimensions of food security (Availability, Access, Stability, Utilization) were developed by the FAO Statistics Division (4). FAOSTAT provides access to some of these indicators' data in the Food security and Nutrition section.

2.1.1 Importance

1. **Alignment with SDG 13 (Climate Action):**
   The project directly addresses the urgent need for climate action, which is a core objective of the 13th Sustainable Development Goal. By focusing on predictive models for climate-related indicators, this project might contribute to the global efforts to mitigate and adapt to climate change.
2. **Alignment with SDG 2 (Zero Hunger):**
   Exploring correlations between predicted indicators and the Global Hunger Index aligns with the goal of achieving zero hunger worldwide. Understanding how climate change impacts food security is critical for addressing this SDG.

- This research addresses critical gaps in our understanding of climate change impacts and their potential consequences. It aligns with global goals, supports sustainable development efforts, and provides valuable tools for planning and decision-making in the face of climate uncertainty.

2.1.2 Why is a thorough exploration of data necessary?

1. High-quality data is essential for developing accurate and reliable predictive models.
2. Thorough data exploration helps identify and address potential errors, inconsistencies, or missing values in the dataset.
3. Proper data exploration allows for the identification of relevant features that capture underlying trends and patterns in the data.

2.2 Data Description

2.2.1 Data Source

We have two sources for our dataset, because we plan to merge both datasets together. The first source is FAOSTAT and the second source is Search for a Dataset - Humanitarian Data Exchange (humdata.org).

2.2.2 Data Format

Both datasets are in .csv file format.

2.2.3 Data Size

For the FAOSTAT dataset the size is 173451 row and 4 columns, and for the Search for a Dataset - Humanitarian Data Exchange (humdata.org) dataset we have 1078768 row and 4 columns.

2.2.4 The reason to choose this data and how it relates to your project

We chose the FAOSTAT dataset because it has been used in previous research in the same field, and we decided to add the Search for a Dataset - Humanitarian Data Exchange (humdata.org) dataset to it, because it has an additional important features that we want to merge with the FAOSTAT dataset features.

2.3 Data Analysis and Insights

In both datasets we have many numbers of indicators of food security for all countries in the word, and for each specific indicator we have many missing values. For example, in the FAOSTAT dataset, we have missing value in all food security indicators as shown in Figure 1. Additionally, we chose 8 just indicators and we explored their correlation together as shown in Figure 2, because they were very important indicators in (3).

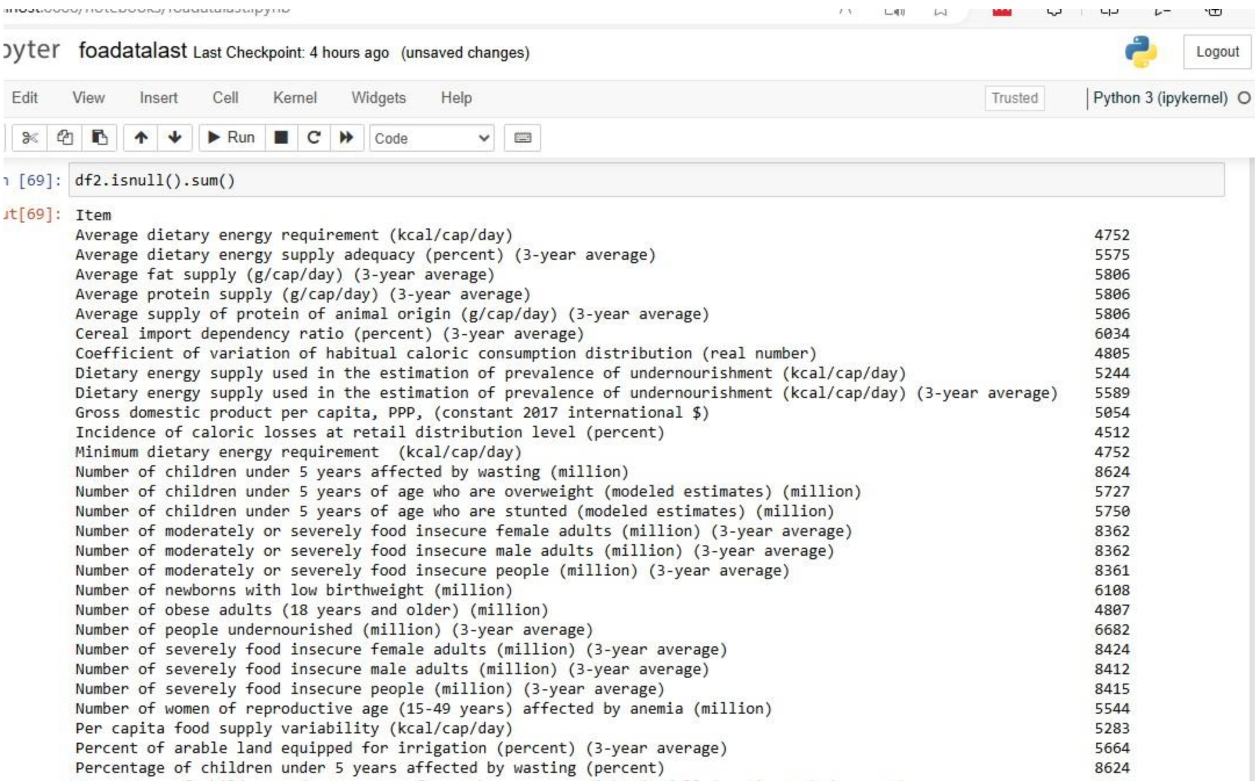

Figure 1: Missing Values for Food Security Indicators in the FAOSTAT Dataset

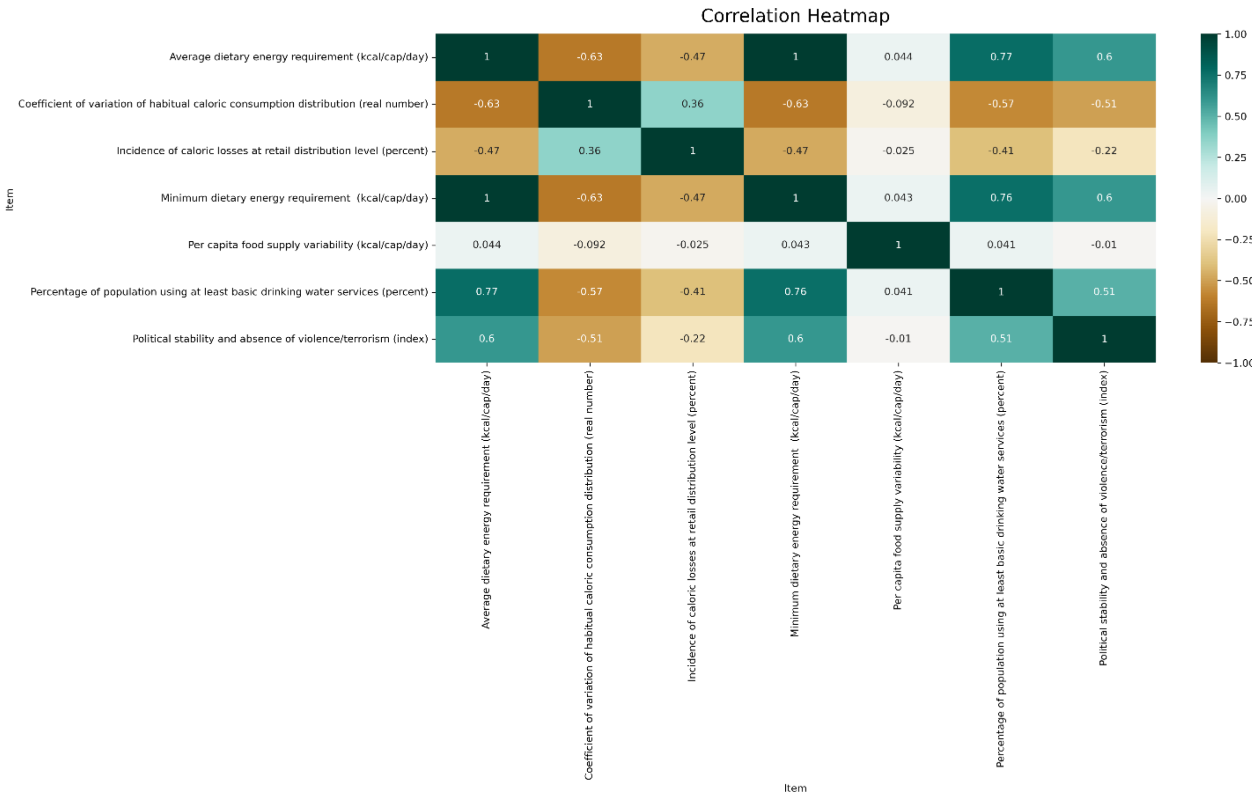

Figure 2: The Correlation Heatmap for 8 indicators in the FAOSTAT Dataset

3 Technology Review

3.1 Introduction

The increasing complexity and scale of climate change pose significant challenges to global food security. Accurately predicting the impacts of climate variability on agricultural productivity is essential for developing effective adaptation strategies. This technology review focuses on the application of a hybrid approach, utilizing both Machine Learning (ML) and Deep Learning (DL) models, particularly those using huge data, in the analysis of climate change effects on food production. The relevance of these technologies lies in their potential to enhance the precision and reliability of climate impact predictions, which is central to the success of this research.

3.2 Technology Overview

Machine Learning (ML) and Deep Learning (DL) models are advanced computational tools designed to identify patterns within large datasets and make predictive analyses based on historical data.

The hybrid approach combines the strengths of Deep Learning (DL) and Machine Learning (ML) models to analyze complex and temporal data related to climate impacts.

3.2.1 Deep Learning:

- **LSTM with Keras:** Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) specifically designed to model sequential data and capture long-term dependencies. In this study, LSTM models are employed to predict indicators such as CO2 emissions, urban population growth, and freshwater withdrawals, where temporal relationships are complex and require a model capable of retaining information over extended periods.

3.2.2 Machine Learning

- **Regression Models:** A variety of ML regression models, including Random Forest, AdaBoost, ExtraTrees, Gradient Boosting, and Support Vector Regression (SVR), are used to predict indicators that do not require the depth of analysis provided by DL models. These models are particularly useful for providing ensemble predictions, which combine the outputs of multiple models to achieve better accuracy and robustness by reducing variance and bias.

3.3 Relevance to the Research Project

The hybrid approach of integrating ML and DL models is highly relevant to this research as it addresses the varying complexities inherent in the data used for climate impact analysis. LSTM models are crucial for capturing the long-term dependencies in time-series data, essential for accurate predictions of climate-related indicators. Meanwhile, ML regression models complement the DL approach by offering reliable predictions in areas

where simpler relationships are sufficient. This dual approach enhances the overall predictive capability and robustness of the research outcomes, directly contributing to more informed decision-making in climate adaptation strategies.

3.4 Comparison and Evaluation

When evaluating the suitability of ML and DL models for this research, several factors were considered, including model accuracy, computational efficiency, and the nature of the data. While traditional statistical models have been used in climate impact studies, the hybrid approach of combining LSTM for time-series forecasting with ensemble ML models for regression tasks provides a more comprehensive solution. LSTM networks excel in handling the sequential nature of climate data, while the ensemble ML methods add value by improving the accuracy of predictions through variance and bias reduction. This approach ensures that the most appropriate model is used for each specific task, thereby maximizing predictive performance.

3.5 Use Cases and Examples

The effectiveness of the hybrid approach has been demonstrated in various studies that utilize both ML and DL models. For instance, LSTM networks have been successfully applied to forecast long-term environmental indicators like CO2 emissions, while ensemble ML methods have been used to predict agricultural yields with high accuracy. These models have been particularly effective in regions where climate variability poses significant risks to food security, providing crucial insights for policy development and adaptation planning.

3.6 Gaps and Research Opportunities

The research addresses critical gaps identified in the literature, such as the lack of comprehensive predictive models for climate change impacts on socio-economic indicators and the correlation with hunger levels. This fills a significant void in our understanding of how climate change affects different regions and populations differently. By addressing this gap, the research not only advances our understanding of these relationships but also provides more nuanced insights into how climate change affects different regions and communities.

3.7 Conclusion

The hybrid approach of combining machine learning and deep learning models, supported by the CMIP6 dataset, represents a major advance in studying the impacts of climate change on agriculture. This methodology not only enhances the accuracy of predictive models, but also provides valuable insights into the complex interactions between climate variables and agricultural productivity. As this research progresses, continued improvement and application of these models will be critical in addressing the global challenge of ensuring food security in the face of climate change and a major step towards achieving Sustainable Development Goal 2 “No Hunger”.

4 References

1. Parry ML, Rosenzweig C, Iglesias A, Livermore M, Fischer G. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Glob Environ Chang. 2004;14(1):53–67.

2. Khan F, Khan F, Liou YA, Khan F, Spöck G, Wang X, et al. Assessing the impacts of temperature extremes on agriculture yield and projecting future extremes using machine learning and deep learning approaches with CMIP6 data. Int J Appl Earth Obs Geoinf. 2024;132(300).

3. Xiong R, Peng H, Chen X, Shuai C. Machine learning-enhanced evaluation of food security across 169 economies. Environ Dev Sustain [Internet]. 2024;(0123456789). Available from: https://doi.org/10.1007/s10668-024-05212-1

4. Tubiello FN. System of Environmental-Economic Accounting for Agriculture, Forestry and Fisheries - Food Security Indicators [Presentation]. 2016;(June):24–6. Available from: https://seea.un.org/sites/seea.un.org/files/food_security_indicators.pdf