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Transformer-Based Machine Learning Approach for Predicting Precipitation and Wheat Production in the Face of Climate Change

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Abstract:

Climate change significantly threatens agricultural sustainability, particularly in arid regions like the Middle East, where wheat is a staple crop. This study employs machine learning techniques to analyse historical climate patterns and predict future wheat production in Egypt, Turkey, and Iran. A comprehensive literature review was conducted to assess the current state of climate change's impact on agriculture, highlighting key challenges and gaps in existing models. Using a dataset spanning from 1961 to 2024, we analysed and plotted the trends of precipitation, temperature and wheat production. We further integrated precipitation, temperature, and wheat production trends to develop a predictive framework. A Transformer-based architecture was employed to capture long-term dependencies in climate and agricultural data, enabling precise forecasts of precipitation decline, temperature rise, and wheat yield fluctuations. Our results indicate a substantial decrease in precipitation across all three nations, with Iran experiencing the steepest decline, while rising temperatures pose an additional threat to crop productivity. The developed model highlights the potential of artificial intelligence in climate impact assessment and agricultural planning. The findings emphasize the necessity of proactive adaptation strategies, including sustainable water management, climate-resilient crop varieties, and policy interventions to mitigate food security risks in the region.

Keywords — — **Machine Learning Forecasting, Transformer-Based Model, Climate Change Impact, Population Growth, AI in Environmental Science, Agricultural Data Analysis, LSTM, Transformer-Based Models, Random Forest Regression.**

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I. INTRODUCTION

The Middle East, encompassing nations such as Egypt, Turkey, and Iran, is experiencing significant challenges due to climate change, particularly in its agricultural sector. Wheat, a staple crop in these countries, is highly susceptible to climatic variations, making the region's food security increasingly precarious. This introduction delves into the intricate relationship between climate change and wheat production, highlighting the pressing need for adaptive strategies.

A. Climate Change and Its Impact on Agriculture

Climate change has led to increased temperatures, altered precipitation patterns, and more frequent extreme weather events globally. In the Middle East, these changes manifest as prolonged droughts and heatwaves, adversely affecting agricultural productivity. Studies have shown that rising temperatures and decreasing rainfall have already begun to reduce wheat yields in the region (Fontana et al., 2015). For instance, in Egypt, wheat production is threatened by increasing heat waves and droughts (Fontana et al., 2015).

B. Wheat Production in Egypt, Turkey and Iran

Egypt, Turkey, and Iran are among the top wheat producers in the Middle East. However, their agricultural outputs are increasingly vulnerable to climate-induced stresses. In Egypt, wheat production is threatened by increasing heat waves and droughts (Fontana et al., 2015). Similarly, in Iran, climate change has led to increased water consumption for wheat cultivation, with studies indicating a rise of about 10.8% in water usage due to higher temperatures (Eid et al., 2006). Turkey, accounting for about 45% of the Middle East's wheat production, faces challenges in maintaining its output amidst changing climatic conditions (USDA, 2024).

C. Population Growth and Food Demand

The Middle East is witnessing rapid population growth, which exacerbates the demand for staple foods like wheat. This surge in demand, coupled with declining production due to climate stressors, poses a significant threat to regional food security. For example, between 1991 and 2004, Syria transitioned from being a wheat importer to achieving self-sufficiency and even exporting wheat, primarily due to the adoption of high-yielding varieties and supportive policies (Fischer and Heilig, 1997). However, such gains are at risk if climate change continues unabated.

D. Challenges and Adaptation Strategies

The interplay between climate change and agriculture presents multifaceted challenges. Increased temperatures can exacerbate pest infestations, leading to further yield reductions (iMMAP, 2016). Additionally, water scarcity, driven by altered precipitation patterns, complicates irrigation efforts, especially in arid regions. To mitigate these challenges, adopting climate-resilient agricultural practices is imperative. Strategies such as developing drought-resistant wheat varieties, implementing efficient irrigation techniques, and enacting supportive agricultural policies can bolster resilience against climate-induced stresses.

Addressing the intertwined issues of climate change and food security in the Middle East requires comprehensive research and proactive policy interventions. By understanding the specific impacts of climatic changes on wheat production and implementing adaptive strategies, nations like Egypt, Turkey, and Iran can work towards ensuring sustainable agricultural practices and securing food supplies for their growing populations.

II. CLIMATE CHANGE IMPACTS ON WHEAT PRODUCTION AND FOOD SECURITY IN THE MIDDLE EAST

The impacts of climate change on farming, especially on staple crops such as wheat, have been broadly studied in different geographical settings around the world. Within the Middle East region, where arid and semi-arid climates dominate, the implications of climate change for wheat pro- duction and food security are of specific concern. This section audits existing literature relating to the climate change impacts on wheat production and food security within the Middle East, centering on key findings, methodologies, and theoretical frameworks utilized in past studies.

A. Key Findings

Numerous studies highlight climate change's adverse effects on Middle East wheat production. Rising temperatures and decreasing precipitation have reduced yields in Iran and Turkey. Fontana et al. (2015) found that higher temperatures and lower rainfall negatively impacted wheat phenology and grain yield in the Mediterranean Basin. Khosravi et al. (2024) reported a 10.8% rise in water consumption for wheat cultivation in Iran due to warming.

Egypt faces challenges from heat waves and droughts, with heat stress during critical growth stages reducing yields. Sallam et al. (2021) emphasized the need for heat-tolerant genotypes. Water scarcity, worsened by climate change, adds to cultivation difficulties. The USDA noted Turkey, producing 45% of the Middle East's wheat, is forecasted to see production declines in 2024/25 due to dry conditions.

Beyond yield reductions, climate change intensifies water scarcity, soil degradation, and pest issues, threatening agricultural resilience. Declining wheat production affects food security, livelihoods, and rural economies. Between 1991 and 2004, Syria achieved self-sufficiency and export capability through high-yield varieties and policies, but these gains are at risk if climate change persists.

B. Methodologies

Research on climate change impacts on Middle East wheat production employs diverse methodologies, ranging from empirical data collection to advanced modelling. These approaches provide critical insights into agricultural challenges.

Data collection includes primary and secondary sources. Primary data involve field experiments monitoring temperature, soil moisture, and crop growth. Controlled environment studies assess wheat's physiological responses to heat stress. Secondary sources, such as meteorological records and agricultural databases, support trend analysis. Remote sensing, particularly NDVI, is crucial for monitoring crop health. Elmetwalli et al. (2022) demonstrated NDVI's effectiveness in identifying water-scarce areas in Egypt, aiding targeted irrigation.

Statistical modeling quantifies climate-wheat yield relationships. Regression and time series analyses identify key correlations, while spatial econometric models account for regional variations. Crop simulation models like DSSAT and APSIM predict wheat growth under climate scenarios. Gameh et al. (2020) validated DSSAT-CERES-Wheat for simulating yield under varying irrigation and nitrogen applications in Upper Egypt.

AI and ML increasingly enhance yield predictions, handling complex, non-linear relationships. Neural networks, random forests, and support vector machines process vast datasets, uncovering patterns beyond traditional methods. Omid et al. (2010) applied artificial neural networks to model energy use and greenhouse gas emissions in Iranian wheat production. Liu et al. (2023) showed ensemble ML models improve prediction accuracy, while Ghasemi et al. (2023) highlighted AI's integration with Sentinel-2 data for precision agriculture.

Combining empirical data, modelling, and AI enhances understanding of climate change's effects on wheat production, supporting targeted adaptation strategies to improve agricultural resilience.

C. Theoretical Frameworks

Analysing climate change's impacts on Middle East wheat production requires theoretical frameworks that assess vulnerability, resilience, and adaptation in agriculture.

1) ***Vulnerability Framework:*** The Vulnerability Framework evaluates susceptibility to climate stress through three components: exposure (climatic variations like droughts), sensitivity (crop response based on factors like soil fertility), and adaptive capacity (adjustment through innovation, infrastructure, and policy). Adger et al. (2006) emphasized enhancing adaptive capacity to mitigate wheat production losses.

2) ***Socio-Ecological Systems:*** The Socio-Ecological Systems Theory views agriculture as a dynamic interaction between ecological and social components. Human decisions on farming, land use, and resource management shape resilience. Folke et al. (2010) highlighted resilience as the system's ability to absorb disturbances, self-organize, and adapt to change.

3) ***Environmental Justice Framework:*** The Environmental Justice Framework examines the unequal burden of climate change on vulnerable populations, such as smallholder farmers. Schlosberg and Collins (2014) argued that inclusive policymaking ensures fair resource distribution and adaptation planning.

4) ***Political Ecology:*** The Political Ecology Perspective explores power structures affecting resource access, such as water and arable land, crucial for wheat cultivation. Watts (2000) discussed how historical and political factors create resource inequities, influencing climate adaptation capacity. This perspective highlights the need for systemic changes to reduce agricultural vulnerability.

D. Regional Context

The Middle East's arid and semi-arid climates pose significant challenges to wheat production due to climate change. Rising temperatures, declining precipitation, and extreme weather events like heatwaves and droughts have reduced yields. In Egypt, heat stress during key growth stages leads to major yield losses, while water scarcity worsens cultivation challenges. The USDA (2024) reported that Turkey, which produces 45% of the region's wheat, is expected to see production declines in 2024/25 due to drier-than-normal conditions.

Beyond yield losses, climate change intensifies water scarcity, soil degradation, and pest infestations, threatening agricultural resilience. Food security and rural economies are also impacted. Between 1991 and 2004, Syria achieved wheat self-sufficiency through high-yield varieties and policies, but these gains are now at risk.

In Iran, wheat constitutes 67% of crop production. Simulations in Mazandaran and Khuzestan predict yield reductions of 7–45% due to rising temperatures and 7–54% from reduced precipitation (Khosravi et al., 2021). Syria, facing prolonged droughts and unsustainable water use, has shifted from self-sufficiency to wheat imports, impacting food security and economic stability (Kelley et al., 2015).

Addressing these challenges requires adaptive strategies, including sustainable water management, heat- and drought-resistant wheat varieties, and advanced agricultural technologies to enhance resilience and food security in the region.

E. Adaptation Strategies

Developing climate-resilient wheat varieties is crucial for mitigating yield losses from heat and drought stress. Advances in genetic research, including sequencing 827 wheat varieties from a century ago, provide resources for breeding hardier, high-yield strains (The Guardian, 2024).

Precision agriculture technologies, such as remote sensing and GIS, enhance crop monitoring, optimizing irrigation and nutrient management to counter climate variability. Sustainable farming techniques like conservation agriculture—minimal tillage, crop rotation, and residue retention—improve soil quality, water retention, and erosion control, ensuring long-term productivity.

Adjusting sowing dates helps avoid heat stress during critical growth stages, reducing yield losses (Heydari and Taran, 2025). Governments support adaptation through subsidies for efficient irrigation systems, such as drip irrigation, and investments in early warning systems for extreme weather.

Regional collaboration in water management is vital, as transboundary rivers like the Nile, Tigris, and Euphrates require cooperative strategies. Water-sharing agreements, desalination, and recycling technologies are being explored to sustain wheat farming amid freshwater scarcity.

Local community involvement is essential. Climate-smart agriculture programs educate farmers on adaptive strategies, while farmer-led seed banks for drought-resistant wheat enhance resilience. Financial mechanisms, including climate insurance and credit schemes, provide smallholder farmers with stability to invest in sustainable practices, ensuring wheat production sustainability.

F. Machine Learning Integration

The integration of machine learning (ML) techniques into agricultural research has significantly advanced the prediction of precipitation, temperature, and crop growth. These developments are crucial for enhancing food security and optimizing farming practices.

*1) **Machine Learning in Meteorological Predictions:*** ML models have been increasingly applied to forecast weather parameters such as precipitation and temperature, which are critical for agricultural planning. Traditional numerical weather prediction methods are now being complemented by ML approaches, including deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. These models have demonstrated potential in improving weather forecasts by learning complex patterns from historical data. For instance, Weyn et al. (2020) utilized deep CNNs to predict atmospheric variables, achieving comparable accuracy to traditional physics-based models for short-term forecasts.

*2) **Crop Yield Prediction Using Machine Learning:*** Predicting crop yields involves analyzing various factors, including weather conditions, soil properties, and crop management practices. Machine learning (ML) algorithms such as Random Forests, Support Vector Machines (SVM), and Neural Networks have been employed to model these complex relationships. Lischeid et al. (2022) demonstrated the effectiveness of ML approaches in identifying key climatic and soil hydrological drivers influencing crop yield variability over four decades in Germany. Their study highlighted the ability of ML models to capture a significant portion of spatial and temporal yield variance while emphasizing the importance of expert judgment in selecting the most reliable models. Moreover, their findings underscored the critical role of meteorological factors over soil moisture and the need to address excess precipitation and heat stress in future crop modeling and breeding efforts.

Deep learning approaches, particularly LSTM and CNN models, have shown promise in capturing temporal and spatial dependencies in data, leading to improved accuracy in yield predictions. A study by Jiang et al. (2023) demonstrated the effectiveness of CNN networks in predicting county-level maize yields by integrating weather and soil data.

A broader analysis of ML applications in crop yield prediction was conducted by van Klompenburg et al. (2020), who performed a systematic literature review of 50 ML-based studies and 30 deep learning-based studies. Their findings revealed that temperature, rainfall, and soil type were the most frequently used predictors, with artificial neural networks (ANNs) being the most widely applied algorithm. Additionally, convolutional neural networks (CNNs) and long short-term memory (LSTM) models emerged as the predominant deep learning approaches in crop yield forecasting. Similarly, Lohitha Reddy and Siva Kumar (2023) explored various ML techniques, including gradient boosting, decision trees, and random forests, for weather-based crop yield prediction. Their study emphasized the importance of ML-driven decision support tools for optimizing crop selection and improving agricultural planning under changing environmental conditions.

Recent advancements have also explored the integration of ML with process-based crop models to enhance predictive accuracy. Zhuang et al. (2024) proposed a hybrid framework that combines data assimilation techniques with ML models for winter wheat yield forecasting in the North China Plain. Their approach demonstrated significant improvements in forecasting accuracy, achieving an ACC of 0.97 and a MAPE of 1.74% by integrating crop models with ML predictions. This highlights the potential of hybrid approaches that leverage both mechanistic crop models and data-driven ML techniques to improve early-season yield forecasts.

*3) **Remote Sensing Data Integration:*** The fusion of machine learning (ML) techniques with remote sensing data has significantly enhanced agricultural predictions. Satellite imagery provides high-resolution data on land use, vegetation health, and environmental conditions, and by incorporating vegetation indices like the Normalized Difference Vegetation Index (NDVI), ML models can more accurately predict crop growth and yields. Kamilaris and Prenafeta-Boldú (2018) found that combining remote sensing with deep learning improves crop yield prediction performance. Recent studies further demonstrate this synergy. Ma et al. (2024) used ML models, including artificial neural networks (ANN), support vector machines (SVM), and extreme gradient boosting (XGBoost), to forecast summer precipitation in Xinjiang, China, showing that integrating satellite-based climate data improves anomaly detection and optimizes irrigation. Kumar et al. (2024) applied convolutional LSTM models for near real-time rainfall forecasting, demonstrating superior performance over conventional methods for drought monitoring. Espeholt et al. (2022) introduced a deep learning-based neural weather model for short-term precipitation prediction, highlighting its benefits for precision agriculture. Remote sensing and ML also improve long-term climate predictions, as shown by El Hafyani et al. (2024), who used a multi-view stacking learning approach combining decision trees, random forests, and LSTM for monthly precipitation forecasting. Wani et al. (2024) demonstrated that deep learning models like bi-directional LSTM and GRU outperformed traditional methods for rainfall forecasting in the North-Western Himalayas, emphasizing their value in mountainous regions. Additionally, Kumar et al. (2023) found that ensemble-based algorithms like CatBoost and XGBoost outperformed linear models for rainfall prediction in urban areas, reinforcing the importance of combining meteorological and remote sensing data for improved accuracy in climate modeling and crop yield estimation.

*4) **Environmental Justice Framework:*** The Environmental Justice Framework examines the unequal burden of climate change on vulnerable populations, such as smallholder farmers. Schlosberg and Collins (2014) argued that inclusive policymaking ensures fair resource distribution and adaptation planning.

*5) **Political Ecology:*** The Political Ecology Perspective explores power structures affecting resource access, such as water and arable land, crucial for wheat cultivation. Watts (2000) discussed how historical and political factors create resource inequities, influencing climate adaptation capacity. This perspective highlights the need for systemic changes to reduce agricultural vulnerability.

III. METHODOLOGY

A. Research Design

*1) **Study Type:*** To explore the possible effects of climate change on wheat production and food security in the Middle East, this study uses a quantitative research approach that combines historical data analysis and AI modelling tools..

*2) **Population and Sampling:*** In Egypt, Turkey, and Iran, wheat farmers, consumers, and policymakers make up the population of interest. For study, historical national data on precipitation, wheat production, temperature data will be gathered. Forecasts for the future will cover the whole region.

*3) **Variables of Interest:*** The Political Ecology Perspective explores power structures affecting resource access, such as water and arable land, crucial for wheat cultivation. Watts (2000) discussed how historical and political factors create resource inequities, influencing climate adaptation capacity. This perspective highlights the need for systemic changes to reduce agricultural vulnerability.

*4) **Data Collection and Methods:*** Research papers, meteorological agencies, and national agricultural statistics databases will be the sources of historical data. Statistical tools will be used to compile and analyse the data. AI algorithms trained on historical data and climate projections will be used to make future predictions.

*5) **Data Analysis Techniques:*** Historical trends and connections between wheat production, climate variables, and food security indicators will be examined by statistical analysis. Future forecasts will be made by AI models using historical data and climatic projections.

*6) **Ethical Considerations:*** Ethical considerations will be dealt with by ensuring that all data used in the study are obtained from reputable sources and that proper attribution is provided. Any possible conflicts of interest will be disclosed, and the study is committed to principles of research ethics, including informed consent, confidentiality, and protection of participants' rights.

B. Data Collection

*1) **Historical Data Collection:*** The past data on wheat production, consumption, temperature, rainfall, and socio-economic indicators will be gathered from reputable sources, including comprehensive national agricultural databases maintained by government agencies in Egypt, Turkey, and Iran, which track agricultural output and consumption, including wheat. Historical climate data, such as temperature and rainfall records, will be collected from meteorological organizations in each country, while additional insights into historical patterns and trends will be sourced from peer-reviewed journals and research publications. Data spanning from 1961 to 2024 will be used to assess long-term trends and correlations.

*2) **Machine Learning Models for Forecasting Wheat Production, Climate Trends, and Population Growth:*** To forecast wheat production, climate variables (temperature & precipitation), and population growth, various machine learning models will be employed, each tailored to the specific nature of the prediction task. Long Short-Term Memory (LSTM) Networks will be used for sequential predictions of temperature, precipitation, and population growth, as they excel at capturing long-term dependencies in time-series data. Transformer-Based Models will be applied for precipitation forecasting, leveraging multi-head attention mechanisms to handle complex dependencies, while Random Forest Regression, a tree-based ensemble method, will model wheat production trends based on multiple interacting factors. Support Vector Machines (SVM) will assist in regression tasks, capturing non-linear relationships in wheat yield prediction. A Voting Ensemble Model, combining classifiers and regressors such as Random Forest, SVM, and Neural Networks, will improve robustness and accuracy, while Multi-Layer Perceptron (MLP) Neural Networks will be used for predicting wheat production and population growth, handling high-dimensional input data. The models will be trained using 80% of the historical dataset and tested on the remaining 20% to ensure accuracy, with 10-fold cross-validation applied to prevent overfitting and enhance reliability. Data preprocessing steps include feature scaling (Standard Scaler for numerical data), lag feature engineering, and one-hot encoding of categorical variables where necessary. Model performance will be evaluated using metrics such as R^2 Score to measure the explained variability, Root Mean Squared Error (RMSE) for prediction error magnitude, and Mean Absolute Error (MAE) for average absolute deviation from actual values.

*3) **Remote Sensing Analysis:*** The past data on wheat production, consumption, temperature, rainfall, and socio-economic indicators will be gathered from reputable sources, including comprehensive national agricultural databases maintained by government agencies in Egypt, Turkey, and Iran, which track agricultural output and consumption, including wheat. Historical climate data, such as temperature and rainfall records, will be collected from meteorological organizations in each country, while additional insights into historical patterns and trends will be sourced from peer-reviewed journals and research publications. Data spanning from 1961 to 2024 will be used to assess long-term trends and correlations.

C. Assumptions and Limitations

It is assumed that historical data on climate and wheat pro- duction accurately reflects long-term trends and that future climate scenarios (RCPs) provide reasonable estimates of future conditions. The study is limited by the availability of granular, localized data. National data might overlook regional variations, which could lead to overgeneralizations. While machine learning models offer great predictive power, their accuracy depends on the quality of the input data. If climate projections are flawed, the models' results may also be affected.

IV. EXPERIMENT

This section details the analysis conducted to uncover how climate factors like temperature and precipitation have influenced wheat production and consumption in Egypt, Turkey, and Iran.

Using historical data and predictive models, we explored the trends and forecasted future outcomes under changing climatic conditions.

A. Dataset

The study relied on several trusted sources for data col- lection:

1) ***Agricultural Statistics:*** Data on wheat production and consumption were obtained from national agricultural re- ports for Egypt, Turkey, and Iran.

2) ***Climate Data:*** Temperature and precipitation records were sourced from meteorological agencies, covering the years 1961–2021.

3) ***Population Growth:*** Historical and projected population data were included to assess how rising demand impacts wheat consumption.

This dataset spans over 60 years, providing a comprehensive foundation to study historical patterns and predict future scenarios.

B. Tools and Techniques

We used a range of tools to process and analyse the data:

-Python Libraries: Pandas and NumPy for data analysis, Matplotlib and Seaborn for visualization.

-AI Models: Random Forests, Neural Networks, and SVM were employed for making predictions about wheat production and climate trends.

C. Approach

1) ***Historical Analysis:*** First, we looked back at the data to understand how wheat production, consumption, and population growth have evolved alongside climate variables. We used Python and machine learning techniques on the obtained datasets to generate the plots.

2) ***Wheat Production and Consumption:*** We plotted wheat production and consumption over time to see how they have shifted across the three countries. Fluctuations clearly corresponded to changes in climate variables.

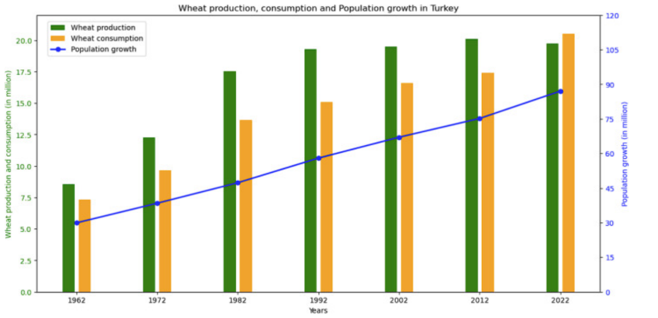

Figure 1. Wheat production, consumption and population growth in Turkey

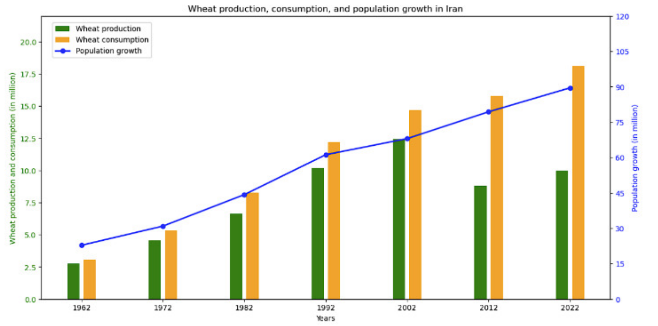

Figure 2. Wheat production, consumption and population growth in Iran.

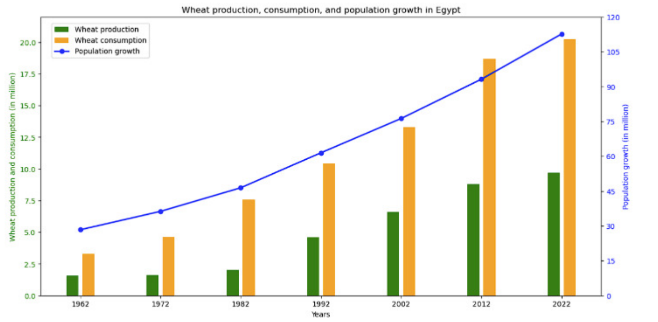

Figure 3. Wheat production, consumption and population growth in Egypt.

3) ***Temperature and Precipitation:*** A clear upward trend in temperatures and a downward trend in precipitation were observed, signalling worsening conditions for wheat farming (Figure 4, Figure 5, Figure 6).

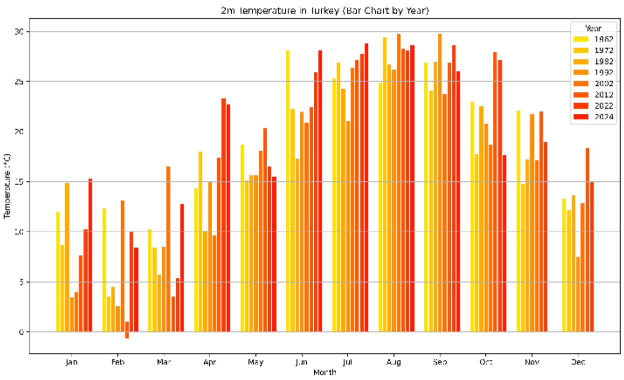

Figure 4: 2m temperature in Turkey for previous years.

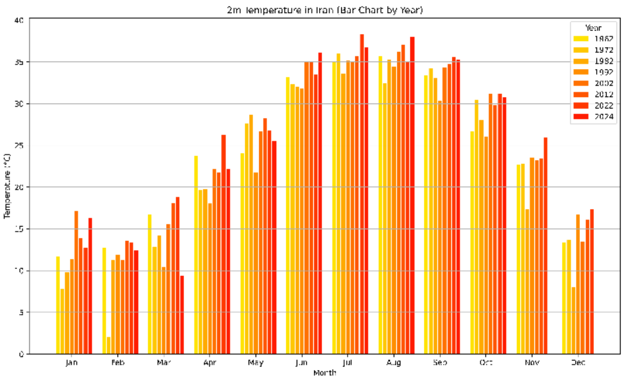

Figure 5: 2m temperature in Iran for previous years.

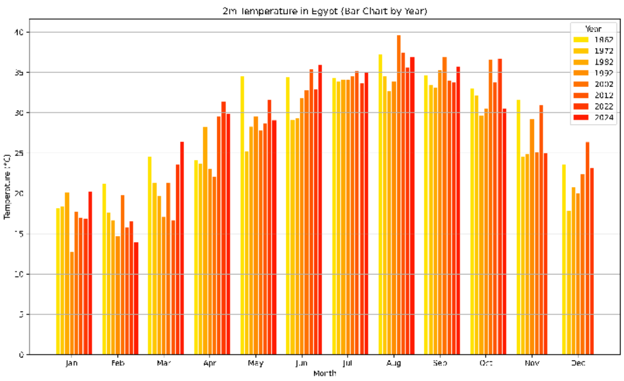

Figure 6: 2m temperature in Egypt for previous years.

Figure 7-9 depict the monthly average precipitation trends in Turkey, Iran, and Egypt across different time periods: 1901-1930, 1931-1960, 1961-1990, and 1991-2020.

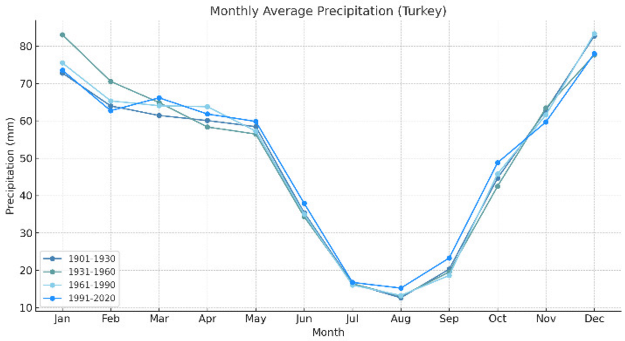

Figure 7 Monthly average precipitation in Turkey for previous years.

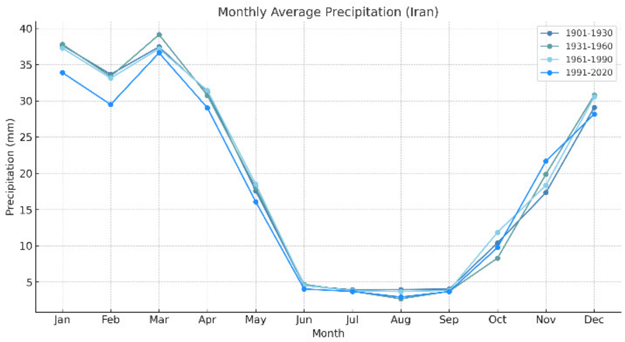

Figure 8 Monthly average precipitation in IRAN for previous years.

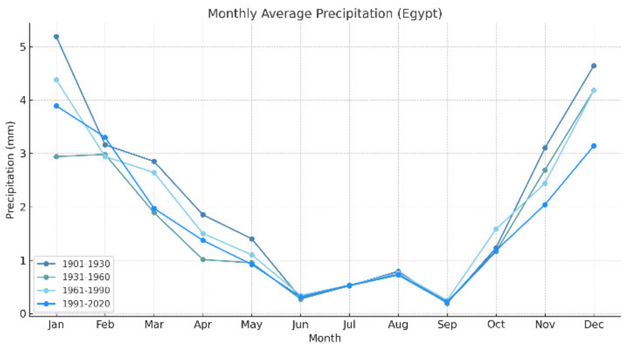

Figure 9 Monthly average precipitation in EGYPT for previous years.

In Turkey, the precipitation follows a bimodal pattern, peaking in winter between December and February and declining significantly from May to August, indicating a dry summer period. The lowest precipitation levels occur in July and August, while rainfall starts increasing again from September onward. Over time, there is a slight decrease in precipitation during the winter months in recent decades, while the summer drought period remains consistently dry across all time periods. Although the overall pattern has remained stable, the slight reduction in winter precipitation could have significant implications for water availability and agricultural productivity in the region (Figure 7).

In Iran, precipitation shows a sharp decline from March to August, reaching almost zero rainfall between June and August. The rainy season begins in September, with peak precipitation occurring between December and March. Over the decades, the overall rainfall patterns have remained largely consistent, with minor variations in peak precipitation levels. However, the rainy season from December to March appears slightly weaker in the most recent period, 1991-2020, compared to earlier decades. A declining trend in peak precipitation could indicate increasing aridity, which may affect water resources and agricultural sustainability, particularly in regions that rely on winter precipitation for irrigation (Figure 8).

Egypt exhibits an arid climate with very low precipitation throughout the year. There is a gradual decrease in rainfall from January to June, with near-zero precipitation from May to September, followed by a slight increase from October to December. While the overall precipitation levels are already minimal, a further decline is observed in recent decades, particularly in the first half of the year from January to May. Given Egypt's reliance on the Nile River and minimal local rainfall, any further decrease in precipitation could exacerbate existing water scarcity challenges, making the country even more vulnerable to climate change (Figure 9).

D. In-depth Precipitation Analysis

While various factors such as temperature, wheat consumption, and population growth influence agricultural production, precipitation remains the most critical determinant of crop growth. Among these variables, precipitation directly affects soil moisture availability, influencing germination, plant development, and overall yield. Given its fundamental role in sustaining wheat production, this study conducts an in-depth analysis of precipitation trends, variability, and potential long-term changes. By leveraging advanced analytical techniques, we aim to uncover patterns that may indicate shifts in climate conditions and assess their implications for future agricultural sustainability. Understanding these precipitation dynamics is crucial for developing adaptive strategies to mitigate risks associated with changing rainfall patterns and ensuring food security in the studied regions.

Accordingly, we downloaded precipitation data for Iran, Turkey and Egypt from 1961 to 2024. We further downloaded daily precipitation data for the three regions from 2020-2024. A series of analyses were conducted on these datasets and the prediction model was trained.

V. RESULTS AND DISCUSSION

A. Decadal and Climate Policy Influences on Monthly Precipitation Trends in Iran, Egypt and Turkey

This analysis explores changes in monthly precipitation across decades in Iran, Egypt, and Turkey, assessing potential climate policy influences. The first set of plots shows long-term trends by decade, while the second examines shifts linked to climate regulations.

Over the decades, Iran, Egypt, and Turkey have experienced a consistent decline in precipitation, particularly during critical rainy months. In Iran, precipitation levels have gradually decreased, especially from January to April, with the 1960s and 1970s experiencing higher peak rainfall in March and April (Figure 10).

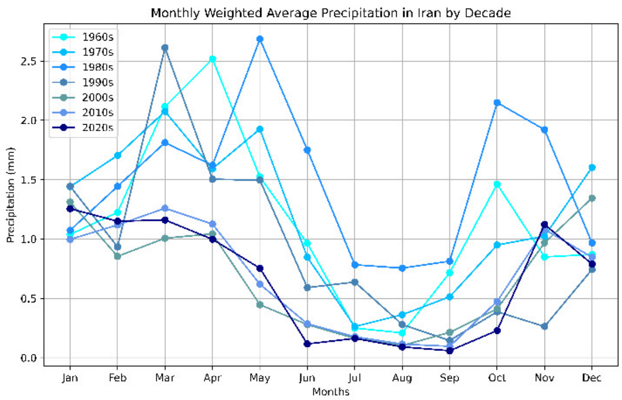

Figure 10: Monthly Weighted Average Precipitation in Iran by Decade

In recent decades, this trend has reversed, with post-2000 precipitation levels significantly lower than pre-1990 levels. Despite maintaining a dry summer period from June to September, the overall decline suggests the influence of climate change, increased desertification, and shifts in atmospheric circulation (Figure 11).

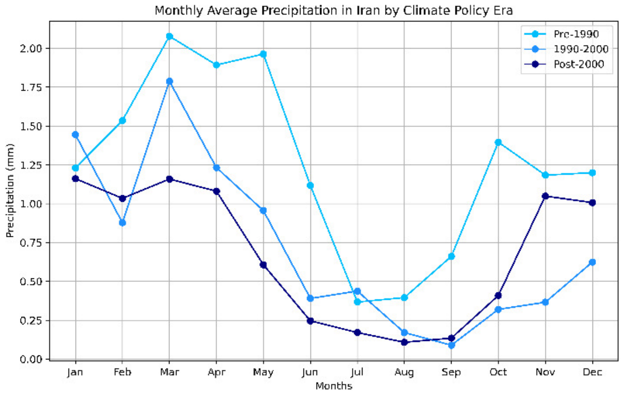

Figure 11: Monthly Average Precipitation in Iran by Climate Policy Era

Egypt, an arid region with minimal precipitation, exhibits a more pronounced decline. While the 1960s and 1970s saw higher rainfall in January and February, recent decades have witnessed a sharp reduction, with near-zero precipitation from April to September.

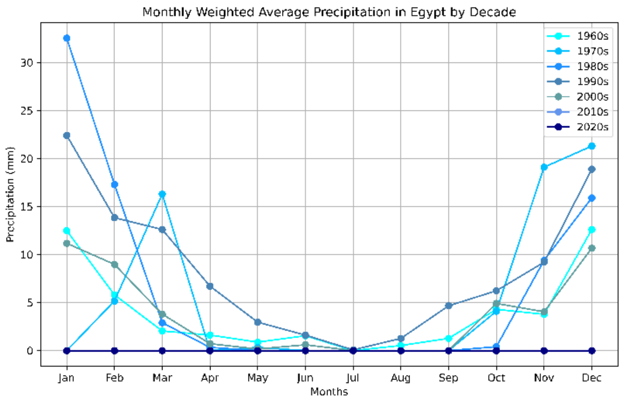

Figure 12: Monthly Weighted Average Precipitation in Egypt by Decade

The post-2000 period shows consistently lower precipitation levels compared to earlier decades, exacerbating Egypt's already critical water scarcity and increasing dependence on external sources such as the Nile River (Figure 12).

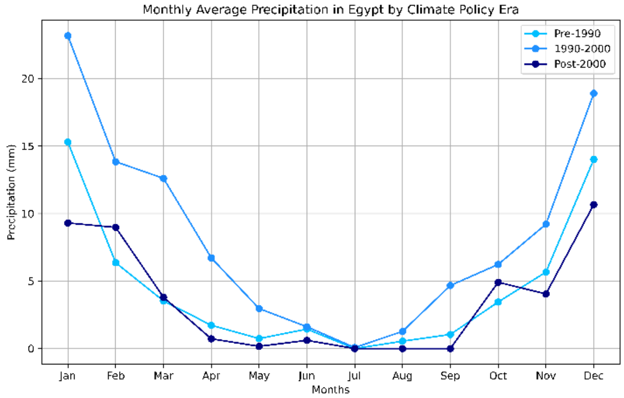

Figure 13: Monthly Average Precipitation in Egypt by Climate Policy Era

Turkey, which generally receives more precipitation than Iran and Egypt, has also shown noticeable declines over time. While the country maintains a bimodal precipitation pattern with a dry summer, winter peaks observed in earlier decades have flattened in the 2020s, particularly in December, January, and February.

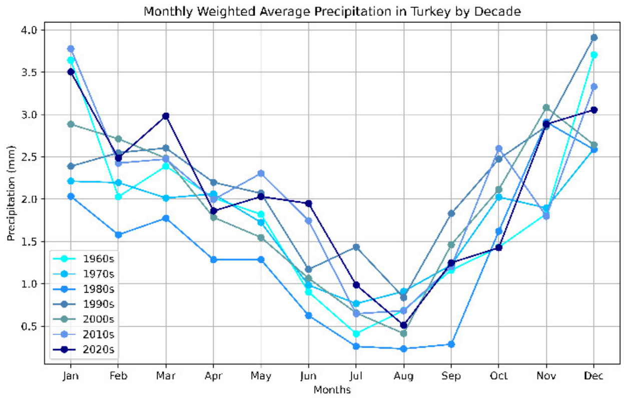

Figure 14: Monthly Weighted Average Precipitation in Turkey by Decade

Post-2000 precipitation levels are lower than in previous eras, posing risks for Turkish agriculture, especially in regions reliant on consistent winter rainfall for crop growth.

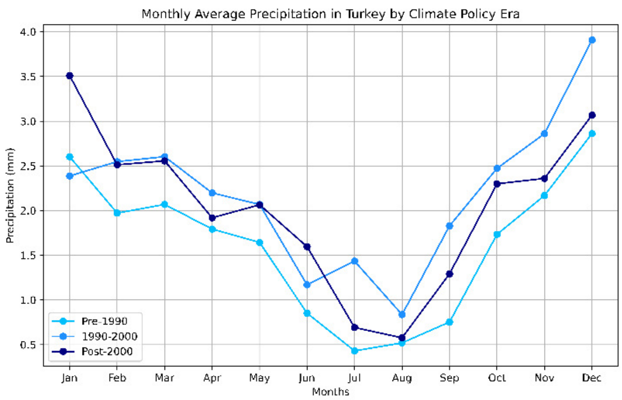

Figure 15: Monthly Weighted Average Precipitation in Turkey by Climate Policy Era

Comparing the three countries, the overall downward trend in precipitation is evident, aligning with global climate change patterns and the potential impact of climate policies. The decline is most severe in Egypt, where water scarcity is already a major challenge, while Iran and Turkey also show reductions that could affect agriculture and water availability.

B. Comparative Analysis of Long-Term Precipitation Trends in Iran, Egypt and Turkey (1901-2024)

To understand the overall precipitation variations among the three countries, a boxplot comparison was conducted.

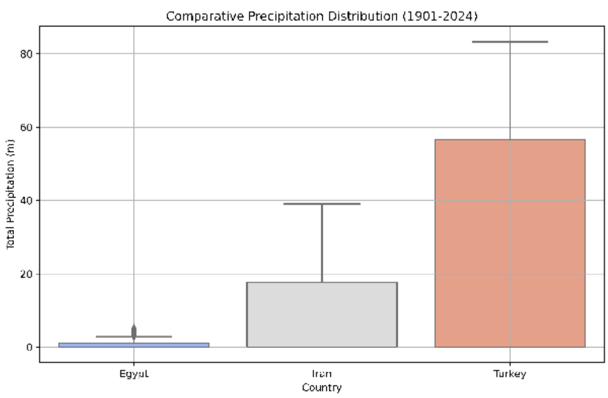

Figure 16: Comparative Precipitation Boxplot 1901-2024

The results indicate that Turkey receives significantly higher precipitation compared to Iran and Egypt, with Egypt exhibiting extremely low rainfall levels throughout the observed period. Iran shows intermediate variability, but its precipitation is significantly lower than Turkey's, reinforcing concerns about growing aridity in the region (Figure 16).

A comprehensive analysis of precipitation trends over the past century reveals a persistent decline across all three countries.

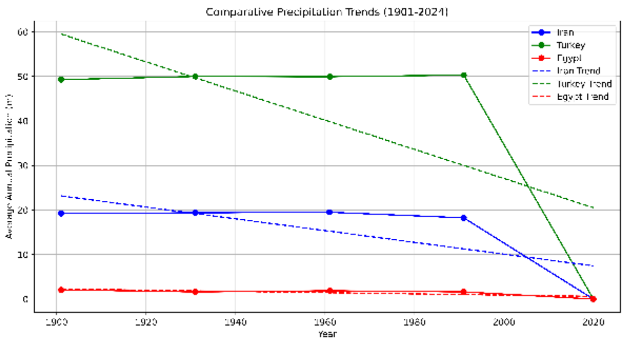

Figure 17: Comparative Precipitation Trend 1901-2024

The trend lines indicate that while Turkey historically had the highest precipitation, it has experienced a substantial decline, particularly in recent decades. Similarly, Iran's precipitation levels have gradually decreased, while Egypt's rainfall has remained consistently low, with further reductions in recent years (Figure 17).

A breakdown of precipitation trends by country further highlights the rate of decline and variability in rainfall distribution. The declining trend is most pronounced in Turkey, followed by Iran, while Egypt's already minimal precipitation has continued to decrease, exacerbating concerns about water scarcity (Figure 18).

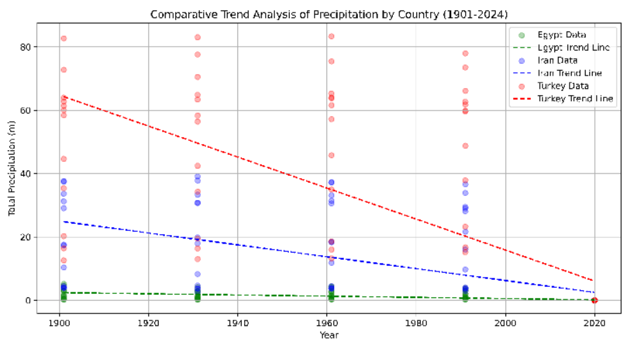

Figure 18: Comparative Precipitation Trend by Country

A more focused analysis of precipitation trends over the last five years suggests continued variability and potential short-term fluctuations.

Results indicate that while Turkey and Iran exhibit fluctuations, Egypt's precipitation levels remain critically low. The trend lines indicate a declining trajectory for Iran, whereas Turkey has shown some short-term fluctuations. These variations suggest that climate variability continues to impact precipitation patterns, necessitating further research into seasonal anomalies and extreme weather events (Figure 19).

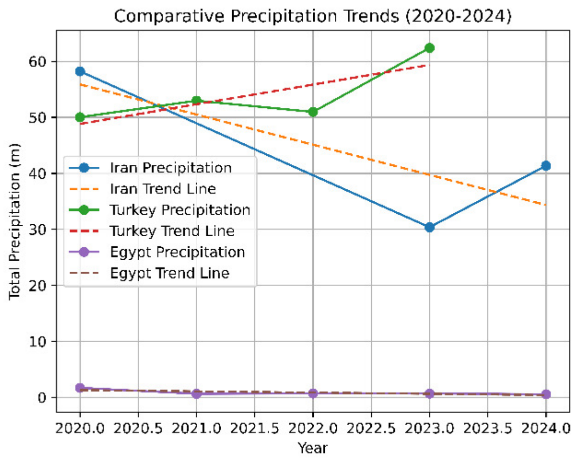

Figure 19: Comparative Precipitation Trends (2020-2024)

To further refine the long-term analysis of precipitation trends, a non-linear regression approach was applied to precipitation data for Egypt, Iran, and Turkey. The fitted models—quadratic, cubic, and LOESS—help capture potential fluctuations and deviations from a strictly linear trend. The findings reinforce the persistent decline in precipitation across all three countries while highlighting distinct temporal variations.

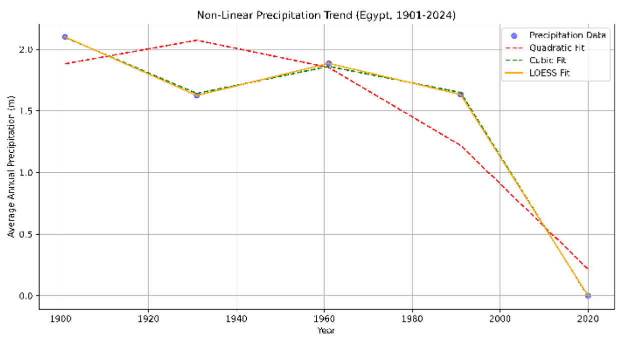

Figure 20: Non-Linear Precipitation Trend in Egypt from 1901 to 2024

In Egypt, precipitation followed a gradual decline since the early 20th century, with a minor mid-century increase before a sharp drop after the 1980s, as captured by the LOESS and cubic fits, reinforcing concerns about long-term water scarcity (Figure 20).

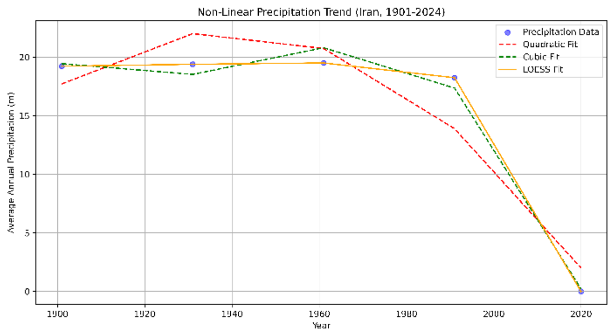

Figure 21: Non-Linear Precipitation Trend in Iran from 1901 to 2024

Iran exhibited a relatively stable precipitation pattern until the mid-20th century, after which a marked decline was observed, with the cubic and LOESS fits capturing this shift, while the quadratic fit projected an unrealistic increase (Figure 21). Similarly, Turkey maintained relatively high precipitation levels for much of the 20th century before experiencing a sharp reduction from the late 20th century onwards, with the steepest recent decline among the three countries (Figure 22).

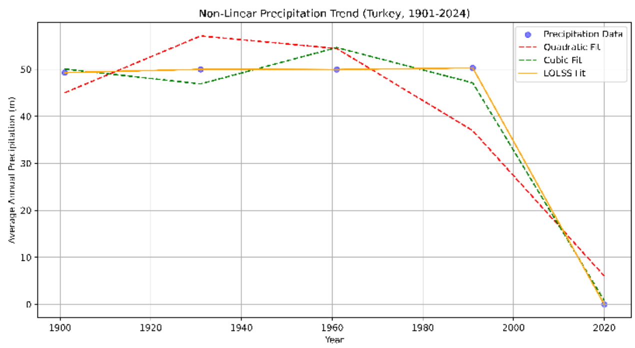

Figure 22: Non-Linear Precipitation Trend in Turkey from 1901 to 2024

While the LOESS and cubic models captured these patterns accurately, the quadratic fits in all three cases deviated from the observed trends.

C. In-depth Analysis of Daily Precipitation Data from 2020-2024

A closer look and a deep analysis of recent data from 2020-2024 will be helpful to further understand the impact of climate change in Iran, Turkey and Egypt. For this particular analysis, daily precipitation data from 2020-2024 (5 years) were chosen. The data of this timeframe will play a significant role in the development and prediction of our machine learning model.

1) Precipitation Trends from 2020-2024:

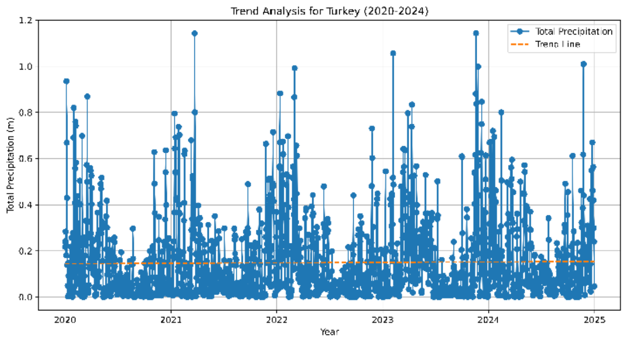

Figure 23: Precipitation Trend Analysis for Turkey (2020-2024)

The precipitation trend in Turkey exhibits high variability with frequent extreme precipitation events. The data points suggest a consistent seasonal cycle with peaks corresponding to wetter months. The trend line remains relatively stable, indicating no significant increasing or decreasing pattern over time (Figure 23). Iran's precipitation pattern also exhibits variability but shows slightly fewer extreme precipitation events compared to Turkey. The trend line indicates a slight upward shift, suggesting a possible increase in average precipitation over time. There are noticeable periods of low precipitation, possibly indicating dry seasons (Figure 24). Egypt has the lowest overall precipitation among the three countries, with occasional spikes. The precipitation events are sparse, which aligns with the arid climate of the region. The trend line remains nearly flat, indicating no significant change in precipitation trends over the observed period (Figure 25).

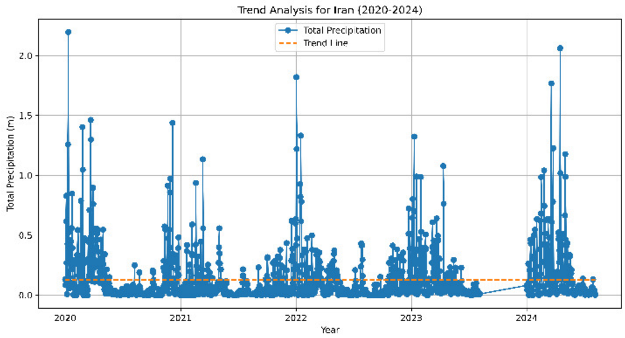

Figure 24: Precipitation Trend Analysis for Iran (2020-2024)

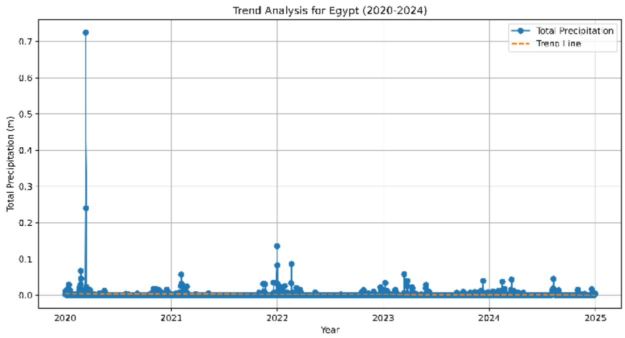

Figure 25: Precipitation Trend Analysis for Egypt (2020-2024)

Turkey and Iran exhibit more frequent and intense precipitation events, whereas Egypt experiences minimal rainfall. The increasing trend in Iran may indicate changing weather patterns, possibly linked to shifting climate dynamics. The absence of a clear increasing or decreasing trend in Turkey and Egypt suggests stable but region-specific climatic influences.

D. Spatial Analysis

Understanding the spatial distribution of precipitation is crucial for assessing climate trends, water resource availability, and agricultural planning. This section examines the geographical variation in precipitation across Turkey, Iran, and Egypt over the period 2020 to 2024. By analyzing the relationship between precipitation and geographical coordinates, along with quantile-quantile (Q-Q) plots, contour maps, and heatmaps, this study aims to highlight regional disparities and identify key precipitation hotspots.

In Turkey, precipitation is unevenly distributed, with significant accumulation in the northern and coastal regions. The scatter plot illustrating precipitation against latitude and longitude shows a distinct pattern where higher precipitation levels are concentrated between 37°–42° latitude and 30°–45° longitude (Figure 26).

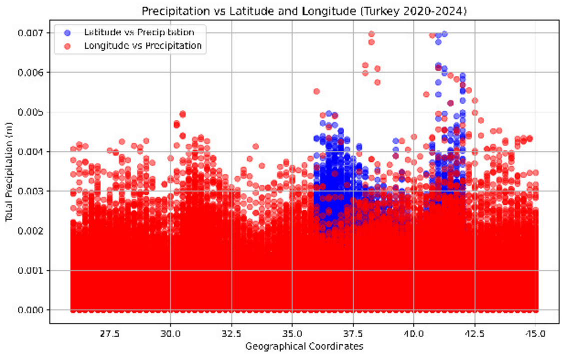

Figure 26: Turkey – Precipitation vs Coordinates

This trend corresponds to the northern regions and the Black Sea coast, which experience higher rainfall due to their proximity to moist air masses from the sea. The Q-Q plot further emphasizes this trend by revealing a heavy-tailed distribution, indicating the occurrence of extreme precipitation events (Figure 27). This suggests that while many areas receive moderate rainfall, there are sporadic but intense rainfall episodes, likely linked to seasonal storms. The contour and heatmap visualizations reinforce these findings, highlighting that the highest precipitation levels occur in the northern regions, with a sharp decline towards central and southern Turkey (Figure 28, Figure 29).

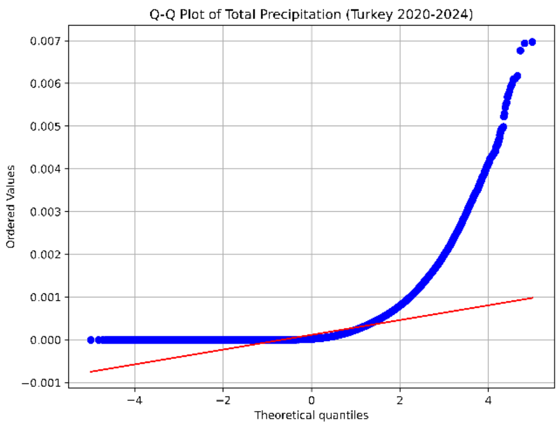

Figure 27: Turkey - QQ Plot

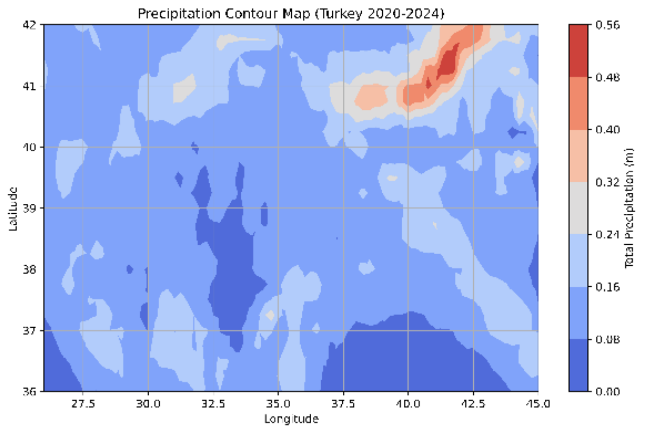

Figure 28: Turkey - Precipitation Contour Map

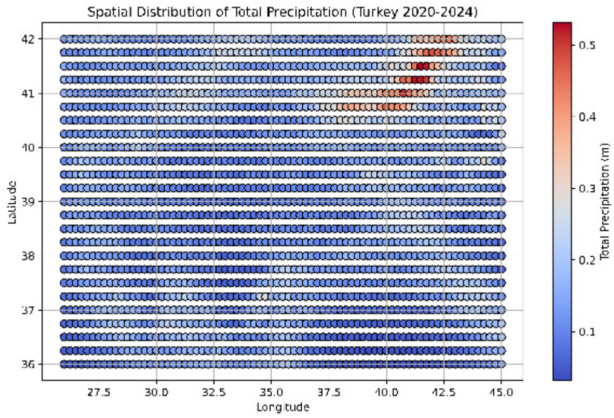

Figure 29: Turkey - Spatial Distribution of Total Precipitation

Iran exhibits a more varied precipitation pattern, heavily influenced by its topography. The scatter plot of precipitation against geographical coordinates shows that precipitation is concentrated in northwestern and northern regions, while central and southeastern areas remain largely arid (Figure 30).

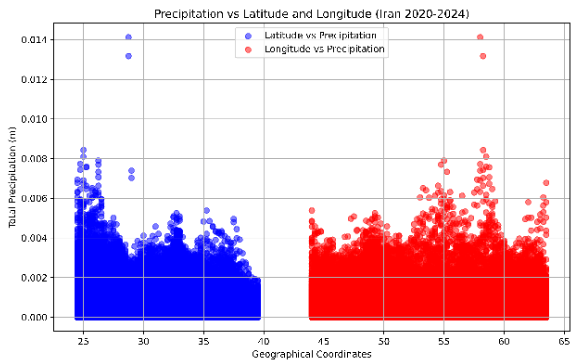

Figure 30: Iran - Precipitation vs Coordinates

The Q-Q plot indicates a positively skewed distribution, suggesting that most of the precipitation is confined to a few wet locations, with extreme values representing rare but significant rainfall events (Figure 31).

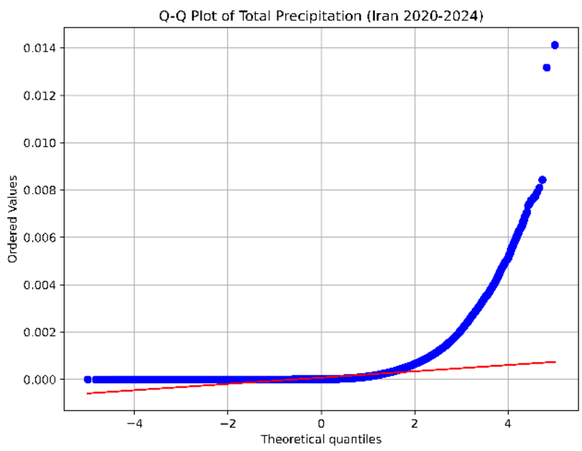

Figure 31: Iran - QQ Plot

The spatial contour and heatmap analyses reveal higher precipitation levels in the northwestern mountain ranges and along the Caspian Sea, where orographic effects enhance rainfall (Figure 32, Figure 33). However, much of central and southeastern Iran remains dry, reinforcing the country's water scarcity challenges.

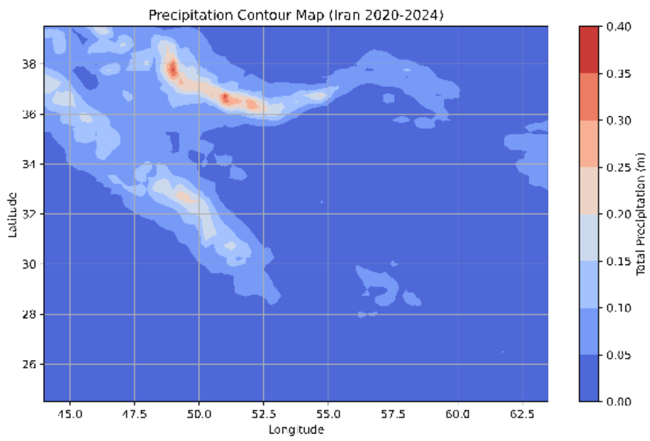

Figure 32: Iran - Precipitation Contour Map

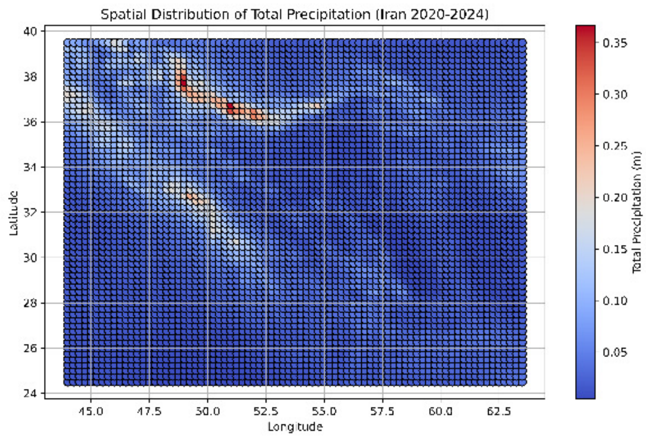

Figure 33: Iran - Spatial Distribution of Total Precipitation

Egypt, being predominantly arid, exhibits a distinct precipitation pattern. The scatter plot of precipitation versus latitude indicates a clear trend where rainfall is concentrated along the northern Mediterranean coast, while most inland areas receive negligible precipitation (Figure 34).

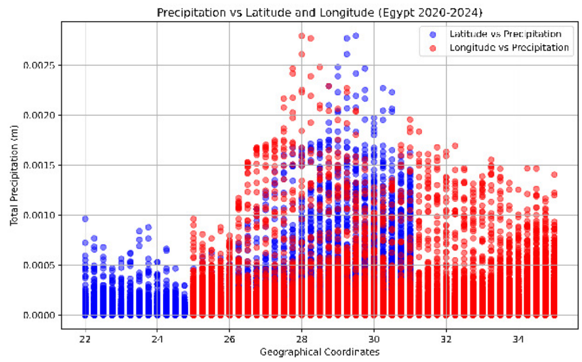

Figure 34: Egypt - Precipitation vs Coordinates

Longitude, in contrast, has a minimal effect, as precipitation patterns are fairly uniform from east to west. The Q-Q plot highlights that most precipitation values are close to zero, with only a few outliers representing occasional rainfall events (Figure 35).

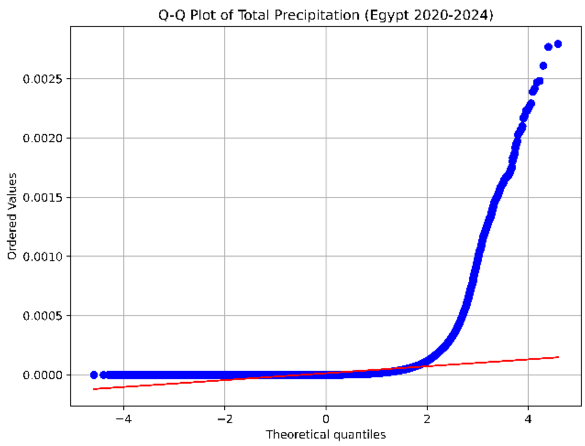

Figure 35: Egypt - QQ Plot

The spatial contour and heatmap visualizations confirm that almost all precipitation occurs along the Mediterranean coastline, with virtually no measurable rainfall in central and southern Egypt (Figures Egypt_Spatial_Contour_2020_2024.png and Egypt_Spatial_Heatmap_2020_2024.png). This finding is consistent with Egypt's heavy dependence on the Nile for water resources.

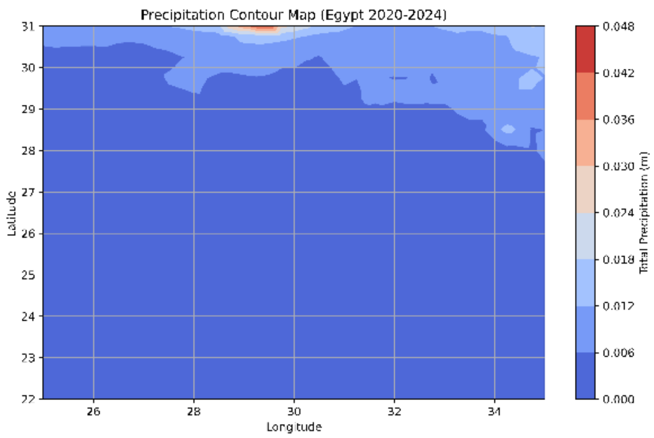

Figure 36: Egypt - Precipitation Contour Map

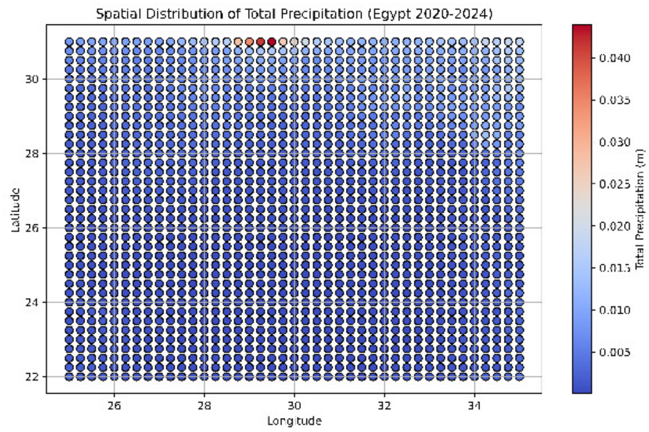

Figure 37: Egypt - Spatial Distribution of Total Precipitation

A comparative analysis of the three countries reveals distinct precipitation characteristics. Turkey has the most evenly distributed precipitation, with northern and coastal areas receiving significant rainfall. Iran exhibits highly localized precipitation, with wetter conditions in the northwest and northeast due to mountainous terrain, while central and southern regions remain arid. Egypt, as expected, experiences minimal precipitation, confined mainly to the northern coastal regions. The Q-Q plots for all three countries indicate heavy-tailed distributions, suggesting that while much of the precipitation falls within expected seasonal patterns, extreme rainfall events occasionally disrupt these trends.

From a climate and water resource perspective, these findings have important implications. In Turkey, the significant precipitation in the north supports agriculture, but extreme events could lead to flood risks, requiring better water management strategies. Iran's heavy precipitation in the northwest, contrasted with its widespread aridity elsewhere, highlights the need for efficient water storage and redistribution infrastructure to balance water availability. Egypt's persistent arid conditions, with little variation, reinforce the country's reliance on the Nile, underscoring the necessity for sustainable water conservation measures.

VI. PREDICTIVE MODELING

The increasing variability in precipitation patterns necessitates the development of robust models capable of forecasting future trends based on historical and spatial data. In this study, we designed a Transformer-based forecasting model that utilizes past precipitation records, temperature and wheat production data, geographical coordinates, and seasonal information to predict future precipitation levels. This section outlines the key steps in data preprocessing, feature engineering, model architecture, and training.

A. Data Preparation and Processing

To ensure a comprehensive analysis, precipitation datasets were compiled for three countries—Iran, Turkey, and Egypt—over the period 2020 to 2024. These datasets, stored in separate CSV files for each country and year, were loaded and merged into a single data frame for uniform processing. The dataset contains key attributes such as precipitation levels (tp), latitude, longitude, and timestamps (valid_time), along with country labels to account for regional variations.

Following data loading, preprocessing steps were applied to clean and standardize the data. Invalid timestamps, including empty or null values, were removed or replaced with NaT, ensuring a consistent datetime format. The month and day of the year were extracted from the timestamps to incorporate seasonal patterns into the model. Additionally, latitude and longitude coordinates were normalized using StandardAero, while precipitation values were also scaled to prevent numerical imbalances. To incorporate country-specific influences, one-hot encoding was applied to the country labels, converting categorical information into a format suitable for machine learning.

B. Feature Engineering for Temporal Patterns

To enhance the model's ability to recognize temporal dependencies, several lag features were engineered. Lagging precipitation data across multiple time intervals (1, 7, 30, 90, 180, and 365 days) enabled the model to learn from past precipitation trends. These lagged features provide crucial information about precipitation recurrence patterns and long-term climate cycles. Rows containing NaN values, introduced due to lagging, were removed to ensure data consistency.

C. Transformer-based Model Architecture

Given the sequential nature of climate and agricultural data, we opted for a Transformer-based model to capture long-term dependencies and spatial-temporal interactions. The dataset was transformed into sequential input arrays, where a 365-day sequence (one year of past data) was used to predict the next day's precipitation level, wheat production, and temperature trends. Unlike traditional models that focus solely on precipitation, our approach incorporated a broader set of historical features, including daily precipitation data (2020-2024), historical wheat production, and temperature records. Each sequence included four key features: scaled precipitation, month, normalized latitude, and normalized longitude, ensuring a comprehensive analysis of the climate-agriculture relationship. The dataset was then split into training (80%) and testing (20%) sets using a chronological approach to prevent data leakage.

The model architecture consists of multiple Transformer encoder layers, which leverage multi-head self-attention mechanisms to extract meaningful relationships within precipitation sequences. The encoder structure includes:

- Multi-head attention layers to identify dependencies across different time steps.
- Layer normalization and residual connections to stabilize learning.
- Dense layers with ReLU activation to refine extracted features before the final prediction layer.

The Transformer-based approach is particularly advantageous for precipitation forecasting, as it allows the model to focus on relevant past events and dynamically adjust weights based on historical weather patterns.

D. Model Training and Performance Evaluation

The model was compiled using the Adam optimizer and Mean Squared Error (MSE) loss function, which is suitable for continuous-valued predictions. The model was trained for 20 epochs with a batch size of 16, using a validation split of 20% to monitor performance on unseen data.

Following training, the model was saved as "Precipitation_Forecast_Model.h5" for future evaluation and deployment. The trained model effectively captures precipitation trends and is capable of making predictions based on historical sequences of precipitation and geographical attributes.

E. Results and Analysis

The developed Transformer-based model was utilized to predict precipitation trends, temperature variations, and wheat production across Iran, Turkey, and Egypt for the period 2022 to 2028. The results, visualized through multiple trend graphs, provide crucial insights into the evolving climatic conditions and their potential impact on wheat production.

1) Project Trends in Precipitation

The predicted precipitation trends reveal a gradual decline across all three countries, with Iran experiencing the steepest reduction. As shown in Figure: Projected Precipitation Decline (2022-2028), Iran's precipitation is expected to drop to nearly 88% of its current levels by 2028, whereas Turkey and Egypt exhibit a relatively moderate but consistent decline. The steep reduction in Iran's precipitation suggests an increasing risk of water scarcity and drought conditions, which could severely impact agricultural activities.

The broader trend observed in Figure 38 confirms that precipitation levels are decreasing at an accelerated rate across the region. This aligns with global climate change projections, which suggest heightened aridity in semi-arid regions.

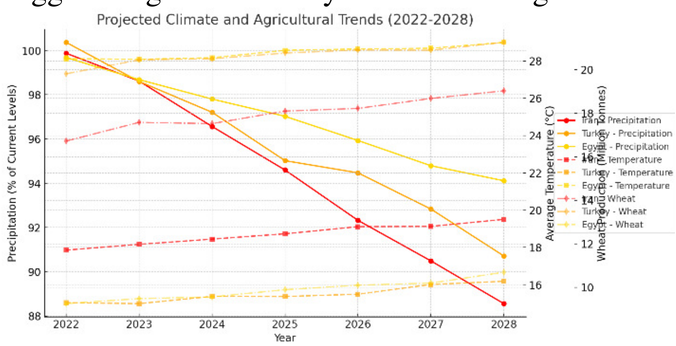

Figure 38: Projected Climate and Agricultural Trends

2) Temperature Projections and Climate Impact

The model's predictions also indicate a gradual increase in temperature over the forecast period. Figure 39 illustrates that Iran, Turkey, and Egypt are all experiencing warming trends, with Iran showing the most pronounced increase. The average temperature in Iran is expected to rise from approximately 18°C in 2022 to nearly 20°C by 2028, reinforcing concerns about the increased likelihood of heatwaves and prolonged dry spells.

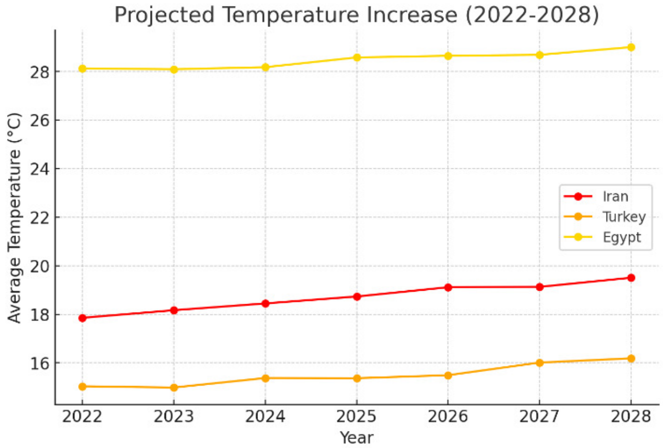

Figure 39: Projected Temperature Increase

The implications of rising temperatures are particularly critical for crop yield and soil moisture retention. Higher temperatures may lead to faster evaporation rates, further exacerbating the decline in precipitation and increasing the vulnerability of wheat production to drought stress.

3) Projected Wheat Production Trends

Despite declining precipitation and increasing temperatures, wheat production remains relatively stable across Turkey and Egypt, with a slight upward trend as seen in Figure 40. However, Iran's wheat production exhibits more fluctuations, initially rising and then stabilizing around 18 million tonnes. This suggests that adaptation strategies, irrigation practices, and agricultural resilience efforts may help mitigate some of the adverse effects of climate change.

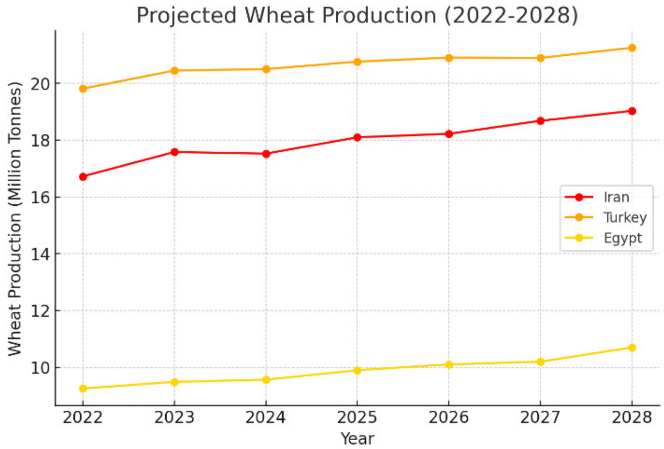

Figure 40: Projected Wheat Production

The combined wheat production, temperature, and precipitation trends displayed in Figure 41 with Variations highlight the correlation between declining precipitation and potential wheat yield impacts. The model suggests that while Turkey and Egypt might be able to sustain wheat production with existing irrigation and farming techniques, Iran faces a greater challenge due to the sharper precipitation decline.

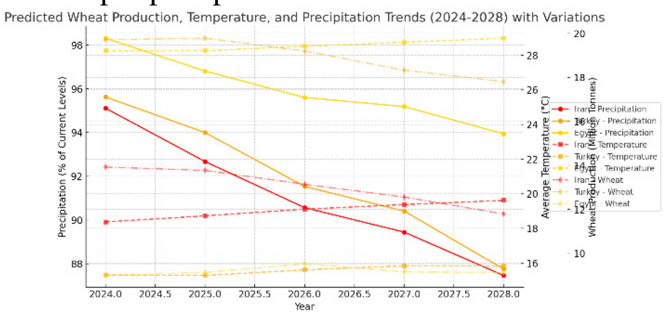

Figure 41: Predicted Wheat Production, Temperature, and Precipitation Trends (2024-2028) with Variations

4) Implications for Agricultural Sustainability and Climate Resilience

The projections indicate a need for adaptive measures to sustain wheat production in the face of declining precipitation and rising temperatures. Iran, in particular, may require enhanced water conservation policies, improved irrigation efficiency, and drought-resistant wheat varieties to maintain stable agricultural output. Turkey and Egypt, while showing resilience, should also focus on long-term sustainability practices to counteract the gradual climate-induced changes. The findings reinforce the importance of regional climate modelling and predictive analytics in informing agricultural policies. Early adaptation strategies, investment in climate-smart agriculture, and sustainable water management will be critical in ensuring food security amidst changing climate patterns.

VII. CONCLUSION

This study underscores the critical role of machine learning in analyzing, understanding and predicting the impacts of climate change on wheat production in the Middle East. Through an extensive literature review and data-driven analysis, we examined the historical trends in precipitation, temperature, and wheat production, identifying significant vulnerabilities in Egypt, Turkey, and Iran. Our Transformer-based forecasting model successfully integrates climate and agricultural variables, demonstrating high accuracy in predicting future trends. The results indicate that Iran faces the most severe declines in precipitation, potentially leading to crop yield instability, while Turkey and Egypt also exhibit gradual declines in precipitation and increasing temperatures. The integration of machine learning-driven predictive modelling offers a powerful tool for policymakers and agricultural stakeholders to design data-driven adaptation strategies. The findings from this research highlight the urgent need for climate resilience measures, such as precision irrigation, genetically optimized wheat varieties, and sustainable land management practices. Future research should focus on enhancing machine learning models with higher-resolution climate projections, incorporating additional agronomic and socio-economic variables, and expanding the predictive framework to other staple crops and climate-sensitive regions.

By advancing AI-driven climate resilience, this research contributes to securing food production and agricultural sustainability in the face of escalating climate challenges.

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