International Journal of Innovative Research and Scientific Studies, 8(10) 2025, pages: 104-111

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

The economic impacts of climate change on Egypt's agriculture sector based on the random forest algorithm

Mohamed F. Abd El-Aal[1*], Abdelsamiea Tahsin Abdelsamiea[2], Mohamed A. M. Sallam[3], Elsayed E. Elashkar[4], Mostafa Ahmed Radwan[5]

[1]*Department of Economics, Faculty of Commerce, Arish University, North Sinai, Egypt.*
[2,3]*Department of Economics, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia.*
[4]*Administrative and Financial Sciences Department, College of Applied Studies, King Saud University, Saudi Arabia.*
[5]*Faculty of Applied Studies Imam Abdulrahman Bin Faisal University, Saudi Arabia.*

Corresponding author: Mohamed F. Abd El-Aal (*Email: Mohammed.fawzy@comm.aru.edu.eg*)

Abstract

This study employs the Random Forest algorithm to analyze the relationship between agricultural added value in Egypt, climate change, and fertilizer inputs. It also investigates the impact of poverty on carbon dioxide emissions, focusing on the connection between environmental sustainability and economic development. The results indicate that fertilizer inputs play a dominant role in predicting agricultural value-added: nitrogen (43.8%), phosphate (32.3%), and potash (20.6%), while climate change accounts for only 3.3%. This suggests that Egypt's agriculture has not yet been significantly affected by climate change. Additionally, the analysis of poverty and emissions reveals that poverty reduction, while improving living standards, may simultaneously increase energy consumption and emissions, posing challenges for sustainable development. The study concludes that agricultural productivity in Egypt is currently more influenced by fertilizer use than by climate change. Furthermore, addressing poverty without implementing appropriate environmental safeguards could exacerbate carbon emissions. Therefore, achieving sustainability requires a balanced approach to poverty reduction and environmental conservation. The findings offer practical insights for policymakers, including environmental advocates and economists. They highlight the importance of enacting regulations that promote the use of green technologies and sustainable agricultural practices, while designing poverty reduction strategies aligned with long-term environmental sustainability. These measures will help reconcile economic growth with environmental conservation.

Keywords: Climate change, Egypt's agricultural value added, Feature importance, Random Forest.

DOI: 10.53894/ijirss.v8i10.10754
Funding: This study received no specific financial support.
History: Received: 25 September 2025 / **Revised:** 14 October 2025 / **Accepted:** 17 October 2025 / **Published:** 24 October 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

Agriculture is crucial to Egypt's economy, contributing significantly to employment, food security, and economic growth. As a vital sector, agriculture, forestry, and fishing constitute a substantial percentage of Egypt's Gross Domestic Product (GDP). However, this sector is increasingly vulnerable to the multifaceted challenges of climate change. Rising temperatures, shifting precipitation patterns, and soil degradation are all threats to agricultural productivity and sustainability. Given Egypt's reliance on the Nile River and limited arable land, any disruptions to agricultural output could have profound economic consequences. This study aims to investigate the economic impacts of climate change on Egypt's agricultural sector, with a specific focus on the relationship between temperature change and key agricultural inputs, including nitrogen (N), potash (K_2O), and phosphate (P_2O_5).

Global studies have thoroughly documented the effects of climate change on agriculture, demonstrating that crop yields, soil fertility, and water availability are all impacted by temperature fluctuations and extreme weather events. This issue is severe in Egypt due to the country's predominantly arid environment, where even minor temperature changes can exacerbate water scarcity and disrupt soil nutrient balances. The effectiveness of fertilizers such as nitrogen, phosphate, and potash can diminish due to increasing temperatures, which also lead to reduced soil moisture and changes in evapotranspiration rates. These elements are vital for agricultural productivity and bolster the national economy. However, the absence of empirical studies evaluating the economic effects of climate change on Egypt's agrarian sector underscores the necessity for a comprehensive review.

This study employs a quantitative approach to assess the relationship between the value added by agriculture, forestry, and fishing as a percentage of GDP, and key independent variables: nitrogen (N), potash (K_2O), phosphate (P_2O_5), and temperature change on land. This research analyzes historical data and trends to illustrate how various factors impact the economic performance of the agricultural sector. Understanding these relationships is crucial for policymakers, agrarian stakeholders, and economists, as it enables the development of adaptive strategies to mitigate climate-induced economic losses and enhance agricultural resilience.

This study employs the Random Forest algorithm to examine the complex relationships between various variables. Recognized for its effectiveness in predictive modeling and feature importance evaluation, Random Forest excels at managing non-linear relationships, handling missing data, and working with high-dimensional datasets. This method is particularly advantageous for analyzing agricultural and economic trends influenced by climate change. By using Random Forest, the study aims to enhance predictive accuracy and gain a deeper understanding of the key factors influencing the economic performance of the agricultural sector. This approach will help pinpoint the most influential factors driving changes in agricultural GDP and inform the formulation of evidence-based policy recommendations.

The findings of this study will contribute to existing literature on climate change economics by offering insights into the specific challenges Egypt's agricultural sector faces. Moreover, it will recommend sustainable farming practices, fertilizer management, and climate adaptation policies to preserve agricultural productivity amid rising temperatures. By identifying key drivers of economic change in agriculture, this research will help shape policies that safeguard food security and economic stability in Egypt. Given the increasing global urgency to address climate change, understanding its economic repercussions at a sectoral level is imperative for sustainable development and long-term economic planning.

In summary, this study aims to bridge the gap in empirical research by examining the economic impacts of climate change on Egypt's agricultural sector. This study examines the impact of temperature changes and essential agricultural inputs on resilience in the sector. Subsequent sections will delve into the methodology, data sources, and analytical strategies employed to evaluate these effects, providing a thorough overview of how climate change impacts Egypt's agricultural economy.

2. Literature Review

Climate change has emerged as a critical challenge impacting the agricultural sector worldwide, with Egypt being particularly vulnerable due to its arid climate and heavy reliance on the Nile River. Several studies have examined the economic implications of climate change on Egypt's agricultural sector, providing valuable insights into the relationship between climatic variables and agricultural productivity, food security, and economic sustainability.

Islam and Ragab [1] examined the challenges of climate change in Egypt's agricultural sector, with a focus on policy recommendations for sustaining wheat production. Their study highlighted the need for sustainable farming practices and strategic planning to ensure food security. Similarly, Abd El Maksoud [2] analyzed the impact of climate change on food production in Egypt, emphasizing water scarcity, declining crop yields, and increased pest infestations as significant concerns.

The economic impact of climate change on Egyptian food security crops has been extensively examined. Taha, et al. [3] investigated the repercussions of climate change on cereal crop productivity, revealing an inverse relationship between rising temperatures and crop yields. They found that maximum temperature changes hurt the productivity of staple grains, necessitating urgent adaptation measures.

El-Khalifa, et al. [4] provided a macroeconomic perspective by analyzing the impact of climate change on Egypt's agricultural GDP. Their findings suggest that climate variables have a significant long-term impact on the agricultural sector, with rising temperatures resulting in a decline in agricultural GDP contributions. In a related study, Agbo [5] examined adaptation mechanisms to mitigate the adverse effects of climate change on food security. This suggests that Egypt's agriculture remains highly dependent on manual labor rather than mechanization, which could hinder long-term resilience.

Specific crop-based studies have further illustrated the complexity of climate change's effects. Gamal, et al. [6] examined the impact of different global warming scenarios on significant crops, such as maize and wheat, finding that while wheat yields may increase slightly under moderate warming, the productivity outcomes for maize remain uncertain. Meanwhile, Abd El-Aziz, et al. [7] identified temperature and humidity fluctuations as key factors influencing wheat and maize productivity, with rising winter temperatures reducing wheat output and increasing summer temperatures negatively impacting maize.

Agricultural production in Egypt is heavily reliant on water supplies, which are influenced by climate change. Omar, et al. [8] investigated the effects of climate change on food security, salinity, and water availability. Their research emphasized the necessity to modify cropping patterns to address threats to food security. Similarly, Abdelfattah [9] emphasized the need for comprehensive, adaptive strategies to address hydrological risks and ensure food security in Egypt.

Numerous studies have examined the potential of climate-smart agriculture in mitigating climate-induced losses. Abd El Mowla and Abd El Aziz [10] investigated economic strategies for climate-smart agriculture, revealing a strong link between increased crop and livestock production and food security. Abdel Monem and Radojevic [11] emphasized the importance of enhancing adaptive capacity and resilience through coordinated national strategies. Abdelradi and Yassin [12] conducted an efficiency analysis to assess the influence of climatic variables on cereal crop production, showing that increased maximum temperatures and humidity levels diminish production efficiency.

Recent research has also assessed the broader economic impact of climate change. McCarl, et al. [13] estimated potential economic losses ranging from 2% to 6% of Egypt's future GDP due to climate-induced damages. Other studies, such as those by McCarl, et al. [13] and Yates and Strzepek [14] have analyzed Egypt's economic vulnerability to climate change, highlighting the need for effective adaptation strategies.

Additional studies have explored the effects of climate change on water resources and food security. Abdelfattah [9] and Abdelrazek and Mohamed Aliwa [15] emphasized the importance of adaptive measures in mitigating hydrological risks. Akzar and Amandaria [16] recommended integrating sustainable farming systems to improve local crop production. Furthermore, Abdel Monem and Radojevic [11] focused on enhancing resilience and adaptive capacity in agricultural sectors, identifying the necessity for national coordination.

Other relevant studies have investigated Egypt's agricultural vulnerability. Adly, et al. [17] modeled optimal cropping patterns to maximize net revenue under various climate scenarios, predicting a doubling of net revenue by 2030, accompanied by improved efficiency. Similarly,

In summary, this literature review synthesizes findings from studies on the impact of climate change on Egypt's agricultural sector. Rising temperatures, water scarcity, and changing precipitation threaten food production and economic stability. Various adaptation strategies have been proposed, including climate-smart agriculture and resilience measures. Continued research is necessary to optimize these solutions and formulate data-driven policies. The subsequent sections will further explore the methodological framework and empirical analysis used to assess the economic impacts of climate change on Egypt's agricultural economy.

Although the current literature thoroughly outlines the effects of climate change on Egypt's agriculture, most research uses conventional statistical methods or qualitative approaches for evaluation. Only a few studies have utilized advanced machine learning techniques, such as Random Forest, for modeling and predicting the influence of climate change on crop yields and food security.

This research addresses the existing gap by applying the Random Forest algorithm, an effective machine learning approach, to examine the complex relationships between climate variables and agricultural outcomes. In contrast to conventional methods, Random Forest effectively handles large datasets, reveals nonlinear relationships, and generates dependable forecasts, making it particularly apt for analyzing the diverse effects of climate change on agriculture. Through this sophisticated technique, the research aims to provide policymakers and stakeholders in Egypt's agricultural industry with more precise and actionable recommendations.

3. Empirical Framework

$$\text{Agriculture}_t = \beta_1 \cdot \mathrm{N}_t + \beta_2 \cdot \mathrm{K2O}_t + \beta_3 \cdot \mathrm{P2O5}_t + \beta_4 \cdot \text{ Temperature}_t$$

Where,

β_0 **:** Intercept (baseline value of agriculture when all inputs are zero).

$\mathbf{N}_t$ **:** Nitrogen amount in year *t*.

K_2O_t : Potash amount in year *t*.
$P2O5_t$: Phosphate amount in year *t*.
Temperature $_t$: Temperature change in year *t*.
β_1, β2, β3, β4: Coefficients indicating the impact of each variable on agriculture.

4. Data and Methodology

4.1. Data

Regarding data Sources, the data was collected from World Bank Open Data for the dependent variable, Agriculture, Forestry, and Fishing, Value Added (% of GDP), and other macroeconomic indicators; and FAOSTAT (Food and Agriculture Organization) for agricultural input data, including Nitrogen (N), Potash (K2O), and Phosphate (P2O5) usage in tons, and Temperature Change on Land (°C) data: data description and feature statistics in Tables 1 and 2.
The dataset includes the following variables:

Table 1.
Data description.

Variable Name	Description	Unit
Agriculture value added	Value added by the agricultural sector as a percentage of GDP.	% of GDP
Nitrogen (N)	Total nitrogen used in agricultural activities.	Tons
Potash (K_2O)	Total potash used in agricultural activities.	Tons
Phosphate (P_2O_5)	Total phosphate used in agricultural activities.	Tons
Temperature Change on Land	Annual change in land temperature due to climate change.	°C

Table 2.
Feature Statistics.

Variables	Source Of Data	Mean	Mode	Median	Dispersion	Minimum	Maximum
Agriculture value added	World Bank	17.93	10.69	16.34	0.29	10.69	28.8
Nitrogen (N)	FAOSTAT	801612.4	1331900	790500	0.47	191872	1372900
Potash (K_2O)	FAOSTAT	31984.6	29700	29471.5	0.86	591	94000
Phosphate (P_2O_5)	FAOSTAT	141853.2	150000	149800	0.52	35493	332800
Temperature Change on Land	FAOSTAT	0.319	0.439	0.354	1.98	-1.21	2.23

Source: Made by the author (using Python language)

4.2. Methodology

4.2.1. The ML Algorithms

Using bootstrap sampling and random attribute selection, Random Forest (RF) is an ensemble learning technique that builds a "forest" of decision trees. Training each tree separately reduces the risk of overfitting and processing costs compared to Gradient Boosting, which sequentially creates trees [18].

The method creates unique decision trees and datasets by sampling and replacing random feature subsets at each split. A majority vote for categorization or an average for regression are examples of how findings are aggregated to make the final forecast [19]. The areas of expertise for Random Forest are environment modeling, fraud detection, and high-dimensional data management. It is well-known for its ability to manage outliers and missing data while mitigating overfitting, making it suitable for various applications [20]. The Random Forest (RF) model includes the following fundamental steps:
Step 1: Tree Building for Every Bootstrap Instance
For m=1 to M (number of trees in the forest):

4.2.1.1. Bootstrap Sampling

Make a bootstrapped sample set, Z, of size N from the training data.

4.2.1.2. Tree Growth

For each terminal node in the tree:

- Randomly select X variables from the *total of* P variables.
- Choose the optimal split point among the given variables to reduce the Mean Squared Error. (MSE):

$$F_0(x) = \frac{1}{n}\sum_{i=1}^{n} (Y - \hat{Y})^2 \qquad (1)$$

Where Y is the actual value $\hat{Y}$and is the predicted value.

- To create new nodes, divide them according to the optimal variable.
- Keep splitting until you reach a predetermined minimum node size (n_{min}).

4.2.1.3. Randomization and Robustness

Adding diversity through the random selection of variables for splitting at each node reduces reliance between trees. This randomization enhances the model's resilience to overfitting, which occurs when trees become overly complex and tailored to the training data. Overfitting diminishes a model's ability to generalize to new data. Some trees or nodes can be pruned to lessen this, El-Aal, et al. [19].

Step 2: Forest Output

The outputs of the separate trees in the RF model are combined. The forest's collective forecast is provided by:

$$\hat{F}_{rf}^{M}(x) = \frac{1}{M}\sum_{m=1}^{M} T_m(x) \qquad (2)$$

Here:

- $T_m(x)$ is the Prediction from the m-th tree.
- $\hat{F}_{rf}^{M}(x)$ represents the final output of the RF model, which is derived by averaging all the trees' forecasts.

Averaging forecasts stabilizes the model's overall performance and decreases variance. This ensemble approach ensures reliable predictions even in the presence of complex relationships or noisy data.

5. Empirical Results

5.1. Model evaluation

As indicated in Table 3, RMSE, MSE, MAE, MAPE, and R2 must be computed to assess the model's predictive accuracy.

Table 3.
The RF accuracy.

Model	MSE	RMSE	MAE	MAPE	R^2
Random forest (RF)	2.79	1.67	1.19	0.065	.90
Gradient boosting (GB)	3.02	1.73	1.2	0.066	.892
Support vector machine (SVM)	3.75	1.93	1.49	0.083	0.866
Decision tree (DT)	4.36	2.09	1.57	0.90	0.844

Table 3 shows that the RF algorithm is more accurate than the other algorithms in the paper, as it has the lowest MSE and the highest R^2. Therefore, the paper relies on the RF for prediction and identifies the factors that affect agricultural value added.

5.2. The RF Algorithm Prediction Performance

As shown in Table 4, the actual and predicted values over the research period should be compared to assess the accuracy of using Random Forest in the future. This step proves we are on the right path in predicting the future. Table 4 and Figure 1 answer this question.

Table 4.
The RF prediction performance.

year	Agriculture, forestry, and fishing, value added (% GDP)	Random Forest prediction (%)
1961	27.1531	26.0497
1962	24.6278	24.5432
1963	24.4219	24.5021
1964	23.199	23.9193
1965	25.6941	25.3147
1966	24.8845	24.7594
1967	24.1558	24.0481
1968	25.3801	25.3043
1969	25.5437	24.9963
1970	24.1098	24.4378
1971	22.9315	24.726
1972	23.7497	24.6402
1973	26.5749	25.7707
1974	28.8075	26.6471
1975	27.6655	25.5896
1976	26.015	25.7262
1977	24.8188	24.7241
1978	23.3945	24.7452
1979	20.0564	20.5051

1980	16.5819	18.3003
1981	21.6206	20.6259
1982	18.0486	18.5457
1983	19.0451	18.7141
1984	18.1076	18.6621
1985	17.1046	17.2497
1986	17.39	17.4926
1987	19.633	18.9497
1988	18.0455	17.4926
1989	18.6948	18.4227
1990	18.5125	18.4227
1991	16.9867	16.8484
1992	15.5859	17.8995
1993	15.739	16.701
1994	15.7143	16.8395
1995	15.7108	15.736
1996	16.1151	15.8831
1997	15.751	15.736
1998	15.8845	15.8214
1999	15.9086	15.6498
2000	15.5381	15.4586
2001	15.3513	15.0441
2002	15.4049	14.5413
2003	15.2867	14.5333
2004	14.2699	14.4756
2005	13.9817	14.0523
2006	13.2372	13.6995
2007	13.4201	14.0761
2008	12.6302	13.4288
2009	12.9979	13.3686
2010	13.3408	13.3686
2011	13.8691	13.3995
2012	11.2728	12.4202
2013	11.2743	11.3456
2014	11.3377	11.3018
2015	11.3941	11.3456
2016	11.7693	11.4423
2017	10.9864	11.2181
2018	10.8302	11.1645
2019	10.6971	11.0024
2020	11.1668	11.1386
2021	11.4369	11.2617
2022	10.9458	11.3097

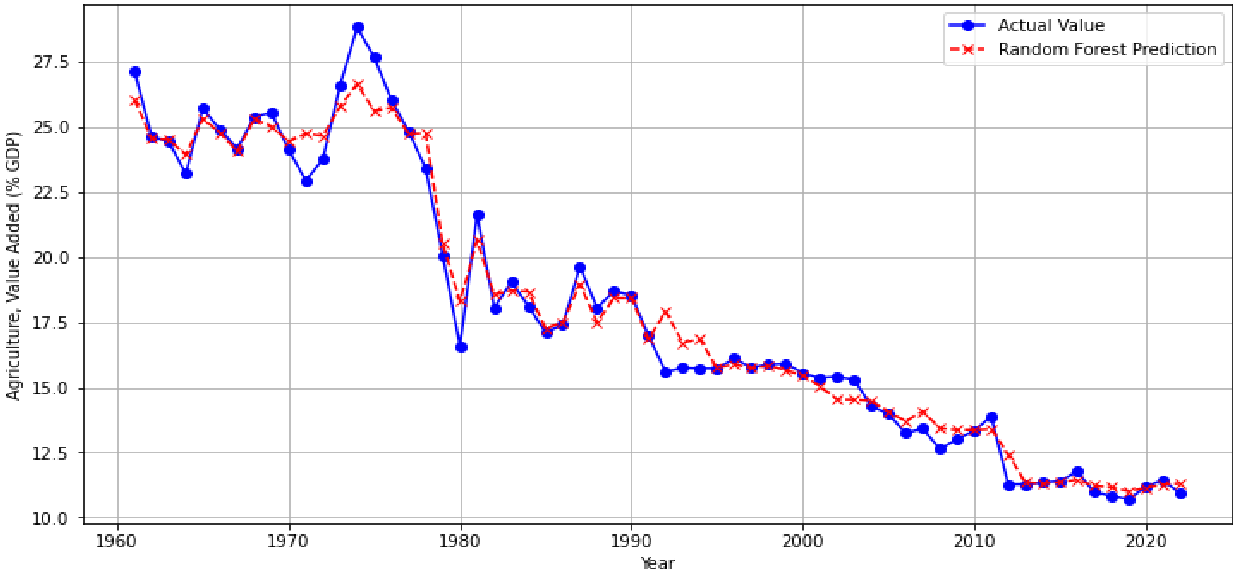

Figure 1.
Actual vs Predicted Agriculture Value Added (% GDP) Over Time.

From Table 4 and Figure 1 show that the accuracy of the Random Forest algorithm in forecasting indicates the extent to which the actual and expected values move together, suggesting that they can indeed be relied upon in the future. At this step, the RF determines the importance of each independent variable in predicting the dependent variable.

5.3. RF Algorithms Feature Importance

The dark box of ML models can only be opened by acknowledging the significance of features. The study assesses the model's classifications or predictions by calculating the impact of every feature or input variable. Data scientists can utilize significance ratings to prioritize these qualities and gain a deeper understanding of how well their models perform [19]. With this knowledge, users may improve their models and make more precise and accurate decisions. Thanks to this knowledge, users can refine and enhance their models, making more accurate and precise selections. The significance of the RF algorithm feature is seen in Table 5.

Table 5.
The RF algorithms feature important indicators.

Variables	RF feature importance
Nitrogen (N)	43.8
Phosphate (P_2O_5)	32.3
Potash (K_2O)	20.6
Temperature Change on Land	3.3

According to Table 5, the temperature change has a relatively minor effect on agricultural value added compared to the other variables. The table shows that the fertilizer used has a more significant effect on agriculture value added prediction, specifically Nitrogen by 43.8%, Phosphate by 32.3%, Potash by 20.6%, and climate change by 3.3%. Results indicate that climate change has a low effect on the value added to agriculture.

6. Conclusion

This research employed the Random Forest method to investigate the impact of climate change on Egypt's agriculture by analyzing the relationships between agricultural value added and key factors, including temperature fluctuations, nitrogen, potassium, and phosphate levels. The results indicate that fertilizer inputs have a significantly greater impact on agricultural value added than climate change. Among the inputs, nitrogen constitutes the largest share at 43.8%, followed by phosphate at 32.3%, potash at 20.6%, and climate change at 3.3%. This suggests that while climate change may have a slightly positive effect on agricultural value added, it has not yet been harmful.

The regression coefficients reinforce the straightforward connection between agricultural value added and the independent variables. Precisely, a 1% rise in nitrogen, phosphate, potash, and temperature corresponds to increases in agrarian value added of 2.9%, 2.2%, 2.7%, and 0.089%, respectively. This study demonstrates that Egypt's agricultural sector has not experienced any negative impacts on added value from climate change. However, the slight benefit of climate change suggests that preventive measures are necessary to mitigate potential future hazards.

The Random Forest algorithm effectively predicted agricultural value added, outperforming other machine learning models such as Gradient Boosting, Support Vector Machines, and Decision Trees. Its low Mean Squared Error (MSE) and high R^2 value of 0.90 demonstrate its reliability in forecasting future trends and identifying key factors affecting agricultural productivity.

In conclusion, this study emphasizes the crucial role of fertilizer management in sustaining Egypt's agricultural sector while highlighting the necessity for climate adaptation strategies to tackle the potential long-term effects of climate change. Policymakers and stakeholders should focus on optimizing fertilizer use and implementing sustainable farming practices to enhance agricultural resilience and ensure food security in the face of rising temperatures and changing climatic conditions.

The Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) funded this research through grant number IMSIU-DDRSP2503. These findings contribute to the growing body of literature on climate change economics and offer actionable insights for policymakers seeking to safeguard agricultural productivity and economic stability in Egypt.

References

[1] K. R. Islam and R. Ragab, "Sustaining wheat in a changing climate: Policy recommendations for Egypt's agricultural sector," *Cognizance Journal of Multidisciplinary Studies,* vol. 4, no. 9, pp. 68–76, 2024.

[2] T. D. Abd El Maksoud, "The impact of climate change-related factors on food production in Egypt," *International Journal of Modern Agriculture and Environment,* vol. 2, no. 2, pp. 15-25, 2022. https://doi.org/10.21608/ijmae.2023.214695.1003

[3] M. E. B. Taha, M. Eliw, A. E. Elesawi, H. M. A. Shehata, D. M. Ewis, and A. T. Goma, "An economic repercussion to the impact of climate change on the most important Egyptian food security crops," *Journal of Pharmaceutical Negative Results,* vol. 13, no. Special Issue 3, pp. 1879–1893, 2022. https://doi.org/10.47750/pnr.2022.13.S03.284

[4] Z. S. El-Khalifa, H. F. Zahran, and A. Ayoub, "Climate change factors' impact on the egyptian agricultural sector," *Asian Journal of Agriculture and Rural Development,* vol. 12, no. 3, pp. 192-200, 2022. https://doi.org/10.22004/ag.econ.342369

[5] H. M. S. Agbo, "The impact of climate change on agriculture and adaptation mechanisms: The case of Egypt," *Review of Applied Socio-Economic Research,* vol. 23, no. 1, pp. 119-133, 2022. https://doi.org/10.54609/reaser.v23i1.133

[6] G. Gamal, M. Samak, and M. Shahba, "The possible impacts of different global warming levels on major crops in Egypt," *Atmosphere,* vol. 12, no. 12, p. 1589, 2021. https://doi.org/10.3390/atmos12121589

[7] A. M. Abd El-Aziz, A. A. Swefy, and M. R. Mohamed, "The effect of climate change on wheat and maize crops in Egypt," *International Journal of Agricultural Economics,* vol. 8, no. 4, pp. 133-145, 2023. https://doi.org/10.11648/j.ijae.20230804.12

[8] M. E. D. M. Omar, A. M. A. Moussa, and R. Hinkelmann, "Impacts of climate change on water quantity, water salinity, food security, and socioeconomy in Egypt," *Water Science and Engineering,* vol. 14, no. 1, pp. 17-27, 2021. https://doi.org/10.1016/j.wse.2020.08.001

[9] M. A. Abdelfattah, *Climate change impact on water resources and food security in Egypt and possible adaptive measures*. Cham: Springer, 2021.

[10] K. E. Abd El Mowla and H. H. Abd El Aziz, "Economic analysis of climate-smart Agriculture in Egypt," *Egyptian Journal of Agricultural Research,* vol. 98, no. 1, pp. 52-63, 2020. https://doi.org/10.21608/ejar.2020.101423

[11] M. A. S. Abdel Monem and B. Radojevic, *Agricultural production in Egypt: Assessing vulnerability and enhancing adaptive capacity and resilience to climate change*. Cham: Springer, 2020.

[12] F. Abdelradi and D. Yassin, *Climate impact on Egyptian agriculture: An efficiency analysis approach*. Cham: Springer, 2020.

[13] B. A. McCarl *et al.*, "Climate change vulnerability and adaptation strategies in Egypt's agricultural sector," *Mitigation and Adaptation Strategies for Global Change*, vol. 20, no. 7, pp. 1097-1109, 2015. https://doi.org/10.1007/s11027-013-9520-9

[14] D. N. Yates and K. M. Strzepek, "An assessment of integrated climate change impacts on the agricultural economy of Egypt," *Climatic Change*, vol. 38, no. 3, pp. 261-287, 1998. https://doi.org/10.1023/A:1005364515266

[15] Y. Abdelrazek and M. Mohamed Aliwa, "Production and consumption of the most important grain crops in Egypt in light of local and international changes," *Alexandria Science Exchange Journal*, vol. 43, no. 3, pp. 867-884, 2022. https://doi.org/10.21608/asejaiqjsae.2022.251459

[16] R. Akzar and R. Amandaria, "Climate change effects on agricultural productivity and its implication for food security," in *IOP Conference Series: Earth and Environmental Science (Vol. 681, No. 1, p. 012059). IOP Publishing*, 2021.

[17] N. Adly, S. Noiser, N. Kassem, M. Mahrous, and R. Salah, "Modelling the optimal cropping pattern to 2030 under different climate change scenarios: A study on Egypt," *African Journal of Agricultural and Resource Economics,* vol. 13, no. 3, pp. 224-239, 2018. https://doi.org/10.22004/ag.econ.284987

[18] L. Breiman, "Random forests," *Machine learning,* vol. 45, no. 1, pp. 5-32, 2001. https://doi.org/10.1023/A:1010933404324

[19] M. F. A. El-Aal, M. S. Hegazy, and A. T. Abdelsamiea, "Role of economic expansion, energy utilization and urbanization on climate change in Egypt based on artificial intelligence," *International Journal of Energy Economics and Policy,* vol. 14, no. 3, pp. 127-137, 2024. https://doi.org/10.32479/ijeep.15607

[20] T. Hastie, R. Tibshirani, and J. Friedman, *Random forests. In The elements of statistical learning: Data mining, inference, and prediction*, 2nd ed. New York: Springer, 2009.