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Artificial intelligence and economic forecasts in climate risks management

Abstract. The physical, financial, and systemic risks associated with climate change continue to increase across global economies. As the frequency and severity of climate-related risks intensify, it becomes increasingly difficult for standard forecasting tools to adequately capture complex ecological-economic interactions. This article examined the role of artificial intelligence (AI) and economic forecasting in managing climate risks. The study demonstrated that the identification and prediction of severe weather events are significantly improved through the use of AI-powered climate models. Explainable AI (XAI) provides additional transparency by enabling analysts and policymakers to better understand the factors influencing predictions generated by drought, flood, and heatwave models. When integrated with economic forecasting frameworks, AI enables comprehensive simulations of how climate challenges propagate through supply chains, labour markets, energy networks, and financial systems. Despite these advantages, AI-based modelling presents several limitations, including data scarcity, limited generalisability, and ethical concerns related to transparency, energy consumption, and inequality. The study concluded that integrating AI with economic forecasting provides a robust interdisciplinary framework for climate risk assessment, policy formulation, and adaptive strategy development. However, the effectiveness of this framework depends on improved governance structures, enhanced data infrastructure, and responsible technological implementation. The research has practical significance in enabling more accurate and early assessment of climate-related impacts on economic systems. The findings are particularly relevant for risk prediction and management in the energy, agricultural, and financial sectors

Keywords: machine learning; explanatory artificial intelligence; agent-based models; climate policy; economic sustainability; innovation

INTRODUCTION

The threat of economic stability, social security, and environmental balance due to climate change is at its peak nowadays. The menace of climate change has turned out to be one of the

most important challenges that the world is currently facing, considering its effects on the infrastructure, agriculture, economy, and society as a whole. Changes in temperature, water resources,

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and the environment are not merely environmental issues, as they affect other sectors as well. While economic and statistical models provide some utility, the inherent complexity of climate processes precludes an accurate representation of real-world dynamics; furthermore, the multifaceted, long-range effects of climate change constrain the efficacy of traditional modelling approaches. Advances in artificial intelligence technology offer some advantages in processing large volumes of data and making more accurate predictions in an uncertain environment (Zaidan, 2025). M. Burke *et al.* (2015) noted that every 1°C increase in average temperature reduces global GDP by approximately 1.2%, threatening economic productivity. This indicates an urgent need for effective climate change mitigation to reduce the negative global economic impacts of rising temperatures. According to T. Papadopoulos & M.E. Balta (2022), the integration of artificial intelligence (AI) and deep learning techniques will increase the resilience of businesses to climate change and will be of great importance in risk management. W.Y. Leong (2025) noted that an AI-driven early warning system deployed in California reduced response time by 40%. J. Cowls *et al.* (2023) while analysing the role that AI can and does play in combating global climate change, have shown that AI can contribute to effectively combating the climate crisis. According to H. Yin *et al.* (2025) AI reduces climate risks through increased resource efficiency, green innovation, implementation of environmental policies and green finance growth.

As noted by Z. Zhang *et al.* (2025), artificial intelligence has the ability to process large amounts of data on climate change, reveal new relationships, and improve the precision of forecasts under uncertain conditions. Y. Mohajarani (2025) observed that, apart from improving forecasts, the integration of economic forecasting allows decision-makers to comprehend the effect of risks on production, markets, business, and economic development. Consequently, the management of climate risks becomes more complete, data-driven, and forward-looking as a result of this change. The integration of artificial intelligence and economic forecasting allows the development of a complex and systematic approach in the management of climate risks,

while at the same time facilitating the modelling of future scenarios and the pre-assessment of the consequences (Mehryar, 2024). In the current economic environment, increased competition, accelerated technological change, and resource constraints make decision-making processes more complex. Wrong or delayed decisions can lead to serious financial losses and weakening of market positions. Inadequate resource management can negatively impact overall performance and long-term stability in uncertain conditions. Given this, the implementation of agile, analytically based, and predictive management mechanisms for organisations to make effective decisions is of particular importance. As a result, as the essence of the problem, with the emergence of modern economic and technological dynamics, the decision-making process within organisations has become increasingly complex and unpredictable. Formulating successful strategies is becoming increasingly difficult for businesses, as they are exposed to both competitive demands and a rapid pace of innovation (Imanova, 2025).

Although climate change, strategic management and decision-making issues are widely studied in the existing scientific literature, a joint and integrated analysis of these topics is insufficient. These elements are considered separately in studies, which does not fully reflect the complexity of the real economic environment. One of the gaps is the insufficient explanation of the mechanisms of interaction between climate risks, resource management and strategic decisions. In practical conditions, these factors operate in close interaction with each other. Climate risks affect resource allocation, while resource constraints shape strategic choices (Batarseh, 2022). These processes jointly determine the overall performance results of the organisation. On the other hand, there is no single conceptual framework for the integration of artificial intelligence-based approaches into the decision-making process. In most studies, the application of these technologies at the management and policy levels is not sufficiently investigated. At the same time, long-term sustainability issues remain in the shadows for many studies. The primary purpose of this study was to assess the economic and organisational

consequences of climate risks, determine the role of artificial intelligence technologies in decision-making, and elucidate the interaction between resource management and strategic planning. The findings are expected to enhance the quality of management decisions and facilitate the formulation of more sustainable development strategies.

MATERIALS AND METHODS

The study covered the period 2000-2025, allowing for the analysis of both long-term climate trends and climate-related economic risk. Selecting this period ensures data consistency across all variables and enables robust analysis of both historical trends and recent developments in climate-related economic impacts. The study used a scientific framework that combines economic forecasting tools, climate datasets, and models to identify key AI methods. The datasets were used to re-examine the first extreme historical temperature anomalies, precipitation indices, drought systems, NASA GISTEMP, and ERA5. These datasets are managed for global impact, reliability, and methodological safety. They provide long-term and robust products. The empirical material of the study consists of climate indicators and macroeconomic variables, including GDP growth, inflation rates and sectoral production data. In addition, peer-reviewed scientific publications (Ozuppek *et al.*, 2025; Ayadi *et al.*, 2025) on climate-economic interactions, machine learning forecasting and agent-based modeling were analysed to establish the theoretical and methodological basis of the study. In the second stage, several forecasting approaches were applied. Traditional econometric models were used as benchmark methods. ARIMA was chosen for its ability to capture linear time dependencies in economic time series. Multiple regression was used to estimate linear relationships between climate variables and economic indicators. Machine learning methods were applied to take into account nonlinear relationships and complex interactions. Gradient Boosting was applied to capture nonlinear interactions between predictors. Long Short-Term Memory (LSTM) networks were utilised for modelling sequential patterns and long-range dependencies present

in the time series. For all the models, training was done using an identical set of data for the period 2000-2023. Uniform preprocessing and estimation methodologies were adopted for ensuring maximum comparability of the results. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2) were utilised for measuring model performance (James, 2021). RMSE measures the mean square deviation between the model-predicted and actual values and is calculated using the following formula:

$$\text{RMSE} = \sqrt{(1/n) \sum (y_i - \hat{y}_i)^2}, \quad (1)$$

where, y_i – the actual observed value; \hat{y}_i – the value predicted by the model; n – the number of observations. MAE measures the average absolute value of the forecast errors, while Coefficient of Determination (R^2) measures the level of variability explained by the model. The formulas for model performance indicators are presented below:

$$\text{MAE} = (1/n) \sum |y_i - \hat{y}_i|. \quad (2)$$

$$R^2 = 1 - (\sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2), \quad (3)$$

where, \bar{y} – the average of the actual values. These metrics were chosen to provide a consistent comparative assessment of forecast accuracy. In particular, the SHAP (SHapley AdDitive exPlanations) method was applied to determine the contribution of individual climate variables to economic forecasts. This approach reduced the opacity of the model and increased its interpretability. An agent-based economic simulation model was developed as part of the study to assess the macroeconomic outcomes. In this model, firms were represented as adaptive agents that adjust their production levels, labour allocation, and pricing strategies in response to climate shocks. Three risk scenarios (low, medium and high intensity) were constructed based on climate variability indicators. Macroeconomic outcomes such as GDP change, inflation and production loss were generated from the interaction of agents within the simulated environment. Statistical evaluation included accuracy measures, F1 score for classification tasks, mean square error and 95%

confidence intervals to ensure the reliability of the results. Ethical considerations included transparency of algorithmic design, use of publicly available data sources, compliance with data protection standards and efforts to minimise computational energy consumption.

AI-enhanced climate modelling. The prediction models that employ artificial intelligence, machine learning, deep learning, and neural networks have greatly enhanced climate modelling. These models can easily identify temperature patterns, rainfall anomalies, atmospheric pressure fluctuations, and ocean currents with greater speed and accuracy than many other models (Lewis, 2024). Furthermore, artificial intelligence has shown promise in improving short-term forecasts, real-time simulations, and pattern recognition with various variables. The study systematically reviewed over 20 scientific publications, covering both traditional numerical climate models and AI-based forecasting approaches, to define methodological frameworks. The study is based on the NASA climate report (NASA information center, 2023), and an analysis of publicly available statistical sources from Statista (Buchholz, 2023). Global temperature data and related climate variables relevant to this study were obtained from international climate data repositories such as the National Oceanic and Atmospheric Administration (NOAA, 2021), the UN Climate Change Program, NASA (2021; 2024), and the World Meteorological Organization (WMO, n.d.). The analytical procedures applied in the study are consistent with the methodological principles described in the selected sources.

Explainable artificial intelligence in climate models. Explainable AI in climate modelling aims to make complex machine learning systems more transparent and understandable. Rather than acting as “black boxes”, explainable models explain how input variables such as greenhouse gas levels, ocean temperatures, or atmospheric conditions affect predictions. By using techniques like feature importance analysis and sensitivity tests, it is possible to identify which factors have the maximum impact on temperature changes or extreme weather occurrences. This improves the reliability of the model and helps in detecting potential bias

while ensuring its compatibility with existing physical principles of climate change.

Economic forecasts using artificial intelligence. In this study, artificial intelligence-based economic forecasting methods were used to assess the impact of climate risks on economic indicators. The dynamic and interdependencies between climate variables and macroeconomic indicators can be detected more accurately through such models. Within the framework of economic forecasting, the growth rate of gross domestic product, energy consumption, inflation rate and production indicators by sectors were selected as the main target variables. The independent variables consisted of long-term temperature anomalies, precipitation variability, frequency of extreme weather events and energy-related climate indicators. By including these variables in artificial intelligence models, the economic consequences of climate risks were predicted.

Agent-based climate-environmental economic models. In this study, an Agent-Based Model (ABM) is developed to estimate the macroeconomic impacts of climate variability over the period 2000-2023. While the framework proposed by Y. Mohajerani (2025) provides conceptual guidance, the model implemented here is independently constructed and calibrated using observed climate and economic data. Due to the model structure and agent behaviours, firms act as adaptive agents that adjust their production levels, division of labour, and pricing strategies in response to climate-induced shocks. Households respond to changes in income and prices by changing their consumption patterns. Climate variables are included as exogenous shocks that affect sector productivity and input costs. Micro-level adaptive behaviours are combined to produce macroeconomic outcomes, including changes in GDP, inflation, and output losses. The study simulated low, medium and high levels of climate risk intensity based on observed data from 2000 to 2023. The resulting macroeconomic outcomes of agent responses for each scenario were determined. The proposed methodology comprehensively explains the relationship between climate and the economy, applies artificial intelligence in an interpretable manner, generates practical implications

for policy and decision-making, and models long-term risks. This provides an integrative, applicable, and analytically robust framework that is different from the existing literature.

RESULTS

Analysis of temperature anomalies

As per the analysis of the temperature records from the National Aeronautics and Space Administration (NASA), the Earth has been experiencing a continuous temperature rise since the end of the 19th century (Buchholz, 2023). The rate at which the Earth has been experiencing temperature rise has accelerated since the year 2000, with visualisations depicting the manifestation of the elevation of the Earth's

temperature. By the end of December 2020, the Earth experienced a temperature deviation of approximately 1.34°C from the baseline temperature of 1880 to present, which falls within the range of 2-2.5°C experienced in the past decades. Temperature anomalies are observed to have significant amplification during the summer season. In June 2020, it was recorded that the global mean temperature anomaly was around 2.07°C higher than the historical base period, which is beyond the previously recorded temperature anomaly of 1.1°C to 1.6 in past years. The rising temperature anomaly continues into 2023, with the temperature anomaly recorded in June being +2.23°C, thus creating a new record Figure 1.

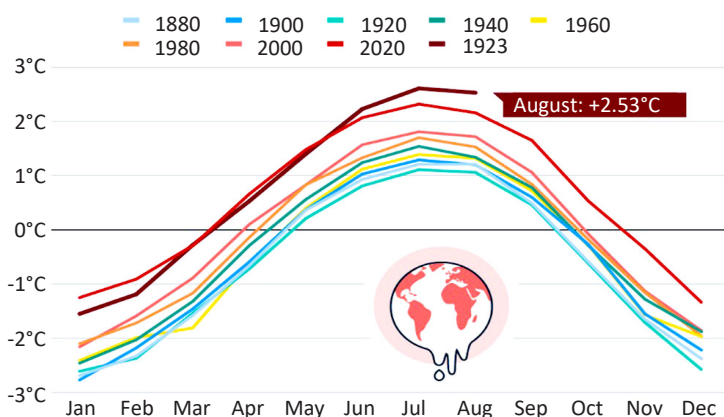


Figure 1. Monthly rate of increase in average temperature (calculated for 1880-2023) in selected years

Source: K. Buchholz (2023)

The summer of 2023, i.e., June-August, marks the period of highest temperature on Earth since systematic temperature recording started in 1880, as per NASA temperature records. This is because the global temperature during these three months of the summer of 2023 was higher than the preceding summer temperature recorded on the Earth's surface. Moreover, as per NASA temperature records, September 2023 marks the highest temperature recorded on Earth and also presents the highest temperature anomaly compared to the long-term average temperature recorded on Earth during September of any given year (NASA information center, 2023). This observation is consistent with the established

phenomenon of rising global temperatures on Earth, as per NASA temperature records. The temperature of 2016 was recorded as it marked the highest deviation of average temperature compared to the reference period of 1880-2015. NASA (2021) estimates show that 2016 and 2020 are the two warmest years on record for the Earth's surface. This is similar to what is observed globally with increasing temperatures on Earth and suggests a large risk of global warming and climatic changes, which are at a critical juncture relative to prior periods. The satellite records of NASA also show that there is a rise of 1.28°C in global air temperatures, which is the highest recorded temperature rise since systematic

temperature measurement began in 1880. In 2024, the Earth's average surface temperature reached a record high and was the warmest year since records began in 1880 (NASA, 2024). The average global surface temperature in 2025 was slightly lower than in 2024, but still higher than in previous years (NASA, 2025). According to the WMO (n.d.), 2025 was the third warmest year on record at the Earth's surface, indicating an increasing trend in surface temperatures and very high levels of global warming. The last three years, 2023-2025, were the three warmest years in all eight data sets.

From the findings discussed above, it is evident that global warming is still on course as a trend in recent years and that its rate is increasing, especially in 2016, 2019, 2020, and 2023. The findings on temperature changes suggest that the rate of risk is increasing. Such changes have posed a challenge to the economy as well as to natural resources. In this respect, the need to employ AI as well as economic forecasting techniques becomes necessary. This is because the

ability of statistical analysis to forecast climate variables accurately is limited. In this respect, the ability of AI-based forecasting techniques to predict climate variables in the study framework was analysed in order to compare the results with the ability of statistical analysis to predict the variables. From the analysis, it can be deduced that the results from the application of machine learning in the study have higher accuracy in the prediction of climate variables.

Model performance and forecast accuracy

Both accuracy indicators and stability criteria were taken into account during model evaluation. In this research, performance metrics such as root mean square error, mean absolute error, and coefficient of determination are used. These performance metrics have been calculated in order to compare the economic forecasting models based on climate variables (Table 1). It is worth noting that all models are based on the same dataset and used the same method of estimation, covering the period from 2000 to 2023.

Table 1. Comparison of model performance (2000-2023)

| Model | RMSE | MAE | R ² |
|---------------------|-------------|-------------|----------------|
| ARIMA | 0.74 | 0.61 | 0.48 |
| Multiple regression | 0.69 | 0.57 | 0.52 |
| Gradient Boosting | 0.41 | 0.34 | 0.78 |
| LSTM | 0.36 | 0.29 | 0.84 |

Note: the model performance indicators presented in Table 1 were calculated using the RMSE, MAE, and R² formulas 1, 2, 3

Source: data generated by the author

Traditional models such as ARIMA and multiple regression, which rely on linear assumptions, were unable to accurately capture sudden temperature changes and extreme weather events, leading to lower forecast accuracy. These models are limited by their linear structure, short memory of past observations, and sensitivity to outliers. Although the addition of non-linear terms or regime-switching terms is possible, this has more limitations in terms of flexibility compared to state-of-the-art machine learning techniques. In contrast, the best performance was achieved by the LSTM model with the following error measures: RMSE = 0.36, MAE = 0.29, and R² = 0.84, signifying the ability to

model long-range dependencies and complex non-linear relationships in the climate data. This is because it is able to retain memory cells over long periods of time, making it very effective for seasonal and sudden changes. These findings are a testament to those of Z. Zhang *et al.* (2025), who found that LSTM was more effective than linear and tree-based methods for predicting economic indicators based on temperature. However, unlike Z. Zhang *et al.* (2025), this study also proves that it is more effective than Gradient Boosting, showing its potential for accurately predicting financial risks related to climate change and its nonlinear and time-dependent nature.

Analysis of the economic impacts of climate variables (XAI results)

Explainable Artificial Intelligence (XAI) analysis was conducted using the SHAP framework to interpret how individual climate variables influence economic forecasts generated by the LSTM model. SHAP values allow identification of both the magnitude and direction (positive or negative) of each variable’s contribution to predicted economic outcomes. The results showed that average temperature increase, precipitation anomalies, and drought duration have the greatest impact on economic forecasts. These

findings indicate that climate risks are transmitted to economic systems mainly through temperature and water-resource channels. In this regard, artificial intelligence-based models enable the achievement of higher forecast accuracy. The analysis shows that average temperature increase was the variable that had the greatest impact on model forecasts, with a total impact share of 34%. Precipitation anomalies accounted for 26%; drought duration for 18%; and the number of extremely hot days and humidity levels had relatively lower, but statistically significant, impacts (Fig. 2).

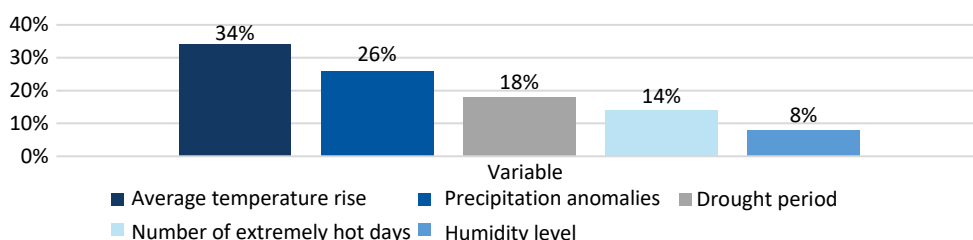


Figure 2. Variables with the main influence (2000-2023)

Source: data generated by the author

The results also corroborate results obtained in prior studies such as E. Ozupek *et al.* (2025) and Z. Zhang *et al.* (2025). At the same time, it is also evident that even though traditional methods and some alternative techniques such as Gradient Boosting are effective in predicting economic indicators that are sensitive to climate change, even better results are obtained when a Long Short-Term Memory Network is applied. The results of the XAI analysis improve model interpretability by clearly quantifying the extent of each predictor’s contribution.

Results of the agent-based economic model

The ABM simulation results quantify the macroeconomic impact of climate variability over the period 2000-2023 and demonstrate how sector-specific shocks affect overall economic outcomes. The model presents results for three levels of observed climate risk intensity. The model explains the mechanism of macroeconomic outcomes by simulating the responses of individual economic entities to climate shocks (Azhar *et al.*, 2025). As the intensity of climate

risks increases, the following changes are observed in the economic system (Table 2).

As can be seen, low-risk years show moderate GDP declines and limited inflation. This also reflects resilience in the economy when climate shocks are mild. This is because adaptive responses by firms and households mitigate short-term impacts, so output losses are minimal. Medium-risk years highlight the cumulative effects of climate shocks. Cumulative climate shocks reduce agricultural output and increase energy demand, which leads to increased costs and deeper production losses. Although firms adjust partially through division of labour and input substitution, the economy is unable to fully absorb repeated shocks. High-risk years demonstrate structural stress. Severe climate shocks create economic structural stress through decreased agricultural productivity, increased energy costs, and increased supply chain fragmentation. As a result, there is a significant decline in gross domestic product (GDP), and inflation rates increase. For instance, there is a decline in GDP of 5.4%, and inflation rates increase to 4.3%.

Output losses are 7.1%. These findings suggest that severe climate events could create persistent economic vulnerabilities. In general, the findings suggest that climate shocks affect the

scale of the economy and price dynamics. Sectoral interventions, along with macroeconomic policy interventions, can reduce vulnerabilities and increase resilience.

Table 2. Macroeconomic outcomes (2000-2023)

| Scenario | GDP change | Inflation | Production loss |
|-------------|------------|-----------|-----------------|
| Low risk | -0.8% | +0.5% | -1.2% |
| Medium risk | -2.6% | +1.9% | -3.8% |
| High risk | -5.4% | +4.3% | -7.1% |

Source: author’s simulation results based on the ABM calibrated for 2000-2023

The results of the study show that artificial intelligence-based models significantly outperform classical approaches in predicting the economic impact of climate variables. Classical studies also noted the decisive impact of temperature increase on economic productivity (Lu, 2023). However, most of the existing literature analyses climate models and economic models separately, presents artificial intelligence methods as a “black box” and does not clearly indicate how the results will be integrated into the decision-making process. The conducted analyses show that climate variables have a direct and measurable impact on economic indicators. It confirms that climate risks, in addition to being an ecological problem, are also a factor of macroeconomic stability. Artificial intelligence models predict these impacts more accurately than classical methods (Sandiponi, 2025). AI methods, on the other hand, make the decision-making process transparent. The results obtained indicate that artificial intelligence models are capable of predicting climate risks 6-12 months in advance, and that climate-informed planning increases the effectiveness of budget expenditure.

The results show that the relationship between climatic variables and economic indicators is non-linear and dynamic. The temperature anomalies have a considerable impact on productivity. The results show that artificial intelligence models can accurately define the relationship. While traditional econometric models are based on stable and linear relationships between variables, the LSTM model facilitated the detection of long-term dependencies over time and non-linear impact mechanisms. Since the impact of climate change is gradual and

sometimes exacerbated after critical thresholds, data-based models provide more appropriate results. This result indicates the need for methodological transformation in climate risk assessment. From a practical perspective, artificial intelligence-based economic forecasting systems can help form early warning mechanisms and timely assessment of risks, especially in the energy, agriculture, and financial sectors, which can ensure a more optimal allocation of resources. E. Ozupek *et al.* (2025) demonstrates that AI has the ability to identify important climatic factors that lead to the onset of drought, which allows for more reliable early warning systems. This approach allows the results to be interpreted not only from a technical but also from a policy perspective. Improvements made by AI, Figure 3.

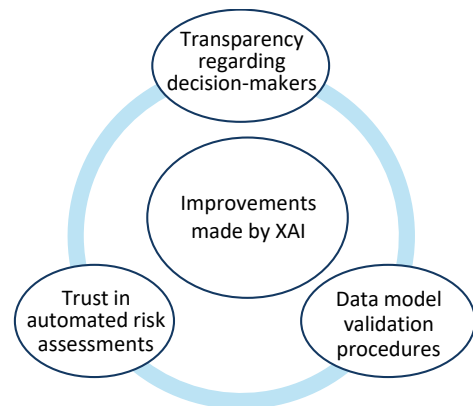


Figure 3. Improvements made by AI
Source: E. Ozupek *et al.* (2025)

Determining the impact of variables through SHAP analysis more clearly shows that climate

factors are a priority risk factor. The results obtained show that climate risks are spread in economic systems not only directly, but also through interaction mechanisms. In particular, the relationship between temperature increase and energy consumption directly affects production costs (Pasqualetto, 2024). This, in turn, increases the price level and inflation. Such chain effects are not sufficiently taken into account in traditional models. Artificial intelligence approaches, on the other hand, can simultaneously process multidimensional interactions between variables. This approach allows for the identification of risks at an earlier stage in the economic decision-making process and the formation of adaptive policy instruments. Thus, artificial intelligence-based economic forecasting both increases analytical accuracy and creates strategic planning opportunities for the systematic management of climate risks.

DISCUSSION

The results of this study are consistent with the results of a number of contemporary scientific studies examining the impact of climate change on the economy. While Y. Mohajerani (2025) shows that high-emission scenarios generate long-term inflationary pressures and supply chain disruptions, this study empirically confirms these mechanisms for the period 2000-2023. Unlike Y. Mohajerani, the current model incorporates interpretable AI to measure the impact of climate variables and generates explicit macroeconomic measures for GDP, inflation, and output losses. M. Azhar *et al.* (2025) examined the impact of climate change on GDP and inflation in developing countries and found that climate shocks lead to a decrease in economic growth and an increase in inflation. The results of this study also show that climate-related risks affect price increases, especially through a decrease in production in the agricultural sector. However, although M. Azhar *et al.* (2025) uses the panel regression method from a methodological point of view, this study simulates the formation of macroeconomic outcomes through agent-based modelling (ABM) based on the interaction of agents at the micro level. A study by T. Ehlers *et al.* (2025) also examined the impact of climate and weather events on various sectors of the economy and showed

that climate risks lead to a decrease in production and an increase in prices. These results are consistent with the results of the current study. However, the authors' study is based on models based on global empirical data used by the Bank for International Settlements. Studies focused on the agricultural sector also show similar results. T. Yusifzada (2024) showed that climate variability is one of the main factors affecting the increase in agricultural prices and empirically substantiated this relationship using a climate condition index. The results of this study also support this idea with a different methodological approach and show that climate shocks cause an increase in food prices. Although T. Yusifzada (2024) uses an index-based empirical approach, this study models agent behaviour and the mechanism of cost transmission throughout the economic system. Recently, studies on the application of artificial intelligence technologies in climate risk assessment have also been widespread. For example, M.K. Khan *et al.* (2023) showed that the application of artificial intelligence technologies in enterprises helps to manage climate risks more effectively. This study also confirms that artificial intelligence-based models play an important role in the analysis and forecasting of climate risks. However, M.K. Khan *et al.* (2023) focused more on risk management at the organisational level, using statistical and machine learning approaches based on empirical data to evaluate the impact of AI implementation on enterprise performance. A study by Y. Wang *et al.* (2025) found that machine learning models performed better than traditional methods in predicting climate risks. While this result is consistent with the results of the current study, the authors used a binary machine learning approach. The results of this study show that the LSTM model provided the highest prediction performance, with a coefficient of determination (R^2) of 0.84. In general, in the existing literature, the economic impacts of climate change have been mainly investigated through either empirical macroeconomic analyses or artificial intelligence-based forecasting methods. This study presents an integrative approach that combines agent-based modelling and machine learning methods to more broadly explain the mechanism of climate risk transmission to the economic system.

The findings are consistent with the recommendations of the UN Technology Mechanism on Climate Change. A new technical paper published by the Technology Implementation Committee (TIC) of the UNFCCC Technology Mechanism explores how AI can serve as a powerful enabler of climate action in developing countries, which are most vulnerable to climate impacts (UNFCCC, 2025). TIC Chair Dietram Opetelt presented the Committee's latest technical paper at the AI for Good Summit in Geneva. The paper, developed in partnership with the United Nations Industrial Development Organization and supported by the Korea International Cooperation Agency, is part of the Technology Mechanism's ClimateAction initiative. It provides a comprehensive guide to policymakers, practitioners, and researchers on the opportunities, risks, and challenges of using artificial intelligence in the mitigation and adaptation of climate change in developing countries (UNFCCC, 2025). There is considerable potential in AI technologies to mitigate greenhouse gas emissions. This is particularly true in minimising energy wastage, optimising energy consumption and distribution, and identifying areas where there is excessive emission in industrial processes. The AI energy management system has the potential to improve the grid, forecast energy demand, and optimise the use of renewable energy sources such as wind and solar energy.

A number of strategic actions are needed to maximise the benefits of using AI in climate action in developing countries (UNFCCC, 2025). First, it is important to increase investments in infrastructure development and programs aimed at building capacity in the field of AI in order to bridge the digital divide. This approach can create conditions for strengthening local experts and expanding technological capabilities. At the same time, improving the quality of climate data is of great importance to support the development and application of AI models. To this end, it is recommended to establish more advanced data collection mechanisms and expand open data initiatives. In addition, it is necessary to form appropriate regulatory frameworks to ensure transparency and accountability in the application of AI technologies. These frameworks can contribute to strengthening AI governance

within the framework of the UN Framework Convention on Climate Change. Another important direction is to build AI systems based on inclusive approaches, which would allow for the elimination of problems such as social inequality and a more equitable distribution of the benefits of climate action. Finally, when implementing AI technologies, special attention should be paid to the efficient use of energy and water resources, and the development of resource-saving and sustainable technological solutions should be encouraged. This approach can help ensure the long-term sustainability of AI systems.

Global near-surface temperature records come from land-based surface meteorological stations as well as from ship-based, buoy-based, and satellite-based observations over the ocean. According to scientific evidence, continued global warming will lead to changes in the intensity, frequency, geographic extent, and duration of extreme weather occurrences. Likewise, AI can be used to optimise the flow of traffic, thereby reducing fuel consumption. In addition, there are promising opportunities for adapting to the effects of climate change with the use of AI (Ayadi *et al.*, 2025). For instance, AI can be used to improve the efficiency of early warning systems for extreme weather occurrences like hurricanes, floods, and droughts (Camps-Valls *et al.*, 2025). In addition, AI-based urban resilience planning can help to elucidate the vulnerabilities of urban infrastructure and optimise land use. Moreover, with the integration of satellite images, AI can aid in biodiversity conservation, water sustainability, and land restoration activities (Jain, 2023). Although the results of this study are reliable, there are certain limitations (UNFCCC & UNIDO, 2025). These limitations include data limitations, model sensitivity, structural simplification, and time constraints. First, it should be noted that the data used are mainly global in scale. It is possible that climate-economic dynamics at the regional and local levels may differ. Second, AI models are sensitive to hyperparameters, so models built with different parameters may produce different results. Agent-based models do not fully reflect real economic behaviour and do not take into account some social factors. Due to time constraints, the model mainly covers short- and medium-term impacts. Long-term

(50-100 years) climate impacts cannot be captured in this study. If there is a lack of inclusiveness in the development of algorithms, there is a possibility of further deepening inequalities. Besides, the energy and water requirements of AI systems are sustainability concerns, especially in regions where there are already existing resource constraints. Limited digital infrastructures, including unreliable internet connectivity, limited computing capacity, and limited human capacity, hinder the development of AI systems. Moreover, developing countries often experience difficulties related to accessing quality and comprehensive climate information, which is essential for creating artificial intelligence models and for informing robust and quality-based decision-making. Without quality information sharing and cybersecurity mechanisms, there is a likelihood of inaccurate information emanating from AI outputs. However, it is important to note that these challenges and limitations do not in any way affect the results' accuracy but, instead, require a more in-depth understanding of the same. It is possible for future research to incorporate alternative models and approaches, such as causality, in order to become more effective. Separately, examining the impact of climate risks on financial stability and capital flows could be considered a promising direction.

CONCLUSIONS

The primary aim of this study was to examine the economic and organisational consequences of climate risks, identify the role of artificial intelligence in the process, and clarify the interaction between the management of resources and strategic planning in relation to climate risks. The study findings show that the objectives were fully realised through the integration of agent-based economic modelling, sophisticated machine learning, and artificial intelligence techniques. The findings point to the fact that climatic factors, such as increased temperatures, inconsistent precipitation, and drought periods, have a quantified effect on macroeconomic performance. Using scenario analysis to examine the period between 2000 and 2023, it is evident that increased risk intensity in climatic factors is linked to lower GDP levels, high inflation rates, and production losses in different sectors.

Agriculture is identified as the most susceptible sector to climatic factors due to its direct exposure to temperature and water risks, while the energy sector reflects the effects of climatic factors in terms of increased costs. These dynamics confirm the structural link between environmental stress and economic vulnerability.

Model comparison further shows that deep learning methods outperform traditional econometric approaches in forecasting climate-related economic outcomes. The superior performance of the LSTM model indicates that nonlinear and time-dependent relationships between climate and economic variables require more flexible analytical frameworks. The use of explainable artificial intelligence techniques provided greater transparency through the quantification of the relative importance of each of the climate indicators on the economic forecasts, thus improving the overall reliability of the results. In conclusion, this study shows that the integration of artificial intelligence with economic forecasting has a significant positive impact on the assessment of climate risks, thus improving the robustness of strategic planning. Future studies need to be conducted to extend the cross-country comparison, include the incorporation of firm-level data, and examine the long-term transition risks under different climate policy scenarios. The improvement of the quality of the data, the ethics of AI, and coordination are important to fully exploit the benefits of the technological progress.

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CONFLICT OF INTEREST

The author declares no conflict of interest related to this study.

REFERENCES

- [1] Ayadi, R., Forouheshfar, Y., & Moghadas, O. (2025). Enhancing system resilience to climate change through artificial intelligence: A systematic literature review. *Frontiers in Climate*, 7, article number 1585331. doi: [10.3389/fclim.2025.1585331](https://doi.org/10.3389/fclim.2025.1585331).
- [2] Azhar, M., Ilyas, S., Ali, S.Y., & Shafiq, A. (2025). Assessing the macroeconomic consequences of climate change: Impacts on GDP growth, inflation volatility, and agricultural productivity in developing economies. *Review Journal of Social Psychology & Social Works*, 3(2), 250-268. doi: [10.71145/rjsp.v3i2.191](https://doi.org/10.71145/rjsp.v3i2.191).
- [3] Batarseh, F.A., et al. (2022). The role of AI in responding to climate challenges. In *Proceedings of the AAAI 2022 Fall Symposium*. doi: [10.48550/arXiv.2212.13631](https://doi.org/10.48550/arXiv.2212.13631).
- [4] Buchholz, K. (2023). *Earth is heating up*. Retrieved from <https://www.statista.com/chart/19048/global-warming-monthly-divergence/>.
- [5] Burke, M., Hsiang, S.M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527, 235-239. doi: [10.1038/nature15725](https://doi.org/10.1038/nature15725).
- [6] Camps-Valls, G., et al. (2025). Artificial intelligence for modeling and understanding extreme weather and climate events. *Nature Communications*, 16, article number 1919. doi: [10.1038/s41467-025-56573-8](https://doi.org/10.1038/s41467-025-56573-8).
- [7] Cowls, J., Tsamados, A., Taddeo, M., & Floridi, L. (2023). The AI gambit: Leveraging artificial intelligence to combat climate change – opportunities, challenges, and recommendations. *AI & Society*, 38, 283-307. doi: [10.1007/s00146-021-01294-x](https://doi.org/10.1007/s00146-021-01294-x).
- [8] Ehlers, T., Frost, J., Madeira, C., & Shim, I. (2025). *Macroeconomic impact of weather disasters: A global and sectoral analysis* (Working Paper No. 1292). Basel: Bank for International Settlements.
- [9] Imanova, M. (2025). Application of strategic management tools in business growth. *Ancient Land International Scientific Journal*, 7(8), 65-76. doi: [10.36719/2706-6185/50/65-76](https://doi.org/10.36719/2706-6185/50/65-76).
- [10] Jain, H., Dhupper, R., Shrivastava, A., Kumar, D., & Kumari, M. (2023). AI-enabled strategies for climate change adaptation: Protecting communities, infrastructure, and businesses from the impacts of climate change. *Computational Urban Science*, 3, article number 25. doi: [10.1007/s43762-023-00100-2](https://doi.org/10.1007/s43762-023-00100-2).
- [11] James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An introduction to statistical learning: With applications in R*. New York: Springer. doi: [10.1007/978-1-0716-1418-1](https://doi.org/10.1007/978-1-0716-1418-1).
- [12] Khan, M.K., Hussain, M.J., Hussain, M.W., Qadeer, A., Armstrong, A., & Li, S. (2025). AI integration for climate risk mitigation: The role of organizational context. *Technological Forecasting and Social Change*, 220, article number 124327. doi: [10.1016/j.techfore.2025.124327](https://doi.org/10.1016/j.techfore.2025.124327).
- [13] Leong, W.Y. (2025). Artificial intelligence-driven analytics for monitoring and mitigating climate change impacts. *Engineering Proceedings*, 108(1), article number 7. doi: [10.3390/engproc2025108007](https://doi.org/10.3390/engproc2025108007).
- [14] Lewis, J.I., Toney, A., & Shi, X. (2024). Climate change and artificial intelligence: Assessing the global research landscape. *Discover Artificial Intelligence*, 4, article number 64. doi: [10.1007/s44163-024-00170-z](https://doi.org/10.1007/s44163-024-00170-z).
- [15] Lu, Q.-B. (2023). Critical review on radiative forcing and climate models for global climate change since 1970. *Atmosphere*, 14(8), article number 1232. doi: [10.3390/atmos14081232](https://doi.org/10.3390/atmos14081232).
- [16] Mehryar, S., Yazdanpanah, V., & Tong, J. (2024). AI and climate resilience governance. *iScience*, 27(6), article number 109812. doi: [10.1016/j.isci.2024.109812](https://doi.org/10.1016/j.isci.2024.109812).
- [17] Mohajerani, Y. (2025). Evolutionary learning in spatial agent-based models for physical climate risk assessment. *arXiv*. doi: [10.48550/arXiv.2509.18633](https://doi.org/10.48550/arXiv.2509.18633).
- [18] NASA information center. (2023). *NASA report: Summer of 2023 has been Earth's hottest since global records began in 1880*. Retrieved from https://spacecoastdaily.com/2023/09/nasa-report-summer-of-2023-has-been-earths-hottest-since-global-records-began-in-1880/?utm_source.
- [19] NASA. (2021). *2020 tied for warmest year on record*. Retrieved from <https://science.nasa.gov/earth/earth-observatory/2020-tied-for-warmest-year-on-record-147794/>.

- [20] NASA. (2024). *Temperatures rising: NASA confirms 2024 warmest year on record*. Retrieved from https://www.nasa.gov/news-release/temperatures-rising-nasa-confirms-2024-warmest-year-on-record/?utm_source.
- [21] NASA. (2025). *NASA releases global temperature data*. Retrieved from <https://www.nasa.gov/news-release/nasa-releases-global-temperature-data/>.
- [22] NOAA. (2021). *2020 global climate assessment. National centers for environmental data*. Retrieved from <https://www.ncei.noaa.gov/news/global-climate-202012>.
- [23] Ozupek, E., Teke, A., Celik, N., & Kavzoglu, T. (2025). Explainable artificial intelligence for meteorological drought forecasting. *Stochastic Environmental Research and Risk Assessment*, 39, 3201-3222. doi: 10.1007/s00477-025-03007-y.
- [24] Papadopoulos, T., & Balta, M.E. (2022). Climate change and big data analytics: Challenges and opportunities. *International Journal of Information Management*, 63, article number 102448. doi: 10.1016/j.ijinfomgt.2021.102448.
- [25] Pasqualetto, A., Serafini, L., & Sproccati, M. (2024). Artificial intelligence approaches for energy efficiency: A review. *arXiv*. doi: 10.48550/arXiv.2407.21726.
- [26] Sandiponi, T. (2025). A review of artificial intelligence applications in climate change mitigation. *International Journal of Environment and Climate Change*, 15(5), 443-449. doi: 10.9734/ijecc/2025/v15i54864.
- [27] UNFCCC & UNIDO. (2025). *Artificial intelligence for climate action: Advancing mitigation and adaptation in developing countries*. Retrieved from https://unfccc.int/ttclear/misc/StaticFiles/gnwoerk_static/AI4climateaction/f2922b97c4cf431996c468e622127eb5/112f8be560ea447dab5ff2e53ab3f6e4.pdf.
- [28] UNFCCC. (2025). *AI and climate action: Opportunities, risks and challenges for developing countries*. Retrieved from <https://unfccc.int/news/ai-and-climate-action-opportunities-risks-and-challenges-for-developing-countries>.
- [29] Wang, Y., Zhang, P., Xie, Y., Chen, L., & Li, Y. (2025). Toward explainable flood risk prediction: Integrating a novel hybrid machine learning model. *Sustainable Cities and Society*, 120, article number 106140. doi: 10.1016/j.scs.2025.106140.
- [30] WMO. (n.d.). *WMO confirm 2025 was one of warmest years on record*. Retrieved from https://wmo.int/news/media-centre/wmo-confirms-2025-was-one-of-warmest-years-record?utm_source.
- [31] Yin, H., Yin, X., & Wen, F. (2025). Artificial intelligence and climate risk: A double machine learning approach. *International Review of Financial Analysis*, 103, article number 104169. doi: 10.1016/j.irfa.2025.104169.
- [32] Yusifzada, T. (2024). Evaluating the global impact of climate change on agricultural inflation: An innovative climate condition index approach. *Environment, Development and Sustainability*, 26(7), 18411-18438. doi: 10.1007/s10668-023-03394-8.
- [33] Zaidan, M.A., Motlagh, N.H., Nurmi, P., Hussein, T., Kulmala, M., Petäjä, T., & Tarkoma, S. (2025). Artificial intelligence for atmospheric sciences: A research roadmap. *arXiv*. doi: 10.48550/arXiv.2506.16281.
- [34] Zhang, Z., Fischer, E., Zscheischler, J., & Engelke, S. (2025). Numerical models outperform AI weather forecasts of record-breaking extremes. *arXiv*. doi: 10.48550/arXiv.2508.15724.

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Штучний інтелект та економічні прогнози в управлінні кліматичними ризиками

Анотація. Фізичні, фінансові та системні ризики, пов'язані зі зміною клімату, продовжують зростати в економіках усього світу. У міру того як частота та інтенсивність кліматичних ризиків посилюються, стандартним інструментам прогнозування стає дедалі складніше адекватно враховувати складні еколого-економічні взаємодії. Метою цієї статті було детально дослідити роль штучного інтелекту (ШІ) та економічного прогнозування в управлінні кліматичними ризиками. Дослідження продемонструвало, що ідентифікація та прогнозування екстремальних погодних явищ суттєво покращуються завдяки використанню кліматичних моделей на основі ШІ. Пояснюваний штучний інтелект забезпечує додаткову прозорість, оскільки дає змогу аналітикам і політикам краще розуміти чинники, що впливають на прогнози, сформовані моделями посух, повеней і хвиль спеки. У поєднанні з моделями економічного прогнозування ШІ забезпечує проведення комплексних симуляцій того, як кліматичні виклики поширюються через ланцюги постачання, ринки праці, енергетичні мережі та фінансові системи. Попри ці переваги, моделювання на основі ШІ має низку обмежень, зокрема дефіцит даних, обмежену узагальнюваність результатів, а також етичні питання, пов'язані з прозорістю, енергоспоживанням і нерівністю. У дослідженні зроблено висновок, що інтеграція ШІ з економічним прогнозуванням формує надійну міждисциплінарну основу для оцінювання кліматичних ризиків, формування політики та розроблення адаптаційних стратегій. Водночас ефективність такого підходу залежить від удосконалення систем управління, розвитку інфраструктури даних і відповідального впровадження технологій. Практична значущість дослідження полягає у можливості більш точного та раннього оцінювання впливу кліматичних змін на економічні системи. Отримані результати є особливо актуальними для прогнозування та управління ризиками в енергетичному, аграрному та фінансовому секторах

Ключові слова: машинне навчання; пояснювальний штучний інтелект; агентно-орієнтовані моделі; кліматична політика; економічна стійкість; інновації