International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 3 (1) 2025

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ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 3(1), 2025

Research Paper

RNN-KNN FUSION FOR PREDICTIVE MODELLING OF CLIMATE-INDUCED ECONOMIC DISRUPTIONS

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Received: 05-6-2025 Accepted: 03-7-2025 Published: 10-7-2025

ABSTRACT

Climate change poses a significant threat to global economic stability, with recent studies estimating that unmitigated climate change could reduce global GDP by 11-14% by 2050. Sectors such as agriculture, insurance, and infrastructure are particularly vulnerable, with crop yields projected to decline by up to 25% and natural disaster damages increasing by over $300 billion annually. Despite this, most climate-related economic assessments remain reactive rather than predictive, relying heavily on manual data aggregation, static models, and domain-specific heuristics. These approaches lack scalability and fail to capture nonlinear climate-economic interactions. To address these limitations, we propose an AI-driven climate impact estimator that integrates historical climate data, socio-economic indicators, and industry-specific metrics to forecast the economic implications of climate change across sectors and geographies. The system utilizes a combination of deep learning for spatiotemporal climate modeling, and ensemble regression techniques for economic impact prediction. Additionally, it incorporates industry-adaptive feature selection and transfer learning to account for varying regional sensitivities and data scarcity. Our experiments on multi-sector datasets demonstrate strong predictive accuracy, with R^2 scores exceeding 0.89 for regression tasks in sectors such as agriculture and energy, and F1 scores above 0.85 for classifying regions by risk level. This approach provides a scalable, data-driven framework for policymakers and businesses to proactively assess and mitigate the economic risks of climate change.

Key words: Climate Risk Modeling, Climate Change Analytics, RNN Feature Extraction, Green Economy Prediction, GDP Loss Estimation

1. INTRODUCTION

Climate change has emerged as one of the most pressing challenges of the 21st century, with far-reaching consequences on ecosystems, societies, and economies. According to the Intergovernmental Panel on Climate Change (IPCC), global surface temperatures have risen by approximately 1.1°C since pre-industrial times, contributing to the increase in extreme weather events, rising sea levels, and shifting climatic zones. These changes are not only environmental but also deeply economic, as they affect resource availability, productivity, and operational stability across multiple industries. The economic toll of climate-related disasters has been steadily rising, with reports from the World Bank estimating that climate change could push over 130 million people into poverty by 2030. Specific industries are already experiencing the impact—agriculture is facing declining yields, coastal infrastructure is threatened by flooding, and energy systems are strained due to increased cooling demands and fluctuating water availability. These disruptions carry direct financial consequences, from increased operational costs to market instability and investor uncertainty, insurance data shows that global insured losses due to natural disasters have exceeded $100 billion annually in recent years, double the average of previous decades.

As risks mount, there is growing pressure on industries, governments, and financial institutions to incorporate climate risk into their decision-making processes. However, quantifying and predicting the economic impact of climate variables remains a significant challenge due to the complexity and dynamic nature of the climate system. In the insurance and reinsurance industry, firms like Swiss Re and Munich Re rely on historical disaster data and actuarial models to estimate future liabilities. However, the volatility introduced by climate change renders

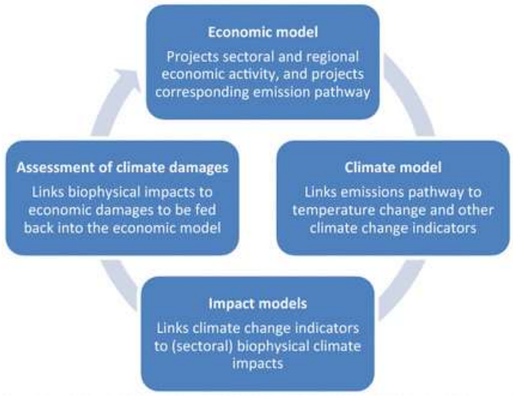

Fig 1. Link of economic and climate changes

traditional models less effective. As weather patterns shift unpredictably, the need for adaptive, forward-looking analytics becomes essential. Real-time climate data integrated with financial forecasting can help these companies dynamically price risks and develop resilient coverage strategies.

Tech companies operating data centers, such as Google and Amazon, are also facing increasing energy and cooling costs due to rising temperatures. Understanding how climate trends affect operational efficiency, resource consumption, and infrastructure lifespan is critical for business continuity. In such high-stakes environments, the application of advanced data analytics is not a luxury but a necessity. It enables companies to model future scenarios, reduce vulnerabilities, and adapt business strategies accordingly. The challenge lies in developing a robust mechanism that can systematically correlate climate indicators such as temperature shifts, rainfall variability, and extreme events with economic performance metrics across diverse industries. In many cases, available data is unstructured, regionally imbalanced, and not directly compatible with economic forecasting models. This gap hinders the development of scalable tools capable of offering actionable predictions at an industry-wide level.

Furthermore, industries lack a unified framework that connects climate projections to business-specific outcomes like crop loss, energy demand, insurance premiums, or infrastructure depreciation. Without such a framework, strategic planning and investment in climate resilience remain speculative and reactive. There is a growing need to define the problem in terms of data integration, modeling precision, and relevance to real-world economic conditions.

2. LITERATURE SURVEY

Tol et al. [1] The study aims to pinpoint key economic sectors impacted and give numerical predictions of potential monetary damages. We used a wide-ranging data set from 1990 to 2020 to evaluate the economic effects of climate change through the use of multiple regression analysis, time-series forecasting, and econometric modeling. Important factors include GDP, agricultural production, healthcare expenditures, and disaster costs. Also, Monte Carlo simulations as well to assess the variability of our forecasts. The analysis shows that by 2050, climate change might cause a yearly decrease of around 2% in global GDP, amounting to a possible loss of $2.5 trillion.

Sumon et al. [2] Machine learning (ML) models offer a powerful tool for predicting and analyzing such impacts, allowing for more efficient decision-making and long-term planning. These models are supposed to analyze patterns in energy production, land use, and emissions to make a more dynamic and predictive understanding of how renewable energy adoption influences CO2 levels. The principal aim of this research project was to develop and curate machine learning algorithms for predicting CO2 emissions based on renewable energy data, using the knowledge to better understand how solar, wind, hydro, and geothermal energy systems affect environmental outcomes.

Tongxi et al. [3] reviewed 226 studies that used statistical models to characterize the impacts of climate change on crop yields. Elaborated on the constraining nature of statistical models in disentangling the complicated yield-climate relationships, which is used to predict or explain. Also discussed common issues related to the use of statistical models, such as strong assumptions that may not hold, and inconsistencies among models.

Zhao et al. [4] This study adopted a provincial computable general equilibrium model by distinguishing different laborers and regions in modelling work to address the aforementioned gap. The study estimates economic costs at different levels under three climate change scenarios (lower (SSP126), middle (SSP245), and higher (SSP585) warming scenarios). Low-income regions located in the southwest part of China (such as Guangxi and Guizhou) would experience the largest economic loss, 3.4–7.1 times higher than high-income regions in China by 2100 under the SSP245 scenario.

Saleem et al. [5] The Agriculture sector encounters severe challenges in achieving the sustainable development goals due to direct and indirect effects inflicted by ongoing climate change. Although many industries are confronting the challenge of climate change, the impact on agricultural industry is huge. Irrational weather changes have raised imminent public concerns, as adequate output and food supplies are under a continuous threat. Food production system is negatively threatened by changing climatic patterns thereby increasing the risk of food poverty.

Wahab et al. [6] This motivates us to explore the impacts of the climate change on recovery of agricultural loans caused by losses in agricultural productivity. Using panel data from 82 districts of Pakistan over a period of 21 years, i.e., 2000–2020, we estimate the sensitivity of agricultural productivity to climate change in each district. Using these sensitivities, we then apply Panel-Corrected Standard Errors (PCSE) Regression to estimate whether climate change sensitivities of agricultural productivity have any impact on the recoveries of agricultural loans across the sampled districts.

Faizan et al. [7] Artificial intelligence (AI) technology have the potential to deal with many of these challenges; massive weather forecasting and imagery dataset can be collected worldwide and analyzed using deep-AI models. This will ultimately provide real-time information regarding changing spatial-temporal dynamics of pests and alert policymakers, producers, and businesses to develop integrated strategy for mitigation of evolving pest infestation.

Bracco et al. [8] Utilized Big data and associated algorithms, coalesced under the field of machine learning (ML), offer the opportunity to study the physics of the climate system in ways, and with an amount of detail, that were previously infeasible. Additionally, ML can ask causal questions to determine whether one or more variables cause or affect one or more outcomes and improve prediction skills beyond classical limits.

Hübner et al. [9] Developed artificial intelligence (AI) is driving transformative changes in many areas, with significant environmental implications. Yet, environmental assessments for specific applications are scarce. This study presents an in-depth life cycle assessment of “Foodforecast,” a machine learning (ML) cloud service designed to reduce food waste in bakeries by optimizing sales forecasting. It covers four impact categories: global warming, abiotic resource depletion, cumulative energy demand, and freshwater eutrophication. The assessment includes both the direct environmental impacts of the ML model and the underlying system hardware, as well as the indirect benefits of avoided bakery returns compared to traditional ordering methods, using real-world case study data.

Materia et al. [10] AI techniques have shown great potential to improve the prediction of

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extreme events and uncover their links to large-scale and local drivers. Machine and deep learning have been explored to enhance prediction, while causal discovery and explainable AI have been tested to improve our understanding of the processes underlying predictability. Hybrid predictions combining AI, which can reveal unknown spatiotemporal connections from data, with climate models that provide the theoretical foundation and interpretability of the physical world, have shown that improving prediction skills of extremes on climate-relevant timescales is possible.

Dugbartey et al. [11] By leveraging machine learning models, big data analysis, and scenario-based forecasting, financial institutions can assess the potential impact of geopolitical instability, environmental shocks, and technological disruptions on financial systems. Additionally, stress testing frameworks enable regulators and policymakers to evaluate the resilience of financial institutions under extreme conditions, ensuring adequate capital buffers and liquidity measures. This research explores how predictive analytics, stress testing, and crisis response strategies can be effectively integrated to enhance financial stability in an era of escalating global uncertainties.

Darwish et al. [12] Artificial intelligence (AI) is significantly contributing to the scientific comprehension of climate change. Although AI and Data science (DS) applications are still in their nascent phases of research, the advancements made thus far indicate significant potential for improved monitoring of human-caused climate effects, enhanced comprehension of the Earth's climate evolution, and more accurate predictions of climate impacts. Computer simulations of intricate climate models are the foundation of the most accurate scientific comprehension of climate processes and predictions of climatic consequences.

3. PROPOSED SYSTEM

The project begins by utilizing the Climate-Risk-Index-1 dataset, which contains country-level data on economic and climate-related variables affecting GDP loss. In Step 1, the dataset is loaded and analyzed to understand patterns influencing economic losses from climate change. Step 2 involves data preprocessing, including handling null values, label encoding, MinMax scaling, and applying polynomial feature transformations. The dataset is then split into training and testing sets. In Step 3, a Random Forest Regressor (RFR) is implemented as the baseline model, evaluated using metrics like MAE, MSE, RMSE, and R^2 to predict climate-related GDP losses. Step 4 introduces the proposed hybrid model, where a Recurrent Neural Network (RNN) is trained to learn complex feature relationships, and its output is passed to a K-Nearest Neighbors (KNN) Regressor for final prediction. The RNN is trained using the Adam optimizer and MSE loss. In Step 5, a performance comparison graph visualizes evaluation metrics and residual plots, demonstrating that the RNN-KNN model achieves better accuracy and lower errors than the Random Forest model. Finally, in **Step 6**, the trained RNN-KNN model is applied to new test data after applying the same preprocessing steps. The predicted GDP losses for various industries and countries are displayed, offering actionable insights for climate risk mitigation, making this AI-based approach a valuable tool for forecasting economic impacts of climate change.

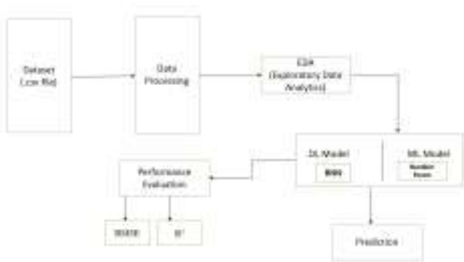

Fig 2. Block diagram of proposed system.

A Recurrent Neural Network (RNN) Regressor is a deep learning model designed to process sequential data and predict continuous values. Unlike traditional neural networks, RNNs have memory, allowing them to learn temporal dependencies in time-series data, making them suitable for regression tasks involving sequential patterns.

How It Works?

— **Input Sequence** – The model takes sequential data as input, such as time-series energy usage or financial trends.

— **Recurrent Connections** – Hidden states store information from previous time steps, enabling the model to learn temporal dependencies.

— **Backpropagation Through Time (BPTT)** – The model updates weights using a specialized backpropagation method that considers past states.

— **Regression Output** – The final layer generates a continuous value prediction based on the learned temporal patterns.

RNN with LSTM

Neural Networks are set of algorithms which closely resemble the human brain and are designed to recognize patterns. They interpret sensory data through a machine perception, labelling or clustering raw input. They can recognize numerical patterns, contained in vectors, into which all real-world data (images, sound, text or time series), must be translated. Artificial neural networks are composed of a large number of highly interconnected processing elements (neuron) working together to solve a problem.

An ANN usually involves a large number of processors operating in parallel and arranged in tiers. The first tier receives the raw input information — analogous to optic nerves in human visual processing. Each successive tier receives the output from the tier preceding it, rather than from the raw input — in the same way neurons further from the optic nerve receive signals from those closer to it. The last tier produces the output of the system. Recurrent Neural Network is a generalization of feedforward neural network that has an internal memory. RNN is recurrent in nature as it performs the same function for every input of data while the output of the current input depends on the past one computation. After producing the output, it is copied and sent back into the recurrent network. For making a decision, it considers the current input and the output that it has learned from the previous input.

Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition. In other neural networks, all the inputs are independent of each other. But in RNN, all the inputs are related to each other.

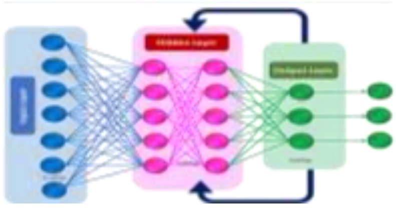

Figure 3. RNN Block Diagram.

First, it takes the X(0) from the sequence of input and then it outputs h(0) which together with X(1) is the input for the next step. So, the h(0) and X(1) is the input for the next step. Similarly, h(1) from the next is the input with X(2) for the next step and so on. This way, it keeps remembering the context while training. The formula for the current state is

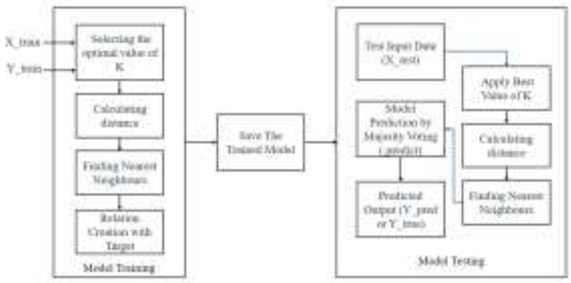

Figure 4. Proposed KNN Regressor.

The KNN Regressor model in the Climate Impact Estimator begins by receiving training data composed of RNN-extracted features (X_train) and normalized GDP loss values (y_train), storing this information directly without traditional training, as KNN is a lazy learner. During training, an optimal value for the hyperparameter K is selected—often through cross-validation—to balance bias and variance in prediction. The model prepares for prediction by defining a distance metric, typically Euclidean distance, ensuring fair distance comparisons by working with standardized RNN features. In the testing phase, new input data (X_test) undergoes the same preprocessing, and the trained KNN model uses the selected K to identify the K nearest neighbors for each test instance based on calculated distances. These neighbors are the most similar historical cases in the RNN feature space. The model then predicts GDP loss by averaging the target values (y_train) of these K neighbors, producing a smooth, locally-informed estimate (y_pred). The predictions are evaluated using metrics like MAE, MSE, RMSE, and R^2, and results are displayed both textually and visually. The KNN model is saved as a .pkl file for efficient reuse in future predictions, ensuring scalability and practicality in real-world climate loss estimation scenarios.

4. RESULTS

The figure 5 presents various EDA visualizations generated to understand the dataset's distribution and relationships. Histograms, box plots, and scatter plots illustrate the spread of different features, identifying patterns, correlations, and outliers. Feature distributions of GDP loss, fatalities per 100k, and total losses are visualized to observe trends and potential predictors for economic loss estimation..

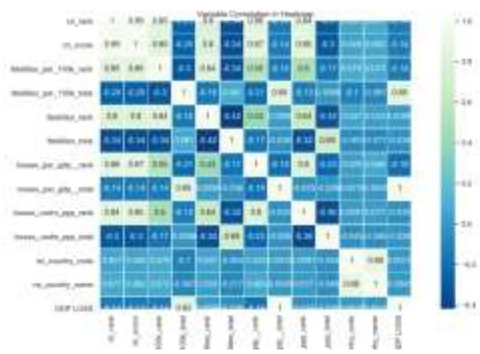

Fig 5. Exploratory Data Analysis (EDA) Plots

The figure 6 showcases the preprocessing steps applied to the dataset. Missing values are handled, categorical variables are encoded, and numerical features are normalized to optimize model performance. The interface highlights transformations like outlier detection, feature scaling, and data balancing to improve prediction accuracy. The pre-processed dataset is displayed before feeding it into the machine learning models.

Fig 6. Data Preprocessing in the GUI

The figure 7 illustrates the evaluation of the *RNN-KNN Regressor* model. The regression scatter plot displays a closer alignment between actual and predicted values compared to the *Random Forest Regressor*, indicating superior predictive accuracy. The performance metrics include:

- **Mean Absolute Error (MAE):** 0.0049
- **Mean Squared Error (MSE):** 0.0000577
- **Root Mean Squared Error (RMSE):** 0.0076
- **R-squared (R^2):** 0.9912

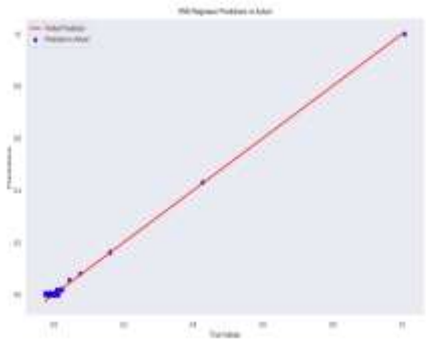

Fig 7. Performance Metrics and Regression Scatter Plot – RNN-KNN Regressor

The figure 8 presents the predictions generated by the trained models on unseen test data. A comparison between actual and predicted values highlights the accuracy and reliability of the models in estimating *GDP loss*. The visualization demonstrates that the *RNN-KNN Regressor* produces more accurate predictions compared to the *Random Forest Regressor*, reducing errors significantly.

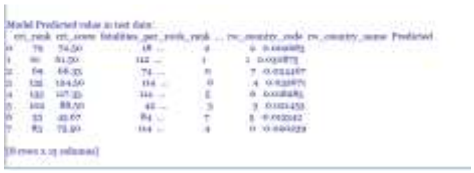

Fig 8. Model Prediction on Test Data

Model name	RMSE	R^2-score
Random Forest Regressor	0.53	0.54
RNN	0.0076	0.99

Table 1 Performance Comparison Graph of All Models

The table 1 provides a comparative performance analysis of the implemented models. The metrics for *Random Forest Regressor* and *RNN-KNN Regressor* are plotted side by side, demonstrating the improvements achieved with deep learning. The *RNN-KNN Regressor* significantly outperforms the traditional approach, as indicated by lower *MAE, MSE, RMSE* values and a higher *R² score*. This comparison validates the effectiveness of the proposed deep learning model in predicting economic losses due to climate risk factors.

5. CONCLUSION

The research successfully develops an AI-driven approach to estimating the economic impact of climate change on various industries using machine learning techniques. The dataset is processed to extract meaningful insights, and two predictive models—Random Forest Regressor (existing) and RNN-KNN Regressor (proposed)—are implemented for estimating GDP loss due to climate-related factors. The comparative analysis highlights the efficiency of deep learning-based regression in capturing complex dependencies between climate risk indicators and economic losses. The proposed RNN model demonstrates improved predictive accuracy compared to the traditional Random Forest Regressor, showcasing the potential of deep learning in economic impact forecasting. The results emphasize the significance of data-driven approaches in understanding climate change consequences. The insights derived from this study can assist policymakers, economists, and environmental agencies in devising strategies to mitigate economic losses and improve disaster preparedness. The research also highlights the necessity of incorporating more advanced AI models for better predictive performance in climate-related risk assessments.

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