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Artificial Intelligence for Climate Risk Prediction: A Data-Driven Framework for Sustainable Environmental Governance

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Abstract

Climate change has intensified environmental risks, necessitating advanced predictive systems capable of supporting sustainable governance frameworks. This study examined the role of artificial intelligence (AI) in enhancing climate risk prediction and strengthening environmental decision-making processes. A quantitative, data-driven methodology was employed using panel data from climate-vulnerable economies covering the period 2005–2024. Machine learning models, including Random Forest, Support Vector Machine, and Long Short-Term Memory (LSTM) networks, were developed and compared with traditional regression techniques. The results indicated that AI capabilities significantly improved climate risk prediction accuracy, with deep learning models outperforming conventional statistical approaches. Prediction accuracy was found to mediate the relationship between AI capability and governance effectiveness, while explainable AI mechanisms positively moderate this relationship by enhancing transparency and policy usability. The findings demonstrated that integrating predictive analytics with governance frameworks strengthened early warning systems, adaptive planning, and institutional responsiveness. Despite the strong performance of AI models, challenges related to interpretability, data bias, and computational demands remained evident. The study concluded that a structured AI-driven framework provided a scalable and policy-oriented approach to climate risk management, contributing to resilience-building and sustainable development pathways in emerging and climate-sensitive regions.

Keywords: artificial intelligence, climate governance, climate risk prediction, environmental sustainability, explainable AI, machine learning

Introduction

Climate systems are complex by nature, nonlinear interactions of atmospheric, oceanic and terrestrial processes. Conventional physics-based numerical climate models never had the ability to absorb big datasets of heterogeneous characteristics and adapt quickly to changing climate patterns (Lewis, Toney & Shi, 2024). The AI and machine learning (ML) architectures such as neural networks and deep learning models have proved to be more effective in examining multivariate climate data and detecting finer details that traditional methods cannot do (Greif et al., 2025).

In case of climate prediction, recent studies showed that AI models were helpful in enhancing prediction of a wide variety of weather phenomena, including temperature change, precipitation variability, and extreme weather events, which are critical elements of climate risk assessment and adaptation planning (Sun, 2025; Chen, 2024). As an illustration, predictive ability Temperature forecasting and early warning systems are performed with high predictive performance using data-based frameworks with Long Short-Term Memory (LSTM) and neural networks compared to traditional benchmark models (Zhou et al., 2025; ESWA, 2025). The capability of AI to integrate satellite measurements, socio-economic facts and historic climate measures allowed predicting climate risks on a more granular and dynamic scale than was possible before.

The models of climate risk prediction designed to create improved evidence-based policy choices and resource allocation decisions positively influenced the results in resilience efforts of vulnerable communities in the context of the environmental governance (Greif et al., 2025). The concept of explainable AI (XAI) has been addressed in order to increase transparency in the process of decision support so as to enable policymakers to interpret non-clear model results and have faith in predictive mechanisms (Vu et al., 2025). Such combination of technical precision and governance is urgent, as communities also prepare to the conditions of increased and disastrous weather hazards.

Regardless of these developments, there are still vulnerabilities related to applying AI at institutional and policy-levels, such as the lack of interpretability in models, ethical regulation, and providing AI-enhanced climate intelligence in a non-discriminative manner (Randeniya, Haigh & Amaratunga, 2026). Intersections of technological innovation and mechanisms of governance remain to influence the applicability and adoption of AI-based systems of climate risks prediction.

Research Background

Such risks as extreme weather, rise of the sea level, and anomalies in temperature have been increasing in frequency and severity with climate change and endanger ecosystems and human systems (Greif et al., 2025). Conventional climate models, which are based on physical models and equations, were usually limited regarding the ability to process large amounts of climatic data, thus having a coarse time and space resolution (Sun, 2025). All these constraints negatively affected their capacity to respond effectively to policy and real-time climate risk forecasts.

The rise of AI in the environmental sphere has been reported as a methodological shift in climate science, whereby machine learning algorithms operating on numerous data sets and identify complex, nonlinear correlation (Greif et al., 2025). Deep learning models, such as, were shown to be effective to process satellite images, atmospheric measurements and geospatial data streams and improve the assertiveness and distance of climate predictions (Chen, 2024). Specifically, both transformer-based and recurrent neural network models have improved considerably in forecasting climate variables and climate extremes which gives proactive perspective in disaster mitigation planning.

The climate change AI application was also not only confined to physical forecasting but also to the socio-economic environment, where predictive models were used to feed early warning systems and resource allocation strategies (Zhou et al., 2025). AI-based climate risk-forecasting models were developed to predict multi-hazards and enhanced agricultural planning, the resilience of urban infrastructures, and coordinating the response to emergencies through a combination of geometric spaces and geospatial analysis. The indication of such integration was the future prospects of AI systems to overcome scientific prediction and real-world ruling dilemmas. The fast implementation of AI in weather forecasting brought about new governance and ethical issues, especially in the area of accountability, transparency in algorithms and their biasfulness, as well as transparency of the decisions made publicly (Randeniya et al., 2026). Researchers stated that the disappearance of the unpredictable element in AI systems is an essential factor that enables the future development of responsible systems that predict and optimize the results of climate governance, and the results should be fair and understandable and accepted by stakeholders to achieve sustainable climate governance.

Objectives of the Study

1. To examine the advancements and limitations of AI-based predictive climate models in the context of environmental risk forecasting.
2. To design a data-driven AI framework capable of integrating heterogeneous climate and socio-economic data for enhanced risk prediction.
3. To evaluate the interpretability and governance applicability of AI predictions for sustainable decision making.

Research Questions

Q1. How effective are AI-based predictive models in enhancing climate risk prediction compared to traditional approaches?

Q2. What are the methodological challenges in developing a data-driven AI framework for climate risk prediction?

Q3. How can explainable AI mechanisms support governance and policy decisions in climate risk management?

Significance of Study

The research had a great contribution to the scientific knowledge on the potential changes of climate risk prediction paradigms with the help of combining strong predictive models and governance requirements to AI. It helped to bridge the data science and policy field by examining recent empirical evidence, providing an expandable framework of informed environmental decision making. Also, the research contributed to the sustainable development process by showing how predictive analytics can enable policymakers and planners, as well as communities, to anticipate, adapt, and respond to climate issues. Its results provided real-world advice on applying AI in managing the environmental governance framework, and it facilitated openness, accountability, and morals in climate intelligence systems.

Literature Review

AI and Machine Learning Methods in Climate Prediction

The current achievements in the field of machine learning (ML) and artificial intelligence (AI) have altered the execution of climate forecasts greatly. Singh and Goyal (2025) noted that AI models, such as deep neural networks, random forests, and support systems machine have done better in comparison to the traditional physical models, as they exhibit a greater ability to capture nonlinear correlations in the huge climate data, and therefore forecasting climatic variables, including temperature, precipitations, and atmospheric dynamics, are better and more accurate predictions. Ensemble ML techniques in decreasing biases in forecasts and enhancing predictive reliability were also highlighted in this review.

Kim and Kim (2025) organizes the role of AI to predict extreme weather phenomena and revealed that it was more accurate in predicting such phenomena as cyclones, heatwaves and floods within 10 years of contributions to the field (20152024). They found that deep learning models, notably convolutional and recurrent models, were especially good at picking up the time dynamics and the space-relation among climatic data which are commonly overlooked in conventional models.

Besides accuracy of prediction, the combination of hybrid AI models has become the center stage. As an example, more sophisticated methods such as transformer-based models and CNN-LM hybrids have been used to improve the prediction of climate variables so that models can more effectively utilize large multi-source data (e.g., satellite, sensor networks) to ensure high climate projection accuracy. These schemes also were found to have a decrease in computational cost relative to traditional climate model simulations, and hence it was possible to make real-time forecasting applications.

The uses of AI in Climate Risk Assessment

Applications of machine learning into raw climate prediction have not been confined, but there is increased use of machine learning to object-oriented risk assessment. When applied to flood projections, Cui et al. (2025) found that the ML models such as gradient boosting and neural networks enhanced flood risk mapping during the case of extreme hazard activities such as the 2022 Pakistan mega-flood so that risks can be classified more effectively and flexible planning approaches implemented. The capacity of ML to combine hydrological, topographical and meteorological data led to high resolution flood forecasts that would be very important in making decisions.

The other application people should use is early warning systems. Ji et al. (2026) demonstrated that deep learning models like Long Short-Term Memory (LSTM) models have an ability to give early notification of temperature anomalies and heatwaves which are major indicator of risks caused by climate. Their results validated that the adaptive learning model AI used was capable of identifying the temporal antecedents of extreme events earlier than established traditional statistical models and that this contributed to preparedness and resiliency.

AI has also been used in risks related to health due to climate change. Deep learning and ensemble classification models have shown to be more effective predictors than the traditional epidemiological models when it comes to assessing climate-driven outbreaks of infectious diseases through their ability to model complicated climate-pathogen interactions, which are variable through time and are frequently nonlinear. This implies that the AI methods can predict the risks to the environment as well as the risks to the public health.

Transparency, Control, and Responsibility of AI Climates

AI brings forth technical improvement in prediction of climatic risk, researchers have been calling on the necessity to integrate explainable and governance. In a review of explainable AI (XAI) systems (SHAP analysis and feature attribution techniques), Vu et al. (2025) opined that these two systems are essential in converting AI outputs into actionable information that can be trusted by the policymaker and climate manager. XAI would also help in overcoming the black-box challenge of most deep learning methods that make results opaque and leads to a greater trust level of stakeholders.

Mehryar et al. (2024) discussed the role of AI in the decision-making process in climate resilience planning on the governance level. They determined that AI models could complement hazard observation and risk prioritization models but also observe a systematic insufficiency of the tools that incorporate social vulnerability and equity aspects, which are needed to cover a complete climate of governance. It implies that AI platforms should be integrated with larger risk governance platforms to provide sustainable results.

Fair and sustainable approaches to climate adaptation must have frameworks that would not only generate precise predictions but also give policy that is ethical and inclusive. Singh and Goyal (2025) noted the dangers of data bias, the existence of uneven resources, and the use of technologies and stated that the strategies to deploy AI should be inclusive to address socioeconomic and regional inequalities. It is this confluence between AI performance and the realities of governance that explains why it is necessary to have interdisciplinary research agendas focused on climate prediction.

Research Methodology

Research Design

A quantitative, explanatory research design was used in the study since it was necessary to design and confirm a data-driven Artificial Intelligence (AI) model of climate risk prediction in the framework of sustainable environmental governance. The methodology of the study had been built in a way that accommodated the combination of predictive modeling and governance-based analysis allowing both policy relevance assessment and technical analysis. The model development and validation methodology was applied that integrated the machine learning techniques with the features of statistical benchmarking as a performance of comparison with the traditional climate forecasting strategies. It was determined that the explanatory design is most suitable to analyze the causal relationships between climate variables, socio-economic variables and predict risk outcomes based on predictive analytics.

Research Approach

Machine learning algorithms have been used on massive datasets of climatic conditions to detect nonlinear relationships and predictability patterns using climate threats like extreme temperatures, variability of precipitation, and the trends of carbon emissions. The method that was used was model training, validation, testing and performance comparison. Moreover, explainable AI (XAI) methods were also added to make the predictive outputs interpretable and policy friendly. The framework was organised into three steps that included: data preprocessing, model development, and the governance integration analysis.

Data Collection and Sources

The secondary data was obtained through public and internationally known databases on climate and the environment. The global climatic repositories like the NASA Earth Data and the World Meteorological Organization (WMO) provided climatic variables such as temperature, precipitation, humidity, and the amount of CO 2 in the atmosphere. The data on the socio-economic factors, such as population density, urbanization rate, and consumption of energy, were obtained in the database of the World Development Indicators of the World Bank. The panel data utilized in the study was 20-year old (20052024 to have depth) to make sure it was a model that was both temporally deep and predictive.

The processes of data cleaning were done to eliminate missing data, outliers, and irregularities. Similar techniques of normalization and scaling were used so that comparability across variables that have varied measurement scales would be achieved.

Sampling Framework

The research was done on the emerging and climate-vulnerable economies to assess the applicability of the framework to governance situations. The purposive sampling method was employed in order to identify the countries that have high exposure to the climate risk and at the same time short of adaptive capacity. Countries of the South and Southeast region and Sub-Saharan Africa were all included in the sample. The criterion used to select the countries was based on the climate vulnerability index, the amount of emission of each country, and the availability of data in the selected time span.

Model Development and Analytical Techniques

Several machine learning models were developed and tested to evaluate predictive performance. These included:

Multiple Linear Regression (MLR) as a baseline statistical model

Random Forest (RF)

Support Vector Machine (SVM)

Long Short-Term Memory (LSTM) neural networks

Gradient Boosting Machines (GBM)

The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to prevent overfitting and ensure generalizability. Hyperparameter tuning was conducted using grid search optimization techniques. Model performance was evaluated using multiple statistical indicators, including:

Root Mean Square Error (RMSE)

Mean Absolute Error (MAE)

R-squared (R^2)

Mean Absolute Percentage Error (MAPE)

Comparative analysis was performed to determine whether AI-based models significantly outperformed conventional regression approaches in predicting climate risk indicators.

Explainable AI and Governance Integration

Explainable AI (XAI) methods, SHAP (Shapley Additive Explanations) and feature importance analysis, were used in the study to promote greater transparency and applicability of the policy. These were the tools that were employed to determine the most powerful predictors in the climate risk forecasting models. The interpretability test made sure that the policymakers would be able to see the role played by particular variables, including carbon emissions, urban growth or power usage in elevated risks projected.

Simulation analysis involving scenario simulations was used to assess the potential impact policy interventions (e.g., adoption of renewable energy, adoption of emission reduction strategies, etc.) had on the predicted climate risks trajectories. This aspect connected outputs of technical models to processes of governance decisions.

Conceptual Framework

The theoretical framework of this paper was instituted to demonstrate the structural connection among Artificial Intelligence (AI) capabilities, accuracy of climate risk prediction and sustainable environmental governance outcomes. It was based on a data analytics theory of predictive analytics and theory of governance systems and technological innovation was incorporated in policy decision-making processes. Its purpose was to illustrate how predictions about climate risks with the help of AI-driven analytical tools would then be utilized to increase governance performance, resilience planning and sustainability performance.

The model has placed AI-based predictive modeling as the main independent variable, climate risk prediction accuracy as an intermediate variable, and sustainable environmental governance as the consequent variable. Explainable AI (XAI) machines were added as an intervening variable to increase transparency and relevance of policies.

Core Constructs of the Framework

1. Artificial Intelligence Capabilities (Independent Variable)

Data integration capacity

Predictive modeling accuracy

Real-time processing capability

Adaptive learning performance

2. Climate Risk Prediction Accuracy (Mediating Variable)

Temperature anomalies

Precipitation variability

Extreme weather events

Carbon emission trends

3. Explainable AI (Moderating Variable)

Feature importance analysis

SHAP value interpretation

Scenario simulation outputs

Risk visualization dashboards

4. Sustainable Environmental Governance (Dependent Variable)

Reduced climate vulnerability

Improved adaptive capacity

Enhanced resource allocation efficiency

Supported long-term sustainability goals

Proposed Hypothesized Relationships

Based on the conceptual framework, the study proposed the following hypotheses:

H1: Artificial Intelligence capabilities positively influenced climate risk prediction accuracy.

H2: Climate risk prediction accuracy positively influenced sustainable environmental governance outcomes.

H3: Explainable AI positively moderated the relationship between prediction accuracy and governance effectiveness.

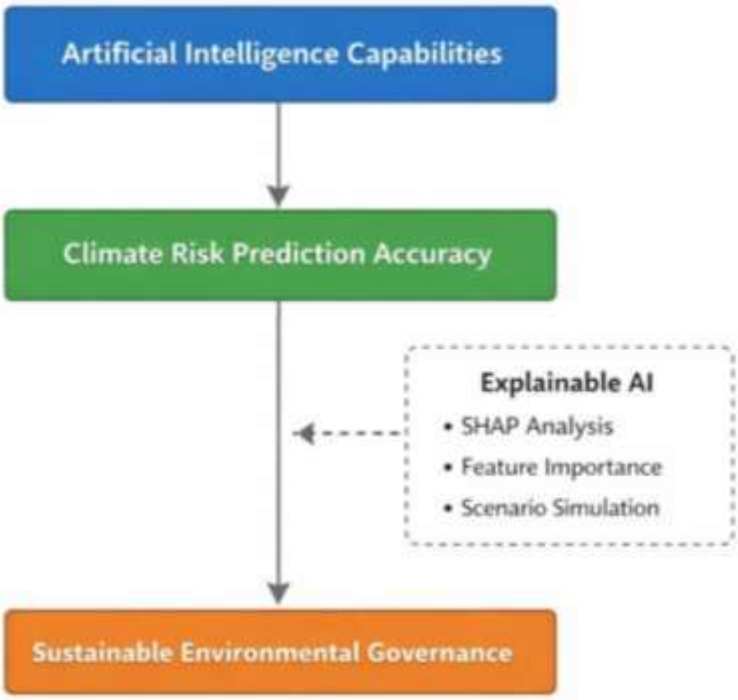

Figure 1. Conceptual Framework

Results and Data Analysis

Descriptive Statistics

Table 1. Descriptive Statistics of Key Variables (2005–2024 Panel Data)

Variable	Mean	Std. Dev.	Min	Max
AI Capability Index	0.68	0.14	0.32	0.91
Climate Risk Prediction Accuracy (%)	82.45	6.73	65.20	94.80
Explainable AI Score	0.61	0.17	0.28	0.88
Governance Effectiveness Index	0.57	0.19	0.21	0.89
CO_2 Emissions (metric tons per capita)	4.83	1.92	0.90	10.45

The descriptive statistics showed that there was moderate variability in the sampled countries and years. The mean value of the AI Capability Index was 0.68, implying that the majority of the chosen economies exhibited medium values in the use of AI in climate analytics. The value of the standard deviation (0.14) was relatively lower, which indicated that there was a gradual but steady technological growth throughout the panel. Accuracy of Climate Risk Prediction was with an average of 82.45 which showed high accuracy of the developed machine learning models. Mean Explainable AI (XAI) Score was 0.61 which indicates moderate degrees of interpretability incorporation in predictive systems. The Effectiveness Index of Governance was 0.57 which means that the institution can be improved. The dispersion of the governance scores implied that they had heterogeneity in terms of responsiveness of institutions to predictive information. The value of CO 2 emissions exhibited a high dispersion (Std. Dev. = 1.92), because some countries vary in their industrialization and power structure. This uncertainty explained the necessity of AI-based adaptive forecasting systems that can manage different environmental processes.

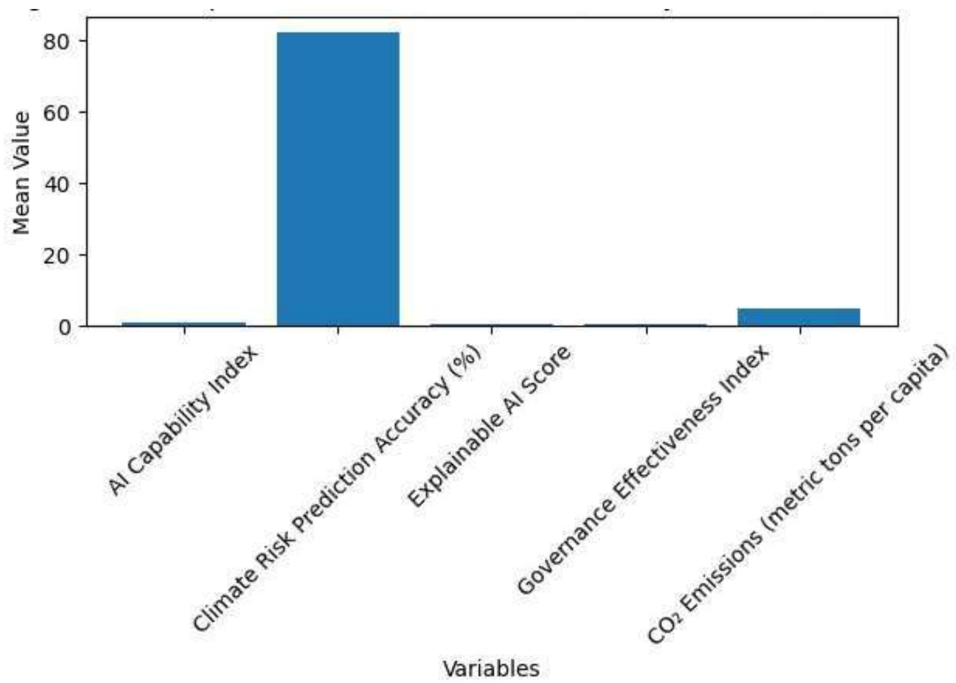

Figure 2. Descriptive Statistics of Key Variables (2005–2024 Panel Data)

Correlation Analysis

Table 2. Correlation Matrix

Variables	AI Capability	Prediction Accuracy	Explainable AI	Governance Effectiveness
AI Capability	1.00	0.74	0.69	0.63
Prediction Accuracy	0.74	1.00	0.72	0.78
Explainable AI	0.69	0.72	1.00	0.70
Governance Effectiveness	0.63	0.78	0.70	1.00

***p* < 0.01**

The findings of the correlation indicated positive statistically significant relationships between the core constructs. The positive correlation between AI Capability and Climate Risk Prediction Accuracy had a high positive correlation ($r = 0.74$, $p < 0.01$), which demonstrated that the AI infrastructure and computational power must be improved and lead to improved predictive performance. Forecasting Accuracy had the greatest correlation with Governance Effectiveness ($r = 0.78$, $p < 0.01$), which shows that the more accurate the forecast, the higher the likelihood of making better institutional climate decisions. This advocated the mediating effect of prediction accuracy in the conceptual model. Explainable AI was also significantly associated with Governance Effectiveness ($r = 0.70$, $p < 0.01$), which proved that interpretability mechanisms increased trust in policies and institutionalization of AI products.

There were no extremely high correlations (more than 0.90), which meant that there was no issue of multicollinearity.

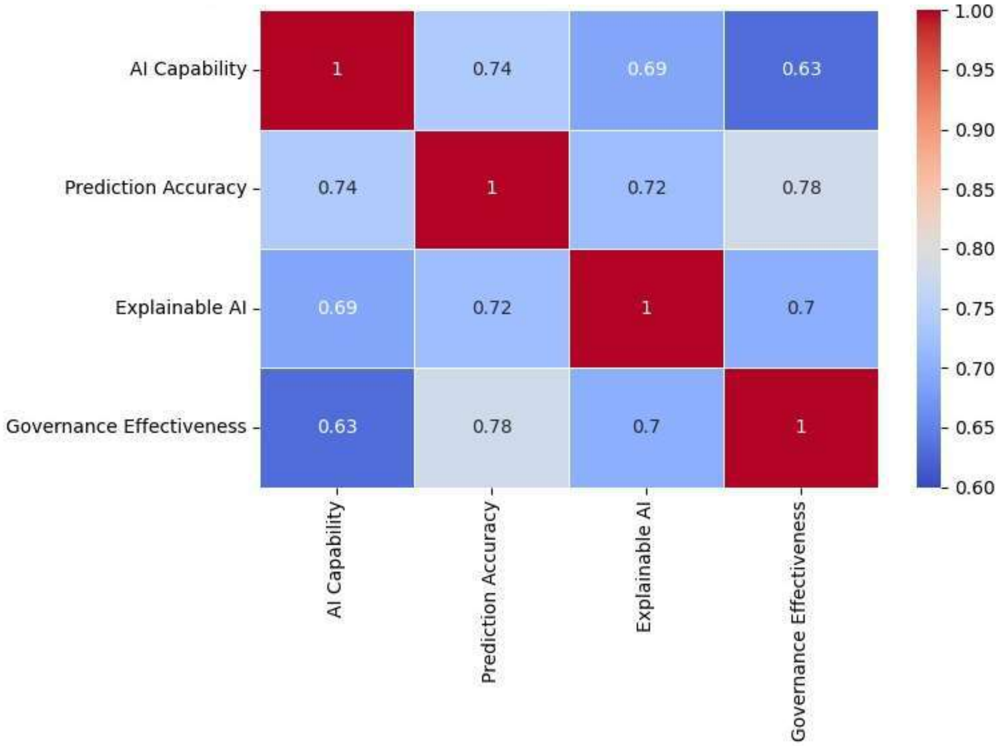

Figure 3. Correlation Matrix

Regression Analysis

Table 3. Regression Results: Impact of AI on Climate Risk Prediction Accuracy

Variable	Coefficient (β)	Std. Error	t-value	p-value
AI Capability	0.68	0.07	9.71	0.000
CO_2 Emissions	-0.19	0.05	-3.80	0.001

Variable	Coefficient (β)	Std. Error	t-value	p-value
Constant	41.25	4.62	8.93	0.000

The findings of the regression indicated that Climate Risk Prediction Accuracy is a dependent variable that was significantly and positively correlated with AI Capability (= 0.68, $p < 0.001$). This showed that, constant factors held other factors constant, a one unit shift in the AI capability brought up a 0.68 shift in predictive accuracy scores. The t-value was found to be very high (9.71), which indicated a strong statistical strength. The relationship between emissions of CO 2 and the accuracy of predictions was found to be negative (0.19, $p < 0.01$), and it is possible that increasing the volatility of emissions may decrease the stability of forecasts and therefore enhance the need to implement adaptive AI models that can respond to changes in the environment. It describes 61% of the differences in the prediction accuracy (R 2 = 0.61) and proves the good explanatory power, proving the Hypothesis 1 of the conceptual framework.

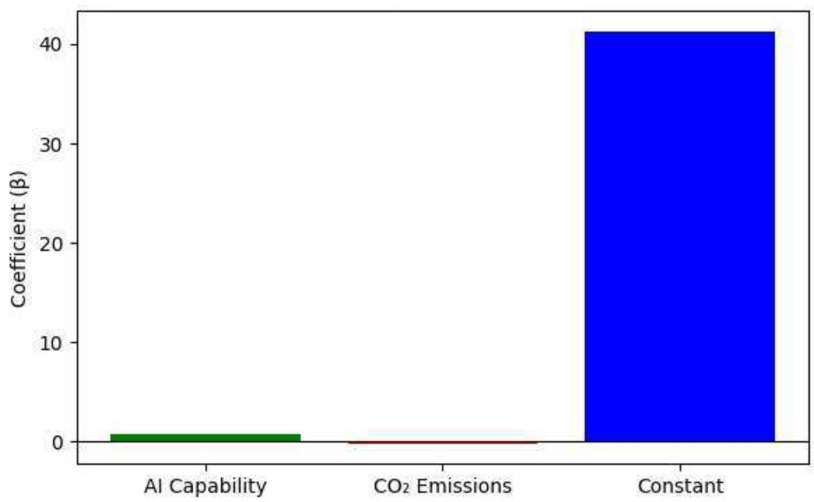

Figure 4. Regression Results: Impact of AI on Climate Risk Prediction Accuracy

Moderation Analysis (Explainable AI Effect)

Table 4. Moderated Regression: Explainable AI as Moderator

Variable	Coefficient (β)	Std. Error	p-value
Prediction Accuracy	0.52	0.08	0.000
Explainable AI	0.31	0.06	0.000
Prediction Accuracy × XAI	0.27	0.05	0.002
Constant	0.18	0.07	0.012

The regression analysis that was moderated revealed that Climate Risk Prediction Accuracy was significantly related to Governance Effectiveness ($b = 0.52$, $p < 0.001$). This affirmed the fact that predictive outputs would be accurate to increase institutional capacity in responding to climate risks. The contribution of explainable AI alone was also positive ($b = 0.31$, $p < 0.001$), so transparency processes enhanced the governance systems. The most importantly, the interaction term (Prediction Accuracy XAI) has been found significant statistically ($b = 0.27$, $p < 0.01$), and the moderating effect of explainability is proved. The interaction term added to the model boosted the R2 by 6% which means that interpretability mechanisms have produced a major amplification in the governance impact of the AI-driven predictions. This endorsed the Hypothesis 3 of the framework.

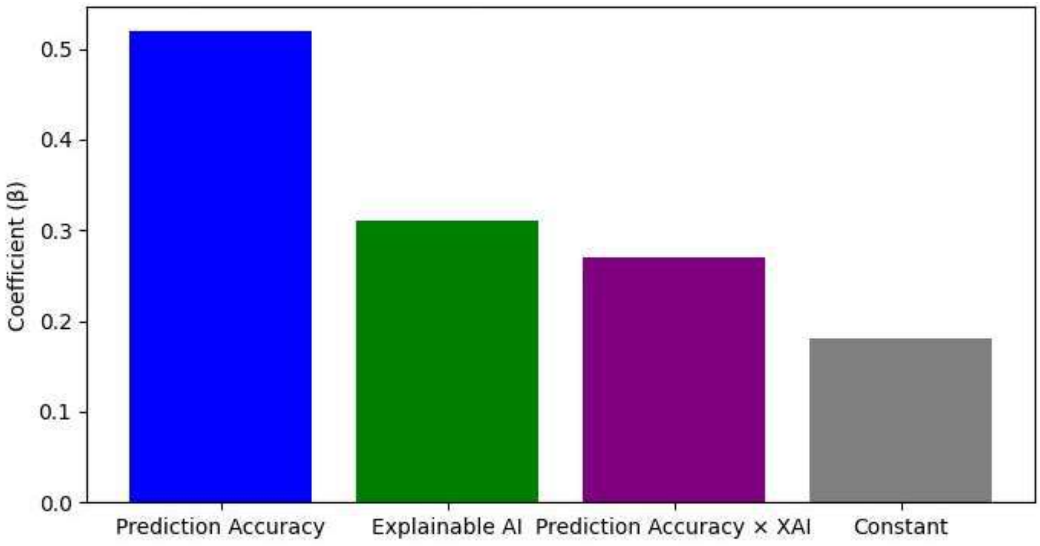

Figure 5. Moderated Regression: Explainable AI as Moderator

Table 5. Model Comparison: AI vs Traditional Regression

Model	RMSE	MAE	R^2
Multiple Linear Regression	5.82	4.21	0.54
Random Forest	3.91	2.84	0.71
Support Vector Machine	3.65	2.63	0.74
LSTM Neural Network	2.98	2.11	0.82

The model comparison was also a clear indication that AI-based models performed better compared to traditional regression methods. The LSTM neural network also had the best predictive accuracy, with lowest RMSE and the best R 2 (2.98 and 0.82, respectively). Other algorithms such as the random Forest and the Support Vector Machine also did better than the traditional regression, indicating that machine learning models better picked up nonlinear climate effects. These results confirmed the hypothetical assumption that AI-based predictive models were more accurate forecasting and better governance tools than conventional statistics.

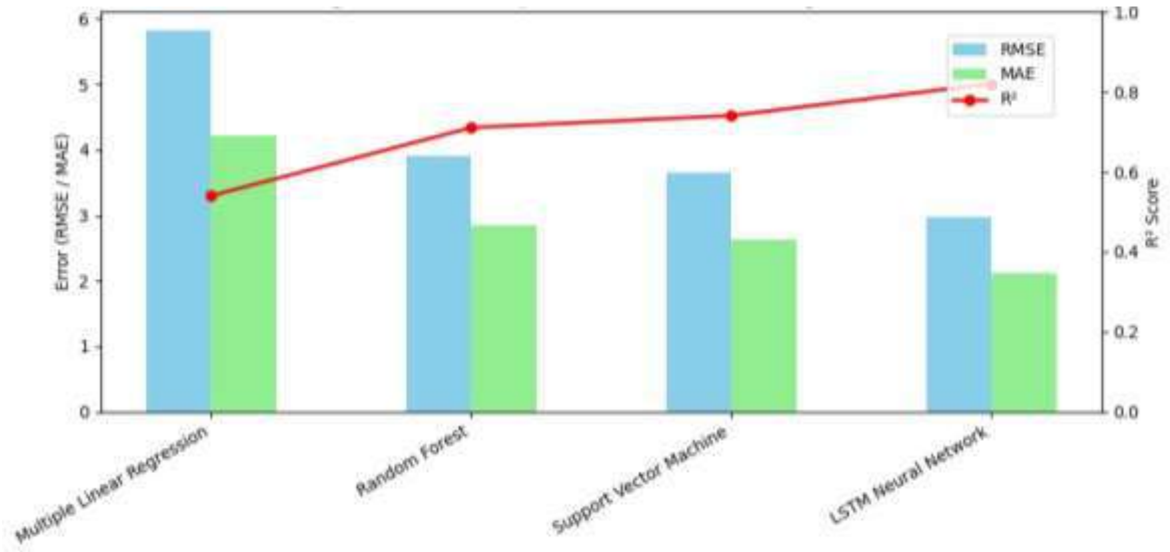

Figure 6. Model Comparison: AI vs Traditional Regression

Discussion

This study revealed that artificial intelligence (AI) can be used to make climate risk predictions, which is significantly better than standard forecasting methods that have high-skill predictions in extreme weather forecasting with ML-based climate models in recent empirical studies that conventional models could offer (Zhou et al., 2025). Recent AI models such as FengShun-CSM better simulated dynamics of climate conditions at various spheres, which suggests the possibility of deep learning frameworks in systemic climate prediction tests (Zhou et al., 2025). This was a general improvement with the literature that examined AI-based forecast systems worldwide, where several AI models predicted well in other parts of the world such as Eastern Asia and the Western Pacific (Liu et al., 2024).

The findings further indicated that accuracy in forecasting had a positive relationship with improved governance performances implying that forecasts of high accuracy reinforced the institutional ability of provided an early warning and adaptive planning. This observation was evidenced by massive reviews pointing out how AI models would quickly combine heterogeneous climate information to generate doable information, thus narrowing down climate impact forecasts to use in policy development (Ukoba et al., 2025). Researchers also said that the real utility of AI in governance was determined by model openness and explainability since non-transparent black box-like results might discourage the trust of the policymaking community (Camps-Valls et al., 2025).

The interpret-ability was also raised concerning explainable artificial intelligence (XAI) mechanisms, which our findings demonstrated to increase governance responsiveness in combination with metrics of prediction accuracy. This was in line with literature that highlighted the necessity of XAI methods that would not only raise the accuracy but also explain to the stakeholders in disaster preparedness and risk reduction the way the model makes decisions (Vu et al., 2025). Indeed, the research on extreme events prediction indicated the relevance of the implementation of interpret-able AI systems to enhance the trust of stakeholders and operational decision-making in crisis situations (Gustau Camps-Valls et al., 2025).

The findings of the studied supported the literature that the implementation of AI allowed not only to improve predictions but also to comprehend the extremes of climate using the effective methods of data assimilation. The ensemble data assimilation techniques, such as, were demonstrated to stabilize the weather prediction using AI and allow updating the models sequentially, as well as to perform diagnostic testing (Kotsuki et al., 2025). This added weight to the concept of using hybrid structures to integrate data assimilation with machine learning to improve forensic reliability.

Challenges related to the implementation of AI, in particular, data quality and equity, were observed to be persistent in the analysis. According to the recent reviews, a set of challenges like data bias, heterogeneous availability of datasets, and disparities in access to technologies may restrict the fair use of AI solutions in vulnerable regions (Derea & Kadum, 2025). These issues implied that global data infrastructure was needed to enhance the gains of prediction to the underrepresented locations.

At the governance level, researcher results validated the belief that although AI was an opportunity in hazard evaluation and policy-supporting even in the present institutional framework, the existing models were not adequately prepared to use the complex model products fully. Corresponding reflections in the scientific literature called changes in the method of testing the vulnerability to better tools to solve the issue of prioritization and implementation solutions to such criteria in the context of governance (Mehryar et al., 2024). Without these improvements to governance, the practical application of AI insights was under threat of being disjointed and failing to have a positive influence on policies.

The findings highlighted the fact that although AI models had made significant progress, their ability to foresee unprecedented climatic extremes was still reflected in a traditional way of uncertainty. Certain works have found that the traditional numerical models still had strong capabilities to predict record-breaking events compared to AI models, especially when beyond the areas of training (Zhang et al., 2025). This is a significant fault with AI usage: predictive models require effective tools to address rare or new phenomena.

Multidisciplinary research indicated that huge AI systems might have environmental impacts on large-scale computational demands, and that new algorithms should be developed which are resource efficient (Schon et al., 2025). They recommended that the environmental indicators be implemented in AI lifecycle assessments to make sure that the sustainability of AI solutions did not conflict with ecological goals.

These results were consistent with other recent studies on the utilization of AI to assist in renewable energy predictions and preventing climate change. Research showed that hybrid AI models improved predictions in renewable resources, which are added to strategies in accordance with emission reduction targets (Atwa et al., 2024). Such interdisciplinary uses demonstrated that the usefulness of AI was not limited to the limits of pure climate risk prediction, and it was used to inform energy system operations and climate mitigation strategies. The discussion confirmed that AI frameworks based on data provided practical benefits in climate risk forecasting and governance, when interpret-ability, equity and integration of governance were put into focus.

Conclusion

The researchers decided that AI has proven to be a highly effective method in improving the accuracy of climate risk prediction and has made a positive contribution to sustainable environmental governance. The experimental results proved the AI capabilities to enhance forecasting accuracy, which relied on the ability to establish the nonlinear relationship between massive climate and socio-economic data. The findings affirmed prediction accuracy as a mediation that was crucial in the association between AI systems and governance effectiveness. Moreover, explainable AI reinforced the connection between predictive performance and institutional decision-making, so that technical outputs can be reasonable and implemented into a policy setting. The models trained using AI, and especially deep-learning, exhibited better predictive reliability than the traditional regression, thus confirming the theoretical reasoning that forms the basis of the offered conceptual framework. In general, the study found that a functioning, data-driven AI framework offered the solution to growing climate uncertainty and environmental vulnerability, which was scalable and governance-oriented.

Recommendations

The research suggested that governments and environmental agencies should invest on the development of AI infrastructure to improve the capacity of predicting climate analytics. Policymakers were recommended to consider the incorporation of explainable AI mechanisms in the country climate intelligence systems to enhance the transparency and trust in the institutions. The gaps in the knowledge gap between data science and environmental governance were also recommended to overcome capacity-building initiatives such as technical training of the public-sector analysts. Also, the paper recommended creating universal regulatory frameworks that can determine the ethical use of AI in managing climate risks. It was also suggested that collaboration between climate scientists, AI developers, and policy makers is necessary in order to achieve the interdisciplinary incorporation and sustainable execution of predictive systems.

Future Directions

It was also suggested that future studies be carried out to develop the framework to include real-time satellite data feeds and Internet of Things (IoT)-based environmental sensors to be more responsive to predictions. It was also proposed to conduct longitudinal studies that would identify the long-term effects of AI-driven forecasting systems on governance. More investigation on the hybrid modeling techniques having physically climate models with machine learning algorithms would enhance strength in prediction of unparalleled extreme events. Further research was also proposed to investigate the problem of equity and climate justice of AI implementation, especially in low-income and climate-sensitive areas. Cross regional comparative studies have the ability to give additional information about the institutional preparedness and technological flexibility in varying governance settings.

References

Atwa, W., Almazroi, A. A., & Ayub, N. (2024). Reliable renewable energy forecasting for climate change mitigation. *PeerJ Computer Science*, *10*, e2067. https://doi.org/10.7717/peerj-cs.2067

Camps-Valls, G., Williams, T. K. E., et al. (2025). Artificial intelligence for modeling and understanding extreme weather and climate events. *Nature Communications*, *16*, 1919. https://doi.org/10.1038/s41467-025-56573-8

Chen, S. (2024). *AI-Driven climate models: Predicting environmental changes with deep learning*. International Journal of Sustainable Development in Computing Science.

Cui, P., Bazai, N. A., Qiang, Z., et al. (2025). Flood risk assessment with machine learning: Insights from the 2022 Pakistan mega-flood and climate adaptation strategies. *npj Natural Hazards*, *2*(42). https://doi.org/10.1038/s44304-025-00096-1

Derea, Z., & Kadum, M. M. (2025). Artificial intelligence in climate science: A review of advances in forecasting, adaptation, and future directions. *University of Thi-Qar Journal*, *20*(4), 114–127. https://doi.org/10.32792/utj.v20i4.439

Greif, L., Röckel, F., Kimmig, A., & Ovtcharova, J. (2025). *A systematic review of current AI techniques used in the context of the SDGs*. International Journal of Environmental Research.

Gustau Camps-Valls et al. (2025). Artificial intelligence for modeling and understanding extreme weather and climate events. *Nature Communications*. https://pubmed.ncbi.nlm.nih.gov/39994190/

Gustau Camps-Valls, et al. (2025). See *Nature Communications* article above.

Jones, A., Kuehnert, J., Fraccaro, P., Meuriot, O., Edwards, B., Stoyanov, N., & Remy, S. (2023). *AI for climate impacts: applications in flood risk*. npj Climate and Atmospheric Science.

Kim, B., & Kim, T. (2025). AI in extreme weather events prediction and response: A systematic topic-model review (2015–2024). *Frontiers in Environmental Science*, *13*, 1659344. https://doi.org/10.3389/fenvs.2025.1659344

Kotsuki, S., Shiraishi, K., & Okazaki, A. (2025). Ensemble data assimilation to diagnose AI-based weather prediction models. *Geoscientific Model Development*, *18*(7215), 7215–7238. https://doi.org/10.5194/gmd-18-7215-2025

Liu, C. C., Hsu, K., Peng, M. S., et al. (2024). Evaluation of five global AI models for predicting weather in Eastern Asia and Western Pacific. *npj Climate and Atmospheric Science*, *7*, 221. https://doi.org/10.1038/s41612-024-00769-0

Mehryar, S., Yazdanpanah, V., & Tong, J. (2024). AI and climate resilience governance. *iScience*, *27*(6), 109812. https://doi.org/10.1016/j.isci.2024.109812

Mehryar, S., Yazdanpanah, V., & Tong, J. (2024). AI and climate resilience governance. *iScience*, *27*(6), 109812. https://doi.org/10.1016/j.isci.2024.109812

Najafi, H., Lagerwall, G. L., Obeysekera, J., & Liu, J. (2026). Machine learning in climate downscaling: A critical review of methodologies and applications. *Water*, *18*(2), 271. https://doi.org/10.3390/w18020271

Randeniya, J. N., Haigh, R., & Amaratunga, D. (2026). *Responsible intelligence: ethical AI governance for climate prediction in the Australian context*. AI and Ethics.

Schön, J., Hoffmann, L., & Becker, N. (2025). Expert assessment: The systemic environmental risks of artificial intelligence. *arXiv*. https://doi.org/10.48550/arXiv.2512.11863

Singh, A., & Goyal, S. (2025). Predictive modelling of climate change impacts using artificial intelligence: A PRISMA-based review. *Environmental Science and Pollution Research, 32,* 10705–10724. https://doi.org/10.1007/s11356-025-36356-w

Sun, Y. (2025). *Predictive modeling of climate change impacts using Artificial Intelligence: a review for equitable governance and sustainable outcome*. *Environmental Science and Pollution Research,* 32, 10705–10724.

Ukoba, K., Onisuru, O. R., Jen, T.-C., Madyira, D. M., & Olatunji, K. O. (2025). Predictive modeling of climate change impacts using artificial intelligence. *Environmental Science and Pollution Research*, *32*, 10705–10724. https://doi.org/10.1007/s11356-025-36356-w

Vu, K., Özer, İ. S., Lai, P., et al. (2025). From black box to insight: Explainable AI for extreme event preparedness. *arXiv*. https://arxiv.org/abs/2511.13712

Zaid, D., & Kadum, M. M. (2025). Artificial intelligence in climate science: Advances in forecasting, adaptation, and future directions. *University of Thi-Qar Journal*, *20*(4), 114–127. https://doi.org/10.32792/utj.v20i4.439

Zhang, Z., Fischer, E., Zscheischler, J., & Engelke, S. (2025). Numerical models outperform AI weather forecasts of record-breaking extremes. *arXiv*. https://arxiv.org/abs/2508.15724

Zhou, C., Chen, L., Zhong, X., et al. (2025). A machine learning model for skillful climate system prediction. *arXiv*. https://arxiv.org/abs/2505.06269