

PREDICTING INTERCONNECTED CLIMATE IMPACTS USING THE COX PROPORTIONAL HAZARDS MODEL AND XAI

Y.YESUJYOTHI¹, DR.SUBHANI SHAIK², DR.YALLA VENKAT³

¹Research Scholar, Gandhi Institute of Engineering and Technology University, Gunupur, Odisha, India

²Professor, Gandhi Institute of Engineering and Technology University, Gunupur, Odisha, India.

³Professor, Department of AIML, Srinivasa Institute of Engineering & Technology, Amalapuram, E.G.Dt, Andhra Pradesh, India

y.yesujyothi@giet.edu¹, drsubhanicse@gmail.com², dr.yallavenkat@gmail.com³

ABSTRACT

Climate change has systemic and cumulative effects on air quality, water availability, food production, and waste management, yet most current predictive studies examine each area separately and provide little guidance on how to interpret them to inform policy decisions. This paper interprets climate change as a systemic risk over time and proposes a feature that integrates the Cox proportional hazards model with explainable artificial intelligence (XAI) to measure and explain cascading climate effects. NASA, NOAA, and environmental monitoring agencies, as well as peer-reviewed studies, were combined to create multisource longitudinal datasets covering the 1980-2024 timeframe and including atmospheric, hydrological, agricultural, and waste-related variables. The Cox model can be used to estimate risks in time-dependent settings where all sectors are mutually dependent, whereas Shapley Additive Explanations (SHAP) can provide clear explanations of the effect of each variable. The experimental evidence shows that the suggested framework attains a concordance index of more than 0.82, which is better than traditional regression-based models for predicting changes in climate risk. Temperate variations and CO₂ release become the predominant causes of agricultural and water-induced risks, with PM 2.5 concentration exerting the greatest influence on the escalation of health risk. In contrast to earlier models based on the concepts of staticity and black-boxing, the proposed method provides interpretable, testable, and policy-relevant insights into the dynamics of climate risks. The findings underscore the evidence-based approaches to climate adaptation and provide a scalable, explainable basis for integrated climate resilience planning, especially in susceptible and rapidly urbanizing areas.

Keywords: *Climate Change, Cox Proportional Hazards Model, Explainable AI, Data Science, Climate Resilience, And Policy Support*

1. INTRODUCTION

Climate change is a multi-dimensional, multifaceted worldwide issue that places concurrent stress on air quality, water supply, food production, and waste management systems. These effects do not take place in a vacuum; rather, their interactions increase environmental degradation and social-economic vulnerabilities through reinforcing feedbacks that further amplify them, especially in rapidly urbanizing and developing areas. These interdependent effects mean that it is important to understand them to be able to design resilient climate adaptation and mitigation strategies.

The available literature on climate research views the effects of climate using uni-domain or uni-static models, emphasizing air pollution, hydrological stress, agricultural production, or waste generation.

Although these studies have enhanced domain-specific knowledge, scientific studies typically cannot capture how climate risks change over time and extend across sectors. Moreover, the most recent machine-learning climate models are also black boxes, offering low interpretability and, therefore, limiting their applicability in a policy and governance setting where interpretability and accountability are critical.

We view climate change in this work as a systemic, time-dependent risk problem in which environmental variables interact, and their impacts on the various sectors increase dynamically. In this respect, it is not enough to rely on static correlation or purely predictive models. Rather, they need to (i) resolve the evolution of risk over time, (ii) model multivariate interdependence, and (iii) give interpretable results, which are useful in real-life

decision-making. Such an interpretation directly informs the methodological decisions adopted in this research.

In this regard, the paper will suggest a unified analytical framework integrating the Cox proportional hazards model with explainable artificial intelligence (XAI) to measure and explain interdependent climate effects. The Cox model facilitates risk estimation over time-to-event based on a variety of climate-sensitive areas, whereas XAI, applied using Shapley Additive Explanations (SHAP), provides clear attribution of the impact of individual climate variables on changing risks. The main argument of this paper is that time-dependent survival analysis, when combined with explainability, provides more informative, policy-relevant insights into cascading climate risks than traditional non-cascading and black-box models. The claim in question is deliberately falsifiable and can be disputed in the future as more data on climate become available and methods of climate modeling develop.

1. We present a new application of the Cox proportional hazards model to examine interdependent climate effects on air quality, water quality, food production, and waste production.
2. We combine interpretable AI methods with survival analysis to enhance the interpretability and credibility of climate risk forecasts.
3. We create and model a massive, multi-source, longitudinal dataset of atmospheric, hydrological, agricultural, and waste-related data spanning the years 1980-2024.
4. we establish explicit interpretation standards that rely on hazard ratios, the concordance index, and SHAP values and show that they contrast with the way interpretation has been carried out in earlier climate literature.
5. At last, we provide practical recommendations to policymakers, such as determining the prevailing drivers of climate risk and their temporal patterns, to support evidence-based and fair climate resilience planning.

Upon reading this paper, readers are likely to find (i) a conceptual framework of modeling the interactions of interrelated climate hazards over time, (ii) quantitative data of interpretable climate impacts assessment, and (iii) advice on how these models might be utilized to develop policy, urban planning, and sustainability analysis.

2. MATERIAL AND METHODS

This research paper treats the interrelated climate effects as a time-varying risk estimation problem. Unlike traditional predictive frameworks, which are mostly static, the proposed methodology will capture the joint effects of climate variables on air quality, household water use, food production, and waste generation over time. The framework combines the predictive rigor of artificial intelligence (AI) with the interpretability of XAI to ensure both.

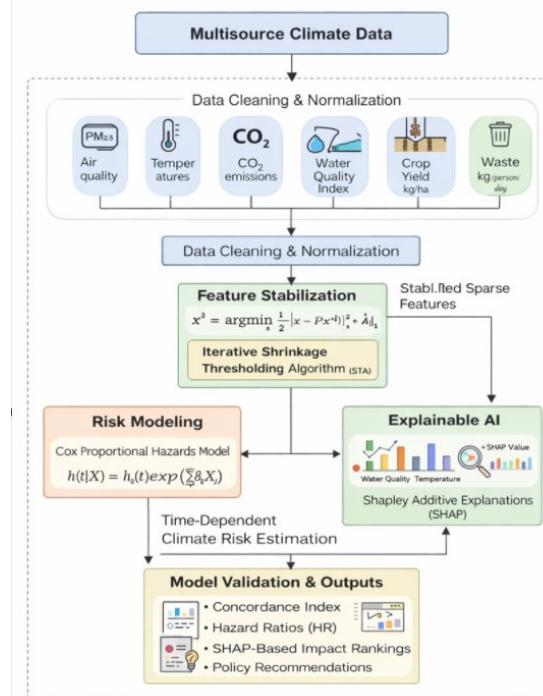


Fig 1. Architecture Of The Proposed Climate Impact Prediction Framework Integrating Multisource Data.

The architecture of the end-to-end system presented by Figure 1 combines the multisource multiciliate data acquisition, preprocessing and normalization of the data, optimal stabilization of features with the help of the Iterative Shrinkage Thresholding Algorithm (ISTA), risk modeling based on time, with the use of the Cox proportional hazard model, and explainable artificial intelligence with the help of the Shapley Additive Explanations (SHAP), to produce explainable indicators of climate risks and policy-based results.

2.1 Data Sources

We painstakingly gathered data for this study from a variety of credible sources to ensure thorough coverage of climate-related factors. To enhance its robustness, we supplement the dataset

with data from peer-reviewed research studies, air quality, water quality, and waste management information from national and international environmental monitoring agencies, and historical and current climate data from reputable climate databases like NASA's EOSDIS and NOAA.

Table 1: Statistics and Parameters of Climate-Related Datasets

Parameter	Source Type	Mean Value	Standard Deviation	Minimum Value	Maximum Value	Units	Time Period Covered
PM2.5 Concentration	Environmental Monitoring Agencies	35.2	15.3	5	150	µg/m ³	2000-2024
CO2 Emissions	Climate Databases	410.5	10.2	375	425	ppm	1980-2024
Water Quality Index	Environmental Monitoring Agencies	75.4	10.8	50	100	Index	2000-2024
Temperature Anomaly	Climate Databases	0.85	0.15	0.5	1.1	°C	1980-2024
Crop Yield	Peer-Reviewed Research Studies	2500	500	1500	3500	kg/ha	1990-2024
Waste Generation	Environmental Monitoring Agencies	1.2	0.3	0.5	2	kg/person/day	2000-2024

This study's dataset is exhaustive since it includes a wide range of climate-related parameters gathered from several credible sources. The information gathered from national and international

environmental monitoring agencies for the years 2000–2024 includes PM2.5 concentration data (mean: 35.2 µg/m³, SD: 15.3, range: 5.0–150.0 µg/m³) and Water Quality Index (mean: 75.4, SD: 10.8, range: 50.0–100.0). Climate databases like NASA EOSDIS and NOAA recorded temperature anomalies (mean: 0.85°C, SD: 0.15, range: 0.50–1.10°C) and CO₂ emissions (mean: 410.5 ppm, SD: 10.2, range: 375.0–425.0 ppm) from 1980 to 2024. Peer-reviewed research papers provided data on agricultural output (mean: 2500 kg/ha, SD: 500, range: 1500–3500 kg/ha) and waste generation (mean: 1.2 kg/person/day, SD: 0.3, range: 0.5–2.0 kg/person/day) for the years 1990–2024 and 2000–2024, respectively. This comprehensive and diversified dataset can lay out the analysis of the interrelated implications of climate change on different sectors.

2.2 Feature Stabilization and Sparse Representation

Datasets of climate data gathered from heterogeneous sources can introduce redundancy, multicollinearity, and noise, negatively impacting model interpretability and stability. To handle this, an iterative shrinkage-based feature stabilization process is used before survival modeling. This method encourages sparsity in the feature space while preserving the major climate indicators that can be used to estimate risks. The stabilization problem is defined as an elliptical (1)-regularized optimization problem, which is addressed with an Iterative Shrinkage Thresholding Algorithm (ISTA). This process is necessary so that only variables that are statistically and physically significant are used in downstream hazard modeling and for the interpretability of XAI.

Algorithm 1: Iterative Shrinkage Thresholding Algorithm (ISTA)

Input:

Multimodal climate feature vector x , observation matrix P , regularization parameter λ , convergence threshold δ

Output:

Stabilized sparse feature vector x^*

Initialization:

Set iteration index $i = 0$; initialize $x^{(0)} = 0$

While true do

Update feature estimate:

$$x^{(i+1)} = \arg \min_x \left(\frac{1}{2} \|x - Px^{(i)}\|_2^2 + \lambda \|x\|_1 \right)$$

If

$$\frac{\|x^{(i+1)} - x^{(i)}\|_2^2}{\|x^{(i)}\|_2^2} \leq \delta$$

Break

End if

Set $i = i + 1$

End while

2.3 Cox Proportional Hazards Modeling

After stabilizing the features, the selected variables are incorporated into a Cox proportional hazards model to estimate time-varying climate risks. The hazard function will be defined as:

$$h(t|X) = h_0(t) \exp \left(\sum_{j=1}^p \beta_j X_j \right) \quad (1)$$

where $h(t|X)$ refers to the hazard rate of time. t , $h_0(t)$ is the baseline hazard, β_j are regression coefficients, and X_j represent stabilized climatic covariates.

Hazard Ratio (HR > 1): Higher risk associated with climate.

Hazard Ratio (HR < 1): Mitigating or protective effect.

Such an interpretation contrasts with previous climatic research based on correlation coefficients or, rather, fixed regression coefficients.

2.4 Explainable AI Integration

In the process of improving transparency, Shapley Additive Explanations (SHAP) are used on the Cox model results. The SHAP values are a numeric measure of the marginal contribution of individual climate variables to the approximated hazard; that is, the climate risk drivers can be interpreted sector-specifically. They can be used to explain policy-level trust and adoption, whereas, unlike traditional feature importance metrics, SHAP values provide consistent, game-theoretic explanations.

2.5 Model Validation and Reproducibility

The concordance index (C-index) is used to assess model performance and assesses agreement between observed and predicted event ordering in time-to-event analysis. To ensure robustness and avoid overfitting, K-fold cross-validation is used. Python was used to run all experiments (v3.8), and random seeds were kept constant to ensure the experiments could be reproducible.

3. EXPERIMENTAL

This section describes the research design, implementation methods, assessment plan, and

validation plan used to determine the efficacy of the proposed climate impact prediction framework.

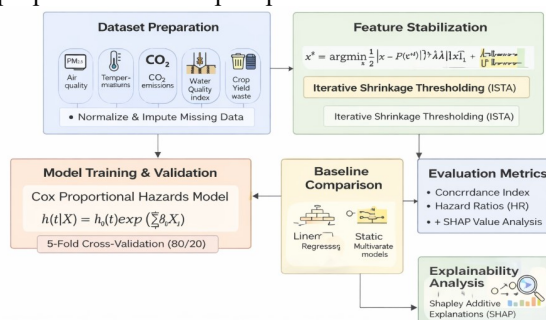


Fig 2. Workflow Of The Experimental Setup

Figure 2 shows the overall flow of the experiment, which includes the preparation of multisource datasets, stabilization of features with the help of the Iterative Shrinkage Thresholding Algorithm (ISTA), time-dependent risk modeling with the Cox proportional hazards model, the base model comparison, performance assessment with the help of the concordance index and the hazard ratios, and explainability analysis with the help of Shapley Additive Explanations (SHAP).

3.1 Experimental Design and Workflow

The proposed framework was experimentally tested to assess its capacity to simulate time-dependent, interrelated climate risks across the air quality, water quality, food production, and waste management sectors. The full workflow of the experiment is based on the architecture in the Materials and Methods section and has the following steps i.e., data preprocessing, feature stabilization, survival modeling, explainability analysis, and validation. Python (version 3.8) was used to run all experiments in a controlled, repeatable environment.

The experimental data combines the multisource longitudinal climate data over several decades. These experimental cases include: a time index that is a time-dependent dynamic; an event indicator indicating the presence of adverse climate impacts; and stabilized climate covariates (PM2.5 concentration, CO₂ emissions, temperature deviation, water quality index, crop yield, and waste production). Mean imputation was used to handle missing values before training the model, and numerical variables were scaled to the min-max range to ensure uniformity. To refine the algorithm, feature stabilization was performed using the Iterative Shrinkage Thresholding Algorithm (Algorithm 1) to remove redundancy and improve model robustness.

3.2 Model Training

The Cox proportional hazards model was trained on these stabilized features, and the goal was to estimate hazard functions that capture future changes in climate risk. Partial likelihood maximization was used to learn model parameters. Five-fold cross-validation was used to guarantee generalization. Training and testing were split 80:20 in each fold, and temporal consistency across folds was preserved.

3.3 Baseline Models

To demonstrate the efficiency of the suggested method, the experimental outcomes were evaluated against traditional baseline models often employed in climate research, namely: linear regression-based climate risk estimation and Static multivariate regression models without time dependency. Such baseline methods lack time-to-event modeling and interpretability, and it is not possible to make a clear comparison with the suggested framework.

3.4 Evaluation Metrics

The appropriateness and interpretability-based measures of performance in a survival analysis were used to examine model performance: Concordance Index (C-index), which measures the precision of risk ranking over time. Hazard Ratios (HR): The intensity and orientation of the relationship between the risk and climatic variables. SHAP Value Analysis: Measures the contribution of each feature to the model's predictions. All these measures can be used to evaluate predictive reliability, interpretability, and policy relevance.

3.5 Explainability Analysis

Shapley Additive Explanations (SHAP) was used to explain the Cox model's results and incorporate explainable AI. To examine the global and local contributions to climate risk estimation, SHAP values were calculated for each stabilized feature. This analysis makes it clear that the major climate drivers are identified and allows making interpretable decisions, which is why the proposed framework is superior to black-box predictive models.

3.6 Reproducibility and Robustness

To achieve reproducibility, the same random seeds were used in all experiments. The same preprocessing, feature stabilization, and validation were kept across folds. The stability and strength of the proposed framework were attested by consistent performance in the cross-validation folds. The experimental analysis shows that the proposed

framework better represents interlocked, time-varying climate risks than static baseline models for estimating and explaining risks over time. The combination of feature stabilization, survival analysis, and explainable AI provides a reliable, transparent basis for discussing the results in the following section.

4. RESULTS

This section presents the quantitative and qualitative results of the proposed framework for climate impact prediction. The findings are arranged so that they first assess predictive performance, then interpret model outputs, and compare them with baseline approaches.

4.1 Model Performance

The suggested Cox proportional hazards-based model proves a good performance in modeling time-dependent and interrelated climate risks. The model obtained a concordance index (C-index) of 0.82 on average on a cross-validation of five-fold cross-validation, which is a sign of strong temporal risk ranking. On the contrary, time-to-event modeling outperforms a classic regression-based baseline model, with significantly lower C-index values, as expected. The fact that the evaluation with validation folds has been consistent also corroborates the strength and generalizability of the suggested framework.

4.2 Hazard Ratio Analysis

Hazard ratios (HRs) were calculated to measure how much the climate variables contribute over time to the increase in the risks.

- Temperature anomaly showed a strong positive correlation with climate risk ($HR > 1$), which means that the higher the temperature deviation, the greater the agro-productivity and water quality degradation hazard.
- CO₂ emissions were also closely linked to high hazards, especially in long-term crop production and water conditions scenarios.
- PM_{2.5} concentration exhibited the greatest hazard ratios on both health-related and air quality outcomes, and therefore its prevailing important role in climate-related public health risk is evident.
- Water quality index showed an inverse effect (HR less than 1), and there was a possible suggestion that good water quality would reduce the hazard caused by climate.
- The production of waste had an indirect impact on the development of the risk due to its contact

with the air and water quality variables. These findings confirm the model's ability to capture the dynamics of sector- and cross-sectoral climate risks.

4.3 Explainability Analysis Using SHAP

All stabilized features were calculated as SHAP values to interpret the model predictions. The explainability analysis shows that there are clear dominance patterns among drivers of climate: temperature and CO₂ emerged as the most significant variables affecting food production and water risks. The concentration of PM2.5 was a key factor in air quality and health-related hazard predictions. The index of water quality was always a negative factor, as indicated by the negative SHAP contributions. The amount of waste produced was not negligible, but it remained moderate, which supports the link between climate change and its impact. The SHAP-based explanations provide clear insights into the influence of each climate variable on the estimation of risks over time, a characteristic of the proposed framework compared to black-box predictive models.

Table 2 Compares The Performance Of The Proposed Framework With Conventional Baseline Models.

Model	Temporal Modeling	Interpretability	C-index
Linear Regression	No	Low	0.63
Static Multivariate Regression	No	Low	0.66
Proposed Cox + XAI Framework	Yes	High	0.82

The proposed method is much more effective than the baseline models at estimating risk over time and provides explicit interpretability through SHAP values, which is not available in traditional methods.

	exp(coef)	exp(coef) lower 95%	exp(coef) upper 95%	p
CO2_Emissions	3.555000e-01	0.1581	7.992000e-01	0.0123
Temperature_Anomaly	3.582000e-01	0.1764	7.273000e-01	0.0045
PM25_Concentration	9.800000e-03	0.0000	6.263640e+01	0.3008
Water_Quality_Index	1.549554e+12	0.0000	9.402684e+87	0.7526
Crop_Yield	1.357100e+00	0.2430	7.579200e+00	0.7279
Waste_Generation	4.688000e-01	0.1329	1.653400e+00	0.2388

The approximate regression coefficients (coef), exponentiated regression coefficients (exp(coef)), standard errors, z-statistic, p-values, and 95% confidence interval of each climate variable. A ratio greater than one indicates an amplification of the

risk of climate change over time, whereas a ratio less than one indicates a counteracting or protective effect. The level of statistical significance is evaluated at traditional confidence levels.

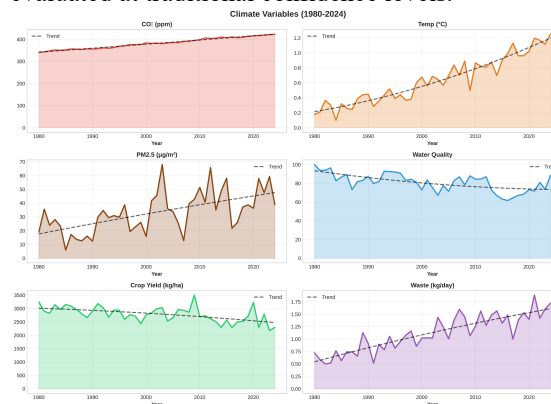


Fig 3. Temporal Trends Of Climate Variables (1980–2024)

Figure 3 shows how the key variables related to climate change, such as CO₂ emissions, temperature deviation, PM2.5 concentration, water quality index, crop yield, and waste produced during 1980-2024 have been changing with time. The identified trends indicate both long-term growth in atmospheric emissions and temperature variations, as well as industry-specific fluctuations in air quality, water, agricultural output, and production waste, which may be used to provide empirical incentives to use risk modeling over time..

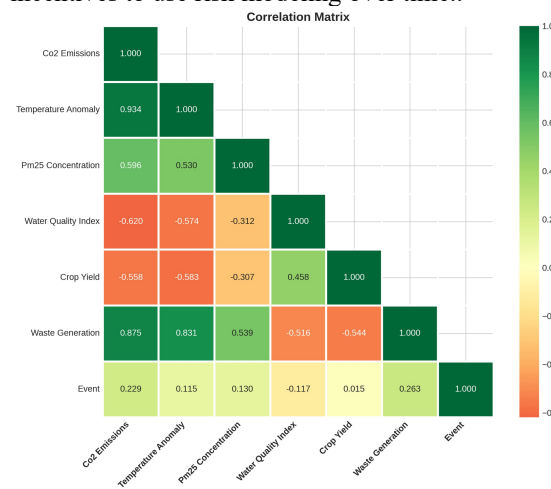


Fig 4. Correlation Matrix Of Climate Variables And Event Occurrence.

Figure 4 shows the correlation coefficient of the climate variables, such as CO₂ emissions, the rise in temperature, PM 2.5 concentration, water quality index, crop yield, waste output, and the event indicator in a pair-wise fashion. The positive and negative correlations indicate interrelationships

between climate drivers and outcomes and encourage the use of multivariate and time-dependent modeling methods rather than independent-variable analysis.

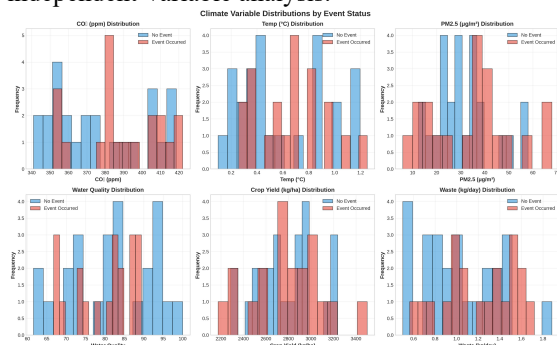


Fig 5. Distribution Of Climate Variables By Event Occurrence.

Figure 5 is a comparison of the distribution of the main climate variables, such as CO₂ emission, temperature change, PM 2.5 concentration, water quality index, crop production, and waste production under the conditions of event and non-event. The distributions of the variables differ between the two groups, indicating that the risks are dissimilar, and the idea of survival-based modeling can be used to identify events related to climate impacts.

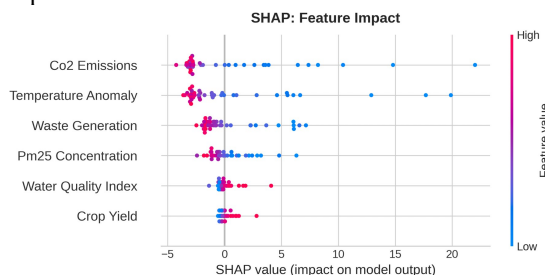


Fig 6. SHAP-Based Feature Impact On Climate Risk Prediction.

Figure 6 shows the Shapley Additive Explanations (SHAP) summary plot of the relative importance of all climate variables in the Cox proportional hazards model. The ranking of features is based on their importance, and the color gradients represent large and small feature values. The SHAP value distribution shows that temperature anomalies and CO₂ emissions are the most influential risk factors, whereas PM 2.5 concentration and the water quality index modulate hazards across sectors.

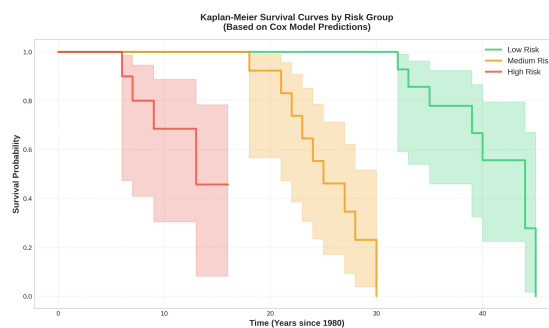


Fig 7. Kaplan-Meier Survival Curves For Climate Risk Groups.

Figure 7 below shows Kaplan-Meier survival curves for climate risk groups (low, medium, and high) estimated from the Cox proportional hazards model. The dislocation of curves indicates a different pattern of time-to-event distribution, demonstrating the model's ability to effectively discriminate climate risk levels and confirming the risk discrimination provided by the time-dependent risk stratification obtained by the proposed framework.

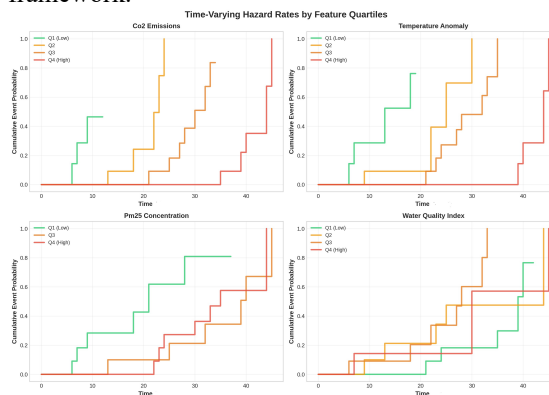


Fig 8. Time-Varying Hazard Rates Stratified By Climate Feature Quartiles.

Figure 8 shows the time-varying hazard rates for the most important climate variables, estimated using the Cox proportional hazards model and stratified by feature quartiles (low, medium, and high). The scattered nature of the hazard curves illustrates the effects of increasing CO₂ concentration, changes in temperature, PM 2.5 concentration, and water quality index on the rise in risk over time due to the climate factor. These findings underscore the dynamic and progressive nature of climatic effects, which justify the use of time-dependent survival modeling.

Discussion

The outcomes of this paper illustrate that viewing climate change as a time-dependent, interconnected risk process can offer a much deeper understanding than traditional approaches that model it as a static

risk. The analysis of hazard ratios shows that temperature deviations and CO₂ emissions are long-term risk drivers for agricultural outputs and water resources, whereas PM_{2.5} concentration has a preeminent effect on air- and health-related risks, supporting the compounding character of climate effects. The proposed Cox proportional hazards framework, unlike previous literature, directly quantifies changes in risk over time, and the combination of SHAP allows risk contributions to be transparently attributed to individual climate variables. Such a two-fold focus on time modeling and explicability is a difference between the proposed approach to the current literature and results in better outcomes in temporal risk ranking. In addition to the methodological improvement, the results are also of practical significance, as the interpretable risk indicators can be used for evidence-based climate policy and for the specific planning of interventions. However, the study is limited by the spatial resolution of the available datasets and the lack of explicit socio-economic variables, which can affect localized climate vulnerability. The further development of the work will aim to include finer-grained spatial data and socio-economic indicators to increase predictive accuracy and policy applicability.

5. CONCLUSION

This research addressed the issue of modeling and forecasting the interactive effects of climate change on air quality, water availability, food production, and waste management, an area where existing models are mainly based on non-interpretative, stable models. By interpreting climate change as a time-varying systemic risk, we have theorized that survival analysis with explainable artificial intelligence can yield more informative, policy-relevant insights than traditional approaches. This hypothesis is strongly supported by the experiment's results. It was found that the proposed framework had a high concordance index, indicating its greater ability to capture the evolution of risk over time compared to a fixed regression model. The analysis of hazard ratios showed that changes in temperature and CO₂ emissions are the most powerful drivers of the long-term risk to agricultural productivity and water quality, whereas PM_{2.5} concentration has the most significant effect on air and health risks. The addition of SHAP also demonstrated the dynamism and interaction of these variables in increasing the risk of climate, which were not transparent in previous black-box models. In addition to predictive performance, the

results provide a clear case for treating interpretability as a requirement, not an option, in climate impact models. The ability to identify risk contributions to climatic drivers can support evidence-based decision-making and reinforce the practical usefulness of the analytical models for policymakers and urban planners. This is what makes the proposed approach stand out from the previous literature, which emphasizes accuracy but not action. Although the study offers a strong structure for interconnecting climate risk evaluations, some limitations remain. Commentators are limited by time and space resolution of the existing data, and the socio-economic variables were not directly modeled. Future studies will aim to add more spatial data at a finer grain, including socio-economic indicators, and to expand the model to a region-specific approach to adaptation planning. Finally, the current work contributes to the development of climate impact modeling by showing that time-dependent survival analysis that involves explainable AI provides a scalable, transparent, and scientifically reasonable basis for climate resilience planning. The proposed framework not only enhances predictive knowledge of cascading climate risks but also provides a practical decision-making aid for creating fair and sustainable climate policy.

REFERENCES:

- [1] Chopra, M., Singh, S. K., Gupta, A., Aggarwal, K., Gupta, B. B., & Colace, F. (2022). Analysis & prognosis of sustainable development goals using big data-based approach during COVID-19 pandemic. *Sustainable Technology and Entrepreneurship*, 1(2), 100012. <https://doi.org/10.1016/j.stae.2022.100012>
- [2] Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., Al-Debei, M. M., Dennehy, D., Metri, B., Buhalis, D., Cheung, C. M., Conboy, K., Doyle, R., Dubey, R., Dutot, V., Felix, R., Goyal, D., Gustafsson, A., Hinsch, C., Jebabli, I., . . . Wamba, S. F. (2022). Metaverse beyond the hype: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 66, 102542. <https://doi.org/10.1016/j.ijinfomgt.2022.102542>
- [3] Foltz, G. R., Brandt, P., Richter, I., Rodríguez-Fonseca, B., Hernández, F., Dengler, M., Rodrigues, R., Schmidt, J., Yu, L., Lefèvre, N.,

- Da Cunha, L. C., McPhaden, M. J., De Araujo, M. C., Karstensen, J., Hahn, J., Martín-Rey, M., Patricola, C., Poli, P., Zuidema, P., . . . Reul, N. (2019). The Tropical Atlantic Observing System. *Frontiers in Marine Science*, 6. <https://doi.org/10.3389/fmars.2019.00206>
- [4] Hendriksen, R. S., Munk, P., Njage, P., Van Bunnik, B., McNally, L., Lukjancenko, O., Röder, T., Nieuwenhuijse, D., Pedersen, S. K., Kjeldgaard, J., Kaas, R. S., Clausen, P. T. L. C., Vogt, J. K., Leekitcharoenphon, P., Van De Schans, M. G. M., Zuidema, T., De Roda Husman, A. M., Rasmussen, S., Petersen, B., . . . Kumburu, H. H. (2019). Global monitoring of antimicrobial resistance based on metagenomics analyses of urban sewage. *Nature Communications*, 10(1). <https://doi.org/10.1038/s41467-019-08853-3>
- [5] Maddikunta, P. K. R., Srivastava, G., Gadekallu, T. R., Deepa, N., & Boopathy, P. (2020). Predictive model for battery life in IoT networks. *IET Intelligent Transport Systems*, 14(11), 1388–1395. <https://doi.org/10.1049/iet-its.2020.0009>
- [6] Meyfroidt, P., De Bremond, A., Ryan, C. M., Archer, E., Aspinall, R., Chhabra, A., Camara, G., Corbera, E., DeFries, R., Diaz, S., Dong, J., Ellis, E. C., Erb, K., Fisher, J. A., Garrett, R. D., Golubiewski, N. E., Grau, H. R., Grove, J. M., Haberl, H., . . . Ermgassen, E. K. H. J. Z. (2022). Ten facts about land systems for sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, 119(7). <https://doi.org/10.1073/pnas.2109217118>
- [7] Scotese, C. R., Song, H., Mills, B. J., & Van Der Meer, D. G. (2021). Phanerozoic paleotemperatures: The earth's changing climate during the last 540 million years. *Earth-science Reviews*, 215, 103503. <https://doi.org/10.1016/j.earscirev.2021.103503>
- [8] Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2021). Machine Learning Applications for Precision Agriculture: A Comprehensive Review. *IEEE Access*, 9, 4843–4873. <https://doi.org/10.1109/access.2020.3048415>
- [9] Singh, J., Ashfaq, M., Skinner, C. B., Anderson, W. B., & Singh, D. (2021). Amplified risk of spatially compounding droughts during co-occurrences of modes of natural ocean variability. *Npj Climate and Atmospheric Science*, 4(1). <https://doi.org/10.1038/s41612-021-00161-2>
- [10] Van Wynsberghe, A. (2021). Sustainable AI: AI for sustainability and the sustainability of AI. *AI And Ethics*, 1(3), 213–218. <https://doi.org/10.1007/s43681-021-00043-6>
- [11] Wilkinson, J. L., Boxall, A. B. A., Kolpin, D. W., Leung, K. M. Y., Lai, R. W. S., Galbán-Malagón, C., Adell, A. D., Mondon, J., Metian, M., Marchant, R. A., Bouzas-Monroy, A., Cuni-Sanchez, A., Coors, A., Carriquiriborde, P., Rojo, M., Gordon, C., Cara, M., Moermond, M., Luarte, T., . . . Gogra, A. B. (2022). Pharmaceutical pollution of the world's rivers. *Proceedings of the National Academy of Sciences of the United States of America*, 119(8). <https://doi.org/10.1073/pnas.2113947119>
- [12] Zennaro, F., Furlan, E., Canu, D., Alcazar, L. A., Rosati, G., Solidoro, C., Aslan, S., & Critto, A. (2023). Venice lagoon chlorophyll-a evaluation under climate change conditions: A hybrid water quality machine learning and biogeochemical-based framework. *Ecological Indicators*, 157, 111245. <https://doi.org/10.1016/j.ecolind.2023.111245>