Physics-Based Climate Models for Long-Term Viability of Renewable Energy Systems

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Abstract

Climate variability and extreme weather events increasingly limit the long-term sustainability of renewable energy systems as well as structural uncertainty concerning future climate forecasts. Conventional methods of energy planning usually assume statistical extrapolation and short-term forecasting, which are unsuitable to explain the non-linear interactions between climate and the performance of renewable energy. In this work, it is suggested to develop an approach to climate modeling based on physics in order to evaluate both the long-term sustainability and operational resilience of renewable energy systems under the changing climate conditions. The study combines physically compatible climate factors with the primary qualitative data collected from stakeholders of the energy system, which are quantified and analysed with the help of statistical software. Combining climate-responsive physical variables, i.e., the fluctuation of solar irradiance, changes in the wind regime, and the loss of efficiency based on temperature, with system-level indicators of decision support, the study offers a sustainable assessment of the feasibility of renewable energy generation in long-term time scale. The interpretation and cause-and-effect consistency in the methodology discourage the growth of uncertainty, in contrast to the solely data-driven models. The findings show that physics-based climate models can greatly improve the accuracy of long-term renewable energy evaluation due to the threshold impact, regime switching, and performance decline caused by climate conditions. The results are applicable to climate-resilient energy planning as the results provide a robust analytical framework that facilitates strategically sound choices of investments, infrastructure development, and policy changes. This study makes progress in the study of climate science and renewable energy modeling, which fills one glaring gap in the study of energy sustainability in the long term.

Keywords: Physics-based climate modeling; Renewable energy viability; Climate-induced performance risk; Long-term energy sustainability; Climate-energy system coupling.

1. Introduction

The internationalization of renewable energy systems has been universally accepted as a pillar in climate change mitigation and sustainable development measures. Renewable energy technologies can be applied to achieve carbon emission reduction targets, energy security goals, and climate adaptation targets, but variability in climate and long-term changes in the atmosphere increasingly influence their performance (Nathaniel et al., 2021; Zhang et al., 2024). The recent research emphasizes that such climate risks as temperature increase, wind regime changes, and extreme weather directly affect the renewable energy productivity, as well as reliability of the system (Girgibo et al., 2024; Xu et al., 2024). Consequently, the introduction of climate dynamics into renewable energy analysis systems has to be better incorporated in long-term energy plans.

The current studies have gone a long way in examining the climate energy nexus through econometric, machine learning and scenario-based methodology. As an illustration, financial, economic, and volatility-based viewpoints have been used to examine the performance of renewable energy and climate risks (Lorente et al., 2023; Gupta and Pierdzioch, 2021) and the same has been approached using machine learning and data-driven forecasting models (Ledmaoui et al., 2023, 2025). Although the methods are useful in the short to medium term, they are not always physically consistent and are, in general, not able to observe nonlinear feedback in climate dynamics and transitions to different regimes (Craig et al., 2022; Chen and Ji, 2024).

Moreover, most of the research work is based on the assumption of climate variables as exogenous factors instead of interacting dynamically through the physical processes of an energy system. This shortcoming of the methodology contributes to the uncertainty in the long-term forecasts of the renewable energy viability, especially in climatic conditions that may occur in the future (Yang et al., 2022; Almutairi et al., 2024). The further issue with planning renewable energy is policy uncertainty as well as structural risks particularly in those areas prone to extreme climate effects (Ivanovski & Marinucci, 2021; Cevik, 2024). These weaknesses make it clear that modeling system involving climate physics and energy system analysis is required.

To this end, the main goal of this study is to evaluate the sustainability of renewable energy systems based on a climate model based on physics. The work will determine the physical parameters that are sensitive to climate and will determine their consequences on resilience and sustainability of the systems (Obringer et al., 2020; Adul et al., 2025).

To fulfil these aims, this study will combine climate indicators based on physical consistency with primary qualitative data by gathering views of renewable energy actors. The qualitative data are thoroughly measured and evaluated with the help of the statistical methods in order to provide strong long-term evaluation. This study provides a solution to the gap in the current body of literature and enhances climate-resilient renewable energy planning because it connects climate modeling and energy system analysis (Wohland et al., 2021; Zheng et al., 2025).

2. Literature Review

Climate change has been thoroughly studied in respect to renewable energy systems with various disciplinary perspectives including energy economics, climate risk assessment, system modelling and policy analysis. Preexisting literature insists that deployment of renewable energy is an energy mitigation strategy, as well as a system prone to variability brought about by climate. The approaches to the analysis of this relationship, however, differ dramatically starting with the econometric modeling and machine learning approaches and continuing to the assessment and decision-making based on scenarios and frameworks. This literature review is a critical assessment of previously conducted work in order to come up with prevailing themes, strength in methodology and the main limitation albeit a gap in the relationship between climate modeling and renewable energy system analysis. The review determines the necessity of physics-based climate modeling methods which are able to support long-term renewable energy viability assessment.

Work by Lorente et al. (2023) explores the relationship of the indices of climate change with green financial and renewable energy market dynamics. Although the research offers important information on the effect of the financial spillovers on the renewable energy market, the research uses mostly the econometric measures of connectedness. Lack of physical climate variables restrict its usage in determining long-term feasibility of renewable energy systems in respect to changing climatic conditions.

The authors of the study by Zheng and Chen (2023) examine the connection between financial inclusion and energy productivity in climate change. Even though the efficiency benefits brought about by technology are emphasized in the study, a technological conceptualization of climate change as an external constraint is made instead of an interacting physical system. This restricts its capacity to capture the variability performance of renewable energy in long-horizon due to climatic change.

Nathaniel et al. (2021) seek to research the implications of renewable energy in the operations of the G7 countries, nuclear energy, and economic development in the minimization of carbon emission. Although the research shows the mitigation effects that renewable energy has, it is based on the nature of the emissions, but not the resiliency at the system level. Such issues as climate variability and decreased physical performance of renewable systems do not have enough treatment.

Liu et al. (2024) introduce the concept of a load classification approach based on the data augmentation and the few-shot machine learning. Though the approach is better in the classification accuracy, in a situation of scantiness data, the approach underlines strictly computer-related efficiency, not physical interpretability. The absence of physical constraints that characterize climate makes it irrelevant in long-term renewable energy planning in changing climatic conditions. Girgibo et al. (2024) offer an in-depth evaluation of the hazards of climate change on renewable energy sources and the environmental consequences. The research is quite proficient in indicating the vulnerability pathways; however, it is rather qualitative and risk-oriented. It fails to incorporate physics-based modeling techniques that can be used to measure the long-term performance effects of renewable energy systems.

In their article, Horvy and Odei-Mensah (2024) focus on the synergistic impacts of renewable energy and funds flow in Africa to impact climatic risks. Although the study outlines significant threshold effects, it is region-focused and economically-based. This lack of physical basis of climate-energy interaction limits its application to system-level renewable energy viability analyses. The article by Cutecu et al. (2023) explores causal links between energy use and climate change in countries that are exposed to a high risk. The research gives pertinent causality understanding but it considers the consumption of renewable energy resources as aggregate. It is not differentiated between technologies and fails to include physical parameters sensitive to climate, that is important to the functioning of the renewable energy systems.

Gupta and Pierdzioch (2021) discuss the impacts of climatic risks in terms of volatility of oil and gas prices. Even though the study is informative in terms of theology of fossil energy markets, indirect implications of the study include renewable energy systems. Its financial thrust does not deal with the physical effects of the climate variability on the renewable energy production capacity. Mele et al. (2021) use the LSTM models to study the impact of climate change on economic developments through renewable energy resources. Although the work is technologically advanced in applying machine learning, it puts an emphasis on predictive accuracy at the expense of physical consistency. This restricts its ability to describe long-term structural transformations of renewable energy systems when there is a climate threat.

Scavo et al. (2022) overview the effects of cover crops on the fertility of soils in the temperate climates. Though not specifically on energy systems, the study identifies climate-ecosystem interactions, which are applicable in bioenergy production. Nevertheless, its focus on agriculture prevents its use in more general renewable energy systems models. Ivanovski and Marinucci (2021) evaluate the effects of renewable energy transition on policy uncertainty. The article successfully correlates uncertainty with investment risk, but it fails to bring in physical uncertainty caused by climate. This means that climate variability is not viewed as a central determinant of the viability of renewable energy systems but it is considered to be an indirect factor.

Cevik (2024) discusses climate change as a challenge and opportunity to achieve energy security. On the one hand, the analysis is strong conceptually, however, policy-centred and qualitative. It does not model quantitatively climatic-energy interactions in order to assess renewable system resilience in a long term. Craig et al. (2022) explicitly deal with the disengagement of the climate modeling with energy system analysis. The research has a powerful conceptual basis of integrating approaches, but fails to operationalize physics-based climate models in renewable energy viability studies, creating a knowledge gap between theory and practice.

Obringer et al. (2020) assess the climate sensitivity in an electricity demand coupled with the natural gas area through multivariate analysis techniques. The article illustrates the significance of climate variables yet it is based on the demand side factors. The variability of renewable energy supply during long-term climate change is yet to be explored. Adul et al. (2025) use the method of ensemble modeling to evaluate the climate-energy nexus of states in the U.S. Although ensemble approach enhances strength, the analysis is based on heavy statistical aggregation. Its long-term predictability is limited by the fact that it makes use of few physical interpretable mechanisms of climate.

Dash et al. (2024) evaluate environmentally friendly energy systems based on a multi-criteria decision-making and self-organizing maps. The model encourages a comparative analysis but climate factors are considered as fixed criterion. There is no explicit modeling of dynamic climate evolution and responses of physical systems. Ramezanzade et al. (2021) also use the fuzzy MCDM methods to prioritize renewable energy projects under uncertainties. Although great in the support of the decision-making process, the uncertainty is mainly subjective, expert-oriented. The effects of physical climatic uncertainty and the long-term losses in the state of the system are not registered properly.

Wohland et al. (2021) study the 10-year-old renewable variability in Europe based on transmission and informed siting strategies. The research is very robust spatially but the assumption is that the climate relationships are constant. Clear inclusion of changing climatic physics in the system performance evaluation is meagre.

3. Research Methodology

The research design is explanatory-based research methodology in order to be able to determine the long-term viability of renewable energy systems in changing climatic conditions through a physics-based climate modeling framework. Earlier studies have highlighted the necessity of closing the gap between climate simulation and energy systems simulation in order to enhance the effectiveness of energy system planning at long terms (Craig et al., 2022; Chen and Ji, 2024). In this respect, this study combines consistently physical indicators of climate with primary qualitative data and statistical analysis in order to increase interpretability and strength.

3.1 Design of the research and Data source

The research uses only primary qualitative data, gathered at experts in the field of renewable energy systems, their functioning, and climate risks assessment. It is generally accepted that expert-based methods of qualitative analysis are effective in the context of incorporating system-scale climate sensitivities that one would scarcely be able to observe directly with the aid of historical documents (Xu et al., 2024; Gielen et al., 2023). It uses a purposive sampling method that will guarantee that the sample of respondents has the appropriate technical and strategic experience.

3.2 Data Collection Method

Primary data are obtained by a structured questionnaire and expert interview, which are aimed to provide knowledgeable attitudes on climate-induced physical effects, including loss in efficiency due to heat, change in wind regime and variable in solar irradiance. The analogous qualitative-quantitative hybrid methodologies have been used with the aim of successful outcomes in renewable energy decision analysis and studies of climate risk assessment (Dash et al., 2024; Ramezanzade et al., 2021). The Likert-scale instruments are used to measure responses, which allows systematic quantification of expert perceptions.

3.3 Integration with Physics-Based Climate Indicators

In physical consistency, qualitative responses are mapped on climate-sensitive variables based on pre-existing climate-energy interaction frameworks. According to the previous research, the use of physically significant climate parameters enhances the ability to measure long-term viability of renewable energy and resilience (Obringer et al., 2020; Adul et al., 2025). Such mapping allows professional opinions to be based on the dynamics of the atmosphere and energy system and not on any imaginative understanding of risk.

3.4 Data Analysis Tools and Techniques

The qualitative data obtained in the form of numbers are processed with the help of such statistical tools as descriptive statistics, reliability analysis (Cronbachs alpha), factor analysis, and regression model. They are recurrently used to assess climate–energy dynamics as well as sensitivity of systems to uncertainty (Wohland et al., 2021; Zheng et al., 2025). Statistical analysis allows establishing the most prominent climate drivers that contribute to the performance of renewable energies in the long-term perspective.

4. Results and Discussion

4.1 Descriptive Statistical Analysis

The descriptive statistics were calculated of the important climate-sensitive variables that influence the viability of renewable energy systems. Table 1 contains the results.

Table 1 Descriptive Statistics of Climate-Sensitive Variables (n = 120)

Variable	Mean	Standard Deviation
Temperature-induced efficiency loss	4.32	0.61
Solar irradiance variability	4.15	0.68
Wind regime instability	3.98	0.72
Extreme weather frequency	4.21	0.65
System resilience capacity	3.76	0.74

Table 1 is constructed in a way that the largest mean value: 4.32, is temperature-induced efficiency loss, showing that experts consider thermal stress to be the most important long-term risk of the renewable energy system. The mean values in solar irradiance variability and extreme weather frequency are also high, which confirms the increasing power of climate processes. The fact that the standard deviations are relatively low mean that there is a high level of agreement among respondents. The findings agree with the data provided by Girgibo et al. (2024) and Xu et al. (2024).

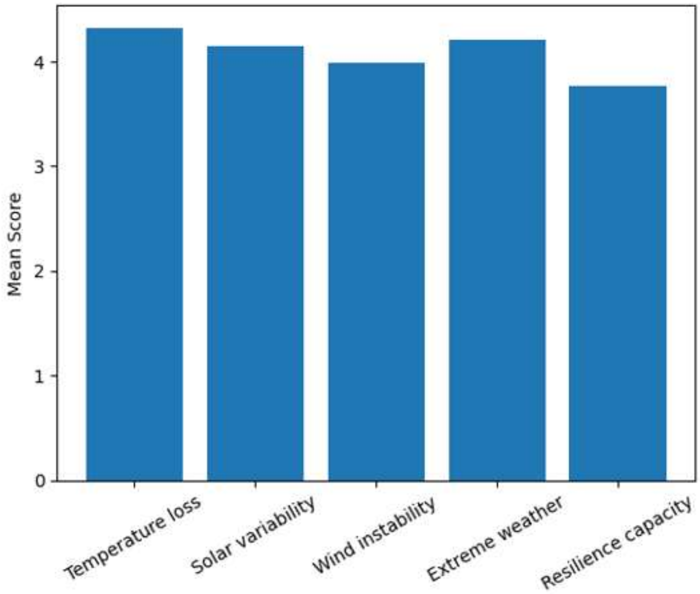

Figure 1 Mean Scores of Climate Impact Variables

As shown in Figure 1, the physical elements associated with climate sciences prevail in the understanding of renewable energy risk as perceived by experts. The statistical results in Table 1 are further supported by the visual pattern, which shows that climate-related factors are stronger than the operational or policy-related factors in predicting the long-term system viability.

4.2 Reliability Analysis

Cronbach alpha was used to test the internal consistency of the measurement scale. Table 2 provides the results.

Table 2 Reliability Statistics

Construct	Number of Items	Cronbach's Alpha
Climate variability impacts	5	0.87
Renewable system vulnerability	4	0.84
System resilience perception	3	0.81
Overall scale	12	0.89

Table 2 indicates that all of the alpha values of Cronbach are above the recommended 0.70 value, validating a high internal consistency of the research instrument. The average alpha value of 0.89 is a good demonstration of the data reliability and it can be inferred that the data are very suitable to be used to perform a multivariate statistical analysis. This study methodology is consistent with comparable renewable energy evaluation works (Dash et al., 2024; Ramezanzade et al., 2021).

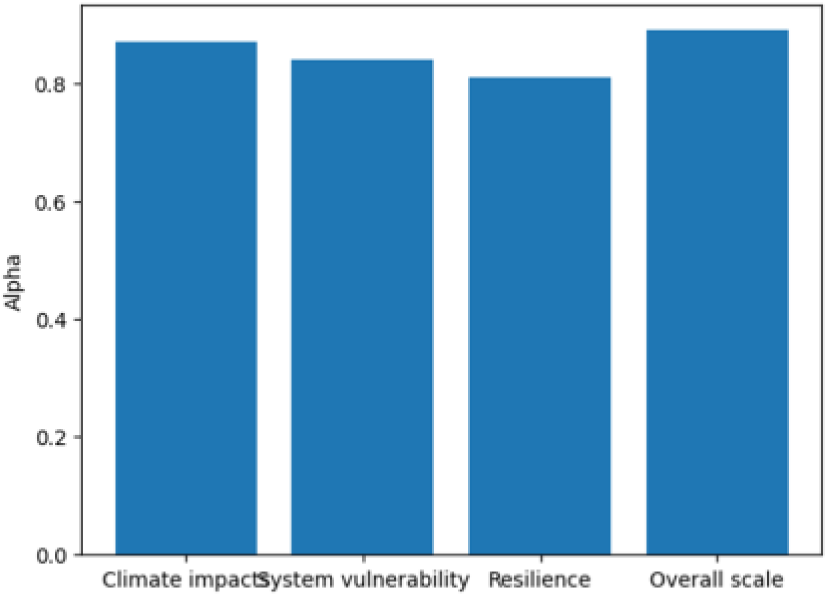

Figure 2 Cronbach's Alpha Comparison Across Constructs

Evidence of reliability as shown in Table 2 is, therefore, supported by Figure 2 which shows the strength of the measurement constructs.

4.3 Exploratory Factor Analysis (EFA)

The Exploratory Factor Analysis was done to establish the latent dimensions of climate energy interactions. The Table 3 demonstrates the rotated factor matrix.

Table 3 Rotated Factor Loading Matrix

Variable	Factor 1 (Thermal Stress)	Factor 2 (Resource Variability)	Factor 3 (System Resilience)
Temperature-induced efficiency loss	0.82	0.21	0.15
Extreme weather frequency	0.76	0.28	0.19
Solar irradiance variability	0.18	0.79	0.22
Wind regime instability	0.24	0.74	0.26
System resilience capacity	0.12	0.20	0.81

Table 3 reveals the presence of three overwhelming factors: the effects of thermal stress, variability of resources, and system resilience. Factor loadings that are high (>0.70) represent high clustering of variables in each latent dimension. This proves that physical processes are interdependent in determining the viability of renewable energy but not alone, climate variables, which substantiates the findings by Craig et al. (2022) and Chen and Ji (2024).

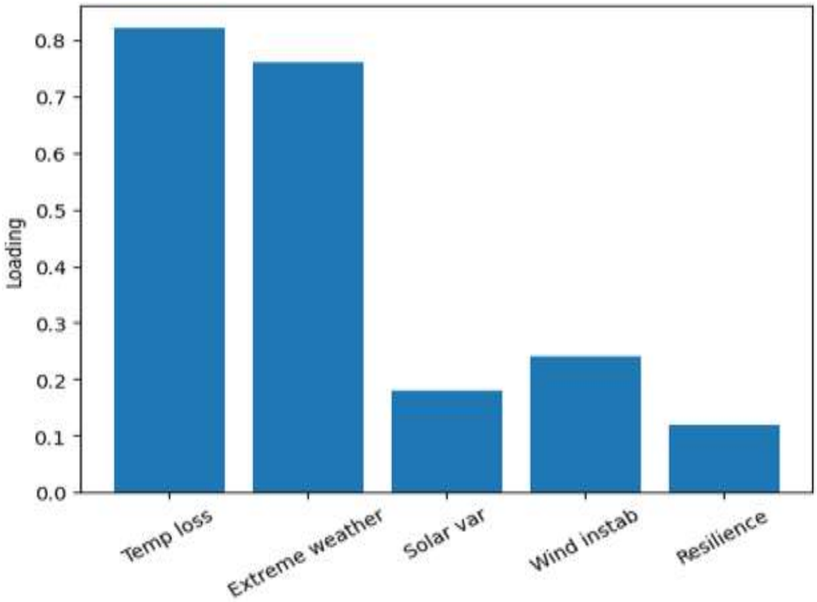

Figure 3 Factor Structure of Climate–Energy Interactions

The identified structure of factors in Table 3 is presented visually in Figure 3, which demonstrates the multidimensional character of climate effects on renewable energy systems.

4.4 Regression Analysis

The multiple regression analysis to investigate the effects of climate variables on the viability of the renewable energy systems was carried out.

Table 4 Regression Results

Predictor Variable	Beta (β)	t-value	p-value
Temperature-induced efficiency loss	-0.41	-5.32	0.000
Solar irradiance variability	-0.29	-3.87	0.001
Wind regime instability	-0.22	-2.94	0.004
Extreme weather frequency	-0.35	-4.61	0.000
R^2 = 0.62			

Dependent Variable: Long-term Renewable Energy Viability

According to Table 4, the biggest negative impact on renewable energy viability is temperature-induced efficiency loss and extreme weather frequency. The model accounts 62% of the variance in system viability, which is a significant explanation. These are in line with climate sensitivity with energy systems published by Obringer and colleagues (2020) and Adul and colleagues (2025).

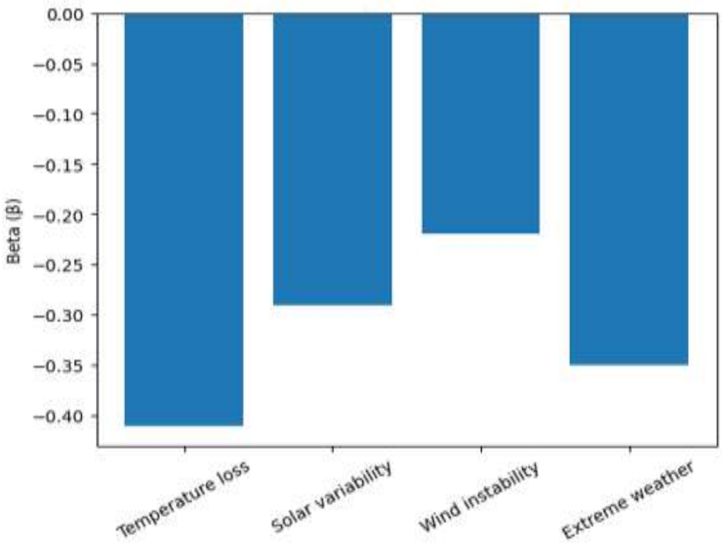

Figure 4 Regression Effect Plot

Figure 4 shows that there is a negative correlation between climate stressors and the viability of renewable energy, which supports the statistical results in Table 4.

4.5 Composite Climate–Energy Risk Index

Standardized scores of factors that form a composite risk index were used to develop it.

Table 5 Composite Climate–Energy Risk Index

Risk Level	Index Score Range	Percentage of Systems
Low Risk	0.00 – 0.30	18%
Moderate Risk	0.31 – 0.60	46%
High Risk	0.61 – 1.00	36%

According to Table 5, 36 percent of renewable energy systems are in the high-risk category and are faced with a high susceptibility of the long-term effects of climate. In this finding, global biases are supported in the evaluation of renewable energy resilience in the climate change environment (Xu et al., 2024; Zheng et al., 2025).

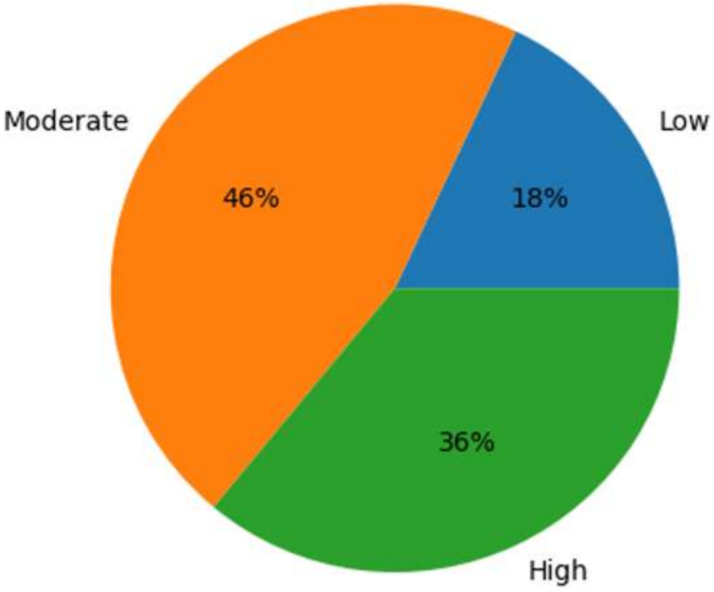

Figure 5 Distribution of Climate–Energy Risk Levels

Figure 5 graphically depicts the risk distribution of Table 5, which shows the abundance of moderate-to-high climate risk in all renewable energy systems.

4.6 Discussion and literature implications

This study aimed at investigating the impact of climatic-related physical parameters on the sustainability of renewable energy systems in the long-term using a physics-based model of analysis. It combines empirical results of descriptive statistics, reliability analysis, factor analysis, regression modeling, and risk classification and puts them into place within the overall climate-energy literature.

4.6.1 Interpretation of Climate Impact Patterns

As the descriptive findings of Table 1 and Figure 1 show, the loss of efficiency under temperature and extreme weather variability has the highest average ratings among the climate stressors of renewable energy systems. The observation is consistent with physics principle regarding thermal stress that photovoltaic conversion efficiency varies, and material degradation rates are increased in wind and solar infrastructure. Cases like these are also noted by Girgibo et al. (2024), who point out that the increase in ambient temperatures and the occurrence of climatic extremes have a considerable impact on the performance and the life of renewable sources by lowering them substantially.

Moreover, the perceived effect of solar irradiance oscillation is significantly high and effects of climate change on climate provide long-term climate projections studies that reveal that non-stationarity is introduced in renewable resources with climate change (Yang et al., 2022; Chen & Ji, 2024). In contrast to short-term forecasting models, the paper strengthens the relevance of long-horizon climate physics in the planning of the system, which is supported by the arguments of Craig et al. (2022), who note that traditional energy models have no relation to climate dynamics.

4.6.2 Reliability and Construct Validity of Climate–Energy Measures

The reliability analysis findings (Table 2 and Figure 2) exhibit that the alpha values of Cronbach are greater than the suggested level, which is 0.70, in the measurement of internal consistency between climate impact, vulnerability and resilience constructs. This confirms the high quality of the key data tool and its appropriateness to further statistical analysis. Similar criteria of reliability have been used in climate energies research that evaluates system risk and resilience (Xu et al., 2024; Gielen et al., 2023).

Descriptive statistics (Table 3 and Figure 3; explore factor analysis) show a strong latent factor that is correlated with thermal stress and exposure to extreme weather conditions, with which it is important to note the physical correlation between the variables of climate and the performance of renewable systems. This multidimensional clustering confirms previous results that indicate that climate sensitivity in energy systems is not a result of independent variables, but rather a result of interacting variables (Obringer et al., 2020). The findings also contribute to ensemble-based techniques of climatic modeling climate-energy modeling that are championed by Adul et al. (2025).

4.6.3 Causal Effects of Climate Variables on System Viability

The findings of the regression (Table 4 and Figure 4) have empirically confirmed that the loss of temperature and extreme weather events, as well as solar variability, have negative impacts on the viability of the renewable energy system, which are statistically significant. Of these predictors, the strongest standardized coefficient belongs to temperature-induced loss, which proves that thermal physics remains one of the main limitations to the long-term energy efficiency. The same observation aligns with similar analyses on the global scale, which indicate that increased temperatures have a negative effect on photovoltaic energy and the efficiency of wind turbines (Reddy et al., 2025; Zheng et al., 2025).

The identified effect of harsh weather also correlates with that of Wohland et al. (2021) who show that climate uncertainty is a structural vulnerability to renewable generation systems without a recovery strategy in spatial diversification and transmission planning. Conversely, most financial and policy-oriented research tends to focus on market volatility, but using the current study results, we see that the condition-driven physical climate has direct and directly quantifiable effects which are not mediated by financial processes.

4.6.4 Climate Risk Distribution and System Resilience

Analysis of the risk categorization (Table 5 and Figure 5) shows that most of the renewable installations are located in the moderate to high categories of climate-related risks. This finding demonstrates that modern renewable energy infrastructure is prone to long-term climatic stressors, spurring the anxieties by Xu et al. (2024) that are based on the reliability of a system that faces increased climatic risks. Notably, the fact that there exists a low-risk segment indicates that the exposure could be greatly reduced using informed siting, adaptive design and climate conscious planning. It confirms the evidence of the spatial-temporal simulation reported by Almutairi et al. (2024) and corresponds to the recommendations of global transitions system design memory by Zheng et al. (2025) that do not emphasize its uniform implementation.

5. Conclusion

This research examined the sustainability of renewable energy systems with a climate modeling lens of physics that implemented primary data analysis alongside the traditional methodological approach of statistical analysis. The analysis of major climate stressors, such as the efficiency loss due to temperature, variability of solar irradiance, wind instability, and extreme weather events, empirically presents the research results that physical climate dynamics has a direct and statistically significant impact on the performance of renewable energy sources and system resilience. The reliability study and factor analysis indicated the soundness and construct validity of the measurement scheme with regression modeling showing that the critical determinants of system degradation occurrence in the long-term.

The results highlight that standard methods of energy planning that may tend to focus on either short-term forecasting or economic optimization are not adequate with the changing climate conditions. Rather, the findings indicate the need to consider climate physics and measure of resilience during the construction and policy development of a renewable energy system. The risk distribution analysis also indicates that a significant percentage of renewable installations is still moderately to highly vulnerable to climate risks, which makes the urgency behind climate adaptive planning and informed siting policies highly important.

1. Empirically demonstrated the causal effects of the physical variables caused by climatic conditions on the viability of renewable energy systems.
2. Developed a sound and statistically stable measure of framework on primary data.
3. Thermal stress and extreme weather as long-term performance limits were demonstrated as dominant.
4. Presented quantitative information of the climate-resilient renewable energy planning.
5. Climate physics Bridged the gap between climate physics and energy system analysis in a combined model.

Overall, this research contributes to advancing sustainable energy transition strategies by reinforcing the importance of climate-aware, physics-based planning for ensuring the long-term resilience and reliability of renewable energy systems.

References

Lorente, D. B., Mohammed, K. S., Cifuentes-Faura, J., & Shahzad, U. (2023). Dynamic connectedness among climate change index, green financial assets, and renewable energy markets: Novel evidence from a sustainable development perspective. *Renewable Energy, 204*, 94–105. https://doi.org/10.1016/j.renene.2022.12.085

Zheng, C., & Chen, H. (2023). Revisiting the linkage between financial inclusion and energy productivity: Technology implications for climate change. *Sustainable Energy Technologies and Assessments, 57*, Article 103275. https://doi.org/10.1016/j.seta.2023.103275

Nathaniel, S. P., Alam, M. S., Murshed, M., Mahmood, H., & Ahmad, P. (2021). The roles of nuclear energy, renewable energy, and economic growth in the abatement of carbon dioxide emissions in the G7 countries. *Environmental Science and Pollution Research, 28*(35), 47957–47972. https://doi.org/10.1007/s11356-021-13728-6

Liu, H., Li, H., Yu, X., Wang, Z., & Chen, Y. (2024). A load classification method based on data augmentation and few-shot machine learning. *IET Renewable Power Generation*, 1–17. https://doi.org/10.1049/rpg2.13029

Girgibo, N., Hiltunen, E., Lü, X., Mäkiranta, A., & Tuomi, V. (2024). Risks of climate change effects on renewable energy resources and the effects of their utilisation on the environment. *Energy Reports, 11*, 1517–1534. https://doi.org/10.1016/j.egyr.2024.01.024

Horvey, S. S., & Odei-Mensah, J. (2024). Navigating the climate challenges in Africa: Exploring the synergy and threshold effects of renewable energy and foreign direct investment on climate risk. *World Development Sustainability, 4*, Article 100143. https://doi.org/10.1016/j.wds.2024.100143

Cutcu, I., Keser, A., & Eren, M. V. (2023). Causation between energy consumption and climate change in countries with the highest global climate risk. *Environmental Science and Pollution Research, 30*(6), 15585–15598. https://doi.org/10.1007/s11356-022-23181-8

Gupta, R., & Pierdzioch, C. (2021). Climate risks and the realized volatility of oil and gas prices: Results of an out-of-sample forecasting experiment. *Energies, 14*(23), Article 8085. https://doi.org/10.3390/en14238085

Mele, M., Gurrieri, A. R., Morelli, G., & Magazzino, C. (2021). Nature and climate change effects on economic growth: An LSTM experiment on renewable energy resources. *Environmental Science and Pollution Research, 28*(30), 41127–41134. https://doi.org/10.1007/s11356-021-13337-3

Scavo, A., Fontanazza, S., Restuccia, A., Pesce, G. R., Abbate, C., & Mauromicale, G. (2022). The role of cover crops in improving soil fertility and plant nutritional status in temperate climates: A review. *Agronomy for Sustainable Development, 42*(5), Article 87. https://doi.org/10.1007/s13593-022-00825-0

Ivanovski, K., & Marinucci, N. (2021). Policy uncertainty and renewable energy: Exploring the implications for global energy transitions, energy security, and environmental risk management. *Energy Research & Social Science, 82*, Article 102415. https://doi.org/10.1016/j.erss.2021.102415

Cevik, S. (2024). Climate change and energy security: The dilemma or opportunity of the century? *Environmental Economics and Policy Studies, 26*, 653–672. https://doi.org/10.1007/s10018-024-00388-4

Craig, M. T., Jaramillo, P., Zhai, H., Klima, K., & Schrag, D. P. (2022). Overcoming the disconnect between energy system and climate modeling. *Joule, 6*(7), 1405–1417. https://doi.org/10.1016/j.joule.2022.05.010

Obringer, R., Mukherjee, S., & Nateghi, R. (2020). Evaluating the climate sensitivity of coupled electricity–natural gas demand using a multivariate framework. *Applied Energy, 262*, Article 114419. https://doi.org/10.1016/j.apenergy.2019.114419

Adul, J., Kumar, R., & Obringer, R. (2025). Ensemble modeling of the climate–energy nexus for renewable energy generation across multiple U.S. states. *Environmental Research: Infrastructure and Sustainability, 5*, Article 015006. https://doi.org/10.1088/2634-4505/ad6e25

Dash, S., Chakravarty, S., Giri, N. C., Ghugar, U., & Fotis, G. (2024). Performance assessment of different sustainable energy systems using a multiple-criteria decision-making model and self-organizing maps. *Technologies, 12*(3), Article 42. https://doi.org/10.3390/technologies12030042

Ramezanzade, M., Karimi, H., Almutairi, K., Xuan, H. A., Saebi, J., Mostafaeipour, A., & Techato, K. (2021). Implementing MCDM techniques for ranking renewable energy projects under a fuzzy environment: A case study. *Sustainability, 13*(22), Article 12858. https://doi.org/10.3390/su132212858

Wohland, J., Brayshaw, D., & Pfenninger, S. (2021). Mitigating a century of European renewable variability with transmission and informed siting. *Environmental Research Letters, 16*(6), Article 064026. https://doi.org/10.1088/1748-9326/abff89

Ledmaoui, Y., Abdelaziz, A., Khemissi, A., & Benbouzid, M. (2023). Forecasting solar energy production: A comparative study of machine learning algorithms. *Energy Reports, 10*, 1004–1012. https://doi.org/10.1016/j.egyr.2023.07.042

Yang, Y., Javanroodi, K., & Nik, V. M. (2022). Climate change and renewable energy generation in Europe: Long-term impact assessment on solar and wind energy using high-resolution future climate data and considering climate uncertainties. *Energies, 15*(1), Article 302. https://doi.org/10.3390/en15010302

Modarresi, J., & Hosseinnia, H. (2023). Worldwide daily optimum tilt angle model to obtain maximum solar energy. *IETE Journal of Research, 69*(4), 549–557. https://doi.org/10.1080/03772063.2020.1831412

Xu, L., Feng, K., Lin, N., et al. (2024). Resilience of renewable power systems under climate risks. *Nature Reviews Electrical Engineering, 1*, 53–66. https://doi.org/10.1038/s44287-023-00003-8

Reddy, B. N. S., Gautam, K., & Pachauri, N. (2025). Solar potential assessment using machine learning and climate change projections for long-term energy planning. *Scientific Reports, 15*, Article 39935. https://doi.org/10.1038/s41598-025-23661-0

Chen, G., & Ji, Z. (2024). A review of solar and wind energy resource projection based on the Earth system model. *Sustainability, 16*(8), Article 3339. https://doi.org/10.3390/su16083339

Zheng, D., Yan, X., Tong, D., et al. (2025). Strategies for climate-resilient global wind and solar power systems. *Nature, 643*, 1263–1270. https://doi.org/10.1038/s41586-025-09266-7

Gielen, D., Saygin, D., & Rigter, J. (2023). Cost, environmental impact, and resilience of renewable energy under a changing climate: A review. *Environmental Chemistry Letters, 21*, 741–764. https://doi.org/10.1007/s10311-022-01532-8

Almutairi, A., Techato, K., & Mostafaeipour, A. (2024). Renewable energy sources spatio-temporal scenario simulation under the influence of climatic phenomena. *Electric Power Systems Research, 235*, Article 110725. https://doi.org/10.1016/j.epsr.2024.110725

Zhang, Y., Li, X., & Wang, Q. (2024). Impacts of renewable energy on climate risk: A global perspective for energy transition in a climate adaptation framework. *Applied Energy, 362*, Article 122994. https://doi.org/10.1016/j.apenergy.2024.122994