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Technical Paper

A Data-Driven Simulation Framework for Sustainable Design: Forecasting Wind Energy Trends in Taiwan

Jang-I Lee[1], Jui-Hung Cheng [1]*, Sung-Ying Tsai [1], and Cheng-Hsien Shen [2]

[1] Department of Mold and Die Engineering, National Kaohsiung University of Science and Technology, Kaohsiung 80778, Taiwan; F114147106@nkust.edu.tw (J.-I L.); F114147167@nkust.edu.tw (S.-Y. T.)
[2] Department of Marine Environment and Engineering, National Sun Yat-sen University, Kaohsiung 80424, Taiwan; M145040020@student.nsysu.edu.tw
* Correspondence: rick.cheng@nkust.edu.tw

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Abstract: This study proposes a data-driven simulation framework for forecasting wind-energy trends in Taiwan and examines how computational prediction can support sustainable design education. The model, implemented in MATLAB, integrates deterministic sinusoidal functions with stochastic variability to emulate seasonal and diurnal wind patterns, producing interpretable and reproducible time-series outputs. Across a three-year simulation span, results illustrate an upward trend in modeled power generation and a reduction in daily fluctuation, suggesting improvements in turbine stability and system efficiency under assumed scenarios. Beyond technical forecasting, the study positions simulation as a design-oriented interpretive medium. Building on prior work in sustainability education, data visualization, and experiential learning, the framework demonstrates how learners can analyze temporal dynamics, recognize long-range energy trajectories, and engage with uncertainty through visual exploration. This dual function-as analytical tool and interpretive interface-highlights how predictive modeling can bridge engineering reasoning with design understanding. By translating complex environmental change into accessible visual forms, the framework supports the development of sustainability literacy and enriches interdisciplinary dialogue around renewable-energy futures.

Keywords: Sustainable design; Renewable energy forecasting; Data-Driven simulation; Environmental visualization; MATLAB modeling; Design education; Predictive interpretation; Renewable-Energy literacy

1. Introduction

The transition toward renewable energy has become a foundational component of global sustainability agendas, requiring not only advancements in engineering but also new frameworks for design interpretation and public communication. As nations move toward decarbonization, design disciplines increasingly play a role in translating complex environmental processes into accessible forms of understanding (Faludi et al., 2023). Wind energy is central to Taiwan's renewable-energy trajectory, yet forecasting its temporal behavior remains difficult due to meteorological uncertainty, highly variable coastal conditions, and the scarcity of long-range datasets. Traditional forecasting approaches often emphasize computational precision, but their outputs can be difficult for non-specialists to interpret, creating a disconnect between technical insight and cultural or educational application.

Recent research in sustainable design and visualization demonstrates that simulation and data-driven representation can help bridge this divide by transforming environmental data into visual and experiential learning artifacts. Mahyar (2024) argues that visualization can "activate interpretive engagement," enabling users to perceive patterns that may otherwise remain buried within numerical outputs. Likewise, Sundman et al. (2025) highlight that experiential learning through simulation allows students and practitioners to treat environmental dynamics as manipulable elements within a design process, thereby developing sustainability literacy and systems thinking. These perspectives reposition simulation from a purely computational instrument to a medium for reflection, interpretation, and creative inquiry.

Motivated by these insights, this study develops a MATLAB-based simulation framework for modeling Taiwan's July wind-power generation from 2024 to 2026. Instead of relying exclusively on incomplete or inconsistent empirical records, the framework employs synthetic yet structured datasets based on deterministic sinusoidal functions and stochastic noise. This approach enables users to explore seasonal and diurnal variability while preserving interpretability and modularity. Once calibrated with real meteorological data, the model can be extended for practical forecasting. More importantly, the structure of the model supports visual exploration, allowing learners and designers to identify temporal patterns, analyze growth trajectories, and understand uncertainty as an integral part of environmental systems.

By situating prediction at the intersection of design reasoning, computational modeling, and cultural meaning-making, this study aligns with contemporary discourse on innovation in design and culture. Forecasting, in this context, becomes both an epistemic practice-revealing structure within complex ecological phenomena-and a creative practice that shapes how renewable-energy futures are imagined, communicated, and collectively negotiated (D'Orto, 2025). The act of simulating environmental change becomes a way of "making sense" of sustainability, transforming raw data into shared narratives that support decision-making, public engagement, and educational development.

Accordingly, this paper pursues three objectives:

(1) To construct a transparent, modular, and interpretable simulation framework for wind-energy forecasting in Taiwan;
(2) To illustrate how data-driven modeling and visualization can support sustainable-design education through experiential and interpretive forms of engagement;
(3) To examine how algorithmic prediction can function as a cultural and communicative process, transforming environmental uncertainty into accessible understanding.

Section 2 introduces the methodological structure, including data generation and simulation workflow. Section 3 presents the results and validation tests. Section 4 discusses implications for design education and cultural interpretation, and Section 5 concludes with reflections on how predictive simulation reshapes the relationship between data, design, and sustainability futures.

2. Materials and Methods

2.1 Simulation Framework Overview

The simulation framework was developed in MATLAB R2024b to model and forecast daily wind-power generation during Taiwan's July southwest-monsoon season. The workflow comprises four interconnected modules: data generation, trend and frequency analysis, visualization, and evaluation. While technically modular, this structure is also pedagogically oriented. Following Bernert et al. (2022), modularity supports "transformative learning processes" by allowing users to isolate, manipulate, and reinterpret each analytical component. Through this configurability, learners can adjust parameters, experiment with alternative assumptions, and observe how computational choices alter the visual and conceptual outcomes. Such flexibility positions the framework not only as an analytical tool but also as a learning environment that can be integrated into design studios, engineering courses, and sustainability-focused instruction.

2.2 Data Generation Model

To emphasize methodological clarity and reproducibility, the study employs synthetically generated datasets rather than relying on incomplete empirical records. Daily power-output sequences were produced for 31 days in July across three model years-2024, 2025, and 2026. The generative equation combines deterministic diurnal oscillation with stochastic variability:

$$P(t) = \mu + A\sin\left(\frac{2\pi t}{T}\right) + \epsilon, \epsilon \sim N(0, \sigma^2) \qquad (1)$$

where $P_t$represents power output (MW) on day t, $A$is the oscillation amplitude, $T = 31$days is the seasonal cycle length, and $\epsilon_t \sim N(0, \sigma^2)$denotes Gaussian noise. Baseline means (μ) of 800, 850, and 900 MW represent projected improvements in turbine efficiency. This deterministic–stochastic hybrid model aligns with interpretability-oriented renewable-energy forecasting practices described by Alahira et al. (2024).

The synthetic structure enables a level of control not possible with raw meteorological data. Users can visualize uncertainty, test contrasting scenarios, and explore how environmental variability becomes a design material-supporting interactive, inquiry-driven learning.

2.3 Trend and Frequency Analysis

Interannual growth trends were examined using linear regression via MATLAB's polyfit function. Slope coefficients for 2024 and 2025 were averaged to approximate the projected trend for 2026. To complement the regression analysis, Fast Fourier Transform (FFT) decomposition was conducted to identify dominant periodic harmonics. This combination of directional regression and spectral interpretation reflects hybrid analytical practices commonly applied in recent energy-trend studies (Kostis et al., 2025).

From a design-interpretive viewpoint, regression highlights long-term trajectories, while FFT reveals underlying rhythmic structures in environmental behavior. These analytical outputs enable learners to interpret temporal patterns not only as numerical characteristics but also as narrative cues that shape the way seasonal energy systems are understood.

2.4 Visualization and Evaluation

Visualization modules were developed to support both analytical insight and pedagogical clarity. Included outputs comprise interannual line-plot comparisons, bar charts summarizing mean generation, fluctuation overlays, comparative statistical plots, and a scatterplot illustrating the relationship between wind speed and power output ($R \approx 0.9$). Following principles of transparency and cognitive accessibility, these visual representations help users examine how algorithmic adjustments influence system stability. As noted by Stenberdt and Makransky (2023), well-designed visual or immersive environments can strengthen mastery experiences and promote environmentally responsible behavior.

Evaluation metrics include mean, standard deviation, minimum, maximum, Mean Squared Error (MSE), and capacity factor (relative to an assumed 1-GW capacity). These indicators-summarized in Table 1-provide structure for interpreting model performance and help transform raw variability into meaningful visual knowledge.

Table 1. Model Parameters and Evaluation Metrics

Parameter	Description	Value/Range	Unit
T	Simulation period	31	days
A	Amplitude of seasonal oscillation	200–240	MW
μ	Baseline mean generation	800–900	MW
σ	Noise standard deviation	35–50	MW

Evaluation Metrics: Mean, Standard Deviation (SD), Maximum, Minimum, Mean Squared Error (MSE), Capacity Factor.

3. Results

3.1 Overview of Simulation Results

The simulated datasets for July 2024–2026 illustrate the dynamic temporal behavior of wind-power generation under the assumed monsoon conditions. As shown in Figure 1, the three annual profiles display a sinusoidal rhythm shaped by diurnal wind cycles, along with a gradual upward shift in mean output. This pattern reflects modeled improvements in turbine performance and overall system efficiency.

Equally notable is the progressive smoothing of the oscillatory amplitude, which indicates reduced fluctuation and increasing stability across the simulated years. The visual interplay between rhythm and refinement creates an intuitive narrative that supports sensemaking-allowing viewers to recognize how environmental patterns evolve over time. Figure 1 therefore serves as both a technical overview and a visual foundation for the analytical results that follow.

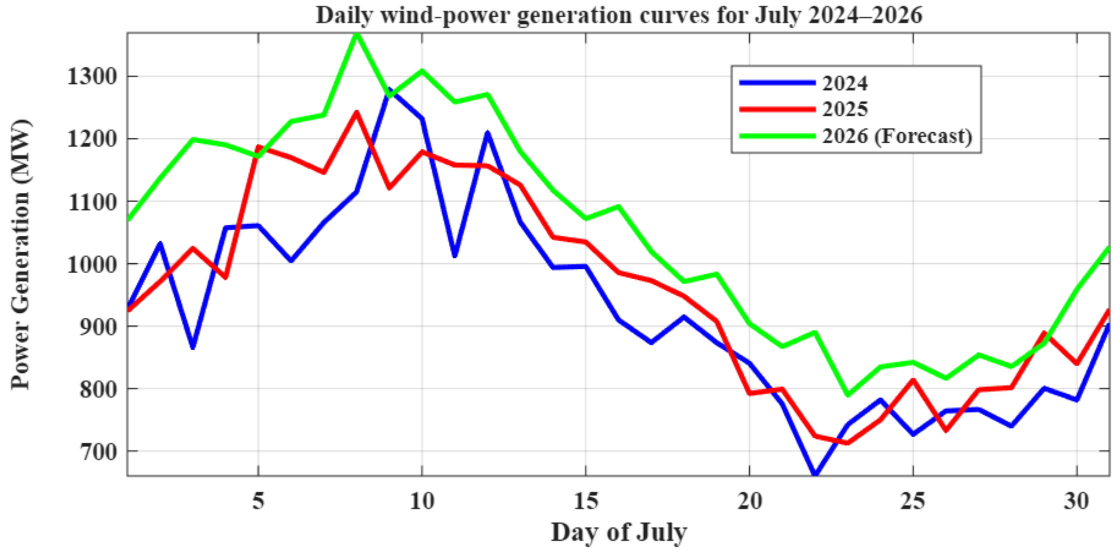

Fig 1. Daily wind-power generation curves for July 2024–2026. The sinusoidal diurnal oscillations and the upward shift in mean output reflect modeled improvements in system efficiency, while the progressive smoothing of amplitude highlights increasing stability. Together, the curves provide a visual narrative of temporal rhythm and refinement, offering viewers an intuitive way to interpret evolving environmental dynamics.

3.2 Annual Mean and Growth Trend

As illustrated in Figure 2, the annual averages-approximately 900 MW in 2024, 970 MW in 2025, and 1050 MW in 2026-reveal a consistent upward trajectory. This trend demonstrates how incremental adjustments to model parameters translate into higher simulated performance and, importantly, how numerical changes can be read visually as part of a broader sustainability narrative.

Regression analysis confirms this growth pattern, validating the use of linear coefficients for short-term forecasting. Together, the numerical trend and the visual clarity of the bar chart exemplify how computational modeling can support interpretive learning, aligning with Redman, Wiek, and Barth's (2021) emphasis on sustainability competencies in education.

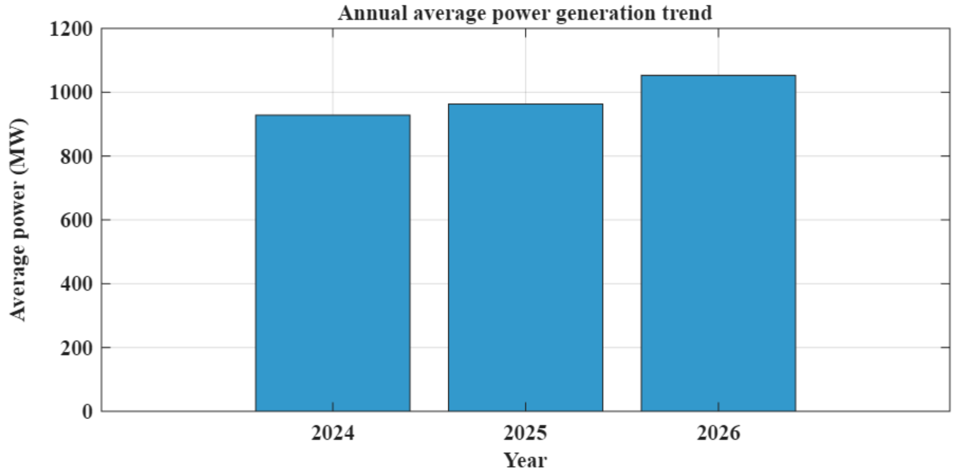

Fig 2. Annual mean wind-power generation for 2024–2026. The upward trend illustrates modeled improvements in system capacity and performance. By presenting year-to-year change in a clear visual format, the chart supports sustainability literacy and helps users connect computational adjustments with interpretable system behavior.

3.3 Variance Analysis and System Stability

Variance analysis further supports the observed stabilization. Standard deviation decreases markedly-from roughly 50 MW in 2024 to 35 MW in 2026-indicating that the simulated system becomes progressively less volatile. Such reduction in fluctuation aligns with iterative calibration processes used in hybrid forecasting approaches.

This pairing of visual observation and statistical confirmation illustrates how uncertainty can be transformed into recognizable patterns. For learners and designers, the decreasing variance provides a concrete example of how algorithmic refinement influences perceived system behavior, offering a bridge between computational reasoning and conceptual understanding.

3.4 Statistical Indicators and Model Reliability

Figure 3 highlights year-to-year changes in statistical indicators, revealing a contraction in variability across the simulated period. Mean Squared Error (MSE) follows a similar downward pattern-decreasing from approximately 2400 MW² in 2024 to 1800 MW² in 2025-indicating improved calibration and model coherence. The capacity factor increases from 0.80 to 0.90, suggesting greater modeled operational efficiency.

These indicators provide quantitative evidence of methodological reliability while also functioning as pedagogical tools. Their clarity supports classroom discussions on calibration, uncertainty reduction, and model validation, demonstrating how statistical reasoning contributes to visual and interpretive understanding within sustainable-energy design.

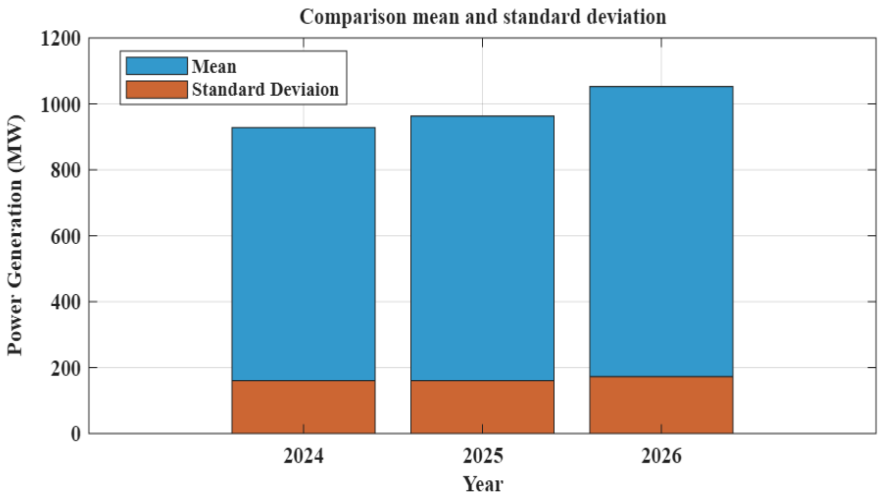

Fig 3. Comparative mean and standard deviation for each simulated year. The narrowing dispersion illustrates reduced variability and improved model reliability. The figure highlights how visual patterns in statistical indicators can support interpretive understanding of system stability within sustainable-energy simulations.

3.5 Wind-Speed Correlation and Physical Interpretation

The correlation analysis in Figure 4 shows consistently high coefficients ($R \approx 0.89$–0.92), reflecting the cubic dependence of turbine output on wind velocity and confirming the physical plausibility of the synthetic datasets. This strong alignment validates the simulation while emphasizing the connection between environmental dynamics and modeled behavior.

Beyond its analytical function, the correlation plot offers a conceptual bridge between aerodynamic mechanics and design interpretation. It allows learners to visualize how changes in wind speed translate into power-output variations, turning an engineering relationship into an accessible interpretive tool for interdisciplinary audiences.

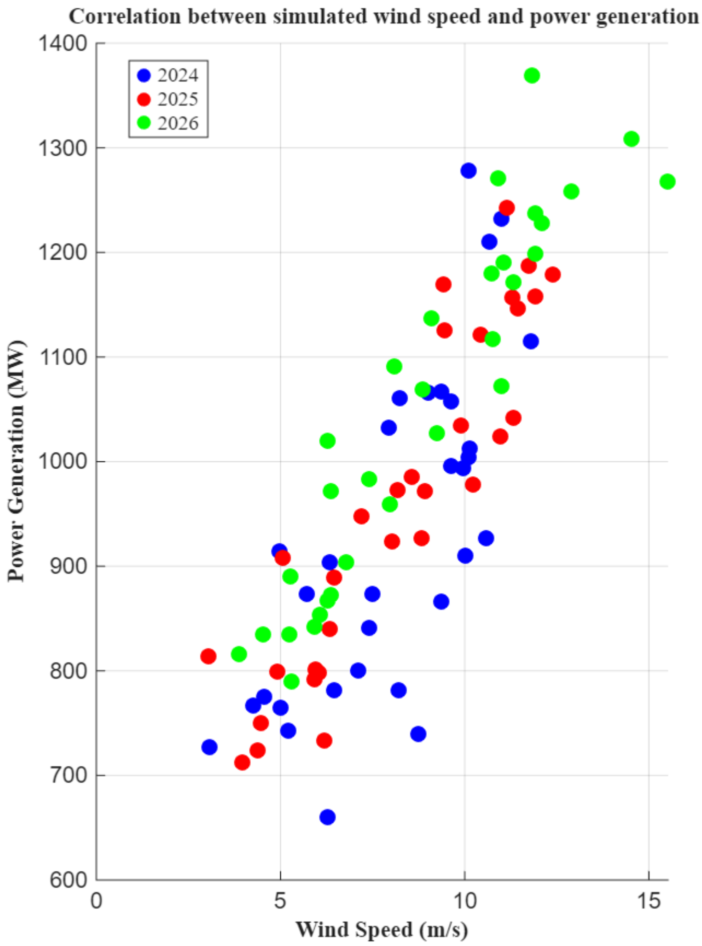

Fig 4. Correlation between simulated wind speed and power generation, showing consistently strong coefficients (R ≈ 0.89–0.92). The alignment reflects the cubic relationship between wind velocity and turbine output, confirming the physical plausibility of the synthetic datasets. The visualization also provides a conceptual bridge between aerodynamic behavior and design-oriented interpretation, helping users connect environmental mechanics with system performance.

3.6 Interpretive Summary

Taken together, the four visualizations illustrate how simulation can represent both quantitative performance metrics and qualitative system behavior within the context of sustainable-energy design. The steady rise in mean output suggests technological advancement, while the reduction in variance reflects increasing system maturity.

When presented in visual or interactive form, these temporal patterns become tools for exploratory analysis, enabling designers, students, and educators to test "what-if" scenarios and engage with the aesthetics of stability, uncertainty, and growth. By translating complex temporal dynamics into interpretable visual narratives, the simulation framework offers an accessible foundation for interdisciplinary sustainability education, where computational modeling and design interpretation operate in tandem.

4. Discussion

4.1 Design Interpretation of Simulation

The simulation framework presented in this study demonstrates how computational modeling can operate not only as an analytical technique but also as a design-oriented interpretive practice. Across Figures 1 through 4, the visual outputs serve as designed representations that translate environmental dynamics into legible patterns. These visualizations function as design artifacts-constructed forms that reveal trajectories of technological improvement, fluctuations in system stability, and indicators of sustainability performance.

By converting numerical behavior into perceptually meaningful structures, the framework aligns with emerging discussions on data aesthetics within sustainable design. As Aeschbach et al. (2025) note, visual patterns can embody both analytical rigor and cultural readability, enabling data to participate in broader interpretive and communicative processes. In this sense, simulation becomes an act of design interpretation: a method of transforming environmental complexity into visual narratives that support reasoning, reflection, and conceptual exploration.

4.2 Educational and Pedagogical Implications

The modular and transparent nature of the framework makes it particularly effective as a pedagogical tool in interdisciplinary settings. Allowing learners to modify parameters, rerun simulations, and compare visual outcomes fosters an experiential mode of learning in which computational reasoning intersects with design thinking. This approach aligns with the development of computational literacy for sustainability, where algorithms serve as instruments for inquiry, experimentation, and creative decision-making (Hu & Mou, 2025).

Within instructional contexts, Figures 2 and 4 are especially useful for cultivating visual reasoning. The bar chart provides a clear entry point for understanding linear growth and long-term system trajectories, while the correlation plot supports discussion on physical principles, uncertainty, and stability. By converting abstract energy behaviors into tangible visual materials, the framework empowers students to construct narratives about renewable-energy systems and engage in interpretive analysis grounded in both data and design (Soares et al., 2024).

4.3 Cultural and Interpretive Dimensions

Beyond educational value, the simulations carry cultural implications tied to how societies conceptualize environmental uncertainty and technological stewardship. Forecasting, in this context, becomes both a scientific and symbolic act-a way of imagining sustainable futures through computational artifacts. The reduction in variance observed from 2024 to 2026, for example, can be interpreted not only as improved model accuracy but as a visual expression of collective aspirations toward ecological stability and technological reliability.

This viewpoint resonates with Donia and Shaw's (2021) framing of design as a mediator of cultural meaning, wherein technological practices embody shared ethical commitments and ecological sensibilities. Consequently, the modeling and visualization of wind energy extend beyond numerical analysis and become part of a cultural dialogue between data, design, and sustainability. The act of prediction thus shapes public imagination and contributes to environmental meaning-making by framing how renewable-energy futures are perceived and communicated.

4.4 Toward Design-Led Sustainability

Integrating computational simulation with design visualization establishes a foundation for design-led sustainability-an approach that merges quantitative modeling with human-centered interpretation. The simulation framework demonstrates how data-driven tools can enable designers to evaluate performance while simultaneously reflecting on the qualitative meanings embedded in system behavior. This synthesis bridges engineering precision with communicative clarity, allowing prediction to function as a mode of design inquiry.

Future developments may incorporate calibration with real meteorological datasets, integration into participatory workshops, and deployment through web-based visualization platforms to support collaborative learning and public engagement. Through these extensions, predictive modeling evolves into an adaptive design strategy-linking computation with culture and environmental data with creative understanding, ultimately supporting interdisciplinary dialogue about sustainable futures.

5. Conclusions

This study developed a MATLAB-based, data-driven simulation framework to demonstrate how computational forecasting can support sustainable design, visualization, and learning. By integrating deterministic and stochastic components, the model reproduced plausible seasonal wind-energy patterns for Taiwan's July monsoon period using synthetic datasets designed for methodological verification. Regression and frequency analyses revealed consistent interannual growth and a measurable reduction in variance, confirming the analytical coherence and stability of the framework.

Beyond technical performance, the findings highlight how numerical results-when expressed through visual and interactive representations-can cultivate sustainability literacy and interdisciplinary engagement. From a design-research perspective, the framework reframes prediction as more than a technical calculation; it becomes a cultural and educational practice. Each visualization, from Figure 1 through Figure 4, operates simultaneously as analytical evidence and as a designed artifact that communicates stability, growth, and environmental adaptation. This dual role positions forecasting within the creative domain of design, enabling educators, learners, and practitioners to treat data as material for reflection, interpretation, and narrative construction.

The main contributions of this study are threefold:

(1) It offers a reproducible and transparent simulation framework adaptable to design-led sustainability research and interdisciplinary instruction;
(2) It demonstrates visual and pedagogical strategies for teaching renewable-energy principles through exploratory, data-driven engagement;
(3) It positions algorithmic modeling as a cultural mediator, showing how computational tools can translate environmental uncertainty into shared understanding and communicative insight.

Future work will integrate real meteorological datasets for empirical calibration, develop web-based visualization interfaces for broader accessibility, and apply the framework within co-design workshops involving policymakers, students, and local communities. As computational tools increasingly shape environmental decision-making, nurturing the dialogue between data interpretation and design imagination becomes essential. By framing prediction as both a scientific and cultural act, this study contributes to the evolving field of Innovation on Design and Culture-where sustainability is not only measured, but also envisioned, communicated, and collectively imagined.

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References

1. Aeschbach, V. M. J., Schwichow, M., & Rieß, W. (2025). Effectiveness of climate change education—A meta-analysis. *Frontiers in Education*, *10*, 1563816.
2. Alahira, J., Nwokediegwu, Z. Q. S., Obaigbena, A., Ugwuanyi, E. D., & Daraojimba, O. D. (2024). Integrating sustainability into graphic and industrial design education: A fine arts perspective. *International Journal of Science and Research Archive*, *11*(1), 2206–2213.
3. Bernert, P., Wanner, M., Fischer, N., & Barth, M. (2022). Design principles for advancing higher education sustainability learning through transformative research. *Environment, Development and Sustainability*, *27*, 20581–20598.
4. Donia, J., & Shaw, J. A. (2021). Ethics and values in design: A structured review and theoretical critique. *Science and Engineering Ethics*, *27*(5), 57.
5. D'Orto, E. (2025). Narrativity and climate change education: Design of an operative approach. *Sustainability*, *17*(4), 1587.
6. Faludi, J., Acaroglu, L., Gardien, P., Rapela, A., Sumter, D., & Cooper, C. (2023). Sustainability in the future of design education. *She Ji: The Journal of Design, Economics, and Innovation*, *9*(2), 157–178.
7. Hu, R., & Mou, S. (2025). Outdoor education for sustainable development: A systematic literature review. *Sustainability*, *17*(8), 3338.
8. Kostis, H. N., Bach, B., Chevalier, F., SubbaRao, M., Jansen, Y., & Soden, R. (2025). What Can Visualization Research Do for Climate? A Workshop Report. *IEEE Computer Graphics and Applications*, *45*(4), 78–88.
9. Mahyar, N. (2024). Harnessing visualization for climate action and sustainable future. *arXiv Preprint*, arXiv:2410.17411. Available online: https://arxiv.org/abs/2410.17411 (accessed on March 20, 2025).
10. Redman, A., Wiek, A., & Barth, M. (2021). Current practice of assessing students' sustainability competencies: A review of tools. *Sustainability Science*, *16*(1), 117–135.
11. Soares, P. H., Kang, M., & Choo, P. (2024). Art and design entanglements for renewable energy education. *Interdisciplinary Journal of Environmental and Science Education*, *20*(1), e2401.
12. Stenberdt, V. A., & Makransky, G. (2023). Mastery experiences in immersive virtual reality promote pro-environmental behavior. *Computers & Education*, *198*, 104760.

13. Sundman, J., Feng, X., Shrestha, A., Johri, A., Varis, O., & Taka, M. (2025). Experiential learning for sustainability: A systematic review and research agenda for engineering education. *European Journal of Engineering Education*, *50*(3), 387–417.