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Techno-Economic and Machine Learning Forecasting of Green Hydrogen: Policy Insights from Costa Rica and the United Kingdom

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Abstract

Green hydrogen is increasingly viewed as a cornerstone of global decarbonization, yet its economic feasibility varies widely due to differences in renewable resource quality, electricity pricing, infrastructure scale, and policy frameworks. This study develops a cross-national modeling framework integrating high-resolution spatial analysis, deterministic techno-economic projections, Monte Carlo simulation, and supervised machine learning to evaluate green hydrogen production in Costa Rica and the United Kingdom. By linking financial modeling, uncertainty quantification, and interpretable learning, the framework estimates Levelized Cost of Hydrogen (LCOH) and Net Present Value (NPV) under region-specific scenarios from 2030 to 2060. Results show that in Costa Rica, Solid Oxide Electrolysis Cell (SOEC) systems at a 3 MW scale achieve a median LCOH of \$4.06/kg H_2 by 2030—outperforming PEM and Alkaline systems—and decline to \$2.84/kg by 2060. Corresponding NPV values rise from \$5.69 million to over \$9 million. In the United Kingdom, 50 MW SOEC projects achieve a median LCOH of \$3.39/kg in 2030 and \$1.39/kg in 2060, with NPVs exceeding \$2.1 billion. SHAP-based analysis confirms electricity price, CAPEX, and capacity factor as dominant cost drivers. This simulation-augmented framework provides a transparent tool for hydrogen investment planning under uncertainty. It demonstrates how emerging economies like Costa Rica can pursue decentralized, sustainability-driven hydrogen strategies by aligning with international partners. In particular, the United Kingdom's offshore wind expertise and financing mechanisms can support Costa Rica's transition through technical cooperation and policy transfer. The results highlight how cross-national collaboration can accelerate equitable, resilient hydrogen development.

Keywords: green hydrogen; Levelized Cost of Hydrogen (LCOH); machine learning; investment analysis; Costa Rica; United Kingdom

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1. Introduction

Green hydrogen is increasingly recognized as a cornerstone of global decarbonization efforts, with the potential to mitigate up to 80 gigatons of CO_2 emissions by mid-century while supporting energy demand in sectors that are difficult to electrify, such as heavy industry, aviation, and long-duration storage (**Hydrogen Council & McKinsey, 2021**). Forecasts indicate that the global hydrogen market could exceed 660 million metric tons annually by 2050, driven by ambitious policy initiatives and the expansion of renewable energy systems. However, this momentum brings considerable uncertainties, including volatile cost projections, substantial infrastructure requirements, and the challenge of equitable deployment across diverse geopolitical contexts. While industrialized nations such as China, Germany, and Japan are advancing rapidly in hydrogen development, countries in the Global South face systemic barriers to aligning hydrogen deployment with broader goals of socio-economic growth and climate equity (**NewClimate Institute, 2023**). **While spatial modeling,**

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stochastic simulation, and machine learning have each been applied to hydrogen cost forecasting, few studies integrate these methods into a unified analytical framework. Fewer still conduct such modeling comparatively across countries with distinct electricity systems, project scales, and policy regimes. This study addresses that gap by systematically combining deterministic techno-economic forecasting, Monte Carlo–based uncertainty analysis, and supervised machine learning in a cross-national assessment of Costa Rica and the United Kingdom.

The UK, for instance, considers hydrogen as a versatile tool to realize its decarbonization agenda, with aspirations of attaining up to 10 GW of low-carbon hydrogen production capacity by 2030 and up to 460 TWh demand by 2050, supported by mechanisms like the Hydrogen Business Model and the Low Carbon Hydrogen Standard (**Royal Academy of Engineering, 2022**). Costa Rica, by contrast, leverages nearly 100% renewable electricity and focuses on hydrogen deployment in transportation and agriculture, with cost estimates between $3.4–5.1/kg depending on the power source (**Stamm et al., 2024**). These contrasting national contexts—policy-driven industrial scaling versus sustainability-centered pilot deployment—offer an ideal platform to explore how technology performance, cost trajectories, and policy frameworks interact under different constraints.

Recent developments highlight Costa Rica's emerging role in global green hydrogen investment. In April 2025, a €25 million initiative supported by the Mitigation Action Facility and GIZ was approved to finance hydrogen infrastructure, regulatory reform, and industrial pilots **(GIZ-MAF, 2025).** Simultaneously, the UK Embassy in San José announced strategic partnerships positioning Costa Rica as a regional hub for UK-led renewable energy and infrastructure projects **(UK Embassy San José, 2024).** This study provides timely spatial and economic modeling that can inform such initiatives by identifying viable production zones, technology trade-offs, and investment conditions.

The technical, policy, and economic feasibility of hydrogen systems has been addressed in several analytical frameworks. **Deloitte (2023)** and **Taghizadeh-Hesary et al. (2022),** for instance, apply LCOH and NPV metrics to evaluate hydrogen production costs under varying assumptions of CAPEX, electricity prices, and financing. In parallel, machine learning has demonstrated potential in improving forecasting and operational modeling. **Mukelabai et al. (2024)** use ML to enhance performance predictions in renewable hydrogen systems, while **Ukwuoma et al. (2024)** highlight the advantages of hybrid ensemble models for biomass-based hydrogen production. These studies show how ML can fine-tune key system parameters, making hydrogen systems more compatible with variable renewable sources and potentially reducing LCOH. However, few studies have explored ML-based projections of LCOH and NPV across countries with divergent resource endowments and infrastructure maturity. Moreover, hydro geographic datasets relevant to hydrogen economics remain regionally confined, limiting the applicability of many stylized models. For example, while solar irradiance models have been developed in contexts such as India **(Sareen et al., 2024)**, **they have not been widely extended to large-scale hydrogen production or used to address intermittency. Most existing models thus remain constrained by national, technological, or methodological silos, limiting their generalizability to diverse deployment environments.**

Machine learning has shown strong potential in optimizing green hydrogen production, particularly for Solid Oxide Electrolysis Cells (SOECs) and electrochemical system dynamics. However, most applications remain confined to technology-specific or laboratory-scale contexts. This study extends machine learning utility to national-scale techno-economic forecasting by applying ensemble models—including Random Forest, XGBoost, and LightGBM—to interpret Levelized Cost of Hydrogen (LCOH) drivers under distinct energy systems in Costa Rica and the United Kingdom. Recent studies, such as **Yang et al. (2025)**, demonstrate that XGBoost models can achieve R^2 values above 0.95 when predicting SOEC performance metrics like hydrogen production rates, voltage, and gas flow optimization. **These findings underscore the technical promise of ML in electrolysis design. Yet, such contributions seldom assess cross-country policy implications or integrate ML into broader investment viability frameworks, as pursued in this study.**

The potential for renewable power generation, particularly wind, solar, and hydropower in Latin America provides a favorable factor for green hydrogen production. Chile, Argentina, and

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Uruguay are some of the countries most likely to assume the role of exporters because those countries provide cheap clean power to produce hydrogen through electrolysis. However, they face a number of challenges such as limited infrastructure, high costs of production, and fragmented regulatory frameworks that inhibit green hydrogen development in these countries. In this regard, specialists recommend increasing the level of cooperation with foreign partners, increasing investments in infrastructure and establishing effective certification systems that would help the market to develop **(Torma et al., 2024).** Furthermore, the established hydrogen policies within the region must embrace social equity and fairness on environmental impacts so that the generated development impacts will be accessible and support a just transition **(Dorn, 2022).** In the view of **Gischler et al. (2023**) regional cooperation, and the public–private sector partnership will be critical for the region in achieving sustainable and socially responsible green hydrogen development to enhance its chance of emerging as a global player in this innovative and important sector.**In this context, Costa Rica's pilot-scale, sustainability-driven strategy offers a valuable example of how smaller economies can align green hydrogen deployment with broader goals of equity and regional integration.**

To address these gaps, this study pursues three guiding questions: (1) How do regional resource quality and policy incentives shape long-run hydrogen costs in Costa Rica and the UK? (2) How can uncertainty and market variability be incorporated into techno-economic modeling of hydrogen systems? (3) What added value does machine learning bring to cost forecasting and policy-relevant scenario analysis in emerging and industrialized contexts?

This study implements a cross-national decision-support framework that integrates spatial resource mapping, deterministic techno-economic forecasting, Monte Carlo–based uncertainty analysis, and supervised machine learning. It evaluates the long-term feasibility of green hydrogen deployment from 2030 to 2060 across Costa Rica and the United Kingdom—two countries with contrasting energy systems and policy regimes. High-resolution wind and solar data are used to adjust regional electricity prices, while Levelized Cost of Hydrogen (LCOH) and Net Present Value (NPV) are estimated for three electrolyzer technologies (PEM, Alkaline, SOEC). Monte Carlo simulations (1,000 draws) are used to assess investment uncertainty, and Latin Hypercube Sampling supports a simulation-augmented machine learning workflow using Random Forest, XGBoost, and LightGBM models. These models accelerate scenario analysis and interpret cost drivers using SHAP-based explainability. While the framework does not introduce novel algorithms, it provides a structured, reproducible approach that clarifies trade-offs among deterministic, probabilistic, and surrogate modeling domains—supporting policy-relevant insights on hydrogen investment planning under uncertainty.

2. Literature Review

2.1. The Role of Green Hydrogen in Global Decarbonization

Green hydrogen is essential for decarbonizing sectors like heavy industry, transport, and flexible power. In Thailand, it could meet 12.2% of energy demand by 2050 with sufficient investment in electrolysers and renewables (**Pradhan et al., 2024**). Globally, demand is expected to grow fifteenfold, with the EU alone requiring 1,300 GW of electrolyser capacity (**Tarvydas, 2022**). It also supports long-duration storage and grid stabilization in renewable-heavy systems.

However, deployment is constrained by high costs and infrastructure gaps. Criticism of blue hydrogen's climate impact has increased interest in rigorous life-cycle standards such as ISO 19870 and independent verification (**Tatarenko et al., 2024**). Public acceptance is also vital—trust-based communication outperforms consultation alone (**Buchner et al., 2025**).

Despite a growing global pipeline, especially in China, many low-emission projects remain unrealized. Progress requires integrated action across policy, infrastructure, and demand—particularly in Latin America (**IEA, 2024a**). Advanced economies are advancing: the EU's hydrogen auctions, the U.S. Inflation Reduction Act, and national strategies in the UK, Australia, and Argentina

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help close the cost gap with fossil fuels (**Bird & Bird LLP et al., 2024**). The UK focuses on industrial clusters, while Costa Rica is piloting decentralized systems adapted to local renewables.

High-resolution solar and wind mapping now underpins regional hydrogen planning by identifying cost-effective electrolysis zones and guiding system design (**Tatarewicz et al., 2023**). This spatial data is crucial for tailoring strategies in countries like Costa Rica and the UK, where renewable potential is unevenly distributed.

These trends underscore the need for comparative, techno-economic evidence to guide hydrogen investment across diverse national contexts—a gap this study aims to fill.

2.2. Overview of Electrolysis Technologies (PEM, Alkaline, SOEC)

Green-hydrogen economics hinges on four main electrolysis routes, each balancing efficiency, capital cost, and grid flexibility. Alkaline electrolysis (AEC) is the work-horse option—60–80 % efficient at 65–100 °C and the lowest CAPEX (≈ US $1,080–1,296 kW^{-1}) but slow to track variable renewables **(El-Shafie 2023).** Proton-exchange-membrane (PEM) stacks deliver 99.999 %-pure H_2 and rapid ramping, ideal for wind- or hydro-linked systems, yet rely on scarce Ir/Pt catalysts that push CAPEX to $2,009–2,506 kW^{-1}.Solid-oxide electrolysis (SOEC) operates at 700–1,000 °C, exploiting waste-heat streams to hit up to 97.6 % (HHV) and just 2.5–3.5 kWh Nm^{-3} electricity use, yet thermal-cycling degradation still curbs commercial rollout **(Norman et al. 2024).** Off-grid trials of **PEM** in Europe and Australia—including unitised regenerative fuel cells—underscore their field readiness for flexible renewables **(Borm & Harrison 2021).**

2.3. Techno-Economic Landscape of Green Hydrogen

Green hydrogen costs depend on electrolyzer type, renewable inputs, and local conditions. This section synthesizes global case studies to assess production pathways and their context-sensitive feasibility.

High-efficiency solid oxide electrolysis (SOEC) systems can reach 97.6% efficiency but are limited by high CAPEX and thermal instability. In South Korea, scaling SOEC from 20 kW to 2 MW cut LCOH to $5.87/kg (**Bui et al., 2023**). In contrast, proton exchange membrane (PEM) and alkaline electrolysis (AEC) are more modular and affordable. PEM excels in variable-grid settings, with LCOH as low as $2.94/kg and CAPEX near $600/kW (**Naqvi et al., 2024**).

Costs vary widely by location and scale. Brazil's 100 MW hybrid system achieved LCOH of $5.29/kg (AEC) and $5.92/kg (PEM), with AEC yielding an IRR close to 29% under $7/kg pricing (**Pinheiro et al., 2025**). In Finland, flexible PEM systems switching to grid exports reached LCOH of $0.65–$2.16/kg, emphasizing operational adaptability (**Javanshir et al., 2024**). Colombia's renewable-powered systems showed LCOH of $7.02–$9.69/kg, with offshore wind deemed unviable due to poor load factors (**Velasquez-Jaramillo et al., 2024**).

Solar systems tend to be costlier. In Australia, a PEM system had an LCOH of $6.36/kg, with 80% of costs from CAPEX and heavy reliance on subsidies (**Rezaei et al., 2024**). In Spain, electricity comprised 70%+ of LCOH ($3.47–$4.43/kg), and public grants >30% improved viability (**Matute et al., 2023b**). A European review reported average costs of $5.02/kg and best-case $2.50/kg, with every 1% system scale-up reducing LCOH by 0.20% (**Weißensteiner, 2025**).

Hybrid and off-grid setups show both promise and challenges. In Brazil, AEC for public transport yielded LCOH of $25–56/MWh and NPV of $21.8 million, aided by co-product revenues (**Alcantara et al., 2025**). In South Africa, solar-based hydrogen cost $2.12/kg, but storage reached 918 ZAR/kg (**Lebepe et al., 2025**). Chilean hydrogen exports to Europe ranged from $3.37–$4.77/kg, while isolated storage added $0.25/kg (**Aldren et al., 2025**). In Indonesia, LCOH spanned $0.48–$82/kg due to geographic and infrastructure differences. A 20% rise in component costs could raise LCOH by 30% (**Prasetyo et al., 2025**).

A sensitivity analysis by **Baral & Šebo (2024)** showed hybrid solar–wind–ORC systems reaching $3.1/kg, potentially falling to $1.46/kg by 2050. CAPEX and capacity factor were the dominant variables, with OPEX having minimal impact.

Overall, these cases affirm the need to match technology with local conditions and support the use of flexible, ML-enhanced modeling frameworks—such as the one in this study—for better forecasting, risk reduction, and policy design.

2.4. Comparative Context: UK and Costa Rica

2.4.1. Renewable Energy Profiles of the UK and Costa Rica

Costa Rica generates approximately 99% of its electricity from renewable sources—primarily hydroelectric (74%), followed by geothermal (13%), wind (11%), and solar (1%). This energy mix ensures a stable, year-round supply from flexible and dispatchable resources. From 2016 to 2021, renewable integration increased significantly, raising the country's energy self-sufficiency to 54%. Such conditions position Costa Rica favorably for green hydrogen production, particularly through off-peak hydro and wind utilization, although regional grid balancing and demand-matching remain key challenges (**IRENA, 2024**).

In contrast, the United Kingdom achieved 50.5% renewable electricity generation in Q3 2024, driven largely by wind (especially offshore and in Scotland), along with solar and biomass. The UK's decarbonizing grid—supported by expanded interconnector capacity and declining fossil-based generation—offers considerable promise for hydrogen production from renewable surpluses. Nonetheless, scaling hydrogen output will depend on reinforcing offshore wind infrastructure, enhancing storage capacity, and deploying more agile grid management systems (**DESNZ, 2024a**).

2.5. National Hydrogen Strategies and Targets

Costa Rica’s 2023 National Green Hydrogen Strategy targets 18–20 kilotonnes of hydrogen demand by 2030 and 420 kilotonnes by 2050, supported by 0.2–1 GW of electrolysis capacity and LCOH projections as low as $1.24/kg, especially from wind energy (**Stamm et al., 2024**). The focus is on domestic use due to high electricity costs and limited export infrastructure. Key partnerships include Ad Astra Rocket and Cavendish S.A., with backing from GIZ and IADB. Political instability, however, threatens long-term planning. The Ad Astra Hydrogen Transportation Ecosystem pilot integrates solar and wind with PEM electrolysis to test leasing and off-take models in Guanacaste (**Ad Astra, 2024**).

The UK Hydrogen Strategy, launched in 2021 and updated in 2024, aims to deliver 10 GW of low-carbon hydrogen by 2030, producing up to 64 TWh annually via green and blue projects. Policy tools include the Net Zero Hydrogen Fund and Low Carbon Hydrogen Standard, supporting deployment in transport, industry, and power (**UK Government, 2021; DESNZ, 2024b**). Regional pilots like Orkney’s BIG HIT project aided early adoption. The hydrogen sector is expected to add £7 billion in GVA and 64,000 jobs by 2030, though challenges in coordination, storage, and distribution persist.

2.6. Modeling and Simulation in Green Hydrogen Project Analysis

Green hydrogen development increasingly relies on advanced modeling, simulation, and AI to optimize system design and forecast metrics like LCOH and NPV under uncertainty—core goals of this study. Tools such as CFD, thermodynamic models, and machine learning are essential for integrating renewables.

Computational Fluid Dynamics (CFD) achieves prediction accuracies up to 95% for flow distribution and polarization curves in electrolyzers (**Shash et al., 2025**). Machine learning (ML), especially tree-based algorithms like Random Forests and Gradient Boosting, outperform traditional regressions in estimating LCOH and NPV, handling complex techno-economic data and enabling real-time optimization across the hydrogen value chain (**Allal et al., 2025**).

High-fidelity models are also being replaced by reduced-order techniques like neural networks and curve-fitting, reducing computational costs while preserving accuracy. In one microgrid case,

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these models yielded an LCOH of $10.81/kg with energy use of 64 kWh/kg, aligning with international benchmarks (**Criollo et al., 2024**).

Together, these simulation and AI tools represent a major shift in hydrogen planning—enhancing precision, scalability, and sustainability (**Motiramani et al., 2025**).

2.7. Machine Learning and Regression-Based Forecasting in Hydrogen Economics

Machine learning (ML) plays an increasingly critical role in modeling green hydrogen costs. Building on **IRENA (2021)**, which identified CAPEX, electricity price, efficiency, and scale as key LCOH drivers, recent studies apply diverse algorithms to improve forecasting and policy planning.

Kabir et al. (2023) used K-Nearest Neighbors and Random Forest to model hydrogen production, highlighting temperature and voltage as key variables. **Kim et al. (2022)** applied CART® to nuclear-powered hydrogen, yielding LCOH estimates around $2.77/kg. **Bassey and Ibegbulam (2023)** emphasized data preprocessing and model explainability, while **Devasahayam (2023)** showed ML's utility in hybrid systems. **Kwon et al. (2024)** developed a deep neural network ($R^2 = 0.9936$) to predict hydrogen demand. **Allal et al. (2025)** found Random Forest effective in ranking cost drivers, and **Alhussan et al. (2023)** introduced a hybrid RNN model for solar hydrogen forecasting.

However, comparative benchmarking across ML models in unified techno-economic frameworks remains rare. Most studies test individual models on isolated datasets, limiting generalizability. Our study addresses this by benchmarking **Random Forest, XGBoost, and LightGBM** on a custom dataset encoding renewable potential, policy incentives, and CAPEX learning for Costa Rica and the UK—offering region-specific insights not previously modeled.

3. Methodology

3.1. Spatial Resource Assessment

This study conducts a spatial analysis of wind and solar energy resources in Costa Rica and the United Kingdom by leveraging geospatial raster datasets and administrative boundary shapefiles. Python (v3.11) was used as the primary analytical platform, employing libraries such as rasterio, geopandas, shapely, and numpy. For each country, high-resolution raster layers representing wind speed or Global Horizontal Irradiance (GHI) were clipped using province- or country-specific polygons to isolate regional resource characteristics.

3.1.1. Zonal Statistics Extraction

To assess solar and wind potential, raster datasets were spatially masked and clipped. The threshold for identifying high-performance zones is defined as the 90th percentile value of valid raster values in a given region, as shown in **Eq. (1)**:

$$T_{90} = \text{Percentile}_{90}(x)$$

- T_{90}: The 90th percentile threshold of the data values.
- X: The vector of valid raster values (e.g., wind speed or solar irradiance) for a given region.

Raster cells with values equal to or exceeding this threshold are defined as part of the top 10% high-performance zone, expressed in **Eq. (2)**:

$$X_{top10\%} = \{ x_i \in \mid x_i \geq T_{90} \}$$

- $X_{top10\%}$: Subset of data values representing the top 10%.
- x_i: Individual raster values within the dataset X

3.2. Offshore Potential Mapping

To delineate offshore resource zones, a 20 km buffer was generated around each administrative unit (province or national region). The offshore area is defined as the difference between the buffered and the original landmass geometries (**Eq. 3**):

$$A_{offshore} = \mathrm{Buffer}\left(A_{region}, 20\mathrm{km}\right) - A_{region}$$

- $A_{offshore}$: The resulting offshore area geometry.
- A_{region}: The original land-based administrative area.
- $\mathrm{Buffer}(A_{region}, 20\mathrm{km})$: Geometric expansion by 20 kilometers.

These areas were rasterized and used to isolate marine wind or solar data for offshore analysis.

3.3. Solar Irradiance Analysis

High-performance solar zones were identified by calculating the 90th percentile of GHI values for each region, following **Eq. (4)**:

$$T_{90}^{solar} = \mathrm{Percentile}_{90}(\mathrm{GHI})$$

- $T_{90solar}$: The 90th percentile of GHI values in a given region.
- GHI: Global Horizontal Irradiance values (in kWh/m²/day).

Pixels meeting or exceeding this threshold were classified as part of the top 10% solar performance zone, as shown in **Eq. (5)**:

$$\mathrm{GHI}_{top10\%} = \left\{ g_i \in \mathrm{GHI} \middle| g_i \geq T_{90}^{solar} \right\}$$

- $\mathrm{GHI}_{top10\%}$: Set of high-performing solar pixels.
- g_i: Individual irradiance values in the dataset.

3.4. Temporal Climate Analysis Using ERA5-Land

To complement the spatial raster analysis, high-resolution hourly climate data for 2000–2019 were extracted using the ERA5-Land reanalysis dataset via Google Earth Engine. Wind resources were processed by calculating hourly wind speed magnitude from the horizontal vector components. Specifically, hourly wind speed was computed as the Euclidean norm of the east–west (u) and north–south (v) components, as shown in **Eq. (6)**:

$$v = \sqrt{u^2 + v^2}$$

Where:

- v is the wind speed magnitude (m/s),
- u is the zonal (east-west) wind component (m/s),
- v is the meridional (north-south) wind component (m/s).

These hourly datasets were excluded from spatial mapping but support validation, interannual variability analysis, and future integration with sensitivity or system modeling frameworks.

3.5. Hydrogen LCOH Modeling

This study estimates the long-run Levelized Cost of Hydrogen (LCOH) for Costa Rica and the United Kingdom from 2025 to 2060 in five-year intervals using a deterministic techno-economic model. The framework integrates annual capital cost reductions, region-specific electricity pricing based on renewable resource quality, and technology-specific operating characteristics. The model excludes hourly dispatch, curtailment, or storage dynamics to focus on long-term structural cost factors across regions.

LCOH is calculated using a standard annuity-based formulation, where capital expenditures are amortized using the Capital Recovery Factor (CRF), and operational expenditures include electricity, water, and fixed O&M costs. The complete expression is given in **(Eq. 7):**

$$\mathrm{LCOH}_{t,r} = \frac{\mathrm{CAPEX}_t \times \mathrm{CRF}}{P_{H_2}} + \left[\left(E_t + E_{\mathrm{steam}}\right) \times C_{\mathrm{elect,r}} \times \mathrm{BoP}\right] + C_{\mathrm{water}} + C_{\mathrm{O\&M}}$$

Where:

- CAPEX_t: Year-specific capital cost ($/kW), reduced annually by a learning rate (3% for PEM and Alkaline; 4% for SOEC)
- CRF:Capital recovery factor (20-year life, 5% discount rate)
- P_{H2}: Annual hydrogen output (300 kg/day × 365)
- E_t: Electricity use per kg H_2 (kWh/kg), scaled by technology-specific voltage
- E_{steam}:Additional 3 kWh/kg for SOEC; 0 for PEM and Alkaline
- $C_{\mathrm{elect},r}$:Region-specific electricity cost ($/kWh).
- BoP: Balance-of-plant penalty (1.05)
- C_{Water}:Water cost ($ 0.0288/kg)
- $C_{\mathrm{O\&M}}$:Fixed O&M ($ 0.02/kg)

CAPEX per unit is calculated as **(Eq. 8):**

$$\mathrm{CAPEX}_t = \mathrm{CAPEX}_0 \times (1 - LR)^{\,t-2025}$$

- CAPEX_0: Initial capital cost
- *LR*: Learning rate (0.03 for PEM/Alkaline; 0.04 for SOEC)

Electrolyzer capacity (kW) is computed based on the 300 kg/day production target and each technology's adjusted efficiency, which derives from nominal voltage.

Annual profit is computed as the difference between revenue and LCOH, defined in **(Eq. 9):**

$$\mathrm{Profit}_t = P_{\mathrm{H}_2}^{\mathrm{sale}} + P_{\mathrm{O}_2} + C_{\mathrm{CO}_2,t} - \mathrm{LCOH}_t$$

Where:

- $P_{\mathrm{H}_2}^{\mathrm{sale}}$: Base hydrogen selling price ($ 3.50/kg).
- P_{O2}: Oxygen credit ($ 2.51/kg).
- $C_{CO2,t}$: Carbon credit (applied only in the UK), growing annually at 4% from $ 0.41/kg in 2025.

Monte Carlo simulations are available to evaluate uncertainty in key parameters using lognormal distributions—±15% for CAPEX and ±20% for electricity prices. However, all baseline projections are deterministic. Although Net Present Value (NPV) is not explicitly calculated, long-term capital amortization is incorporated through the Capital Recovery Factor (CRF), allowing for life-cycle cost comparisons without discounting individual cash flows. The Monte Carlo simulations are implemented solely for sensitivity analysis and do not affect the core LCOH trajectory. Country-specific financial assumptions, electricity pricing structures, and policy factors are detailed in **Supplementary Tables 1** (UK) and **2** (Costa Rica). Technology performance parameters, including voltage-based degradation and steam requirements for SOEC, are summarized in **Supplementary Table 3.**

3.7. Regional Electricity Price Adjustments

To reflect spatial variation in wind and solar resources, electricity prices are adjusted using a composite Renewable Resource Score. The regional score is computed as a weighted average of wind and solar quality **(Eq. 10):**

$$\mathrm{Score}_r = 0.6 \times \mathrm{Wind}_r + 0.4 \times \mathrm{Solar}_r$$

This score is normalized by the national average to produce a quality adjustment factor for each region, shown in **(Eq. 11):**

$$\text{Qual}_r = \frac{\text{Score}_r}{\overline{\text{Score}}}$$

Where:

- Score_r: Composite renewable resource score in region rrr, derived from wind and solar availability (defined previously in Eq. 9).
- $\overline{\text{Score}}$: National average of all regional scores.
  The effective electricity price used in LCOH calculations is then computed in **(Eq. 12):**

$$C_{elec,\, r} = \left(\text{PPA}, t + P_{\text{grid}} \right) \times \text{Qual}_r$$

Where:

- $P_{PPA,t}$: Power purchase agreement price in year ttt, declining by 1% annually
- P_{grid}: Grid access fee ($ 0.001/kWh in UK; 0 in Costa Rica)
- Qual_r: Resource-based multiplier

This adjustment ensures that regions with higher renewable potential face lower electricity costs, improving their LCOH outcomes accordingly. These spatial adjustments—based on ERA5-derived solar and wind data scaled by the composite score—enable geographic differentiation in electricity costs without requiring explicit grid dispatch modeling. A full description of modeling assumptions and limitations is provided in Section 4.

3.8. Techno-Economic Evaluation Using LCOH and NPV Metrics

This study evaluates the economic viability of green hydrogen production in Costa Rica and the United Kingdom using two complementary indicators: the Levelized Cost of Hydrogen (LCOH) and the Net Present Value (NPV). LCOH values are derived from a deterministic techno-economic model that accounts for regional electricity prices (adjusted using ERA5-based wind and solar resources), electrolyzer performance, and national incentive schemes. These precomputed LCOH projections serve as inputs to the NPV analysis and are not recalculated during the NPV simulation.

The NPV framework builds on these cost inputs to assess long-term investment performance over a 20-year operational horizon (2030–2060). It incorporates stochastic variation in wholesale hydrogen prices, oxygen and carbon co-product credits, electricity tariffs, and plant load factors. This structured, dual-indicator approach captures both unit cost efficiency and investment attractiveness under country-specific policy and market conditions. Key assumptions and input distributions for each country are presented in **Table 1** (UK) and **Table 2** (Costa Rica).

3.8.1. Net Present Value (NPV) Simulation Framework

The NPV is calculated using Monte Carlo simulation with 1,000 draws per country–technology pair. The simulation uses annual LCOH projections as fixed cost inputs and computes the discounted sum of net revenues over the project lifetime calculating using **(Eq.13):**

$$\text{NPV} = \sum_{t=1}^{T} \frac{\left(P_{\text{H}_2} + P_{\text{C}fD} + P_{\text{O}_2} + P_{\text{CO}_2} - \text{LCOH}_t - \text{CAPEX}_{\text{ann}} \right) \times Q_{H_2,t}}{(1 + \text{r})^{t}}$$

Where:

- $\text{LCOH}t$: Annual levelized cost per kg of hydrogen (imported from prior model)
- $Q_{H_2,t}$: Hydrogen output adjusted by stochastic load factors (±5%)
- P_{H_2}: Hydrogen market price (uniform distribution)
- P_{CfD}: Strike price top-up (UK only; triangular distribution)

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- P_{O_2}, P_{CO_2} Revenues from oxygen and carbon credits (log-normal distributions)
- $CAPEX_{ann}$: Annuitized capital cost per kg (adjusted for subsidies)
- *r:* Real discount rate (5% for Costa Rica, 6% for the UK)

This formulation isolates the impact of market uncertainty and fiscal incentives on investment performance while preserving consistency with regional LCOH projections from the deterministic cost model.

Table 1. Key Quantitative Data for UK Hydrogen Production, Pricing, and Financial Modeling.

Data type	Value / distribution in MC run	Reference
Wholesale H_2 price 2025 – 2050	3.0 – 4.8 US $ kg^{-1} (≙ £112→£71 MWh^{-1})	UK Hydrogen Strategy (2021a)
CfD / HPBM strike premium	Triangular 5–7 US $ kg^{-1} (mode = 6)	DESNZ HPBM IA (2023)
Oxygen-gas credit	Log-normal μ = 2.51 US $ kg^{-1}, σ = ±20 %	GasWorld price index (2023)
Carbon credit (UK-ETS)	Log-normal μ = 0.50 US $ kg^{-1}, σ = ±25 %	UK-ETS Authority (2024)
Electricity tariff draw	0.0516 – 0.0774 US $ kWh^{-1} (4–6 p/kWh)	UK Hydrogen Strategy (2021a)
Installed CAPEX 2025	PEM/Alk 1 500 US $ kW^{-1}; SOEC 1 900 US $ kW^{-1}	Lichner (2024); IEA (2024b)
CAPEX grant (Net-Zero Hydrogen Fund + GIGA)	15 % of EPC	DESNZ NZHF guidance (2024c)
Plant size & utilisation	**50 MW; 6,000 h y^{-1} (±5 %)**	**Hydrogen Europe (2024)**
Discount rate (real)	6 %	HM Treasury Green Book (2022)
Monte-Carlo runs	1 000	Custom Simulation

Table 2. Key Quantitative Data for Costa Rica Hydrogen Production, Pricing, and Financial Modeling.

Category	Variable	Value / distribution in MC run	Reference
Fiscal incentives	Adjusted CAPEX grant	15 % write-down	MINAE (2025)
Revenue	H_2 wholesale price	3.0 – 4.0 US $ kg^{-1}	MINAE (2022)
Revenue	O_2 credit (log-normal)	μ = 2.51 US $ kg^{-1}, σ = 20 %	Del Valle Gamboa, 2018
Revenue	CO_2 credit (log-normal)	μ = 0.30 US $ kg^{-1}, σ = 30 %	ICAO (2024)

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Electricity	Tariff draw	0.04 – 0.06 US $ kWh^{-1}	ICE (2022)
Electricity	OPEX electricity share	70 % of OPEX	Assumption
Electricity	Base price in deterministic LCOH	0.15 US $ kWh^{-1}	Assumption
OPEX	OPEX subsidy	10 % reduction	MINAE (2025)
Technical	Plant size	3 MW$_e$; 300 kg H_2 d^{-1}	Del Valle Gamboa, 2018
Technical	Full-load hours	4 000 h yr^{-1} ± 5 %	Del Valle Gamboa, 2018
Finance	Discount rate	5 % real	Assumption
Finance	Plant life	20 years	Assumption
Simulation	Monte-Carlo draws	1 000 iterations	Custom

3.9. Simulation-Augmented Machine Learning Framework for LCOH Forecasting

A hybrid workflow couples deterministic techno-economic simulations with tree-based surrogate models—Random Forest, XGBoost and LightGBM—to enable rapid, high-fidelity LCOH estimation across thousands of scenarios.

3.9.1. Synthetic Data Generation

Latin hypercube sampling (LHS) produces 300 stratified draws of four uncertain inputs for Costa Rica—subsidy-adjusted CAPEX (1 500–3 000 $/kW), electricity price (0.04–0.10 $/kWh), fixed OPEX (0.015–0.030 $/kg H_2) and capacity factor (0.25–0.55)—and 500 draws of six inputs for the UK, adding a binary subsidy flag and technology-specific annual degradation rate. Each sample represents a plausible techno-economic future without rerunning the full mechanistic model for every point.

3.9.2. High-Fidelity LCOH Estimation

Each LHS draw is evaluated by the deterministic LCOH model, which computes annual cost as **(Eq. 14):**

$$\mathrm{LCOH} = \mathrm{CRF}\frac{\mathrm{CAPEX}_{adj} \times P_{plant}}{m_{\mathrm{H}_2}} + \mathrm{OPEX} + p_e E_{spec}(t)$$

Where:

- CRF: capital recovery factor, r(1+r)n/((1+r)n−1), with discount rate r and lifetime n=20.
- CAPEX_{adj}: subsidy-adjusted CAPEX (UK only applies a discount factor when subsidy flag = 1).
- P_{plant}: nameplate capacity (3 000 kW for CR; 50 000 kW for UK).
- mH2: annual hydrogen output in kg, P_{plant}×8760 h×CF/Espec(t).
- OPEX: fixed operating cost ($/kg H_2).
- p_e: electricity price ($/kWh).
- E_{spec}(t): specific energy use per kg H_2, which degrades linearly over time according to technology-specific voltage drop ΔV).

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Province- and region-level solar (GHI mean, top 10% mean) and wind metrics (onshore/offshore mean, max, top 10% mean) are merged into each scenario. Missing wind values in Costa Rica are imputed using column means. National NPV summary statistics (mean, P10, P90) are also appended. Latin hypercube sampling follows the adaptive and multi-dimensional design strategies outlined by **Borisut & Nuchitprasittichai (2023)**.

3.9.3. Surrogate Training, Tuning & Validation

Feature matrices—comprising LHS inputs, resource metrics, and NPV values—are standardized by z-scoring and split 80/20 for training and testing. Random Forest hyperparameters (e.g., number of estimators, maximum depth, minimum samples per split) are optimized via five-fold grid search, while XGBoost and LightGBM use fixed, tabular-optimized settings. Model accuracy is assessed via MAE, RMSE, R^2, and ΔMAE relative to a naïve mean predictor. The top-performing Random Forest for each country and technology is interpreted using SHAP summary and dependence plots, revealing electricity price, CAPEX, and capacity factor as the dominant cost drivers.

4. Modeling Assumptions and Limitations

The modeling framework applies deterministic LCOH calculations and Monte Carlo–based NPV analysis to assess green hydrogen viability across Costa Rica and the United Kingdom, but several limitations should be noted. Temporal resolution is coarse: the model operates in five-year intervals and excludes hourly dispatch, curtailment, and storage, relying on annual average electricity inputs. Spatial granularity is limited to provinces (Costa Rica) and regions (UK), without accounting for land-use constraints, infrastructure bottlenecks, or grid congestion.

Electricity prices are adjusted by regional renewable resource quality using a static multiplier, but temporal variability, peak pricing, and intermittency effects are not modeled. Electrolyzer degradation is treated as linear voltage decay without stack failure modeling. CAPEX learning, BoP penalties, and OPEX values are fixed per technology and spatially uniform. Carbon pricing is included only for the UK and treated deterministically. Financial assumptions such as discount rate and subsidy levels are held constant throughout the modeling horizon.

NPV is calculated via Monte Carlo simulations over a 20-year horizon, varying H_2 prices, electricity tariffs, co-product credits, and utilization rates. However, the model omits firm-level cash flow schedules, tax treatment, reinvestment, and financing structure. Machine learning surrogates assume input independence, apply mean imputation for missing regional values, and do not capture structural correlations or feedbacks. SHAP-based interpretation improves transparency but reflects model-internal associations rather than causal economic mechanisms (**Rodgers et al., 2023**; **Zhao et al., 2021**).

Lifecycle emissions, ESG indicators, and environmental sustainability metrics are excluded, limiting the framework's application for regulatory compliance or sustainable finance evaluation.

4. Sensitivity Analysis for Green Hydrogen Economic Models

To assess the robustness of green hydrogen production costs under uncertainty, a Monte Carlo–based sensitivity analysis was conducted for both Costa Rica and the United Kingdom. The analysis focused on estimating the (LCOH) by propagating uncertainty across key techno-economic parameters and regional resource characteristics.

For each country, 1,000 synthetic project scenarios were simulated per electrolyzer technology—PEM, Alkaline, and SOEC—across all national regions. The simulation framework sampled input variables from uniform distributions within plausible bounds derived from literature and techno-economic assumptions. Core uncertain inputs included capital expenditure (CAPEX, 1,500–3,000 $/kW), electricity pricing (adjusted for regional solar and wind quality), fixed operating expenditures (OPEX), water costs, and balance-of-plant (BoP) performance penalties. For SOEC, additional steam energy demand was included. For the UK, grid fees and voltage degradation effects were also varied using technology-specific degradation rates.

Regional solar irradiance and wind speed data were used to compute resource-quality weights, enabling electricity price adjustments for each province or nation. The LCOH was computed for each draw using a discounted cash flow approach over a 20-year plant life with country-specific discount rates (5% for Costa Rica, 6% for the UK). The capital recovery factor (CRF) was applied to convert CAPEX into an annualized cost stream. Energy efficiency degradation was applied linearly over time for PEM, Alkaline, and SOEC systems, based on initial voltage and degradation coefficients.

For each scenario, the resulting LCOH value captured the combined effect of economic, technical, and regional factors. Results were then grouped by technology and region to evaluate central tendencies, variability, and percentile-based performance bands (P10, P50, P90).

5. Results

5.1. Wind and Solar Energy Potential in Costa Rica

A spatial analysis of Costa Rica's wind and solar resources reveals substantial regional variation, underscoring the country's diverse renewable energy potential. As shown in **Figure 1**, Guanacaste emerges as the most promising province for both wind and solar energy. It exhibits a mean onshore wind speed of 6.59 m/s, a maximum wind speed of 19.17 m/s, and a top 10% wind zone average of 11.20 m/s. In contrast, Limón shows the lowest onshore wind resource, with a mean wind speed of 2.40 m/s and a top 10% zone average of only 4.18 m/s. Offshore wind is also favorable in Guanacaste, with a mean of 6.00 m/s, and peak speeds up to 11.87 m/s in the best zones. Meanwhile, Limón again has the lowest offshore wind potential, with a mean of 3.32 m/s and a top 10% mean of 3.97 m/s.

For solar energy, Guanacaste records the highest mean GHI at 5.27 kWh/m²/day, and a top 10% zone average of 6.73 kWh/m²/day. Other high-performing regions include Puntarenas (4.68 kWh/m²/day mean, 6.16 top 10%) and Heredia (4.67 mean, 6.23 top 10%). By contrast, San José and Cartago have slightly lower mean GHI values, both around 4.65–4.67 kWh/m²/day, although top 10% zones still exceed 6.07–6.13 kWh/m²/day.

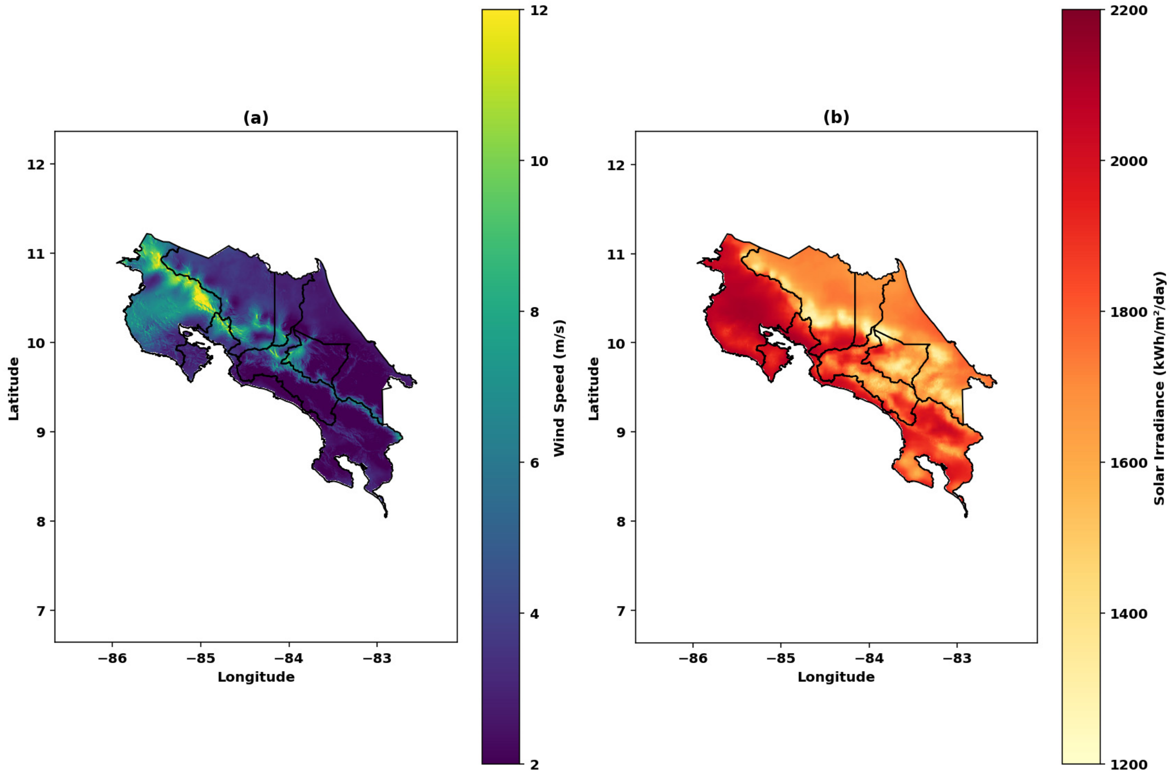

Figure 1. Wind and Solar Maps of Costa Rica. **Caption:** This figure illustrates the spatial distribution of wind speed (panel a) and solar irradiance (GHI) (panel b) across Costa Rica. Panel (a) shows wind speeds ranging from 2–12 m/s, with Guanacaste exhibiting the strongest values. Panel (b) presents solar irradiance from from 1200–2200 kWh/m²/year, again with Guanacaste recording the highest GHI. Both maps include provincial boundaries to support geographical context and aid in identifying priority areas for renewable energy development.

5.2. Solar and Wind Energy Potential Across the United Kingdom and Northern Ireland

Renewable resource availability in the United Kingdom varies considerably by region. As shown in **Figure 2**, England and Wales demonstrate the highest solar potential, with mean GHI values of 2.73 and 2.67 kWh/m²/day, respectively. Northern Ireland and Scotland follow with 2.44 and 2.35 kWh/m²/day. The top 10% zones in each region exceed 2.56–2.98 kWh/m²/day, offering meaningful solar generation potential in targeted sites.

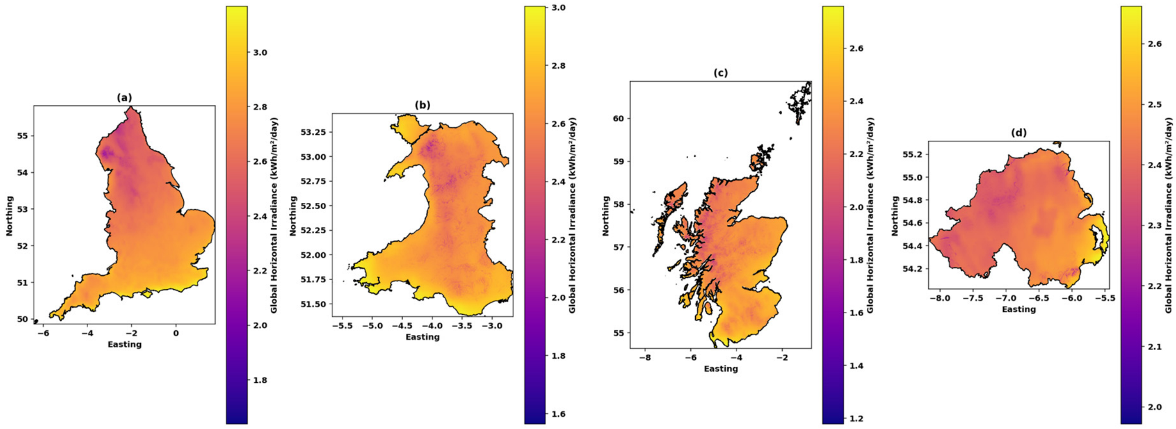

Figure 2. Solar Potential (GHI) for England, Wales, Scotland, and Northern Ireland. **Caption:**This figure displays the Global Horizontal Irradiance (GHI) for four regions of the United Kingdom: England, Wales, Scotland, and Northern Ireland. Each region's solar potential is shown in a separate subplot, labeled (a) for England, (b) for Wales, (c) for Scotland, and (d) for Northern Ireland, with individual colorbars representing the average daily solar irradiance (kWh/m²/day). The plasma colormap is used to visualize varying levels of solar energy intensity, with brighter regions indicating higher irradiance levels. These maps provide valuable insights for assessing the regional solar potential essential for renewable energy planning.

Wind resources are shown in **Figure 3**, with all UK regions exhibiting robust onshore wind speeds. Northern Ireland has the highest mean onshore speed at 9.00 m/s, followed by Scotland (8.66 m/s), Wales (8.57 m/s), and England (8.17 m/s). Top 10% zones in Scotland and Northern Ireland exceed 11 m/s, while peak offshore values reach over 16 m/s. Offshore wind is particularly strong in Scotland, which has the strongest offshore wind resource, with a mean speed of 10.58 m/s and top 10% zones averaging 11.31 m/s. England's offshore wind potential is slightly lower, with a mean of 9.42 m/s and top 10% zones at 10.22 m/s.

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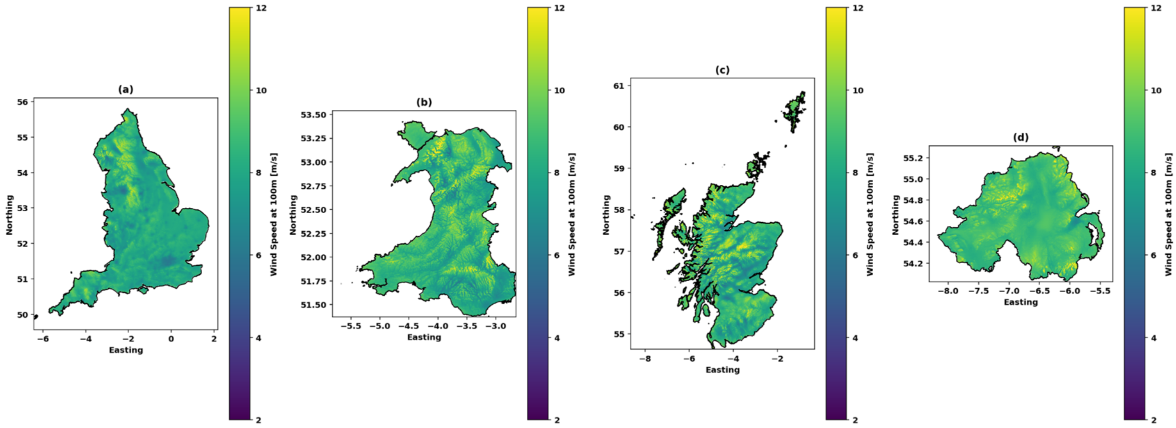

Figure 3. Wind Speed (100m Height) for England, Wales, Scotland, and Northern Ireland. **Caption:**Figure 3 presents the wind speed data at 100 meters height across England, Wales, Scotland, and Northern Ireland. Each subplot, labeled (a) for England, (b) for Wales, (c) for Scotland, and (d) for Northern Ireland, shows the wind speed distribution with individual colorbars. The viridis colormap is used to visualize wind speed variations, where brighter areas indicate stronger wind speeds. These maps are essential for evaluating the feasibility of onshore wind energy generation, highlighting regions with higher wind potential.

Together, these results underscore Guanacaste's dominance in Costa Rica for both wind and solar development, while also highlighting the UK's offshore wind advantage and moderate solar potential. Detailed regional statistics for both countries—including wind speed ranges, GHI levels, and top-performing zones—are provided in **(see Supplementary Table 4)**.

5.3. LCOH Estimations for Costa Rica and the United Kingdom

Hydrogen production cost projections for 2030 reveal marked contrasts between Costa Rica and the United Kingdom, shaped by differences in renewable resource quality, electricity pricing structures, and capital cost assumptions. These patterns are illustrated in Figure 4, which compares the Levelized Cost of Hydrogen (LCOH) across regions and electrolyzer technologies.

In Costa Rica, modeled 2030 LCOH values range from 2.41 to 5.94 $/kg depending on region and technology. The lowest cost is achieved in Guanacaste using SOEC, at 2.41 $/kg, benefiting from high solar and wind resource quality and SOEC's lower electricity intensity. The highest cost appears in Limón with Alkaline electrolysis, at 5.94 $/kg, due to elevated electricity tariffs and reduced efficiency under local conditions. Provincial averages are 5.06 $/kg for Alkaline, 4.73 $/kg for PEM, and 3.29 $/kg for SOEC, indicating a clear cost advantage for SOEC under current assumptions.While 2030 serves as a representative mid-term benchmark, model projections indicate steady LCOH declines through 2060. By then, national average LCOH falls to 4.50 $/kg for Alkaline, 4.20 $/kg for PEM, and 2.84 $/kg for SOEC. Minimum values reach as low as 1.96 $/kg, particularly in high-resource provinces such as Guanacaste, whereas the maximum remains elevated at 5.37 $/kg in cost-challenged regions.

In the United Kingdom, 2030 LCOH values are both lower and more regionally consistent. The lowest cost is observed in Northern Ireland with SOEC (2.14 $/kg), driven by strong wind resources, falling PPA prices, and favorable carbon credit integration. England records the highest 2030 LCOH with Alkaline electrolysis at 3.66 $/kg. National mean values are 3.58 $/kg for Alkaline, 3.40 $/kg for PEM, and 2.19 $/kg for SOEC.By 2060, average UK LCOH values drop substantially across all technologies: to 2.38 $/kg for Alkaline, 2.26 $/kg for PEM, and 1.39 $/kg for SOEC. The lowest projected value reaches 1.35 $/kg, reflecting continued cost declines and robust wind deployment, while the maximum falls below 2.50 $/kg.

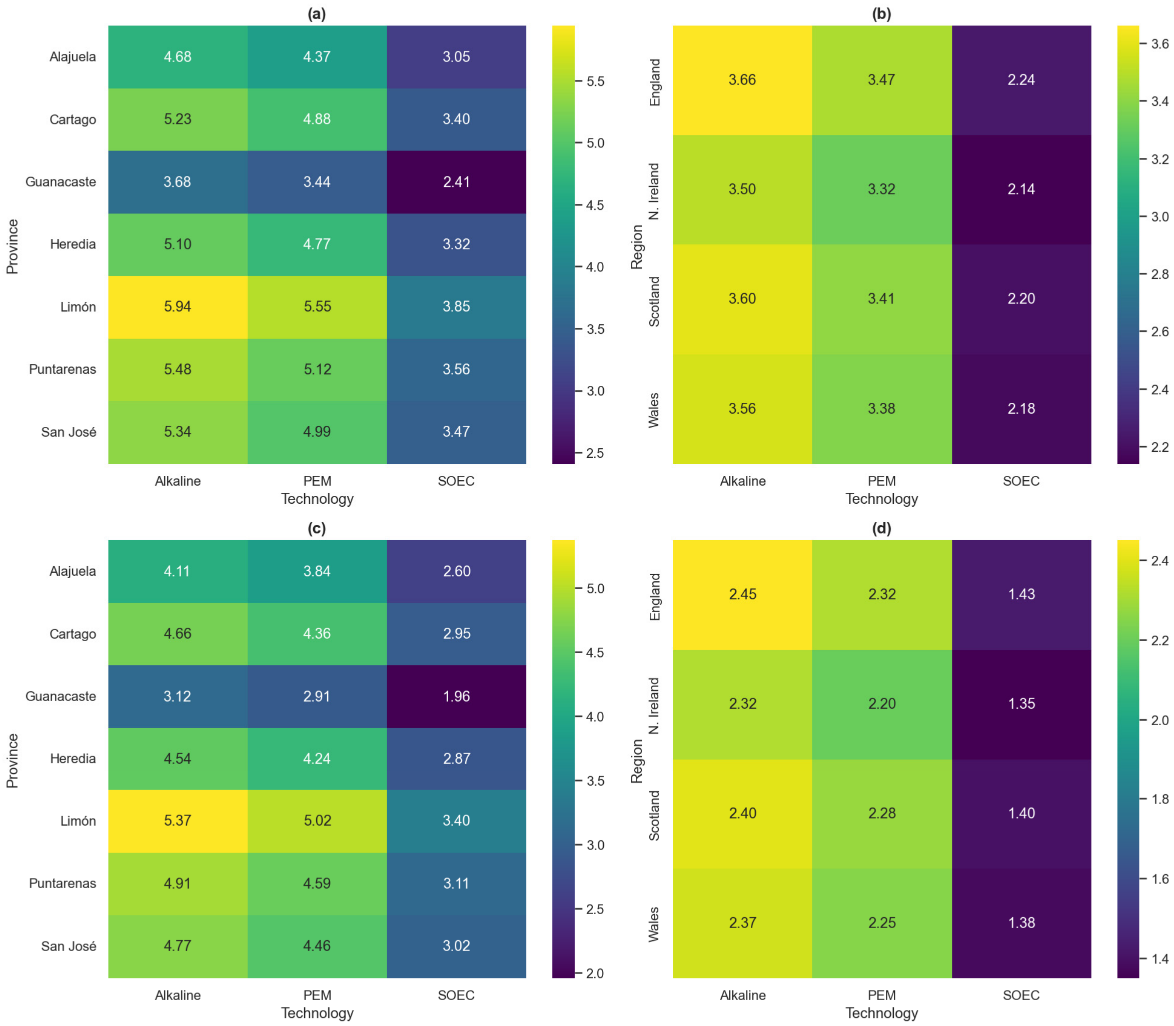

Figure 4. Levelized Cost of Hydrogen (LCOH) Across Regions in Costa Rica and the United Kingdom for 2030 and 2060. **Caption:**Heatmaps show modeled LCOH ($/kg H_2) by technology: Proton Exchange Membrane (PEM), Alkaline, and Solid Oxide Electrolysis Cell (SOEC). Subfigures (a) and (b) display mid-term projections for 2030; subfigures (c) and (d) show long-term estimates for 2060. Color intensity reflects cost efficiency, with darker shades indicating lower values. Data highlight persistent regional disparities in Costa Rica and sustained competitiveness in the United Kingdom.

Overall, the United Kingdom exhibits stronger cost competitiveness across all technologies in both 2030 and 2060, reflecting the benefits of structured policy support, lower electricity prices, and widespread wind deployment. By contrast, Costa Rica shows long-term potential—particularly in provinces like Guanacaste—but remains hindered by persistently high electricity tariffs and regional disparities. These structural constraints limit its ability to achieve cost parity with international hydrogen benchmarks, despite gradual improvements over time.

5.4. NPV Comparison for Hydrogen Production in Costa Rica and the United Kingdom

A harmonized Monte Carlo framework was applied to evaluate the investment performance of green hydrogen projects in Costa Rica and the United Kingdom for three electrolyzer technologies: Alkaline, Proton Exchange Membrane (PEM), and Solid Oxide Electrolysis Cells (SOEC). Simulations included 1,000 randomized draws per country–technology pair, incorporating uncertainty in hydrogen, oxygen, and carbon credit prices, electricity tariffs, capital expenditures, and load factors. Figure 5 summarizes the resulting Net Present Value (NPV) distributions for the benchmark years 2030 and 2060.

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In Costa Rica, all technologies yield positive investment returns under current conditions. In 2030, the highest mean NPV is achieved by SOEC at $2.48 million, followed by PEM at $2.08 million and Alkaline at $1.97 million. By 2060, expected profitability improves significantly across all technologies due to cost declines and efficiency gains. Mean NPVs increased to $5.69 million for SOEC, $4.82 million for PEM, and $4.59 million for Alkaline. Despite relatively high electricity prices and small-scale systems (300 kg/day), these results suggest that Costa Rican projects remain financially viable, especially with moderate policy support.

In contrast, the United Kingdom shows substantially higher NPVs, reflecting the advantages of utility-scale projects (50 MW), lower electricity costs, and strong policy incentives such as Contracts for Difference. In 2030, SOEC again leads with a mean NPV of $496.83 million, followed by PEM at $441.90 million and Alkaline at $429.56 million. These values more than doubled by 2060, reaching $1.04 billion for SOEC, $940.19 million for PEM, and $919.53 million for Alkaline. The tight P10–P90 intervals across all cases reflect a relatively stable investment environment.

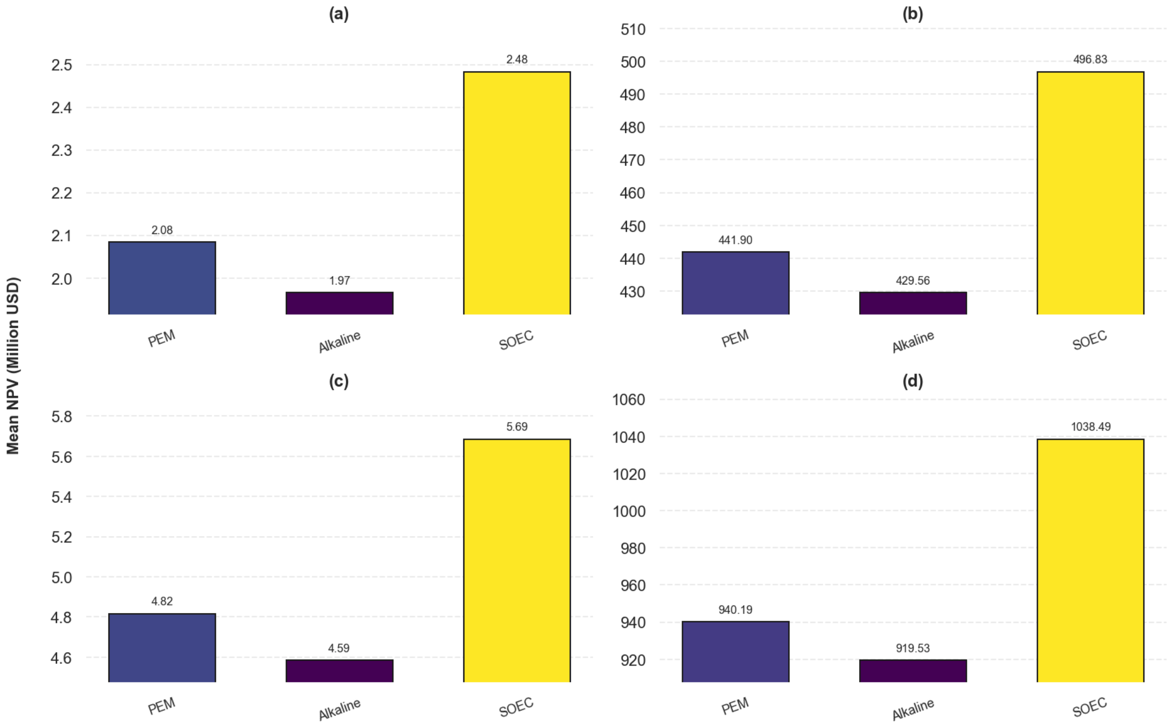

Figure 5. Net Present Value (NPV) Comparison for Green Hydrogen Production in Costa Rica and the United Kingdom (2030 and 2060). **Caption:** This figure presents the mean Net Present Value (NPV) outcomes from Monte Carlo simulations for green hydrogen projects in Costa Rica and the United Kingdom, under three electrolyzer technologies—PEM, Alkaline, and SOEC. Subplots (a) and (b) show investment performance for the year 2030, while (c) and (d) reflect projections for 2060. Costa Rica models assume a 300 kg/day system with moderate subsidy support, while UK scenarios are based on 50 MW-scale installations with enhanced fiscal incentives. Results indicate substantially higher NPVs in the United Kingdom due to economies of scale, favorable electricity pricing, and policy mechanisms such as Contracts for Difference.

These findings underscore how **scale, electricity pricing, and fiscal mechanisms** fundamentally shape green hydrogen investment prospects. While Costa Rica's systems remain profitable on a smaller scale, achieving global competitiveness will require scaling, regional coordination, and export market development. The UK, by contrast, demonstrates strong economic potential already under way, driven by structural and financial enablers that amplify project viability over time.

5.5. Machine Learning Model Performance Comparison

To evaluate the accuracy and generalizability of machine learning models in predicting the Levelized Cost of Hydrogen (LCOH) across national and technological contexts, this study tested three ensemble methods: Random Forest, XGBoost, and LightGBM. Model performance was assessed using three key metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2)—for each electrolyzer type (PEM, Alkaline, SOEC) in both Costa Rica and the United Kingdom.

As summarized in **Figure 6,** LightGBM consistently outperformed other models across all technologies and countries. In Costa Rica, LightGBM achieved high predictive accuracy despite the smaller-scale dataset. For PEM systems, it attained a MAE of 0.119, RMSE of 0.156, and R^2 of 0.986 across provinces. Alkaline models followed closely (MAE: 0.120, RMSE: 0.164, R^2: 0.986), while SOEC yielded MAE: 0.123, RMSE: 0.159, and R^2: 0.988.

In the United Kingdom, LightGBM again emerged as the top performer. For PEM electrolyzers, it recorded a MAE of 0.189, RMSE of 0.245, and R^2 of 0.989. Alkaline systems showed slightly lower performance (MAE: 0.213, RMSE: 0.271, R^2: 0.986), likely reflecting greater variability in resource inputs and capital expenditures. SOEC models also demonstrated strong predictive ability (MAE: 0.218, RMSE: 0.278, R^2: 0.987), confirming the robustness of the machine learning framework across all three technologies and national settings.

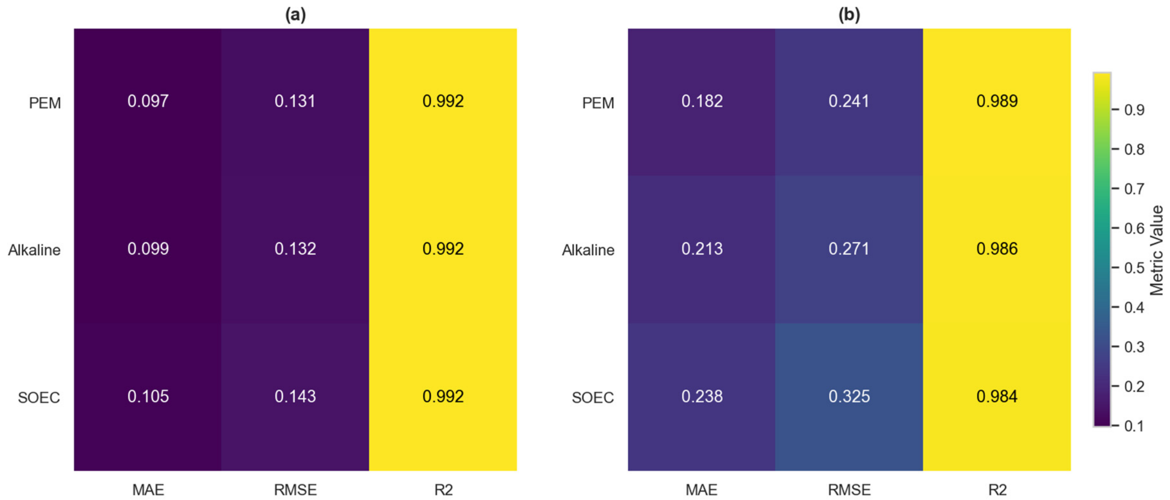

Figure 6. Machine Learning Error Metrics Comparison for Costa Rica and the United Kingdom. **Caption:** This figure presents the performance of the best machine learning models in predicting the Levelized Cost of Hydrogen (LCOH) for Costa Rica and the United Kingdom, across three electrolyzer technologies: PEM, Alkaline, and SOEC. Each heatmap displays three evaluation metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2)—with values annotated in each cell. Color intensities, based on the Viridis colormap, indicate relative metric magnitudes, using a consistent scale across both subplots. A shared vertical colorbar reflects the value gradient, enabling direct visual comparison between countries and technologies.

SHAP-based feature importance analysis across all models confirmed the dominant influence of electricity price, CAPEX, and capacity factor on LCOH predictions. These findings not only enhance model transparency but also provide actionable insights for policymakers aiming to reduce hydrogen production costs through targeted incentives and infrastructure investment.

5.6. Sensitivity Analysis of Hydrogen Economics in Costa Rica and the United Kingdom

Monte Carlo simulations were conducted to assess the sensitivity of the (LCOH) to techno-economic uncertainties across three electrolyzer technologies: (PEM), Alkaline, and (SOEC). Each simulation included 1,000 randomized draws per country–technology pair, varying capital

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expenditure (CAPEX), electricity prices, efficiency degradation rates, operational costs, and balance-of-plant penalties. National LCOH distributions and interquartile ranges are presented in **Figure 7** and summarized in **(see Supplementary Table 7)**.

In Costa Rica, SOEC outperformed both PEM and Alkaline technologies, yielding a median LCOH of \$4.06/kg H_2, compared to \$6.01/kg for PEM and \$6.44/kg for Alkaline. The 10th–90th percentile range for SOEC remained relatively narrow (\$3.06–5.22/kg), indicating lower cost volatility. In contrast, PEM and Alkaline exhibited broader uncertainty intervals (e.g., Alkaline: \$4.86–8.21/kg), driven primarily by their sensitivity to fluctuating electricity prices and capital costs.

In the United Kingdom, SOEC again produced the lowest median LCOH (\$3.39/kg), followed by PEM (\$5.19/kg) and Alkaline (\$5.51/kg). The dispersion patterns were similar to Costa Rica, with SOEC showing the tightest spread (\$2.92–3.89/kg) relative to PEM (\$4.45–5.92/kg) and Alkaline (\$4.73–6.34/kg). This reinforces SOEC's comparative resilience to uncertainty, largely due to higher baseline efficiency and reduced exposure to electricity price volatility.

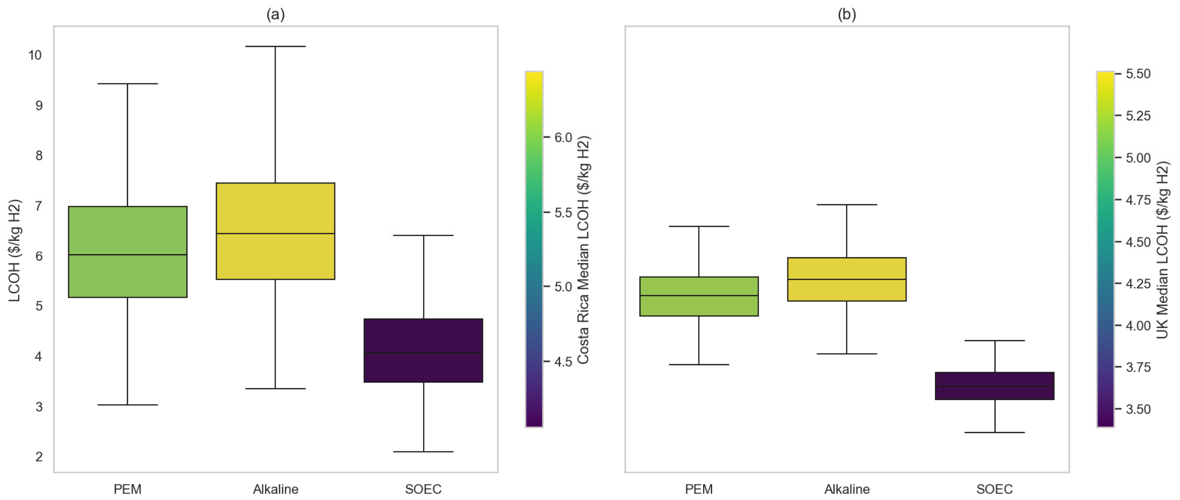

Figure 7. Monte Carlo–Based Sensitivity Analysis of LCOH by Technology in Costa Rica and the United Kingdom. **Caption***:* This figure presents the distribution of Levelized Cost of Hydrogen (LCOH) estimates for three electrolyzer technologies—PEM, Alkaline, and SOEC—based on 1,000 Monte Carlo simulations per category. Panel (a) shows results for Costa Rica; panel (b) shows results for the United Kingdom. Boxplots represent the interquartile range and variability of LCOH under techno-economic uncertainty, while color shading (Viridis palette) encodes the median LCOH per technology within each country. Independent colorbars allow visual comparison of cost distribution scales across national contexts. SOEC consistently outperforms in both countries, with lower central values and reduced spread.

The consistent cost advantage and lower dispersion of SOEC across both national contexts highlights its robustness under variable cost assumptions and its strategic value for long-term hydrogen planning. Country-level differences—particularly the higher median LCOH in Costa Rica—stem largely from differential electricity tariffs, learning rates, and resource quality scaling. This is further supported by SHAP-based machine learning interpretation in **Supplementary Figures 1 and 2,** which consistently identify electricity price, CAPEX, and capacity factor as dominant cost drivers across regions and technologies.

Together, these results highlight the techno-economic tradeoffs and model robustness that inform strategic decision-making across national hydrogen pathways.

6. Discussion

This comparative modeling study demonstrates how national conditions, system scale, and policy design influence green hydrogen viability in Costa Rica and the United Kingdom. Despite Costa Rica's abundant low-cost renewables, small-scale deployments (3 MW) remain financially

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constrained—even under optimistic scenarios—highlighting the persistent cost barriers identified by **Henry et al. (2023)**. In contrast, the UK leverages structured subsidy stacking through the Hydrogen Production Business Model (HPBM), Net Zero Hydrogen Fund, and UK-ETS credits to support 50 MW projects with NPVs exceeding $800 million across technologies. These outcomes align with Costa Rica's decentralized hydrogen vision in the *Estrategia Nacional de Hidrógeno Verde 2022–2050* (**MINAE, 2022**) but emphasize the need for targeted incentives. In the UK, large-scale investment is enabled by offshore wind expansion and blended finance mechanisms such as the Net Zero Hydrogen Fund (**Department for Business, Energy & Industrial Strategy, 2021**; **DESNZ, 2024b**). Ultimately, national policy architecture, system size, and technological preferences—particularly the adoption of SOEC systems—will be key drivers of hydrogen competitiveness.

Machine learning techniques—particularly ensemble models such as Random Forest, XGBoost, and LightGBM—enabled scalable estimation of hydrogen production costs under complex uncertainty, serving as surrogate estimators beyond the scope of deterministic simulations (see Section 3.9). Among these, LightGBM consistently delivered the highest predictive accuracy across all electrolyzer types and national contexts. In Costa Rica, it achieved R^2 values up to 0.988, with MAEs ranging from 0.119 to 0.123. In the United Kingdom, performance remained similarly strong, with R^2 values up to 0.989 and MAEs between 0.189 and 0.218, despite greater variability in capital costs and resource conditions. These results should be interpreted within the constraints of the modeling framework, which includes fixed five-year intervals, region-averaged electricity prices, and surrogate models that abstract from detailed physical system dynamics. SHAP-based feature attribution consistently identified electricity price, CAPEX, and capacity factor as the most influential variables shaping LCOH outcomes. This interpretability underscores the utility of hybrid modeling approaches for informing investment prioritization, technology selection, and subsidy allocation. Together with the Monte Carlo–based NPV simulations, these surrogate models reveal how policy design, project scale, and geographical context interact to shape financial feasibility under uncertainty.

These findings reinforce the value of hybrid simulation–machine learning approaches not only for cost forecasting, but also for informing technology design, risk-adjusted investment, and policy development in green hydrogen systems. This aligns with prior studies: **Chen et al. (2023)** emphasized machine learning's role in uncovering policy-relevant energy dynamics, while **Shash et al. (2025)** demonstrated that combining CFD, thermodynamic models, and AI can boost predictive accuracy above 95% and lower operational costs. This study extends the work of **Navarro Jiménez and Zheng (2024)** by adopting a cross-national scope, incorporating model explainability, and linking Monte Carlo simulations with ML forecasting to better support decision-making under uncertainty. It also responds to broader systemic challenges outlined by **Jayachandran et al. (2024)**, including electrolyzer inefficiencies, storage risks, and underdeveloped infrastructure—barriers that manifest differently across national contexts. In Costa Rica, decentralized grids limit centralized hydrogen deployment, necessitating modular, locally optimized systems. The UK, by contrast, faces regulatory and financial complexity in scaling offshore infrastructure, contributing to elevated LCOH and NPV volatility. These structural contrasts underscore the need to integrate advanced modeling with infrastructure planning. The U.S. *National Clean Hydrogen Strategy and Roadmap* (**DOE, 2023**) and recent work by **Mullanu et al. (2024)** echo this need, highlighting the role of AI and digital–physical integration in optimizing hydrogen system development—an approach embedded in the framework presented here.

Further perspective comes from **Müller et al. (2023)**, who used a GIS-based least-cost framework to assess hydrogen viability in Kenya, highlighting the importance of spatial planning—especially in LMICs—to align production, transport, and end-use zones. This supports Costa Rica's decentralized hydrogen strategy, where regional hubs could reduce transmission costs and address terrain and infrastructure fragmentation. Beyond national strategies, Costa Rica and the United Kingdom offer complementary strengths for bilateral cooperation. Costa Rica's renewable decentralization and environmental leadership, combined with the UK's financial and regulatory expertise, create opportunities for joint pilot projects, electrolyzer strategy exchange, and co-development of ML-based forecasting tools. Offshore wind collaboration in Guanacaste could be accelerated through UK infrastructure experience, while institutions such as GIZ, IADB, and the UK Infrastructure Bank could support inclusive innovation, blended finance, and transnational knowledge transfer.

While this study integrates high-resolution spatial data, techno-economic simulation, and machine learning, it does not incorporate empirical calibration using operational datasets such as SCADA records or electrolyzer performance logs—reflecting the pre-commercial status of hydrogen infrastructure in Costa Rica. The surrogate models developed here are intended for scenario exploration and cost driver interpretation, not for generalization across geographies or replication of physical system behavior such as dynamic ramping or real-time control. Hourly dispatch, intra-day variability, and operational dynamics are also excluded. These abstractions reflect a deliberate emphasis on long-term investment analysis and policy planning. Rather than modeling plant-level physics, the study focuses on infrastructure-scale insights by integrating geospatial scaling, stochastic forecasting, and interpretable machine learning (via SHAP), offering a complementary perspective to dynamic system-level models.

Beyond national comparisons, this study identifies global priorities for scaling hydrogen systems—most notably the creation of open-access, interoperable datasets to improve transparency, comparability, and reproducibility in techno-economic modeling. The lack of standardized data remains a key barrier to validation and policy alignment. Benchmarking machine learning models across diverse geographic and economic contexts is equally essential to ensure their transferability. In decentralized settings like Costa Rica, integrating demand-side forecasting will be critical for effective project planning and infrastructure design. For example, Colombia's national hydrogen roadmap (**Rodríguez-Fontalvo et al., 2024**) targets 9 Mt/a by 2050 and a 1.2% global market share through a $244 billion investment—leveraging tropical renewables similar to Costa Rica. In contrast, the UK emphasizes offshore energy, carbon pricing, and blended finance mechanisms to scale its hydrogen sector. These divergent strategies underscore the need for context-specific approaches tailored to national capabilities and constraints. This study demonstrates that combining techno-economic analysis with machine learning offers a scalable, adaptable framework to guide investment, policy design, and deployment across varied global settings.

7. Conclusion

This study presents an integrated, cross-national framework for evaluating the techno-economic feasibility of green hydrogen production in Costa Rica and the United Kingdom, combining spatial resource assessment, deterministic LCOH and NPV modeling, Monte Carlo simulation, and machine learning. Results demonstrate that national conditions—particularly electricity pricing, policy incentives, and project scale—profoundly shape hydrogen viability. While Costa Rica offers abundant renewable resources, high electricity tariffs and decentralized infrastructure constrain cost competitiveness, especially at pilot scale. In contrast, the United Kingdom benefits from structured policy mechanisms, large-scale systems, and lower energy costs, enabling stronger investment returns and more consistent LCOH outcomes.

Among electrolyzer technologies, Solid Oxide Electrolysis Cells (SOEC) consistently outperformed PEM and Alkaline systems across both countries, offering lower median costs and reduced sensitivity to uncertainty. Machine learning models—especially LightGBM—proved highly accurate in forecasting LCOH, with SHAP-based interpretation confirming electricity price, CAPEX, and capacity factor as dominant cost drivers. These findings reinforce the strategic value of hybrid simulation–ML frameworks for guiding hydrogen investment decisions under uncertainty.

Beyond national comparisons, this study highlights broader implications for global hydrogen strategy. Interoperable data, geospatial planning, and interpretable AI tools are essential for ensuring equitable, cost-effective hydrogen deployment—particularly in emerging economies. Joint ventures between countries with complementary strengths, such as Costa Rica's renewable base and the UK's policy expertise, offer promising pathways for advancing decentralized, resilient hydrogen systems.

Future work should incorporate operational data as pilot projects scale, and expand modeling to include demand-side dynamics, hourly variability, and system integration challenges. As hydrogen markets evolve, the ability to merge high-resolution data with transparent, explainable models will be critical to accelerating just and sustainable energy transitions.

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