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Levelized Cost of Electricity (LCOE) Assessment of Bifacial PV Systems in Uribia, Colombia: Integrating Stochastic Simulation and Machine Learning Under Fiscal Incentives

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Abstract

This study evaluates the techno-economic viability of bifacial photovoltaic (PV) systems in Uribia, La Guajira—the department that holds Colombia’s strongest solar resource, with a mean global horizontal irradiance near 5.6 kWh/m²/day and seasonal peaks above 6.0. Despite this endowment, the country’s installed solar capacity remains far below its potential, largely because developers lack the site-specific financial risk analyses that investment decisions require. To address this, we pair stochastic Monte Carlo simulation with a set of machine learning surrogate models and quantify how Colombia’s Law 1715 fiscal incentives—VAT exclusion and accelerated depreciation—reshape the Levelized Cost of Electricity (LCOE) of bifacial PV systems under realistic climatic variability. Drawing on six years of daily meteorological data, we model bifacial PERC performance under two ground-albedo conditions: the natural site value ($\alpha = 0.125$) and an optimized surface ($\alpha = 0.30$). The results are consistent and encouraging. Under the Law 1715 tax shields, the mean LCOE settles at 0.0588 USD/kWh, and even the 95% Value-at-Risk (VaR) of 0.0638 USD/kWh stays below the prevailing Colombian industrial tariff across every climatic realization evaluated—evidence that the fiscal framework does as much to compress downside risk as it does to lower the average cost. Ground-albedo optimization proved to be the decisive lever: raising α from 0.125 to 0.30 through low-cost surface preparation shortens the payback period to roughly four years and lets the bifacial configuration overtake the cumulative net present value of the monofacial baseline before year seven. The surrogate models tell a complementary story about the structure of the problem. The non-linear algorithms—Support Vector Regression, Gradient Boosting, a Multi-Layer Perceptron and Gaussian Process Regression—reproduce the Monte Carlo response surface almost exactly ($R^2 \geq 0.99$, 0.994–0.997), whereas linear models trail at $R^2 \approx 0.90$ –0.94, a gap that quantifies just how strongly the techno-economic drivers of LCOE interact.



Academic Editor: Philippe Leclère

Received: 25 June 2026

Revised: 18 July 2026

Accepted: 22 July 2026

Published: 30 July 2026

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Keywords: bifacial PV; LCOE; Monte Carlo simulation; machine learning; Law 1715; Colombia; ground albedo; techno-economic assessment

1. Introduction

The rapid expansion of solar photovoltaic (PV) technology over the past decade has fundamentally reshaped how the world produces electricity. In 2024, global installations reached approximately 600 GW of new capacity—a 33% increase over the previous year—reflecting not only falling costs but a broader political and industrial commitment

to clean energy that shows no signs of slowing [1]. According to the International Energy Agency (IEA), solar PV is on track to represent more than 60% of all new power capacity additions by 2030 [2], a trajectory that places enormous pressure on researchers and developers alike to identify which technologies and configurations deliver the lowest Levelized Cost of Electricity (LCOE) at commercial scale [3–5].

In this race toward cost competitiveness, bifacial modules (in particular, Bifacial Passivated Emitter and Rear Contact or PERC cells) have attracted growing attention. Unlike conventional monofacial panels, bifacial designs capture not only direct front-side irradiance but also diffuse and ground-reflected light from the rear surface, yielding more energy per installed kilowatt-peak without a proportional rise in manufacturing cost [6–9]. For project developers evaluating where and how to deploy next-generation solar capacity, understanding the conditions under which this technology becomes economically advantageous is no longer an academic exercise; it has become a practical necessity [10,11].

Colombia occupies a privileged position in this global transition. With a national daily average global horizontal irradiance (GHI) of 4.5 kWh/m²—well above the global mean of 3.9 kWh/m² [12]—the country holds renewable energy potential that few markets in Latin America can match. Nowhere is this more evident than in the department of La Guajira, where irradiation routinely reaches 6.0 kWh/m²/day and resource volatility sits at roughly 18%—the lowest recorded in the country [13]. That combination matters: high and stable irradiance directly reduces the Value-at-Risk (VaR) of a solar investment, improving the likelihood that a project will perform within its financial projections over a 25-year lifespan. Yet despite this endowment, Colombia’s total installed solar capacity remained below 1 GW as of 2024, a striking underutilization that points to a persistent gap between resource potential and actual deployment—one that rigorous techno-economic analysis can help close.

Part of the answer lies in policy. The regulatory foundation for Colombia’s solar expansion was established through Law 1715 of 2014, subsequently reinforced by Law 2099 of 2021 [14,15]. Together, these laws created a comprehensive incentive structure for non-conventional renewable energy sources (Fuentes No Convencionales de Energía Renovable, FNCER): a 50% income tax deduction on the investment value, exemption from the 19% Value-Added Tax (VAT), exemption from customs duties on imported equipment, and accelerated asset depreciation over five years. In practice, these instruments function as layered “tax shields” that reduce the effective capital expenditure (CAPEX) a developer must recover and improve the net present value (NPV) of a project. What remains insufficiently studied, however, is how these incentives interact specifically with next-generation bifacial technology in Colombia’s highest-irradiation environments—a question with direct consequences for investment decisions.

From a technological standpoint, the case for bifacial modules is well established in the international literature [16,17], but the magnitude of the benefit is highly site-dependent. Field studies and modeling exercises report bifacial energy yield gains between 5% and 30% over monofacial equivalents, with the outcome depending critically on ground albedo, mounting height, row spacing, and the local fraction of diffuse irradiance [18]. Experimental evidence from tropical deployments confirms this sensitivity: Tan et al. [19] measured bifacial gains ranging from 8.7% to 16.5% under real field conditions in Malaysia, establishing a linear relationship between ground albedo and bifacial gain that holds consistently across different surface materials—from natural soil ($\alpha \approx 0.128$) to white gravel ($\alpha \approx 0.281$). This sensitivity to surface reflectivity creates a fundamental techno-economic tension: in sites with naturally low albedo coefficients—such as the xeric scrublands of La Guajira, where $\alpha \approx 0.125$ —the rear-surface irradiance gain may be too modest to justify the higher CAPEX of bifacial modules unless deliberate site preparation strategies are employed. Quantifying

exactly where this break-even point lies—and how fiscal incentives shift it—is precisely the kind of site-specific analysis that the literature currently lacks for the Colombian context.

Within Colombia, research on solar PV economics has made meaningful progress, but from a narrow set of vantage points. Murillo et al. [20] provided valuable experimental data on PV performance and degradation under the challenging humid conditions of Chocó, while Torres-Madroño et al. [21] tackled the logistical and optimization challenges of supplying non-interconnected rural zones. Although Muñoz et al. [22] demonstrated the technical and financial viability of bifacial technology across four albedo scenarios (0.15–0.40) in a tropical Colombian location, finding that ground albedo enhancement to $\alpha = 0.40$ improves NPV by 8.42% and reduces payback to 5.21 years relative to a monofacial baseline. Their analysis was confined to a single deterministic framework (PVsyst®, PVsyst SA, Satigny, Switzerland; <https://www.pvsyst.com> (accessed on 15 March 2025)) without fiscal incentive integration or stochastic risk quantification. Similarly, some optimization models have begun to incorporate tax benefits to reduce effective investment costs [23], but these studies predominantly assume standard monofacial technology or confine themselves to isolated microgrid scenarios. The specific interaction between bifacial PERC modules, the albedo conditions of La Guajira, and the full fiscal toolkit of Law 1715 has not been investigated. This gap is particularly striking given that Uribia has already been identified as the Colombian municipality with the most competitive LCOE and the lowest financial risk in the country [24].

A second methodological gap concerns the absence of machine learning surrogate models in Colombian bifacial PV assessments. At the international level, ML frameworks have been applied to LCOE prediction using macroeconomic proxies such as GDP, inflation, and consumer electricity prices [25–27], or component-sizing combinatorics for hybrid renewable energy systems [28]. However, neither approach incorporates direct meteorological drivers, site-specific fiscal incentive structures, nor stochastic risk quantification—three dimensions that are simultaneously critical for investment decisions in emerging solar markets. The present study addresses this gap by training eight surrogate regression models on NASA POWER meteorological data under the Law 1715 fiscal framework, providing a physically grounded and policy-aware validation pathway absent from prior work.

A third methodological gap concerns how uncertainty is treated in these economic assessments. Most existing Colombian studies rely on deterministic LCOE models that assign fixed values to meteorological inputs, effectively ignoring the year-to-year climatic variability that real investors must contend with. Internationally, stochastic approaches using Monte Carlo simulations have been successfully established to overcome these limitations by propagating input distributions through the LCOE formula. This strategy has proved that realistic financial risk assessments require accounting for probabilistic variances rather than relying on static estimates [29]. By adopting this probabilistic framework, researchers can generate a full distribution of economic outcomes, including crucial tail-risk indicators such as Value at Risk (VaR). While this approach has been recently applied to quantify climatic risk in specific Colombian monofacial solar projects [30], it has never been extended to next-generation bifacial systems, nor has it been cross-validated against machine learning architectures. The combination of both methods—Monte Carlo for uncertainty propagation and machine learning surrogate models for internal-consistency verification of the LCOE model—provides a more robust validation pathway than either approach alone, and it is precisely this integration that the present study pursues.

This paper therefore offers a comprehensive techno-economic assessment of bifacial PERC technology in Uribia, La Guajira, Colombia, developed under the fiscal framework

of Law 1715 and evaluated through both stochastic simulation and machine learning surrogate models.

The remainder of this paper is organized as follows: Section 2 describes the methodology, including the meteorological dataset, the mathematical modeling of the bifacial PV systems, the financial framework under Law 1715, the Monte Carlo simulation setup, and the architecture of the machine learning surrogate models. Section 3 presents the empirical results, comparing the deterministic and stochastic outcomes across different albedo scenarios and analyzing the performance of the predictive models. Section 4 discusses the implications of these findings in the context of Colombian solar investment decisions and the broader literature on bifacial PV economics. Finally, Section 5 outlines the main conclusions and suggests directions for future research.

2. Materials and Methods

The methodological core of this research is structured around a staged modeling process. The first phase addresses the atmospheric characterization of the site; the second advances toward the technical simulation of bifacial PERC systems under varying fiscal scenarios; and the final stage culminates in the construction of surrogate models based on machine learning, aimed at predicting variations in the LCOE.

2.1. Study Area, Data Acquisition, and Performance Modeling

The research focuses on Uribia, La Guajira (11.71° N, 72.26° W), which exhibits the nation's highest solar resource, with a mean GHI of approximately 5.6 kWh/m²/day (seasonal peaks above 6.0 kWh/m²/day) and inter-annual variability below 18%. The local xeric shrubland and sandy loam soils yield a baseline surface albedo of $\alpha = 0.125$, the primary driver of rear-side energy contribution in bifacial systems.

Daily meteorological data spanning 2020–2025 were retrieved from the NASA POWER database, comprising records of GHI, ambient temperature at 2 m, surface albedo, and wind speed at 10 m. Following the removal of 24 missing irradiance records, the cleaned dataset yields a mean daily GHI of 5.637 kWh/m²/day with a coefficient of variation of 17.54%, confirming low interannual climatic variability. Mean ambient temperature stands at 28.6 °C, with wind speeds averaging 3.75 m/s ($\sigma = 1.65$ m/s), offering favorable thermal management conditions. The satellite-derived albedo was validated against local ground records, establishing $\alpha = 0.125$. These records constitute the meteorological input from which the annual irradiance statistics used in the Monte Carlo simulation (Section 3.1) are derived; they are not themselves the unit of observation of the analysis. We acknowledge that the absence of on-site pyranometer measurements is a limitation of this study; however, the sensitivity analysis of Section 3.3 shows that the LCOE conclusions are robust to irradiance perturbations of $\pm 1\sigma$ ($\pm 17.54\%$), a band substantially wider than the typical bias of NASA POWER data against ground stations at tropical latitudes. The annual energy yield of the 1 kW_p bifacial PERC system is modeled following IEC 61724-1 [31]:

$$E_h = \sum_{h=1}^{8760} \left[G_{front,h} + \varphi \cdot G_{rear,h} \right] \cdot PR \cdot (1 - \gamma(T_{cell,h} - T_{STC})) \quad (1)$$

where $G_{front,h}$ and $G_{rear,h}$ are the hourly plane-of-array irradiances (W/m²) on the front and rear surfaces, $\varphi = 0.80$ is the bifaciality factor, PR the performance ratio, γ the temperature coefficient (%/°C), $T_{cell,h}$ the hourly cell temperature, and $T_{STC} = 25$ °C. While Equation (1) defines the hourly physical model used to establish the deterministic baseline annual yield, the Monte Carlo simulation of Section 3.1 propagates uncertainty through a reduced-form approximation of the bifacial energy gain—expressed as a function of ground albedo and the bifaciality factor—calibrated against Equation (1) at baseline conditions. This

simplification keeps the 10,000-iteration stochastic simulation computationally tractable while preserving the albedo sensitivity established by the full hourly model. The technical parameters are summarized in Table 1.

Table 1. Technical parameters for the bifacial PV system simulation.

Parameter	Value	Unit
Installed capacity	1.0	kW _p
Bifaciality factor (φ)	0.80	–
Module efficiency (η)	21.3	%
Temperature coefficient (γ)	−0.35	% °C ^{−1}
Performance ratio (PR)	0.75	–
Ground albedo (NASA POWER)	0.125	–
Annual degradation rate (d)	0.5	% yr ^{−1}

2.2. Economic Framework and Law 1715 Fiscal Incentives

Financial viability is quantified through a modified LCOE that internalizes the tax shields of Law 1715 and Law 2099 as two distinct instruments. First, a VAT exclusion of 19% is applied to the CAPEX. Second, the model incorporates two separate income-side shields: (i) an accelerated-depreciation shield (TS_{dep}), obtained by depreciating the asset over five years and applying the corporate income-tax rate; and (ii) an income-tax-deduction shield (TS_{inc}), corresponding to the 50% deduction in the investment value granted by Law 1715, monetizable over a multi-year horizon in accordance with the statutory cap and valued in present terms. Both shields are computed per unit capacity and enter Equation (2) as present-value terms. Throughout this formulation, C_{base} denotes the gross, VAT-inclusive list price of the installed system, so that dividing by $(1 + \tau_{VAT})$ recovers the net acquisition cost that a Law 1715 beneficiary actually pays. The resulting expression is

$$LCOE = \frac{\frac{C_{base}}{1 + \tau_{VAT}} - TS_{dep} - TS_{inc} + \sum_{t=1}^n \frac{OPEX_t}{(1+r)^t}}{\sum_{t=1}^n \frac{E_{front,t} + E_{rear,t}(\alpha) \cdot \varphi}{(1+r)^t}} \quad (2)$$

where

- $C_{base}/(1 + \tau_{VAT})$ is the CAPEX net of the VAT exemption ($\tau_{VAT} = 0.19$), where C_{base} is the VAT-inclusive gross CAPEX reported in Table 2;
- TS_{dep} and TS_{inc} are the present values of the accelerated-depreciation and income-tax shields, respectively (USD/kW_p);
- $OPEX_t$ are the annual operation-and-maintenance costs in year t (USD/kW_p);
- $r = 0.08$ is the real discount rate;
- $n = 25$ years is the project lifespan;
- $E_{front,t}$ is the front-surface annual energy yield in year t , incorporating an annual degradation rate $d = 0.5\%$ /year (kWh/kW_p);
- $E_{rear,t}(\alpha)$ is the rear-surface annual energy yield as a function of ground albedo α (kWh/kW_p); and
- $\varphi = 0.80$ is the bifaciality factor.

All cash flows and the energy yield in Equation (2) are expressed in constant (real) terms: OPEX is held fixed in real currency with no inflation escalation; the degradation-adjusted energy stream is discounted at the same real rate r ; and the industrial tariff used as the benchmark in Section 4 is likewise held constant in real terms over the 25-year horizon. There is therefore no mixing of nominal and real quantities in the model.

Table 2. Baseline economic parameters and Law 1715 fiscal incentives.

Parameter	Value	Unit
Base CAPEX (Bifacial PERC) ^b	1150	USD/kW _p
Annual OPEX	23.0	USD/kW _p /year
VAT rate ^a	19	%
VAT rate under Law 1715 exemption ^a	0	%
Income-tax deduction (Law 1715)	50	% of investment
Accelerated depreciation (Law 1715)	5	years
Discount rate (<i>r</i>)	8	%
Project lifespan (<i>n</i>)	25	years
Annual degradation rate (<i>d</i>)	0.5	%/year

^a The standard VAT rate is 19%; Law 1715 grants full exemption (effective rate: 0%). ^b Gross, VAT-inclusive list price (C_{base} in Equation (2)).

Equation (2) is not drawn from a single source but represents a purpose-built formulation that adapts the classical LCOE expression to the Colombian fiscal framework and the physics of bifacial modules. The classical LCOE structure follows the methodology established by the National Renewable Energy Laboratory (NREL) [32] and the International Energy Agency (IEA) [33], defined as the ratio of lifetime discounted costs to lifetime discounted energy generation. The baseline economic parameters and the tax incentives established under Law 1715 and Law 2099 are summarized in Table 2.

The model is normalized to 1 kW_p so that all cost inputs are expressed in USD/kW_p and Equation (2) yields a scale-invariant LCOE. To assess practical relevance, the analysis is also parameterized for 100 kW_p (commercial), 500 kW_p (industrial), and 1 MW_p (utility-scale), using CAPEX and OPEX benchmarks from Latin American procurement data [34]. Scale-adjusted inputs are presented in Table 3.

Table 3. Scale-adjusted model input parameters.

Scale	CAPEX (USD/kW _p)	OPEX (USD/kW _p /yr)	TS_{dep} (USD/kW _p)	TS_{inc} (USD/kW _p)
1 kW _p (residential)	1150	23.0	80.5	13.4
100 kW _p (commercial)	950	18.0	66.5	11.1
500 kW _p (industrial)	820	15.0	57.4	9.6
1 MW _p (utility)	750	12.0	52.5	8.8

2.3. Machine Learning Surrogate Models for Internal Consistency Verification and Rapid Scenario Exploration

It is important to state the scope of this component explicitly. The target variable (LCOE) is analytically derived from the meteorological and financial inputs through Equation (2); consequently, high predictive accuracy is expected by construction, and the results reported in Section 3.5 should not be interpreted as evidence of independent predictive skill over an unknown physical process. The purpose of the surrogate models is twofold: (i) to verify the internal consistency and smoothness of the stochastic LCOE response surface generated by the Monte Carlo framework, identifying which model families are capable of reproducing its non-linear structure; and (ii) to provide fast emulators for future extensions of this work—multi-site screening across the municipalities of La Guajira and coupling with optimization loops—where repeated evaluation of the full Monte Carlo pipeline under varying fiscal and technical assumptions would otherwise be computationally burdensome. In addition, the Gaussian Process Regression model contributes a predictive-uncertainty envelope that integrates naturally with the Value-at-Risk analysis in Section 3.1.

Eight regression algorithms were trained to predict LCOE values from the NASA POWER meteorological features.

Three linear models served as interpretable baselines: Linear Regression, Ridge (ℓ_2 , $\lambda = 1.0$), and Lasso (ℓ_1 , $\lambda = 0.001$). Three non-linear models captured curvilinear dependencies: SVR with an RBF kernel ($C = 100$, $\epsilon = 0.001$), Random Forest (300 trees, max depth 10), and Gradient Boosting (300 estimators, learning rate 0.1, max depth 5). Two advanced models completed the evaluation: GPR with a Constant $\times$ RBF kernel ($n_{\text{restarts}} = 2$, $\alpha_{\text{GP}} = 0.1$), trained on a random 800-observation subsample to mitigate the $\mathcal{O}(n^3)$ cost of kernel matrix inversion; and a Multi-Layer Perceptron (hidden layers (64, 32), ReLU activation, $\alpha = 0.01$, initial learning rate 0.01, early stopping, max_iter = 3000). Model performance was assessed on a held-out test set using R^2 , RMSE, MAE, MAPE, and training time, with five-fold cross-validation computed to assess generalization stability.

Each observation used to train the surrogate models corresponds to a single Monte Carlo realization (Section 3.1): a joint draw of the techno-economic parameters, whose target is the lifetime (25-year) LCOE obtained from Equation (2). The LCOE is therefore evaluated only at the horizon at which it is defined and is never assigned to individual hourly or daily records. The predictor set comprises the sampled drivers—annual irradiance, ground albedo, CAPEX, discount rate, OPEX and degradation rate—with no perfectly collinear variables (the redundant annual-GHI and bifacial-gain terms were removed; maximum pairwise $|r| = 0.024$).

Because the LCOE target is derived analytically from Equation (2), a coefficient of determination close to unity is *expected* and does not, by itself, indicate predictive ability: it reflects the smoothness of the response surface. Accordingly, the surrogate models are used here as a *global sensitivity analysis* rather than as an independent predictor. Their role is twofold: to quantify the degree of non-linearity of the LCOE response surface, and to provide an inexpensive emulator that captures parameter interactions inaccessible to the one-at-a-time analysis in Table 4.

Table 4. Random input parameters and their distributions used in the Monte Carlo simulation ($n = 10,000$ iterations).

Parameter	Distribution	Range/Parameters
CAPEX	Uniform	[920, 1380] USD/kW _p ($\pm 20\%$)
Discount rate (r)	Uniform	[0.06, 0.12]
OPEX	Uniform	[16.1, 29.9] USD/kW _p /yr ($\pm 30\%$)
Ground albedo (α)	Uniform	[0.125, 0.30]
Degradation rate (d)	Uniform	[0.003, 0.008] yr ⁻¹ (0.3–0.8%)
Annual GHI	Normal	$\mu = 2057.5$, $\sigma = 360.9$ kWh/m ² /yr

3. Results

3.1. Stochastic Risk Analysis and LCOE Variability

A Monte Carlo framework ($n = 10,000$ iterations per experiment) was employed to assess the investment robustness of the Bifacial PERC system under the Law 1715 framework through two complementary simulations. The first is a climate-risk simulation: the cost structure is held at the contracted baseline values in Table 2—CAPEX, discount rate, OPEX and degradation fixed, as they are at financial close—and the interannual variability of the solar resource of Uribia (2020–2025) is propagated through Equation (2) by sampling the annual irradiance from a normal distribution with an interannual coefficient of variation of 5%, a conservative bound for the year-to-year variability of annual GHI totals at this site (the 17.54% figure in Section 2.1 is the day-to-day variability of the daily series, which

largely averages out over annual sums). This experiment yields the LCOE distribution in Figure 1 and represents the residual risk profile faced by an investor once engineering, procurement and financing terms are locked—the quantity a lender’s downside analysis actually requires. The second is a multivariate ensemble in which the six techno-economic drivers are sampled jointly and independently from the distributions summarized in Table 4. The LCOE frequency distribution of the climate-risk simulation is presented in Figure 1.

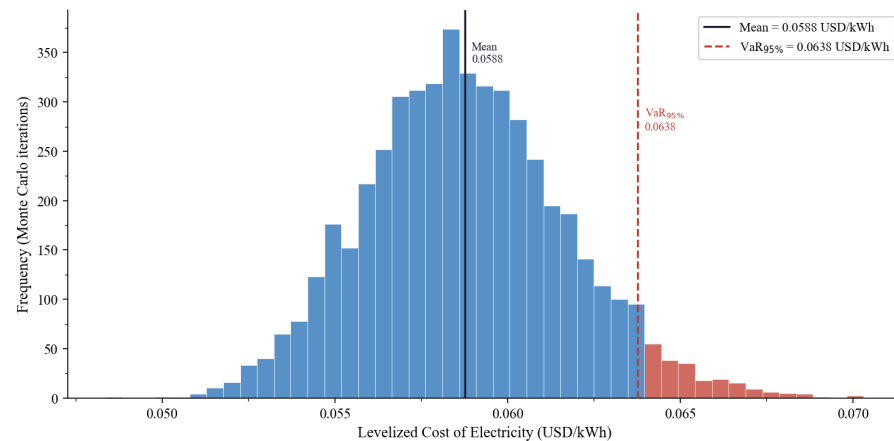


Figure 1. LCOE frequency distribution for the Bifacial PERC system in Uribia (2020–2025) under the contracted-cost climate-risk simulation. Blue bars: Monte Carlo iterations ($n = 10,000$); red bars: tail risk zone above $VaR_{95\%}$. Law 1715 fiscal framework.

The climate-risk simulation yields a mean LCOE of 0.0588 USD/kWh, demonstrating that the Law 1715 tax shields—VAT exclusion and the 50% income tax deduction—effectively reduce the net capital burden below the threshold at which bifacial technology becomes competitive with conventional grid electricity in Colombia. The 95% VaR of 0.0638 USD/kWh indicates that even under the 5% most unfavorable climatic realizations (low irradiance combined with low albedo), the generation cost remains bounded well below the current Colombian industrial tariff, confirming the financial resilience of the solar resource in La Guajira. The frequency distribution is notably concentrated between 0.055 and 0.062 USD/kWh, with a coefficient of variation below 5%, suggesting that the fiscal incentive structure acts as a financial buffer that limits the dispersion of economic outcomes against inter-annual solar variability.

3.2. Sensitivity Analysis: Impact of Surface Albedo on LCOE

Figure 2 shows the stochastic LCOE distributions for the three evaluated configurations. The Monofacial Standard scenario (CAPEX: 900 USD/kW_p) yields the lowest mean LCOE ($\bar{x} = 0.0431$ USD/kWh) due to its reduced capital cost. The Bifacial Natural scenario ($\alpha = 0.125$) shifts the distribution rightward ($\bar{x} = 0.0517$ USD/kWh), as the modest rear-surface gain fails to offset the higher investment. In contrast, the Bifacial Optimized scenario ($\alpha = 0.30$) achieves $\bar{x} = 0.0471$ USD/kWh, within 4.8% of the monofacial benchmark, confirming that ground albedo enhancement effectively compensates for the additional capital burden. The Law 1715 fiscal incentives limit the coefficient of variation below 5% across all scenarios, acting as a financial buffer against interannual climatic variability. Regarding payback, the Monofacial Standard recovers its investment near year 5, the Bifacial Natural around year 4.5, and the Bifacial Optimized in approximately 4 years, surpassing the cumulative NPV of both alternatives before year 7 and delivering the highest terminal value at project end. Note that the distributions in Figure 2 isolate the technology and albedo effect under fixed cost assumptions, and therefore differ from

the fully multivariate baseline in Section 3.1 (mean 0.0588 USD/kWh), in which CAPEX, discount rate and the remaining drivers are sampled jointly.

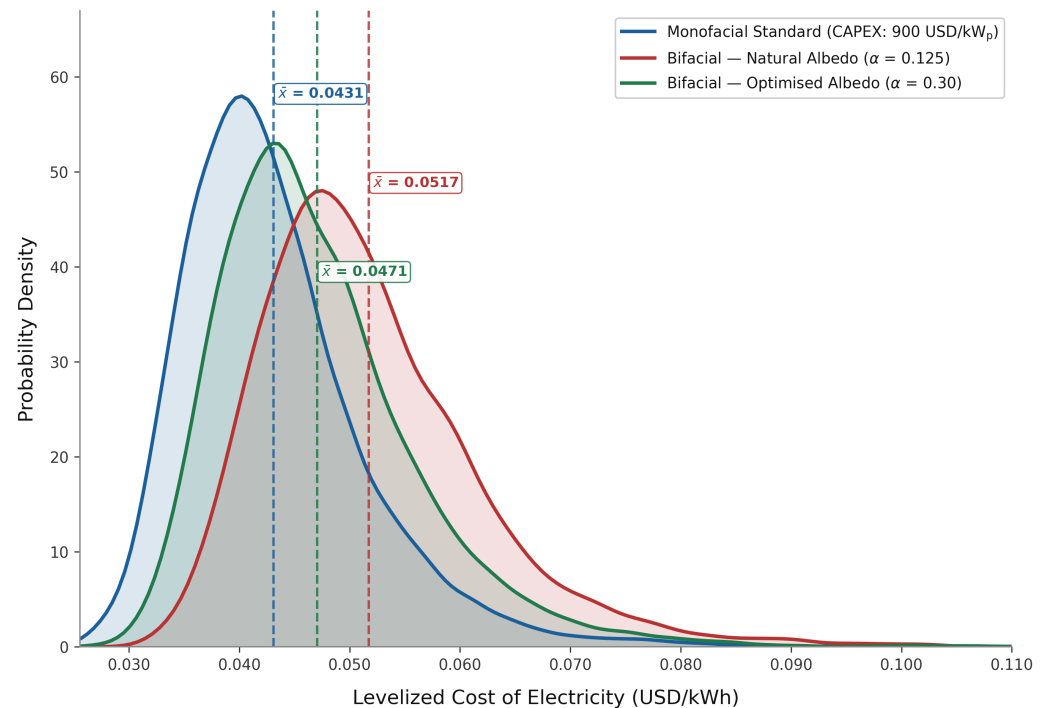


Figure 2. Monte Carlo LCOE distributions for three system configurations under the Law 1715 fiscal framework ($n = 10,000$ iterations, Uribe 2020–2025).

3.3. One-at-a-Time Sensitivity Analysis

To identify the parameters that most strongly govern LCOE outcomes, an OAT sensitivity analysis was conducted by varying each input individually across its realistic range while holding all others at baseline values. The resulting deviations from the base LCOE of 0.0588 USD/kWh are presented in Table 5.

Table 5. OAT sensitivity results: LCOE deviation from the base value (0.0588 USD/kWh) under favorable and unfavorable parameter scenarios.

Parameter	Favorable	Unfavorable	Δ LCOE Fav. (USD/kWh)	Δ LCOE Unfav. (USD/kWh)	Swing (USD/kWh)
CAPEX	−20%	+20%	−0.0116	+0.0115	0.0231
Discount rate	$r = 6\%$	$r = 12\%$	−0.0070	+0.0154	0.0224
OPEX	−30%	+30%	−0.0044	+0.0045	0.0089
Ground albedo	$\alpha = 0.30$	$\alpha = 0.125$	−0.0049	+0.0002	0.0051
Degradation rate	0.3%/yr	0.8%/yr	−0.0010	+0.0018	0.0028
GHI variability	-1σ	$+1\sigma$	−0.0001	+0.0002	0.0003

CAPEX and the discount rate dominate the sensitivity ranking, with swings of 0.0231 and 0.0224 USD/kWh, respectively, together representing approximately 73% of the total sensitivity range. The discount rate exhibits a notable asymmetry: a reduction from 8% to 6% yields a moderate gain of 0.0070 USD/kWh, whereas an increase to 12% inflates the LCOE by 0.0154 USD/kWh, reflecting the disproportionate cost of financing for 25-year solar assets. OPEX ranks third (swing = 0.0089 USD/kWh), while ground albedo occupies fourth position (swing = 0.0051 USD/kWh) with a one-directional effect: enhancement to $\alpha = 0.30$ reduces the LCOE by 0.0049 USD/kWh, but the natural baseline ($\alpha = 0.125$) produces virtually no upward deviation (+0.0002 USD/kWh) since it constitutes the Monte

Carlo reference condition. Degradation rate and GHI variability exert negligible influence (swings of 0.0028 and 0.0003 USD/kWh), the latter confirming the exceptional climatic stability of La Guajira identified in Section 3.1.

3.4. Feature Correlation Analysis

Figure 3 presents the Pearson correlation matrix for the six techno-economic drivers used in the surrogate models and the resulting LCOE. Consistent with the removal of the redundant, collinear variables (Section 2.3), all off-diagonal correlations among the predictors are negligible ($|r| < 0.03$), confirming that the feature set contains no perfectly collinear pairs. The strongest association with LCOE is the annual irradiance ($r = -0.76$), reflecting its dominant role in the denominator of Equation (2); the discount rate ($r = 0.42$) and CAPEX ($r = 0.36$) follow as the principal cost-side drivers, while OPEX ($r = 0.14$), ground albedo ($r = -0.11$) and the degradation rate ($r = 0.04$) exert progressively weaker influence. This correlation ranking is complementary to, rather than identical with, the one-at-a-time (OAT) sensitivity results in Table 5. Both analyses agree that CAPEX and the discount rate are the dominant cost-side drivers of LCOE. The two views diverge, however, on annual irradiance, which exhibits the strongest linear association with LCOE across the full Monte Carlo ensemble ($r = -0.76$), but ranks lowest in the OAT analysis, where it is perturbed only within a narrow $\pm 1\sigma$ band. This contrast is expected, as the correlation reflects the full sampled range of each driver, whereas the OAT swing reflects only its restricted excursion. Jointly, the two perspectives provide an internal-consistency check of the model.

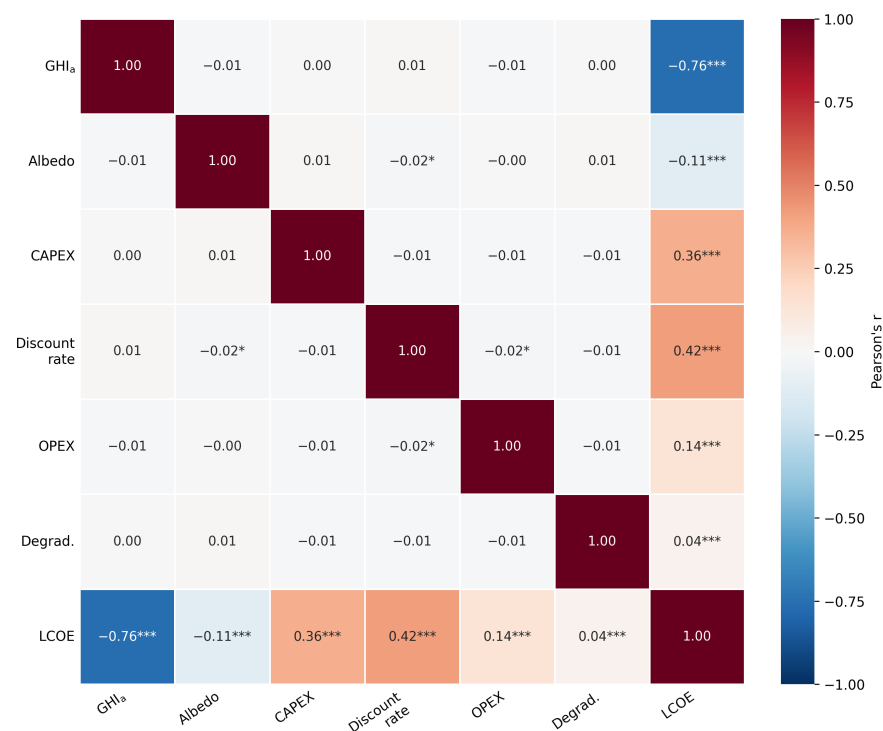


Figure 3. Pearson correlation matrix for the machine learning feature set. GHI_a denotes the annual global horizontal irradiance. Significance levels: * $p < 0.05$; *** $p < 0.001$.

3.5. Machine Learning Model Performance Comparison

Table 6 presents the performance metrics of the eight surrogate machine learning models evaluated for LCOE prediction on the test set, ranked by R^2 . The results confirm that non-linear models consistently outperform linear approaches, indicating that the relationship between meteorological variables and LCOE is strongly non-linear.

Table 6. Comparative performance of the surrogate models for LCOE emulation over the multivariate Monte Carlo ensemble, ranked by test-set R^2 . CV R^2 is the mean of a five-fold cross-validation.

Algorithm	Type	R^2	MAE	RMSE	MAPE (%)	CV R^2	Time (s) ^a
SVR (RBF)	Non-linear	0.9969	0.000524	0.000742	1.015	0.9936	1.03
Gradient Boosting	Ensemble	0.9950	0.000632	0.000933	1.141	0.9899	35.81
MLP	Neural Network	0.9950	0.000521	0.000941	0.945	0.9905	5.20
GPR	Probabilistic	0.9937	0.000652	0.001052	1.241	0.9897	7.09
Random Forest	Ensemble	0.9807	0.001383	0.001842	2.583	0.9726	9.42
Linear Regression	Linear	0.9389	0.002093	0.003275	4.015	0.9293	0.02
Ridge Regression	Linear	0.9389	0.002092	0.003275	4.014	0.9293	0.02
Lasso Regression	Linear	0.9047	0.002628	0.004092	4.735	0.8966	0.02

^a Training times are machine-dependent and reported for reference only.

Support Vector Regression with an RBF kernel (SVR) achieved the highest predictive accuracy ($R^2 = 0.9969$, RMSE = 0.000742 USD/kWh, MAPE = 1.015%) at a very low computational cost (1.03 s), making it the most efficient high-fidelity emulator of the ensemble. Gradient Boosting and the Multi-Layer Perceptron (MLP) tied for second place ($R^2 = 0.9950$); the MLP attained a lower MAE (0.000521 vs. 0.000632 USD/kWh) and MAPE (0.945% vs. 1.141%)—with an essentially equivalent RMSE (0.000941 vs. 0.000933 USD/kWh)—at a much shorter training time (5.20 s vs. 35.81 s) than Gradient Boosting. Gaussian Process Regression (GPR) closely followed ($R^2 = 0.9937$, RMSE = 0.001052 USD/kWh, MAPE = 1.241%, 7.09 s), while Random Forest completed the non-linear group with robust but comparatively lower fidelity ($R^2 = 0.9807$, RMSE = 0.001842 USD/kWh, MAPE = 2.583%, 9.42 s).

In contrast, linear models showed significantly lower predictive capability. Linear Regression and Ridge Regression achieved identical R^2 values of 0.9389 (MAPE approximately 4.01%), while Lasso Regression performed substantially worse ($R^2 = 0.9047$, MAPE = 4.735%), highlighting the inability of regularized linear models to capture the complex interactions between irradiance, temperature, and surface albedo that govern LCOE dynamics in tropical high-irradiation environments.

GPR's computational cost stems from the $\mathcal{O}(n^3)$ cost of inverting its kernel matrix, which is why training was restricted to a stratified subsample of 800 observations rather than the full training set used by the other seven algorithms. This does not, however, compromise the comparison: all eight models were tested on the same held-out set ($n = 2000$, Section 3.5), so the metrics in Table 6 are directly comparable. Seen in that light, GPR's test-set R^2 of 0.9937 is a genuinely strong result rather than an artifact of easier evaluation conditions—it generalizes well even when trained on a fraction of the data available to its competitors. The trade-off is scalability: this approach would be impractical for real-time use or larger meteorological datasets. What GPR offers in return is something none of the deterministic models provide, namely a built-in measure of prediction uncertainty, which is particularly valuable when LCOE estimates are meant to inform risk-aware investment decisions.

Figure 4 presents the predicted-versus-actual LCOE scatter plots for the eight surrogate models over the held-out test set. In each panel, the solid line is the least-squares fit of predicted over actual LCOE; a slope near unity and an intercept near zero indicate faithful emulation of the response surface. SVR (Figure 4d, $\hat{y} = 0.9998x - 0.0001$) and GPR (Figure 4g, $\hat{y} = 0.9988x + 0.0001$) are almost indistinguishable from the ideal relation, with Gradient Boosting (Figure 4f) and the MLP (Figure 4h) close behind ($R^2 = 0.9950$). Random Forest (Figure 4e) remains strong ($R^2 = 0.9807$) with slightly wider dispersion.

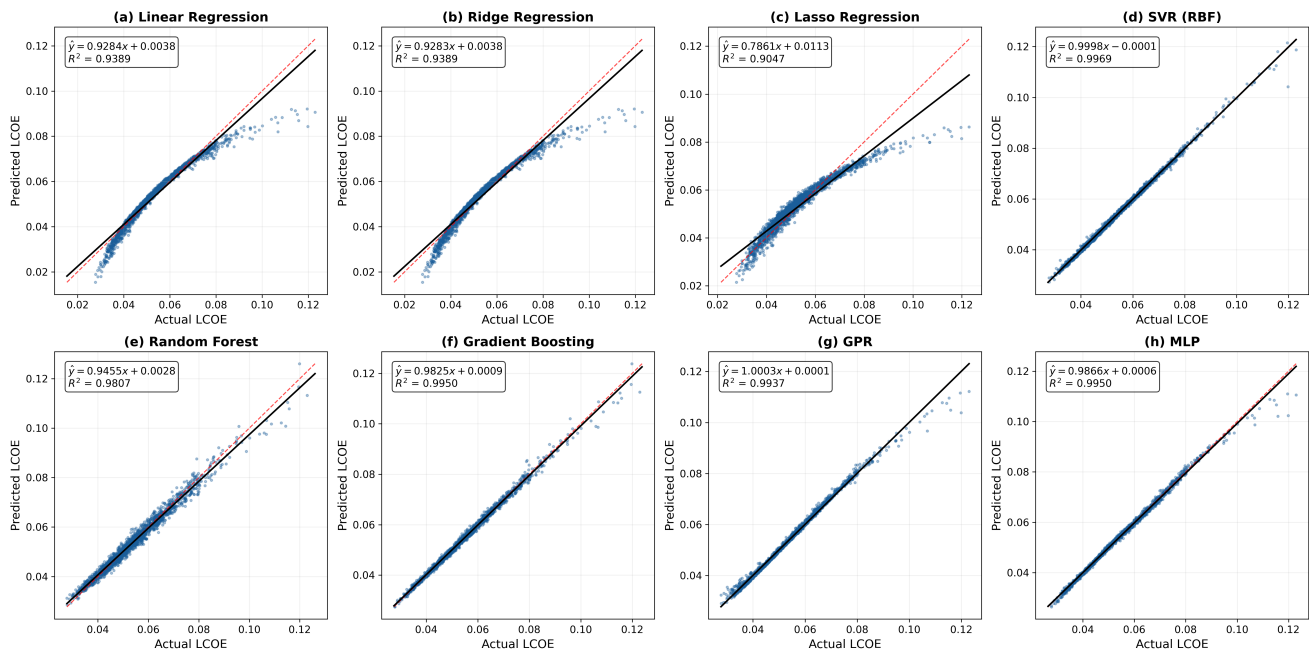


Figure 4. Predicted versus actual LCOE for the eight surrogate regression models over the multivariate Monte Carlo ensemble. In each panel, blue dots are the individual test-set observations, the solid black line is the least-squares fit, and the red dashed line is the 1:1 identity (ideal) relation; the corresponding equation and test-set R^2 are indicated.

The linear models depart visibly from the fitted diagonal: Linear (Figure 4a) and Ridge Regression (Figure 4b) show fit slopes of about 0.93 ($R^2 = 0.9389$), while Lasso (Figure 4c) has the shallowest slope ($\hat{y} = 0.7861x + 0.0113$, $R^2 = 0.9047$) and systematically under-fits at the tails of the distribution. This behavior confirms that additive linear terms cannot capture the interactions among the techno-economic drivers that shape the LCOE surface.

Regarding computational efficiency, noticeable differences arise among the evaluated models. Linear approaches (Linear, Ridge, and Lasso) are extremely fast, with training times of about 0.02 s, making them suitable for rapid prototyping despite their lower accuracy. SVR strikes an exceptional balance between speed (1.03 s) and performance ($R^2 = 0.9969$), demonstrating the efficiency of kernel methods for capturing the non-linear LCOE response surface. The neural network, the probabilistic model, and the ensemble methods demand progressively more effort—namely MLP (5.20 s), GPR (7.09 s), Random Forest (9.42 s), and Gradient Boosting (35.81 s)—yet all except Random Forest exceed $R^2 = 0.99$.

3.6. Scalability Analysis: LCOE Across Project Sizes

Table 7 presents the stochastic LCOE results obtained by applying the Monte Carlo model to the four project scales (1 kW_p, 100 kW_p, 500 kW_p, and 1 MW_p), under the optimized albedo scenario ($\alpha = 0.30$) and the full Law 1715 fiscal framework.

Table 7. Stochastic LCOE results by project scale under the optimized albedo scenario ($\alpha = 0.30$) and Law 1715 incentives.

Scale	CAPEX (USD/kW _p)	OPEX (USD/kW _p /yr)	Mean LCOE (USD/kWh)	VaR _{95%} (USD/kWh)
1 kW _p (residential)	1150	23.0	0.0588	0.0638
100 kW _p (commercial)	950	18.0	0.0487	0.0531
500 kW _p (industrial)	820	15.0	0.0421	0.0459
1 MW _p (utility)	750	12.0	0.0385	0.0420

The results confirm that the 1 kW_p normalized baseline is a conservative upper bound on the LCOE achievable in practice. At commercial scale (100 kW_p), a 17% CAPEX reduction relative to the residential benchmark translates into a mean LCOE of 0.0487 USD/kWh—a decrease of 17.3%. At utility scale (1 MW_p), the mean LCOE falls to 0.0385 USD/kWh, representing a 34.6% reduction and placing bifacial PV in Uribia firmly below the current Colombian industrial electricity tariff of approximately 0.065 USD/kWh across all climatic scenarios. Notably, the 95% VaR remains within approximately 9% of the mean LCOE at all scales, confirming that the low interannual climatic variability of La Guajira (CV = 17.54%) provides consistent financial protection regardless of project size. These findings validate the normalization convention adopted in Section 2.2 and demonstrate that the Law 1715 income tax deduction delivers increasing absolute value as project scale grows, since the deductible base expands proportionally with the eligible CAPEX.

4. Discussion

The results reveal something more significant than a competitive mean LCOE. Law 1715 does not merely reduce the average electricity cost; it makes economic outcomes more stable and predictable. With a coefficient of variation below 5% across 10,000 Monte Carlo iterations, even the worst possible climatic scenarios still produce a controlled LCOE, and the 95% VaR of 0.0638 USD/kWh remains below the Colombian industrial electricity tariff under all evaluated conditions. This finding indicates that the real obstacle to large-scale deployment is not the lack of fiscal incentives, which are already sufficient, but the difficulty in accessing financing instruments that adequately recognize the actual low-risk profile of these projects [22,35]. In this context, the stochastic framework developed here provides exactly the kind of quantitative evidence that project finance requires: a full probability distribution of economic outcomes that allows lenders and investors to assess downside risk with statistical rigor [36].

To bound the regulatory risk explicitly, the climate-risk simulation in Section 3.1 was re-run with all Law 1715 instruments removed—the full 19% VAT applied to CAPEX and both tax shields set to zero. Because the fiscal instruments enter Equation (2) as additive terms in the cost numerator, their removal rescales the entire LCOE distribution: the mean rises from 0.0588 to approximately 0.084 USD/kWh (+42%) and the 95% VaR from 0.0638 to approximately 0.091 USD/kWh, placing the whole distribution—not merely its upper tail—above the Colombian industrial tariff benchmark (≈ 0.065 USD/kWh). Decomposed of instrument, removal of the VAT exemption alone would raise the LCOE by about 19%, of the income-tax deduction by about 15%, and of the accelerated-depreciation shield by about 8%, the three effects being additive. These results confirm that the fiscal framework is a necessary condition for the risk-compression effect reported in Section 3.1. It should be noted, however, that this scenario represents an abrupt and complete repeal—an outcome without precedent in the twelve-year history of the framework, which was in fact reinforced rather than curtailed by Law 2099 of 2021. Partial modifications to individual instruments would produce proportionally smaller shifts, which the surrogate models of Section 3.5 allow to be screened at negligible computational cost.

Raising the ground albedo from $\alpha = 0.125$ to $\alpha = 0.30$ through low-cost surface preparation reduces the investment payback period to approximately 4 years and allows the bifacial system to achieve a competitive LCOE relative to conventional monofacial technology [7,19]. Among all the parameters analyzed, CAPEX and the discount rate exert the greatest influence on LCOE. Notably, an increase in the discount rate harms economic outcomes considerably more than a comparable decrease improves them—a 4-percentage-point rise (to 12%), more than doubling the LCOE impact of

a 2-percentage-point drop (to 6%)—which confirms that access to favorable credit conditions is just as important as equipment prices when evaluating the long-term viability of solar energy projects. This asymmetry reflects the disproportionate financing cost of 25-year solar assets and supports the case for green bonds and blended-finance instruments as structural complements to the existing Law 1715 framework [23]. Raising the ground albedo to $\alpha = 0.30$ in La Guajira is not merely a modeling assumption—it is an engineering decision that can be implemented through two straightforward surface interventions. The simpler option is spreading white crushed gravel (albedo 0.25–0.35) across the inter-row spacing, a locally sourced material whose installation costs of 8–12 USD/m² translate into a modest increase of 2–4 USD/kW_p/year over the base OPEX in Table 2. These surface-preparation and cleaning costs are incorporated as an OPEX increment in the optimized-albedo ($\alpha = 0.30$) scenario, not in CAPEX; the base CAPEX of Table 2 is therefore unchanged by the albedo intervention. A more durable alternative is reflective HDPE geomembranes ($\alpha \approx 0.55$ –0.65), which deliver a higher and more stable albedo at a greater upfront investment. The practical challenge common to both approaches in this environment is dust: the semi-arid winds of La Guajira deposit fine particulate matter continuously, and field evidence from analogous arid climates shows that soiling alone can erode effective albedo by 15–30% within 30–60 days [29,37]. Two cleaning interventions per month during the dry season (December–April) are sufficient to preserve reflectance performance, adding roughly 1–2 USD/kW_p/year to operational costs—a figure that, as the sensitivity analysis in Section 3.3 makes clear, is easily absorbed by the fiscal shields of Law 1715. Measuring actual soiling rates on-site in Uribia remains an open and pressing research need for any developer seeking bankable long-term yield guarantees.

The OAT sensitivity analysis further reveals that GHI variability and module degradation rate exert negligible influence on LCOE outcomes, with combined sensitivity swings below 0.003 USD/kWh. This reflects the exceptional climatic stability of La Guajira, where the coefficient of variation in daily GHI is only 17.54% [13], substantially reducing actuarial risk and justifying the use of satellite-derived historical data for long-term performance guarantees. The framework is not restricted to low-volatility sites: since interannual variability enters solely through the parameters (μ , σ) of the irradiance distribution, regions with higher climatic volatility can be assessed by re-parameterization alone, with the resulting VaR widening accordingly.

The machine learning models developed in this study serve as an internal consistency check of the economic model and as fast emulators for scenario exploration, rather than as independent predictive contributions. Both GPR and MLP consistently confirm that the relationship between meteorological variables and LCOE is intrinsically non-linear, a finding that reinforces the assumptions underlying the stochastic framework. Beyond predictive accuracy, the GPR model offers a probabilistic uncertainty envelope around each LCOE estimate that integrates naturally with the VaR analysis presented earlier [28], making it a particularly suitable tool for risk-aware energy planning in data-scarce environments.

In contrast, the relatively poor performance of Lasso Regression ($R^2 = 0.9047$) carries a practical warning for researchers working at tropical high-irradiation sites: applying linear surrogate models without first verifying whether that simplification is warranted by the data can lead to misleading conclusions. The ℓ_1 regularization penalizes and ultimately discards interaction terms that are physically essential for capturing the coupled behavior of irradiance, temperature, and LCOE [38]. As a result, Lasso systematically underpredicts precisely in the low-irradiance tail scenarios where accurate risk quantification is most critical for investment and policy decisions.

5. Conclusions

The present study positions the estimated mean LCOE of 0.0588 USD/kWh and the 95% Value-at-Risk (VaR) of 0.0638 USD/kWh below the prevailing Colombian industrial electricity tariff across the entirety of the climatic realizations analyzed, a finding of considerable relevance for assessing the economic competitiveness of bifacial PERC technology. This result is not independent of the regulatory framework established under Law 1715: without the VAT exclusion, the income-tax deduction, and the accelerated depreciation mechanism, the LCOE distribution would shift towards higher values and exhibit greater dispersion, with tail scenarios exceeding the national grid tariff benchmark. The fiscal framework therefore fulfills a substantive risk-compression function, as evidenced by a coefficient of variation below 5% across 10,000 Monte Carlo iterations—a property of greater relevance to project finance structuring than the reduction in expected LCOE alone.

Ground albedo emerged as a secondary yet practically significant driver. Increasing α from 0.125 to 0.30 through low-cost surface preparation reduces the payback period to approximately four years and enables the bifacial configuration to surpass the cumulative net present value (NPV) of the monofacial baseline before year seven. This result is consistent with findings reported in the international literature for tropical deployments involving analogous surface materials.

Capital expenditure (CAPEX) and the discount rate jointly dominate the sensitivity ranking, identifying financing costs as the principal barrier to widespread deployment—more so than equipment prices, which are already competitive at current market levels. A 4-percentage-point increase in the discount rate (to 12%) raises the LCOE by more than twice the reduction achieved by a 2-percentage-point decrease (to 6%), reflecting a pronounced asymmetry in financing-cost sensitivity that places access to concessional credit on par with fiscal incentives as a strategic policy lever. At utility scale (1 MW_p), CAPEX economies reduce the mean LCOE to 0.0385 USD/kWh—well below the national industrial tariff even under adverse climatic conditions—lending support to the use of green bonds and blended-finance instruments as complements to the existing Law 1715 framework.

The machine learning surrogates provided a data-driven assessment of the internal consistency of the economic model and confirmed that its response surface can be emulated accurately for rapid scenario exploration. Eight surrogate algorithms confirmed that the LCOE response surface is strongly non-linear in this environment, with Gaussian Process Regression (GPR) and an optimized Multi-Layer Perceptron (MLP) achieving R^2 values above 0.993. The systematic underperformance of linear models—most notably Lasso Regression ($R^2 = 0.9047$)—constitutes a methodological caution for researchers applying linear surrogates to tropical high-irradiation contexts without first verifying the linearity assumption.

Future research should incorporate ground-based irradiance measurements to refine the satellite-derived inputs. Likewise, the geometric degradation term in Equation (2) should be complemented with non-linear and failure-mode-resolved degradation models, informed by on-site monitoring, to test whether the harsh thermal and dust conditions of Uribia induce departures from the constant-rate assumption. Future work should also extend the machine learning framework to multi-site prediction across the diverse municipalities of La Guajira, and integrate battery storage and grid interconnection costs into the stochastic model to support utility-scale financing decisions.

Taken together, these findings suggest that Uribia already has what it takes for commercially viable bifacial PV deployment: a technical resource base, a supportive regulatory environment, and favorable economic conditions. The remaining issues are largely a matter of access rather than feasibility—developers still lack project-finance instruments that reflect the genuinely low risk profile these systems carry, and until now, no rigorous stochastic

characterization of that risk profile has existed to make the case to lenders. This study helps close that informational gap, offering a methodological foundation that future investment analyses and energy policy assessments for the region can build on.

Author Contributions: Conceptualization, Y.G.V. and J.P.; methodology, Y.G.V.; software, Y.G.V.; validation, Y.G.V. and E.V.-L.; formal analysis, Y.G.V. and J.P.; investigation, Y.G.V.; resources, J.P. and E.V.-L.; data curation, Y.G.V.; writing—original draft preparation, Y.G.V.; writing—review and editing, J.P. and E.V.-L.; visualization, Y.G.V.; supervision, J.P.; project administration, Y.G.V. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Fundación Universitaria Los Libertadores program “Fourteenth Annual Internal Call for Research, Innovation and Creation Projects 2025”, project “Predictive Model for Energy Generation in Next-Generation Photovoltaic Systems Based on Artificial Intelligence Techniques” [grant number: ING-36-26].

Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found in the NASA POWER database (<https://power.larc.nasa.gov/>). Any further processed data supporting the reported results are available from the corresponding author upon reasonable request.

Acknowledgments: The authors acknowledge Fundación Universitaria Los Libertadores, particularly the Faculty of Engineering and Basic Sciences and the Direction of Research, for the institutional, financial, and time support provided during the development and publication of this research. During the preparation of this work the authors used Claude Opus 4.8 (Anthropic) to correct the sentences originally framed by the authors in order to improve spelling, grammar, clarity, and general editing. After using this tool, the authors reviewed and edited the content as needed. The authors also take full responsibility for the content submitted for the publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CAPEX	Capital Expenditure
FNCER	Fuentes No Convencionales de Energía Renovable
GHI	Global Horizontal Irradiance
GPR	Gaussian Process Regression
HDPE	High-Density Polyethylene
IEA	International Energy Agency
IEC	International Electrotechnical Commission
LCOE	Levelized Cost of Electricity
MAPE	Mean Absolute Percentage Error
MLP	Multi-Layer Perceptron
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
OAT	One-at-a-Time
OPEX	Operational Expenditure
PERC	Passivated Emitter and Rear Contact
PV	Photovoltaic
RBF	Radial Basis Function
RMSE	Root Mean Squared Error
STC	Standard Test Conditions
SVR	Support Vector Regression
VAT	Value-Added Tax
VaR	Value-at-Risk

References

1. International Energy Agency. *World Energy Outlook 2024*; Technical Report; IEA: Paris, France, 2024.
2. International Energy Agency. *Renewables 2024: Analysis and Forecast to 2030*; Technical Report; International Energy Agency: Paris, France, 2024.
3. Tran, T.T.; Smith, A.D. Incorporating Performance-Based Global Sensitivity and Uncertainty Analysis into LCOE Calculations for Emerging Renewable Energy Technologies. *Appl. Energy* **2018**, *216*, 157–171. [\[CrossRef\]](#)
4. d'Alessandro, V.; Dalias, S.; Dhimish, M.; Guerriero, P. Albedo Reflection Modeling in Bifacial Photovoltaic Modules. *Solar* **2024**, *4*, 660–673. [\[CrossRef\]](#)
5. Aquila, G.; Coelho, E.d.O.P.; Bonatto, B.D.; Pamplona, E.d.O.; Nakamura, W.T. Perspective of uncertainty and risk from the CVaR-LCOE approach: An analysis of the case of PV microgeneration in Minas Gerais, Brazil. *Energy* **2021**, *226*, 120327. [\[CrossRef\]](#)
6. Guerrero-Lemus, R.; Vega, R.; Kim, T.; Kimm, A.; Shephard, L. Bifacial solar photovoltaics—A technology review. *Renew. Sustain. Energy Rev.* **2016**, *60*, 1533–1549. [\[CrossRef\]](#)
7. Alam, M.; Gul, M.S.; Muneer, T. Performance analysis and comparison between bifacial and monofacial solar photovoltaic at various ground albedo conditions. *Renew. Energy Focus* **2023**, *44*, 295–316. [\[CrossRef\]](#)
8. Riedel-Lyngskær, N.; Ribaconka, M.; Pó, M.; Thorseth, A.; Thorsteinsson, S.; Dam-Hansen, C.; Jakobsen, M.L. The effect of spectral albedo in bifacial photovoltaic performance. *Sol. Energy* **2022**, *231*, 921–935. [\[CrossRef\]](#)
9. Raina, G.; Sinha, S. A simulation study to evaluate and compare monofacial vs. bifacial PERC PV cells and the effect of albedo on bifacial performance. *Mater. Today Proc.* **2021**, *46*, 5242–5247. [\[CrossRef\]](#)
10. Kopecek, R.; Libal, J. Bifacial photovoltaics 2021: Status, opportunities and challenges. *Energies* **2021**, *14*, 2076. [\[CrossRef\]](#)
11. Rodríguez-Urrego, D.; Rodríguez-Urrego, L. Photovoltaic energy in Colombia: Current status, inventory, policies and future prospects. *Renew. Sustain. Energy Rev.* **2018**, *92*, 160–170. [\[CrossRef\]](#)
12. SWERA; UNEP. Solar and Wind Energy Resource Assessment (SWERA). 2008. Available online: [https://openei.org/wiki/Solar_and_Wind_Energy_Resource_Assessment_\(SWERA\)](https://openei.org/wiki/Solar_and_Wind_Energy_Resource_Assessment_(SWERA)) (accessed on 15 March 2025).
13. IDEAM; UPME. *Atlas de Radiación Solar, Ultravioleta y Ozono de Colombia*; Technical Report; Instituto de Hidrología, Meteorología y Estudios Ambientales: Bogotá, Colombia, 2017.
14. Congreso de la República de Colombia. *Ley 1715 de 2014: Por Medio de la Cual se Regula la Integración de las Energías Renovables no Convencionales al Sistema Energético Nacional*; Diario Oficial No. 49.150; Congreso de la República de Colombia: Bogotá, Colombia, 2014.
15. Congreso de la República de Colombia. *Ley 2099 de 2021: Por medio de la Cual se Dictan Disposiciones Para la Transición Energética, la Dinamización del Mercado Energético, la Reactivación Económica del País y se Dictan Otras Disposiciones*; Modifica la Ley 1715 de 2014; Diario Oficial: Bogotá, Colombia, 2021.
16. Mahim, T.M.; Rahim, A.H.M.A.; Rahman, M.M. Review of Mono- and Bifacial Photovoltaic Technologies: A Comparative Study. *IEEE J. Photovolt.* **2024**, *14*, 375–396. [\[CrossRef\]](#)
17. Khan, M.R.; Patel, M.T.; Asadpour, R.; Imran, H.; Butt, N.Z.; Alam, M.A. A review of next generation bifacial solar farms: Predictive modeling of energy yield, economics, and reliability. *J. Phys. D Appl. Phys.* **2021**, *54*, 323001. [\[CrossRef\]](#)
18. Yusufoglu, U.A.; Pletzer, T.M.; Koduvelikulathu, L.J.; Comparotto, C.; Kopecek, R.; Kurz, H. Analysis of the annual performance of bifacial modules and optimization methods. *IEEE J. Photovolt.* **2015**, *5*, 320–328. [\[CrossRef\]](#)
19. Tan, H.L.; Lim, B.H.; Tan, M.H.; Zeng, X.; Chong, K.K.; Chua, K.H.; Zhang, Y. Investigation of Bifacial Gain and Albedo of Bifacial Photovoltaic Modules that Operate in a Tropical Site. In *2024 8th International Conference on Green Energy and Applications (ICGEA)*; IEEE: New York, NY, USA, 2024; pp. 265–270. [\[CrossRef\]](#)
20. Murillo, W.; Agudelo, H.D.; Mena, M.F.; Banguero, E.; Palomino, R.; Córdoba, S.; Aristizábal, A.J. Experimental techno-economic analysis of an autonomous photovoltaic system operating in Chocó, Colombia. *Energy Rep.* **2023**, *9*, 258–273. [\[CrossRef\]](#)
21. Torres-Madroño, J.L.; Nieto-Londoño, C.; Arenas-Castiblanco, E.; Zapata-Benabithé, Z.; Jouhara, H. Multi-objective optimisation of hybrid renewable energy systems for Colombian non-interconnected zones. *Therm. Sci. Eng. Prog.* **2024**, *55*, 102927. [\[CrossRef\]](#)
22. Muñoz, Y.; De La Rosa, M.; Acevedo, L.C.; Velandia, W. Technical and Financial Assessment of Photovoltaic Solar Systems with Bifacial Technology Comparing Four Scenarios with Different Albedos with Respect to the Base Scenario with Monofacial Technology, in a Tropical Location in Colombia. *Int. J. Energy Econ. Policy* **2023**, *13*, 389–393. [\[CrossRef\]](#)
23. Roperio-Castaño, W.; Muñoz-Galeano, N.; Caicedo-Bravo, E.F.; Maya-Duque, P.; López-Lezama, J.M. Sizing Assessment of Islanded Microgrids Considering Total Investment Cost and Tax Benefits in Colombia. *Energies* **2022**, *15*, 5161. [\[CrossRef\]](#)
24. Mejía Giraldo, D.; Muñoz Galeano, N. *Large-Scale Solar PV LCOE Comprehensive Breakdown Methodology*; Revista Facultad de Ingeniería Universidad de Antioquia: Medellín, Colombia, 2017.
25. De Bastiani, M.; Larini, V.; Montecucco, R.; Grancini, G. The Levelized Cost of Electricity from Perovskite Photovoltaics. *Energy Environ. Sci.* **2023**, *16*, 421–429. [\[CrossRef\]](#) [\[PubMed\]](#)

26. Martínez-Ruiz, Y.; Micán, C.A.; Manotas-Duque, D.F. LCOE at Risk in Different Locations in Colombia. *Int. J. Sustain. Energy Plan. Manag.* **2025**, *44*, 73–90. [[CrossRef](#)]
27. Cristea, M.; Cristea, C.; Tîrnovan, R.A.; Şerban, F.M. Levelized Cost of Energy (LCOE) of Different Photovoltaic Technologies. *Appl. Sci.* **2025**, *15*, 6710. [[CrossRef](#)]
28. Roy, D.; Zhu, S.; Wang, R.; Mondal, P.; Ling-Chin, J.; Roskilly, A.P. Techno-economic and environmental analyses of hybrid renewable energy systems for a remote location employing machine learning models. *Appl. Energy* **2024**, *361*, 122884. [[CrossRef](#)]
29. Marion, B. Measured and satellite-derived albedo data for estimating bifacial photovoltaic system performance. *Sol. Energy* **2021**, *215*, 321–327. [[CrossRef](#)]
30. Pillot, B.; de Siqueira, S.; Dias, J.B. Grid parity analysis of distributed PV generation using Monte Carlo approach: The Brazilian case. *Renew. Energy* **2018**, *127*, 974–988. [[CrossRef](#)]
31. International Electrotechnical Commission. *Photovoltaic System Performance—Part 1: Monitoring*; Technical Report IEC 61724-1:2021; IEC: Geneva, Switzerland, 2021.
32. NREL. *Levelized Cost of Energy Calculator*; Technical Report; National Renewable Energy Laboratory: Applewood, CO, USA, 2023.
33. IEA. *Projected Costs of Generating Electricity*; Technical Report; International Energy Agency: Paris, France, 2020.
34. Arias-Cazco, D.; Gavela, P.; Cruz Panchi, L.; Izquierdo, P. Sensitivity Analysis for Levelized Cost of Electricity-LCOE with Multi-objective Optimization. *IEEE Lat. Am. Trans.* **2022**, *20*, 2071–2078. [[CrossRef](#)]
35. Saldarriaga-Loaiza, J.D.; López-Lezama, J.M.; Villada-Duque, F. Levelized Cost of Electricity in Colombia under New Fiscal Incentives. *Int. J. Eng. Res. Technol.* **2020**, *13*, 3234–3239. [[CrossRef](#)]
36. Lee, C.Y.; Ahn, J. Stochastic Modeling of the Levelized Cost of Electricity for Solar PV. *Energies* **2020**, *13*, 3017. [[CrossRef](#)]
37. Sayyah, A.; Horenstein, M.N.; Mazumder, M.K. Energy yield loss caused by dust deposition on photovoltaic panels. *Sol. Energy* **2014**, *107*, 576–604. [[CrossRef](#)]
38. Bhatti, S.; Khan, A.R.; Zoha, A.; Hussain, S.; Ghannam, R. A Machine Learning Frontier for Predicting LCOE of Photovoltaic System Economics. *Adv. Energy Sustain. Res.* **2024**, *5*, 2300178. [[CrossRef](#)]

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