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LCOE at Risk in Different Locations in Colombia

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ABSTRACT

The development of renewable energy (RE) projects is closely tied to the financial attractiveness of these investments. Despite the extensive literature, most studies focus on a static analysis, which is no longer adequate for dealing properly with the uncertainty associated with RE projects. This study proposes a stochastic model based on the levelized cost of energy (LCOE) and the application of VaR (value at risk) and CvaR (conditional value at risk) measures for risk assessment. Using a hypothetical case consisting of a solar farm with a rated capacity of 10 MWp, the analysis was conducted for nine Colombian municipalities. The irradiation levels at each site were considered the sole source of uncertainty. In addition, the Colombian regulatory framework was considered, represented by accounting and tax benefits. The results obtained from this work made it possible to evaluate the effect of resource behavior on the financial risk level of PV projects. The results provide a ranking of the nine assessed municipalities from a financial point of view and highlight the influence of considering solar resources as a risk factor on the project´s financial expected performance.

Keywords

Renewable energy;
LCOE;
Financial risk assessment;
PV farm

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1 Introduction

The interest on reducing greenhouse gases and climate change impacts related to carbon emissions from fossil fuel-based energy sources has been gaining attention [1,2]. This concern was incorporated in the Paris Agreement, which commits to limiting the temperature increase to 1.5 C. Added to the above, global energy consumption grew by 2.2% in 2023, well above its average growth rate in 2010-2019 (+1.5%/year) [3,4]. This is after previous reports showed that the average growth rate of energy consumption in 2018 had been nearly double that of 2010 [5]. In this context, energy scarcity situations have occurred worldwide. For example, the recent energy crisis in Europe resulted from Russia's dependence on gas and liquefied natural gas (LNG) imports [1], or the energy supply suspensions of up to 12 hours in October and November 2024 associated with the low level of water reservoirs affecting the operation of hydroelectric plans [6].

Thus, as the concern to reduce fossil fuel-based energy sources increases, so do the global energy demand and the multiple energy crises in different countries resulting from dependence on a single energy source. To address this challenge, governments in several countries have developed policies and long-term incentives to increase the implementation of renewable energy (RE) projects, thereby making RE generation more competitive [7,8]. Because of the above, the global energy generation landscape has transformed in recent decades, shifting from traditional energy production based on fossil fuel sources to RE sources.

In this regard, countries have adopted a twofold transition strategy: firstly, to reduce the environmental impact and secondly, to enhance energy security through an increase in their energy generation capacity and diversification of energy sources. Consequently, RE is progressively substituting fossil fuels as the primary

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energy source, contributing to decreased greenhouse gas (GHG) emissions [9–11]. Thus, wind, solar, biomass, geothermal, and oceanic sources have been growing as RE sources to meet electricity demand [7,8].

In the case of Colombia, the country has an electricity mix based almost completely on renewable sources [12]. With a share of 67.25%, hydropower is the main source of energy, followed by 30.72% of thermal power generation with fossil fuels resources [13]. Although the high participation of its water sources makes the electricity mix of Colombia different of most countries of the world, it also represents a high climatic vulnerability, which implies great challenges in terms of supplying the demand. In the Colombian electricity market, variations in energy prices as well as in electricity production have a close relationship with the level of hydroelectric dams and the behavior of the "El Niño" Southern Oscillation (ENSO) weather phenomenon, which can negatively affect the available resource for hydro generation [14–16]. Therefore, during dry seasons, it is required to supplement the power generation sources with other energy sources.

In this concern, the Colombian government is pursuing a strategy focused on diversifying its electricity generation matrix by incorporating RE sources to reduce its high dependency on hydropower energy generation plants. Based on this purpose, the country is seeking to maintain a country with a clean electricity mix while ensuring the energy supply in dry seasons. To that end, the Colombian government has promoted the RE projects based on the approval of Law 1715, enacted in 2014 [17,18]. Law 1715 promotes the use and generation of electricity from RE sources based on accounting and tax incentives [17,19]. As mentioned by Granados et al. [18], "the significance of this law is considerable because Colombia's power generation capacity is reliant on water resources, which have been impacted by dry seasons and climate change". Additionally, the implementation of generation systems based on RE aligns to reduce GHG emissions in Colombia by 20% for the year 2030 [17].

Research studies conducted in the last decades have led to the expansion of solar photovoltaic (PV) technology from both an academic perspective and in terms of solar project implementation [18]. Additionally, advancements in the technologies and equipment required for the implementation of PV systems have turned them into one of the cleanest, smartest, and most economical means of power generation [20]. Consequently, PV technology has become one of the fastest-growing technologies worldwide [18]. This expansion of PV systems is also reflected in the shifts observed in the Colombian power generation matrix, which has transitioned from a less than 1% share of the energy generation matrix in 2020 to a more than 6% share in 2024, adding more than 745MW to the current Colombian electricity system [21,22]. Currently, solar generation is the most important RE source in Colombia. This is not only due to the country's current installed solar power, but also the number of registered projects and the expected power derived from those solar projects.

In the framework of financial project valuations, interest in RE projects represents huge investment opportunities. The levelized cost of energy (LCOE) is used to assess the competitiveness or relevance of different locations for energy generation projects [8,23,24]. Although the benefits of PV systems are widely recognized and the associated costs are significantly decreasing, a careful study of the solar irradiance at the project site is highly relevant to improving the decision-making process [8]. According to Martínez-Ruiz et al. [23], in addition to classical methods, more sophisticated techniques for assessing risk and uncertainty have been considered in the financial analysis of energy projects. Risk and uncertainty assessment in LCOE has also been studied in recent years from the perspective of power generation portfolios, and lastly, from the integration of LCOE and Value at Risk (VaR) and Conditional Value at Risk (CVaR) as risk measures [8]. In this concern, Aquila et al. [8] suggests using CVaR-LCOE for the analysis of PV systems to conduct comparisons in different regions of the same country.

Then, considering the importance of PV projects for Colombia's electricity mix, as well as the literature highlighting the relevance of incorporating risk assessment as an integral part of the financial valuation of these projects, this study is focused on analyzing the influence of solar resource variability on the financial feasibility of PV projects in Colombia. CVaR is widely used to assess the uncertainty and risk in power systems [8,25]. However, Colombia's tropical climate gives rise to solar resource behavior that differs significantly from the other studied contexts. Based on the above, his study seeks to answer the research question: *Is the solar resource a critical risk factor in PV projects, particularly in countries with tropical climatic conditions like Colombia?*

Therefore, this study aims to perform a financial feasibility analysis for a PV farm project in Colombia using a stochastic model based on the LCOE and applying VaR and CvaR measures for risk assessment. For this purpose, nine Colombian municipalities were considered possible locations for the PV project. The remainder of the paper is organized as follows: first, the literature background is presented; second, the methodology for the LCOE-at-risk analysis is detailed. Section 4 presents the main results, and Section 5 discusses the findings and outlines the main conclusions.

2 Literature background

PV energy has emerged as one of the fastest-growing alternatives for power generation. This growth is driven, on one hand, by the environmental benefits associated with PV technologies, and on the other, by the significant reduction in installation and maintenance costs over recent years [24,26]. As a result, the deployment of PV systems has expanded globally across both developed and developing countries [26,27]. In parallel, challenges related to the installation and operation of PV systems have also intensified [26]. Among these challenges, the dependence on solar resources and their inherent variability—leading to intermittent energy generation—have been recognized as critical factors in the evaluation of PV system performance [7,26].

Recent research underscores the importance of understanding the effects of local solar radiation behavior on PV system performance [7,8]. This implies the necessity of incorporating the uncertainty derived from local solar radiation into PV system evaluations, whether by assessing the impact on technical variables or from a financial and cost-benefit analysis perspective [8]. As outlined in the Introduction Section, the present study aligns with the latter perspective, contributing to the growing body of research aimed at integrating uncertainty considerations into financial analyses of PV systems.

Two distinct approaches for incorporating financial criteria into PV system assessments are identified in the literature. The first approach involves using financial criteria within multicriteria decision-making (MCDM) frameworks to compare and select PV system locations, or to benchmark PV systems against other renewable energy technologies. These assessments typically complement financial metrics with demographic, technical, and system performance criteria [11,26,28]. Commonly used financial indicators include Initial Investment, Net Present Value (NPV), Payback Period, and Annual Operating Cost [26,28]. Although meteorological factors, such as Solar Radiation, are included as criteria in these models [26], the explicit influence of solar resource variability on financial outputs is not directly quantified within this framework.

The second approach, which frames this study, involves analyzing the impact of uncertainty and risk associated with PV systems on financial decision-making criteria [8]. Monte Carlo Simulation (MCS) is the most widely used technique to model uncertainty in this context. MCS enables the modeling of input parameters based on probability distributions to assess their influence on financial variables, such as NPV or LCOE, defined as model outputs [7,8]. Both technical performance factors and climatic behavior are typically modeled as sources of uncertainty [27].

The financial implications of uncertainty in PV systems have been primarily studied using NPV and LCOE as decision criteria [8,24]. NPV focuses on investor perspectives, reflecting the returns over the operational life of the PV system, whereas LCOE quantifies the lifecycle energy cost, facilitating comparisons of locations, technologies, and energy sources based on competitiveness [8,23,27]. Moreover, LCOE enables the incorporation of policy impacts into cost assessments [8].

In a 2024 study, Hwang et al. [27] conducted a literature review revealing that most research employing LCOE has historically adopted a deterministic approach. In a deterministic model all input variables are treated as fixed, known values, and the output variable is obtained through a single calculation without incorporating uncertainty or variability [29]. Although widely applied in the valuation of RE projects, the deterministic approach has been criticized in the literature for its assumption of predefined cash flows [23]. In contrast, stochastic models incorporate probability distributions to represent uncertainty in the input variables of the RE projects and then generate a range of possible outcomes. Authors such as Aquila et al. [8] and Andrade et al. [7], Hwang et al. [27] noted that the incorporation of stochastic methods to model uncertainty in LCOE calculations remains limited. Recent literature, therefore, has begun to emphasize the need for stochastic assessments, focusing on two primary perspectives: (i) modeling the influence of technical and economic factors—such as capacity, capital expenditure, and operation and maintenance costs—on LCOE [27,30]; and (ii) modeling the influence of climatic factors, notably solar resource variability, on LCOE [7,8].

Focusing on the latter, Aquila et al. [8] developed one of the few studies that explicitly modeled the impact of climatic variability on LCOE using stochastic analysis and risk assessment. Their work evaluated PV site selection in Brazil by considering solar radiation uncertainty. Similarly, Andrade et al. [7] investigated the impact of solar radiation variability in the context of PV-powered green hydrogen production. Both studies highlight that while literature offers a robust body of work analyzing NPV under climatic uncertainty [8], research specifically addressing LCOE through stochastic, risk-oriented approaches remains scarce [7,8].

The results from these studies demonstrate that incorporating risk analysis based on climatic variability across regions—even within the same country—can enhance the evaluation of PV system competitiveness from a financial risk perspective, offering decision-makers more valuable insights compared to analyses based solely on average LCOE values.

As uncertainty analysis has evolved, more sophisticated risk measures such as VaR and CVaR have been proposed for use in PV system assessments [8,23]. MCS remains the primary modeling technique for such analyses. Specifically, the Weibull probability distribution has been identified, through Anderson-Darling testing and p-value assessments, as a suitable model for solar radiation data in several cities across Brazil [7,8], a country with geographic conditions comparable to Colombia. Additionally, Weibull distributions have been used to model solar irradiation of German cities [7], while Triangular distributions were applied in earlier research focused on Colombia [23].

3 Methods

The methodology was developed from a hypothetical case study based on a PV farm with a rated capacity of 10 MWDC, whose clean energy production is equivalent to the consumption of 6.000 Colombian households. The study was conducted to compare, from a financial perspective, the feasibility of installing a PV farm in 9 locations in different regions in Colombia. The financial assessment was conducted by evaluating the LCOE to identify, from a risk perspective, the locations with the most favorable costs for a PV installation in the country. In each case, the analyses were carried out from two approaches: (I) the deterministic LCOE, and (II) the LCOE at risk by applying measures of financial risks. For the second approach, the source of uncertainty was purely based on the solar resource of the selected sites, whose behaviors were simulated by applying MCS. Figure 1 details a flow chart of the methodology.

3.1 Site selection

The locations selected for this study were chosen based on inclusion and exclusion criteria, primarily considering the status of PV projects in Colombia. The criteria included the current installed PV capacity, the number of registered PV projects, the irradiation levels, and the volatility of the solar resource. It is important to emphasize that the selection of the locations is solely intended for conducting a financial risk assessment, focusing on areas where PV projects are already being developed and considering the solar resource potential. This selection does not imply a recommendation for optimal locations for future PV installations in Colombia.

3.1.1 Current installed PV capacity

The installed PV capacity accounts for 8% of Colombia's total electricity mix. As of early 2023, an additional 952 MW were added to the installed capacity through PV projects [31], resulting in a total nominal PV capacity exceeding 1,200 MW. A total of 87 operational PV projects are distributed across 16 of Colombia's 32 regions. However, 90% of the installed solar capacity is

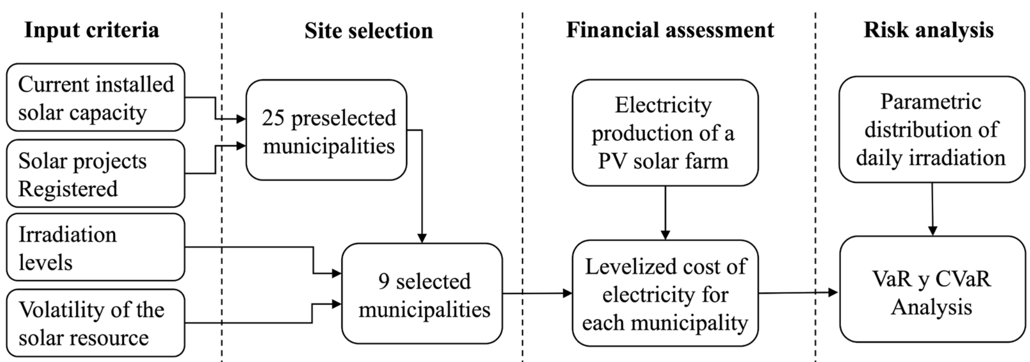

Figure 1. Workflow of the methodology.

Source: Own elaboration.

concentrated in just 7 regions: Cesar (24%), Caldas (15%), Córdoba (14%), Meta (11%), Tolima (9%), Magdalena (9%), and Valle del Cauca (8%).

El Paso, a municipality in the Cesar region, holds the highest PV installed capacity in Colombia, with 218 MW generated by two PV projects. It is followed by La Dorada, in the Caldas region, with 185 MW across two operational PV projects. Other municipalities such as San Carlos (in Córdoba), Puerto Gaitán (in Meta), Pivijay (in Magdalena) and La Gloria (in Cesar) contribute 100 MW, 97.5 MW, 90 MW and 80 MW, respectively, to the installed PV capacity of Colombia. The remaining 494 MW (39% of the total PV capacity) is distributed among 52 municipalities, with individual capacities ranging from 6.75 kW to 50.47 MW.

3.1.2 Registered solar projects

According to the Unidad de Planeación Minero Energética (UPME) [31], Colombia currently has 60 PV projects registered in phase 2 (with prefeasibility studies) and phase 3 (with the execution schedule and environmental licenses), representing a potential PV capacity of 4,284 MW. Among these, Barrancabermeja, located in the Santander region, stands out as the municipality with the highest number of registered projects, totaling five PV initiatives with a combined capacity of 375 MW. Additionally, a significant 300 MW PV farm is under development in Guaduas, projected to become operational by the end of 2025. Other notable projects include those in Ponedera (Atlántico), Sahagún (Córdoba), and Montelíbano (Córdoba), with nominal capacities of 200 MW for Ponedera and Sahagún, and 135 MW for Montelíbano. In the case of Villavicencio, Puerto Boyacá and Armero, it is expected the registered projects inject a total of 696 MW to the National Interconected System (SIN, for its acronym in Spanish) across 8 PV projects by 2026.

At this stage, specific locations were pre-selected for this study based on two inclusion criteria: *(i) municipalities with existing PV installed capacity and registered PV projects; and (ii) municipalities with the highest ratio of MW installed or registered per project.* Table 1 lists the 25 pre-selected locations for this study.

As can be seen, municipalities such as El Paso, Chinú (Córdoba), and Villavicencio (Meta) not only have existing installed PV capacity but are also being considered for the development of new PV projects. Meanwhile, other locations such as Ponedera, San Carlos, San Juan del Cesar (La Guajira) and Barrancabermeja, have a potential installed or registered capacity ranging from 75 to 200 MW per PV project.

3.1.3 Solar irradiation and resource volatility

To refine the selection process, the locations preselected in Table 1 were analyzed based on their solar resource potential to determine the final sites for financial assessment. Two additional inclusion criteria were introduced: *(iii) locations with the highest solar resource potential,* measured in terms of irradiation levels (kWh/m^2-day) and *(iv) locations with the highest daily irradiation volatility,* recognizing that the source of uncertainty in this study is strictly based on the solar resource behavior of the locations.

These additional criteria were evaluated using historical data spanning a 24-year period, from 2000 to 2023 [33]. For each of the 25 pre-selected locations (i), the solar resource potential was calculated as the average daily irradiation over the specified horizon. On the other hand, the volatility of the solar resource was calculated as the standard deviation of the logarithmic returns, based on a dataset of 137,886 observations (k) spanning the past 24 years, as shown in Equation 1 [34].

$$Daily\,irradiation\,returns = In\left(\frac{Irradiation_k}{Irradiation_{k-1}}\right)\forall k>1 \quad (1)$$

Table 2 lists the nine final locations selected for the financial assessment, providing details on the region, average daily irradiation and solar resource volatility.

3.1.4 Distribution selection for irradiation modeling

The behavior of the daily solar irradiation at selected locations was modeled using parametric distributions. Previous studies have applied parametric models —such as Weibull and Triangular— for modeling the solar resource in Colombian or in countries with climatological conditions similar to those of Colombia [7,8]. Based on this literature and considering the statistical properties of the historical data, this study adopted a parametric modeling approach to describe the daily behavior of the solar irradiation, supported by two main arguments: (i) the climatic features of the solar resource in Colombia, and (ii) the application of goodness of-fit-and robustness tests.

Colombia's geographic location over the equatorial line results in a notable solar stability throughout the year, with no marked seasons [35,36]. As a result, daily

Table 1. Preselected locations and status of installed/registered solar capacity.

Region	Municipality	Inclusion criterion*	Current		Potential	
			Installed capacity	Rate MW/ Project	Registered capacity	Rate MW/ Project
Atlántico	Ponedera	2	-	-	200	200
Bolivar	Cartagena	1	12.9	6.5	19.8	9.9
Boyacá	Puerto Boyacá	2	-	-	277	92.3
Caldas	La Dorada	1	185	92.5	150	150
Cesar	El Paso	1	218	109	259.9	86.6
	La Gloria	2	80	80	-	-
Cordoba	Chinú	1	19.8	9.9	119.4	59.7
	Montelibano	1	9.9	9.9	135	135
	Planeta Rica	1	39.3	13.1	9.9	9.9
	Sahagun	2	-	-	200	200
	San Carlos	2	100	100	-	-
Cundinamarca	Guaduas	1	19.8	9.9	300	300
	Nariño	2	-	-	100	100
Huila	Neiva	1	1.6	1.6	29.8	14.9
La Guajira	El Molino	2	-	-	181.3	181.3
	San Juan	2	-	-	100	100
	Uribia	2	-	-	76	76
Magdalena	Pivijay	2	90	90	-	-
	Zona Bananera	1	9.9	9.9	9.9	9.9
Meta	Villavicencio	1	16	16	300	300
Risaralda	Balboa	2	-	-	80	80
Santander	Barrancabermeja	2	375	75	-	-
	Giron	2	-	-	99.9	99.9
Sucre	Since	1	18.5	18.5	19.9	19.9
Tolima	Armero	1	19.9	19.9	210	70

1: Municipalities with both high current and potential capacity; 2: Municipalities with high current or potential rate of MW/Project

Source: Own elaboration based on data collected from UPME [31] and Sinergox [32].

Table 2. Selected locations and additional information.

Location	Region	Daily average irradiation (kWh/m^2)	Daily volatility of the solar resource
Ponedera	Atlántico	5.41	22%
El Paso	Cesar	5.41	20%
San Carlos	Córdoba	5.01	26%
Chinú	Córdoba	5.13	28%
Montelíbano	Córdoba	4.67	23%
Neiva	Huila	4.28	26%
San Juan	La Guajira	5.28	18%
Villavicencio	Meta	4.33	30%
Barrancabermeja	Santander	5.18	23%

Source: Own elaboration based on data collected from National Aeronautics and Space Administration (NASA) [33].

solar irradiation does not exhibit extreme or highly variable patterns. This characteristic leads to stable behavior of the solar resource, with not heavy tails, for the analyzed sites. The historical behavior from 2000 to 2023 of daily solar irradiation is shown in Figure 2 for each selected location. As observed in historical data, the daily irradiation distributions do not display unusual or complex histogram shapes that would necessarily suggest the use of empirical distributions or non-parametric techniques. Conversely, the histograms exhibit unimodal shapes that align with classical parametric distributions.

To evaluate the daily irradiation behavior at each selected location, a statistical analysis was conducted. The Anderson-Darling (AD) test was applied to identify the parametric probability distribution that best represents the daily irradiation patterns for each site. The AD statistic is often used to select the parametric distribution that best describes the behavior of a variable. In this work, the AD statistic was chosen as the primary metric for assessing goodness-of-fit due to its sensitivity to detect deviations in the tails of the distribution [37]. This characteristic is particularly relevant when conducting a risk assessment [38,39], which is the purpose of this study.

In addition to the AD test, two other goodness-of-fit statistics were applied to test the robustness of the results: Kolmogórov-Smirnov (KS), Cramer-von Mises (CvM), as defined by D'Agostino [40]. Six parametric distributions were evaluated for each selected location: Normal, Lognormal (3-parameters), Weibull, Weibull (3-parameters), Gamma, Gamma (3-parameters). Goodness-of-fit tests were performed using Minitab v22 (AD test) and Python's SciPy library (KS and CvM tests).

3.2 Financial assessment

This section presents the methodology used to evaluate the financial viability of installing a PV farm at each selected location, as described in Section 3.1. The analysis compared the deterministic and stochastic LCOE values based on the electricity production potential of the PV farm at each location. Additionally, a financial

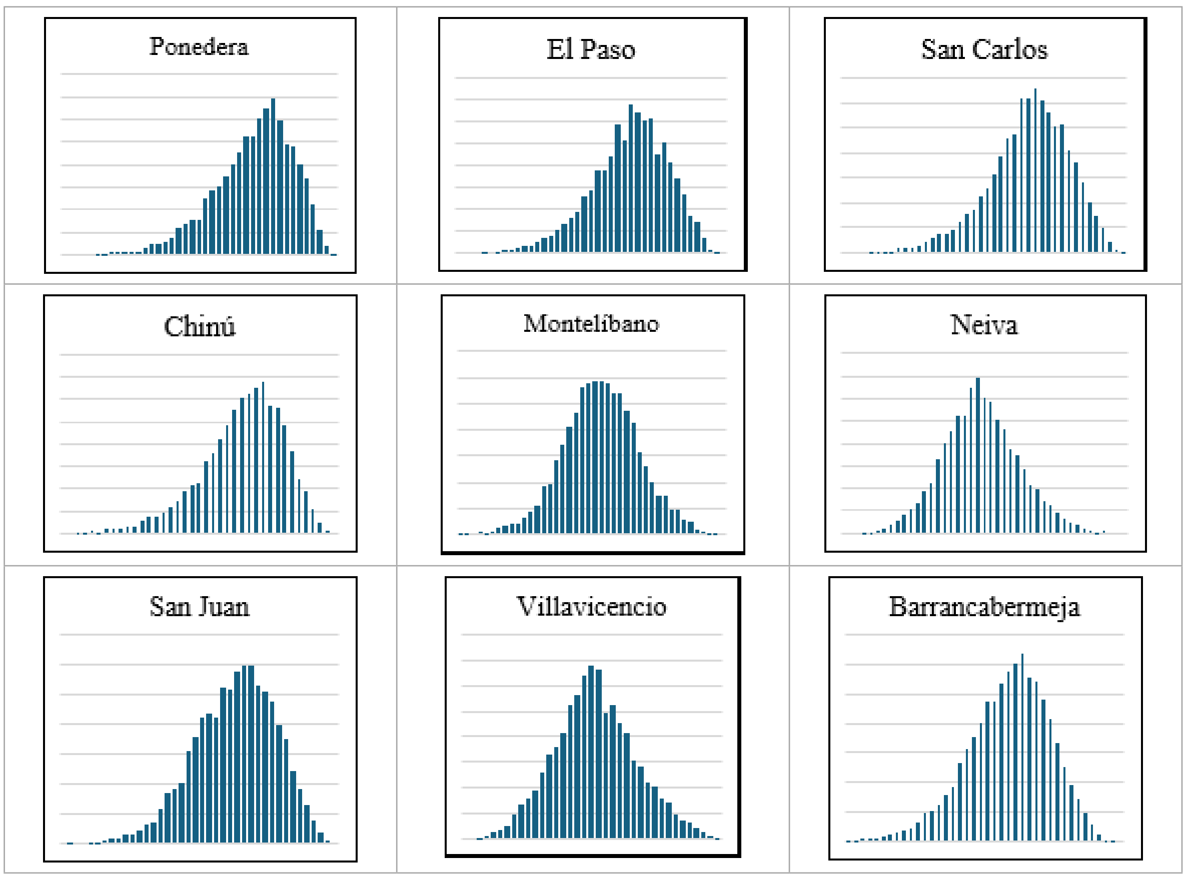

Figure 2. Historical histograms of daily solar irradiation for selected locations.

Source: Own elaboration based on historical data collected from NASA [33].

risk assessment was conducted to quantify the impact of solar resource volatility on the LCOE scenarios.

3.2.1 Electricity production of the PV farm

The electricity production for each location was determined using the peak sun hours (*PSH*) (note that PSH = daily irradiation (kWh/m^2)/standard irradiance (1 kW/m^2)), along with the technical specifications of the PV array. For all locations, the PV farm was designed to meet a total electricity demand () of 34,000 kWh/day, equivalent to the electricity consumption of approximately 6,000 traditional Colombian households. The number of panels required for the PV array () at each location *i* was estimated based on the minimum daily average irradiation, ensuring the minimum peak sun hours (*m_PSH*) were sufficient for producing the electrical requirements of the solar farm. Table 3 details the minimum daily average irradiation registered at each location during the last 24 years.

The N_{panels_i} was calculated from Equation 2, where the nominal power of the selected PV panel (*PP*) and the efficiency (η) of the panel were assumed to be 570 Wp and 90%, respectively.

$$N_{panels_i} = \frac{m\_PSHi * PP * \eta}{1000 * T_{consumption}} \forall i \tag{2}$$

In the stochastic approach, solar irradiation was simulated for each day (*k*) over a 25-year horizon (*j*) to calculate the PSH for each location. The simulation was performed using the parametric distribution assigned to the solar irradiation characteristics of each site. Subsequently, the annual electricity production (AEP) (kWh) of the PV farm was determined for each location *i* using Equation 3 [17].

Table 3. Minimum daily average irradiation of the selected locations.

Set *i*	**Municipality**	**Minimum daily average irradiation (kWh/m^2)**
1	Ponedera	5.41
2	El Paso	5.41
3	San Carlos	5.01
4	Chinú	5.13
5	Montelíbano	4.67
6	Neiva	4.28
7	San Juan	5.28
8	Villavicencio	4.33
9	Barrancabermeja	5.18

Source: Own elaboration based on data collected from NASA [33].

$$AEP_{i,j} = N_{panels_i} * \sum_{k=1}^{365} \frac{PSH_{i,j,k} * PP * \eta}{1000} \forall i, j \tag{3}$$

The $AEP_{i,j}$ was used for the calculation of the deterministic and stochastic LCOE, as is specified in the next subsection.

3.2.2 Levelized cost of electricity

The financial assessment was conducted under the premise of evaluating the same PV farm at each selected location. To this aim, LCOE (USD/MWh) criteria was calculated to determine the ranking of sites with the greatest financial potential for developing a PV project in Colombia. Table 4 presents the financial parameters considered for the LCOE calculation [31,32].

It is worth noting that all financial parameters were considered equal for all locations, given that the sites under analysis belong to the same country, and capital and operating expenditures do not vary sharply from one place to another. Likewise, the financial assessment was conducted from the perspective of a single investor, with a weighted average cost of capital (WACC) of 10.78% in COP$ [43–45]. The LCOE was estimated using Equation 3, following the traditional mathematical formula commonly applied in the literature [8] but adapted to reflect a cash-flow-based approach [19]. Additional parameters used in the calculation are detailed below.

$$LCOE_i = T\_CAPEX_i + \frac{\sum_{j=1}^{26} \frac{T\_O\&M_{i,j} - TAX_{i,j} + WCI_{i,j}}{(1+WACC)^j}}{\sum_{j=1}^{25} \frac{AEP_{i,j} * (1+PPI_j) * (1-Tax_{rate})}{(1+WACC)^j}} \forall i, j \tag{4}$$

Where:

- T_CAPEX. Total capital expenditures.
- T_O&M. Total operating and maintenance costs. O&M costs were annually indexed according to the consumer price index (CPI).
- WCI. Working capital investment.

Table 4. Financial parameters for the PV project.

Parameter	**Notation**	**Units**	**Value**
Total installation costs	CAPEX	USD/kW	876
Operating and maintenance costs	O&M	USD/kW/yr	7.4
Working Capital policy	WC	month over O&M	1
TAX		%	35%
Exchange rate	ER	COP$/USD	4,251

Source: [41,42]

- AEP. Annual electricity production, which was indexed according to the producer price index (PPI). Its impact as a tax generator was also considered.
- TAX. Represents the tax deduction resulting from the T_O&M, depreciation (Dep), and tax shield (TS) within the project. It does not represent the actual tax liability, but rather the reduction in tax burden attributable to these factors. The computation of TAX is formulated by Equation 4.

$$TAX_{i,j} = \left(T\_O\,\&\,M_{i,j} + Dep_{i,j} + TS_{i,j}\right) * Tax_{rate}\ \forall i \qquad (5)$$

As depicted in Equation 3, LCOE was calculated not only considering the cost flows but also from a cash flows perspective. In this regard, factors such as the impact of depreciation as non-cash expenditure, tax shields, and working capital recovery, to name but a few, were considered. It also considered the effect of the amount of electricity produced as a tax's generator. Accounting and tax incentives of Law 1715 [46] were also included in the LCOE calculation, considering that regulatory framework directly affects the cash flow of the PV project. Among the incentives incorporated into the financial model were the accelerate depreciation, exemption of value added tax (IVA, for its acronym in Spanish) and income tax deduction. All these factors suggest a more accurate outcome of the LCOE, rather than solely focusing on the CAPEX and OPEX.

3.3 Financial risk measurement

This study also involved the application of risk measures, namely VaR and CVaR to obtain scenarios of risk in the worst conditions and considering a 99% confidence level. These metrics provided a detailed understanding of the maximum LCOE that can be observed at each location due to fluctuations in solar resource availability. By incorporating these measures, the analysis provides a reliable framework for decision-making, enabling the identification of the role of the solar resource as a critical risk factor for PV projects, particularly in countries with tropical climatic conditions like Colombia.

4 Results

Tables 5, 6 and 7 details the results obtained in the AD, KS and CvM tests, respectively. As described in the Methods Section, these three goodness-of-fit statistics were applied to each selected location to identify the best-fitting distribution among the six parametric alternatives evaluated. The highlighted values indicate the two best-fitting distributions for each location, corresponding to the lowest values for each goodness-of-fit statistic.

The results obtained show that, in most locations, the parametric distributions suggested by the AD test were consistent with the results of the KS and CvM tests. The distributions under comparison were always among the top candidates, and the few differences in test values were minor. In cases where discrepancies occurred, they were typically among similar distribution families. Indeed, in eight out of nine locations, the three goodness-of-fit favored the same two distributions for representing the behavior of daily solar irradiation. Barrancabermeja was the only location where the AD-based selection (Weibull 3-parameter) differed from the distributions favored by the KS and CvM tests. Therefore, the Weibull 2-parameter distribution

Table 5. Anderson-Darling statistic results.

Anderson-Darling statistic						
Municipality	**Normal**	**Lognorm_3p**	**Weibull_2p**	**Weibull_3p**	**Gamma_2p**	**Gamma_3p**
Ponedera	69.67	70.03	14.34	2.53	150.35	87.47
El paso	32.48	32.53	1.25	1.56	86.90	46.56
San Carlos	38.85	38.90	3.41	2.11	111.31	63.46
Chinú	72.40	72.69	16.96	0.47	172.88	102.71
Montelíbano	2.87	2.87	29.16	14.35	21.76	7.52
Neiva	6.73	2.90	43.54	22.05	9.79	2.89
San Juan	19.69	19.90	2.11	2.11	58.87	31.89
Villavicencio	6.79	2.84	27.19	12.87	13.91	2.77
Barrancabermeja	24.86	25.02	0.39	0.37	77.92	46.78

Source: Own elaboration using Minitab v22.

Table 6. Kolmogórov-Smirnov statistic results.

Kolmogórov-Smirnov statistic						
Municipality	**Normal**	**Lognorm_3p**	**Weibull_2p**	**Weibull_3p**	**Gamma_2p**	**Gamma_3p**
Ponedera	0.06	0.06	0.02	0.01	0.08	0.07
El Paso	0.04	0.04	0.01	0.01	0.06	0.05
San Carlos	0.04	0.05	0.01	0.02	0.08	0.06
Chinú	0.06	0.06	0.02	0.01	0.09	0.07
Montelíbano	0.01	0.01	0.04	0.03	0.03	0.01
Neiva	0.03	0.02	0.05	0.04	0.03	0.02
San Juan	0.03	0.04	0.02	0.01	0.05	0.04
Villavicencio	0.03	0.02	0.05	0.03	0.03	0.02
Barrancabermeja	0.04	0.04	0.01	0.68	0.06	0.04

Source: Own elaboration using Python (SciPy).

Table 7. Cramer-von Mises statistic results.

Cramer-von Mises statistic						
Municipality	**Normal**	**Lognorm_3p**	**Weibull_2p**	**Weibull_3p**	**Gamma_2p**	**Gamma_3p**
Ponedera	11.17	10.78	1.99	0.30	24.82	15.74
El Paso	4.95	4.55	0.12	0.24	13.85	9.80
San Carlos	5.94	6.45	0.41	0.40	17.95	11.33
Chinú	11.48	11.30	2.29	0.05	28.50	17.28
Montelíbano	0.35	0.35	4.39	2.11	3.24	0.46
Neiva	1.18	0.53	6.91	3.63	1.61	0.55
San Juan	3.10	3.87	0.33	0.33	9.33	5.22
Villavicencio	1.17	0.48	4.57	2.32	2.20	0.48
Barrancabermeja	3.96	4.33	0.04	1,523.56	12.57	6.01

Source: Own elaboration using Python (SciPy).

was selected, as it provided a more robust and consistent fit across all tests. Table 8 summarizes the top 2 distributions identified by each of the three analyzed tests. The last column presents the final distribution selected for each location for modeling the daily irradiation:

The QQ-plot was additionally employed as a visual criterion for selecting the parametric distribution. Panels (a–i) in Figure 3 display the QQ-plots corresponding to the parametric distribution chosen for each location.

In summary, four parametric distributions were identified to simulate the daily irradiation levels across the nine selected locations: Weibull 3-parameters, Weibull 2-parameters, Normal, and Gamma 3-parameters. Table 9 details of the parametric distributions selected for each location, along with the corresponding input parameters to each case.

Figure 4 shows the histograms of daily irradiation obtained for each location from the simulation of 50,000 scenarios by using the Statistics and Machine Learning Toolbox-MATLAB® version 2023B.

As observed, despite the differences in the probability distribution used for the simulation, the behavior of the daily irradiation simulation did not reflect abrupt changes from one location to another. Conversely, the mean daily irradiation values range approximately from 4 to 5.5 kWh/m^2, with overlapping histograms. This exhibits the climatic characteristics of Colombia, whose irradiation levels do not vary sharply from one region to another due to the geographic location of the country.

Some differences can be observed relative to the locations with the lowest and highest irradiation levels. For instance, Neiva recorded minimum daily irradiation levels as low as 1 kWh/m^2. On the other hand,

Table 8. Selected distribution for each location.

Municipality	**AD**	**CvM**	**KS**	**Selected distribution**
Ponedera	Weibull_3p	Weibull_3p	Weibull_3p	Weibull_3p
	Weibull_2p	Weibull_2p	Weibull_2p	
El Paso	Weibull_2p	Weibull_2p	Weibull_2p	Weibull_2p
	Weibull_3p	Weibull_3p	Weibull_3p	
San Carlos	Weibull_3p	Weibull_3p	Weibull_2p	Weibull_3p
	Weibull_2p	Weibull_2p	Weibull_3p	
Chinú	Weibull_3p	Weibull_3p	Weibull_3p	Weibull_3p
	Weibull_2p	Weibull_2p	Weibull_2p	
Montelíbano	Normal	Lognorm_3p	Lognorm_3p	Normal
	Lognorm_3p	Normal	Normal	
Neiva	Gamma_3p	Lognorm_3p	Lognorm_3p	Gamma_3p
	Lognorm_3p	Gamma_3p	Gamma_3p	
San Juan	Weibull_3p	Weibull_3p	Weibull_3p	Weibull_3p
	Weibull_2p	Weibull_2p	Weibull_2p	
Villavicencio	Gamma_3p	Lognorm_3p	Gamma_3p	Gamma_3p
	Lognorm_3p	Gamma_3p	Lognorm_3p	
Barrancabermeja	Weibull_3p	Weibull_2p	Weibull_2p	Weibull_2p
	Weibull_2p	Normal	Normal	

Ponedera and El Paso can reach irradiation levels of up to 7.7 and 7.9 kWh/m^2/day. An interesting behavior is observed for Villavicencio, where daily irradiation levels can drop to as low as 0.07 kWh/m^2 in a day but can also reach up to 8.92 kWh/m^2-day within the same year. This aligns with the high volatility estimated for this location (see Table 2), as Villavicencio exhibited the highest standard deviation among all municipalities when analyzing the historical solar irradiation behavior for this site.

As mentioned in Section 3, the financial parameters were kept constant during the construction of the financial model. Consequently, any differences in the LCOE results for the selected locations are solely attributed to variations in the behavior of the solar resource under both deterministic and stochastic analysis. Table 10 summarizes the results obtained for all locations for both analyses and main descriptive statistics from the simulation. Information about the ranking of locations with the most favorable LCOE, is also related in Table 10. The financial evaluation and risk analysis results were converted into U.S. dollars (USD) for easier comparison. However, all calculations and simulations were originally conducted in Colombian pesos (COP) to accurately reflect the project's local economic and financial context.

The solar resource variability results in differences in the LCOE outcomes for both deterministic and stochastic results, where the probability distributions of the LCOE exhibit a normal behavior with a kurtosis of approximately 3.0 in all cases. This leads to LCOE scenarios without heavy tails or extreme outliers, which is closely tied to the climatic conditions of Colombia, where variations in solar irradiation are generally stable and not highly volatile.

As expected, there is a clear inverse relationship between the amount of solar resources and the LCOE behavior. The highest and lowest LCOE were obtained for the locations with the lowest and highest daily average irradiation, respectively. For example, El Paso was classified as the location with the most favorable LCOE among all sites considered. With an average of 5.41 kWh/m^2 of daily irradiation, a price of USD 51.23 per MWh is, on average, the energy sales price that would make the project financially feasible in this location. On the other hand, for Neiva, bilateral contracts and spot prices would have to exceed the threshold of USD 67.44 per MWh for this project to be financially attractive in

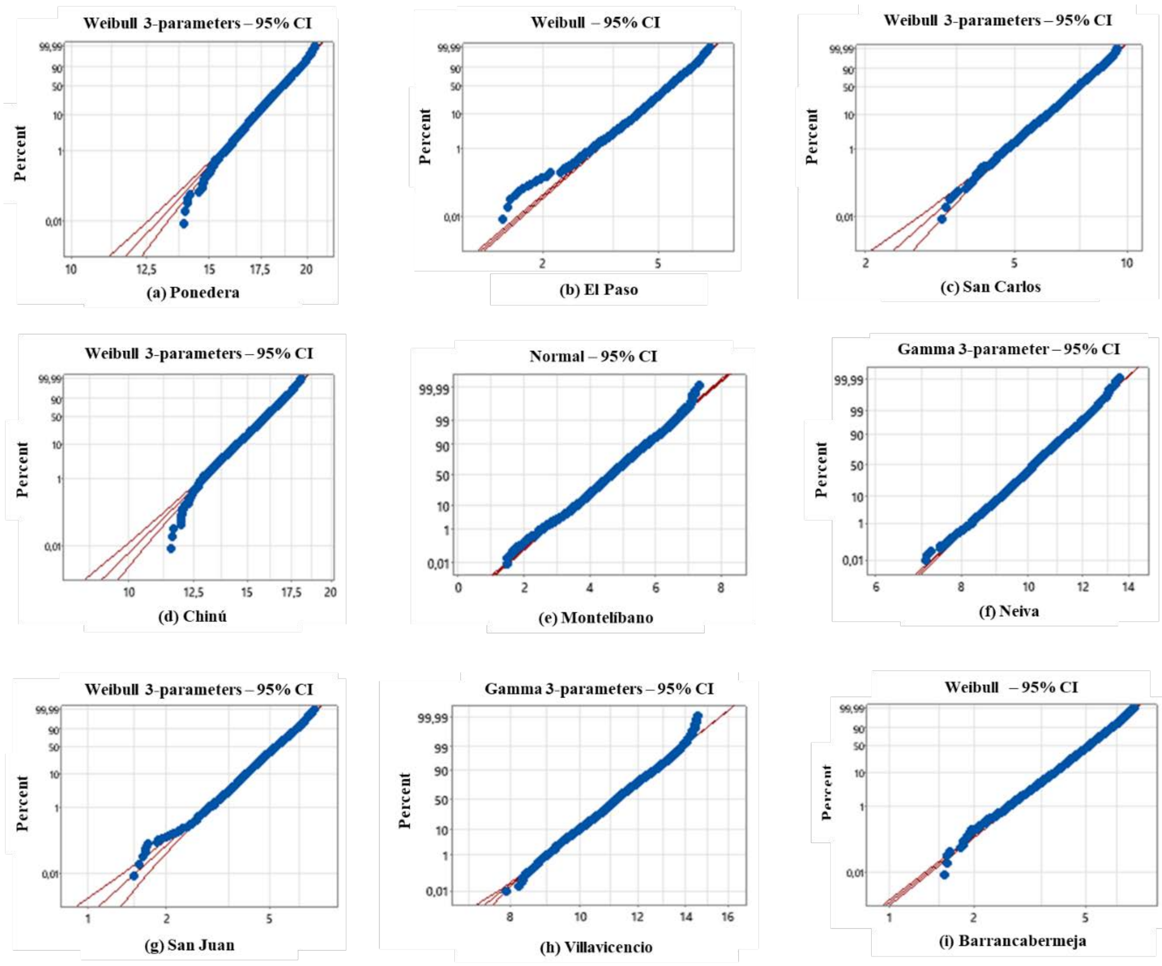

Figure 3. Parametric distribution test (QQ-plots).

Source: Generated using Minitab v22.

Table 9. Input arguments of parametric distributions.

Municipality	**Distribution**	**Input parameters***
Ponedera	Weibull 3-parameters	a = 24.072; b = 18.9527; c = –13.1183
El Paso	Weibull	a = 7.4331; b = 5.7673
San Carlos	Weibull 3-parameters	a = 9.7759; b = 7.7261; c = –2.3361
Chinú	Weibull 3-parameters	a = 19.7724; b = 16.3274; c = –10.7557
Montelíbano	Normal	μ = 4.6653; σ = 0.8440
Neiva	Gamma 3-parameters	a = 136.1605; b = 0.0754; c = –5.9935
San Juan	Weibull 3-parameters	a = 7.0249; b = 5.6397; c = 0.0048
Villavicencio	Gamma 3-parameters	a = 116.2857; b = 0.0975; c = –7.0068
Barrancabermeja	Weibull	a = 6.67753; b = 5.46228.

For Weibull, Weibull 3-parameters, and Gamma 3-parameters distribution, a: shape, b: scale, c: threshold. For normal distribution, μ: mean and σ: deviation

Source: Own elaboration using Minitab v22.

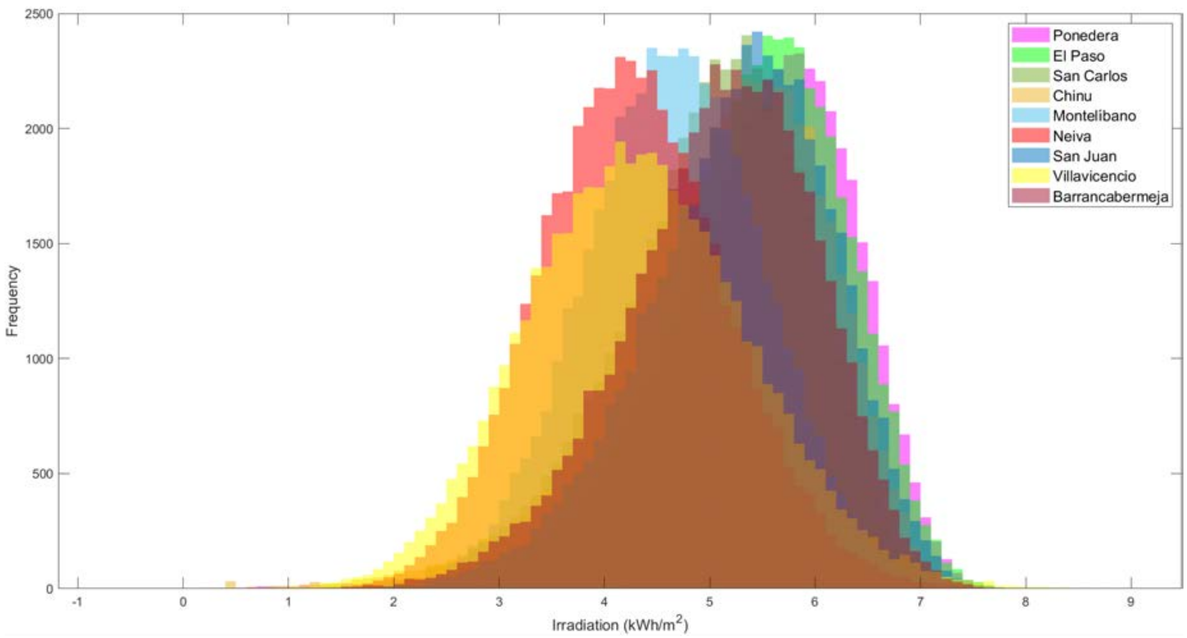

Figure 4. Histogram daily irradiation for each site.

Source: Generated using Matlab R2023B.

Table 10. LCOE results for location. All values in USD$/MWh unless otherwise indicated.

Ranking	**Deterministic**	**Mean**	**Median**	**Standard Deviation**	**Kurtosis (adim.)**	**Min.**	**Max.**
1. El Paso	51.24	51.23	51.23	0.42	3.01	49.57	53.16
2. Ponedera	51.25	51.23	51.22	0.48	3.01	49.12	53.29
3. San Juan	52.49	52.49	52.48	0.46	3.00	50.34	54.49
4. Chinú	54.01	53.99	53.98	0.55	3.00	51.81	56.43
5. Barrancabermeja	54.39	54.39	54.38	0.50	3.00	52.33	56.62
6. San Carlos	55.36	55.36	55.36	0.52	2.99	53.22	57.71
7. Montelíbano	59.42	59.46	59.45	0.56	2.98	57.29	61.73
8. Villavicencio	63.95	63.99	63.98	0.81	3.01	60.79	67.66
9. Neiva	64.76	64.78	64.77	0.69	2.95	61.68	67.44

Source: Own elaboration using Matlab R2023B.

the worst-case scenario. This, considering that the average daily irradiation of Neiva was the lowest among the locations considered in the study, with a value of 4.2 kWh/m^2.

An interesting result was obtained in Villavicencio, since this municipality had the highest standard deviation for the LCOE, explained by the volatility of the solar resource in this location. Thus, the maximum LCOE values for Villavicencio are too close to the maximum LCOE values for Neiva, which is the location with the highest average LCOE and with the last position in the ranking. Although the mean and minimum LCOE for Villavicencio differ by 0.79 and 0.90 USD/MWh, respectively, when compared to Neiva, the maximum LCOE scenarios are nearly identical for both locations. This suggests that, in terms of uncertainty, Villavicencio emerges as the least favorable location for the development of a PV farm. Figure 5 provides an overview of the LCOE simulations for the analyzed locations.

The results illustrated in Figure 5 show clear differences in LCOE outcomes across the nine analyzed

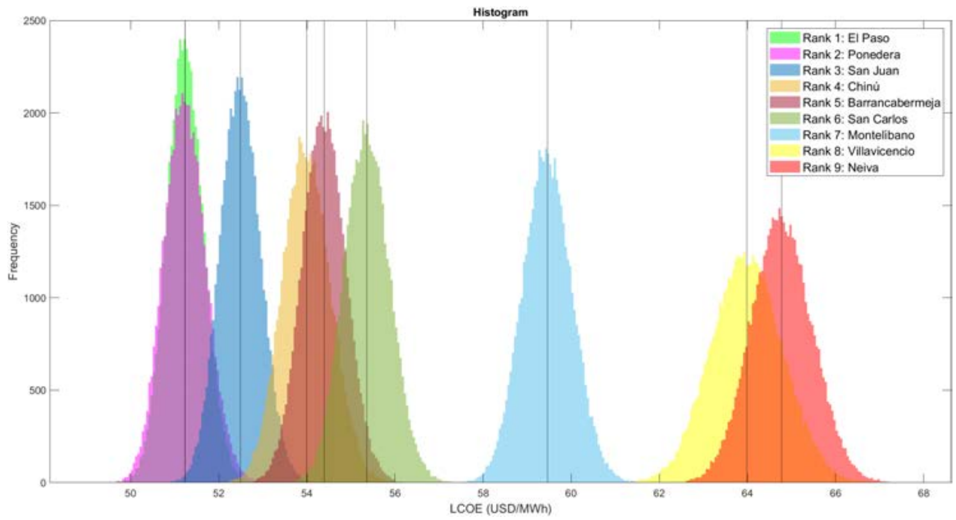

Figure 5. Histogram: daily irradiation for each site.

Source: Generated using Matlab R2023B.

locations, largely explained by site-specific characteristics. For instance, El Paso and Ponedera exhibited the most favorable LCOE results with lower dispersion, followed by San Juan. Although Chinú, Barrancabermeja and San Carlos are not ranked among the top 3, these locations still present levelized costs that can be considered competitive when compared to those of the most financially attractive sites . In contrast, Montelíbano represents an intermediate case, with an average LCOE of 59.46 USD/MWh, ranking sixth overall. Meanwhile, Villavicencio and Neiva appear as the least attractive locations, with higher average LCOE values and a wider distribution, which reflect greater financial uncertainty. Regarding financial risk analysis, Table 11 details the results for the VaR and CVaR measures of the LCOE at 99% confidence level for each location.

As is shown in Table 11, it is noteworthy that the extreme risk values are remarkably similar among the cities that are near ranked. For instance, El Paso and Ponedera exhibit the same level of financial risk despite being in different regions of Colombia (Cesar and Atlántico, respectively). The maximum LCOE for these municipalities is approximately 52 USD per MWh at a 99% confidence level. Similarly, in the deterministic case, the difference between the LCOE of Villavicencio and Neiva is 0.81 USD/MWh. Meanwhile, the 99% CVaR of the LCOE for Villavicencio indicates that, in the worst 1% possible scenarios, the average LCOE will be at least 66.19 USD/MWh. In the case of Neiva, this measure is only 0.45 USD/MWh higher. This underscores that, although the ranking suggests one location may appear more attractive than another for developing a PV project, the differences in financial risk between certain locations become less pronounced and do not represent significant variations from one position in the ranking to the next. Figure 6 shows the irradiation map of Colombia, along with the geographic location and LCOE ranking of the nine analyzed sites.

In summary, the ranking of sites with the most favorable LCOE remains consistent across both deterministic and the financial risk assessment. Both analyses suggest that the LCOE patterns identified are closely linked to the investment dynamics of PV projects outlined in Section 3. These patterns highlight that the northern region of Colombia (Cesar, Atlántico, and Guajira)

Table 11. VaR and CVaR measures of LCOE. All values in USD$/MWh.

Ranking	VaR 99%	CVaR 99%
1. El Paso	52.23	52.38
2. Ponedera	52.39	52.56
3. San Juan	53.58	53.74
4. Chinú	55.29	55.51
5. Barrancabermeja	55.58	55.75
6. San Carlos	56.62	56.80
7. Montelíbano	60.79	60.99
8. Villavicencio	65.89	66.19
9. Neiva	66.41	66.64

Source: Own elaboration using Matlab R2023B.

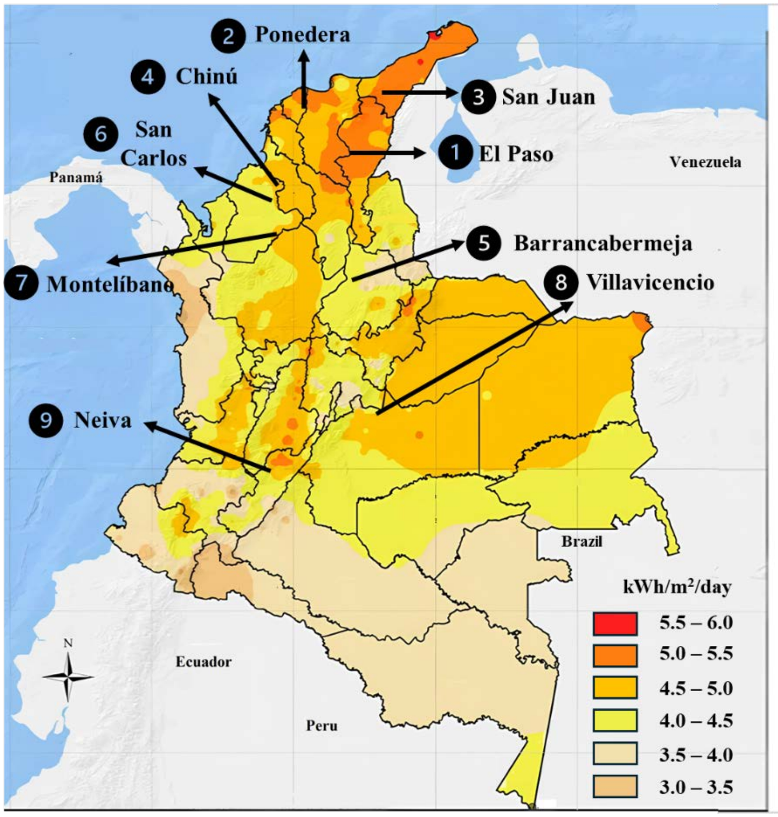

Figure 6. Irradiation map of Colombia and LCOE ranking with the analyzed sites.
Source: Own elaboration based on a base map from Instituto de Hidrología y Meteorología y Estudios Ambientales (IDEAM) [47].

offers the most favorable conditions for developing PV projects when considering solar resource behavior as the primary differentiating factor among cities. However, the results obtained are strongly influenced by the geographical location of Colombia, where irradiation levels and climatic conditions does not vary significantly due to the absence of distinct seasons. Consequently, investors might consider prioritizing other factors —such as logistical feasibility, existing infrastructure, or community acceptance— when selecting a PV project site, as the financial risk profiles of certain locations are nearly indistinguishable.

5 Discussion and Conclusions

This study aimed to investigate whether solar resource constitutes a critical risk factor in the site selection decision for solar farms in countries with tropical climate conditions, using Colombia as a reference case. Financial evaluation of a PV farm project in Colombia for nine different locations considering a deterministic approach based on LCOE and later, complementing this approach with estimation of VaR and CVaR measures to perform a risk assessment of the project in each location. In this regard, the results showed that solar resource variability influences the performance of the project in terms of the LCOE in each location. However, from a stochastic perspective, the extreme risk values are similar among the municipalities evaluated. So that, the financial risk profiles of the projects suggest that locations are equally viable from a risk perspective.

Thus, by comparing the ranking of nine locations in Colombia based on deterministic LCOE versus CVaR-LCOE, it was found that although the solar resource is a key factor in defining the location, it does not represent a significant risk factor in this decision. This contrasts with previous studies conducted in countries with geographical and climatic characteristics similar to Colombia such as [8], in which comparable analyses concluded that the location ranking for PV systems is altered when the uncertainty derived from solar resource behavior is considered.

Consequently, the notion that the risk derived from uncertainty in solar resource behavior constitutes a critical risk factor for the performance of PV systems is not generalizable, not even among locations with shared geographical features. This was evident when comparing the findings from Colombia with those from previous studies conducted in Brazil. Thus, while solar irradiation remains a crucial factor for PV site selection, as consistently supported in existing literature [7,8,27], this study shows that it does not always qualify as a critical risk factor in all cases. The solar resource was confirmed as influential in this study, but not in a way that introduced significant differences among the evaluated sites.

The relatively stable irradiation levels observed in Colombian cities reflect the consistent solar resource behavior characteristic of tropical regions. Consequently, abrupt changes in LCOE scenarios attributable to solar resource behavior are mitigated in the financial risk assessment for the ranking definition. Consequently, for future studies, factors such as logistical considerations, infrastructure availability, or community acceptance, could be incorporated into the project feasibility analysis to have a comprehensive view.

In this regard, the results reported herein are not at odds with the understanding that solar irradiation can influence the technical conditions and the stability of energy production capacity. On the contrary, these results reinforce the conclusions of prior studies such as [2,5], by highlighting the influence of solar irradiation in the deterministic LCOE results and their relevance to compare sites for possible location of PV systems. However, results derived from this study suggest that the risk generated by the behavior of solar irradiation in different locations may be relatively homogeneous and therefore may not constitute a decision-making criterion in some specific context. In other words, it is not that the evaluated locations are risk-free, but rather that risk levels are homogeneous among them, making it a non-differentiating factor for decision-making. Given this, it should be clearly stated that, in other contexts, such risk derived from the irradiation behavior could indeed represent a relevant criterion for site selection, as shown in previous studies.

The use of parametric distributions allowed modeling the uncertainty in the behavior of the solar irradiation for the nine municipalities studied. The statistical tests performed confirmed that, for the cases studied, parametric distributions adequately reflect the behavior of this variable. These results suggest that the irradiation behavior cannot be homogeneously modeled with a single distribution. Instead, an individualized statistical analysis is required for each case. In this regard, further analysis could be conducted that considers empirical techniques such as bootstrapping as an alternative for modeling solar irradiation in tropical countries such as Colombia, to compare the influence on the results when parametric and non-parametric approaches are used.

In addition, future research could apply this methodology to countries with more volatile solar resources. Comparing LCOE rankings derived from deterministic and stochastic perspectives may offer valuable insights, particularly in scenarios where a high presence of solar resources does not necessarily compensate for the riskiest scenarios of LCOE. Finally, modeling solar resources using empirical distributions could also be of interest. Especially for those locations where solar behavior exhibits particular patterns that cannot be adequately captured through parametric distributions.

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