Assessing Photovoltaic Capacity Factor Variability Using Long-Term Satellite Derived Solar Resource Data Under Brazilian Climate

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Abstract

- Accurate photovoltaic (PV) energy yield assessment is fundamental to mitigating financial risk and ensuring reliable performance contract expectations.
- TMY-based methods are widely used for project design but often underestimate uncertainty by smoothing interannual and seasonal solar resource variability. Long-term satellite-derived time-series data provide a more realistic basis for evaluating historical weather variability and its impact on PV performance.
- Capacity Factor (CF) translates this variability into a metric directly linked to system performance and financial return, while Coefficient of Variation (COV) provides a normalized measure of uncertainty across locations and timescales.
- Monthly-resolution analysis reveals limitations on annual-only predictions, improving short-term performance expectations and uncertainty bound for operational and contractual assessments
- In this work, 27 years of NSRDB data (1998 - 2024) are analyzed across multiple Brazilian locations to derive probabilistic CF distributions and quantify solar resource variability, supporting more robust project design and financial decision-making.

Probabilistic Framework and Site Selection

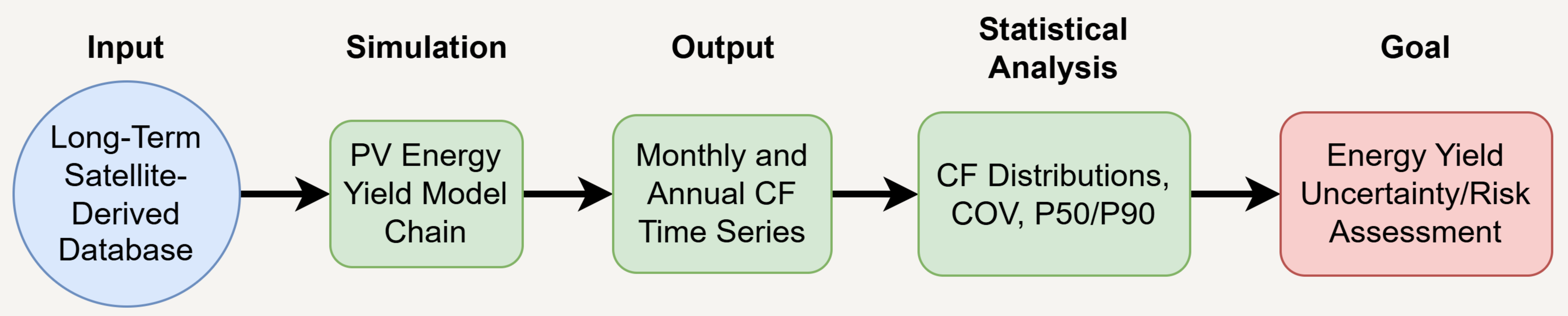

Figure 1: Diagram of the Probabilistic Framework.

$$CF = \frac{\sum_{i=1}^{n} E_{out,daily,i}}{P_{ac} * 24 * D} \quad (1)$$

$$COV_{intramonthly} = \frac{\sqrt{\frac{1}{D}\sum_{i=1}^{n}(CF_{d,i} - \widetilde{CF})}}{\widetilde{CF}_m} \quad (2)$$

$$COV_{interannual} = \frac{\sqrt{\frac{1}{Y}\sum_{i=1}^{n}(CF_{m,i} - \widetilde{CF}_y)}}{\widetilde{CF}_y} \quad (3)$$

- $E_{out,daily,i}$ is the modeled daily AC PV energy yield; P_{ac} is the inverter nominal power capacity; D is the number of days in the analyzed month; and Y is the number of years. COV is calculated at two scales: monthly (using all the daily CF per month) and annual (using monthly CF of the specific month across all dataset years).

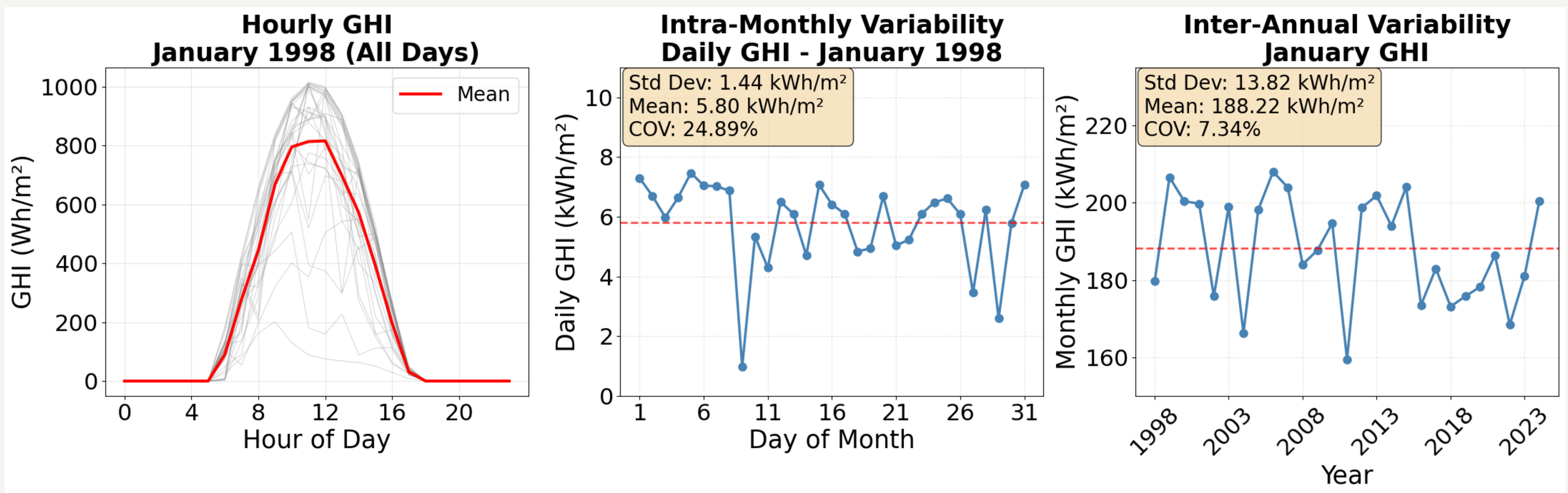

Figure 2: Visual concept of COV estimative for solar resource.

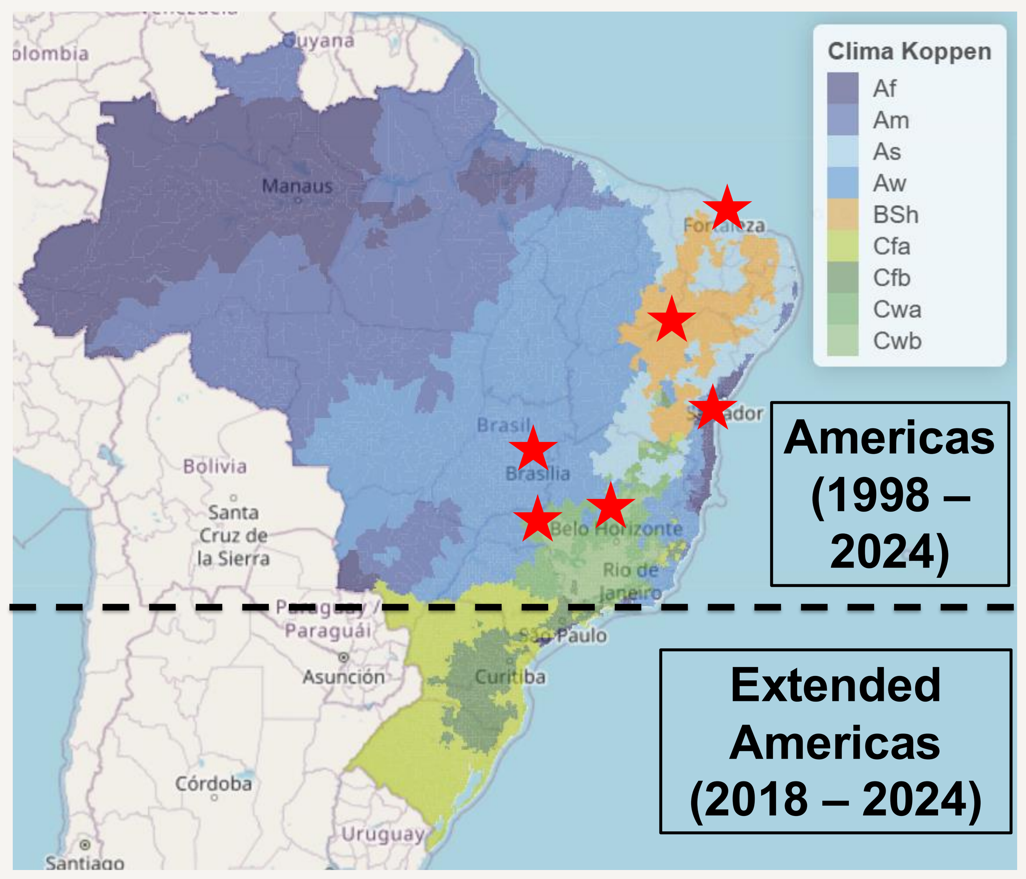

Figure 3: Sites analyzed from Brazil overlayed on Köppen-Geiger Climate Classification map [1] .

- **Six locations across Brazilian territory** and **four across the U.S.** were selected to provide a geographically diverse dataset.
- Simulated PV systems were configured as both **Fixed-tilt** and **1-Axis Tracking** installations, using Bifacial 700 Wp modules, 1 MWp of rated capacity, and a 1.3 DC/AC ratio.
- Fortaleza, Brazil is used as the representative case study for detailed results and analysis.
- Interannual monthly and yearly CF distributions are analyzed over 27 years (1998–2024) using NSRDB.

Application and Key Findings

- The monthly P50-P90 spread is **substantially larger** than annual averages suggest, especially during winter and spring, indicating that annual-only assessments underestimate short-term financial risk.
- At the annual scale, TMY aligns closely with P50 but shows a gap of **0.8–1.3 percentage** points for P90, being critical for financing and performance guarantees. At the monthly scale, the TMY-to-P50-P90 distance varies with seasonal patterns, further amplifying project financial risk.

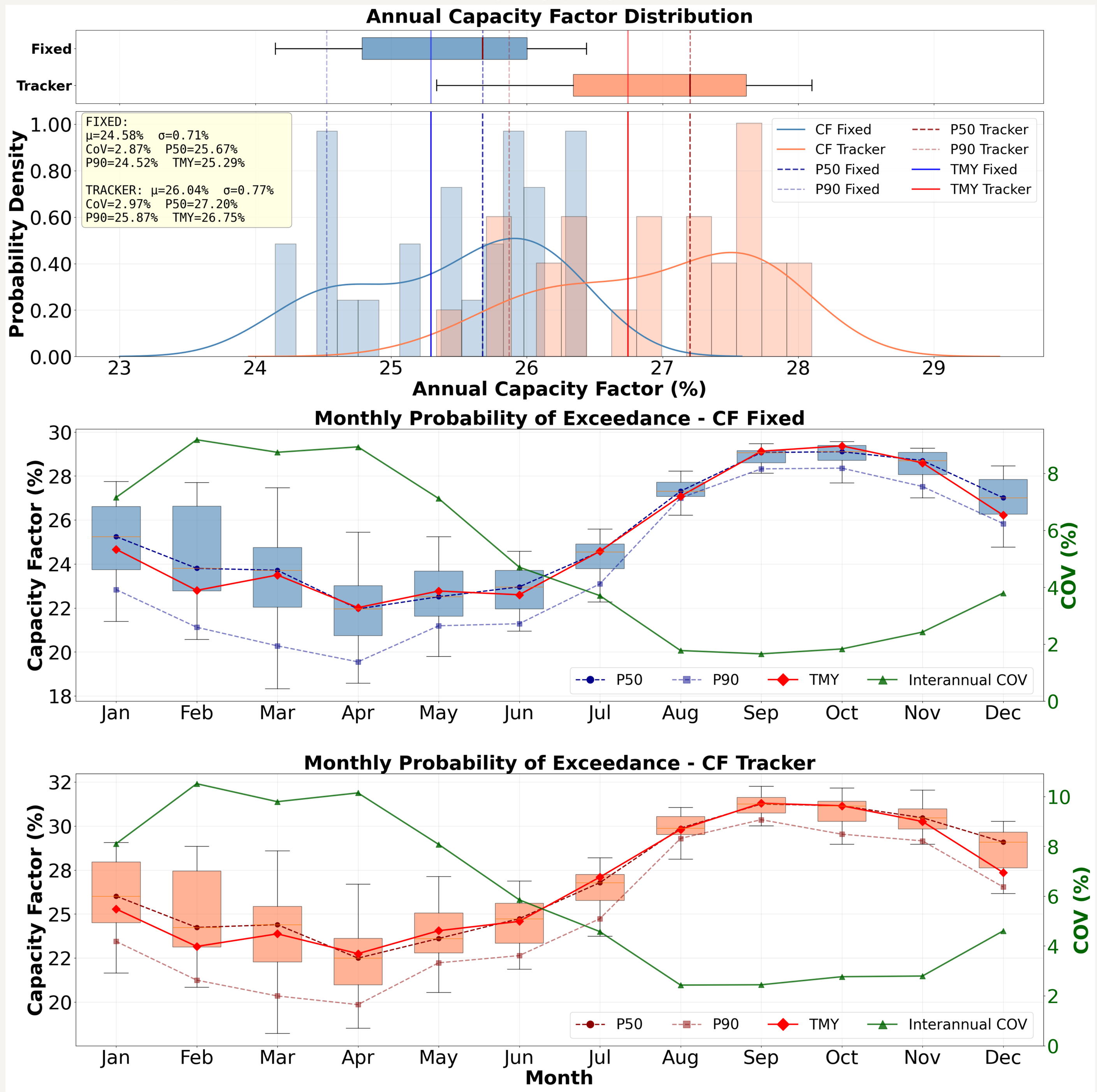

Figure 4: Monthly and Yearly Fixed and 1-Axis Tracker CF distributions.

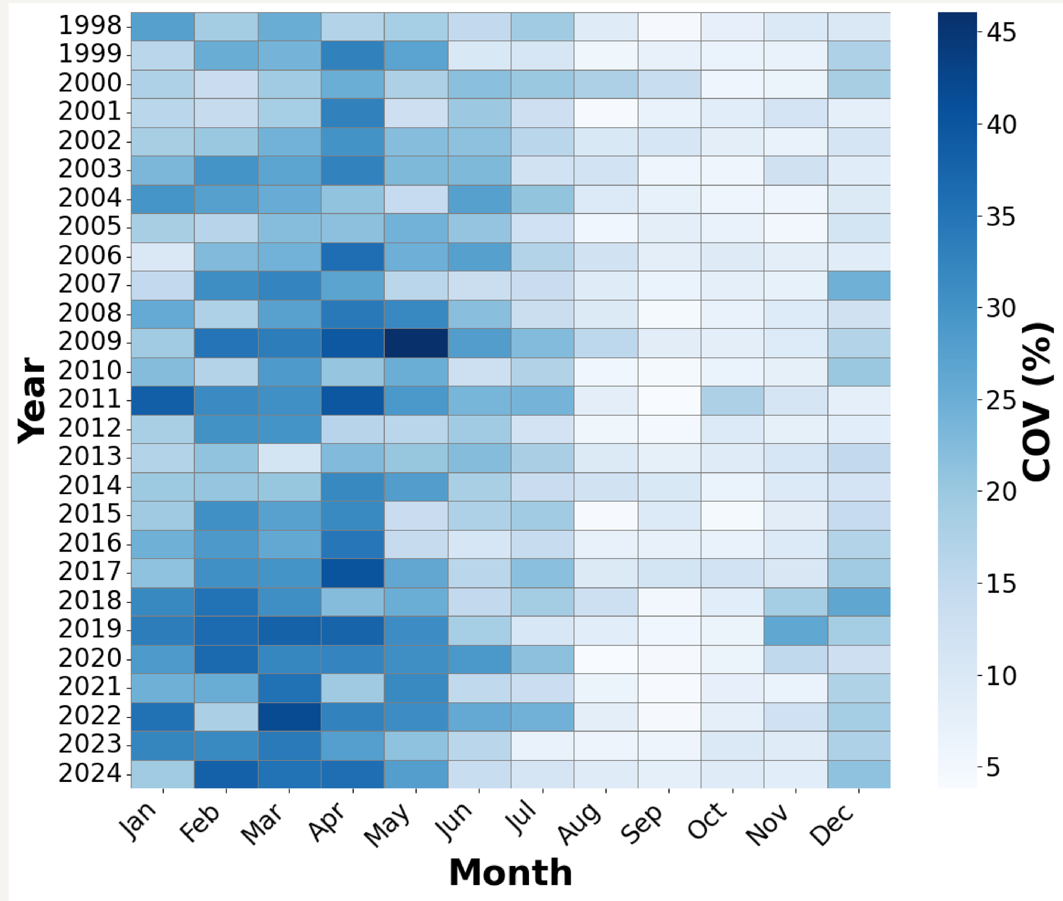

Figure 5: CF Tracker COV matrix heatmap.

- Comparing the CF from Fixed and 1-Axis Tracker PV Systems, despite the tracker gain of **5.24%**, it also brought more uncertainty (**~0.1 percentage points**).
- Monthly interannual variability shows string seasonality, with COV reaching as high as **8-10%** during lower-production months (mainly Jan-Apr) and dropping to **only 2-3%** during peak production month (Aug-Nov).
- A seasonal COV metric derived from monthly means better captures site-specific solar resource stability, improving yield comparisons across climates. Monthly performance guarantees and merchant revenue are more sensitive to seasonal resource structure than to annual average variability.

Table 1: Results summary from different locations.

Cities	KG Lat-Lon	Mean Yearly GHI (kWh/m²/year)	Fixed / Tracker Annual Mean CF	Tracker Gain	Worst Intra Monthly Mean COV	Worst Interannual Monthly COV	Fixed / Tracker Interannual COV of Yearly CF
Fortaleza	As (-3.73°, -38.52°)	2250	24.6 % / 25.9 %	5.2 %	29.4 % (Apr)	11.0 % (Feb)	2.9 % / 3.0 %
Petrolina	BSh (-9.39°, -40.50°)	2313	25.5 % / 27.0 %	5.8 %	20.6 % (Dec)	8.4 % (Jan)	2.9 % / 3.3 %
Salvador	Af (-12.97°, -38.47°)	2098	23.3 % / 24.3 %	4.3 %	30.6 % (May)	9.9 % (May)	2.5 % / 2.9 %
Brasília	Aw (-15.77°, -47.92°)	2076	23.1 % / 24.3 %	5.3 %	28.6 % (Nov)	11.9 % (Oct)	2.8 % / 3.1 %
Uberlândia	Cwa (-18.91°, -48.26°)	2076	23.1 % / 24.3 %	3.4 %	28.5 % (Nov)	10.7 % (Jan)	2.7 % / 3.0 %
Belo Horizonte	Cwb (-19.91°, -43.94°)	2025	22.5 % / 23.7 %	5.1 %	32.2 % (Nov)	13.9 % (Jan)	3.3 % / 3.8 %
Miami	Am (25.76°, -80.19°)	1928	21.5 % / 22.6 %	5.4 %	31.2 % (Dec)	11.2 % (Dec)	3.0 % / 3.2 %
El Paso	Bsh (31.77°, -106.46°)	2183	24.8 % / 26.4 %	6.7 %	27.9 % (Dec)	8.1 % (Oct)	2.1 % / 2.1 %
Albuquerque	BSk (35.10°, -106.62°)	2066	23.7 % / 25.1 %	6.2 %	31.6 % (Dec)	8.9 % (Oct)	1.5 % / 1.4 %
Seattle	Cfb (47.60°, -122.33°)	1283	14.8% / 15.2%	2.6 %	72.3 % (Dec)	21.0 % (Jan)	4.6 % / 4.8 %

Summary and Conclusions

- CF variability was analyzed for simulated 1 MWp bifacial fixed-tilt and 1-axis tracking PV systems across six Brazilian and four U.S. locations with distinct Köppen-Geiger climate classifications, demonstrating that long-term satellite-derived time-series provides a more robust basis than TMY alone for uncertainty quantification and financing risk assessment.
- Despite tracker CF gains of up to 6%, interannual variability increased by **0.1–0.5 percentage** points relative to fixed-tilt systems, reflecting a trade-off between energy gain and resource uncertainty.
- Seasonal COV analysis revealed location-dependent uncertainty patterns throughout the year, highlighting that site selection must account for seasonal resource structure and monthly uncertainty, as locations with similar annual GHI can present significantly different financial risk profiles.

REFERNCES: [1] Köppen Brasil, "Köppen climate classification for brazilian cities," GitHub Pages. [Online]. Available: https://koppenbrasil.github.io/. [Accessed: May, 2026].

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