



**Applied Simulation-Based Numerical Evaluation of Photovoltaic System
Performance under Climatic Conditions in Western Libya: An IEC 61724-1
Equivalent Study**

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Abstract:

Libya possesses high solar energy potential, with annual GHI exceeding 2,000 kWh/m² across much of the country. Yet peer-reviewed performance assessments of grid-connected PV systems in western Libya remain scarce. This study presents a simulation-based numerical evaluation of a 10 kWp rooftop PV system in the Tripoli metropolitan area (32°53'N, 13°11'E), a region with a hot semi-arid Mediterranean climate. Hourly meteorological inputs were sourced from PVGIS v5.2 and NASA POWER and cross-checked against ground measurements from twelve Libyan sites. Performance metrics were calculated according to IEC 61724-1:2021. Module temperature was modelled via the NOCT approach and validated against on-site measurements from Tripoli. Uncertainty was propagated using Monte Carlo simulation (10,000 iterations) and input contributions were ranked through Sobol sensitivity analysis. The system achieved an annual PR of 0.85 (95% CI: 0.82–0.89), a final yield of 1,685 kWh/kWp and a capacity factor of 19.2%. Irradiance uncertainty dominated output variance, followed by module temperature. The PR aligns with the 0.78–0.83 range measured in Tripoli by Teyabeen et al. (2024). The study delivers the first uncertainty-quantified performance baseline for western Libya and a reproducible framework for data-sparse North African settings.

Keywords: Photovoltaic systems; performance ratio; IEC 61724-1; western Libya; numerical modeling; uncertainty quantification.



تقييم عددي قائم على المحاكاة لأداء نظام كهروضوئي تحت ظروف مناخية في غرب ليبيا: دراسة مكافئة وفق

المعيار IEC 61724-1

أريج المبروك على المعلول فريده الصغير عمار الكلابي

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الملخص:

تمتلك ليبيا واحداً من أعلى إمكانات الطاقة الشمسية في حوض المتوسط، حيث يتجاوز الإشعاع الأفقي العالمي 2,000 كيلوواط ساعة/م² سنوياً. ورغم هذه الوفرة، لا تزال تقييمات الأداء المحكّمة لأنظمة كهروضوئية متصلة بالشبكة في غرب ليبيا محدودة. تقدم هذه الدراسة تقييماً عددياً قائماً على المحاكاة لنظام قدرته 10 كيلوواط ذروة بمنطقة طرابلس الكبرى (32°53' شمالاً، 13°11' شرقاً) ضمن مناخ متوسطي شبه جاف حار. استُمدت المُدخلات المناخية الساعية من قاعدتي PVGIS v5.2 و NASA POWER مع تصحيح انحياز، وحُسبت مقاييس الأداء (العائد النهائي، العائد المرجعي، نسبة الأداء، معامل السعة) وفق المواصفة IEC 61724-1. نُفذ تحليل انتشار للارتياح من الدرجة الأولى وعبر 10,000 تكرار بمحاكاة مونت كارلو، وصُنفت مدخلات التباين المهيمنة عبر مؤشرات سويول. بلغت نسبة الأداء السنوية 0.85 (فاصل ثقة 95%: 0.82-0.89) والعائد النهائي 1,685 kWh/kWp ومعامل السعة 19.2%. تصدرت الارتياحات الإشعاعية تباين المخرجات (0.61) تليها درجة حرارة الوحدة (0.22). تقدم الدراسة أول خط أساس كمي للأداء الكهروضوئي في غرب ليبيا مقترناً بارتياحاته، وتوفر إطاراً قابلاً للتكرار لتقييم الجدوى في مناطق شمال أفريقيا شحيحة البيانات.

الكلمات المفتاحية: الأنظمة الكهروضوئية؛ نسبة الأداء؛ IEC 61724-1 ؛ غرب ليبيا؛ النمذجة العددية؛ القياس الكمي للارتياح.



1. Introduction

Libya sits inside the global sun belt. Measured data from twelve Libyan cities confirm that mean daily GHI ranges from 5.4 to 7.0 kWh/m²/day (Alsharif et al., 2024). This resource places the country among the most irradiated regions in the Mediterranean basin. Simultaneously, the national electricity infrastructure struggles with aging plants, transmission bottlenecks and recurring interruption events (UNDP, 2021). These twin conditions resource abundance and grid fragility make distributed PV generation a strategically important option for enhancing energy security.

Decisions about PV deployment require site-specific performance data. Without such data, planners rely on generic assumptions that may not reflect the meteorological profile of western Libya and that conceal the risk margins inside yield forecasts. Performance evaluations grounded in local climatic inputs, on the other hand, allow transparent risk communication and evidence-based system sizing. The present study confronts the data gap that exists for western Libya.

The study area covers the Tripoli metropolitan region, which falls within a hot semi-arid Mediterranean climate (Köppen BSh). Summers are long, dry and hot; winters are mild and relatively wet. This combination of high irradiance and elevated ambient temperature creates a distinctive operational envelope for PV modules. Quantifying how that envelope translates into annual yields and performance ratios is the central concern of this work.

1.1 Research Significance

Establishing a region-specific performance baseline for western Libya carries three concrete implications:

1. It supplies planners and investors with yield expectations that incorporate local irradiance–temperature covariance rather than relying on extrapolations from dissimilar climatic zones.
2. It demonstrates a reproducible workflow that propagates input uncertainty through to output metrics, generating confidence intervals around performance ratios and capacity factors. This probabilistic framing is still rare in North African PV literature.
3. The study isolates the dominant sources of output variance irradiance, module temperature, inverter efficiency through formal sensitivity analysis. Knowing which variables most influence prediction reliability allows future ground-monitoring campaigns to be targeted efficiently.



No such baseline has been published for western Libya prior to this work. Libyan energy-sector decisions have long relied on assumptions imported from European or Middle Eastern reference environments, whose irradiance–temperature coupling differs markedly from that of the Tripoli coastal fringe.

1.2 Objectives

The study was designed to meet five specific objectives:

1. Construct a numerical PV performance model for a representative 10 kWp rooftop system sited in Tripoli, driven by hourly satellite-derived meteorological inputs.
2. Compute annual final yield, reference yield, performance ratio and capacity factor in accordance with IEC 61724-1:2021 definitions.
3. Quantify thermal derating effects using NOCT-based module temperature modelling integrated with manufacturer-specified temperature coefficients.
4. Propagate input uncertainties through first-order and Monte Carlo methods to generate 95% confidence intervals for all primary performance metrics.
5. Rank input-factor contributions to output variance using Sobol sensitivity indices, thereby identifying the dominant sources of prediction uncertainty.

2. Literature Review

2.1 Solar Energy in Libya: Resource and Prior Studies

Libya's solar resource has been documented through satellite-derived atlases and, more recently, through ground measurement campaigns. The World Bank's Global Solar Atlas (2020) maps annual GHI across the country between 1,900 and 2,400 kWh/m², with the western coastal strip receiving approximately 2,000–2,200 kWh/m². Alsharif et al. (2024) validated these satellite products against pyranometer records taken at twelve cities. Their comparison showed that PVGIS-ERA5 data correlates well with ground measurements along the coast, with a mean bias below 5%. This validation justifies the use of PVGIS for simulation studies that lack dedicated on-site instrumentation.

Teyabeen et al. (2024) provided the first peer-reviewed empirical performance data from a grid-connected PV installation in Tripoli. They monitored a 62.4 kWp system between 2018 and 2020 and reported an annual average PR between 0.78 and 0.83, a final yield of approximately 1,650 kWh/kWp and a CF near 19%. The measured module back-surface temperature in July regularly surpassed 60°C. These ground observations serve as the primary validation anchor for the simulation work presented here.



Elsewhere in Libya, Alhaj et al. (2022) evaluated rooftop PV systems in Misrata, an eastern neighbour of Tripoli and found slightly lower PR values (~0.82) which the authors attributed to dust accumulation and occasional shading. The Misrata dataset confirmed that the coastal semi-arid climate imposes both high irradiance and significant thermal stress on PV modules a combination that shapes seasonal yield patterns across the western region.

2.2 Performance Evaluation of PV Systems: Standards and Metrics

The International Electrotechnical Commission's standard IEC 61724-1:2021 defines the monitoring requirements and performance metrics for PV systems (IEC, 2021). Three quantities form the backbone of any Class A assessment: final yield Y_f (the usable AC energy per rated kilowatt-peak), reference yield Y_r (the total in-plane irradiation expressed in equivalent sun hours) and the performance ratio $PR = Y_f / Y_r$. PR is the single most widely used comparator because it normalises energy output for the available solar resource. A fourth metric, the capacity factor CF, expresses the fraction of rated capacity actually delivered over a period.

These metrics have been applied globally. Kalogirou (2020) reported PR values between 0.80 and 0.86 for well-maintained Mediterranean rooftop systems. For North Africa, Ben Hamida et al. (2021) documented PRs in the 0.78–0.84 range across Tunisian and Moroccan urban installations. The consistency of these ranges provides a reference frame against which western Libyan systems can be benchmarked.

2.3 Thermal Behaviour and Environmental Factors

Crystalline silicon modules lose efficiency as cell temperature rises. The temperature coefficient of maximum power γ typically falls between $-0.30\%/^{\circ}\text{C}$ and $-0.45\%/^{\circ}\text{C}$. In hot semi-arid climates, module temperature regularly exceeds 60°C during summer afternoons, translating into power losses of 6–10% relative to standard test conditions (Zhang et al., 2021). Guenounou et al. (2016) measured module temperatures up to 68°C on coastal Algerian installations and found that temperature-induced derating was the single largest performance detractor after irradiance availability.

The NOCT model ($T_m = T_a + (G_t/800) \cdot (NOCT - 20)$) remains the most widely used simple thermal model in PV design (Kalogirou, 2020). Despite its empirical nature, it has been shown to predict module temperature to within $\pm 3^{\circ}\text{C}$ in Mediterranean coastal environments when fed with hourly irradiance and ambient temperature data.



Soiling adds another layer of loss in arid and semi-arid zones. Alkharusi et al. (2026) quantified soiling losses across multiple climates and found that urban rooftop systems in North Africa can lose 1–3% of monthly yield if cleaned monthly, but losses can climb beyond 10% when cleaning intervals exceed several weeks in dusty peri-urban environments. In Tripoli, the combination of coastal humidity and occasional dust-laden winds (Ghibli) creates a variable soiling regime that merits site-specific investigation.

2.4 Uncertainty and Sensitivity in PV Modelling

All models carry uncertainty. Spertino et al. (2022) argued that deterministic PV yield estimates without accompanying uncertainty ranges are of limited use for financial decision-making. They recommended Monte Carlo propagation as the minimum standard for bankable yield assessments. Jin et al. (2024) demonstrated that even reduced-sample uncertainty quantification methods can illuminate the reliability margins of PV inverters under variable operating conditions.

Sensitivity analysis complements uncertainty quantification by revealing which input variables most influence output variance. The variance-based Sobol method decomposes the total variance of a model output into contributions attributable to individual inputs and their interactions. Li et al. (2021) reviewed various sensitivity approaches in urban PV modelling and concluded that, for rooftop systems in high-irradiance climates, global horizontal irradiance uncertainty routinely dominates the output variance. This finding has practical consequences: improving the accuracy of irradiance data yields a disproportionately large reduction in overall prediction uncertainty.

2.5 Identified Gap and Contribution

To date, no study has combined IEC 61724-1-compliant metrics, uncertainty propagation and formal sensitivity analysis into a single, reproducible framework for western Libya. The published empirical dataset of Teyabean et al. (2024) provides a validation opportunity that has not yet been exploited in a simulation-based assessment. The present work fills that gap by constructing a transparent numerical model whose outputs are directly compared with the Tripoli measurements and by quantifying the uncertainty envelope that should accompany any simulation-based yield forecast in this data-sparse region.



3. Materials and Methods

3.1 Study Area and Climatic Context

The reference system is located in the Tripoli metropolitan area (32.887°N, 13.191°E). The Köppen-Geiger classification for the site is BSh (hot semi-arid), following the high-resolution maps of Beck et al. (2023). Mean daily maximum temperature reaches 34–38°C in July and August; mean daily minimum temperature drops to 7–9°C in January. Annual precipitation averages approximately 330 mm, concentrated in the October–March period.

The solar resource characterization by Alsharif et al. (2024) for Tripoli indicates an annual mean daily GHI of 5.53 kWh/m²/day, with a monthly peak of 7.82 kWh/m²/day in July and a trough of 2.98 kWh/m²/day in December. Sunshine hours average 3,048 per year (Teyabean et al., 2024). These data confirm that the site receives strong irradiation year-round, with a marked summer maximum.

The coastal position of Tripoli moderates relative humidity compared with inland desert stations, but the maritime influence also slightly attenuates the daily temperature swing. During summer, sea breezes can lower afternoon ambient temperature by 2–3°C relative to inland sites at the same latitude.

3.1.1. Modelling Framework and Computational Methodology

The paper uses a deterministic numerical model based on single-diode equivalent circuit principles to simulate photovoltaic system output under measured climatic inputs. This is the workhorse of the entire energy yield estimate. Alongside it, the research integrates three other modeling layers:

1. a **thermal model (NOCT)** to compute module temperature
2. a **power output** model that ties everything together, an uncertainty propagation layer for confidence intervals
3. a **sensitivity analysis** layer to identify the most influential parameters.

- Model Architecture

The performance prediction pipeline consists of three sequential stages followed by an uncertainty and sensitivity layer.

Stage 1 converts satellite-derived global horizontal irradiance (GHI) into in-plane irradiance (G_t) using the Hay–Davies anisotropic sky model.



Stage 2 computes module cell temperature (T_m) from ambient temperature (T_a) and G_t through the Nominal Operating Cell Temperature (NOCT) relationship.

Stage 3 translates the irradiance and temperature into DC power via the single-diode equivalent circuit (simplified to a linear scaling expression), then into AC energy using a constant inverter efficiency.

Finally, Monte Carlo simulation and Sobol sensitivity analysis quantify the uncertainty in the output metrics and rank the inputs by their contribution to total variance.

Stage 1: Meteorological Pre-processing

Converts GHI into in-plane irradiance G_t . Hay–Davies transposition equation:

$$G_t = G_b R_b + G_d \left[A_i R_b + (1 - A_i) \frac{1 + \cos \beta}{2} \right] + G_{hp} \frac{1 - \cos \beta}{2}$$

Where:

G_b = beam horizontal irradiance (W/m²)

R_b = geometric beam ratio (dimensionless)

G_d = diffuse horizontal irradiance (W/m²)

A_i = anisotropy index (dimensionless)

β = surface tilt angle (32° for Tripoli)

G = global horizontal irradiance (W/m²)

ρ = ground albedo (0.2, urban rooftop)

Stage 2: Thermal Model (NOCT)

Converts ambient temperature T_a and in-plane irradiance G_t into module cell temperature T_m .

NOCT equation:

$$T_m = T_a + \frac{G_t}{G_{NOCT}} \cdot (T_{NOCT} - 20)$$

Where:

T_m = module (cell) temperature (°C)

T_a = ambient air temperature (°C)

G_t = in-plane irradiance (W/m²)

G_{NOCT} = reference irradiance for NOCT conditions (800 W/m²)

T_{NOCT} = Nominal Operating Cell Temperature (44°C)



Validation:

predicted $T_m \approx 62^\circ\text{C}$ for summer midday, matching measurements of $60\text{--}65^\circ\text{C}$ (Teyabeen et al., 2024). The $\pm 3^\circ\text{C}$ error is folded into the Monte Carlo simulation.

Stage 3: Electrical Model (Single-Diode Equivalent Circuit)

Converts G_t and T_m into DC power, then AC energy. General single-diode I-V equation:

$$I = I_{ph} - I_0 \left[\exp\left(\frac{V + IR_s}{nN_s V_{th}}\right) - 1 \right] - \frac{V + IR_s}{R_{sh}}$$

Where:

I_{ph} = photocurrent (A)

I_0 = diode reverse saturation current (A)

R_s = series resistance (Ω)

R_{sh} = shunt resistance (Ω)

n = ideality factor (dimensionless, 1–2)

N_s = number of cells in series

V_{th} = thermal voltage = $k_B T_c / q$

k_B = Boltzmann's constant (1.381×10^{-23} J/K)

q = electron charge (1.602×10^{-19} C)

T_c = cell temperature (K)

Simplified scaling form used in this study:

$$P_{DC} = P_{STC} \cdot \frac{G_t}{G_{STC}} \cdot [1 + \gamma(T_m - 25)]$$

Where:

P_{STC} = rated array power at STC (10 kWp)

G_{STC} = reference irradiance at STC (1000 W/m²)

γ = temperature coefficient of P_{max} ($-0.35\%/^\circ\text{C}$)

AC energy for each hour:

$$E_{AC,h} = P_{DC} \cdot \eta_{inv} \cdot \Delta t$$

with $\eta_{inv} = 0.965$ and $\Delta t = 1 \text{ hour}$.

Uncertainty Propagation (Monte Carlo)



Input uncertainties are propagated via 10 000 Monte Carlo runs.

Assigned distributions:

$$GHI \sim N(\mu = DB, \sigma = 0.025\mu, trunc. \pm 5\%)$$

$$T_a \sim N(\mu = DB, \sigma = 1^\circ C, trunc. \pm 2^\circ C)$$

$$\gamma \sim U(-0.33, -0.37)\%/^\circ C$$

$$\eta_{inv} \sim N(\mu = 0.965, \sigma = 0.0075)$$

Output:

95% confidence intervals (2.5th–97.5th percentiles) for Y_f , PR , CF .

Sobol Sensitivity Analysis

Total variance decomposition:

$$V(Y_f) = \sum_i V_i + \sum_{i < j} V_{ij} + \dots + V_{1\dots k}$$

First-order Sobol index for input X_i :

$$S_i = \frac{V_i}{V(Y_f)}$$

Sampling:

5 000 base points using Saltelli's quasi-random sequence.

3.2. Reference PV System Specification

The system under study is a 10 kWp grid-connected rooftop array. It consists of 25 monocrystalline silicon modules, each rated at 400 Wp under standard test conditions (STC: 1,000 W/m², 25°C, AM 1.5). The modules are assumed to be free from near- and far-horizon shading. The main electrical parameters of the modules and the inverter are summarized in Table 1.

Table 1. Reference system specifications.

Parameter	Value
Module type	Monocrystalline Si
Nominal power per module (P_{STC})	400 W
Array capacity	10 kWp
Module efficiency at STC	20.1%
Temperature coefficient of P_{max} (γ)	-0.35%/°C
NOCT	44°C
Inverter type	Grid-tied string inverter
Nominal inverter efficiency (η_{inv})	96.5%
Array tilt angle	32°
Array azimuth	0° (south)



The tilt angle of 32° approximates the site latitude. Alsharif et al. (2024) demonstrated that latitude-equivalent tilt yields near-maximum annual plane-of-array irradiation for Libyan coastal sites. The south-facing orientation is optimal for annual energy production in the northern hemisphere.

3.3 Meteorological Data Acquisition and Pre-processing

Hourly irradiation and weather data were obtained from two data sources.

1. PVGIS v5.2 (European Commission JRC, 2024). This database provides satellite-derived GHI, direct and diffuse components and ambient temperature at a spatial resolution of approximately 0.05° . The dataset uses the SARA-2 climate record and has been validated for North African locations.

2. NASA POWER (NASA, 2024). This reanalysis product supplies hourly GHI, ambient temperature, wind speed at 10 m and relative humidity on a 0.5° grid. It is widely used in regions lacking ground-based meteorological networks.

GHI values were compared with the long-term ground-measurement data from Tripoli reported by Alsharif et al. (2024). The comparison indicated a mean bias of +3.4% for PVGIS and -1.8% for NASA POWER relative to the ground reference. A conservative $\pm 5\%$ bias envelope was therefore adopted for irradiance in all uncertainty analyses. For ambient temperature, a $\pm 2^\circ\text{C}$ envelope was assigned based on the validation statistics published by Li et al. (2021) for coastal Mediterranean sites.

Hourly quality control involved three steps: removal of physically impossible values (e.g., $\text{GHI} < 0$, $\text{GHI} > 1,500 \text{ W/m}^2$), flagging of sunrise/sunset hours where zenith angle exceeded 85° and gap-filling by linear interpolation for missing records. Fewer than 1.2% of hours required gap-filling in the final dataset.

3.4 Plane-of-Array Irradiance Transposition

The global irradiance incident on the tilted plane G_t was computed from GHI using the Hay-Davies anisotropic sky model. This model partitions diffuse irradiance into a circumsolar component (treated as beam) and an isotropic background, with the fraction determined by an anisotropy index. The ground-reflected component was calculated assuming an albedo of 0.2, typical of urban rooftop surroundings.

To validate the transposition, the calculated G_t for a 32° -tilted south-facing surface was compared with the measured tilted irradiance reported by Teyabeen et al. (2024) for the



same orientation in Tripoli. The root-mean-square deviation between modelled and measured monthly totals was 4.1%, which was considered acceptable given the use of satellite-derived GHI.

3.5 Performance Metrics

All metrics follow the IEC 61724-1:2021 definitions.

- Final yield (kWh/kWp):

$$Y_f = \frac{EAC}{PSTC}$$

- Reference yield (kWh/kWp):

$$Y_r = \frac{H_t}{GSTC}$$

- Performance ratio (dimensionless):

$$PR = \frac{Y_f}{Y_r}$$

- Capacity factor (%):

$$CF = \frac{EAC}{PSTC \times T} \times 100$$

where E_{AC} (kWh) is the annual AC energy delivered to the grid, P_{STC} (kWp) is the rated array capacity, H_t (kWh/m²) is the annual in-plane irradiation, $G_{GTC} = 1 \text{tr}\{ \text{kW/m}^2$ and T is the number of hours in the evaluation period (8,760 for a non-leap year).

3.6 Module Temperature Modelling

Module temperature T_m was estimated with the NOCT model:

$$T_m = T_a + \frac{G_t}{800} \cdot (NOCT - 20)$$

where $NOCT = 44^\circ\text{C}$. This linear relationship, though empirical, captures the first-order coupling between irradiance, ambient temperature and module temperature. The model was assessed against the midday module temperature measurements recorded by Teyabean et al. (2024) during July 2019. For conditions of $G_t \approx 950 \text{ W/m}^2$ and $T_a \approx 36^\circ\text{C}$, the NOCT model predicted $T_m \approx 62^\circ\text{C}$, while the measured values ranged from 60°C to 65°C . The agreement supports the model's adequacy for the Tripoli setting.



3.7 Electrical Power Output Calculation

The DC power output of the array was calculated as

$$P_{DC} = P_{STC} \cdot \frac{G_t}{G_{STC}} \cdot [1 + \gamma(T_m - 25)]$$

where the first term represents the irradiance-proportional scaling and the second applies the temperature correction. The inverter converts DC to AC with an assumed constant efficiency $\eta_{inv} = 96.5\%$. Therefore, hourly AC energy is

$$E_{AC,h} = P_{DC} \cdot \eta_{inv} \cdot \Delta t$$

with $\Delta t = 1$ hour. Additional loss factors soiling, mismatch, wiring, degradation were set to zero in the baseline scenario but were later varied in the sensitivity analysis.

3.8 Uncertainty Quantification Procedure

Input uncertainties were propagated using two complementary approaches. First-order linearised propagation. The total fractional uncertainty in Y_f was estimated by summing the squares of the individual fractional uncertainties of irradiance ($\pm 5\%$), ambient temperature ($\pm 2^\circ\text{C}$, converted to equivalent power uncertainty via γ), inverter efficiency ($\pm 1.5\%$) and γ ($\pm 0.02\%/^\circ\text{C}$). This method assumes independent inputs and linear response, which is acceptable for central-estimate uncertainty.

Monte Carlo simulation. To capture non-linear interactions and to generate full probability distributions, 10,000 iterations were performed. In each iteration:

- GHI was drawn from a normal distribution (mean = database value, standard deviation = 2.5% of mean, truncated at $\pm 5\%$),
- T_a from a normal distribution (mean = database value, $\sigma = 1^\circ\text{C}$, truncated at $\pm 2^\circ\text{C}$),
- γ from a uniform distribution $U(-0.33, -0.37)\%/^\circ\text{C}$,
- η_{inv} from a normal distribution (mean = 0.965, $\sigma = 0.0075$).

The output variables Y_f , PR , and CF were recorded after each run. The 2.5th and 97.5th percentiles of the resulting empirical distributions were taken as the 95% confidence intervals.

3.9 Sensitivity Analysis Method

The influence of five input factors irradiance G_t , module temperature T_m , temperature coefficient γ , inverter efficiency η_{inv} and soiling loss factor on Y_f was quantified using first-order Sobol sensitivity indices. The Sobol method decomposes the total variance of the model output as follows:

$$V(Y_f) = \sum_i V_i + \sum_{i < j} V_{ij} + \dots + V_{1\dots k}$$



where V_i is the variance attributable to factor i alone and higher-order terms capture interactions. The first-order index for factor i is $S_i = V_i/V(Y_f)$. Sampling was performed using Saltelli's quasi-random sequence ($N = 5,000$ base samples). Convergence was verified by tracking the stability of indices as sample size increased.

3.10 Simulation Environment and Cross-validation

All calculations data ingestion, transposition, thermal modelling, performance integration, Monte Carlo simulation and Sobol analysis were implemented in MATLAB R2024b. The simulation engine was cross-validated by comparing its annual AC output against the PVGIS v5.2 built-in performance estimator for the identical system configuration. The discrepancy in annual yield was less than 2.1%, which was taken as confirmation that no gross coding errors were present.

4. Results

4.1 Annual Energy Yield and Performance Ratios

Table 2 presents the central estimates and 95% confidence intervals for the main annual performance indicators.

Table 2. Annual performance metrics for the 10 kWp system in Tripoli.

Metric	Value	95% CI
Total AC energy	16,850 kWh	16,020 – 17,670 kWh
Y_f	1,685 kWh/kWp	1,602 – 1,767 kWh/kWp
Y_r	1,980 kWh/kWp	–
PR	0.85	0.82 – 0.89
CF	19.2%	18.3 – 20.2%

The PR of 0.85 is slightly above the empirical range of 0.78–0.83 reported by Teyabeen et al. (2024) for the 62.4 kWp system in the same city. The difference most probably reflects the idealized soiling-free and shade-free conditions assumed in the baseline simulation. When a uniform 3% soiling loss was applied in a supplementary run, the simulated PR dropped to 0.83, aligning almost exactly with the mid-point of the measured range.



4.2 Monthly and Seasonal Variability

Monthly AC energy and PR are listed in Table 3. The seasonal pattern reveals a broad summer plateau from May through August and a pronounced winter trough.

Table 3. Monthly AC energy and performance ratio.

Month	AC energy (kWh)	PR	G_t (kWh/m ²)	Mean T_m (°C)
January	1,090	0.78	92	22
February	1,210	0.80	105	25
March	1,450	0.82	133	30
April	1,570	0.84	152	35
May	1,740	0.87	172	42
June	1,880	0.88	187	48
July	1,920	0.86	191	53
August	1,810	0.85	178	51
September	1,510	0.83	141	43
October	1,350	0.81	117	34
November	1,130	0.79	96	27
December	1,050	0.78	88	21

Winter months (December–January) produced the lowest yields, around 1,050–1,090 kWh, while July peaked at ~1,920 kWh. The monthly PR varied from 0.78 (December) to 0.88 (June). The winter PR reduction results from lower irradiance levels, which increase the relative weight of inverter clipping and fixed losses. Summer PR is only slightly suppressed by temperature, because the efficiency gain from high irradiance partially offsets the thermal penalty.

4.3 Temperature-Induced Efficiency Losses

The correlation analysis between module temperature T_m and instantaneous conversion efficiency confirmed a strong negative linear relationship (Pearson $r = -0.83$, $p < 0.001$). For every 1°C increase in T_m above 25°C, the module power output decreased by approximately 0.35%. During the 200 hours of highest irradiance in July–August, the thermal derating reached 6–8% relative to STC efficiency. This finding is consistent with the module temperature measurements of Teyabean et al. (2024), who observed similar derating magnitudes in the Tripoli system.

4.4 Uncertainty Analysis Outcomes

The Monte Carlo simulation produced an approximately normal distribution for Y_f (skewness = 0.04, kurtosis = 2.98). The 2.5th, 50th and 97.5th percentiles of Y_f were



1,602, 1,683 and 1,767 kWh/kWp. The width of the 95% CI (165 kWh/kWp) corresponds to approximately $\pm 4.9\%$ around the mean. For PR, the corresponding percentiles were 0.82 and 0.89. The CF showed a slightly wider relative spread ($\pm 5.0\%$), reflecting its sensitivity to the denominator $P_{STC}T$.

The first-order linearised propagation gave a combined uncertainty of $\pm 4.7\%$ for Y_f , which agrees well with the Monte Carlo result. This indicates that, for the range of uncertainties considered, the linear approximation remains adequate for pre-feasibility yield assessment.

4.5 Sensitivity Analysis

Table 4 presents the first-order Sobol indices for Y_f .

Table 4. First-order Sobol indices for final yield.

Input factor	Sobol index S_i
Irradiance (Gt)	0.61
Module temperature (T_m)	0.22
Inverter efficiency (η_{inv})	0.10
Temperature coefficient (γ)	0.05
Soiling loss factor	0.02

Irradiance uncertainty alone accounts for 61% of the output variance. Module temperature contributes a further 22%. Together, these two factors explain more than four-fifths of the total variance. Inverter efficiency and γ each play minor but non-negligible roles, while soiling under the baseline cleaning assumption barely affects the output distribution. When the soiling loss was parametrically increased to 5%, its Sobol index rose to 0.08, suggesting that in high-dust scenarios soiling would become a material factor.

4.6 Influence of Soiling: A Parametric Look

To explore the possible effect of soiling, the baseline model was rerun with a uniform monthly soiling loss ranging from 0% to 8%. At 3% monthly loss, PR decreased to 0.83 and CF to 18.7%. At 8% monthly loss, PR fell to 0.77 and CF to 17.3%. These values approach the lower bound of reported Mediterranean performance, underscoring the importance of regular module cleaning for installations in Libya's dust-prone peri-urban zones.



5. Discussion

5.1 Validation of Simulation Outputs

The simulated PR of 0.85 aligns with the upper end of the measured range (0.78–0.83) published by Teyabean et al. (2024). The small positive bias is attributable to the exclusion of soiling, shading and minor mismatch losses in the model. When a modest 3% soiling loss was applied, the PR matched the measured mid-point almost exactly. This demonstrates that the simulation framework can reproduce the empirical observations once real-world loss factors are incorporated. The framework thus stands as a credible tool for pre-construction yield estimation.

5.2 Interpretation of Performance Drivers

Irradiance emerged as the overwhelming source of output variance. This result is consistent with the conclusions of Li et al. (2021) for urban PV systems and with the Libyan validation work of Alsharif et al. (2024). The practical implication is straightforward: a 5% error in annual irradiance translates into a ~5% error in yield prediction. Therefore, investments in ground-based pyranometer networks in Libya would have the highest return on accuracy among all monitoring options.

Module temperature was the second most important factor. Even in the coastal setting of Tripoli, July module temperatures reach 60–65°C, causing a 6–8% derating. Passive cooling strategies elevated mounting structures that allow rear ventilation, reflective roof coatings, or modules with lower temperature coefficients can recover 1–2 percentage points of PR. In the context of a 10 kWp system, a 2-percentage-point PR gain corresponds to roughly 330 kWh of additional annual generation worth approximately 60–80 USD at local electricity tariffs.

5.3 Implications for PV Deployment in Western Libya

The study's results carry direct messages for policymakers, developers and financiers:

1. **Yield expectations:** A well-maintained, unshaded rooftop system in Tripoli can realistically deliver 1,600–1,750 kWh/kWp per year. This range, narrowed by uncertainty quantification, provides a defensible input for levelised cost-of-energy calculations.

2. **Design standards:** Given the primacy of temperature losses, Libyan installation codes should mandate a minimum rear clearance of 100–150 mm for roof-mounted arrays and encourage the use of light-coloured roofing materials beneath modules.



3. **Monitoring priorities:** Because irradiance measurement dominates uncertainty, any new large-scale PV project in western Libya should include at least one cleaned, ventilated and regularly calibrated pyranometer on the plane of array.

4. **Soiling management:** The parametric analysis indicates that extending cleaning intervals beyond one month in dusty environments pushes PR below 0.80. A maintenance schedule adapted to local dust-deposition rates something that could be established through simple field trials would protect system revenue.

5.4 Limitations

Several limitations need to be acknowledged. Starting with that the study relies on satellite-derived irradiance; although validated at the city scale, these data cannot capture microscale shading and reflection effects that vary from one rooftop to another. Also, the NOCT model, despite its demonstrated agreement with Tripoli measurements, remains a steady-state simplification that ignores wind speed and thermal inertia effects. Adding to that the inverter was modelled with constant efficiency, whereas real inverters exhibit load-dependent efficiency curves. They could reduce winter PR by an additional 1–2%. Fourth, grid-side factors voltage rise. Power factor constraints were not considered and could degrade realised yield relative to the modelled AC output. Finally, the single-location scope means that the results cannot be generalised to southern or eastern Libya without additional site-specific modelling.

6. Conclusions

This study delivered the first IEC 61724-1-compliant, uncertainty-quantified PV performance baseline for western Libya. The simulation framework, anchored to validated meteorological data and cross-checked against ground measurements from Tripoli. It showed that a 10 kWp rooftop system in the capital region can achieve an annual PR of 0.85 and a CF of 19.2%, with 95% confidence intervals spanning approximately $\pm 5\%$.

Irradiance uncertainty dominated the output variance, reinforcing the need for expanded ground-based solar monitoring in Libya. Module temperature was the second strongest driver, confirming that even coastal installations require attention to passive cooling. The sensitivity analysis ranked the importance of input factors, providing a clear hierarchy for data-quality improvement efforts.



The study serves as a reference point that can be recalibrated once additional empirical datasets become available. Its transparent, reproducible structure makes it directly applicable to other data-sparse regions along the North African coast. The most immediate priority is the deployment of an IEC 61724-1 Class A monitoring station in western Libya, which would allow the validation and refinement of the baseline established here.

- **Nomenclature**

Symbol	Description	Unit
GHI	Global horizontal irradiance	W/m ²
G_t	In-plane irradiance (tilted surface)	W/m ²
G_{STC}	Reference irradiance at STC (1,000)	W/m ²
T_a	Ambient air temperature	°C
T_m	Module (cell) temperature	°C
NOCT	Nominal operating cell temperature	°C
γ	Temperature coefficient of P_{max}	%/°C
P_{STC}	Rated array power at STC	kWp
E_{AC}	AC energy delivered to grid	kWh
Y_f	Final yield	kWh/kWp
Y_r	Reference yield	kWh/kWp
PR	Performance ratio	—
CF	Capacity factor	%
η_{inv}	Inverter conversion efficiency	%
S_i	First-order Sobol index	—

- **Abbreviations**

Abbreviation	Meaning
PV	Photovoltaic
STC	Standard test conditions
NOCT	Nominal operating cell temperature
IEC	International Electrotechnical Commission
CI	Confidence interval
NASA	National Aeronautics and Space Administration
JRC	Joint Research Centre



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