

Stochastic–dynamic Modelling of Performance Degradation in a Grid-connected Rooftop Photovoltaic System

Dani Yuniawan^{1,*}, Vetty Kartikasari¹, Rahman Arifuddin², & Effendi Mohamad³

¹Department of Industrial Engineering, Faculty of Engineering, Universitas Merdeka Malang, Jalan Terusan Raya Dieng No. 62-64, Malang 65146, East Java, Indonesia

²Department of Electrical Engineering, Faculty of Engineering, Universitas Merdeka Malang, Jalan Terusan Raya Dieng No. 62-64, Malang 65146, East Java, Indonesia

³Faculty of Industrial and Manufacturing Technology and Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

*Corresponding author: dani.yuniawan@unmer.ac.id

Abstract

This study investigates the effects of climatic variability and long-term module degradation on the technical performance of a 100-kWp grid-connected rooftop photovoltaic system installed on a university campus in a humid tropical climate. A 65-month observational dataset covering January 2020 to May 2025 was combined with 10,000 Monte Carlo iterations and a dynamic feedback model to estimate energy yield, performance ratio (PR), and performance degradation over a 25-year operating period. The simulated annual energy yield ranged from 111 to 129 MWh yr⁻¹ (P10–P90), with a median specific yield of approximately 1,200 kWh kWp⁻¹ yr⁻¹, while the PR remained within 0.75–0.80. A literature-informed two-stage degradation scenario—0.55% yr⁻¹ during Years 1–10 and 1.00% yr⁻¹ during Years 11–25—resulted in an estimated cumulative energy loss of 8.7% relative to the no-degradation baseline. Sobol sensitivity analysis identified the PR residual as the dominant contributor to annual energy-yield variance, followed by irradiance, temperature, and degradation. By preserving irradiance–temperature dependence through paired bootstrap resampling and incorporating time-dependent degradation, the proposed framework provides a more realistic representation of both short-term uncertainty and long-term performance decline. Applications to other humid tropical locations require site-specific inputs and independent validation.

Keywords: campus rooftop pv; degradation modelling; energy yield uncertainty; monte carlo simulation; performance ratio; stochastic-dynamic modelling; tropical climate.

Introduction

The speed of the global transition toward low-carbon energy systems has positioned solar photovoltaic (PV) technology as a strategic component in distributed energy generation and institutional decarbonisation. University campuses in emerging economies, such as Indonesia, are particularly valuable due to their concentrated diurnal load profiles, long asset lifecycles, and alignment with the national renewable energy targets (Tarigan, 2024; Wenten et al., 2024; Wongwan et al., 2024).

Rooftop PV (rPV) systems operating in humid tropical regions are plagued by many technical uncertainties. More specifically, high variability in solar resources due to monsoon dynamics, high ambient temperatures, and persistent humidity collectively influence instantaneous energy output, performance ratio (PR), and long-term degradation behaviour (Islam et al., 2024; Mohamad Radzi et al., 2025; Yadav et al., 2025). Apart from that, temperature-induced efficiency losses and moisture-related degradation mechanisms are important in humid tropical regions as they produce site-specific degradation patterns (Atia et al., 2023; Rajput et al., 2024; Hasan et al., 2026). Conventional feasibility studies use single-year meteorological data and constant PR assumptions to deterministically assess PV performance. However, these studies often underestimate energy yield uncertainty and the risks of long-term environmental exposure (International Energy Agency Photovoltaic Power Systems Programme [IEA PVPS], 2020; Prilliman et al., 2023). Contemporary stochastic PV modelling uses Monte Carlo (MC) simulation to integrate climatic and operational uncertainties into probabilistic energy yield assessments (Al-Hanoot et al., 2025; Prilliman et al., 2023). However, these

studies are temporally static as they assess short-term climate variability independently from the dynamics of long-term system degradation. This not only limits their ability to capture the cumulative interactions between climate variability and temperature-driven efficiency losses, but system degradation over multiple decades of operations. As such, system-dynamics approaches are increasingly used in energy transition planning (Chayjan et al., 2024) as they explicitly represent the feedback structures and cumulative effects required to model the evolution of system degradation and capacity. Nevertheless, campus-scale PV performance assessments do not integrate MC-based stochastic uncertainty propagation into dynamic degradation modelling. To date, correlation-preserving bootstrap resampling of tropical the National Aeronautics and Space Administration's (NASA) Prediction of Worldwide Energy Resources (POWER) data has not been integrated with a two-stage dynamic degradation scenario (2S-DDS) for campus-scale rPV assessments. This methodological gap facilitates producing probabilistic performance frameworks that can be applied at campuses in developing economies. Apart from that, degradation-responsive and reliability-oriented models indicate that static representations become invalid as system degradation evolves. Therefore, environmental exposure and degradation must be modelled as time-dependent processes (Shen et al., 2025; Kladas et al., 2025).

Reliable solar resource characterisation is fundamental for probabilistic modelling. Satellite-derived datasets, such as the NASA POWER database, provide useful and accurate location-dependent data for energy yield assessments in regions that do not have long-term ground data (Harsarapama et al., 2020; Mutlu, 2025). Nevertheless, the uncertainty arising from the choice of climatic data and its statistical treatment must be explicitly acknowledged in the modelling framework to avoid implicit bias in energy yield estimations. University campuses in humid tropical regions are analytically valuable sites at which to examine hybrid models that integrate stochastic climatic variability with dynamic performance evolution. In Indonesia, the rPV framework is governed by the Ministry of Energy and Mineral Resources' (MEMR) Regulation No. 2/2024, which replaced Regulation No. 26/2021 and places greater emphasis on quota-based approval and on-site use of the generated energy (MEMR, 2024). This changed the operational plans outlined in the Regulation No. 26/2021 (Tarigan, 2024). It is, therefore, essential to develop performance evaluation frameworks that integrate uncertainty quantification, degradation analysis, and reliability considerations to support long-term investments and operational planning (IEA PVPS, 2020; Obatola & Junjie, 2024).

The present study addressed this research gap by proposing a hybrid stochastic-dynamic framework with which to evaluate the long-term technical performance of a 100-kWp grid-connected rPV system installed at a university campus in a humid tropical region. The proposed framework integrates (1) multi-year satellite-derived solar-based meteorological data (Harsarapama et al., 2020; Mutlu, 2025) with dependence-preserving climate resampling (Zheng et al., 2025), (2) temperature-dependent PR modelling that is consistent with empirical PV behaviour in high thermal stress conditions (Islam et al., 2024; Qu et al., 2024), (3) MC simulation to probabilistically estimate annual energy yields (Al-Hanoot et al., 2025; Prilliman et al., 2023), and (4) a 2S-DDS of PV system performance in its early phase and its decline in the degradation phase in humid tropical regions (Atia et al., 2023; Mohamad Radzi et al., 2025). By correlating stochastic climate drivers with time-dependent degradation mechanisms, the proposed framework outperforms conventional deterministic and static probabilistic approaches as it facilitates physically-consistent propagation of uncertainty across both short-term operational variabilities and long-term degradation dynamics. The resulting probabilistic-dynamic representation provides engineering-relevant indicators of reliability and yields a more realistic performance estimation of PV systems in humid tropical regions.

The present study is scientifically novel due to three distinct contributions. Firstly, it developed a correlation-preserving paired bootstrap resampling strategy that maintains the empirical irradiance-temperature covariance. This prevents artificial decorrelation from occurring, which would skew the results of the temperature-dependent performance modelling. It is also unlike extant stochastic PV studies that treat global horizontal irradiance (GHI) and ambient temperature as independent, random variables. Secondly, it directly embedded a 2S-DDS into the probabilistic MC structure. This enabled both short-term climate variability and long-term degradation uncertainty to consistently propagate in a single computational framework. Lastly, it built a modelling architecture that can be applied to PV systems in humid tropical regions. As such, it is a reproducible and scalable tool that can be used to assess campus-scale PV performance in developing economies.

Materials and Methods

The present study proposed a hybrid stochastic-dynamic modelling framework comprising three sequential stages, namely, stochastic characterisation of tropical solar resources (Stage A), probabilistic PV energy yield modelling via MC simulation (Stage B), and dynamic long-term performance evolution that takes degradation and reliability feedbacks into consideration (Stage C). The proposed architecture ensures direct mapping between climate variabilities,

behaviours in the 2S-DDS, and explicit uncertainty propagation, which is consistent with the recent PV performance assessment practices in humid tropical regions (Islam et al., 2024; Mohamad Radzi et al., 2025; Rajput et al., 2024).

Figure 1 depicts the proposed framework and the flow of information between the three stages. As seen, Stage A establishes the empirical stochastic drivers based on multi-year satellite-derived solar-based meteorological data, then in Stage B, it uses MC simulation to propagate climatic and operational uncertainty into the probabilistic energy yield distributions. Lastly, in Stage C, it embeds the stochastic outputs into a dynamic representation of the PV system to estimate its long-term performance and degradation. The proposed three-stage framework aligns with the current practice in PV engineering, in which probabilistic energy yield assessments, P10–P90 risk indicators, and lifetime performance metrics are increasingly prioritised (IEA PVPS, 2020; Prilliman et al., 2023; Al-Hanoot et al., 2025).

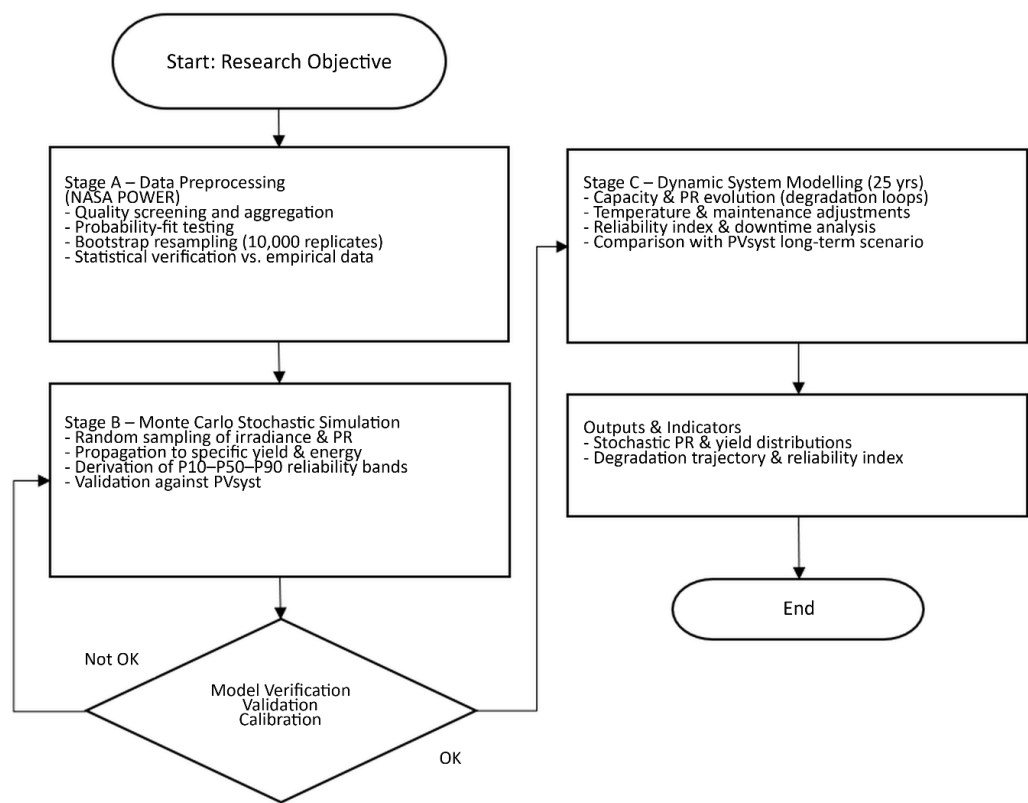


Figure 1 The proposed hybrid stochastic-dynamic framework for assessing the technical performance of a grid-connected rPV system at a university campus in a humid tropical region.

Study Site and PV System Configuration

The present study examined a 100-kWp grid-connected rPV system at Universitas Merdeka Malang (UNMER) in Indonesia (7.96°S, 112.62°E), which is located in a humid monsoon-prone tropical region. According to the site-specific information from the NASA POWER database, the region has high relative humidity, pronounced seasonal cloud cover, and persistently elevated ambient temperatures. The PV module is mounted on the rooftop of a campus building. Its installed capacity was set to remain within the transformer’s limits while matching the campus’ energy demands. This is consistent with existing campus-scale rPV systems in Southeast Asia (Tarigan, 2024; Wongwan et al., 2024).

The grid-connected rPV system operates without battery storage, which is common among rPV systems at university campuses and matches the configurations used for the PVsyst-based validation in the present study (Ates & Singh, 2021; Khan et al., 2022; Shukla et al., 2024). The methodological boundary was restricted to technical performance and degradation assessments. Economic optimisation, tariff design, and policy-scenario analysis were not examined to avoid conflating techno-economic uncertainty with climatic variability and degradation dynamics. Nevertheless, future studies may examine these aspects as they are relevant under the current MEMR Regulation No. 2/2024 and its transitional provisions (MEMR, 2024). The performance indicators evaluated were annual and lifetime energy yield, PR, degradation estimations, and risk metrics, namely, the P10, P50, and P90 probabilistic thresholds. These align with the current best practice for PV-based energy yield and uncertainty assessments (IEA PVPS, 2020; Prilliman et al., 2023).

Stage A - Solar Resource Data and Pre-processing

Stage A characterises the stochastic variability of the solar resource at the study site and prepares the irradiance-temperature inputs for the probabilistic energy yield modelling. The hourly solar-based meteorological data from 2020–2025 were obtained from the NASA POWER database for the coordinates of UNMER (7.96°S, 112.62°E). This included the GHI, diffuse horizontal irradiance, direct normal irradiance, near-surface air temperature, wind speed, and relative humidity. Although the NASA POWER database provides useful GHI and temperature inputs for renewable-energy assessments in regions where long-term ground data is limited, its accuracy remains location- and variable-dependent (Harsarapama et al., 2020; Mutlu, 2025). An hourly file of the location of the rPV system was extracted via the POWER Data Access Viewer and labelled “NASA_POWER_Malang_2020_2025_hourly_PVsyst.csv”. It comprised data from 1 January 2020 to 30 May 2025 and contained 49200 hourly records pre-quality control. Implausible values, such as a negative GHI or irradiance beyond the extra-terrestrial limits, as well as missing entries flagged as –999 were removed. This yielded a total of 47448 records (96.4%) for the annual aggregation and bootstrap resampling.

Table 1 provides a summary of the key characteristics of the data. As seen, it spanned six calendar years (2020–2025) and yielded 65 months of observational data as the record stop on 30 May 2025. When the annual totals were calculated using Eq. (1), 2025 was entered as a partial year of observation and was confined to the bootstrap pool. Its annual GHI was derived only from the available January to May data and it was explicitly flagged as a partial year estimate. This method yielded the broadest possible observational base for the bootstrap resampling, while ensuring that the decreased seasonal coverage of the Year 2025 was apparent.

Table 1 Data characteristics

Parameter	Description	Value
Data source	NASA POWER database	Accessed 2025
Primary file	NASA_POWER_Malang_2020_2025_hourly_PVsyst.csv	49,200 records
Coordinates	Latitude, Longitude	7.96°S, 112.62°E
Valid data period	After quality control	2020-01-01 to 2025-05-30
Temporal resolution	Hourly average	24 obs./day
Key variables	GHI (W·m ⁻²), T2M (°C)	NASA POWER standard
Data completeness	Valid records	96.4% (47,448/49,200)

The raw hourly irradiance data was first aggregated into daily totals, then annual totals to present the inter-annual solar variability in a form that was suitable for engineering applications and PV feasibility analysis (Dobos et al., 2012; IEA PVPS, 2020). Eq. (1) was used to compute the annual GHI H_t from the daily GHI:

$$H_t = \sum_{d=1}^{D_t} GHI_{t,d} \quad (1)$$

where H_t is the aggregated GHI (kWh m⁻²), $GHI_{t,d}$ is the daily GHI on day (d), and D_t is the number of valid daily observations available in the calendar year (t). The full year totals were calculated from between 2020–2024. However, as the record stops on 30 May 2025, its sum was treated as a partial year and was not extrapolated or directly compared with the full year totals.

Figure 2 depicts the pseudo-day index. As seen, the valid daily observations from between 1 January 2020 to 30 May 2025 were concatenated. Therefore, 65 months of temporal variability were displayed without implying that it was a complete six-year record. The P10, P50, and P90 probabilistic thresholds served as the empirical daily-GHI reference quantiles, which were calculated from the available observations.

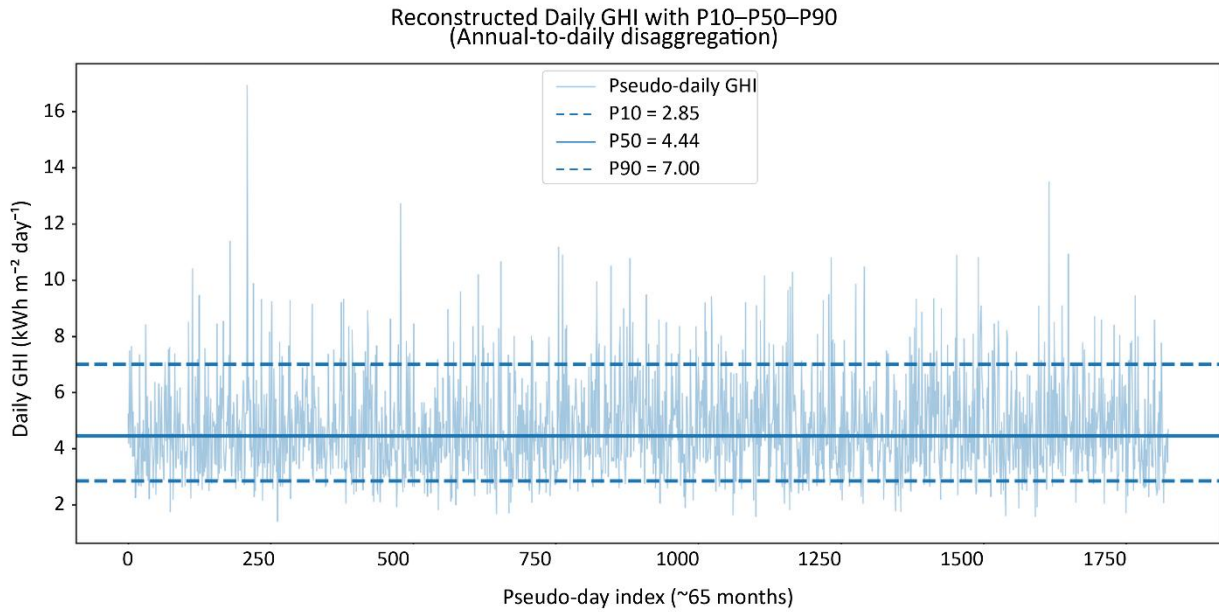


Figure 2 The reconstructed daily GHI sequence at UNMER from 1 January 2020 to 30 May 2025 ($n = 65$ months), with empirical P10, P50, and P90 probabilistic thresholds. The pseudo-day axis preserves the available observational sequence and does not represent six complete calendar years.

As the available data spans a limited number of years, a non-parametric bootstrap resampling procedure was applied to the annual GHI data to preserve the empirical distribution of solar variability without imposing a fitted parametric distribution (Prilliman et al., 2023). The bootstrap resampling was conducted on paired annual observations (H_t, T_t) to maintain the physical coupling between the irradiance and temperature. Here, T_t is the annual mean ambient temperature, rather than irradiance alone. This is because dependence among renewable energy drivers should be retained (Zheng et al., 2025). Eq. (2) was used to derive a climatic pair from the empirical set for each MC iteration (i):

$$(H^*(i), T^*(i)) \sim \text{Empirical}\{(H_1, T_1), \dots, (H_T, T_T)\} \quad (2)$$

By resampling irradiance and temperature as pairs, the procedure retains their observed covariances and avoids artificial decorrelation in the temperature-dependent performance model (Prilliman et al., 2023; Zheng et al., 2025). The output of Stage A is an ensemble of paired annual irradiance-temperature $(H^*(i), T^*(i))$, and serves as the stochastic drivers for the MC-based energy yield simulation in Stage B. Therefore, scenario-generation methods must retain dependence between the renewable energy drivers to avoid producing physically inconsistent uncertainties (Zheng et al., 2025).

Stage B - Stochastic Performance and Energy-yield Modelling

Stage B propagates the climatic uncertainty produced in Stage A into probabilistic distributions of PV energy yield *via* MC simulation. The standard irradiance-to-yield relationship, adopted in PV performance assessment, was used to determine the specific annual energy yield for each i (Dobos et al., 2012; IEA PVPS, 2020; Prilliman et al., 2023).

It is worth clarifying that the P10, P50, and P90 probabilistic thresholds denote the 10th, 50th, and 90th percentiles of the simulated annual energy yield distribution. As such, the larger percentile values would map to the higher energy yield scenarios, in line with the statistical percentile convention. However, some in the PV industry and several energy yield assessment guidelines (IEA PVPS, 2020; Dobos et al., 2012) consider P90 as an exceedance-based energy yield, where the output was surpassed in 90% of the years. This is a conservative, low estimate that correlates with the P10 probabilistic threshold in the present study, where it is considered the lower-bound (pessimistic) energy yield scenario, P50 is the median or most likely scenario, and P90 is the upper-bound (optimistic) scenario. This was applied consistently under the statistical percentile convention. The specific annual energy yield for each Monte Carlo iteration was calculated using Eq. (3):

$$Y(i) = H^*(i) \times PR(i) \quad (3)$$

where $H^*(i)$ is the bootstrapped annual GHI and $PR(i)$ is the temperature-dependent formulation. Eq. (4) defines the temperature-driven PR:

$$PR(i) = PR_{ref} [1 - \gamma(T^*(i) - T_{ref})] + \varepsilon(i) \quad (4)$$

where PR_{ref} is the reference PR at the reference temperature T_{ref} , γ is the temperature coefficient of the performance loss ($^{\circ}\text{C}^{-1}$), $T^*(i)$ is the bootstrapped annual mean temperature from Stage A, and $\varepsilon(i)$ is a residual stochastic term that captures mismatch, soiling, and assumed inverter and wiring losses (Youssef et al., 2021). The residual stochastic term was sampled using Eq. (5):

$$\varepsilon(i) \sim N(0, \sigma^2) \quad (5)$$

Temperature-driven efficiency reductions in crystalline-silicon-based PV modules located in high thermal stress conditions are well documented (Islam et al., 2024; Qu et al., 2024; Youssef et al., 2021; Ziar, 2024). Eq. (6) was used to keep the PR values within the empirical limits and ensure realistic operations:

$$PR_{min} \leq PR(i) \leq PR_{max} \quad (6)$$

with $PR_{min} = 0.60$ and $PR_{max} = 0.95$. These limits spanned conservative loss conditions and high-performing operational conditions derived from long-term grid-connected and tropical PV assessments. These were modelling limits rather than an empirical confidence interval for the PV module located at UNMER (Aarich et al., 2024; Islam et al., 2024; Mohamad Radzi et al., 2025). Eq. (7) was used to calculate the annual alternating current (AC) energy yield at the installed capacity (P_{inst}) (kWp):

$$E(i) = Y(i) \times P_{inst} \quad (7)$$

where $E(i)$ is the annual energy yield (kWh·year⁻¹) at i , $Y(i)$ is the specific energy yield (kWh·kWp⁻¹·year⁻¹), and P_{inst} is the nominal capacity of the system (kWp). This formulation is compatible with the probabilistic P50/P90 practices of international PV yield-uncertainty guidelines and industry tools (Dobos et al., 2012; IEA PVPS, 2020; Prilliman et al., 2023).

NumPy's MT19937 pseudo-random generator was used to perform the Monte Carlo (MC) simulations for 10000 iterations with a fixed seed ($n = 42$) to ensure reproducibility. The convergence analysis was based on the running mean, variance, and the P10, P50, and P90 probabilistic thresholds. The annual energy statistics stabilised after 6000 iterations, with relative changes < 1%, which aligns with the recommended ensemble sizes for probabilistic PV assessment (Prilliman et al., 2023; Dobos et al., 2012; IEA PVPS, 2020). The probabilistic outputs were recorded in terms of P10, P50, and P90 annual energy yields, which facilitates direct interpretability for the subsequent risk and performance analyses.

Stage C – Dynamic Performance Evolution and Degradation Modelling

In Stage C, the time-dependent degradation was superimposed as a deterministic degradation layer on the stochastic annual yields derived from Stage B. In humid tropical regions, degradation occurs in two stages, with slow degradation in early-life followed by rapid degradation due to humidity-induced stress and material fatigue (Jordan & Kurtz, 2013; Atia et al., 2023; Islam et al., 2024; Rajput et al., 2024). Eq. (8) provides the effective capacity of the PV in operational t :

$$C(t) = \begin{cases} C_0(1 - \delta_1)^t, & 1 \leq t \leq 10 \\ C_0(1 - \delta_1)^{10}(1 - \delta_2)^{(t-10)}, & 11 \leq t \leq T \end{cases} \quad (8)$$

where C_0 is the initial installed capacity (kWp), t is the operational year, δ_1 is the annual degradation rate for Years 1–10, and δ_2 is the rate for Years 11–25. The values $\delta_1 = 0.55\% \text{ yr}^{-1}$ and $\delta_2 = 1.0\% \text{ yr}^{-1}$ are literature-informed assumptions of environmental exposure in humid tropical regions rather than on-site measured estimates (Atia et al., 2023; Rajput et al., 2024; Mohamad Radzi et al., 2025). Eq. (9) was used to calculate the annual AC energy yield for MC i and t . The higher second-stage rate indicates the possibility that accumulated moisture ingress, corrosion, delamination, microcracking, and potential-induced degradation accelerates performance loss over extended operation. These mechanisms occur in humid tropical regions (Atia et al., 2023; Islam et al., 2024; Mohamad Radzi et al., 2025; Hasan et al., 2026). The transition at Year 10 served as a modelling boundary in the scenario analysis, not a universal physical breakpoint or a value derived from the PV system at UNMER.

$$E_{i,t} = \eta_{ref} H^*(i) PR_i(t) C_t \quad (9)$$

where $E_{i,t}$ is the annual energy yield (kWh yr⁻¹), η_{ref} is an effective conversion coefficient that combines plane-of-module geometry and system efficiencies, $H^*(i)$ is the bootstrap-sampled annual irradiance from Stage A, $PR_i(t)$ is the temperature-dependent PR from Stage B, and C_t is the effective capacity in t from Equation (8). This formulation ensured that (i) short-term variability was governed by the stochastic climate drivers, (ii) the long-term degradation was governed by the deterministic degradation, and (iii) the sources of uncertainty were not counted twice. Eq. (10) was used to calculate the cumulative lifetime energy yield for i :

$$E_i^{life} = \sum_{t=1}^T E_{i,t} \quad (10)$$

where $E_{i,t}$ is the annual energy yield in t from Equation (9), and $T = 25$ years is the assumed lifetime of the PV system. This formulation embedded (i) stochastic annual baseline energy, (ii) year-specific degradation capacity, and (iii) temporal progression across the 25-year operational horizon.

These degradation-aware lifetime outputs formed the basis of the subsequent cumulative energy and capacity analyses (Figures 8 and 9), as well as the lifetime correlation and annual energy yield sensitivity analyses. This separation prevented the deterministic degradation assessments from being treated as an independently sampled source of annual uncertainty (IEA PVPS, 2020; Prilliman et al., 2023).

Stochastic Convergence and Variance Validation

The numerical robustness was assessed by examining the convergence of the annual energy yield indicators to determine if 10000 iterations provide stable P10, P50, and P90 probabilistic estimates with negligible MC sampling drift, which is in line with the PV uncertainty-assessment guidelines (Prilliman et al., 2023; IEA PVPS, 2020; Al-Hanoot et al., 2025). The convergence was assessed by examining the running mean, standard deviation, and empirical percentiles as the cumulative number of iterations increased. After 6000 iterations, changes in the running mean and variance were $< 1\%$, while the percentile curves indicated negligible additional drift (Figure 3). Therefore, the specified simulation was numerically stable. However, this does not conclusively prove that model-form bias did not occur or prove that the underlying climate sample was representative (Prilliman et al., 2023; Dobos et al., 2012).

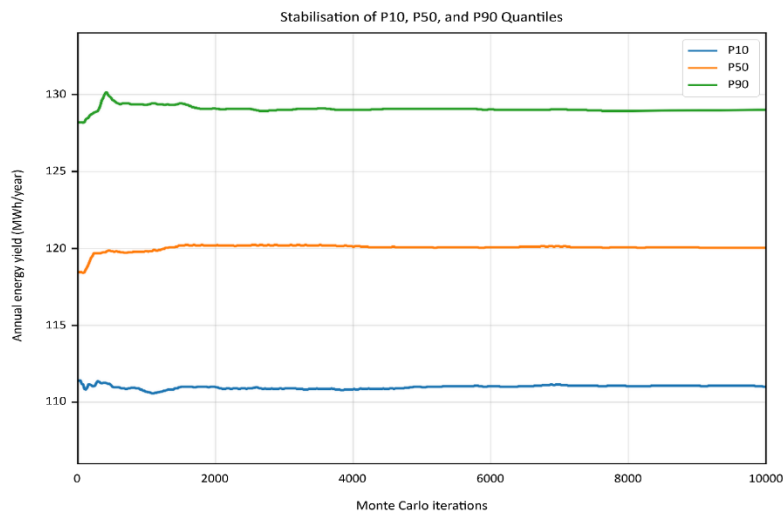


Figure 3 The P10, P50, and P90 probabilistic thresholds stabilised as the number of MC iterations increased. All the empirical probabilistic thresholds exhibited asymptotic convergence after 6000 iterations, with a relative drift of $< 1\%$ thereafter. This confirmed the distributional stability of the 10000-iteration ensemble and the adequacy of the ensemble size for probabilistic PV performance assessment.

The observed convergence was consistent with the results of probabilistic PV studies that use MC simulations to estimate the energy yield distributions (Prilliman et al., 2023; Al-Hanoot et al., 2025; Dobos et al., 2012). Stabilisation of the central tendency and tails indicates numerically well-behaved sampling within the stated model. However, this does not validate the structure of the model. Furthermore, numerical convergence should not be confused with representativeness of long-term inter-annual climate variability. As Stage A is based on 65 months of observations from January 2020 to May 2025, the bootstrap pool is limited by the conditions observed during that period. It cannot generate climatic conditions outside that range. As such, low-frequency variability may be underrepresented. Therefore, the reported P10–P90 probabilistic thresholds are conditional uncertainty limits for the observed climate period, rather than unconditional estimates of long-term climate risks. It is recommended that future assessments use longer observational records to examine low-frequency climate variability.

Consistency Check Against PVsyst Simulation

The physical consistency of the proposed stochastic-dynamic framework was examined by benchmarking the median (P50) annual energy yield against the results of the PVsyst 7.4 simulation, which is a widely used deterministic simulation tool for PV modules (Ates & Singh, 2021; Khan et al., 2022; Shukla et al., 2024). The parameters of the MC formulation,

namely, hourly meteorological data from the NASA POWER database from 2020–2025, installed capacity (100 kWp), and loss factors for shading, soiling, mismatch, inverter efficiency, and wiring, were used to configure the PVsyst model to ensure methodological comparability (Harsarapama et al., 2020; IEA PVPS, 2020). As the proposed stochastic-dynamic model and the PVsyst simulation relied on the same hourly meteorological data from the NASA POWER database and comparable system loss assumptions, the comparison examined methodological consistency rather than independent model validation. A genuinely independent validation would require a wholly separate meteorological dataset, or PV system outputs measured in the long-term with parameter-independent calibrations. Therefore, this is acknowledged as a limitation of the present study. Differences have been observed between the energy yield and the simulated outputs. As such, the present comparison is a measure of consistency rather than an independent empirical validation (Ates & Singh, 2021; Shukla et al., 2024).

The comparison focused on the P50 probabilistic threshold of the simulated annual energy yield distribution as it represents the median energy yield scenario in the statistical-percentile convention used in the present study (Dobos et al., 2012; IEA PVPS, 2020). The difference between the MC P50 and the PVsyst reference output was < 2%. As both calculations used the same meteorological data and comparable system loss assumptions, it indicates methodological consistency rather than the absence of systematic bias or independent validation (Ates & Singh, 2021; Khan et al., 2022).

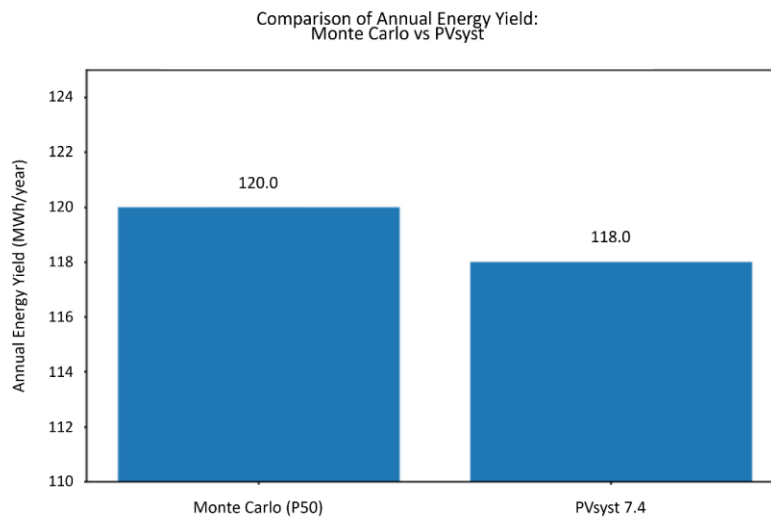


Figure 4 A comparison of the annual AC energy yield of the MC P50 probabilistic threshold and the PVsyst 7.4 deterministic simulation for a 100-kWp rPV system at UNMER. As the difference was < 2%, it indicates consistency between the proposed stochastic-dynamic model and standard engineering simulations.

Therefore, the internal methodology was consistent between the temperature-dependent PR model (Eq. (4)), the paired climate resampling (Eq. (2)), and the energy yield formulation (Eq. (7)). However, this should not be interpreted as independent evidence of physical realism as the benchmark simulation model uses the same hourly meteorological data from the NASA POWER database and comparable system loss assumptions as the proposed stochastic-dynamic model (Youssef et al., 2021; Harsarapama et al., 2020; Prilliman et al., 2023). The proposed stochastic-dynamic framework, nevertheless, extends the deterministic comparison by reporting the P10 and P90 probabilistic thresholds for annual energy yield in the climatic and operational variabilities represented in the model (IEA PVPS, 2020; Al-Hanoot et al., 2025).

Dynamic Modelling of Long-term Performance and Degradation

Eq. (10) was used to determine the lifetime performance of the PV system by aggregating its annual energy yields over a 25-year operational horizon. Eq. (8) was used to deterministically apply degradation, with scenario rates of 0.55% yr⁻¹ for Years 1–10 and 1.0% yr⁻¹ for Years 11–25. Figure 8 depicts the cumulative P10, P50, and P90 probabilistic energy yield estimations, while Figure 9 depicts the common deterministic capacity estimations.

Sensitivity and Correlation Analysis

Integrated correlation and variance-based sensitivity analyses were used in the proposed stochastic-dynamic framework to identify the dominant sources of uncertainty in the annual and lifetime energy yields. The purpose was

to decompose the total output variance into contributions from individual variables, while preserving the physical couplings between the climatic drivers and PV performance. This aligns with the best practice for probabilistic PV-based energy yield assessments (Saltelli et al., 2010; Prilliman et al., 2023; IEA PVPS, 2020).

A Pearson correlation matrix was used to quantify the pairwise linear correlations between the GHI, ambient and module temperatures, temperature-dependent PR, degradation parameters, and energy yields for both single-year and 25-year operational horizons (Prilliman et al., 2023; IEA PVPS, 2020). The correlation analysis facilitated an initial screening of potential variance drivers and indicated which variables most closely correlated to short- and long-term energy yields.

The variance-based global sensitivity analysis was conducted using Sobol indices, which decompose output variances into first-order contributions (S_1), which are the direct contributions of each variable in the decomposition assumptions, and total-order contributions (S^T), which includes the interactions (Saltelli et al., 2010; Prilliman et al., 2023). Variance-based sensitivity analysis captures the effects of non-linear interactions when the input assumptions are satisfied (Saltelli et al., 2010). The Sobol decomposition was applied to the annual energy yields across the 10000 iterations in Stage B, while correlation screening was used to separately examine the lifetime variables in Stage C (Prilliman et al., 2023; IEA PVPS, 2020). Standard Sobol decomposition assumes mutually independent inputs (Saltelli et al., 2010). Stage A intentionally retains the observed dependences between irradiance and ambient temperature. Therefore, the reported first-order and total-order indices were used as approximate screening measures rather than exact independent-effect estimates. The Pearson correlation coefficients (r) complement this as they do not require input independence, as they describe associations rather than causations.

Campus Load Data and Boundary Validation

The 100-kWp PV system was examined to determine if its energy yield was proportionate to the campus' energy demands. The load data was used only to define the operational boundaries, not to calibrate the proposed stochastic-dynamic model. This makes it possible to apply the proposed framework in other humid tropical regions with site-specific inputs (Wongwan et al., 2024). As seen in Table 2, the campus' energy demand data comprised its monthly electricity bills from 2021–2025, short-term hourly on-site energy demand measurements during normal academic operating hours, and a reconstructed hourly profile scaled to the billing totals. The monthly electricity bills constrained the annual consumption and seasonal magnitude, whereas the hourly on-site measurements described the diurnal energy demand pattern, including the base load, morning ramp-up, midday peak, and afternoon decline. As these were on-site measurements, the results described the dataset used in the present study rather than literature-informed results.

Table 2 Summary of campus electricity demand data used for boundary validation.

Data source	Period covered	Temporal resolution	Purpose in analysis
Electricity billing records	2021–2025	Monthly (kWh)	Constraining annual and monthly energy demand magnitude
On-site load measurements	Short-term campaign during normal academic operation	Hourly	Derivation of normalised typical daily load shape
Reconstructed load profile	Scaled to billing data	Hourly (representative)	Assessment of PV sizing plausibility and PV–load temporal alignment

The reconstructed profile was derived by normalising the measured hourly on-site patterns to the daily totals and scaling them to match the monthly electricity bills. This yielded a representative hourly load profile that reflected both the diurnal energy demand pattern and the seasonal magnitude constraints (Tarigan, 2024; Wongwan et al., 2024; Adita & Setiawan, 2023). Figure 5 presents the resulting representative diurnal load profile.

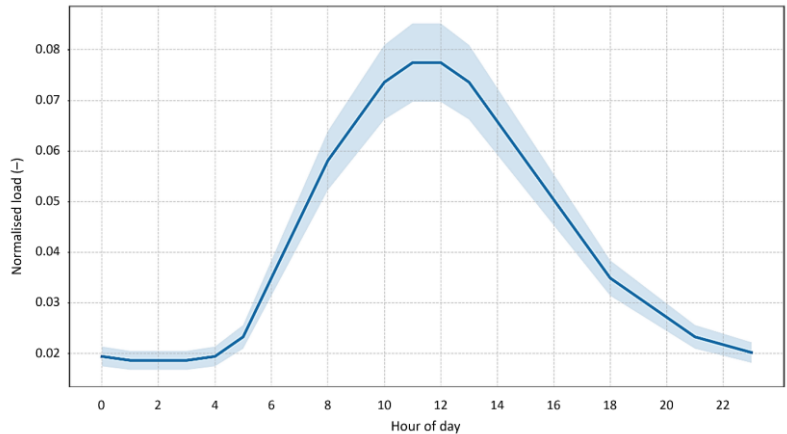


Figure 5 The campus' normalised typical daily load profile derived from hourly on-site measurements and scaled to the monthly electricity bills (2021–2025), showing the diurnal energy demand pattern relevant to rPV integration.

As seen in Figure 5, the pronounced midday peak (10:00–14:00) correlates with academic activity and cooling loads, with a peak-to-base ratio of approximately 2.5:1, and most energy demand occurring between 06:00–18:00. This profile is favourable for the on-site use of diurnal PV-based energy yield, and resembles the load patterns of campuses located in humid tropical regions (Wongwan et al., 2024; Adita & Setiawan, 2023). The annual energy demand of the campus was 1200 MWh. The P50 PV-based energy yield was 120 MWh. Therefore, the energy penetration was 10%. This modest share is consistent with roof- and grid-connected PV systems for campuses (Wongwan et al., 2024; Adita & Setiawan, 2023). Therefore, it has limited exposure to transformer-capacity constraints. However, its voltage and power-quality compliance should still be examined in a dedicated grid-impact study as PV module placement and penetration may result in network losses and affect voltage profiles (Le Thi Minh & Duong, 2024).

A time-resolved analysis of PV self-consumption lies beyond the scope of the present study. However, it would be a useful next step to optimise operations (Tarigan, 2024; Wongwan et al., 2024). The short-term inverter data of the existing 100-kWp PV system was only used to qualitatively determine the energy yield magnitude and PR range. It was not used to calibrate the parameters (Prilliman et al., 2023; IEA PVPS, 2020; Ates & Singh, 2021; Khan et al., 2022).

Campus Measured PV Data and Validation Status

The availability and use of on-site PV system data was documented to clarify the scope and limitations of empirical validations. Unlike the comprehensive NASA POWER dataset used in Stage A, the on-site PV system data was temporally limited and unsuitable for the long-term statistical calibration of the proposed stochastic-dynamic model (Prilliman et al., 2023; IEA PVPS, 2020). The available measurement data comprised the short-term AC energy records of the existing 100-kWp rPV system, which was acquired by monitoring the inverter during normal operations in tropical monsoon conditions (Table 3) (Ates & Singh, 2021; Khan et al., 2022; Shukla et al., 2024). Recent monitoring of a 1.05-MW rPV system at a university further illustrated the value of system-level PR and energy yield indicators when satisfactorily complete operational records are available (Muñoz-Rodríguez et al., 2025).

Table 3 Summary of measured PV production data used for qualitative validation.

Data source	Location / system	Period covered	Temporal resolution	Data completeness	Purpose in analysis
Inverter monitoring logs	100 kWp rooftop PV, UNMER	Mar–Aug 2022	Hourly AC energy (kWh)	85–90% of expected records	Short-term production plausibility check
Inverter monitoring logs	100 kWp rooftop PV, UNMER	Jan–May 2023	Hourly AC energy (kWh)	80–95% of expected records	Seasonal variation illustration and order-of-magnitude comparison with P50 simulation
Inverter monitoring logs	100 kWp rooftop PV, UNMER	Selected weeks in 2024	Hourly AC energy (kWh)	Campaign-based, partial days	Spot-check of instantaneous performance (PR range, peak power)

The measured PV system data spanned 8–12 months across the dry and wet seasons. However, the data contained monitoring interruptions and did not provide complete seasonal coverage. As such, it cannot be used to robustly estimate long-term PR distributions, inter-annual variability, or empirical degradation trends (Prilliman et al., 2023; Islam et al., 2024; Mohamad Radzi et al., 2025). Therefore, the data was only used to determine if the simulated energy yields, seasonal patterns, and PR ranges were plausible, not to fit the parameters or to shape the probability distributions (Prilliman et al., 2023; IEA PVPS, 2020; Wongwan et al., 2024). The model parameters used in Eqs. (2), (4), (5), and (8) were obtained from the meteorological data and literature-informed PV system-performance rather than the short-term on-site measurements (Atia et al., 2023; Rajput et al., 2024; Yadav et al., 2025; Islam et al., 2024). This prevented parameter calibration using incomplete data. Nevertheless, site-specific inputs and external validation are required to apply the proposed stochastic-dynamic framework to another campus.

Results

Probabilistic Annual Energy Yield and Production Risk

Two complementary examinations were conducted before the probabilistic outputs were analysed. The difference between the MC P50 probabilistic estimate and the PVsyst 7.4 result was $< 2\%$ (Figure 4). A comparison with the inverter-based data (Table 3) also placed the simulated annual yield, seasonal energy yield pattern, and PR range within the operational bounds of the 100-kWp rPV system at UNMER.

The 10000-iteration MC ensemble produced a nearly symmetric annual energy yield distribution, with a slight right skew and moderate dispersion (Figure 6).

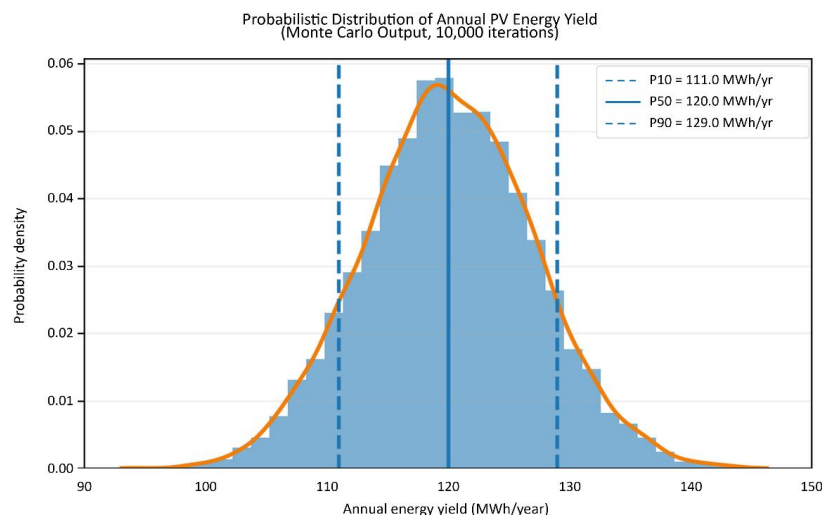


Figure 6 The distribution of the annual PV-based energy yield (histogram + KDE) with the P10, P50, and P90 probabilistic thresholds.

The simulated annual energy yield thresholds were 111 MWh yr⁻¹ at P10, 120 MWh yr⁻¹ at P50, and 129 MWh yr⁻¹ at P90. Under the present study's statistical percentile convention, P10 is the lower energy yield probabilistic threshold, P50 is the median, and P90 is the upper. The P10–P90 range was 18 MWh yr⁻¹, which is equivalent to $\pm 7.5\%$ relative to P50. When this was normalised to the 100-kWp installed capacity, the P50 energy yield was 1200 kWh kWp⁻¹ yr⁻¹, with a P10–P90 range of 1110–1290 kWh kWp⁻¹ yr⁻¹.

Temperature-correlated Performance Ratio Behaviour

Figure 7 depicts four related diagnostics while distinguishing their data scopes. Figure 7(a) used the observed NASA POWER-based diurnal data, Figure 7(b) presents the model-derived cell-temperature-PR correlation, Figure 7(c) used the 10000 MC system-level iterations, and Figure 7(d) depicts the paired annual bootstrap outputs.

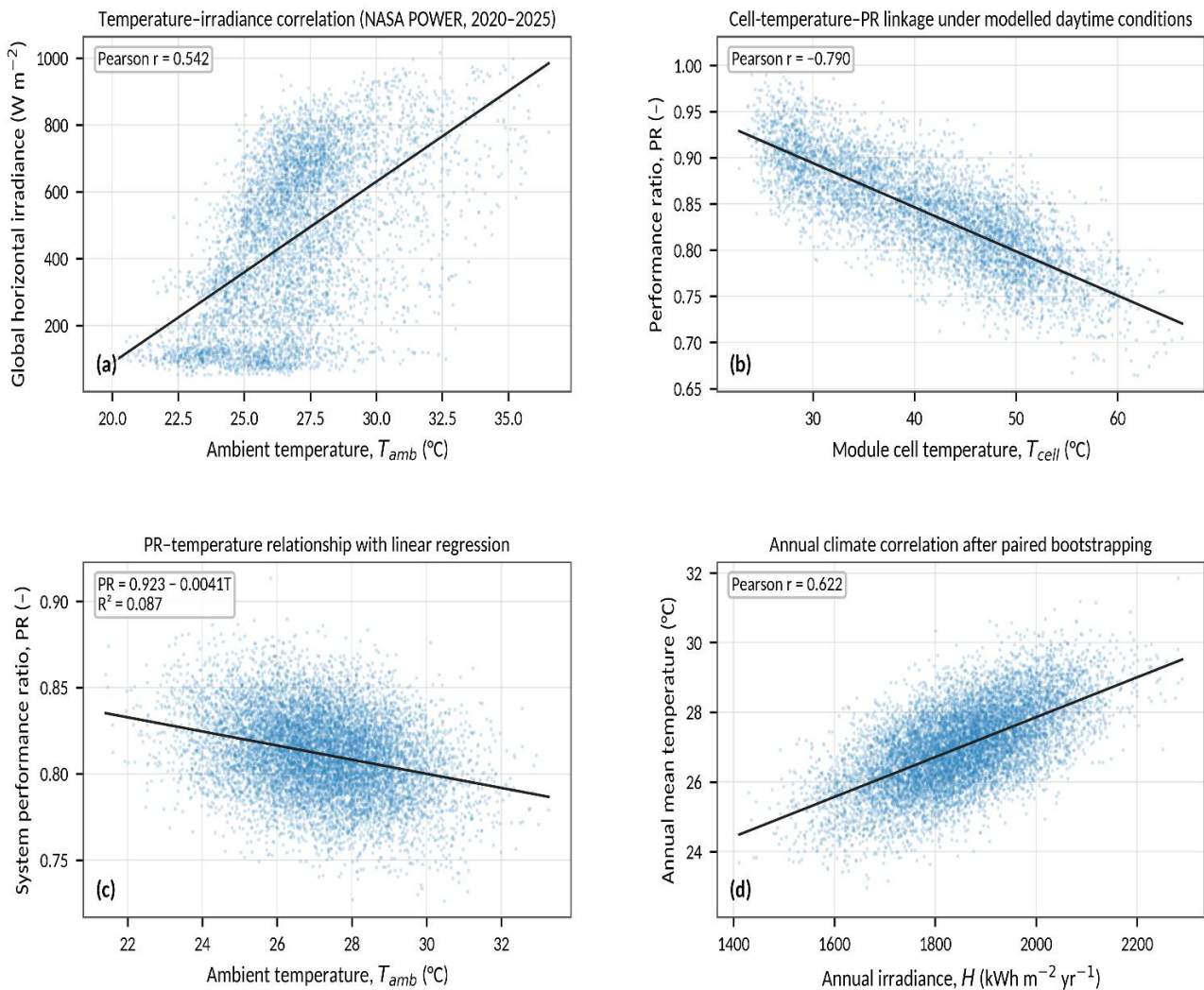


Figure 7 The results of the temperature-irradiance-PR diagnostic. Figure 7(a) depicts the observed ambient temperature versus the diurnal GHI obtained from the NASA POWER database ($\text{GHI} > 50 \text{ W m}^{-2}$), Figure 7(b) depicts the model-derived cell temperature versus the diurnal PR, Figure 7(c) depicts the ambient temperature versus the rPV system's PR across 10000 MC iterations, and Figure 7(d) depicts the bootstrapped annual irradiance versus the annual mean ambient temperature, indicating that covariance was preserved.

Figure 7(a) depicts a moderate positive correlation between the ambient temperature and the diurnal GHI from the NASA POWER database ($\text{GHI} > 50 \text{ W m}^{-2}$), with Pearson $r = 0.542$. It characterises the observed high-solar-hour correlation rather than the annual bootstrap distribution.

Figure 7(b) depicts a strong negative correlation between the model-derived diurnal module cell temperature and PR (Pearson $r = -0.790$). These points combined meteorological data from the NASA POWER database with the present study's temperature-dependent PR formulation. Therefore, it should not be interpreted as independent field measurements of PR. Figure 7(c) depicts a negative correlation between ambient-temperature-PR at the system level across the 10000 MC iterations. The fitted relation ($\text{PR} = 0.923 - 0.0041T$; $R^2 = 0.087$) indicates a modest direct trend, while the dispersion reflects the residual operational variability used in Equation (4). Figure 7(d) depicts that the paired annual bootstrap resampling retained a positive irradiance-temperature correlation (Pearson $r = 0.622$). Therefore, the $H^*(i)$, $T^*(i)$ pairs preserved the empirical covariance structure that was used as the stochastic input in Stage B.

Long-term Dynamic Performance and Two-stage Degradation

The 2S-DDS rates defined in Eq. (8) were used to generate the capacity and lifetime energy yields over the 25-year operational horizon. These estimations were literature-informed rather than degradation rates measured by monitoring the rPV system located at UNMER in the long-term. Figure 8 depicts the cumulative P10, P50, and P90 energy yield estimations obtained by applying the common deterministic capacity factors seen in Equation (8) to the three annual

energy yield quantiles. Totalling the annual capacity factors over the 25-year operational horizon yielded a lifetime-energy deficit of 8.7% relative to a no-degradation scenario, with 13.6% of that deficit occurring in Years 1–10, and 86.4% in Years 11–25. Figure 9 depicts the single deterministic 2S-DDS estimation specified by Equation (8). The normalised capacity decreases to 94.6% in Year 10 and 81.4% in Year 25, which corresponds to capacity losses of 5.4% and 18.6%, respectively. As the degradation rates were fixed rather than sampled, this capacity estimation is common to the P10, P50, and P90 energy scenarios.

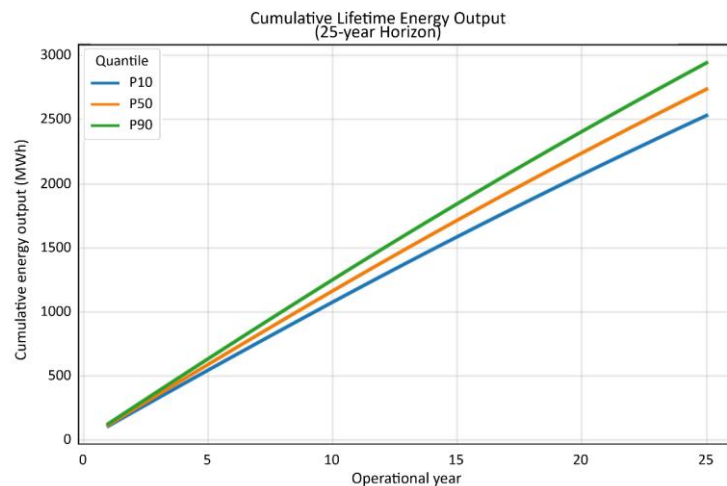


Figure 8 The cumulative P10, P50, and P90 lifetime energy yields after applying the deterministic 2S-DDS over the 25-year operational horizon.

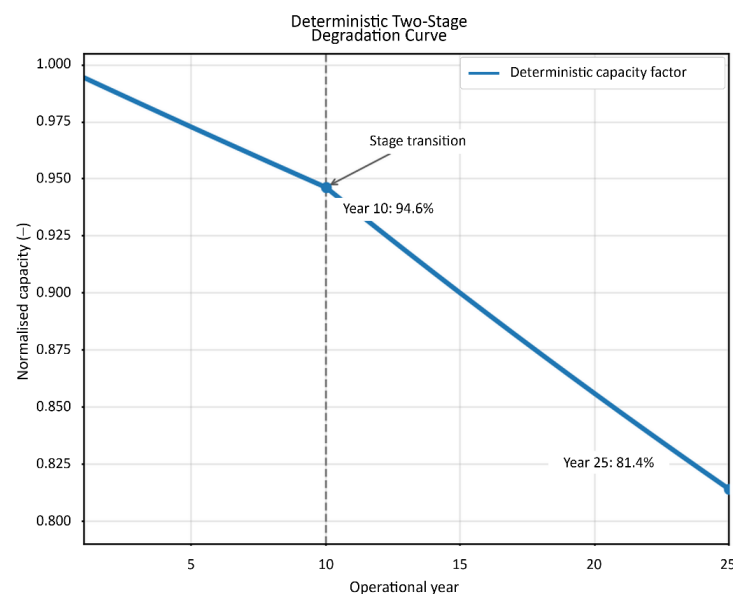


Figure 9 The deterministic 2S-DDS estimation of normalised PV system capacity over a 25-year operational horizon.

Dominant Drivers of Uncertainty: Sensitivity and Correlation Analysis

Figure 10 depicts the correlation matrix of the 25-year operational horizon. As seen, the lifetime energy yield positively correlates with PR ($r = 0.953$), availability ($r = 0.908$), and GHI ($r = 0.705$), and negatively correlates with the degradation factor ($r = -0.869$). These coefficients describe pairwise correlations within the model's output and do not represent the independent variance shares.

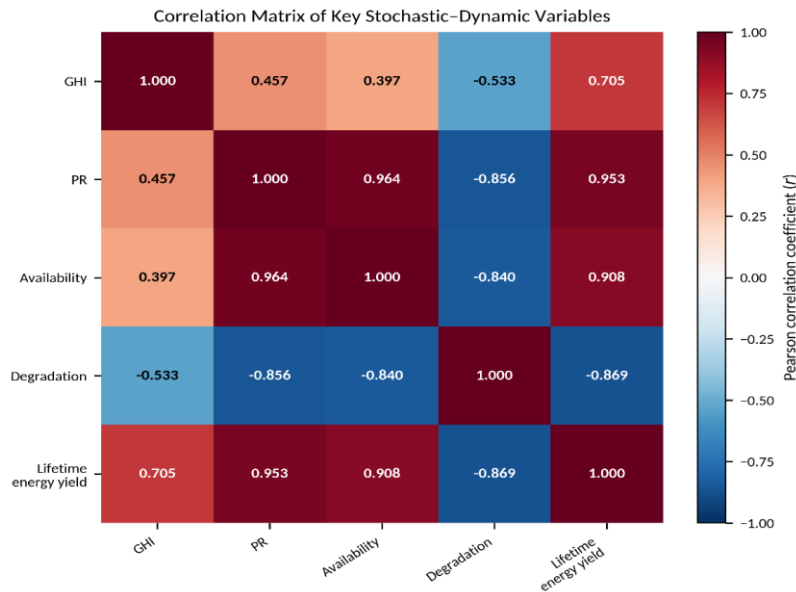


Figure 10 The Pearson correlation matrix of the key stochastic–dynamic variables and lifetime energy yield over the 25-year operational horizon of a 100-kWp rPV system at a university campus in a humid tropical region.

Figure 11 depicts the Sobol variance decomposition of annual energy yield. The PR residual was the largest contributor ($S_1 = 0.45$; $S^T = 0.55$), followed by irradiance ($S_1 = 0.22$; $S^T = 0.30$), temperature ($S_1 = 0.15$; $S^T = 0.24$), and degradation ($S_1 = 0.10$; $S^T = 0.16$).

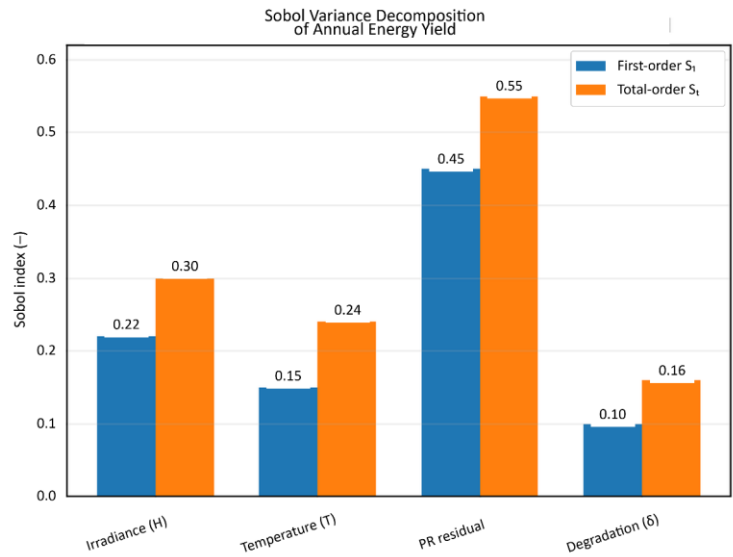


Figure 11 The Sobol variance decomposition of annual energy yield, with the S_1 and S^T sensitivity indices.

A separate dependence-aware Sobol decomposition of the lifetime energy yield over a 25-year operational horizon was not performed. Therefore, the lifetime correlation coefficients seen in Figure 10 are correlations rather than causal or independent variance contributions.

Discussion

Probabilistic Energy-yield Uncertainty and Model Credibility

The close agreement between the results of the PVsyst simulation and its qualitative consistency with the inverter-based on-site measurements support the physical plausibility of the simulation. However, this should be interpreted as consistency and plausibility examinations rather than independent empirical validation as the proposed stochastic–dynamic model and the PVsyst model used the same hourly meteorological data from the NASA POWER database and

comparable system loss assumptions. Similar differences between the observed energy yields and predictions by PVsyst, SAM, and PVLIB models have been observed (Shukla et al., 2024).

The $\pm 7.5\%$ P10–P90 range indicates that a single deterministic estimate could conceal meaningful downside and upside energy yield-related risks. Therefore, P10 aligns with a conservative budget and grid-connections, whereas P50 is the moderate plan, and P90 is the upper energy yield scenario (Dobos et al., 2012; IEA PVPS, 2020; Prilliman et al., 2023). The normalised energy yields were within the ranges reported for rPV and PV systems in humid tropical regions (Islam et al., 2024; Mohamad Radzi et al., 2025; Yadav et al., 2025; Wongwan et al., 2024; Tarigan, 2024).

The observed distribution reflects three interacting sources in the proposed stochastic-dynamic model. More specifically, the paired resampling retains inter-annual irradiance fluctuations and their correlations with temperature, the temperature-dependent PR formulation constrains energy yield in hot, high-irradiance years, and the residual term represents operational losses, such as soiling, mismatch, inverter-efficiency variation, and wiring losses (Youssef et al., 2021; Aarich et al., 2024; Yadav et al., 2025).

Temperature–irradiance Coupling and Performance-ratio Implications

The positive GHI-temperature correlation and the negative temperature-PR correlation indicate that the climatic drivers cannot be treated as independent. Therefore, preserving their covariance through paired bootstrap resampling avoids non-physical combinations, such as high irradiance with anomalously low temperature, which would overestimate the PR and energy yield (Prilliman et al., 2023; Zheng et al., 2025).

The estimated decrease in PR of 0.4–0.5 percentage points per °C aligns with the thermal responses of crystalline-silicon-based PV modules. In humid tropical regions, elevated module cell temperatures decrease open-circuit voltage and increase resistive and mismatch losses. As such, some of the additional solar resource is offset by thermal penalties (Youssef et al., 2021; Qu et al., 2024; Ziar, 2024). The simulated PR band of 0.75–0.80 lies within range for PV systems in humid tropical regions. However, it should not be interpreted as a universal benchmark for PV systems in humid tropical regions as the measured PR varies according to technology, site, maintenance, and monitoring period (Islam et al., 2024; Mohamad Radzi et al., 2025). Rooftop PV (rPV) systems, similarly, face performance penalties from elevated module cell temperatures and soiling, while the magnitude remains site-specific (Yadav et al., 2025).

Long-term Degradation and Dominant Uncertainty Drivers

The segmented estimations depict why a constant degradation rate may overstate late-life energy availability. The accelerated losses after Year 10 inversely correlates with a cumulative increase in energy yield and places most of the lifetime degradation in Years 11–25. This is consistent with the results of field and reliability studies that correlate environmental exposure in humid tropical regions with progressive material and electrical degradation (Atia et al., 2023; Rajput et al., 2024; Mohamad Radzi et al., 2025; Hasan et al., 2026). However, as the adopted rates were literature-informed rather than on-site measurements, these estimations should be interpreted as a degradation scenario rather than a deterministic projection for the rPV system at UNMER.

The annual Sobol results identified the PR residual as the largest contributor to variance, with irradiance, temperature, and degradation contributing progressively less. As seen in Figure 10, there are strong pairwise correlations between lifetime energy yield and PR, availability, and degradation over the 25-year operational horizon. However, the correlated-input structure prevents these coefficients from being interpreted as independent effects. Therefore, a dependence-aware lifetime sensitivity analysis is required before a shift in the dominant variance drivers can be claimed.

Implications for Tropical Campus PV Planning

The probabilistic annual energy yield results indicate that solely relying on single deterministic values underestimates the energy yield risks to PV systems in humid tropical regions. Therefore, for planning purposes, capacity sizing and reliability assessments should be based on percentile metrics, such as the P10 and P50 probabilistic thresholds, rather than median values alone. This would ensure that downside scenarios are taken into consideration during budgeting, reserve planning, and grid-integration (IEA PVPS, 2020; Prilliman et al., 2023).

The dominance of the PR residual in the annual Sobol decomposition indicates that operational-loss control is, at the very least, as important as resource characterisation. In practice, this indicates that it is important to select modules with lower temperature coefficients as well as to improve the ventilation and soiling of PV systems in humid tropical

regions, where dust and particulates decrease its transmittance (Tripathi et al., 2025; Kumar et al., 2025). Apart from that, proactive operations and maintenance are required to maintain high system availability (Islam et al., 2024; Mohamad Radzi et al., 2025; Yadav et al., 2025). The five-year operational data from a 120-kWp rPV system in Central Java, similarly, identify temperature, humidity, dust, shading, and maintenance as significant determinants of its long-term performance in Indonesia's climatic conditions (Umam et al., 2025). At the balance-of-system level, inverter topology and control strategies may also affect conversion performance and harmonic quality. However, these mechanisms were not explicitly resolved in the annual energy yield model (Nouira & El Badsy, 2025).

The behaviour of the 2S-DDS observed in the simulations highlights the need for degradation-aware lifetime planning. More specifically, assuming a constant degradation rate risks overstating the availability of energy in the late-life phase and may bias long-term financial estimations, carbon accounting, and reinvestment schedules (Jordan & Kurtz, 2013; Rajput et al., 2024). Therefore, integrating time-dependent degradation into the roadmaps of PV systems at campuses would yield more realistic estimates of cumulative energy, as well as indicate when performance refurbishments or repowering would be beneficial. It would also align the lifetime of the PV module with infrastructure plans of the campus (Shen et al., 2025; Kladas et al., 2025; Atia et al., 2023).

From a regulatory standpoint, Indonesia's current rPV framework is governed by MEMR Regulation No. 2/2024, which replaced Regulation No. 26/2021. For newly-approved systems, the excess electricity exported to the *Izin Usaha Penyediaan Tenaga Listrik* (IUPTLU) grid is not credited against a customer's electricity bills, as the export-import arrangements approved under Regulation No. 26/2021 are subject to a 10-year transitional provision (MEMR, 2024; Tarigan, 2024). Therefore, the P10, P50, and P90 probabilistic scenarios should be interpreted as data for self-consumption and capacity planning rather than forecasts of net-metering revenue. More specifically, with an annual campus energy demand of 1200 MWh, the P10 energy yield of 111 MWh only satisfies 9.3% of the energy demand. Meanwhile, actual self-consumption still depends on time-based matching between the energy yield of the PV system and the load. Apart from that, although the P90 energy yield of 129 MWh represents a higher energy yield scenario, there is no guarantee that the energy can be exported to the grid. Therefore, these scenarios support capacity and operational planning in a quota-based, self-consumption-oriented regulatory framework.

Study Limitations and Generalisability

Although this study focuses on a single Indonesian campus, the proposed stochastic-dynamic framework can be applied to campuses in humid tropical regions with similar diurnal load patterns and operational planning horizons. This would facilitate site-specific adaptations of climatic inputs and PV system parameters, while maintaining a consistent probabilistic structure, which would support comparative assessments and portfolio-level planning in humid tropical regions (Wongwan et al., 2024).

The main limitations of the present study lie in its reliance on satellite-derived meteorological data and literature-informed degradation parameters, which may differ from long-term on-site measurements. Therefore, future studies should integrate extended ground-based monitoring, refine the empirical characterisation of degradation in local climatic conditions, and explicitly model maintenance and component replacement schedules, as well as economic performance. Nevertheless, the proposed stochastic-dynamic framework is a practical, reproducible tool that can be used to improve the performance and reliability of PV systems in humid tropical regions, which are plagued by climatic uncertainty. It can also be readily applied to PV systems with similar load and climate characteristics.

Conclusion

The present study proposed a hybrid stochastic-dynamic framework with which to assess the long-term technical performance of a 100-kWp grid-connected rPV system at a university campus in a humid tropical region. The proposed framework integrated multi-year climatic data from the NASA POWER database, MC-based uncertainty propagation, and a 2S-DDS to represent both inter-annual variability and time-dependent degradation over a 25-year operational horizon. The results of the probabilistic simulation revealed that the annual energy yield was 111–129 MWh yr⁻¹ (P10–P90), with a median specific energy yield of 1200 kWh kWp⁻¹ yr⁻¹. The simulated PR and specific energy yield levels were plausible and consistent with field reports from humid tropical regions (Islam et al., 2024; Mohamad Radzi et al., 2025). The < 2% difference in the results of the PVsyst simulation was interpreted as internal methodological consistency as both the calculations used the same hourly meteorological data from the NASA POWER database and comparable system loss assumptions (Ates & Singh, 2021; Khan et al., 2022).

Over the 25-year operational horizon, the literature-informed degradation rates of 0.55–1.0% yr⁻¹, which were scenario estimations rather than on-site measurements, revealed an estimated cumulative energy loss of 8.7%, which was relative to a no-degradation scenario. This highlights the importance of taking non-linear degradation into account during long-term PV performance assessments (Atia et al., 2023; Mohamad Radzi et al., 2025; Rajput et al., 2024). As for the annual energy yield, the Sobol analysis identified the PR residual as the largest contributor to variance. This was followed by irradiance, temperature, and degradation. Apart from that, the results of the lifetime correlation analysis revealed significant correlations between PR, availability, and degradation. However, these correlations should not be interpreted as independent contributors to variance. Therefore, operational conditions, thermal management, and degradation-aware planning are critical for sustaining the performance of PV systems in humid tropical regions, together with resource-based assessments (IEA PVPS, 2020; Prilliman et al., 2023; Yadav et al., 2025).

Acknowledgement

The authors gratefully acknowledge Universitas Merdeka Malang for the institutional and administrative support provided during this research. Funding: This research was funded by the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia, through the Directorate General of Research and Development and the Directorate of Research and Community Service, under DIPA No. SP DIPA-139.04.1.693320/2025, Revision 04; contract No. 128/C3/DT.05.00/PL/2025; derivative contract No. 018/LL7/DT.05.00/PL/2025; and institutional subcontract No. 13/Kontrak/LPPM/UM/V/2025.

Data Availability

The meteorological data was obtained from the NASA POWER database (<https://power.larc.nasa.gov/>). The specific dataset (NASA_POWER_Malang_2020_2025_hourly_PVsyst.csv) spans 1 January 2020 to 30 May 2025 for coordinates 7.96°S, 112.62°E. The Python scripts implementing Stages A to C, configuration files, and data processing workflows are provided in Supplementary Material S1. All the codes ensure complete reproducibility (Python 3.11, fixed seed = 42).

Nomenclature

i	Monte Carlo / bootstrap iteration index
t	Operational year index (year)
d	Daily index within year t (day)
$GHI_{t,d}$	Global horizontal irradiance on day d of year t (kWh·m ⁻² ·day ⁻¹)
H_t	Annual global horizontal irradiance in year t (kWh·m ⁻² ·yr ⁻¹)
$H^*(i)$	Bootstrapped annual irradiance at iteration i (kWh·m ⁻² ·yr ⁻¹)
$T^*(i)$	Bootstrapped annual mean ambient temperature at iteration i (°C)
T_{ref}	Reference temperature for PR modelling (°C)
$PR(i)$	Temperature-dependent performance ratio at iteration i
PR_{ref}	Reference performance ratio at the reference temperature
PR_{min}	Lower bound of performance ratio
PR_{max}	Upper bound of performance ratio
γ_T	Temperature coefficient of performance ratio (°C ⁻¹)
$\varepsilon(i)$	Stochastic residual loss term at iteration i
η_{ref}	Calibrated irradiance-to-yield conversion factor
$Y(i)$	Specific annual energy yield at iteration i (kWh·kWp ⁻¹ ·yr ⁻¹)
P_{inst}	Installed PV capacity (kWp)
$E(i)$	Annual energy yield at iteration i (kWh·yr ⁻¹)
$E_{i,t}$	Annual energy yield at iteration i in year t (kWh·yr ⁻¹)
C_0	Initial installed capacity at commissioning (kWp)
C_t	Effective capacity after degradation in year t (kWp)
δ_1	Early-life degradation rate (years 1–10) (yr ⁻¹)
δ_2	Ageing-phase degradation rate (years 11–25) (yr ⁻¹)
D_t	Number of days in year t (day)

*In the dataset implementation, ambient temperature is recorded as T_{amb} in the NASA POWER export file and corresponds to $T^*(i)$ in the stochastic model.

Compliance with ethics guidelines

The authors declare they have no conflict of interest or financial conflicts to disclose.

This article contains no studies with human or animal subjects performed by the authors.

References

- Aarich, N., Bakkour, M., Errahimi, F., & Benhmida, M. (2024). Assessment the long-term performance ratio maps of three grid-connected photovoltaic systems in the Moroccan climate. *Energy for Sustainable Development*, 79, 101388. <https://doi.org/10.1016/j.esd.2024.101388>
- Adita, N., & Setiawan, E. A. (2023). Analysis of performance and economic value of thin film and monocrystalline photovoltaic systems in the tropical area of Jakarta. *International Journal of Electrical, Computer, and Biomedical Engineering*, 1(1), 33–43. <https://doi.org/10.62146/ijecbe.v1i1.19>
- Al-Hanoot, A. K., Mokhlis, H., Mekhilef, S., Alghoul, M., Al Aqil, M., & Alhanut, M. (2025). Monte Carlo simulation for real-world energy yield analysis of car park solar PV system installations in harsh environments. *Results in Engineering*, 28, 106996. <https://doi.org/10.1016/j.rineng.2025.106996>
- Ates, A. M., & Singh, H. (2021). Rooftop solar photovoltaic (PV) plant—One year measured performance and simulations. *Journal of King Saud University - Science*, 33(3), 101361. <https://doi.org/10.1016/j.jksus.2021.101361>
- Atia, D. M., Hassan, A. A., El-Madany, H. T., Eliwa, A. Y., & Zahran, M. B. (2023). Degradation and energy performance evaluation of mono-crystalline photovoltaic modules in Egypt. *Scientific Reports*, 13, 13066. <https://doi.org/10.1038/s41598-023-40168-8>
- Chayjan, M. R., Dehghanian, F., & Kakhki, M. D. (2024). Modeling residential photovoltaic adoption: A system dynamics approach for solar energy expansion. *Energy Policy*, 189, 114133. <https://doi.org/10.1016/j.enpol.2024.114133>
- Dobos, A., Gilman, P., & Kasberg, M. (2012). P50/P90 analysis for solar energy systems using the System Advisor Model (NREL/CP-6A20-54488). National Renewable Energy Laboratory. <https://www.nrel.gov/docs/fy12osti/54488.pdf> (accessed 15 September 2026).
- Harsarapama, A. P., Aryani, D. R., & Rachmansyah, D. (2020). Open-source satellite-derived solar resource databases: Comparison and validation for Indonesia. *Journal of Renewable Energy*, 2020, 2134271. <https://doi.org/10.1155/2020/2134271>
- Hasan, A. A. Q., Zuhdi, A. W. M., Al-Shetwi, A. Q., Islam, M. A., Sankar, K. P., Idris, M. I., & Alkaws, G. (2026). Investigating long-term degradation and defects of solar photovoltaic modules in tropical climates: A case study of Malaysia. *IET Renewable Power Generation*, 20(1), e70198. <https://doi.org/10.1049/rpg2.70198>
- International Energy Agency Photovoltaic Power Systems Programme. (2020). Uncertainties in yield assessments and PV LCOE (Report T13-18:2020). IEA PVPS. https://iea-pvps.org/wp-content/uploads/2021/01/Report-IEA%E2%80%93PVPS-T13-18_2020-Uncertainties-in-Yield-Assessments-and-PV-LCOE-1.pdf (accessed 15 September 2026).
- Islam, M. I., Jadin, M. S. B., Al Mansur, A., & Alharbi, T. (2024). Electrical performance and degradation analysis of field-aged PV modules in tropical climates: A comparative experimental study. *Energy Conversion and Management: X*, 24, 100719. <https://doi.org/10.1016/j.ecmx.2024.100719>
- Jordan, D. C., & Kurtz, S. R. (2013). Photovoltaic degradation rates — an analytical review. *Progress in Photovoltaics: Research and Applications*, 21(1), 12–29. <https://doi.org/10.1002/pip.1182>
- Khan, M. A., Islam, N., Khan, M. A. M., Irshad, K., Hanzala, M., Pasha, A. A., & Mursaleen, M. (2022). Experimental and simulation analysis of grid-connected rooftop photovoltaic system for a large-scale facility. *Sustainable Energy Technologies and Assessments*, 53, 102773. <https://doi.org/10.1016/j.seta.2022.102773>
- Kladas, A., Herteleer, B., & Cappelle, J. (2025). A degradation-responsive framework for long-term PV power estimation. *Advanced Theory and Simulations*, 8(11), e202500631. <https://doi.org/10.1002/adts.202500631>
- Kumar, H., Yadav, S., Chaudhary, A., Sharma, S., & Kuradiya, A. (2025). Mitigating dust deposition effects on solar panels: An experimental approach using hydrophobic coating and vibration. *Environmental Science and Pollution Research*, 32(36), 21758–21768. <https://doi.org/10.1007/s11356-025-36946-8>
- Le Thi Minh, C., & Duong, M. Q. (2024). Reducing overall active power loss by placing solar and wind generators in a distribution power system using wild horse optimizer algorithm. *Journal of Engineering and Technological Sciences*, 56(5), 571–582. <https://doi.org/10.5614/j.eng.technol.sci.2024.56.5.2>
- Ministry of Energy and Mineral Resources of the Republic of Indonesia. (2024). Regulation of the Minister of Energy and Mineral Resources No. 2 of 2024 concerning rooftop solar power plants connected to the electricity network of holders of business licenses for the provision of electricity for public purposes. <https://jdih.esdm.go.id/dokumen/download?id=2024abspmesdm2.pdf> (accessed 15 September 2026).

- Mohamad Radzi, P. N. L., Mekhilef, S., Mohamed Shah, N., Akhter, M. N., Hassani, S., Albaker, A., & Wahyudie, A. (2025). Performance evaluation and degradation analysis of grid connected photovoltaic systems for energy efficient buildings in tropical climates. *Scientific Reports*, 15, 39103. <https://doi.org/10.1038/s41598-025-26765-9>
- Muñoz-Rodríguez, F. J., Gómez, P., Fernández-Carrasco, J. I., Tina, G. M., & Jiménez-Castillo, G. (2025). A new approach to analyse from monitored data the performance, matching capability and grid usage of large rooftop photovoltaic systems: Case study of the 1.05 MW photovoltaic system installed at the University of Jaén. *Renewable Energy*, 239, 121947. <https://doi.org/10.1016/j.renene.2024.121947>
- Mutlu, A. (2025). Comparative evaluation of NASA, ERA5, and observational data for accuracy and reliability. *Theoretical and Applied Climatology*, 156(7), 367. <https://doi.org/10.1007/s00704-025-05605-w>
- Nouira, I., & El Badsy, B. (2025). Comparative analysis of DTC-controlled TSTPI and FSTPI inverters for low-power photovoltaic applications. *Journal of Engineering and Technological Sciences*, 57(5), 599–612. <https://doi.org/10.5614/j.eng.technol.sci.2025.57.5.3>
- Obatola, S. O., & Junjie, T. (2024). A data-driven approach to grid-connected PV system reliability assessment: Combining deep learning and hybrid optimization. *Energy Reports*, 12, 5582–5593. <https://doi.org/10.1016/j.egyr.2024.11.041>
- Prilliman, M. J., Hansen, C. W., Keith, J. M. F., Janzou, S., Theristis, M., Scheiner, A., & Ozakyol, E. (2023). Quantifying uncertainty in PV energy estimates final report (NREL/TP-7A40-84993). National Renewable Energy Laboratory. <https://www.nrel.gov/docs/fy23osti/84993.pdf> (accessed 15 September 2026)
- Qu, H., Gao, B., Kong, Q., & Xu, Z. (2024). Experimental study of the effect of ambient temperature on the output characteristics of PV-PCM systems. *Journal of Energy Storage*, 88, 111535. <https://doi.org/10.1016/j.est.2024.111535>
- Rajput, P., Singh, D., Singh, K. Y., Karthick, A., Shah, M. A., Meena, R. S., & Abdul Zahra, M. M. (2024). A comprehensive review on reliability and degradation of PV modules based on failure modes and effect analysis. *International Journal of Low-Carbon Technologies*, 19, 922–937. <https://doi.org/10.1093/ijlct/ctad106>
- Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance based sensitivity analysis of model output: Design and estimator for the total sensitivity index. *Computer Physics Communications*, 181(2), 259–270. <https://doi.org/10.1016/j.cpc.2009.09.018>
- Shen, Y., Fouladirad, M., & Grall, A. (2025). Mathematical modeling of solar farm performance degradation in a dynamic environment for condition-based maintenance. *Reliability Engineering & System Safety*, 257, 110778. <https://doi.org/10.1016/j.ress.2024.110778>
- Shukla, A., Yadav, S. K., Yaqub, A., Singh, J., & Singh, R. B. (2024). Performance assessment of a 1 MW grid-connected rooftop solar photovoltaic (GCRPV) plant on an institutional building in composite climate of Northern India. *International Journal of Ambient Energy*, 45(1), 2392167. <https://doi.org/10.1080/01430750.2024.2392167>
- Tarigan, E. (2024). Techno-Economic Analysis of Residential Grid-Connected Rooftop Solar PV Systems in Indonesia Under MEMR 26/2021 Regulation. *International Journal of Energy Economics and Policy*, 14(1), 412–417. <https://doi.org/10.32479/ijeep.15277>
- Tripathi, A. K., Aruna, M., Sharma, S., Kumar, C., & Didwania, M. (2025). Performance assessment of solar PV panels under varying environmental conditions: A laboratory and field-based approach for sustainable energy in mining operations. *Environmental Science and Pollution Research*, 33, 15156–15175. <https://doi.org/10.1007/s11356-025-35983-7>
- Umam, M. F., Patria, M. F. A., Affandi, D. M., Nugraha, D. H., Kurniawan, H. D., & Ramadani, H. P. (2025). Performance evaluation of 120 kWp on-grid photovoltaic power plants after five years of operation. *Indonesian Journal of Energy*, 8(2), 177–189. <https://doi.org/10.33116/ije.v8i2.278>
- Wenten, I. G., Khoiruddin, K., & Siagian, U. W. R. (2024). Green energy technologies: A key driver in carbon emission reduction. *Journal of Engineering and Technological Sciences*, 56(2), 143–192. <https://doi.org/10.5614/j.eng.technol.sci.2024.56.2.1>
- Wongwan, W., Pleerux, N., Thanomsat, N., & Moukomla, S. (2024). Technical and Economic Potential of Solar Energy on Rooftops: A Case Study at Lampang Rajabhat University, Thailand. *International Journal of Geoinformatics*, 20(2), 82–94. <https://doi.org/10.52939/ijg.v20i2.3069>
- Yadav, D., Yadav, S. K., Varma, V., Khatoon, S., Singh, J., Singh, R. B., Hasnain, S. M. M., Paramasivam, P., & Tufa, M. A. (2025). Experimental analysis of elevated temperature and soiling loss on the rooftop PV modules performance under composite climatic conditions. *Scientific Reports*, 15, 42035. <https://doi.org/10.1038/s41598-025-25846-z>
- Youssef, M., Sharma, D. K., El Bahir, L., & Hassboun, T. (2021). Temperature prediction-based realistic performance analysis of various electrical configurations of solar PV panels. *Solar Energy*, 228, 612–624. <https://doi.org/10.1016/j.solener.2021.09.084>

- Zheng, K., Sun, Z., Song, Y., Zhang, C., Zhang, C., Chang, F., Yang, D., & Fu, X. (2025). Stochastic scenario generation methods for uncertainty in wind and photovoltaic power outputs: A comprehensive review. *Energies*, 18(3), 503. <https://doi.org/10.3390/en18030503>
- Ziar, H. (2024). A global statistical assessment of designing silicon-based solar cells for geographical markets. *Joule*, 8(6), 1667–1690. <https://doi.org/10.1016/j.joule.2024.02.023>