

# CREATING BANKABLE ENERGY PRODUCTION ESTIMATES FOR UTILITY-SCALE SOLAR PROJECTS



Part of the Bridging Solar PV Performance and Financial Models for Utility-Scale Projects Series

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## Introduction

Accurate energy production forecasting is fundamental to the bankability of utility-scale solar PV projects, as even modest forecasting errors can materially affect project revenues, debt coverage, and investor returns. Consider a hypothetical 250 MWac utility-scale solar photovoltaic (PV) project in Arizona that fails to meet its forecasted P50 energy output by 5 percent in its second year of operation, triggering debt covenant issues and falling short of equity investors' expected returns. Similar discrepancies are frequently observed across the solar PV industry, exposing a significant financial challenge: a large gap between forecasted performance and actual energy production in utility-scale solar PV projects.

By year-end 2025, global solar PV capacity had reached approximately 3.0 TWac, after an estimated 698 GW of new PV capacity was installed in 2025 [1]. At this scale, even modest gaps between forecasted and actual energy production can translate into tens of billions of dollars of financial exposure. Despite the considerable value at stake, a troubling trend continues: recent operating data show that PV sites are underperforming P50 production expectations by

approximately 8.6% on a weather-adjusted basis [2]. This gap reflects the combined effects of modeling assumptions, including soiling, shading, clipping losses, operational factors such as DC health issues, curtailment, degradation, overly optimistic availability assumptions, and other project-specific factors. Collectively, these effects create a gap between technical performance forecasts and financial expectations, ultimately adding risk and cost to solar PV projects.

This paper is part of E3 Consulting's 'Bridging Solar PV Performance and Financial Models for Utility-scale Projects' white paper series, which examines how technical assumptions, operating realities, and financial structures interact across the solar PV project lifecycle. Within that broader series, this paper focuses on the foundation of bankable solar PV production estimates for utility-scale projects. We discuss solar resource assessment and the technical assumptions that convert a project design into bankable energy forecasts used for financing. We explain how P-value forecasts are developed and used, why actual performance can deviate from those forecasts, and how uncertainty in solar resource data, modeling

assumptions, degradation, deferred maintenance, and evolving PV module technologies can compound over a project's operating life. The white paper series is intended for developers, independent engineers, lenders, tax equity investors, asset owners, and operators seeking to improve forecast credibility and reduce the gap between expected and realized energy production. The paper concludes with actionable recommendations for improving the credibility and bankability of production forecasts.

## Technical Performance Forecasts and Financial Modeling

Development of utility-scale solar projects relies on two parallel, yet siloed processes: technical performance forecasting and financial modeling. Engineers use software such as PVsyst to model the project configuration, including modules, inverters, and mounting systems, to estimate annual energy production over a 30- to 40-year operating life. Long-term irradiance data is used to characterize resource variability and to calculate probability-of-exceedance (P-values). In parallel, a financial model converts these forecasts into revenue projections and aggregates them with capital expenditures (CAPEX) budgets, depreciation schedules, operating expenses (OPEX) budgets, debt service coverage ratio (DSCR), and equity returns.

Financiers typically rely on a single set of simplified performance projections. In doing so, the nuances of performance variability and long-term degradation are standardized or simplified, thereby masking important risks. Historically, standardized assumptions were sufficient when solar Power Purchase Agreement (PPA) prices and the leveled



cost of energy (LCOE) were declining, as they have for most of the past two decades. However, policy changes, supply chain disturbances, and higher financing costs have recently driven prices upward, narrowing profit margins. Under these tighter economic conditions, there is less operating margin, and a 5 to 10 percent revenue shortfall can markedly erode equity returns or breach debt covenants.

Conflicting stakeholder priorities further compound these challenges: developers typically focus on minimizing initial costs and capturing incentives, while financiers seek stable and long-term cash flows; both are important for advancing sustainable, profitable projects. Consequently, the gap between technical forecasts, which can underestimate real-world losses or overstate system efficiencies, and financial models that often assume idealized output has far-reaching consequences for project success.

### Solar Resource Analysis

Most utility-scale energy models rely on third-party solar resource or meteorological data providers, such as SolarAnywhere, Solargis, Vaisala, and similar bankable platforms. These providers typically supply a Typical Meteorological Year (TMY) file or, in some cases, a Typical Global Horizontal Irradiance Year (TGY) file. These files are created using long-term satellite-derived data and include hourly or sub-hourly values for irradiance and meteorological variables such as global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), ambient temperature, wind speed, and humidity. These datasets are useful for estimating expected 1-Year P50 production, but they represent “typical” meteorological conditions and do not fully capture year-to-year weather variability, extreme events, or site-specific weather conditions. Utility-scale developers often use on-site MET stations and 12-month measurement campaigns to capture site-specific conditions such as irradiance, temperature, wind speed, soiling, and albedo. The GHI measurements from these campaigns are then used in a site-adaptation, or measure-correlate-predict (MCP) analysis to calibrate long-term satellite-derived data and produce a tuned TGY file. Site adaptation reduces site-specific bias and epistemic resource uncertainty,

although it does not eliminate long-term weather variability or measurement uncertainty.

For finance-grade satellite datasets, long-term annual GHI uncertainty is around  $\pm 4.5$  percent at a 95 percent confidence level in well-validated regions. Still, it can be materially higher in complex climates or locations with limited high-quality ground validation [3] [4]. Stakeholders either rely on a single weather data provider, average GHI across providers, or use a site-adapted TGY file. These methods may establish a reasonable long-term solar-resource estimate based on GHI but do not fully capture uncertainty in plane-of-array (POA) irradiance, which is the sunlight that reaches the PV modules. POA depends on GHI, DNI, DHI, orientation or tracking geometry, and albedo. The DNI uncertainty for these weather data files typically falls around  $\pm 8.5$  percent at approximately a 95 percent confidence level, while DHI uncertainty is less commonly reported as a standalone value because it is often derived from GHI and DNI. DNI has a material influence on

POA irradiance, particularly for single-axis tracking systems, where tracker orientation increases the contribution of direct-beam irradiance.

Assuming a reasonable correlation of 0.8 between GHI and DNI uncertainties, and accounting for tracker efficiency and POA uncertainties, POA can be estimated at approximately  $\pm 5.6$  percent for a typical tuned TGY file at a 95 percent confidence level. E3 modeled a  $\pm 60^\circ$  tracker system with 1 module in portrait orientation and a 30 percent ground coverage ratio (GCR) in PVsyst to estimate monthly POA values at a project location in the United States, using tuned TGY and TGY/TMY files from four widely used weather data providers. **Figure 1**, **Figure 2**, and **Figure 3** compare monthly GHI, DHI, and PVsyst-calculated POA irradiance for the ground-tuned TGY and four anonymized, widely used weather-provider datasets, labeled WP1 through WP4. It includes a 2-sigma (95 percent confidence) envelope around the tuned TGY, based on the associated uncertainties in GHI, DHI, and POA respectively.

**Figure 1: Monthly GHI Comparison Across Weather Datasets**

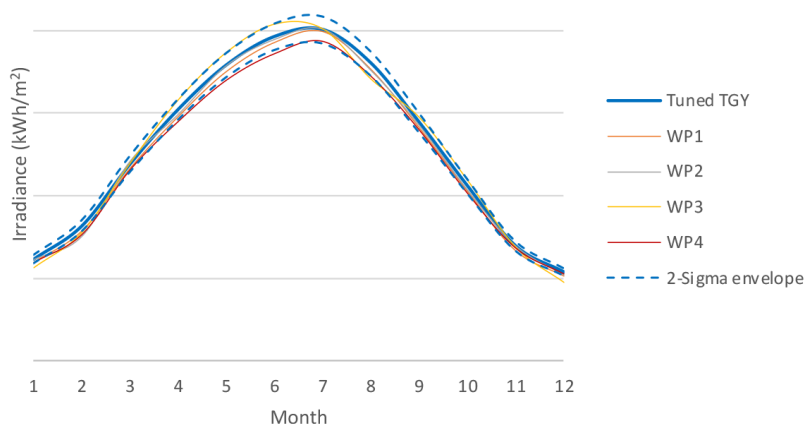


**Figure 2: Monthly DHI Comparison Across Weather Datasets**

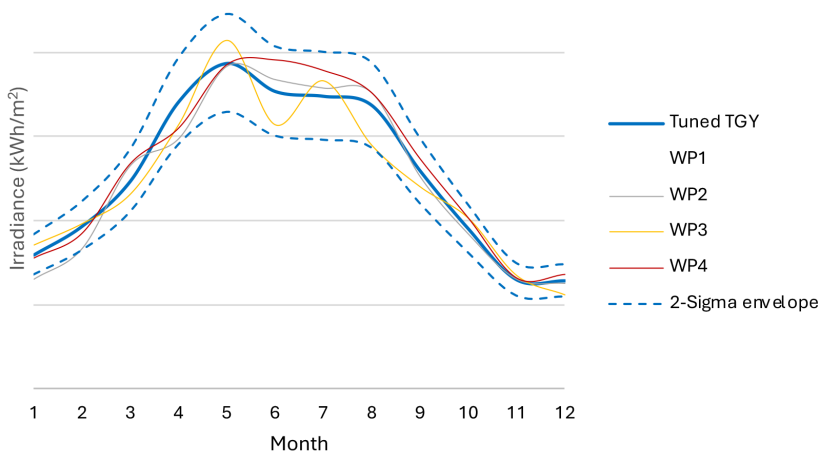
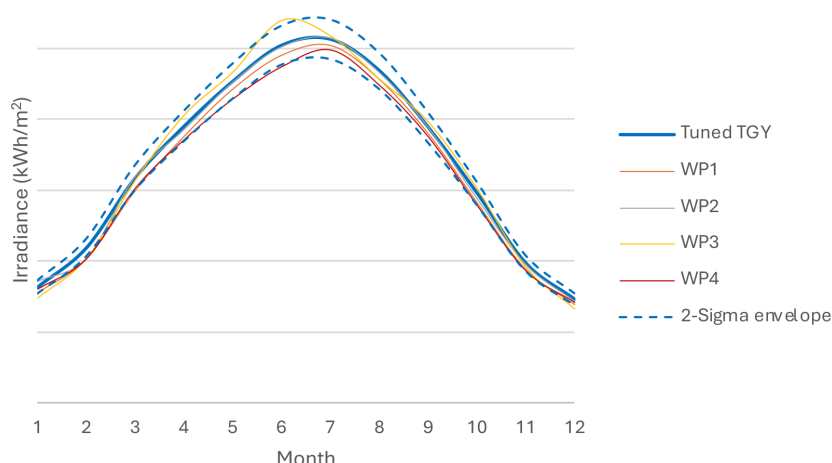


**Figure 3: Monthly POA Comparison Across Weather Datasets**



Figures 1 through 3 illustrate that the weather datasets are closely aligned on a monthly basis and generally remain within the tuned TGY's 2-sigma envelope. In contrast, **Figure 2** shows material variability in DHI, particularly from May through August, when the monthly values and seasonal profiles differ more noticeably among the datasets. This DHI variability does not translate directly into POA irradiance because diffuse irradiance is only one component of incident irradiance, and its contribution depends on array orientation, tracker position, sky-diffuse transposition, albedo, and the relative contribution of direct irradiance. Similar differences in the DNI profiles, although not shown separately, would also affect the resulting POA irradiance because single-axis tracking systems are particularly sensitive to the DNI component.

**Figure 3** shows that these differences in irradiance composition result in greater separation in modeled POA irradiance during the higher-resource months. WP3 produces the highest POA values in early summer, while WP4 produces the lowest values, despite the comparatively close GHI profiles shown in **Figure 1**. The POA results remain within the tuned TGY's 2-sigma envelope. This shows that similar GHI values across weather datasets do not necessarily produce similar modeled energy potential. Differences in the GHI–DNI partition, albedo, tracker geometry, and transposition produce distinct POA estimates even when monthly GHI is closely aligned.

For finance-grade energy assessments, weather-file selection should reflect the resulting POA irradiance, rather than GHI alone. Leaving residual POA uncertainty out of the analysis makes the P50 case appear more certain than it is and can leave insufficient margin in P90/P95 estimates. That bias can carry through to debt sizing, equity IRR, and NPV at financial close.

GHI-based selection methods, including maximum-likelihood [5] or similar representative weather approaches, are useful for early-stage screening as GHI is widely available and typically has lower uncertainty than DNI or DHI. However, selecting a weather file based only on GHI can miss differences that become apparent after transposition to POA. E3 recommends a POA-informed solar resource methodology that documents GHI and DNI uncertainties and the assumptions regarding their correlation. This provides a more defensible basis for selecting the weather file used in production estimates.

#### Downside Risk and P-values

Production risks in utility-scale solar PV projects fall into two broad categories: risks outside the owner's control and risks that project stakeholders can influence through design, procurement, construction, and asset management. Solar resource variability is the clearest uncontrollable risk: year-to-year changes in irradiance, temperature, snow, smoke, and other weather conditions can be characterized statistically but cannot be

altered by the project owner. In contrast, the following factors can be influenced through project decisions and operating practices:

- Equipment Quality
- BOM Selection
- Construction and Commissioning Quality
- Monitoring
- Maintenance Practices
- Corrective Maintenance Response
- Spare Parts Availability
- Degradation Management

These factors directly influence realized energy production and, unlike weather variability, can be mitigated through engineering, procurement, contractual, and operational controls. Some performance drivers fall between these two categories. Soiling, curtailment, equipment failure, and climate-driven degradation cannot always be prevented, but their effect on production can often be reduced through design choices, operating practices, contracts, maintenance, and monitoring. Production-risk analysis must therefore distinguish uncertainty that must be quantified and financially absorbed from risks that project stakeholders can mitigate through engineering and operational controls. Within this framework, production forecast uncertainty can be further categorized as follows:

#### Solar Resource Variability and Weather-Data Uncertainty

Solar resource uncertainty has two distinct components: aleatoric and epistemic uncertainty. Aleatoric uncertainty reflects the natural year-to-year variability in weather conditions, including irradiance, temperature, wind speed, snow, smoke, and other site conditions. This uncertainty cannot be eliminated because future weather is inherently variable, even when long-term historical datasets are available. TMY or TGY files are useful because they represent typical long-term conditions. Still, they do not capture the full range of annual weather outcomes that a project may experience during its operating life. Epistemic uncertainty, by contrast, reflects uncertainty caused by limitations in the weather dataset itself. This includes satellite model uncertainty, ground-sensor

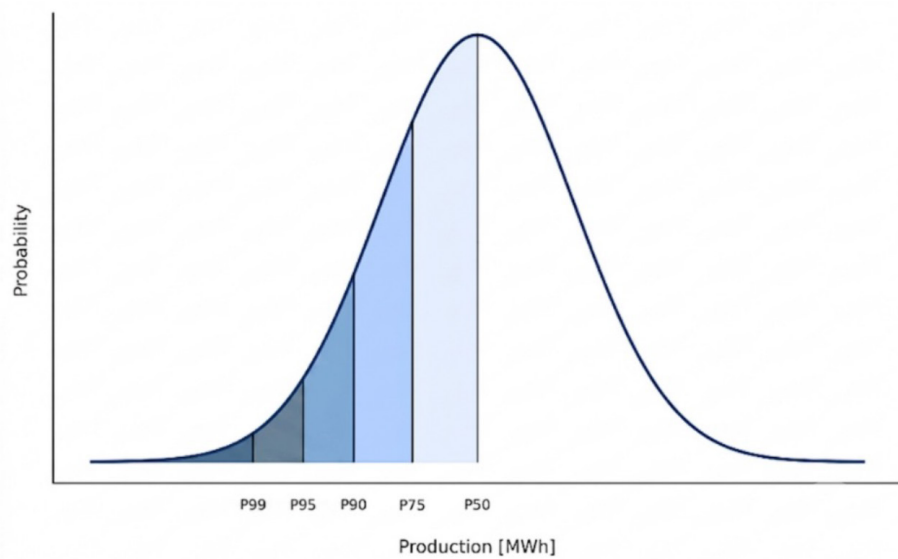
calibration, measurement quality, measurement period, data gaps, and site adaptation methods. A short-term on-site measurement campaign reduces epistemic uncertainty by calibrating long-term satellite data to site observations; it does not eliminate future weather variability and measurement uncertainty. Therefore, finance-grade downside analysis should separately account for both long-term weather variability and the uncertainty of the selected weather dataset, including GHI, DNI, and the resulting POA irradiance. In practice, downside calculations often rely on GHI variability and GHI model uncertainty. For tracking systems, this understates total resource uncertainty because DNI uncertainty and transposition also affect POA irradiance. Leaving those effects out makes the P50 case look more certain than it is and narrows the margin represented by the P90 or P95 estimate.

### Energy Modeling and Project-Specific Parameter Uncertainty

Energy-model uncertainty is primarily epistemic, arising from how the weather file, system design, equipment specifications, and technical assumptions are converted into expected plant output. Module and inverter parameters are typically based on manufacturer data or independent laboratory assessments, but the final energy estimate also depends on less certain assumptions. These include tracker behavior, bifacial gain, albedo, soiling, snow, shading, mismatch, thermal behavior, clipping, system availability, degradation, and O&M response assumptions. Some of these inputs are supported by test data or operating history, while others are based on benchmarks, empirical models, or engineering judgment. Because these assumptions are uncertain rather than fixed, a bankable downside analysis should assign defensible ranges to the material inputs and carry those ranges through the production estimate.

Together, solar-resource variability, weather-data uncertainty, and energy-model uncertainty form the basis of the probabilistic downside analysis used to derive P-values. However, the treatment of influenceable operational and lifecycle risks requires additional care, because these risks are not always well represented by a single statistical adjustment.

**Figure 4: Standard P-values based on Normal Distribution**



### P-values

To quantify the impact of these uncertainties, the industry commonly uses probability-of-exceedance (p-value) estimates. These values estimate the probability that actual energy production will exceed a given production level. In practice, P-values are typically calculated using a parametric method that combines key variability and uncertainty inputs through a root-sum-square approach and assumes annual energy production is approximately normally distributed.

**Figure 4** illustrates industry-standard P-values based on a normal distribution, where the standard deviation represents the cumulative uncertainty resulting from weather-resource variability, weather-data uncertainty, and energy-modeling assumptions.

Common P-values used in solar project finance include:

- **P50: Median or optimistic estimate with 50 percent probability of actual production exceeding it.**
- **P90: Conservative estimate with 90 percent probability of exceedance, typically used for debt sizing.**
- **P95: Conservative estimate, typically used for ITC-related downside sensitivity and tax equity risk assessment.**
- **P99: Highly conservative estimate, typically used for stress testing.**

P-values rely on the assumption that input uncertainties follow a normal distribution and that all sources of uncertainty are

independent and measurable. In practice, underlying inputs can be uneven, correlated, or biased, such as by overly optimistic modeling assumptions or unidentified climate or project risks. This can produce a non-normal distribution curve for the performance forecast. In addition, P-values primarily reflect changes in weather data and modeling assumptions, with the system always available. However, actual long-term performance depends on operational availability, equipment reliability, soiling, and degradation. These limitations can leave important project risks outside the P-value calculation. P-values are only as reliable as the uncertainty inputs, distributions, and correlations used to derive them. Operational availability, equipment reliability, degradation, soiling variability, and other lifecycle risks therefore need separate quantitative or scenario-based treatment when they are not explicitly included.

Monte Carlo methods extend the conventional parametric framework by allowing correlated and non-normal uncertainties to be carried through long-term production forecasts [6]. This is useful when degradation, mismatch, and other inputs interact in ways that are not well represented by a normal distribution. The result is a more realistic range of long-term production forecasts that can be used directly in financial downside analysis. By adopting such frameworks, the industry can successfully bridge the gap between technical and financial

stakeholders, advancing a unified, data-driven understanding of production uncertainties and their economic impacts.

### Operational Degradation

Solar PV projects are built with the expectation that output will decline steadily as PV modules degrade. Sunlight, heat, and similar environmental stresses cause microscopic damage that accumulates over time, reducing the production capacity each year. Other balance-of-system (“BOS”) components, such as inverters, trackers, and cables, also wear out or fail and are expected to be replaced, increasing availability losses and causing nonlinear performance drops. Technical forecasts typically model the decline as a linear percentage reduction in capacity from the initial production estimate over the project’s lifetime. The percentage value is based on the PV module’s warranted maximum year-on-year degradation, which is now between 0.4 and 0.5 percent per year.

PV module manufacturers typically provide a two-stage linear-warranty degradation structure as follows:

**Initial degradation (Year 1):** 1.0 to 2.0 percent, accounting for light-induced degradation (LID) for technologies that are exposed to LID, like p-type crystalline solar cell technologies.

**Year-on-year degradation (Year 2 onward):** Linear decline below 0.4 to 0.5 percent per year, with output warranted to remain above ~87 percent of the rated capacity after 25 to 30 years of operation.

The PV module manufacturer’s warranty represents a controlled estimate of module degradation and does not account for the cumulative effects of real-world conditions on system performance. These warranties do not account for operational stress factors, such as soiling, electrical imbalances, equipment wear and tear, and site-specific weather conditions, which can lead to increased degradation losses over time. Additionally, field data from operating utility-scale solar PV projects indicate that, while systems generally degrade in a near-linear manner, the observed rates exceed the warranty assumptions for PV modules [7]. These datasets suggest that actual system performance differs from the module’s guaranteed degradation by about 0.2 percent [8, 7].

**Figure 5: System Degradation over Project Lifetime**

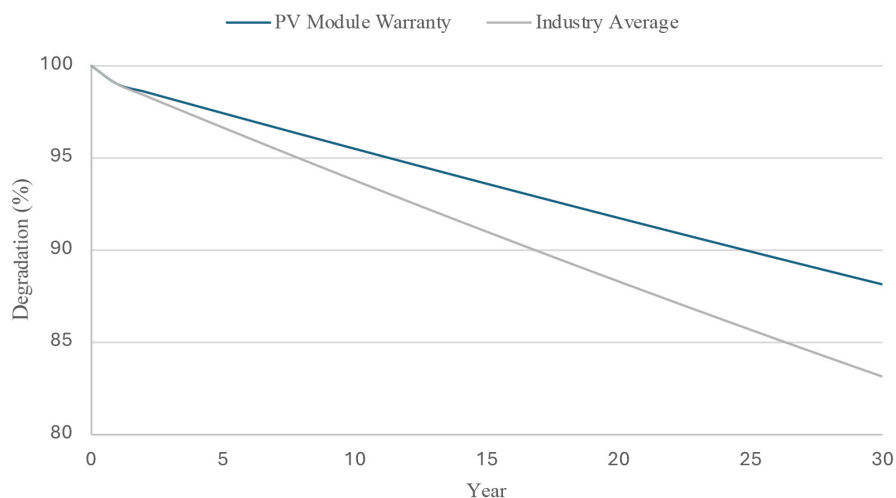


**Figure 5** compares two performance forecast scenarios: one using a 0.4 percent year-on-year degradation rate based on typical PV module warranties, and another using a reasonable 0.6 percent rate based on the field data. A 0.2-percentage-point difference in the degradation assumption yields approximately 3 percent less cumulative energy over the modeled system life. For a 250 MW plant with a 30-year PPA priced at \$30/MWh, this deficit represents approximately \$6.0 million in present value terms. Although newer PV module technologies may ultimately show lower degradation than the technologies represented in these field studies, they do not yet have the same depth of long-term operating history. The available field data still show system-level degradation above module-warranty assumptions, with BOS degradation contributing to the difference. Industry observations suggest that each new technology cycle has a steep learning curve. Higher initial failure rates often characterize these learning curves, and rapid technology cycles can render some technologies obsolete before they are fully stable.

In addition, the degradation warranty for PV modules is provided under Standard Test Conditions (STC), which are 1000 W/m<sup>2</sup> irradiance, 25°C ambient temperature, and 1.5 Air Mass Index. Verification of module degradation under STC conditions requires the developer and the module manufacturer to agree on a certified test laboratory to test field modules. STC measurement uncertainty and manufacturers’ contractual verification requirements make it difficult to substantiate degradation-warranty claims in practice. As these effects are not captured in module warranties, including an additional degradation factor for BOS, such as 0.2 percent, remains a reasonable approach to support more robust performance forecasts and reduce downside risk in long-term cash flow projections. Lastly, individual modules in the field degrade at different rates, introducing uncertainty in system-level degradation. Energy assessments should include this degradation uncertainty in downside production estimates and the associated P-value assumptions.

### Deferred Maintenance Leading to Nonlinear Degradation

Effective operations and maintenance (O&M) strategies are critical to sustaining long-term energy production and financial returns from utility-scale solar PV projects. But insufficient maintenance budgets, often based on overly optimistic views of wear and tear, defer required maintenance and increase availability and degradation losses. For example, inadequate module cleaning results in immediate soiling losses. Over time, persistent, localized soiling increases the risk of hotspots and irreversible cell damage, which directly reduces module efficiency and plant DC capacity. Deferred maintenance of essential BOS components, such as inverters, trackers, and data acquisition systems, leads to unexpected downtime, lower availability, and increased failure rates, especially during the late-stage wear-out phase of the asset lifecycle. [8].

In short, deferred maintenance, whether due to inadequate budgets or neglect in asset management, accelerates component aging and introduces non-linear performance degradation that linear warranty-based assumptions fail to capture. Reducing these risks requires a carefully planned and adequately funded O&M program. The associated budget should address both anticipated wear and unforeseen maintenance problems.

### **PV Module Technology and Climate Impacts on Degradation**

Passivated emitter and rear contact (PERC) monocrystalline silicon modules became mainstream around 2018, offering efficiency gains over standard monocrystalline PV modules. It was followed by tunnel oxide passivated contact (TOPCon) technology, which began to scale commercially around 2023. This technology offers higher efficiency potential and works well with existing PERC manufacturing lines. The industry is now exploring next-generation designs, which include Heterojunction Technology (HJT), perovskite, and tandem solar cells. These cells combine different materials to exceed current efficiency limits. This pace of innovation has outpaced much of the available degradation data, which is still largely based on older module technologies. Newer designs have not yet accumulated the same depth of long-term field history. Their degradation behavior is therefore not always fully represented in current performance models or warranty assumptions. In addition, the linear PV module's warranted degradation rates are based on controlled laboratory stress tests and do not account for the real-world effects of UV exposure, moisture ingress, and corrosive environments, which vary widely by geography. For instance, UV-Induced Degradation (UVID) has become a major concern for TOPCon and HJT solar modules. Reported average power losses range from 2.0 to 3.5%, which exceeds the acceptable limit of 1.0% for a 120 kWh/m<sup>2</sup> exposure [9]. These climate-related stressors affect different module designs in various ways and are greatly impacted by the quality of the Bill of Materials (BOM). Accordingly, degradation models must account for module technology, BOM configuration, and site-specific environmental exposure.

### **E3's Actionable Recommendations**

Developing a bankable production forecast requires more than selecting a weather file and applying standard loss assumptions. The analysis should reflect how resource uncertainty, equipment performance, degradation, maintenance, and operating data affect expected energy production over the project life. The following recommendations focus on the areas where stronger technical assumptions and better project controls can improve forecast credibility and reduce downside risk:

**POA-Informed Solar Resource Assessment:** Select weather datasets based on the POA irradiance and not on GHI agreement alone. For single-axis tracker and bifacial systems, the comparison should also account for DNI, DHI, albedo, tracker geometry, and the transposition model.

**Apply Transparent Uncertainty Analysis:** Document the material uncertainty inputs used in the production estimate, including the basis for each assumption, the range or distribution applied, and any known correlations. When the inputs are correlated, asymmetric, or non-normal, use Monte Carlo or scenario analysis in addition to the conventional root-sum-square method. The basis and exclusions for the P50, P90, P95, and P99 estimates should be clearly stated.

### **Use Lifecycle- and Technology-Specific Degradation Assumptions:**

Model degradation at the system level rather than relying solely on the module warranty curve. The forecast should distinguish initial degradation, mid-life behaviour, and late-life wear-out, while also accounting for module mismatch and balance-of-system ageing. Technology- and climate-specific effects, such as LID, UVID, moisture ingress, corrosion, and thermal stress, should be evaluated where relevant to the project.

**Strengthen Equipment and Bill-of-Materials Quality Assurance:** Implement comprehensive BOM controls and an end-to-end QA program, including raw-material traceability, in-line quality control, factory audits, reliability scorecards, independent

accelerated life testing, and pre-shipment inspections. Project stakeholders should apply enhanced quality-assurance and risk-control measures to emerging PV technologies with limited long-term field experience.

**Align O&M Budgets and Spare Parts with Lifecycle Risk:** Develop O&M budgets that reflect changing maintenance requirements over the operating life rather than assuming constant annual expenditure. Financial plans should include preventive maintenance, corrective repairs, increased late-life labor requirements, strategic spare parts, and reserves for major component replacements, such as inverters, cabling, and monitoring equipment.

### **Establish Proactive Monitoring and Periodic Model Recalibration:**

Use SCADA analysis, IV-curve tracing, thermography, electroluminescence, soiling studies, and fault analytics to identify emerging performance issues. Recalibrate the production forecast at least annually, and whenever material forecast-to-actual deviations are identified. Material forecast-to-actual deviations should also trigger root-cause analysis and corrective action.

### **Integrate Technical Forecasts with Financial and Contractual Models:**

Ensure that the financial model uses the same production, uncertainty, availability, degradation, and O&M assumptions as the technical assessment. Material revisions to the production forecast should flow directly into debt sizing, DSCR analysis, reserve requirements, return expectations, and downside cases. EPC, equipment supply, warranty, and O&M agreements should conform to the assumptions used in the bankable energy forecast.

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## References

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- [1] International Energy Agency Photovoltaic Power Systems Program (IEA PVPS), "Snapshot of Global PV Markets," 2026.
- [2] kWh Analytics, "Solar Risk Assessment," 2025.
- [3] Clean Power Research, "SolarAnywhere Validation Data Version 4.1," 2026.
- [4] M. Sengupta, Y. Xei, A. Lopez, A. Habte, G. Maclaurin and J. Shelby, "The National Solar Radiation Data Base (NSRDB)," Renewable and Sustainable Energy Reviews, Elsevier, 2018.
- [5] R. Kharait, J. Newmiller, J. Moore and C. Chan, "Maximum Likelihood Estimation (MLE) Approach for Determining Most Representative Solar Resource Data Set for United States," IEEE Photovoltaic Specialists Conference (PVSC), 2021.
- [6] A. Joshi and R. Kharait, "Parametric vs Monte Carlo Uncertainty Analysis for Distinct U.S. PV Locations," 13 May 2026. [Online]. Available: [https://pvpmc.sandia.gov/app/uploads/sites/243/dlm\\_uploads/2026/05/Session10\\_RounakKharait.pdf](https://pvpmc.sandia.gov/app/uploads/sites/243/dlm_uploads/2026/05/Session10_RounakKharait.pdf). [Accessed 03 08 2026].
- [7] C. Deline, M. Muller, R. White, K. Perry, M. Springer, M. Deceglie and D. Jordan, "Availability and Performance Loss Factors for U.S. PV Fleet Systems," National Renewable Energy Laboratory (NREL), Colorado, Denver, 2024.
- [8] M. Bolinger, W. Gorman, D. Millstein and D. Jordan, "Plant-level performance and degradation of 31 GWdc of utility-scale PV in the United States," Energy Analysis & Environmental Impacts Division, Lawrence Berkeley National Laboratory, Berkeley, California, 2022.
- [9] A. Sinha, J.-N. Jauber and T. Karin, "UV-Induced Degradation Susceptibility of Industrial N-Type Silicon High-Efficiency PV Modules," IEEE, Seattle, Washington, 2024.