

Physics-based modeling of climate-induced degradation in crystalline silicon PV modules for performance-loss prediction

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Abstract. Global photovoltaic (PV) growth requires accurate lifetime prediction and long-term reliability frameworks to ensure economic viability and greenhouse gas emission reduction. Conventional degradation models, which depend on historical performance trends, often fail to capture location-specific climatic variability or the coupled physical and chemical mechanisms that govern real-world material aging. This work presents a physics-based, multi-mechanism framework that links environmental stressors directly to performance loss in field-aged crystalline silicon PV modules. The model combines weather-driven encapsulant photo-oxidation kinetics with Shockley–Read–Hall recombination and metallization corrosion to predict the degradation of PV electrical parameters. We calibrated model parameters against long-term field I–V data using non-linear least-squares optimization. We propagated uncertainty through Monte Carlo sampling and quantified parameter influence via Sobol global sensitivity analysis. The calibrated model reproduced the measured degradation trajectories with high fidelity ($R^2 = 0.918$ for I_{sc} , 0.841 for V_{oc} , and 0.934 for P_{max}). The model predicted an 80% of initial performance threshold at 13.69 years and an overall P_{max} degradation rate of 1.78%/year over a 25-year operating period. Sensitivity analysis identified yellowing kinetics as the dominant contributor to long-term power loss, with defect-generation parameters gaining influence as the module ages. The climatic sensitivity analysis result show that the temperature has an important effect due to its contribution towards enhancing the kinetic rates that control the deterioration process and energy loss. However, the influence of irradiation and humidity has a relatively smaller effect compared to the temperature influence on reaction kinetics.. By replacing empirical extrapolation with mechanism-based prediction, the model identifies dominant failure modes and provides a physically interpretable basis for climate-specific PV material optimization and reliability forecasting.

Keywords: PV Lifetime, Material Physics, Climate Stressors, Performance Modeling, Reliability

1 Introduction

Solar photovoltaic (PV) systems are central to the global energy transition and greenhouse gas (GHG) emission reduction. Crystalline silicon (c-Si) PV technology dominates the global solar PV market owing to its high conversion efficiency, technological maturity, and relatively low manufacturing cost [1]. Despite substantial improvements they are subject to degradation mechanisms driven by environmental stressors, with significant implications for energy yield and GHG emissions [2]. Life-cycle assessment studies demonstrate that PV module degradation rate directly influences GHG emissions, and lower degradation rates reducing environmental burden [3]. Non-linear degradation patterns and location-specific climate conditions further affect GHG emissions, and climate change projections suggest GHG emissions from PV electricity could increase by up to 105% by 2100 under worst-case scenarios [4]. Comprehensive reviews of c-Si failure modes highlight the importance of understanding degradation mechanisms to extend module operational lifetimes beyond current 25-year warranties [5]. Degradation can weaken PV's emissions-reduction contribution: reduced generation may be offset by fossil electricity or additional and replacement modules, which add emissions across the energy and equipment life cycles [4]. Future warming is projected to accelerate thermal degradation in mono-Si modules, increasing weighted average degradation rates by up to 0.1%/year by 2059 and raising energy costs by approximately 10% [6, 7].

Silicon photovoltaic materials undergo complex defect evolution governed by environmental stressors and kinetic pathways [8]. Recent research on crystalline silicon photovoltaic degradation reveals significant variability in performance loss rates and underlying mechanisms. Field studies demonstrate degradation rates ranging from 0.01-0.47%/year for well-maintained systems, with an overall average of 0.27%/year [9], while technology-specific analysis shows polycrystalline silicon at 0.36%/year, monocrystalline at 0.77%/year, and amorphous silicon at 0.57%/year. However, severely degraded systems can exhibit much higher rates, with one 15-year Mediterranean study reporting 2.56%/year for polycrystalline modules [10]. Key degradation mechanisms include encapsulant yellowing causing optical losses and interconnect corrosion increasing series resistance, both driven by moisture, oxygen, and light exposure [10, 11]. Multiple degradation mechanisms contribute to optical losses, including encapsulant delamination, internal haze formation from glass-encapsulant interactions, and corrosion of various module components [12]. Research demonstrates that EVA encapsulant discoloration significantly impacts photovoltaic module performance through coupled photo-chemical and photo-physical processes [13]. Field studies of 25-year-old modules show that EVA discoloration accounts for 83.5% of failure modes, causing 22.2% degradation in short-circuit current (I_{sc}) and 21.3% in maximum power, with degradation rates varying linearly with discoloration area [14]. UV-induced yellowing in photovoltaic modules results from complex chemical degradation processes that significantly impact optical performance. The yellowing process involves chromophore formation through UV absorber photodegradation, which can cause up to 4% decrease in photogenerated current after accelerated aging [15]. These optical losses stem from discoloration caused by additive interactions and polymer structural changes, including competing cross-linking and chain scission mechanisms influenced by oxygen and temperature [16]. The lifetime-equivalent defect density concept quantifies these relationships, showing how defect density changes directly affect bulk carrier lifetime in crystalline silicon under various stress conditions [17]. SRH recombination occurs when defects act as traps that successively capture electrons and holes, with longer lifetimes indicating better solar cell performance [18]. In silicon solar cells with short SRH lifetimes, non-radiative exciton recombination becomes increasingly problematic, substantially limiting optimal base doping levels and reducing photoconversion efficiency [19].

Accurate prediction of long-term performance PV remains a critical challenge for system

designers, reliability engineers and investors. Traditional degradation models often rely on empirical degradation rates, typically ranging from 0.3% to 1.0% per year. While useful for financial assessments, such approaches provide limited insight into the underlying physical mechanisms driving performance loss. A more rigorous methodology requires coupling semiconductor behavior with environmental and chemical degradation processes. Multiphysics simulations have become essential tools for understanding these complex degradation pathways, enabling systematic exploration of charge transport mechanisms, thermal effects, mechanical stress, and device architecture optimization to enhance both performance and stability [20]. Advanced modeling approaches using accelerated aging show promise for laboratory to field correlation, with acceleration factors of 143.36 demonstrated under controlled conditions [21]. These findings highlight the critical need for physics-based degradation models beyond empirical approaches. [22] developed a dynamic time evolution method that converts continuous time reliability models into incremental versions using equivalent stress duration concepts, enabling concurrent device circuit aging simulations with natural aging feedback that reduces overestimation by 32%. [23] created a TCAD-to-SPICE framework using identical physical models for BTI and HCD aging, calibrated with experimental data and compatible with cycle-by-cycle input excitations for DVFS and random activity analysis. [24] introduced ComphU, a compact physics-aware framework for nanowire nFET aging that models experimental I-V characteristics under BTI and HC stress using simplified Distribution Function modeling. [25] demonstrated an analytical framework spanning from microscopic degradation physics to aged I-V characteristics, representing devices as equivalent ballistic MOSFET chains to propagate local degradation without computationally intensive self consistent calculations.

c-Si are the most installed PV technology worldwide. understanding their degradation is critical to assure module performance overtime. Cumulative effects of annual degradation affect lifetime energy production, levelized cost of electricity (LCOE), and bankability assessments used by investors and insurers. Warranty terms are linked to expected degradation rates; Unexpected degradation can influence risk premiums, financial terms and warranty liabilities. Degradation is also intrinsically linked to manufacturing economics: robust modules which incur less performance loss over the lifetime can demand higher prices to offset increased production costs, while modules which degrade more quickly incur greater lifecycle costs and devalue manufacturing improvements. For these reasons, understanding and accurately modeling c- Si degradation is important for reliable energy generation, maintaining warranty promises, and developing competitive manufacturing cost targets. This work develops a multi-scale framework that connects temperature-dependent semiconductor properties, encapsulant aging, and moisture-induced corrosion to module electrical performance. A physics-informed computational framework was developed to predict the long-term power degradation of crystalline silicon photovoltaic (PV) modules over a 20-year operating period. The model integrates environmental stressors, moisture ingress, and defect-related trap generation into a unified degradation assessment methodology. Unlike conventional approaches that rely exclusively on empirical degradation rates, the proposed framework incorporates physically meaningful degradation mechanisms and their dependence on environmental conditions.

2 Methodology

This section presents the complete methodology used to model PV module degradation. The workflow begins by identifying the underlying physical mechanisms responsible for degradation, followed by applying these mechanisms into the corresponding electrical performance parameters. To ensure robustness and consistency, the model calibrated using measured field data, after which sensitivity analysis and model validation are performed.

2.1 Optical degradation

The progressive optical degradation of photovoltaic encapsulants is governed by a coupled chain of photo-chemical and photo-physical processes that linked environmental stressors. The discoloration kinetics of Ethylene-Vinyl-Acetate (EVA) are described by a stress-accelerated rate law in which UV irradiance, humidity, and temperature jointly drive the formation of chromophoric species, yielding a yellowing index $Y(t)$ that increases linearly with exposure time under constant conditions. The yellowing equation can be derived by combining chemical reaction kinetics (Arrhenius law) with multi-stress acceleration (Eyring model) and a bounded damage evolution term. Each component has a clear physical interpretation.

$$\frac{dY}{dt} = k_Y \exp\left(-\frac{E_{aY}}{k_B T}\right) \left(\frac{RH}{RH_0}\right)^{m_Y} \left(\frac{G}{G_0}\right)^{n_Y} (1 - Y) \quad (1)$$

where K_Y - intrinsic discoloration rate constant under reference conditions, $\left(\frac{G}{G_0}\right)^{n_Y}$ - UV-dose acceleration term, m -quantifies sensitivity of chromophore formation to UV intensity, UV drives photolysis of additives and formation of conjugated degradation products, $\left(\frac{RH}{RH_0}\right)^{m_Y}$ - humidity acceleration term. $\exp\left(-\frac{E_{aY}}{k_B T}\right)$ - Arrhenius temperature dependence, E_a is the activation energy for discoloration reactions. $(1-Y)$ the saturation term.

Integrated Form

$$Y(t) = 1 - (1 - Y_0) \exp\left[-\int_0^t k_Y e^{-E_{aY}/(k_B T(\tau))} \left(\frac{RH(\tau)}{RH_0}\right)^{m_Y} \left(\frac{G(\tau)}{G_0}\right)^{n_Y} d\tau\right]. \quad (2)$$

Where Y_0 — initial yellowing index,

The accumulation of photo-oxidation products—represented by the discoloration index $Y(t)$ increases the effective absorption coefficient and thereby reduces transmitted light. The optical transmittance of the encapsulant was modeled using a Beer–Lambert law formulation, according to Step 2. Beer–Lambert law

$$T = e^{-\alpha L} \quad (3)$$

where T - optical transmittance, (α) - absorption coefficient, (L) - encapsulant thickness.
hence,

$$\alpha(t) = \alpha_0 + \alpha_Y Y(t)$$

where (α_Y) = increase in absorption caused by complete yellowing, (α_0) = absorption coefficient of new encapsulant. Substitute these into Beer–Lambert law.

$$T(t) = \exp[-(\alpha_0 + \alpha_Y Y(t))L] \quad (4)$$

2.2 Defect density (N_t) and recombination

The non-saturating defect-growth model that the classical Peck–Arrhenius–irradiance formulation applied to defect kinetics.

$$N_d(t) = N_{d0} + A_d \exp\left(-\frac{E_d}{k_B T}\right) RH^n \left(\frac{UV}{UV_{ref}}\right)^m t \quad (5)$$

where N_{d0} - initial defect density, E_d - Activation Energy for Defect Density Growth, A_d - base defect-generation rate under reference conditions Shockley-Read-Hall (SRH) Theory: Impact of

N_t , capture cross-section (σ), and thermal velocity (v_{th}) on minority carrier lifetime (τ). For a single trap level with density $N_t(t)$, the lifetime becomes

$$\tau_{SRH}(t) = \frac{1}{\sigma_t v_{th} N_t(t)} \quad (6)$$

where the thermal velocity v_{th} , $v_{th} = \sqrt{\frac{3k_B T}{m^*}}$

The product $\sigma_t v_{th} N_t(t)$, represents the total recombination probability per unit time.

2.2.1 Corrosion and Series Resistance Environmental stress—particularly humidity and temperature drives metallization corrosion, gridline thinning, and contact degradation. This is modeled through a corrosion index

$$C(t) = A_c R H^n t \exp\left(-\frac{E_c}{kT}\right) \quad (7)$$

where; E_c - activation energy for corrosion, A_c - pre-exponential factor for corrosion.

The resulting increase in series resistance is modeled as

$$R_s(t) = R_{s0} + \alpha C(t) \quad (8)$$

where α quantifies the impact of corrosion on metallization resistance.

2.3 Energy degradation modeling

The energy degradation model is developed from changes in electrical parameters, which are linked to degradation-induced changes in material properties and the underlying material physics.

2.3.1 Short-Circuit Current The short-circuit current is computed by spectrally integrating the incident photon flux over the solar spectrum, weighted by the module's time-dependent optical transmittance and internal quantum efficiency. Mathematically,

$$I_{sc}(t) = I_{sc0} T(t) \sqrt{\frac{\tau_{SRH}(t)}{\tau_{SRH,0}}} = I_{sc0} \exp[-\alpha_Y Y(t)] \sqrt{\frac{N_{t0}}{N_t(t)}}.$$

2.3.2 Open-Circuit Voltage The open-circuit voltage is obtained from the diode equation and reflects the balance between photogeneration and recombination. It is expressed as

$$V_{oc}(t) = \frac{k_B T(t)}{q} \ln\left(\frac{I_{sc}(t)}{J_0(t)} + 1\right) \quad (9)$$

where $I_{sc}(t)$ - the short-circuit current and $J_0(t)$ is the saturation current.

$$J_0(t) = J_{00} \sqrt{\frac{N_t(t)}{N_{t0}}}. \quad (10)$$

2.3.3 Fill factor The fill factor is highly dependent on the development of series resistance and recombination effects in the solar cell. With continued degradation, the increase in R_s results in a decrease in the slope of the I–V characteristic curve in the area of maximum power. A drop in and improvement in recombination cause a reduction in the available current. The approximation for the FF is

$$FF(t) \approx FF_{id}(t) \left[1 - \frac{R_s(t) I_{sc}(t)}{V_{oc}(t)}\right] \quad (11)$$

2.3.4 Power Degradation Model The maximum power output of the device is expressed as the product of the degraded short-circuit current, open-circuit voltage, and fill factor

$$P_{\max}(t) = V_{oc}(t) I_{sc}(t) FF(t). \quad (12)$$

Substitute everything

$$P_{\max}(t) = \left\{ \frac{k_B T(t)}{q} \ln \left(\frac{I_{sc}(t)}{J_0(t)} + 1 \right) \right\} \times \left\{ I_{sc0} \exp[-\alpha_Y Y(t)] \sqrt{\frac{N_{t0}}{N_t(t)}} \right\} \times FF_{id}(t) \left[1 - \frac{R_s(t) I_{sc}(t)}{V_{oc}(t)} \right]. \quad (13)$$

2.4 Parameter optimization and weighted calibration

Model calibration was performed by minimizing a weighted multi-objective residual function using a bounded non-linear least-squares (*scipy.optimize.least_squares, trf*) procedure implemented via SciPy's Trust Region Reflective (TRF) algorithm with Jacobian scaling. The optimisation minimizes a weighted multi-objective residual function constructed from the differences between measured and model-predicted normalized values of P_{max} , I_{sc} , V_{oc} , FF . Unit weights were applied to the I_{sc} , V_{oc} and FF residuals, while the P_{max} residuals were scaled by a factor of 1.20 to increase sensitivity to long-term power loss. At each iteration, the concatenated residual vector was evaluated and passed to the TRF solver, which enforces physically meaningful parameter bounds and ensures numerical stability through tight convergence tolerances $\mathbf{ftol} = 10^{-6}$, $\mathbf{xtol} = 10^{-6}$. All eight kinetic and coupling parameters were constrained within experimentally and literature-supported ranges to prevent the optimizer from exploring non-physical regions of the parameter space. To ensure numerical stability and prevent parameter boundaries from collapsing during fit iterations, we minimize a weighted multi-objective residual function. The objective function minimises the difference between predicted and measured normalised values across all available field measurement dates. Parameter uncertainty was propagated via Monte-Carlo sampling of the model parameters. For every sample, the full climate-to-rate-to-electrical chain was re-evaluated, yielding empirical 2.5th – 97.5th percentile bands on the normalised performance curves.

2.5 Uncertainty quantification

The unified degradation model brings together optical, electrical, and kinetic parameters, all of which evolve under environmental forcing (temperature, relative humidity, and irradiance). Because these parameters shift and interact over time, their effect on the model's outputs isn't constant; it changes nonlinearly depending on how far along the module is in its aging process. This is where sensitivity analysis becomes useful, and it does two things for us here: it tells us which degradation mechanisms dominate at different stages of aging, and it surfaces parameter interactions that a single-mechanism model simply wouldn't catch. We use Monte Carlo simulation to generate the uncertainty envelope, and Sobol indices to trace how that uncertainty moves through the model. A variance-based Sobol global sensitivity analysis using the SALib framework used to look at how variance is distributed across parameters under micro climatic variability. It applied to all 11-parameter vectors that includes both the internal kinetic parameters and the environmental scaling multipliers. First-order indices (S_i) tell us how much each parameter contributes on its own, while total-order indices (S_{Ti}) capture that plus any interaction effects with other parameters. This analysis is implemented on the Monte Carlo set at each field measurement date, this gives information how sensitivity actually shifts as the module ages.

2.6 Validation procedure

Model predictions were evaluated at each field measurement date without temporal smoothing or post-processing. Residuals were inspected to confirm the absence of systematic bias. The agreement between predicted and measured trajectories was used to assess whether the model correctly captures the coupled evolution of optical, electrical, and resistive degradation mechanisms under real outdoor conditions. To indicate the model accurately reproduces the measured degradation trajectories model skill was quantified by the coefficient of determination (R^2), root-mean-square error (RMSE) and mean absolute error (MAE) computed between predicted and measured normalised values at all available field measurement dates.

3 Results and discussion

3.1 Climatic conditions used as environmental inputs

Figure 1 presents the environmental conditions used as inputs to the physics-based degradation model, comprising the measured solar irradiance (G), relative humidity (RH), and PV module surface temperature (Tsurf). The module surface temperature was used rather than ambient temperature because it more directly represents the thermal conditions experienced by the PV cells and encapsulant during outdoor operation. These site-specific environmental variables provide the principal forcing conditions for the modeled degradation processes, with Tsurf governing thermally activated degradation through Arrhenius-type kinetics, irradiance driving photo-induced degradation, and RH representing moisture-related stress associated with hydrolysis, corrosion, and delamination.

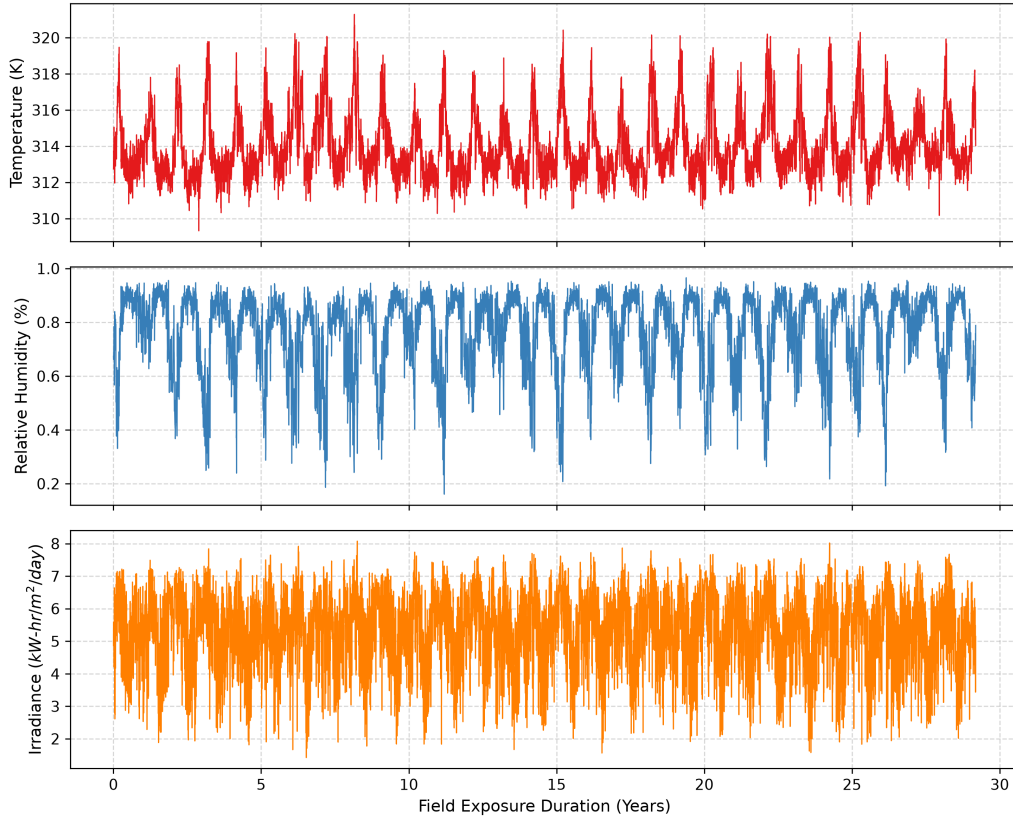


Figure 1: Site-specific environmental conditions used as inputs to the model.

3.2 Parameter calibration and estimated kinetic constants

All eight kinetic and coupling parameters were calibrated within physically meaningful bounds, and the resulting optimized values are summarized in Table 1. The resulting parameters line up well with what we’d expect from each degradation mechanism. Encapsulant yellowing drives an exponential drop in transmittance, which explains the long-term I_{sc} losses we see. Defect generation, through a slow buildup of recombination centers, accounts for the more gradual decline in V_{oc} . And corrosion explains the rising series resistance behind the fill-factor losses. What’s notable is that these three mechanisms each affect a different electrical parameter, yet they all feed into P_{max} so the fact that one consistent parameter set reproduces all four metrics at once is a strong indication the model is capturing the real underlying physics, not just curve-fitting. Generally, the calibrated parameters provide a multi-mechanism representation of PV degradation, linking environmental exposure to optical attenuation, defect-related recombination, and resistive losses. The optimization algorithm maintained stability even under high-variance weather inputs (T, RH, G), confirming its suitability for long-term field data.

Table 1: Optimized model parameters for crystalline-silicon PV module degradation

Parameters	Value
E_{aY}	0.3536 eV
E_d	0.1953 eV
E_c	0.22 eV
$\log k_Y$	6.976
$\log A_d$	0.450
$\log A_c$	0.5437
α_Y	14.37 m ⁻¹
α_c	0.456

3.3 Sensitivity analysis

The combined Sobol sensitivity analysis in Figure 2 evaluates the contributions of kinetic and environmental parameters to the variance of (P_{max}) predictions at different exposure times. The results show that (E_{aY}) remains the dominant parameter, with total-order sensitivity indices of approximately 0.52–0.60, indicating the strong influence of EVA yellowing kinetics on long-term power degradation. The sensitivity to E_d increases from approximately 0.38 at year 6 to 0.48 at year 20, while $\log(k_Y)$ increases from approximately 0.38 to 0.53, suggesting an increasing contribution of optical and defect-related degradation kinetics with aging. γT , E_c and $\log(A_d)$ show moderate but smaller contributions. In contrast, the direct sensitivities to irradiance, and relative humidity parameters γG , and γRH) are very small within the investigated parameter ranges. This indicates that the irradiance and relative humidity primarily influence degradation through the associated kinetic processes rather than acting as dominant independent sources of (P_{max}) variance. Overall, the results support the use of a coupled environmental–kinetic degradation framework and demonstrate that the long-term power loss is governed predominantly by the degradation kinetics activated by environmental exposure.

3.4 Validation

The model show high coefficients of determination ($R^2 = 0.934$ for P_{max} , 0.918 for I_{sc} , and 0.84 for V_{oc} together with the low RMSE and MAE values. The strong agreement between the

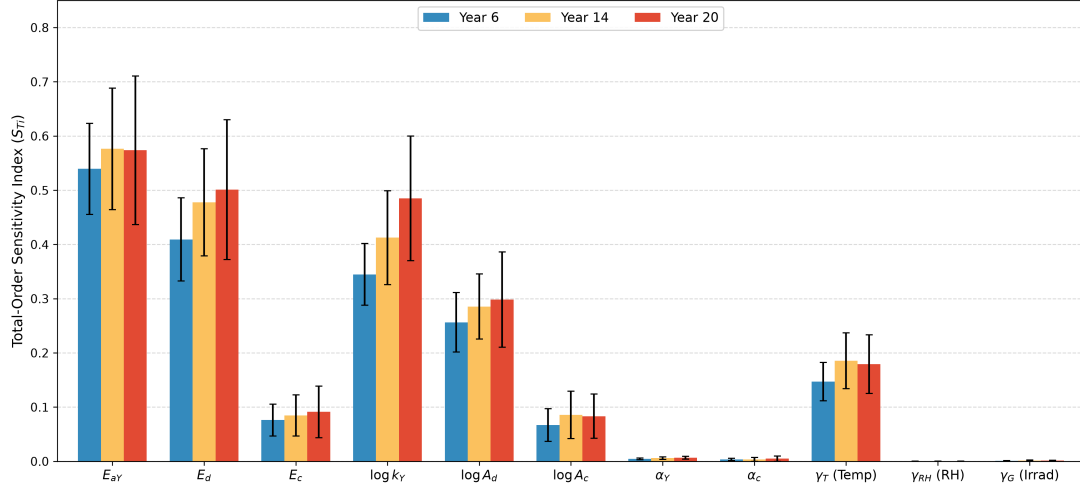


Figure 2: Combined Sobol sensitivity analysis of kinetic and environmental parameters for P_{max} degradation at selected exposure times

modeled and measured trajectories for P_{max} , I_{sc} , V_{oc} demonstrates that the framework accurately captures the dominant ageing mechanisms governing optical losses, current-generation decline, and defect-density-driven voltage degradation. the slightly lower but still robust R^2 for FF reflects the more complex dependence of fill factor on defect generation and the progressive increase in series resistance. Overall, the results demonstrate that the unified degradation model provides reliable, physically consistent predictions across all electrical parameters. As presented in Table 2, the model achieved high R^2 , indicating high predictive accuracy and strong physical consistency across all degradation channels.

Table 2: Model accuracy assessment across key performance parameters

Parameter	R^2	RMSE	MAE
I_{sc}	0.918	0.0195	0.0152
V_{oc}	0.841	0.0149	0.0123
FF	0.470	0.0058	0.0043
P_{max}	0.934	0.0228	0.0198

3.5 Optical degradation

EVA encapsulant aging shows a clear a rising yellowing index and the declining optical transmittance. This driven by long-term photo-oxidation and thermo-oxidation that generate carbonyls, chromophores, and acetic acid. These chemical species increase the absorption coefficient in the blue-UV region, reducing the photon flux reaching the silicon cell and lowering the carrier-generation rate. The resulting optical losses directly suppress I_{sc} and indirectly reduce V_{oc} through the diode relation linking photogenerated current and recombination. Acetic-acid-induced metallization corrosion further elevates series resistance, degrading fill factor. Together, these coupled optical, chemical, and electrical mechanisms produce the measured monotonic decline in P_{max} , demonstrating that encapsulant discoloration is a primary driver of long-term PV module power loss under field conditions.

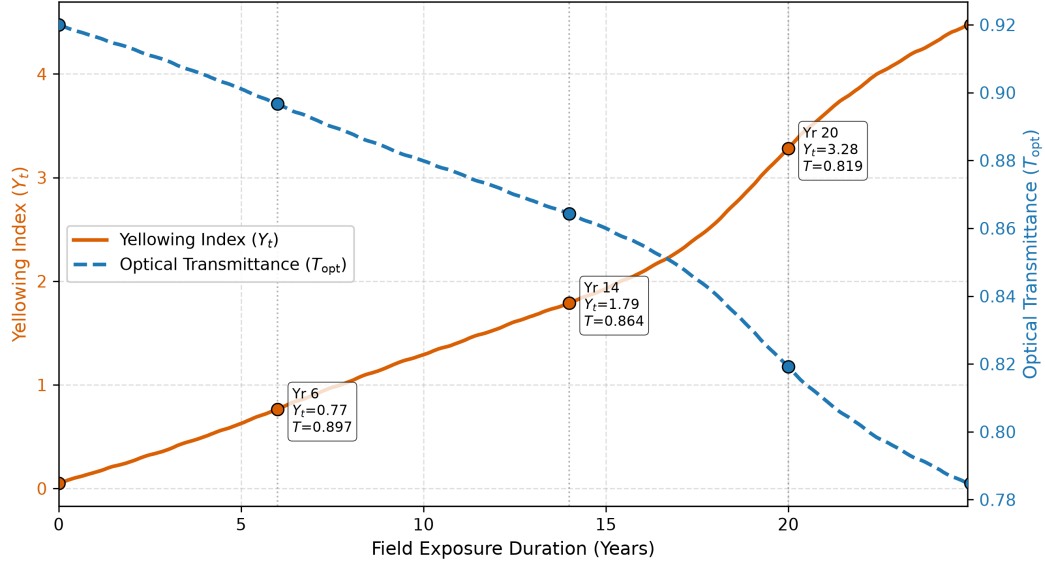


Figure 3: Evolution of encapsulant yellowing and optical transmittance during long-term exposure.

3.6 Performance loss metrics

Figure 4. Calibrated physics-based degradation trajectories for normalized I_{sc} , V_{oc} , FF , P_{max} compared with field measurements and the 95% Monte Carlo confidence band. Solid lines represent the model output for each parameter; shaded regions denote the corresponding 95% Monte Carlo confidence bands, obtained by propagating parameter uncertainty through the calibrated model. Red markers indicate field-measured values at each inspection date. The model produces smooth, monotonic declines across all metrics, driven by defect-generation-induced recombination, corrosion-related series-resistance growth, and encapsulant yellowing-induced optical losses. The Monte Carlo ensemble produces smooth confidence bands that quantify the uncertainty in the predicted degradation trajectories. For all three electrical parameters, the measured points lie largely within the 95% confidence regions, indicating that the model adequately captures the observed field variability. The V_{oc} band remains relatively narrow, reflecting the constrained defect-generation and recombination parameters. In contrast, the I_{sc} band is wider, consistent with its greater sensitivity to optical-transmittance losses and EVA yellowing. The P_{max} band progressively widens with operating time because uncertainty propagates through the coupled optical, recombination, and resistive degradation pathways. Overall, the results demonstrate that the model provides stable, uncertainty-aware predictions and adequately represents the dominant degradation mechanisms. The narrow confidence bands across all trajectories indicate strong parameter identifiability and confirm that the calibrated kinetics accurately represent the dominant physical drivers of PV module degradation under real operating conditions.

3.7 Combined results

The model reproduces degradation trajectories of all four electrical metrics with high fidelity. Encapsulant-yellowing generate the observed exponential decline in optical transmittance, driving the long-term reduction in I_{sc} . Defect-generation kinetics capture the gradual increase in recombination centers responsible for the monotonic loss in V_{oc} . Corrosion-related parameters account for the rise in series resistance, producing the measured fill-factor deterioration. When

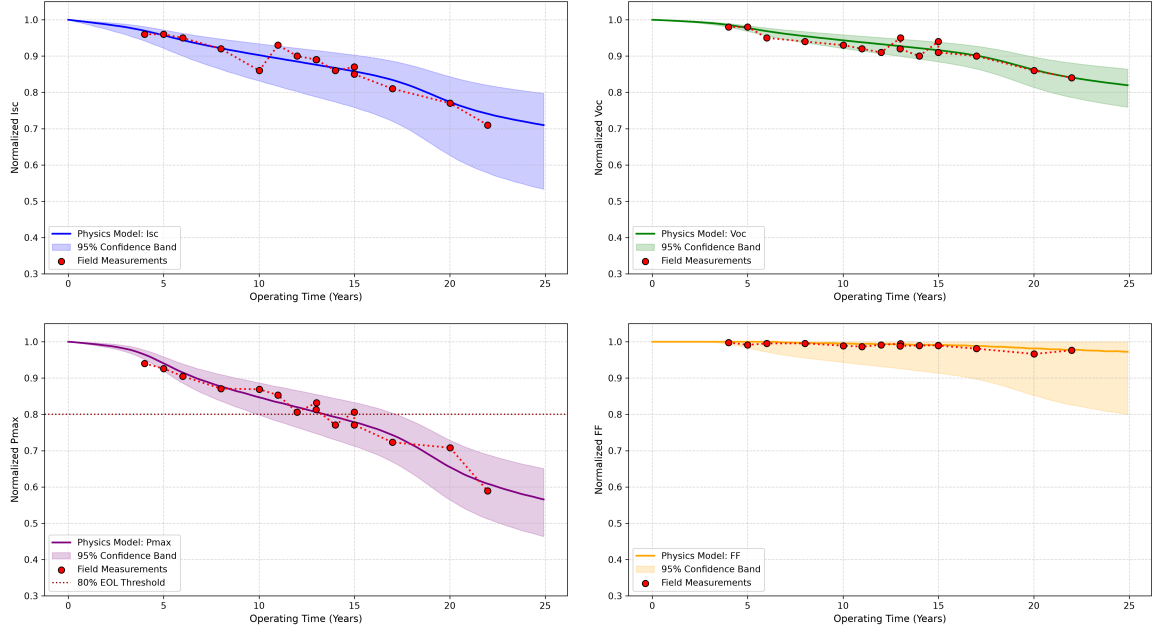


Figure 4: Physics-based prediction of normalized I_{sc} , V_{oc} , FF, and P_{max} degradation over a 25-year operating period.

combined, these mechanisms yield a smooth, internally consistent decline in P_{max} that closely matches field data and intersects the 80% of initial performance threshold at the experimentally observed timeframe. The combined and comparative degradation behavior of the electrical parameters was presented in Figure 5 to visualize the degradation of each parameters with respect to others

4 Discussion

The results demonstrate that the model good predictive capability over the extended operating lifetime of the PV modules. The obtained performance degradation can be attributed to the collective effects of environmental exposure on the optical, electrical, and semiconductor properties of the module. At the optical level, progressive EVA discoloration and yellowing increase parasitic absorption within the encapsulant, so reducing the optical transmittance of incident solar radiation to the silicon cells. The resulting reduction in photon flux reaching the cell decreases photogeneration and carrier collection, contributing primarily to the observed reduction in I_{sc} . At the semiconductor level, prolonged thermal, irradiance, and moisture exposure raises the formation and evolution of electrically active defects within the silicon and at relevant interfaces. These defects introduce recombination centers that enhance Shockley–Read–Hall (SRH) recombination, thereby reducing the minority-carrier lifetime (τ) and diffusion length. The resulting reduction in carrier lifetime limits the collection of photogenerated carriers and contributes to decreases in I_{sc} and V_{oc} . Since V_{oc} is related to the carrier concentration through the diode relation, increased recombination reduces the excess carrier concentration and consequently lowers V_{oc} . In similarly, aging-induced degradation of metallization, contacts, solder joints, and interconnections can increase the series resistance (R_s). The increase in R_s produces greater resistive losses ($I^2 R_s$), particularly under high-current operating conditions, thereby reducing V_{mp} , I_{mp} , and the fill factor (FF). Consequently, the combined effects of optical attenuation, enhanced recombination, increased resistive losses progressively reduce I_{sc} , V_{oc} , FF, and

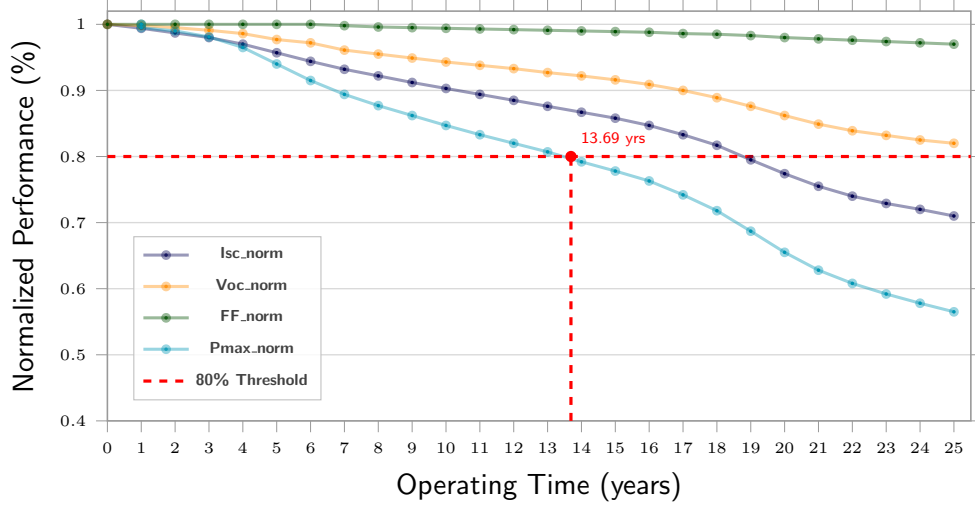


Figure 5: Longitudinal degradation trajectories of normalized electrical parameters (I_{sc} , V_{oc} , FF , and P_{max}) over 25 operating years with 80% threshold for P_{max} .

ultimately P_{max} . The good agreement between the simulated trajectories and long-term field measurements indicates that the coupled physics-based framework sufficiently represents these interacting degradation pathways over extended outdoor exposure.

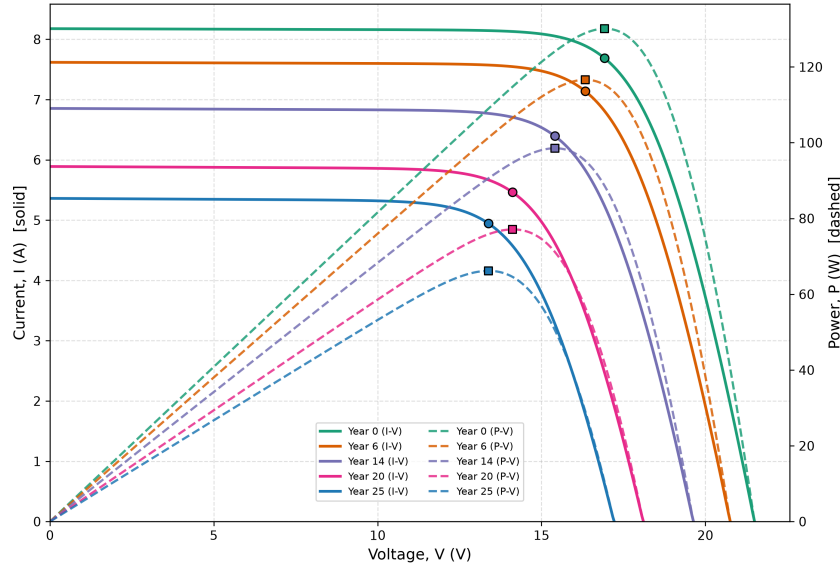


Figure 6: Modeled single-diode I-V and P-V characteristics of the PV module at different field-exposure years

The outdoor degradation behavior of the PV module was evaluated using a physics-based single-diode model. In Figure 6, the modeled I-V and P-V curves are shown for several exposure times (Year 0, 6, 14, 20, and 25). As the exposure time grows, the V_{oc} , I_{sc} and P_{max} progressively declines. The bend in the I-V curve becomes softer too. This points to a weaker fill factor as the module ages. This behavior is fit with degradation mechanisms captured in the single-diode parameters (increased series resistance, reduced shunt resistance, and enhanced

recombination). These effect reduces current output and reduced peak power over the module's service lifetime. The model trajectory crosses the 80% level at approximately 13.69 years (Figure 5), closely matching the measured degradation trend and the observed crossing of the 80% warranty threshold. This agreement shows the model's capability to capture the long-term degradation behavior and provides confidence in its application for PV module lifetime assessment under the investigated climatic conditions. The modeled performance degradation over 25 years shows that P_{max} experiences the greatest reduction, declining by 44.52% from its initial value, corresponding to an average degradation rate of (1.78%/yr). This is followed by I_{sc} (29.03%) at (1.16%/yr), while V_{oc} declines by 18.15 at 0.73/yr. In contrast, FF shows only a 4.50 reduction, corresponding to 0.18/yr. The higher degradation of Pmax shows the combined effects of local environmental stressors, on the optical losses, carrier-recombination and collection losses, and resistive degradation. The results demonstrate that current degradation is a major contributor to long-term power loss. While the relatively small FF reduction indicates a comparatively weaker contribution from resistive losses over the modeled period. The result further demonstrates the importance of incorporating site-specific environmental conditions into PV lifetime and energy-yield assessments.

5 Conclusion

This study developed a physics-based approach to predict the performance loss of aged crystalline silicon PV modules. A multi-mechanistic physics-based model of I_{sc} , V_{oc} , FF and P_{max} degradation as a function of temperature, humidity and irradiance history at the site is used. Unlike empirical approach that extrapolate the past degradation rates, this model takes into account encapsulant photo-oxidation kinetics, Shockley-Read-Hall recombination mechanism and metallization corrosion. The model has been calibrated to field-measured IV data over a long period of time and accurately reproduces I_{sc} , V_{oc} , FF and P_{max} . This has yielded the following R^2 values: 0.918 for I_{sc} , 0.841 for V_{oc} , 0.934 for P_{max} and 0.470 for FF. Thus, there is some room for improvement in the model as far as FF is concerned. As the fit for the latter parameter has proven to be relatively weak, one could expect that the resistive and shunt pathways of the degradation are not sufficiently constrained in the corrosion-based model and require further modification. Furthermore, the Monte Carlo uncertainty analysis combined with the Sobol sensitivity analysis has shown that the EVA yellowing rate (Eay) is the key factor affecting Pmax over long periods of time, whereas the defect generation parameters (Ed) gain importance with age. The model calibrated for the particular field site indicates that the module reaches the 80% of initial performance threshold at 13.69 years and the Pmax degradation rate of 1.78%/year for 25 years. These results show that current collapse driven mainly by optical attenuation and recombination, while the series resistance contribution is small. Thus, the models can be as accurate as the empirical ones while providing further information about the underlying mechanisms that control the process at each climate.

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