

Performance Modeling of Tandem Photovoltaics: A Yearlong Outdoor Degradation Analysis of a GaAs//Si Minimodule

Martin Springer^{✉,*}, Robert Witteck[✉], Timothy J. Silverman[✉], John F. Geisz, William E. McMahon[✉],
and Emily L. Warren[✉]

National Laboratory of the Rockies, Golden, Colorado 80401, USA

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We present a performance modeling and degradation analysis framework for tandem photovoltaic modules, building upon established procedures for crystalline silicon devices and adapting them to account for the spectral sensitivity of multijunction technologies. The methodology employs filter criteria to select outdoor measurements close to standard test conditions (STC) under stable spectral and ambient conditions, followed by normalization of power production data with corrections for temperature, irradiance, and precipitable water vapor. We demonstrate this framework using a mechanically stacked four-terminal gallium arsenide (GaAs)//silicon (Si) tandem solar minimodule deployed outdoors from October 2019 to January 2021 in Golden, Colorado, USA. We determined degradation rates of $-4.1 \pm 0.2\%$ /year for the GaAs subcell and $-2.5 \pm 0.9\%$ /year for the Si subcell, with analysis of individual performance metrics indicating that packaging degradation, particularly delamination, was the dominant failure mode. Simulations using PVcircuit, an open-source equivalent-circuit solver, confirmed these findings. The presented methodology provides a reproducible foundation for performance modeling and degradation analysis of emerging tandem technologies.

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I. INTRODUCTION

Crystalline silicon (c-Si) photovoltaic (PV) technology is one of the lowest-cost options for renewable energy generation and remains the dominant PV technology, with a market share of over 96% [1,2]. However, current technologies are limited by the single-junction design, which has a theoretical maximum efficiency of 29.6% [3]. A recent analysis has shown that improvements in average cell efficiencies in mass production take only three years to reach the efficiencies of champion cells fabricated under laboratory conditions [4,5]. The International Technology Roadmap for Photovoltaic (ITRPV) suggests that Si-based tandem cells and modules will enter mass production around the year 2026 to keep up with this rapid development and the ever-increasing demand for higher-efficiency cell and module designs [6]. Such multijunction technologies can surpass the theoretical efficiency limit for single-junction devices and have the potential to achieve

power conversion efficiencies above 40% [7], thus making nonconcentrating tandem technologies and, in particular, metal-halide-perovskite-based tandems a popular option for future high-efficiency solar cells. However, these new technologies have the potential to introduce new degradation mechanisms that may lead to accelerated performance loss and elevated degradation rates. Thus, current research priorities are evolving toward improving the reliability and long-term performance of tandem devices [8].

The development and commercial adoption of new systems depends on precise power output predictions and reliable degradation rate assumptions for forecasting system behavior. Degradation rates directly affect the yield of a PV system over its anticipated service life and therefore its future cash flow—which has significant financial consequences on whether or not to pursue a new development project [9]. Currently, system performance analysis relies on appropriate rating procedures, such as the International Electrotechnical Commission (IEC) 62670-3 [10] standard, which was developed for single-junction devices. Such rating procedures require the translation of outdoor measurements into standard-test-condition (STC) power ratings. Existing methods for single-junction devices do not adequately take into account the impact of spectral irradiance on the power output of multijunction devices. Only recently, procedures have been proposed to translate outdoor tandem module current density-voltage $J(V)$ measurements to STC power ratings [11]. Such a translation

*Contact author: martin.springer@nlr.gov

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is helpful to properly assess device performance over time and extract adequate degradation rates for tandem devices.

In this work, we build upon the filtering methodology proposed in Ref. [11] and develop a performance-modeling methodology to analyze long-term degradation in tandem PV modules. A tandem minimodule, comprising a gallium arsenide (GaAs) top cell and a silicon (Si) bottom cell, was fabricated and exposed to outdoor conditions for 14 months to exemplify our performance modeling approach. These semiconductor materials were selected for their robustness compared to metal-halide perovskites, allowing degradation effects to be distinguished at the module level. The module was encapsulated using a low-temperature vacuum lamination process and edge sealant, mimicking typical perovskite tandem encapsulation methods [12]. However, the filtering methodology proposed in Ref. [11], which is tailored to dual-axis tracked systems, proved unsuitable for our analysis of a fixed-tilt device. We enhanced this approach by incorporating angle-of-incidence effects and expanding spectral-mismatch bounds, creating a new filter set optimized for fixed-tilt mounting conditions. Using this refined process, we identified that degradation primarily affects the module current, indicating a failure in the module packaging. These findings underscore the importance of addressing both cell-specific degradation mechanisms and the risks posed by modifications to established module fabrication methods when analyzing novel tandem technologies such as perovskites.

II. METHODS

In this section, we detail the methods employed to assess the long-term performance and degradation of tandem solar modules. We begin by detailing the tandem minimodule fabrication of our example GaAs//Si tandem device that is used to exemplify the performance modeling methodology, and then describe the outdoor deployment and data acquisition setup. For this analysis, we expanded upon the rigorous set of filtering criteria first introduced in Ref. [11] for dual-axis tracked systems. These criteria were used to select measurement points that are close to STC and that occur under stable ambient conditions. Our approach ensures an accurate reflection of the performance of the minimodule for a fixed-tilt racking setup. Furthermore, we explain the normalization process of the raw power production data, which included corrections for temperature and irradiance variations, as well as an additional adjustment based on precipitable water vapor (PWV) to account for spectral influences on the GaAs top cell. The section also covers the extraction of subcell temperature coefficients from the outdoor data and the application of linear regression analysis to determine degradation rates for both the top and bottom subcells. Finally, we

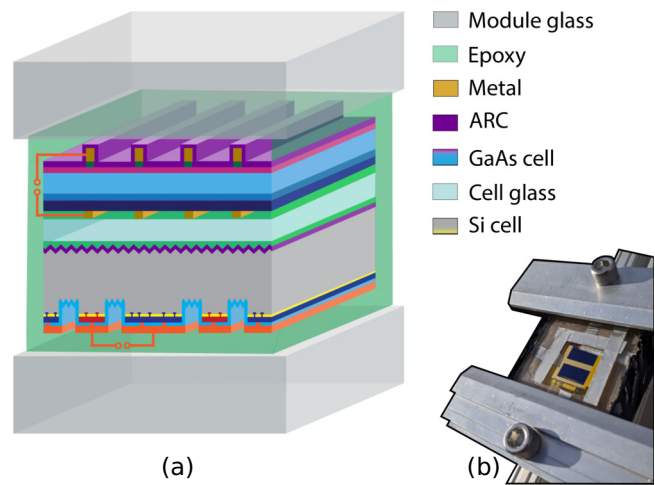


FIG. 1. (a) An illustration of the GaAs//Si four-terminal (4T) rear heterojunction tandem solar minimodule. (b) A picture of the packaged cell, mounted in a fixed-tilt configuration during outdoor deployment in Golden, Colorado, USA.

discuss the use of PVcircuit [13], an open-source modeling tool, to simulate the performance of the tandem minimodule and validate our experimental findings.

A. Tandem module fabrication

The mechanically stacked four-terminal (4T) GaAs//Si tandem device was fabricated using methods similar to those published previously for cell-level performance analysis [14–17]. The GaAs top cell was grown using metal-organic chemical vapor deposition (MOCVD) in an inverted rear-heterojunction structure. The Si bottom cell was a poly-Si on oxide (POLO) interdigitated back contact (IBC) device fabricated at the Institute for Solar Energy Research in Hamelin, Germany (ISFH) [18]. The tandem cell had an aperture area of 1 cm².

The tandem cell was packaged for outdoor conditions by laminating the subcells into a glass-glass package. To contact the GaAs device, the nonactive areas of the device were insulated using Kapton tape, and the front and rear bus bars were contacted using silver (Ag) paste and connected to metal tape with conductive adhesive on it. The contacts of the Si cell were also contacted using Ag paste connected to the metal tape. An illustration of the contacted cell is shown in Fig. 1(a).

We used ethylene vinyl acetate copolymer (EVA) as an encapsulant along with two layers of textured low-iron solar glass to form the minimodule packaging. We cut a sheet of release liner into a frame around the cell to provide support during the lamination. Masking tape around the stack provided additional support and prevented encapsulant leakage. We added a polyisobutylene (PIB) edge sealant around the perimeter of the minimodule to seal the cells against moisture. The stack was laminated at

125 °C with pressure increments of 1 psi increased every 30 s for a total of 5 min. This lamination temperature is lower than the typical 145 °C used for c-Si modules and aims to mimic the more gentle encapsulation approach used for perovskite cells. The stack was supported during lamination by a surrounding metal frame of the same height as the finished minimodule. After lamination, we removed the masking tape and soldered two insulated wires to each piece of bus-bar tape. Any excess tape was removed. The exposed metal was insulated with silicone sealant. The ends of the wires were connected to an eight-pin waterproof automotive connector. The other end of the automotive connector was connected to the measuring device.

B. Outdoor deployment

The minimodule was deployed from October 2019 to January 2021 at the outdoor test facility at the National Laboratory of the Rockies (NLR) in Golden, Colorado, USA. The test site was located at 39.7404°N, 105.1778°W at an elevation of 1798 m. We used a 40° fixed-tilt mounting configuration, facing due south for the module orientation. A picture of the minimodule is shown in Fig. 1(b). The minimodule temperature was measured with a thermocouple attached to the rear side of the minimodule. Spectral and meteorological measurement data were obtained from the Solar Radiation Research Laboratory (SRRL), located about 200 m away from the test site. Global tilt (40° facing south) spectral data were measured with an EKO MS-710 WISER spectroradiometer. The ambient air temperature and relative humidity were measured with a Vaisala probe mounted in a naturally aspirated radiation shield. The wind speed was measured by a three-cup anemometer and wind vane mounted 1.83 m above ground. Further details regarding the sensors can be found in Ref. [19].

We attached a programmable direct current load (MDL302 load module in a MDL001 mainframe) from B&K Precision to each cell. The loads trace a $J(V)$ curve nominally every 5 min, with voltage and current measured by separate Keithley 2700 benchtop multimeters with 7702 multiplexer modules. Between $J(V)$ measurements, the loads were set to the constant resistance passing through the maximum power point of the most recent $J(V)$ curve. The minimodule was deployed during the COVID-19 pandemic, which resulted in limited on-site access. Hence, any problems with the measuring equipment or data acquisition took longer to resolve. This caused gaps in the data set, especially in the spring and summer months of 2020. The data set was prescreened to eliminate data recorded during periods of rain or snow [20].

C. Degradation analysis

A typical PV module degradation analysis involves three primary steps: filtering, normalization, and data

analysis [21]. The first two steps are concerned with translating outdoor module measurements into STC power ratings. The filtering step helps to ensure that outdoor measurements with stable ambient conditions close to STC are used for the module performance evaluation. The normalization step provides a dimensionless performance metric to monitor the module performance over time. Typically, additional temperature and irradiance corrections are performed to reduce the variability in the raw data by translating the outdoor conditions to STC. This step requires knowledge of the temperature coefficients of the cells. In this work, we extracted the temperature coefficients from the outdoor data and compared them with coefficients obtained from temperature-dependent external quantum efficiency (EQE) measurements. The data can then be analyzed to extract performance trends, such as the degradation rate (or temperature coefficient). In this work, we focused on extracting a degradation rate, which we define as a rate of change, with a negative value indicating a decrease in performance.

1. Filtering

Outdoor $J(V)$ measurements taken during stable ambient conditions close to STC are required for the performance and degradation analysis. We used data filtering to select measurement points that fulfilled those criteria. We started by applying the filter set proposed in Ref. [11] to our data set and found that the filter criteria eliminated almost all of our data. This reference filter set was derived from criteria defined in IEC 62670-3 [10] for concentrator PV but was modified for a tandem module on a dual-axis tracking system mounted in Freiburg, Germany. Thus, we had to modify some of the filter criteria to account for our fixed-tilt mounting configuration and deployment location in Golden, Colorado, USA. The modified filter set is summarized in Table I and each modification is discussed in detail in Sec. III B. Filters with the same restriction range as in the reference filter set are marked with an asterisk (*).

TABLE I. The filter criteria to select stable outdoor measurements close to STC: the asterisk (*) indicates filters that are equal to the reference filter set in Ref. [11].

	Filter parameter	Restriction
1*	G_{POA} variation before-after $J(V)$	$\leq 1\%$
2*	G_{POA} min-max variation 10 min	$\leq 10\%$
3*	G_{POA} min-max variation 30 min	$\leq 40\%$
4	Average wind speed	0.5 – 5 m/s
5	$G_{\text{DNI}}/G_{\text{POA}}$	> 0.8
6	Spectral matching ratio (SMR)	1 ± 0.09
7	Angle of incidence (AOI)	$\pm 30^\circ$
8*	G_{POA} range (degradation rate)	$G_{\text{ref}} \pm 200 \text{ W/m}^2$
9	G_{POA} range (temperature coefficient)	$G_{\text{ref}} \pm 10 \text{ W/m}^2$

Here, G_{POA} is the global plane-of-array irradiance, with a reference irradiance, G_{ref} , of 1000 W/m². The first three filter criteria ensure steady irradiance conditions by specifying the maximum allowed variation of G_{POA} in a time frame of up to 30 min around the measurement time of the $J(V)$ curve. Filter 4 ensures steady module temperature measurements by filtering out data points during wind gusts or no air movement. Filter 5 limits the amount of diffuse irradiance by specifying a ratio of direct normal irradiance, G_{DNI} , to G_{POA} . Filter 6 limits the variation in the spectral matching ratio (SMR), which is used to quantify the impact of different spectral irradiance compositions on the power output and is defined as

$$\text{SMR} = \frac{J_{\text{sc,top}} J_{\text{sc,bot,ref}}}{J_{\text{sc,bot}} J_{\text{sc,top,ref}}}. \quad (1)$$

Here, $J_{\text{sc,top}}$ and $J_{\text{sc,bot}}$ are the measured short-circuit current density of the top and bottom cell, respectively, and $J_{\text{sc,top,ref}}$ and $J_{\text{sc,bot,ref}}$ are the short-circuit current density under the global standard spectrum (AM1.5G). The SMR provides a simple metric to quantify how closely the outdoor spectrum matches the AM1.5G spectrum.

Because our tandem module was deployed on a fixed-tilt system instead of a tracked system (as in the reference filter

set), we included a new filter criterion based on the angle of incidence (AOI). Finally, we limited the range of the maximum deviation from the reference irradiance. We used the range definition from the reference filter set of ± 200 W/m² for the degradation analysis, but used a tighter range of ± 10 W/m² for the extraction of temperature coefficients, as explained below.

2. Normalization

We normalized the raw power production data by calculating a dimensionless performance ratio (PR). The PR is typically based on the rated power of a module or system at STC and corrected for temperature and irradiance variations in the outdoor data to reduce the variability of the raw power production data (see IEC 61724-1:2021 [22]). Our approach is based on the typical metrics used for c-Si PV [21] but is augmented by an additional correction based on precipitable water vapor (PWV). This addition accounts for temperature-correlated changes in the incident spectrum that affect the GaAs top cell [23] and consequently the tandem cell performance. We further expanded on that approach by incorporating the air mass (AM) into the PWV correction [24]. Summarizing the listed corrections, the PR for each subcell can be obtained as

$$\text{PR} = \frac{P}{P_{\text{STC}} \times \frac{G_{\text{POA}}}{G_{\text{ref}}} \times [1 + \gamma_{P_{\text{mp}}} \times (T_{\text{cell}} - T_{\text{ref}})] \times [1 + \beta_{\text{PWV}} \times (\text{PWV} \times \text{AM} - \text{PWV}_{\text{ref}} \times \text{AM}_{\text{ref}})]}, \quad (2)$$

where P is the subcell power measured under outdoor conditions, P_{STC} is the power of the subcell at STC, $\gamma_{P_{\text{mp}}}$ is the relative maximum power temperature coefficient in %/°C, T_{cell} is the cell temperature in °C, and T_{ref} is the reference temperature of 25 °C. We incorporated the PWV correction through the factor β_{PWV} , which corrects the short-circuit current density J_{sc} for spectral influence. PWV_{ref} and AM_{ref} are the reference values of 14.2 mm and 1.5, respectively.

We used the Sandia PV Array Performance Model (SAPM) to estimate the cell temperature based on the measured module temperature [25],

$$T_{\text{cell}} = T_{\text{module}} + \frac{G_{\text{POA}}}{G_{\text{ref}}} \Delta T, \quad (3)$$

where T_{module} is the measured rear-side module temperature, and the representative module and mounting parameter $\Delta T = 3^\circ\text{C}$ for a glass-glass module in an open rack configuration.

3. Temperature coefficients

Thermal transient measurements at STC were not available for the given data set. Thus, we extracted the temperature coefficients and PWV correction factors directly from the outdoor measurements. We used the narrowly filtered data set around STC with all nine filter criteria from Table 1 and divided it further into subsets, as shown in Fig. 2.

We split the long observation time frame into subsets to mitigate the impact of degradation on the determination of the correction coefficients. We searched for subsets of consecutive measurements that showed a strong gradient in PWV and cell temperature. For the PWV correction, we only considered subsets with a ΔPWV of greater than 5 mm and data points with cell temperatures in the range of 23 °C–27 °C. These criteria limited us to one suitable subset for the PWV correction, as shown in Fig. 2(a). We performed the PWV correction before fitting the temperature coefficients; therefore, no restrictions on the PWV values were necessary for the temperature subsets [Fig. 2(b)]. This allowed us to extract four suitable subsets for the temperature correction with a ΔT of greater than 15 °C.

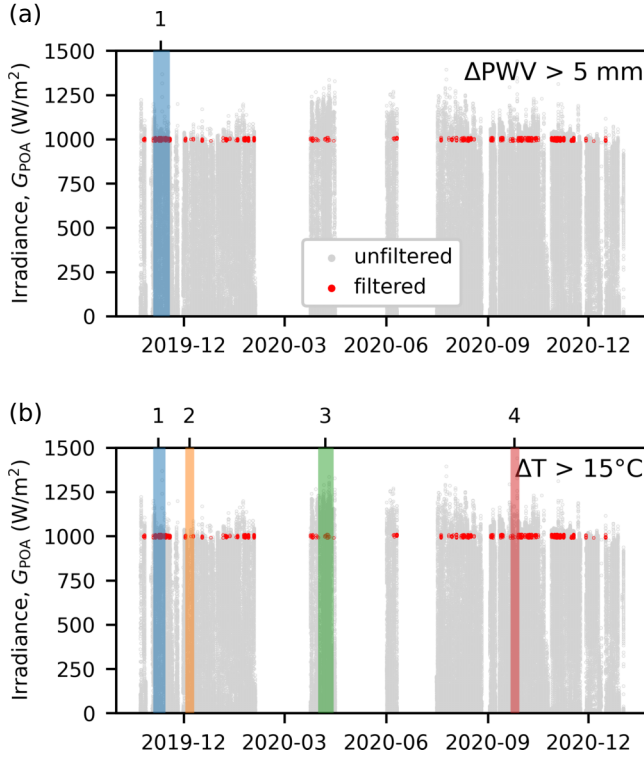


FIG. 2. An illustration of the data subsets used for (a) the extraction of the PWV correction coefficient and (b) the temperature coefficients. The gray dots show the irradiance values of the unfiltered data set and the colored dots show the filtered data set. Only subsets of the filtered data points (indicated by the colored areas) were used for the extraction of the module performance correction coefficients. In this way, we minimized the impact of module performance degradation on the correction coefficient.

We used the Theil-Sen estimator [26] for a robust linear regression analysis of both correction coefficients. To calculate the PWV correction factor, β_{PWV} , we analyzed the irradiance-corrected short-circuit current density, $J_{sc}(G_{ref}/G_{POA})$, as a function of $PWV \times AM$. Using β_{PWV} , we corrected for the impact of PWV on J_{sc} and P_{mp} , as outlined in Ref. [23]. A regression analysis was performed to obtain the short-circuit current (I_{sc}), the open-circuit voltage (V_{oc}), and the maximum power point (P_{mp}) temperature coefficients, $\alpha_{I_{sc}}$, $\beta_{V_{oc}}$, and $\gamma_{P_{mp}}$, respectively. Each regression analysis was conducted for each subset and the mean values of the fits were subsequently used for calculations involving the temperature coefficients.

4. Data analysis

Various methods exist to account for seasonal and environmental effects when extracting degradation rates of PV systems [27]. Typically, those approaches need several years of outdoor data and focus on the analysis of single-junction devices. Because our 14-month data set is for a

tandem device, we used the following robust regression approach for our analysis.

We used an insolation-weighted average, aggregated at daily frequency, to calculate the degradation rate. The GaAs top cell shows fairly linear degradation behavior, for which this approach seems to work reasonably well. The Si bottom cell shows a stronger seasonal component in cell performance. Hence, we decided to use only the overlapping months of October to December in 2019 and 2020 to extract the degradation rates. In this way, we were able to mitigate the impact of seasonal effects on the calculation of the degradation rates. Similar to the linear regression analysis of the temperature coefficients, we used the Theil-Sen estimator [26] to extract a linear fit of the time-series data.

In addition to calculating the degradation rate for the PR, we also calculated individual degradation rates for the module performance metrics J_{sc} and V_{oc} and the fill factor (FF), which provided us insight into the likely degradation mechanisms of the tandem minimodule.

D. Performance modeling approach

We modeled the output voltage, V_{cell} , and current density, J_{cell} , of the individual top and bottom solar cells using PVcircuit, a PYTHON library of optoelectronic models for tandem and multijunction solar cells [28,29]. PVcircuit is an NLR-developed open-source equivalent-circuit solver that employs a diode model and thus depends on the individual subcell diode parameters. We obtained these diode parameters by fitting a single diode model to $J(V)$ measurements of individual solar cells at STC. Therefore, we filtered all $J(V)$ data from the outdoor data set in accordance with the filter criteria 1–9 specified in Table I and limited the module temperature to $24.5^\circ\text{C} < T_{mod} < 25.5^\circ\text{C}$ to closely approximate STC.

In order to take the temperature dependence of the J_{sc} and the recombination current density J_0 into account, PVcircuit requires the temperature dependence of the band gap. Using the method of Rau *et al.* [30], we extracted the band gap from EQE measurements at various device temperatures. For the top cell, we employed the EQE data for a GaAs cell with identical structure grown at NLR from Perl *et al.* [31]. We determined a band gap of 1.41 eV at 25°C . For the bottom cell, we measured the EQE for a temperature range from $20^\circ\text{C} - 65^\circ\text{C}$ of an IBC solar cell equivalent to the one used in the tandem device. We determined a band gap of 1.15 eV at 25°C . For further details on the modeling approach, see Ref. [32].

III. RESULTS AND DISCUSSION

First, we present the minimodule performance measurements before outdoor deployment. Second, we discuss the modified filter criteria and showcase their impact on the data retention of our outdoor measurement data set. Third,

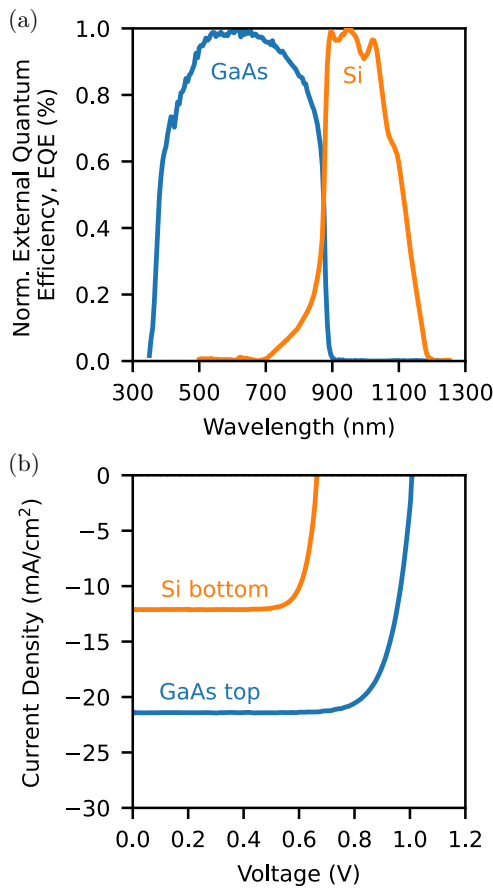


FIG. 3. (a) The normalized external quantum efficiency measurements for each cell. (b) The measured current density-voltage ($J(V)$) curves for the GaAs top and Si bottom cell under simulated AM1.5G illumination.

we compare the employed methods for the determination of the temperature coefficients. Fourth, we present the dimensionless PR and the degradation rate results. Finally, we compare our findings from the outdoor analysis with the modeling effort and discuss the underlying degradation mechanisms. Before presenting the results, we note several limitations of the present data set that are inherent to the early-stage nature of tandem PV technologies. The investigated GaAs//Si minimodule represents an immature device concept, particularly with respect to its packaging design and was not optimized for long-term field deployment. Accordingly, the objective of this study is not to establish technology-specific reliability metrics or lifetime projections for GaAs//Si tandems but to demonstrate a transferable performance modeling and degradation analysis framework applicable to tandem PVs more broadly.

A. Module performance measurements

The initial performance measurements are summarized in Fig. 3. The EQE shown in Fig. 3(a) and the $J(V)$ measurements shown in Fig. 3(b) were obtained for each

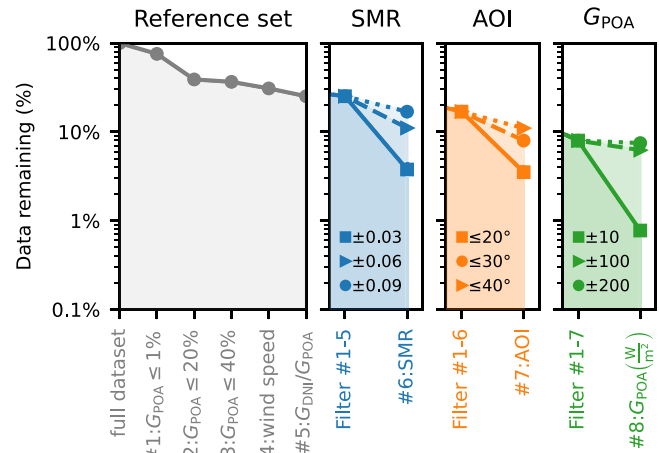


FIG. 4. The data retention is shown through cumulative application of each filter criterion. Different ranges for the spectral matching ratio (SMR), angle of incidence (AOI), and global plane-of-array irradiance (G_{POA}) filter criteria were explored. Note that the starting point for each filter criterion is based on the selected parameters summarized in Table I.

subcell of the mechanically stacked 4T device. The EQE measurements were normalized for each subcell. For the $J(V)$ curves, one example of an outdoor measurement was taken with conditions close to STC. Each cell was measured individually while the other cell was biased at the maximum power point [33]. The 4T device design allowed us to utilize combinations that are not current matched.

B. Filter criteria

We had to modify the proposed filter criteria from Ref. [11] to account for our fixed-tilt mounting configuration and deployment location. We illustrate the effect of our modifications in Figs. 4 and 5, which provide a visualization of data retention and filtered data exemplified by irradiance measurements, respectively. In Fig. 4, the reference filter set plot shows the cumulative application of the first five filter criteria defined in Ref. [11], which eliminated almost 70% of our outdoor measurement data. The same information is displayed in more detail in Fig. 5. Here, the gray data points represent the unfiltered data set, whereas the colored data points indicate the remaining data after cumulatively applying each filter criterion. Each row (I–IV) in Fig. 5 explores a different filter criterion in detail. These criteria are also shown in the data retention plot (Fig. 4).

In the first row (I) of Fig. 5, we applied the complete reference filter set. The effect of applying the first five filters (1–5) is shown in, Fig. 5(I)(a). The first three criteria specify restrictions for the allowed variation in the G_{POA} in the time frame around the measurements. These filters eliminate any rapid changes in irradiance caused by conditions such as intermittent clouding. Filter 4 restricts the wind

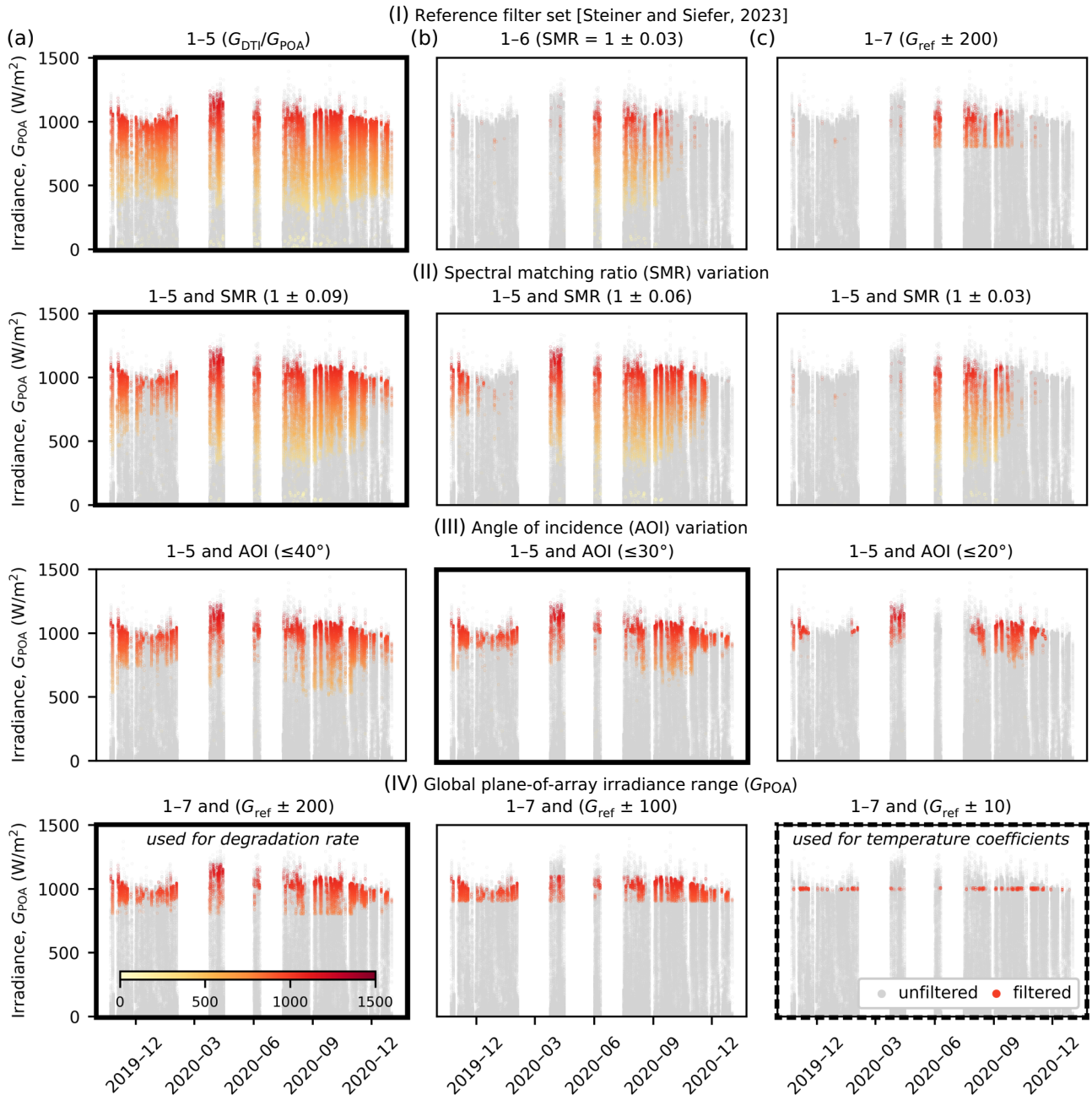


FIG. 5. An illustration of the individual filter criteria and variation of filter parameters through measured irradiance. The label on each subplot indicates the filter sets used to produce the colored data. Row I showcases the impact of the reference filter set defined in Ref. [11] on data retention and collocation. Rows II–IV explore different ranges for the spectral matching ratio (SMR), the angle of incidence (AOI), and the global plane-of-array irradiance (G_{POA}) filter criteria, respectively, with the goal of increasing the data retention over the course of outdoor deployment. The bold frames indicate the selected filter criteria specified in Table I.

speed to avoid rapid changes in module temperature and filter 5 limits the amount of diffuse irradiance by specifying a ratio between G_{DNI} and G_{POA} .

In Fig. 5(I)(b), we show the application of the SMR filter (6). In our case, the proposed SMR restriction of 1 ± 0.03 in Ref. [11] eliminated almost all data points in the winter and spring months, leaving us with a data cloud concentrated in the summer and fall months. Especially

when applying the G_{POA} range filter, as shown in Fig. 5(I)(c), only a very small subset (approximately 2% of the initial data set) remained for any module performance characterization. This data set would be sufficient if we were only interested in the performance of the module during the summer months. However, to extract an annual degradation rate, we need filter criteria that ensure a consistent data distribution throughout the entire year.

TABLE II. The temperature coefficients ($\alpha_{I_{sc}}$, $\beta_{V_{oc}}$, and $\gamma_{P_{mp}}$) and the precipitable water vapor correction coefficient (β_{PWV}) for the GaAs top and Si bottom cell obtained from the outdoor measurements and the PVcircuit model.

	GaAs		Si		Units
	Outdoor	Model	Outdoor	Model	
$\alpha_{I_{sc}}$	0.12 ± 0.03	0.05	0.08 ± 0.28	0.11	%/°C
$\beta_{V_{oc}}$	-0.18 ± 0.01	-0.17	-0.27 ± 0.01	-0.30	%/°C
$\gamma_{P_{mp}}$	-0.17 ± 0.04	-0.17	-0.29 ± 0.30	-0.30	%/°C
β_{PWV}	0.15	...	-0.05	...	%/mm

Thus, in Figs. 5(II)(a)–5(II)(c), we explored different restrictions for the SMR filter criterion and settled on using 1 ± 0.09 for our modified filter criteria set summarized in Table I. Opening this restriction seemed to be a necessary trade-off to sufficiently increase the availability of outdoor measurements throughout the year for the degradation analysis. By increasing the restriction from 1 ± 0.03 to 1 ± 0.09 , we could increase data retention from 3.7% to 17%, as indicated in Fig. 4.

The results for the next filter criterion based on the AOI are shown in Figs. 5(III)(a)–5(III)(c). We decided to limit the AOI to $\pm 30^\circ$, which seemed to be a good trade-off between data availability and stringency of the restriction and should ensure negligible current losses for fixed-tilt mounted modules with a clean surface [34].

Lastly, we explored different restrictions for the range criterion of G_{POA} around STC, as shown in Figs. 5(IV)(a)–5(IV)(c). We used the same criterion ($\pm 200 \text{ W/m}^2$) as in the reference filter set to calculate the degradation rate but we used a stricter criterion ($\pm 10 \text{ W/m}^2$) to extract the temperature coefficients of the module.

In summary, we had to modify the proposed filter criteria from Ref. [11] to improve the data retention for our fixed-tilt mounted minimodule in Golden, Colorado, USA. We did this by increasing the SMR restriction from 1 ± 0.03 to 1 ± 0.09 but we introduced an additional filter criterion to restrict the AOI $\pm 30^\circ$. The bold axes around the subplots in Fig. 5 highlight our modified filter set and the complete filter criteria are summarized in Table I. Ultimately, we are left with about 10% of the initial data points for the degradation analysis and about 1% for the calculation of temperature coefficients (Fig. 4), which is discussed next.

C. Temperature coefficients

The PWV correction coefficients and temperature coefficients for the GaAs top and Si bottom cell are summarized in Table II. We compared the coefficients obtained from the outdoor measurement data set with the calculated coefficients from the reference measurements in Ref. [31], as elaborated in Sec. II D.

We obtained a tight standard deviation for the top cell throughout all three temperature coefficient fits and good agreement for $\beta_{V_{oc}}$ and $\gamma_{P_{mp}}$ with the reference coefficients. The I_{sc} temperature coefficient extracted from the outdoor measurement data set is higher than the reference coefficient. Even after filtering, the I_{sc} data show the greatest variability in the outdoor measurements, which could explain this discrepancy.

The variability in the measurement data is shown in Fig. 6. This figure depicts the linear regression fits for all three temperature coefficients ($\alpha_{I_{sc}}$, $\beta_{V_{oc}}$, and $\gamma_{P_{mp}}$) for the GaAs top and Si bottom cell. The markers are the filtered outdoor data after applying all nine filter criteria specified in Table I. The dotted lines are the linear regression fits of the temperature coefficients for each subset, as depicted in Fig. 6. The solid lines are the mean value of the individual fits from the subsets. These mean values are also reported in Table II. Note that we choose this subset approach to mitigate the degradation effects from the temperature coefficient extraction from the outdoor measurements.

The Si bottom cell exhibits seasonally affected performance, leading to greater uncertainty in the $\alpha_{I_{sc}}$ and $\gamma_{P_{mp}}$ temperature coefficient fits for the bottom cell. In contrast, the V_{oc} data shows almost no spread and we obtain good agreement with the reference coefficient as well as only low uncertainty for the $\beta_{V_{oc}}$ temperature coefficient fit.

The dashed black lines in Fig. 6 indicate the results from modeling the temperature dependence with PVcircuit. We can see that the extraction of diode parameters close to STC and the temperature dependence from indoor EQE measurements delivered reasonably good approximations of the temperature dependence in the model when compared to the measurement.

D. Degradation rates

We used a dimensionless performance ratio to determine the degradation rate of the GaAs top cell and the Si bottom cell. In Fig. 7, we illustrate the performance degradation of the tandem module over the deployed time frame. The dots show the insolation-weighted daily averages of the remaining data points after applying filter criteria 1–8 from Table I. The colored dots indicate the overlapping months of the first and second years of outdoor exposure. We used those data points to extract the linear degradation rates. The gray dots indicate the remaining data points throughout the period of outdoor exposure.

The seasonal variation in Fig. 7 is due to a variation in spectral content. In the summer, the air mass decreases, so the spectra become more “blue-rich,” which increases the ratio $J_{sc,top}/J_{sc,bottom}$. Because this can seasonally change the tandem cell efficiency, our degradation-rate analysis was done using data from the same months in two consecutive years [27]. This results in a relative degradation rate of $-4.1 \pm 0.2\%/year$ for the GaAs top cell and $-2.5 \pm$

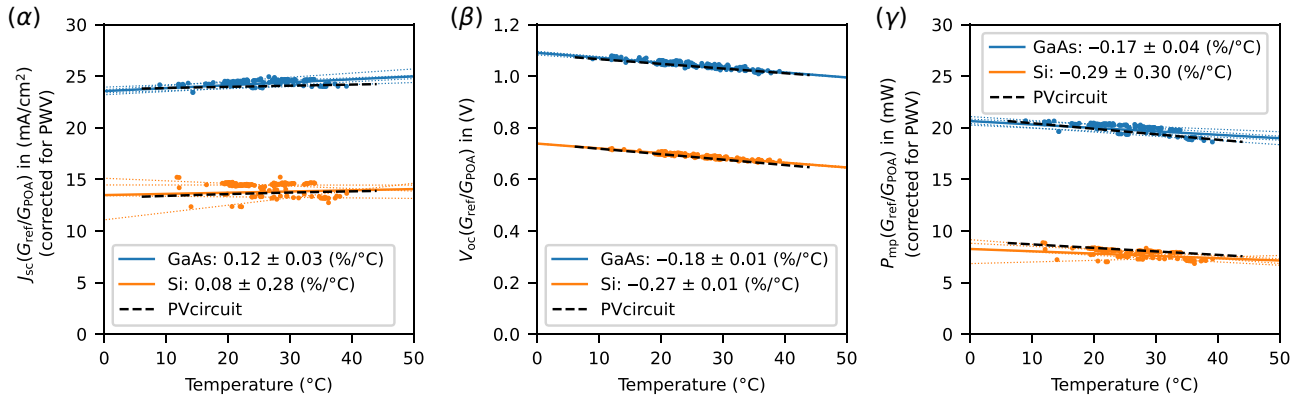


FIG. 6. Regression analysis of the relative temperature coefficients for the short-circuit current density (α), the open-circuit voltage (β), and the maximum power point (γ). The dots indicate the filtered outdoor measurement data used for the fits. The dashed lines are the individual fits for each subset and the solid lines indicate the mean of the subset fits. The dashed black lines illustrate the temperature coefficients obtained from the reference measurement sets via PVcircuit.

0.9%/year for the Si bottom cell. The seasonal variation and larger spread of the performance data for the Si bottom cell leads to a significantly larger standard error of $\pm 0.9\%$ /year. This is caused by the short time frame of the overlapping months and is expected to reduce with longer data sets and multiyear degradation analysis.

In Fig. 8, the individual degradation rates are shown for the main parameters extracted from the $J(V)$ measurements. We present the relative rate of change in the figure legends as well as the absolute change over the deployment time frame inside the parentheses. Again, we only used the data points from the overlapping months to extract

the degradation rates. We obtained the highest degradation rates for the short-circuit current density [Fig. 8(a)], with -2.7% /year for the GaAs top cell and -2.5% /year for the Si bottom cell. For the open-circuit voltage shown in Fig. 8(b), we see a slight decrease of -0.6% /year for the GaAs top cell and a slight increase of 0.8% /year for the bottom cell. Similarly, we obtained slight reductions in fill factor for both cells. We extracted -0.6% /year for the GaAs top cell and -0.7% /year for the Si bottom cell, which are significantly smaller than the seasonal variation within the measurements.

Consequently, we saw the strongest degradation in the short-circuit current density, which we can correlate with the degradation of the module packaging [35]. We observed a delamination between the front glass and the encapsulation layer, which is likely the main degradation mechanism of the tandem minimodule and contributed to the elevated degradation rates. The minimodule was produced in a larger research effort also considering emerging tandem technologies as perovskite//Si, which are sensitive to elevated temperatures during lamination [12]. Therefore, a lower-than-typical lamination temperature was used to create this package. While the lower temperature is not necessary for the GaAs//Si cell, this minimodule provided an opportunity to test the long-term performance of the packaging approach. Unfortunately, the lower lamination temperature was insufficient to protect the cell in the long term, leading to the high degradation rates reported above. Since long-term outdoor exposure data of tandem cells are still rare, we did not have another data set available to repeat our degradation analysis.

Historically, several important PV degradation mechanisms were first identified through outdoor exposure rather than through standardized indoor testing. In CdTe technologies, long-term operational studies have revealed

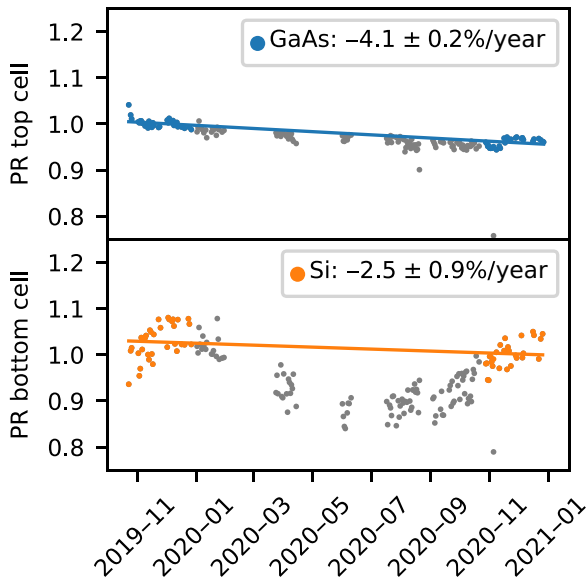


FIG. 7. The performance degradation of the tandem minimodule shown for the GaAs top cell and Si bottom cell through the normalized performance ratio (PR).

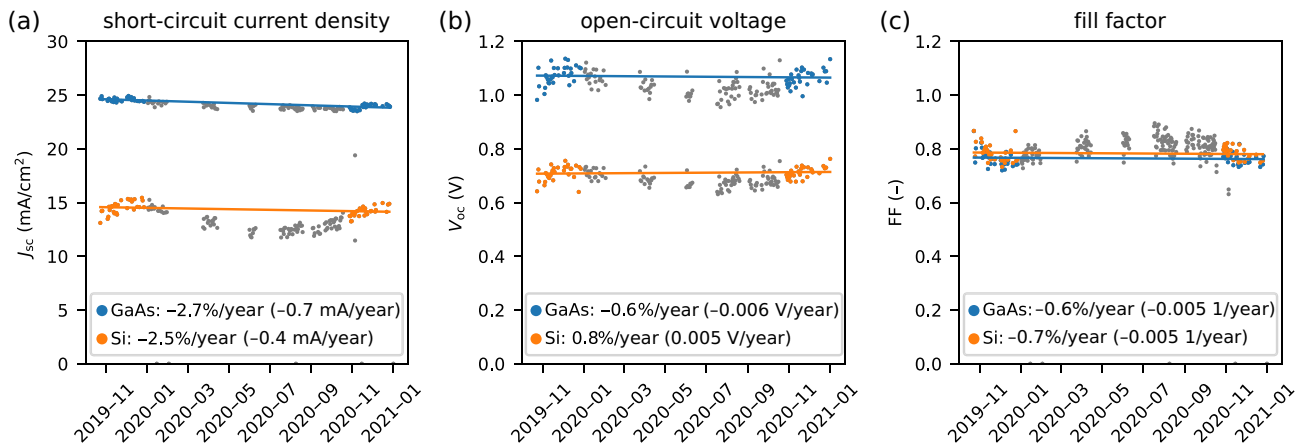


FIG. 8. The individual degradation rates of the main characteristics of the $J(V)$ measurements. The legends indicate the relative rate of change in %/year and the absolute change in units per year. (a) Short-circuit current density; (b) open-circuit voltage; (c) fill factor.

strong bias- and history-dependent metastable effects that complicate performance assessment and cannot be isolated by a single accelerated stress protocol [36]. Similarly, outdoor testing has demonstrated degradation modes that depend on field-representative operating conditions: CdTe modules operated outdoors at open circuit degraded rapidly, while identical modules operated at maximum power point showed no measurable degradation over the same exposure period [37]. More broadly, major reliability issues such as potential-induced degradation, light- and elevated-temperature-induced degradation, and polymer backsheets cracking were all discovered only after extensive field deployment, with corresponding accelerated tests developed years to decades later [38–40]. For emerging technologies, including tandem and perovskite PVs, recent assessments emphasize that existing stress tests do not act as a “time machine” and have no established relationship to field service; numerous examples exist where devices pass indoor tests but fail within the first year outdoors [41]. These precedents highlight that outdoor testing is not merely a validation step but a necessary discovery tool for identifying field-relevant degradation modes and informing the subsequent design of appropriate accelerated tests.

E. Performance modeling

Finally, we compared the measured module power to the simulated module power of PVcircuit. In Fig. 9, we show an identity plot of the filtered data points around STC for the measured and simulated module power. The GaAs top cell delivers the higher module power, which results in data points collocating in the top-right part of the figure, whereas the Si bottom cell data points are collocated in the lower left. Both data clouds are located around

the identity line, with the Si bottom cell results showing a slightly better agreement between the simulated and measured data.

The PVcircuit model takes the measured J_{sc} data as a modeling input and does not account for cell or packaging degradation. All other diode parameters such as the series resistance and diode saturation current density are constants in our simulations. Because the simulated and measured power data show good agreement over the course of field deployment, a reduction in the short-circuit

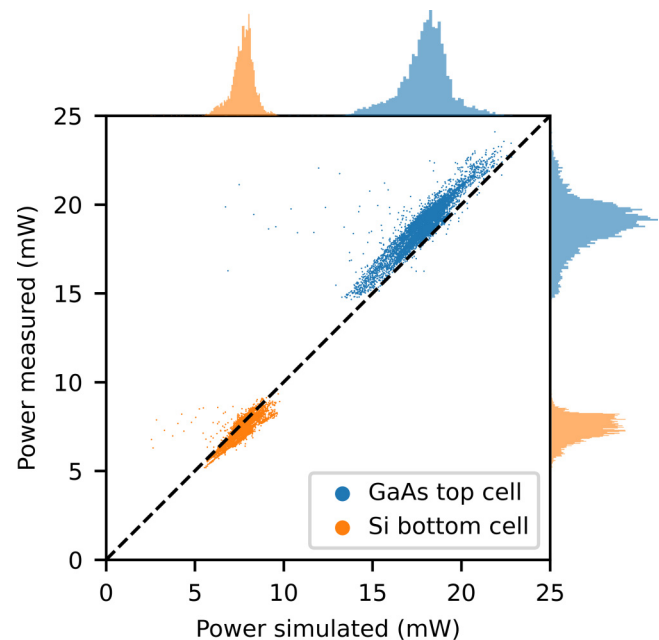


FIG. 9. The identity plot of the measured module power versus the simulated module power from PVcircuit for the top and bottom cells. Histograms of the data sets are plotted along the figure axes.

current could explain the observed performance degradation in the measured outdoor data. This is in alignment with the identified delamination failure mode in the module packaging, which is known to mainly reduce the short-circuit current. Thus, the modeling results confirm that the packaging degradation mode is a main contributor to the observed performance degradation.

IV. CONCLUSIONS

We developed and demonstrated a modular outdoor performance modeling and degradation analysis framework for tandem minimodules, using a GaAs//Si 4T prototype as a case study. To enable robust degradation analysis, we translated outdoor $J(V)$ measurements to STC conditions, but found no agreed-upon standards for tandem modules. Spectral variations have a greater impact on multijunction than single-junction devices, making established methods (e.g., IEC 61724-1:2021) unsuitable. While a recent publication [11] has proposed filter criteria for dual-axis systems, applying them to our fixed-tilt system removed all winter and spring data, substantially reducing the usable deployment time for our analysis. We therefore introduced a modified filter set emphasizing year-round data retention.

We applied this approach to a GaAs//Si tandem minimodule data set, exemplifying a methodology that is broadly applicable to other tandem technologies (e.g., perovskite/Si). By normalizing the top- and bottom-cell performance, we obtained degradation rates (defined as the relative rate of change) of $-4.1 \pm 0.2\%$ /year for the GaAs top cell and $-2.5 \pm 0.9\%$ /year for the Si bottom cell. We were able to extract those degradation rates by comparing months of similar spectral irradiance. With our 14-month data set, this enabled year-to-year comparisons for two months. In principle, the efficiencies and degradation rates can be different for different months of the year because the spectral content (“blue-rich” versus “red-rich”) changes. To determine the year-to-year degradation rate for all months of the year would require at least a two-year data set and would minimize the uncertainty in the degradation-rate results.

Analysis of $J(V)$ characteristics showed the largest degradation in the short-circuit current. Postdeployment inspection of the module packaging revealed delamination between the front glass and encapsulant, likely caused by the lower-than-typical lamination temperatures used in the prototype fabrication, leading to early packaging failure and elevated degradation rates. Subsequent PVcircuit simulations, with all cell parameters besides J_{sc} held constant, confirmed good agreement with measured data, supporting packaging degradation as the primary failure mode. These findings suggest that III-V//Si technologies are ready for extended outdoor deployment, provided that robust module packaging is ensured. This is especially important for

emerging technologies such as perovskite//Si tandem modules that are susceptible to elevated temperatures during the packaging process.

In summary, our presented methodology provides a reproducible foundation toward bankable performance modeling and degradation analysis of emerging multijunction technologies.

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DATA AVAILABILITY

The data that support the findings of this paper are openly available [43].

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