

# Accurate Modeling of Module Temperature for Ground-Mounted PV and Its Impact on Degradation

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**Abstract**—This article presents thermal models for simulating the photovoltaic module temperature. In particular, the study focuses on investigating a more accurate thermal model using transient simulation methods for smaller time steps and explicit terms to account for radiative heat exchange with the sky-dome. Accurate modeling of module temperature for ground-mounted systems is essential, as module temperature directly impacts system performance, efficiency, reliability, and financial outcomes. The accurate thermal model was applied to model the thermal performance of a unique East–West (EW) facing ground-mounted system. This resulted in a 38% reduction in root-mean-square error between modeled and measured temperatures. Heat transfer coefficients were determined using fits to field data, and found to be comparable to those previously found for modules mounted on single-axis trackers (SAT). Thus, since the heat coefficients are similar and the plane-of-array irradiance is lower, modules installed on ground-mounted EW systems operate at lower temperatures than those installed on SAT. Based on the accurate thermal model results in this study, the impact this has on module degradation is explored, with modules mounted on the EW system simulated to experience up to a 40% reduction in the rate of some degradation modes in Australia across different climate regions.

**Index Terms**—Light-induced degradation, PV module degradation, PV mounting systems, reliability, UV-induced degradation.

## I. INTRODUCTION

THE rate of photovoltaic (PV) deployment is increasing exponentially, with over 570 GWp installed in 2024 [1]. This has been accompanied by a rapid reduction in module costs, reaching around 10 cents/Wp [2]. However, the majority of PV system costs come from other components, such as mounting

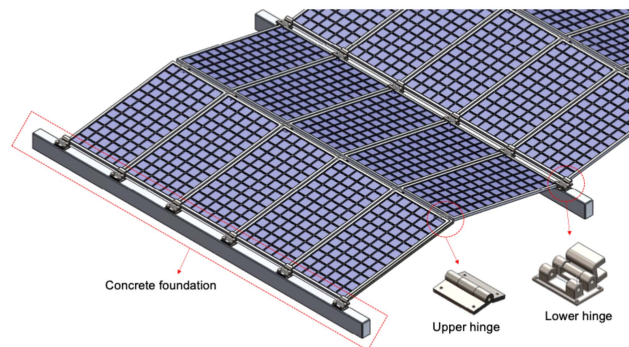


Fig. 1. Layout of MAV of 5B Australia Pty Ltd.

and deployment costs. Moreover, some countries are constrained by land area, so maximizing the energy density of solar farms can minimize nontechnical costs while achieving maximum output. While current mounting types are dominated by tracking systems [3], this has created an opportunity to develop and adopt mounting systems that prioritise low cost, rapid deployment, and high ground-coverage ratios.

### A. East–West Mounting Systems

The recent development in East–West (EW) types of fixed tilt mounting systems includes products, such as Jurchen Technology’s PEG [4], Erthos’s Earth Mount [5], and 5B’s MAVERICK (MAV) [6]. As these products are quite distinct from standard fixed-tilt or tracking systems, improving models for these technologies is crucial to accurately simulate system output, and remain competitive against dominant mounting system types like single-axis trackers (SAT). The schematic example of an EW system is shown in Fig. 1. Due to its low tilt angle, it allows a higher ground cover ratio compared to SAT, which allows significantly higher energy density per land area. Moreover, as the system is prefabricated in the factory, it can reduce deployment time and be more easily assembled at the end of its life.

### B. Thermal Modeling of PV Modules

Module temperature is one of the most significant factors affecting module output after plane-of-array (POA) irradiance, resulting in 3%–5% losses [7]. It also significantly impacts module degradation, which is often neglected in yield simulations. Standard PV temperature models typically use simple linear

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relationships with POA irradiance and ambient temperature ( $T_{\text{amb}}$ ) [8]. These simplifications result in significant uncertainty in simulated module temperature ( $T_m$ ), particularly when default temperature coefficients are applied across different sites.

Furthermore, PV module temperature estimation is dominated by steady-state models, using solar irradiance and weather conditions in energy balance equations or data-driven approaches [9]. Early industrial practice relied heavily on the nominal operating cell temperature (NOCT) formulation, which provides an approximate rise above ambient temperature under a nominal irradiance and wind condition, and is still embedded in tools, such as SAM [10]. More detailed steady-state formulations emerged with the Faïman model, now widely used due to its simplicity and empirical robustness. Faïman [8] measured irradiance, wind speed, and module back-surface temperatures across seven glass-front, Tedlar-backed modules, and fitted two empirical coefficients capturing combined convective and radiative losses. Its dominance stems from this simplicity, but it embeds numerous assumptions. Studies have shown that the model does not explicitly represent wind direction, module construction, tilt, or seasonal effects, which reduces its generality. For instance, Barykina and Hammer [11] applied the Faïman model to evaluate four module technologies across five climates and found that parameter values varied seasonally and by site, with cross-site application producing bias below 3.5 °C in most cases and up to 4.5 °C in one instance.

Recent work has focused on improving the physical representation of heat transfer processes, particularly radiative exchange with the sky dome. Standard linear models generally lump radiative losses into empirical coefficients, but sky radiation is a major component of nighttime and low-wind cooling, and is nonlinear. Motivated by earlier formulations, such as Swinbank and Fuentes, and aided by the availability of ERA5 and other re-analysis datasets, several researchers have begun incorporating explicit longwave terms. A notable contribution is the Sandia report, which demonstrates that including longwave radiation exchange with the sky significantly improves accuracy even though this adds some complexity to the model [12].

Because steady-state models assume instantaneous thermal equilibrium, they perform well for long averaging windows but degrade under fast changes in irradiance and wind. They typically overestimate short-term fluctuations because they neglect thermal mass. This has led to growing interest in transient models for both fixed-tilt and SAT systems. One influential approach is the Prilliman transient method, which uses a weighted moving-average of past steady-state predictions to reflect the module's delayed thermal response, with weighting derived from 3-D finite-element analysis of thermal mass and wind-dependent convective behavior. This has been shown to reduce error and variability in performance models [13]. Other studies have explored numerical integration of the thermal balance, such as the Euler solution, used by Jones and Underwood [15] to compute temperature from heat capacity and time-varying radiative and convective fluxes. While these methods improve accuracy under rapidly changing or overcast conditions, they require more data and careful initialization [15]. Module degradation is a

significant concern for utility-scale solar panels, with multiple studies concluding that typical yield forecasts underpredict degradation. These models typically assume a simple linear degradation with time, often based on the manufacturer's warranty. More complex models, which account for weather and operating conditions at sites, have been reported in the literature [8], [11], [12], [13] but have not yet been incorporated into mainstream yield modeling programs. The primary factors contributing to module degradation are: 1) temperature, 2) humidity, and 3) exposure to ultraviolet (UV) light [15].

### C. Thermal Modeling of the 5B MAV

In this article, we focused on simulating the module's temperature when mounted on the 5B MAV, a prefabricated mounting system designed for rapid deployment, and on a SAT, one of the most commonly used mounting types. The MAV consists of "waves" of modules with opposing 10° tilts (see Fig. 1). Due to its design, the MAV suffers little or no shading loss from neighboring modules despite having a high ground cover ratio of over 80%.

Determining the accurate temperature coefficients is crucial to understanding the performance of these new mounting systems. We first fit an advanced thermal model to the measured module temperature of a MAV system and then simulate the system. Those calculated temperature coefficients are then compared for the temperature-dependent degradation modes of MAV and SAT systems. Therefore, this study focuses on the following.

- 1) Development of a transient thermal model incorporating explicit sky-dome radiative heat exchange.
- 2) Validation of the model against field measurements.
- 3) Determination and comparison of heat transfer coefficients for EW and SAT mounting systems.
- 4) Demonstration that EW systems operate at lower module temperatures due to reduced POA irradiance.
- 5) Quantification of the impact of reduced temperature on module degradation across Australian climates.

## II. METHODOLOGY

### A. Site Location and Data Collection

Monitoring data were obtained from a 5B test site located near Bungendore in New South Wales, Australia (35.175 °S, 149.522 °E) from September 2022 to June 2023, as shown in Fig. 2. The location has low soiling (<3%/year), which therefore would be less likely to impact the temperature measurement and the POA. The MAV is normally deployed with its module aligned NE–SW. The modules are Jinko JKM315PP-72, with an efficiency of 16.23% ± 0.49% under standard test conditions, a power output of 315 W, a thermal coefficient of −0.40%/K, and a nominal operating temperature (NOCT) of 45 °C ± 2 °C, as specified in the datasheet.

Local weather data were obtained from a weather station located ~50 m from the main site. This data included global horizontal irradiance (GHI), POA for the two module orientations, ambient temperature ( $T_{\text{amb}}$ ), wind speed (ws), and the direction, which were measured 1.8 m above the ground. The

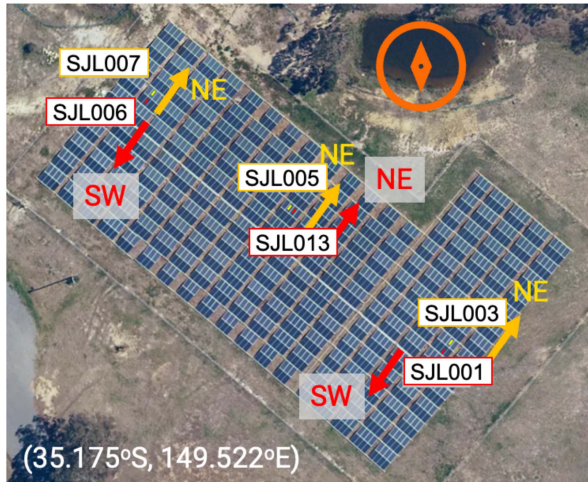


Fig. 2. Birds-eye view of the site at Bungendore in New South Wales, Australia (35.175 °S, 149.522 °E).

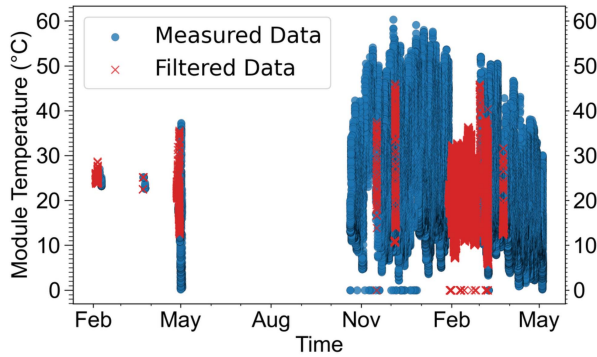


Fig. 3. Example of data filtering of *Thermocouple's* Measurements for module temperature from module SJL001. Due to hardware errors, some data points are missing.

data were recorded at 5-min intervals. The module temperature ( $T_m$ ) was monitored using four thermocouples attached to their rear, along with a fifth sensor located in the air space underneath as defined in international electrotechnical commission standard 61853-2. These sensors provide data at slightly irregular intervals, typically 3 min. System output data were monitored at the inverter level, with DC current, voltage, and power measured at 5-min intervals.

Downwelling irradiance data on a horizontal plane were obtained from the ERA5 reanalysis dataset, accessed from the climate data store [16]. This data is relatively low resolution (approx. 8 km pixel size) and on an hourly basis. Simulations were performed on a 5-min basis. Data with differing timesteps were aligned with linear interpolation.

Data filtering was performed using the *pvanalytics* package in *pvlib-python* [17] to detect sensor faults and data outside physical limits. Custom routines were also developed to detect and remove data associated with hardware faults. Fig. 3 illustrates some of the data excluded through this process. In this case, data were excluded where the sensor gave lower readings throughout the middle of the day than the measured ambient temperature. Site inspection revealed that the sensor had detached.

## B. Thermal Models

Data from one of the central modules on the Bungendore site was used to fit coefficients for several thermal models of increasing complexity. For all models, the heat into the modules, corrected for the energy extracted as electricity, is described by the following equation:

$$Q_{in} = \Phi_m \alpha - \frac{P_{electrical}}{A_m} \quad (1)$$

where  $\Phi_m$  is the POA irradiance on the front of the modules,  $\alpha$  is the absorption coefficient of the modules (assumed to be 0.9 in all cases),  $P_{electrical}$  is electrical power output, and  $A_m$  is the module area. However, when the on-site inverters were undersized, this resulted in clipping throughout the middle of the day. Therefore, the  $P_{electrical}$  can be expressed as follows:

$$P_{electrical} = \frac{P_{inv,dc}}{N_m} \cdot \frac{2\Phi_m}{\Phi_m + \Phi_{m,opp}} \quad (2)$$

where  $P_{inv,dc}$  is the DC power measured at the inverter,  $N_m$  is the number of modules connected to the inverter, and  $\Phi_{m,opp}$  is the measured POA irradiance for the modules of opposing alignment for MAV. This is required as modules facing both NE and SW directions were connected to the same inverter. For SAT in comparison,  $\Phi_m = \Phi_{m,opp}$ .

There are several thermal models in the literature, including Faïman with radiative loss [8], [12], which is similar to the model proposed in this study. However, it does not include transients unless the Prilliman model [13] is subsequently applied. Our study includes the new numerical transient process, which improved the accuracy further, where custom coding is required to perform a fitting process using these models, as we describe. Finally, we have done this for a system that is distinct from any of the systems for which these models have reported results.

Five thermal models were used in this work where the model complexity increased by considering additional heat transfer mechanisms and transient effects.

1) *U<sub>C</sub>-Single Heat Transfer Coefficient*: The simplest thermal model used in this article uses a constant transfer coefficient to account for heat exchange between modules and the ambient. Such models are widely used, including being the default setting for simulation programs, such as PVsyst. The transfer of thermal energy is given by

$$Q_{out,constant} = (T_m - T_{amb}) \cdot U_C \quad (3)$$

where  $T_m$  is the simulated module temperature,  $T_{amb}$  is the ambient temperature, and  $U_C$  is the heat transfer coefficient [ $W/m^2 \cdot ^\circ C$ ].

2) *U<sub>V</sub>-Double Heat Transfer Coefficient*: The first extension to the most basic model is the inclusion of a second heat transfer coefficient to account for the impact of wind speed. The heat exchange between the module and the ambient then becomes

$$Q_{out,convective} = (T_m - T_{amb}) \cdot (U_C + U_V \cdot ws) \quad (4)$$

Where  $ws$  is wind speed, and both  $U_C$  [ $W/m^2 \cdot ^\circ C$ ] and  $U_V$  [ $W \cdot s / m^3 \cdot ^\circ C$ ] are constant heat transfer coefficients.

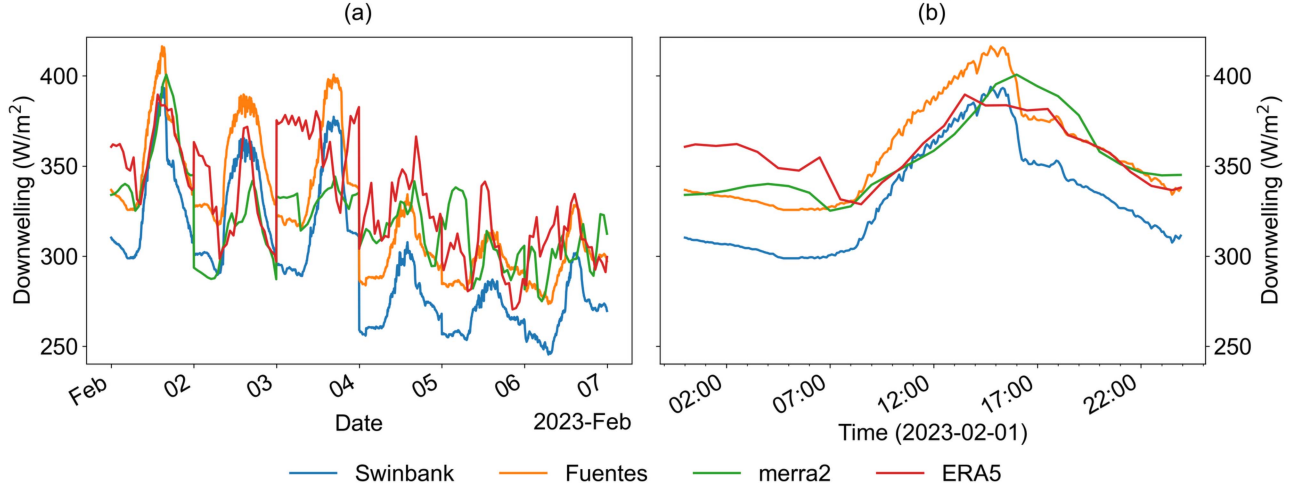


Fig. 4. Line plot of downwelling as calculated using the Swinbank and Fuentes models, as well as using climate reanalysis data from the ERA5 and MERRA2 datasets over (a) a week and (b) a day.

3) *Including Radiative Heat Transfer With Sky Dome:* This approach introduces an additional term to account for net radiative heat transfer with the sky dome

$$Q_{\text{out.sky}} = \text{vf} \cdot \varepsilon \cdot (\sigma \cdot T_{\text{module}}^4 - q_{\text{dr}}) \quad (5)$$

where  $\text{vf}$  is the effective view factor (assumed 0.989 [12]);  $\varepsilon$  is the emissivity (assumed 0.88 [18]), and  $\sigma$  is the Stefan–Boltzmann constant [ $5.6703 \times 10^{-8} \text{ W}/(\text{m}^2 \cdot \text{K}^4)$ ].  $q_{\text{dr}}$  is long wavelength downward radiation on a horizontal plane, which can be estimated in several ways. The most straightforward are models, such as the Swinbank [19] or Fuentes [20] methods, which estimate sky temperature (and hence downward radiation) based solely upon the ambient temperature. Alternatively, the long-wavelength flux on a horizontal surface can be extracted from a climate reanalysis dataset, such as ERA5 [21] or MERRA2. It should be noted that these datasets are hourly and have a resolution of  $8 \times 8 \text{ km}^2$ . Fig. 4 presents downwelling data calculated using each of these data sources. While the reanalysis datasets better account for cloud cover, there are significant issues with the MERRA2 data over this time period, likely as a result of missing measurements. Of the four potential sources of downwelling data, ERA5 allowed for the most accurate thermal model and is therefore used for all results in this article.

4) *Including Transient Effects:* More accurate thermal modeling is made possible by accounting for transient effects on the module temperature, rather than assuming that the modules are always at steady state. Two methods were employed in this article.

The first method employed was that of Prilliman et al. [13], which reflects the transient behavior using a weighting function,  $P$  (6) calculated from wind speed measurements ( $\text{ws}$ ), module unit mass ( $m_u$ ), and specific coefficients ( $a_0 = 0.0046$ ,  $a_1 = 0.00046$ ,  $a_2 = -0.00023$ , and  $a_3 = -1.6 \times 10^{-5}$ ). These coefficients have been shown to work effectively across a variety of PV modules [13]

$$P = a_0 + a_1 \times \text{ws} + a_2 \times m_u + a_3 \times \text{ws} \times m_u. \quad (6)$$

An exponentially weighted moving average of steady-state temperatures is then applied, using weights given by  $e^{-P \times t_i}$ , where  $t_i$  represents the past time in seconds. This method integrates steady-state temperature data  $T_{\text{ss},i}$  to provide a more accurate current temperature prediction. The weighted moving average temperature prediction  $T_{\text{MA},i}$  is expressed as

$$T_{\text{MA},i} = \frac{\sum_{i=2}^{t_i \leq 1200} T_{\text{ss},i} \times e^{-P \times t_i}}{\sum_{i=2}^{t_i \leq 1200} e^{-P \times t_i}}. \quad (7)$$

The Prilliman temperature model implementation used in this study is provided by the *pvlb* library [17]. This function calculates the transient state temperature using inputs of modeled steady-state temperature, wind speed, and the module's unit mass. For this study, the module's unit mass was  $13.65 \text{ kg}/\text{m}^2$  from a module mass of  $26.5 \text{ kg}$  and an area of  $1.94 \text{ m}^2$ , with an assumed value of specific heat capacity of  $833 \text{ J}/\text{kg} \cdot \text{K}$  as utilized by McIntosh et al. [22].

Another approach to accurately model the transient temperature behavior of solar modules is using an explicit numerical method, such as the Runge–Kutta method. Starting with an initial steady modeled temperature distribution, the temperature at each time step is iteratively updated, considering the thermal mass of the module and the conditions at the previous timestep (s). The rate of heat is initially independent of the module temperature and only depends on the heat fluxes in and out of the module. Higher order numerical methods can be used to obtain more accurate results, though at the cost of computation time. More details on how the Runge–Kutta method was applied are provided in the Supplementary Material.

There were several gaps in the filtered and interpolated 5-min data, which presented a problem for transient simulations. To resolve these issues, two approaches were used. In the first instance, linear interpolation was applied for data gaps of less than 20 min. Second, when data gaps were up to 1 h, data were backfilled. Such an approach enabled the simulated temperature to reach a steady state before the first actual data point was

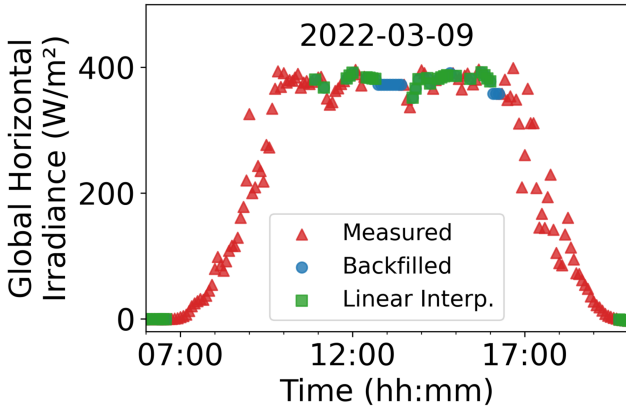


Fig. 5. Irradiance data measured on site on the 9<sup>th</sup> of March 2022 and interpolated to 5-min intervals. The black dots indicate data points with actual measurements (original), where blue dots represent linearly interpolated values for small gaps in the left figure. Red dots represent points where backward filling was applied.

reached. An example of the interpolation method is shown in Fig. 5.

This approach prioritizes data continuity for transient simulations, while any filled points were excluded from the assessment of error metrics to prevent skewed results. Fig. 5 presents the original irradiance measurements along with the interpolated data points introduced by the two methods in two typical days. These additional points help smooth transitions from steady-state to transient simulations and mitigate numerical solver errors that are particularly pronounced at the onset of the transient phase. Only the original data points were considered when evaluating the fits. Fitting the heat transfer coefficients for each of the models was performed based on least squares minimization using the *Scipy* library in Python. The flowchart of the methodology is shown in Fig. 6.

More complex models, including the effect of wind direction and heat exchange with the ground, have been investigated by McIntosh et al. [22]. However, they did not provide a significant increase in modeling accuracy.

### C. Simulating Module Temperature and Degradation

Once the coefficients for the thermal models were obtained, simulations of module temperature were carried out for other locations to investigate potential differences between the temperature of modules mounted on MAV and SAT systems, and how this might impact module degradation.

Satellite-derived weather data provided by SolarGIS was used for two sites within Australia: Bannerton in Victoria (33.8637 °S, 151.2021 °E) and Clare in Queensland (19.8397 °S, 147.2104 °E). While both locations have excellent solar resources, the increased humidity in tropical Queensland is expected to increase module degradation. Fig. 7 presents the monthly average insolation, peak temperature, and relative humidity for each location.

MAV and SAT systems were simulated using the *pvlb* library with DC:AC ratios of 1.3 and 1.5, respectively. The modules used were Longi LR5-72HBD-570M bifacial panels connected

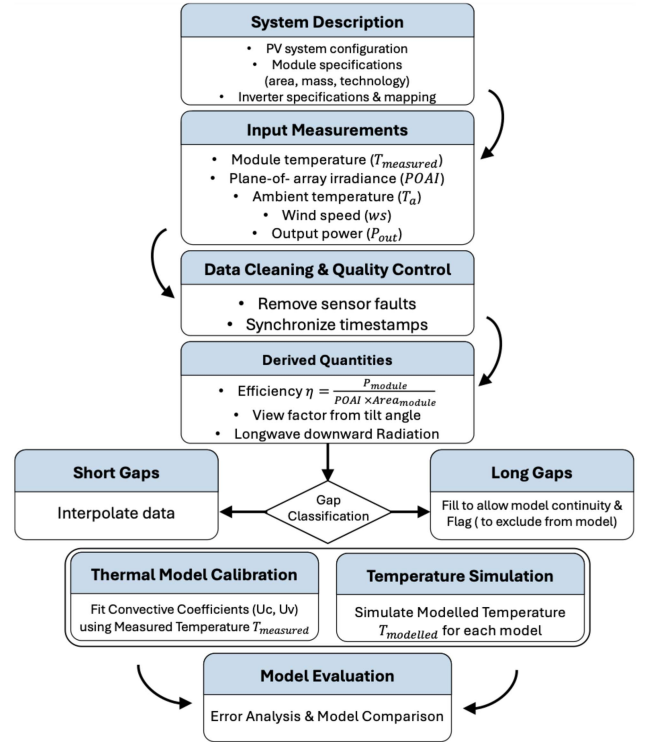


Fig. 6. Flowchart of the methodology.

to SMA Sunny Central 2.5 MW inverters. This work considered two degradation modes: thermal and UV-induced degradation.

1) *Thermal Degradation*: Thermal degradation is usually driven by the thermal stress due to the module temperature variation throughout the day. The thermal degradation rate constant,  $k_{TD}$ , can be calculated as follows:

$$k_{TD} = A_{TD}(\Delta T)^\theta C_N \exp\left(-\frac{E_{TD}}{k_B \times T_{TD,MAX}}\right) \quad (8)$$

Where  $A_{TD}$  is prefactor constant for the thermal degradation (assumed to be 2.04 [23]),  $\Delta T$  is the difference in minimum and the maximum module temperature,  $\theta$  is a constant that denotes the effect of temperature difference on power degradation (assumed to be 2.24),  $C_N$  is cycling rate, (assumed 1 [15]),  $E_{TD}$  is Activation energy for the thermal degradation (0.43 eV) [23],  $k_B$  is Boltzmann constant ( $8.62 \times 10^{-5}$  eV/K),  $T_{TD,max}$  is the module temperature in Kelvin.

2) *Photodegradation*: High temperature and relative humidity can also lead to photodegradation (PD) when PV modules are exposed to UV radiation. The PD rate,  $k_{PD}$  can be calculated using the equation as follows:

$$k_{PD} = A_{PD} (UV)^X (1 + RH_{eff}^X) \exp\left(-\frac{E_{PD}}{k_B \times T_m}\right) \quad (9)$$

Where  $A_{PD}$  is prefactor constant, UV is amount of UV radiation in  $W/m^2$  on a tilted plane,  $X$  is a correction factor that denotes the impact of UV radiation on degradation,  $E_{PD}$  is activation energy of photodegradation, and  $T_m$  is module's temperature (in Kelvin).

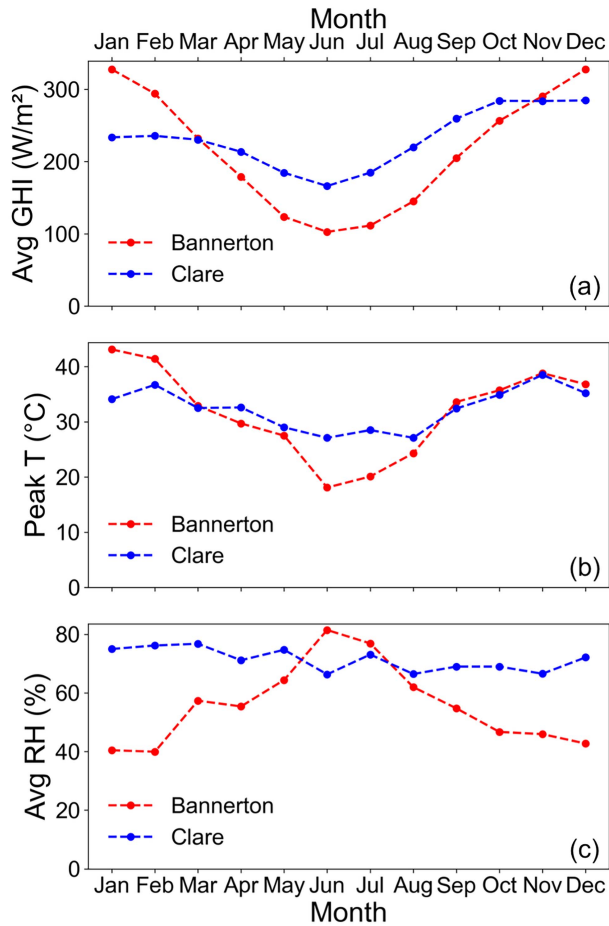


Fig. 7. Monthly (a) average Insolation, (b) peak temperature, and (c) average humidity for sites at Bannerton and Clare.

The values used for PD are assumed to be constant, as suggested in Kaaya et al. [23]. The in-plane UV radiation was modeled in three steps: 1) calculation of UV fraction from GHI, 2) decomposition of UV into direct and diffuse components, and 3) transposition to POA irradiance [22].

#### D. Mapping

The operating condition depends strongly on location, which results in variations in temperature, relative humidity, and insolation. Using weather data from different regions across Australia, degradation is mapped for each of the degradation modes described above. Single-axis tracking (SAT) and MAV mounting systems are compared to see the susceptibility of degradation to each mounting type. Spatial maps of thermal and PD modes for SAT and MAV across Australia were generated to compare the expected differences in degradation rates.

### III. RESULTS AND DISCUSSION

#### A. Thermal Model Comparison

Before comparing degradation modes, a comprehensive evaluation of different thermal models for PV modules was conducted. The models compared are described in Section II-B. The

North-facing module at the centre of the system was selected as the reference module for determining the fitting coefficients of the thermal models. Table I presents these fitted coefficients,  $U_C$  and  $U_V$ , as well as the mean bias error (MBE) and centred root-mean-square error (CRMSE) for each model in a manner similar to Driesse and Polo [24]. The simplest model used was the PVSyst default value in version 8.0.6 ( $U_C = 29 \text{ W/m}^2 \cdot ^\circ\text{C}$ ) setting for an open rack, which neglected the effects of wind speed. This method is intended to simulate cell temperature using Sandia cell-to-module conversion. The Faïman model, using either default ( $U_C = 25 \text{ W/m}^2 \cdot ^\circ\text{C}$  and  $U_V = 1.2 \text{ W} \cdot \text{s/m}^3 \cdot ^\circ\text{C}$ ) or fitted coefficients, accounts for the effects of wind speed. Finally, radiative transfer, according to [8], was used for both the steady-state and transient sky simulations without introducing any additional fitting variables. The MBEs present for the fitted models result from, including overnight data.

Fig. 8 presents scatter plots for models based on the basic Faïman model and those that include radiative heat transfer. The data is separated into “day” (POA irradiance  $> 20 \text{ W/m}^2$ ) and “night” (POA irradiance  $< 20 \text{ W/m}^2$ ). The error metrics for different time periods (all day, daytime, and nighttime) are also available in Table I of the Supplementary Material.

The resulting error metrics are displayed in Fig. 9. The primary impact of including sky transfer is a more accurate simulation during periods of low module temperature, particularly overnight. Considering that the inclusion of transient effects significantly reduces the scatter in the results, it is worth noting that the improvement between the transient and steady-state models is even more pronounced when radiative transfer is also taken into account, aligning with the findings of McIntosh et al. [22].

A comparative analysis of residual density distributions was conducted to evaluate the impact of incorporating sky radiation and transient effects on model accuracy, as illustrated in Fig. 2 of the Supplementary Material, which presents the histogram plots of residuals for the different models under consideration, from the least accurate [Faïman ( $U_C$  only)] to the most accurate [Transient (RK4) Faïman + Sky model]. The comparison reveals significant differences in the residual distributions of the two models.

This plot supports the impact of the sky models in improving simulation accuracy overnight. The single heat coefficient model exhibits two separate distributions, one with a significant negative shift. In contrast, the improved model, which incorporates sky temperature and transient effects, produces a single, sharp distribution centred around 0. The residuals during the daytime periods exhibit a less radical transformation, but there is a clear reduction in the standard deviation.

#### B. Validation Across the Field

The fitting coefficients derived from the SJI005 module, oriented North-East and centrally located, were used to simulate module temperatures for four other modules throughout the site and compared to the measured values. This was done to check how transferable the improved thermal model was for a single site. Fig. 3 of the Supplementary Material shows that this model

TABLE I  
COEFFICIENTS AND ERROR METRICS FOR THERMAL MODELS APPLIED TO MEASURED DATA

| Model                                      | Coefficient |       | MBE   |       | CRMSE |      |      |       |
|--------------------------------------------|-------------|-------|-------|-------|-------|------|------|-------|
|                                            | $U_c$       | $U_v$ | ALL   | Day   | Night | ALL  | Day  | Night |
| PVSyst default                             | 29          | 0     | 1.89  | 1.91  | 1.87  | 2.33 | 3.02 | 1.59  |
| Faiman - $U_c$ only                        | 33.85       | 0     | 1.15  | 0.26  | 1.87  | 2.39 | 2.87 | 1.59  |
| Faiman default                             | 25          | 1.2   | 2.09  | 2.37  | 1.87  | 2.32 | 2.98 | 1.59  |
| Faiman                                     | 26.02       | 3.35  | 1.15  | 0.26  | 1.87  | 2.26 | 2.62 | 1.59  |
| Faiman + Sky                               | 15.66       | 3.67  | -0.07 | -0.25 | 0.08  | 1.9  | 2.6  | 1.02  |
| Transient (Prilliman) Faiman               | 24.34       | 3.82  | 1.23  | 0.36  | 1.93  | 2.2  | 2.49 | 1.63  |
| Transient (Prilliman) Faiman + Sky         | 14          | 4.1   | -0.01 | -0.1  | 0.06  | 1.7  | 2.27 | 1.02  |
| Transient (RK4) Faiman + Sky<br>[our work] | 13.89       | 4.09  | -0.01 | -0.05 | 0.03  | 1.48 | 1.91 | 1.01  |

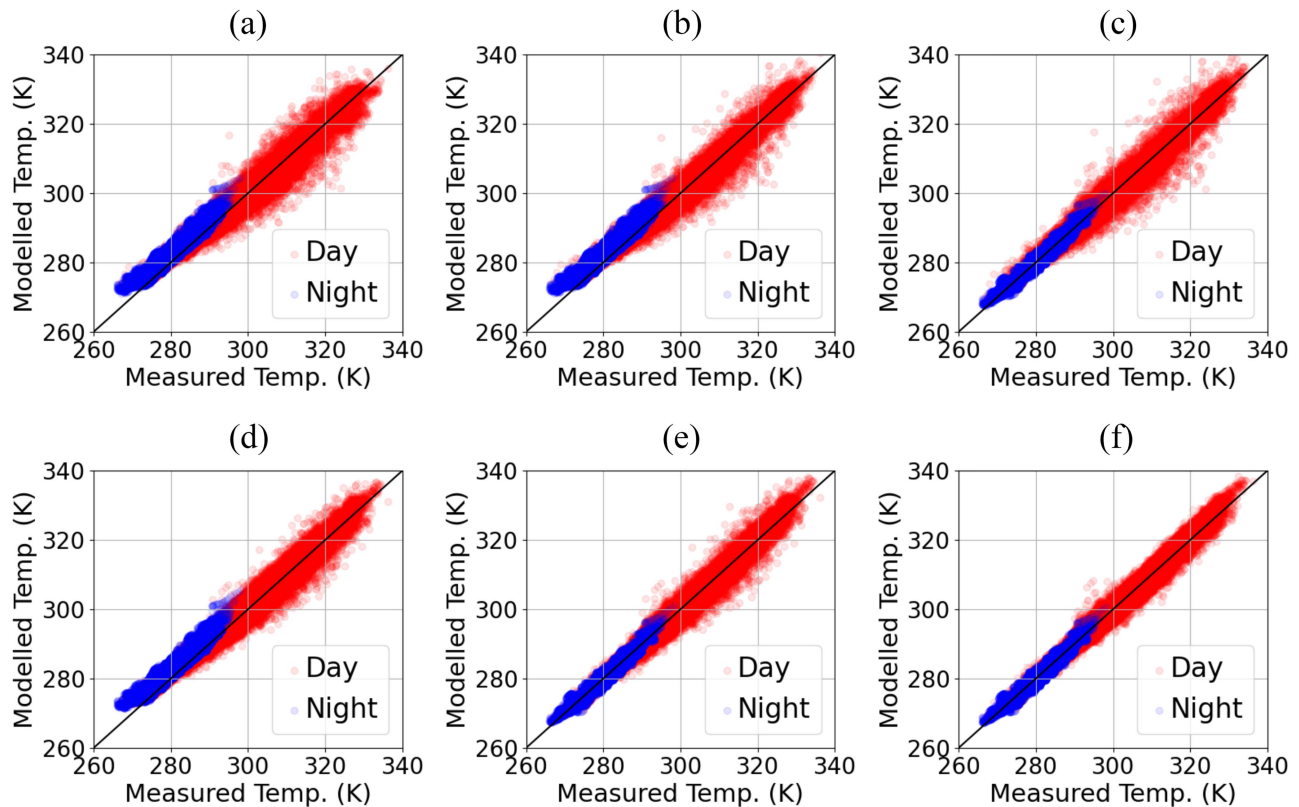


Fig. 8. Predicted versus measured module temperature ( $T_m$ ) for various thermal models. (a) Faiman ( $U_c$  only). (b) Faiman. (c) Transient (Prilliman) Faiman. (d) Faiman + Sky. (e) Transient (Prilliman) Faiman + Sky. (f) Transient (RK4) Faiman + Sky.

yielded errors within acceptable limits across all simulated modules. The model performs consistently across both orientations, with generally lower errors observed for the South-West-facing modules due to their reduced POA irradiance. Incorporating longwave radiative exchange with the sky leads to a systematic reduction in error for all modules, most notably during night-time conditions, while the inclusion of transient effects further reduces daytime CRMSE by better capturing rapid thermal responses. The module located near the eastern edge

of the array (SJI003) exhibits slightly higher errors across all model formulations, likely reflecting enhanced and nonuniform airflow cooling effects, with a greater sensitivity to the wind-dependent heat transfer term. The error reduction trends observed in our study are consistent with previous studies, including SAT analyses in Denver by McIntosh et al. [25] and fixed-tilt systems in Albuquerque reported by Driesse and Polo [24]. In all cases, adding radiative heat exchange and transient effects leads to systematic improvements over the base Faiman model,

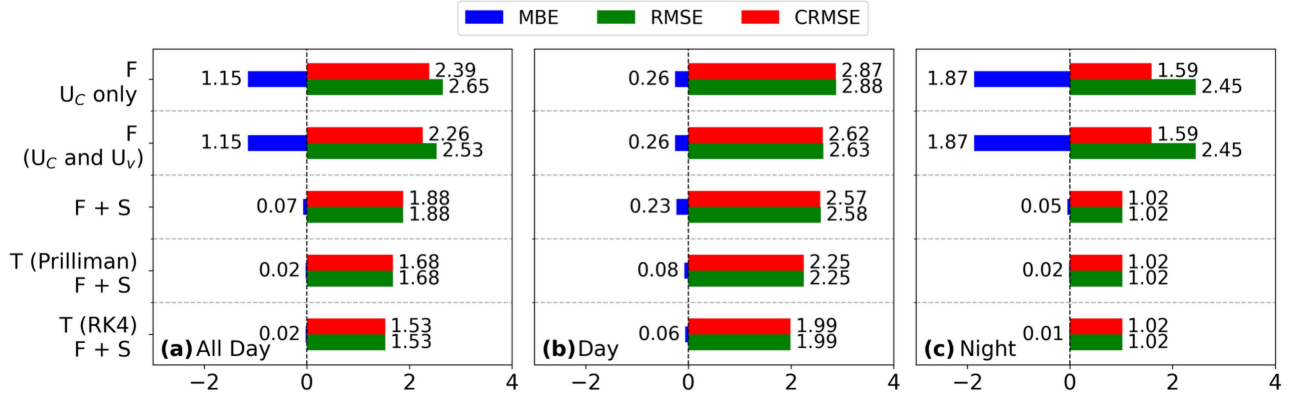


Fig. 9. Error metrics for selected models. The MBE, root-mean-square error (RMSE) and corrected root-mean-square error (CRMSE) are displayed for (a) the entire dataset, as well as (b) during day and (c) night periods. F, S, and T present Faiman, sky, and transient models, respectively.

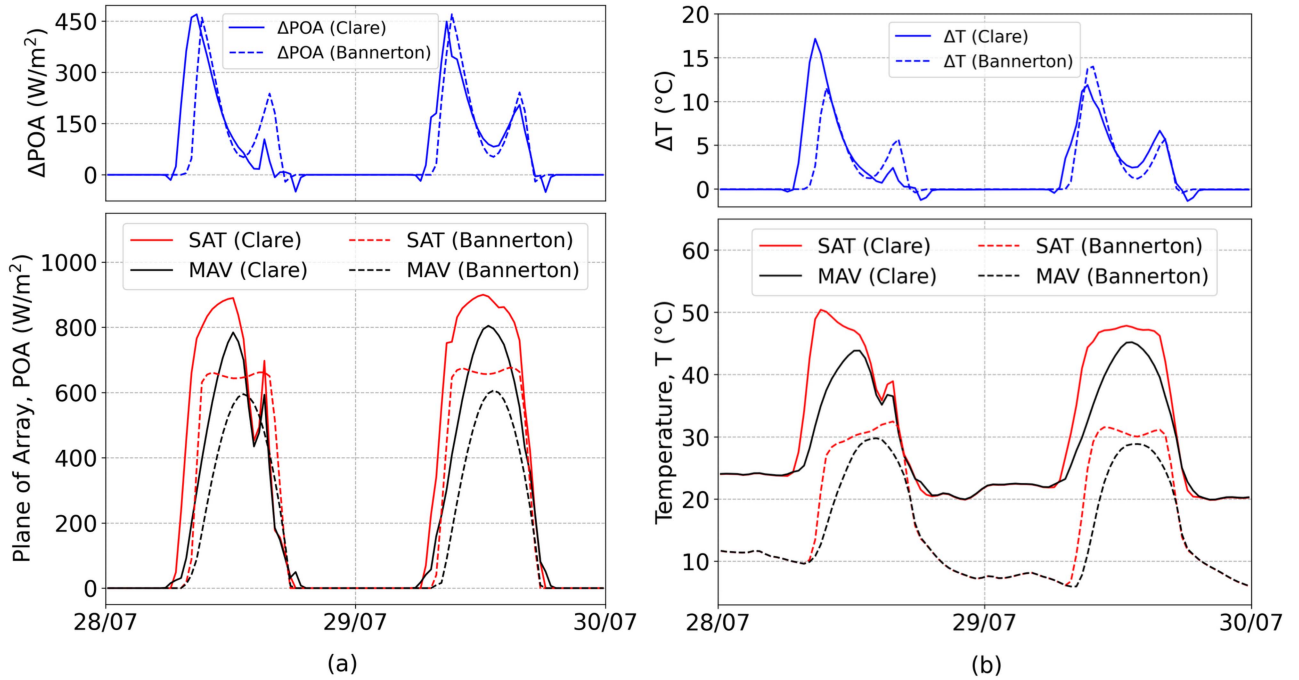


Fig. 10. Examples of (a) Irradiance and (b) module temperature with different mounting systems on the 28<sup>th</sup> and 30<sup>th</sup> of July 2023.

supporting the general applicability of the proposed approach across climates and mounting configurations.

### C. Simulated Operating Temperatures and Effect on Degradation for the 5B MAV

It is instructive to compare the coefficients obtained in this work with those for an SAT system reported by McIntosh et al. [22]. Despite the fits being performed for different locations, the  $U_C$  (13.95 c.f., 15.0) and  $U_V$  (3.96 c.f., 3.4) values are comparable. Some care should be taken with this comparison as the two fits used different downwelling models.

This means that modules mounted on MAV will generally have lower operating temperatures due to reduced POA. In this section, we use the thermal coefficients above to simulate

MAV and SAT operating temperatures in various locations and system configurations and the subsequent impact on module degradation.

### D. Module Temperature

Fig. 10 compares the POA and module temperatures ( $T$ ) on different mounting systems at Bannerton and Clare, Australia. Since the SAT system tracks the sun, it has a higher POA irradiance than an MAV system, leading to both a higher energy yield per module and a higher module temperature. This effect is enhanced by the bifacial gain, which is significantly higher for SAT relative to MAV systems [35]. However, the increase in POA also leads to higher module temperature, resulting in a peak difference.

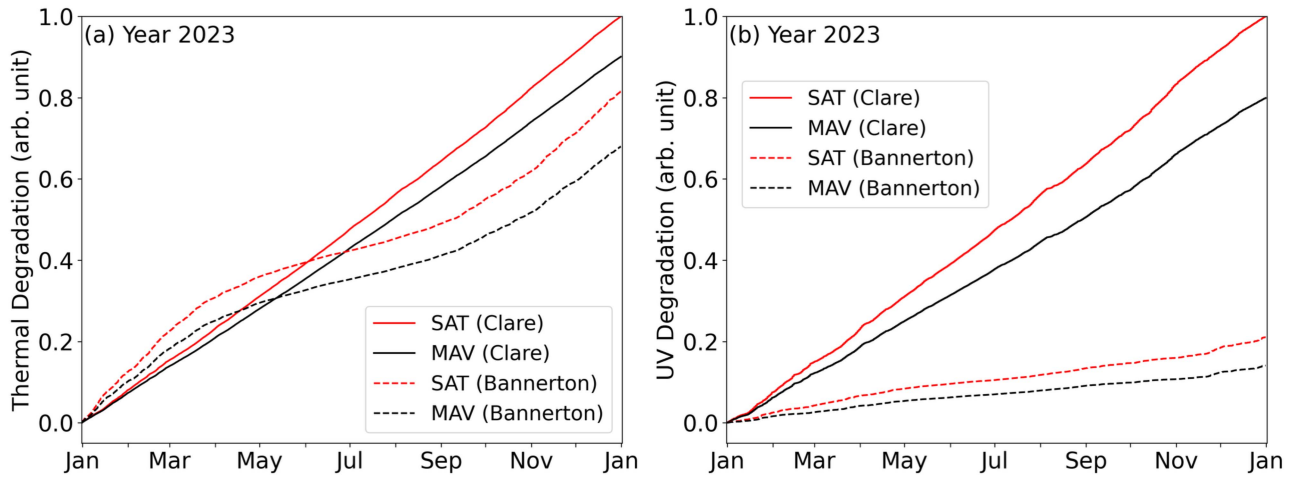


Fig. 11. Comparison of (a) thermal and (b) photo (UV) degradations at Clare and Bannerton on both MAV (West only) and SAT mounting systems.

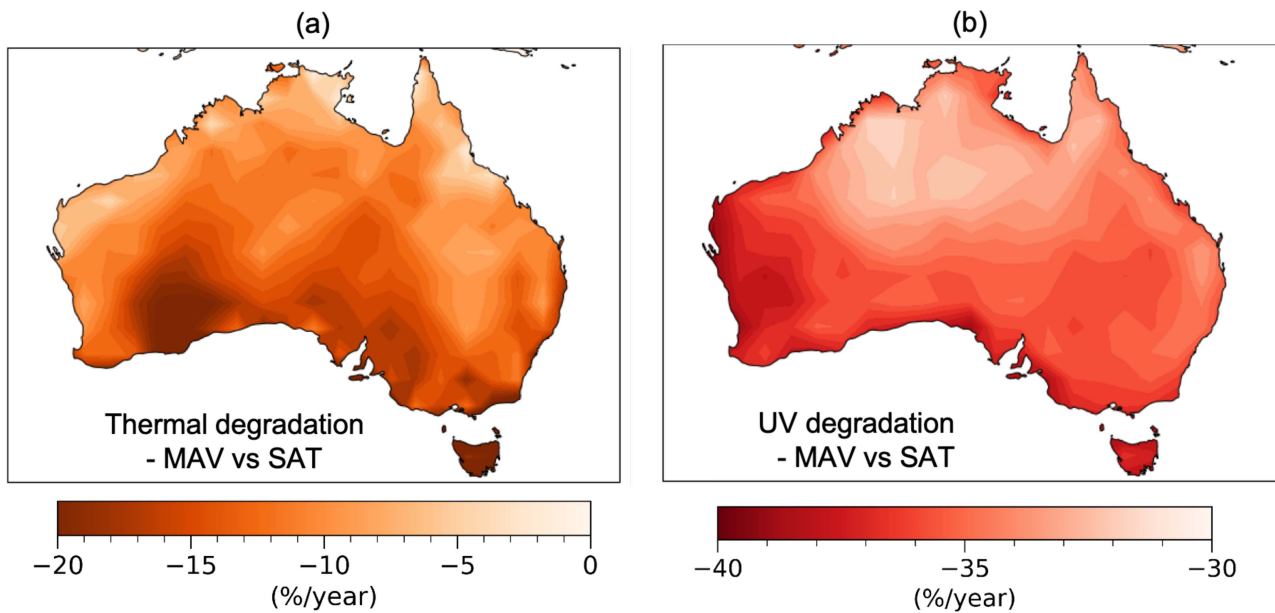


Fig. 12. Simulated reduction in degradation comparison for a module mounted on MAV compared with SAT in Australia for (a) thermal degradation and (b) UV degradation.

1) *Degradations Due to Different Modes:* Fig. 11 presents simulated thermal degradation and PD for both SAT and MAV systems in Bannerton. As anticipated, degradation peaks during summer, coinciding with the highest temperatures and incident irradiance levels. Furthermore, degradation can be accelerated due to clipping or curtailment, as shown in (1), where the  $Q_{in}$  is higher because of the lower amount of electricity delivered, resulting in higher operating temperatures of the module. The higher operating temperature and increased UV exposure on the SAT systems result in a systematically greater degradation rate compared to the MAV.

2) *Mapping of Relative Degradation:* As the POA depends on the location and the mounting systems, this can consequently lead to variations in module temperature and UV exposure. This section compares the thermal and PD of the MAV and SAT

mounting systems. Fig. 12(a) and (b) show the relative differences in thermal and PD between MAV and SAT, respectively. MAV was found to be less susceptible to both degradation mechanisms. Thermal degradation was more significantly different in Australia's Southern and Southwestern regions.

As most parts of Australia have high irradiance with high UV exposure, while MAV could still suffer from photo-degradation, the relative degradation of SAT was more significant. Our work therefore demonstrates that, despite differences in specific yield due to lower POA from the fixed orientations, there is still a strong benefit of reduced degradation in PV modules with lower operating temperatures. Therefore, such orientations may be preferred in remote locations, which would require higher operation and maintenance costs due to higher logistics costs.

#### IV. CONCLUSION

This study demonstrates high-accuracy thermal modeling using the Faiman model, including radiative heat transfer with a sky dome and transient effects on an East–West facing ground-mounted system, i.e., MAV by 5B Australia. Compared to the conventional method of using Faiman model values, our work demonstrated significantly higher accuracy in module-temperature prediction. Using the improved thermal model, the module temperatures are compared between the MAV and the SAT in locations in Bannerton and Clare, Australia. The work demonstrated that modules on the SAT system experience hotter temperatures due to higher POA. Furthermore, such can transition to more severe degradation due to thermal and photo degradation. Lastly, based on the geographical variation in Australia's climate, the work revealed relative degradation differences between the two mounting systems.

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