Comparative evaluation of PVGIS, PVsyst, and SAM models for predicting solar power output in equatorial tropical climates

Fabian Alonso Lara Vargas[1,3], Miguel Angel Ortiz Padilla[1], Alvaro Torres Amaya[2], Carlos Vargas Salgado[3]
[1]Department of Electronics Engineering, ITEM Group, Universidad Pontificia Bolivariana, Monteria, Colombia
[2]Department of Technological Sciences, TICES Group, Universidad Pedagógica y Tecnológica de Colombia, Tunja, Colombia
[3]University Institute of Energetic Engineering, Universitat Politècnica de Valéncia, Valencia, Spain

Article Info

Article history:

Received Oct 10, 2024
Revised Oct 22, 2025
Accepted Nov 16, 2025

Keywords:

Photovoltaic simulation
PVGIS
PVsyst
SAM
Tropical climate

ABSTRACT

Accurate evaluation of energy production in photovoltaic (PV) systems is critical for renewable projects, especially in tropical climates where environmental factors such as temperature significantly affect performance. Although commercial simulation tools exist (photovoltaic geographic information system (PVGIS), PVsyst, and system advisor model (SAM)), previous studies have identified notable deviations between their predictions and actual data, particularly in tropical climates. Moreover, these investigations are usually limited to short periods (one year) and do not systematically compare multiple tools under interannual conditions. This study evaluates the accuracy of PVGIS, PVsyst, and SAM in predicting the energy production of a PV installation in a tropical equatorial climate for 24 months to identify the most suitable tool for this context. Monthly energy production data were collected from a PV plant in Monteria, Colombia, equipped with 240 modules and two 36 kW inverters. Simulations were performed using the most recent PVGIS, PVsyst, and SAM versions. Accuracy was evaluated using metrics such as root mean square error (RMSE) and mean absolute error (MAE). SAM showed the highest accuracy, with an overall RMSE of 1,993.71 kWh and MAE of 1,615.87 kWh, followed by PVGIS (RMSE: 2,076.65 kWh, MAE: 1,830.84 kWh) and PVsyst (RMSE: 3,546.18 kWh, MAE: 3,250.17 kWh). The results highlight that SAM provides estimates closer to the real data and less dispersion than other tools. This study contributes to the renewable energy field by systematically comparing simulation tools in an understudied tropical context. The findings emphasize the importance of selecting appropriate software according to the specific environmental conditions of the project, thus optimizing the design and efficiency of PV systems in tropical regions.

Corresponding Author:

Fabian Alonso Lara Vargas
Department of Electronics Engineering, ITEM Group, Universidad Pontificia Bolivariana
Monteria, Colombia
Email: fabian.lara@upb.edu.co

1. INTRODUCTION

The increasing demand for renewable energy sources is driven by the growing global population, technological advancements, and the need for sustainable and environmentally friendly energy solutions [1]. Rapid population growth, rising living standards, and technological advancements have increased energy demand [2]. Consequently, a shift towards sustainable and low-carbon energy systems has become necessary

[3]. The transition to renewable energy sources, particularly solar power, is an essential response to the urgent need for sustainable energy sources [4]. Despite its promise, fully harnessing the potential of solar energy for global energy consumption requires addressing several challenges [5]. To attain a sustainable future, the role of solar power in expanding the renewable energy sector is crucial [6]. Realizing solar energy's full potential requires addressing challenges and investing in research and development [7].

The development of initial photovoltaic (PV) systems relied heavily on empirical methods and essential calculation tools, with limited use of specialized simulation software [8]. Today, the photovoltaic geographic information system (PVGIS), PVSyst, and the system advisor model (SAM) are among the most widely used software packages for designing and simulating PV systems [9]. PVsyst is a prominent tool for estimating the energy performance of both conventional and composite systems [10]. It has been widely used to analyze losses due to shading, while PVGIS and SAM are employed for comparisons and the inclusion of solar tracking systems [11]. The primary technical indicators for measuring the energy performance of a PV plant are the performance ratio and energy production [12].

PVGIS calculates the energy output from various PV systems in nearly any global location [13]. SAM, a free techno-economic software model, aids professionals in the renewable energy sector by modeling multiple renewable energy systems [14]. PVsyst, specifically designed for PV systems development, can import meteorological and personal data from various sources [15].

The performance of solar PV systems is significantly influenced by environmental conditions, including solar irradiance, ambient temperature, humidity, wind speed, and particulate matter such as dust and smoke, so tropical climates can represent a challenge for these performance [16]. For instance, ambient temperature negatively affects the efficiency of solar panels by increasing their operating temperature and reducing their conversion efficiency [17]. While increased module temperatures in sunny climates can decrease instantaneous efficiency, this is often compensated for by longer solar hours, resulting in higher total daily production [18]. Thus, to optimize energy production and system reliability, it is crucial to consider these environmental factors in the design, installation, and predictive modeling of solar PV systems [19].

Numerous PV system analyses use simulation programs such as PVGIS, PVsyst, and SAM [6], [20]. However, empirical validations in tropical climates reveal notable deviations. For instance, a case study in Ghana demonstrated that PVsyst simulations overestimated annual energy production by approximately 10% compared to measured data, emphasizing the influence of unaccounted environmental stressors on predictive accuracy. Notably, this analysis did not incorporate cross-validation with PVGIS or SAM and was limited to a one-year timeframe [21]. Research conducted in Indonesia similarly identified that PVsyst predictions were negatively impacted by elevated ambient temperatures, leading to decreased monthly performance ratios (indicating the efficiency of a PV system under actual conditions compared to ideal conditions) during peak heat periods. However, the study's conclusions were constrained by its single-year scope [22]. Furthermore, Mohammadi and Gezegin [20] compared PVGIS and PVsyst with a grid-connected system in Turkey and concluded that PVGIS had the highest consistency in a high-radiation climate [20].

Contrasting database performances within SAM were observed in a Brazilian PV plant assessment [23]. The NSRDB dataset exhibited minimal deviation (-1.21%) from actual generation data, whereas the Meteonorm database introduced a substantial overestimation (+11.18%). This disparity highlights the critical role of meteorological data sources in simulation outcomes, though the study omitted comparisons with other software tools [23]. Additionally, a comparison between PVSyst and SAM revealed that SAM had lower annual error and deviation values [15].

The above studies were conducted over one-year analysis periods. However, environmental conditions may vary yearly due to natural or anthropogenic causes [24], affecting the PV panel temperature [25] and, consequently, the system's performance [26]. These collective findings underscore two critical gaps in current simulation practices: (i) the frequent exclusion of multi-software validation to identify tool-specific biases (more than two programs) and (ii) the predominance of short-term (one-year) analyses, which may fail to capture interannual climatic variability.

This study asks, what are the deviations in energy production predictions from PVGIS, PVsyst, and SAM software compared to actual data from a rooftop PV installation in a tropical climate, throughout analysis longer than one year? This research fills this gap by conducting a 24-month longitudinal comparison of PVGIS, PVsyst, and SAM in a tropical location, incorporating metrics like mean absolute error (MAE) and root mean square error (RMSE) to quantify deviations caused by environmental variability. This study hypothesizes that PVGIS, PVsyst, and SAM will show average cumulative deviations of less than 10% relative to measured data. The conclusions of this study could contribute to optimizing the design of photovoltaic systems in tropical climates, reducing costs due to overestimation of production. This paper is organized as follows: the first section methods, analyzes the site location and the data acquisition process, then the section on results and discussions compares the evaluation metrics, including the RMSE and MAE, between the actual and simulated data, interpreting the findings. The final section presents the conclusions, summarizing the key insights and implications for future research.

2. METHOD

This section outlines the methodology used for the analysis. Figure 1 shows the methods used to develop the simulations. Data were collected from the rooftop PV installation using a proprietary communication system of the inverter solar equipment. This system sends the operating data to a cloud platform in CSV format via GSM. Ambient temperature data were obtained from meteostad.net for the Garzones Montería Weather Station in XLS format. The data were filtered for missing or outliers. Simulations were conducted using PVGIS, PVsyst, and SAM. The annual energy production data from the plant were compared with the simulations for each software program. The actual and simulated energy production data were evaluated using RMSE and MAE metrics.

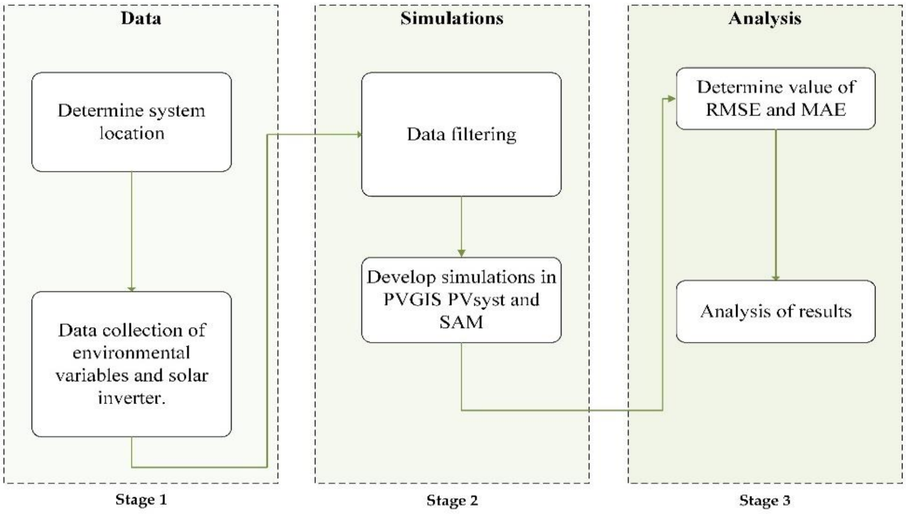

Figure 1. Overall methodology flowchart

2.1. Location of the system

The solar PV power plant in Monteria, Colombia (8° 48' 13,5" S, - 75° 51' 0,45" O), located on the rooftop of a building in Montería, Colombia as shown in Figure 2, a region known as for its tropical climate and high relative humidity, varying between 76 and 82% [27]. The technical characteristics of the plant solar PV are listed in Table 1. The solar inverters were placed inside an inverter room on the same floor as the PV module.

Figure 2. Roof-mounted PV plant

Table 1. Technical specifications of PV system components

Item	Specifications
Module PV	LR6-720PH(SI) LONGI
Solar inverter	Yaskawa PVI 36TL-480
Module rated maximum power	400 W
Module open circuit voltage	36.2 V
Module current at Pmax	11.05 A
Inverter power input voltage range	540-800 VDC
Inverter ambient temperature range	(-25 °C to +60 °C)
Continuous output power	36 kW
System no of modules	240
Inverter peak efficiency	98%
Tilt	9º
Number of inverters	2
Azimut	N 28°O
Number of modules per inverter	120
Transformer for coupling to the electrical network	80 kVA 460 V/120 V

2.2. Data acquisition

The internal information from the solar inverters is transmitted through a GSM module, which sends data to a cloud-based computer system for downloading and analysis as shown in Figure 3. Monthly temperature data were obtained from the Los Garzones weather station near the solar PV plant using the Meteostat.net website.

During the two years of monitoring, maintenance activities required the disconnection of data transmission, and these days were excluded from the analysis. To avoid introducing possible inaccuracies, missing values were left unfilled. This method is consistent with suggestions from earlier research [28], prioritizing maintaining data integrity over filling in missing values, especially in applications requiring high-precision modeling [29].

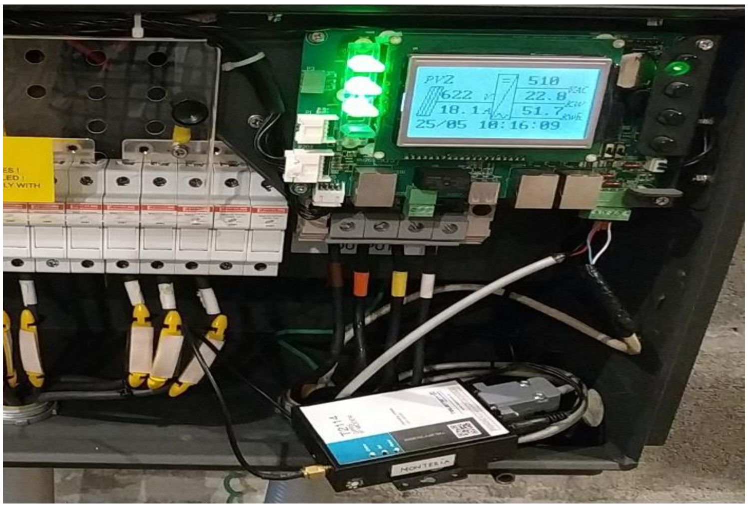

Figure 3. The internal data transmission system for solar investors is based on GSM

2.3. Simulations

The simulations were carried out using the program versions and meteorological databases indicated in Table 2. In particular, PVGIS 5.2 and SAM 2017.9.5 were used together with the NSRDB database, while PVsyst 7.4 was run with the Meteonorm 8.1 database. These versions were selected due to their widespread use in solar resource studies.

Table 2. Versions and databases of the analyzed programs

Metric	PVGIS	PVsyst	SAM
Version	5.2	7.4	2017.9.5
Database	NSDRB	Meteonorm 8.1	NSDRB

2.4. Evaluation metrics

RMSE measures the magnitude of the errors between the values predicted by the model ($V_{predicted}$) and the actual values (V_{target}). It is calculated by taking the square root of the average of the squared differences between these values. A lower RMSE indicates higher model accuracy. The calculation method is presented in (1) [30].

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(V_{predicted} - V_{target})^2} \quad (1)$$

Model validation is a crucial aspect of scientific research, and various methods are used. MAE and Spearman correlation coefficients are some of the most widely used techniques for model validation. These methods apply to different fields and have been proven effective in assessing models' accuracy. MAE measures the average magnitude of errors in a set of predictions without considering their direction. In contrast, the correlation coefficients quantify the degree to which the two variables are linearly related [31]. The method for calculating MAE is presented in (2), while the Spearman correlation is depicted in (3).

$$MAE = \frac{1}{n}\sum_{k=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

Where n denotes the number of observations, y_i represents the actual value, and $\hat{y}_i$ denotes the predicted value. The RSME and MAE provide a clear perspective when comparing the electricity production data from the case study's PV plant with those obtained from the PVsyst, PVGIS, and SAM simulations.

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \quad (3)$$

For (3), n corresponds to the total number of observations in the data set, and d_i is the difference between the x and y ranges for each observation.

2.5. Experiment design

The research design focused on collecting data on the electricity production of solar inverters over two years. The unit of measurement was the monthly energy production. Additionally, ambient temperature data were collected monthly over the same two years.

- Data collection frequency: monthly (accumulated energy production and averaged ambient temperature).
- Measurement periods: March 2021 to February 2022 (Period 1) and March 2022 to February 2023 (Period 2).
- Location: rooftop of a five-story building with solar inverters located within an enclosed installation.
- Operating period: the plant operated almost continuously, with minimal downtime (five days in the first and four days in the second year).
- Energy production hours: between 6 AM and 6 PM, the inverters automatically switched off outside this timeframe.
- Ambient temperature data source: Los Garzones weather station, less than 2 km from the PV plant.

The primary objective of the experimental design was to evaluate the difference between the actual production of the PV plant over two years and the results of the simulations using PVGIS, PVsyst, and SAM. The comparison of the data collected in both scenarios aimed to identify the distinctions and similarities between the resulting data Figure 4. It is essential to note the limitations associated with the experiment that are listed below:

- The experiment's outcomes are influenced by the unique climatic and geographical features of the location where the study is conducted (Monteria, Colombia).
- This could restrict the applicability of the findings to other areas with unique environmental conditions, such as elevated altitudes or extended periods of drought. Secondly, the analysis did not consider factors like dust accumulation and pollution on panels or the effects of shading, even though these could impact the temperature of the modules and the absorption of irradiance.
- No allowance was made for cable temperature losses, panel degradation, roof floor temperature, and maintenance periods, which could add deviations in the final results.

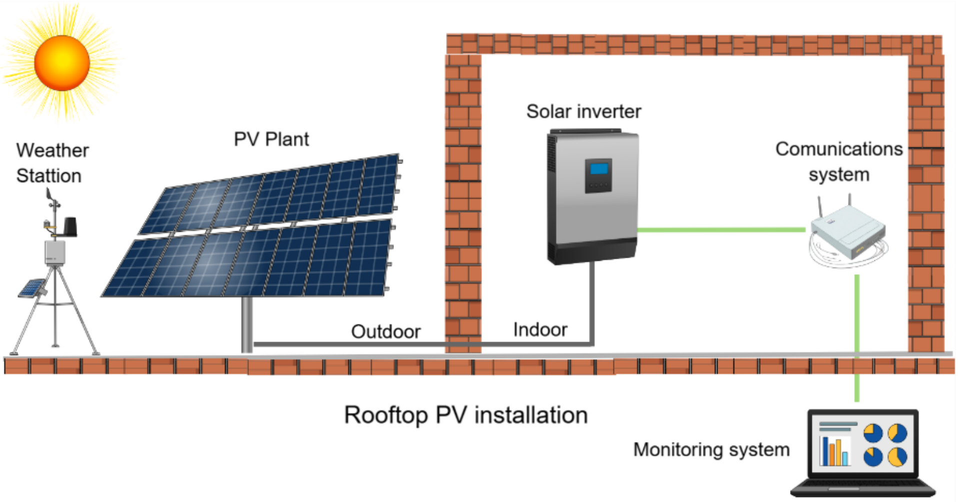

Figure 4. Description of the experiment

3. RESULTS AND DISCUSSION

After processing the solar PV plant production data and environmental factors, power generation decreased from Period 1 to Period 2 from 127,211 kWh per year to 100,645 kWh per year, coinciding with an average increase in ambient temperature of 0.7 °C during Period 2 (Figure 5). The Spearman correlation between ambient temperature and energy production was 0.55 for Period 1 and 0.53 for Period 2; this decrease could result from the increase in ambient temperature for Period 2. The correlation of the temperature data between the measurement periods was 0.85.

Simulations using PVsyst, PVGIS, and SAM predicted an annual energy production of 152,432 kWh for PVsyst, 100,299 kWh for PVGIS, and 117,321 kWh for SAM as shown in Figure 6. The highest correlation between the simulations was found between PVGIS and PVsyst, with a correlation coefficient of 0.65, which proves that the results of both tools are in close agreement with each other, as demonstrated in previous studies [20]. Both periods reflect an inverse correlation between ambient temperature and energy production, where significant increases in ambient temperature tend to coincide with decreases in energy production.

This pattern suggests that, in addition to the higher average temperatures, other environmental or operational factors may be affecting the efficiency of the PV system during Period 2. This is related to the fact that the inverter installation is on the rooftop and is enclosed without air conditioning, which can significantly increase the operating temperature of the inverters and decrease their efficiency due to the temperature derating process in Figure 4. The variability in energy production associated with temperature fluctuations underscores the need to implement design and operational strategies that minimize the thermal impact on solar modules and inverter installations.

The RMSE between the actual data and simulation results showed that for Period 1, the lowest error was for the simulation developed in SAM, with a value of 1,621.17 kWh; for Period 2, the lowest error was for the simulation developed in PVGIS, with a value of 1,680.99. Additionally, the best performance for MAE was for SAM, with 1,278.70 in Period 1, and for PVGIS, it was 1,419.00 in Period 2 as shown in Table 3.

When analyzing the simulation models in SAM, PVGIS, and PVSyst, the superiority of SAM can be justified based on the overall results of the key statistical metrics: RMSE and MAE. When considering both analysis periods, SAM shows superior performance, with an overall RMSE of 1,993.71 kWh and an overall MAE of 1,615.87 kWh, compared to PVGIS, which presents an overall RMSE of 2,076.65 kWh and an overall MAE of 1,830.84 kWh. PVSyst, on the other hand, showed a significantly lower performance, with an overall RMSE of 3,546.18 kWh and an overall MAE of 3,250.17 kWh. These values indicate that the SAM predictions are, on average, closer to the actual values and present a lower dispersion, reaffirming its superior accuracy and reliability in the PV energy production simulation as shown in Table 4. The findings of this study align with previous research in tropical regions, highlighting variability in the accuracy of simulation models.

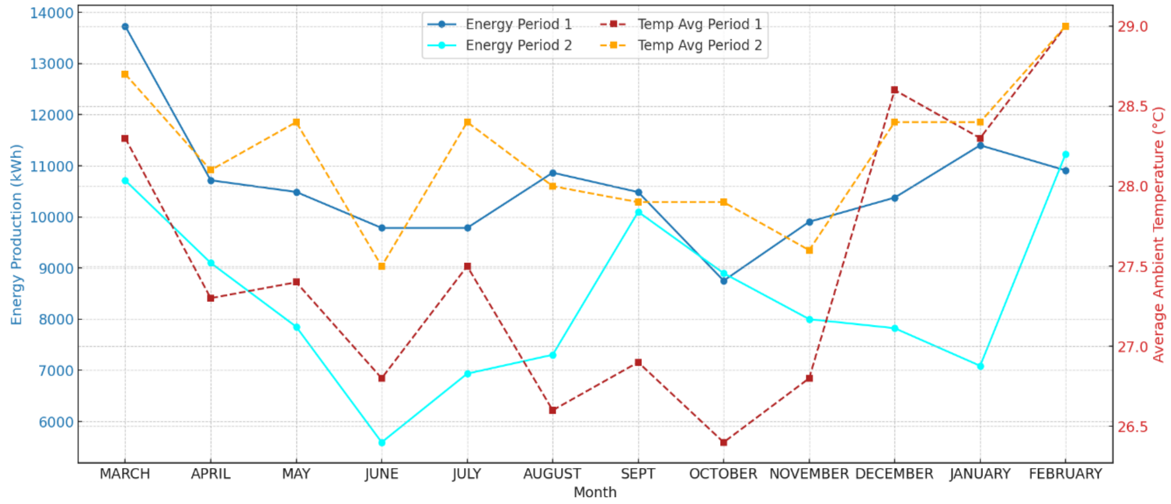

Figure 5. Comparative graph of average temperature and energy production during the periods of analysis

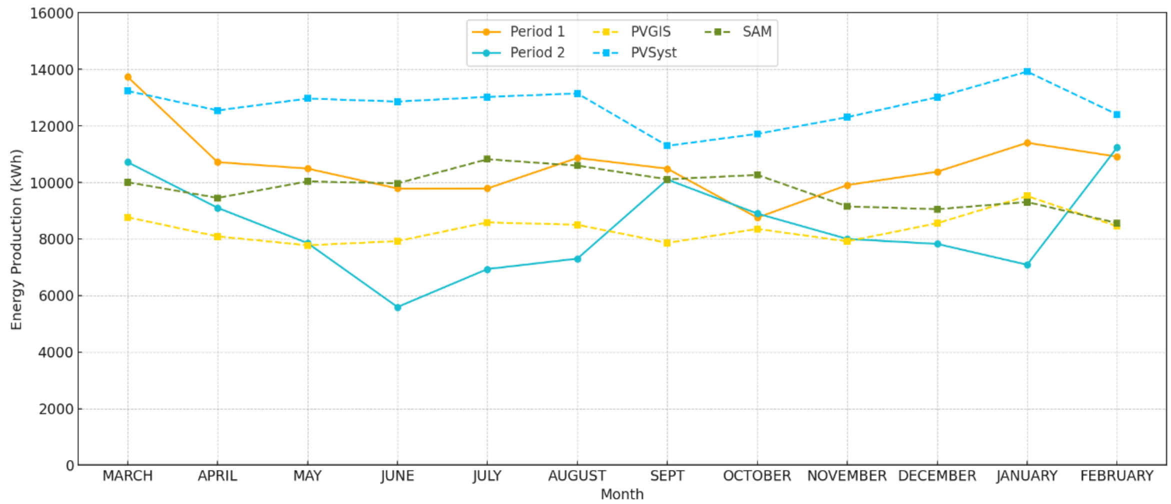

Figure 6. Comparison of actual and simulated energy production

Table 3. Comparing the RMSE and MAE of the actual data with the simulations

Metric	Period 1			Period 2		
	PVGIS	PVSyst	SAM	PVGIS	PVSyst	SAM
RMSE	2,472.30	2,337.85	1,621.17	1,680.99	4,754.50	2,366.24
MAE	2,242.67	2,184.75	1,278.70	1,419.00	4,315.58	1,953.04

Table 4. Average percentage deviation between measured data and simulations

Metric	PVGIS	PVsyst	SAM
Period 1	-21.2%	51%	17%
Period 2	-0.34%	51.98%	-23.03%
Average	-10.7%	51.7%	-3%

An increase in the ambient temperature causes higher temperatures in the PV modules, which decreases the efficiency and overall system performance, as demonstrated by Roga *et al.* [32] and as shown in Figures 5 and 6. In addition, Sekyere *et al.* [21] evaluated a 20 MW PV system in Ghana. They found that PVsyst overestimated annual energy production by approximately 10% compared to measured data, a pattern similar to that observed in this study for Period 1 and Period 2, see Table 3. This study extends these results by including multi-platform comparisons (PVGIS, SAM, and PVsyst) and a 24-month evaluation period, which allows for capturing interannual climate variabilities not considered in previous studies such as Sekyere *et al.* [21] and Kumara *et al.* [22].

In addition, Mohammadi and Gezegin [20] compared PVGIS and PVsyst in a grid-connected system in Turkey, concluding that PVGIS showed greater consistency in climates with high irradiance. This study corroborates those results (Table 3) but highlights that SAM outperforms both in equatorial contexts with high humidity and intermittent cloudiness (as in Monteria, Colombia). On the other hand, Sancar and Yakut [15] reported that SAM had a lower annual error in its calculations than PVsyst, which is corroborated in this study (Table 3). On the other hand, the deviation in the SAM measurements reported by Paula [23] of -1.21% in Brazil is close to those reported in this study (Table 3), using the same NSRDB meteorological database. The accuracy of SAM in this context could be attributed to these key methodological factors:

i) Improved model: SAM is designed to model the performance of solar systems by considering local climatic conditions, which inherently include factors such as cloudiness and humidity. This allows for more accurate predictions of power generation [33]. This contrasts with PVGIS, which uses static satellite data that is less sensitive to diurnal variations [34], and with PVsyst, whose thermal loss model does not adequately consider the effect of high humidity on panel degradation [35].
ii) Meteorological database management: SAM allows the integration of multiple data sources (NSRDB, Meteonorm) and prioritizes hourly rather than daily records, which reduces errors in regions with abrupt irradiance patterns common in equatorial climates [36].

While SAM exhibited superior overall performance, its predictive accuracy decreased during periods with ambient temperatures exceeding 28 °C. This limitation suggests the influence of unmodeled thermal effects such as solar inverter cooling, panel maintenance cycles, and hardware degradation rates. Future research should incorporate (1) validation across diverse tropical regions (e.g., Southeast Asia), (2) long-term longitudinal analyses (5-10 years) to capture climate variability patterns, and (3) comparative assessments with tools like HOMER or custom models developed for specific regional conditions. Implementing real-time monitoring systems could enhance model accuracy by enabling dynamic adjustments. These results highlight the critical dependence of simulation tools' accuracy on specific environmental conditions, establishing the necessity of climate-adapted simulation tool selection in photovoltaic system design.

4. CONCLUSION

This study assessed the accuracy of the commercial simulation tools PVGIS, PVSyst, and SAM in predicting the energy output of a photovoltaic system in a tropical climate. The findings revealed significant variations in the precision of these tools compared with actual production data, highlighting the importance of selecting appropriate simulation software based on specific environmental conditions. SAM demonstrated superior performance with a global RMSE of 1,993.71 kWh and a global MAE of 1,615.87 kWh, indicating that its predictions were, on average, closer to the actual production data and exhibited less dispersion compared to PVGIS (global RMSE: 2,076.65 kWh, global MAE: 1,830.84 kWh) and PVSyst (global RMSE: 3,546.18 kWh, global MAE: 3,250.17 kWh). These results underscore the robustness and reliability of SAM in providing more accurate simulations, which is crucial for optimizing the efficiency and sustainability of PV systems in tropical climates. This study contributes to the body of knowledge on renewable energy by providing a critical comparison of simulation tools, thereby enabling professionals and researchers to make informed decisions based on the accuracy of simulations under specific conditions.

ACKNOWLEDGEMENTS

This research is part of a doctoral thesis entitled “Optimization of the energy management of a hybrid solar photovoltaic plant with lithium-ion battery storage system using genetic algorithms.” The authors gratefully acknowledge Universidad Pontificia Bolivariana Monteria for providing data access to the photovoltaic system.

FUNDING INFORMATION

One of the authors, F.A.L.V., was granted a scholarship by the Universidad Pontificia Bolivariana through Act 58 of 25 October 2023 for studies at the Universitat Politécnica de Valencia. This work was also supported by: a grant of the Cátedra de Transición Energética Urbana- funded by Ajuntament de València-Las Naves and Fundació València Clima i Energia; and the RES4CITY project, financed by the European Union under Grant Agreement No. 101075582.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Fabian Alonso Lara Vargas	✓	✓	✓	✓		✓		✓	✓	✓			✓	
Miguel Angel Ortiz Padilla	✓			✓						✓	✓			
Alvaro Torres Amaya		✓			✓	✓				✓				
Carlos Vargas Salgado	✓	✓			✓							✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data supporting this study's findings are available on request from the corresponding author, [FALV]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

REFERENCES

[1] F. A. L. Vargas, C. V. Salgado, J. Á. León, D. D. Bello, D. “Optimizing bifacial solar modules with trackers: advanced temperature prediction through symbolic regression,” *Energies*, vol. 18, 2019. https://doi.org/10.3390/en18082019.

[2] J. Tovar-Facio, B. Cansino-Loeza, and J. M. Ponce-Ortega, “Management of renewable energy sources,” *Sustainable Design for Renewable Processes: Principles and Case Studies*, pp. 3–31, Jan. 2022, doi: 10.1016/B978-0-12-824324-4.00004-4.

[3] L. T. C. Montoya, S. Lain, M. Issa, and A. Ilinca, “Renewable energy systems,” *Hybrid Renewable Energy Systems and Microgrids*, pp. 103–177, Jan. 2021, doi: 10.1016/B978-0-12-821724-5.00013-1.

[4] C. Breyer, *et al.* “Solar photovoltaics demand for the global energy transition in the power sector,” *Progress in Photovoltaics: Research and Applications*, vol. 26, no. 8, 2018, doi: 10.1002/pip.2950.

[5] L. Kruitwagen, K. T. Story, J. Friedrich, L. Byers, S. Skillman, and C. Hepburn, “A global inventory of photovoltaic solar energy generating units,” *Nature*, vol. 598, no. 7882, 2021, doi: 10.1038/s41586-021-03957-7.

[6] S. Ponnada, *et al.*, “Renewable energy: introduction, current status, and future prospects,” in *Green Energy Harvesting: Materials for Hydrogen Generation and Carbon Dioxide Reduction*, 2022. doi: 10.1002/9781119776086.ch1.

[7] K. Obaideen *et al.*, “Solar energy: applications, trends analysis, bibliometric analysis and research contribution to sustainable development goals (SDGs),” *Sustainability*, vol. 15, no. 2, p. 1418, Jan. 2023, doi: 10.3390/su15021418.

[8] A. D. C. Lima, C. Schardong, F. Schaf, and L. Michels, “Mathematical models used in photovoltaic system design software: a systematic review and a new proposal,” in *2022 14th Seminar on Power Electronics and Control, SEPOC 2022*, 2022. doi: 10.1109/SEPOC54972.2022.9976460.

[9] A. Roshana, A. Inbamani, S. Sujeev Rithan, R. Krishnakumar, and J. M. Vishal, “Design and investigation of grid associated PV framework using PVSYST Software,” in *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation, ICAECA 2021*, 2021. doi: 10.1109/ICAECA52838.2021.9675711.

[10] S. Oliveira-Pinto and J. Stokkermans, “Assessment of the potential of different floating solar technologies – overview and analysis of different case studies,” *Energy Convers Manag*, vol. 211, 2020, doi: 10.1016/j.enconman.2020.112747.

[11] N. M. Kumar, S. Chakraborty, S. K. Yadav, J. Singh, and S. S. Chopra, “Advancing simulation tools specific to floating solar photovoltaic systems – comparative analysis of field-measured and simulated energy performance,” *Sustainable Energy Technologies and Assessments*, vol. 52, p. 102168, Aug. 2022, doi: 10.1016/J.SETA.2022.102168.

[12] E. Solomin, E. Sirotkin, E. Cuce, S. P. Selvanathan, and S. Kumarasamy, “Hybrid floating solar plant designs: a review,” *Energies (Basel)*, vol. 14, no. 10, p. 2751, May 2021, doi: 10.3390/en14102751.

[13] UE, “Empezando con PVGIS,” https://joint-research-centre.ec.europa.eu/photovoltaic-geographical-information-system-pvgis/getting-started-pvgis_en.

[14] Department of Energy, “System Advisor Model (SAM),” https://sam.nrel.gov/.

[15] M. R. Sancar and K. Yakut, “Comparative analysis of SAM and PVsyst simulations for a rooftop photovoltaic system,” *International Journal of Engineering and Innovative Research*, vol. 5, no. 1, 2023, doi: 10.47933/ijeir.1209413.

[16] T. Atyia and M. Qasim, “Evaluating the impact of weather conditions on the effectiveness and performance of pv solar systems and inverters,” *NTU Journal of Renewable Energy*, vol. 5, no. 1, 2023, doi: 10.56286/ntujre.v5i1.551.

[17] H. H. Jo, J. Kim, and S. Kim, "Enhancing the power generation performance of photovoltaic system: impact of environmental and system factors," *Appl Therm Eng*, vol. 240, 2024, doi: 10.1016/j.applthermaleng.2023.122221.
[18] S. M. Ruiz, M. V. Chamorro, G. V. Ochoa, J. F. Villegas, and C. A. Peñaloza, "Effects of environmental conditions on photovoltaic generation system performance with Polycrystalline panels," *Int J Adv Sci Eng Inf Technol*, vol. 11, no. 5, 2021, doi: 10.18517/IJASEIT.11.5.9335.
[19] S. Vunnam, M. Vanithasri, and R. Alla, "An outline of solar photovoltaic systems impact on environment," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 5, 2023, doi: 10.11591/eei.v12i5.5584.
[20] S. A. D. Mohammadi and C. Gezegin, "Design and simulation of grid-connected solar PV system using PVSYST, PVGIS and HOMER Software," *International Journal of Pioneering Technology and Engineering*, vol. 1, no. 01, 2022, doi: 10.56158/jpte.2022.24.1.01.
[21] C. K. K. Sekyere, F. Davis, R. Opoku, E. Otoo, G. Takyi, and L. Atepor, "Performance evaluation of a 20 MW grid-coupled solar park located in the southern oceanic environment of Ghana," *Clean Eng Technol*, vol. 5, 2021, doi: 10.1016/j.clet.2021.100273.
[22] I. N. S. Kumara, M. Ashari, A. S. Sampeallo, and A. A. G. A. Pawitra, "Simulated energy production and performance ratio of 5 MW grid-connected photovoltaic under tropical savannah climate in Kupang timor Island of Indonesia," *International Journal of Engineering and Technology Innovation*, vol. 7, no. 2, 2017.
[23] J. F. S. de Paula "Análise comparativa de desempenho de um sistema fotovoltaico simulado com as ferramentas pvsyst e sam (system advisor model)," Aug. 2022. doi: 10.59627/cbens.2022.1183.
[24] Ş. Sağlam, "Meteorological parameters effects on solar energy power generation," *WSEAS Transactions on Circuits and Systems*, vol. 9, no. 10, 2010.
[25] S. Dubey, J. N. Sarvaiya, and B. Seshadri, "Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world – a review," *Energy Procedia*, vol. 33, pp. 311–321, Jan. 2013, doi: 10.1016/J.EGYPRO.2013.05.072.
[26] M. N. R. Nazeri, M. F. N. Tajuddin, T. S. Babu, A. Azmi, M. Malvoni, and N. M. Kumar, "Firefly algorithm-based photovoltaic array reconfiguration for maximum power extraction during mismatch conditions," *Sustainability (Switzerland)*, vol. 13, no. 6, 2021, doi: 10.3390/su13063206.
[27] IDEAM, "Climatología aeronáutica aerodromo Los Garzones skmr Monteria," Bogota, 2013.
[28] M. S. Roy, B. Roy, R. Gupta, and K. D. Sharma, "On-device reliability assessment and prediction of missing photoplethysmographic data using deep neural networks," *IEEE Trans Biomed Circuits Syst*, vol. 14, no. 6, 2020, doi: 10.1109/TBCAS.2020.3028935.
[29] C. B. Storlie, T. M. Therneau, R. E. Carter, N. Chia, J. R. Bergquist, J. M. Huddleston, and S. Romero-Brufau "Prediction and inference with missing data in patient alert systems," *J Am Stat Assoc*, vol. 115, no. 529, 2020, doi: 10.1080/01621459.2019.1604359.
[30] T. O. Hodson, "Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not," *Geoscientific Model Development*, vol. 15, no. 14, pp. 5481–5487, Jul. 2022, doi: 10.5194/gmd-15-5481-2022.
[31] Z. Dayev, A. Kairakbaev, K. Yetilmezsoy, M. Bahramian, P. Sihag, and E. Kıyan, "Approximation of the discharge coefficient of differential pressure flowmeters using different soft computing strategies," *Flow Measurement and Instrumentation*, vol. 79, 2021, doi: 10.1016/j.flowmeasinst.2021.101913.
[32] S. Roga, A. Lokesh, S. Jain, A. A. N. Vinay, R. Chauhan, C. Karthik, and Y. Kumar, "Assessment of sessional solar energy using PVsyst and SAM," *Renewable Energy Optimization, Planning and Control. Studies in Infrastructure and Control*. Springer, Singapore 2023. doi: 10.1007/978-981-19-8963-6_10.
[33] S. Dragićević, V. Vujičić, and M. Marjanović, "Analiza rada solarne elektrane u NTP Čačak – system advisor model (SAM) modelovanje i poređenje sa stvarnim rezultatima," *Energija, ekonomija, ekologija*, vol. XXIV, no. 4, pp. 52–56, Dec. 2022, doi: 10.46793/EEE22-4.52D.
[34] K. Kulesza, A. Martinez, and N. Taylor, "Assessment of typical meteorological year data in photovoltaic geographical information system 5.2, based on reanalysis and ground station data from 147 European Weather Stations," *Atmosphere (Basel)*, vol. 14, no. 12, 2023, doi: 10.3390/atmos14121803.
[35] M. Bălăceanu, N.S. Popa, V. Nae, M.C. Târhoacă, and M.-O. Popescu, "The influence of environmental factors on a photovoltaic Panel–PVsyst Simulation," *Electrotehnica, Electronica, Automatica*, vol. 72, no. 2, pp. 3–12, Jun. 2024, doi: 10.46904/eea.23.72.2.1108001.
[36] H. Baraki, C. Schwarzbach, S. Jakob, A. Jahl, and K. Geihs, "SAM: A semantic-aware middleware for mobile cloud computing," in *IEEE International Conference on Cloud Computing, CLOUD*, 2018, doi: 10.1109/CLOUD.2018.00054.

BIOGRAPHIES OF AUTHORS

Prof. Fabian Alonso Lara Vargas is a full professor at the Faculty of Electronic Engineering at the Universidad Pontificia Bolivariana in Colombia. Obtained a degree in electronic engineering at the Universidad Pontificia Bolivariana in Colombia in 2004, a specialization in industrial control and instrumentation at the same university in 2009, a master's degree in management of computer projects at the University of Pamplona in Colombia in 2016, and is a Ph.D. student in design, manufacturing, and management of industrial projects, at the Universitat Politecnica de Valencia in Spain. He is a professor at Universidad Pontificia Bolivariana, Campus Monteria, Colombia. His research interests include genetic algorithms, symbolic regression, floating photovoltaic solar energy, and storage. He can be contacted at email: fabian.lara@upb.edu.co.

Prof. Miguel Angel Ortiz Padilla received a B.Sc. degree in electrical engineering from the Universidad de Los Andes, Colombia, in 2014 and an M.Sc. degree in electrical engineering from the Universidad de Los Andes, Colombia, in 2017. He specializes in the fields of power and energy and renewable energies. He has a background in computer programming using the Python language and employs innovative methodologies and a STEM approach to education. He has been teaching at Universidad Pontificia Bolivariana Seccional Montería since 2019 and has been an electronic engineering program faculty member since 2021. He can be contacted at email: miguel.ortizp@upb.edu.co.

Prof. Dr. Alvaro Torres Amaya received a B.S. degree in electronic engineering from Universidad Pedagógica y Tecnológica de Colombia in 2007, an M.S. degree in electronic engineering from Escuela Colombiana de Ingeniería, Bogotá, Colombia, 2015, and PhD in electrical and computer engineering from Universidade Tecnológica Federal do Paraná, Curitiba, Brazil, 2023. He is currently a full professor at Universidad Pedagógica y Tecnológica de Colombia. His research interests include eolic and photovoltaic systems, energy efficiency, and electric vehicles. He can be contacted at email: alvaro.torres@upb.edu.co.

Prof. Dr. Carlos Vargas Salgado received a Ph.D. in industrial engineering and production, Valencia, Spain. Professor of the Department of Electrical Engineering of the UPV. Since 2005, he has been linked to the Institute of Energy Engineering of the UPV, where projects have been carried out in renewable energies (isolated and grid-connected microgrids based on photovoltaic, wind, and biomass gasification with battery storage). He can be contacted at email: cavarsa@upvnet.upv.es.