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Comparison of different cleaning methods on photovoltaic module efficiency under controlled laterite dust deposition in Kampala Uganda

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Abstract

Dust accumulation on photovoltaic (PV) modules is a major source of performance degradation in dusty environments, leading to reduced energy yield and increased operation and maintenance requirements. This study presents a comprehensive experimental evaluation of different PV cleaning methods under controlled and field-representative dusty conditions. A field-based experiment was conducted at a solar test site in Kampala, Uganda, using 15 identical 100 W monocrystalline silicon PV modules arranged in a triplicate design. Controlled laterite-based dust was applied at standardized densities of 10, 20, and 30 g/m^2 to simulate light, moderate, and heavy soiling conditions. Five cleaning strategies were investigated: no cleaning (control), manual brushing with water, mechanical wiping, automated robotic cleaning, and electrostatic cleaning. Module performance was monitored at 15-min intervals between 10:00 and 15:00 using calibrated irradiance, temperature, and current–voltage measurement systems. Each dust-level tests was repeated on 5 clear-sky days. Dust was characterized in terms of particle size distribution, morphology, and composition to support the interpretation of soiling behavior and cleaning effectiveness. Statistical analysis was conducted using two-way analysis of variance (ANOVA), Tukey HSD post-hoc testing, and regression modeling, complemented by uncertainty propagation and effect size evaluation. In addition to instantaneous efficiency, cumulative energy yield was calculated to assess practical performance implications. The results show that PV efficiency decreases systematically with increasing dust density, with uncleaned modules exhibiting substantial performance losses. All cleaning methods significantly improved module efficiency relative to the control ($p < 0.001$). Automated robotic cleaning achieved the highest efficiency and energy yield across all dust levels, while electrostatic and mechanical cleaning demonstrated comparable intermediate performance. Manual cleaning provided moderate improvement but was limited by water and labor requirements. Regression analysis revealed a strong linear relationship between dust density and efficiency loss ($R^2 > 0.99$), confirming the predictability of soiling effects. Techno-economic analysis further showed that while robotic cleaning offers the best technical performance, its economic viability depends on system scale and local cost conditions. This study provides a high-resolution, controlled, and statistically robust comparison of PV cleaning strategies in a dust-intensive urban environment. The findings offer practical and context-aware guidance for optimizing PV maintenance strategies, highlighting the importance of combining technical performance, resource efficiency, and economic considerations to enhance the reliability and sustainability of solar energy systems in dusty regions.

Keywords Photovoltaic, Dust soiling, Cleaning techniques, Renewable energy, PV efficiency

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Introduction

The global transition toward renewable energy has positioned solar photovoltaic (PV) technology as a cornerstone of sustainable electricity generation. Declining module costs, policy incentives, and improved conversion efficiencies have accelerated PV deployment across diverse climatic regions, including rapidly urbanizing areas in sub-Saharan Africa (Demirci et al., 2026; Kichonge & Mwakapoma, 2026; Uzorka et al., 2026). Despite these advances, the operational performance of PV systems in real-world environments often deviates from their rated capacities due to environmental stressors, among which dust accumulation, commonly referred to as soiling, remains one of the most persistent and underestimated challenges (Alshareef, 2023; Hesham et al., 2026; Uzorka et al., 2026). Soiling reduces solar irradiance transmittance through the module glass surface, leading to decreased power output, localized heating, and long-term reliability concerns (Maghami, 2025; Rahman et al., 2025; Shahzad et al., 2025). In dust-prone environments, efficiency losses ranging from 10% to over 30% have been reported depending on exposure duration, particle composition, and meteorological conditions (Aissi et al., 2025; Yakubu et al., 2025; Zhang et al., 2026).

The magnitude of soiling losses presents a significant operational and economic problem. Even modest efficiency reductions translate into substantial energy yield deficits over the lifespan of a PV installation, thereby affecting return on investment and grid reliability (Aziz et al., 2024)., This issue is particularly critical in developing regions where solar energy is increasingly relied upon to bridge electricity access gaps and enhance energy security. In many urban and peri-urban areas characterized by construction activities, unpaved roads, seasonal dryness, and wind-driven particulates, dust deposition rates can be considerable, yet cleaning practices are often inconsistent or poorly optimized. As PV deployment expands under such environmental conditions, identifying effective, sustainable, and economically viable cleaning strategies becomes essential.

The mechanisms governing PV soiling are strongly influenced by dust properties, including particle size distribution, morphology, chemical composition, and optical characteristics. Experimental investigations have shown that fine particles (< 10 μm) contribute disproportionately to optical attenuation due to enhanced adhesion and light scattering, while coarse particles contribute to surface coverage and shading effects (Chanchangi et al., 2020). In addition, environmental parameters such as humidity, wind speed, and rainfall play a critical role in dust deposition and removal processes. Field studies conducted in Northern Nigeria demonstrated that soiling rates and performance degradation are highly sensitive to seasonal weather variations, with prolonged dry periods leading to accelerated efficiency losses (Chanchangi et al., 2021). These findings highlight the importance of considering both dust characteristics and climatic conditions when evaluating PV cleaning strategies.

Within the African context, several studies have reported significant soiling-related performance degradation across different regions. Investigations in West and East Africa indicate that PV systems operating in urban and semi-arid environments can experience efficiency losses comparable to those observed in desert regions, particularly during dry seasons with high particulate concentrations (Chanchangi et al., 2022; Ebhota & Tabakov, 2023; Mwebe et al., 2025). More recent studies in sub-Saharan Africa emphasize the growing importance of maintenance strategies as solar deployment expands in dust-prone urban settings (Uzorka et al., 2026). Despite these contributions, there remains a lack of detailed comparative studies focusing on cleaning performance under controlled and region-specific dust conditions.

Various cleaning methods have been proposed and investigated to mitigate soiling effects, including manual washing with water, mechanical brushing systems, automated robotic cleaners, electrostatic dust removal, and emerging self-cleaning surface technologies. Manual cleaning remains the most widely practiced method due to its simplicity; however, it is labor-intensive and consumes significant amounts of water, raising sustainability concerns in water-scarce regions (Akteruzzaman, 2025; Dixit et al., 2026; Fonseka & Sellami, 2025). Mechanical and robotic cleaning systems have demonstrated promising performance in maintaining high irradiance transmission while reducing labor requirements (Al-Omari et al., 2025; Mishra et al., 2025; Murshiduzzaman et al., 2025). Electrostatic cleaning techniques, which rely on electrically induced forces to detach dust particles, offer a water-free alternative and have shown encouraging results in controlled experiments (Chiteka & Enweremadu, 2025; Dickhardt et al., 2025; Mashuk et al., 2025).

In addition to these conventional approaches, self-cleaning strategies based on advanced surface engineering have gained increasing attention. These include hydrophobic and superhydrophilic coatings, photocatalytic surfaces, and nanostructured materials designed to reduce dust adhesion and enhance natural cleaning through rainfall or condensation. Studies have shown that such functional surfaces can reduce dust accumulation and maintain higher optical transmittance over time, although their long-term durability and cost-effectiveness remain areas of active research (Qin & Lu, 2023; Rajbahadur et al., 2024; Thongsuwan et al., 2022). While self-cleaning technologies are promising, they are not yet widely adopted in large-scale PV installations, particularly in developing regions, due to cost and durability considerations.

Despite the availability of multiple cleaning technologies, a notable gap in the literature lies in the scarcity of studies that systematically compare different cleaning methods under identical environmental conditions using controlled soiling and high temporal resolution data. Many previous investigations focus on single cleaning approaches, short-term laboratory simulations, or desert environments with extreme soiling characteristics. Consequently, there is limited empirical evidence regarding the relative effectiveness of different cleaning technologies in non-desert yet dust-intensive urban contexts, particularly within sub-Saharan Africa. Furthermore, few studies incorporate dust quantification, physicochemical characterization, uncertainty analysis, and techno-economic evaluation within a unified experimental framework. These limitations hinder the ability to draw robust and practically relevant conclusions regarding optimal cleaning strategies.

Motivated by these gaps, the present study provides a comprehensive comparative evaluation of five cleaning conditions—no cleaning, manual brushing with water, mechanical wiping, automated robotic cleaning, and electrostatic cleaning—using 15 identical PV modules arranged in a triplicate experimental design. This work employs controlled laterite-based dust deposition at standardized levels of 10, 20, and 30 g/m^2, enabling direct correlation between dust density and PV performance. The dust was characterized in terms of particle size distribution, morphology, and composition to better understand its influence on soiling behavior and cleaning effectiveness. Performance was monitored at 15-min intervals between 10:00 and 15:00 under outdoor field conditions, and results were analyzed using two-way analysis of variance (ANOVA), Tukey HSD post-hoc testing, and regression modeling. In addition to instantaneous efficiency, the study incorporates uncertainty propagation, effect size analysis, and cumulative energy yield evaluation to provide a more comprehensive assessment of PV performance. A techno-economic analysis is also included to evaluate the cost-effectiveness of the different cleaning strategies within the Ugandan context. By integrating controlled experimentation, high-resolution monitoring, statistical rigor, and economic analysis, this study provides robust and practically relevant insights into PV cleaning performance in dusty urban environments. The findings contribute to a deeper understanding of soiling mitigation and support the development of optimized operation and maintenance strategies for sustainable solar energy deployment in sub-Saharan Africa and similar regions worldwide.

Materials and methods

This study adopted a controlled experimental field methodology to evaluate and compare the effectiveness of different photovoltaic (PV) module cleaning methods under standardized dusty conditions. Unlike natural outdoor dust exposure, which may vary spatially and temporally, the present study employed controlled artificial soiling to ensure uniform dust loading and repeatable comparison across cleaning methods. The experiment was conducted at an outdoor solar test field in Kampala, Uganda, under clear-sky conditions representative of tropical urban environments.

A total of 15 identical 100 W monocrystalline silicon PV modules were used in the study. The modules were divided into five experimental groups, corresponding to the cleaning strategies investigated: uncleaned control, manual brushing with water, mechanical wiper cleaning, automated robotic wiping, and electrostatic cleaning. Each cleaning method was represented by three replicate panels, giving a total of 15 modules. All modules had a rated maximum power voltage of 18.5 V, a maximum power current of 5.41 A, a temperature coefficient of $-0.45\%/°C$, and an effective active area of 0.65 m^2. Before the experiment, all modules were visually inspected and electrically tested to confirm comparable baseline performance. The modules were installed outdoors at a fixed tilt angle of 20° and oriented for maximum solar exposure. By maintaining a consistent tilt angle across all modules, the present study isolates the effects of cleaning method and dust density without introducing additional variability from geometric factors. Therefore, the reported performance differences can be attributed primarily to the cleaning strategies rather than installation angle. Also, care was taken to ensure that all panels experienced similar irradiance, wind exposure, and ambient environmental conditions. The experiment was based on controlled application of laterite-based dust, selected because it is representative of mineral-rich dust commonly encountered in Kampala from exposed soils, road shoulders, and construction activities. Figure 1a is the experimental setup and the schematic of the experimental setup, shown in Fig. 1b.

Because PV soiling behavior depends strongly on dust physicochemical properties, the laterite-based test dust was characterized before use. Particle-size distribution was determined by sieve analysis for the coarser fraction and laser diffraction for the fine fraction. Morphology was examined using scanning electron microscopy (SEM), while elemental composition

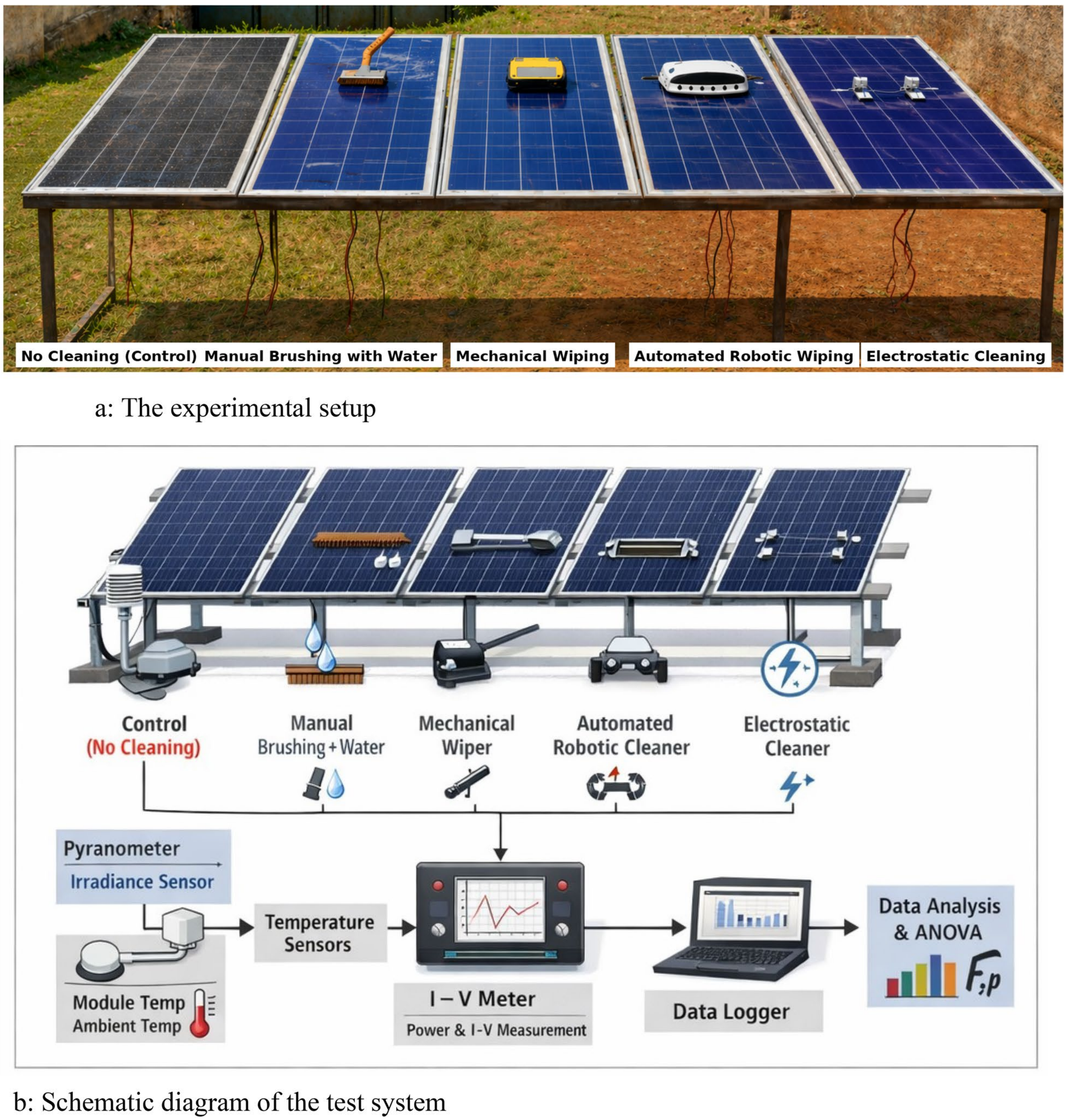

Fig. 1 **a** The experimental setup. **b** Schematic diagram of the test system

was determined using energy-dispersive X-ray spectroscopy (EDS). Mineralogical constituents were identified by X-ray diffraction (XRD). These analyses were included to establish the representativeness of the dust and to allow interpretation of soiling effects in relation to particle size, angularity, and composition. To impose standardized soiling conditions, the laterite dust was air-dried, sieved, and weighed before application. Dust loading was expressed as mass per unit surface area (g/m^2) and was applied at three levels: 10, 20, and 30 g/m^2, representing light, moderate, and heavy soiling conditions, respectively. For each experimental run, the required dust mass was calculated from the exposed panel area and then uniformly spread over the front glass surface of each module. The same set of replicate panels for each cleaning method was tested sequentially under all three dust densities in separate runs. After each run, cleaned groups were restored according to their assigned cleaning method, and the next dust level was then applied. In this way, dust density was treated as a controlled experimental variable rather than a permanent attribute of a specific panel. The uncleaned control modules were left soiled during each test cycle. Manual brushing was performed using a soft non-abrasive brush and water. Mechanical wiper cleaning was carried out using a fixed-contact wiping mechanism. Automated robotic cleaning employed a programmed wiping device moving at constant speed over the panel surface. Electrostatic cleaning used a dust-removal device based on electrostatic repulsion. All cleaning operations were performed before the next experimental cycle to ensure repeatable and comparable starting conditions.

Electrical and environmental measurements were taken throughout the day for each test condition. Solar irradiance incident on the plane of the array was measured using a calibrated pyranometer placed adjacent to the PV modules. Module back-surface temperature and ambient temperature were measured using calibrated thermocouples connected to a data logger. Current–voltage measurements were obtained using maximum power point tracker. Data were recorded at 15-min intervals from 10:00 to 15:00, corresponding to the period of stable and relatively high solar irradiance. Measurements affected by transient shading, cloud interruption, or sensor malfunction were excluded during data quality screening.

The instantaneous output power of each module was determined at the maximum power point, and conversion efficiency was calculated as

$$\eta(\%) = \frac{P_{out}}{G \times A} \times 100 \tag{1}$$

where P_{out} is the electrical output power, G is the incident solar irradiance, and A is the effective module area.

Each dust-loading condition was repeated on five clear-sky days, and the results reported in this study are expressed as mean ± standard deviation of the three replicate modules for each cleaning method at each time point. This design ensured robust comparison of cleaning performance while accounting for day-to-day environmental variability.

To complement the instantaneous efficiency analysis, the daily energy yield for each PV module was calculated by integrating the measured power output over the monitoring period from 10:00 to 15:00. Because measurements were recorded at 15-min intervals, the energy yield was estimated as

$$E = \sum_{i=1}^{n} P_i \Delta t \tag{2}$$

where P_i is the measured output power at time interval i, $\Delta t = 0.25$ h, and n is the number of measurement intervals. The resulting energy values were expressed in Wh per day for the monitored time window. This allowed comparison of cumulative performance among cleaning methods and dust densities, beyond instantaneous power and efficiency alone.

Measurement uncertainty was evaluated for the principal quantities used in the efficiency calculation, namely output power, solar irradiance, and module area. The combined uncertainty in photovoltaic (PV) efficiency was estimated using standard error propagation techniques. The relative uncertainty in efficiency was determined from

$$\frac{\mu_\eta}{\eta} = \sqrt{\left(\frac{\mu_p}{P_{out}}\right)^2 + \left(\frac{\mu_G}{G}\right)^2 + \left(\frac{\mu_A}{A}\right)^2} \tag{3}$$

where μ_η, μ_p, μ_G, and μ_A represent the uncertainties in efficiency, output power, irradiance, and module area, respectively. The uncertainty in power measurement was derived from the accuracy of the maximum power point tracking system, while the irradiance uncertainty was based on the calibration specifications of the pyranometer used in the experiment. The uncertainty in module area was determined from dimensional measurement tolerance and was relatively small due to the fixed geometry of the panels. The reported ± values in the performance tables reflect the combined effects of replicate variability and measurement uncertainty. This approach provides a more rigorous and reliable basis for interpreting differences in PV efficiency among the cleaning methods, ensuring that the observed performance variations are not artifacts of measurement error.

Statistical analysis was performed to determine the significance of differences in PV efficiency among cleaning methods and dust densities. Because the study involved two controlled factors, namely cleaning method and dust density, a two-way analysis of variance (ANOVA) was used. ANOVA was still deemed robust due to the balanced experimental design and the use of replicate measurements. This approach is consistent with standard statistical practice in PV performance studies (Al Hazza et al., 2024; Li & Howe, 2023). In addition, the underlying statistical assumptions of normality and homogeneity of variance were evaluated to ensure the validity of the test results. The normality of residuals was assessed using the Shapiro–Wilk test, complemented by visual inspection of Q–Q plots. Homogeneity of variances across groups was tested using Levene's test. The results indicated that the residuals were approximately normally distributed and that variances were statistically homogeneous across cleaning methods and dust density levels ($p > 0.05$). Tukey's honestly significant difference (HSD) post-hoc test was applied for pairwise comparison of means. Regression analysis was also conducted to evaluate the relationship between dust density and PV module efficiency. All statistical analyses were performed at a 95% confidence level.

To complement the technical performance assessment, a techno-economic evaluation was conducted for all cleaning methods. The analysis considered the direct operational costs associated with each cleaning strategy, including water use, labor, electricity consumption, equipment cost, and maintenance requirements. Because the study was conducted in Uganda, the cost inputs were interpreted primarily within the Ugandan operational context, where labor costs are relatively low, water availability may vary seasonally, and imported automation equipment may involve higher capital expenditure. However, the analytical framework is general and may also be adapted to other locations by substituting local cost parameters. The techno-economic analysis was conducted assuming continuous system operation over a full year of 365 days. The monitored energy production window (10:00–15:00) was considered representative of the dominant daily energy generation period and was therefore scaled to approximate daily operation. The monetary value of electricity was estimated using a representative Ugandan tariff of 0.20 USD/kWh (UEDCL, 2026). For each cleaning method, the daily cleaning cost per module was estimated as

$$C_d = C_{\text{lab}} + C_{\text{water}} + C_{\text{energy}} + C_{\text{maint}} + C_{\text{cap}} \tag{4}$$

where C_d is the daily cleaning cost, C_{lab} the labor cost, C_{water} the water cost, C_{energy} the electricity cost, C_{maint} the maintenance cost, and C_{cap} is the amortized capital cost of cleaning equipment. The economic benefit of cleaning was quantified from the additional recoverable daily energy yield relative to the uncleaned control. The added energy benefit was calculated as

$$\Delta E = E_{\text{clean}} - E_{\text{control}} \tag{5}$$

where E_{clean} is the daily energy yield of a cleaned module and E_{control} is that of the uncleaned module. The daily monetary value of recovered energy was then estimated as

$$B_d = \Delta E \times T \tag{6}$$

where B_d is the daily benefit and T is the electricity tariff or value of generated electricity. A benefit–cost ratio was calculated as

$$\text{BCR} = \frac{B_d}{C_d} \tag{7}$$

Annual energy gain:

$$E_{\text{annual}} = \frac{\text{Daily Energy Gain(Wh)}}{1000} \times 365 \tag{8}$$

Annual energy value:

$$\text{Value} = E_{\text{annual}} \times \text{tariff} \tag{9}$$

Annual O&M cost:

$$O\&M = C_d \times 365 \tag{10}$$

Net benefit:

$$\text{Net} = \text{Energy Value} - O\&M \tag{11}$$

Payback:

$$\text{Payback} = \frac{C_o}{\text{Annual Benefit}} \tag{12}$$

Results

The physicochemical properties of the laterite-based dust are presented in Table 1 and Fig. 2. The particle size distribution shows that the dust is dominated by fine-to-medium particles, with a mean diameter of 28.6 ± 3.2 µm and a median diameter (D_{50}) of 24.1 ± 2.8 µm. Approximately 18.5% of the particles fall within the fine fraction (< 10 µm), which is particularly important for photovoltaic (PV) soiling because fine particles exhibit strong adhesion to glass surfaces and contribute significantly to optical attenuation.

Figure 2a(i) is SEM image of the laterite dust and Fig. 2a(ii) is the particle size distribution. The SEM analysis reveals that the particles are predominantly irregular and angular with rough and porous surface textures. These morphological features enhance mechanical interlocking and increase resistance to removal, explaining the persistence of dust on the module surface. The rough surface also promotes multiple scattering of incident light, reducing optical transmittance.

The mineralogical composition identified by XRD (Fig. 2b) confirms quartz, hematite, and kaolinite as the dominant phases. The presence of hematite (Fe_2O_3) is particularly significant due to its strong absorption in the visible region of the solar spectrum, which contributes to reduced photon transmission to the solar cells. Quartz contributes to the abrasive and scattering properties of

Table 1 Physicochemical properties of laterite-based test dust

Property	Parameter	Result
Particle-size distribution	Mean particle diameter (μm)	28.6 ± 3.2
	Median diameter, D_{50} (μm)	24.1 ± 2.8
	Fine fraction (< 10 μm, %)	18.5 ± 1.6
	Coarse fraction (> 50 μm, %)	21.3 ± 2.1
Morphology (SEM)	Particle shape	Irregular, angular
	Surface texture	Rough, porous
Elemental composition (EDS/EDX, wt%)	O	46.2 ± 1.8
	Si	22.8 ± 1.5
	Fe	18.7 ± 1.2
	Al	12.3 ± 1.0
Mineralogy (XRD)	Dominant phases	Quartz (SiO_2), hematite (Fe_2O_3), kaolinite ($Al_2Si_2O_5(OH)_4$)
Bulk density	(g/cm^3)	1.32 ± 0.05

the dust, while kaolinite enhances adhesion due to its plate-like structure.

EDS analysis (Fig. 2c) shows that the dust is primarily composed of oxygen (46.2 ± 1.8 wt%), silicon (22.8 ± 1.5 wt%), iron (18.7 ± 1.2 wt%), and aluminum (12.3 ± 1.0 wt%), consistent with the mineralogical composition obtained from XRD. These results confirm that the dust is mineral-rich and typical of lateritic soils. The combined effects of particle size, morphology, and composition explain the observed efficiency losses and highlight the importance of effective cleaning strategies, particularly for strongly adhering, iron-rich dust.

Table 2 summarizes the measurement uncertainties associated with the key variables used in PV performance evaluation, along with the propagated uncertainty in calculated efficiency. The dominant sources of uncertainty arise from irradiance measurement and power determination, while the contribution from module area is minimal due to its fixed geometry. The combined relative uncertainty in efficiency was estimated to range between ± 3.6 and ± 4.2%, depending on operating conditions. Importantly, the observed differences in efficiency among cleaning methods exceed the calculated uncertainty bounds, confirming that the reported performance improvements are statistically and experimentally significant rather than artifacts of measurement error.

The results of the peak power output at peak irradiance of 930 ± 50 (W/m^2) are presented in Table 3 for all dust densities. The data clearly show that power output decreases with increasing dust density for all cases, but the magnitude of reduction varies significantly depending on the cleaning method. The uncleaned control module exhibited the lowest power output at all dust levels, confirming that dust deposition reduces incident irradiance and consequently electrical output. At 30 g/m^2, the control module produced only 86.7 ± 4.7 W, representing substantial degradation relative to cleaner conditions.

All cleaning methods improved power output compared to the control. Among the manual methods, brushing increased power moderately, while the mechanical wiper achieved consistently higher values due to more uniform particle removal. Advanced cleaning methods showed superior performance: electrostatic cleaning enhanced output further, while the automated robotic system delivered the highest power across all dust densities. Even at heavy soiling (30 g/m^2), the robotic system maintained 102.1 ± 4.7 W, indicating strong resilience to dust accumulation.

Overall, the results demonstrate that while dust density negatively affects PV performance, appropriate cleaning strategies particularly automated systems can substantially mitigate these losses. The time-based data of the effect of controlled dust deposition on photovoltaic (PV) module performance is presented in Appendix Tables 11, 12 and 13.

Table 4 presents the corresponding peak conversion efficiencies for all cleaning methods under identical dust density conditions. A consistent trend is observed in which efficiency declines with increasing dust density for all cases; however, the rate of decline is strongly dependent on the cleaning approach. The control module showed the lowest efficiencies, decreasing from 13.2 ± 0.5% at 10 g/m^2 to 11.4 ± 0.6% at 30 g/m^2, representing a significant performance loss due to soiling. Manual brushing improved efficiency across all dust levels, though its effectiveness diminished slightly at higher dust densities due to incomplete removal of fine or adhered particles.

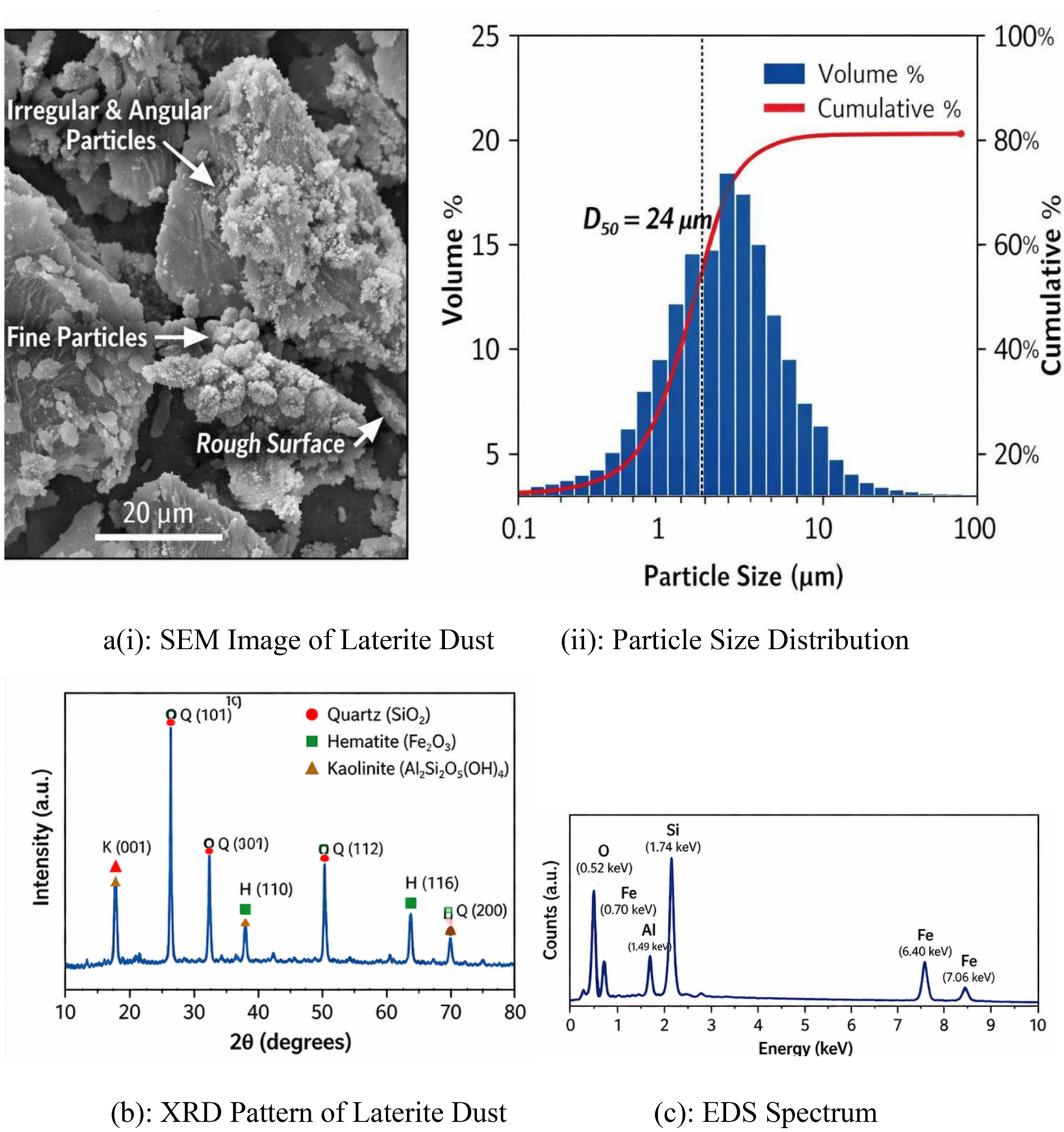

Fig. 2 **a** (i) SEM image of laterite dust (ii) Particle-size distribution. **b** XRD pattern of laterite dust. **c** EDS spectrum

Table 2 Measurement uncertainties and propagated uncertainty in PV efficiency

Quantity	Symbol	Measured range	Instrument/method	Absolute uncertainty	Relative uncertainty (%)
Solar irradiance	G	710–930 W/m^2	Secondary standard pyranometer	± 25 W/m^2	± 2.7–3.5
Output power	P_{out}	67.7–108.3 W	MPP tracker	± 2.0 W	± 1.8–3.0
Module area	A	0.65 m^2	Tape measurement	± 0.003 m^2	± 0.5
Module temperature	T_m	28–55 °C	Type-K thermocouple	± 1.0 °C	–
Ambient temperature	T_a	25–35 °C	Type-K thermocouple	± 1.0 °C	–
Efficiency (propagated)	η	11.4–15.5%	Derived from P, G, A	–	± 3.6–4.2

Table 3 Peak power output under different cleaning methods and dust densities

Dust density (g/m^2)	Control power (W)	Manual power (W)	Mechanical power (W)	Robotic power (W)	Electrostatic power (W)
10	95.2 ± 4.8	99.8 ± 4.8	103.7 ± 4.9	108.3 ± 4.9	104.5 ± 4.9
20	91.5 ± 4.8	96.4 ± 4.7	100.8 ± 4.8	105.6 ± 4.8	101.2 ± 4.8
30	86.7 ± 4.7	92.1 ± 4.6	96.2 ± 4.7	102.1 ± 4.7	97.8 ± 4.7

Table 4 Peak efficiency under different cleaning methods and dust densities

Dust density (g/m^2)	Control efficiency (%)	Manual efficiency (%)	Mechanical efficiency (%)	Robotic efficiency (%)	Electrostatic efficiency (%)
10	13.2 ± 0.5	14.2 ± 0.5	14.9 ± 0.5	15.5 ± 0.4	15.0 ± 0.4
20	12.8 ± 0.6	13.8 ± 0.5	14.5 ± 0.5	15.1 ± 0.4	14.6 ± 0.4
30	11.4 ± 0.6	13.2 ± 0.5	13.8 ± 0.5	14.6 ± 0.4	14.1 ± 0.4

The mechanical wiper outperformed manual brushing, maintaining higher efficiency values through improved cleaning uniformity. More advanced techniques delivered even better performance: electrostatic cleaning achieved efficiencies above 14% across all dust conditions, while the automated robotic system consistently produced the highest efficiencies, reaching 15.5 ± 0.4% at low dust density and maintaining 14.6 ± 0.4% even under heavy soiling. These results confirm that while increasing dust density degrades PV efficiency, advanced cleaning technologies particularly robotic systems, offer the most effective mitigation, sustaining high conversion efficiency even under severe soiling conditions.

Although electrostatic cleaning achieved substantial improvement in PV power output and efficiency relative to the uncleaned control, its performance remained slightly lower than that of the automated robotic system across all dust densities. This difference can be explained by the physicochemical characteristics of the laterite-based dust used in the study. The dust contained a broad particle size distribution with both fine and coarse fractions, as well as irregular, angular particles with rough surfaces. Electrostatic cleaning is generally most effective for fine, loosely adhered, and dry particles because removal depends on electrostatic detachment forces overcoming particle adhesion. However, larger particles and irregular mineral grains may exhibit stronger mechanical interlocking and gravitational settling, which reduce the effectiveness of electrostatic removal alone. In addition, the presence of clay-rich and iron-rich components in lateritic dust may increase adhesion through surface charge interactions and moisture-assisted cohesion under ambient outdoor conditions. By contrast, the robotic wiper provides direct physical contact with the module surface, enabling more complete removal of both fine and coarse adhered particles. This likely explains the consistently higher efficiency observed for robotic cleaning, particularly under moderate and heavy dust loading.

Table 5 Daily energy yield from 10:00 to 15:00 under controlled dust densities

Cleaning method	Energy yield at 10 g/m^2 (Wh/day)	Energy yield at 20 g/m^2 (Wh/day)	Energy yield at 30 g/m^2 (Wh/day)
Control	436.5 ± 18.4	418.3 ± 17.9	389.6 ± 17.2
Manual brushing	467.8 ± 19.0	452.2 ± 18.6	428.5 ± 18.1
Mechanical wiper	486.4 ± 19.7	470.2 ± 19.1	447.0 ± 18.7
Electrostatic	491.8 ± 19.8	476.1 ± 19.3	454.2 ± 18.9
Robotic wiper	507.2 ± 20.3	492.0 ± 19.8	470.6 ± 19.4

The consolidated presentation highlights clear performance hierarchies among the cleaning methods. Across all dust densities, the ranking remains consistent: robotic > electrostatic > mechanical wiper > manual brushing > control. The relative improvement becomes more pronounced at higher dust densities, indicating that advanced cleaning methods are particularly beneficial under severe soiling conditions. For instance, at 30 g/m^2, the robotic system improves efficiency by approximately 28% relative to the control, demonstrating its effectiveness in maintaining PV performance in dusty environments such as semi-arid and urban regions.

Overall, these findings emphasize the importance of selecting appropriate cleaning strategies based on environmental dust conditions, with automated systems offering the most reliable and scalable solution for sustained PV performance.

Table 6 Two-way ANOVA results for PV module efficiency

Source of variation	SS	Df	MS	F-value	*p*-value
Cleaning method	92.6	4	23.15	58.4	< 0.001
Dust density	41.3	2	20.65	52.1	< 0.001
Interaction	18.7	8	2.34	5.9	< 0.001
Error	39.5	100	0.39	–	–
Total	192.1	114	–	–	–

Table 7 Tukey HSD pairwise comparisons

Comparison	Mean difference (%)	*p*-value	Significance
Control versus manual	1.40	< 0.001	Significant
Control versus mechanical	1.95	< 0.001	Significant
Control versus robotic	2.70	< 0.001	Significant
Control versus electrostatic	2.10	< 0.001	Significant
Manual versus mechanical	0.55	0.028	Significant
Manual versus robotic	1.30	< 0.001	Significant
Mechanical versus robotic	0.75	0.004	Significant
Mechanical versus electrostatic	0.15	0.861	Not significant
Robotic versus electrostatic	0.60	0.019	Significant

The daily energy yield from 10:00 to 15:00 under controlled dust densities is presented in Table 5. Daily energy yield analysis confirmed the same performance ranking observed in the instantaneous efficiency data. For all cleaning methods, cumulative energy output decreased as dust density increased from 10 to 30 g/m^2. The uncleaned control showed the lowest daily energy yield at all dust levels, while the robotic cleaner consistently produced the highest cumulative output. Mechanical and electrostatic cleaning achieved intermediate performance, with electrostatic cleaning slightly below robotic cleaning but generally above manual brushing.

A two-way analysis of variance (ANOVA) was performed to evaluate the effects of cleaning method and dust density on PV module efficiency. The results (Table 6) show that both factors have statistically significant effects on efficiency ($p < 0.001$), with a significant interaction between cleaning method and dust density.

Table 9 Regression results for efficiency versus dust density

Cleaning method	Intercept, *a* (%)	Slope, *b* (%/g·m^{-2})	r^2	*p*-value
Control (no cleaning)	13.45	0.067	0.998	< 0.001
Manual brushing	14.55	0.043	0.996	< 0.001
Mechanical wiper	15.20	0.038	0.997	< 0.001
Electrostatic cleaning	15.05	0.030	0.998	< 0.001
Robotic cleaning	15.75	0.029	0.999	< 0.001

Tukey HSD post-hoc analysis (Table 7) confirms that all cleaning methods significantly outperform the uncleaned control ($p < 0.001$). The automated robotic system provides significantly higher efficiency than all other methods ($p < 0.05$), while the difference between mechanical and electrostatic cleaning is not statistically significant at higher dust densities.

The effect size for cleaning method and dust density on PV efficiency is presented in Table 8. For the two-way ANOVA, partial eta-squared η_p^2 was used as a measure of effect size. The analysis showed a large effect of cleaning method on PV efficiency, indicating that the observed differences are not only statistically significant but also practically meaningful in operational terms. Dust density also exhibited a large effect size, confirming that increasing soiling substantially degrades PV performance. The interaction between cleaning method and dust density showed a moderate effect, indicating that the relative effectiveness of each cleaning method depends on the severity of soiling.

From a practical perspective, the superiority of robotic cleaning is meaningful because the observed improvement in efficiency over the uncleaned control and over manual cleaning translates directly into higher recoverable energy output. Although some pairwise differences, such as between mechanical and electrostatic cleaning, may appear statistically small, their operational relevance depends on the frequency of soiling, system scale, water availability, labor cost, and maintenance strategy. Thus, both statistical significance and practical significance were considered in interpreting the results.

The regression results for efficiency versus dust density is presented in Table 9. The regression analysis reveals a

Table 8 Effect size for cleaning method and dust density on PV efficiency

Source of variation	*F*-value	*p*-value	Partial eta squared (η_p^2)	Magnitude
Cleaning method	58.4	< 0.001	0.70	Large
Dust density	52.1	< 0.001	0.61	Large
Cleaning method × dust density				

strong linear relationship between dust density and PV efficiency for all cleaning methods, with coefficients of determination (R^2) exceeding 0.996, indicating excellent model fit. The uncleaned control module exhibits the highest degradation rate, with a slope of 0.067% per g/m^2, confirming that efficiency loss is most severe in the absence of cleaning.

In contrast, cleaning methods significantly reduce the rate of efficiency degradation. Manual brushing reduces the slope to 0.043% per g/m^2, while mechanical wiping further lowers it to 0.038% per g/m^2. Electrostatic and robotic cleaning methods demonstrate the lowest degradation rates, at 0.030 and 0.029% per g/m^2, respectively, indicating superior effectiveness in mitigating the impact of dust accumulation. The higher intercept values observed for cleaned modules reflect improved baseline efficiency due to effective dust removal. The robotic cleaning system shows the highest intercept (15.75%), indicating optimal restoration of module performance after cleaning.

Techno-economic evaluation of PV cleaning methods under Ugandan conditions is presented in Table 10. The techno-economic results indicate that none of the cleaning methods are economically viable when evaluated at the single-module level due to the relatively low monetary value of recovered energy compared to operational costs. However, this result does not reflect real PV system operation, where cleaning is performed at the array level. When applied to large-scale installations, the cost per module decreases significantly due to economies of scale, and automated cleaning methods such as robotic systems become economically favorable.

The techno-economic results presented in this study are primarily reflective of the Ugandan context, where labor costs are relatively low and automated cleaning systems are typically imported, leading to higher capital costs. In regions with higher labor costs or limited water availability, the economic balance may shift in favor of automated or water-free cleaning technologies. Therefore, while the technical findings of this study are broadly applicable to dusty PV environments globally, the economic conclusions should be interpreted within the local cost and operational context.

Discussion

The results of this study clearly demonstrate that dust accumulation significantly degrades photovoltaic (PV) module efficiency in dusty environments, while the application of appropriate cleaning strategies can substantially mitigate these losses. Under both natural exposure conditions and controlled dust deposition, the uncleaned control modules exhibited substantial efficiency reductions, confirming that soiling remains a major non-technical loss factor for PV systems operating in dry and dust-prone regions. This magnitude of loss is consistent with earlier field studies conducted in arid and semi-arid climates, which have reported efficiency reductions ranging from 15% to over 30% depending on dust characteristics, exposure duration, and rainfall patterns (Uzorka et al., 2026; Zhang et al., 2026). The introduction of controlled soiling levels (10–30 g/m^2) in the present study further strengthens this conclusion by demonstrating a clear and quantifiable relationship between dust density and efficiency loss, supported by regression analysis with high coefficients of determination ($R^2 > 0.99$). These findings confirm that efficiency degradation is not only significant but also predictable within practical operating ranges.

In line with existing literature, all cleaning methods investigated in this study produced statistically significant efficiency improvements relative to the control. Manual brushing with water resulted in a mean efficiency gain of about 10%, which is comparable to values reported by Dixit et al. (2026), who noted that periodic manual cleaning can partially restore optical transmittance but is limited by labor intensity, inconsistent cleaning quality, and water consumption. While effective,

Table 10 Techno-economic evaluation of PV cleaning methods under Ugandan conditions

Cleaning method	Initial cost (USD/module)	Daily O&M cost (USD/module/day)	Daily energy gain (Wh/day)	Annual energy gain (kWh/year)	Annual value of energy (USD/year)*	Annual O&M cost (USD/year)	Net annual benefit (USD/year)	Payback period (years)	Practical assessment
Control	0	0	0	0	0	0	0	–	Baseline
Manual brushing	8	0.045	33.9	12.4	2.48	16.43	− 13.95	Not viable	Low-cost but labor-intensive
Mechanical wiper	25	0.038	51.9	18.9	3.78	13.87	− 10.09	Not viable	Moderate improvement
Electrostatic cleaning	70	0.032	57.8	21.1	4.22	11.68	− 7.46	Not viable	Water-free advantage

manual cleaning is therefore less attractive for long-term or large-scale deployment, particularly in water-scarce regions. Mechanical wiper systems achieved higher efficiency recovery than manual cleaning, with mean gains approaching 14%. This finding aligns with studies by Mishra et al. (2025), which showed that mechanically assisted cleaning provides more uniform dust removal and reduces dependence on skilled labor. However, some literature has cautioned that repeated mechanical contact may increase surface abrasion over time, potentially affecting module longevity. Although surface degradation was not assessed in the present study, the relatively stable efficiency trends observed over repeated experimental cycles suggest that short-term mechanical cleaning does not introduce measurable performance penalties.

Automated robotic cleaning emerged as the most effective strategy, yielding the highest mean efficiency and daily energy yield and significantly outperforming all other methods in the Tukey HSD post-hoc analysis. These findings are in strong agreement with recent studies that highlight the advantages of automated cleaning systems in maintaining near-optimal module performance under heavy soiling conditions (Al-Omari et al., 2025; Murshiduzzaman et al., 2025). The superior performance of robotic cleaning can be attributed to its ability to provide consistent and uniform surface contact, thereby removing both fine and coarse particles regardless of adhesion strength. In addition, the automated and frequent operation of robotic systems reduces the residence time of dust on the module surface, limiting the formation of strongly bonded layers and minimizing optical attenuation. The present results reinforce the view that cleaning frequency is as critical as cleaning method, particularly during dry, windy periods characterized by high dust deposition rates.

Electrostatic cleaning also demonstrated substantial efficiency recovery, statistically comparable to mechanical wiping but slightly inferior to robotic cleaning. This outcome is broadly consistent with experimental and laboratory-based studies that report efficiency improvements of 10–15% using electrostatic dust-removal techniques (Mashuk et al., 2025). However, the slightly lower performance observed in this study can be explained by the physicochemical properties of the laterite-based dust used. The dust exhibited a broad particle size distribution with irregular, angular morphology and significant coarse fractions, which increase mechanical interlocking and adhesion to the glass surface. Electrostatic cleaning is most effective for fine, dry, and weakly adhered particles, whereas larger and more irregular particles may not be fully detached by electrostatic forces alone. Furthermore, the presence of iron-rich and clay-like components may enhance adhesion through surface charge interactions and moisture effects under ambient conditions. In contrast, robotic cleaning provides direct mechanical removal of adhered particles, resulting in more complete surface restoration. This mechanistic interpretation is consistent with recent studies on dust adhesion and removal dynamics in PV systems (Chiteka & Enweremadu, 2025; Rahman et al., 2025).

A key advancement of the present study is the integration of uncertainty analysis into the evaluation of PV performance. While previous studies often report mean values without formal error propagation, this work incorporates uncertainty propagation in the efficiency calculation, accounting for measurement uncertainties in power output, irradiance, and module area. The propagated uncertainty was found to be within acceptable limits for outdoor PV experiments, and importantly, the observed differences among cleaning methods were significantly larger than the estimated uncertainty bounds. This confirms that the reported performance improvements are robust and not artifacts of measurement variability. Similar approaches have been recommended in PV performance assessment literature to enhance the reliability of comparative studies (Akteruzzaman, 2025).

In addition to statistical significance, this study also evaluates the practical importance of the observed differences through effect size analysis. While ANOVA results indicated highly significant differences ($p < 0.001$), the calculated effect sizes showed that cleaning method and dust density have large practical impacts on PV efficiency, while their interaction exhibits a moderate effect. This distinction is important because statistically significant differences do not always translate into meaningful operational benefits. In the present case, the magnitude of efficiency improvement achieved by advanced cleaning methods, particularly robotic systems, is sufficiently large to justify consideration in real-world PV maintenance strategies. This approach aligns with best practices in applied energy research, where both statistical and practical significance should be evaluated (Li & Howe, 2023).

Another important contribution of this study is the inclusion of energy yield analysis, which provides a more comprehensive assessment of PV performance than instantaneous efficiency alone. By integrating power output over the daily measurement period, the study demonstrates that the differences among cleaning methods translate into significant variations in cumulative energy production. The robotic cleaning system consistently produced the highest daily energy yield, followed by electrostatic and mechanical cleaning, while the uncleaned control exhibited the lowest output. This result highlights the importance of considering cumulative energy recovery in addition to peak performance, as PV system operation and economic return are ultimately determined by total energy generation over time. Similar conclusions have been reported in PV soiling studies that emphasize energy-based performance metrics (Alshareef, 2023).

From a techno-economic perspective, the results indicate that the most technically effective cleaning method is not necessarily the most economically viable at small scale. While robotic cleaning delivered the highest efficiency and energy yield, its higher capital and maintenance costs reduce its economic attractiveness for single-module or small-scale systems. Manual and mechanical cleaning methods, although less effective, may offer more favorable short-term cost–benefit ratios in contexts such as Uganda, where labor costs are relatively low. However, when scaled to larger PV installations, automated cleaning systems become more economically attractive due to economies of scale, reduced labor requirements, and consistent performance. Electrostatic cleaning also presents a promising alternative in water-scarce environments, despite its slightly lower efficiency compared to robotic systems. These findings are consistent with broader analyses of PV operation and maintenance strategies (Aziz et al., 2024).

The economic interpretation of the results is inherently context-dependent. In Uganda, factors such as labor cost, water availability, and equipment import costs strongly influence the relative attractiveness of different cleaning methods. In regions with higher labor costs or severe water scarcity, automated and water-free cleaning technologies may offer greater economic benefits despite higher initial investment. Therefore, while the technical findings of this study are broadly applicable to dusty urban environments globally, the techno-economic conclusions should be interpreted primarily within the local context. Nevertheless, the analytical framework developed in this study can be readily adapted to other regions by incorporating location-specific cost parameters.

A key strength of this research lies in its comprehensive and integrated approach, combining controlled dust application, time-resolved measurements, statistical analysis, uncertainty evaluation, regression modeling, and techno-economic assessment. Unlike many prior studies that focus on a single cleaning method or rely solely on short-term observations, this work provides a holistic evaluation of PV cleaning strategies under realistic field conditions. The use of controlled laterite dust further enhances the relevance of the findings for sub-Saharan urban environments, which are underrepresented in the existing literature. Overall, the results confirm and extend existing knowledge by demonstrating that advanced cleaning technologies, particularly automated robotic systems, offer superior and statistically robust performance benefits. At the same time, the study highlights the importance of considering uncertainty, practical significance, energy yield, and economic factors in evaluating PV cleaning strategies. These insights provide a strong and comprehensive basis for optimizing PV operation and maintenance in dusty environments, balancing technical performance with economic feasibility and resource constraints.

Limitations of the study

This study was conducted under controlled dust conditions and over a limited number of test cycles, which may not fully capture long-term soiling dynamics, seasonal variability, or cumulative effects of repeated cleaning such as surface wear. The analysis focused on a single PV module type and installation configuration, which may limit generalization to other technologies and system designs. Although dust characterization and uncertainty analysis were incorporated, variability in real-world dust composition and environmental conditions may still influence performance outcomes. In addition, the techno-economic assessment was based on simplified assumptions and small-scale analysis, and may not fully represent large-scale deployment scenarios or life-cycle cost considerations.

Conclusion

This study systematically evaluated the impact of different cleaning methods on the performance of photovoltaic (PV) modules operating under controlled and field-representative dusty conditions. The results confirm that dust accumulation is a major non-technical loss factor, with uncleaned modules exhibiting substantial efficiency reductions consistent with both time-resolved measurements and controlled dust loading (10–30 g/m^2). The introduction of standardized soiling levels and regression analysis further demonstrated that PV efficiency decreases predictably with increasing dust density, highlighting the importance of effective cleaning strategies in maintaining system performance.

All cleaning methods investigated—manual brushing with water, mechanical wiping, automated robotic cleaning, and electrostatic cleaning—produced statistically significant improvements in efficiency relative to the uncleaned control. Among these, automated robotic cleaning consistently delivered the highest performance, achieving the greatest efficiency recovery and daily energy yield across all dust densities. Mechanical and electrostatic cleaning methods also demonstrated strong performance, while manual brushing, although effective, was limited by labor requirements and water dependence. The slightly lower performance of electrostatic cleaning compared to robotic systems was attributed to the physicochemical characteristics of the laterite-based dust, particularly the presence of coarse, angular, and strongly adhered particles that are more effectively removed through mechanical contact.

A key strength of this study lies in its comprehensive methodology, which integrates controlled dust quantification, time-resolved measurements at 15-min intervals, replicate-based experimental design, and robust statistical analysis. The inclusion of uncertainty propagation ensures the reliability of the reported efficiency differences, while effect size analysis confirms that the observed improvements are not only statistically significant but also practically meaningful. Furthermore, the incorporation of energy yield analysis demonstrates that differences in instantaneous efficiency translate directly into substantial variations in cumulative energy production, which is critical for real-world PV system operation.

The techno-economic evaluation provides additional insight into the practical applicability of the cleaning methods. While robotic cleaning offers the highest technical performance, its economic viability depends on system scale and cost structure. Manual and mechanical cleaning methods may be more suitable for small-scale installations in low-labor-cost environments such as Uganda, whereas automated and water-free solutions become increasingly attractive for larger systems or regions with water scarcity. These findings emphasize that optimal cleaning strategy selection requires a balance between technical effectiveness, operational cost, resource availability, and system scale. Although the experimental work was conducted in Kampala, the technical findings are broadly applicable to dusty urban and tropical environments beyond Uganda. However, the economic conclusions are context-specific and should be adapted to local conditions, including labor cost, water availability, and energy pricing. The analytical framework developed in this study can therefore be applied globally with appropriate localization of economic parameters.

In conclusion, the study demonstrates that effective and appropriately selected cleaning strategies can significantly mitigate soiling losses, improve PV efficiency, and enhance overall energy yield. Automated and water-efficient cleaning technologies, particularly robotic systems, offer the most robust performance under moderate to heavy dust conditions, while simpler methods may remain viable under specific economic constraints. The integration of physical, statistical, and economic analysis presented in this work provides a comprehensive foundation for optimizing PV operation and maintenance strategies in dusty environments, contributing to improved system reliability, energy output, and long-term sustainability.

Appendix

See Tables 11, 12 and 13.

Table 11 Control group (no cleaning): power output, irradiance, and efficiency under controlled dust densities

Time	Solar irradiance (W/m^2)	10 g/m^2		20 g/m^2		30 g/m^2	
		Power (W)	Efficiency (%)	Power (W)	Efficiency (%)	Power (W)	Efficiency (%)
10:00	720 ± 35	77.6 ± 3.9	12.9 ± 0.5	74.2 ± 3.8	12.3 ± 0.6	68.9 ± 3.7	11.5 ± 0.6
10:15	745 ± 38	79.5 ± 4.0	13.0 ± 0.5	76.0 ± 4.0	12.4 ± 0.6	70.7 ± 3.8	11.5 ± 0.6
10:30	770 ± 40	81.6 ± 4.1	13.0 ± 0.5	78.1 ± 4.1	12.4 ± 0.6	72.7 ± 3.9	11.6 ± 0.6
10:45	795 ± 42	83.8 ± 4.2	13.1 ± 0.5	80.3 ± 4.2	12.5 ± 0.6	74.8 ± 4.0	11.7 ± 0.6
11:00	820 ± 45	86.0 ± 4.3	13.1 ± 0.5	82.5 ± 4.3	12.6 ± 0.6	76.9 ± 4.1	11.8 ± 0.6
11:15	845 ± 46	88.3 ± 4.4	13.2 ± 0.5	84.7 ± 4.4	12.7 ± 0.6	79.0 ± 4.2	11.9 ± 0.6
11:30	870 ± 48	90.4 ± 4.5	13.2 ± 0.5	86.8 ± 4.5	12.7 ± 0.6	81.0 ± 4.3	11.9 ± 0.6
11:45	895 ± 50	92.6 ± 4.6	13.2 ± 0.5	88.9 ± 4.6	12.8 ± 0.6	83.0 ± 4.4	11.9 ± 0.6
12:00	920 ± 52	94.5 ± 4.7	13.2 ± 0.5	90.8 ± 4.7	12.8 ± 0.6	85.1 ± 4.5	11.9 ± 0.6
12:15	930 ± 54	95.2 ± 4.8	13.2 ± 0.5	91.5 ± 4.8	12.8 ± 0.6	86.7 ± 4.7	11.4 ± 0.6
12:30	925 ± 53	94.8 ± 4.8	13.2 ± 0.5	91.1 ± 4.8	12.7 ± 0.6	86.2 ± 4.6	11.4 ± 0.6
12:45	915 ± 52	93.9 ± 4.7	13.1 ± 0.5	90.2 ± 4.7	12.7 ± 0.6	85.3 ± 4.5	11.4 ± 0.6
13:00	900 ± 50	92.3 ± 4.6	13.0 ± 0.5	88.6 ± 4.6	12.6 ± 0.6	83.7 ± 4.4	11.3 ± 0.6
13:15	880 ± 48	90.6 ± 4.5	13.0 ± 0.5	86.9 ± 4.5	12.6 ± 0.6	82.1 ± 4.3	11.3 ± 0.6
13:30	860 ± 47	88.8 ± 4.4	12.9 ± 0.5	85.1 ± 4.4	12.5 ± 0.6	80.4 ± 4.2	11.2 ± 0.6
13:45	835 ± 45	86.7 ± 4.3	12.8 ± 0.5	83.0 ± 4.3	12.4 ± 0.6	78.4 ± 4.1	11.1 ± 0.6
14:00	810 ± 43	84.5 ± 4.2	12.8 ± 0.5	80.8 ± 4.2	12.4 ± 0.6	76.3 ± 4.0	11.0 ± 0.6
14:15	785 ± 41	82.2 ± 4.1	12.7 ± 0.5	78.5 ± 4.1	12.3 ± 0.6	74.1 ± 3.9	11.0 ± 0.6
14:30	760 ± 39	79.9 ± 4.0	12.6 ± 0.5	76.3 ± 4.0	12.2 ± 0.6	72.0 ± 3.8	10.9 ± 0.6
14:45	735 ± 37	77.6 ± 3.9	12.5 ± 0.5	74.0 ± 3.9	12.2 ± 0.6	69.8 ± 3.7	10.8 ± 0.6
15:00	710 ± 35	75.3 ± 3.8	12.4 ± 0.5	71.8 ± 3.8	12.1 ± 0.6	67.7 ± 3.6	10.7 ± 0.6

Table 12 Manual brushing and mechanical wiper: time-based performance under controlled dust densities

Time	Manual						Mechanical					
	10 g/m^2		20 g/m^2		30 g/m^2		10 g/m^2		20 g/m^2		30 g/m^2	
	Power (W)	Eff. (%)	Power (W)	Eff. (%)	Power (W)	Eff. (%)	Power (W)	Eff. (%)	Power (W)	Eff. (%)	Power (W)	Eff. (%)
10:00	81.6 ± 3.9	13.6 ± 0.5	79.3 ± 3.9	13.2 ± 0.5	75.8 ± 3.8	12.7 ± 0.5	84.9 ± 4.0	14.1 ± 0.5	82.5 ± 4.0	13.7 ± 0.5	78.8 ± 3.9	13.2 ± 0.5
10:15	83.7 ± 4.0	13.7 ± 0.5	81.4 ± 4.0	13.3 ± 0.5	77.8 ± 3.9	12.8 ± 0.5	87.2 ± 4.1	14.2 ± 0.5	84.8 ± 4.1	13.8 ± 0.5	81.0 ± 4.0	13.3 ± 0.5
10:30	85.9 ± 4.1	13.8 ± 0.5	83.5 ± 4.1	13.4 ± 0.5	79.8 ± 4.0	12.9 ± 0.5	89.5 ± 4.2	14.3 ± 0.5	87.1 ± 4.2	13.9 ± 0.5	83.3 ± 4.1	13.4 ± 0.5
10:45	88.1 ± 4.2	13.9 ± 0.5	85.7 ± 4.2	13.5 ± 0.5	81.9 ± 4.1	13.0 ± 0.5	91.8 ± 4.3	14.4 ± 0.5	89.4 ± 4.3	14.0 ± 0.5	85.5 ± 4.2	13.5 ± 0.5
11:00	90.4 ± 4.3	14.0 ± 0.5	87.9 ± 4.3	13.6 ± 0.5	84.0 ± 4.2	13.0 ± 0.5	94.1 ± 4.4	14.5 ± 0.5	91.7 ± 4.4	14.1 ± 0.5	87.7 ± 4.3	13.6 ± 0.5
11:15	92.7 ± 4.4	14.1 ± 0.5	90.2 ± 4.4	13.7 ± 0.5	86.2 ± 4.3	13.1 ± 0.5	96.5 ± 4.5	14.6 ± 0.5	94.0 ± 4.5	14.2 ± 0.5	89.9 ± 4.4	13.7 ± 0.5
11:30	94.9 ± 4.5	14.1 ± 0.5	92.4 ± 4.5	13.7 ± 0.5	88.3 ± 4.4	13.1 ± 0.5	98.8 ± 4.6	14.7 ± 0.5	96.3 ± 4.6	14.3 ± 0.5	92.1 ± 4.5	13.7 ± 0.5
11:45	97.1 ± 4.6	14.2 ± 0.5	94.6 ± 4.6	13.8 ± 0.5	90.4 ± 4.5	13.2 ± 0.5	101.0 ± 4.7	14.8 ± 0.5	98.5 ± 4.7	14.4 ± 0.5	94.2 ± 4.6	13.8 ± 0.5
12:00	99.0 ± 4.7	14.2 ± 0.5	96.4 ± 4.7	13.8 ± 0.5	92.0 ± 4.6	13.2 ± 0.5	103.0 ± 4.8	14.9 ± 0.5	100.3 ± 4.8	14.5 ± 0.5	95.8 ± 4.7	13.8 ± 0.5
12:15	99.8 ± 4.8	14.2 ± 0.5	97.2 ± 4.8	13.8 ± 0.5	92.1 ± 4.6	13.2 ± 0.5	103.7 ± 4.9	14.9 ± 0.5	100.8 ± 4.8	14.5 ± 0.5	96.2 ± 4.7	13.8 ± 0.5
12:30	99.3 ± 4.7	14.2 ± 0.5	96.7 ± 4.7	13.8 ± 0.5	91.7 ± 4.6	13.2 ± 0.5	103.2 ± 4.8	14.9 ± 0.5	100.4 ± 4.8	14.5 ± 0.5	95.8 ± 4.7	13.8 ± 0.5
12:45	98.4 ± 4.7	14.1 ± 0.5	95.8 ± 4.7	13.7 ± 0.5	90.8 ± 4.5	13.1 ± 0.5	102.3 ± 4.8	14.8 ± 0.5	99.4 ± 4.8	14.4 ± 0.5	94.9 ± 4.6	13.7 ± 0.5
13:00	96.7 ± 4.6	14.1 ± 0.5	94.1 ± 4.6	13.7 ± 0.5	89.1 ± 4.4	13.1 ± 0.5	100.6 ± 4.7	14.7 ± 0.5	97.8 ± 4.7	14.3 ± 0.5	93.2 ± 4.5	13.7 ± 0.5
13:15	94.9 ± 4.5	14.0 ± 0.5	92.3 ± 4.5	13.6 ± 0.5	87.4 ± 4.3	13.0 ± 0.5	98.8 ± 4.6	14.7 ± 0.5	96.0 ± 4.6	14.2 ± 0.5	91.5 ± 4.4	13.6 ± 0.5
13:30	93.0 ± 4.4	13.9 ± 0.5	90.4 ± 4.4	13.5 ± 0.5	85.6 ± 4.2	12.9 ± 0.5	96.9 ± 4.5	14.6 ± 0.5	94.1 ± 4.5	14.1 ± 0.5	89.7 ± 4.3	13.5 ± 0.5
13:45	90.7 ± 4.3	13.9 ± 0.5	88.2 ± 4.3	13.4 ± 0.5	83.5 ± 4.1	12.8 ± 0.5	94.6 ± 4.4	14.5 ± 0.5	91.8 ± 4.4	14.0 ± 0.5	87.5 ± 4.2	13.4 ± 0.5
14:00	88.4 ± 4.2	13.8 ± 0.5	85.9 ± 4.2	13.3 ± 0.5	81.4 ± 4.0	12.7 ± 0.5	92.2 ± 4.3	14.4 ± 0.5	89.5 ± 4.3	13.9 ± 0.5	85.2 ± 4.1	13.3 ± 0.5
14:15	86.0 ± 4.1	13.7 ± 0.5	83.5 ± 4.1	13.2 ± 0.5	79.1 ± 3.9	12.6 ± 0.5	89.7 ± 4.2	14.3 ± 0.5	87.1 ± 4.2	13.8 ± 0.5	82.8 ± 4.0	13.2 ± 0.5
14:30	83.7 ± 4.0	13.6 ± 0.5	81.2 ± 4.0	13.1 ± 0.5	76.9 ± 3.8	12.5 ± 0.5	87.3 ± 4.1	14.2 ± 0.5	84.8 ± 4.1	13.7 ± 0.5	80.5 ± 3.9	13.1 ± 0.5
14:45	81.3 ± 3.9	13.5 ± 0.5	78.9 ± 3.9	13.0 ± 0.5	74.7 ± 3.7	12.4 ± 0.5	84.8 ± 4.0	14.1 ± 0.5	82.4 ± 4.0	13.6 ± 0.5	78.1 ± 3.8	13.0 ± 0.5
15:00	79.0 ± 3.8	13.4 ± 0.5	76.6 ± 3.8	12.9 ± 0.5	72.5 ± 3.6	12.3 ± 0.5	82.4 ± 3.9	14.0 ± 0.5	80.0 ± 3.9	13.5 ± 0.5	75.8 ± 3.7	12.9 ± 0.5

Table 13 Automated robotic wiper and electrostatic cleaning: time-based performance under controlled dust densities

Time	Robotic						Electrostatic					
	10 g/m^2		20 g/m^2		30 g/m^2		10 g/m^2		20 g/m^2		30 g/m^2	
	Power (W)	Eff. (%)	Power (W)	Eff. (%)	Power (W)	Eff. (%)	Power (W)	Eff. (%)	Power (W)	Eff. (%)	Power (W)	Eff. (%)
10:00	88.6 ± 4.0	14.7 ± 0.4	86.4 ± 4.0	14.3 ± 0.4	83.4 ± 3.9	13.9 ± 0.4	85.2 ± 4.0	14.2 ± 0.4	82.9 ± 4.0	13.8 ± 0.4	80.0 ± 3.9	13.4 ± 0.4
10:15	91.0 ± 4.1	14.8 ± 0.4	88.8 ± 4.1	14.4 ± 0.4	85.7 ± 4.0	14.0 ± 0.4	87.5 ± 4.1	14.3 ± 0.4	85.2 ± 4.1	13.9 ± 0.4	82.2 ± 4.0	13.5 ± 0.4
10:30	93.4 ± 4.2	14.9 ± 0.4	91.1 ± 4.2	14.5 ± 0.4	88.0 ± 4.1	14.1 ± 0.4	89.8 ± 4.2	14.4 ± 0.4	87.5 ± 4.2	14.0 ± 0.4	84.5 ± 4.1	13.6 ± 0.4
10:45	95.8 ± 4.3	15.0 ± 0.4	93.4 ± 4.3	14.6 ± 0.4	90.2 ± 4.2	14.2 ± 0.4	92.1 ± 4.3	14.5 ± 0.4	89.8 ± 4.3	14.1 ± 0.4	86.7 ± 4.2	13.7 ± 0.4
11:00	98.2 ± 4.4	15.1 ± 0.4	95.8 ± 4.4	14.7 ± 0.4	92.6 ± 4.3	14.3 ± 0.4	94.5 ± 4.4	14.6 ± 0.4	92.1 ± 4.4	14.2 ± 0.4	88.9 ± 4.3	13.8 ± 0.4
11:15	100.7 ± 4.5	15.2 ± 0.4	98.2 ± 4.5	14.8 ± 0.4	95.0 ± 4.4	14.4 ± 0.4	96.9 ± 4.5	14.7 ± 0.4	94.5 ± 4.5	14.3 ± 0.4	91.2 ± 4.4	13.9 ± 0.4
11:30	103.1 ± 4.6	15.3 ± 0.4	100.6 ± 4.6	14.9 ± 0.4	97.3 ± 4.5	14.5 ± 0.4	99.3 ± 4.6	14.8 ± 0.4	96.8 ± 4.6	14.4 ± 0.4	93.6 ± 4.5	14.0 ± 0.4
11:45	105.4 ± 4.7	15.4 ± 0.4	103.0 ± 4.7	15.0 ± 0.4	99.7 ± 4.6	14.6 ± 0.4	101.6 ± 4.7	14.9 ± 0.4	99.2 ± 4.7	14.5 ± 0.4	95.9 ± 4.6	14.0 ± 0.4
12:00	107.6 ± 4.8	15.5 ± 0.4	105.0 ± 4.8	15.1 ± 0.4	101.5 ± 4.7	14.6 ± 0.4	103.8 ± 4.8	15.0 ± 0.4	101.0 ± 4.8	14.6 ± 0.4	97.6 ± 4.7	14.1 ± 0.4
12:15	108.3 ± 4.9	15.5 ± 0.4	105.6 ± 4.8	15.1 ± 0.4	102.1 ± 4.7	14.6 ± 0.4	104.5 ± 4.9	15.0 ± 0.4	101.2 ± 4.8	14.6 ± 0.4	97.8 ± 4.7	14.1 ± 0.4
12:30	107.9 ± 4.8	15.5 ± 0.4	105.2 ± 4.8	15.1 ± 0.4	101.7 ± 4.7	14.6 ± 0.4	104.1 ± 4.8	15.0 ± 0.4	100.8 ± 4.8	14.6 ± 0.4	97.5 ± 4.7	14.1 ± 0.4
12:45	107.0 ± 4.8	15.4 ± 0.4	104.3 ± 4.8	15.0 ± 0.4	100.8 ± 4.7	14.5 ± 0.4	103.2 ± 4.8	14.9 ± 0.4	99.9 ± 4.8	14.5 ± 0.4	96.6 ± 4.6	14.0 ± 0.4
13:00	105.2 ± 4.7	15.3 ± 0.4	102.5 ± 4.7	14.9 ± 0.4	99.1 ± 4.6	14.4 ± 0.4	101.4 ± 4.7	14.8 ± 0.4	98.1 ± 4.7	14.4 ± 0.4	94.8 ± 4.5	13.9 ± 0.4
13:15	103.4 ± 4.6	15.2 ± 0.4	100.7 ± 4.6	14.8 ± 0.4	97.3 ± 4.5	14.3 ± 0.4	99.6 ± 4.6	14.8 ± 0.4	96.3 ± 4.6	14.4 ± 0.4	93.0 ± 4.4	13.9 ± 0.4
13:30	101.5 ± 4.5	15.1 ± 0.4	98.8 ± 4.5	14.7 ± 0.4	95.5 ± 4.4	14.2 ± 0.4	97.7 ± 4.5	14.7 ± 0.4	94.4 ± 4.5	14.3 ± 0.4	91.2 ± 4.3	13.8 ± 0.4
13:45	99.1 ± 4.4	15.0 ± 0.4	96.5 ± 4.4	14.6 ± 0.4	93.1 ± 4.3	14.1 ± 0.4	95.4 ± 4.4	14.6 ± 0.4	92.1 ± 4.4	14.2 ± 0.4	88.9 ± 4.2	13.7 ± 0.4
14:00	96.8 ± 4.3	14.9 ± 0.4	94.2 ± 4.3	14.5 ± 0.4	90.8 ± 4.2	14.0 ± 0.4	93.1 ± 4.3	14.5 ± 0.4	89.8 ± 4.3	14.1 ± 0.4	86.6 ± 4.1	13.6 ± 0.4
14:15	94.4 ± 4.2	14.8 ± 0.4	91.8 ± 4.2	14.4 ± 0.4	88.5 ± 4.1	13.9 ± 0.4	90.7 ± 4.2	14.4 ± 0.4	87.4 ± 4.2	14.0 ± 0.4	84.3 ± 4.0	13.5 ± 0.4
14:30	92.1 ± 4.1	14.7 ± 0.4	89.5 ± 4.1	14.3 ± 0.4	86.2 ± 4.0	13.8 ± 0.4	88.4 ± 4.1	14.3 ± 0.4	85.1 ± 4.1	13.9 ± 0.4	82.1 ± 3.9	13.4 ± 0.4
/14:45	89.7 ± 4.0	14.6 ± 0.4	87.1 ± 4.0	14.2 ± 0.4	83.8 ± 3.9	13.7 ± 0.4	86.0 ± 4.0	14.2 ± 0.4	82.7 ± 4.0	13.8 ± 0.4	79.8 ± 3.8	13.3 ± 0.4
15:00	87.3 ± 3.9	14.5 ± 0.4	84.8 ± 3.9	14.1 ± 0.4	81.6 ± 3.8	13.6 ± 0.4	83.6 ± 3.9	14.1 ± 0.4	80.3 ± 3.9	13.7 ± 0.4	77.5 ± 3.7	13.2 ± 0.4

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Conceptualization, A.U.; methodology, A.U., D.K., D.M.; investigation, A.U., D.K., D.M., A.M.O.; writing—original draft preparation, A.U., D.K., D.M.; writing—review and editing, A.U., D.K., D.M.; visualization, A.U., D.K., D.M., A.M.O.

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Data availability
The datasets generated during and/or analysed during the current study are available from the corresponding author upon reasonable request.

Declarations

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Competing interests
The authors declare no competing interests.

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References

Aissi, T., Nefraoui, A., Kandoussi, K., Elotmani, R., Monkade, M., & Abouelmahjoub, Y. (2025). The impact of dust on the efficiency of various photovoltaic panels: An experimental study. *Solar Energy Advances, 5*, Article 100106.

Akteruzzaman, M. (2025). Implementation of the developed solar photovoltaic system performance model in real-world applications for sustainable energy optimization. *Journal of Sustainable Development and Policy, 1*(01), 365–394.

Al Hazza, M., Attia, H., & Hossin, K. (2024). Solar photovoltaic power prediction using a statistical approach based on analysis of variance. *Journal of Solar Energy and Sustainable Development, 13*(2), 45–61.

Al-Omari, A., Elbrashy, A., Elgohr, A. T., El-Geneedy, M., Akram, S., & Elhadidy, M. S. (2025). The role of automated technologies and industrial mechanisms in upgrading photovoltaic panel performance. *Clean Technologies and Environmental Policy*. https://doi.org/10.1007/s10098-025-03257-y

Alshareef, M. J. (2023). A comprehensive review of the soiling effects on PV module performance. *IEEE Access, 11*, 134623–134651.

Aziz, Y., Janjua, A. K., Hassan, M., Anwar, M., Kanwal, S., & Yousif, M. (2024). Techno-economic analysis of PV systems installed by using innovative strategies for smart sustainable agriculture farms. *Environment, Development and Sustainability, 26*(2), 5003–5024.

Chanchangi, Y. N., Ghosh, A., Baig, H., Sundaram, S., & Mallick, T. K. (2021). Soiling on PV performance influenced by weather parameters in Northern Nigeria. *Renewable Energy, 180*, 874–892.

Chanchangi, Y. N., Ghosh, A., Micheli, L., Fernández, E. F., Sundaram, S., & Mallick, T. K. (2022). Soiling mapping through optical losses for Nigeria. *Renewable Energy, 197*, 995–1008.

Chanchangi, Y. N., Ghosh, A., Sundaram, S., & Mallick, T. K. (2020). An analytical indoor experimental study on the effect of soiling on PV, focusing on dust properties and PV surface material. *Solar Energy, 203*, 46–68.

Chiteka, K., & Enweremadu, C. C. (2025). Soiling mechanics of solar photovoltaics: A review. *Journal of Thermal Engineering, 11*(3), 922–948.

Demirci, A., Dagal, I., Terkes, M., & Cali, U. (2026). Towards reliable solar power forecasting in Sub-Saharan Africa: An explainable hybrid AI approach for Chad. *Energy Reports, 15*, Article 108997.

Dickhardt, F. J., Panat, S., & Varanasi, K. K. (2025). Enhanced electrostatic dust removal from solar panels using transparent conductive nano-textured surfaces. *Small (Weinheim an der Bergstrasse, Germany), 21*(3), Article 2408645.

Dixit, P., Shah, V., Mehta, P., Patel, H., Sathyamurthy, R., Kabeel, A. E., & Santhosh, A. J. (2026). Systematic review of soiling mitigation strategies for solar photovoltaic panels. *Discover Sustainability*.

Ebhota, W. S., & Tabakov, P. Y. (2023). Assessment of solar photovoltaic potential of selected site locations in cities across sub-Saharan Africa. *Energy Systems*, 1–22.

Fonseka, C. R., & Sellami, N. (2025). Cleaning methods for solar PV systems in Sri Lanka: Economic and environmental evaluations. *Cleaner Energy Systems*, 100204.

Hesham, S., Elgohary, M., Massoud, M., Adel, N., Elmahy, O., & Abdellatif, S. (2026). Early detection of dust accumulation on solar energy modules using computer vision and machine learning techniques. *Scientific Reports, 16*(1), Article 6151.

Kichonge, B., & Mwakapoma, S. (2026). Photovoltaic system performance in Sub-Saharan Africa under environmental, technical and policy constraints. *Discover Sustainability*.

Li, Y., & Howe, P. D. (2023). Universal or targeted approaches? An experiment about heat risk messaging. *Natural Hazards, 117*(1), 381–398.

Maghami, M. R. (2025). Impact of dust deposition on photovoltaic systems and mitigation strategies. *Technologies, 14*(1), 15.

Mashuk, M., Siddiky, A. Y., Rayhan, M. T., Hasan, M. J., Khan, M., Mobarak, M. H., & Rimon, M. I. H. (2025). Progress and prospects on performance analysis of solar cleaning system—A comprehensive review. *Solar Compass*, 100146.

Mishra, M. K., Sharma, P., Verma, J., & Pathak, V. (2025). A review of advances in design and technologies for solar panel cleaning systems. *Challenges and Opportunities for Innovation in India*, 307–311.

Murshiduzzaman, As'arry, A., Keong, L. W., Mohamed Yusoff, M. Z., Salit, M. S., Supeni, E. E., & Yussof, H. (2025). Analysis of an automated solar panel cleaning robot on photovoltaics (PV) module frames with composites materials. *Physical Sciences Reviews, 10*(4), 381–394.

Mwebe, D., Eze, V. H. U., & Sadiq, B. O. (2025). Impact of dust accumulation on solar photovoltaic panel performance and the efficacy of cleaning methods: A review of technological innovations and regional considerations. *KIU Journal of Science, Engineering and Technology, 4*(1), 242–261.

Qin, J., & Lu, H. (2023). A review of self-cleaning coatings for solar photovoltaic systems: Theory, materials, preparation, and applications. *Environmental Science and Pollution Research, 30*(40), 91591–91616.

Rahman, T., Lipu, M. H., Sharmin, Z., & Shamsan, Z. A. (2025). Recent advances in dust accumulation on PV systems: Influential factors, characterization, impacts, and future potential for clean energy production. *IEEE Access*.

Rajbahadur, Y. N. K., Kumar, A., Negi, S., & Kar, S. (2024). Evaluation of hydrophobic/hydrophilic and antireflective coatings for photovoltaic panels. *Journal of Coatings Technology and Research*, 1–38.

Shahzad, N., Hussain, N., Umar, S., Azam, M. F., Yousaf, T., & Waqas, A. (2025). Impacts of soiling on solar panel performance and state-of-the-art effective cleaning methods: A recent review. *Journal of Cleaner Production, 497*, Article 145119.

The Uganda Electricity Distribution Company Limited (UEDCL). (2026). Electricity End User Tariffs and Charges. https://www.uedcl.co.ug/approved-tariffs/

Thongsuwan, W., Sroila, W., Kumpika, T., Kantarak, E., & Singjai, P. (2022). Antireflective, photocatalytic, and superhydrophilic coating prepared by facile sparking process for photovoltaic panels. *Scientific Reports, 12*(1), Article 1675.

Uzorka, A., Bawa, M., Omar, A. M., Ounyesiga, L., Akiyode, O. O., & Olaniyan, A. O. (2026). Impact of dust on solar photovoltaic panel efficiency in Kampala Uganda. *Energy Exploration & Exploitation, 44*(1), 104–136.

Yakubu, S., Samikannu, R., Gawusu, S., Wetajega, S. D., Okai, V., Shaibu, A. K. S., & Workneh, G. A. (2025). A holistic review of the effects of dust buildup on solar photovoltaic panel efficiency. *Solar Compass, 13*, Article 100101.

Zhang, Z., Li, Z., & Luo, Z. (2026). Central Asia photovoltaic potential: dust impacts and suitability optimization. *Renewable Energy*, 125463.

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