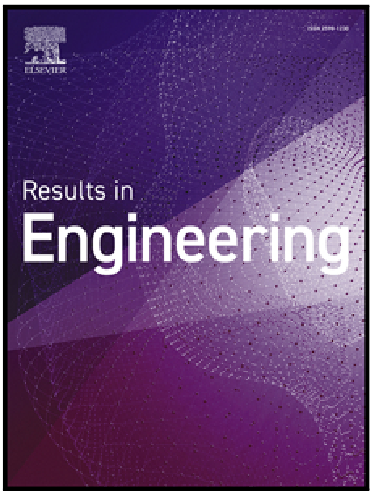

Soiling assessment and cleaning decision analysis for a photovoltaic feasibility study: a case study in a high dust-loaded mining environment

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Highlights

- One-year soiling campaign at a Moroccan mine showed 0.30%/day rate and 5.8% loss
- Dynamic cleaning combines soiling, weather, and economics for optimal decisions
- Dynamic cleaning yields $230k gain and +2.6 pp net revenue with 14 cleanings/year
- It outperforms the best fixed and threshold-based cleaning by +1.1 pp and +0.1 pp
- Dynamic cleaning gives highest NPV ($82.27 M, +4.1%) using market electricity price

Soiling assessment and cleaning decision analysis for a photovoltaic feasibility study: a case study in a high dust-loaded mining environment

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Abstract

Soiling of photovoltaic (PV) modules remains a major operational challenge, as it lowers energy yield and financial performance. Although regular cleaning mitigates soiling losses, selecting an appropriate cleaning strategy is critical, since suboptimal decisions may lead to unnecessary energy losses or excessive operational costs. This study presents a one-year soiling and meteorological measurement campaign conducted as part of a feasibility study for a large-scale PV project at a mining site in Morocco. Ground-based measurements are integrated into a performance model of a simulated 44 MWp PV power plant. Results show an average daily soiling rate (ΔSR) of 0.30%/day, resulting in an annual energy loss of 4,442 MWh (100.9 MWh/MWp), equivalent to 5.8% of potential energy production. A dynamic cleaning decision approach has been employed, combining soiling levels, weather conditions, and economic factors to optimize cleaning timing. Cleaning is triggered only when the projected energy recovery outweighs the associated cleaning expenses. The proposed dynamic cleaning strategy reduces losses to 1.9%, recovering 2,990 MWh annually and generating an economic gain of approximately \$230,000 (\$5.23/kW/year) relative to the no-cleaning scenario. Compared to the best fixed-frequency and threshold-based approaches, the dynamic approach increases net revenue by 1.1 and 0.1 percentage points, respectively, demonstrating its effectiveness for practical PV operation and feasibility assessment. In addition, a detailed economic analysis based on Levelized Cost of Electricity and Net Present Value has been performed to further evaluate the financial viability of the proposed strategy.

Keywords: Photovoltaic, Dust deposition, Soiling monitoring, Soiling mitigation, cleaning optimization.

Nomenclature

Symbols

α	Temperature coefficient of short-circuit current
CC	Cleaning cost (\$/cleaning)
CNC	Completeness of natural cleaning (-)
d	Discount rate (%)
E	Annual energy production (MWh)
E_{Clean}	Output energy of clean solar field (MWh)
E_{Loss}	Energy loss due to soiling (MWh)
E_{Soiled}	Output energy of soiled solar field (MWh)
El_{Price}	Electricity selling price (\$/MWh)
$I_{sc_{Clean}}$	Short-circuit current of clean module (A)
$I_{sc_{Soiled}}$	Short-circuit current of soiled module (A)
N	Project lifetime (Years)
N_c	Number of cleaning operations (-)
RD	Linear degradation rate (%)
RL	Revenue loss due to soiling (\$)
RL_{acc}	Cumulative revenue loss due to soiling (\$)
SL	Soiling loss (%)
$SLAfter$	*Soiling loss after rainfall (%)*
$SLBefore$	*Soiling loss before rainfall (%)*
SLR	*Soiling loss reduction (%)*
SR	*Soiling ratio (-)*
SR_{opt}	*Soiling ratio under optimized cleaning schedule (-)*

STC	*Standard test conditions*
$T_{mod_{Clean}}$	*Back-of-module temperature of clean module (°C)*
$T_{mod_{Soiled}}$	*Back-of-module temperature of soiled module (°C)*
T_{STC}	*Module temperature at standard test conditions (°C)*
ΔSR	*Soiling Rate (%/day)*

Abbreviations

AC	Alternating Current
CAPEX	CAPital Expenditures
CdTe	Cadmium Telluride
DC	Direct Current
HSE	Health, Safety and Environment
LCoE	Levelized cost of electricity
IEC	International Electrotechnical Commission
MWp	Megawatt-peak
NPV	Net present value
NREL	National Renewable Energy Laboratory
OPEX	Operating Expenses
O&M	Operation and Maintenance
PPA	Power Purchase Agreement
PV	Photovoltaic
O&M	Operation and Maintenance
SCADA	Supervisory Control and Data Acquisition
STC	Standard Test Conditions

1. Introduction

As global efforts to fight climate change accelerate, tripling renewable energy capacity by 2030 has become a key goal to help reach the global 1.5 °C ambition and advancing the energy transition [1]. In 2024, significant progress was made, with 585 GW of new renewable capacity added, the highest annual increase so far [2]. Solar PV was the main driver of this expansion, contributing around 452 GW of new capacity. Thanks to its low cost, strong production capacity, and scalability, solar PV is anticipated to remain the leading renewable technology in the coming years in terms of growth [1].

In light of solar PV's current dominance in renewable energy development, it is crucial to identify sites for its construction [3,4]. Desert regions, with their high solar resource and vast available land, are well placed to support this expansion [5,6]. However, operating solar PV plants in desert environments comes with specific challenges [7]. One of the most critical is soiling, the deposition of dust and particles on solar modules, potentially leading to notable energy losses if not properly managed [8–11]. Globally, it is estimated that soiling causes energy losses of at least 4% to 7% in solar PV systems, leading to financial losses of over 4 to 7 billion euros each year [12].

In this context, numerous studies have been conducted and reviews were published on impact of soiling on PV [12–18]. The literature uniformly supports the idea that the presence of soiling leads to a significant reduction in energy production, representing a major economic challenge for PV plants. Consequently, site-specific mitigation and maintenance planning are essential to address this issue and maintain economic viability. Cleaning is an efficient approach to minimizing the impact of soiling. However, frequent cleaning can substantially raise operational expenditure, often representing a non-negligible share of operation and maintenance (O&M) budgets. Consequently, determining the appropriate cleaning schedule becomes a crucial techno-economic decision that requires meticulous consideration to find a good trade-off between the performance of the solar power plant and the costs associated with cleaning [19]. This means that obtaining site-specific information regarding soiling is crucial for optimizing site selection, plant design, O&M decisions, and, thus, also the cleaning schedule planning [20–26].

A number of studies have been conducted to identify the most effective cleaning strategies and frequencies for PV systems across different regions in the world. For instance, Micheli et al [27] investigated the appropriate cleaning schedule for a 1 MWp PV power plant in southern Spain, which had an annual soiling loss of 2.8% assuming no manual cleaning operations. Their findings suggested that adopting one cleaning scenario provided the best economic outcome, leading to the lowest values of both levelized cost of electricity (LCoE) and net present value (NPV). In another study, Urrejola et al [28] assessed the economic feasibility of a cleaning strategy for a PV system in Santiago, Chile, characterized by significant soiling degradation. They determined that the critical cleaning period was 45 days at that site, irrespective of cleaning costs and energy prices. You et al [29] used the NPV to determine the optimal cleaning interval for PV systems in seven cities around the world. Their study revealed that in Doha (UAE), where soiling was high, the most effective cleaning intervals were found to be 17 days for machine-assisted cleaning and 23 days for manual cleaning. At Malibu, on the other hand, optimal intervals were 70 days for manual cleaning and 49 days for machine-assisted cleaning. Rodrigo et al. [30] developed a method to determine the optimal cleaning schedule for a PV system in Aguascalientes, central Mexico, by minimizing the LCoE. Their study indicated that performing cleaning once per year is adequate for both residential and commercial systems in that area. Additionally, optimal cleaning schedules for large-scale PV installations were observed to fall between 12 and 31 days.

These studies contribute to the understanding of optimal cleaning practices for PV technology, focusing on the economic viability and effectiveness of different cleaning schedules. The occurrence of soiling demonstrates pronounced fluctuations over time and across seasons [31,32]. Its effective impact often being more significant during seasons of high system efficiency, typically characterized by high solar irradiance and low ambient temperatures. Despite this, the variability and seasonality of soiling and their effective impact are sometimes overlooked or underestimated in cleaning optimization strategies. In addition, electricity market conditions, which directly influence the economic value of recovered energy, are often neglected. To address these gaps, an adaptive and dynamic cleaning approach that accounts for both environmental and economic trends is essential. Furthermore, the long-term impact of different cleaning strategies on the economic viability of PV plants is rarely evaluated, and many existing approaches are not designed in a way that facilitates practical implementation by O&M teams, limiting their applicability in real-world PV plant operations.

While numerous studies have evaluated soiling impacts across different climatic zones, relatively few have focused on PV performance in dust-intensive industrial environments such as mining sites, where human-induced dust emissions significantly compound natural soiling processes. Temporal characterization of soiling in these environments remains limited. Additionally, the effectiveness of natural cleaning by rainfall, a critical factor in reducing cleaning costs, has received limited quantitative analysis despite its substantial influence on optimal cleaning schedules. Moreover, comparative techno-economic analyses evaluating dynamic cleaning strategies against conventional fixed-frequency and threshold-based approaches are scarce in the literature.

The deployment of large-scale PV power plants by industries as a means of mitigating carbon dioxide emissions has grown substantially, with the mining sector being no exception. Mining sites are characterized by high dust emissions, making soiling of PV panels particularly problematic and call for optimized cleaning strategies tailored to such environments.

In this context, this work addresses the identified knowledge gaps by advancing the understanding of soiling dynamics in dust-intensive industrial environments and by proposing a data-driven dynamic cleaning decision approach. Unlike conventional fixed-frequency or threshold-based methods, the proposed strategy triggers cleaning only when the projected economic benefit exceeds the cleaning cost, thereby ensuring a direct and measurable impact on project profitability.

Building on the preliminary short-term soiling assessment reported in an earlier study by members of the current research team [33], the methodological contribution of this study lies in extending the analysis to a full-year characterization of soiling variability in a dust-intensive mining environment, capturing seasonal trends and quantifying natural cleaning effectiveness using Soiling Loss Reduction (SLR) and Completeness of Natural Cleaning (CNC) metrics. Moreover, the full-year soiling dataset is integrated into a PV performance model to quantify seasonal energy losses under realistic operating conditions. A dynamic cleaning decision approach is implemented that explicitly links measured soiling data with energy production, cleaning costs, and electricity prices. This strategy is systematically compared with conventional fixed-frequency and threshold-based approaches through a comprehensive techno-economic assessment using cleaning net revenue, LCoE, and NPV metrics. The results provide actionable insights for project developers, operators, and owners of solar power plants in dust-prone industrial environments.

This paper is organized as follows: Section 2 presents an overview of the experimental site, including details of weather conditions, and describes the methodology used to measure soiling on site. Section 3 clarifies the procedure proposed to model the PV power plants, describes the methodology employed to estimate energy and revenue losses due to soiling, and outlines the cleaning decision approach. Section 4 reports the results of the annual soiling measurement campaign, including analysis of natural cleaning effectiveness (SLR/CNC), yield analysis of the simulated PV plant highlighting soiling impacts, comparative analysis of cleaning approaches (dynamic vs. fixed-frequency vs. threshold-based), and economic evaluation using LCoE and NPV metrics. The paper concludes with a summary of the main findings and their implications for solar plant operations in mining and industrial environments.

2. Weather and PV soiling measurements

2.1. Weather parameter measurement

This study was carried out on a mining site in Morocco, for a one-year period from July 1, 2022 to June 30, 2023, the precise details of which are confidential. The site represents a typical dust-intensive industrial environment, where anthropogenic emissions from mining activities intensify natural soiling processes, making it a representative test field for assessing soiling and evaluating PV soiling management strategies.

In order to collect relevant data, a weather station (see Fig. 1) was installed to record global horizontal irradiance (GHI), global tilted irradiance at 30° (GTI) as well as various other weather factors such as ambient temperature (T_{amb}), relative humidity (RH), wind speed (WS), wind direction (WD), rain, and atmospheric pressure (BP).

Fig. 1. The weather station installed at the studied mining site.

The weather parameters obtained during the measurement campaign that are used in this study are shown in Fig. 2. The analysis reveals that the site examined has substantial solar potential, as evidenced by a cumulative irradiation of around 1921 kWh/m^2/year for global horizontal irradiance (GHI) and around 2230 kWh/m² for global tilted irradiance (GTI). Meteorological data recorded at an hourly resolution showed that ambient temperatures were particularly high during the summer, reaching a maximum of 44°C. Wind speed and relative humidity are key factors influencing the accumulation of soiling on PV modules [17]. During the campaign, the average relative humidity was 50.6%, and the maximum hourly wind speed reached 11.3 m/s, predominantly from the north-east. The total recorded rainfall was 200.6 mm/year, concentrated mainly between December 2022 and March 2023.

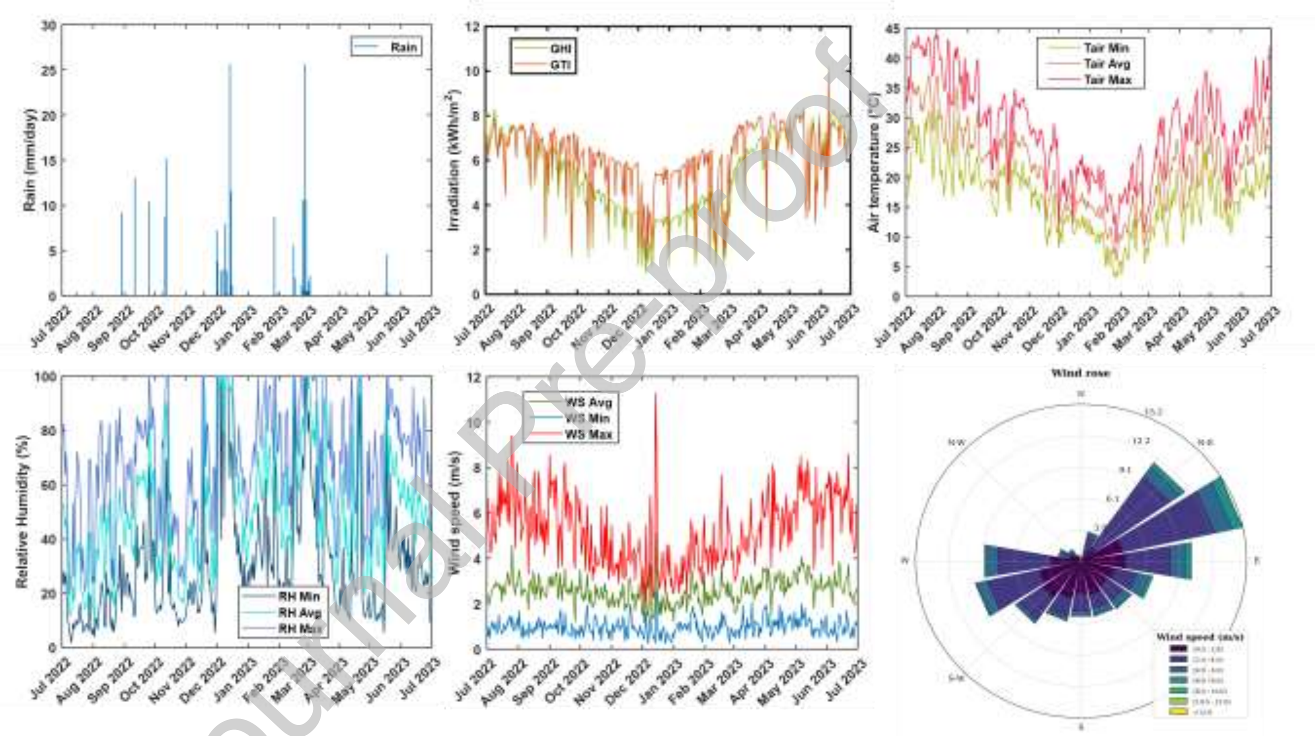

Fig. 2. The daily values of the measured weather parameters at the mining site.

2.2. PV soiling measurement

A PV soiling monitoring station was installed at the site (Fig. 3) following the dual-module methodology detailed in IEC 61724-1 standard, "method 2: short-circuit current reduction due to soiling" [34]. The system employed two thin-film CdTe PV panels (Calyxo CX3 75W) mounted at 30° tilt, south-facing orientation, alongside a thermopile pyranometer in the same plane. CdTe technology was selected for its reduced sensitivity to non-uniform soiling distribution compared to crystalline modules [35].

The soiling ratio SR was calculated following Eq. 1, with daily values derived from one-minute measurements averaged over the 10:00-15:00 window when irradiance exceeded 500 W/m². Data quality control procedures, including outlier removal and calibration against clean-module conditions, were implemented as described in [33].

Fig. 3. The soiling station installed at the studied mining site.

$$SR(t) = \frac{I_{sc_{Soiled}(t)} \times (1 + (T_{STC} - T_{mod_{Soiled}(t)}) \times \alpha)}{I_{sc_{Clean}(t)} \times (1 + (T_{STC} - T_{mod_{Clean}(t)}) \times \alpha)} \quad (1)$$

where $I_{sc_{Soiled}}$ and $I_{sc_{Clean}}$ represent the short-circuit currents of the soiled and clean PV modules, respectively, without applying temperature correction., T_{STC} denotes the module temperature under standard test conditions (STC), typically 25°C. $T_{mod_{Soiled}}$ and $T_{mod_{Clean}}$are the measured soiled and clean PV module temperatures, respectively. α corresponds to the module's temperature coefficient for I_{sc} as provided by the PV module manufacturer.

3. PV power plant model and cleaning decision approach

3.1. The modeling of the PV power plant

To simulate the energy yield of the proposed solar plant, the Python library "PVLib" was employed [36]. PVLib provides a wide range of functions and classes specifically designed to simulate the performance of PV power systems. Its utility and prominence within the PV research community have been widely recognized [37–41]. The flowchart in Fig. 4 gives a general workflow of the modeling steps of the PV plant using PVLib. For a comprehensive description of the mathematical implementation and Python functions employed in the utilized models, refer to [42].

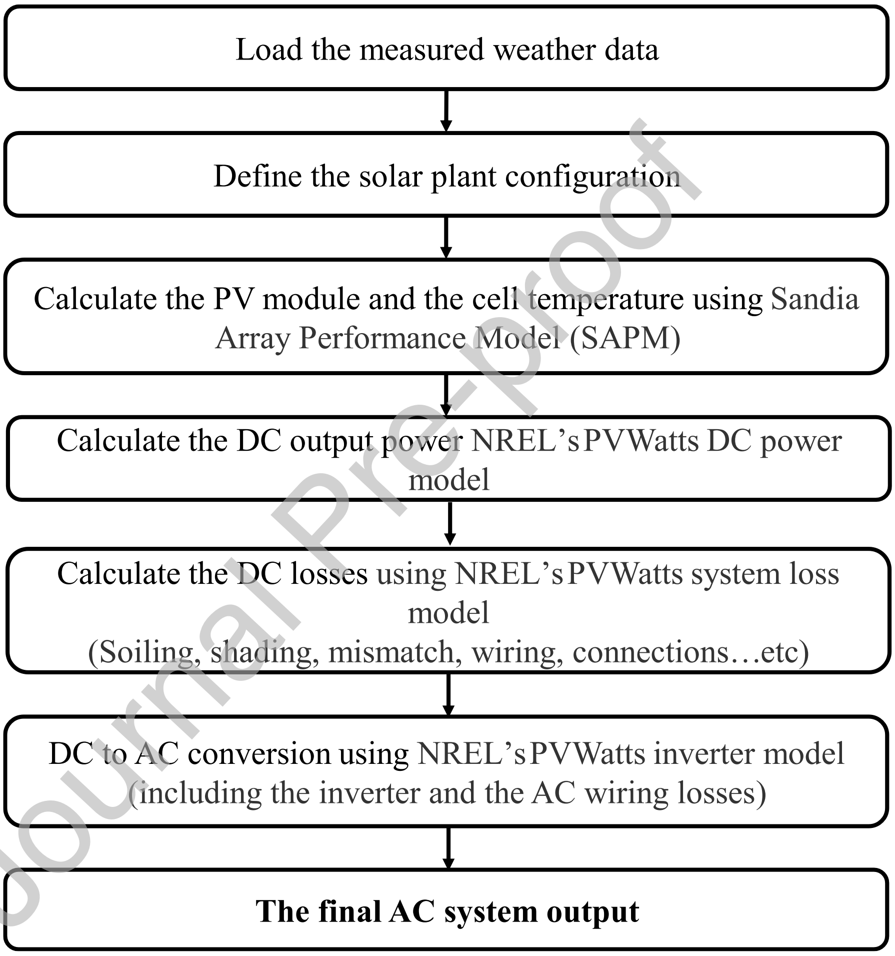

Fig. 4. The PV system modeling workflow.

The default loss assumptions of the original PVWatts model [43] were primarily used, with the exception of the soiling parameter (see section 3.2).

Table 1 provides the configuration of the simulated PV power plant along with the specifications of the PV modules under STC.

Table 1. The simulated PV plant configuration and the specifications of the used PV module.

PV plant capacity	44 MWp
Installation type	Fixed ground mounted PV
Tilt angle/ Orientation	30°/ South-facing
PV technology	Monofacial monocrystalline
PV maximum power (P_{MAX})	540 W
PV maximum power voltage (V_{MP})	41.64 V
PV maximum power current (I_{MP})	12.97 A
PV open circuit voltage (V_{OC})	49.60 V
PV short circuit current (I_{SC})	13.86 A
P_{MAX} temperature coefficient (γ_p)	-0.350 %/°C
I_{SC} temperature coefficient (α_{IscMod})	+0.045 %/°C

3.2.The energy and the revenue loss due to soiling

Energy loss was estimated using NREL's PVWatts system loss model, as implemented in PVLib [43,44]. This model was applied to simulate a 44 MWp utility-scale plant over a full annual cycle. The approach uses the temporal resolution of the measured soiling data rather than assuming constant monthly or an average value of annual soiling losses, thereby capturing seasonal performance variations critical to mining site operations. Two parallel scenarios were simulated using measured weather data and plant configuration: (i) a permanently clean reference case (SR = 1.0), and (ii) a realistic operation scenario incorporating measured daily SR profiles. Daily energy loss (E_{Loss}, MWh) was computed as the difference between these scenarios (Eq. 2):

$$E_{Loss} = E_{Clean} - E_{\mathrm{Soiled}} \tag{2}$$

Daily revenue loss RL was calculated by multiplying E_{Loss} by the local electricity price El_{Price}, as shown in Eq. 3

$$RL = E_{Loss} \times El_{\mathrm{Pr}ice} \tag{3}$$

It should be noted that local electricity prices are affected by multiple factors, including policy and regulatory frameworks, technical considerations, power plant business models, and Power Purchase Agreement (PPA) terms. However, specific electricity tariffs for individual projects typically remain confidential, limiting public access to this information. Variability in electricity prices significantly affects cleaning decisions: higher electricity prices mean that energy recovered from cleaning generates greater economic returns, while lower prices reduce these benefits. This relationship has been confirmed through sensitivity analysis by Micheli et al. [45], who examined the effects of electricity price and cleaning cost on the optimal number of cleanings. They found that the most favorable conditions for more frequent cleaning occur when high electricity prices are combined with low cleaning costs, which minimize soiling losses and maximize energy yield.

According to the SolarPower Europe report on Moroccan solar investment opportunities [46], average electricity prices have shown notable fluctuations, declining from \$108.48/MWh in 2021 to \$97.54/MWh in 2022, before rising again to \$121/MWh in 2024. Based on this recent market data, an electricity price of \$121/MWh has been adopted for this study.

3.3. Cleaning decision approach

This study employs the dynamic cleaning decision approach developed in [33]. The cleaning is initiated once the cumulative revenue loss since the last cleaning (RL_{acc}) surpasses the estimated on-site cleaning cost CC. This logic ensures that interventions occur only when financially justified, and considers the temporal variability of soiling across seasons, fluctuations in dust generation caused by human activities, and the influence of natural cleaning events that can restore performance without additional cost.

For this feasibility study, covering 365 days without manual cleaning of the soiled module, the measured daily SR was post-processed to simulate economically optimal cleaning dates using the approach detailed in [33]. The day-to-day variation in SR was first evaluated to distinguish between soiling accumulation and natural recovery effects. Based on this variation, an optimal SR time series (SR_{opt}) was reconstructed by resetting SR to unity at each proposed cleaning date and propagating the daily SR changes between successive cleaning events . The resulting SR_{opt}

therefore represents the expected SR profile under an economically optimized cleaning schedule derived from site-specific measured conditions rather than predetermined cleaning intervals.

Fig. 5 shows the flowchart describing the steps involved in simulating the SR_{opt} to identify the most favorable cleaning dates for the feasibility analysis.

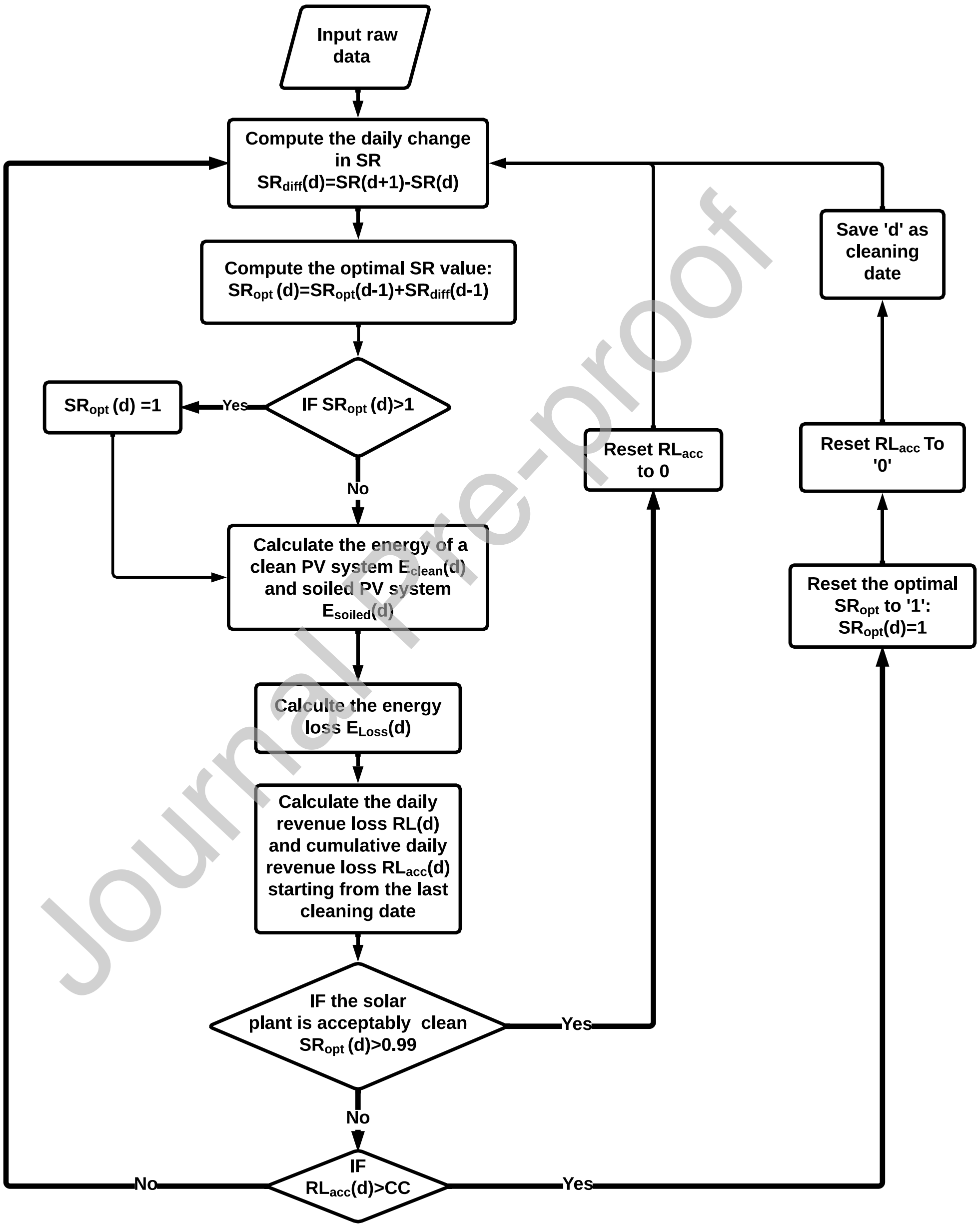

Fig. 5. The cleaning approach employed in this study (based on [33]).

4. Results and discussion

4.1. Soiling and rain data analysis

This section reports the findings of the annual soiling measurement campaign conducted from July 1st, 2022 to June 30, 2023 at the mining site. The year-long monitoring period enables identification of extreme soiling periods, seasonal patterns, and natural cleaning events characteristic of dust-intensive industrial environments, providing the temporal coverage necessary for reliable PV feasibility assessments and O&M planning. Fig. 6 depicts the daily *SR* measurements obtained from the soiling station installed at the study site, along with the corresponding daily rainfall data obtained from the weather station.

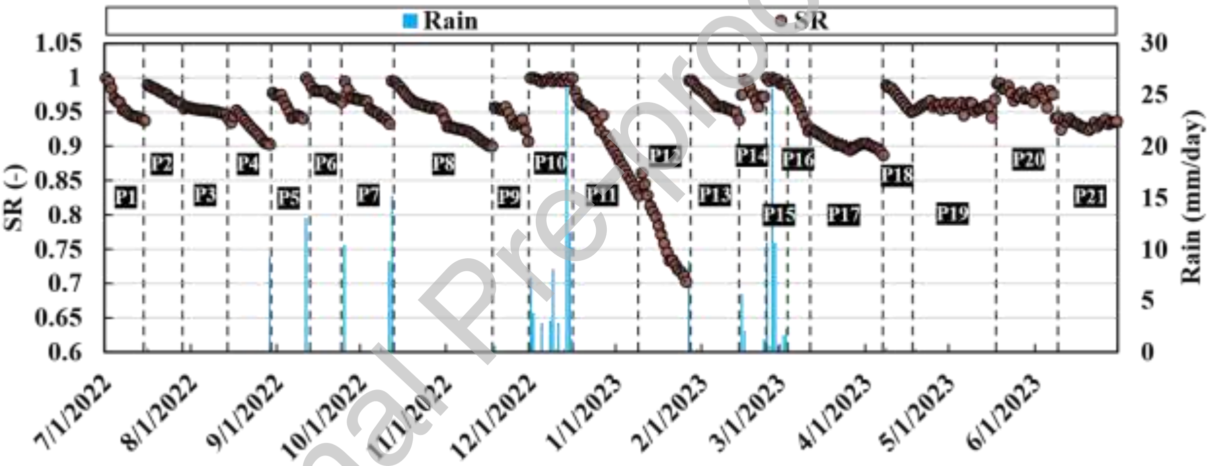

Fig. 6. The daily SR measured during the study period at the mining site.

As shown in Fig. 6, during rain-free periods, the *SR* gradually decreases due to the continued accumulation of soiling. However, minor variations in *SR* can still occur, potentially influenced by other weather factors such as wind. These factors can either promote or inhibit the accumulation of soiling.

It is apparent that rainfall contributes to partial or complete performance recovery. To further assess the impact of natural cleaning on soiling, given its implications for optimizing cleaning operations, two metrics found in the literature were calculated: Soiling Loss Reduction (SLR) and Completeness of Natural Cleaning (CNC) [40,47]. These metrics are defined as follows:

$$SLR = SL_{Before} - SL_{After} \tag{4}$$

$$CNC = \frac{SL_{Before} - SL_{After}}{SL_{Before}} \tag{5}$$

Where Soiling Loss (*SL*) is calculated as follows:

$$SL[\%] = (1 - SR) \times 100 \tag{6}$$

Positive CNC values below 1 indicate partial cleaning, with a value of 1 representing complete cleaning of the PV module. A value of 0 denotes no cleaning, while negative values suggest that rainfall contributed to additional soiling, as might occur with events like red rain [48].

For this analysis, only rainfall events occurring after a significant level of *SL* were considered. Days with low *SL* values, specifically those in which rainfall occurred shortly after a previous rain event (i.e., when $SL < 3\%$) were excluded to ensure that only meaningful cleaning events were analyzed and to minimize uncertainties associated with low *SL* levels, as noted in [47]. This filtering process resulted in 17 rain events selected from an initial total of 40.

The findings from this analysis are summarized in Table 2 and illustrated in Fig. 7. Table 2 summarizes the selected rain events along with their corresponding SLR and CNC values. Fig. 7 shows the scatter plots of the SLR versus the initial SL before the rain event as a function of rain and the scatter plots of the CNC versus rain sum as a function of SL before the rain.

The results of this analysis reveal that, in general, higher rainfall tends to result in greater SLR and higher CNC. However, it is evident that rainfall quantity alone does not fully explain the observed variations in cleaning effectiveness. A crucial factor influencing both SLR and CNC is the initial soiling level prior to the rain event (*SL* before). As shown in Table 2 and further illustrated in Fig. 7a, there is a clear positive correlation between *SL* before and the corresponding SLR: when the module is more soiled prior to the rain, the absolute reduction in soiling loss tends to be higher. This relationship is expected, as higher initial soiling levels offer greater potential for recovery. For instance, the event on January 27, 2023, with a *SL* before of 29.71%, achieved a SLR of 29.35%, nearly a complete recovery (CNC=0.99). However, Fig. 7b reveals that the natural cleaning efficiency is more complex and not easily predictable based solely on the initial soiling level and the amount of rainfall. Although CNC generally tends to increase with higher rainfall amounts, no clear rainfall threshold can be identified that guarantees complete cleaning. This complexity emphasizes the need for extended measurement campaigns across regions with diverse climatic conditions, to capture the full range of influencing factors. Furthermore, incorporating additional environmental measurement parameters, such as dew sensors to quantify moisture formation patterns, could provide valuable insights into dust particle adhesion mechanisms and their influence on natural cleaning effectiveness.

Table 2. Summary of selected rain events along with the corresponding rainfall amount, SL before, SL after, SLR, and CNC.

Day	**Rainfall [mm/day]**	**SL Before [%]**	**SL After [%]**	**SLR [%]**	**CNC [-]**
7/16/2022	0.4	6.22	1.03	5.19	0.83
8/29/2022	9.2	9.65	2.16	7.49	0.78
9/11/2022	13.0	5.98	0.00	5.98	1.00
9/25/2022	10.4	3.54	0.50	3.04	0.86
10/11/2022	8.8	6.66	0.49	6.17	0.93
11/18/2022	0.6	9.99	4.28	5.71	0.57
12/1/2022	7.2	9.23	0.00	9.23	1.00
1/27/2023	8.8	29.71	0.36	29.35	0.99
2/15/2023	5.6	6.10	2.48	3.62	0.59
2/16/2023	2.0	2.48	0.33	2.15	0.87
2/24/2023	10.6	2.76	0.00	2.76	1.00
4/8/2023	0.4	11.26	1.11	10.15	0.90
4/18/2023	0.2	4.99	4.57	0.42	0.08

4/19/2023	0.2	4.57	4.30	0.27	0.06
5/17/2023	0.4	5.75	3.20	2.55	0.44
5/18/2023	4.6	3.20	0.82	2.38	0.74
6/1/2023	0.2	3.52	1.55	1.97	0.56

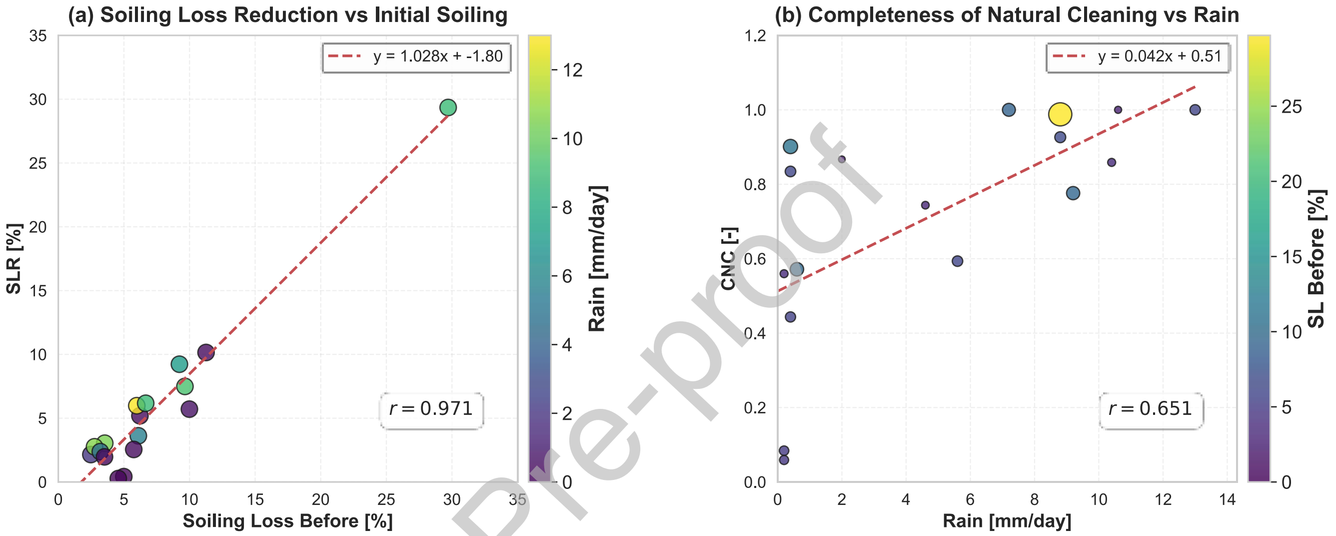

Fig. 7. (a) Scatter plot of Soiling Loss Reduction (SLR) versus initial soiling level (SL before) for different rain intensities. (b) Scatter plot of Completeness of Natural Cleaning (CNC) versus rain amount, as a function of initial soiling level (SL before).

Having analyzed the effectiveness of natural cleaning by rainfall events, it is equally important to understand the variability and dynamics of soiling accumulation between the natural cleaning period. Throughout the study period, notable variations in the rate of soiling accumulation were observed. To assess this variability, 21 distinct periods (P1 to P21; see Fig. 6) were identified based on changes in the trend of *SR* and the noticeable impact of natural cleaning events. To quantify the daily accumulation rate for each time period, the soiling rate (ΔSR: %/day) was determined as the absolute value of the slope from a linear regression of *SR* over time. Table 3 summarizes the ΔSR values for each period and provides the weighted average ΔSR. These results give insight into the soiling accumulation variability observed during the different time periods of the study.

Table 3. The ΔSR measured for each period.

Period	Period length (days)	Average ΔSR value (%/day)
P1: 07/01/2022 – 07/15/2022	15	0.43
P2: 07/16/2022 – 07/26/2022	11	0.24
P3: 07/27/2022 – 08/15/2022	20	0.10
P4: 08/16/2022 – 08/29/2022	14	0.43
P5: 08/30/2022 – 09/10/2022	12	0.40
P6: 09/11/2022 – 09/24/2022	14	0.23
P7: 09/25/2022 – 10/11/2022	17	0.32
P8: 10/12/2022 – 11/17/2022	37	0.26
P9: 11/18/2022 – 11/30/2022	13	0.34
P10: 12/01/2022 – 12/13/2022	13	0
P11: 12/14/2022 – 01/09/2023	27	0.66
P12: 01/10/2023 – 01/26/2023	17	0.97
P13: 01/27/2023 – 02/14/2023	19	0.30
P14: 02/15/2023 – 02/23/2023	09	0.29
P15: 02/24/2023 – 03/03/2023	08	0
P16: 03/04/2023 – 03/11/2023	08	0.89
P17: 12/03/2023 – 04/07/2023	27	0.14
P18: 04/08/2023 – 04/17/2023	10	0.45
P19: 04/18/2023 – 05/17/2023	30	0.03
P20: 05/18/2023 – 06/07/2023	21	0.19
P21: 06/08/2023– 06/30/2023	23	0.12
The weighted average ΔSR value		**0.30**

The period between December 14, 2022, and January 26, 2023, exhibited significant soiling accumulation, primarily attributed to the recorded high soiling rate values (ΔSR = 0.66%/day and ΔSR = 0.97%/day for P11 and P12, respectively). Furthermore, this accumulation was further exacerbated by the extended duration of approximately 44 days without any effective natural cleaning events. The process of soiling accumulation during the monitoring period was further investigated by documenting the condition of the soiling station under different accumulation states, along with the corresponding *SR* values, as shown in Fig. 8. The visual records clearly show that the rate of accumulation of soiling particles was remarkably high, occurring even in short time intervals. In a single month, the SR decreased substantially from 0.91 to 0.70 (i.e., a 21% loss due to soiling). However, on January 27, 2023, a rainfall of 8.8 mm/day restored the *SR* to a value of 0.99. Although other periods (e.g., P1, P4, P5, P16) also experienced high ΔSR values ranging from 0.40%/day to 0.89%/day, SR did not reach extremely low levels due to intermittent precipitation that partially or fully restored the performance. In contrast, soiling accumulation during periods P10 and P15 was insignificant (ΔSR = 0%/day), mainly thanks to the occurrence of considerable and continuous rainfall events throughout these periods. The remaining periods had low to moderate ΔSR values that were not as significant, although not negligible. The daily average ΔSR value for the entire study period, weighted by the duration of each period, was approximately 0.30%/day. It should be noted that in the context of mine sites, the rate of soiling accumulation is influenced by environmental factors including the effects of the mining activities, which may account for the observed variability pattern in soiling rates at the study site. Moreover, it is worth noting that the average ΔSR value observed over the annual cycle is significantly higher than the results reported in previous studies conducted in high-soiling regions of Morocco [49,50], but without proximate industrial activities. This elevated soiling rate indicates that mining site environments experience substantially greater particle accumulation than typical conditions, likely driven by anthropogenic dust emissions associated with extraction, processing, and transportation operations.

Fig. 8. The soiling station under different soiling conditions with the corresponding SR values.

4.2. Soiling effect on the PV plant energy production

Building upon the annual soiling characterization (Section 4.1), this section evaluates the effect of measured soiling profiles on a simulated 44 MWp PV plant at the mining site. Fig. 9 shows the total monthly AC energy produced by the plant under two scenarios: permanently clean and soiled (cleaned only by natural effects such as rain). In the clean solar field scenario, the highest monthly energy production was observed in March 2023, amounting to 7530 MWh, while the lowest was observed in December, with a total of 4513 MWh. On the other hand, considering the soiling impact, the maximum monthly power production was recorded in April 2023, reaching 7047 MWh, while the minimum was recorded in December, which was 4353 MWh. These results point out the substantial influence of the soiling factor on the monthly energy production profile.

The month of January exhibited the highest energy loss due to soiling, exceeding 1 GWh, equivalent to roughly 18 % of energy production during that month. This significant loss is primarily attributed to the prolonged period of high soiling rate accumulation with no intervening rain or cleaning events, which allowed the soiling to build up and significantly reduce system performance.

In contrast, the lowest energy losses were observed in February 2023, totaling approximately 145.8 MWh. This sharp reduction in loss is likely due to a rain event on January 27, 2023, which effectively cleaned the panels and restored their performance. Additionally, overall energy production in February was relatively low, which further reduced the absolute magnitude of energy loss due to soiling.

It should be noted that absolute energy losses are affected not only by the degree of soiling but also by weather conditions, including solar irradiance and temperature, which influence overall energy production. As a result, the same level of soiling may lead to smaller energy losses during months with lower irradiance, since the energy yield is already reduced due to unfavorable weather.

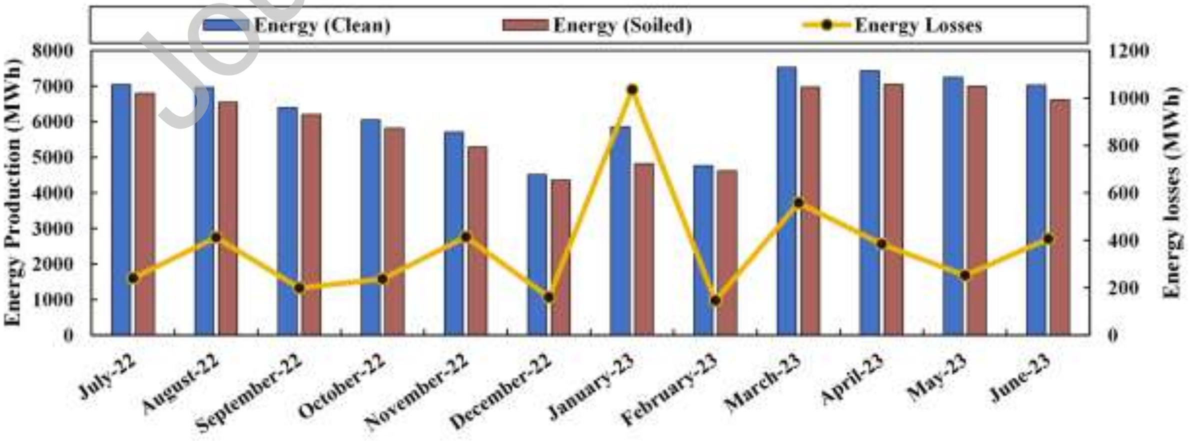

Fig. 9. The monthly energy production in the case of clean and soiled solar field.

Fig. 10 shows the total energy production generated by the proposed PV plants during the study period under clean and soiled conditions. In the absence of soiling, the solar field produced a total energy output of 76518 MWh. When the effects of soiling were considered, the total output decreased to 72076 MWh, corresponding to a loss of 4442 MWh, or approximately 5.8% of the annual energy production.

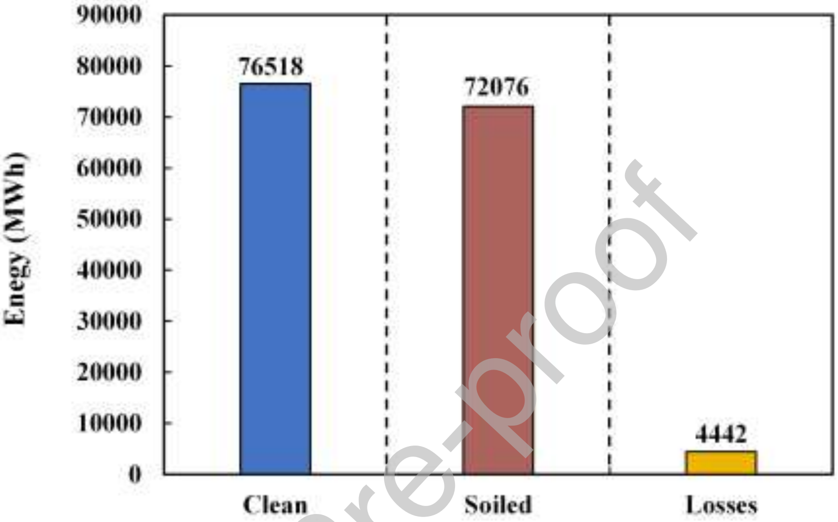

Fig. 10. Total energy production for both clean and soiled solar fields.

4.3. Cleaning decision

As previously stated, the proposed approach recommends cleaning when the cumulative revenue loss exceeds the cost of cleaning *CC*, as cleaning on such days is both economically justified and operationally beneficial. In this study, a cleaning cost of $9460 (approx. $215/MWp) is used, based on recent studies conducted in Morocco [33,51].

In this analysis, it is assumed that manual cleaning operations are carried out during night hours, and the adopted cleaning cost reflects the number of workers and equipment required to clean a 44 MWp PV plant within 8-hour nighttime period using local labor costs. However, it is important to note that the selection of an optimal cleaning method is a separate topic that requires further study in future work, as it depends on numerous parameters including PV plant configuration, local costs, health, safety and environmental (HSE) factors, and the social impact of the project. Therefore, determining the most appropriate cleaning method should precede the optimization of cleaning schedules. For the sake of simplicity, and in line with recent works on soiling and cleaning in Morocco [33,51], this study adopts the cost estimate mentioned above, focusing on evaluating the impact of cleaning schedules on the overall viability of PV plant operation rather than to determine the optimal cleaning method.

Fig. 11 shows the cumulative daily revenue loss due to soiling (RL_{acc}) and the corresponding cleaning dates recommended by the algorithm. A total of 14 cleaning operations were proposed over the 1 year study period. Each cleaning date is triggered when the RL_{acc}exceeds the CC threshold (represented by the green dashed line). After each cleaning event, or whenever rainfall achieves an acceptable performance recovery, the RL_{acc} is reset to zero.

The duration between two consecutive cleaning operations (referred to as the cleaning period) varies depending on the soiling accumulation rate observed during each interval (see Fig. 6 and Table 2), as well as the frequency of natural cleaning events. Specifically, shorter intervals (i.e., more frequent cleanings) are observed during periods of high soiling accumulation and infrequent rainfall, whereas longer intervals are observed when natural cleaning events are more frequent or when the soiling accumulation rate is relatively low. This dynamic adjustment highlights the effectiveness of the proposed cleaning approach in adapting to environmental conditions to maintain plant performance while minimizing unnecessary costs.

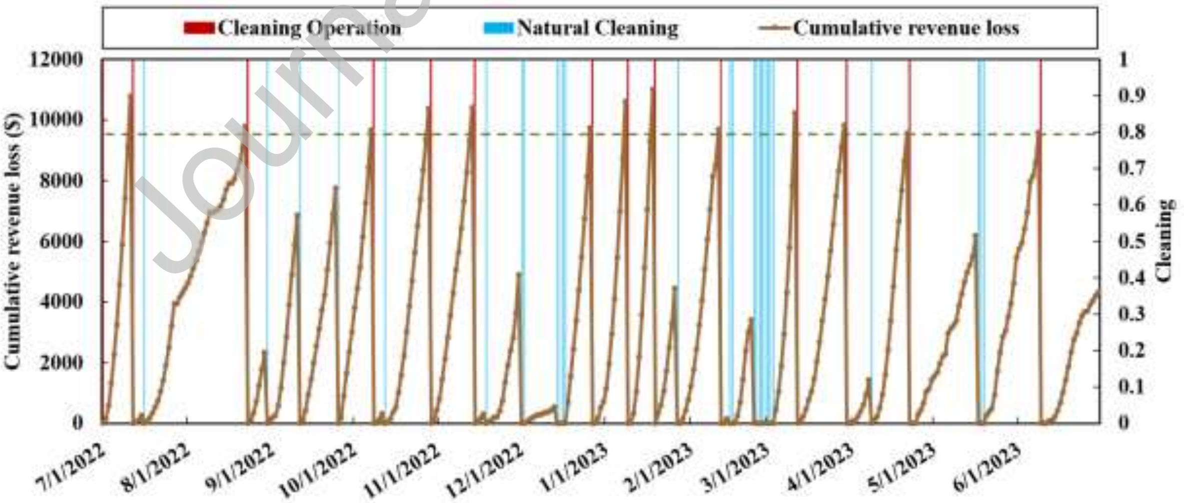

Fig. 11. Daily cumulative revenue loss due to soiling over the annual measurement campaign, showing the 14 cleaning operations (red vertical lines) and natural cleaning events (light blue lines) determined using the dynamic decision algorithm.

Fig. 12 shows the daily energy losses due to soiling under two scenarios: No cleaning and following the proposed cleaning schedule. This figure highlights the negative effects of soiling and underscores the importance of an appropriate cleaning strategy. The analysis indicates that the maximum daily energy loss, around 66 MWh, occurred on January 26, 2023. This result is consistent with expectations, as this period typically experiences high soiling accumulation and no rainfall. The losses on this day are the result of cumulative soiling over 43 days since the last rainfall on December 15, 2022, resulting in a total energy loss of approximately 1182 MWh. Fortunately, the rainfall event on January 27, 2023, with around 8.8 mm/day of precipitation, effectively cleaned the solar panels, restoring their performance at no additional cost. Although energy losses due to soiling were lower in the following periods due to a reduced soiling accumulation rate and occasional rain events, the losses remained significant. Hence, it is crucial to establish a suitable cleaning policy that manages the trade-off between revenue losses caused by soiling and the corresponding cleaning expenses.

As shown in Fig. 12, the proposed cleaning schedule successfully maintains the energy loss due to soiling within acceptable limits. Under the proposed cleaning schedule, the maximum daily energy loss from soiling was about 20 MWh, observed on March 11, 2023. Over the full evaluation period, total energy losses reached 1452 MWh, corresponding to a reduction in average annual soiling losses from 5.8% to 1.9% due to the scheduled cleanings.

It is important to note that the cleaning algorithm may sometimes schedule a cleaning shortly before a natural cleaning event occurs. This can be attributed to the decision algorithm used in the feasibility studies, which does not account for future precipitation due to the potential uncertainty and variability in rainfall patterns from year to year. Feasibility studies are primarily used to provide preliminary understanding of various factors, including optimal cleaning frequency, seasonal variations in cleaning intervals, associated costs, and expected economic benefits. In contrast, for operational solar power plants, O&M teams can employ weather forecasting tools to enhance the cleaning decision-making process, as also discussed [52].

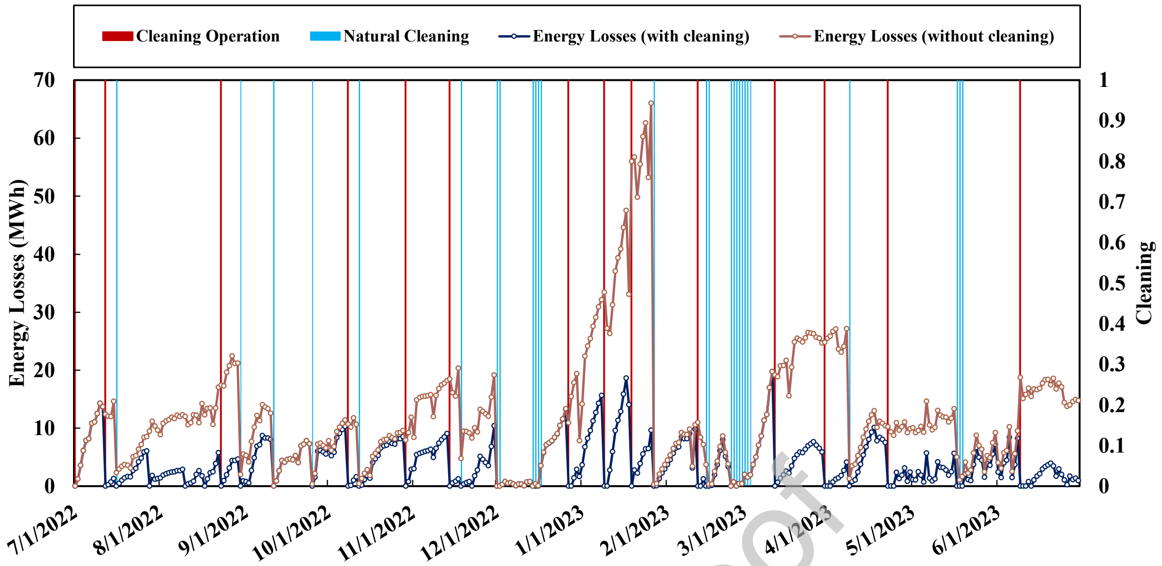

Fig. 12. The daily energy loss due to soiling in two scenarios: without any cleaning and when the proposed cleaning schedule is applied. Natural cleaning events (light blue) and scheduled cleaning operations (red) are indicated with vertical lines.

To assess the economic benefits of the proposed cleaning approach, the net revenue metric was employed. This metric allows us to assess the balance between energy revenues generated and total cleaning costs. It is particularly relevant for this evaluation as it reflects only two key parameters affected by cleaning: the value of the energy produced, which is dependent on the local electricity market, and the cleaning expenses. This simplicity makes it an effective and practical indicator for comparing cleaning strategies. However, this metric does not truly reflect the real revenue of a PV project as more detailed economic analysis is required and could incorporate additional operational, maintenance, and financial costs, as well as potential degradation or availability impacts. Net revenue can be simplistically defined as follows:

$$\mathrm{Net\_Re}venue = E \times El_{\mathrm{Price}} - N_C \times CC \qquad (7)$$

Here, E denotes the total AC energy produced by the PV plant over the analysis period. El_{Price} is the unit electricity price per MWh, while N_C is the annual number of cleaning actions and CC corresponds to the cost of a single cleaning operation.

Table 4 summarizes the total energy generated and the estimated net revenue for the no-cleaning and proposed cleaning scenarios.

Table 4. The total produced energy and the net revenue for no cleaning and with-cleaning scenarios.

Metric	**No cleaning**	**With cleaning**	**Relative improvement (%)**
Total produced AC energy (MWh)	72076	75066	–
Gain in AC energy (MWh)	–	2990	+4.1
Net revenue ($\$\times10^3$)	8721	8951	–
Economic gain ($\$\times10^3$)	–	230	+2.6

The net revenue of the proposed solar plant was assessed for two conditions: (i) using the dynamic cleaning schedule and (ii) assuming no cleaning at all. Although the no-cleaning scenario incurs no cleaning costs (Nc=0), its net revenue is still lower than that obtained with the dynamic cleaning approach, which required 14 cleaning operations (Nc=14). This confirms that the proposed approach effectively balances cleaning expenses against the revenue losses caused by soiling. Overall, the economic gain achieved by following the recommended schedule is approximately \$230,000, corresponding to about \$5.23/kW/year.

4.4. Comparative analysis between conventional cleaning schedules approaches and dynamic cleaning.

Traditionally, solar plant operators have relied on two predominant approaches for PV plants cleaning: fixed cleaning frequencies and threshold-based strategies triggered when predefined soiling loss thresholds measured by soiling sensors are exceeded. Such soiling sensors are increasingly being installed in PV plants and implemented in Supervisory Control and Data Acquisition (SCADA) systems to align with the IEC 61724-1 standards for PV plants performance monitoring [34]. However, these methods often fail to keep the optimal performance and the economic viability of the solar plant. Fixed cleaning frequencies , while simple to implement, do not consider the site-specific variability of soiling rates leading to cleaning schedules that may result in unnecessary interventions or prolonged performance losses. threshold-based strategies that rely solely on soiling loss measurements might be able to capture soiling rate variability but fail to keep the economic balance between cleaning costs and energy production losses, in particular if an inadequate threshold is selected. For this reason, the dynamic cleaning approach proposed in this work aimed to achieve a trade-off between cleaning costs and potential energy production losses as the proposed method considers the particular economic impact of each potential cleaning operation.

To assess the economic benefits of the three main approaches, the net revenue factor was calculated (defined in Eq. 7) for each approach and then compared with the “no-cleaning” scenario to calculate the economic gain that is the difference between the net revenue of each scenario and the net revenue of no cleaning scenario. The results of this comparative analysis are presented in Table 5 and Table 6, for the dynamic cleaning versus the fixed cleaning frequency and the dynamic cleaning versus the threshold-based approach, respectively.

The results shown in Tables 5 and 6 demonstrate clear benefits of dynamic cleaning over fixed cleaning frequency and threshold-based cleaning approaches. The dynamic cleaning achieved the highest economic gain of approximately \$230,000 compared with the no-cleaning scenario, representing a 2.6 percentage-point increase in net revenue. This outperforms the best fixed frequency (1-month cleaning at \$134,000, or 1.5 percentage-point increase) by 1.1 percentage points and slightly exceeds the best threshold-based approach (6% SL threshold at \$218,000, or 2.5 percentage-point increase) by 0.1 percentage points.

In terms of operational efficiency, dynamic cleaning required 14 cleanings per year compared with 12 cleanings for the best fixed frequency approach (1-month cleaning), representing only two additional interventions. When compared with the best threshold-based approach (6% soiling loss threshold), which required 11 cleanings per year, dynamic cleaning involved only three more interventions but offered a higher economic return.

The dynamic cleaning approach also performed favorably in terms of energy loss management, with a total energy loss of 1452 MWh, lower than both the 1-month fixed cleaning schedule (2394 MWh) and the SL threshold approach (1776 MWh). Notably, it reduced energy losses by 969 MWh (40.5%) compared to the 1-month schedule, and by 351 MWh (19.8%) relative to the SL threshold-based approach.

Table 5. Comparative analysis of dynamic cleaning approach versus fixed frequency cleaning frequencies. Values are shown as absolute numbers for the reference case (No cleaning) and as percentage changes for all cleaning strategies. **Bold** values indicate the cleaning strategies with the highest economic gain.

	No cleaning	**Dynamic cleaning**	**1 Week cleaning**	**2 weeks cleaning**	**1 month cleaning**	**2 months cleaning**	**4 months cleaning**
Number of cleaning per year	0	**14**	53	27	**12**	6	3
Total produced AC energy (MWh)	72076	**+ 4.1 %**	+5.1 %	+4.3 %	**+2.8 %**	+2.0 %	+0.9 %
Total energy loss (MWh)	4442	**-67.3 %**	-84.8 %	-69.4 %	**- 46.7 %**	-34.0 %	-16.8 %
Net Revenue ($\$\times10^3$)	8721	**+2.6 %**	+1.3 %	-2.9 %	**+ 1.5 %**	+1.4 %	+0.7 %
Economic gain ($\$\times10^3$)	-	**230**	117	102	**134**	126	62

Table 6. Comparative analysis of dynamic cleaning approach versus threshold-based approach with various SL thresholds. Values are shown as absolute numbers for the reference case (No cleaning) and as percentage changes for all cleaning strategies. **Bold** values indicate the cleaning strategies with the highest economic gain

	No cleaning	**Dynamic cleaning**	**2% SL threshold**	**4% SL threshold**	**6% SL threshold**	**8% SL threshold**	**10% SL threshold**
Number of cleaning per year	0	**14**	41	17	**11**	7	3
Total produced AC energy (MWh)	72076	**+4.1 %**	+5.3 %	+4.1 %	**+3.7 %**	+2.8 %	+2.4 %
Total energy loss (MWh)	4442	**-67.3 %**	-87.2 %	-66.5 %	**-60.0 %**	-47.6 %	-38.7 %
Net Revenue ($\$\times10^3$)	8721	**+2.6 %**	+0.9 %	+2.3 %	**+2.5 %**	+2.2 %	+2.1 %

Economic gain (\$×10^3)	-	**230**	81	197	**218**	190	180

These results demonstrate that even when compared directly to the best conventional alternatives, dynamic cleaning provides a superior balance between cleaning frequency, energy production, and economic returns, as cleaning interventions are triggered based on economic impact rather than fixed schedules or simple thresholds. The dynamic approach therefore maximizes net revenue while ensuring efficient allocation of operational resources. For practical implementation, the dynamic cleaning algorithm could be integrated into existing SCADA systems with automated notifications triggering whenever the calculated economic value of potential energy recovery exceeds cleaning costs. Such implementation would enable solar plant operators to systematically optimize maintenance operations, ultimately improving plant profitability throughout its operational lifetime.

4.5. LCoE and NPV Assessment of Cleaning Approaches

This section aims to assess the economic impact of different cleaning approaches using two widely accepted financial evaluation metrics: the LCoE and the NPV. These indicators are essential in evaluating the financial viability of solar projects, particularly when comparing operational strategies that influence energy production and operational costs.

The LCoE quantifies the cost of producing electrical energy per MWh over the lifetime of a power plant. It is particularly relevant in feasibility assessments and commonly used to benchmark the cost-competitiveness of utility-scale PV projects against other energy generation technologies [27,51,53]. NPV, on the other hand, is used to assess the profitability of an investment by comparing the present value of all expected cash inflows with the present value of the associated cash outflows over the project lifetime [25,54]. The equations 8 and 9 are for LCoE and NPV calculation, respectively:

$$LCoE = \frac{CAPEX + \sum_{n=0}^{N} (OPEX + Nc \times CC) \Big/ (1+d)^n}{\sum_{n=0}^{N} E \times (1-R_D)^n \Big/ (1+d)^n} \qquad (8)$$

$$NPV = -CAPEX + \sum_{n=0}^{N} \frac{El_{\mathrm{Price}} \times E \times (1 - R_D)^n - (OPEX + N_c \times CC)}{(1+d)^n} \tag{9}$$

Table 7 summarizes the key techno-economic parameters used in the LCoE and NPV calculations for the different scenarios considered.

Table 7.Values, units and references of the key techno-economic parameters used for LCoE and NPV calculation.

Parameter	Unit	Symbol	Value	Reference
PV plant DC capacity	MW		44	
Annual energy production per scenario	MWh	E	**No cleaning:** 72076 **Dynamic cleaning:** 75066 **1 Month cleaning**: 74123 **6% SL threshold:** 74741	
Capital expenditures	$/kW	$CAPEX$	876	[55]
O&M expenditures, cleaning excluded	$/kW/year	$OPEX$	16.3	[27]
Cleaning Cost	$/MWp/cleaning	CC	215	[51]
Electricity Price	$/MWh	El_{Price}	121	[46]
Number of cleaning operations per scenario	#	Nc	**No cleaning:** 0 **Dynamic cleaning:** 14 **1 Month cleaning**: 12 **6% SL threshold:** 11	
Discount rate	%	d	5	[56]
Linear degradation	%	R_D	0.8	[57]
Project lifetime	years	N	30	

In this analysis, only the dynamic cleaning approach and the best-performing conventional alternatives were considered, based on the findings from the previous section. The results of the LCoE and NPV calculations for each scenario are presented in Table 8, while Fig. 13 shows the relative improvements in both LCoE and NPV when compared with the no-cleaning scenario. Positive values indicate a positive impact, while negative values represent a negative impact.

Table 8. LCoE and NPV calculation results for each cleaning scenario.

Scenario	NPV [$×10^6]]	LCoE [$/MWh]

No cleaning	79.05	46.95
1 Month cleaning	80.88	47.32
6% SL threshold	82.14	46.79
Dynamic cleaning	82.27	47.00

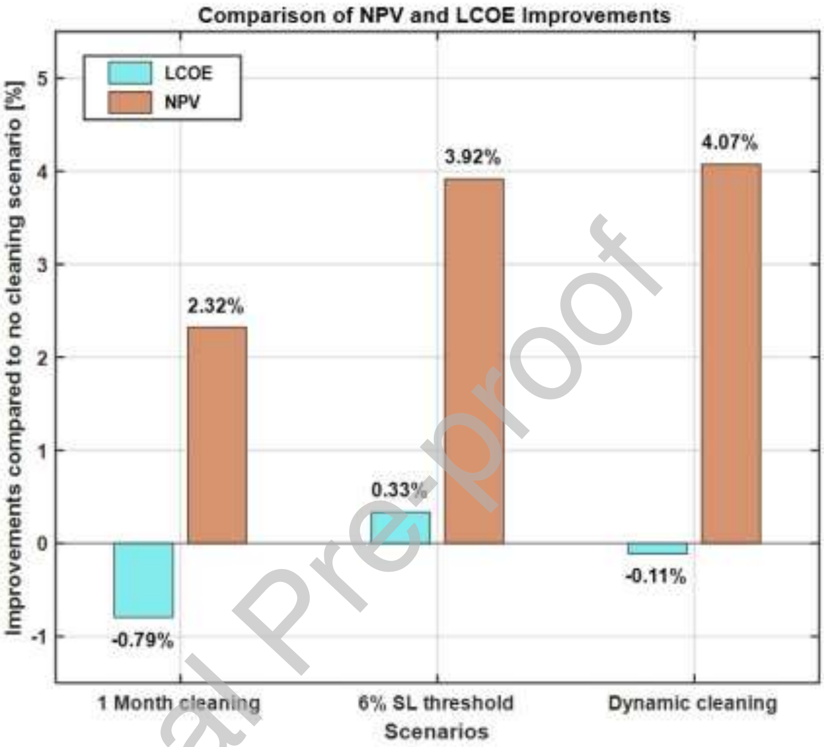

Fig. 13. The improvement in percentage of NPV and LCoE for various cleaning scenarios compared to the no-cleaning scenario.

As shown in Table 8 and Fig. 13, in terms of NPV, all considered cleaning scenarios improve the financial viability of the PV plant when compared to the no-cleaning baseline. The highest NPV is obtained with the dynamic cleaning approach with approximately $82.27M , which represents a 4.07% improvement over the no-cleaning scenario. This slightly outperforms the 6% SL threshold approach, which reached an NPV of $82.14 million (3.92% improvement), and exceeds the monthly fixed cleaning schedule with an NPV of $81.81 million (2.32% improvement).

When examining the LCoE metric, the 6% SL threshold approach shows the best performance at $46.79/MWh, representing a 0.33% improvement compared to the no-cleaning scenario.

Dynamic cleaning ranks second with \$47.00/MWh (-0.11%), while the monthly fixed cleaning schedule performs worst at \$47.32/MWh (-0.79%). However, it is important to note that this analysis assumes full cleaning efficiency during strong rainfall events and no accumulation of persistent or cemented soiling. In practice, certain soiling types may leave residual deposits that are not completely removed by natural cleaning processes. As a result, the long-term performance of a system without cleaning operation could degrade more significantly over time. Future research should therefore focus on modeling the cumulative effects of persistent soiling and the interannual variability of soiling conditions, as these factors play a critical role in accurately representing long-term PV performance.

While LCoE remains a useful metric for estimating the cost of generating electricity, especially in early project stages, it does not fully capture the economic benefit of operational optimizations like cleaning strategies. This is mainly because LCoE is strongly influenced by installation and O&M costs, which reduce the relative impact of cleaning optimization on the overall cost of electricity. On the other hand, NPV is more relevant for evaluating cleaning approaches, as it is directly affected by electricity price assumptions in addition to O&M costs. This difference explains why LCoE and NPV respond differently to cleaning strategies.

The dynamic cleaning recommendation adapts to market energy tariffs, making it more efficient than fixed or threshold-based approaches. This price sensitivity allows operators to prioritize cleaning actions during periods of high electricity prices, maximizing revenue recovery and further improving financial outcomes. This adaptability explains why dynamic cleaning achieves the highest NPV.

To recap, the results demonstrates that effective soiling management strategies should consider not only the direct cost of cleaning and energy recovery but also how these factors interact with market conditions to impact long-term profitability.

Conclusions

In this study, a soiling measurement campaign was conducted as part of the feasibility assessment for a large-scale solar project at a mining site in Morocco. The campaign covered the period from July 1, 2022, to June 30, 2023, with the aim of characterizing the temporal evolution of soiling. The results reveal significant temporal fluctuations, driven mainly by seasonal effects and the level of mining activity. The average daily soiling rate, represented by ΔSR, was approximately 0.30%/day, resulting in a total energy loss of 4442 MWh. This corresponds to 5.8% annual energy loss in the absence of cleaning, highlighting the significant impact of soiling under mining-site conditions. Consequently, the implementation of cleaning operations should take into account both the level and the seasonality of soiling at the site in order to maximize performance and reduce costs. Using the dynamic cleaning decision approach, 14 cleaning operations per year are proposed, with cleaning intervals varying according to soiling levels, weather conditions, local cleaning costs, and electricity market trends. This strategy reduces annual soiling losses from 5.8% to 1.9%, recovering 2,990 MWh and generating an economic gain of approximately $230,000 ($5.23/kW/year).

Compared to conventional methods, the dynamic strategy significantly outperformed both the fixed-frequency (monthly) and the threshold-based (6% SL) cleaning approaches. It delivered a 2.6 percentage-point increase in net revenue compared to the no-cleaning baseline, outperforming the best fixed schedule (1-month cleaning at 1.5 percentage points) by 1.1 percentage points and slightly exceeding the best threshold-based approach (6% SL at 2.5 percentage points) by 0.1 percentage points. In terms of energy loss management, dynamic cleaning achieved a 67.3% reduction in AC energy losses relative to the no-cleaning baseline, corresponding to 20.6 percentage points greater reduction than the monthly schedule (46.7%) and 7.3 percentage points greater reduction than the 6% SL threshold approach (60.0%).

The financial assessment using NPV and LCoE metrics further confirmed the advantages of the dynamic approach. Although the 6% SL threshold approach showed a slightly lower LCoE, this indicator is strongly influenced by installation and O&M costs, thereby limiting the apparent effect of cleaning optimization on the final value. In contrast, NPV directly reflects revenue generation and is affected by both O&M costs and electricity price assumptions. From this perspective, the dynamic cleaning approach achieved the highest NPV of $82.27 million, corresponding to a 4.07% improvement compared to the no-cleaning scenario. These results indicate that soiling mitigation strategies should account not only for cleaning costs and energy recovery, but also for electricity price effects in order to maximize long-term profitability.

The dynamic cleaning decision approach which considers economic factors alongside soiling rates, provides a practical methodology that can be integrated into existing SCADA systems, enabling solar plant operators to make optimal cleaning decisions and systematically improve plant profitability throughout its operational lifetime.

While this study provides a comprehensive soiling assessment and cleaning decision analysis for the considered PV feasibility study, several aspects could be further explored in future work. Extending the analysis over multiple years would help capture interannual variability in soiling behavior and rainfall patterns. Incorporating short-term weather forecasting into the cleaning decision framework could improve real-time operational planning. Additionally, future research could examine the long-term effects of persistent or cemented soiling that are not fully removed by natural cleaning events. Finally, a more realistic economic assessment could be achieved by incorporating the variability of local cleaning costs and electricity prices using real historical data, such as long-term market prices or available PPA data, to better reflect variable market conditions.

Author contribution statement

Abdellatif Ghennioui: Conceptualization, Methodology, Data curation, Writing- Original draft preparation. **Mounir Abraim**: Conceptualization, Methodology, Data curation, Writing- Original draft preparation. **Fatima Zahra Ouchani:** Methodology, Writing- Reviewing and Editing. **Leonardo Micheli:** Validation, Writing- Reviewing and Editing. **Stefan Welber:** Validation, Writing- Reviewing and Editing. **Natalie Hanrieder:** Validation, Writing- Reviewing and Editing. **Mohamed Boujoudar:** Data curation, Methodology. **Omaima El Alani:** Data curation, Writing- Reviewing and Editing. **Farid Abdi**: Investigation, Validation. **Hicham Ghennioui**: Investigation, Validation.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used AI assistance in the editing and refinement of text. Specifically, OpenAI’s ChatGPT that was used to help improve the clarity and academic writing style. All data, analytical interpretations, and core technical content were developed by the authors. The AI tool was used solely to improve the presentation and readability of existing content. The authors reviewed and edited all AI-suggested modifications as needed and take full responsibility for the content of the publication.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: