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Soiling Loss Quantification of Roof-Top Mounted Solar Module in Mombasa Using Digital Imagery Techniques

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Abstract

Photovoltaic cells' output performance is negatively impacted by the particles that are deposited on the solar panels which scatter and absorb solar energy. The particles cause shading on the PV modules and when they are densely sparse on the PV panel and depending on their light transmittance, could adversely reduce the intensity the amount of irradiance reaching the PV cells. This study quantified soiling loss of rooftop solar photovoltaic using images of soiled PV panels in Mombasa County, Kenya. This study estimated a significant intensity of soiling of rooftop mounted modules in Mombasa. A pilot study was conducted on the roof-top of s Laboratory at Technical University of Mombasa for 90 days using two fixed angle and azimuth modules; One of them was cleaned everyday while the other was left soiled for the entire period. In the setup, high resolution pictures were taken daily for 90 days for dust pixel analysis. The analysis of the pixels revealed that soiling reduced pixel intensity on the panel by 10 per cent. Clean panel had an average pixel intensity of 132.47 in the first day. After 30, 60 and 90 days, the pixel intensity of soiled panels were 148.96, 151.96 and 148.42, respectively. It was observed that the particles that collected on the surface of the PV module reduced optical characteristics of the panel for the first two months before the onset of rain in the third month. The highest loss of 19.34 was witnessed in the second month.

Key Words: PV Soiling loss, Solar PV metrology, Irradiance attenuation, Digital image processing, Autocorrelation measurements, Technical University of Mombasa, Kenya

Introduction

Solar photovoltaic (PV) power generation has been growing at an accelerating rate and is now a major contributor to the global electricity generation industry. Currently, theoretical conversion efficiency of panels stands at around 30% (Alharbi & Kais, 2015). According to Bhattacharya & John (2019), laboratory experiments have estimated conversion efficiencies at 33%. Besides these low conversion efficiency, solar photovoltaic performance is also affected by environmental factors like temperature, humidity and soiling (Aboagye et al., 2021; Shahzad et al., 2025). Soiling is the deposition of birds' droppings, dust, sand and other foreign particles on the surface of a PV panel (Shaik et al., 2023). Dust deposition on the module not only absorb, transmit, attenuate, scatter or reflect the incoming radiation but it also degrades the panel (Smestad et al., 2020). The blocked radiation leads to reduced power production by the panel. The higher the accumulated dust the lower the irradiance received and the lower the power generated. Soiling affects the performance of the panel where power reduces with increase in dust deposition (Alshareef, 2023). This results in a reduction in the photovoltaics' power production, reduced energy output of the panel and finally reduced financial return on investment (Pouladian-Kari et al., 2022).

Unlike other PV losses, soiling is sometimes reversible. Controlled soiling maximizes the

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panel's performance, lowers the levelized cost of energy (LCOE), and boosts revenue. There is a need to mitigate this impact of soiling by cleaning the panels. Cleaning has cost implications (Zeedan et al., 2021). Traditional approaches for soiling quantification typically rely on measuring the difference in power output between soiled and clean PV panels (Adekanbi et al., 2024). Although these methods provide direct power loss data, they are often expensive, requires additional sensors, cannot easily be scaled to large solar farms and it is difficult to develop preventive maintenance strategies based solely on the methods (Hasan et al., 2022). In response to these aforementioned challenges, recent research has proposed image-based soiling detection as a promising alternative (Yang et al., 2020). These methods rely on digital photographs of PV modules, processed using computer vision and image analysis techniques, to estimate the level and impact of soiling. Image-based techniques are cost-effective, non-invasive, and scalable, particularly well-suited to roof-top PV installations in resource-constrained settings (Haider Ali, 2024).

A lot of research on image processing has been done globally, however, Hachicha et al., (2019) cautioned that solar PV findings cannot be taken to represent the global outlook of soiling or findings cannot be generalized to other regions. These authors added that efforts to generalize performance of solar PV due to soiling calls for empirical data in different environments. Therefore, more empirical data is needed to validate the accuracy of image-based models against actual power output data, particularly in Kenya's coastal region. Coast region is synonymous with high humidity combined with salt spray and airborne dust which exacerbate the soiling effect (Molelu & Charo, 2024). Therefore, this study is intended to empirically quantify impact of soiling on the transmittance of roof-top photovoltaic panels in Mombasa, Kenya.

Theoretical background

Effect of soiling on the PV module

Soiling reduces both short circuit current (I) and open circuit voltage (V). Despite the I-V curve of both the clean and dusty panels having the same shape, short circuit current of the clean panel is in most cases slightly higher than that of the soiled panel (Al Siyabi et al., 2021). The deposited dust has the effect of raising the temperature of the panel. The increased temperature can substantially reduce the open circuit voltage (V) of the panel thereby impacting on the power output (P). Consequently, soiling causes a reduction in P-V curves. P-V of the clean panel is slightly higher than that of the dusty panel (Bessa et al., 2021). Lasfar et al., (2021) conducted an experiment to investigate soiling intensity on a solar panel. The experiment was carried out in Nouakchott, Toujoumine and Mauritania. They compared two panels; one cleaned while the other was uncleaned. They observed that dust decreased power output by about 21.57%. Similarly, Kumar et al., (2021) set up an experiment to investigate power loss due to dust. They noted that soiling caused an attenuation decrease from 38% to 24% for dust densities 12.5 g/m^2 at 0° and 40°, respectively.

Image capture techniques

Real world objects are described in three-dimension coordinates (3D). This is the global location which is independent of camera location. Cameras capture by transforming 3-dimensional world coordinates into 2-dimensional image plane. This change in position is achieved by object rotation which aligns the world axes with the orientation of the camera (Figure 1) or translation which changes the world coordinate system's origin to the location of the camera (Jackman et al., 2021).

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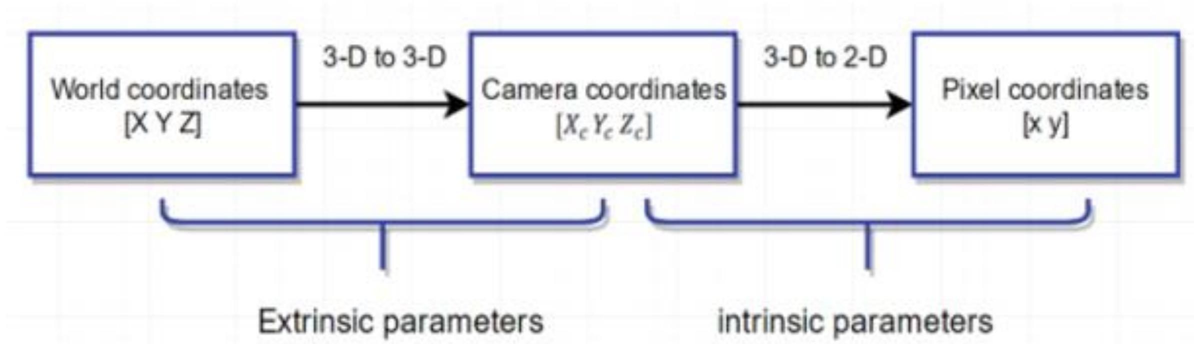

Figure 1. Extrinsic and intrinsic camera parameters (Jackman et al., 2021)

Jim and Yang, (2020) proposed the use of digital image processing as a non-contact, low-cost method for monitoring soiling. Their research used a prototype in the laboratory and developed an algorithm to test for soiling quantification. The result was able to show the correlation between camera angle and soiling index. However, its accuracy in real life scenario required externally exposed panels. Jim and Yang, (2024) expanded their work of Jim and Yang (2020) by incorporating various image features in a machine-learning regression model to predict P-V soiling loss. The new model was trained and tested using P-V performance data and raw panel images collected in the field over several months, covering real-time soiling loss levels up to about 28%. The results showed that the new method could reliably predict the soiling loss when the images were taken under similar settings. However, this training used amorphous panels.

Materials and Methods

This section comprises of soiling measurements set up, empirical data collection, image processing and quantification of dust. Python software was used to quantify soiling intensity on the surface of a solar panel. Data was collected for 3 months from January 2025 to March 2025 on a solar learning kit mounted on the roof-top about 9m high (Figure 1).

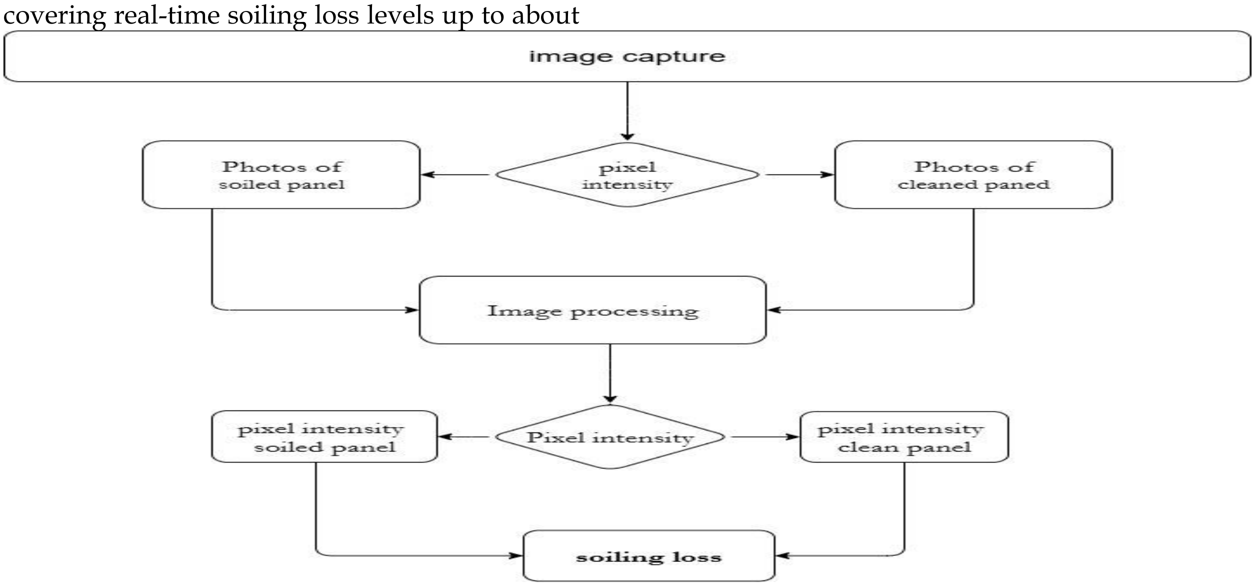

Figure 2. Soiling quantification flowchart used during the experiment period

Image Acquisition

The study was conducted on a setup that was designed, fabricated and installed on the roof-top of the Renewable Energy Laboratory at Technical University of Mombasa (TUM) (Figure 2).

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Photographs were captured at exactly 1pm on daily basis for a duration of three months. Two modules' images of both cleaned and soiled photovoltaic panels placed side by side were captured simultaneously. A high-resolution camera of oppo Reno 12 was used. The tripod was fixed with the distance between the camera and the panel at about 1m. The camera was fixed at around 7 degrees to the panel. Captured images were stored with date-stamped file names for easy tracking.

Figure 3. Photos of roof-top solar PV mounted on top of the Renewable Energy Laboratory building at Technical University of Mombasa, Kenya

Preprocessing

After acquisition, the images were standardized to ensure comparability. Both images were resized to equal dimensions of 512 × 512 pixels for ease of computation and memory requirements. To reduce computational complexity, Red, Green and Blue (RGB) images were converted to grayscale using the weighted sum in the tool in the software used following the equation below:

$$\mathrm{I}(x, y) = 0.2989 \cdot \mathrm{R}(x, y) + 0.5870 \cdot \mathrm{G}(x, y) + 0.1140 \cdot \mathrm{B}(x, y) \quad (1)$$

Where: I (x, y) is the grayscale intensity at pixel (RGB) (x, y). This models the human visual response by assigning greater weight to pixel green (G), which is more perceptually dominant.

Line graphs and pixel intensity

Pixel intensity line graphs were generated for both clean and soiled panels to visualize the distribution of grayscale values. For the clean panel, intensities were expected to cluster around lower values due to the darker, uniform glass surface. In contrast, the soiled panel line graph was expected to shift toward higher values, corresponding to brighter patches of accumulated particles.

Pixel intensity was used to illustrate how much light was absorbed or reflected by the panel surface. The grayscale image's pixel intensity ranged between 0 and 255, and it was handled as a 2D object.

These values were used to characterize the object's average grayscale image pixel intensity. A shift of the graph towards zero illustrates that images are dark whereas the shift towards the right indicated that images were white. The average grayscale image pixel intensity was stored as a CSV file using Pandas, available in Python software. Drops in mean grayscale image pixel intensity value illustrated increase in soiling and vice versa.

Mean (M) pixel intensity was used to estimate the average value of brightness of all pixels in an image according to the following equation by Bijaksana & Tahcfulloh, (2022):

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$$I_{Mean} = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} I(x, y) \tag{2}$$

Where I_{Mean} is the average of all the pixel values and N are the number of pixels and the number of occurrences respectively.

The average pixel intensities for both clean and soiled panels were computed by the python software using the following equations:

$$I_{Cleaned} = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} I(x, y) \tag{3}$$

and

$$I_{Soiled} = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} I(x, y) \tag{4}$$

$$intensity\ loss = I_{Soiled} - I_{Cleaned} \tag{5}$$

Soiling losses index

The intensity of soiling was quantified by soiling loss percentage. It was estimated using the following equation:

$$\text{Soiling Losses \%} = \left[\frac{(\mathrm{I_{Cleaned}} - \mathrm{I_{soiled}})}{\mathrm{I_{Cleaned}}}\right] \times 100\ \% \tag{6}$$

Where, I_{soiled} and $I_{Cleaned}$ refers to the pixel intensity averages of the dust and clean panels, respectively. The index ranged from 0 to 1. The value 0 indicates there is no soiling whereas 1 means that the panel is completely soiled. A times series graph was plotted to illustrate daily soiling loss and the overall soiling accumulation rate.

Line graph analysis

Line graph analysis was used to show occurrences of pixel intensity against the average pixel intensity values. It was used to show both soiled and cleaned panels. This analysis was conducted for different days of the experiment. Line graph of the module was investigated on January 1st and day 30th of every month for three months in the year 2025. The results were plotted and average pixel intensity for both cleaned and soiled panels determined.

Results and Discussion

Grayscale Image Comparison

Grayscale photos showed clear distinctions between images of soiled and clean PV solar panels upon visual inspection (Figure 3). Clean PV solar panel showed uniformly darker surface while soiled PV solar panel had erratic patches and brilliant white spots that were caused by dust collection and dispersion. These variations were as a result of surface particles physically changing optical paths.

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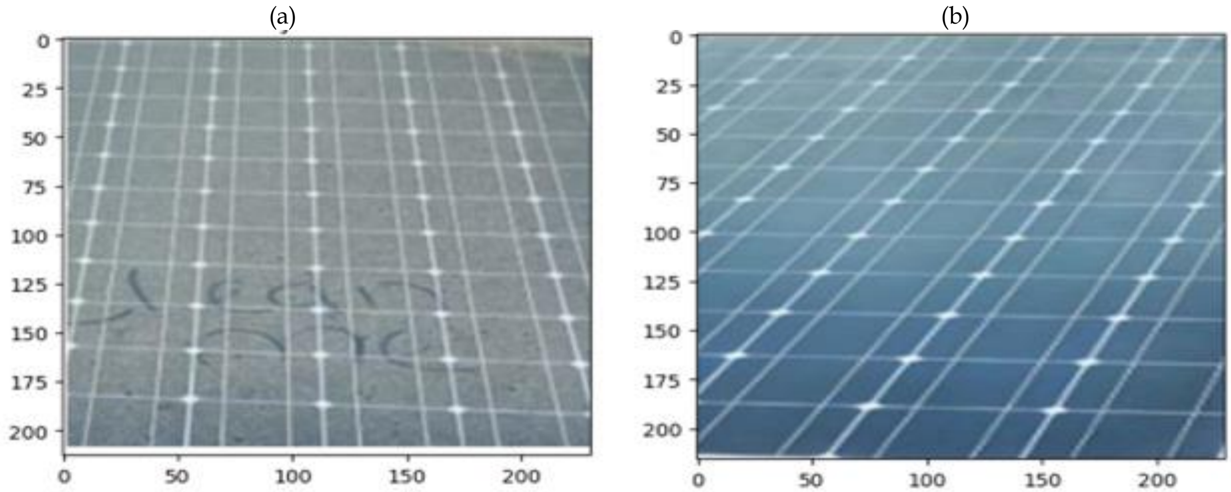

Figure 4. Images of (a) soiled and (b) cleaned module observed during the study period

Day-One line graph

Results of Day-One line graph was found out that pixel intensity was the same for both the panels (Figures 4 and 5).

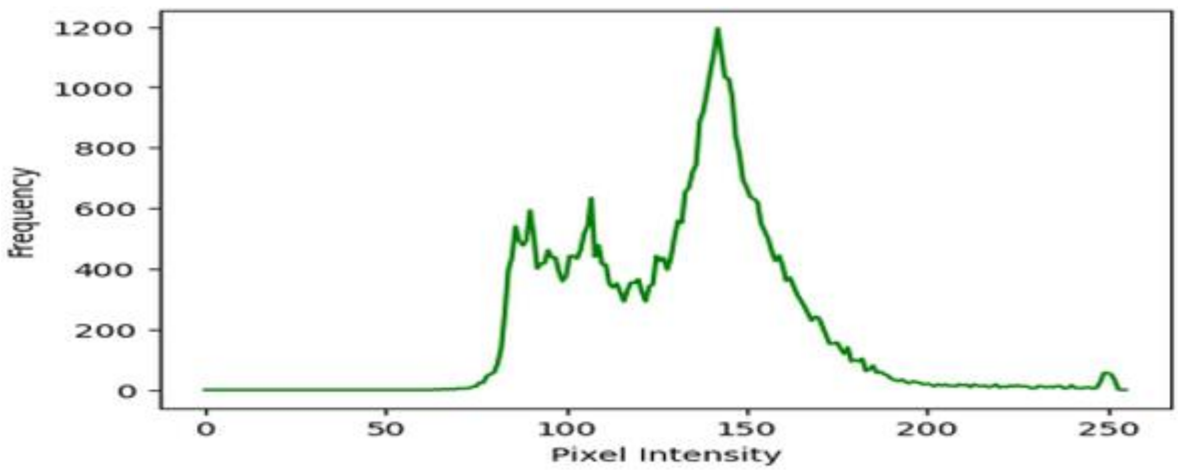

Figure 5. Line graph of pixel intensity for Day-One of the experiments for soiled PV panel

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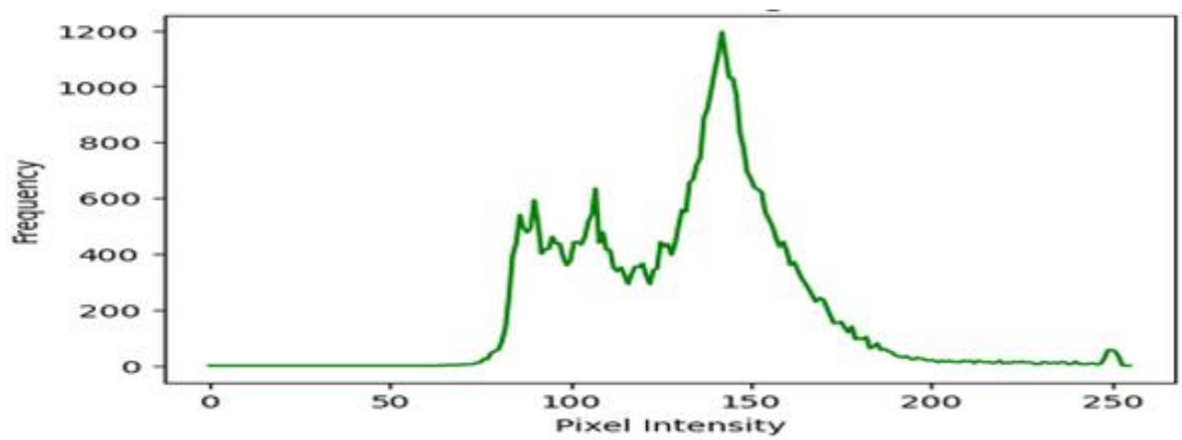

Figure 6 Line graph of pixel intensity for Day-One of the experiments for clean PV panel

Both panels showed the same mean pixel intensity values clustered between 80 - 150 forming a sharp trimodal peak. Their average pixel intensity was found to be 132.06. The contrast between them was estimated using the following equation and found to be zero because they had the same pixel intensity.

$$\text{Contrast} = \mathrm{I}_{\text{soiled}} - \mathrm{I}_{\text{Cleaned}} \tag{7}$$

$$= 132.06 - 132.06 = 0$$

An average value of 132.06 was in the mid gray which was expected because in clean panels irradiance was not blocked by foreign materials on the surface of the panel from reaching the solar cell. Clean panel therefore, illustrated a good optical surface for irradiance penetration. The relatively low spread of intensity levels indicated that the pixel values were tightly clustered around the mean.

Thirty-Day line graph

After a period of one month there was a shift in the graph of soiled and clean panels. The clean panel had an average pixel intensity of around 132.43 which was in the range between 60 and 185 but the spread was broadened. That low pixel intensity showed that clean panel was seen towards 0. Clean panels seemed to have a peak overshoot towards 250 mark (Figure 6). These were the bright spots on the panel. The panel was non-uniform in pixel distribution. Soiled panel after one month on the other hand had average pixel intensity of 148.96 (Figure 7).

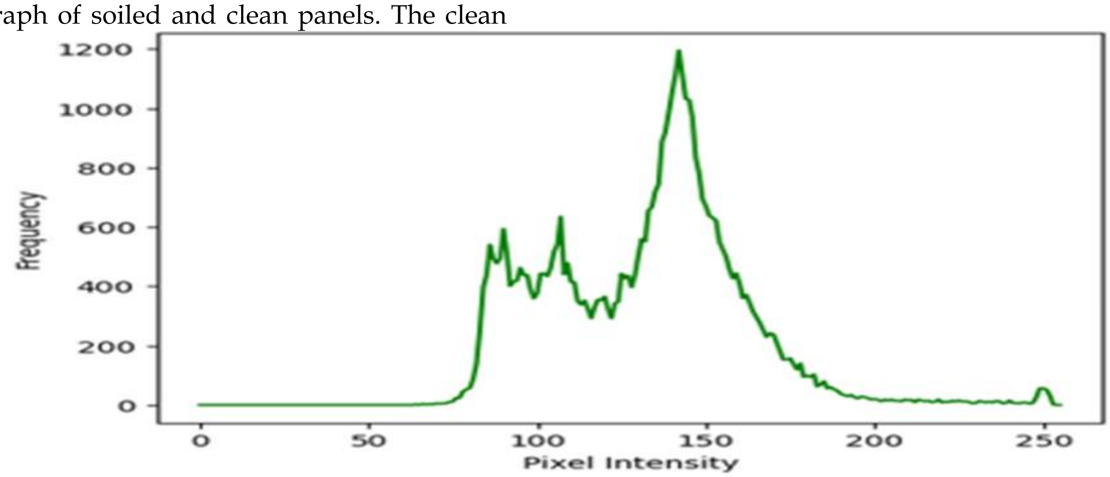

Figure 7. Line graph of pixel intensity for clean PV panel after 30 days of the experiment

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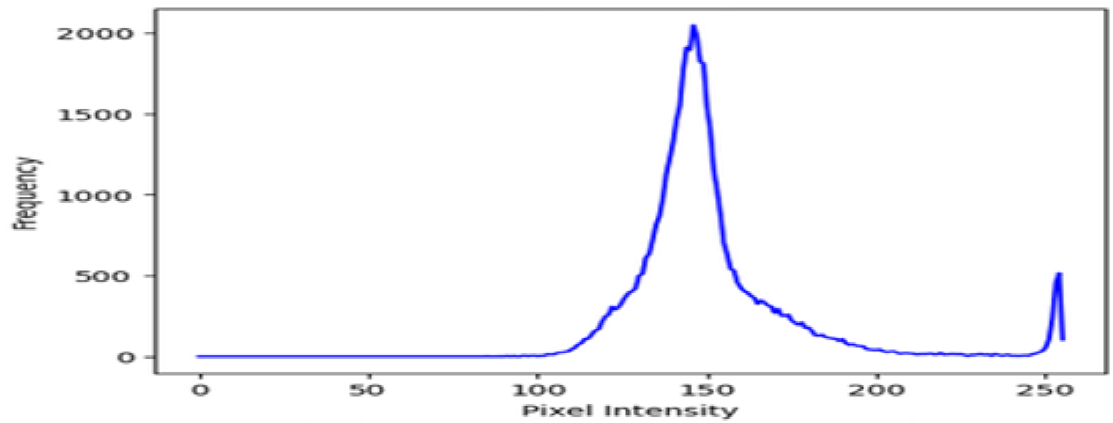

Figure 8. Line graph of pixel intensity for soiled PV panel after 30 days of the experiment4.4 Line graphs after 60 Days

There was a large variation in efficiency between soiled and clean PV panels. The clean PV panel had an average pixel intensity of around 133.27 which was in the range between 63 to 189 but the spread was broadened. That variation in pixel intensity was due to changing irradiance. This low pixel intensity value illustrated that clean PV panel surface allowed absorption of light rather than scattering it. Multiple peaks observed in Figure 8 were due to reflections occasioned by white lines on the material of the panel. Clean PV panel seemed to have a peak overshoot towards 250 marks. These were due to the bright spots on the panel. The PV panel was non-uniform in pixel distribution.

Soiled PV panels experienced the effect of soiling (Figure 9). It had average pixel intensity of 151.96 which was in the range between 113 to 201. The graph was towards 250 marks. Soiling accumulation resulted in shift in amplitude. There was a noticeable peak between 150–170 range, and the distribution was biased toward higher pixel intensity values for the soiled PV panel. This illustrates that as accumulation of dust rises on the image, brightness and reflectance too increases making the uniformity and clarity of the panel reduce Soiled PV panel.

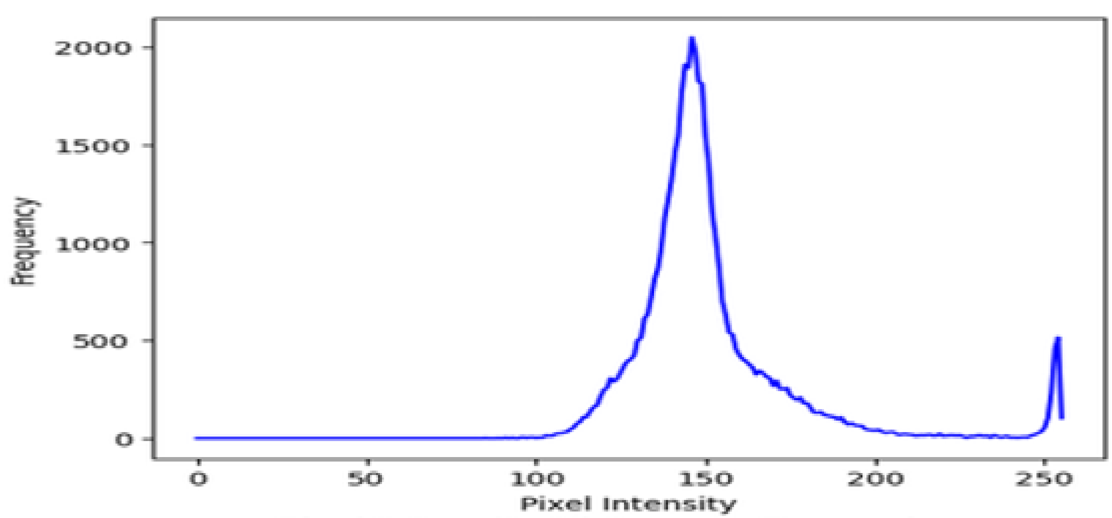

Figure 9. Line graph of pixel intensity for soiled PV panel after 30 days of the experiment

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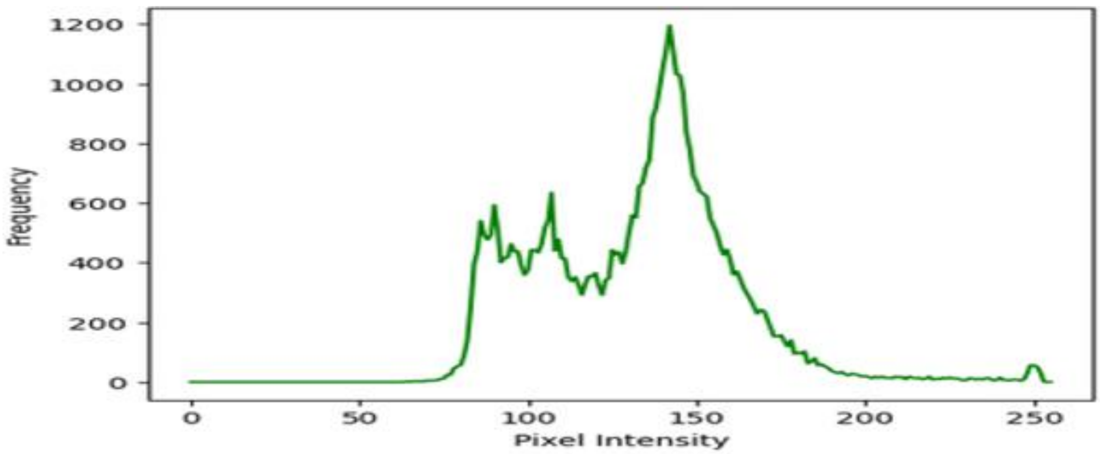

Figure 10. Line graph of pixel intensity for clean PV panel after 30 days of the experiment

Line graphs after 90 Days

Figures 10 and 11 show line graphs of pixel intensity for soiled and clean PV panels after 90 days, respectively.

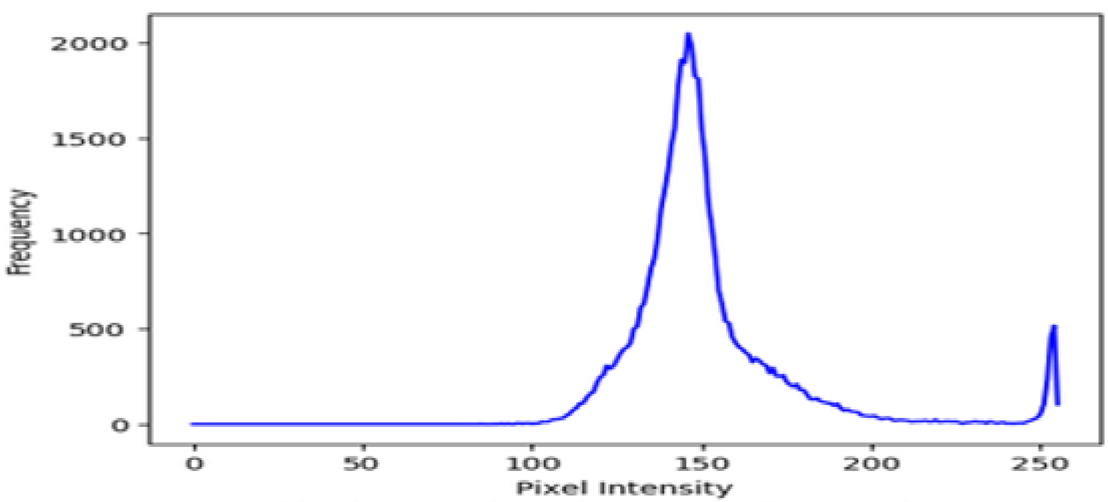

Figure 11. Line graph of pixel intensity for soiled PV panel after 90 days of the experiment

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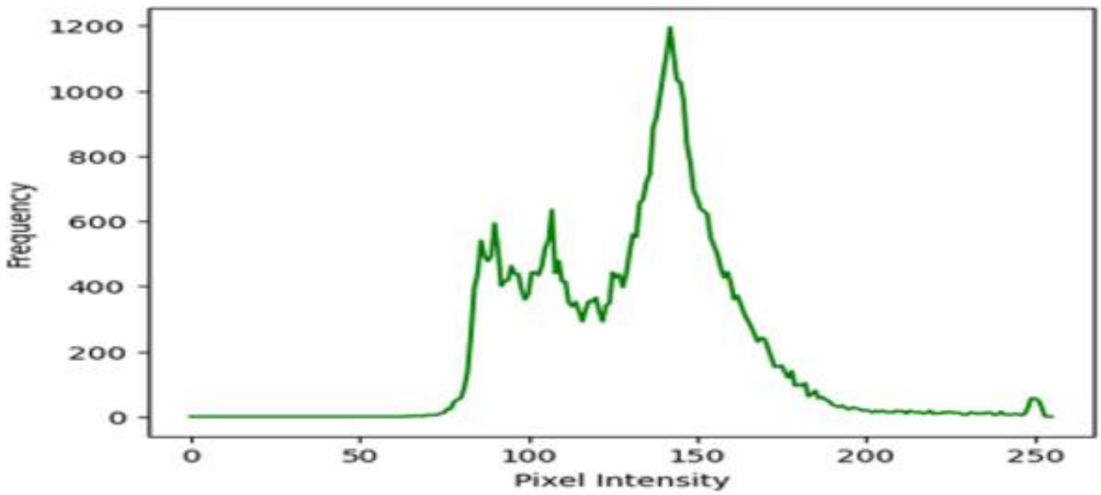

Figure 12. Line graph of pixel intensity for clean PV panel after 90 days of the experiment

There was a large variation in efficiency between soiled and clean PV panels. The clean PV panel had an average pixel intensity of around 131.27 which was in the range between 63 to 171 but the spread was broadened. That variation in pixel intensity was due to changing irradiance. This low pixel intensity value illustrated that clean PV panel surface allowed absorption of light rather than scattering it. Multiple peaks observed in Figure 11 were due to reflections occasioned by white lines on the material of the panel. Clean PV panel in figure 11 seemed to have a peak overshoot towards 250 marks. These were due to the bright spots on the panel. The panel was non-uniform in pixel distribution.

Soiled PV panels experienced the effect of soiling. It had average pixel intensity of 148.42 which was in the range between 113 to 198. The graph was towards 250 mark. Soiling accumulation resulted in shift in amplitude. There was a noticeable peak between 149 –167 range, and the distribution was biased toward higher pixel intensity values for the soiled PV panel. This illustrates that as accumulation of dust rises on the image, brightness and reflectance too increases making the uniformity and clarity of the panel to reduce.

Average pixel intensity variation for the three months

The average daily variation due to pixel intensity was computed from the difference between soiled and clean pixel intensity for 90 days (Figure 12). The loss was estimated as shown in equation 8 and illustrated in Figure 13. The per centage pixel loss was calculated (Table 1) using equation 9:

$$\text{Pixel lost} = \text{Av. Pixel Intensity of soiled PV panel} - \text{Av. Pixel Intensity clean PV Panel} \tag{8}$$

$$Pixel\ \text{Loss}\ (\%) = \frac{Pixel_{(Cleaned)} - Pixel_{\text{(soiled)}}}{Pixel_{(Cleaned)}}\ \text{X}\ 100\% \tag{9}$$

The average pixel intensity losses increased steadily before dropping in the last days after the onset of rain. Monthly average losses for the month of January were 12.5, for February it was 14.0 and the month of March it was 13.1. This steady increase between January and end of February was due to increased soiling. The month of March, soiling reduced due to increased rains.

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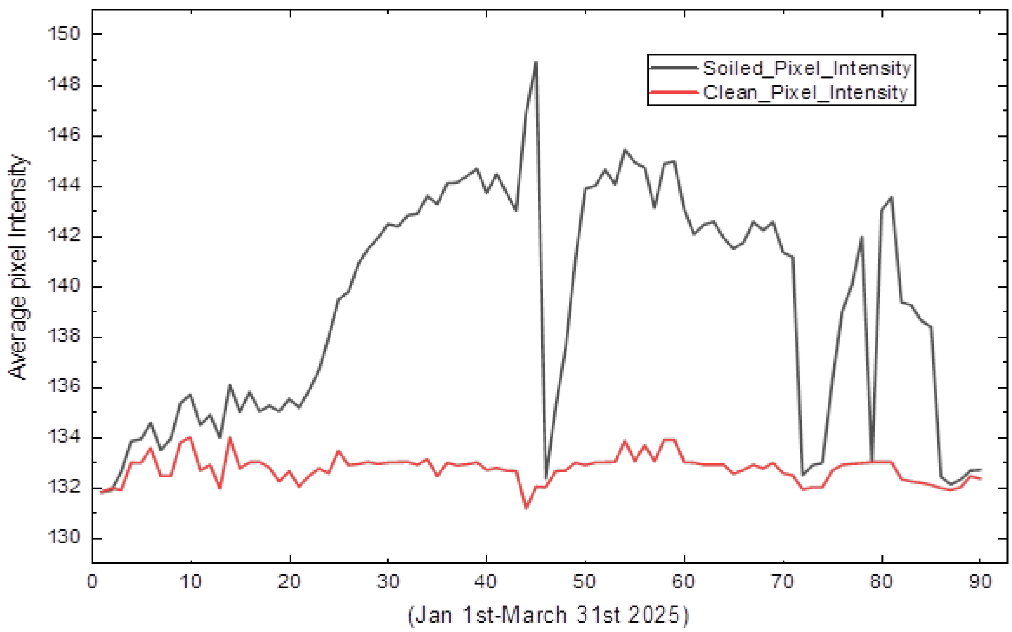

Figure13. Variation of average pixel intensity for three months observed over the study period.

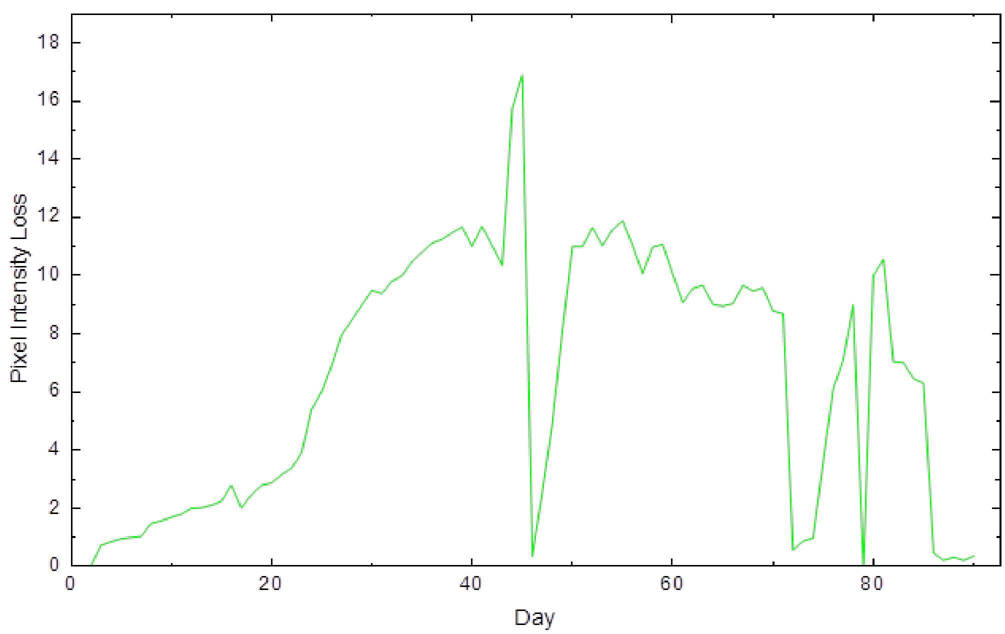

Figure 14. Pixel intensity loss (%) due to soiling for 3 months observed over the study period

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Table 1. Summary of pixel loss (%) observed over the study period

Parameter	Cleaned Day 1	Soiled (30 days)	Soiled (60 days)	Soiled (90 days)
Pixel intensity variation %	0	12.5	14.0	13.1

Overlaid line graph (Clean vs Soiled)

When the histograms of the clean and soiled PV panels were overlaid, the contrast in pixel intensity distribution became immediately visible (Figure 14). The clean panel showed a sharp, narrow peak centered at 133.67 indicating uniform surface reflectance and minimal variation across pixels. In contrast, the soiled PV panel exhibits a broader peak around 152, shifted distinctly to the right due to increased brightness caused by dust scattering and reflection. The overlap between the two distributions occurs only in the 137–143 range, accounting for roughly 13% of total pixels, which confirms that soiling significantly alters the overall brightness profile of the solar PV panel. This demonstrates that grayscale intensity analysis can effectively distinguish clean from soiled surfaces.

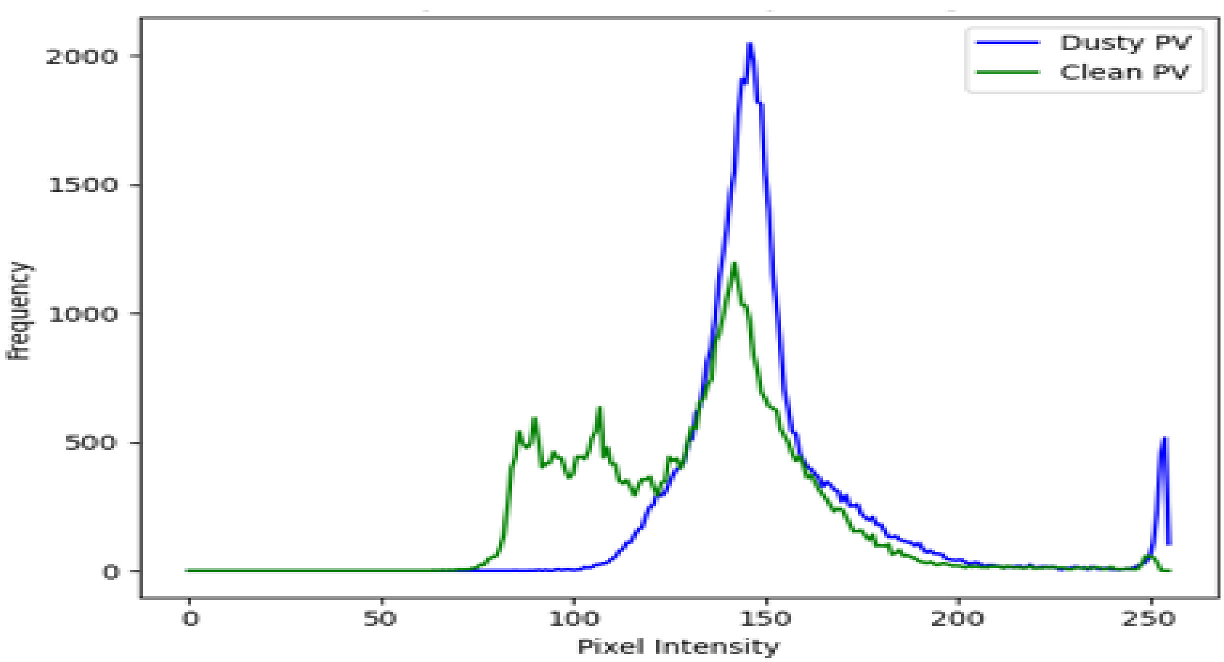

Figure 15. Overlay of soiled and clean PV line graph

Conclusion

This study found that soiling reduces pixel intensity on the panel. Clean panel had an average pixel intensity of 132.47 in the first day. After 30, 60 and 90 days, the pixel intensity of soiled panels were 148.96, 151.96 and 148.42, respectively. It was noted that soiling reduced optical characteristics of the panel for the first two months before the onset of rain in the third month. The highest loss of 19.34 was witnessed in the second month. This study therefore, recommends future work in this field should involve conducting field study for one year to take care of variation in seasons. It should also be conducted in different locations for effective comparison.

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