The Relationship between PM2.5 and Solar Cell Electricity Generation Using Aerosol Optical Depth (AOD)

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Abstract

This study analyses the relationship between PM2.5 concentrations, derived from Aerosol Optical Depth (AOD), and solar power generation at a solar farm owned by a "Private Owner" in Samut Prakan Province, Thailand. Most existing research emphasizes directly measuring dust accumulation on panels or converting AOD values into particulate matter levels, with limited focus on seasonal variations or applying remote sensing data, such as AOD, to assess solar energy impacts. This research seeks to address these gaps by examining the effects of dust across seasons using satellite-derived data. PM2.5 data from pollution monitoring stations of the Pollution Control Department, AOD data from the MCD19A2.061 product, and solar power generation data from the Electricity Generating Authority of Thailand (EGAT) in 2022 are utilized. The results indicate a negative correlation between PM2.5 concentrations and solar power generation during the summer (R^2 = -0.7), meaning that as PM2.5 levels increase, solar power generation decreases. A regression equation used for power prediction achieved an accuracy of R^2 = 0.97. In contrast, a positive correlation is observed during the winter (R^2 = 0.6), suggesting that as PM2.5 levels increase, solar power generation increases, with a prediction accuracy of R^2 = 0.93. No significant correlation is found during the rainy season (R^2 = -0.07), likely due to other influencing factors. When predicting solar power generation in different areas, the distinct physical and seasonal factors unique to each location should be considered.

Keywords: Aerosol Optical Depth (AOD), PM2.5, Solar Farm, Solar Power

1. Introduction

Thailand has joined the global effort to achieve the Sustainable Development Goals (SDGs) by committing to Goal 7. This goal aims to ensure universal access to affordable and clean energy and to increase the share of renewable energy in the global energy mix. Thailand is working towards this goal by implementing various initiatives to improve energy efficiency and expand access to clean energy [1]. Renewable energy, particularly solar power, has gained significant attention in Thailand. Solar panels play a crucial role in converting sunlight into electricity. Thanks to declining costs and technological advancements, solar panel systems have become more accessible, leading to a surge in domestic electricity producers in recent years [2][3] and [4].

Air pollution poses the most significant threat to human health. However, health impacts are not the only concern. Air pollution also hinders economic growth due to additional costs, including those associated with climate change [5]. Particulate matter affects the intensity of solar radiation [6]. Dust particles in the atmosphere and accumulated on the surface of solar panels harm solar power generation. The dust can block sunlight from reaching the solar cells, reducing efficiency [7][8][9][10][11][12][17] and [18].

Some studies examine dust's impact on solar panel power generation, such as the impact of PM2.5 dust on solar cell power generation and the dust effect on photovoltaic module surface to photovoltaic power generation. Both studies investigated the accumulation of PM2.5 dust on solar panels, collecting data over specific intervals. The impact of PM2.5 dust on solar cell power generation measured dust accumulation at 15, 30, and 60-day intervals, finding that dust buildup significantly reduced power output.

Similarly, the dust effect on photovoltaic module surface to photovoltaic power generation gathered data every 7, 14, 30, and 60 days and observed that accumulated dust reduced sunlight exposure and power output. These studies collectively indicate dust accumulation directly impacts solar panel efficiency [7] and [8].

The studies have extensively examined the impact of dust and particulate matter on solar energy generation. In an experimental study on the effect of dust on power lost in solar photovoltaic modules, researchers analyzed various types of dust using a scanning electron microscope. They identified that delicate dust layers can significantly reduce solar power output, with reductions reaching as low as 3.88W and up to 60% in desert conditions. Similarly, modeling the impacts of PM2.5 concentration on PV power outputs developed a model to simulate how PM2.5 levels affect solar power in Beijing, revealing that high PM2.5 concentrations can decrease PV power output by as much as 30%. The effect of dust deposition on the performance of multi-crystalline photovoltaic modules found that different pollutants, including ash, sand, and silica, affect PV output to varying degrees, with ash causing a 25% reduction in module voltage. Finally, the effect of particulate matter on solar photovoltaic power generation in the Republic of Korea showed that PM2.5 and PM10 levels reduced solar electricity generation by over 10% under typical conditions and over 20% during high pollution events. These studies underscore the significant effect that airborne particles can have on diminishing solar energy efficiency [9][10][11] and [12].

According to statistics on airborne particulate matter in Thailand, the levels have been found to exceed established standards [13]. Thailand has established a network of air quality monitoring stations that provide accurate and high-resolution time series data. However, due to the point-based nature of these measurements, spatial resolution remains insufficient for comprehensive dust monitoring and surveillance [14]. Remote sensing technology has increasingly been used to measure particulate matter concentrations [15]. Remote sensing can provide detailed spatial and temporal information, such as aerosol optical depth. However, a drawback of remote sensing is the potential for measurement uncertainties [16]. Research has utilized remote sensing and modeling techniques to assess the impact of dust on solar energy output. The impact of aerosols on solar radiation and solar energy in Egypt. They used Earth observation Aerosol Optical Depth (AOD) data and radiation transfer modeling, finding that under severe dust conditions (AOD > 3.5), solar output was reduced by 64 to 107 kWh/m², with daily energy losses exceeding 4 kWh/m² [17]. Similarly, forecasting the impact of dust on solar energy in India. They demonstrated that continuous dust storms caused elevated AOD values, reducing power output by 76 watts/m² for photovoltaic installations and 275 watts/m² for concentrating solar power plants [18]. Both studies confirm a strong correlation between high AOD levels and substantial reductions in solar power generation [17] and [18].

Most existing research focuses on directly measuring dust accumulation on solar panels or developing equations to convert AOD values into particulate matter concentrations, often prioritizing the monitoring of PM2.5 due to its health impact. These studies rarely explore the seasonal variations that could influence dust levels and, in turn, affect solar cell efficiency over time. Additionally, there is limited application of remote sensing-derived data, such as AOD, for further analysis in other areas, particularly its impact on solar energy production. This study aims to fill these gaps by examining the effects of dust on solar panel performance using satellite data, incorporating seasonal influences, and emphasizing AOD's broader applicability.

The Electricity Generating Authority of Thailand (EGAT) initiated a solar power generation data collection project in 2021, focusing on various solar farms nationwide. Among these, *"Private Owner"* located in Thaibanmai Subdistrict, Mueang District, Samut Prakan Province, was selected as a case study. The nearest air quality monitoring station to this solar farm is Station 18t at Samut Prakan Provincial Hall, Pak Nam Subdistrict, Mueang District, Samut Prakan Province. The average annual PM10, PM2.5, and Total Suspended Particulate (TSP) concentrations at this station from 2021 to 2023 were 52, 31.33, and 0.08, respectively. Due to its relatively high average dust concentration compared to other solar farms, this location was chosen for research.

Researchers estimated dust concentrations using AOD data from the MCD19A2 V6.1 product of the MODIS instrument on Terra and Aqua satellites. The accuracy of these AOD-derived dust concentrations was validated by comparing them with ground-based PM2.5 measurements from the Pollution Control Department, using a geospatial matching technique. A correlation analysis was then conducted to examine the relationship between the validated PM2.5 concentrations and solar power generation from the solar farm. This study aims to find the relationship between PM2.5 levels from the optical depth of particulate matter and the energy output from solar panels in the study area and to provide guidance for planning and management in the energy industry for solar farms, provide valuable insights for optimizing the operation and maintenance of solar power plants in regions with high levels of atmospheric dust.

2. Data and Methodology

In the data and methodology section, this study aims to analyze the relationship between PM2.5 values and solar panel electricity generation. The research utilizes reliable datasets, including ground-based PM2.5 measurements, satellite-derived AOD, and solar power generation data. The methodology involves data conversion, validation, and correlation analysis to examine how particulate matter affects solar energy production. The key steps in the study are summarized in Figure 1.

2.1 Scope of the Area

For this study, the name of the company will be kept confidential. It is called *"Private Owner"* in Thaibangmai Subdistrict, Mueang Samut Prakan District, Samut Prakan Province.

2.1.1 Topography

The area is primarily lowland, divided into three parts: the lowland along both banks of the Chao Phraya River, the coastal lowland in the south, which is subject to tidal flooding and has high salinity during the dry season, making it suitable for nipa palm and firewood forests, and the vast lowland in the north and east, which is suitable for agriculture [19].

2.1.2 Climate

Samut Prakan Province experiences a tropical monsoon climate influenced by the northeast and southwest monsoons. The northeast monsoon brings cool and dry conditions, while the southwest monsoon results in high humidity and abundant rainfall. The hottest month is April, and the coldest month is December [19]. The scope of the *"Private Owner"* area in Thai Bang Mai Subdistrict, Mueang Samut Prakan District, Samut Prakan Province. Solar farms in the surrounding provinces of Bangkok and the central region of Thailand, as supplied by EGAT, consist of:

1. Tianguan Spinning Co., Ltd.
2. Tirathai Public Co., Ltd.
3. T.P.N Packaging Co., Ltd.
4. S.T.B Textil Industry Co., Ltd.
5. Premium Pack Group Co., Ltd.
6. Sum Hitechs Co., Ltd.
7. K. K. Kased Dulakarn Banpong Co., Ltd.
8. Xin Yuan Da Rubber Co., Ltd.

Due to the variability in physical factors such as temperature across different provinces, districts, and sub-districts, the research team focused on a single solar farm owned by *a "Private Owner"* to isolate the impact of dust on power generation. Given the limitations in obtaining consistent and accurate data for other factors, a time-series comparison was adopted instead of a spatial comparison.

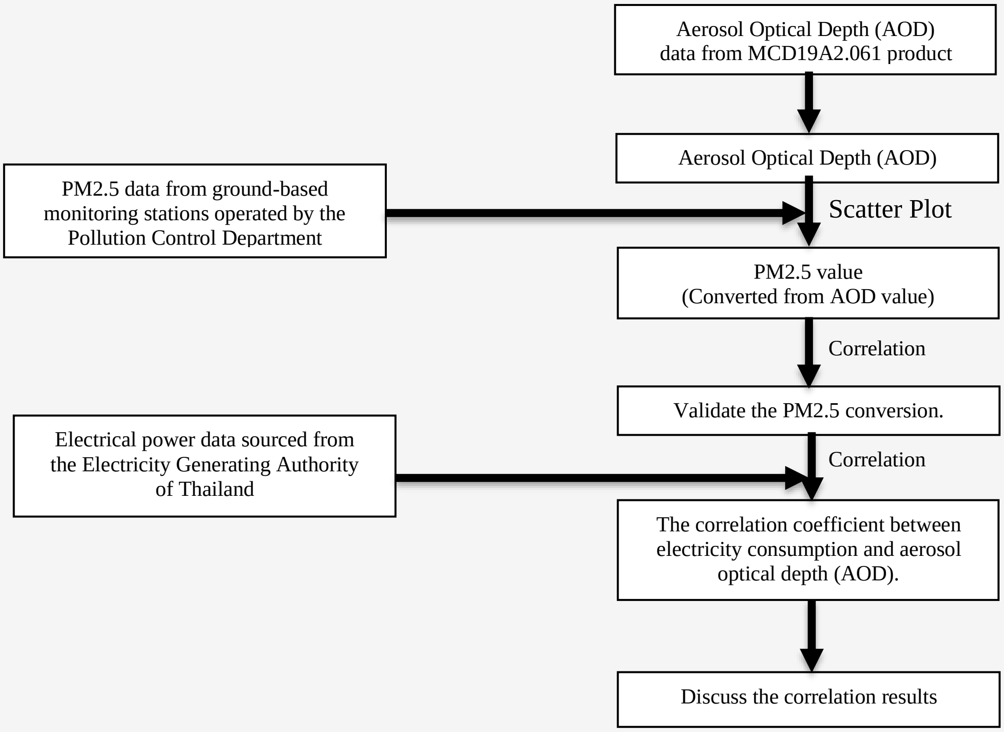

Figure 1: Relationship between PM2.5 and solar cell electricity generation study workflow

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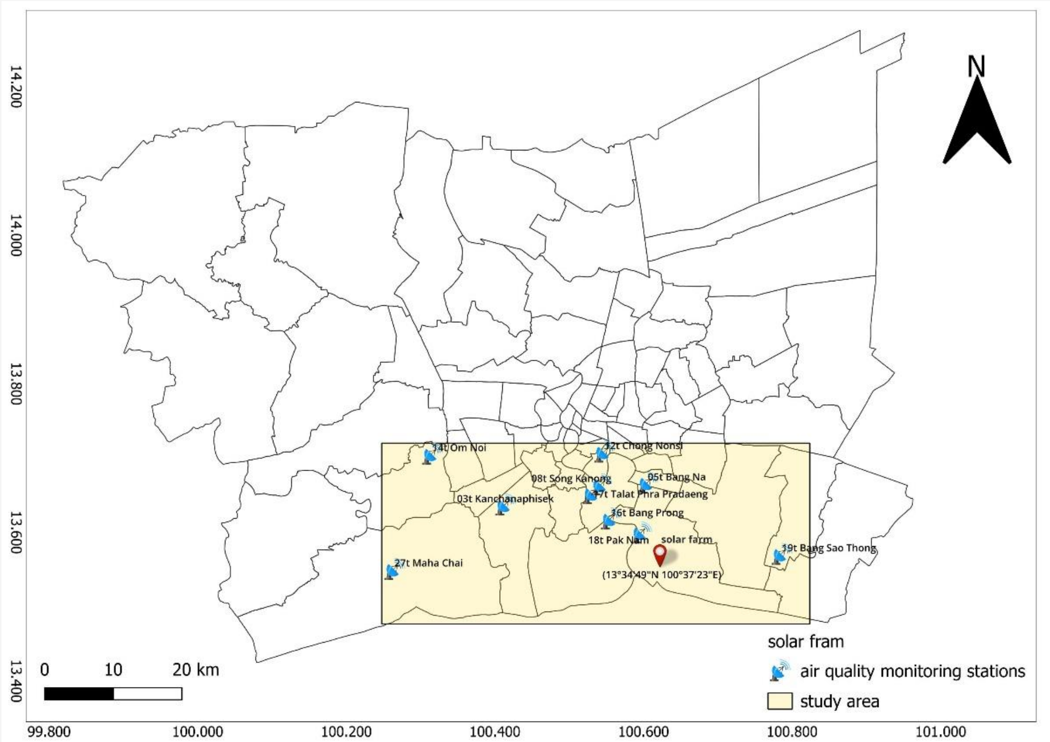

Figure 2: Map of air quality monitoring stations

Moreover, the proximity of the solar farm to Station 18t in Pak Nam Subdistrict, Mueang District, Samut Prakan Province, which has a relatively high annual average dust concentration, made it an ideal location for this study, as shown in Figure 2.

2.2 Scope of the Contents

2.2.1 Analyze the concentration of PM2.5 particulate

Analyze the concentration of PM2.5 particulate matter using remote sensing technology. Validate these results against ground-based PM2.5 measurements from calibrated monitoring stations. Subsequently, establish a correlation between the converted dust values derived from aerosol optical depth and the power output of solar panels.

2.2.2 Data used

This study used Ground-based PM2.5 concentration data from the Pollution Control Department in 2024. Most stations only measured PM2.5 concentrations, with limited data availability for PM10 and TSP. Consequently, due to its more comprehensive dataset, the analysis focused solely on PM2.5, enabling a robust validation of converted AOD values. This research focused solely on the impact of PM2.5 on solar power generation at a single solar farm owned by *a "Private Owner"* It did not investigate the influence of other physical factors on solar panel performance, nor did it calculate the correlation between dust levels and power generation at a larger scale, such as the entire Samut Prakan Province or Thailand. Moreover, the study could not fully control for other variables affecting dust measurements and solar power output. Electricity generation data for *"Private Owner"* located in Pak Nam Subdistrict, Mueang District, Samut Prakan Province, was obtained from EGAT for the year 2025. Since the data was sourced from EGAT and not directly from the company, conducting on-site investigations regarding panel installation, cleaning procedures, energy measurement times, or internal factory power consumption was impossible. This information is generally not publicly accessible.

AOD data from the MCD19A2 V6.1 product of the MODIS instrument on Terra and Aqua satellites, accessed via Google Earth Engine. In our research, we utilized the Optical_Depth_047 band, which is particularly sensitive to small particles, making it well-suited for detecting delicate particulate matter such as PM2.5, the primary focus of our study. The narrower valid range of this band (-100 to 6000), compared to other bands, enhances its precision in identifying fine particles. The MODIS Blue band (0.47 μm) captures AOD over land. It is optimized to retrieve data at lower altitudes, except for smoke or dust events above 4.2 km. A static value of 0.02 is applied for atmospheric correction in these high-altitude cases.

This band's properties align well with our environmental analysis, suggesting that AOD measurements from this specific band are sufficiently accurate when evaluated within the broader context of our study area [20].

2.2.3 Other physical factors affecting

Other physical factors affecting solar panel power output and PM2.5 monitoring, such as cloud cover, light intensity, wind speed, and rainfall, could not be controlled in this study [21][22] and [23].

2.3 Data

The study period was one year, from February 2022 to February 2023. The data used for the study is shown in Table 1.

2.4 Methodology

2.4.1 Data collection

1. Collect data on the locations of air quality monitoring stations and dust concentrations of sample stations distributed in the study area. The principle of selecting representative stations is similar to selecting Ground Control Point (GCP) points for georeferencing. In this case, using *n* = 3, the result is ten representative stations, as shown in Equation 1.

$$G_n = \frac{(n+1)(n+2)}{2}$$

Equation 1

Where:

G_n = Numbers of data points to be collected

n = Polynomial order number

2. Collect data on the boundary of the study area and define the study area to cover the distribution of monitoring stations.
3. Collect daily electricity consumption data and calculate the monthly average.
4. Download satellite imagery from Google Earth Engine
5. Import the study area boundary and set the zoom level for display.
6. Retrieve satellite imagery from the MCD19 A2_GRANULES product, selecting the desired date, band, and study area.
7. Create a function to scale the image values by multiplying by 0.001.
8. Create a variable to store the image with AOD values and apply the scaling function.
9. Clip the image to the study area.
10. Create a time series graph of AOD values.
11. Display the AOD map and save the map image.
12. Extract AOD values at the exact locations of the monitoring stations. Researchers utilized data from all stations within the study area. The inspection tool was employed in Google Earth Engine (GEE) to extract AOD values. Clicking on each station's exact coordinates retrieved the corresponding AOD values. These extracted AOD values were subsequently used for analysis.
13. Import the shapefile of dust monitoring stations and the location of the A. solar farm.
14. Extract AOD values at the station and solar farm locations.

2.4.2 Transforming AOD data into PM concentrations

Record AOD values at each station's location in a Microsoft Excel spreadsheet, as shown in Table 2. Record PM2.5 values from the same monitoring station, as shown in Table 3. Interpolation of PM2.5 values was performed using the Inverse Distance Weighting (IDW) method to estimate monthly PM2.5 concentrations at the *"Private Owner"* solar farm location. Extracting monthly AOD values at the *"Private Owner"* solar farm location, as shown in Table 4.

Table 1: Data used for the study

No.	Dataset	Variable	Data Source	Unit	Temporal Detail	Spatial Resolution
1	MCD19A2.061: Terra & Aqua MAIAC Land Aerosol Optical Depth	AOD	Google Earth Engine	-	Daily (12 hours)	1,000 m
2	Dust Data	PM 2.5	Pollution Control Department	µg/cu.m.	Monthly (2022-2023)	-
3	Electricity Generation Data	Solar power generation	Electricity Generating Authority of Thailand	kWh	Monthly (2022-2023)	-

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Table 2: AOD values at each monitoring station

Station	Feb. 2022	Mar. 2022	Apr. 2022	May 2022	Jun. 2022	Jul. 2022	Aug. 2022	Sep. 2022	Oct. 2022	Nov. 2022	Dec. 2022	Jan. 2023	Feb. 2023
03t	0.66	0.37	0.33	0.38	0.52	0.22	0.17	0.54	0.47	0.09	0.34	0.23	0.53
05t	0.24	0.29	0.59	0.49	0.08	0.42	0.26	0.63	0.30	0.50	0.28	0.49	0.51
08t	0.10	0.20	0.34	0.47	0.02	0.29	0.28	0.36	0.36	0.13	0.30	0.55	0.24
12t	0.60	0.58	0.37	N/A	0.05	0.45	0.30	0.54	0.37	0.15	0.36	0.46	0.48
14t	0.53	0.45	0.26	0.46	0.00	0.33	0.13	0.26	0.15	0.41	0.35	0.43	0.51
16t	0.13	0.27	0.35	0.54	0.18	0.33	0.30	0.32	0.32	0.17	0.33	0.47	0.60
17t	0.18	0.18	0.37	0.38	0.05	0.32	0.23	0.54	0.39	0.15	0.33	0.55	0.48
18t	0.23	0.21	0.05	0.39	0.42	0.38	0.29	0.41	0.30	0.46	0.28	0.47	0.56
19t	0.56	0.09	0.52	0.49	0.58	1.36	0.56	0.37	0.30	0.22	0.19	0.48	0.62
27t	0.47	0.36	0.49	0.36	0.30	0.10	0.18	0.42	0.28	0.23	0.48	0.45	0.47
Average	**0.37**	**0.30**	**0.37**	**0.44**	**0.22**	**0.42**	**0.27**	**0.44**	**0.32**	**0.25**	**0.32**	**0.45**	**0.50**

Table 3: PM2.5 values from at each monitoring station

Station	Feb.2 022	Mar. 2022	Apr. 2022	May2 022	Jun. 2022	Jul. 2022	Aug. 2022	Sep. 2022	Oct. 2022	Nov. 2022	Dec. 2022	Jan. 2023	Feb. 2023
03t	35.4	28.84	37.1	22.71	21.1	20.4	20.7	22.7	29.8	31.7	37.8	38.5	66.7
05t	30.8	22.79	31.9	18.52	14.2	13.7	14.8	16.7	25.7	26.4	30.7	34.5	39.5
08t	31.5	23.48	31.8	18.74	15.0	16.0	17.9	18.5	26.6	n/a	31.4	33.2	39.3
12t	27.3	21.07	25.6	19.55	17.6	16.2	18.9	16.6	25.7	22.6	26.1	24.1	39.7
14t	30.8	23.42	33.2	20.13	17.5	16.9	18.1	18.3	28.1	31.0	34.3	39.1	40.1
16t	28.2	18.82	26.7	13.97	12.9	10.6	11.6	13.1	22.7	22.6	21.3	NA.	31.7
17t	24.3	16.97	23.8	12.61	10.7	9.68	10.6	11.3	19.7	20.6	23.2	26.0	30.8
18t	37.1	27.81	37.2	23.42	19.0	19.5	20.3	21.8	31.2	31.6	35.0	39.0	48.5
19t	29.3	21.84	30.9	18.35	16.8	17.4	18.6	19.1	25.7	27.1	28.1	29.0	36.2
27t	28.2	16.74	29.1	16.45	11.6	11.2	12.4	14.0	26.5	29.4	34.0	35.9	35.8
Average	**30.3**	**22.18**	**30.7**	**18.45**	**15.7**	**15.1**	**16.4**	**17.2**	**26.2**	**27.0**	**30.2**	**33.3**	**40.8**

Table 4: Monthly AOD and PM2.5 values derived from IDW at the *"Private Owner"* solar farm locations

Month/year	AOD	PM2.5 from IDW (µg/cu.m.)	Month/year	AOD	PM2.5 from IDW (µg/cu.m.)
February 2022	0.26	36.220	September 2022	0.332	21.417
March 2022	0.189	27.373	October 2022	0.273	30.407
April 2022	0.402	36.265	November 2022	0.302	31.335
May 2022	0.603	22.495	December 2022	0.252	34.383
June 2022	0.344	18.574	January 2023	0.530	38.248
July 2022	0.381	19.422	February 2023	0.598	48.063
August 2022	0.294	19.539			

AOD values at the solar farm location were paired with the corresponding PM2.5 values obtained from IDW interpolation. A scatter plot was created with AOD on the x-axis and PM2.5 on the y-axis. The equation from the scatter plot with the highest R^2 value converted AOD values, as shown in Table 5. Based on the tests and comparisons using all five equations, A polynomial trend is used for a complex pattern of change and non-static data. The polynomial equation was found to yield the highest R^2 value. To convert dust values at the *"Private Owner"* solar farm from February to May 2022 using a quadratic polynomial equation with an $R^2 = 0.956$, as shown in equation 2 and Table 6.

$$y = -282.81AOD^2 + 209.03AOD - 0.9569$$

Equation 2

To Convert dust values at the *"Private Owner"* solar farm from June 2022 to October 2023 using a quadratic polynomial equation with an $R^2 = 0.710$ as shown in Equation 3 and Table 7.

$$y = 1677.6AOD^2 - 1173.3AOD + 223.57$$

Equation 3

To Convert dust values at the solar farm from November 2022 to February 2023 using a quadratic polynomial equation with an $R^2 = 0.999$, as shown in Equation 4 and Table 8.

$$y = 364.01AOD^2 - 270.69AOD + 79.645$$

Equation 4

Table 5: R^2 values for the relationship between AOD and PM2.5 across different equation types

Equation tyeps	R^2 values		
	Summer	Rainy	Winter
Polynomial	0.956	0.710	0.999
Exponential	0.188	0.515	0.780
Linear	0.217	0.480	0.756
Logarithmic	0.102	0.514	0.694
Power	0.086	0.551	0.718

Table 6: PM2.5 derived from AOD for February 2022 to May 2022

Month/year	AOD	PM2.5 from AOD (µg/cu.m.)
February 2022	0.260	34.273
March 2022	0.189	28.448
April 2022	0.402	37.370
May 2022	0.603	22.256

Table 7: PM2.5 derived from AOD for June 2022 to October 2022

Month/year	AOD	PM2.5 from AOD (µg/cu.m.)
June 2022	0.344	18.475
July 2022	0.381	20.065
August 2022	0.294	23.625
September 2022	0.332	18.946
October 2022	0.273	28.289

Table 8: PM2.5 derived from AOD for November 2022 to February 2023

Month/year	AOD	PM2.5 from AOD (µg/cu.m.)
November 2022	0.302	31.096
December 2022	0.252	34.547
January 2023	0.530	38.430
February 2023	0.598	47.944

Table 9: Accuracy assessment of PM2.5 estimations

Dates	PM2.5 sources	AOD	Monitoring Stations
February 2022 to May 2022	AOD	1.000	-
	Monitoring stations	0.977	1.000
June 2022 to October 2022	AOD	1.000	-
	Monitoring stations	0.842	1.000
November 2022 to February 2023	AOD	1.000	-
	Monitoring stations	0.999	1.000

2.4.3 Verification of the accuracy of PM2.5 values obtained from AOD

The R^2 value indicates that the estimated PM2.5 values derived from AOD data are reasonably accurate. Calculate the correlation coefficient (R^2) as shown in Table 9.

2.4.4 Analysis of the correlation between PM2.5 levels and electricity consumption

Microsoft Excel was used to analyze the correlation between PM2.5 values converted from AOD and electricity consumption. A scatter plots were created to find the regression equation, then check the R^2 value. If R^2 is more significant than 0.6, it is considered a strong correlation. Subsequently, all data will be aggregated for seasonal analysis.

3. Result and Discussion

3.1 Correlation between PM2.5 Levels, Derived from AOD, and Solar Power Generation in the Study Area

February to May 2022: The analysis indicates that PM2.5 levels, derived from AOD values, negatively correlate with average solar power generation, with a coefficient of -0.7 from February to May 2022, as shown in Table 10. This implies that an increased AOD or PM2.5 levels leads to decreased solar power output. This finding is consistent with the impact of airborne particulate matter obstructing sunlight and reducing the efficiency of solar panels, as shown in Table 11.

June to October 2022: The analysis of the period from June to October (the rainy season) indicates that PM2.5 levels, derived from AOD values negatively correlate with average solar power generation, with a coefficient of -0.24, as shown in Table 12. This negative correlation suggests that as AOD or PM2.5 levels increase, the average solar power output decreases during the rainy season. However, the lower correlation compared to the period from February to May (the summer) may reflect other factors, such as increased cloud cover during the rainy season, which affects power generation differently than in the summer, as shown in Table 13.

November 2022 to February 2023: From November 2022 to February 2023, which corresponds to the winter, the correlation between AOD values and solar power generation from the solar farm is 0.6, as shown in Table 14, indicating a positive relationship. This positive correlation suggests that the solar power output is also low when AOD or PM2.5 levels are low.

Table 10: Correlation Matrix of PM2.5, AOD, and solar power generation (Feb. to May 2022)

	PM2.5 from IDW	AOD	PM2.5 from AOD	Average Solar Power
PM2.5 from IDW	1.00			
AOD	-0.47	1.00		
PM2.5 from AOD	0.98	-0.48	1.00	
Average Solar Power	-0.68	-0.32	-0.68	1.00

Table 11: Monthly PM2.5 and solar power generation data (Feb. to May 2022)

Month/year	PM2.5 from IDW (μg/cu.m.)	AOD	PM2.5 from AOD (μg/cu.m.)	Average Solar Power (kWh)
February 2022	36.22	0.26	34.27	2,887.95
March 2022	27.37	0.189	28.45	3,205.50
April 2022	36.27	0.402	37.37	2,678.30
May 2022	22.50	0.603	22.26	2,992.94

Table 12: Correlation Matrix of PM2.5, AOD, and Solar power generation (June to October 2022)

	PM2.5 from IDW	AOD	PM2.5 from AOD	Average Solar Power
PM2.5 from IDW	1.00			
AOD	-0.69	1.00		
PM2.5 from AOD	0.84	-0.82	1.00	
Average Solar Power	-0.48	0.373	-0.24	1.00

Table 13: Monthly PM2.5 and solar power generation data (Jun. to Oct. 2022)

Month/year	PM2.5 from IDW (μg/cu.m.)	AOD	PM2.5 from AOD (μg/cu.m.)	Average Solar Power (kWh)
June 2022	18.57	0.344	18.48	3,220.28
July 2022	19.42	0.381	20.06	3,043.13
August 2022	19.54	0.294	23.62	2,957.73
September 2022	21.42	0.332	18.95	2,555.89
October 2022	30.41	0.273	28.29	2,781.17

Table 14: Correlation Matrix of PM2.5, AOD, and solar power generation (Nov. 2022 to Feb.2023)

	PM2.5 from IDW	AOD	PM2.5 from AOD	Average Solar Power
PM2.5 from IDW	1.00			
AOD	0.87	1.00		
PM2.5 from AOD	0.99	0.87	1.00	
Average Solar Power	0.62	0.53	0.59	1.00

Table 15: Monthly PM2.5 and solar power generation data (Nov. 2022 to Feb. 2023)

Month/year	PM2.5 from IDW (μg/cu.m.)	AOD	PM2.5 from AOD (μg/cu.m.)	Average Solar Power (kWh)
November 2022	31.33	0.302	31.10	2,563.76
December 2022	34.38	0.252	34.55	2,021.55
January 2023	38.25	0.53	38.43	2,139.79
February 2023	48.06	0.598	47.94	2,942.77

Table 16: R^2 values for the relationship between AOD and PM2.5 across different equation types

Equation types	R^2 values		
	Summer (February to May 22)	**Rainy (June to October 22)**	**Winter (November 2022 to February 2023)**
Polynomial	0.972	0.074	0.939
Exponential	0.443	0.057	0.382
Linear	0.459	0.058	0.354
Logarithmic	0.390	0.054	0.297
Power	0.376	0.054	0.324

Despite PM2.5 levels being the highest during the year, this may be associated with clearer skies and fewer clouds, which could enhance the amount of sunlight reaching the solar panels compared to other seasons, resulting in the observed positive correlation, as shown in Table 15.

3.2 Guidelines for Planning and Managing the Energy Industry for Solar Farms

From the analysis of the relationship between PM 2.5 dust and electricity generated from solar cells, we can estimate the energy output from solar farms (*y*) and manage it seasonally using the equations as shown in Equation 5, Equation 6, Equation 7 and Table 16.

February to May 2022: The analysis of the relationship between PM2.5 levels derived from AOD and solar power generation at the solar farm from February to May 2022 (the summer) indicates that Polynomial Regression explains this relationship better than other equations. The Polynomial Regression model achieved an R^2 value of 0.970, considered very high. This equation can accurately predict solar power output in the study area. However, it is essential to consider varying atmospheric and environmental factors when applying them in other places, as shown in Equation 5.

$$y = -5.6793(PM2.5)^2+315.55(PM2.5) -1{,}207.4$$

Equation 5

June to October 2022: The analysis of the relationship between PM2.5 levels derived from AOD and solar power generation at the solar farm from June to October 2022 (the rainy season) reveals that Polynomial Regression has an R^2 value of 0.074, considered very low. This indicates that the model does not effectively explain the relationship between PM2.5 levels and solar power generation. The low R^2 value suggests that other factors may significantly impact power generation during this period or that the data may exhibit high variability that cannot be explained by the linear or nonlinear models used in this analysis.

Exploring alternative analytical methods or collecting additional data that reflects various influencing factors may be necessary to achieve more reliable results. The energy output from solar farms for rainy season can be estimated from Equation 6.

$$y = -3.1693(PM2.5)^2 + 133.15(PM2.5) + 1{,}558.4$$

Equation 6

November 2022 to February 2023: The analysis of the relationship between PM2.5 levels derived from AOD and solar power generation at the solar farm from November 2022 to February 2023 (the winter) indicates that Polynomial Regression provides a better explanation of this relationship than other equations. The Polynomial Regression model achieved an R^2 value of 0.939, which is considered very high. This equation can accurately predict solar power output in the study area. However, it is essential to consider varying atmospheric and environmental factors when applying them in other places. The equation obtained from the analysis is shown in Equation 7.

$$y=9.3757(PM2.5)^2 - 714.32(PM2.5) - 15{,}651$$

Equation 7

4. Discussion

4.1 Correlation between PM2.5 Levels from AOD and Solar Energy Output in the Study Area

In the summer, PM2.5 levels were negatively correlated with solar energy production in the study area. This means that as PM2.5 levels increase, the amount of solar energy produced decreases. This is consistent with the impact of airborne particulate matter obstructing sunlight and reducing the efficiency of solar panels [7][8][9][10][11][12][17] and [18]. This occurs due to the interaction of atmospheric particles with sunlight, which may involve absorption, scattering, or reflection [25]. During the rainy season, PM2.5 levels derived from AOD negatively correlated with the average solar energy output, with a correlation value of -0.24. This indicates that as AOD or PM2.5 levels increase, the average amount of solar energy produced decreases.

However, the low correlation value may suggest the influence of other factors, such as the high cloud cover during the rainy season [26], which also affects solar energy production. In the winter, the correlation between PM2.5 levels and solar energy output from solar farms was 0.6, indicating a positive correlation. This means that when PM2.5 levels are low, the amount of solar energy produced also tends to be high. This correlation may be related to the clear skies and low cloud cover typical of winter extending into early summer [26].

The season with the lowest average monthly solar energy output is winter, at 2,416,97 kWh. When compared to PM2.5 levels, this period has the highest PM2.5 concentrations among all seasons. Winter is characterized by high atmospheric pressure, which prevents air from rising vertically, leading to poor air circulation and the accumulation of airborne particulate matter. This accumulation reduces solar energy production, particularly in December, when PM2.5 levels are at their highest [23]. The season with the highest average monthly solar energy output is summer, at 2,941.17 kWh. Compared to PM2.5 levels, summer has a lower average PM2.5 concentration than winter but higher than the rainy season. This may be related to the amount of solar radiation, a key factor in solar energy production [27]. Summer has the highest average solar radiation intensity in Samut Prakan Province.

The relatively low correlation between PM2.5 levels from AOD and solar energy output in the study area can be attributed to other factors that directly affect solar energy production. These factors include the amount and intensity of sunlight, weather conditions and cloud cover, the orientation and angle of the solar panels, and high temperatures, which can reduce the efficiency of the solar panels [21] and [22]. These studies collectively highlight the significant impact of particulate matter, especially PM2.5, on solar energy efficiency, reinforcing the importance of considering air quality in solar power planning and operations. We found that the season significantly affects the levels of PM 2.5 dust, which also plays an essential role in the relationship between PM 2.5 dust and the electricity generated from solar cells. This is consistent with previous research conducted by others that found similar results. The power output decreased for monocrystalline solar panels and polycrystalline panels.

These findings demonstrate that dust accumulation significantly diminishes the energy output of solar panels [7] and [8], found that dust particles can reduce solar panel power output by approximately 20-60% [9] [10] [11] and [12]. Remote sensing methods have shown significant reductions in solar energy output due to dust, and findings highlight the considerable impact of dust on solar energy production, underscoring the importance of monitoring and forecasting dust levels to optimize energy generation [17] and [18], as shown in Table 17.

Additionally, this can be explained by the fact that the study area has only ten monitoring stations for dust measurements. Furthermore, wind influence can cause discrepancies between satellite measurements and ground-based observations, leading to potential inaccuracies in dust data conversion. The analysis was based on average monthly data for only 13 months, which may not be sufficiently detailed. A more thorough study should include daily data over multiple years and increase the number of representative monitoring stations.

4.2 Guidelines for Planning and Managing the Energy Industry for Solar Farms

The scatter plot graph with Polynomial Regression analysis indicates an excellent R^2 value. For forecasting electrical energy production in the study area using the equation and PM2.5 dust data converted from AOD values, it is possible to predict the amount of electrical energy that solar cells can generate. This benefits solar farms needing to plan and manage their energy resources.

The equations to use are $y = -5.6793(PM2.5)^2 + 315.55(PM2.5) - 1{,}207.4$ for summer, and $y = 9.3757(PM2.5)^2 - 714.32(PM2.5) - 15651$ for winter. However, for forecasting in other areas, it is necessary to determine the appropriate equation for that specific region due to varying physical factors such as light intensity, seasons, cloud cover, and other elements, which affect dust levels and the energy production capacity of solar cells differently.

During the rainy season, $y = -3.1693(PM2.5)^2 + 133.15(PM2.5) + 1{,}558.4$ for the rainy season, it is impossible to predict the amount of electrical energy solar cells can produce. Other factors may have a more impact significant impact on energy production during this time than PM2.5 dust levels, or the data might exhibit high variability that cannot be explained by the simple linear or nonlinear equations used in this analysis. It may be necessary to consider alternative analytical methods or to gather additional data that fully reflects the various factors to obtain more reliable results. The rainy season experiences cooler temperatures than the summer, leading to higher electricity generation efficiency. High humidity during the rainy season facilitates the dissipation of heat accumulated in solar panels, further enhancing cell performance.

Table 17: Seasonal variation of IDW, AOD, PM2.5 derived from AOD, and average solar power

Season	Month/year	IDW (µg/cu.m.)	AOD	PM2.5 from AOD (µg/cu.m.)	Average Solar Power (kWh)
Summer	Feb. 2022	36.220	0.26	34.273	2,887.952
	Mar. 2022	27.373	0.189	28.448	3,205.501
	Apr. 2022	36.265	0.402	37.370	2,678.301
	May 2022	22.495	0.603	22.256	2,992.942
			Average	**30.587**	**2,941.174**
Rainy	Jun. 2022	18.574	0.344	18.475	3,220.277
	Jul. 2022	19.422	0.381	20.065	3,043.128
	Aug. 2022	19.539	0.294	23.625	2,957.726
	Sep. 2022	21.417	0.332	18.946	2,555.894
	Aug. 2022	30.407	0.273	28.289	2,781.166
			Average	**21.880**	**2,911.638**
Winter	Nov. 2022	31.335	0.302	31.096	2,563.761
	Dec. 2022	34.383	0.252	34.547	2,021.548
	Jan. 2023	38.248	0.53	38.430	2,139.795
	Feb. 2023	48.063	0.598	47.944	2,942.771
			Average	**38.004**	**2,416.969**

Additionally, the southwest monsoon influences Thailand's rainy season, resulting in extensive cloud coverage, particularly cumulonimbus and nimbostratus clouds. These cloud types cause rainfall and, on some days, heavy precipitation, leading to reduced solar irradiance across the country compared to other seasons. Consequently, the intensity of sunlight reaching solar panels decreases, resulting in lower energy production. The solar irradiance distribution is quite similar across all regions of Thailand. The average annual solar irradiance for the entire country is 17.5 MJ/m2-day. This fluctuation may be why the equation cannot be used for forecasting [7] [28] and [29].

4.3 Limitations

1. The study area has only ten monitoring stations for dust measurements, which may not adequately represent the variability of PM2.5 concentrations across a larger region.

2. The equations and methods used in the analysis may not capture all relevant factors influencing solar energy production, such as the concentration of other pollutants or environmental variables.

3. The analysis relies on average monthly data over only 13 months, which may not sufficiently reveal long-term trends in solar energy production or PM2.5 levels.

4. Geographical Factors: Geographic characteristics of the study area, such as terrain and the proximity of industrial activities, may influence both PM2.5 levels and solar energy generation.

5. Weather Variability: Variations in weather conditions, including temperature and humidity, can impact solar energy production and may not be fully accounted for in this study.

6. Discrepancies Between Remote and Ground Measurements: Wind effects may create discrepancies between satellite data and ground-based observations, leading to potential inaccuracies in dust data conversion.

7. Due to the flexibility of polynomial fitting in analyzing data trends, it is instrumental in cases where data values are uncertain. Compared to exponential fitting, which is suitable for data that increases or decreases exponentially, and linear fitting, which is ideal for consistently increasing or decreasing data, polynomial fitting in scatter plots can better analyze and predict the distribution and uncertainty of AOD values. Since the AOD values were obtained through interpolation, an approximation method using polynomial fitting allows for more effective analysis and prediction of AOD values with distribution and variability.

5. Conclusion

This study emphasizes the seasonal influence of PM2.5 on solar energy production, using AOD data to investigate dust impacts across summer, rainy, and winter periods. Results showed that summer had the highest solar output (2,941.174 kWh monthly), linked to lower PM2.5 levels and higher solar radiation. Conversely, winter had the lowest output (2,416.969 kWh) despite clearer skies and atmospheric conditions trapping dust.

The rainy season showed a weaker negative correlation between PM2.5 and solar production, likely due to cloud cover interference. Polynomial regression analysis effectively predicted solar output, accurately capturing non-linear relationships between seasonal dust levels and solar efficiency. Findings suggest that seasonal dust variability significantly affects solar power, highlighting the importance of high-resolution data and accurate dust measurements for optimizing solar panel performance.

6. Suggestion

From our study, if we want to continue in the future, we should conduct additional studies as follows to increase the accuracy. Therefore, we propose to do the following:

1. Use of High-Frequency Data: Daily data should be analyzed to improve accuracy, mainly focusing on specific days with the highest and lowest dust levels rather than relying on daily averages. This approach provides more precise insights into dust impacts on solar power generation.

2. Expansion of Dust Monitoring Stations: Increasing the number of dust measurement stations can enhance the granularity and accuracy of dust level estimations and their effects on solar panel efficiency.

3. Higher-Resolution Satellite Data: Selecting satellites with higher resolution than the MCD192A2.061 (Terra & Aqua MALAC Land Aerosol Optical Depth) will improve the precision of AOD data, leading to more reliable assessments of dust impacts on solar power.

4. Incorporation of Additional Data Layers: Future studies should consider including AOD uncertainty (AOD_uncertainty) and quality assessment layers (AOD_QA) to ensure data quality. These layers will help assess the reliability and uncertainty of AOD data for a more accurate analysis.

5. Consideration of Local Environmental Factors: When adapting this research approach to other regions, it is crucial to account for unique geographical and climatic factors. Key considerations include the number and placement of dust monitoring stations, sunlight intensity, wind speed, rainfall frequency, cloud cover, airflow obstructions, and shadows from surrounding structures. These elements are vital for accurately evaluating the impact of dust on solar energy production across different areas.

6. Advancement of Renewable Energy Planning: These insights highlight the significance of air quality in renewable energy planning. Developing localized dust management strategies will be essential to maximize the efficiency of solar power generation, thereby contributing to cleaner and more sustainable energy solutions.

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