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Impact of Climate Variability on Solar Power Plant Electricity Production in Lombok Island

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Abstract. Indonesia, located in the equatorial region, possesses vast solar energy potential reaching up to 200,000 MW. However, its utilization remains significantly low at only 0.08% of the total potential. In remote regions like Lombok Island, solar power plants serve as a strategic solution for clean and sustainable electricity, especially where access to fossil fuels is limited and costly. This study investigates the impact of local temperature variation on the efficiency and power output of PLTS in Lombok, a tropical region with high solar irradiance (4–6 kWh/m²/day) and elevated daytime temperatures (26–33°C). Using temperature and solar radiation data from 2019 to 2024, along with electricity output records from three major Solar Power Plant facilities (Pringgabaya, Selong, Sengkol, each 7 MWp), the research applies statistical correlation and regression modeling to quantify the relationships among temperature, irradiance, and energy output. The findings are expected to reveal a negative correlation between increased ambient temperature and photovoltaic efficiency due to rising electrical resistance in solar cells. Conversely, higher irradiance generally enhances power output, although its benefits may be offset by excessive heat. This study also incorporates Dipole Mode Index (DMI) analysis to understand the regional climatic influence on local temperature trends. DMI is selected due to its direct representation of the Indian Ocean Dipole (IOD) phenomenon, which significantly affects weather patterns, sea surface temperature, and consequently, regional thermal variations in the Indonesian maritime continent. By focusing on DMI, this research captures a dominant mode of interannual climate variability that is particularly relevant to temperature fluctuations in Lombok. Furthermore, the study provides quantitative results for the Lombok region, including the percentage impact of each variable on power production. It also analyzes the seasonal and intraseasonal variations of temperature and solar radiation to identify periods of optimal and suboptimal solar plant performance. These findings are expected to support predictive energy output modeling and inform technical recommendations such as thermal mitigation strategies and material optimization for improving solar power performance in tropical environments. These insights are crucial for supporting Indonesia's energy transition and achieving greater integration of renewable sources in its national energy mix.

Keywords: *Solar Power Plant, Photovoltaic Efficiency, Local Temperature, Solar Irradiance, Dipole Mode Index (DMI), Tropical Climate, Renewable Energy*

1 Introduction

Energy plays a fundamental role in supporting economic development, technological advancement, and societal well-being. In Indonesia, the continuous rise in energy demand driven by rapid urbanization, population growth, and industrial activities has intensified the need for reliable and sustainable energy sources. Despite the nation's vast renewable energy potential, particularly in solar energy, fossil fuels still dominate the energy mix. This dependency not only poses long-term sustainability challenges but also contributes significantly to greenhouse gas emissions and global warming (IPCC, 2023).”.

Indonesia has an estimated solar energy potential exceeding 200,000 MW, with average daily solar radiation levels ranging from 4 to 6 kWh/m² (EBTKE, 2021). However, only a small fraction of this potential has been harnessed, with installed solar capacity accounting for less than 0.1% of the total. This gap between potential and utilization is even more pronounced in remote and non-interconnected areas, where fuel transportation costs and energy access remain persistent issues. In these regions, the adoption of solar power plants (PLTS) offers a promising solution for decentralized, clean, and cost-effective electricity supply (IRENA, 2020).

Lombok Island, part of the West Nusa Tenggara Province, represents a compelling case study for solar energy deployment. With its favorable solar irradiance and limited access to fossil fuels, PLTS development in Lombok can contribute significantly to local energy resilience and Indonesia's broader transition to renewable energy (IRENA, 2020). However, a critical technical challenge in the tropical climate of Lombok is the high ambient temperature, which can negatively affect the efficiency and output of photovoltaic (PV) systems. Elevated temperatures increase the internal resistance in PV cells, leading to reduced voltage and overall conversion efficiency (Skoplaki and Palyvos, 2009).

Understanding how temperature and other environmental factors such as solar irradiance influence PLTS performance is essential for optimizing system design, forecasting energy production, and improving operational reliability. Moreover, regional climate phenomena such as the Indian Ocean Dipole (IOD) also play a role in modulating irradiance and temperature patterns, thereby indirectly affecting solar energy output (Saji, 1999). This study aims to analyze the impact of local temperature variation on the efficiency and output of PLTS in Lombok, while also examining the influence of IOD-driven climate variability. The IOD is specifically selected for this analysis because it is the dominant mode of interannual climate variability over the Indian Ocean and exerts a strong influence on rainfall, cloud cover, and surface temperature across Indonesia, including the Lesser Sunda Islands (Ashok, 2003). Compared to ENSO, the IOD has a more direct and localized impact on the Indonesian maritime continent, making it particularly relevant for understanding short- to medium-term fluctuations in solar irradiance and thermal conditions in Lombok. By integrating statistical analysis and Python-based simulations, this research seeks to offer technical insights and recommendations for enhancing PLTS performance in tropical regions.

2 Methodology

2.1 Study Area

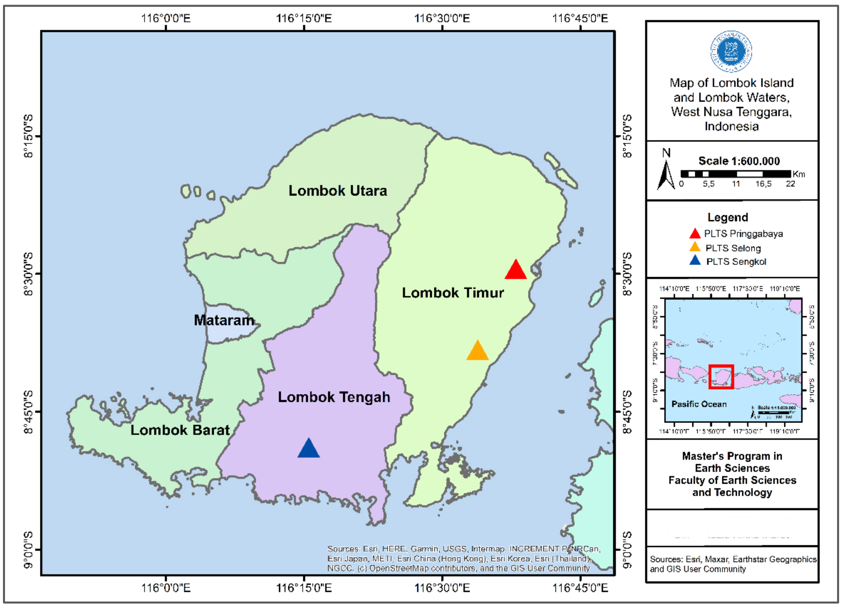

Figure 1. Map of Lombok Island (115°46' – 119°5' East Longitude and 8°10' – 9°5' South Latitude)

The research focuses on Lombok Island (115° 46' – 119° 5' E and 8° 10' – 9° 5' S) in West Nusa Tenggara, Indonesia. The island has 4–6 kWh/m²/day solar irradiance and 26–33°C temperatures. It relies on PLTS due to limited fossil fuel logistics. Three 7 MWp PLTS Pringgabaya, Selong, and Sengkol are the case study sites.

2.2 Data Sources

This study utilizes data from three primary sources: (1) meteorological data, including daily temperature and solar irradiance from 2019 to 2024, obtained from BMKG and other relevant institutions; (2) operational data from three selected solar power plants in Lombok PLTS Pringgabaya, PLTS Selong, and PLTS Sengkol each with an installed capacity of 7 MWp, covering performance metrics such as electrical output and efficiency; and (3) supporting scientific literature and prior studies that provide context and empirical evidence regarding the influence of environmental variables on photovoltaic performance.

2.3 Data Analysis

The data collected are analyzed using statistical and simulation-based approaches to understand the relationship between environmental variables and PLTS performance. First, Pearson correlation is applied to quantify the degree of association between ambient temperature, solar irradiance, and power output (Mukaka, 2012). Following this, a linear regression model is constructed to represent the influence of temperature (T) and irradiance (G) on the electrical power output (Pout) of the system. The model is expressed as:

$$P_{out} = \beta_0 + \beta_1 T + \beta_2 G + \varepsilon$$

where *Pout* is the electrical power output, *T* is ambient temperature, *G* is solar irradiance, β_0, β_1, and β_2 are the regression coefficients, and ε is the residual error (Montgomery, 2012). To complement the analysis, Python-based simulations are used to model PLTS behavior under varying environmental conditions, helping to validate the statistical findings and support performance forecasting (Mohamed, 2022).

3 Result

3.1 Time Series Analysis of Key Variables

Figure 1. shows the monthly variation of surface shortwave radiation, air temperature, electricity production at three photovoltaic power plants (PLTS Sengkol, PLTS Selong, and PLTS Pringgabaya), and the Dipole Mode Index (DMI) from 2019 to early 2024. All three sites exhibit similar seasonal patterns in solar radiation (Figure 1.a), with peak values typically occurring during the dry season when cloud cover is minimal. Although radiation levels are relatively consistent across locations, PLTS Selong tends to receive slightly less incoming solar energy, likely due to local microclimatic differences.

Meanwhile, based on Figure 1.b, air temperatures fluctuate between 25°C and 28°C, with Selong often recording slightly cooler values compared to the other sites. The seasonal cycle of temperature is well-aligned with the tropical climate characteristics of the region. These temperature differences may play a role in panel efficiency, as higher temperatures can reduce photovoltaic performance.

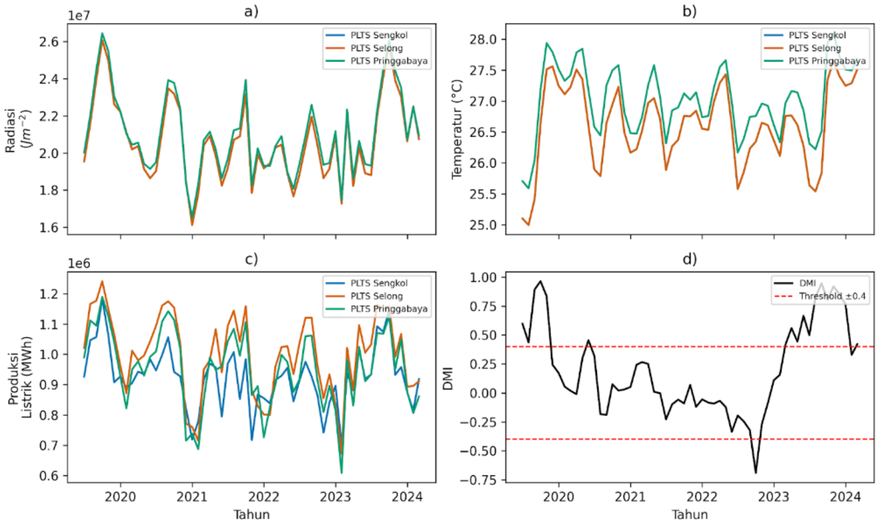

Figure 2. Monthly time series of key variables from 2019 to early 2024 at three photovoltaic power plants. The plots show: (a) surface shortwave radiation (J/m²), (b) 2-meter air temperature (°C), (c) electricity production (MWh), and (d) the Dipole Mode Index (DMI).

Electricity production generally mirrors the radiation trends, with higher output during periods of stronger solar radiation (Skoplaki and Palyvos, 2009). Interestingly, PLTS Selong consistently produces more electricity than the other two sites, even when radiation levels are comparable or lower. This suggests that other factors such as system design, technology type, or maintenance practices may contribute to better performance (Jordan and Kurtz, 2013). A noticeable dip in production occurs in 2021 and late 2022 across all sites, potentially linked to weather disruptions or operational constraints.

Meanwhile, the DMI time series highlights distinct ocean-atmospheric events. Positive IOD phases are evident in early 2019 and again in late 2022 to 2023, surpassing the +0.4 threshold, while negative phases dominate parts of 2021. These large-scale climate anomalies may affect cloud cover and rainfall, indirectly influencing solar energy availability at the local level (Saji, 1999).

3.2 Correlation Between Electricity Production and Climatic Variables

Figure 2 illustrates the Spearman correlation between electricity production and three climatic variables Dipole Mode Index (DMI), solar radiation, and air temperature across three photovoltaic power plants: PLTS Selong, PLTS Pringgabaya, and PLTS Sengkol. The aim is to identify which environmental factors most influence the variability in monthly electricity output.

Among the three variables, solar radiation shows the strongest and most consistent correlation with electricity production. The correlation coefficients are high, ranging from $\rho = 0.61$ at Selong and Sengkol, to $\rho = 0.70$ at Pringgabaya. These values indicate a strong positive monotonic relationship, confirming that increased solar radiation is closely associated with higher electricity production. This result aligns with the fundamental operating principles of photovoltaic (PV) systems, which convert incident solar energy into electricity (Duffie & Beckman, 2013).

In contrast, the Dipole Mode Index (DMI) exhibits a weak positive correlation with electricity output, ranging from $\rho = 0.16$ to 0.33. While positive IOD events are known to reduce cloud cover and enhance insolation over parts of the Indonesian region (Saji et al., 1999), their influence on solar energy output appears indirect in this context. This may be due to the temporal lag between ocean-atmospheric anomalies and their manifestation in surface weather conditions, such as changes in cloudiness or precipitation patterns that directly affect irradiance (Ummenhofer, 2009).

For air temperature, the relationship with electricity production is weak or even negative. At PLTS Selong, the correlation is slightly negative ($\rho = -0.15$), while the values are nearly zero at Pringgabaya ($\rho = 0.09$) and Sengkol ($\rho = -0.03$). This suggests that temperature does not exhibit a consistent monotonic influence on output. Elevated ambient temperatures are known to reduce the efficiency of PV modules due to increased internal resistance and reduced open-circuit voltage (Skoplaki & Palyvos, 2009). While Lombok's high irradiance contributes positively to output, the thermal stress may partially offset these gains, especially during peak daytime heat.

Overall, the analysis confirms that solar radiation is the most dominant environmental driver of electricity production in the three PLTS locations. DMI may serve as a secondary, climate-scale indicator influencing seasonal irradiance patterns but is less directly impactful than local radiation measurements. Meanwhile, temperature exerts a marginal or counterproductive effect. These findings emphasize the importance of site-specific irradiance monitoring and thermal management in PV system design and forecasting for tropical regions like Lombok. Incorporating both real-time and climate-scale indicators can enhance energy planning and system resilience in the face of environmental variability.

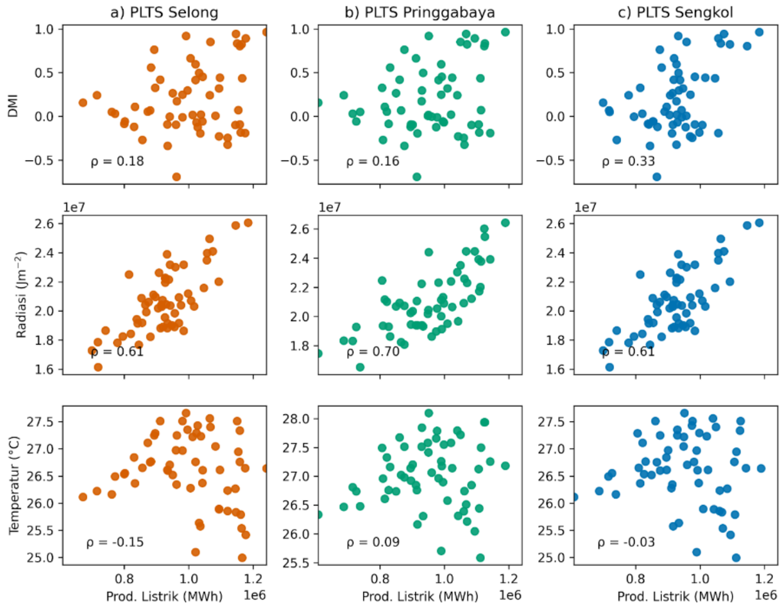

Figure 3. Spearman correlation between monthly electricity production and three climatic variables at PLTS Selong (left column), PLTS Pringgabaya (middle column), and PLTS Sengkol (right column). Each subplot displays the scatter distribution and corresponding Spearman's ρ value, indicating the strength and direction of the monotonic relationship.

3.3 Regression Analysis of Electricity Production

The regression model explains 54.2% of the variability in electricity production at PLTS Selong, with solar radiation emerging as the strongest and most significant predictor (coefficient = 102,100; $p < 0.001$). This confirms the direct influence of solar input on photovoltaic performance. Air temperature shows a significant negative effect (coefficient = −42,800; $p = 0.001$), suggesting that higher temperatures reduce panel efficiency. Meanwhile, DMI has no significant influence ($p = 0.356$), indicating a weak or indirect role in affecting power output. Overall, the results highlight that electricity production at PLTS Selong is primarily driven by solar radiation, with temperature playing a secondary, inhibitory role, and DMI contributing minimally.

The regression model for PLTS Pringgabaya explains 55.9% of the variation in monthly electricity production, with solar radiation as the only statistically significant predictor ($p < 0.001$). Its strong positive coefficient (103,400) confirms that higher radiation levels drive increased output. In contrast, temperature and DMI show no significant effect ($p = 0.151$ and 0.226, respectively), indicating minimal direct influence. While these variables may have indirect roles, their impact is not clearly captured by this model. Overall, solar radiation is the dominant factor influencing electricity production at this site.

The regression model for PLTS Sengkol explains 62.4% of the variability in electricity production, with solar radiation emerging as the most significant predictor (coefficient = 72,860, $p < 0.001$). This confirms a strong positive link between solar input and power output. Air temperature has a significant negative effect (coefficient = −24,980, $p = 0.005$), likely due to reduced panel efficiency at higher temperatures. Meanwhile, DMI shows a positive but non-significant association ($p = 0.206$), suggesting a weak or indirect influence. In summary, solar radiation is the key driver, temperature has a notable negative impact, and DMI does not significantly affect electricity production at this site.

Table 1. Summary of multiple linear regression results for monthly electricity production at PLTS Selong, Pringgabaya, and Sengkol. The table presents the model fit statistics (R^2 and adjusted R^2), regression coefficients for each predictor (DMI, temperature, and radiation), their statistical significance, and the identified main driver at each site.

	PLTS Selong	PLTS Pringgabaya	PLTS Sengkol
R^2	0.542	0.559	0.624
Adj. R^2	0.516	0.534	0.603
Coef(DMI)	−33,180	-40,560	31,060
Sig.(DMI)	No	No	No
Coef(Temp)	−42,800	−17,470	−24,980
Sig.(Temp)	Yes (p=0.001)	No	Yes (p=0.005)
Coef(Rad)	102,100	103,400	72,860
Sig.(Rad)	Yes (p<0.001)	Yes (p<0.001)	Yes (p<0.001)
Main Driver	Radiation	Radiation	Radiation

3.4 Composite analysis based on the phases of the Indian Ocean Dipole (IOD)

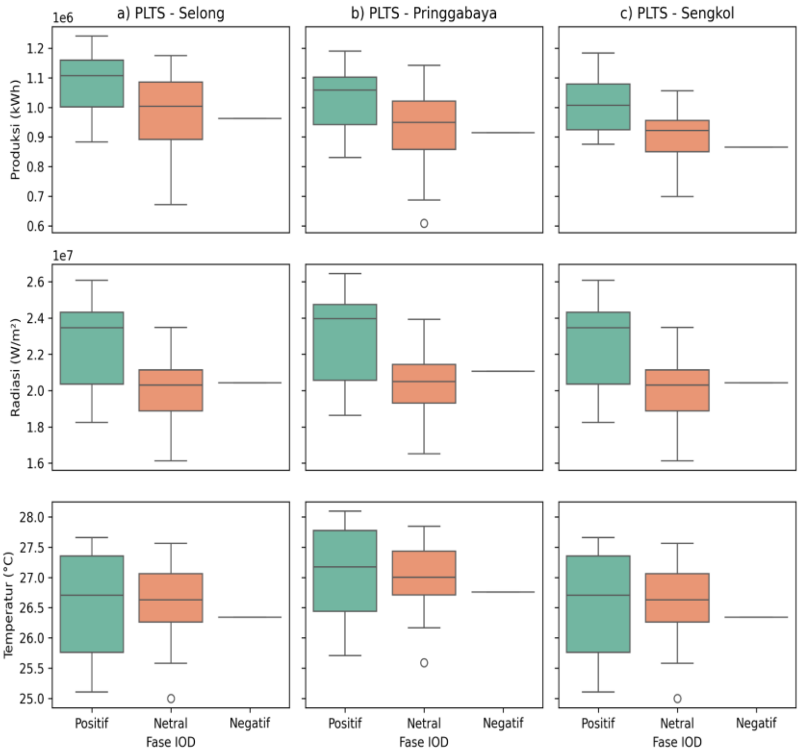

Figure 4. Boxplots of electricity production, solar radiation, and temperature during Positive, Negative, and Neutral IOD phases at each solar power plant

The boxplots illustrate the distribution of electricity production, solar radiation, and temperature at three solar power plant Selong, Pringgabaya, and Sengkol across different IOD phases: Positive, Neutral, and Negative. The findings consistently demonstrate that all observed solar power plant show increased electricity production during Positive IOD phases. This trend is attributed to elevated solar radiation levels, likely resulting from reduced cloud cover and precipitation during these periods.

Solar radiation exhibited a coherent pattern across all solar power plant sites, with the highest values recorded during Positive IOD phases and the lowest during Negative phases. This supports the conclusion that Positive IOD conditions enhance solar irradiance by reducing atmospheric cloudiness over southern Indonesia. As a result, solar radiation emerges as the principal driver of increased electricity output in the region.

In contrast, ambient temperature showed no statistically or visually significant variation between IOD phases. Although slightly higher temperatures were observed during Positive IOD phases, the differences generally less than 1°C were insufficient to exert a notable influence on photovoltaic efficiency. Thus, temperature is not considered a dominant factor affecting electricity production in this context.

Table 2. Table of mean and standard deviation distribution across IOD phases at the Selong solar power plant

	electricity production		Radiation		Temperature	
	mean	Std	Mean	Std	Mean	Std
IOD-	9,620136E+05	NaN	20422656	NaN	26,343536	NaN
Netral	9,804418E+05	131011,722901	20141344	1,721842E+06	26,629969	0,583842
IOD+	1,074822E+06	116.145,062826	22603930	2,708388E+06	26,560953	0,905984

Table 3. Table of mean and standard deviation distribution across IOD phases at the Pringgabaya solar power plant

	electricity production		Radiation		Temperature	
	mean	Std	Mean	Std	Mean	Std
IOD-	9,141697E+05	NaN	21071360	NaN	26,757599	NaN
Netral	9,340360E+05	125621,947478	20472468	1,736856E+06	27,003904	0,507377
IOD+	1,023375E+06	111087,6125	22998384	2,703049E+06	27,072998	0,807892

Table 4. Table of mean and standard deviation distribution across IOD phases at the Sengkol solar power plant

	electricity production		Radiation		Temperature	
	mean	Std	Mean	Std	Mean	Std
IOD-	8,655040E+05	NaN	20422656	NaN	26,343536	NaN
Netral	9,024956E+05	85826,800316	20141344	1,721842E+06	26,629969	0,583842
IOD+	1,009072E+06	106014,784669	22603930	2,708388E+06	26,560953	0,905984

Tables 2 to 4 present the mean and standard deviation values of electricity production, solar radiation, and temperature at three solar power plants Selong, Pringgabaya, and Sengkol classified by IOD phases (negative, neutral, and positive).

Across all locations, the positive IOD phase consistently shows the highest average values for both electricity production and solar radiation, supporting the observation that reduced cloud cover during this phase enhances solar irradiance and thus increases solar power plants output. For example, at Selong solar power plants, the average electricity production rises from 9.62×10^5 MWh (IOD−) to 1.07×10^6 MWh (IOD+), accompanied by an increase in radiation from 2.04×10^7 to 2.26×10^7 J/m². Similar trends are observed at other sites.

In contrast, temperature variations across IOD phases are relatively small. Although temperatures tend to be slightly higher during the positive IOD phase, the standard deviations remain under 1°C and the differences between phases are minor for example, at Pringgabaya, temperature increases only from 26.76°C to 27.07°C. These subtle changes suggest that, while solar radiation is highly responsive to IOD phase shifts, air temperature is much less so, and its direct role in influencing solar power plant performance appears comparatively limited.

It is worth noting that the temperature data used in this study still contains seasonal signals, which may mask finer-scale variations. For future research, applying signal processing techniques such as seasonal decomposition or digital filtering could help isolate interannual temperature fluctuations and more clearly reveal the IOD's climatic impact at the local level. However, for the scope and objectives of this study, the current data processing and analysis are considered sufficient to capture the dominant trends affecting PLTS performance.

Overall, the results highlight the critical role of regional climate variabilityparticularly IOD phases in influencing solar energy generation. Positive IOD phases, which are characterized by warmer sea surface temperatures in the western Indian Ocean and cooler temperatures in the east, tend to reduce cloud cover and enhance solar radiation over parts of Indonesia, especially in the southern and central islands such as Lombok. These effects are linked to a weakening of the Walker circulation and eastward shift of convection zones, leading to drier and sunnier conditions in the region (Saji et al., 1999; Ashok et al., 2003). Conversely, negative IOD events often increase cloudiness and rainfall, which can diminish solar irradiance and reduce power output.
Several studies have noted that the Lesser Sunda Islands—including Lombok, Sumbawa, and Bali—are particularly sensitive to IOD-driven anomalies due to their location within the maritime continent's transitional climate zone (Yuan et al., 2008; Hendon et al., 2012). The modulation of radiation by IOD events not only impacts short-term electricity generation but also has implications for system planning, such as battery storage sizing and capacity factor estimation. These insights are valuable for optimizing solar power system performance in tropical climates, particularly when designing systems that account for interannual atmospheric variability and integrating long-term climate risk into energy planning.

4 Conclusions

This study demonstrates that regional climate variability, particularly the Indian Ocean Dipole (IOD), plays a significant role in influencing the performance of solar power plants (PLTS) in Lombok Island. Through statistical and simulation-based analysis, it was found that the Dipole Mode Index (DMI) has a moderate correlation with solar radiation and a weaker correlation with both electricity production and temperature. During positive IOD phases, increased solar radiation resulting from reduced cloud cover was consistently associated with higher electricity generation across all PLTS sites.

However, ambient temperature showed only minor variations across IOD phases and did not significantly impact photovoltaic efficiency, indicating that temperature is not a dominant factor in output variation within the tropical setting of Lombok. The results confirm that solar radiation is the primary environmental driver affecting PLTS performance, while the influence of temperature is relatively limited.

These findings provide useful insights for improving forecasting and operational strategies for solar power in tropical climates. Future solar development in regions like Lombok should incorporate regional climate indices, such as DMI, into system planning and energy modeling to better anticipate seasonal variations in solar energy potential.

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