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Climate-Driven Projections of Solar Energy Potential in Indonesia Using CMIP6 Models

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Abstract. Indonesia possessed significant solar energy potential, positioning it as a key resource in the nation's pathway toward achieving net-zero carbon emissions by 2060. However, climate variability introduced uncertainties that could affect long-term solar energy production and investment planning. This study investigated the projected impacts of climate change on Indonesia's solar photovoltaic (PV) potential for the period 2030–2060, using outputs from five global climate models (GCMs) participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6). Two emission scenarios were considered: SSP1-2.6 (low emissions) and SSP5-8.5 (high emissions). Key climate variables influencing PV performance's surface downwelling shortwave radiation, near-surface air temperature, and the wind speed were analyzed. The model outputs were re-gridded to a 0.25° spatial resolution and bias-corrected using statistical downscaling. The results revealed spatially variable responses of PV potential to future climate change, with a projected decrease during the rainy season and an increase during the dry season in specific regions. These findings underscored the importance of incorporating climate projection uncertainties into national renewable energy strategies to ensure adaptive and resilient solar energy development in Indonesia under future climate conditions.

Keywords: *CMIP6, climate change, solar photovoltaic potential, probabilistic projections, SSP scenarios, Indonesia, renewable energy, ensemble model.*

1 Introduction

Greenhouse gas emissions from human activities had caused global warming, with global surface temperatures reaching 1.1°C above the 1850–1900 baseline during the 2011–2020 period. Global greenhouse gas emissions continued to rise, driven by uneven contributions from unsustainable energy use, land use and land-use change, as well as varying lifestyles and consumption production patterns across regions, countries, and individuals. Public awareness and a broad range of mitigation actions had supported global efforts to address anthropogenic climate change, including the utilization of renewable energy [1].

Among ASEAN countries, Indonesia possessed the most abundant solar energy potential. Furthermore, Indonesia had committed to addressing climate change and achieving net-zero carbon emissions by 2060. According to the national energy plan, out of 443 GW of total renewable energy potential, 208 GW was derived from solar energy sources [2]. In line with this national commitment, the state electricity company (PLN) also adopted a net-zero emissions strategy in its planning and investment decisions. The strategy focused on reducing fossil fuel dependence and promoting renewable energy-based technologies and ecosystems, including the development of solar power plants (PLTS) as outlined in the 2021–2030 Electricity Supply Business Plan (RUPTL) [3].

Among various renewable energy options, solar energy was considered one of the most promising due to its high reliability and significant utilization potential [4]. However, its sensitivity to future weather variability posed uncertainties that could complicate energy planning and negatively affect investment in the energy sector. Solar radiation affected by cloud cover and aerosol concentrations served as a direct indicator of solar energy potential. In addition, meteorological factors such as air temperature and wind speed also influenced solar energy generation [5]. Increased variability in future weather conditions was projected to raise uncertainties in power output and amplify the need for energy storage and grid stabilization services [6]. Therefore, it was necessary to consider various future climate change scenarios to ensure the sustainable development of the solar energy sector.

Previous studies had investigated the impact of climate change on solar energy potential in various countries. On a global scale, average solar energy availability between 2006 and 2100 was projected to decline, except for increases in East Asia, Europe, Central Africa, and Central America. These projections exhibited significant spatial variation even within the same region [5]. For instance, research in Africa suggested a decline in annual solar energy potential in most regions, with reductions reaching up to 6% in the Horn of Africa, driven by reduced solar radiation and increased temperatures [7]. Similarly, studies in Brazil indicated that climate change would likely result in significantly reduced rainfall and higher temperatures compared to the late 20th century [8].

Additional research assessed changes in solar energy potential between 1961–1990 and 2036–2065, revealing that increased air temperature and cloudiness could reduce photovoltaic (PV) power output. For example, PV potential was projected to decrease by 4% in the Arabian Peninsula by mid-century, while increases of 5% and 3% were projected for central Europe and the Atacama Desert, respectively. Meanwhile, southeastern Australia was expected to see a 2% decline, eastern China and Southeast Asia a 2% increase, and northwest Africa a 2% decrease [6]. Despite these global efforts, limited research had been

conducted using the latest climate change scenarios to evaluate future solar energy potential in Indonesia.
The development of climate models had significantly enhanced assessments of future climate risks. The latest outputs from the Coupled Model Intercomparison Project Phase 6 (CMIP6) provided improved data quality compared to the previous CMIP5 generation [9]. However, no comprehensive study had yet applied CMIP6 projections to assess Indonesia's solar energy potential. Therefore, this study aimed to analyze projected changes in solar energy potential in Indonesia for the period 2030–2060 under the latest IPCC emission scenarios, using an ensemble analysis of five CMIP6 global climate models.

2 Data

This study focused on the administrative region of Indonesia and employed climate projections based on two Shared Socioeconomic Pathways (SSPs): SSP1-2.6, representing a low-emission (best-case) scenario, and SSP5-8.5, representing a high-emission (worst-case) scenario. The analysis covered two distinct periods: a historical baseline (1980–2014) and a future projection period (2030–2060). Climate data were sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP6) through the Earth System Grid Federation (ESGF) portal (https://aims2.llnl.gov/search/cmip6/).

Five CMIP6 global climate models were selected based on their development by leading climate research institutions, featuring a range of spatial resolutions from medium to high, and demonstrating strong performance in simulating both historical climate conditions and future projections. The selected models are listed in Table III.1, along with their respective spatial and temporal resolutions. The primary climate variables used in this study included surface downwelling shortwave radiation (I, in W/m²), near-surface air temperature (T, in °C) at 2 meters, and near-surface wind speed (WS, in m/s) at 10 meters. These variables are critical inputs for estimating photovoltaic (PV) power output and assessing solar energy potential.

Comparisons were made to evaluate the reliability of the CMIP6 model outputs with observational reanalysis data from the ERA5 dataset, obtained through the Copernicus Climate Data Store (CDS) (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview). The ERA5 dataset provided reference values for T, I, and WS at a spatial resolution of 0.25° × 0.25° (latitude × longitude), and was used as the observational baseline for bias correction.

The outputs of the five selected CMIP6 models were regridded to ensure consistency in spatial resolution into a common resolution of 0.25° × 0.25° using bilinear interpolation [10]. In addition, a bias correction method using the delta-change approach was applied to improve or adjust the projections of the global climate model (GCM) to enhance accuracy. The delta-change method was relatively simple and easy to implement, involving the calculation of the bias in the mean values of the climate model data during the historical period compared to observational data (in this study, the ERA5 dataset). The derived bias was then directly or proportionally subtracted from the projected future climate data to correct the bias in the prediction period [1].

Table 1 Five Selected CMIP6 Global Climate Models

Model Name	*Model Centre*	Temporal Resolution	Spatial Resolution	
			Grid Size (Lon x Lat)	*Re-gridded (Lon x Lat)*
CSIRO	Commonwealth Scientific and Industrial Research Organisation, Australia	Day	1,875° x 1,25°	0,25° x 0,25°
NCAR	National Center for Atmospheric Research, USA		0.94° x 1.25°	
MIROC	Model for Interdisciplinary Research on Climate, Japan		1.39° x 1.41°	
MRI	Meteorological Research Institute, Japan		1.11°x1.12°	
MPI-HR	Max Planck Institute for Meteorology, Germany		1.85°x1.88°	

3 Methodology

3.1 Calculation of PV Potential

Photovoltaic (PV) potential represents the fraction of power output that a PV module may produce under real field conditions relative to standardized test conditions (Dutta et al., 2022). In this study, monthly estimates of PV potential were calculated using climate variables obtained from five CMIP6 global climate models (GCMs) under both SSP1-2.6 and SSP5-8.5 emission scenarios. The required input variables included surface downwelling shortwave radiation (I), near-surface air temperature (T), and near-surface wind speed (WS), all of which were processed for the period 2030–2060. The PV potential was estimated by multiplying the incident solar radiation by a performance ratio (PR), which accounts for efficiency losses due to temperature and other environmental factors. The calculation followed the method proposed by Dutta et al. (2022), and was expressed as:

$$PV_{pot} = P_R \frac{I}{I_{STC}} \tag{1}$$

Where *I* is the Surface Downwelling Shortwave (SW) Radiation, ISTC is the SW radiation at standard conditions, which is 1000 W/m2 [2]. Based on the research of Dutta et al. (2022), PR was the performance ratio that takes into account the effect of PV cell temperature (Tcell), that is:

$$P_R = 1 - \gamma(T_{cell} - T_{STC}) \tag{2}$$

Here, *Tstc* is the standard cell temperature (25°C), and γ is the temperature coefficient, typically 0.005 $°C^{-1}$ for monocrystalline silicon PV cells, which are among the most widely used types. The cell temperature Tcell was modeled as a function of ambient air temperature (T), solar radiation (I), and wind speed (WS), using the empirical relationship.

$$T_{cell} = c_1 + c_2 T + c_3 I - c_4 WS \tag{3}$$

The coefficients used for this equation, as suggested by Dutta et al. (2022), were specific to monocrystalline silicon solar cells : c_1 = 4,3ºC, c_2 = 0,943, $c3$ = 0,028ºCW^{-1} m^2 dan $c4$ = 1,528ºcm^{-1}s which are used for monocrystalline silicon solar cells [2].

These calculations allowed for monthly estimation of PV potential across Indonesia, accounting for projected changes in climate conditions and their impact on solar energy generation efficiency

3.2 Probability Analysis

A probability analysis was conducted to enhance the confidence level in assessing photovoltaic (PV) potential across different regions using data from five CMIP6 global climate models. This approach evaluated the agreement among models in projecting areas with high PV potential. Specifically, the analysis identified locations where the estimated PV potential exceeded a predefined threshold, indicating a high probability of solar energy development based on consistent projections across the ensemble of climate models. Regions with stronger inter-model agreement were considered to have more robust potential for future solar energy deployment under varying climate scenarios.

Table 2. Scientific interpretation of probability value

Probability Value	Number of Models in Agreement (out of 5)	Scientific Interpretation
100%	5 models	All models consistently indicated that the region exceeded the threshold.
80%	4 models	Four models suggested that the region likely exceeded the threshold.
60%	3 models	Three models indicated moderate agreement on exceeding the threshold.
40%	2 models	Two models showed limited agreement regarding exceedance.
20%	1 model	Only one model suggested that the threshold was exceeded.

4 Results

4.1 Comparison of CMIP6 global climate model data with ERA5

To evaluate the CMIP6 global climate models, a comparison was conducted with ERA5 reanalysis data (Dutta et al., 2022).

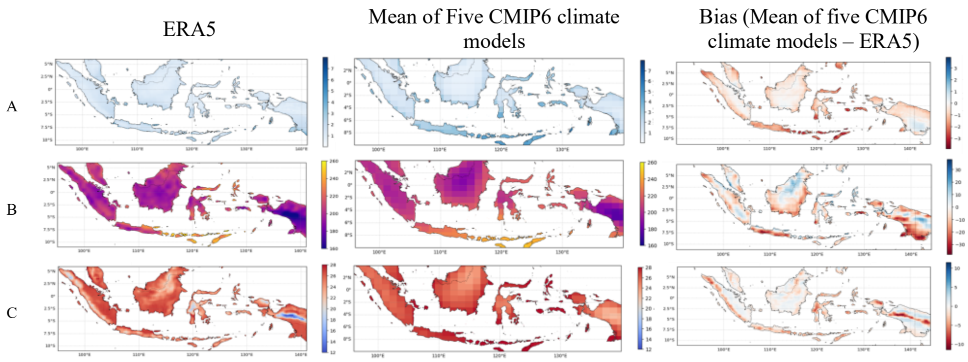

Figure 1. The spatial distribution between ERA5 reanalysis data, the multi-model mean of five CMIP6 climate models, and the bias, was analyzed for energy-related variables, including (a) wind speed (m/s), (b) solar radiation intensity (W/m²), and (c) surface air temperature, during the historical period from 1980 to 2014.

The evaluation of CMIP6 global climate models by comparing them with ERA5 reanalysis data was a common approach to assess the models performance in representing climate conditions (Dutta et al., 2022). The analysis showed that the average biases of these three parameters were relatively low across most land areas of Indonesia, The negative bias was particularly evident in southern Java, Bali, Nusa Tenggara, southern Kalimantan, coastal areas of Sulawesi, Maluku, and southern Papua. This negative bias appeared consistently across all three variables. Meanwhile, the positive bias over land areas was relatively limited, appearing sporadically only in parts of western Sumatra and northern Kalimantan, especially for temperature and radiation variables. The bias calculation results were used to correct the model data in estimating future potential projections. Therefore, the application of bias correction methods was an essential step in improving the accuracy of model data, ensuring that the simulation results better reflected the actual climate conditions over the Indonesian land areas.

4.2 Change in Photovoltaic (PV) Potential

In general, when observed from the spatial patterns, all five climate models indicated that PVpot values decreased in the future period compared to the historical PVpot values.

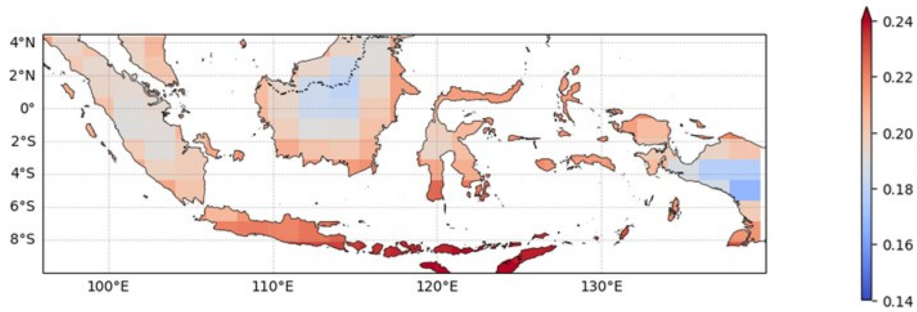

Figure 2. The spatial distribution of the average PVpot fraction values across Indonesia during the historical period from 1980 to 2014

Based on Figure 2, During the historical period from 1980 to 2014, based on the analysis of five CMIP6 climate models, regions with the highest average PVpot fraction approximately 0.24, represented by dark red were located in East Nusa Tenggara (NTT), West Nusa Tenggara (NTB), and Bali. Areas with moderate average PVpot fractions ranging from approximately 0.18 to 0.21 and shown in grey to orange were found in Sumatera, northern Java, East Kalimantan, and northern Sulawesi. Regions with low potential, indicated by blue, appeared in Central Kalimantan and West Papua. In the future period, from 2030 to 2060, the PVpot analysis was conducted using three SSP emission scenarios, as illustrated in the following figure.

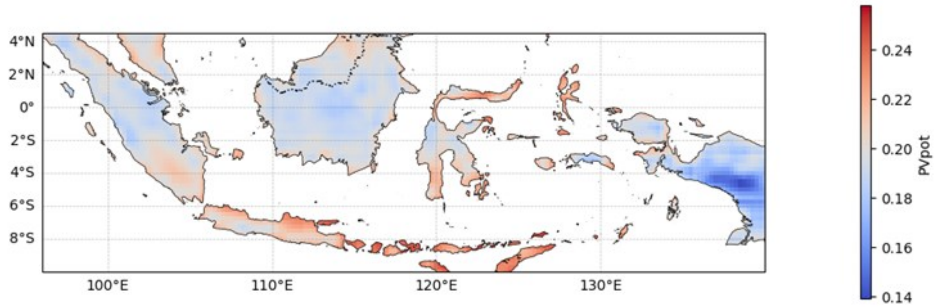

Figure 3. The spatial distribution of the average PVpot fraction in Indonesia during the future period from 2030 to 2060 under the SSP1-2.6

Figure 3 illustrated the average fraction of PVpot values under the low-emission scenario (SSP1-2.6). Compared to the historical period, during the future period from 2030 to 2060, a greater extent of areas exhibited lower PVpot values, as indicated by the blue shading. Regions with moderate to high PVpot values were located in Bali, East Nusa Tenggara (NTT), and West Nusa Tenggara (NTB).

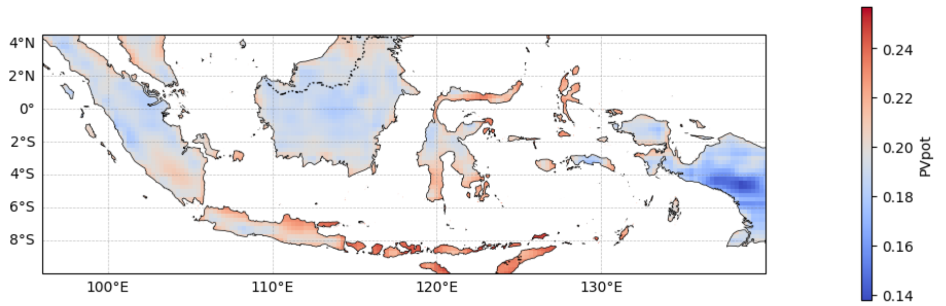

Figure 4. The spatial distribution of the average PVpot fraction in Indonesia during the future period from 2030 to 2060 under the SSP 5-8.5

Figure 4 showed the average fraction of PVpot values under the high emission scenario, SSP5-8.5. Compared to the historical period, during the future period from 2030 to 2060, regions with moderate to high PVpot values were also located in Madura, Bali, East Nusa Tenggara (NTT), West Nusa Tenggara (NTB), and Central Sulawesi.

In general, Figure 5 presented the projected seasonal changes in photovoltaic (PV) potential across Indonesia for the period 1980-2014 and 2030–2060. Each map represented a different season, illustrating the spatial and temporal variability in solar energy potential.

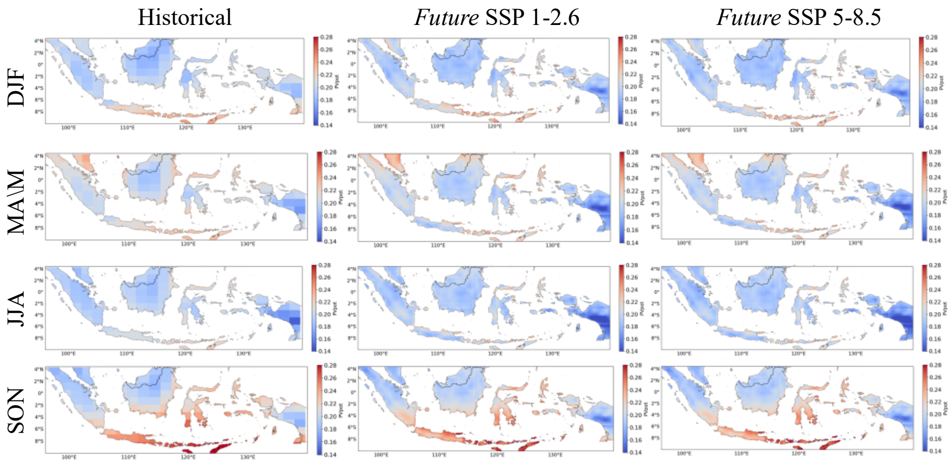

Figure 5. Seasonal Changes in PV potential Five Model CMIP6

Each map represented a different season for both the historical and future projection periods, with variations in PVpot values reflecting changes in solar energy potential influenced by factors such as solar radiation, air temperature, and wind speed. These factors affected the efficiency of solar panels in generating energy across different regions and seasons. The transitional season (SON) appeared to be the most stable and promising period for solar energy across most of Indonesia's land regions. The land areas of Bali and Nusa Tenggara showed consistent positive potential, even under the high-emission scenario (SSP5-8.5), indicating that these regions were suitable for long-term solar energy development. To illustrate the overall statistical changes in PV potential values, a density plot analysis was conducted.

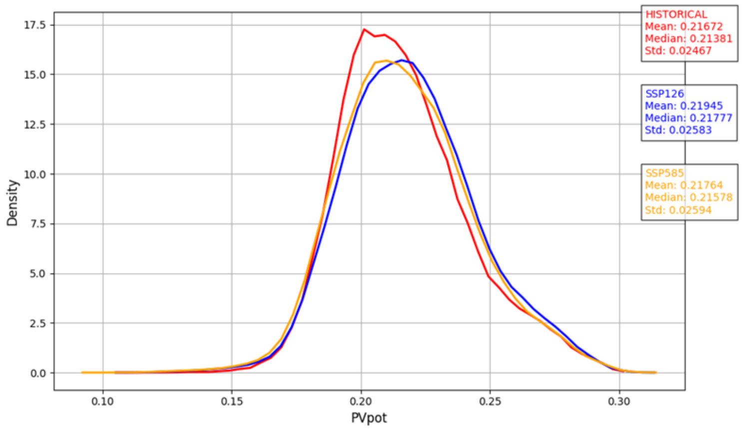

Figure 6. Distribution of photovoltaic (PV) potential values from historical period (1980–2014) and future period (2030-2060) under SSP1-2.6 and SSP 5-8.5

According to Figure 6, based on the PV potential density plot, the highest mean value was observed under the SSP1-2.6 scenario (0.21945), followed by SSP5-8.5 (0.21764), while the lowest value was recorded in the historical period (0.21672). These results indicated that, on average, PV potential slightly increased in future scenarios. Specifically, the mean PV potential under SSP1-2.6 increased by approximately 1.26% compared to the historical period, whereas under SSP5-8.5, the increase was around 0.42%. In terms of standard deviation, the highest value was observed under SSP5-8.5 (0.02594), followed by SSP1-2.6 (0.02583), with the lowest in the historical period (0.02467). These findings suggested that as emission scenarios intensified, the spatial variability of PV potential also increased, reflecting higher uncertainty in future solar energy potential, particularly under the high-emission scenario SSP5-8.5.

These observations were consistent with previous studies, which reported that under the low greenhouse gas emission scenario (SSP1–2.6), most regions globally experienced slight increases in PV potential, with an average rate of change of approximately 0.03% per decade. Notably, southeastern China and India exhibited significant upward trends exceeding 0.1% per decade, corresponding to an overall increase of around 5% in China and 1% in India for the period 2025–2100 compared to 1990–2014. In contrast, under the high-emission scenario (SSP5–8.5), a more pronounced global decrease in PV potential was projected, averaging approximately 0.26% per decade, with reductions of up to 3–4% in regions such as the Sahara Desert. Globally, PV potential under SSP5–8.5 was estimated to be 1.5% lower than in the historical period (1990–2014). These results supported the conclusion that while low-emission scenarios may lead to modest improvements in solar energy potential, high-emission trajectories could result in reduced and more uncertain PV potential, both regionally and globally [12].

4.3 Probability of (PV) Potential

The spatial distribution of the probability of agreement among the five CMIP6 models regarding areas where PV potential exceeded a predefined threshold, for the projection period 2030–2060 under SSP1-2.6 and SSP5-8.5, respectively.

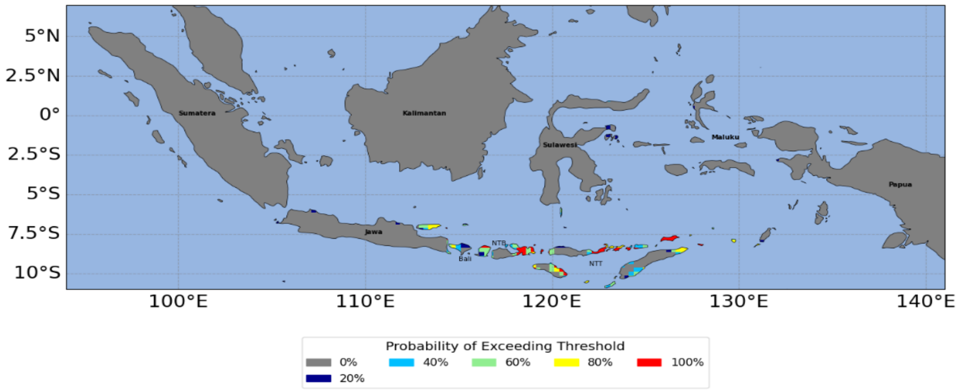

Figure 7. Probability of agreement among the five CMIP6 models regarding areas where PV potential exceeded a predefined threshold, for the projection period 2030–2060 under SSP1-2.6

Under the SSP1-2.6 scenario, high inter-model agreement (80–100%) was concentrated in the southern coastal areas of West Nusa Tenggara (NTB) and East Nusa Tenggara (NTT), particularly across the smaller islands of NTT. Moderate agreement (40–60%) was identified in Bali, Madura, and parts of eastern Java, indicating reasonably promising potential despite the lack of full consensus among models. In contrast, Sumatra, Kalimantan, Sulawesi, and Papua were dominated by low agreement levels (<20%), reflecting projection uncertainty likely influenced by local climatic factors such as high precipitation, persistent cloud cover, and elevated humidity.

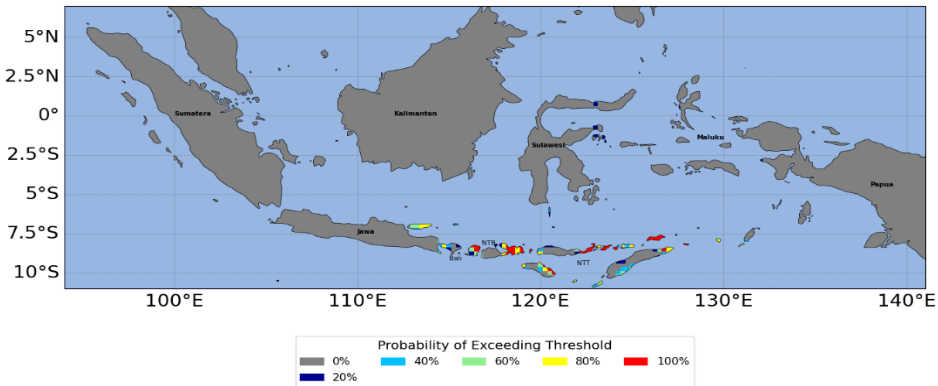

Figure 8. Probability of agreement among the five CMIP6 models regarding areas where PV potential exceeded a predefined threshold, for the projection period 2030–2060 under SSP 5-8.5

In comparison, the SSP5-8.5 scenario exhibited a significant expansion of areas with high agreement regarding solar energy potential. Regions with 80–100% probability extended across a broader portion of NTT, including the eastern parts such as Sumba Island, as well as several smaller islands near southern NTB and Bali. Areas with moderate agreement became more limited compared to SSP1-2.6, primarily appearing in eastern Madura and a small portion of NTT. Nevertheless, Sumatra, Kalimantan, and Papua continued to show low levels of model agreement, consistent with the patterns observed under the SSP1-2.6 scenario.

Overall, the CMIP6 multi-model ensemble provided a robust signal for identifying regions with promising solar energy potential. The high level of agreement in drier southern regions, particularly NTB and NTT, strengthened the scientific basis for prioritizing solar development in these areas. These findings also supported informed decision-making for future renewable energy planning and policy development in Indonesia.

5 Conclusions

The probability analysis based on agreement among five CMIP6 models indicated that the West Nusa Tenggara (NTB) and East Nusa Tenggara (NTT) regions were the highest priority locations for solar energy development in Indonesia during the 2030–2060 period. The strong inter-model consensus in these regions reinforced the confidence that investments in solar energy infrastructure would have positive and sustainable impacts. Consequently, national energy planners and stakeholders such as PLN were advised to focus on the development of large-scale solar power plants (PLTS) in NTB and NTT, supported by the necessary grid infrastructure.

The Madura and Bali regions showed moderate potential for solar energy development, suggesting that more adaptive strategies to local climate variability were required. In these areas, medium-scale solar PV installations were considered an effective approach. Meanwhile, Kalimantan, Sulawesi, and Maluku regions exhibited lower prospects based on the national spatial analysis. However, further studies with higher spatial resolution were recommended to identify potential local opportunities that may have been overlooked in the broader analysis.

6 References

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