Assessment of solar PV power potential over Asia Pacific region with remote sensing considering meteorological factors

Cite as: J. Renewable Sustainable Energy 11, 013502 (2019); https://doi.org/10.1063/1.5059335
Submitted: 20 September 2018 . Accepted: 24 December 2018 . Published Online: 14 January 2019

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Submitted: 20 September 2018 · Accepted: 24 December 2018 · Published Online: 14 January 2019

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ABSTRACT

The intensity of solar radiation (SR) is one of the most important required inputs for the estimation of photovoltaic (PV) power station output. Meanwhile, the efficiency of solar PV systems is affected by meteorological factors such as temperature, dust, precipitation, and snow. Meteorological data from satellites provide a viable way for estimating PV potential due to its advantage in spatial coverage and temporal resolution. This paper presents a new approach to adjust SR data from satellites based on the cloud optical thickness (CLOT) before evaluating the solar PV power \( P_{\text{PV}} \) potential, with the effective efficiency of solar cells computed based on temperature, dust, precipitation, and snow. The objective of this study is to evaluate the over-all spatiotemporal solar PV potential in the Asia Pacific region which will holistically include limiting meteorological factors and identify which factor contributes most significantly to the decrease in solar PV potential in selected cities in the region. First, SR and CLOT data from Advanced Himawari Imager 8 and a SKYNET station were processed to derive the correction factor for solar radiation data. Second, satellite data for temperature (MOD11), precipitation (global satellite mapping of precipitation), dust (MOD04), and snow cover (MOD10) were processed to derive the effective solar PV efficiency. Finally, maps showing the seasonal PV power potential over the Asia Pacific region were generated, with selected cities zoomed in for detailed analysis using mean monthly values from March 2016 to February 2017. The results showed that the maximum theoretical \( P_{\text{PV}} \) in the region was estimated to be 1.9 GW per 17.5 km² effective pixel area. Moreover, \( P_{\text{PV}} \) decreased by maximum values of 180 MW, 550 MW, and 225 MW due to temperature, dust, and snow, respectively. For Beijing, Tokyo, and Jakarta, the major contributor to the decrease in \( P_{\text{PV}} \) is dust, while Khabarovsk is consistently affected by snow effects. Initial validation of the model shows over- and underestimation of solar PV output compared to the actual values by as high as 30%. However, very high values of coefficient of determination (>-0.90) show promising results of the model. The contribution of this study is two-fold: regional-scale assessment of \( P_{\text{PV}} \) potential and investigation of the collective effect and individual contributions of dust, temperature, and snow to the decrease in \( P_{\text{PV}} \) potential.

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NOMENCLATURE

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( A_{\text{cell}} )</td>
<td>total aggregated pixel area allocated for the installation of solar PV panels</td>
</tr>
<tr>
<td>Dust._Decr</td>
<td>contribution of dust to the decrease in theoretical solar PV power</td>
</tr>
<tr>
<td>( E_{\text{gen}} )</td>
<td>equivalent generated output energy in kWh</td>
</tr>
<tr>
<td>( P_{\text{PV}} )</td>
<td>solar photovoltaic power</td>
</tr>
<tr>
<td>( P'_{\text{PV}} )</td>
<td>total effective solar photovoltaic power output</td>
</tr>
<tr>
<td>( P'_{\text{PV, X}} )</td>
<td>effective solar PV power output considering X individual meteorological factors</td>
</tr>
<tr>
<td>R'</td>
<td>adjusted solar radiation data from AHI8</td>
</tr>
<tr>
<td>sc</td>
<td>snow cover</td>
</tr>
</tbody>
</table>

LST._Decr | contribution of temperature to the decrease in theoretical solar PV power |

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I. INTRODUCTION

Energy is an indisputable necessity for the modern society. As the world’s population increases, the demand for energy also rises since the population growth rate is recognized as an important driver of energy (US EIA, 2017) to ensure a better life environment and technological and economic development (Sampaio and Gonzalez, 2017). However, the annual total greenhouse gas (GHG) emissions from the global energy supply sector continue to increase as well. It was reported that the combustion of fossil fuels continues to dominate the global energy market that is striving to meet the ever-increasing demand for heat, electricity, and transport fuels (Sims et al., 2007). In Asia alone, the reliance on fossil fuels is 86% in the energy mix which is 5% higher than the global average in 2014 (AIB, 2017). For sustainable development, however, there is a need for an efficient way of extracting energy from renewable sources. One such alternative is solar—a low carbon resource with both scalability and technological maturity to meet the fast-growing global demand for electricity (Chander et al., 2015). Solar photovoltaic (PV) contributed to an annual market increase in about 50%, making it the world’s leading source of additional power generating capacity of at least 75 GW in 2016 (REN21, 2017).

Meteorological data from satellites provide a viable way for estimating the PV potential due to its advantage in spatial coverage and temporal resolution. For instance, the SolarGIS database that was used to determine the potential of selected renewable energy sources in the Greater Mekong Subregion contains irradiance values in the 30-min time-step calculated from the Meteosat first generation (MFG) satellite and elevation from Shuttle Radar Topography Mission (SRTM) (ADB, 2015). Moreover, Higurashi and Nakajima (1999) acknowledged that the use of data from satellites was very effective while performing a large-scale study of aerosol optical properties.

The theoretical solar PV potential is not reached due to several limiting meteorological factors including the effects of dust, temperature, precipitation, snow, and clouds. Both the increase in temperature (Menes-Rodriguez et al., 2005) and dust deposition (Goossens et al., 1993) contribute to the decrease in the PV solar efficiency. Meanwhile, insolation is directly related to the cloud cover (Kim et al., 2017). Moreover, it has also been observed that the snow cover reduces the overall performance of solar modules mounted at different tilt angles (NAIT, 2016). The objective of this study is to evaluate the overall spatiotemporal solar PV potential in the Asia Pacific region (APR) using remote sensing that will holistically include such limiting factors and identify which contributes most significantly to the decrease in the solar PV potential in selected cities in the region. The approach used in this study utilized various remote sensing satellite products for solar radiation, cloud optical thickness (CLOT), land surface temperature (LST), precipitation, dust, and snow.

Previous studies on solar PV power potential investigated the effects of the above-mentioned meteorological factors separately and their methods applied in local settings or very small areas. For instance, such experiments were done on the roof of a building (Paudyal and Shree, 2016 and NAIT, 2017) and in a laboratory environment under controlled conditions (Beattie et al., 2012; Chander et al., 2015; El-Shobokshy and Hussein, 1993; and Goossens et al., 1993). As such, this study contributes to the body of knowledge by providing a method for regional-scale assessment of $P_{PV}$ potential and investigating the collective effect and individual contributions of dust, temperature, and snow to the decrease in $P_{PV}$ potential.

II. METHODOLOGY

A. Data description

Derived products from Advanced Himawari Imager 8 (AHI8) are downloaded via the Japan Aerospace Exploration Agency (JAXA) Himawari Monitor (cor:java.jp/pree/index.html). These two products are the Shortwave Radiation (SWR) and the Cloud Property (CLOT) both at spatial and temporal resolutions of 5km and 10 min, respectively. The daily Aerosol Optical Depth (AOD) from the MODIS aerosol product (MOD04_L2) at a...
resolution of 10 km was used to extract dust information (Levy et al., 2013). For LST data, the MODIS Land Surface Temperature and the Emissivity 8-day global product (MOD11 L3) at a resolution of 1 km were used (Wan, 1999). To extract precipitation rate data, the daily average rainfall estimates from global satellite mapping of precipitation (GSMaP) at a resolution of 0.1° × 0.1° were used (Okamoto et al., 2005). Finally, the monthly snow cover was extracted from the monthly Global 0.05° CMG (version 6) MODIS L3 dataset (Hall et al., 2001). The period analyzed for this study is one complete year, starting from March 2016 to February 2017 since the SWR data from AHI8 are only available from March 2016. The seasons defined in this study were MAM (March to May), JJA (June to August), SON (September to November), and DJF (December to February).

B. Methods

The general methodology adopted in this study is shown in Fig. 1. First, the SWR data from AHI8 were adjusted to generate \( R' \). The adjustment process entailed the use of CLOT data to fit the original SWR data with the ground data observations (http://atmos2.cr.chiba-u.jp/skynet/chiba/chiba.html) and derive the correction factor for solar radiation data (CFSR) via a non-linear regression technique by Principe and Takeuchi (2018). SWR data were then adjusted using CFSR to generate \( R' \). The technique of adjusting the solar radiation values derived from AHI-8 using CLOT data worked well during the summer and winter seasons since \( R' \) has a smaller absolute difference to the SKYNET data (Table 1). It performed unsatisfactorily, however, during spring and autumn seasons when, most probably, the cloud cover is not a major factor affecting SWR. Nonetheless, the technique’s effectiveness to adjust the solar radiation values during the summer (JJA) is worth noting since the peak of solar intensity is expected and the discrepancy between the ground- and satellite-based values is at a maximum during this season compared to other seasons of the year.

1. Computation of solar PV power output and decrease in solar cell efficiency

The theoretical solar PV power (\( P_{PV} \)) output in megawatts (MW) is computed using Eq. (1), where \( A_{cell} \) is the total aggregated pixel area allocated for the installation of solar PV panels, \( \eta \) is the conversion efficiency of the solar cell, and \( R' \) is the adjusted solar radiation data from AHI8

\[
P_{PV} = A_{cell} \eta R'.
\]

Equation (1) is adapted from the original model equation in the study by Liu et al. (2017) where the modifications include the merging of two separate variables for the number of PV cells (N) and the area of a single PV cell (\( S_a \)) to a single variable \( A_{cell} \). Moreover, in Eq. (1), we considered the adjusted solar radiation \( R' \) instead of the actual intensity of solar radiation \( R \) since this study did not use the ground-observed values of solar radiation but used instead the satellite-derived values as adjusted to fit with the actual ground data.

The decrease in solar cell efficiency due to temperature (\( \Delta T \)), dust (\( \Delta d \)), and snow (\( \Delta s \)) is computed using Eqs. (2), (3), and (4), respectively. The over-bar in these equations indicates the computation of mean values over the evaluation period. \( \Delta T \) is computed using the typical nominal operative cell temperature (NOCT) with NOCTmax set at 45°C and the temperature coefficient of efficiency \( (d\eta/dT = 0.094) \) (Chander et al., 2015) at every 4th day for each season with \( n \) being the total number of days.

---

**FIG. 1.** The general methodology used in this study. The theoretical solar PV power potential (\( P_{PV} \)) was derived using the adjusted shortwave radiation (SWR). The effect of temperature (\( \Delta T \)) was derived using the LST product from MOD11, while the effect of dust (\( \Delta d \)) was derived from a binary technique considering rainfall (cleaning agent) and non-rainfall (the dust effect is not eliminated) events using GSMaP rainfall rate data and AOD data (representing dust) from MOD04. Moreover, the effect of snow (\( \Delta s \)) was derived from snow cover percentage data of MOD10. Such effects of meteorological factors on the efficiency of solar PV cells were then used to compute for the effective solar PV power potential (\( P'_{PV} \)). The computed \( P'_{PV} \) was in turn validated against the outputs from actual solar PV installations. Finally, maps of solar PV potential were generated.


\[ \Delta \eta_d = 0.094 \left( \sum_{i=1}^{n} \Delta \eta_i \right) \]

\[ \Delta \eta_s = 0.0016 \left( \sum_{i=1}^{n} \Delta \eta_s \right) \]

The effective solar PV power output considering the individual meteorological factors \( P_{PV,X} \) in MW was computed as

\[ P_{PV,X} = \eta_{cell} \eta \left( 1 - \Delta \eta_X \right) \]

where subscript \( X \) denotes the meteorological components (e.g., \( d = \) dust, \( s = \) snow, and \( t = \) temperature).

The total effective solar photovoltaic power output \( P_{PV} \) in MW was computed as

\[ P_{PV} = \eta_{cell} \eta \left( 1 - \Delta \eta_d - \Delta \eta_s \right) \]

In this study, the final spatial resolution of the raster data used was 5 km and it was assumed that only 70% of the pixel area will be utilized for solar PV installation with a PV cell efficiency of 13% (for thin-film cells) according to Sampaio and Gonzalez (2017). The type of solar cell based on thin film silicon was selected since it offers a promising value of significantly lowering the costs of producing energy from solar PV, thereby attracting future investors and users of this technology (Chen and Sopori, 1999).

### 2. Comparison of computed solar PV power with actual reported outputs

The computed seasonal solar PV power was compared with the actual generated PV output data from the installations published in the website of PVOutput.org (https://pvoutput.org). The website offers a free service platform to share, compare, and monitor live solar photovoltaic (PV) and energy consumption data (PVOutput.org, 2018). Since the reported actual outputs were in energy units (kWh), the computed \( P_{PV} \) in MW must be converted to kWh using the following equation:

\[ E_{gen}(\text{kWh}) = P_{PV} \times TSH \times TSPA \times 1000/\text{EPA}. \]

where \( E_{gen} \) is the equivalent generated output energy in kWh; \( P_{PV} \) is the total effective solar photovoltaic power output in MW; TSH is the average total sunshine hours; TSPA is the total solar panel area used in the actual installation in \( \text{m}^2 \); and EPA is the effective pixel area (for this study, \( \text{EPA} = 5000 \text{ m} \times 5000 \text{ m} \times 0.7 = 175 \times 10^7 \text{ m}^2 \) or 17.5 km²).

The description of the two solar PV installations used in this study for validation purposes is shown in Table II. Only this limited number of actual solar PV systems was used because there were only a few installations in the Asia Pacific region with data in PVOutput.org and most of them did not have data for periods covered in this study. Meanwhile, the TSH data were obtained from different sources including the Australian Government Bureau of Meteorology for Signal Hill (2005), and the Thai Meteorological Department for Bangkok Soladin (2014).

The estimated values of solar PV output were assessed using the percentage prediction error (PPE) as given by Kim et al. (2017) in the following equation:

\[ \text{PPE} = \frac{|V_P - V_M| \times 100}{V_M} \]

where \( V_P \) and \( V_M \) are the predicted (estimated) and measured (actual) values, respectively. Equation (8) implies that the lower the value for PPE is the better the estimation is.

### III. RESULTS AND DISCUSSION

Satellite data were processed to produce three sets of PV solar potential products for the Asia Pacific region: theoretical, effective (considering individual meteorological factors), and

<table>
<thead>
<tr>
<th>Name</th>
<th>Location</th>
<th>System size (kW)</th>
<th>Number of panels</th>
<th>Orientation</th>
<th>Tilt (deg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal Hill</td>
<td>Perth, Australia</td>
<td>3.36</td>
<td>16</td>
<td>NE</td>
<td>18</td>
</tr>
<tr>
<td>Bangkok Soladin</td>
<td>Bangkok, Thailand</td>
<td>0.65</td>
<td>5</td>
<td>S</td>
<td>15</td>
</tr>
</tbody>
</table>

### TABLE I. Absolute differences in solar radiation between SKYNET and AH8 original (AH8) and adjusted (AH8Cor) SWR data

<table>
<thead>
<tr>
<th>Season</th>
<th>AH8—SKYNET</th>
<th>AH8Cor—SKYNET</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spring</td>
<td>21.29</td>
<td>30.87</td>
</tr>
<tr>
<td>Summer</td>
<td>61.99</td>
<td>15.85</td>
</tr>
<tr>
<td>Autumn</td>
<td>12.69</td>
<td>42.56</td>
</tr>
<tr>
<td>Winter</td>
<td>9.80</td>
<td>7.85</td>
</tr>
</tbody>
</table>
total effective. Moreover, zoomed in analysis for selected cities in the region was performed to determine which among the factors are significantly affecting the PV solar potential. The equivalent generated output energy ($E_{gen}$) is also compared with the actual output of solar PV installations in two locations within the Asia Pacific region. Finally, the limitations and possible sources of error of the technique used in this study for the estimation of $P_{PV}$ are also presented.

A. Theoretical solar PV power potential

The satellite-derived mean theoretical seasonal solar photovoltaic output power maps for the Asia Pacific Region are generated using Eq. (1). Meanwhile, Fig. 2 shows the solar PV power output in selected cities in the Asia Pacific region. Among these 20 cities examined, Brunei and Muara, Sydney, Manila, and Taipei, have the highest estimated solar PV power during SON (1204.73 MW), DJF (1487.3 MW), MAM (1473.57 MW), and JJA (1243.94 MW) seasons, respectively.

The corresponding spatial distribution maps in the Asia Pacific region during the different seasons are shown in Fig. 3. The theoretical solar PV potential is high during the JJA season in most of the region, except in Southern Australia and mountainous areas in India, Nepal, Myanmar, and Bhutan. Since $A_{cell}$ and $\eta$ are assigned with fixed values, the variation of $P_{PV}$ is solely dependent on $R^0$ the value of which varies according to the surface topology, zenith angle, atmospheric gases, and clouds, among others (Gokmen et al., 2016; Lee et al., 2018; Gupta et al., 2016; and Frouin and Murakami). Since the effects of clouds and the clear atmosphere were already accounted in the algorithm to estimate SWR from AHI8 (Frouin and Murakami, 2007), topographic shading and short sunshine hours (in the case of Australia) are possible reasons for the low $P_{PV}$ potential during the said season. Meanwhile, Australia has very high potential during DJF and SON with a potential of about 1.6 GW for both seasons, the highest among the Asia Pacific countries. Australia experiences an average sunshine hour of up to 11 h during these seasons (Australian Government Bureau of Meteorology, 2005) which translates to more solar irradiance available for solar energy conversion by PV systems.

B. Decrease in solar PV power potential due to temperature

The satellite-derived seasonal decrease in solar photovoltaic output power due to temperature for the Asia Pacific Region was generated using Eqs. (1), (2), and (5). The corresponding spatial distribution maps during the different seasons are shown in Fig. 4. The maximum decrease in $P_{PV}$ was 180 MW, about 9.4% of the theoretical potential. During the DJF season, most of the area in Australia experiences a decrease in solar PV potential due to the high temperature, with some portions in the northwest area affected during the MAM season. It can also be observed from Fig. 4 that during the JJA season, areas in northern China and southern Mongolia in the Gobi Desert have a notable decrease in solar PV potential. The reason was that in these areas, LST can reach up to 50 °C during the summer season. Some parts of India, Thailand, Myanmar, and Cambodia experience a decrease in $P_{PV}$ potential during the MAM season.

As can be seen in Fig. 4, the effect of the temperature on solar PV performance was very negligible in many parts of the region. This can be attributed to the use of LST to estimate the actual temperature of the solar cells ($T_{cell}$). Thermal radiance coming from the land surface is retrieved by the satellites which are then used to estimate LST on the theoretical basis that the total radiance emitted by the ground increases rapidly with temperature (Mildrexler et al., 2011). As such, the direct use of LST in place of $T_{cell}$ may result in an error in the estimation of temperature effects on $P_{PV}$ potential. LST was used in this study since actual long-term $T_{cell}$ data were not available for the whole Asia Pacific Region. For future work, the conversion of LST to $T_{cell}$ can be done by first linking the LST to air temperature ($T_{air}$) and $T_{air}$ to $T_{cell}$ following the studies of Li et al. (2008), Jin and Dickinson (2010), Mildrexler et al. (2011), and Gokmen et al. (2016). Finally, wind can also affect $P_{PV}$...
potential in terms of its cooling effect on PV systems (Gokmen et al., 2016). In the current model, the effect of temperature seemed to be very negligible, but if $T_{\text{cell}}$ is used instead of LST, it is expected to get very high temperature values which will degrade the solar cell efficiency down to 0. As such, wind speed will be considered in the future model update. Rainfall may also help in cooling down solar panels, but the solar-driven rainwater cooling device is not efficient and cost-effective especially for solar PV installations for domestic houses (Wu and Xiong, 2014). For this reason, rainfall was not considered as a cooling agent for solar PV systems.

C. Decrease in solar PV power potential due to dust

Using Eqs. (1), (3), and (5), maps for the satellite–derived seasonal decrease in solar photovoltaic output power due to dust for the Asia Pacific Region were generated. The corresponding spatial distribution maps during the different seasons are shown...
FIG. 4. Decrease in mean seasonal solar PV power (in megawatts) due to temperature in the Asia Pacific region: (a) DJF; (b) MAM; (c) JJA; and (d) SON. The areas in circles are where the temperature has a relatively high impact on the decrease in solar PV output compared to other areas in the region for that season.
FIG. 5. Decrease in mean seasonal solar PV power (in megawatts) due to dust in the Asia Pacific region: (a) DJF; (b) MAM; (c) JJA; and (d) SON. The areas in circles are where dust have a relatively high impact on the decrease in solar PV output compared to other areas in the region.
FIG. 6. Decrease in mean seasonal solar PV power (in megawatts) due to snow in the Asia Pacific region: (a) DJF; (b) MAM; (c) JJA; and (d) SON. The areas in the latitudes above ~30°N and below ~30°S are where snow have an impact on the decrease in solar PV output.
FIG. 7. Total effective mean seasonal solar PV power (in megawatts) in the Asia Pacific region: (a) DJF; (b) MAM; (c) JJA; and (d) SON.
in Fig. 5 which reveals that almost all countries in the region suffer from the effects of dust. The effects are severe in East Asia (except in Japan and Korea) during the JJA season. Australia is consistently affected by dust especially during DIF and MAM seasons. The southern part of Australia also experienced severe effects from dust during the SON season. Finally, the maximum decrease in solar PV power potential due to dust was 550 MW. It seems that the precipitation rate in the region is not enough to serve as a cleaning agent for solar cell installations. Manual scheduled cleaning of the solar PV systems is therefore suggested for these areas.

The interaction between rainfall and dust affects the output power of solar cells. Depending on its intensity, rainfall can either promote or impede the accumulation of dusts on a PV module. Kimber et al. (2006) suggested a minimum of 20 mm/day of rain to clean a PV system from dusts. Meanwhile, even the size of dust particles affects PV power output. Dust of finer particles is distributed in a more uniform manner than that for the coarser ones, thus minimizing the voids between particles through which light can pass (El-Shohokshy and Hussein, 1993). Such dust and rainfall characterization will therefore be considered in updating the current model.

D. Decrease in solar PV power potential due to snow

Using Eqs. (1), (4), and (5), maps for the satellite-derived seasonal decrease in solar photovoltaic output power due to snow for the Asia Pacific Region were generated. The corresponding spatial distribution maps during the different seasons are shown in Fig. 6 which shows that areas with latitudes above ~30°N and below ~30°S were affected by this limiting factor. Areas in North East and North West China, Mongolia, Russia, Japan, and Korea were significantly affected compared to other areas in the region during DIF and MAM seasons. The same is true for New Zealand during JJA and SON seasons. The maximum decrease in the solar PV potential was computed at 225 MW, which is about 12% of the theoretical $P_{PV}$ which is below the maximum snow effect set in the model (i.e., 16%). As such, there is a possible underestimation of snow effects. For future work, we plan to vary the threshold level to efficiently model the snow dynamics in the region.

For an optically thick layer, the Bouguer-Lambert law predicts an exponential decrease in solar irradiance with the depth (Perovich, 2007) which will yield lower $P_{PV}$. Due to its better spatial resolution and temporal coverage, the snow cover product from MODIS (MOD10) was used instead of the snow depth with the assumption that the two are highly correlated. However, in the model update, we plan to derive the snow depth from the snow water equivalent (SWE) product of the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) (Chang and Rango, 2000).

E. Total effective solar PV power

Combining the effects of temperature, dust, and snow gives the total effective $P_{PV}$ as facilitated by Eq. (6). Maps for the satellite-derived total effective seasonal solar photovoltaic output power for the Asia Pacific Region were generated and are shown in Fig. 7. Moreover, Fig. 8 shows the percent decrease in $P_{PV}$ during different seasons at selected cities in APR. The cities of Ulaanbaatar (−12%), Khabarovsk (−16%), Dhaka (−9%), and Beijing (−13%) have the highest percentage decrease in $P_{PV}$ during the SON, DJF, MAM, and JJA seasons, respectively.

As snow and temperature cannot be controlled, significant efforts should be devoted to reducing dust emission. Such a reduction in dust effects will result in a saving of at most 167 MW of energy during the JJA season in Beijing. This amount of energy can support about 6 families of 6 in China for a month based on the reported electric power consumption according to The World Bank (2014).

F. Effects of temperature, dust, and snow on the decrease in solar PV potential in selected cities in the Asia Pacific region

The cities of Beijing (China), Tokyo (Japan), Khabarovsk (Russia), and Jakarta (Indonesia) were selected to see the percent contribution of the three meteorological factors considered in
this study to the overall decrease in solar PV potential with respect to the theoretical values. Figure 9(a) shows that in Beijing’s case, dust is a major contributor to the decrease in $P_{PV}$ for all seasons except in DJF where snow cover is the only factor affecting the said decrease. In Tokyo’s case [Fig. 9(b)], the major contributor varies with the season. Snow is the major factor during SON; snow and dust have equal contributions during DJF; dust is the major
contributor during MAM; during JJA, there is no significant decrease in $P_{PV}$ (snow’s impact is very small at 0.01\% and is highly unlikely to be present during this season).

Khabarovsk is consistently affected by snow effects except in JJA when dust is the only contributing factor to the decrease in $P_{PV}$ [Fig. 9(c)]. Finally, in the case of Jakarta [Fig. 9(d)], the only contributing factor is the dust. The case of Jakarta is the same for the other cities in the region with tropical climate. It can be seen in Figs. 9(a)–9(d) that temperature has no effect on the decrease in $P_{PV}$ for the four cities that were examined. In fact, except in extreme cases such as in desert areas, $\Delta T$ is very negligible for most cities in the Asia Pacific region. As stated previously, this result may change if an actual $T_{cell}$ is computed and reflected in the model instead of LST.

**G. Comparison of estimated and actual solar PV outputs**

Table III shows the summary of the estimated and actual solar PV outputs for the two installations in Australia and Thailand with their corresponding PPE values. Moreover, Fig. 10 shows the bar charts for Table III. The model underestimated
that dealt with the derivation of for different locations. Finally, the coefficient of efficiency for snow needs to be care-
which are useful for the analysis of dust effects on solar panels. use the Angstrom coefficient data to determine AOD values
can also represent other aerosol particles aside from fine and
scheme used for dust analysis also has its limitations since AOD
is the dust.

The maximum decrease in $P_{PV}$ due to the three meteorologi-
parameters was reached except for snow (the threshold is 16%, but the computed is 12%). It is therefore necessary to
investigate this underestimation by considering a more compre-
ensive analysis of snow dynamics in the region and how it can
be incorporated in the model. Although model improvements
are still needed, this paper has demonstrated how different
temperate data can be used to assess the solar PV power
potential in a regional scale. The excellent temporal resolution
of AHI8 should also be maximized to produce the estimated
solar PV power output for every hour at the least. After refining
the model, the next step for this study is to include the geomor-
phological and building/roof type factors in the computation of
$P_{PV}$ to consider the tilt and shadow effects.

Globally, it is apparent that there is a strong movement,
from government and non-government institutions, pushing for
clean energy alternatives. Solar power from PV cells is one of
such alternative that is now becoming a more popular choice.
This technology is continually progressing to provide a more
affordable and more efficient system for the advantage of both
the electricity producers and consumers, leading to more stake-
holders participating in this industry. Therefore, the output of
this study can be useful in planning for small-scale (e.g., solar
rooftop) or large-scale solar PV projects (e.g., solar farms) in a
solar-rich region of Asia Pacific.

ACKNOWLEDGMENTS

SWR, CLOT, and GSMaP products were supplied by the
P–tree System, Japan Aerospace Exploration Agency (JAXA).
The authors would like to thank the Hitachi Global Foundation
for their support in this research endeavor.

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IV. CONCLUSIONS

This paper presented a method for incorporating different
remote sensing satellite data to investigate the limiting effects
of temperature, dust, and snow on the total effective efficiency
of the solar PV cells and the corresponding output power
potential. The theoretical mean seasonal solar PV power was
also derived for the Asia Pacific region with the maximum value
at $\sim$ 19.9 GW per EPA of 17.5 km². The results of this study show a
noticeable significant decrease in $P_{PV}$ in Australia for DJF and
MAM seasons and a slight decrease during SON. The same can
be observed during JJA in China, Mongolia, and Russia.

Different cities are affected differently by temperature,
dust, and snow. For Beijing, the major contributor to the decrease in $P_{PV}$ is dust, except in DJF when snow is the major
contributor. For Tokyo, the effect varies with the season but
mainly dust during MAM. Khabarovsk is consistently affected by
snow effects except in JJA when dust is the only contributing
factor. Finally, in the case of Jakarta, the only contributing factor
is the dust.

The maximum decrease in $P_{PV}$ due to the three meteorologi-
parameters was reached except for snow (the threshold is
16%, but the computed is 12%). It is therefore necessary to
investigate this underestimation by considering a more compre-
ensive analysis of snow dynamics in the region and how it can
be incorporated in the model. Although model improvements
are still needed, this paper has demonstrated how different
temperate data can be used to assess the solar PV power
potential in a regional scale. The excellent temporal resolution
of AHI8 should also be maximized to produce the estimated
solar PV power output for every hour at the least. After refining
the model, the next step for this study is to include the geomor-
phological and building/roof type factors in the computation of
$P_{PV}$ to consider the tilt and shadow effects.

Globally, it is apparent that there is a strong movement,
from government and non-government institutions, pushing for
clean energy alternatives. Solar power from PV cells is one of
such alternative that is now becoming a more popular choice.
This technology is continually progressing to provide a more
affordable and more efficient system for the advantage of both
the electricity producers and consumers, leading to more stake-
holders participating in this industry. Therefore, the output of
this study can be useful in planning for small-scale (e.g., solar
rooftop) or large-scale solar PV projects (e.g., solar farms) in a
solar-rich region of Asia Pacific.

ACKNOWLEDGMENTS

SWR, CLOT, and GSMaP products were supplied by the
P–tree System, Japan Aerospace Exploration Agency (JAXA).
The authors would like to thank the Hitachi Global Foundation
for their support in this research endeavor.

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the generated energy MAM and JJA in Signal Hill and JJA and
SON seasons in Bangkok Soladin.

The values of PPE range from 10% to 38% with an average
value of 22% for Signal Hill and 19% for Bangkok Soladin. This
result is close to but better than the reported monthly averaged
PPE value (23.6%) by Kim et al. (2017) who considered a “practical
model” (similar in some respect to our model) for daily predic-
tion of solar PV power generation in South Korea. Moreover, it
can be seen in Fig. 10 that there is a good linear correlation
between the estimated and actual values as indicated by the
very high values (0.94, 0.99) of $R^2$. The values, however, are quite
far from the 1:1 line indicating a very low agreement in the abso-
lute values of the two sets of data. This can be an indication that
“rotation” factors should be introduced in the model equations
to fit these data points to the 1:1 line. Such a rotation factor can be
derived from the solar PV cell efficiency and coefficients of
efficiencies both of which were set to fixed values. The conver-
sion from power (MW) to energy (KWh) units can also be a
source of error; specifically, it is assumed that sunshine hours
are equivalent to the actual number of hours that the solar cells
are producing power. The assumption was done since no informa-
tion on the actual operating hours is available in PVOutput.org.

The model needs more refinement as indicated by unsatis-
factory values of PPE. The sources of error can be attributed to the
fixed values set for the solar PV cell efficiency (33%) and
efficiencies of efficiency (0.094, 0.3, and 0.16 for temperature,
dust, and snow, respectively). For instance, the published peak
efficiencies for the solar cells used in Signal Hill and Bangkok
Soladin are 16.9% and 13.1%, respectively. Such an efficiency rate
is a possible reason why the estimated values relatively agreed
well with the actual values in Bangkok Soladin. Using the
satellite-derived LST to estimate the actual solar cell tempera-
ture may also introduce significant error since LST itself has
limitations due to mixed-pixel issues, complicated surface
structures, and topographic effects (Wan, 1999). It is therefore
recommended to convert LST to solar panel temperature.
Several studies have used explicit equations to derive the oper-
ating temperature of a PV module ($T_{cell}$) from ambient air tem-
perature such as the studies of Alsayed et al. (2013) and Gokmen
et al. (2016), but as far as we know, there has been no study yet
that dealt with the derivation of $T_{cell}$ directly from LST. This is
therefore a subject of our future work. The binary masking
scheme used for dust analysis also has its limitations since AOD
can also represent other aerosol particles aside from fine and
course dusts (e.g., water vapor, etc.). As a future work, we will
use the Angstrom coefficient data to determine AOD values
which are useful for the analysis of dust effects on solar panels.
Finally, the coefficient of efficiency for snow needs to be care-
fully considered and adjusted if needed since snow types vary
for different locations.

IV. CONCLUSIONS

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