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Interannual Variability of the Solar Resource across Australia

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Abstract

Interannual variability, a measure of uncertainty of the solar resource from one year to the next, is a source of financial risk for PV investments. This paper utilises the satellite-derived gridded global horizontal and direct normal irradiance data products available from the Australian Bureau of Meteorology (BoM) to calculate interannual variability. This data set spans a period of 26 years (1990-2016) enabling characterisation of temporal variability of the solar resource across the continent of Australia. The results from this study indicate that the south eastern and central coastal regions of Queensland experience the highest levels of interannual variability, ranging between 3.5\% and 6.5\% for global horizontal irradiance (GHI). These results differ from previous published results of interannual variability across Australia due to a significant rainfall event which occurred across Queensland in the summer of 2010/11, a period not included in previous analyses. These results highlight the importance of including outlying years in the calculation of interannual variability. Finally, the findings presented in this paper can be used to quickly gauge the level of interannual variability of the solar resource and its potential impact on annual estimates of photovoltaic system performance, improving the understanding of weather related risk for PV projects.

1. Introduction

Within the solar energy industry, it is not uncommon to use either a single year of weather data (i.e. a Typical Meteorological Year (TMY) weather file) or a single set of annual and monthly estimates of the solar resource to undertake pre-feasibility site assessments or to produce estimates of solar energy system performance. Similarly, monthly and annual maps of the solar resource are also commonly employed for pre-feasibility site assessment as evident by the increase in online renewable energy resource maps (AREMI, 2017; IRENA, 2017; Pfenninger & Staffell, 2016; The World Bank Group & Solargis, 2016).

Besides the magnitude of the solar resource, knowledge of the uncertainty of the solar resource at any given location is essential for accurate analysis of system performance, financial viability, and optimal system design and deployment of solar energy systems (Schnitzer, Thuman, & Johnson, 2012; Sengupta et al., 2015). Whilst the variability and uncertainty of the solar resource over hours, minutes and seconds are important for power system operation and impacts on generator electricity market revenue and revenue risk; the uncertainty of annual and monthly energy yield estimates are the key indicators of a projects viability and risk and will
therefore be the focus of this paper. In this context, the uncertainty of the solar resource with respect to annual and monthly energy yield predications is typically described by the following two components:

- The interannual variability of the solar resource; and
- The inherent uncertainty of the data used to quantify the solar resource.

The first component, the interannual variability of the solar resource is the measure of uncertainty of the solar resource from one year to the next, including the uncertainty of the resource in the same month across different years, and therefore the uncertainty associated with monthly and annual energy yield predictions (Schnitzer et al., 2012). This is typically calculated by integrating hourly solar resource data over a month or year, and analysing the variability across a range of years. Existing studies undertaken outside of Australia, have shown that the cumulative solar resource during any one year is independent of the solar resource of the previous years (Gueymard & Wilcox, 2011; T. Tomson, 2008). Within the Australian context, existing studies have investigated the variance of the solar resource utilising a variety of data products, however the focus of these studies has primarily been on the study of intra-annual variability, the study of the variability of the solar resource with time resolutions less than a year. Only one study was located which analysed the interannual variability of the solar resource across Australia (Davy & Troccoli, 2012).

The interannual variability study from (Davy & Troccoli, 2012) examined the effects that the El Nino Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) had on global horizontal irradiance (GHI) in order to establish the role for seasonal forecasting of solar power. The study concluded that the main impact of ENSO occurred during winter over a large part of eastern Australia, whilst little impact was observed during summer, concluding that the ENSO phenomenon may account for solar energy changes of more than 10% in some locations on a seasonal basis. The equivalent analysis for IOD, again showed no statistically significant impacts during summer, however a region of enhanced solar radiation during winter was observed for IOD positive years in comparison to IOD negative years. These results imply that the variability, and not just the average magnitude, of the solar resource on a seasonal basis can have implications for the siting of large scale solar generation plants. However, because the focus of the study was to examine the effects of ENSO and IOD on the variability of GHI for seasonal forecasting purposes, the interannual variability of GHI over the entire period studied was not reported; rather the variability was reported for ENSO specific years and for IOD positive vs. IOD negative years. In addition, the study only focused on the GHI component of the solar resource. This leaves scope for this study to be replicated in order to (1) calculate the interannual variability for GHI across all years of available data; and (2) calculate the interannual variability for direct normal irradiance (DNI) and global irradiance at latitude tilt (GTI) to better reflect the insolation experienced by concentrating and tracking solar energy systems and fixed tilt systems for DNI and GTI respectively. Typically, GTI stands for the global tilted irradiance, which in this study is defined as the plane of array irradiance for a fixed tilt system orientated north, with a tilt angle equivalent to the latitude angle.

The other limitations of the study from (Davy & Troccoli, 2012) was the use of the ERA-Interim and NCEP reanalysis data products (a reanalysis is an estimate of the atmospheric state obtained by combining observations with physical models) over the 19-year period spanning from 1989
to 2008. The use of reanalysis datasets are a limitation when more accurate satellite derived irradiance data products exist for Australia. Conclusions from (Boilley & Wald, 2015) have shown that reanalysis datasets often predict clear sky conditions when actual conditions are cloudy, and vice versa, therefore limiting their use in variability studies. Further it was concluded that satellite data offers less uncertainty than reanalysis data and should be preferred where available. There is therefore scope for an interannual variability study to be reconducted using the more accurate satellite derived irradiance data set. Further, a significant one in a 30 to 40-year rainfall event occurred across Queensland in the summer of 2010-2011, but was excluded from the (Davy & Troccoli, 2012) study, limiting the usefulness of their conclusions, again leaving scope to reconduct an interannual variability analysis for Australia which includes this period of below average solar resource.

Other studies undertaken on solar resource variability across Australia have focused on intra-annual variability, i.e. the study of variability with time intervals less than a year. For example, a second study from (Davy & Troccoli, 2014) used the BoM’s daily gridded satellite derived irradiance data between 2007 and 2012 to determine optimum locations for augmenting the BoM existing network of irradiance ground stations. As part of the study the authors assessed the daily variability of GHI, indicating that higher levels of variability on the daily level occur over the south-eastern regions of Australia. Similarly, the variability of the direct normal (DNI) component of the solar resource at an hourly level has also been studied (Elliston, MacGill, Prasad, & Kay, 2015; Prasad, Taylor, & Kay, 2015). The study by (Prasad et al., 2015) analysed recent trends of the DNI component of the solar resource using the BoM hourly gridded satellite data from 1990 to 2012. The study concluded that the deseasonalised DNI anomalies were significant for all seasons over the west, southeast and north-eastern regions of Australia. Another study by (Elliston et al., 2015), used the BoM satellite derived irradiance dataset over the period 1998 to 2010 to characterise the frequency and duration of rare events such as extended periods of heavy cloud cover and low solar insolation across Australia. As part of this study, the intra-annual variability of the DNI component was assessed using the standard deviation of the hourly anomalies to show how the DNI component deviated from the long-term climatology. These results indicated that the largest deviations in the hourly variability of the DNI component occur across the northern and southern regions of Australia. An almost identical result was reported by (Prasad et al., 2015) using the extended satellite derived dataset from 1990 to 2012. The results of these studies are important for quantifying and understanding the intra-annual variability of the solar resource across Australia at various time intervals. However, it should be reiterated that the focus of these studies has been on variability over days or hours, rather than interannual variability i.e. the variability of the solar resource from year to year. Further each of these studies have focused on one aspect of the solar resource, either GHI or DNI, none of these studies have assessed the variability of irradiance on a tilted plane i.e. GTI.

Outside of Australia, the most relevant work on interannual variability of the solar resource was presented by (Gueymard & Wilcox, 2011) for the United States. Their study presented a methodology to assess both the interannual and spatial variability of the solar resource geospatially. Using the method presented by (Gueymard & Wilcox, 2011) for interannual variability, this paper aims to complement the existing literature on intra-annual variability of

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1 An anomaly is the difference between a specific value of irradiation and the calculated long-term average.
the solar resource over Australia, by reporting the annual and monthly interannual variabilities for GHI, DNI and GTI. DNI and GTI have been chosen for inclusion in this study, rather than focusing on GHI alone, as they better reflect the insolation conditions experienced by tracking, concentrating solar energy systems and fixed tilt solar energy systems.

2. Data Sources

The BoM gridded satellite derived data is processed by the Australian Bureau of Meteorology from satellite imagery sourced from the Geostationary Meteorological Satellites, MTSAT and Himawari-8 series operated by Japan Meteorological Agency and from GOES-9 operated by the National Oceanographic & Atmospheric Administration (NOAA) for the Japan Meteorological Agency. The data is available over numerous temporal time frames, including: instantaneous hourly GHI and DNI in W/m², average hourly GHI and DNI in W/m² averaged over the period 1995 to 2011, and daily and monthly averages of solar exposure in MJ/m²/day. Each of the gridded satellite derived data products span the entire region of Australia (latitudes: -10.05° to -43.95°, Longitudes: 112.05° to 153.95°) with spatial resolutions of 0.05° (≈5km) (Bureau of Meteorology, 2016b). The accuracy of the hourly gridded satellite derived irradiance data products from the BoM are presented in Table 1.

Table 1: Statistical metrics of the bias and uncertainty of the BoM hourly gridded satellite derived irradiance data products as reported by the Australian BoM (Bureau of Meteorology, 2016b)

<table>
<thead>
<tr>
<th></th>
<th>GHI (W/m²)</th>
<th>DNI (W/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MBE (W/m²)</td>
<td>-1</td>
<td>-3</td>
</tr>
<tr>
<td>RMSE (W/m²)</td>
<td>76</td>
<td>172</td>
</tr>
</tbody>
</table>

The second component of the uncertainty of the solar resource, the inherent uncertainty of the data used to quantify the solar resource, results from the accuracy of the method used to generate the solar resource data; whether that data is measured by ground based sensors or modelled by satellite based solar models. The BoM metadata (Bureau of Meteorology, 2016b) estimated the accuracy of the satellite derived data products by comparing the satellite derived data to the 1-minute averaged measurements of GHI and DNI from the BoM surface-based instruments. The reported mean bias difference (MBD) and the root mean squared difference (RMSD), calculated on an annual basis across all surfaces sites are reproduced in Table 1. These statistics indicate that the satellite derived DNI data product has on average twice the level of uncertainty of the GHI data product when referenced to the ground-based measurement data.

The accuracy of the hourly gridded satellite data from the BoM has been independently assessed by a number of authors over the course of its development (Blanksby, Bennett, & Langford, 2013; Copper & Bruce, 2015; Delghani, Prasad, Sherwood, & Kay, 2014). The study from (Copper & Bruce, 2015) demonstrated a strong correlation between the normalised root mean squared deviation of the BoM’s hourly gridded satellite data and the satellite derived clearness index, with reported Pearson correlation coefficients of -0.91 and 0.89 for GHI and DNI respectively. This study also reported the existence of significant differences between the frequency distributions of the satellite derived and ground measured DNI data products, a
phenomenon which has been reported for other satellite derived DNI data products across the globe (Ineichen, 2011). These known issues within the gridded satellite data set will simply be acknowledged and accepted for the work presented in this study.

3. Methodology

The interannual variability of GHI, GTI and DNI in this study are characterised by the method presented by (Gueymard & Wilcox, 2011). The method utilises the coefficient of variation (CoV), the ratio of the standard deviation (σ) of the annual or monthly anomalies divided by the corresponding long term climatological annual or monthly mean (μ), \[ \text{CoV} (%) = \frac{\sigma}{\mu}; \] in conjunction with the assumption that the monthly and annual anomalies of the solar resource are normally distributed. Due to the assumption of normality, this method dictates a 66% likelihood that the solar resource for any given year or month will be within the range defined by \( \mu \pm \sigma \). For a 95% likelihood (i.e. “bankable data”), again working under the assumption of normality, the results presented in this paper can be multiplied by 1.96, as the assumption of normality dictates that a 95% likelihood corresponds to \( \mu \pm 1.96\sigma \) (Gueymard & Wilcox, 2011).

The methodology presented by (Gueymard & Wilcox, 2011) can be applied in the Australian context by utilising the BoM hourly gridded satellite derived datasets to generate spatial grids of monthly and annual averages of the solar resource (both GHI and DNI) in kWh/m²/day and for the GHI component by directly using the monthly grids of solar exposure available from the BoM’s website in MJ/m²/day (Bureau of Meteorology, 2017).

For this analysis, monthly and annual average grids were calculated from grids of daily solar exposure, for each day within the analysis period (1990 to 2016, both years inclusive), in units of kWh/m²/day. The grids of daily solar exposure were calculated by summating the hourly satellite derived grid of GHI and DNI over each day. It should be noted that the metadata for the BoM satellite derived irradiance data products reports that the temporal coverage of the hourly gridded satellite data is not 100% complete (Bureau of Meteorology, 2016b). Most notably, the metadata indicates that no values are reported for hours early and late in the day for the period up until 30/06/1994 with sparser values reported during the period of July 2001 to June 2003. Although not reported in the metadata, it was also observed that only 17 days’ worth of data exists for the month of November 2009.

In this analysis, missing hourly data was handled in one of two ways. The first method was performed using a subset of the data (1995-2000, 2004-2008 and 2010-2016), excluding the years that were reported to have a large fraction of missing data. The second method substituted missing data with their corresponding hourly climatology grid (i.e. long term hourly monthly averages); also sourced from the BoM (Bureau of Meteorology, 2012). For the first method, the exclusion of years of data from an interannual variability analysis may have implications for the calculated value if the excluded years happen to be outlying years i.e. well above or below average. In such a case the calculated values of interannual variability would be underestimated. For the second method, as with any analysis that utilises data filling, the data filling method impacts the results presented. In this case, filling the missing hourly data with long term hourly monthly climatologies reduces the calculated interannual variabilities.

The methodology used to calculate the monthly and annual averages of the solar resource, including the filled data, was tested in comparison to the monthly average grids of solar
exposure in MJ/m²/day, downloaded directly from the BoM website – Climate Maps service (Bureau of Meteorology, 2017). Throughout the remainder of this paper, the GHI grids downloaded from the BoM Climate Maps will be referred to as the monthly “solar exposure” grids, whilst the calculated monthly averages of GHI, DNI and GTI will be referred to as the “calculated” grids.

The results of a comparison between the solar exposure and calculated grids of GHI for the location of Melbourne Airport are presented in Figure 1. These results indicate significant discrepancies between the monthly solar exposure and calculated grids when no data filling method was applied; justifying the need to either exclude or fill these time periods. Conversely, when data filling was applied, Figure 1 illustrates a strong correlation between the monthly solar exposure and calculated grids, highlighting the potential of the data filling method proposed. It should be noted that some of the discrepancies observed between the solar exposure and the filled calculated grids can be attributed to the fact that the BoM’s archived grids of daily and monthly solar exposure prior to 2016, were not reprocessed when the BoM undertook a major update of all hourly satellite derived global and direct normal data products in 2016 (Bureau of Meteorology, 2016a).

![Figure 1: Monthly time series of solar exposure (red) and calculated averages with (green) and without (blue) data filling for the location of Melbourne. The yellow regions highlight the time frames with sparse or missing data.](image)

The BoM does not offer a gridded data product for global irradiance at latitude tilt (GTI). For this study, the monthly and annual averages of GTI were calculated from hourly grids of GTI, which were in turn calculated from the hourly GHI and DNI satellite derived gridded data from the BoM. The calculation process was undertaken via batch processing in python, utilising the ‘location’, ‘solarposition’ and ‘irradiance’ libraries, available within the python version of the PV_LIB toolbox from the PV Performance Modelling Collaborative (PVPMC) (Andrews, Stein, Hansen, & Riley, 2014; Sandia Corporation, 2012). The Perez irradiance transposition model (Loutzenhiser et al., 2007; Richard Perez, Ineichen, Seals, Michalsky, & Stewart, 1990; R. Perez, Seals, Ineichen, Stewart, & Menicucci, 1987) was selected as the specific irradiance transposition model used in this study.
4. Results

Figure 2 plots the annual interannual variability of GHI for the time periods of (a) 1995-2000, 2004-2008 and 2010-2016 (i.e. excluding the years with a significant fraction of missing data); (b) 1990 to 2016 with data filling; and (c) 1990 to 2016 with data filling, excluding 2010 and 2011. It should be noted that the small regions of high interannual variabilities reported across South Australia are primarily due to regions of salt lakes, where the satellite derived irradiance methodology cannot easily distinguish the salt lakes from cloud cover. These regions of high anomalies should be ignored in the results presented.

When comparing the results from Figure 2 (a) and (b), regardless of the analysis method chosen, the results indicate higher levels of interannual variability across the south eastern and central coastal regions of Queensland (3.5% to 6.5%) in comparison to the rest of Australia which experiences interannual variabilities on the order of 2.0% to 3.5%. The driver of the higher variability reported across the south eastern and central coastal region of Queensland in this study, was due to the extreme weather events that occurred over this region in December 2010 and January 2011. During this period Queensland experienced its highest levels of recorded rainfall, exceeding the previous records set in the mid 1970’s. Figure 3 presents an example of the annual differences observed for the location of Brisbane, Queensland, for each year over the analysis period, in comparison to the long-term average. This figure highlights the low level of annual irradiance experienced in 2010 and 2011 in Brisbane.

![Figure 2: Annual GHI interannual variability (%) calculated using time periods (a) 1995-2000, 2004-2008 and 2010-2016; (b) 1990-2016 and (c) 1990-2009 and 2012-2016](image)

![Figure 3: Annual differences from the long-term average for Brisbane, Queensland.](image)

If 2010 and 2011 were excluded from the geospatial analysis, the calculated interannual variabilities across Queensland would drop significantly and be comparable to the rest of
Australia as per Figure 2 (c). These results highlight both the importance of including outlying years in the calculation of interannual variabilities and the potential limitation of calculating interannual variabilities using a dataset which covers a limited period. In the case of the BoM’s satellite derived irradiance, the filled dataset covers a period of 27 years. It is conceivable that this dataset may not yet encompass one in thirty, forty or fifty-year extreme weather events which could have an influence on the calculated interannual variability. Similarly, the influence of the December 2010 – January 2011 rain event in Queensland may have a disproportional impact on the calculated interannual variability across Queensland, if this was indeed a one in a 35-year event, when the dataset used to calculate the interannual variability only currently encompasses 27 years. Further, given the difference in the results presented within this study to the conclusion that variability had little impact across summer in the study by (Davy & Troccoli, 2012), these maps of interannual variability should be recalculated on a periodic basis as new data is released.

This raises the question of how many years of data is required before the solar radiation components stabilise and converge to their long-term means, such that interannual variability can be calculated. This question was investigated by (Gueymard & Wilcox, 2011) using measured irradiance data from four locations in the United States. Their study found that GHI was almost always within ±5% of the long-term mean, whereas they found that it took many years for DNI to stabilise and fall within the ±5% range. An identical analysis to the one presented by (Gueymard & Wilcox, 2011) was undertaken for the location of Brisbane using the 1990-2016 filled satellite dataset, demonstrating similar results, as presented in Figure 4. In this figure, both positive and negative annual anomalies are sorted separately in decreasing order of magnitude. As outlined by (Gueymard & Wilcox, 2011) this analysis illustrates the hypothetical case where, by chance, a measurement station would start operating during the best (or worst) year, followed by the second best (or worst year) and so on.

Figure 4: Number of years needed to stabilise GHI (blue) and DNI (green). Data: Brisbane 1990-2016 filled satellite dataset. Yellow shaded region highlights ±5% range; Red shaded region highlights ±2% range.

For the location of Brisbane, this type of analysis further highlights the effect that the extreme weather event of 2010 and 2011 had on the calculated variability of the solar resource. The results in Figure 4 indicate that six (three positive and three negative anomaly years) and sixteen years respectively would be required before GHI and DNI stabilise within the ±5% region.
Fourteen and twenty-four years respectively would be required for the calculated mean to stabilise within ±2%. Therefore, the reduced dataset that excludes periods of missing data should be suitable to calculate the global horizontal interannual variability, but more years of data would ideally be required to adequately calculate the direct normal long-term mean and hence its interannual variability.

To understand the seasonal variability, the analysis was also undertaken on the monthly bins of data (e.g. the 27 Januaries, 27 Februaries...). In this case results are presented for the reduced data set which excluded years with a high fraction of missing data. The results using the full dataset, with data filling applied, are presented within the appendix. The results in Figure 5, indicate that significant changes in the pattern of variability occur across the months and seasons of the year, with the highest levels of monthly interannual variability occurring across the tropical and Equatorial climate regions of Northern Australia during summer. Conversely, this region of Australia experiences the lowest levels of monthly interannual variabilities across winter. Again these results are very different to the results presented in the study by (Davy & Troccoli, 2012) which concluded that the main impact of ENSO occurs during winter over a large part of Australia and little impact was observed over the continent during summer. The results in Figure 5 also highlight that the magnitude of the monthly interannual variability significantly exceeds the annual interannual variability.

Similar conclusions can be drawn from the analysis using the full dataset as presented in the appendix.

![Figure 5: Interannual variability (% of monthly GHI (kWh/m²/day) 1995-2000, 2004-2008 and 2010-2016](image)

The results of the annual analysis for the GTI and DNI components of the solar resource are presented in Figure 6. This analysis reveals that similar geographical patterns of variability occur for all three components of the solar resource; however, the magnitude of the variability in the DNI component is on average double the variability observed for GHI and GTI, as
observed by comparing Figure 6 (b) for DNI to Figure 6 (a) and Figure 2 (b) for GTI and GHI respectively. These results indicate that the energy output from tracking or concentrating solar systems, which are dependent primarily on DNI, are likely to suffer at twice the level of interannual variability in comparison to fixed tilt solar energy systems, which are better represented by the variability in GHI and GTI.

![Figure 6: Annual GTI and DNI interannual variability (%) calculated using the calculated (1995-2000, 2004-2008 and 2010-2016) GTI and DNI gridded datasets.](image)

Further, in comparison to Figure 2 (b), Figure 6 also indicates that both GTI and DNI experience higher levels of annual variability across the coastal regions of NSW and Victoria, similar in magnitude to the levels of variability observed across Queensland. This highlights the importance of accounting for the increased variability of the DNI component in the calculation of GTI interannual variability. Hence, the use of GHI interannual variability as a proxy for GTI interannual variability will be a conservative estimate. Overall, the interannual variability analysis reveals that the highest levels of variability occur across the coastal regions of eastern Australia, with the lowest levels of variability occurring across the north-western region of Australia.

Figures of the monthly interannual variabilities for GTI and DNI are presented within the Appendix. The results from these comparisons show similar geospatial trends as the results for GHI presented in Figure 5.

5. Conclusions

This paper utilised the satellite-derived gridded global horizontal and direct normal irradiance data available from the Australian Bureau of Meteorology (BoM) to characterise the interannual variability of the solar resource across Australia. The results highlighted that the south eastern and central coastal regions of Queensland experienced the highest levels of GHI interannual variability ranging between 3.5% and 6.5%. This result was shown to be driven by an extreme rainfall event that occurred across this region in December 2010 – January 2011. Further, the results presented in this study were found to differ from the previous published results of interannual variability across Australia (Davy & Troccoli, 2012), likely caused by the 2010/11 rainfall event not being captured by the dataset used in the previous study. These results highlight the importance of including outlying years in the calculation of interannual variability.
The findings presented in this paper can be used to quickly gauge the level of interannual variability of the solar resource and its potential impact on annual estimates of photovoltaic system performance, improving the understanding of weather related risk for PV projects. It is recommended that the maps presented in this paper are recalculated on a periodical basis as new data is released. This will (a) limit the impact of extreme one in 30/40/50-year events have on the calculated interannual variability, which maybe currently encompassed within a limited temporal dataset and (b) include any one in 30/40/50-year extreme events which may occur but have not yet been captured by the dataset.

References


Appendix

Figure 7: Interannual variability (%) of monthly GHI (kWh/m²/day) 1990 – 2016

Figure 8: Annual GTI and DNI interannual variability (%) calculated using the calculated (1990-2016) GTI and DNI gridded datasets.
Figure 9: Interannual variability (%) of monthly DNI (kWh/m²/day) 1995-2000, 2004-2008 and 2010-2016

Figure 10: Interannual variability (%) of monthly DNI (kWh/m²/day) 1990-2016
Figure 11: Interannual variability (%) of monthly GTI (kWh/m$^2$/day) 1995-2000, 2004-2008 and 2010-2016

Figure 12: Interannual variability (%) of monthly GTI (kWh/m$^2$/day) 1990-2016