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Sven Killinger, David Lingfors, Yves-Marie Saint-Drenan, Panagiotis Moraitis, Wilfried van Sark, et al.. On the search for representative characteristics of PV systems: Data collection and analysis of PV system azimuth, tilt, capacity, yield and shading. *Solar Energy*, 2018, 173, pp.1087 - 1106. 10.1016/j.solener.2018.08.051 . hal-01882680

**HAL Id: hal-01882680**

**<https://hal.science/hal-01882680v1>**

Submitted on 5 Jul 2019

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Article in *Solar Energy* · August 2018

DOI: 10.1016/j.solener.2018.08.051

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# On the search for representative characteristics of PV systems: Data collection and analysis of PV system azimuth, tilt, capacity, yield and shading

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## Abstract

Knowledge of PV system characteristics is needed in different regional PV modelling approaches. It is the aim of this paper to provide that knowledge by a twofold method that focuses on (1) metadata (tilt and azimuth of modules, installed capacity and specific annual yield) as well as (2) the impact of shading.

Metadata from 2,802,797 PV systems located in Europe, USA, Japan and Australia, representing a total capacity of 59 GWp (14.8% of installed capacity worldwide), is analysed. Visually striking interdependencies of the installed capacity and the geographic location to the other parameters tilt, azimuth and specific annual yield motivated a clustering on a country level and between systems sizes. For an eased future utilisation of the analysed metadata, each parameter in a cluster was approximated by a distribution function. Results show strong characteristics unique to each cluster, however, there are some commonalities across all clusters. Mean tilt values were reported in a range between 16.1° (Australia) and 35.6° (Belgium), average specific annual yield values occur between 786 kWh/kWp (Denmark) and 1,426 kWh/kWp (USA South). The region with smallest median capacity was the UK (2.94 kWp) and the largest was Germany (8.96 kWp). Almost all countries had a mean azimuth angle facing the equator.

PV system shading was considered by deriving viewsheds for  $\approx 48,000$  buildings in Uppsala, Sweden (all ranges of solar angles were explored). From these viewsheds, two empirical equations were derived related to irradiance losses on roofs due to shading. The first expresses the loss of beam irradiance as a function of the solar elevation angle. The second determines the view factor as a function of the roof tilt including the impact from shading and can be used to estimate the losses of diffuse and reflected irradiance.

*Keywords:* PV system characteristics, Metadata, Shading, Data analysis

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## 1. Introduction

With 402.5 GW of installed photovoltaic (PV) capacity globally (IEA, 2018), the integration of the large amounts of energy generated by the numerous distributed solar power systems into the electricity supply system is an issue ever gaining in importance. Modelling of the power generated by those decentralised solar systems is of utmost importance for several issues ranging from energy trading to network flow control. The estimation and forecast of PV power is made difficult by the fact that only a minority of systems continuously report their generation and are publicly accessible.

Different strategies have been proposed to overcome the lack of reporting (e.g. upscaling approaches or power simulations based on satellite derived irradiance); an extensive literature overview is provided in Bright et al. (2017b). Within this paper, the estimation of the aggregated power generated in a given region by a fleet of unknown PV systems is referred to as regional PV power modelling. Knowledge of PV system characteristics is required in the different regional PV modelling approaches to reconstruct the missing power measurements (Lorenz et al., 2011; Saint-Drenan et al., 2016). Some studies assign simplified assumptions of the PV system characteristics. This can result in over-exaggerated grid impacts (Bright et al., 2017a). Unfortunately in most cases, characteristics from PV systems are either unknown or

only accessible for a small number of stakeholders (inverter manufacturers, monitoring solutions providers, etc.). As a result, progress in the area of regional PV power estimation or forecasting can be considered sub-optimal as potential contributors like universities or small companies are partially excluded from access to larger datasets of measurements or metadata. This is still the case despite grid integration of solar energy being considered a strategic societal issue. Therefore, it is the aim of this paper to offer any stakeholders the possibility to develop activities on this research field by collecting, analysing and disseminating metadata on millions of PV systems installed worldwide. To begin, we must establish which metadata are the most important.

Saint-Drenan (2015) carried out a sensitivity analysis and found that the four most influential characteristics impacting PV output generation are: (1) tilt angle and (2) azimuth angle of PV modules, (3) installed capacity and (4) total efficiency (represented herein as the specific annual yield). Furthermore, (5) shading is of crucial influence on the PV power generation but is not accessible from PV system metadata. The impact of shading can only be accessed with considerable effort, e.g. simulations that consider digital elevation models (DEM) including buildings, trees and other obstacles, by analysing PV power profiles or even weekly performance ratios (see Paulescu et al. (2012); Freitas et al. (2015); Lingfors et al. (2018); Tsafarakis et al. (2017) for further reading). Due to its significant influence, a shading analysis complements the focus of this study.

These five identified characteristics are the cen-

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66 tral focus of this paper because of their general 99  
67 importance for regional PV modelling approaches. 100  
68 The overall aim of this paper is to achieve a full re- 101  
69 producibility of the five characteristics so that they 102  
70 can be used in regional PV power modelling appli- 103  
71 cations such as nowcasting or forecasting, but also 104  
72 in power simulations that are used for energy sys- 105  
73 tem analysis, studying the grid impact, defining the 106  
74 PV power potential etc.

### 75 1.1. Related work

76 The relevant literature for this research has three 111  
77 prominent categories: (1) metadata analysis with 112  
78 intention to improve regional PV power simula- 113  
79 tions, (2) PV performance due to specific yield, and 114  
80 (3) models that consider shading analysis. 115

81 **Category 1:** Examples of literature using meta- 116  
82 data to improve regional PV power simulations. 117  
83 [Schubert \(2012\)](#) provides a useful guidebook for 118  
84 the simulation of PV power that sketches impor- 119  
85 tant parts of the simulation chain and delivering 120  
86 assumptions for characteristics. An overview of dif- 121  
87 ferent characteristics of tilt, azimuth, the module 122  
88 and installation type are given together with sug- 123  
89 gested weights. However, these weights seem to be 124  
90 assumptions with no datasets being cited as an em- 125  
91 pirical basis and so using these weights in PV sim- 126  
92 ulations raise questions of trust. 127

93 Datasets are used by [Lorenz et al. \(2011\)](#), who 128  
94 evaluated the representativeness of a set of ref- 129  
95 erence PV systems to predict regional PV power 130  
96 by analysing the orientation and module types of 131  
97  $\approx 8,000$  systems in Germany. The authors note 132  
98 that their dataset seem to have a disproportionate 133

share of large PV systems and so do not fully rep-  
resent a larger portfolio.

The problem of poor representativeness was by-  
passed in [Saint-Drenan \(2015\)](#); [Saint-Drenan et al. \(2017\)](#) by feeding a PV model with metadata statis-  
tics from a larger sample of PV systems as opposed  
to a smaller and unrepresentative subset. They de-  
rived joint probabilities of azimuth and tilt from  
35,000 systems and clustered them by their sys-  
tem size and geographic location. These empiric  
distributions were then used to estimate the char-  
acteristics of all 1,500,000 PV systems installed in  
Germany at that time. [Saint-Drenan et al. \(2018\)](#)  
complemented their earlier research by reproduc-  
ing it for more European countries using statistical  
distributions from 35,000 PV systems in Germany  
and 20,000 in France. This demonstrates the sig-  
nificant potential of generating representative sta-  
tistical distributions with intended use in regional  
PV power simulations.

[Kühnert \(2016, pp. 80-85\)](#) followed a similar ap-  
proach and derived statistical distributions for tilt  
and azimuth from  $\approx 1,300$  PV systems in Germany.  
Based on this portfolio, the author evaluated the  
representativeness should PV systems be clustered  
into different geographic regions and system sizes.  
The authors quantitatively derived recommenda-  
tions between the two extremes of (1) a portfolio  
covering all PV systems and (2) a high number of  
subclasses with a very small number of PV systems.  
From this, we observe that there must be a well  
considered clustering approach in order to derive  
representative subclasses.

[Killinger et al. \(2017c\)](#) detailed a regional PV  
power upscaling approach which estimated the

134 power of  $\approx 2,000$  target PV systems based on 45  
135 continuously measured PV systems in Freiburg, 170  
136 Germany. Whereas the azimuth and tilt of the 45 171  
137 measured systems were known in their case, both 172  
138 parameters were derived through a geographic in- 173  
139 formation system (GIS) based approach for the tar- 174  
140 get PV systems. 175

141 Furthermore, [Pfenninger and Staffell \(2016\)](#) use 176  
142 PV power measurements and incorporate metadata 177  
143 from 1,029 systems in 25 European countries to de- 178  
144 rive empirical correction factors for PV power sim- 179  
145 ulations. A comparison between the analysed tilt 180  
146 and latitude showed an trend towards steeper an- 181  
147 gles at higher latitudes, indicating that metadata 182  
148 might vary with the geographic location. 183

149 PV system metadata is thus used to successfully 184  
150 improve regional PV power upscaling across Europe 185  
151 in [Pfenninger and Staffell \(2016\)](#); [Killinger et al. \(2017c\)](#); [Saint-Drenan \(2015\)](#); [Saint-Drenan et al. \(2017, 2018\)](#); [Kühnert \(2016\)](#). These works applied 186  
152 information of azimuth, tilt, installed capacity and 187  
153 the geographic location from PV systems to esti- 188  
154 mate the power output of a larger PV fleet for sim- 189  
155 ilar geographies and different countries. They stand 190  
156 as an powerful and excellent example for how rep- 191  
157 resentative metadata distribution statistics can be 192  
158 employed. It is these examples that guide the first 193  
159 usage of our vast dataset towards deriving repre- 194  
160 sentative metadata distributions. 195  
161  
162

163 **Category 2:** Excerpts of literature that analyse 198  
164 the performance of PV systems. Performance is 199  
165 more complex than just tilt and azimuth as it is 200  
166 inherently influenced by other components, such as 201  
167 soiling and meteorology. 202

168 [Nordmann et al. \(2014\)](#) found a positive correla- 203

tion between specific annual yield and incoming ir-  
radiance, as well as an observed negative correlation  
between system performance and ambient temper-  
ature. Their data was obtained via web-scraping of  
Solar-Log (2,914 systems in the Netherlands, Ger-  
many, Belgium, France and Italy) and collected by  
participants of the IEA task (>60,000 systems in  
the USA).

[Moraitis et al. \(2015\)](#) observed an increasing yield  
with decreasing latitude from  $\approx 20,000$  systems in  
Netherlands, Germany, Belgium, France and Italy,  
also achieved using web-scraping techniques. We  
therefore expect to observe geographical differences  
due to latitude and climate.

[Taylor \(2015\)](#) explored the generation of 4,369  
distributed systems in the UK to derive the per-  
formance ratio and degradation rate. To allow re-  
producibility, the analysis of the performance ratio  
was enriched by approximating it with distribution  
functions. We intend to extend this style of analysis  
to PV system metadata.

[Leloux et al. \(2012a\)](#) examined data from residen-  
tial PV systems in Belgium; [Leloux et al. \(2012b\)](#)  
focused on France. In Belgium, specific annual  
yield was analysed for 158 systems in 2009 and  
normalised by a factor which compared the incom-  
ing irradiance in this year to a 10 year average.  
The mean value was 836 kWh/kWp. The same ap-  
proach led to a mean value of 1,163 kWh/kWp for  
1,635 systems in 2010 in France. Weibull distribu-  
tions were used throughout both papers to approxi-  
mate the specific yield and performance indicators;  
Weibull distributions were selected for visual simi-  
larity and not for robustness of fit — we aim to use a  
more statistically rigorous approach to distribution

204 type selection. Furthermore, a relative distribution 238  
205 was provided for combinations of tilt and azimuth. 239  
206 Additionally, the installed capacity was analysed in 240  
207 France, showing a high number of systems with 3 241  
208 kWp or slightly less. The reason for this is due to 242  
209 tax credits being denied for system sizes  $> 3$ kWp 243  
210 and a strongly increased VAT for such system sizes 244  
211 (Leloux et al., 2012b). The legal framework can 245  
212 thus have a strong influence on characteristics of 246  
213 PV systems. Further studies exist which analyse 247  
214 the specific energy of PV systems. However, most 248  
215 of these studies are limited to a particular region 249  
216 and less of them propose a parametric approxima- 250  
217 tion of the data studied. 251

218 **Category 3** — the impact of shading in many ar- 252  
219 ticles is only considered in a highly simplified man- 253  
220 ner, e.g. by setting irradiance values zero above 254  
221 a certain solar zenith angle (Lingfors and Widén, 255  
222 2016), restricting simulations and analyses to time 256  
223 steps with certain solar zenith angles (Elsinga and 257  
224 van Sark, 2015; Elsinga et al., 2017; Jamaly et al., 258  
225 2013; Killinger et al., 2016; Saint-Drenan et al., 259  
226 2017; Yang et al., 2014; Bright et al., 2015), ap- 260  
227 plying constant losses (Mainzer et al., 2017) or as- 261  
228 suming a linear decrease in the PV power values 262  
229 (Schubert, 2012). Several authors expect improve- 263  
230 ments in their results, when the influence of shading 264  
231 is better represented (Bright et al., 2017a,b; Pareek 265  
232 et al., 2017) 266

### 233 1.2. Contribution 267

234 Considering the lessons and outcomes of the dif- 268  
235 ferent studies described in our literature review, we 269  
236 see a clear need for the production of a represen- 270  
237 tative set of distributions to appropriately repre- 271

sent PV system metadata. Currently, further ad-  
vancements in regional PV power models in the ab-  
sence of significant knowledge of metadata is hin-  
dered due to several reasons. Firstly, implementa-  
tion is hindered due to lack of access to PV sys-  
tem datasets. Empirically derived distributions  
of these PV system parameters could replace this  
need, though currently are only provided for per-  
formance indicators (Taylor, 2015) and the specific  
annual yield (Leloux et al., 2012a). Secondly, with  
exception of a few studies (e.g., Saint-Drenan et al.  
(2015)), the issue of sample representativeness is  
often omitted. This is a major omission, for exam-  
ple, a studied dataset including a majority of roof-  
mounted PV system has to be generalised in order  
to represent a fleet of systems encompassing a lot  
of rack-mounted PV systems. Thirdly, most of the  
identified studies focused on particular PV system  
characteristics; an integrated analysis encompass-  
ing all five key characteristics is required. Further-  
more, the influence of shading is in most articles  
excessively simplified or more commonly excluded.  
Lastly, studies are mostly limited to a specific coun-  
try and it is currently difficult to make comparisons  
between countries to assess applicability. A holistic  
overview of important parameters of metadata for  
multiple countries is clearly missing.

The objective of this paper is to address the afore-  
mentioned limitations by following the goals below:

1. To collect and process as many data sources  
as feasible of four identified key metadata pa-  
rameters (tilt, azimuth, installed capacity and  
specific annual yield) for PV systems installed  
worldwide (section 2),

- 272 2. To explore the characteristics of these key pa- 305  
273 rameters and their associated interdependen- 306  
274 cies ([section 3.1](#)), 307
- 275 3. To propose a a clustering approach to allow 308  
276 representative generalisation of our datasets 309  
277 ([section 3.2](#)), 310
- 278 4. To provide an eased access to the character- 311  
279 istics of each key parameter by fitting distri- 312  
280 bution functions to the observed probabilities 313  
281 ([section 4](#)), 314
- 282 5. To propose a method that evaluates the im- 315  
283 pact of shading ([section 5.1](#)) and which derives 316  
284 generalised findings for improved consideration 317  
285 and implementation ([section 5.2](#)). 318

286 The influence of meteorological conditions, panel  
287 degradation and soiling are not considered within  
288 this research, beyond those losses that are inher-  
289 ently and statically contained within the specific  
290 annual yield. Whilst they are highly interesting  
291 topics and research avenues that could be explored,  
292 we are more keenly interested in comparisons and  
293 parametrisations of PV system metadata and re-  
294 serve such topics for future research, more ideas of  
295 which are presented in [section 6](#). A summary of the  
296 paper is then given in [section 7](#). In the [Appendix](#)  
297 [A](#), the forms of the distributions used in this paper  
298 are defined and their fitted variables provided.

## 299 **2. Collection and processing of PV system** 300 **metadata**

301 An intensive effort has been conducted to iden- 336  
302 tify, collect and prepare good sources of PV sys- 337  
303 tem metadata. Some of the major monitoring 338  
304 companies and inverter manufacturers have been 339

305 contacted. In parallel, free information on sev-  
306 eral solar portals have also been used to gather  
307 our dataset either by downloading or web-scraping  
308 techniques. Ultimately, we obtained a dataset con-  
309 taining 2,802,797 PV systems located in Europe,  
310 USA, Japan and Australia, which represents a to-  
311 tal capacity of 59 GWp (14.8% of installed capacity  
312 worldwide). Every system in our records reported  
313 an installed capacity. However, the other param-  
314 eters were not always reported. The systems in  
315 our database that reported a valid tilt/azimuth only  
316 have a relative share from the worldwide installed  
317 capacity of 1.7%. Geographic position was almost  
318 as often reported as installed capacity and the re-  
319 lative share is 14.5%. The specific annual yield has  
320 a relative share of 11%. Further detail of the pa-  
321 rameter shares and subsequent quality filtering are  
322 found in [Table A.5](#).

323 An overview of the regions covered by our study,  
324 the characteristics of the datasets and their sources  
325 are provided in [Table 1](#). For some countries, data is  
326 derived from multiple sources. It shouldn't be ruled  
327 out that systems could be listed multiple times,  
328 leading to duplicates in the analysis. Due to the  
329 nature of reporting, a single PV system may not  
330 have the same metadata in different datasets and  
331 so it is accepted that this is an inherent error. The  
332 inhomogeneous nature of the datasets motivated us  
333 to apply some preprocessing operations to ensure  
334 that only valid system measurements are considered  
335 in our analysis and all datasets are in a consistent  
336 format. Some of these operations act as quality fil-  
337 ters. They were developed based on our empiric  
338 experiences with the datasets and are shortly justi-  
339 fied where presented.



Table 1: Regions, parameters and data sources. “Rest of Europe” contains different European countries not already listed with less than 1,000 systems each. The cumulated capacity is given in MWp and, where available, as a relative share of the total installed capacity in a region (own calculations based on [IEA \(2018\)](#) with data from 2016 and [National Grid UK \(2018\)](#) in case of UK with data from 2018).

Region	No. systems	Tilt & azi. ( ° )	Capacity (kW/kWp)	Spec. ann. yield (kWh/kWp)	Cumulated Capacity (MWp) / % of total	Source
–	–					–
Australia	4,055	✓	✓	×	30 / 0.42	pvoutput.org
Austria	385	✓	✓	2012-2016	4 / 0.33	solar-log.com
	280	✓	✓	×	2 / 0.14	suntrol-portal.com
	268	✓	✓	2015-2017	2 / 0.17	sonnenenertrag.eu
	112	✓	✓	2015-2017	1 / 0.04	pvoutput.org
Belgium	4,535	✓	✓	2012-2016	149 / 3.93	solar-log.com
	3,365	✓	✓	2015-2017	17 / 0.45	bdpv.fr
	541	✓	✓	2015-2017	12 / 0.32	sonnenenertrag.eu
Denmark	933	✓	✓	2012-2016	7 / 0.80	solar-log.com
	630	✓	✓	×	4 / 0.42	suntrol-portal.com
	542	✓	✓	2015-2017	2 / 0.27	pvoutput.org
France	20,935	✓	✓	2015-2017	93 / 1.17	bdpv.fr
	558	✓	✓	2012-2016	8 / 0.10	solar-log.com
Germany	1,664,967	×	✓	2012-2016	41,478 / 98.76	bundesnetzagentur.de
	23,536	✓	✓	2012-2016	547 / 1.30	solar-log.com
	6,561	✓	✓	×	124 / 0.29	suntrol-portal.com
	6,447	✓	✓	2015-2017	112 / 0.27	sonnenenertrag.eu
Italy	2,506	✓	✓	2012-2016	30 / 0.15	solar-log.com
	1,068	✓	✓	2015-2017	9 / 0.04	pvoutput.org
	358	✓	✓	2015-2017	11 / 0.06	sonnenenertrag.eu
Japan	5,233	✓	✓	2012-2017	42 / 0.09	jyuri.co.jp
Netherlands	7,180	✓	✓	2015-2017	31 / 1.08	pvoutput.org
	1,115	✓	✓	2012-2016	14 / 0.49	solar-log.com
	917	✓	✓	2015-2017	9 / 0.31	sonnenenertrag.eu
	290	✓	✓	×	2 / 0.07	suntrol-portal.com
Rest of Europe	1,191	✓	✓	2012-2016	23 / –	solar-log.com
	566	✓	✓	2015-2017	5 / –	pvoutput.org
	133	✓	✓	2015-2017	2 / –	sonnenenertrag.eu
UK	18,543	✓	✓	2015-2016	58 / 0.45	microgen-database.sheffield.ac.uk
	2,286	✓	✓	2015-2017	9.5 / 0.07	pvoutput.org
USA	1,020,585	✓	✓	2017	16,521 / 32.39	openpv.nrel.gov
	2,176	✓	✓	2015-2017	17 / 0.03	pvoutput.org

**Longitude and latitude:** In cases where this information was not provided, the geographical coordinates were derived from OpenStreetMap using other given information such as the zip-code, city name, state name, etc. Erroneous locations outside the specific region are set NA. For confidentiality reasons geographic information was provided separately from the other parameters in case of the 18,543 systems from Sheffield Solar. The derived longitude and latitude are not required to be highly accurate to suit the needs of this paper as they are purely used for trend analysis when studying rough relationships to other parameters and for visualization purposes. The ability to allocate a PV system to a specific country is certain in all cases.

**Tilt and azimuth:** Unfortunately, this important metadata is not available from all sources. In case of Australia the provided data was imprecise ( $45^\circ$  steps in the azimuth) and thus estimated by the approach described in Killinger et al. (2017b) and improved in Killinger et al. (2017a) as the PV power data was available. As Australia is on the southern hemisphere, azimuth angles were transformed to normalise the angles expressed for both hemispheres. Within this paper, we consider  $-90^\circ$  to be east,  $90^\circ$  to be west, with  $0^\circ$  representing south in the Northern hemisphere and north in the Southern hemisphere. Multi-array systems are not considered in this paper. In a few of the listed datasets, an excessive amount of tilt values with  $0^\circ$  or  $1^\circ$  and azimuth values of  $-180^\circ$  are reported. E.g. the Australian dataset reported 36% of all systems having a tilt angle  $\leq 1^\circ$ . Visual inspections based on aerial images and results from the aforementioned parametrisation, however, showed that

such small tilt angles were very rare and regularly incorrectly reported. From previous work with various datasets, we know that such boundary values are sometimes used as a default when data is missing. As we have no quality control measures on the data, the validity of the data at these boundary values is in question and so are removed from consideration. Tilt  $\leq 1^\circ$  or  $> 89^\circ$  and azimuth  $< -179^\circ$  or  $> 179^\circ$  are thus set NA.

**Specific annual yield:** There are many instances of systems reporting a specific annual yield of 0 kWh/kWp. Without further information from the datasets, it is not possible to distinguish whether this is a default value for missing data or a valid measurement. We expect that both cases regularly occur and so we must remove any input of 0 kWh/kWp from our analysis. Furthermore, the specific yield of a system is set NA if it was installed within the year of consideration to ensure that a full year of generation is the basis for the annual yield. In order to compensate annual meteorological fluctuations within a dataset of a country, all values within a year are divided by the ratio between the mean value from all systems in this year and the average of the mean values from all reported years. A similar approach is applied in Leloux et al. (2012a). In datasets reporting a continuous time series, the specific annual yield was derived by the summation of the normalised PV power values. Only systems which have less than 10 days /  $\approx 2.7\%$  of missing time steps in their generation data are considered. The vast minority of systems in the datasets reported specific annual yield values that significantly exceed any meteorological potential. We believe that such values are either erroneous reports

of either yield or the installed capacity, as the latter is used in some datasets to derive the former through division. Whereas Taylor (2015) applied a statistical based upper limit for outliers, a fixed limit of 2,000 kWh/kWp was used in this paper. The fixed value was chosen to ensure a reliable filtering even though the quality and range of values may differ for the various datasets. A threshold value of 2,000 kWh/kWp acknowledges the increasing risk of erroneous data beyond this value and is a very cautious limit with the aim of avoiding any erroneous filtering. In fact, this limit was only exceeded in 2.65% of all systems that reported a yield value from openpv.nrel.gov where we observed the largest values within the study and only for 0.084% of all systems in this study.

Please note that, regarding the installed capacity, no pattern was recognised that led us to believe that there were any systematic quality issues. The same applies for the other parameters that were only available for some datasets, such as information about the network connection for Germany as visualised in Figure 2. Hence, the data was taken on an as-is basis in these cases.

A summary of the impact of our proposed quality control criteria is provided in the appendix in Table A.5 where percentages of removed data are presented. Data from pvoutput.org were strongly affected by the filtering of the low tilt values and justify the need of such a quality control. There is a significantly higher share of systems filtered by  $< -179^\circ$  when compared to the filter for azimuths  $> 179^\circ$ . This is because south is defined as  $180^\circ$  in some datasets and are therefore transformed by subtracting  $180^\circ$ . Invalid entries in the

same datasets were defined as  $0^\circ$  and subsequently filtered post-transformation by the lower threshold value for azimuth values. Insufficient information was given to derive the exact location for PV systems, mostly from pvoutput.org. All valid parameter entries that have passed the quality control are used for the analysis in the next two sections.

### 3. Analysis of PV system metadata

#### 3.1. Analysis of parameters and dependencies

The datasets presented in section 2 are very inhomogeneous with large differences in the number of systems in each region and the availability of parameters. Before starting to explore individual clusters, typical ranges of these parameters and potential dependencies between them shall be studied on a global dataset. The general principle of the global dataset is that every region has the same weight. Consider Table 1, should all data be used to make global statistics, the results would be biased towards the countries with more data (USA and Germany). Therefore, a normalisation method must be employed to weight countries equally. Its derivation follows the following procedure:

(1) Specific annual yield is the only parameter that exists multiple times for each PV system. To evenly weight all systems, only one normalised specific yield value per system is considered by randomly selecting a year. This procedure was preferred to others such as e.g. taking the mean value for all values of a system in order to conserve system specific variability between years. (2) For each combination of two parameters (e.g. tilt and specific annual yield) the algorithm counts the number

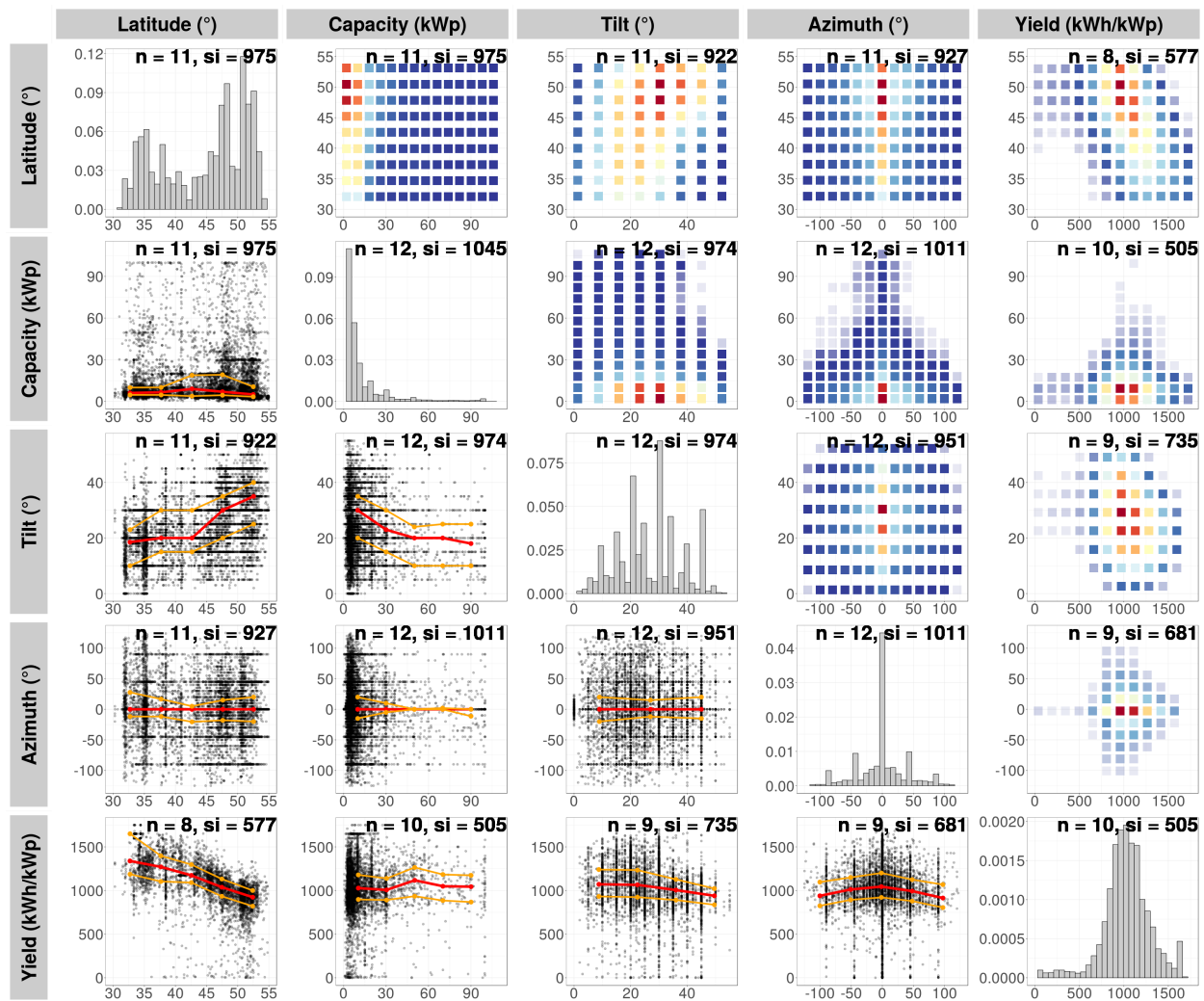


Figure 1: Hybrid graphic with plots of the different parameter pairs from the global dataset. The plots below the diagonal are scatter plots with the 25%, 50% and 75% quantiles as coloured lines. Plots on the diagonal are 1D-histograms of that parameter. Plots above the diagonal are 2D-histograms of the parameter pairs; the change in colour from white to red is an indication of probability and its distribution. The 2D-histograms and scatter plots have the parameter of their column on the x-axis and the parameter of their row on the y-axis. Note that each scatter and 2D-histogram pair have opposite axes but are identical data. 1D-histograms are the only exception with having displayed the density on the y-axis. For reasons of simplification the absolute value of the latitude is taken in these plots to make results from the northern and southern hemisphere comparable. The bold number in each plot shows the number of countries ( $n$ ) which are considered in the plot as well as the sampling size ( $si$ ).

478 of couples per region that have valid reports in both 482 statistical relevance. (3) The smallest number of  
 479 parameters that have passed the quality control in 483 complete couples from all regions is taken to de-  
 480 [section 2](#). Only regions with a sample size of at 484 fine the sample size for the global dataset. This  
 481 least 500 complete couples are considered to ensure 485 way, the same number of complete couples is taken

486 from each region. Therefore, all of the data is con- 521  
487 sidered for the region with the smallest number of 522  
488 complete couples. In all other regions, the same 523  
489 number of couples is randomly selected. To avoid 524  
490 under-representation of larger systems, the selec- 525  
491 tion probability is linearly weighted with installed 526  
492 capacity, not frequency. 527

493 The significant advantage of this procedure is 528  
494 that regional characteristics are evenly weighted 529  
495 and the availability for each pair of parameters is 530  
496 individually considered. The disadvantage is that 531  
497 many systems are randomly banned due to the re- 532  
498 gion with least availability. We applied different 533  
499 methods of sub-sampling the data, however, the re- 534  
500 sulting global data was quite insensitive to differ- 535  
501 ent sampling procedures indicating the robustness 536  
502 of our approach. 537

503 Results from the global dataset are displayed 538  
504 in [Figure 1](#) and the following observations can be 539  
505 made: 540

506 **Latitude:** To have a robust quantity of data, 541  
507 PV systems in latitudes between  $30^\circ$  and  $55^\circ$  are 542  
508 studied. Latitude does not show any obvious in- 543  
509 fluence to the installed capacity or azimuth angle. 544  
510 The tilt angle shows a tendency to increase with 545  
511 an increasing latitude, corroborating the same ob- 546  
512 servation by [Pfenninger and Staffell \(2016\)](#) between 547  
513 the latitude ranges in the study. This finding agrees 548  
514 with studies showing that systems should have a 549  
515 smaller tilt closer to the equator in order to opti- 550  
516 mize their annual yield ([Šúri et al., 2007](#)). It is still 551  
517 surprising since many systems in our analysis are 552  
518 installed on roofs and strongly depend on the roofs' 553  
519 inclination. It can be suggested that the roof pitch 554  
520 has a tendency to be steeper at higher latitudes in 555

our datasets and agrees with similar observations in  
Europe ([McNeil, 1990](#), p. 883). Furthermore, a lin-  
ear decline in the specific annual yield is observed  
with an increasing latitude. This occurs in accor-  
dance to the tendency of a higher solar potential in  
regions closer to the equator ([Šúri et al., 2007](#)).

**Installed capacity:** Within the plot, only sys-  
tems  $< 100$  kWp are displayed for ease of visuali-  
sation. Even though the sampling weights in pref-  
erence of larger systems, there is a clear concentra-  
tion of smaller system sizes. There is a visual trend  
towards smaller tilts with an increasing installed  
capacity. Furthermore, there is a clear observation  
that larger capacity systems are consistently ori-  
ented towards the equator whereas smaller systems  
have a much broader range of orientation. A depen-  
dency between the installed capacity and the spe-  
cific annual yield cannot be observed in the global  
dataset. Despite that, we would expect that the  
efficiency of larger systems is usually higher and  
systems better maintained. Most likely, this trend  
is invisible here since data from many geographic  
regions were sampled. This hypothesis is checked  
in [section 4](#). The finding that PV system size has  
interdependencies on the other parameters can be  
reaffirmed with everyday observations; smaller sys-  
tems are in most cases mounted on the roof of res-  
idential buildings, medium systems are typically  
found on farming houses or industrial buildings,  
and large systems are mounted on a rack on the  
ground.

**Tilt:** Tilt in the dataset mainly occurs in a range  
up to  $50^\circ$  and is often reported in steps of  $5^\circ$ ,  
though reporting steps of  $10^\circ$  are also common. No  
discernible trend between tilt and azimuth is ob-

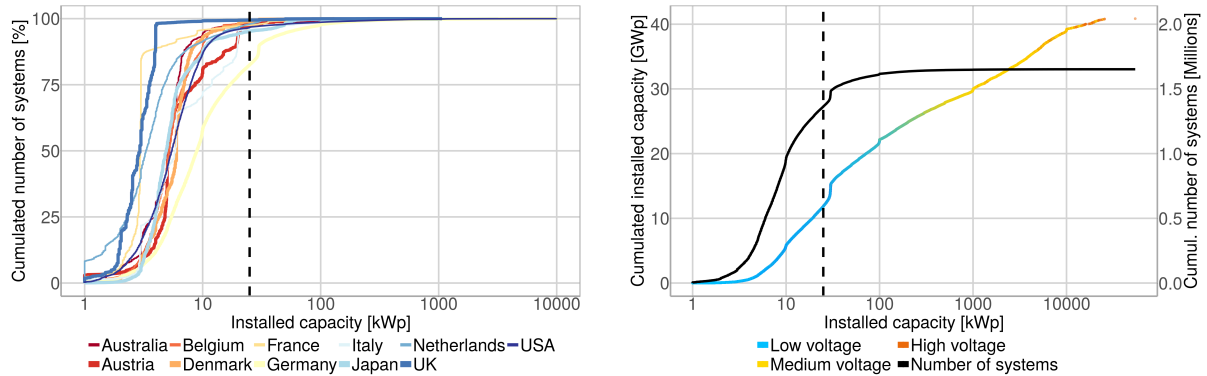


Figure 2: The installed capacity and its relationship to the relative share of systems for different countries (left). The line width and colours vary to simplify the differentiation. The cumulative installed capacity in case of Germany is shown in the right plot represented by the coloured line (colouration indicating the network connection) whereas the black line represents the cumulative number of systems. The dashed line indicates 25 kWp, which is used to sub-categorise the data in [section 3.2](#).

566 served, however the 2D-histogram shows a signifi- 577 est 15°.  
 567 cant density peak around the most frequent combi-  
 568 nation of azimuth and tilt with a radially decreasing 578  
 569 probability, this was also observed by [Saint-Drenan](#) 579  
 560 (2015); [Killinger et al. \(2017c\)](#). A decrease in the 580  
 561 specific annual yield can be seen with an increas- 581  
 562 ing tilt. This might be caused by the finding that 582  
 563 tilt is usually smaller for decreasing latitudes which 583  
 564 occur in combination with an increased specific an- 584  
 565 nual yield.

566 **Azimuth:** There is a significant peak of azimuth 587  
 567 angles pointing south (north in Australia). It is 588  
 568 probable that this distinct peak is due to the tar- 589  
 569 geted approach of solar installers who favour equa- 590  
 570 torial orientated rooftops due to performance ben- 591  
 571 efits. Indeed, azimuth angles tend towards reach- 592  
 572 ing a higher specific annual yield with systems ori- 593  
 573 ented towards 0°. In general, outliers reach a range 594  
 574 of +/- 100° with discrete reporting intervals being 595  
 575 visible in the 1D-histogram and scatter plot, e.g. 596  
 576 databases only requiring azimuth reported to near- 597

**Specific annual yield:** The 1D-histogram of  
 yield shows the most distinct shape of all param-  
 eters with a peak around 1,000 kWh/kWp. Fur-  
 thermore, there is a small peak at 1,650 kWh/kWp  
 which is caused by PV systems in southern re-  
 gions of the USA. It is not possible with the lim-  
 ited latitude study area to infer that the regression  
 of specific yield with latitude will extend towards  
 the equator; climatic regions are expected to be  
 far more influential on the specific yield whereby  
 around the equator there is a significant presence  
 of clouds, and around the tropics there tends to be  
 desert. It is probable that the secondary peak above  
 1,650 kWh/kWp is for systems installed in particu-  
 larly arid regions found in southern USA, however,  
 climatic influence is outside the scope of this paper  
 and is reserved for future study. The specific an-  
 nual yield has the most visually recognisable trends  
 to all other parameters, demonstrating the strong  
 inter-relationship. There is a need for a more de-

tailed multi-variable analysis between specific annual yield and the other parameters. However, due to its extra complexity it falls outside the scope of this paper.

### 3.2. Representativeness of clusters

In the previous section, important characteristics of PV systems and their dependencies were derived. With exception of the annual specific yield and installed capacity in Germany, metadata of all the installed systems within the different regions is not known (e.g. we have access to 4,055 systems from Australia when there are an estimated 1.8 million installed). This restriction questions the representativeness and re-usability of our observations when using the statistics of a subset of systems to infer the statistics of the remainder because some characteristics could be over- or underrated in our datasets. To achieve representation, a solution is to sub-categorise metadata from the PV systems into smaller and more homogeneous clusters. By doing so, an end-user can use the statistics of the clusters and weight them individually by the probability of occurrence. Prior to an approximation of metadata in [section 4](#), it is the objective within this section to define groupings or clusters of PV system that allow the derivation of representative characteristics.

The interdependency analysis reveals two dominating parameters which show multiple dependencies to others: (1) The installed capacity and (2) a geographical influence (c.f. absolute latitudes are used to account for hemispheres). These two findings are in accordance with [Kühnert \(2016\)](#); [Saint-Drenan \(2015\)](#); [Saint-Drenan et al. \(2017\)](#) who analysed azimuth and tilt for different classes

of installed capacity and multiple regions. Such a separation has the benefit to acknowledge the impact from these two dominating parameters on others, while still allowing us to derive meaningful statistics within a chosen cluster. As [Kühnert \(2016\)](#) evaluates, a balance must be found between the number and size of the clusters, in order to guarantee that each class includes a sufficient number of data to be representative.

The left plot in [Figure 2](#) provides further insights into the system size and its relative share for different countries in this paper. Differences can be observed between countries but all show a heightened concentration towards small scale systems with a relative share between 60% (Germany) and 99% (UK) of systems < 10 kWp. Whereas most datasets only cover a selection of systems within a country, the dataset in case of Germany ([bundesnetzagentur.de](#)) covers the vast majority of systems and is detailed on the right plot. Almost one million out of the 1.6 millions German systems are smaller than 10 kWp but in total, with an aggregated capacity of  $\approx 5$  GWp, they only represent  $\approx 12\%$  of the installed capacity. Another 650,000 systems occur in a range between 10 and 100 kWp and cover additional  $\approx 17.5$  GWp. Only 35,000 systems are > 100 kWp yet are responsible for half of the total installed capacity.

On the search of a threshold value to split the datasets into representative clusters, a system size of 25 kWp was chosen by considering: (1) An installed capacity of 25 kWp is an adequate size between typical roof mounted systems and larger plants, particularly as larger capacities are linked to larger physical space requirements. (2) So even



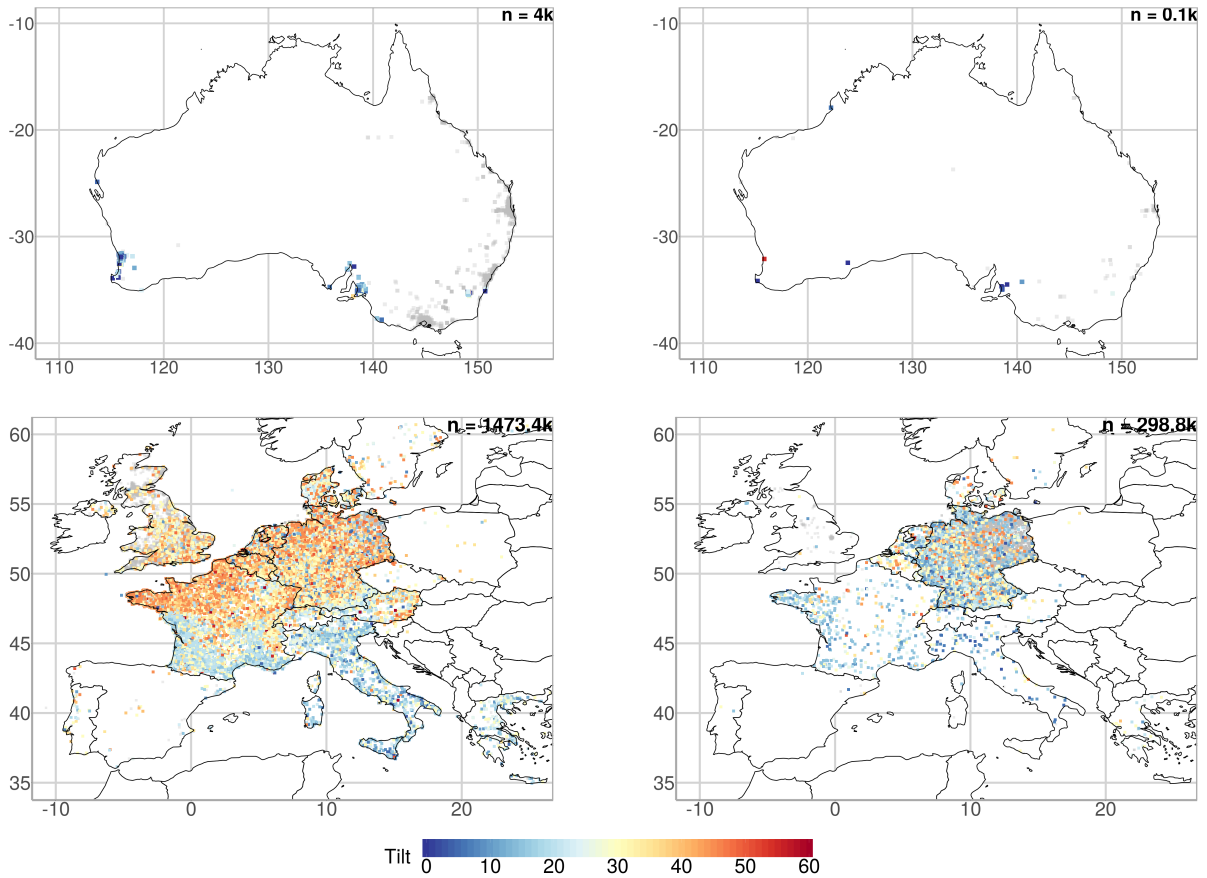


Figure 3: Maps for Australia (top) and Europe (bottom). The left column shows systems  $\leq 25$  kWp and the right column systems  $> 25$  kWp. Systems which do not report tilt are in grey colour.

667 though the number of larger systems is rather low in  
 668 most countries, their strong contribution to the total  
 669 power generation and the knowledge that characteristics  
 670 change with the system size justify a consideration  
 671 in a separate cluster. The threshold value of 25 kWp  
 672 is displayed as a dashed vertical line in Figure 2. If the  
 673 threshold value were higher, only a small number of  
 674 systems would be left in the upper cluster and the  
 675 derivation of representative statistics impeded. (3) Several  
 676 threshold values were trialled in our analysis. A value  
 677 of 25 kWp was finally decided upon as it satisfied the  
 678 aforementioned criteria and passed visual inspection by  
 679 producing dis-

680 tinct distribution curves.

681 Both the impact of system size and the geographical  
 682 influence can be studied in respect to the tilt angle  
 683 of systems in Figure 3 and Figure 4. All regions show  
 684 a tendency towards smaller tilt angles for system sizes  
 685  $> 25$  kWp. Especially for systems  $\leq 25$  kWp in  
 686 Europe, the dependency between latitude and tilt can  
 687 be observed by an increasing tilt angle from Italy to  
 688 Denmark. However, it should be noted that the spatial  
 689 influence is not only limited to a pure geographical  
 690 relationship; the spatial impact depends on regulations  
 691 and incentives which often occur on a national level.  
 692 The policy situation



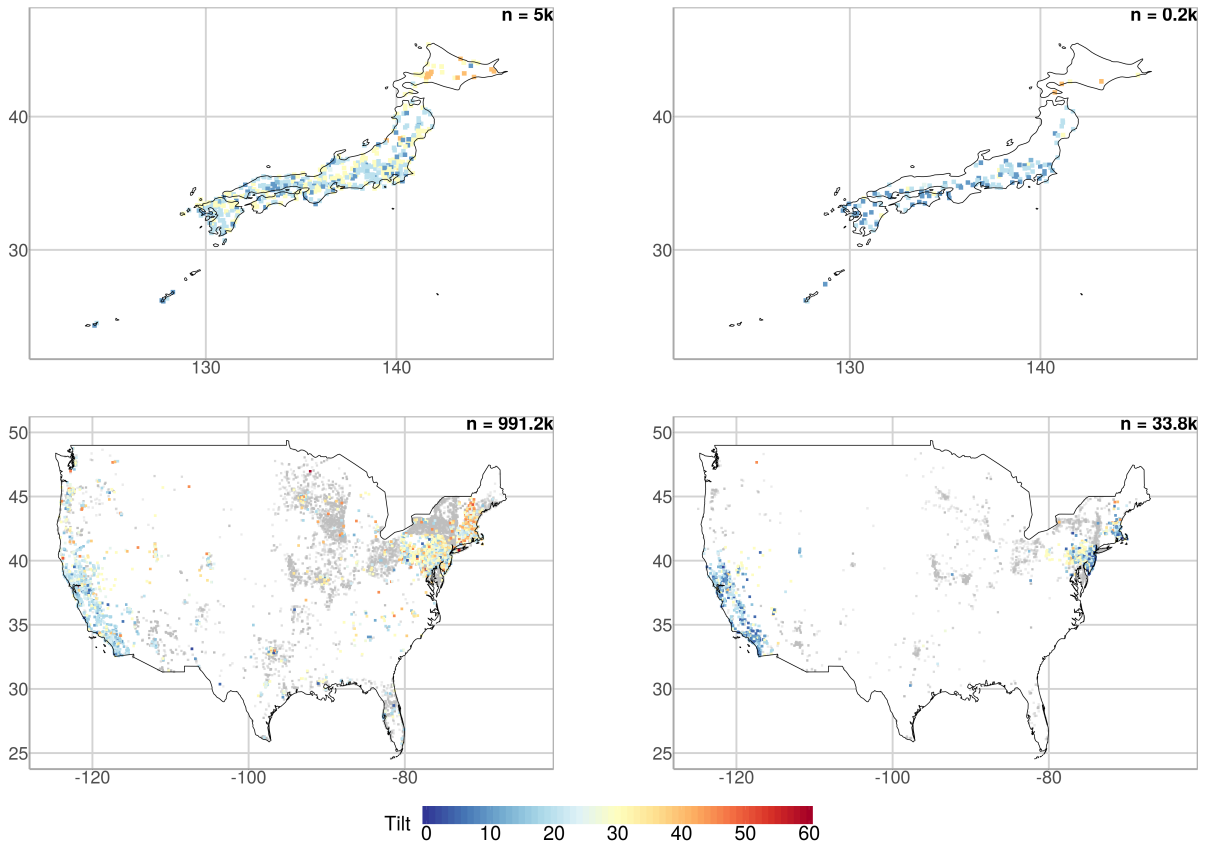


Figure 4: Maps for Japan (top) and the USA (bottom). The left column shows systems  $\leq 25$  kWp and the right column systems  $> 25$  kWp. Systems which do not report tilt are in grey colour.

693 in France leads to a high number of 3 kWp systems 706  
 694 (see [Leloux et al. \(2012b\)](#) in [section 1.1](#)). In Ger- 707  
 695 many, there are changing regulations and feed-in 708  
 696 tariffs for systems  $> 30$  kWp resulting in an in- 709  
 697 crease in the black line of the right plot in [Figure 2](#). 710  
 698 Furthermore, the UK had a higher feed-in tariff for 711  
 699 systems  $\leq 4$  kWp up until January 2016 and has 712  
 700 since moved to  $\leq 10$  kWp ([ofgem, 2018](#)). These are 713  
 701 such examples of significant policy-specific regional 714  
 702 influence that can impact upon the characteristics 715  
 703 of PV systems.

704 There are many opportunities as to how we sub- 718  
 705 categorise the data into clusters. Many of which

could be explored in order to derive meaningful 706  
 information depending on the approach. Options 707  
 include separating by climatic region or grouping 708  
 by policy similarities. However with respect to the 709  
 aforementioned aspects, a clustering at a country 710  
 level seems advisable for the following reasons: (1) 711  
 National regulations and incentives have a visually 712  
 evident impact on the occurrence of different sys- 713  
 tem sizes which may itself influence other metadata. 714  
 (2) A geographical influence was observed on mul- 715  
 tiple parameters. Countries limit this influence by 716  
 their size. The only exception of this strategy is the 717  
 USA. The enormous geographic area of this country 718

719 results in a inhomogeneous pattern of the specific  
720 annual yield. This is a direct consequence of the  
721 heterogeneity of the solar resource within a country.  
722 The USA was thus split at  $37.5^\circ$  N into a northern  
723 and a southern component. The same approach  
724 could be applied to Australia, however, the sample  
725 size of available data is too low. Further subdivi-  
726 sions e.g. by the latitude for systems  $\leq 25$  kWp in  
727 France (see tilt in [Figure 4](#)), could be considered  
728 but exceed the scope of this paper and is a focus  
729 of future work. (3) There is a certain convenience  
730 to clustering by countries. Many of the studies pre-  
731 vious focused mainly on a single country, this is  
732 indicative of a researchers interests and data avail-  
733 ability. We feel that, whilst there are many options  
734 of clustering that can be explored, a preliminary  
735 study at a country level is of most interest.

736 The region ``Rest of Europe'' is not be consid-  
737 ered further due to its inhomogeneous portfolio of  
738 systems across different countries in Europe. The  
739 clusters, defined by their belonging to a region and  
740 system size, are used in the next section to derive  
741 representative distributions for the metadata.

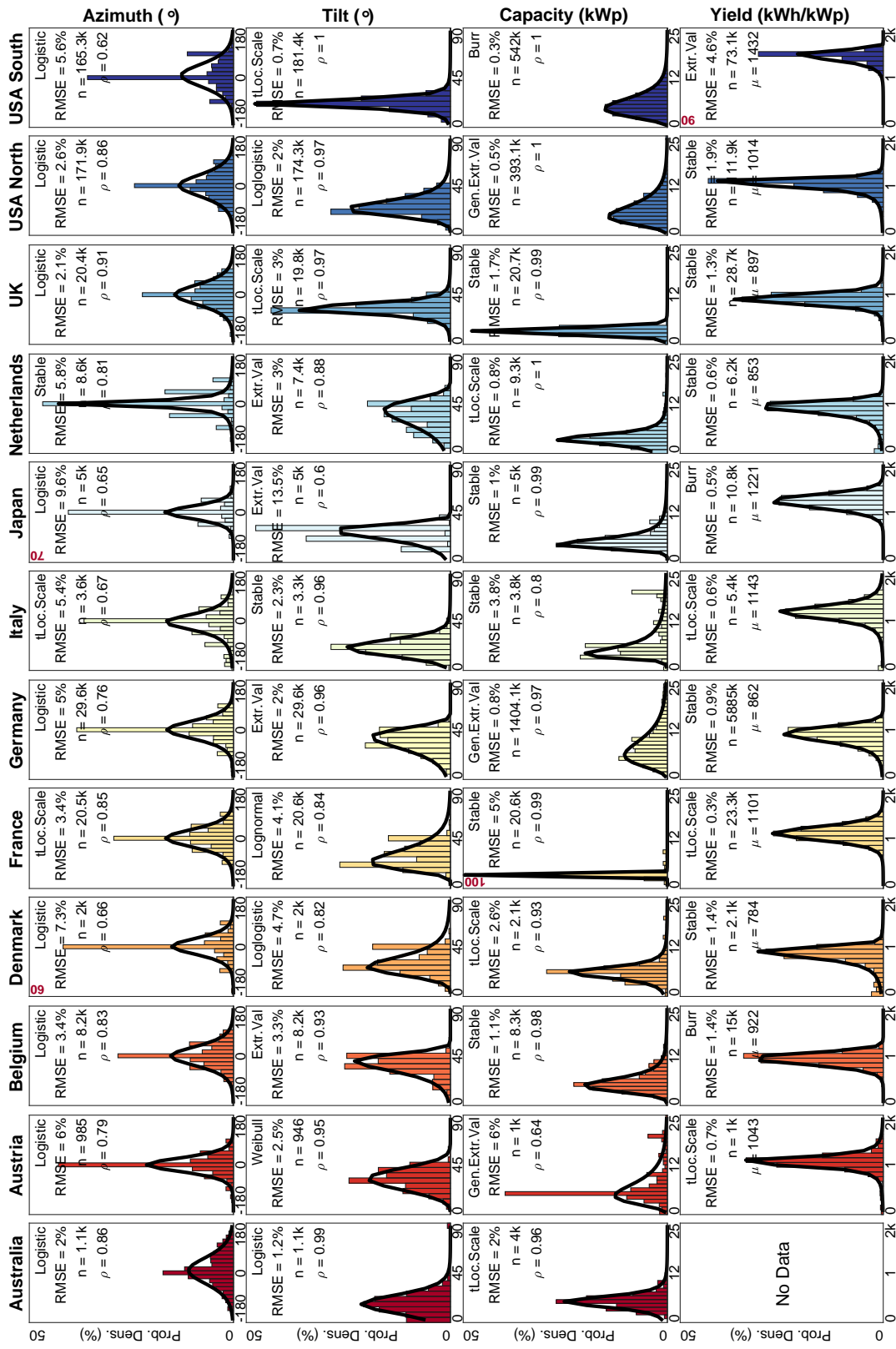


Figure 5: Histograms of real data (bar) with approximated probability distributions (line) for the different clusters (columns) and parameters (rows), where capacity is the installed capacity and yield is the specific annual yield. All systems reported within this figure have a capacity  $\leq 25$  kWp, see appendix for the same plot for  $> 25$  kWp. Within each of the axes is reported the name of the best fitting distribution type (see section 4.1 for detail), the root mean squared error (RMSE) between the scatter of real data in the histogram against the fitted probability density distribution, the number of data points considered for that cluster ( $n$ ), and the Pearson correlation coefficient ( $\rho$ ) of the linear regression. The mean value  $\mu$  is shown in place of  $\rho$  for Yield. All y-axes are scaled between 0% and 50% probability except where a bold red value is assigned to the individual axis.

#### 4. Approximation of parameters in clusters

The intentions of parametrisation are twofold. Firstly, we want to discover whether or not the parameters (tilt, azimuth, capacity and yield) can be represented with simple parametric distributions. Secondly, we want to explore the relative differences between clusters through comparison between probability distributions. We concede that simple distribution fitting has weaknesses such as not appropriately capturing a more complex relationship offered by non-parametric fitting, however, reproducibility of the statistics is encumbered with added complexity. For our first presentation of the substantial volume of PV system data collected, we focus on simple distribution fitting as interesting comparisons and individual cluster insights can be drawn, and we are able to comment on the ability for these complex parameters to be represented as such.

##### 4.1. Methodology of fitting the distributions

In order to enable the utilisation of the aggregated statistics of each cluster (defined in [section 3.2](#)) and for each parameter (defined in [section 3.1](#)), individual distributions are fitted to the real-world probability density histograms. The results are presented in [Figure 5](#) ( $\leq 25$  kWp) and [Figure A.10](#) ( $> 25$  kWp). The total number of available data varies between clusters and parameters; there is no further processing beyond the criteria described in [section 2](#); all possible data available is used. Differences in data within a cluster are due to some PV sites not reporting one or more parameters. There are up to 6 years of reported

specific annual yield (2012-2017). The normalised value within each year is taken as an individual sample and so there are up to  $6n$  more samples for this parameter.

For each cluster and for each parameter, many different distribution types were fitted to the probability density. Distributions were fit using the inbuilt FITDIST function of the software Matlab® ([Matlab, 2018](#)). There are 23 parametric distribution types available, of which all are fitted to the data. Where distribution types require only positive values (for parameters with negative bins) or values between 0 and 1, the data is scaled to satisfy the distribution requirements and allowed to re-scale so that as many distributions could be tested; note that no distribution requiring this treatment was found to be best fitting, and so no further discussion is made regarding this normalising process. Probability density functions are then scaled to only exist between the x-axis limits as indicated in the figure, for example, the tilt distributions are only relevant between  $0^\circ$  and  $90^\circ$ . This means that the sum of all probabilities between the prescribed x-axis range must be equal to 1. This is important as some distributions facilitate values way outside of the bin limits resulting in the sum of probabilities between the bins of interest  $\neq 1$ , and so would not fit the histogram. The disclaimer is, therefore, that these distributions *must* be scaled before use and not be extrapolated beyond the specified bin ranges else risk persisting an under/overestimation about the scaling factor, defined as

$$s = \frac{1}{\sum_a^b p_{a:b}}, \quad (1)$$

807 where  $s$  is the scaling factor,  $p$  is the probability  
 808 at each bin between the lower and upper bin limit,  
 809  $a$  and  $b$ , respectively. The resultant fitted distribu-  
 810 tion is then plotted against the real probability den-  
 811 sity and tested for linear fit; the root mean squared  
 812 error (RMSE, percentage) and Pearson correlation  
 813 coefficient ( $\rho$ , dimensionless) are derived. A per-  
 814 fectly fitted distribution would result in  $y = x$  with  
 815  $\rho = 1$  and an RMSE= 0%. The distribution type  
 816 with the lowest RMSE was selected for the plot.  
 817 Should there be more than one distribution type  
 818 that has the same RMSE, then the type with low-  
 819 est  $\rho$  is selected. Should there still be more than  
 820 one distribution type after this, one of the remain-  
 821 ing types is selected at random.

822 The exact parameterisation for each distribution 841  
 823 presented in Figure 5 and Figure A.10 are detailed 842  
 824 in Table A.4. Each distribution has up to 4 co- 843  
 825 efficients and are employed using different equa- 844  
 826 tions, not all 23 parametric distributions are de- 845  
 827 tailed, only those that featured within the study. 846  
 828 Whilst Table A.4 details the parameterisation of 847  
 829 the coefficients, it is Table A.3 that explains how 848  
 830 to use those values to form the distribution. Fur- 849  
 831 thermore, the mean or median values of the whole  
 832 dataset, exclusive of the 25 kWp separation, are 850  
 833 presented in Table 2.

#### 834 4.2. Discussion of the distributions

835 The following discussion about clusters and dis- 854  
 836 tributions mainly refers to Figure 5 with systems 855  
 837  $\leq 25$  kWp unless explicitly noted otherwise. The 856  
 838 reason for this is that the vast majority of systems 857  
 839 are within the  $\leq 25$  kWp category, and so are of 858  
 840 most interest. However, important differences to 859

Table 2: Mean or median value extracted from entire data set (without separation by capacity size) for each of the parameters of tilt angle, azimuth angle, system capacity and specific annual yield.

Country	Tilt ( ° ) mean	Azi. ( ° ) mean	Cap. (kWp) median	Yield (kWh/kWp) mean
Australia	16.1	8.58	5.00	-
Austria	31.1	-0.34	5.15	1,040
Belgium	35.6	-1.69	5.20	921.5
Denmark	30.0	0.48	6.00	786.0
France	28.7	-0.28	2.96	1,101
Germany	31.6	-2.46	8.96	870.2
Italy	19.8	-15.9	5.88	1,142
Japan	23.8	-1.20	4.92	1,222
Netherlands	32.5	0.77	3.30	855.2
UK	31.8	-1.07	2.94	896.7
USA North	25.2	0.42	5.81	1,005
USA South	19.9	9.33	5.26	1,426

851 system sizes  $> 25$  kWp are mentioned and can be  
 852 observed in Figure A.10.

853 It is important to note that only rough dependen-  
 854 cies between parameters, regions and system sized  
 855 can be considered with this clustering approach.  
 856 The more intricate and established interdependen-  
 857 cies have not been explored within this paper as it  
 858 is beyond the scope of the initial objective. The  
 859 authors reserve this for future work.

##### 851 4.2.1. Azimuth angle

852 The most noticeable feature of the azimuth ob-  
 853 servations is the significant probability of an equa-  
 854 torial facing PV system. This is unsurprising as  
 855 it offers the best annual specific yield by receiving  
 856 maximum system efficiency at peak solar position.  
 857 The topic of extreme probability of an equatorial  
 858 orientated system was discussed in section 3.1; the  
 859 prevalence of  $0^\circ$  is true of all sites for both  $< 25$  and  
 $> 25$  kWp. The Japan and Netherlands clusters

860 have exaggerated angles of  $-45^\circ$  or  $+45^\circ$ , assumed  
861 to be a result of overly simplified reporting.

862 The distributions could not capture the probabil-  
863 ity of  $0^\circ$  with exception of the Netherlands where  
864 a Stable distribution fitted best. Even with large  
865 sample sizes for the USA North and south clusters,  
866 a distribution could not be fitted that satisfied the  
867 observed probability for an azimuth angle of  $0^\circ$ .  
868 Perhaps a more complex or bespoke distribution  
869 type is needed to suitably express the probability  
870 distribution of azimuth angle with reproducible ac-  
871 curacy. This large proportionality of  $0^\circ$  was also  
872 observed by [Saint-Drenan et al. \(2018\)](#), who fitted  
873 a normal distribution in similar magnitudes to the  
874 logistical distribution fitted in this article. That  
875 said, there is an argument that the significant  $0^\circ$  az-  
876 imuth feature is exaggerated when considering the  
877 UK cluster. The majority of the data within the UK  
878 cluster is from Sheffield Solar. Their users report  
879 the system metadata, however, there is a feedback  
880 to the user reporting system performance analysis  
881 on a monthly basis, inclusive of a nearest-neighbour  
882 performance analysis of a system of similar meta-  
883 data. Users are encouraged to verify their reported  
884 metadata and is often double checked with satellite  
885 imagery; the result is much more accurate report-  
886 ing of metadata for the UK cluster leading to the  
887 smoothness of distribution fit. With improved PV  
888 system metadata reporting, we see a wider spread  
889 of azimuth about  $0^\circ$ .

#### 890 4.2.2. Tilt angle

891 The tilt angle across all clusters is rather unique  
892 per cluster with 7 different distribution types be-  
893 ing found as the best fitting among 10 clusters. We

894 previously discussed the gentle increase of tilt an-  
895 gles with latitude. Solar installers can mount the PV  
896 panels with a steeper tilt angle to that of the roof at  
897 higher latitudes through arrangement of the mount-  
898 ing brackets; this is not expected to be overly com-  
899 mon practise. The predominant factor for smaller  
900 roof integrated systems is expected to be the phys-  
901 ical roof angle, which is influenced by local archi-  
902 tectural styles. We suspect this is the case, partic-  
903 ularly when considering France in [Figure 3](#) where  
904 there exists a distinct change in the tilt for the  $\leq 25$   
905 kWp systems at roughly  $47.5^\circ$  latitude. Note that  
906 France and Denmark have similar distributions de-  
907 spite France having a significant number of systems  
908 south of that  $47.5^\circ$  roof tilt feature. Furthermore,  
909 Belgium and the Netherlands share similar climate  
910 and latitude yet feature distinctive distributions.

911 Interestingly, the Australian cluster consisting of  
912 the second lowest number of observations has the  
913 second most accurate fit after USA South. This  
914 is in part due to the smoothness of the distribu-  
915 tions and accuracy of method in which the tilt is  
916 obtained (see [section 2](#)). The USA cluster has excel-  
917 lently fitted distributions suggesting accurate mea-  
918 surement, particularly for the USA South cluster  
919 where the tilt distribution is fitted with  $\rho = 1$  and  
920 RMSE=0.7%. The Japan cluster evidently suffers  
921 from reporting to the nearest  $10^\circ$ , and so we suggest  
922 to avoid using a best-guess approach to collecting  
923 metadata as it leads to biased distributions. The  
924 tendency for larger system sizes having smaller tilt  
925 angles, introduced in [section 3.1](#), can be confirmed  
926 when comparing [Figure 5](#) and [Figure A.10](#). The  
927 only exception is Denmark, which reports only a  
928 small number of systems  $> 25$  kWp.

929 Within the distributions, the smallest mean tilt 963  
930 angles were reported in Australia (16.07°), Italy 964  
931 (19.81°) and USA South (19.89°). The largest 965  
932 mean tilt values were reported in Belgium (35.58°) 966  
933 and closely followed by the UK, Germany and Aus- 967  
934 tria (31°). 968

### 935 4.2.3. *Installed capacity*

936 The most obvious observation from the installed 971  
937 capacity is the extreme peak within the French clus- 972  
938 ter. Of all 20.6k systems ( $\leq 25$  kWp and  $> 25$  973  
939 kWp), 73.74% of them report an installed capacity 974  
940 of 3 kWp when rounded to nearest integer, though 975  
941 note that the French dataset reported to a high dec- 976  
942 imal precision. The best fitting distribution cannot 977  
943 appropriately represent this extreme despite a very 978  
944 high  $\rho = 0.99$ ; the RMSE value of 5% is indicative 979  
945 of the Stable distribution assigning 100% probab- 980  
946 ity to 3 kWp. This distribution is, therefore, very 981  
947 limited even if it does most accurately capture the 982  
948 data for France. As discussed when defining the 983  
949 clusters, this peak in capacity is a direct response 984  
950 to regulations within that country. This is further 985  
951 observed in the UK database, with the vast major- 986  
952 ity of systems being  $\leq 5$  kWp due to the nature of 987  
953 the feed-in tariff rate. The north and south USA 988  
954 clusters demonstrate the power of a larger and con- 989  
955 sistent sample size reporting RMSE 0.5% and 0.3%, 990  
956 respectively, with both reporting  $\rho = 1$ . Interest- 991  
957 ingly, the distribution type between USA clusters 992  
958 are distinct from each other, with a slightly in- 993  
959 creased probability of smaller systems in the south. 994  
960 This is expected to be a result of more rooftop solar 995  
961 in the sunnier States, though this is speculation. 996

962 The shape of the distribution functions for sys-

tem sizes  $> 25$  kWp (Figure A.10) differ to systems  
 $\leq 25$  kWp and show an heightened concentration of  
systems  $< 50$  kWp. Australia is an exception and  
reports many systems with an installed capacity of  
 $\approx 100$  kWp.

The mean values of capacity are too heavily in-  
fluenced by the presence of large systems (cf. 2b),  
and so the median value is reported to reduce bias.  
From the distributions, the country with smallest  
capacity median is the UK (2.94 kWp) and the  
largest is Germany (8.96 kWp). The fact that  
the German data reveals such a high median is re-  
flective of the thorough nature of data collection  
whereby nearly all systems are reported; we have  
very few large systems reported from the UK as  
the database is primarily used for rooftop solar and  
so this statistic is not overly representative.

### 980 4.2.4. *Specific annual yield*

981 The most noticeable detail of the specific annual  
982 yield distribution fits is the smoothness of the his-  
983 tograms of raw data. This is perceived to be of  
984 two reasons. Firstly, the sample size is typically  
985 much larger ( $n = 5.885$ m for the German clus-  
986 ter). Secondly, the data is digitally recorded and  
987 not reliant on human reporting. The mean  $\mu$  is  
988 presented in place of the correlation coefficient so  
989 as not to over busy the plot, though for complete-  
990 ness, all sites reported  $\rho \geq 0.98$  except USA South  
991 with  $\rho = 0.93$ . Recall that the specific annual yield  
992 is normalised for inter-annual differences and so we  
993 can directly compare clusters. Each cluster exhibits  
994 reasonably unique subtle traits, it is expected that  
995 the larger the share of equatorial orientated systems  
996 with more optimal tilts, the larger the specific yield,



1097 however, it is also a function of local meteorology 1032  
1098 and climate local to the systems and not just lat- 1033  
1099 itude, orientation and tilt. More questions can be  
1100 derived from these distributions than are really an- 1034  
1101 swered. For example, consider the German cluster. 1035  
1102 There is a substantial tail towards lower specific 1036  
1103 annual yields that is not observed in other clusters. 1037  
1104 Germany is known to be a mature market when it 1038  
1105 comes to PV, and so is this tail indicative of age- 1039  
1106 ing systems, or perhaps all clusters would present 1040  
1107 this pattern given as large a sample size? The USA 1041  
1108 South cluster has an unexplainable peak at exactly 1042  
1109 1650 kWp/kWh. The only other country within our 1043  
1110 study that is comparable to southern USA in terms 1044  
1111 of climate and land availability is Australia, alas, 1045  
1112 we have no data for this cluster to gain insight to 1046  
1113 this peak. We would expect to observe much higher 1047  
1114 yields in Australia akin to southern USA. 1048

1115 [Leloux et al. \(2012a\)](#) found that of 158 sys- 1049  
1116 tems in Belgium, the mean specific annual yield was 1050  
1117 836 kWh/kWp. Our analysis of 15k specific an- 1051  
1118 nual yields finds the mean to be 921.5 kWh/kWp. 1052  
1119 [Leloux et al. \(2012b\)](#) applied the same approach 1053  
1120 for 1,635 systems in France resulting in a mean of 1054  
1121 1,163 kWh/kWp. Our analysis of 23.3k systems 1055  
1122 places the mean value at 1,101 kWh/kWp. When 1056  
1123 comparing [Figure 5](#) and [Figure A.10](#), the expected 1057  
1124 trend towards higher specific annual yield values for 1058  
1125 larger systems (see [section 3.1](#)) can be confirmed for 1059  
1126 Denmark, France, Germany, Japan, Netherlands, 1060  
1127 UK and USA North. The other four countries in- 1061  
1128 stead show a decrease in the mean specific annual 1062  
1129 yield for systems  $> 25$  kWp. 1063

1130 From the distributions, we find the smallest 1064  
1131 mean specific annual yield is in Denmark (786.0 1065

kWh/kWp) and largest in USA south (1,426 kWh/kWp).

#### 4.3. Using the distributions

As we have observed that each cluster and parameter can be generally represented by a probability distribution, our discussion can shift towards the usage of these statistics in regional PV power modelling approaches. Generally, the cited publications in [section 1.1](#) (category 1) not only emphasize the practical relevance of statistical distributions in regional PV power modelling approaches, but also sketch the procedure of how these statistics can be used and therefore serve as good examples. One of these publication is [Saint-Drenan et al. \(2018\)](#), which provides detailed information about how fitted distributions can be applied in a regional power simulation and therefore serves as a good example.

We foresee that the fitted distributions from the previous section can be used to randomly sample the desired metadata of a portfolio of systems in a specific cluster. As pointed out in [section 3.2](#), this cluster can then be weighted individually by the probability of occurrence (as can be derived e.g. from [Figure 2](#)). To reproduce the distributions, one must extract the appropriate distribution variables from [Table A.4](#), apply them in the expression from [Table A.3](#), and scale the result according to [Eq. \(1\)](#). We state that the data we have is not representative enough to derive global distributions as there are too many features that can influence the PV system characteristics from regions we do not have access to. The derived distribution functions should only be used for their specific clusters, or for clusters with particularly similar climates and policies.



1066 The usage of the fitted distributions is sketched 1101  
1067 in a practical example, assuming that the PV power 1102  
1068 generation in Germany is of interest. 1103

1069 1) In Germany, the installed capacity, geographic 1104  
1070 location and specific annual yield of all PV systems 1105  
1071 is known (see [section 2](#)) and should not been sam- 1106  
1072 pled if one wishes realistic outputs, though may be 1107  
1073 sampled for theoretical purposes. 1108

1074 2) For each PV system, tilt and azimuth is as- 1109  
1075 signed by sampling the fitted distribution from the 1110  
1076 relevant cluster. E.g. a system with 10 kWp will 1111  
1077 use the distributions from the cluster for systems  $\leq$  1112  
1078 25 kWp. In this example we can extract the data 1113  
1079 from [Table A.4](#) such that the German cluster has a 1114  
1080 Logistic distribution for azimuth with location co- 1115  
1081 efficient of -0.1366 and scale parameter of 20.6455. 1116  
1082 The distribution can be recreated using the logis- 1117  
1083 tic function defined in [Table A.3](#). Please note that 1118  
1084 there is a high risk that the sampled characteristics 1119  
1085 won't accurately predict the metadata for a specific 1120  
1086 PV system. It is the objective to use these distribu- 1121  
1087 tions to simulate larger PV portfolios and we expect 1122  
1088 to derive representative characteristics for that ap- 1123  
1089 plication. 1124

1090 3) The direct usage of yield is more complicated 1125  
1091 for two reasons. Firstly, in contrary to azimuth, tilt 1126  
1092 and installed capacity, it is not an input param- 1127  
1093 eter in the simulation chain but instead indicates 1128  
1094 the power generation, which is the typical output 1129  
1095 of a simulation. Secondly per definition, the spe- 1130  
1096 cific annual yield sums the PV power generation 1131  
1097 over a whole year. In many application however, 1132  
1098 simulations may cover a different time span. How 1133  
1099 can yield be used in simulating the regional PV 1134  
1100 power generation then? When making the simplify- 1135

ing assumption that the meteorological conditions  
are relatively similar within a cluster, the observed  
specific annual yield can be interpreted as a mea-  
sure that expresses relative performance differences  
between PV systems. For instance, a PV system  
with a yield of 600 kWh/kWp can be said to be  
less efficient than a PV system with a yield of 800  
kWh/kWp. For usage in a simulation, a conver-  
sion from yield into an performance factor is there-  
fore necessary. A potential method of conversion is  
to take the range of yields (0 to 2000 kWh/kWp)  
and align it to typical ranges of the performance  
ratio, though taking care to centre the mean yield  
against the mean performance ratio (said to have  
a wide distribution centred about 0.74 as derived  
from 5,000 systems in the Netherlands ([Tsafarakis  
et al., 2017](#); [Reich et al., 2012](#))). A direct linear  
conversion could then be applied. For example, a  
system in Germany with yield 870.2 kWh/kWp (the  
mean for this cluster) could be assigned a perfor-  
mance ratio of 0.74. This performance ratio can  
then be applied as a correction factor to either the  
output power or the system capacity, and therefore  
facilitating representative differences between sys-  
tems.

4) The individual PV power generation for each  
system can be simulated by considering the sampled  
system characteristics as well as the known installed  
capacity, efficiency of the specific system and its ge-  
ographic location. Within such a simulation, other  
inputs will be needed such as the local irradiance  
or ambient temperature. Please note, if consider-  
ing such a large number of systems is too compu-  
tational intense, instead a smaller number could be  
randomly chosen and then used within an upscaling

1136 approach.

1137 5) Finally, the total power in Germany can then  
1138 be derived by aggregating the simulated power from  
1139 all systems.

## 1140 5. Shading on roofs

### 1141 5.1. Methodology of the shading analysis

1142 An objective in this paper is to derive gener-  
1143 alised findings of how to consider the impact of  
1144 shading. We aim to achieve that in a more so-  
1145 phisticated manner than the overly simplified man-  
1146 ner presented in category 3 from [section 1.1](#). It is,  
1147 however, not the aim to study differences of shad-  
1148 ing in rural or urban areas all over the world in  
1149 this paper. This shading analysis is performed on  
1150  $\approx 48,000$  buildings in the city of Uppsala, Swe-  
1151 den (N59.9°,E17.6°). Uppsala provides a variety  
1152 of different buildings (44% residential, 2.2% indus-  
1153 tries, 5.7% commercial and services, 49% other) and  
1154 therefore allows studying differences in the impact  
1155 of shading. The average height of the buildings  
1156 studied here are  $6.4 \pm 4.1$  m, which may be com-  
1157 pared to a study on 12 US cities of various size  
1158 (29,498 to 1,066,354 buildings) with average build-  
1159 ing height ranging from 4.1 to 9.7 m ([Schlöpfer](#)  
1160 [et al., 2015](#)). The analysis is not limited to any  
1161 country specific influences because all combination  
1162 of solar angles are considered; climate does not in-  
1163 fluence this shading study. The above reasons em-  
1164 phasise the general representativeness of Uppsala  
1165 and were reason for its selection.

1166 The shading analysis is realised by using the  
1167 method in [Lingfors et al. \(2017\)](#), which was cross-  
1168 validated in [Lingfors et al. \(2018\)](#). Inputs to

1169 the model are low-resolution LiDAR data (0.5-1  
1170 pts/m<sup>2</sup>) and building footprints, provided by the  
1171 [Swedish Land Survey \(2015, 2016\)](#). The model does  
1172 the following:

- 1173 1. Finds a simple roof shape from a template of  
1174 roof types using linear regression on LiDAR  
1175 data;
  - 1176 (a) within the footprint of the examined  
1177 building and,
  - 1178 (b) within building footprints of similar shape  
1179 in its proximity,
- 1180 2. Each roof now consists of 1-4 facets depending  
1181 on the roof type (1 for flat or shed, 2 for gabled  
1182 and 4 for hipped or pyramidal). If LiDAR data  
1183 are insufficient, the roof type cannot be deter-  
1184 mined and the building is excluded from fur-  
1185 ther analysis. The number of roof facets are  
1186  $>90,000$  (cf. number of buildings). However,  
1187 around 1,000 facets which are  $> 20$  m above  
1188 ground are excluded, as there is an increased  
1189 risk of these roofs being misrepresented due to  
1190 noise in the LiDAR data.
- 1191 3. After some filtering of the LiDAR data sur-  
1192 rounding the building, a triangulated irregu-  
1193 lar network (TIN) is produced representing ob-  
1194 jects, predominantly trees and other buildings  
1195 that may shade the roof.
- 1196 4. Using the TIN as input, a viewshed (a map  
1197 showing what parts of the sky are visible from  
1198 the perspective of a point on the roof) at every  
1199  $0.5 \text{ m} \times 0.5 \text{ m}$  section of the roof is calculated  
1200 to determine whether there are objects block-  
1201 ing the direct solar path. The resolution of the  
1202 viewshed is limited to solar elevation angles,

$\alpha_s$ , of 2.5, 7.5, ..., 87.5°, and solar azimuth angles,  $\gamma_s$ , of -180, -170, ..., 170° where 0° is due south. Since the sky sectors are angular-equal, they are not equal in size (see dotted lines in Figure 6). Hence, the contribution of diffuse irradiance from each sky sector depends on its size and the angle-of-incidence of the irradiance from the sky sector onto the plane.

5. For each combination of  $\alpha_s$  and  $\gamma_s$  the mean shading of the whole roof facet is calculated, noting that roofs can be partially shaded. This is illustrated in the *viewsheds* of Figure 6. For a discrete point of the roof, each element of the sky would be either shaded or not shaded corresponding to black or white (0 or 1), respectively, in the left panel of Figure 6. However, if the mean of all points of the roof are considered, the viewshed would be blurred (grey) as illustrated in the right panel of Figure 6. The mean viewshed displayed on the right of Figure 6 is only for illustrative purposes and can be considered to gain understanding as to how the beam, diffuse and reflected irradiance subcomponents are affected by shading for the general region of all facets within this study. Results of the shading analysis are presented in section 5.2.

### 5.2. Deriving a simplified shading model

The main results from the shading analysis on  $\approx 48,000$  buildings in Uppsala, Sweden, are presented in Figure 7. The colour of each bin in the left panel of Figure 7 represents the average ratio of all roof facets being visible to a sky sector, defined

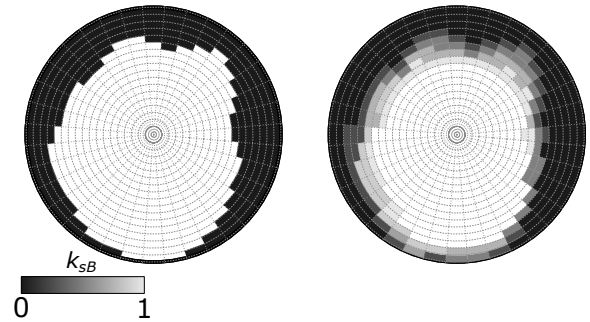


Figure 6: Polar diagrams of viewsheds, where the displayed angles represent the azimuth angle, and the radius the elevation angle. Left) illustrates the viewshed of a single point on the roof. Right) the mean viewshed of all the points on the roof is illustrated. The dotted lines mark the sky sectors for which the viewshed analysis was conducted from their respective centre points. Note that the right plot is purely illustrative and not used within any of the modelling stages.

by the corresponding solar elevation angle and solar azimuth intervals. This visibility is here referred to as the *beam shade index*,  $k_{sB} \in [0, 1]$  (see Figure 6), where 0 means the roof facet is fully shaded. The dashed lines illustrate the solar path for Uppsala, Sweden. However, the corresponding solar path could be over-layered for an arbitrary site to visualise the implication of shading for that site. From the left panel of Figure 7 it is also clear that the solar azimuth has very little importance, which is logical as shading should be as likely from any direction when a large portfolio of buildings is considered.

In the right panel of Figure 7, the average ( $\times$ -marked) and percentiles (dashed) of  $k_{sB}$  for all roofs are presented as a function of only the solar elevation angle, hence it differs from the left panel by not considering the azimuth angle. The thin red lines

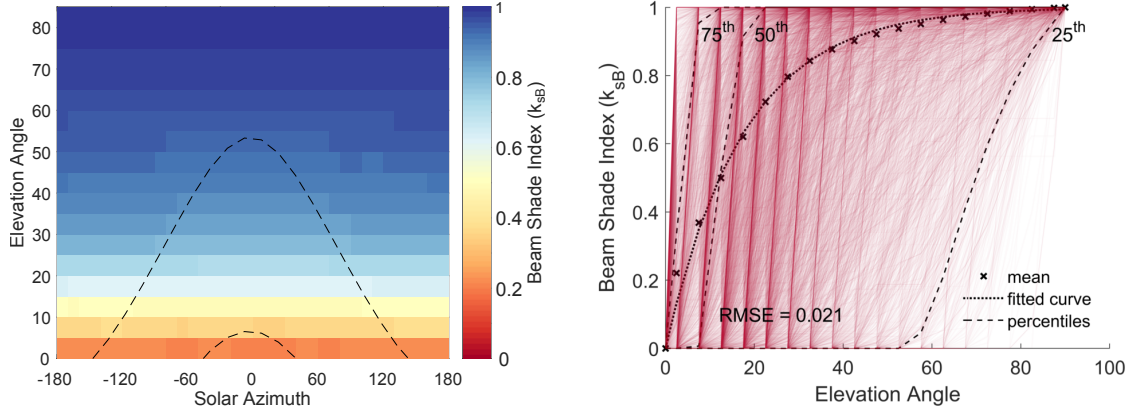


Figure 7: To the left, the mean shade index of all studied roof facets are presented at bins of a viewshed defined by the solar elevation angle and solar azimuth. To the right, the shade index is plotted against the solar elevation angle. Every shade index profile from each studied facet are indicated with a red solid line. The mean shade index of all facets is indicated with crosses, with fitted curve represented by a dotted line as presented in Eq. (2). The RMSE between the means and fitted curve is 0.021. The dashed lines represent the different percentiles.

1254 represent 10,000 individual roofs. Many of these 1269  
 1255 lines jumps from 0 to 1 when going from one ele- 1270  
 1256 vation angle to the next, meaning that from being 1271  
 1257 entirely obscured, the roof becomes entirely visible 1272  
 1258 when the elevation angle is increased by  $5^\circ$ . The 1273  
 1259 mean beam shade index,  $\bar{k}_{sB}$ , of all the roof facets 1274  
 1260 can be represented by a fitted curve (dotted), de- 1275  
 1261 rived as a function of the solar elevation angle,  $\alpha_s$ : 1276

$$\bar{k}_{sB} = 1 - e^{-\alpha_s/17.5}. \quad (2)$$

1262 The average beam irradiance that will fall on a 1279  
 1263 tilted roof, if shading is considered, could then be 1280  
 1264 calculated as: 1281

$$B_T = \bar{k}_{sB} \frac{\cos \theta}{\cos \theta_Z} B_H, \quad (3)$$

1265 where  $B_H$  is the unshaded beam irradiance on the 1285  
 1266 horizontal plane,  $\theta$  is the angle between the incident 1286  
 1267 irradiance and the normal of the roof plane and  $\theta_Z$  1287  
 1268 is the solar zenith angle. 1288

Assuming similar shading properties, i.e., vegeta-  
 tion and urban density, as in Uppsala, this function  
 may be used in any area to determine the impact of  
 shading on roofs as a function of the solar elevation  
 angle. It gives a better estimation than solely as-  
 suming a cut-off solar elevation angle for the beam  
 irradiance, which is a method commonly used for  
 PV potential studies.

On the other hand, the red lines of figure in the  
 right panel, representing individual buildings, re-  
 veals the variation in shading among the buildings.  
 Thus, studies of higher detail where, for instance,  
 the implications in a low-voltage grid due to shad-  
 ing on PV modules are studied require a method  
 that reproduces these variations.

If the global irradiance on a shaded roof is of in-  
 terest, one also needs to consider the diffuse ( $D_T$ )  
 and reflected ( $R_T$ ) irradiance subcomponents on  
 the tilted plane, which both depend on the view  
 factor (visible fraction of the sky,  $f_{sky} \in [0, 1]$ ) from

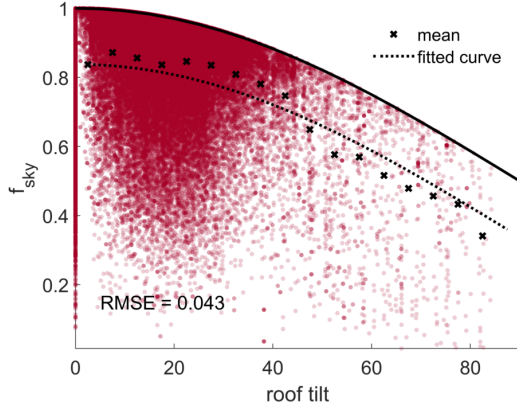


Figure 8: The mean  $f_{sky}$  as a function of the roof tilt (marked with x) and a fitted curve (dotted) presented in Eq. (4). The solid line represents the first term of Eq. (4)

1289 the perspective of the roof. I.e., the viewshed of the  
 1290 roof should be considered (see Figure 6). The view  
 1291 factor  $f_{sky}$  represents the ratio of the isotropic dif-  
 1292 fuse irradiance from the sky hemisphere and reaches  
 1293 a value of 1 for a horizontal surface if there are no  
 1294 shading objects.

1295 The values of  $f_{sky}$  for > 90,000 studied roof  
 1296 facets are presented in Figure 8. A fitted curve  
 1297 (with an RMSE of 0.043 with respect to the means,  
 1298 indicated by black crosses) was derived with the  
 1299 function:

$$\bar{f}_{sky} = \frac{1 + \cos(\beta)}{2} - C, \quad (4)$$

1300 where the first term is the view factor for a free sky  
 1301 and  $C$  is a constant representing the contribution  
 1302 from shading objects, here found to be 0.162. This  
 1303 equation may be used to calculate the diffuse and  
 1304 reflected irradiance following equations (6) and (10)  
 1305 in Lingfors et al. (2017), respectively.

1306 In Figure 9 the losses due to shading are pre-  
 1307 sented for the three irradiance subcomponents (cal-

1308 culated individually for each roof facet), sorted with  
 1309 respect to decreasing diffuse irradiance losses. In  
 1310 this analysis, hourly instantaneous Global Hori-  
 1311 zontal Irradiance (GHI) and Direct Normal Irradi-  
 1312 ance (DNI) data from 2014 for Uppsala were used  
 1313 (SMHI, 2015).  $B_T$  was calculated through Eq. (3),  
 1314 if we let  $\bar{k}_{sB}$  here represent the mean value of  $k_{sB}$   
 1315 for all points on the individual roof facet.  $D_T$ ,  
 1316 as well as  $R_T$ , were calculated through equations  
 1317 (6) and (10) in Lingfors et al. (2017), respectively,  
 1318 using the  $f_{sky}$  derived for each roof facet. These  
 1319 equations, adapted for the conventions used in the  
 1320 present paper, can be expressed as:

$$D_T = D_H \left[ (1 - A_i) f_{sky} + \frac{\cos \theta}{\cos \theta_Z} A_i \right], \quad (5)$$

1321 and

$$R_T = (B_H + D_H) \rho (1 - f_{sky}), \quad (6)$$

1322 where  $A_i$  is the anisotropy index and  $\rho$  is the surface  
 1323 albedo, here assumed to be 0.2 for all surfaces (i.e.,  
 1324 ground, trees, buildings etc.).

1325 Hence, Eqs. (2) and (4) in the present paper  
 1326 were not used here, but could be valuable in future  
 1327 studies where, for instance, the level of detail of the  
 1328 building topography in a city is unknown or the  
 1329 time for making detailed simulations is limited, yet  
 1330 the impact of shading on solar power generation is  
 1331 of interest.” The in-fold figure illustrates the nega-  
 1332 tive correlation between diffuse ( $D_T$ ) and reflected  
 1333 ( $R_T$ ) irradiance. The diffuse irradiance decreases  
 1334 (i.e., the losses increase) with a decreasing  $f_{sky}$ ,  
 1335 while instead the reflected irradiance increases (i.e.,  
 1336 negative losses in Figure 9). From Figure 8, it is  
 1337 clear that  $f_{sky}$  decreases with an increasing roof tilt,

1338 leading to a higher contribution of reflected irradiance  
 1339 for a highly tilted roof. The mean losses due  
 1340 to shading (expressed in relation to the unshaded  
 1341 global irradiance) for the whole building portfolio  
 1342 are 7.3%, 3.6%, 6.3% and  $-2.7\%$  for the global,  
 1343 beam, diffuse and reflected irradiance, respectively,  
 1344 where the minus sign is indicative of an added con-  
 1345 tribution to the total irradiance, since trees, build-  
 1346 ings etc. adds to the total reflective area seen by  
 1347 the roof when shading is considered. Hence, dif-  
 1348 fuse losses contribute the most for Uppsala, which  
 1349 has an annual clear-sky index of 0.63 (calculated as  
 1350 the global horizontal irradiation for 2014 divided by  
 1351 the clear-sky irradiation for the same period (In-  
 1352 ichten and Perez, 2002)). One should also remem-  
 1353 ber that all roofs in Uppsala were considered. If  
 1354 only roofs with installed PV systems on them were  
 1355 considered, the losses would most likely be lower.  
 1356 It is likely that the present method over-estimates  
 1357 the reflected irradiance at clear conditions as all  
 1358 trees and buildings seen by a roof could also be  
 1359 themselves shaded, therefore, offering reduced re-  
 1360 flected irradiance. To consider this is a complex  
 1361 matter and needs extensive research. For instance  
 1362 ray-tracing could be incorporated in the model but  
 1363 at a computational cost.

## 1364 **6. Future advancements beyond the scope of** 1365 **this work**

1366 The main objective of the paper was to fit dis-  
 1367 tributions to selected metadata and approximate  
 1368 functions that describe the impact of shading. This  
 1369 enables replication of these characteristics and al-  
 1370 lows a usage in regional PV power modelling ap-

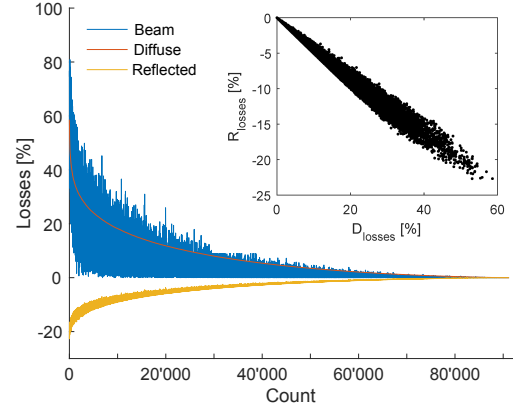


Figure 9: Beam and diffuse irradiance losses and the added contribution from reflected irradiance to the global irradiance considering shading on the  $> 90,000$  studied roof facets. The in-folded figure illustrates the negative correlation between the losses of diffuse and reflected irradiance when shading is considered.

1371 approaches with suitable representativeness. The un-  
 1372 derlying basis for the approximations are numerous  
 1373 datasets with metadata and simulated results from  
 1374 a model in the case of shading. Background infor-  
 1375 mation and references for further reading are pro-  
 1376 vided in the related sections. Furthermore, the level  
 1377 of accordance of the fitted distributions and func-  
 1378 tions with the original data is expressed by error  
 1379 metrics and limitations of the procedure are criti-  
 1380 cally discussed. Naturally, with such a considerable  
 1381 and detailed database of information, we cannot  
 1382 cover all aspects in a single paper. We have opted  
 1383 to present an overview in a manner that enables  
 1384 the user to engage with the findings. That said,  
 1385 we have identified several interesting topics during  
 1386 our work that we would like to study in more de-  
 1387 tail, however are beyond the scope of this paper's  
 1388 objectives.

- **Focus on specific parameters:** The whole



dataset offers so much information that it is im-  
possible to evaluate all specific parameters in  
detail within one paper. This data could po-  
tentially be used to study various performance  
indicators, e.g. by including irradiance infor-  
mation in specific regions and the age of the  
systems (provided for most systems).

- **Dependencies between parameters:** In  
this paper we have qualitatively discussed pair-  
wise dependencies between parameters. Fur-  
thermore, we have applied a quantitative ap-  
proach to individual parameters by fitting dis-  
tribution functions. The next step will be  
to quantitatively incorporate dependencies be-  
tween multiple (two and more) parameters, e.g.  
by joint distributions, multivariate models, etc.  
By that, the complex relations should be better  
represented.

- **Complex distributions:** The azimuth an-  
gle presented irregularities with a wide base  
and tall  $0^\circ$  peak and on occasion presented  
a trimodality that is certainly not-able to be  
captured by standard parametric distribution  
types with satisfaction. Whilst we dispute the  
validity of much of the measured data due  
to reporting simplifications, there is scope to  
analyse the distributions in a more statistically  
rigorous manner. There is scope to combine  
distributions and to enable multi-modal, non-  
parametric definition of the non-conformal pa-  
rameters, notably the tilt and azimuth. We  
intend to make available the actual probability  
distribution for the reader to draw their own  
conclusions, see our invitation for collaboration

below.

- **Cluster refinement:** Influence of climatic re-  
gion may influence certain parameters, partic-  
ularly the specific annual yield. It is probable  
that the specific annual yield is not only a func-  
tion of latitude (as we have demonstrated with  
a general regression between  $30^\circ$  and  $50^\circ$  of lat-  
itude), however, it is a function of the climatic  
region where those sites are situated. There  
is a lack of data within the  $0^\circ$  to  $30^\circ$  latitude  
band with which to successfully analyse this  
hypothesis. Further steps could be to replace  
the clusters by country with clusters by climate  
region using maps such as the Köppen-Geiger  
classifications, or perhaps by mean irradiance  
using a dataset such as NASA SSE.

- **Shading:** As mentioned in [section 5.2](#) the re-  
sults on shading from the present study can  
be used on a large portfolio of buildings, while  
for smaller areas one may want to produce re-  
alistic viewsheds for a few buildings to study  
the impact from shading. One simple approach  
would be to provide a database of viewsheds  
such as the one produced in this study, from  
which samples could be randomly drawn. To  
avoid the need of a database, another approach  
could be to design a model that can reproduce  
the distribution of shading profiles, perhaps  
stochastically using Markov chains to create  
statistically appropriate skylines. While the  
solar elevation angle is probably the most in-  
fluential parameter, other factors such as the  
type of roof or height of the building would  
most likely also have an impact. Hence, a set

of building specific parameters would satisfy as inputs to such a model.

• **Invitation for collaboration and data**

**access:** This work would not have been possible without support from many sides mentioned in the acknowledgements. Gathering this data has proven difficult at times, and finding the correct person to approach was not straight forward. Therefore, we would like to extend an invitation to the reader. Should you have good ideas of how to use this data, or have large data itself, particularly in countries that we have not detailed, we encourage you to get in contact with either Sven Killinger (sven.killinger@ise.fraunhofer.de, svnkllngr@gmail.com), Jamie Bright (jamie.bright@anu.edu.au, jamiebright1@gmail.com) or Nicholas Engerer (nicholas.engerer@anu.edu.au). Much of the data is confidential and so we cannot share it, however, the aggregated statistics are available. Should you wish to have access to the real distributions presented in the work, they are available on request, should they be publicly released, all communications will be made through our ResearchGate project. You are encouraged to follow that project for updates and communications (Bright et al., 2018).

**7. Summary**

Knowledge of PV system characteristics is needed in the different regional PV modelling approaches but are either unknown or only accessible for a small

number of stakeholders. The aim of this paper was to provide knowledge of PV system characteristics through data collection, analysis and distribution fitting of PV system characteristics. The structure presented was twofold and focused on (1) metadata (tilt and azimuth of modules, installed capacity and specific annual yield) as well as (2) the impact of shading.

We considered 2,802,797 PV systems located in Europe, USA, Japan and Australia, which represented a total capacity of 59 GWp (14.8% of installed capacity worldwide). Interdependencies of the installed capacity and the geographic location to the other parameters tilt, azimuth and specific annual yield were observed. To acknowledge the impact from these two dominating parameters (installed capacity and geographic location) on others and to allow a derivation of meaningful statistics, a clustering of systems on a country-basis with additional separation by systems sizes  $\leq 25$  kWp and  $> 25$  kWp was introduced. For eased future utilisation of the analysed metadata, each parameter in a cluster was approximated by a distribution function. Results show strong characteristics unique to each cluster, however, there are some commonalities across all clusters. The smallest mean tilt values were reported in Australia ( $16.1^\circ$ ), USA South and Italy ( $19.8$  and  $19.9^\circ$ , respectively). The largest mean tilt values were reported in Belgium ( $35.6^\circ$ ), the UK ( $31.8^\circ$ ) and Germany ( $31.6^\circ$ ). We find the smallest mean specific annual yield is in Denmark ( $786.0$  kWh/kWp) and largest in south USA ( $1,426$  kWh/kWp), this corresponds well to the climatic differences between  $30$  and  $50^\circ$  latitude within the study. The region with smallest me-



1526 dian capacity was UK (2.94 kWp) and the largest 1561  
1527 was Germany (8.96 kWp). Almost all countries 1562  
1528 had a mean azimuth angle normal to the equa- 1563  
1529 tor. The number of equatorially-orientated sys- 1564  
1530 tems was significantly higher than any other ori- 1565  
1531 entation, such that no distribution type could ap- 1566  
1532 propriately capture this characteristic. That said, 1567  
1533 it is expected that the number of systems with az- 1568  
1534 imuth of  $0^\circ$  are exaggerated due to lacking preci- 1569  
1535 sion of PV system metadata reporting, and per- 1570  
1536 haps the statistical distributions are more realistic 1571  
1537 than the data suggests, particularly when consid- 1572  
1538 ering the reduced peak from higher accuracy meta- 1573  
1539 data, such as that from the UK. Capacity demon- 1574  
1540 strated the most cluster-unique characteristics. As  
1541 each cluster represented a country, it also captures 1575  
1542 national policy incentives that clearly influence the  
1543 overall capacity distributions. The feed-in tariffs of  
1544 France, Germany and the UK have clear impact on  
1545 the PV system size. The shape of the distributions  
1546 of specific annual yield offered the most similarity 1578  
1547 between clusters, with the location/mean being pri- 1579  
1548 marily a function of climate through latitude. Dis- 1580  
1549 semination of clusters by climate may reveal more 1581  
1550 insightful differences. All of the distributions that 1582  
1551 are presented in the paper can be obtained from the 1583  
1552 tables in the appendix. 1584

1553 Shading was considered by computing the view- 1585  
1554 shed of individual roof facets of  $\approx 48,000$  buildings 1586  
1555 in Uppsala, Sweden, which meant that  $> 90,000$  1587  
1556 facets were analysed. Two empirical equations 1588  
1557 were derived and presented. The first represents 1589  
1558 the beam irradiance subcomponent, describing the 1590  
1559 mean ratio of a roof that is shaded as a function 1591  
1560 of the solar elevation angle. The second determines 1592

the view factor as a function of the roof tilt includ-  
ing the impact from shading and can be used to es-  
timate the losses of diffuse and reflected irradiance.  
These equations are believed to better take shading  
into consideration than the coarse estimates used  
today. For the specific meteorological conditions of  
Uppsala, we also showed in this study that losses  
of diffuse irradiance due to shading are higher than  
that of beam on an annual basis and should not be  
neglected for sites of similar cloudiness as in Upp-  
sala (annual clear-sky index of 0.63).

Several interesting research topics beyond the  
scope of this paper were sketched and the offer for  
future collaborations expressed.

## 8. Conflict of interest

The authors declare no conflicts of interest.

## Acknowledgement

The authors would like to thank the Australian  
Renewable Energy Agency (ARENA) for support-  
ing this work (Research and Development Pro-  
gramme Funding G00854). Part of this work is  
performed within the framework of the IEA-PVPS-  
Task 13 “Performance and Reliability of Photo-  
voltaic Systems” (IEA-PVPS, 2018). We would  
also like to acknowledge the Jyukankyo Research  
Institute Inc. and particularly Mr Takahiro Tsurusaki,  
Managing Director, COO, for the collaborative  
spirit shown and for the provision of data for  
Japan. The authors would like to thank those  
researchers that were approached who warmly in-  
vited the call for collaboration, however, were un-  
able to contribute directly. Dr Joao Gari da Silva

1593 Fonseca Jr, Assistant Professor at the University 1626  
 1594 of Tokyo, was invaluable in guiding us to the  
 1595 Japanese dataset. Rodrigo Palma-Behnke, Direc- 1627  
 1596 tor and Assistant Professor of Solar Energy Re- 1628  
 1597 search Center, Universidad de Chile, was able to 1629  
 1598 provide the international collaborative effort with 1630  
 1599 large scale PV systems information within Chile 1631  
 1600 that was unfortunately outside the scope of this 1632  
 1601 project. Dr Jan Kleissl, Professor at UCSD, USA, 1634  
 1602 for directing us to databases within the USA. We 1635  
 1603 would like to thank Dr Rodrigo Alonso Suárez of 1636  
 1604 UDELAR, Uruguay, and Ricardo Bessa of INESC 1638  
 1605 TEC, Portugal, who demonstrated collaborative 1639  
 1606 spirit but were not able to obtain the data relevant 1640  
 1607 for the study. David Trebosc and the bdpv plat- 1641  
 1608 form team are thanked for their engagement, high 1642  
 1609 value work and their exemplary policy of openness, 1644  
 1610 which highly contributed to present work. Daniel 1645  
 1611 Decker from the Federal Network Agency in Ger- 1646  
 1612 many is thanked for the provision of the dataset 1648  
 1613 and his kind support. We would like to thank 1649  
 1614 Mr Ruppel and Mr Ausburg (SMA) for their ef- 1650  
 1615 forts in gathering plant information while preserv- 1652  
 1616 ing the anonymity of the plants of the sunny por- 1653  
 1617 tal. Lastly, we are mostly appreciative to those 1654  
 1618 websites that allowed us to freely download their 1655  
 1619 data: openpv.nrel.gov, pvoutput.org, solar-log.com, 1656  
 1620 sonnenertrag.eu, suntrol-portal.com. Another site 1658  
 1621 not used within the study that is an excellent source 1659  
 1622 is <https://www.californiadgstats.ca.gov/>, however, 1660  
 1623 the USA data collected from openpv.nrel.gov was 1662  
 1624 feared to already incorporate this data and so po- 1663  
 1625 tential duplication was avoided. 1664

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## Appendix A. Approximation of parameters in clusters: continued

The appendix is a continuation of [section 4](#) and provides histograms together with fitted distribu-

1837 tions of azimuth, tilt, specific annual yield and in-  
1838 stalled capacity for system sizes  $> 25$  kWp in [Fig-](#)  
1839 [ure A.10](#). [Table A.4](#) presents the coefficients of the  
1840 fitted distributions, while distinguishing between  
1841 systems  $\leq 25$  kWp and  $> 25$  kWp. All distri-  
1842 bution functions are defined in [Table A.3](#) and can  
1843 be replicated with help of the parametrised coeffi-  
1844 cients. It is important that the user reads carefully  
1845 [section 4](#) in order to appropriately use the distribu-  
1846 tions. A summary of the impact of our proposed  
1847 quality control criteria from [section 2](#) is provided  
1848 in the appendix in [Table A.5](#) where percentages of  
1849 removed data are presented.

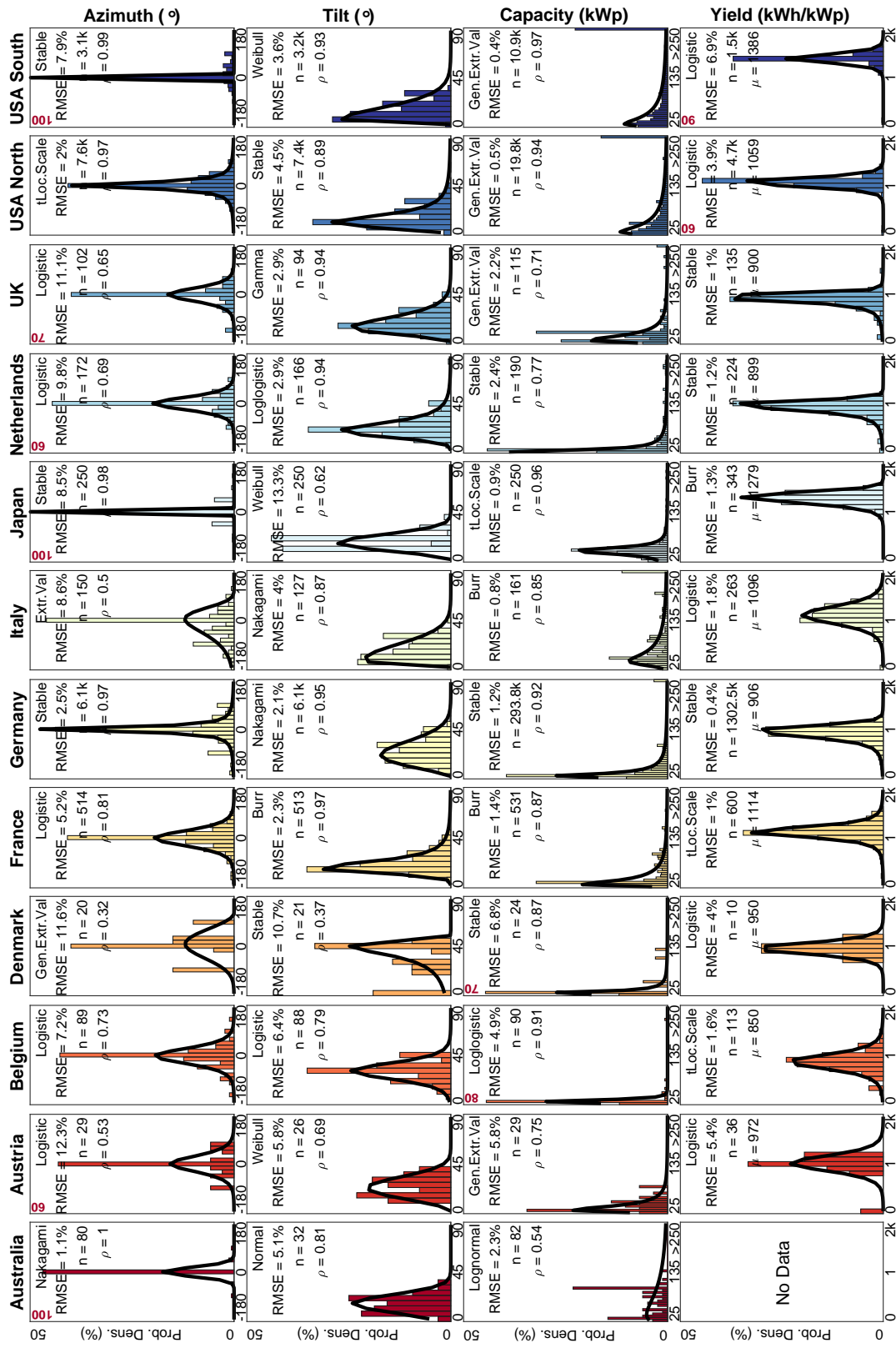


Figure A.10: Histograms of real data (bar) with approximated probability distributions (line) for the different clusters (columns) and parameters (rows), where capacity is the installed capacity and yield is the specific annual yield. All systems reported within this figure have a capacity > 25 kWp, see section 4 for complete derivation. Within each of the axes is reported the name of the best fitting distribution type, the root mean squared error (RMSE) between the scatter of real data in the histogram against the fitted probability density distribution, the number of data points considered for that cluster ( $n$ ), and the Pearson correlation coefficient ( $\rho$ ) of the linear regression. The mean value  $\mu$  is shown in place of  $\rho$  for Yield. All y-axes are scaled between 0 and 50% probability except where a bold red value is assigned to the individual axis.

Table A.3: Definition of the probability density distributions used in the research. The coefficients correspond to those presented in Table A.4. The distribution name corresponds to the same Matlab® distribution names and readers are encourage to read the detailed descriptions at [www.mathworks.com/help/stats/continuous-distributions.html](http://www.mathworks.com/help/stats/continuous-distributions.html). Each coefficient is defined. The equation is provided from the Matlab® documentation. Note that the Stable distribution is not explicitly a probability density function, but a characteristic function.

Distribution Name	Coeff. 1	Coeff. 2	Coeff. 3	Coeff. 4	Probability Density Function, $f(x ...)$
Burr type XII	$\alpha$ Scale	$c$ Shape 1	$k$ Shape 2	-	$f(x \alpha, c, k) = \frac{\frac{kc}{\alpha} \left(\frac{x}{\alpha}\right)^{c-1}}{\left(1 + \left(\frac{x}{\alpha}\right)^c\right)^{k+1}}$
Extreme Value	$\mu$ Location	$\sigma$ Scale	-	-	$f(x \mu, \sigma) = -\sigma^{-1} \exp\left(\frac{x-\mu}{\sigma}\right) \exp\left(-\exp\left(\frac{x-\mu}{\sigma}\right)\right)$
Gamma	$a$ Shape	$b$ Scale	-	-	$f(x a, b) = \frac{1}{b^a \Gamma(a)} x^{a-1} \exp\left(-\frac{x}{b}\right)$
Generalized Extreme Value	$k$ Shape	$\sigma$ Scale	$\mu$ Location	-	$f(x k, \mu, \sigma) = \left(\frac{1}{\sigma}\right) \exp\left(-\left(1 + k\frac{(x-\mu)}{\sigma}\right)^{-\frac{1}{k}}\right) \left(1 + k\frac{(x-\mu)}{\sigma}\right)^{-1 - \frac{1}{k}}$
Inverse Gaussian	$\mu$ Scale	$\lambda$ Shape	-	-	$f(x \mu, \lambda) = \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left(-\frac{\lambda}{2\mu^2 x} (x - \mu)^2\right)$
Logistic	$\mu$ Location	$\sigma$ Scale	-	-	$f(x \mu, \sigma) = \frac{\exp\left(\frac{x-\mu}{\sigma}\right)}{\sigma(1+\exp\left(\frac{x-\mu}{\sigma}\right))^2}$
Loglogistic	$\mu$ Log Loc.	$\sigma$ Log Scale	-	-	$f(x \mu, \sigma) = \frac{1}{\sigma} \frac{1}{x} \frac{\exp\left(\frac{\log(x)-\mu}{\sigma}\right)}{\left(1+\exp\left(\frac{\log(x)-\mu}{\sigma}\right)\right)^2} \frac{1}{\Gamma(\mu)} x^{2\mu-1}$
Lognormal	$\mu$ Log Loc.	$\sigma$ Log. Scale	-	-	$f(x \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$
Nakagami	$\mu$ Shape	$\omega$ Scale	-	-	$f(x \mu, \omega) = 2\left(\frac{\mu}{\omega}\right)^\mu \frac{1}{\Gamma(\mu)} x^{2\mu-1} \exp\left(-\frac{\mu x^2}{\omega}\right)$
Normal	$\mu$ Location	$\sigma$ Scale	-	-	$f(x \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$
Stable	$\alpha$ Shape 1	$\beta$ Shape 2	$\gamma$ Scale	$\delta$ Location	$E(e^{itX}) = \exp\left(-\gamma^\alpha  t ^\alpha (1 + i\beta \text{sgn}(t) \tan \frac{\pi\alpha}{2} ((\gamma t )^{1-\alpha} - 1) i\delta t)\right)$
t Location-Scale	$\mu$ Location	$\sigma$ Scale	$\nu$ Deg. of Freedom	-	$f(x \mu, \sigma, \nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sigma\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \left(\frac{\nu + \left(\frac{x-\mu}{\sigma}\right)^2}{\nu}\right)^{-\left(\frac{\nu+1}{2}\right)}$
Weibull	$a$ Scale	$b$ Shape	-	-	$f(x a, b) = \frac{b}{a} \left(\frac{x}{a}\right)^{b-1} \exp\left(-\left(\frac{x}{a}\right)^b\right)$

Table A.4: The distribution coefficients corresponding to the definitions in Table A.3. The left side is for capacities  $\leq 25$  kWp and the right side is for  $> 25$  kWp.

Cluster	Parameter	Dist. Type	Coef. 1	Coef. 2	Coef. 3	Coef. 4	Dist. Type	Coef. 1	Coef. 2	Coef. 3	Coef. 4
Australia	Azimuth	Logistic	8.3472	34.2603			Nakagami	28.0028	0.2537		
	Tilt	Logistic	15.0891	6.0136			Normal	14.6875	8.4183		
	Capacity	tLocationScale	4.9355	1.4855	3.2434		Lognormal	4.3491	0.8328		
Austria	Azimuth	Logistic	0.4566	17.6159			Logistic	0.6107	19.9366		
	Tilt	Weibull	34.6425	3.6381			Weibull	26.2683	2.7083		
	Capacity	GeneralizedExtremeValue	0.1633	2.9111	4.8713		GeneralizedExtremeValue	0.4337	8.5691	33.5998	
	FLH	tLocationScale	1.0668	0.0971	2.0439		Logistic	1.0144	0.1090		
Belgium	Azimuth	Logistic	-1.2365	24.3969			Logistic	-3.5828	19.3034		
	Tilt	ExtremeValue	39.8100	7.8703			Logistic	29.6932	5.1091		
	Capacity	Stable	1.4734	0.9578	1.3688	4.8772	Loglogistic	3.3900	0.0905		
Denmark	FLH	Burr	0.5814	9.2775	5.8277		tLocationScale	0.8570	0.1623	3.8904	
	Azimuth	Logistic	1.5526	20.6455			GeneralizedExtremeValue	-0.3684	49.6733	-13.0930	
	Tilt	Loglogistic	-1.1441	0.2256			Stable	0.9410	-1.0000	6.5572	41.6962
Denmark	Capacity	tLocationScale	5.7414	1.5014	2.3622		Stable	0.9767	1.0000	2.8140	28.6026
	FLH	Stable	1.2818	-0.8035	0.0948	0.8767	Logistic	0.9500	0.0778		
	Azimuth	tLocationScale	0.3346	34.5161	5.4215		Logistic	-2.2831	19.1336		
France	Tilt	Lognormal	-1.2139	0.4144			Burr	16.5673	5.0314	0.6793	
	Capacity	Stable	0.4000	0.5250	0.0345	3.0118	Burr	27.9585	19.1798	0.0934	
	FLH	tLocationScale	1.1011	0.1416	7.6129		tLocationScale	1.1194	0.1111	2.9295	
Germany	Azimuth	Logistic	-0.1366	23.0048			Stable	1.0309	-0.0002	9.9430	-0.2506
	Tilt	ExtremeValue	38.0648	9.6547			Nakagami	1.1890	0.0887		
	Capacity	GeneralizedExtremeValue	0.1143	3.5745	6.2413		Stable	0.7373	1.0000	5.2331	30.8089
Germany	FLH	Stable	1.6611	-0.9423	0.1152	0.9086	Stable	1.5803	-0.8322	0.0902	0.9530
	Azimuth	tLocationScale	-5.2371	32.9151	2.1254		ExtremeValue	4.4388	46.3326		
	Tilt	Stable	1.8917	1.0000	5.5359	19.0462	Nakagami	0.6147	0.0448		
Italy	Capacity	Stable	0.9088	0.9411	1.5384	4.4130	Burr	37.2635	8.0048	0.1480	
	FLH	tLocationScale	1.1774	0.1415	2.5624		Logistic	1.1096	0.1246		
	Azimuth	Logistic	-0.7254	15.9481			Stable	0.4045	0.0010	0.2121	0.0007
Japan	Tilt	ExtremeValue	27.6791	6.4206			Weibull	18.9055	2.6245		
	Capacity	Stable	1.3094	0.9774	1.0384	4.4144	tLocationScale	48.0538	7.9913	1.4353	
	FLH	Burr	1.3730	11.1707	2.7755		Burr	1.4833	13.7688	5.1025	
Netherlands	Azimuth	Stable	1.0309	0.0001	11.2285	0.0294	Logistic	-0.3912	15.7031		
	Tilt	ExtremeValue	38.8465	11.6153			Loglogistic	3.0459	0.2311		
	Capacity	tLocationScale	3.2381	1.3462	1.6898		Stable	0.6078	1.0000	3.7179	28.2348
UK	FLH	Stable	1.3553	-0.8354	0.0893	0.9334	Stable	1.4819	-0.9477	0.0760	0.9577
	Azimuth	Logistic	0.2461	26.0886			Logistic	-0.8287	16.4894		
	Tilt	tLocationScale	31.5952	4.6591	3.3818		Gamma	3.9484	4.5939		
UK	Capacity	Stable	1.8937	-0.0544	0.5898	2.9504	GeneralizedExtremeValue	0.5210	10.8742	35.6490	
	FLH	Stable	1.6851	0.0000	0.0776	0.9035	Stable	1.3744	-0.8038	0.0638	0.9395
	Azimuth	Logistic	0.4600	28.1468			tLocationScale	0.1686	12.6681	1.2295	
USA North	Tilt	Loglogistic	-1.2944	0.2061			Stable	1.3001	1.0000	4.8192	10.6480
	Capacity	GeneralizedExtremeValue	0.0868	2.5493	4.6450		GeneralizedExtremeValue	1.1806	31.0335	45.3525	
	FLH	Stable	1.3201	-0.7411	0.0666	1.0628	Logistic	1.0679	0.0575		
USA South	Azimuth	Logistic	8.5676	29.3711			Stable	0.4000	0.4410	0.2829	0.0822
	Tilt	tLocationScale	20.4150	3.8106	3.0306		Weibull	0.1647	1.3876		
	Capacity	Burr	0.3092	2.5724	2.2109		GeneralizedExtremeValue	1.2834	38.6717	49.6038	
USA South	FLH	ExtremeValue	1.4898	0.0963			Logistic	1.4035	0.0579		



Table A.5: Percentages of reported (Rep.) and filtered data due to the quality control procedure sketched in section 2 for tilt, azimuth, installed capacity (Capa.), geographic location (Loca.) and specific annual yield. Numbers are given as percentage and in relation to the total number of systems that were available in each dataset.

Region	Tilt		Azimuth		Capa. Rep.	Loca. Rep.	Yield		Source
	Rep.	$\leq 1^\circ$ $> 89^\circ$	Rep.	$< -179^\circ$ $> 179^\circ$			Rep.	$= 0$ $> 2000$	
Australia	26.95	0.00	26.95	0.00	100.00	96.40	0.00	0.00	pvoutput.org
Austria	100.00	2.34	100.00	2.60	100.00	100.00	0.00	0.00	solar-log.com
	100.00	0.71	100.00	0.00	100.00	100.00	0.71	0.00	suntrol-portal.com
	100.00	1.87	100.00	1.12	100.00	100.00	0.00	39.93	sonnenenerg.eu
	83.04	28.57	93.75	6.25	100.00	67.86	0.00	0.30	pvoutput.org
Belgium	100.00	1.65	100.00	0.99	100.00	95.77	0.00	0.00	solar-log.com
	100.00	0.48	100.00	0.48	100.00	100.00	0.00	67.74	bdpv.fr
	100.00	1.48	100.00	0.74	100.00	99.63	0.00	41.47	sonnenenerg.eu
Denmark	100.00	2.25	100.00	2.57	100.00	100.00	0.00	0.00	solar-log.com
	100.00	0.63	100.00	0.00	100.00	100.00	1.27	0.00	suntrol-portal.com
	93.54	11.62	98.34	4.43	100.00	68.45	0.00	0.74	pvoutput.org
France	100.00	0.25	99.99	0.61	100.00	100.00	0.17	60.23	bdpv.fr
	100.00	4.84	100.00	5.02	100.00	63.44	0.00	0.00	solar-log.com
Germany	0.00	0.00	0.00	0.00	100.00	99.78	0.00	0.26	bundesnetzagentur.de
	100.00	2.30	100.00	2.77	100.00	100.00	0.10	0.00	solar-log.com
	100.00	0.76	100.00	0.00	100.00	100.00	1.01	0.00	suntrol-portal.com
	100.00	1.72	100.00	1.13	100.00	99.97	0.03	39.36	sonnenenerg.eu
Italy	100.00	3.63	100.00	4.71	100.00	86.91	0.00	0.00	solar-log.com
	86.42	26.12	96.35	4.59	100.00	78.84	0.00	1.03	pvoutput.org
	100.00	1.40	100.00	0.56	100.00	100.00	0.00	41.15	sonnenenerg.eu
Japan	100.00	0.00	100.00	0.32	100.00	100.00	0.00	0.00	iyuri.co.jp
Netherlands	92.08	18.44	97.09	7.08	100.00	55.06	0.00	0.35	pvoutput.org
	100.00	1.26	100.00	1.79	100.00	100.00	0.09	0.00	solar-log.com
	100.00	0.55	100.00	0.55	100.00	100.00	0.00	52.02	sonnenenerg.eu
	100.00	0.69	100.00	0.00	100.00	100.00	0.34	0.00	suntrol-portal.com
Rest of Europe	100.00	7.30	100.00	13.18	100.00	72.88	0.00	0.00	solar-log.com
	88.16	32.33	96.29	21.38	100.00	62.37	0.00	3.06	pvoutput.org
	100.00	3.76	100.00	5.26	100.00	100.00	0.00	36.09	sonnenenerg.eu
UK	99.15	0.06	100.00	0.08	100.00	100.00	0.00	0.21	microgen-database.sheffield.ac.uk
	81.71	16.23	97.16	4.64	100.00	62.07	0.00	0.28	pvoutput.org
USA	37.56	0.05	35.59	0.00	100.00	94.51	0.03	0.00	openpv.nrel.gov
	93.57	20.63	98.30	7.54	100.00	65.53	0.00	0.44	pvoutput.org