Methodology of Köppen-Geiger-Photovoltaic climate classification and implications to worldwide mapping of PV system performance

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ABSTRACT

Photovoltaic (PV) already proves but even more promises to be massively deployed worldwide. To evaluate the performance of PV systems globally and assess risk due to different climate conditions, we propose a methodology for the global Köppen-Geiger-Photovoltaic (KGPV) climate classification that divides the globe into 12 zones with regard to the temperature, precipitation and irradiation, and standardizes the evaluations of the performance in regions with similar climatic conditions. Additionally, we present implications of KGPV to simulated PV performance using monthly data, for current and future operation of PV systems worldwide including climate change scenarios. A set of electrical and thermal performance indicators of crystalline silicon PV modules in different KGPV zones is analyzed and their evolution over time due to climate changes caused by high greenhouse gas emissions discussed. Results show that the KGPV scheme proves to be a convenient methodology to relate the KGPV climate zones with PV performance.

1. Introduction

Nowadays, solar photovoltaic (PV) systems are a viable and competitive option for the transition to sustainable energy systems. This technology can be used in any location and at any scale (in residential, commercial and also industrial sectors), offering us countless opportunities to produce renewable electrical energy for our needs. Trend studies present an exponential growth in total installed capacity together with further increase of efficiency and further decrease of the system prices, which boost the interest of broader communities across the globe and attracts new stakeholders to the variety of markets (ETIP-PV, 2017; IEA PVPS, 2018). The global installed capacity of PV systems reached 480 GW in 2018 (IRENA, 2019) and is projected to surpass the 1 TW by 2021–2022 (SolarPower Europe, 2018).

To support and expand the worldwide deployment of solar PV energy, the PV community raised interest in the understanding and improvement of the long-term performance and reliability of PV modules and systems under different climate conditions (e.g. SOLARTRAIN (Weiß et al., 2017), Pearl-PV (Reinders et al., 2018)) and as mentioned in (Haegel et al., 2019), adopted PV module designs related to specific climate stresses will be needed.

In this regard, a simplification of the problem can be addressed by categorizing the regions with similar climate conditions. Examples of categorization of certain climate zones for single locations or single

countries have been presented in the literature: Jordan et al. have defined the Desert, Hot & Humid, Moderate and Snow climate zones for the study of the PV modules degradation (Jordan et al., 2016); Kohl et al. classified ground measurement stations into Maritime, Moderate, Arid, Alpine and Tropical (Koehl et al., 2018); Eder et al. have correlated indoor and outdoor conditions defining the climate zones as Tropical, Arid, Moderate and Alpine (Eder et al., 2018); and Dash et al. categorized regions across India using temperature and irradiation (Dash et al., 2017).

However, according to our knowledge, no global climate classification scheme for PV existed, which could help stakeholders to easily analyze the regions of their interest. The PV community has been mostly using the Köppen-Geiger (KG) climate classification scheme (Kottek et al., 2007), which is composed of three letters for each location: (1) main climate, (2) seasonal precipitation type and (3) level of heat. This scheme is widely used because of the easy understanding of categories but unfortunately includes only temperature and precipitation, while letters (2) and (3) provide not significant information for PV.

Furthermore, the lack of standardization of climate zones brings confusion in the community since different terms are used to name the climate of specific regions.

Those issues motivated us to develop a new climate classification scheme combining temperature, precipitation and irradiation, called as

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Nomenclatures**Symbols**

Az	Azimuth angle of PV modules installation [°]
B_{PoA}	direct irradiance at PoA [W/m^2]
D_{PoA}	diffuse irradiance at PoA [W/m^2]
f_{AR}	angular reflection losses
f_{sh}	shading losses
f_{snow}	snow losses
f_{soil}	soiling losses
f_{spec}	spectral losses
f_{temp}	temperature losses
Gd	geographical data (latitude, longitude and altitude)
GHI_{ERA}	monthly average of daily irradiation from ERA-Interim [Wh/m^2]
G_{PoA}	global plane-of-array irradiance [W/m^2]
G_{eff}	effective irradiance in PoA [W/m^2]
H_{ann}	annual global horizontal irradiation [Wh/m^2]
H_{eff}	annual effective irradiation at PoA [Wh/m^2]
k_{cdaily}	daily clear sky index
k_{Ross}	Ross coefficient [$^{\circ}C\ m^2/W$]
η_{BoS}	balance of system efficiency
$Prec_{ann}$	annual precipitation [mm]
$Prec_{th}$	precipitation threshold to define the dryness of the

	location [mm]
P_{STC}	nominal output power at STC [W]
R_{PoA}	ground-reflected irradiance at PoA [W/m^2]
UCF	unit capacity factor

Greek symbols

β	tilt angle of PV modules installation [°]
γ	power-temperature coefficient [%/°C]

Subscripts

PoA	plane-of-array

Abbreviations

I-zones	irradiation-zones
KG	Köppen-Geiger
KGPV	Köppen-Geiger-Photovoltaic
NOC	nominal operating conditions
PL	performance loss factor
PV	photovoltaic
STC	standard test conditions
SSP	shared socio-economic pathway
TP-zones	temperature-precipitation-zones

the Köppen-Geiger-Photovoltaic (KGPV) climate classification. The KGPV scheme is based on the KG climate classification but extended by the solar irradiation since this variable is the primary one for solar PV energy production. Accordingly, it includes two classification levels: the Temperature-Precipitation (TP-) zones and the Irradiation (I-) zones. Preliminary results for the US and Chile were presented in (Ascencio-Vásquez et al., 2018). Hereby, we present an update of the scheme and also the worldwide KGPV map composed by 12 climate zones.

The usefulness of the KGPV scheme can be proved by comparing the climate zones with relevant PV indicators, such as the energy yield, performance ratio or module operating temperature. According to it, the need for a tool for PV performance modelling is needed. Different alternatives of PV performance assessment over large geographical regions have been already proposed by several research groups (Bora et al., 2018; Dubey et al., 2013; Huld et al., 2010; Kim et al., 2015;

Louwen et al., 2017; Wild et al., 2015). Some of them are already available to the customer as commercial (e.g. PVSyst (PVSyst, 2019)) or freeware tool (e.g. PVGIS (Huld et al., 2010; Huld and Gracia Amillo, 2015; Urraca et al., 2017), PVWatts (NREL and Dobos, 2014) or external library PVLIB (Stein et al., 2016)). However, due to the complexity of combining available tools with a climate classification scheme, we combine existing models to create an in-house tool for the estimation of PV indicators.

Fig. 1 illustrates the main components, climate variables and factors taken into account for the simulation of a PV system. The parameters affecting the PV performance can be grouped in solar irradiance (extra-terrestrial irradiance, beam irradiance, diffuse irradiance, etc.), weather data (ambient temperature, wind speed and direction, precipitation, clouds, etc.), local conditions (soiling, shading, ground albedo, etc.) and PV module data (mounting, angular-reflection losses, spectral losses,

Fig. 1. Scheme of climate modelling and electrical modelling for PV systems.

etc.). At system level, the PV modules are connected in strings to an inverter that converts the electricity from the direct (DC) to alternating current (AC) and regulates the voltage to the one determined by the electrical grid to dispatch the energy to the power system.

Having both, the climate classification and the PV performance, bring us the possibility to standardize the evaluations per climate zone. The validity of the model is made by comparing ground measurements of irradiance and temperature from the Baseline Surface Radiation Network (BSRN) stations (Driemel et al., 2018).

Finally, to prove the applicability of our methodology, the climate zones and PV indicators are projected towards 2100, using the dataset “SSP5-8.5” developed in the frame of the Scenario Model Intercomparison Project (ScenarioMIP) (O’Neill et al., 2016).

This paper is divided into six sections: first, the datasets are described as well as the methodology to handle the global gridded data; then, the Köppen-Geiger-Photovoltaic climate classification is defined, and followed by the methodology to calculate the performance of PV systems; consequently, the mapping of worldwide PV performance is shown and analysed in view of the new KGPV zones; finally, we evaluate the evolution of PV indicators towards 2100 under the published climate change projections.

2. General approach and datasets used

The main steps to achieve the global climate classification and global PV performance modelling are illustrated in Fig. 2, where temporal- and spatial-aggregations need to be carried out to combine global gridded datasets for ambient temperature, precipitation and irradiation.

2.1. Global gridded climate datasets

The precipitation data is taken from the dataset called “GPCPv2018” and generated by the Global Precipitation Climatology Centre (GPCC) of the German Weather Service (Schamm et al., 2016), which integrates the largest number of precipitation stations worldwide (Duan et al., 2017). This dataset is given with a high resolution ($0.1^\circ \times 0.1^\circ$) and is based on measurements by national meteorological and hydrological services, regional and global data collections as well as stations of World Meteorological Organisation (WMO).

The ambient temperature data was taken from the “CRU TS4.01” dataset of the Climatic Research Unit (CRU), University of East Anglia (Harris et al., 2014), based mainly on the stations network of the WMO, as well as the GPCPv2018. From this dataset, we have extracted the daily average ambient temperature ($T_{amb_{avg}}$) for each month to be used

in the climate classification scheme, and the monthly maximal and minimal temperature ($T_{amb_{max}}$ and $T_{amb_{min}}$) to model the daylight ambient temperature as a function of time (T_{amb}) for the PV performance modelling.

Regarding the irradiation data, several data source comparisons and evaluations have been carried out, since the inaccuracy of the estimations can be high (Jones et al., 2017; Urraca et al., 2018c, 2018a, 2018b, 2017). While for temperature and precipitation, thousands of ground-based measurements are available and integrated into large datasets, for solar irradiation no global dataset based on ground-measurements exist, because the ground stations are not equally spread around the world. For example, the Baseline Surface Radiation Network (BSRN) includes only 76 stations worldwide including pyranometers, pyrhemometers, etc. mainly located in the northern hemisphere (Driemel et al., 2018; WRMC-BSRN, 2019).

Due to the lack of the irradiation data, two alternatives to derive the solar data over large regions or globally have been developed: (i) satellite-based models, which estimate the irradiation from the satellite data combined with the ground measurements (Amillo et al., 2018); and (ii) reanalysis models, which are based on large computational coupled models (Atmospheric and Ocean-Wave models) where irradiation is calculated from millions of climate measurements from different sources, such as, ground stations, satellites or aircrafts (Zhang et al., 2016). In this work, we have taken the global horizontal irradiation (GHI) from the reanalysis-based dataset ERA-Interim (Uppala et al., 2011) provided by the European Centre for Medium-Range Weather Forecasts (ECMWF).

The validation of the synthetic T_{amb} and synthetic GHI is made by comparison with 22 stations BSRN installed around the World (see Table A1 in Appendix). All measurements when GHI is lower than 30 W/m^2 and higher than 1300 W/m^2 are neglected.

The climate variables projected towards the year 2100 are derived from the “SSP5-8.5” climate change scenario, created by the Institute Pierre Simon Laplace (IPSL) (Boucher et al., 2018). The details of this world scenario are presented in (Kriegler et al., 2017; O’Neill et al., 2016; Riahi et al., 2011). The simulations are applied for the time period of 2015 to 2100 on monthly basis and a spatial resolution of $250 \text{ km} \times 250 \text{ km}$.

2.2. Temporal- and spatial- aggregation

Since we obtain datasets from different providers and also in different formats, temporal and spatial adjustments are needed to aggregate all the data. We aim a long-term evaluation, thus, it is relevant

Fig. 2. General concept used in our approach.

to define a representative time period from which the historical data can be extrapolated and used to estimate the near-future. To choose the time range of historical data, we have evaluated (and relabelled) six climate zones defined by the KG scheme (Kottke et al., 2007): A-Tropical, B-Desert, C-Steppe, D-Temperate, E-Cold and F-Polar climates. The average ambient temperature per each climate zone has been calculated on annual basis. As already reported in climate change reports (IPCC, 2018), rising temperature trends are evident from the middle of the 20th century in all climate zones and they are shown in Fig. 3. Precipitation and irradiation show no clear trend nor pattern.

The evolution of temperature across the full period can be divided into two linear segments: the data before and after 1990 (see Fig. 3). Accordingly, we selected the time period for the climate classification from 1990 to 2016, where the data is averaged on monthly basis. The temporal aggregation is followed by spatial aggregation. The datasets are resampled to a generic global grid resolution, ranging from 180°E to 180°W in Longitude and 90°S to 90°N in Latitude, with a resolution of $0.5^\circ \times 0.5^\circ$ after applying a bilinear interpolation.

3. The Köppen-Geiger-Photovoltaic climate classification scheme

The aggregated datasets generate the map of the KGPV climate classification scheme presented in Fig. 4. The developed climate classification divides the Globe according to two classification levels: first, the *TP*-zones are defined following the threshold criteria proposed by (Kottke et al., 2007) and relabelled as A-Tropical, B-Desert, C-Steppe, D-Temperate, E-Cold and F-Polar climates; and second, the *I*-zones are defined as L-Low, M-Medium, H-High and K-Very High irradiation zones. The 30th, 50th and 80th percentiles (1130, 1560 and 2070 kWh/m², respectively) of the global values (excluding Antarctica) for annual global horizontal irradiation (H_{ann}) are chosen as the thresholds for *I*-zones. Those values were empirically defined for Europe based on the weather conditions on the continent. They also present a reasonable categorization in the rest of the World. Both threshold criteria and order of classification are presented in Fig. A1 in Appendix.

Combining six *TP*-zones and four *I*-zones, we get 24 possible KGPV climate zones designated with two letters. However, less important

zones can be neglected due to two main reasons:

- Land-Surface ratio (LS_r): this indicator is defined as the portion of land per climate zone over the global land surface and given in percentage (see Table 1),
- Population Density: since large PV systems are usually installed in or next to populated areas (Bollinger and Gillingham, 2012; Dharshing, 2017; Graziano and Gillingham, 2015), we use this indicator to identify the unpopulated zones, where is less probable to install PV systems. The global population density data has been taken from (Center for International Earth Science Information Network - CIESIN - Columbia University, 2018), and correlated with the climate zones to get the average population density per climate zone (see Table 2).

To reduce the 24 zones, we define a surface-population density indicator by multiplying the land-surface ratio by the population density per climate zone (which represent roughly the number of people per climate zone) and neglect small areas with low population to get 12 climate zones (represented as the highest 11 values in Table 3, plus one zone for Polar climates). The neglected zones are relabelled to the closest neighbouring zone in view of the irradiation criterion as shown in Table 4. As an exception, the climate zone “FL” (Polar climate with Low Irradiation) is included in the map as a representative of all the Polar zones.

4. Worldwide PV performance modelling

Besides the climate classification, we have developed a comprehensive PV performance modelling using global gridded monthly data to calculate thermal and electrical indicators at any location. The highest uncertainty comes from ERA-Interim data due to the modelling of the cloudiness (Urraca et al., 2018b). However, also other models used for clear sky, decomposition and transposition modelling can introduce more uncertainties because they are validated only for specific locations around the world (Hofmann and Seckmeyer, 2017a). The selection of models is based on uncertainty studies (Lave et al., 2015;

Fig. 3. Evolution of the ambient temperature per climate zone calculating a 10-years rolling mean. The trend lines represent the linear regression with 95% of confidence interval extrapolated to 2030 2020 for the three data periods: 1950–2016 (black dashed line), 1950–1989 (black solid line) and 1990–2016 (coloured solid line). Grey areas represent the time period selected to monthly average the climate variables (from 1990 to 2016). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 4. Köppen-Geiger-Photovoltaic climate classification with the 12 most relevant climate zones (Antarctica excluded). The first letter indicates the Temperature-Precipitation (TP)-zones: A-Tropical, B-Desert, C-Steppe, D-Temperate, E-Cold and F- Polar. The second letter indicates the Irradiation (I)-zones: K-Very High, H-High, M-Medium and L-Low irradiation.

Table 1
Land Surface Ratio per climate zone indicating the portion of land-surface for each climate zone over the total sum.

Land-Surface Ratio		I-zones			
		L	M	H	K
TP-zones	A – Tropical	0.04%	2.80%	11.11%	1.77%
	B – Desert	0.00%	0.17%	3.36%	12.05%
	C – Steppe	0.01%	1.20%	5.25%	4.44%
	D – Temperate	0.76%	4.54%	7.58%	0.84%
	E – Cold	20.24%	10.12%	2.10%	0.10%
	F – Polar	8.95%	1.17%	0.61%	0.80%

Table 2
Population Density per climate zone representing the average of population density for each climate zone over the Globe.

Population Density [people/km ²]		I-zones			
		L	M	H	K
TP-zones	A – Tropical	28.36	23.64	80.53	67.71
	B – Desert	0.00	3.92	31.07	13.98
	C – Steppe	0.48	11.11	81.29	25.77
	D – Temperate	149.99	143.98	129.07	73.92
	E – Cold	4.71	29.29	41.29	16.23
	F – Polar	0.04	0.28	8.62	1.62

Table 3
Surface-Population Density indicator per climate zone calculated by multiplying Tables 1 and 2.

Surface-Population Density indicator		I-zones			
		L	M	H	K
TP-zones	A – Tropical	0.59	0.66	8.95	1.20
	B – Desert	0.00	0.01	1.04	1.68
	C – Steppe	0.00	0.13	4.26	1.14
	D – Temperate	1.14	6.53	9.79	0.62
	E – Cold	0.95	2.96	0.87	0.02
	F – Polar	0.00	0.00	0.05	0.01

Table 4
Assumptions applied on KGPV labelling procedure merging to most relevant zones next to them indicated by the arrows. Different colours label TP-zones.

Selected Zones		I-zones			
		L	M	H	K
TP-zones	A – Tropical	→	→	✓	✓
	B – Desert	→	→	✓	✓
	C – Steppe	→	→	✓	✓
	D – Temperate	✓	✓	✓	←
	E – Cold	✓	✓	←	←
	F – Polar	✓	←	←	←

Skoplaki and Palyvos, 2009; Urraca et al., 2018b), privileging simplicity to reduce processing speed.

To get the long-term performance of PV systems, we simulate a typical day (from sunrise to sunset) for each month. Daily values are multiplied by the number of days in each month and summed up to the annual value. Performance modelling is done in three stages: the selection of input parameters, the modelling of temperature and irradiation, and the modelling of PV performance.

Fig. 5. Flowchart for definition of initial variables and parameters.

4.1. Input parameters

The first stage is presented in Fig. 5, where we define the models with initial parameters and input variables. From the timestamp and geographical data of the location (denoted as *Gd*, including the latitude, longitude and altitude), we calculate the sun position (*SP*), Sun Azimuth angle (*SunAz*) and Sun Zenith angle (*SunZen*), using the NREL SPA Algorithm (Reda and Andreas, 2008). The orientation (or azimuth angle, denoted as *Az*) and inclination angle (or tilt, denoted as β) of fixed-mounted PV modules is considered optimal once the PV module or system produces the maximal annual energy output (Palmer et al., 2018). Optimal position (OP), including *Az* and β angles worldwide, are calculated by using a 3-order polynomial empirical model as reported in (Jacobson and Jadhav, 2018).

We define the following parameters for the PV system model:

- Balance of System Efficiency (η_{BOS}): overall efficiency of all the system components except PV modules, including cabling, inverter, transformer, etc.,
- Power-temperature coefficient (γ): parameter given by the PV manufacturer, which indicates the relative impact of the module temperature on the output power,
- Nominal output power at STC (P_{STC}): expected output power of the PV module at Standard Test Conditions (STC: $G_{STC} = 1000 \text{ W/m}^2$, $T_{STC} = 25^\circ\text{C}$),
- Module Temperature at NOC (T_{NOC}): parameter given by the PV manufacturer, which indicates the module temperature at Nominal Operating Conditions (NOC: $G_{NOC} = 800 \text{ W/m}^2$, $T_{amb} = 20^\circ\text{C}$)
- Ground albedo (*Alb*): parameter defined as the fraction of global incident irradiance reflected from the ground to the PV module and it can be wavelength-dependent.

4.2. Solar irradiance and ambient temperature modelling

Global Plane-of-Array Irradiance (G_{PoA}) for a typical day of each month is calculated from ERA-Interim irradiation data (GHI_{ERA}). First, we model the Clear Sky Global Horizontal Irradiance (GHI_{CS}) using the Simplified-Solis Model (Ineichen, 2008) from pre-processed data and formulas included in the PVLIB python package (Stein et al., 2016).

To get the *GHI* as a function of time (denoted as GHI_t), we calculate a Daily Clear Sky Index (k_{daily}) defined as the ratio of the GHI_{ERA} and the daily sum of $GHI_{CS}(t)$ for a typical day of each month (see Eq. (1)). The GHI_t is calculated hourly from sunrise to sunset by multiplying GHI_{CS} and k_{daily} (see Eq. (2)).

$$k_{daily} = \frac{GHI_{ERA}}{\int_{day} GHI_{CS}(t) dt} \quad (1)$$

$$GHI_t = k_{daily} \times GHI_{CS}(t) \quad (2)$$

Once the GHI_t is calculated, we implement the Erbs decomposition model (Erbs et al., 1982), to obtain the diffuse horizontal irradiance (DHI_t) and direct normal irradiance (DNI_t), needed for the PV performance calculation (Kirm et al., 2015). Then, the transposition of irradiances has to be applied since the PV modules are tilted. The Angle of Incidence (AOI) for tilted modules is calculated and integrated into the Hay-Davies transposition model (Loutzenhiser et al., 2006) to obtain the Plane-of-Array (PoA) irradiance (G_{PoA}) composed by: B_{PoA} - Direct Irradiance at PoA, D_{PoA} - Diffuse Irradiance at PoA and R_{PoA} - Ground-Reflected Irradiance at PoA.

Additionally, the incident irradiance reaching the tilted PV modules can be affected by the following local environmental factors:

- Shading losses (f_{sh}): due to obstacles that block the solar ray paths, such as buildings, mountains, trees, etc. (Das et al., 2017),
- Soiling losses (f_{soil}): dust is accumulated on the surface, reducing the absorption of rays (Cordero et al., 2018),

Fig. 6. Flowchart for calculation of the effective solar irradiation on the Plane-of-Array.

- Snow losses (f_{snow}): during winter time a layer of snow or ice can get accumulated on the panels surface reducing the absorption of rays considerably (Andrews et al., 2013),
- Spectral losses (f_{spec}): given as a mismatch between the spectral response of the PV module and the actual spectrum of the incident irradiance (Martín and Ruiz, 1999),
- Angular-Reflection losses (f_{AR}): reflection of the sun at larger incident angles can decrease the penetration of the light into the module (Martín and Ruiz, 2005).

Finally, the Effective Irradiance in PoA (G_{eff}) is composed by the sum of each PoA component weighted by the loss factors as shown in Eq. (3). All the steps are summarized in Fig. 6.

The ambient temperature is modelled using two sinusoidal functions during the daylight time (Waichler and Wigmosta, 2003), where the minimum temperature is set at the sunrise and the maximal temperature is located at the middle between noon and sunset.

$$G_{eff} = (B_{PoA} + D_{PoA} + R_{PoA}) \times f_{sh} \times f_{soil} \times f_{snow} \times f_{spec} \times f_{AR} \quad (3)$$

4.3. PV performance modelling and performance indicators

Module temperature losses are estimated through the Module operating temperature (T_{mod}) calculated using the Ross model (Skoplaki and Palyvos, 2009), which uses the Nominal Operating Condition (NOC) values to calculate the Ross Coefficient (k_{Ross}). For c-Si, the Module Temperature at NOC (T_{NOC}) is typically 44°C , deriving in a k_{Ross} equal to $0.03^\circ\text{C m}^2/\text{W}$. The T_{mod} as function of time is calculated as:

$$T_{mod} = T_{amb} + k_{Ross} \times G_{eff}. \quad (4)$$

T_{mod} strongly affects the power and energy production, since high operating temperatures generate thermal losses and decrease the efficiency of the PV module (Bogenrieder et al., 2018; Dash and Gupta, 2015; Hegedus, 2013; Schweiger et al., 2017). This phenomenon is expressed by the power-temperature coefficient (γ). The temperature loss factor (f_{temp}) is calculated as:

$$f_{temp} = \gamma \times (T_{mod} - T_{STC}). \quad (5)$$

Fig. 7. Flowchart for PV System Performance modelling.

The PV energy output (E_{PV}) of the simulated PV system depends on climate variables, PV module characteristics and long-term degradation of the PV module materials and system components, and it can be calculated as:

$$E_{PV} = \int G_{eff}(t) \times \frac{P_{STC}}{G_{STC}} \times (1 + f_{temp}(t)) \times \eta_{BoS}(t) \times PL_i(t) dt, \quad (6)$$

where $PL_i(t)$ is the total Performance Loss factor, defined as the reduction of the PV system performance over time.

Then, from the synthetic data generated, we calculate several performance indicators (yield, performance ratio, module operating temperature, etc.) that can help to compare and evaluate technologies depending on the location and climate zones for the PV deployment worldwide. Typically, long-term PV assessments are represented by the indicators expressed in the IEC standards (International Electrotechnical Commission, 1998), thus, we calculate the reference energy yield (Y_r), final energy yield (Y_f) and performance ratio (PR) using standard formulas. We also include the Unit Capacity Factor (UCF) to characterize the availability of the annually produced energy, which can support the comparison among conventional and renewable

power sources, or in terms of reliability, to identify zones with long operating stress for PV modules.

Additionally, four thermal indicators are calculated from annual basis: the average, maximal and minimal module temperature, as well as the daily cycling temperature. Those indicators are not related only to the decrease or increase of performance but also to the degradation processes of PV systems (Lindig et al., 2018) and PV materials (Eder et al., 2018). The calculation formulas are presented in Table A1. The flowchart for the PV performance modelling and calculation of indicators is procedure is presented in Fig. 7.

5. Worldwide PV performance mapping

Our methodology is used to simulate a PV system with crystalline silicon (c-Si) modules, since this technology has the highest market share (Philipps and Warnuth, 2019). The c-Si PV modules are typically characterized by a power-temperature coefficient (γ) equivalent to $-0.45\%/^{\circ}\text{C}$ and the module temperature at Nominal Operating Conditions (T_{NOC}) equal to 44°C , deriving in a Ross coefficient (k_{Ross}) of $0.03^{\circ}\text{C m}^2/\text{W}$. The balance-of-system efficiency (η_{BoS}) was selected to be 85% for all locations in the world. In this case study, shading, soiling and snow losses are excluded and the Performance Loss factor (PL) representing degradation is neglected. Spectral and angular-reflection losses are calculated for each location using the coefficients given in (Martín and Ruiz, 2005, 1999).

Fig. 8 shows the worldwide mapping of Performance Ratio (PR) for a typical PV system with c-Si PV modules. In Fig. A2(a and b), the Final Energy Yield (Y_f) and the maximal Module Operating Temperature (T_{modmax}) are also plotted.

The synthetic data in hourly resolution calculated from ERA-Interim is correlated with ground measurements (GHI and T_{amb}) of 22 stations from the BSRN (more details in Table A1). The data from BSRN stations is aggregated to hourly basis for a typical day per month. Each station is compared to the closest simulated point in the spatial grid.

The scatter plots of both variables in Fig. 9a and b, justify the good agreement between simulated and measured data. The coefficient of determination (R^2), root-mean-squared-error (RMSE) and mean-bias-error (MBE) are indicated in the figures. The modelling in all locations present considerable low RMSE and MBE. Despite the relatively high R^2 , the uncertainty varies from location to location.

Fig. 8. Worldwide mapping of Final Energy Yield for a PV system with typical c-Si PV modules. Parameters used: $k_{Ross} = 0.03^{\circ}\text{C m}^2/\text{W}$; $\gamma = -0.45\%/^{\circ}\text{C}$; $\eta_{BoS} = 85\%$.

Fig. 9. Comparison of hourly synthetic data from ERA Interim and hourly measured data from 22 stations of the BSRN. (a) Ambient Temperature, (b) Global Horizontal Irradiance. Legends indicate the R^2 , RMSE and MBE for each station.

6. Implications of the KGPV zones to PV performance indicators

One location per KGPV zone was selected to analyse and compare the PV performance of a typical c-Si PV system (see the geographical distribution in Fig. A3). For comparison between deserts, we also included additionally the Atacama Desert-Chile and the Gibson Desert-Australia. In Table 5 we present the simulated PV indicators per climate zone (complementary explanation of indicators is presented in Table A2).

Regarding the final energy yield (Y_f), the highest production occurs as expected at locations with high irradiances (like deserts and steppes). However, due to higher temperatures, the Performance Ratio (PR) in desert areas is lower. Concerning the Unit Capacity Factor (UCF), which represents the percentage of time over one year when the PV system is under operation (Kirm et al., 2017), in places with high irradiation and large amount of sun hours during the year, the UCF can reach over 20%, though in cloudy places, such as the Cold or Temperate climates, it can hardly get over 14%. Tropical climate presents UCFs of 16–18% despite the high irradiation, which is mainly due to the tropical

rain and cloud periods along the year and constant high ambient temperatures. In Minnesota-USA, we got an average UCF of 15%, but the temperature cycling (ΔT_{mod}) is extremely high which could accelerate the PV module degradation. Notably, Atacama Desert-Chile presents the highest Y_f and UCF with relatively low temperatures, which is highly favourable for PV technologies, while Gibson Desert-Australia and Phoenix-USA present also high solar resources in terms of Y_f and UCF, but high temperatures can be harmful for the long-term operation.

7. Application under SSP5-8.5 climate change scenario

Once defined the KGPV map and PV performance modelling structured, we evaluate the evolution of land-surface per climate zone and also the future operation of PV systems in view of the climate change scenarios.

7.1. KGPV zones towards 2100

First, the proposed climate classification is calculated from 2015 to

Table 5

Simulated performance indicators for selected cities in each KGPV climate zone. ($k_{Ross} = 0.03 \text{ } ^\circ\text{C m}^2/\text{W}$; $\gamma = -0.45 \text{ } ^\circ\text{C}/^\circ\text{C}$; $\eta_{BoS} = 85\%$).

KGPV	City	Country	Tilt	H_{ann}	H_{eff}	Y_r	Y_f	PR	UCF	T_{ann}	T_{modavg}	T_{modmax}	T_{modmin}	ΔT_{mod}
AK	Jos	Nigeria	11.6	2073	2120	2023	1556	0.796	0.178	26.03	39.13	59.56	15.62	43.94
AH	Bangkok	Thailand	15.6	1811	1856	1783	1368	0.789	0.156	29.39	40.89	56.76	21.56	35.19
BK	Phoenix	USA	28.5	1986	2175	2057	1582	0.805	0.197	22.52	36.69	65.23	4.31	60.92
BH	Garagum	Turkmenistan	31.5	1788	2037	1938	1542	0.836	0.176	16.27	28.56	61.86	-2.84	64.70
CK	Marrakesh	Morocco	27.4	2116	2334	2209	1740	0.821	0.198	18.51	32.66	59.22	4.11	55.11
CH	Almeria	Spain	30.2	1941	2186	2073	1653	0.831	0.188	16.41	29.94	58.02	4.49	53.53
DH	Atlanta	USA	28.7	1707	1866	1783	1438	0.837	0.164	17.06	28.42	51.60	0.50	51.10
DM	Ljubljana	Slovenia	34.0	1346	1454	1403	1176	0.876	0.134	9.75	18.29	46.01	-4.03	50.04
DL	Berlin	Germany	36.4	1150	1280	1242	1038	0.878	0.118	10.52	17.77	46.31	-1.43	47.74
EM	Minnesota	USA	34.4	1440	1658	1592	1331	0.884	0.152	6.21	16.14	50.07	-17.41	67.48
EL	Moscow	Russia	37.4	1044	1150	1119	943	0.890	0.117	7.58	14.48	44.56	-9.29	53.85
BK	Atacama	Chile	23.4	2392	2518	2346	1861	0.824	0.232	15.37	31.79	51.84	8.52	43.33
BK	Gibson	Australia	24.0	2184	2325	2201	1684	0.796	0.192	24.80	39.07	62.82	8.23	54.59

- Tilt Optimal tilt angle for fixed mounting [°].
- H_{ann} Annual Global Horizontal Irradiation [kWh/m²].
- H_{eff} Annual Effective Irradiation at Plane-of-Array [kWh/m²].
- Y_r Reference energy yield [kWh/kWp].
- Y_f Final energy yield [kWh/kWp].
- PR Performance Ratio.
- UCF Unit Capacity Factor.
- T_{ann} Annual average ambient temperature [°C].
- T_{modavg} Annual average module operating temperature [°C].
- T_{modmax} Annual maximal module operating temperature [°C].
- T_{modmin} Annual minimal module operating temperature [°C].
- ΔT_{mod} Annual module operating temperature cycling [°C].

Table A1 Details of BSRN stations used for the validation of GHI and T_{amb} .

Label	Location	Latitude	Longitude	Elevation	Time frame
BIL	Oklahoma, USA	36.6	−97.5	317	1993–09 to 2017–05
CAB	Cabauw, Netherlands	52.0	4.9	0	2005–02 to 2019–05
CAR	Carpentras, France	44.1	5.1	100	1996–09 to 2018–12
CNR	Pamplona, Spain	42.8	−1.6	471	2009–07 to 2019–02
DAA	De Aar, South Africa	−30.7	24.0	1287	2000–06 to 2019–02
DAR	Darwin, Australia	−12.4	130.9	30	2002–03 to 2015–01
E13	Oklahoma, USA	36.6	−97.5	318	1994–01 to 2017–05
FUA	Fukuoka, Japan	33.6	130.4	3	2010–04 to 2019–04
GAN	Gandhinagar, India	23.1	72.6	65	2014–06 to 2019–01
GOB	Gobabeb, Namibia	−23.6	15.0	407	2012–05 to 2019–05
GUR	Gurgaon, India	28.4	77.2	259	2014–07 to 2019–01
HOW	Howrah, India	22.6	88.3	51	2014–10 to 2019–01
ILO	Ilorin, Nigeria	8.5	4.6	350	1992–09 to 2005–07
LIN	Lindenberg, Germany	52.2	14.1	125	1994–10 to 2017–01
LRC	Virginia, USA	37.1	−76.4	3	2014–12 to 2019–05
PAL	Palaiseau, France	48.7	2.2	156	2003–06 to 2019–02
PAY	Payerne, Switzerland	46.8	6.9	491	1992–10 to 2019–03
REG	Regina, Canada	50.2	−104.7	578	1995–01 to 2011–12
SAP	Sapporo, Japan	43.1	141.3	17	2010–04 to 2019–04
SBO	Sede Boger, Israel	30.9	34.8	500	2003–01 to 2012–12
TAT	Tateno, Japan	36.1	140.1	25	1996–02 to 2019–03
TIR	Tiruvallur, India	13.1	80.0	36	2014–08 to 2019–01

2100 using the SSP5-8.5 scenario (Kriegler et al., 2017; O'Neill et al., 2016; Riahi et al., 2011). To evaluate the trends of the percentage of global land-surface for each climate zone, indicated as Land-Surface ratio (LS_r), we calculate a 10-years rolling mean and relative values compared to the reference period ranging from 2015 to 2024. Fig. 10a and b show the relative changes in the climate zones (TP -zones and I -zones, respectively).

Triggered by the rising temperature, the warmer TP -zones, such as A -Tropical, B -Desert and C -Steppes, will increase the LS_r under the SSP5 scenario. Vice versa, F -Polar and E -Cold areas decrease their areas along the time.

On the other hand, the tendencies of I -zones do not follow a clear trend. This situation can be related with the work of (Wild et al., 2015), where differences in the evolution of cloud coverage and anthropogenic air pollution influenced by climate mitigation actions were detected at regional levels. Therefore, the land-surface ratio of I -zones evidence changes per period and it cannot be treated as the evolution of ambient temperature, since the changes are more locally dependent.

7.2. PV performance towards 2100

Fig. 11(a and b) show the evolution of the ambient temperature (T_{amb}) and global horizontal irradiation (GHI) for locations indicated

previously. Those climate variables affect directly the performance of PV systems. In all cases, T_{amb} increases, but GHI behaves different depending on the location. The combination of both variables is expressed by the PV module operating temperature (T_{mod}) and the Performance Ratio (PR) (see Fig. 11(c and d)). For example, under SSP5 scenario, Ljubljana-Slovenia will increase both T_{amb} and GHI , and for this reason, the rise of T_{mod} will lead to decrease in the PR . Minnesota-USA is showing the fastest PR reduction due to the fast rising temperature. In Jos-Nigeria, GHI drops significantly, limiting the decrease of PR only to 1.8% in 2100.

In general, results indicate a really slight reduction of performance of PV systems due to the climate change, which can reach only 0.04% year, causing a decrease of 1.2% after 30 years lifetime operation for a PV system. Comparing with a typical 0.5%/year degradation rate, the climate change can be considered as minor issue for energy production from c-Si PV modules.

8. Discussion

The versatile and adaptable structure of the combined KGPV scheme and PV performance modelling allows an easy integration of new climate variables, i.e. wind speed, relative humidity or ultra-violet

Table A2

PV Performance indicators in annual basis for correlation with KGPV climate zones.

Symbol	Name	Definition	Formula	Unit	Ref.
Y_r	Reference energy yield	Global PoA irradiation normalized by the standard irradiance value	$Y_r = \frac{f_{year} G_{eff}}{G_{STC}}$	[kWh/kWp]	(International Electrotechnical Commission, 1998)
Y_f	Final energy yield	PV energy production normalized by the nominal output power at STC	$Y_f = \frac{E_{PV}}{P_{STC}}$	[kWh/kWp]	(International Electrotechnical Commission, 1998)
PR	Performance Ratio	Quality factor of the PV system regardless of the mounting position and location	$PR = \frac{Y_f}{Y_r}$	[%]	(International Electrotechnical Commission, 1998)
UCF	Unit Capacity Factor	Percentage of time over one year when the PV system is under operation.	$UCF = \frac{E_{PV}}{365 \times 24 \times P_{STC}}$	[%]	(Kim et al., 2017)
$T_{mod,avg}$	Average Module Operating Temperature	Daylight average temperature reached by the PVMs along the year	$T_{mod,avg} = T_{mod}^-$	[°C]	–
$T_{mod,min}$	Minimal Module Operating Temperature	Average minimal temperature reached by the PV modules along the year	$T_{mod,min} = \min(T_{mod})$	[°C]	–
$T_{mod,max}$	Maximal Module Operating Temperature	Average maximal temperature reached by the PV modules along the year	$T_{mod,max} = \max(T_{mod})$	[°C]	–
ΔT_{mod}	Module operating temperature cycling	Difference between the Average maximal temperature and minimal temperature reached by the PV modules along the year	$\Delta T_{mod} = T_{mod,max} - T_{mod,min}$	[°C]	–

Fig. 10. 10-years rolling mean evolution of the Land-Surface ratio for (a) TP-zones and (b) I-zones.

irradiation etc., and expands the usage of the model on the reliability and degradation of specific materials and components of a PV system, as well as for climate change studies.

During the validation and review of previous PV performance modelling, we came up with the following findings:

- Irradiation models, such as Clear Sky, Decomposition and Transposition have to be improved and validated worldwide or at least in some specific climate zones.
- Our selection of the Simplified-Solis model (for estimation of Clear Sky Irradiance) and Erbs model (for transposition of irradiances) has been based on simplicity. New models (e.g. (Hofmann and Seckmeyer, 2017b; Ineichen, 2018)) can provide better results but require the inclusion of more climate variables, which can again,

propagate more uncertainty or increase the computation resources needed.

- Transposition models need further validation for global applications and for different fixed mounting positions, as well as for tracking systems.
- The sun position algorithm is of minor importance due to really low calculation uncertainties (Hofmann and Seckmeyer, 2017a; Reda and Andreas, 2008), but horizon shadings due to mountains or even close obstacles can largely increase the accuracy of outcomes, especially in urban environments or highlands.
- For the energy output calculation, we kept the simplest model using the irradiance and ambient temperature. For future calculations, wind speed and non-linearity responses should be considered.

Fig. 11. Evolution of relevant PV performance indicators for c-Si PV modules under the SSP5-8.5 climate change scenario. Annual differences of 10 years rolling mean for: (a) Ambient Temperature, (b) Global Horizontal Irradiation, (c) Maximal Module Operating Temperature and (d) Performance Ratio.

Fig. A1. Thresholds for the second KGPV classification level to set (a) the Temperature-Precipitation (TP-) zones based on the criteria from KG scheme, and (b) the thresholds for Irradiation (I-) zones based on the Annual Global Horizontal Irradiation.

In addition, the climate change evaluation carried out has brought us new challenges regarding the PV performance over the course of the century. In the future, it will be important to include the GHG emissions and atmospheric composition to understand why P_R and T_{mod} are changing in specific locations; is the changing because of the increase/decrease in pollution? Are they directly correlated with climate mitigation actions?

9. Conclusion

We are proposing a new Köppen-Geiger-Photovoltaic classification scheme with 12 climate zones to standardize the evaluation of PV systems around the World. The proposed scheme is based on the widely used Köppen-Geiger classification scheme, upgraded with information of the solar irradiation, the most important parameter for photovoltaics.

Fig. A2. Worldwide mapping of (a) final Energy Yield and (b) Maximal Module Operating Temperature for a PV system with c-Si PV modules. Parameters used: $k_{Ross} = 0.03\text{ }^{\circ}\text{C m}^2/\text{W}$; $\gamma = -0.45\%/^{\circ}\text{C}$; $\eta_{BoS} = 85\%$.

Fig. A3. Cities representing each KGPV zone in the Northern hemisphere. Additionally, Atacama desert-Chile and Gibson desert-Australia are included in our study. The first letter indicates the Temperature-Precipitation (TP)-zones: A-Tropical, B-Desert, C-Steppe, D-Temperate, E-Cold and F- Polar. The second letter indicates the Irradiation (I)-zones: K-Very High, H-High, M-Medium and L-Low irradiation.

The KGPV classification scheme divides the Earth, first, into Tropical (A), Desert (B), Steppe (C), Temperate (D), Cold (E) and Polar (F) climates, and then into Low (L), Medium (M), High (H) and Very High (K) irradiation zones. The 24 possible climate zones were reduced by the population density and land-surface ratio to only 12 climate zones of the KGPV scheme to keep the classification simple and easily understandable. With this approach we suggest to sacrifice less relevant zones (microclimates) to make the model friendlier to use.

The presented KGPV classification scheme is given in a resolution of $0.5^\circ \times 0.5^\circ$, which is enough to keep the computational time in reasonable time frames and evaluate the KGPV climate zones and PV performance globally through the combination of existing irradiance and PV performance models.

The proposed structure is modular and can be easily updated with new models and input data, as well as with new evaluation parameters. In the paper, we are presenting the analysis of performance indicators for the c-Si technology for each climate zone from an electrical and thermal point of view. The uncertainty of the model largely depends on the quality of the input data and can deviate largely from the acceptable values in specific locations like high mountains and coastal regions. However, the developed model together with the used irradiation database proves to be a reliable tool for PV performance modelling.

We have calculated several PV indicators regarding the electrical performance of PV modules and systems. Complementing the typical performance indicators, Performance Ratio (PR) and final Energy Yield (Y_f), we include the Unit Capacity Factor (UCF) to compare the availability of PV power plants over a year. Furthermore, we introduced thermal indicators to compare locations according to the module operating temperature T_{mod} . Our study showed that the best location for PV is Atacama Desert-Chile area because of the very high irradiation and high numbers of sun hours due to the relative vicinity to the equator (for example, in comparison to the desert area of Phoenix). However, the highest PR values we obtained in Moscow (EL climate zone - Cold climate with low irradiation) but the annual energy production is lower due to the lower irradiation levels.

Moreover, we have applied our schemes (KGPV climate classification and PV performance modelling) to climate change scenarios. We considered the highest greenhouse gas emission scenario, the SSP5-8.5 under the frame of ScenarioMIP, to evaluate the performance of c-Si PV modules over the 21st century, concluding that cities or climate zones will have different climate evolution due to climate mitigation actions, but anyway due to the global rising temperature under this scenario, the Performance Ratio of c-Si PV modules can decrease in all locations, between 0.5% and 1% by 2050 and between 2% and 3% by 2100. Finally, KGPV classification together with the PV performance analyses can be a powerful tool to make long-term degradation and Levelized cost of energy (LCOE) analyses, and world classification mapping of PV performance including climate change scenarios.

Declaration of Competing Interest

The authors declare no conflicts of interest.

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Author contributions

J.A.V. worked on data processing, simulations and analyses. K.B. and M.T. discussed the results and helped to improve the schemes. All the authors discussed the results and contributed, read and commented the manuscript.

Appendix

Description of shared research data

The Köppen-Geiger-Photovoltaic climate classification and generated data for the worldwide PV performance ($k_{ross} = 0.03^\circ\text{C m}^2/\text{W}$; $\gamma = -0.45\%/^\circ\text{C}$; $\eta_{BoS} = 85\%$) presented in this work is available as Mendeley data. The given data cover the annual average values for the years between 1990 and 2016. Every point on the global map is represented as a row with the following variables:

- Latitude in decimal degrees,
- Longitude in decimal degrees,
- KGPV: Köppen-Geiger-Photovoltaic climate classification,
- Y_f : Final Energy Yield [kWh/kWp],
- H_{ann} : Annual Global Horizontal Irradiation [kWh/m²],
- H_{eff} : Annual Effective Irradiation at Plane-of-Array [kWh/m²],
- PR: Performance Ratio [-],
- UCF: Unit Capacity Factor [-],
- $T_{amb,avg}$: Annual average module operating temperature [$^\circ\text{C}$],
- $T_{mod,max}$: Annual maximal module operating temperature [$^\circ\text{C}$],
- Tilt: Optimal tilt angle for fixed mounting [$^\circ$].

References

- Amillo, A.G., Ntsangwane, L., Huld, T., Trentmann, J., 2018. Comparison of satellite-retrieved high-resolution solar radiation datasets for South Africa. *J. Energy Southern Africa* 29, 63–76. <https://doi.org/10.17159/2413-3051/2018/v29i2a3376>.
- Andrews, R.W., Pollard, A., Pearce, J.M., 2013. The effects of snowfall on solar photovoltaic performance. *Sol. Energy* 92, 84–97. <https://doi.org/10.1016/j.solener.2013>.

- 02.014.
- Ascencio-Vásquez, J., Brecl, K., Topič, M., 2018. Köppen-Geiger-Photovoltaic Climate Classification. In: IEEE 7th World Conference on Photovoltaic Energy Conversion, WPEC 2018 - A Joint Conference of 45th IEEE PVSC, 28th PVSEC and 34th EU PVSEC, pp. 2270–2275. <https://doi.org/10.1109/PVSC.2018.8547952>.
- Bogenrieder, J., Hüttner, M., Luchscheider, P., Hauch, J., Camus, C., Brabec, C.J., 2018. Technology-specific yield analysis of various photovoltaic module technologies under specific real weather conditions. *Prog. Photovolt. Res. Appl.* 26, 74–85. <https://doi.org/10.1002/ppp.2921>.
- Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. *Market. Sci.* 31, 900–912. <https://doi.org/10.1287/mksc.1120.0727>.
- Bora, B., Kumar, R., Sastry, O.S., Prasad, B., Mondal, S., Tripathi, A.K., 2018. Energy rating estimation of PV module technologies for different climatic conditions. *Sol. Energy* 174, 901–911. <https://doi.org/10.1016/j.solener.2018.09.069>.
- Boucher, O., Denvil, S., Caubel, A., Foujols, M.A., 2018. IPSL IPSL-CM6A-LR model output prepared for CMIP6 CMIP. *Earth Syst. Grid Feder.* <https://doi.org/10.22033/ESGF/CMIP6.1534>.
- Center for International Earth Science Information Network - CIESIN - Columbia University, 2018. Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 10.
- Cordero, R.R., Damiani, A., Laroze, D., MacDonell, S., Jorquera, J., Sepúlveda, E., Feron, S., Llanillo, P., Labbe, F., Carrasco, J., Ferrer, J., Torres, G., 2018. Effects of soiling on photovoltaic (PV) modules in the Atacama Desert. *Sci. Rep.* 8, 1–14. <https://doi.org/10.1038/s41598-018-32291-8>.
- Das, S.K., Verma, D., Nema, S., Nema, R.K., 2017. Shading mitigation techniques: state-of-the-art in photovoltaic applications. *Renew. Sustain. Energy Rev.* 78, 369–390. <https://doi.org/10.1016/j.rser.2017.04.093>.
- Dash, P.K., Gupta, N.C., 2015. Effect of temperature on power output from different commercially available photovoltaic modules. *Int. J. Eng. Res. Appl.* 5, 5.
- Dash, P.K., Gupta, N.C., Rawat, R., Pant, P.C., 2017. A novel climate classification criterion based on the performance of solar photovoltaic technologies. *Sol. Energy* 144, 392–398. <https://doi.org/10.1016/j.solener.2017.01.046>.
- Dharshing, S., 2017. Household dynamics of technology adoption: a spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. *Energy Res. Social Sci.* 23, 113–124. <https://doi.org/10.1016/j.erss.2016.10.012>.
- Driemel, A., Augustine, J., Behrens, K., Colle, S., Cox, C., Cuevas-Agulló, E., Denn, F.M., Duprat, T., Fukuda, M., Grobe, H., Haefelin, M., Hodges, G., Hyett, N., Iijima, O., Kallits, A., Knap, W., Kustov, V., Long, C.N., Longenecker, D., Lupi, A., Maturilli, M., Mimouni, M., Ntsangwane, L., Ogihara, H., Olano, X., Olefs, M., Omori, M., Passamani, L., Bueno Pereira, E., Schmithusen, H., Schumacher, S., Sieger, R., Tamlyn, J., Vogt, R., Vuilleumier, L., Xia, X., Ohmura, A., König-Langlo, G., 2018. Baseline surface radiation network (BSRN): structure and data description (1992–2017). *Earth Syst. Sci. Data* 10, 1491–1501. <https://doi.org/10.5194/essd-10-1491-2018>.
- Duan, Q., Hsu, K.-L., Ashouri, H., Sorooshian, S., Miao, C., Sun, Q., 2017. A review of global precipitation data sets: data sources, estimation, and intercomparisons. *Rev. Geophys.* 56, 79–107. <https://doi.org/10.1002/2017rg000574>.
- Dubey, S., Sarvaiya, J.N., Seshadri, B., 2013. Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world - a review. *Energy Procedia* 33, 311–321. <https://doi.org/10.1016/j.egypro.2013.05.072>.
- Eder, G.C., Voronko, Y., Dimitriadis, S., Knöbl, K., Újvári, G., Berger, K.A., Halwachs, M., Neumaier, L., Hirschl, C., 2018. Climate specific accelerated ageing tests and evaluation of ageing induced electrical, physical, and chemical changes. *Prog. Photovolt. Res. Appl.* 1–16. <https://doi.org/10.1002/ppp.3090>.
- Erbs, D.G., Klein, S.A., Duffie, J.A., 1982. Estimation of the diffuse radiation fraction for hourly, daily and monthly-average global radiation. *Sol. Energy* 28, 293–302. [https://doi.org/10.1016/0038-092X\(82\)90302-4](https://doi.org/10.1016/0038-092X(82)90302-4).
- ETIP-PV, 2017. The true competitiveness of Solar PV: A European case study.
- Graziano, M., Gillingham, K., 2015. Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. *J. Econ. Geogr.* 15, 815–839. <https://doi.org/10.1093/jeg/lbu036>.
- Haegel, N.M., Atwater, H., Barnes, T., Breyer, C., Burrell, A., Chiang, Y.-M., De Wolf, S., Dimmler, B., Feldman, D., Glunz, S., Goldschmidt, J.C., Hochschild, D., Inzunza, R., Kaizuka, I., Kroposki, B., Kurtz, S., Leu, S., Margolis, R., Matsubara, K., Metz, A., Metzger, W.K., Morjaria, M., Niki, S., Nowak, S., Peters, I.M., Philipps, S., Reindl, T., Richter, A., Rose, D., Sakurai, K., Schlattmann, R., Shikano, M., Sinke, W., Sinton, R., Stanbery, B.J., Topic, M., Tumas, W., Ueda, Y., van de Lagemaat, J., Verlinden, P., Vetter, M., Warren, E., Werner, M., Yamaguchi, M., Bett, A.W., 2019. Terawatt-scale photovoltaics: transform global energy. *Science* 364, 836–838. <https://doi.org/10.1126/science.aaw1845>.
- Harris, I., Jones, P.D., Osborn, T.J., Lister, D.H., 2014. Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 dataset. *Int. J. Climatol.* 34, 623–642. <https://doi.org/10.1002/joc.3711>.
- Hegedus, S., 2013. Review of photovoltaic module energy yield (kWh/kW): comparison of crystalline Si and thin film technologies. *Wiley Interdiscipl. Rev.: Energy Environ.* 2, 218–233. <https://doi.org/10.1002/wene.61>.
- Hofmann, M., Seckmeyer, G., 2017a. Influence of various irradiance models and their combination on simulation results of photovoltaic systems. *Energies* 10. <https://doi.org/10.3390/en10101495>.
- Hofmann, M., Seckmeyer, G., 2017b. A new model for estimating the diffuse fraction of solar irradiance for photovoltaic system simulations. *Energies* 10. <https://doi.org/10.3390/en10020248>.
- Huld, T., Gottschalg, R., Beyer, H.G., Topič, M., 2010. Mapping the performance of PV modules, effects of module type and data averaging. *Sol. Energy* 84, 324–338. <https://doi.org/10.1016/j.solener.2009.12.002>.
- Huld, T., Gracia Amillo, A.M., 2015. Estimating PV module performance over large geographical regions: the role of irradiance, air temperature, wind speed and solar spectrum. *Energies* 8, 5159–5181. <https://doi.org/10.3390/en8065159>.
- IEA PVPS, 2018. Trends 2018 in Photovoltaic Applications (No. IEA PVPS T1-34:2018). International Renewable Energy Agency.
- Ineichen, P., 2018. High turbidity Solis clear sky model: development and validation. *Rem. Sens.* 10. <https://doi.org/10.3390/rs10030435>.
- Ineichen, P., 2008. A broadband simplified version of the Solis clear sky model. *Sol. Energy* 82, 758–762. <https://doi.org/10.1016/j.solener.2008.02.009>.
- International Electrotechnical Commission, 1998. IEC61724:1998, Photovoltaic system performance monitoring-guidelines for measurement, data exchange and analysis.
- IPCC, 2018. Special Report: Global Warming of 1.5 °C. Intergovernmental Panel on Climate Change.
- IRENA, 2019. Renewable Capacity Statistics 2019. International Renewable Energy Agency, Abu Dhabi.
- Jacobson, M.Z., Jadhav, V., 2018. World estimates of PV optimal tilt angles and ratios of sunlight incident upon tilted and tracked PV panels relative to horizontal panels. *Sol. Energy* 169, 55–66. <https://doi.org/10.1016/j.solener.2018.04.030>.
- Jones, P.D., Harpham, C., Troccoli, A., Gschwind, B., Ranchin, T., Wald, L., Goodess, C.M., Dorling, S., 2017. Using ERA-interim reanalysis for creating datasets of energy-relevant climate variables. *Earth Syst. Sci. Data* 9, 471–495. <https://doi.org/10.5194/essd-9-471-2017>.
- Jordan, D.C., Kurt, S.R., VanSant, K., Newmiller, J., 2016. Compendium of photovoltaic degradation rates: photovoltaic degradation rates. *Prog. Photovolt. Res. Appl.* 24, 978–989. <https://doi.org/10.1002/ppp>.
- Kirn, B., Brecl, K., Topič, M., 2015. A new PV module performance model based on separation of diffuse and direct light. *Sol. Energy* 113, 212–220. <https://doi.org/10.1016/j.solener.2014.12.029>.
- Kirn, B., Čepin, M., Topič, M., 2017. Effective load carrying capability of solar photovoltaic power plants - case study for Slovenia. In: 27th European Safety and Reliability Conference, ESREL 2017. Portorož, Slovenia. <https://doi.org/10.1201/9781315210469-408>.
- Koehl, M., Heck, M., Wiesmeier, S., 2018. Categorization of weathering stresses for photovoltaic modules. *Energy Sci. Eng.* 6, 93–111. <https://doi.org/10.1002/ese3.189>.
- Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F., 2007. World map of the Köppen-Geiger climate classification updated. *Hydrol. Earth Syst. Sci.* 11, 1633–1644. <https://doi.org/10.5194/hess-11-1633-2007>.
- Kriegler, E., Bauer, N., Popp, A., Humpenöder, F., Leimbach, M., Streffer, J., Baumstark, L., Bodirsky, B.L., Hilaire, J., Klein, D., Mouratiadou, I., Weindl, I., Bertram, C., Dietrich, J.P., Luderer, G., Pehl, M., Pietzcker, R., Piontek, F., Lotze-Campen, H., Biewald, A., Bonsch, M., Giannousakis, A., Kreidenweis, U., Müller, C., Rolinski, S., Schultes, A., Schwanitz, J., Stevanovic, M., Calvin, K., Emmerling, J., Fujimori, S., Edenhofer, O., 2017. Fossil-fueled development (SSP5): an energy and resource intensive scenario for the 21st century. *Global Environ. Change* 42, 297–315. <https://doi.org/10.1016/j.gloenvcha.2016.05.015>.
- Lave, M., Hayes, W., Pohl, A., Hansen, C.W., 2015. Evaluation of global horizontal irradiance to plane-of-array irradiance models at locations across the United States. *IEEE J. Photovolt.* 5, 597–606. <https://doi.org/10.1109/JPHOTOV.2015.2392938>.
- Lindig, S., Kaaya, I., Weis, K.A., Moser, D., Topič, M., 2018. Review of statistical and analytical degradation models for photovoltaic modules and systems as well as related improvements. *IEEE J. Photovolt.* 8, 1773–1786. <https://doi.org/10.1109/JPHOTOV.2018.2870532>.
- Loutzenhiser, P.G., Maxwell, G.M., Strachan, P.A., Manz, H., Frank, T., Felsmann, C., 2006. Empirical validation of models to compute solar irradiance on inclined surfaces for building energy simulation. *Sol. Energy* 81, 254–267. <https://doi.org/10.1016/j.solener.2006.03.009>.
- Louwen, A., de Waal, A.C., Schropp, R.E.I., Faaij, A.P.C., van Sark, W.G.J.H.M., 2017. Comprehensive characterisation and analysis of PV module performance under real operating conditions. *Prog. Photovolt. Res. Appl.* 25, 218–232. <https://doi.org/10.1002/ppp>.
- Martín, N., Ruiz, J.M., 2005. Annual angular reflection losses in PV modules. *Prog. Photovolt. Res. Appl.* 13, 75–84. <https://doi.org/10.1002/ppp.585>.
- Martín, N., Ruiz, J.M., 1999. A new method for the spectral characterisation of PV modules. *Prog. Photovolt. Res. Appl.* 7, 299–310. [https://doi.org/10.1002/\(SICI\)1099-159X\(199907/08\)7:4<299::AID-PIP260>3.0.CO;2-0](https://doi.org/10.1002/(SICI)1099-159X(199907/08)7:4<299::AID-PIP260>3.0.CO;2-0).
- NREL, Dobos, A.P., 2014. PVWatts version 5 manual. *Nat. Renew. Energy Lab. (NREL)* 20. <https://doi.org/10.2172/1158421>.
- O'Neill, B.C., Tebaldi, C., Van Vuuren, D.P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.F., Lowe, J., Meehl, G.A., Moss, R., Riahi, K., Sanderson, B.M., 2016. The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.* 9, 3461–3482. <https://doi.org/10.5194/gmd-9-3461-2016>.
- Palmer, D., Gottschalg, R., Betts, T., Koumpli, E., Cole, I., 2018. A GIS-based method for identification of wide area rooftop suitability for minimum size PV systems using LiDAR data and photogrammetry. *Energies* 11, 3506. <https://doi.org/10.3390/en1123506>.
- Philipps, S., Warnuth, W., 2019. Photovoltaics Report, updated: 14 March 2019. Fraunhofer ISE.
- PVSyst, 2019. PVSyst Software [WWW Document]. URL <https://www.pvsyst.com/> (accessed 4.1.19).
- Reda, I., Andreas, A., 2008. Solar position algorithm for solar radiation applications (revised). *United States*. <https://doi.org/10.2172/15003974>.
- Reinders, A., Moser, D., van Sark, W., Oreski, G., Pearsall, N., Scognamiglio, A., Leloux, J., 2018. Introducing 'PEARL-PV': Performance and Reliability of Photovoltaic Systems: Evaluations of Large-Scale Monitoring Data. 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion, WPEC 2018 - A Joint Conference of 45th IEEE

- PVSC, 28th PVSEC and 34th EU PVSEC.
- Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N., Rafaj, P., 2011. RCP 8.5—a scenario of comparatively high greenhouse gas emissions. *Clim. Change* 109, 33. <https://doi.org/10.1007/s10584-011-0149-y>.
- Schamm, K., Ziese, M., Raykova, K., Becker, A., Finger, P., Meyer-Christoffer, A., Schneider, U., 2016. GPCC Full Data Daily Version 1.0: Daily Land-Surface Precipitation from Rain Gauges built on GTS based and Historic Data. <https://doi.org/10.5065/D6V69GRT>.
- Schweiger, M., Herrmann, W., Gerber, A., Rau, U., 2017. Understanding the energy yield of photovoltaic modules in different climates by linear performance loss analysis of the module performance ratio. *IET Renew. Power Gener.* <https://doi.org/10.1049/iet-rpg.2016.0682>.
- Skoplaki, E., Palyvos, J.A., 2009. Operating temperature of photovoltaic modules: a survey of pertinent correlations. *Renew. Energy* 34, 23–29. <https://doi.org/10.1016/j.renene.2008.04.009>.
- SolarPower Europe, 2018. Global Market Outlook For Solar Power / 2018 – 2022.
- Stein, J.S., Holmgren, W.F., Forbess, J., Hansen, C.W., 2016. PVLIB: Open Source Photovoltaic Performance Modeling Functions for Matlab and Python. In: IEEE 43rd Photovoltaic Specialists Conference, pp. 3–8. <https://doi.org/10.1109/PVSC.2016.7750303>.
- Uppala, S.M., Healy, S.B., Balmaseda, M.A., de Rosnay, P., Isaksen, L., van de Berg, L., Geer, A.J., McNally, A.P., Matricardi, M., Haimberger, L., Dee, D.P., Dragani, R., Bormann, N., Hersbach, H., Vitart, F., Kobayashi, S., Andrae, U., Beljaars, A.C.M., Poli, P., Monge-Sanz, B.M., Peubey, C., Thépaut, J.-N., Delsol, C., Hólm, E.V., Simmons, A.J., Köhler, M., Bechtold, P., Berrisford, P., Balsamo, G., Park, B.-K., Fuentes, M., Bidlot, J., Bauer, P., Tavalato, C., Kållberg, P., Morcrette, J.-J., 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q. J. R. Meteorolog. Soc.* 137, 553–597. <https://doi.org/10.1002/qj.828>.
- Urraca, R., Gracia-Amillo, A.M., Huld, T., Martínez-de-Pison, F.J., Trentmann, J., Lindfors, A.V., Riihelä, A., Sanz-Garcia, A., 2017. Quality control of global solar radiation data with satellite-based products. *Sol. Energy* 158, 49–62. <https://doi.org/10.1016/j.solener.2017.09.032>.
- Urraca, R., Huld, T., Gracia-Amillo, A., Martínez-de-Pison, F.J., Kaspar, F., Sanz-Garcia, A., 2018a. Evaluation of global horizontal irradiance estimates from ERA5 and COSMO-REA6 reanalyses using ground and satellite-based data. *Sol. Energy* 164, 339–354. <https://doi.org/10.1016/j.solener.2018.02.059>.
- Urraca, R., Huld, T., Lindfors, A.V., Riihelä, A., Martínez-de-Pison, F.J., Sanz-Garcia, A., 2018b. Quantifying the amplified bias of PV system simulations due to uncertainties in solar radiation estimates. *Sol. Energy* 663–677. <https://doi.org/10.1016/j.solener.2018.10.065>.
- Urraca, R., Huld, T., Martínez-de-Pison, F.J., Sanz-Garcia, A., 2018c. Sources of uncertainty in annual global horizontal irradiance data. *Sol. Energy* 170, 873–884. <https://doi.org/10.1016/j.solener.2018.06.005>.
- Waichler, S.R., Wigmosta, M.S., 2003. Development of hourly meteorological values from daily data and significance to hydrological modeling at H. J. Andrews experimental forest. *J. Hydrometeorol.* 4, 251–263. [https://doi.org/10.1175/1525-7541\(2003\)4<251:DOHMFV>2.0.CO;2](https://doi.org/10.1175/1525-7541(2003)4<251:DOHMFV>2.0.CO;2).
- Wei, K.-A., Saile, S., Keiner, A., Bauermann, P., Oreski, G., Gottschalg, R., Moser, D., Topić, M., Lagunas, A.R., Chiantore, P., van Iseghem, M., 2017. Training the next generation of PV Reliability experts - New Marie-Sklodowska Curie (MSCA) project SOLAR-TRAIN. 33rd European Photovoltaic Solar Energy Conference and Exhibition. Amsterdam, The Netherlands.
- Wild, M., Folini, D., Henschel, F., Fischer, N., Müller, B., 2015. Projections of long-term changes in solar radiation based on CMIP5 climate models and their influence on energy yields of photovoltaic systems. *Sol. Energy* 116, 12–24. <https://doi.org/10.1016/j.solener.2015.03.039>.
- WRMC-BSRN, 2019. World Radiation Monitoring Center - Baseline Surface Radiation Network [WWW Document]. URL <https://www.pangaea.de/ddi?request=bsrn/BSRNEvent&format=html&title=BSRN+Stations> (accessed 3.7.19).
- Zhang, X., Liang, S., Wang, G., Yao, Y., Jiang, B., Cheng, J., 2016. Evaluation of the reanalysis surface incident shortwave radiation products from NCEP, ECMWF, GSFC, and JMA using satellite and surface observations. *Rem. Sens.* 8. <https://doi.org/10.3390/rs8030225>.