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Modelling the global photovoltaic potential on land and its sensitivity to climate change

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Abstract

Solar photovoltaic (PV) energy is fundamental for decarbonizing the global economy and supporting the renewable energy transitions that are needed to combat climate change. Potential solar power production at a given location is a function of climatic variables that will change over time and so climate change needs to be accounted for in PV potential estimation. The future potential of PV in response to climate change has not previously been assessed consistently and globally across alternative scenarios. We develop global gridded estimates of PV potential between 2020 and 2100 as a function of spatial, climatic, technological and infrastructural conditions. We find a global technical potential of 175 111 T W h yr^{-1} in 2050, which changes by between ca. −19% (high-emission scenario) and +16% (low-emission scenario), with larger geographic variations within these scenarios. We perform a sensitivity analysis to identify key uncertainties and assess the scope for emerging PV technologies to offset negative climate impacts. We find that suboptimal orientation and temperature losses have the largest negative effects (reducing PV potential by up to ca. 50% and ca. 10% respectively), but that new technologies may be able to generate gains of more than 200% if successfully deployed worldwide. Solar power can make an important contribution to energy production over the coming decades and the demand for renewable energy could be met by PV deployment on between 0.5% and 1% of the global land area, provided its deployment accounts for the location-specific impacts of climate change.

1. Introduction

Solar energy is one of the most abundant and clean alternatives to conventional hydrocarbon fuels, and one of the most promising for facilitating global access to economic, reliable, and secure energy. However, the potential of solar energy has been consistently underestimated in the past and remains uncertain in the future (Creutzig *et al* 2017, Poddar *et al* 2021, Zakiah *et al* 2021). Rapid technological development, policy support, and increasing costs of competing forms of energy have so far all helped solar photovoltaics (PV) to outperform projections (Schmidt *et al* 2012, Creutzig *et al* 2017, Mohan *et al* 2022). These factors will remain crucial, but future deployment will also depend on the effects of climate change on PV energy generation by altering ambient temperature, incident solar radiation, and other environmental conditions. The lack of comprehensive assessments of PV potential across climate change scenarios has hampered robust estimation not only of present but also of future PV energy production, which could be valuable to inform investment (Adeh *et al* 2019, Feron *et al* 2021). Several studies have attempted to fill this gap using projections from general circulation models (GCMs) indicating potential climate impacts of approximately 0% to −2% in PV potential at the global scale

(Gernaat *et al* 2021). Regional studies suggest decreases in PV potential of approximately −20% in South Asia and Latin America and −34% in Sweden, on the basis of regional climate model projections (Perera *et al* 2020, Yalew *et al* 2020). While the impact of variation in solar radiation has been investigated in these previous studies, other important parameters that determine PV potential have been study-specific, focusing on particular places, technologies, or policies (Drury *et al* 2009, Gagnon *et al* 2018, Yang *et al* 2019, 2022, Poddar *et al* 2021, Zakiah and Aditya 2021, Danso *et al* 2022). No global projections have been made for a range of GCMs and climate change scenarios, which also account for uncertainties in some of the key variables that determine PV potential globally across space and time.

We model gridded global projections of PV energy potential in response to key environmental and technological factors (Durusoy *et al* 2020). We validate the model with respect to currently-installed PV sites around the world and investigate model parameter sensitivity to understand associated uncertainties (Jaxa-Rozen and Trutnevyte 2021). In doing so, we address the following research questions:

1. What is the global PV potential in various climate change scenarios accounting for key environmental and technological factors?
2. What is the sensitivity of modelled PV potential to each of these factors?
3. What are the expected climate impacts on currently installed PV sites and can new PV technologies offset negative impacts?

2. Methods

We developed a PV energy yield estimation model by modifying the global solar atlas (GSA) algorithm (ESMAP2.0 2019), which allows exploration of PV potential responses to a range of environmental and technological factors (Kawajiri *et al* 2011, Green *et al* 2021, ESMAP2.0 2019); see also details in the next section and table 1. Modifications were made to include the spatial influence of air temperature and orientation: PV efficiency has been found to decline by around 0.4% for every 1 °C increase in temperature above 25 °C, while the direction and tilt angle of a PV panel determines the amount of absorbed incident radiation and varies with latitude (Kawajiri *et al* 2011, Korfiati *et al* 2016). Wind could play an important role (positive or negative, depending on the balance of its effects on temperature and soiling), but wind speed data have very large uncertainties that make reliable projections impossible at this scale, and so these are not included. We modelled changes in the PV potential until 2100 under scenarios of low (RCP2.6), medium (RCP4.5, RCP6.0) and high (RCP8.5) climate change, assessing climate impacts on current PV sites across these scenarios and exploring how emerging PV technologies might offset negative impacts.

2.1. Data used

The environmental and technological factors included in the analysis were PV module temperature, PV module technology, and energy losses associated with dust, snow, orientation, conversion from DC to AC, DC and AC cabling, inverter power mismatching, and downtime of PV modules and transformers (Kawajiri *et al* 2011, Cordero *et al* 2018, Dhimish and Tyrrell 2022, ESMAP2.0 2019). The required input climatic variables of global incident solar radiation (k W h m^{-2} per day) and air temperature (°C) were obtained from two independent sources for the historic period and projected future scenarios. We used the 35 year period of 1970–2005 to compute averaged recent historical PV potential, with data from the CRU JRA observational dataset (providing daily means) (Harris 2022). Projected data (for RCPs 2.6, 4.5, 6.0 and 8.5) were obtained from four GCMs used in CMIP5: HadGEM2-ES, MIROC5, GFDL-ESM2M and IPSL-CM5A-LR, as these are frequently used climate models for global studies (Gernaat *et al* 2021) and the bias adjusted models in ISIMIP2b (the second simulation round of the second phase of ISIMIP) given by Lange and Büchner (2017). However, solar radiation does not show substantial differences among the scenarios and the GCMs. Conversely, GFDL-ECM2M has larger variations in the temperature across all RCPs, while HadGEM2-ES is less sensitive as compared to other GCMs (section A1.1 and figures A2, A3). For these GCMs, we took a multi-model mean for temperature and solar radiation for the respective RCPs and for the whole time series (2020–2100) and these data were used as input to the PV potential modelling (more details in section A1.1 and figures A2, A3, including on the limited variation among the GCMs, which prompted our use of mean values). The data were bias-corrected and derived from the Inter Sectoral Impact Model Intercomparison Project (ISIMIP2b) database (www.isimip.org/). The choice of CMIP5 reflected the availability of CMIP5 bias-corrected data at the time the study was undertaken, with bias-corrected CMIP6 data only becoming available at a later stage and having less influence on results than several other parameters. These projections were available at 0.5° × 0.5° spatial resolution, and so the PV energy potential was estimated at this resolution.

2.2. PV energy potential and model development

The theoretical PV energy potential was calculated for the ice-free land area of the world based on

Table 1. Details of the parameters included and the technologies used in the PV potential modelling, with their effects on modelled PV potential showing its sensitivity to each. The ranges in brackets capture possible effects while the default value, usually at the lower end of these ranges, represents a global standard value in which site-specific variation is averaged out. Further explanation is given in the text.

Parameter	Explanation	Values//losses	Effects on modelled PV potential	Reference
Orientation loss	Due to suboptimal orientation reducing incident solar, e.g. where topography or latitude limits orientation options.	0.5 (0.1–50) (%)	−1.11 to +1.01%	Global Solar Atlas (ESMAP2.0 2019)
Mismatch losses	Mainly due to the differences between the power generated from PV modules connected in series, which can arise as a result of environmental factors such as pollution and shading.	0.3 (0.1–15) (%)	−1.01 to +1.0%	
DC cabling losses	Connections from PV modules to inverters mainly cause losses due to corrosion and overheating.	2 (0.5–15) (%)	−1.12 to +1.02%	
Losses in inverter (conversion of DC to AC)	Usually calculated against the generic parameters of the most commonly used Sandia Inverter Model.	2.2 (2–15) (%)	−1.04 to +1.02%	
Availability (Downtime losses)	Sudden failure, depend on maintenance and repair timings	0.5 (0.1–10) (%)	+1.04 to +1.02%	
Losses due to dirt and soiling	Vary with the intermittent cleaning of solar panels.	3.5 (2–10) (%)	−1.26 to +1.04%	
AC cabling losses	Due to sudden voltage drop caused by a loose connection or corrosion or any other type of resistance which leads to energy losses in the wire	0.5 (0.2–3.5) (%)	−1.10 to +1.01%	
Transformer losses	Sudden failure	0.9 (0.2–3.5) (%)	−1.27 to +1.01%	
PV module temperature		18.5 °C above ambient temperature at standard test condition (STC)		Kawajiri *et al* (2011)
The ideal PV module temperature, at which efficiency losses due to heat are negligible		25 °C		
α—loss for every 1 °C increase above 25 °C of the combined PV module and air temperature		0.4%		

the geographic variation in global solar radiation (k W h m^{-2} yr^{-1}). Furthermore, technical PV potential was derived by considering several environmental and technological factors and conversion efficiencies by modifying the GSA algorithm (ESMAP2.0 2019) to include the spatial influence of temperature (Kawajiri *et al* 2011). Equation (1) penalises the PV potential by 0.4% for every 1 °C rise above 25 °C in the PV module surface temperature, and otherwise remains as in the GSA.

The technical PV energy potential of ground-mounted solar panels was calculated as:

$$E = \begin{cases} A.r.I.PR.\left[1 - \left\{\left(T_{A_{avg}} + T_m - 25\,^{\circ}\mathrm{C}\right).\alpha\right\}\right] \\ \quad .\left(1 - z_i\right),\ T_{A_{avg}} + T_m > 25\,^{\circ}\mathrm{C}) \\ A.r.I.PR.\left(1 - z_i\right),\ T_{A_{avg}} + T_m \leq 25\,^{\circ}\mathrm{C}) \end{cases} \quad (1)$$

where, E —energy (k W h), A —total solar panel Area (m^2), r—solar panel yield or efficiency (%), I—mean solar radiation on tilted panels (shadings not included) (k W h m^{-2}), PR —performance ratio (a coefficient for the constant losses from different environmental and technological factors), z_i—orientation loss, $T_{A_{avg}}$ —ambient temperature, T_m —PV module temperature (18.5 °C for conventional *Si* PV technology) and α—reduction in efficiency for every 1 °C increase in the temperature (a value of around 0.004).

The CMIP5 data have a lower climate sensitivity than many of the CMIP6 models (Zelinka *et al* 2020, Hausfather *et al* 2022), and hence the effect of temperature on PV potential is likely to be lower in our results compared with CMIP6.

A few technological parameters that incur energy losses at constant levels were used to calculate a performance ratio (PR) and the associated uncertainty was quantified using univariate sensitivity analysis (see table 1). This analysis involved changing each parameter in the model by ± 1% across its range and recording changes in the model outcomes in each case. We therefore present results using the global standard (default) values along with uncertainties derived across the ranges given in table 1 and below. Dirt and soiling on the surface of the PV module absorb, scatter and reflect a fraction of solar radiation to the environment and this reduces the amount and intensity of the sunlight penetrating the surface of the PV module and adds 2%–10% (default: 3.5%) to the angular reflectivity losses. Mismatch losses due to different maximum power points of the PV modules connected to the inverter results in heat losses, varying between 0.1 and 15% (default: 0.3%). However, minimizing these losses is possible if the same class of module is grouped and connected to the inverter (Wurster and Schubert 2014). DC cabling losses for decentralised connections from the modules to the inverters depend on the PV power plant topology, smaller string connections in the roof-top PV causes smaller current flows and so lower losses, whereas large-scale installations require combiner boxes leading to longer current paths and thus higher losses (0.5%–15%, default 2.0%) (Ekici and Kopru 2017).

Inverter losses are associated with the performance of inverters for the conversion from DC to AC (2–15%, default 2.2%), while AC cabling losses (0.2%–3.5%, default 0.5%) and transformer losses (0.2%–3.5%, default 0.9%) are associated mainly with large-scale ground-mounted PV power plant topology, where the AC outputs from the inverter are connected to grids through the transformer. Availability of the PV power supply determines downtime losses and is affected by failures or shutdowns of PV plants themselves or associated power grids (0.1%–10%, default 0.5%).

In addition to constant losses affecting the PR, PV module temperature (a combination of ambient temperature and a standard temperature gain occurring at the surface of the module) was considered as a spatial variable (see table 1). PV panel orientation also causes varying losses if not aligned optimally with incident radiation. Optimal alignment is not always possible due to latitude (and topography, but our analysis does not have the spatial resolution required to account for this), and so we consider an optimal latitude tilt facing toward the equator with the additional standard in-situ PV paneltilt of 35–40 degrees to maximise PV production (Del Cueto 2002, González-González *et al* 2022).

2.3. Model validation and climate change impacts on the existing PV sites

To validate the PV model, a large random sample of existing global PV sites was selected and stratified by the PV installed capacity and size of site (small, medium, large), with observed PV yields at these sites then compared to those estimated by the model (Kruitwagen *et al* 2021). Observed yields were from 2018 (although installation dates varied across the preceding few years and were not always available, suggesting slight differences in efficiencies), while the PV baseline model used a long-term climatic average (i.e. 1970–2005). The scatter plot and the box plot shown in figure 1 below were used to represent the fit between the actual and modelled PV potential of different PV sites (more details in the results). In addition, the Adjusted R-squared, p-value, SE (standard error), F-statistic, and MAPE (mean absolute percentage error) for the individual sample class of small, medium and large PV sites were computed to assess the model performance (table A1). We also projected climate impacts on existing PV sites with major installed capacities globally by comparing mean PV potential for the current and future climate change scenarios.

3. Results

3.1. PV energy potential model validation

Overall the model performed well in estimating the PV potential for the current PV sites, achieving an R^2 of 0.695, with greater accuracy achieved for small sites (R^2 0.726), and lesser for medium (R^2 0.6) and large (R^2 0.598) sites (more details about the metrics are given in table A1). These results are associated with the increasing variation among small, medium and large sites that is caused by the vulnerability of larger sites to environmental and technical effects that change production substantially (figure 1(a)). The median values for the PV

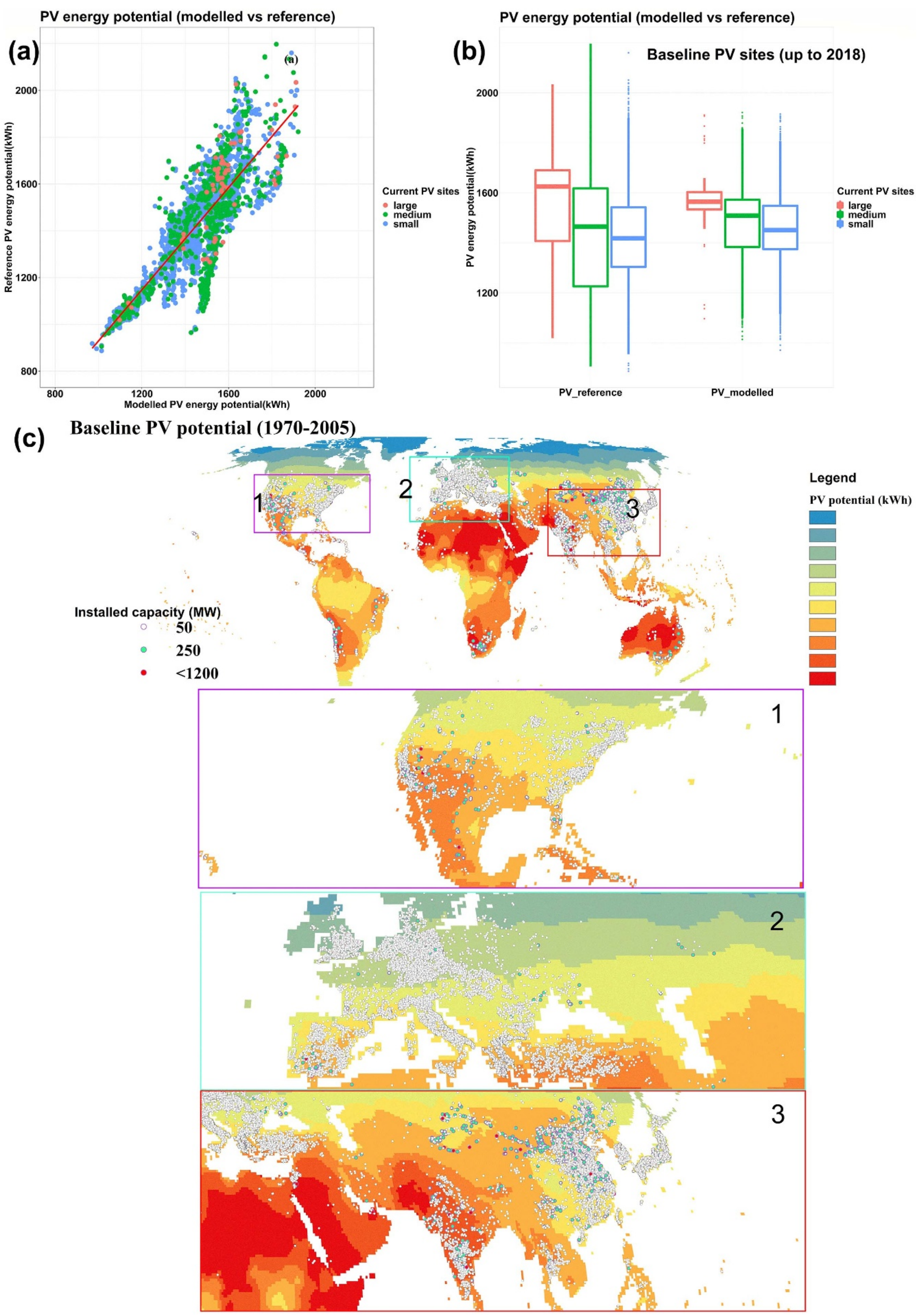

Figure 1. PV potential model validation with the actual PV installed locations a, b, c. (a) Scatter plot showing the relationship between the actual and the modelled PV potential for a large stratified random sample, (b) boxplot showing the comparison of modelled vs actual PV potential for the minimum, 1st quartile, median, 3rd quartile, and maximum, (c) current PV installations up to 2018 (Kruitwagen *et al* 2021) and modelled baseline (1970–2005) potential globally. The regions 1, 2, and 3 are zoomed in of 1(c).

potential of large, medium and small PV sites in both the modelled and the reference PV potential follow the same relative pattern, with the model slightly underestimating the PV potential for large sites and slightly overestimating the potential for medium and small sites (figure 1(b)). The tendency of the PV potential model to underestimate for large sites is due to the strict accounting for spatial parameters such as temperature and other environmental and technological parameters in the modelling, which can be partially ameliorated in large installations. The interquartile range is higher in the reference than the modelled data since every site has specific characteristics including varying technologies, which the generic PV model does not account for (figure 1(b)). Some discrepancy between observational and modelled PV is therefore to be expected, but overall the model performs well.

The baseline PV potential along with the potential from current PV installations are presented in figure 1(c). PV energy has huge potential under Arid and semi-arid climates (1283–1921 k W h) due to abundant sunshine. Dust storms and low precipitation may contribute to dust accumulation and so reduce PV efficiency, but conversely wind that does not carry dust particles can help to clean previously accumulated dust (Mussard *et al* 2018). The PV energy potential in tropical regions ranges from 1487–1854 k W h, although this might be inconsistent in some regions due to humid conditions, high temperatures, and frequent dust storms (Ye *et al* 2013). The PV energy potential in temperate regions has a larger range (971–1830 k W h) due to larger variations in weather conditions.

Regions at high altitudes such as the Andes and Himalayas have greater PV potential than the temperate regions of China, Denmark, Japan and the USA (ESMAP 2020). A small and moderate range of PV potential was found in the cold (1089–1667 k W h) and polar (1590–1625 k W h) climate zones due to fewer sunny days in these regions (figure 1(c)). Thus, the selection of sites and PV technology will play a crucial role in optimising the benefits from the high PV potential zones. Nevertheless, the global PV potential range of 802–2010 kWh is smaller than might be expected, because the distribution of temperature partially countervails the distribution of solar radiation (see figure A4 for mean PV potential for different countries in the baseline scenario). Thus, the difference between the countries with the highest PV potential (Nigeria) and the lowest (Greenland) is only just over a factor of 2 (ESMAP. 2019) (see figure 1).

The leading PV potential regions are the Middle East and North Africa (1711 k W h, mainly Egypt, Libya, Saudi Arabia, Yemen and Oman), South Asia (1663 k W h, Afghanistan, Pakistan, India, and Nepal), and Sub-Saharan Africa (1657 k W h, mainly Niger, Mauritania, Chad, Sudan, Ethiopia, Kenya, Namibia, South Africa, Botswana and Madagascar). Moderate potential occurs in East Asia and Pacific (1563 k W h, mainly Australia and China), Latin America and Caribbean (1457 k W h, mainly Brazil, Peru, Mexico, and Guatemala), and the lowest potential occurs in North America (1116 k W h, mainly USA) and Europe and Central Asia (1011 kWh mainly Spain, Turkey and Portugal).

3.2. Uncertainty and sensitivity analysis

The PV model was calibrated for large-scale ground-mounted PV systems with free-standing installations usually assembled on fixed tilted infrastructures connected to the power grid with additional cabling and transformer setups. This calibration was found to have associated uncertainties for different ranges of the parameters as set out in table 1. Figure 2(a) shows the PV potential when varied across the uncertainty ranges of different losses including minimum, maximum and default losses considered (see table 1). Figure 2(b) reflects the sensitivity of these parameters to every 1% change away from the default values (table 1). Orientation was found to be the most uncertain variable in the PV modelling, leading to the highest differences between the maximum and minimum PV potential even though its sensitivity was not the highest. Transformer and AC cable losses resulted in the lowest difference for the computed PV potential (see figure 2(a)).

Overall PV potential estimates were found to be sensitive (for every 1% change in the values) to dust, soiling and snow (−1.25%−+1.03%), transformer (−1.27%−+1%), orientation (−1.11%−+1.05%), DC (−1.12%−+1.02%) and AC cabling (−1.10%−+1%), invertor (−1.03%−+1.02%), downtime (−1.04%−+1.01%), and mismatch parameters (−1.01%−+1%) (figure 2(b)).

3.3. PV potential for climate change scenarios and climate change impacts on existing global PV sites

The PV potential in different climate change scenarios is presented in figure 3 (Saxena *et al* 2023), which indicates that Sub-Saharan Africa, the Middle East and North Africa, Latin America and Caribbean are the regions with the highest PV potential, while Europe and high-latitude countries suffer from a lack of solar radiation that causes lower PV potential. The general patterns for PV potential are similar across the climate change scenarios, but PV potential declines in the high-emission scenario compared with the low-emission scenario mostly in South Asia and Middle East and North Africa. Figure 4 shows future climate change impacts on the 50 highest-capacity PV installations worldwide, referring to the amount of electricity they produce (Kruitwagen *et al* 2021). The largest PV sites in the US, South Africa, India, China, Spain, Germany and Ireland all have reduced PV potential for all climate change scenarios. However, other locations (such as some sites in Brazil and China) show gains in PV potential across the climate change scenarios. Overall, the mean PV potential at the existing sites changes by between ca. −19% and +16%, with a maximum decrease in RCP8.5 and a maximum increase in RCP2.6.

Some of the Chinese PV sites observed an increase in PV potential across the scenarios as they receive more solar radiation and have lower temperatures in the climate scenarios. However, other Chinese

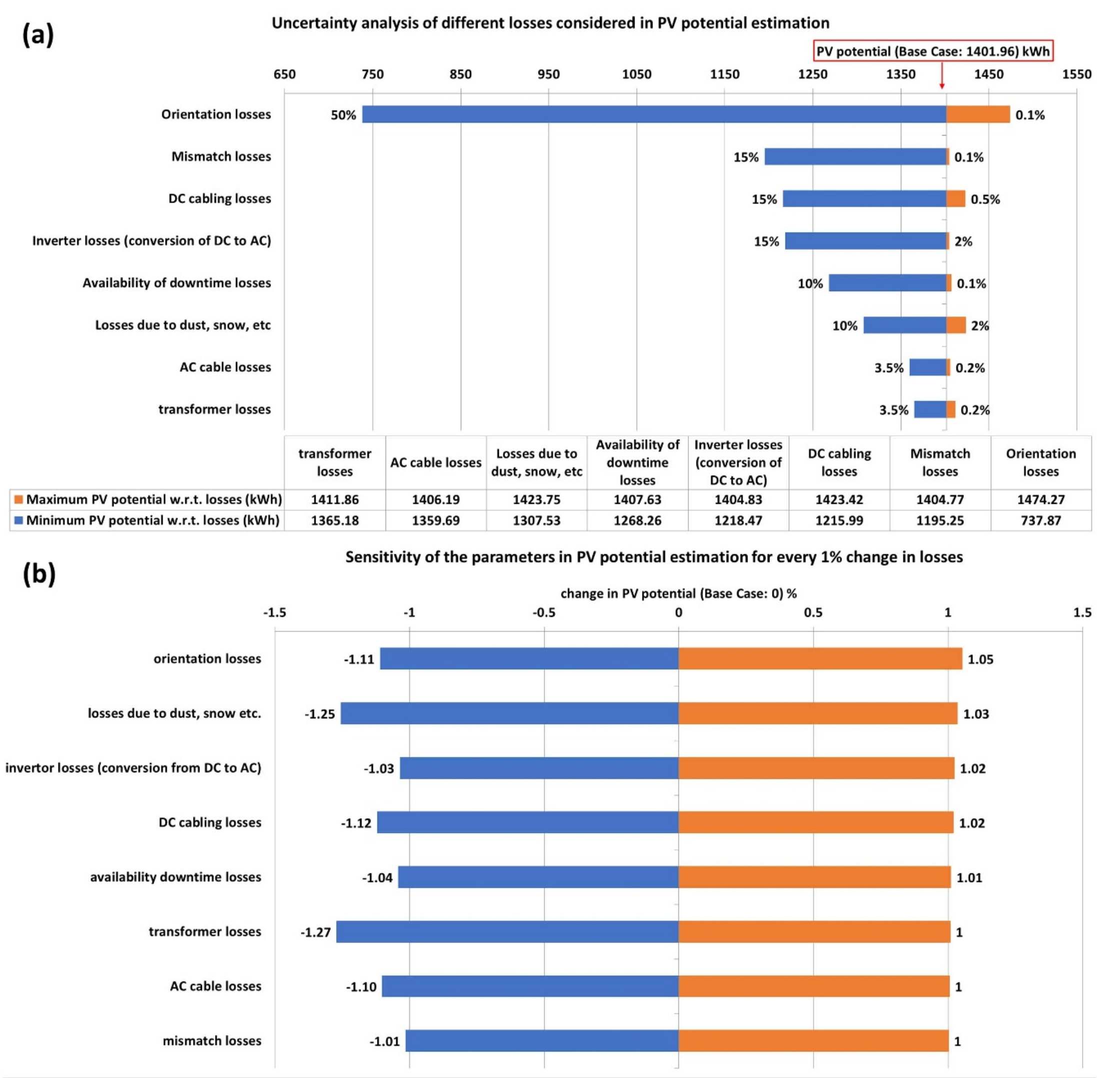

Figure 2. PV potential model parameter testing a, b (a) uncertainty analysis, (b) sensitivity analysis.

sites experience a decline in PV potential due either to less solar radiation (cloudiness), over irradiance (Zamalloa-Jara *et al* 2023) or to an increase in temperature. Of note is that reductions in PV potential are more prevalent in RCP4.5 and RCP8.5, while gains are more prevalent in RCP2.6 and RCP6.0. A greater PV potential decline in South Asia (up to 12%), Europe and Central Asia (up to 11%), and North America (up to 9%) and a moderate decline in East Asia and Pacific (up to 5%), Latin America and Caribbean (up to 4%), and Middle East and North Africa (up to 3%) were mainly attributable to the high-emission scenarios while Sub-Saharan Africa indicated both an increase from 0.4% (RCP2.6) to a lesser decline of up to 2% (RCP8.5) in the PV potential.

3.4. Potential of various PV module technologies

The technical PV potential (PV module efficiency combined with environmental and technological factors) was explored for alternative PV technologies, based on data from Green *et al* (2021). The most commonly used technologies along with their efficiencies (%) are presented in table 2. When used to model future potential, these technologies generated between ca. −58 and +212% of the 2100 values for the conventional *Crystalline Silicon* based technology. The lowest values were obtained for *Organic* panels and the highest for *III–V cells multijunctions*. Results varied widely due to uncertain estimations of technical potential, but rapid improvements in efficiency and the use of new technologies suggest that they have the potential to compensate for the negative climate impacts on PV energy generation.

4. Discussion

Mitigating climate change requires a rapid energy transition from conventional fossil fuels to renewable energy sources, and solar PV power has immense potential to facilitate this transition. Hence, it is crucial to estimate future PV potential that considers both changing climatic conditions and developments in PV module technologies (Cherp *et al* 2021, Way *et al* 2022).

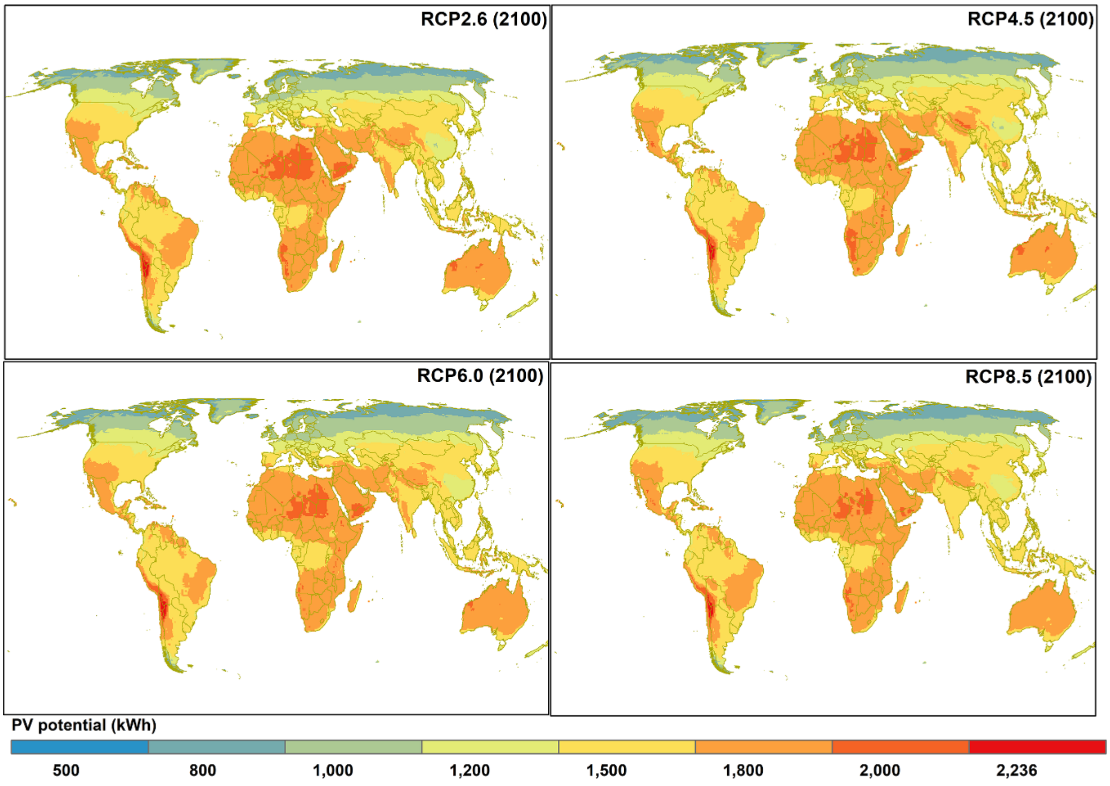

Figure 3. PV potential in different RCP scenarios. Data are averages for the years 2091–2100.

The PV potential modelled here is consistent with the results of previously published studies regarding spatial patterns and maxima (e.g., Sahara desert, western Africa, the Andes and Himalayas) and minima (e.g. high northern latitudes such as Iceland or Greenland (Kawajiri *et al* 2011, Gernaat *et al* 2021, ESMAP2.0 2019)). The global sum of solar PV power generation was computed as 1199 TWh, which is slightly lower than the 1244 TWh estimated by Kruitwagen *et al* (2021) for the same PV locations in the year 2020 using fewer parameters. Conversely, the IEA estimated an even lower value of 824 TWh for the year 2020 (IEA 2022).

We also identify substantial uncertainties in future projections, with orientation losses having the greatest negative uncertainties and PV technologies having the greatest positive uncertainties. These uncertainties were large compared to the climate change impacts and uncertainties among scenarios (figure A2) and GCMs (figure A3), suggesting that improved technology has the potential to comfortably offset climate change impacts. PV module technologies are already improving rapidly from conventional Silicon-based to thin film, multijunction, perovskites, organic and quantum dot technologies with improved efficiency and lower costs, and better estimates of their future capacities and infrastructural needs are a priority for further research (Creutzig *et al* 2017, Way *et al* 2022, Haegel *et al* 2023).

Climate uncertainties may of course be larger given other data. Many of the CMIP6 models have higher climate sensitivity than the CMIP5 models used here (Zelinka *et al* 2020, Hausfather *et al* 2022), and so our results are likely to be conservative concerning the temperature effects on PV potentials. Moreover, considering only four GCMs does not cover the full range of climate model uncertainty per emissions scenario. Our results show moderate to large climate impacts on the PV potential in different world regions, but mainly in high-emission scenarios, as also found by other studies (Zhao *et al* 2020, Dutta *et al* 2022, Matera *et al* 2022). Earlier research does give more detail in specific regions, but is less comparable globally, across parameter values, or across scenarios. Notwithstanding more detailed regional impacts, we find that the chief uncertainty regarding the temperature response of PV potential to future climate scenarios arises from different emissions scenarios rather than variations within them.

Geographically, some locations show different sensitivities in PV potential toward temperature changes, with cooler world regions being less sensitive to temperature increases than hotter regions (see figure A1). PV potential can be maximised across these regions by using PV technologies that are adapted to local climatic conditions both now and in the future (e.g., *amorphous Si* or *CdTe* based PV cells are less sensitive to temperature and good for hotter regions such as Africa, Australia, and Middle

Figure 4. Climate change impacts on current PV sites with the largest installed capacities worldwide (lower and upper plots). The bars show differences between present-day modelled PV potential and future modelled potential under climate scenarios (abbreviations used in the figure are ISO country codes: IN—India, CN—China, DE—Germany, JO—Jordan, ES—Spain, US—United States, MX—Mexico, IR—Ireland, BR—Brazil, and ZA—South Africa). Data are averages for the years 2091–2100.

Table 2. Change in technical PV potential for various PV module technologies relative to the conventional Silicon based PV technology for the year 2100. Data are averages of the years 2091–2100.

S.no	PV technology	Efficiency range (%) (Green *et al* 2021)	PV potential relative to *crystalline Silicon* (%)
1	*Silicon*	10.5–26.7	—
2	*III–V cells*	18.4–29.1	+8.9 to +75.2
3	*Thin film chalcogenide*	10–23.35	−12.5 to −4.7
4	*Amorphous microcrystalline Si*	10.2–11.9	−55.4 to −2.8
5	*Dye sensitized*	8.8–11.9	−55.4 to −16.1
6	*Organic*	9.7–11.2	−58 to −7.6
7	*Perovskite*	11.7–37.9	+11.4 to +41.9
8	*Multijunctions with crystalline Silicon*	20.1–39.2	+46.8 to +91.4
9	*III–V cells multijunction*	32.8–38.8	+45.3 to +212.3
10	*Amorphous nanocrystalline silicon (a Si nc Si) Multijunctions*	12.7–14.0	−47.5 to +20.9

East whereas *Si* based cells, being more sensitive to temperature, are good for cooler regions of Antarctica and the Himalayas). Thus, designing region-specific PV technology scenarios would provide additional information regarding the global future PV energy potential, providing important background information for large-scale investments. Since technological development correlates with economic growth, which varies between countries, the exploration of socio-economic developments -jointly with region-specific PV- would allow a nuanced estimation of the differential rates of PV uptake across the world. Further, some uncertainties in the PV potential were not accounted for in the work presented here, including high solar radiation that could occur at higher latitudes for some parts of the year (i.e. approx. above 50°) and atmospheric aerosol loads that might affect PV potential, especially in North India, China, the Gulf regions and West Africa. Countries with humid and tropical climates (e.g., Africa, the Pacific, Indonesia, Malaysia and the Philippines), mountainous regions with snow cover and deserts with high surface reflectance may also have additional uncertainties in the estimation of PV potential (ESMAP2.0 2019).

Widespread deployment of solar PV would also be subject to constraints from other land uses that are not considered here, and from requirements for PV panel processing, including the mining and recycling of metals and minerals (Sovacool *et al* 2020). Because of the need for land, PV installations can conflict with agriculture, food production and nature protection, which themselves require considerable areas of land globally. Mining for PV is less of an issue for food production (unless it spoils water) but has local effects on biodiversity and people, with further social issues being dependent on how PV deployment locations are decided and run. Multifunctional land uses such as agri-voltaics have the potential to reduce these constraints, but also require further research (Arneth *et al* 2019, Joshi *et al* 2021, Um 2022, Yeligeti *et al* 2023). Nevertheless, PVs are area efficient, supporting the UN Sustainable Development Goals and have an immense potential to produce clean energy with fewer trade-offs than the alternatives.

Data availability statement

Any data that support the findings of this study is included within the article and appendix.

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.17605/OSF.IO/8UV2S, URL: https://osf.io/8uv2s/.

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Appendix

A1.1. Variations in climate data in RCPs across GCMs

PV infrastructure is planned based on current climate conditions which may change in the future. The spatial distribution of most PV resources is based on observed changes in the climate. Understanding climatic variability and trends is essential for analysing its implications for the global PV potential. Solar radiation (primary) and air temperature (secondary) variables are projected for different RCP scenarios using different GCMs (GFDL-ECM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5). The box plots (figure A2) show a five-number statistical summary of the data set of the stratified random sample locations: minimum (end of the line, bottom), first quartile (bottom of the box), median (midline in the box), third quartile (top of the box) and maximum (end of the line, top). The median of solar radiation in the GFDL-ECM2M model is consistently low across all RCP scenarios compared to other GCMs.

However, the overall range of solar radiation varies across the scenarios and the GCMs. GFDL-ECM2M in RCP4.5, HadGEM2-ES in RCP2.6, IPSL-CM5A-LR in RCP6.0 and MIROC5 in RCP8.5 showing the highest stretch in both directions i.e. low and high. The lower quartile is always lower in the case of GFDL- ECM2M while the higher quartile is relatively higher in HadGEM2-ES (RCP2.6 and 6.0) and IPSL-CM5A-LR (RCP4.5 and 8.5) model projections. While in MIROC5, the lower and higher quartile lies consistently between the highest and lowest values of the respective quartiles of radiation from different GCMs across all scenarios, which indicates insufficient representation of climate change variation. However, solar radiation does not show substantial differences among the scenarios and the GCMs. Conversely, GFDL-ECM2M has larger variations in the temperature across all RCPs, while HadGEM2-ES is less sensitive as compared to other GCMs. Looking at the differences in the climatic variables across the GCMs we decided to take a multi-model mean for temperature and solar radiation in the respective RCPs and for the whole time series (2020–2100) and to use these as input to the PV potential modelling.

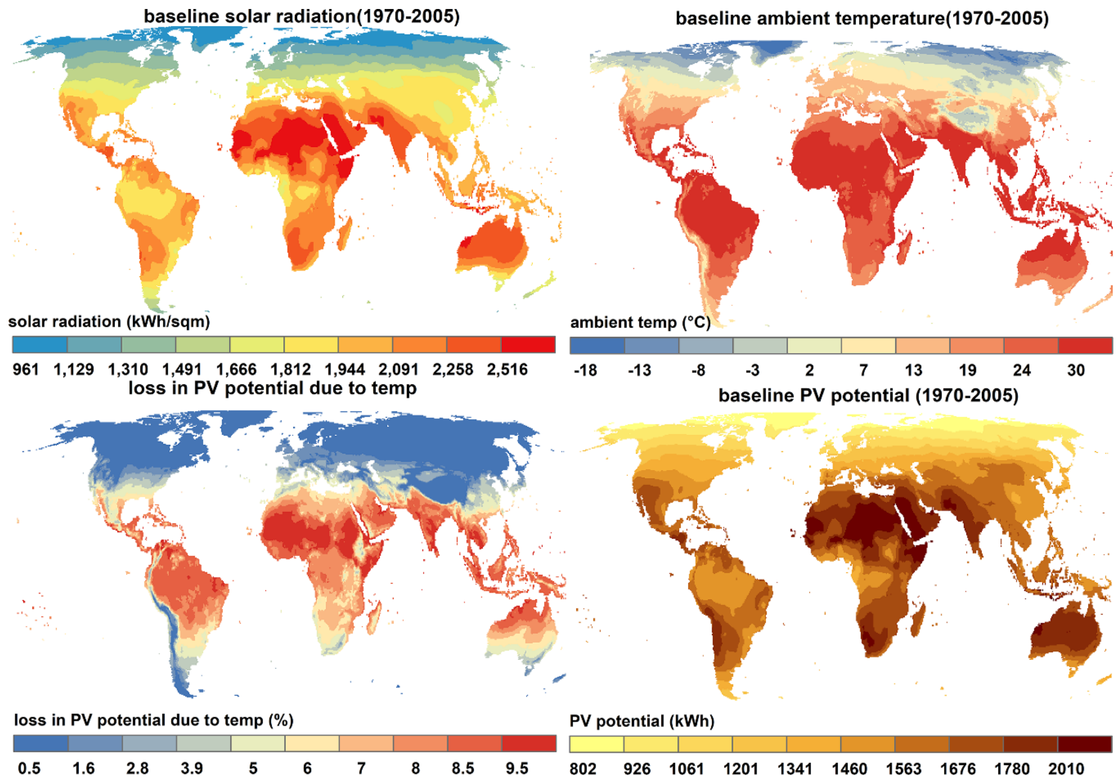

Figure A1. Baseline climate data for 1970–2005. a, b, (a) Long-term annual mean solar radiation, (b) long-term mean air temperature, (c) losses in PV potential due to temperature variations, (d) annual PV potential for the baseline.

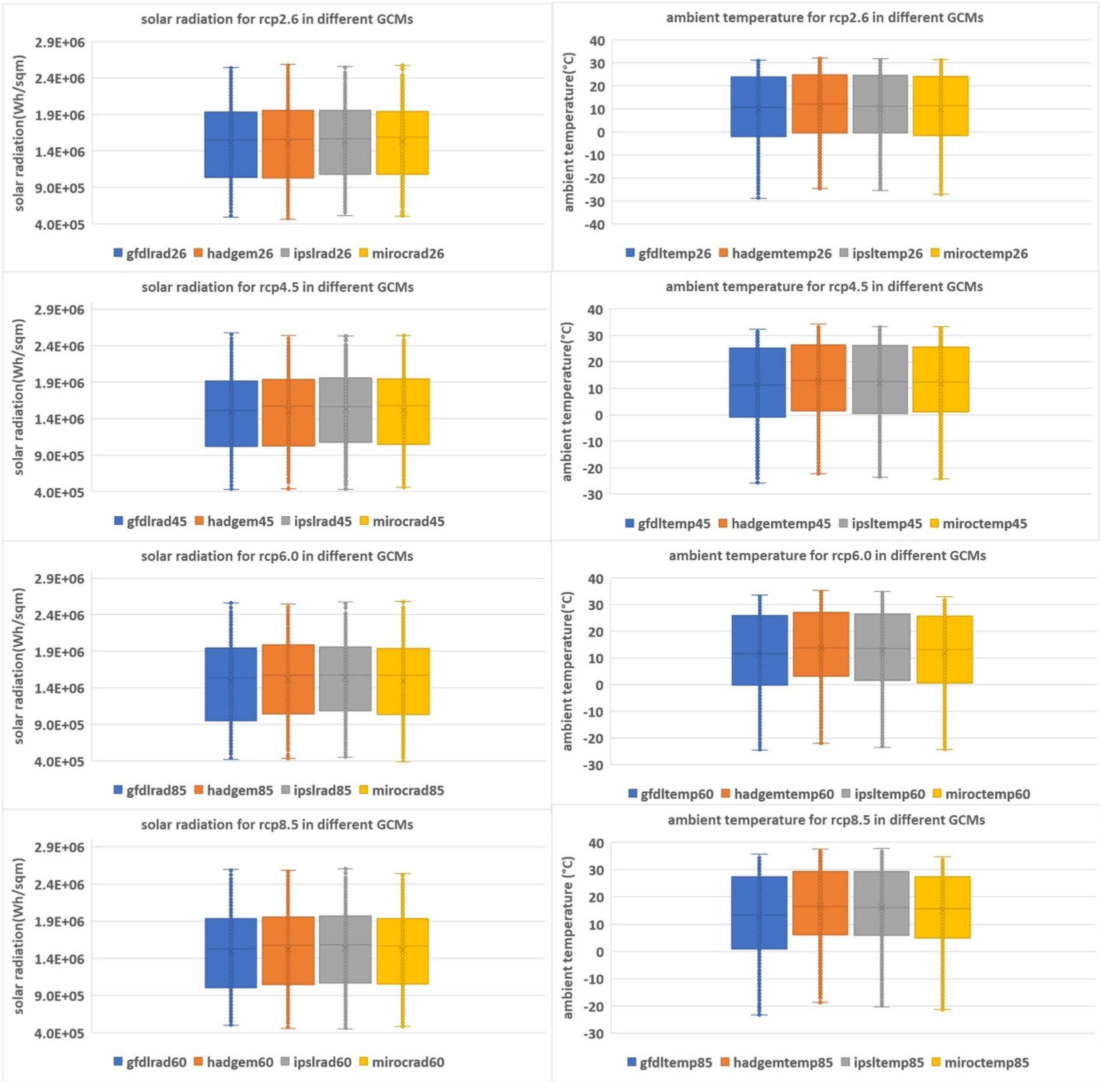

Figure A2. The box plots show a five-number statistical summary of the data set of the stratified random sample locations: minimum (end of the line, bottom), first quartile (bottom of the box), median (midline in the box), third quartile (top of the box) and maximum (end of the line, top). Box plot showing the variations across the GCM models' projections for the solar radiation and the air temperature in various climate change scenarios. a, b, c, d, e, f, g, h (a) Global annual solar radiation in rcp2.6, (b) global annual solar radiation in rcp4.5, (c) global annual solar radiation in rcp6.0, (d) global annual solar radiation in rcp8.5, (e) global mean air temperature in rcp2.6, (f) global mean air temperature in rcp4.5, (g) global mean air temperature in rcp6.0, (h) global mean air temperature in rcp8.5.

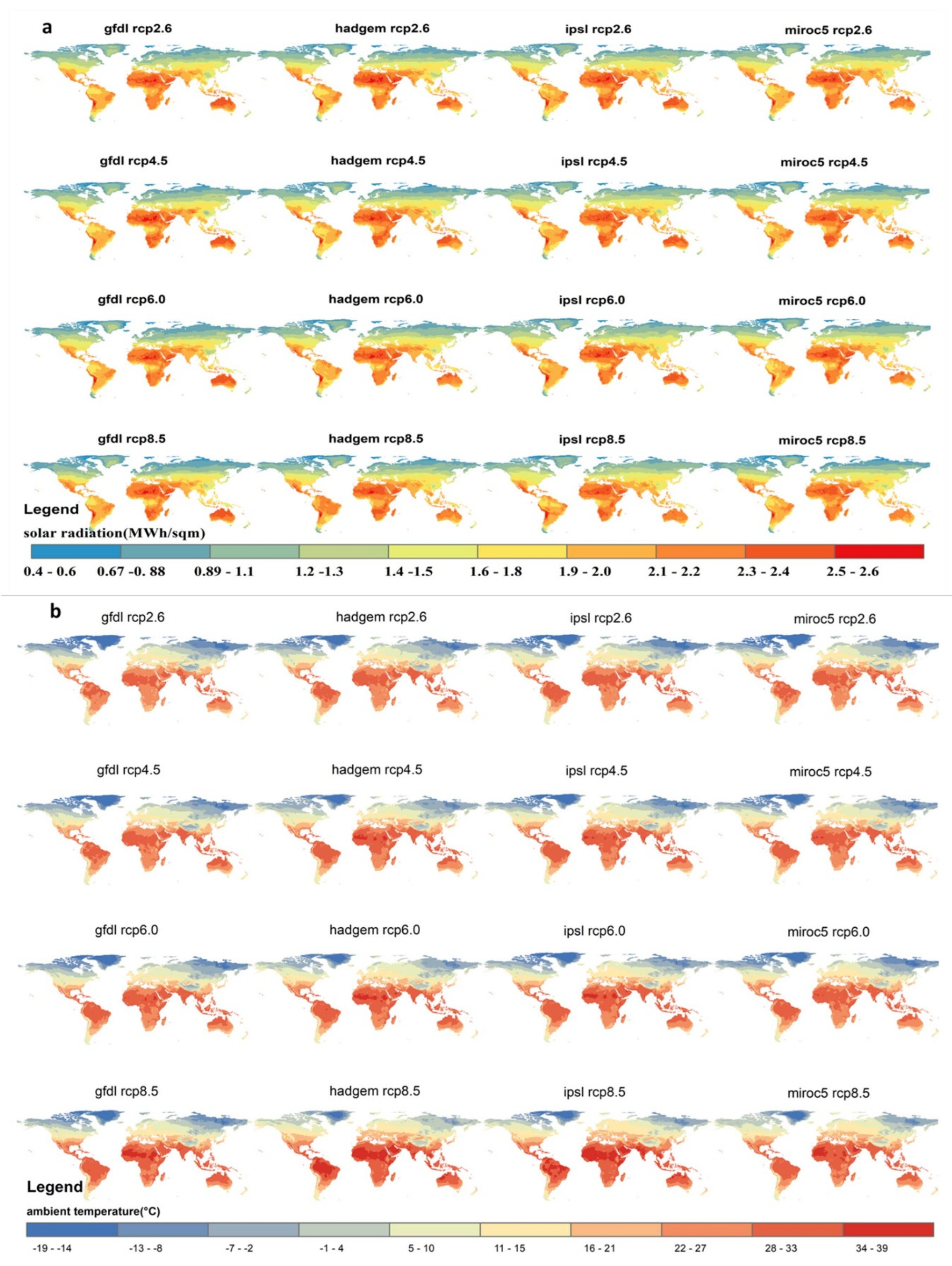

Figure A3. GCM model projections for the solar radiation and the air temperature in various climate change scenarios. a, b, (a) Global annual solar radiation, (b) global annual mean air temperature.

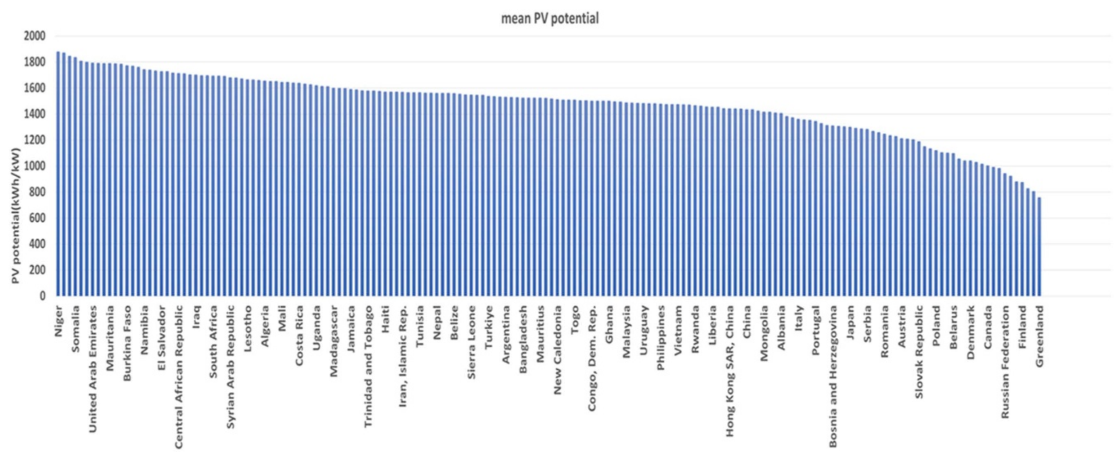

Figure A4. Global mean PV potential for different countries in the baseline scenario.

Table A1. Statistics used for the validation of PV potential model using different samples of the PV sites of small, medium, and large scale and in different climate zones (arid, temperate, tropical and cold).

	Adjusted *R*-squared (R^2)	*p*-value	Std. Error	F-statistic	MAPE(mean absolute percentage error)
Overall	0.695	$<2.2\times10^{-16}$	0.0113	9208 on 1 and 4033 DF	5%
Small-size	0.726	$<2.2\times10^{-16}$	0.0119	8416 on 1 and 3178 DF	4.6%
Medium-size	0.6	$<2.2\times10^{-16}$	0.0308	1221 on 1 and 789 DF	6.6%
Large-size	0.598	$<2.2\times10^{-16}$	0.110	92 on 1 and 62 DF	4.9%

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