

Article

Implications of CMIP6 GCM-Based Climate Variability for Photovoltaic Potential over Four Selected Urban Areas in Central and Southeast Europe During Summer (1971–2020)

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Abstract

In the last two decades, the utilization of solar energy has been growing rapidly worldwide, mainly due to the increasing adoption of photovoltaic (PV) systems. Since solar energy is one of the most weather-dependent renewable energy sources, an increasing number of meteorological studies have focused on PV potential (PV_{pot}) and its projected changes under global warming. GCM outputs disseminated through the Coupled Model Intercomparison Project (CMIP) are often applied in energy-related urban climate studies, as they can be downscaled either statistically or dynamically. It is essential to evaluate raw (not bias-corrected) GCM data, which helps to determine the uncertainties in the GCM simulations before downscaling. Despite their coarse resolution, some studies even rely directly on the GCM grid cell time series to represent individual locations. Accordingly, this study evaluates 10 CMIP Phase 6 (CMIP6) GCMs with respect to some atmospheric variables (air temperature, solar radiation, and wind speed, which are the primary drivers of PV_{pot}) in four lowland grid cells representing four major urban areas in Central and Southeast Europe: Belgrade (Serbia), Budapest (Hungary), Vienna (Austria), and Prague (Czechia). The use of solar energy has increased significantly in most of these regions in recent years; however, it remains less studied than in Western Europe. ERA5 reanalysis is used as the reference dataset. We analyzed the boreal summer (JJA) days of three overlapping 30-year time periods: 1971–2000, 1981–2010, and 1991–2020. Our main findings are as follows: GCMs tend to overestimate solar radiation and underestimate maximum near-surface air temperature relative to ERA5 in all time periods and in all the four urban areas, which leads to a significant overestimation of the number of JJA days with high PV_{pot} ($PV_{pot,90}$). $PV_{pot,90}$ is increasing from 1971–2000 to 1991–2020 in the vast majority of GCMs, in all the four regions. EC-Earth3 and its different configurations (EC-Earth3-Veg, EC-Earth3-CC) are considered the most accurate GCMs relative to ERA5.

Keywords: photovoltaic potential (PV_{pot}); Central and Southeast Europe; Coupled Model Intercomparison Project Phase 6 (CMIP6); general circulation models (GCMs); reanalysis datasets; ERA5; ERA5-Land; GCM evaluation



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1. Introduction

Due to rising prices and the depletion of fossil fuels, as well as the need to meet climate protection goals such as those outlined in the Paris Agreement [1], renewable energy sources are gaining increasing importance [2]. For example, the commitment of the European Union (EU) to renewable energy is evident in its target to achieve a 42.5% share of renewables in its energy mix by 2030 according to the Renewable Energy Directive EU/2023/2413 [3]. Solar energy is the most abundant renewable resource worldwide, which can be utilized to some extent in all regions of the Earth, including the polar regions [4,5].

In recent years, significant developments in solar energy have taken place worldwide. In 2024, the photovoltaic (PV) sector recorded another year of unprecedented growth [6]. According to the latest International Renewable Energy Agency (IRENA) report [7], the global installed PV capacity exceeded 1.8 TW in 2024, with Asia and Europe as the two leading markets, accounting for approximately 60% and 20% of the global PV capacity, respectively. In 2024, Germany, Spain, and Italy were the leading European countries in the use of solar energy [7]. However, the PV market is also emerging in the eastern part of Central Europe. In 2024, the installed PV capacity reached 8.5 GW in Austria, 4.2 GW in Czechia, and 7.7 GW in Hungary [7]. Hungary—where solar energy can theoretically generate the highest amount of the renewable electricity [8]—has the highest share of PV electricity in the electricity mix globally (24.6%) [6]. Meanwhile Austria and Hungary rank 3rd and 9th, respectively, in installed PV capacity per capita among the EU-27 member states [9]. According to governmental energy strategies, Czechia, Hungary, and Austria have ambitious plans to further increase installed PV capacity in the near future: to 7 GW by 2030 in Czechia [10], and to 12 GW by 2030 in Hungary [11]. In Austria, achieving carbon neutrality would require increasing installed PV capacity to 41 GW by 2040 [12]. Serbia, a non-EU country, also plans to increase its installed PV capacity [13]. Therefore, assessing PV potential (PV_{pot}) in Central and Southeast Europe is an important task.

PV systems exhibit vulnerability to climate change impacts, such as changes in the mean values of atmospheric variables (i.e., near-surface air temperature (tas), surface downwelling shortwave radiation ($rsds$), near-surface wind speed (wsp), and near-surface humidity), making the assessment of their performance under changing climatic conditions an important research topic in the field of renewable energy [14]. For that purpose, analyzing outputs from different generations of general circulation models (GCMs) disseminated through the different phases of the Coupled Model Intercomparison Project (CMIP) has gained increasing popularity in recent years. Several studies have assessed PV_{pot} on global or continental scales by analyzing GCM simulation outputs from CMIP3 [15,16], CMIP5 [17], and CMIP6 [18,19]. On a global scale, [20] compared CMIP5 and CMIP6 simulation outputs under various future scenarios and found that CMIP6 GCMs show slightly better performance than their previous versions in CMIP5. At the regional scale, [21,22] explored CMIP6 projections for China, while [23] focused on Northern Europe. GCMs are also used to analyze PV_{pot} for individual locations, such as the Canary Islands [24].

While numerous previously mentioned studies have discussed PV_{pot} analysis, the majority have concentrated on the future trends and paid relatively little attention to the validation of PV_{pot} . For example, [18] found that CMIP6 GCMs underestimate tas , slightly overestimate $rsds$ and underestimate wsp in Central Europe compared to ERA5, but they did not mention the evaluation of PV_{pot} itself. There are several studies evaluating atmospheric variables in GCM simulations. According to [25], CMIP6 GCMs underestimate maximum near-surface air temperature ($tasmax$) in Europe compared to ERA5 reanalysis. Li et al. [26] assessed the surface energy budget of CMIP6 GCMs at the regional scale and found that most GCMs overestimate $rsds$ in Eurasia. He et al. [27] found that GCMs overestimate $rsds$ in Europe mainly in summer, and that the EC-Earth3 and its different configurations

(EC-Earth3-Veg and EC-Earth3-CC) showed the best agreement with *rsds* measurements. The study by [28] showed a lack of agreement among CMIP6 GCM simulations in representing *wsp* over Europe, with some GCMs overestimating and others underestimating the observed values. In contrast, [29] found a clear underestimation of *wsp* by the CMIP6 GCMs in Europe.

GCMs cannot reliably reproduce regional climate; therefore, GCMs are often the subject of statistical or dynamical downscaling, e.g., Ref. [30]. Machine learning-based downscaling methods are already well established in renewable energy research [31]. However, in some cases, biases inherent in the driving of GCMs can propagate into downscaled simulations, as errors may be transferred from the coarse GCM grid to the finer regional grid [32]. In other cases, GCM and RCM tendencies may differ from each other [30]. Consequently, choosing the best-performing GCMs relative to a reference dataset is also essential for downscaling.

Since there are a limited number of climatological studies on PV_{pot} in the eastern part of Central Europe, see, e.g., Refs. [21,33,34] and in Southeast Europe [35], this study aims to analyze raw time series at a small number of GCM grid cells in this region. These grid cells are characterized by relatively similar low-elevated topography (thus, terrain smoothing by GCMs is less important) and climatic conditions, corresponding to the Cfa/Dfa (humid subtropical/hot-summer humid continental) and the Cfb/Dfb (temperate oceanic/warm-summer humid continental) climate types according to the Köppen–Geiger classification. GCM simulation outputs are examined over 30-year time periods between 1971 and 2020 to assess the ability of the GCMs to reproduce meteorological variables that primarily affect PV_{pot} . The most accurate GCMs relative to the ERA5 reanalysis will be selected as potential candidates for future dynamical downscaling.

The paper is organized as follows: Section 2 describes the study locations, the data, and the methods used in this study; Section 3 presents our results, including the evaluation of the temporal variability of the meteorological variables (*tasmax*, *rsds*, and *wsp*) and PV_{pot} . Section 4 presents the discussion and conclusions, along with suggestions for future research.

2. Materials and Methods

2.1. The Study Locations

The selected GCM grid cells located in lowland areas cover densely populated urban areas. For simplicity, each selected GCM grid cell is hereafter referred to by the name of the major city located within it. However, a GCM grid cell—covering an area of $1.25^\circ \times 1.25^\circ$ —cannot be considered to accurately represent the city itself. The coordinates and labels of the GCM grid cells from southeast to northwest are as follows: 44.75° N and 20.5° E, Belgrade (Serbia), 47.5° N and 19° E, Budapest (Hungary), 48.25° N and 16.5° E, Vienna (Austria), and 50° N and 14.5° E, Prague (Czechia), as shown in Figure 1. Belgrade and Budapest have Cfa/Dfa climate types, while Vienna and Prague have Cfb/Dfb climate types according to the Köppen–Geiger classification.

Because the selected grid cells are located in lowlands, there is no distortion due to terrain smoothing by GCMs. This approach helps to avoid masking meaningful spatiotemporal variability. Furthermore, the selection of the GCM grid cells minimizes the influence of complex, mountainous terrain that cannot be adequately resolved by GCMs.

All selected locations are characterized by transitional climatic position between Atlantic maritime influences from the west and continental air masses from Eastern Europe and Eurasia. This transitional setting results in seasonal variability in temperature, precipitation, and shortwave solar radiation, which are further modified by local topography and urban effects [36]. These metropolitan areas show the climatic gradient within Central and

Southeast Europe, from increasingly continental and subtropical influences in Belgrade and Budapest to more oceanic conditions in Vienna and Prague. This climatic gradient strongly influences regional climate variability and sensitivity to climate change, particularly with respect to rising temperatures and changing precipitation regimes observed over recent decades [37].

Belgrade is located further southeast, at the confluence of the Sava and Danube rivers, where continental and subtropical influences overlap. This is the warmest and wettest metropolitan area in the study, with an average temperature of $\sim 23^{\circ}\text{C}$ in July and annual precipitation of ~ 700 mm. Precipitation maxima typically occurring in late spring and early summer. The area experiences more than 2000–2100 sunshine hours annually, which is the highest value among the four locations [38]. Budapest is situated in the central part of the Carpathian Basin. Precipitation has a summer maximum linked to convective activity, while the annual total of sunshine duration exceeds 2000 h [39].

Vienna is located at the eastern margin of the Alps, along the Danube Valley, where Atlantic and continental influences interact. Summers are moderate, and precipitation is distributed evenly throughout the year. The sunshine duration is approximately 1900 h annually [40]. Prague is located in the Bohemian Basin. Precipitation maxima occur in summer and are linked to frontal and convective systems. The annual sunshine duration in Prague is ~ 1700 h [41], which is the lowest value among the four locations.

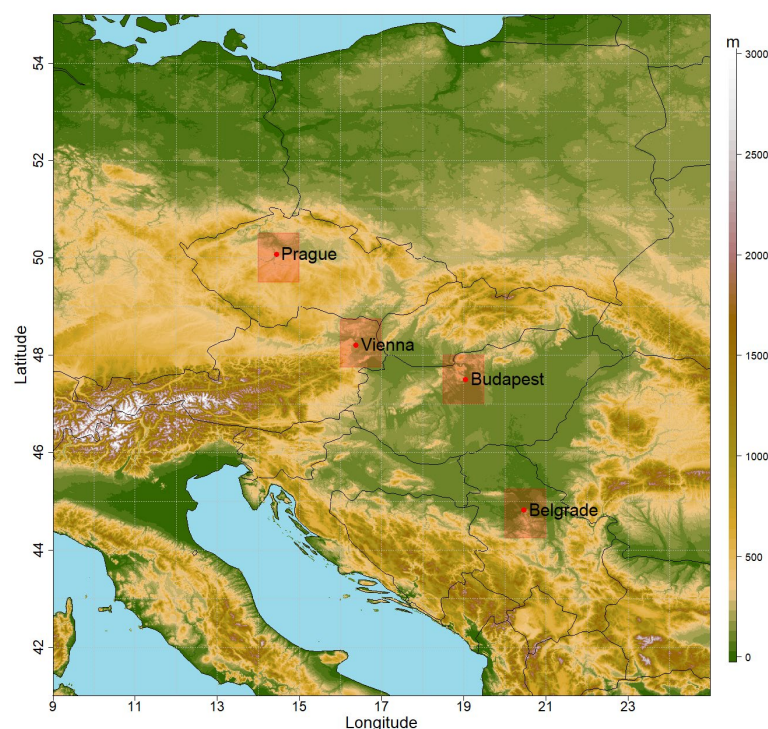


Figure 1. Topography map of Central and Southeast Europe based on GMTED2010 elevation data (m) [42]. The four examined GCM grid cells are indicated by red squares. For simplicity, these are referred to by the names of the major cities located within them, which are marked with red dots.

2.2. Data

2.2.1. CMIP6 GCMs

Daily data of the 10 GCMs from CMIP6 [43] were downloaded for the time period 1971–2020 from the ESGF node (<https://esgf-node.ornl.gov/>; last accessed on 30 January 2026). The list of GCMs can be found in Table 1.

Only GCMs with a horizontal resolution finer than $1.25^{\circ} \times 1.25^{\circ}$ were included in the analysis. The GCM outputs were bilinearly interpolated to the exact geographic

coordinates of the four selected locations (labelled as Belgrade, Budapest, Vienna, and Prague), obtaining one time series per location. These four time series were examined in this study.

The following three overlapping 30-year time periods were examined: 1971–2000, 1981–2010, and 1991–2020. For this purpose, historical GCM simulation outputs were used between 1971 and 2014. Although, the historical time period extends to 2014 for the CMIP6 GCMs, the current climatological normal is 1991–2020 [44]. Therefore, SSP2-4.5 and SSP5-8.5 [45] simulation outputs were applied for the time period 2015–2020. Accordingly, two versions of the 1991–2020 time period are considered hereafter referred to as 1991–2020 (SSP2-4.5) and 1991–2020 (SSP5-8.5). Only boreal summer days were considered in the analysis, corresponding to June, July, and August (30 + 31 + 31 = 92 days), hereinafter referred to as JJA days, resulting in a total of $92 \times 30 = 2760$ daily values for each time period and for each city.

The following variables were examined (their short names and units are given in parentheses): the maximum near-surface air temperature (*tasmax*, K; converted to °C), the surface downwelling shortwave radiation (*rsds*, W/m²), and the eastward and the northward near-surface wind components (*uas* and *vas*, m/s). Near-surface wind speed (*wsp*, m/s) was calculated as the square root of the sum of the squared wind components according to Equation (1):

$$wsp = \sqrt{uas^2 + vas^2}. \quad (1)$$

Table 1. List of the GCMs and their components used in this study. The number of vertical levels is in parentheses regarding the atmospheric and ocean model components. This information was obtained from the metadata of the GCM NetCDF files and from the CMIP6 source ID repository (https://wcrp-cmip.github.io/CMIP6_CVs/docs/CMIP6_source_id; last accessed on 30 January 2026).

GCM	Developer	Original Horizontal Resolution (Lat × Lon)	Model Components							
			Atmospheric	Aerosol	Atmospheric Chemistry	Land Surface	Land Ice	Ocean	Ocean Biogeochemistry	Sea Ice
BCC-CSM2-MR [46]	CHN	~1.12° × 1.13°	BCC-AGCM3-MR (46)	-	-	BCC_AVIM2	-	MOM4 (40)	-	SIS2
CMCC-CM2-SR5 [47]	ITA	~0.94° × 1.25°	CAM5.3 (30)	MAM3	-	CLM4.5 (BGC mode)	-	NEMO3.6 (50)	-	CICE4.0
CMCC-ESM2 [48]	ITA	~0.94° × 1.25°	CAM5.3 (30)	MAM3	-	CLM4.5 (BGC mode)	-	NEMO3.6 (50)	BFM5.1	CICE4.0
EC-Earth3 [49]	EU	~0.7° × ~0.7°	IFS cy36r4 (91)	-	-	HTESSEL	-	NEMO3.6 (75)	-	LIM3
EC-Earth3-Veg [49]	EU	~0.7° × ~0.7°	IFS cy36r4 (91)	-	-	HTESSEL, LPJ-GUESS v4	-	NEMO3.6 (75)	-	LIM3
EC-Earth3-CC [49]	EU	~0.7° × ~0.7°	IFS cy36r4 (91)	-	TM5	HTESSEL, LPJ-GUESS v4	-	NEMO3.6 (75)	PISCESv2	LIM3
GFDL-CM4 [50]	USA	1° × 1.25°	GFDL-AM4.0.1 (33)	inter active	-	GFDL-LM4.0.1	GFDL-LM4.0.1	GFDL-OM4p25 (75)	GFDL-BLINGv2	GFDL-SIM4p25
GFDL-ESM4 [51]	USA	1° × 1.25°	GFDL-AM4.1 (49)	inter active	GFDL-ATM CHEM4.1	GFDL-LM4.1	GFDL-LM4.1	GFDL-OM4p5 (75)	GFDL-COBALTv2	GFDL-SIM4p5
MPI-ESM1-2-HR [52]	GER	~0.94° × ~0.94°	ECHAM6.3 (95)	prescribed MACv2-SP	-	JSBACH 3.20	none/prescribed	MP1OM 1.63 (40)	HAMOCC6	unnamed
MRI-ESM2-0 [53]	JPN	~1.12° × 1.13°	MRI-AGCM 3.5 (80)	MASINGAR mk2r4	MRI-CCM2.1	HAL1.0	-	MRI.COM4.4 (61)	MRI-COM4.4	MRI-COM4.4

2.2.2. Reanalysis Datasets: ERA5 and ERA5-Land

ERA5 [54] was used as the reference dataset, and ERA5-Land [55] was also evaluated against it. ERA5 is the fifth-generation atmospheric reanalysis produced by ECMWF within the Copernicus Climate Change Service. It provides a globally consistent dataset of atmospheric, land, and ocean variables by combining numerical weather prediction models with a wide range of observations. ERA5 has a horizontal resolution of about 31 km (0.25°), covers the time period from 1950 to present, and is available at hourly and daily temporal resolutions. Daily values were downloaded from <https://cds.climate.copernicus.eu/datasets/derived-era5-single-levels-daily-statistics> (last accessed on 30 January 2026).

ERA5-Land is a land-only reanalysis dataset derived from ERA5, designed to provide a more detailed representation of land-surface processes. ERA5-Land uses the same atmo-

spheric forcing as ERA5 but is produced with an enhanced land surface model. ERA5-Land has a higher spatial resolution of approximately 9 km (0.1°) and focuses on variables such as soil moisture, soil temperature, snow, evaporation, and surface fluxes. Like ERA5, ERA5-Land is available at daily resolution from <https://cds.climate.copernicus.eu/datasets/derived-era5-land-daily-statistics> (last accessed on 30 January 2026).

For each city, the nearest grid cell and its surrounding neighbours were selected, and their spatial mean values were calculated. By computing these spatial means, representative time series were obtained for the areas comparable to the GCM grid cells ($1.25^\circ \times 1.25^\circ$) derived from the interpolated GCM outputs.

The following ERA5/ERA5-Land variables were downloaded, corresponding to the variables available for the GCMs: the maximum air temperature at 2 m based on the hourly air temperature at 2 m ($t2m$, K), the surface downwelling shortwave radiation ($ssrd$, originally provided in J/m^2), and the eastward and northward wind components at 10 m ($u10$ and $v10$, m/s). The variables $u10$ and $v10$ were compared with the corresponding GCM variables uas and vas . Wind speed (wsp) was calculated according to Equation (1). The variables $ssrd$ and $t2m$ were converted to W/m^2 and $^\circ\text{C}$, respectively, to ensure comparability with $rsds$ and $tasmax$. Henceforth, the abbreviations $tasmax$, $rsds$, uas , and vas will be used for the atmospheric variables.

Climate Data Operator (CDO; <https://code.mpimet.mpg.de/projects/cdo>; last accessed on 30 January 2026) software (version 2.5.0) was used for data preprocessing, while all subsequent data analysis and visualization were conducted in R programming language [56].

2.3. Evaluation Methods for GCMs

2.3.1. Distribution-Based GCM-Evaluation Using Daily Atmospheric Variables Influencing PV_{pot}

At first, a probability distribution-based comparison was carried out between the GCMs and the ERA5-Land relative to ERA5 for each calendar day ($N = 92$ days for JJA), for each atmospheric variable, location, and time period. For each calendar day, empirical distributions were constructed from the corresponding 30-year time series. The distributions of the GCM simulations and the reanalyses were then compared using the Wasserstein distance of order 1 (W_1) [57] defined by Equation (2) as follows:

$$W_1(F_N, G_N) = \int_{\mathbb{R}} |F_N(x) - G_N(x)| dx, \quad \forall x \in \mathbb{R}, \quad (2)$$

where F_N and G_N denote the empirical cumulative distribution functions (ECDFs) of the GCM simulations (or ERA5-Land) and ERA5, respectively. All observations were equally weighted in the ECDFs.

In general, the Wasserstein distance measures the “optimal transport cost” required to transform one distribution into another [58]. Thus, the value of zero indicates perfect match with the distribution of ERA5. The Wasserstein distance was computed using the *wasserstein1d* function implemented in the R package *transport* [59].

The comparison of the distributions resulted in a total of 92 distance matrices, corresponding to the 92 JJA days, for each variable, location, and time period. To summarize these results, the Wasserstein distances were averaged over the 92 JJA days for each GCM–ERA5 and ERA5-Land–ERA5 comparison.

2.3.2. Mean Seasonal Courses-Based GCM-Evaluation of Daily Atmospheric Variables Relevant to PV_{pot}

The mean seasonal (JJA) courses of the atmospheric variables were examined by computing the mean values for each JJA day over the 30-year time periods, hereinafter referred to as mean daily values. This procedure provides time series for each GCM and reanalysis consisting of 92 values for each variable, location, and time period. The mean seasonal courses of the GCMs and the ERA5-Land were compared against the ERA5 computing Pearson correlation coefficients (r) and the ratio of standard deviations (sd ratio). The latter is defined as the ratio of the standard deviation of the given GCM (or ERA5-Land) time series to the standard deviation of ERA5.

The r compares the shape of the mean seasonal courses of the GCMs (and the ERA5-Land) against the ERA5, where $r = 1$ means perfect (linear) correlation, while $r = -1$ means perfect inverse (linear) correlation. The sd ratio quantifies the variability of the mean seasonal courses. If sd ratio = 1 for a given GCM or the ERA5-Land, then it captures the same variability as ERA5. Both r and the sd ratio are dimensionless; therefore, those are directly comparable across variables, despite the variables having different physical units.

2.3.3. PV_{pot} -Based GCM-Evaluation

The mean daily PV_{pot} values were calculated from the mean daily values of $tasmax$, $rsds$, and wsp for monocrystalline silicon PV module using the energy rating method based on Equation (3) [60]:

$$PV_{pot} = P_R \cdot \frac{rsds [W/m^2]}{1000 [W/m^2]}. \quad (3)$$

The $rsds$ (W/m^2) represents the surface downwelling shortwave radiation reaching PV modules under field conditions. The $rsds$ is divided by $1000 W/m^2$, i.e., the $rsds$ incidents on the PV module under standard test conditions (STC). The P_R (performance ratio) is a dimensionless metric that can be calculated using Equation (4):

$$P_R = 1 - \gamma [^\circ C^{-1}] \cdot (T_{cell} [^\circ C] - 25 [^\circ C]), \quad (4)$$

where T_{cell} is the temperature of the PV module under field conditions ($^\circ C$), from which $25^\circ C$ —corresponding to the T_{cell} under STC—is subtracted. The γ is an efficiency factor [61], whose value for monocrystalline silicon PV module is $0.005^\circ C^{-1}$.

The T_{cell} was calculated based on the regression formula (Equation (5)) provided by TamizhMani et al. [62] for monocrystalline silicon PV module:

$$T_{cell} = 0.942 \cdot T_a [^\circ C] + 0.028 [^\circ C \cdot W^{-1} \cdot m^2] \cdot rsds [Wm^{-2}] - 1.509 [^\circ C \cdot m^{-1} \cdot s] \cdot wsp [m \cdot s^{-1}] + 3.9 [^\circ C], \quad (5)$$

where T_a denotes air temperature, for which $tasmax$ is used in this study.

In this study, PV_{pot} was used as a simplified climate-based indicator to compare GCMs against the reference dataset (ERA5), rather than as an estimate of actual PV electricity production. This means that Equations (3)–(5) do not account for site-specific factors affecting the actual PV electricity production, such as inverter losses, panel inclination, panel orientation, spectral response, or system configuration. The PV_{pot} formulation is intended to capture the influence of key meteorological variables (tas or $tasmax$, $rsds$, and wsp) on PV performance.

According to Equations (3)–(5), PV_{pot} increases with increasing $rsds$ and P_R . The P_R increases with decreasing T_a . Higher $rsds$ —e.g., due to reduced cloud cover or lower aerosol concentration—generally enhances PV_{pot} ; however, $rsds$ also increases T_{cell} , which leads to a reduced P_R ; therefore, lower PV_{pot} . The wsp lowers T_{cell} , consequently, increasing wsp increases PV_{pot} .

Finally, the GCMs were evaluated based on the number of days with high PV_{pot} ($PV_{pot,90}$) following the concept of Feron et al. [17]. To calculate $PV_{pot,90}$, the base value was defined as the 90th percentile of the 92 ERA5 mean daily PV_{pot} values for 1971–2000, for each location. The mean daily PV_{pot} values from the GCMs and ERA5-Land were compared against these location-specific base values for each time period. If the PV_{pot} values exceed the base value on more (less) than 10 days within the selected time period and location, the given GCM or ERA5-Land overestimates (underestimates) the frequency of $PV_{pot,90}$ relative to ERA5 (1971–2000). Thus, the base value is fixed for each location as the 90th percentile of the 92 ERA5 mean daily PV_{pot} values for 1971–2000.

3. Results

3.1. GCM-Performance Based on Distributions of Daily Atmospheric Variables Relevant to PV_{pot}

Differences between the probability distributions of daily atmospheric variables derived from the GCMs (and ERA5-Land) relative to ERA5 were quantified using Wasserstein distance of order 1. These distances were computed for each calendar day (JJA) and subsequently averaged over the 92 JJA days for each time period and location.

According to Figure 2, no distinct improvement or deterioration in GCM performance relative to ERA5 can be identified over time. In cases of *tasmax* and *rsds*, Wasserstein distances remain broadly similar across the analyzed time periods, indicating that the agreement between GCM simulations and ERA5 does not change substantially over time (Figure 2a,b). However, a slight improvement can be observed for *uas* and *vas* during 1981–2010 compared to the other time periods (Figure 2c,d). In addition, GCM performance is very similar for the two scenarios in the most recent time period (1991–2020 SSP2-4.5 and SSP5-8.5).

Spatial differences among the four locations are more pronounced than temporal differences. However, no systematic patterns are observable with respect to the variables, except for *rsds*. The Wasserstein distances for *rsds* tend to decrease from southeast to northwest across the four locations (Figure 2b). Wasserstein distances have similar ranges for *uas* and *vas*; however, even individual GCMs do not exhibit consistent performance between *uas* and *vas* across the locations (Figure 2c,d).

Based on the magnitude of the Wasserstein distances for *tasmax* and *rsds*, ERA5-Land shows greater similarity to ERA5 than the GCM simulations (Figure 2a,b). This advantage of the ERA5-Land is less pronounced for *uas* and *vas* (Figure 2c,d).

Table 2 summarizes the mean Wasserstein distances of the 10 GCMs relative to ERA5 to evaluate GCM performance. The relatively stable values across the analyzed time periods indicate that the differences between the GCM simulations and the ERA5 remain constant over time.

Figure 3 presents the GCM rankings relative to ERA5, quantified by Wasserstein distances averaged over the time periods 1971–2000, 1981–2010, and 1991–2020 (SSP2-4.5) across the four locations. Since the aim of this study was to identify GCMs with relatively high skill in reproducing PV_{pot} , no formal statistical significance tests were performed to assess whether the Wasserstein distances of individual GCMs (or ERA5-Land) differ significantly from each other. Instead, the Wasserstein distances were used to indicate the relative position of the GCMs in terms of their similarity to ERA5.

For *tasmax* and *rsds*, the GCMs can visually be divided into two groups exhibiting higher and lower accuracy relative to ERA5 (Figure 3a,b). For *uas* and *vas*, GCM rankings are highly inconsistent across the two variables (Figure 3c,d). Despite the absence of a single outstandingly accurate GCM, EC-Earth3 and its different configurations (EC-Earth3-Veg, EC-Earth3-CC) are among the most accurate GCMs. The two reanalyses exhibit the highest degree of similarity to each other for all variables, consistent with the individual cases

presented in Figure 2. The Wasserstein distances and GCM rankings remain very similar when 1991–2020 (SSP5-8.5) is used as the final averaging time period (see Figure S1a–d).

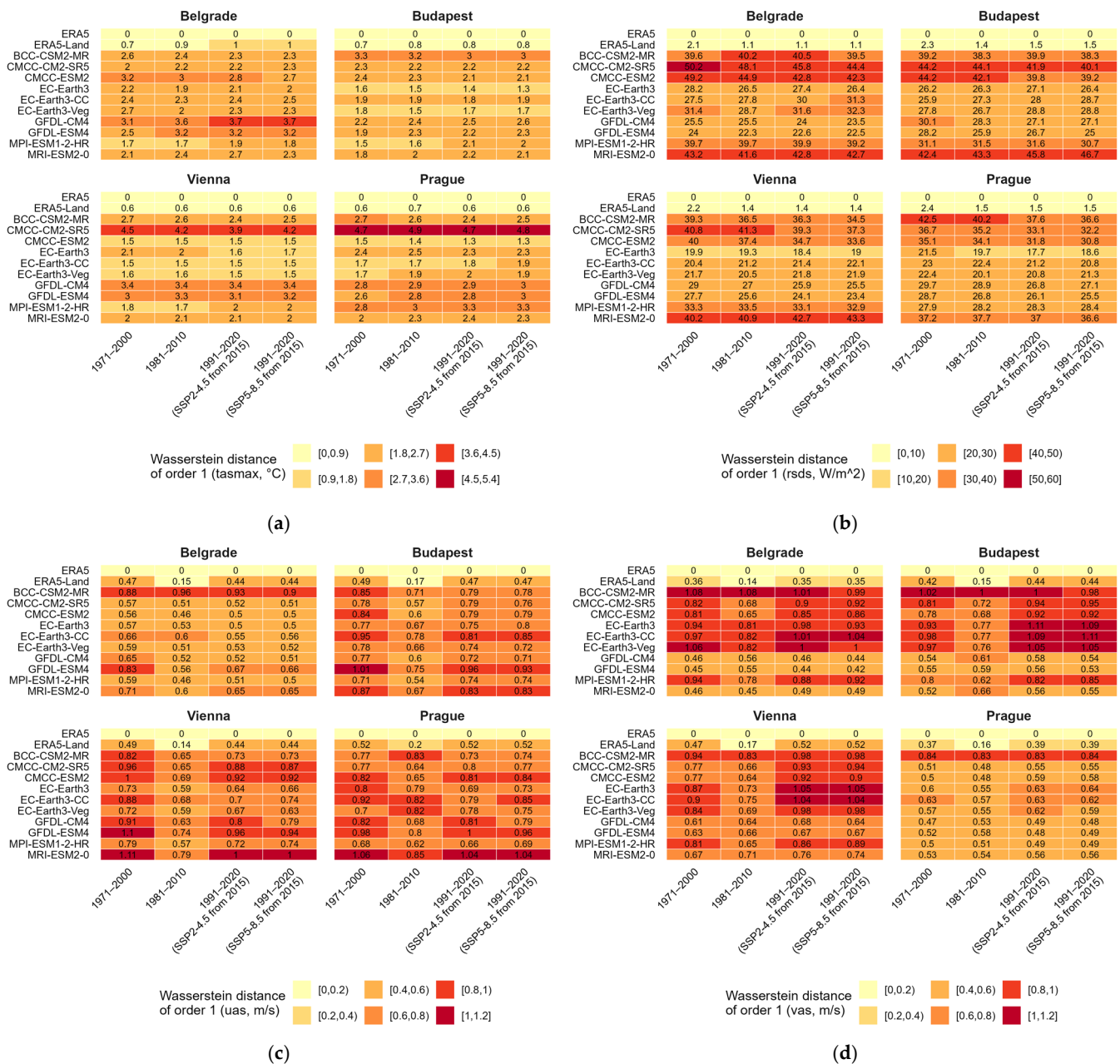


Figure 2. Wasserstein distance values averaged over the 92 JJA days of the GCMs and ERA5-Land relative to ERA5 for locations labelled as Belgrade, Budapest, Vienna, and Prague, for the time periods 1971–2000, 1981–2010, 1991–2020 (SSP2-4.5), and 1991–2020 (SSP5-8.5), for (a) maximum near-surface air temperature (*tasmax*), (b) surface downwelling shortwave radiation (*rsds*), (c) eastward near-surface wind (*uas*), and (d) northward near-surface wind (*vas*) components. The colour categories are comparable across the four variables only in terms of being defined by the same number of intervals. However, Wasserstein distance values are directly comparable between *uas* and *vas* because their physical units are the same. The similarity of the distributions decreases from yellow to red shades.

Detailed rankings relative to ERA5 based on Wasserstein distance for each variable, time period, and location—corresponding to Figure 2—are provided in Figure S1. It must be emphasized that differences between the top-performing GCMs in Figures 3 and S1 are relatively small. Therefore, the ranking primarily indicates the GCMs with relatively high skill and it should not be interpreted as a definitive performance order.

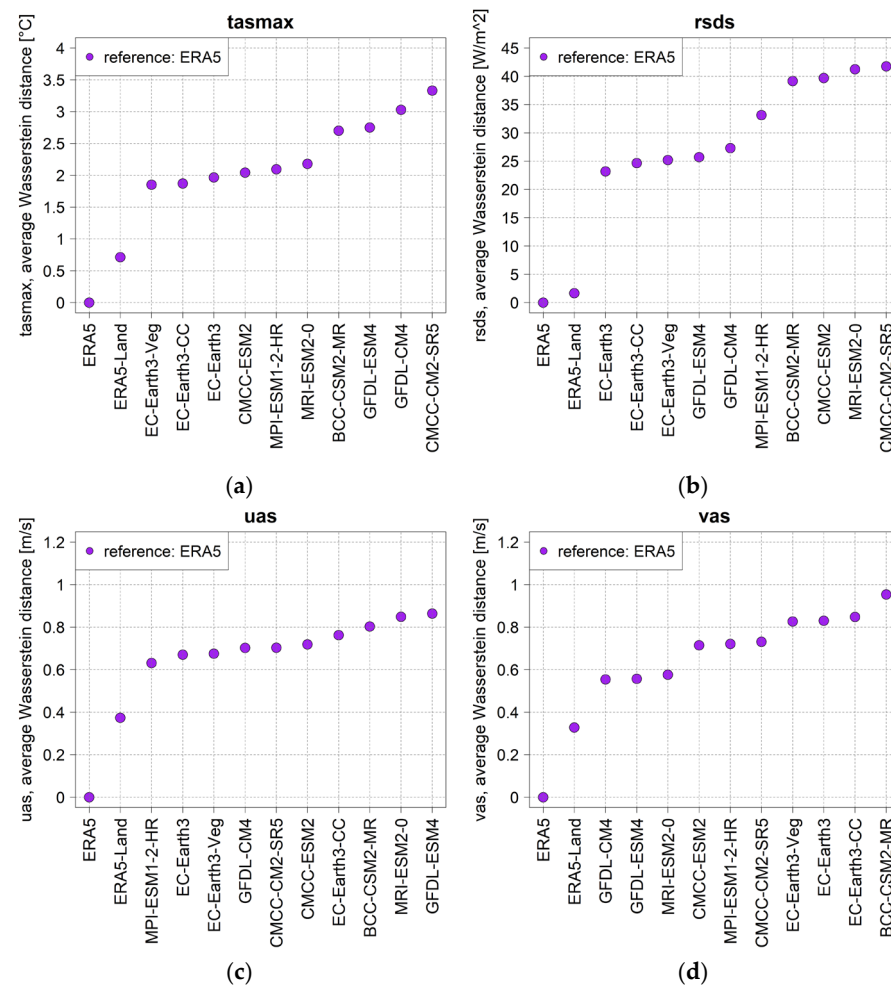


Figure 3. GCM rankings based on the mean Wasserstein distances between the distributions of daily atmospheric variables of the GCMs relative to ERA5 for (a) maximum near-surface air temperature (*tasmax*), (b) surface downwelling shortwave radiation (*rsds*), (c) eastward near-surface wind (*uas*), and (d) northward near-surface wind (*vas*) components. ERA5-Land was also included in the ranking. The Wasserstein distances were averaged over three time periods: 1971–2000, 1981–2010, and 1991–2020 (SSP2-4.5), across four locations labelled as Belgrade, Budapest, Vienna, and Prague.

Table 2. Mean Wasserstein distances of the 10 GCMs relative to ERA5 for each time period and location. The spatial mean was computed based on the four locations, while the temporal mean was computed based on the time periods 1971–2000, 1981–2010, and 1991–2020 (SSP2-4.5). Similar results were obtained when 1991–2020 (SSP5-8.5) was used instead of 1991–2020 (SSP2-4.5).

Variables	Time Period	Belgrade	Budapest	Vienna	Prague	Spatial Mean
<i>tasmax</i> [°C]	1971–2000	2.4	2.1	2.4	2.5	2.4
	1981–2010	2.5	2.1	2.4	2.6	2.4
	1991–2020 (SSP2-4.5)	2.6	2.1	2.3	2.6	2.4
	1991–2020 (SSP5-8.5)	2.5	2.1	2.3	2.6	2.4
	Temporal mean	2.5	2.1	2.4	2.6	
<i>rsds</i> [W/m²]	1971–2000	36	34	31	31	33
	1981–2010	35	33	30	29	32
	1991–2020 (SSP2-4.5)	35	34	30	28	32
	1991–2020 (SSP5-8.5)	34	33	29	28	31
	Temporal mean	35	33	30	29	

Table 2. Cont.

Variables	Time Period	Belgrade	Budapest	Vienna	Prague	Spatial Mean
<i>uas</i> [m/s]	1971–2000	0.7	0.8	0.9	0.8	0.8
	1981–2010	0.6	0.7	0.7	0.7	0.7
	1991–2020 (SSP2-4.5)	0.6	0.8	0.8	0.8	0.8
	1991–2020 (SSP5-8.5)	0.6	0.8	0.8	0.8	0.8
	Temporal mean	0.6	0.8	0.8	0.8	
<i>vas</i> [m/s]	1971–2000	0.8	0.8	0.8	0.6	0.8
	1981–2010	0.7	0.7	0.7	0.6	0.7
	1991–2020 (SSP2-4.5)	0.8	0.9	0.9	0.6	0.8
	1991–2020 (SSP5-8.5)	0.8	0.9	0.9	0.6	0.8
	Temporal mean	0.8	0.8	0.8	0.6	

3.2. GCM-Performance Based on Mean Seasonal Courses of Daily Atmospheric Variables

The mean seasonal (JJA) courses of ERA5, ERA5-Land, the 10 GCMs, and the GCM-ensemble mean are presented for each variable, location, and time period in Figure S2. In general, the GCMs tend to underestimate *tasmax* at locations labelled as Vienna and Prague in all time periods (Figure S2a), while overestimation is observable for *rsds* in all four locations and time periods (Figure S2b). The GCMs tend to underestimate *uas* and *vas* in all locations and time periods except in 1981–2010 (Figure S2c,d).

According to Figure S2, the shape and variability of the mean seasonal courses show considerable similarity over time and across locations. These characteristics are quantified by the Pearson correlations coefficient (r) and the ratio of standard deviations (*sd ratio*) as shown in Figure 4, thereby enabling the comparison of the GCM performance across variables. In general, the shape of the mean seasonal courses of the GCMs and ERA5-Land is the most similar to ERA5 for *tasmax* and *rsds* ($r \cong 0.6$ – 0.8 in 1971–2000, 1981–2010, and $r \cong 0.4$ – 0.8 in 1991–2020; Figure 4a,b). (For *rsds* the mean seasonal courses largely overlap; Figure S2b) Meanwhile substantially weaker ($r < 0.5$) or even negative correlations are found for *uas* and *vas* (Figure 4c,d).

The *sd ratio* mostly exceeds 1.2 for *rsds* and *tasmax*, indicating larger variability in the GCMs relative to ERA5 in 1971–2000 and 1981–2010 (Figure 4a,b). However, in case of *tasmax* and *vas*, the *sd ratio* decreases below 1 for the last time period, which is more pronounced for 1991–2020 (SSP5-8.5). The spread of the GCMs for *tasmax* and *uas* increases over time, while the largest inter-location differences are observed for *uas* and *vas*.

According to Figure 4, with respect to individual GCM performance, EC-Earth3, EC-Earth3-Veg, and EC-Earth3-CC are among the most accurate GCMs ($r \cong 0.6$ – 0.8 , $sd \cong 1$ – 1.4) relative to the ERA5 for *rsds*. However, for *tasmax*, the *sd ratio* decreases below 1 in 1991–2020. Consequently, GCMs may reproduce that variable more accurately in 1981–2010 than in the time periods 1971–2000 and 1991–2020. This can explain why Wasserstein distances in Figure 2 were smaller for *uas* and *vas* in 1981–2010 than for the preceding and succeeding time periods. Besides EC-Earth3 and its different configurations, GFDL-ESM4 and GFDL-CM4 perform relatively well for *tasmax* and *vas*, respectively. The 10 GCMs reproduce the mean seasonal course of *uas* the least accurately. Consistent with the findings in Section 3.1, no single GCM outperforms the others simultaneously across all variables, locations, and time periods.

According to Figure 4, the r values of the GCM ensemble mean are similar to those of the best performing individual GCMs. However, its *sd ratio* is typically below 1, as ensemble averaging reduces the amplitudes of the variability.

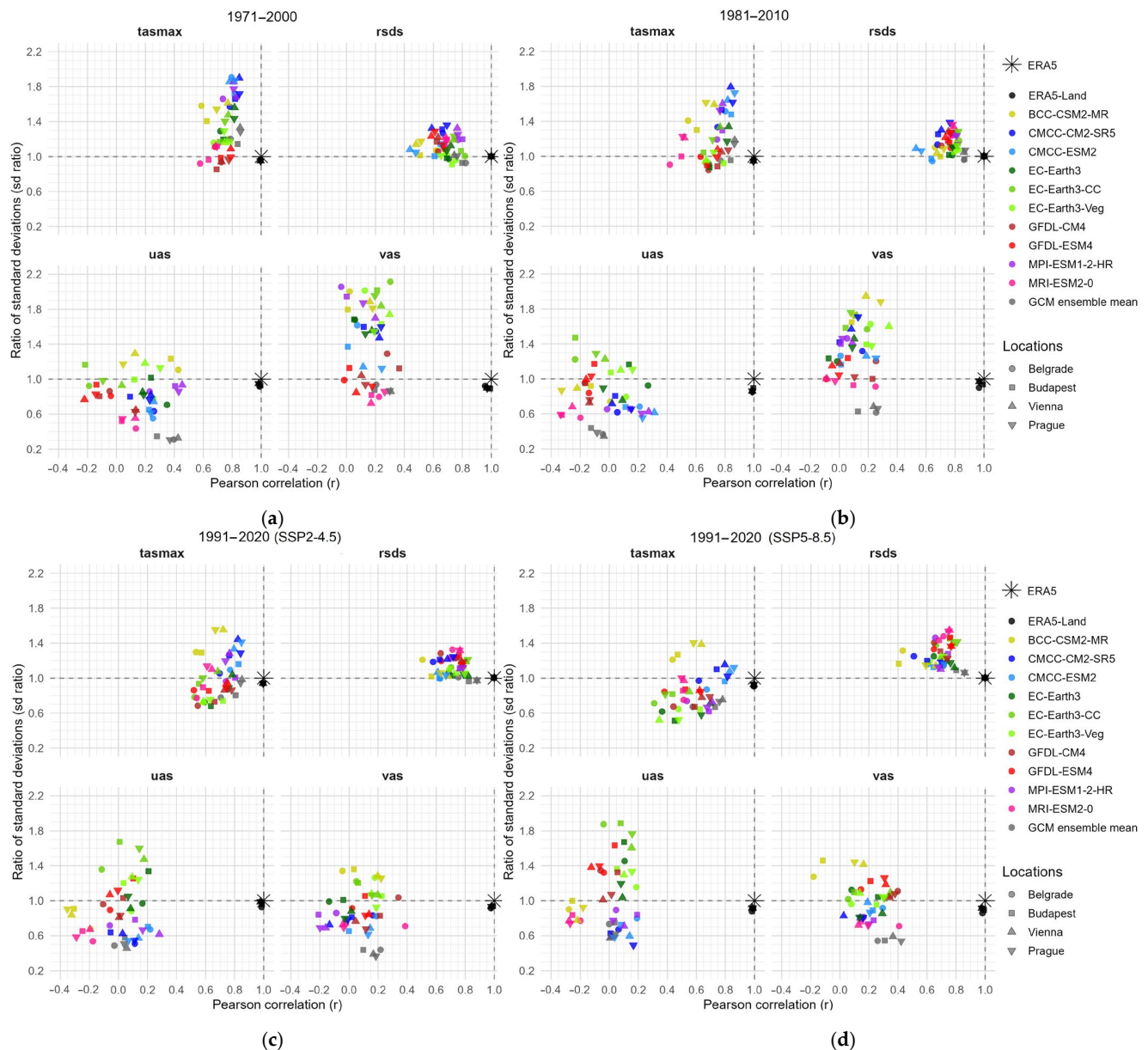


Figure 4. Pearson correlation coefficients (r) and the ratio of standard deviations (sd ratio) based on the mean seasonal (JJA) courses for maximum near-surface air temperature (*tasmax*), surface downwelling shortwave radiation (*rsds*), eastward near-surface wind (*uas*), and northward near-surface wind (*vas*) components for (a) 1971–2000, (b) 1981–2010, (c) 1991–2020 (SSP2-4.5), and (d) 1991–2020 (SSP5-8.5), for all locations (denoted by different symbols). The dashed lines show the perfect agreement with the ERA5 (reference dataset).

The mean seasonal courses of ERA5 and ERA5-Land are very similar (Figure S2), with the largest discrepancies observed for *uas* and *vas* (Figure 4).

3.3. GCM-Performance Based on PV_{pot}

The mean seasonal courses of PV_{pot} are shown in Figure S3. In most cases, the GCM simulations produce higher PV_{pot} values than ERA5, indicating a tendency to overestimate PV_{pot} . In contrast, the differences between the PV_{pot} values for the ERA5 and ERA5-Land are negligibly small, resulting in almost overlapping courses in Figure S3.

According to Equation (3), PV_{pot} is a dimensionless ratio varying within a relatively small range (0.13–0.32) for all time periods and locations. Consequently, to get physically interpretable values, the number of days with high PV_{pot} ($PV_{pot,90}$) was assessed.

Figure 5 summarizes the relative changes in $PV_{pot,90}$ compared with the $PV_{pot,90}$ obtained from ERA5 for 1971–2000 (base value) for each location. For 1971–2000, the values obtained from the GCM simulations and ERA5-Land indicate how accurately $PV_{pot,90}$ is reproduced relative to ERA5. A value of 0% would indicate perfect agreement with ERA5.

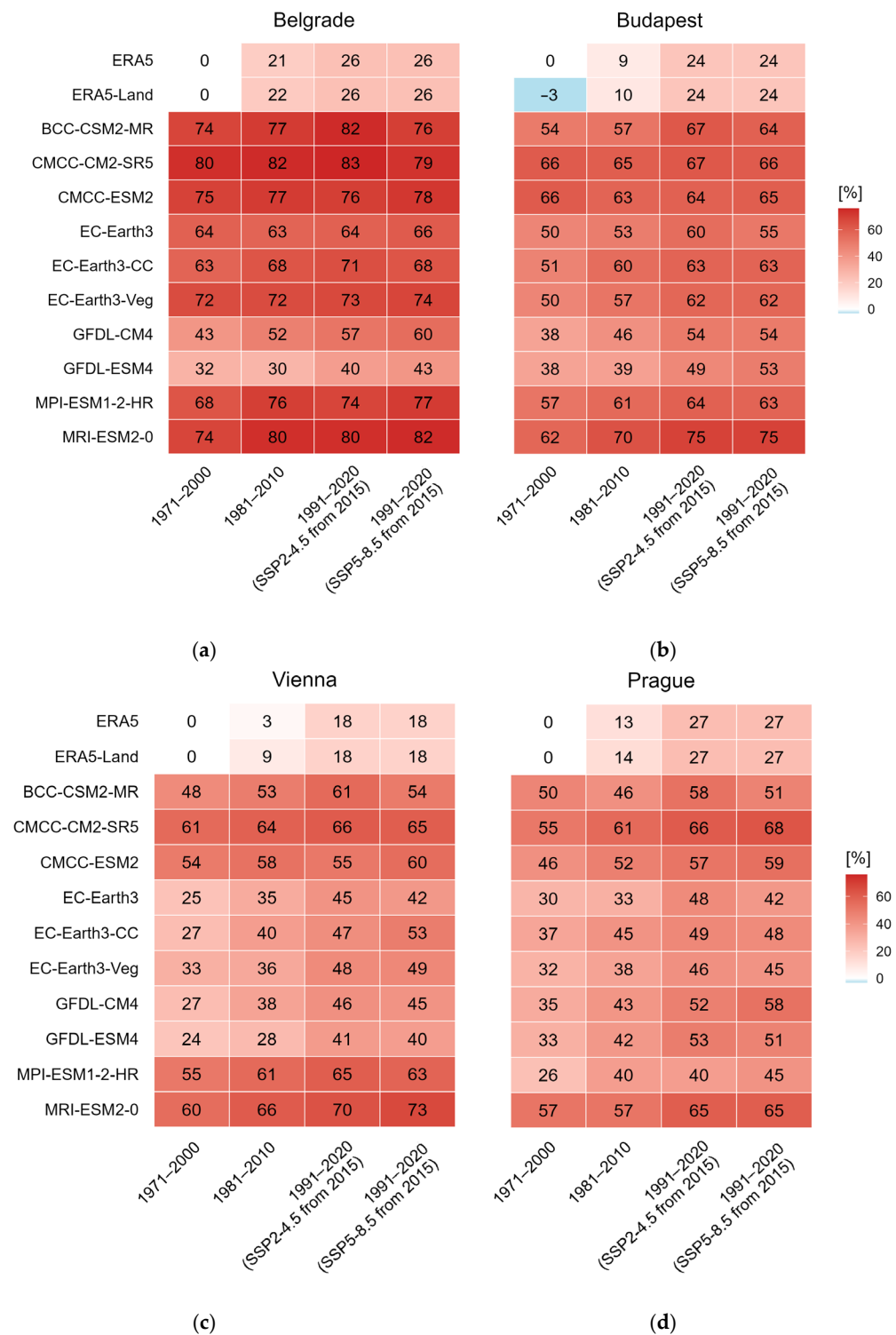


Figure 5. The relative changes in the number of days with high PV_{pot} ($PV_{pot,90}$) compared with the ERA5 $PV_{pot,90}$ values in 1971–2000 (base value) for the locations labelled as (a) Belgrade, (b) Budapest, (c) Vienna, and (d) Prague, and for the time periods 1971–2000, 1981–2010, 1991–2020 (SSP2-4.5), and 1991–2020 (SSP5-8.5).

ERA5-Land reproduces the ERA5 values almost perfectly for Belgrade, Vienna, and Prague (Figure 5a,c,d), while a small underestimation is observed for Budapest (−3%). In contrast, all GCM simulations substantially overestimate $PV_{pot,90}$ for 1971–2000 (reference time period). The overestimations—i.e., GCM biases—range from 24% to 80% depending on the GCM and the location.

ERA5 indicates a systematic increase in $PV_{pot,90}$ from 1971–2000 to 1991–2020. According to Figure 5, $PV_{pot,90}$ increases over time by 24–27% in Belgrade, Budapest, and Prague, while by 18% in Vienna. For example, in Prague, the number of days with high PV_{pot} increased from 10 days (1971–2000) to 35 days (1991–2020), calculated as $10 \text{ days} + (92 \text{ days} \times 0.27)$. This indicates an actual increase in favourable conditions for PV production in the study locations.

Although, most of the GCMs reproduce this increasing tendency from 1971–2000 to 1991–2020, they systematically overestimate $PV_{pot,90}$ across all analyzed time periods, while the increase in $PV_{pot,90}$ is generally smaller than that observed in ERA5. There are only slight differences in $PV_{pot,90}$ for the time periods 1991–2020 (SSP2-4.5) and 1991–2020 (SSP5-8.5).

The largest overestimations occur for Belgrade and Budapest (Figure 5a,b), while smaller, but still considerable overestimations occur for Vienna and Prague (Figure 5c,d). Across all time periods and locations, GFDL-ESM4 is considered one of the most accurate GCMs, while EC-Earth3, EC-Earth3-Veg, and EC-Earth3-CC perform relatively well for Vienna and Prague for all time periods.

ERA5-Land reproduces very similar $PV_{pot,90}$ values compared to ERA5; however, in 1971–2000, ERA5-Land contained only 7 days with high PV_{pot} relative to the base value for the GCM grid cell labelled as Budapest, calculated as 10 days − $(92 \text{ days} \times 0.03)$ (Figure 5b).

4. Discussion and Conclusions

The evaluation of GCM performance is a popular topic in climate research. However, GCM evaluation with respect to PV_{pot} remains limited for our study locations (the eastern part of Central Europe [33,34] and Southeast Europe [35]). Existing studies typically provide only broad statements for this region based on multi-model ensembles, e.g., Refs. [17,18,63].

The main objective of this study was to evaluate GCM performance with respect to daily atmospheric variables that primarily drive PV_{pot} . GCM rankings may fluctuate across regions, time periods, and variables see, e.g., Refs. [64–66] and Figure 3. Therefore, to gain a deeper understanding of the GCMs—which are often regarded as black boxes [67]—we restricted the analysis to GCM grid cells with similar topographical (Figure 1) and climatic conditions.

The use of the nearest grid cell to represent a specific location in GCM outputs is not an uncommon practice in climate studies; e.g., the nearest GCM grid cells were used for climate risk assessment in Taiwan [68]. This approach also formed the basis of a city-specific ranking of CMIP6 GCMs in Indonesia to support urban-scale climate applications [69].

The GCM evaluation comprised three steps. In the first step, the distributions of daily atmospheric variables mainly affecting PV_{pot} (t_{max} , $rsds$, uas , and vas) obtained from GCMs and ERA5-Land were compared with those of ERA5. The ERA5 reanalysis product is widely used as a reference dataset in PV_{pot} -related studies, e.g., Refs. [18–20]. To compare the datasets—without making any assumptions about their underlying distributions—the Wasserstein distance was calculated, which has proven to be an effective metric for evaluating GCM performance [70,71].

In the second step, the mean daily values of the atmospheric variables were examined, and no pronounced outliers were detected (Figure S2). In the third step, PV_{pot} was computed, with a key step being the assessment of T_{cell} . The PV_{pot} values obtained from the GCM simulations and ERA5-Land were then compared with those obtained from ERA5.

To calculate T_{cell} , a linear regression model [62] was used, in which T_{cell} is a linear function of tas , $rsds$, and wsp . This approach has been widely adopted in PV_{pot} studies worldwide, e.g., Refs. [17–19,72]. According to TamizhMani et al. [62], this linear regression model can be applied across different regions, as the coefficients are largely independent of site location. Korab et al. [73] evaluated several formulas for estimating T_{cell} in Poland (Central Europe). They concluded that TamizhMani's equation is one of the best for estimating T_{cell} . In this study, humidity was not considered in the calculation of T_{cell} (Equation (5)). Although increasing humidity may reduce PV_{pot} [74], this atmospheric variable was not included in the present study. This simplification is common in PV_{pot} calculations (see e.g., Refs. [17,18,30]), as the influence of humidity on PV_{pot} is generally negligible. Equation (5) was formulated using daily maximum air temperature, rather than daily mean temperature, as it better represents daytime thermal conditions relevant for PV module operation, while daily averages also include nighttime temperature values.

Several studies expressed changes in PV_{pot} in percentage terms, e.g., Refs. [18,19], which can be difficult to interpret physically, as the base PV_{pot} value itself is already expressed as a percentage. Consequently, the number of days with high PV_{pot} , thus $PV_{pot,90}$ [17] based on ERA5 (1971–2000) was analyzed. We found that all GCMs overestimate $PV_{pot,90}$ for 1971–2000. One possible reason behind this GCM biases is the overestimation of $rsds$ values in the GCMs relative to ERA5 (Figure S2b). Underestimation of $tasmax$ by the GCMs relative to ERA5 contributes to the overestimation of the PV_{pot} . This may explain the smaller $PV_{pot,90}$ values in cases of Vienna and Prague (Figure 5c,d). The overestimation of wind speed reduces air temperature therefore also increases the PV_{pot} (Figure S2c,d). These results are in accordance with the findings of [18].

The relatively small discrepancy between ERA5 and ERA5-Land for $rsds$, compared to the much larger spread among the GCM simulations (e.g., Figure S1), can be explained by the fundamentally different nature of these datasets. The $rsds$ is an inherently uncertain variable, strongly controlled by cloud cover, which remains one of the largest sources of bias in GCMs [75]. Systematic cloud representation errors propagate directly into biases in simulated surface radiation fields, leading to substantial inter-model spread in GCM-based $rsds$ estimates [76]. In contrast, ERA5 and ERA5-Land are produced within the same data assimilation framework, differing primarily in their land surface representation rather than in their atmospheric component. ERA5-Land was generated to better represent land processes, while largely preserving the atmospheric forcing of ERA5 [55]. Consequently, atmospheric variables controlling cloudiness—and thus $rsds$, $tasmax$ —remain highly consistent between the two products, resulting in a small Wasserstein distance (see Figures 2 and S1). Because PV_{pot} is primarily influenced by $tasmax$ and $rsds$ (e.g., Ref. [20]), the PV_{pot} values of ERA5 and ERA5-Land are also very similar (see Figure S3). This interpretation is supported by independent validation studies showing that both ERA5 and ERA5-Land exhibit similar performance in simulating incoming shortwave radiation and agree well with global reference datasets [77].

The 30-year time periods 1991–2020 (SSP2-4.5) and 1991–2020 (SSP5-8.5) differ from each other only in five years. No significant differences were obtained between them based on Wasserstein distances, r , and sd ratio values. However, the examination of $PV_{pot,90}$ enabled us to distinguish them since $PV_{pot,90}$ is slightly smaller for 1991–2020 (SSP5-8.5) than for 1991–2020 (SSP2-4.5) in case of the majority of the GCMs (Figure 5). This may be explained by the higher $tasmax$ values in the SSP5-8.5 scenario than in SSP2-4.5, which reduces PV_{pot} .

Our main findings based on the selected GCM grid cells representing lowland, highly populated urban areas in Central and Southeast Europe during JJA days, are as follows:

- Spatial differences among the analyzed locations are more pronounced than temporal differences, particularly for *rsds*, where Wasserstein distances decrease from southeast to northwest across the study region (Figure 2).
- For *uas*, and *vas*, the GCM simulations exhibit comparatively poorer performance than for *tasmax* and *rsds*, based on the magnitude of the Wasserstein distances. Furthermore, for *tasmax* and *rsds*, ERA5-Land shows greater similarity to ERA5 than the GCM simulations. This is not the case for *uas* and *vas*, where some GCMs exhibit smaller Wasserstein distances to ERA5 than ERA5-Land (Figure 3).
- Although the GCMs overestimate *rsds* values relative to ERA5 (Figure S2b), the shape and variability of the *rsds* mean seasonal course are reproduced reasonably well by the GCMs ($r \cong 0.4\text{--}0.8$; $sd\ ratio \cong 1\text{--}1.4$) (Figure 4b).
- The GCMs show a transition from overestimation to underestimation of the variability of the mean seasonal courses of *tasmax* and *vas* over time (from 1971–2010 to 1991–2020) relative to ERA5. In contrast, the variability of *uas* in the GCM simulations changes in the opposite direction (Figure 4a,c,d).
- Since PV_{pot} is mainly influenced by *rsds* and *tasmax* according to Equation (5), and the GCMs tend to overestimate *rsds*, while underestimating *tasmax* relative to ERA5, PV_{pot} is also overestimated by the GCM simulations compared to ERA5. Consequently, the number of days with high PV_{pot} ($PV_{pot,90}$) is also overestimated, which can be interpreted as a GCM bias.

The $PV_{pot,90}$ values obtained from ERA5 show an increase over time. The GCMs reproduce this increasing tendency from 1971–2000 to 1991–2020; however, the increase in $PV_{pot,90}$ is generally smaller than that observed in ERA5. As it was pointed out in Section 3.2, the GCM ensemble mean may reduce the variability of daily mean seasonal courses; therefore, we avoid computing PV_{pot} based on GCM ensemble means.

Furthermore, selecting the best-performing individual GCM is essential for statistical or dynamical downscaling. Although no individual GCM outperformed others across all four variables, time periods, and locations, the EC-Earth3 and its different configurations (EC-Earth3-Veg, EC-Earth3-CC) were chosen as the best-performing GCMs due to their relatively accurate performance with respect to *rsds* and *tasmax*, which are the most important variables calculating PV_{pot} . Future plans include dynamical and statistical downscaling of the previously mentioned GCM simulations for more detailed studies.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/urbansci10040204/s1>, Figure S1: GCM rankings based on mean Wasserstein distances averaged over 92 JJA days of the GCMs and the ERA5-Land relative to the ERA5 in 16 cases, thus for four locations labelled as Belgrade (1st row), Budapest (2nd row), Vienna (3rd row), and Prague (4th row), and three time periods: 1971–2000 (1st column), 1981–2010 (2nd column), 1991–2020 (SSP2-4.5) (3rd column), and 1991–2020 (SSP5-8.5) (4th column), for (a) maximum near-surface air temperature (*tasmax*), (b) surface downwelling shortwave radiation (*rsds*), (c) eastward near-surface wind (*uas*), and (d) northward near-surface wind (*vas*) components. Figure S2: Seasonal mean courses for (a) maximum near-surface air temperature (*tasmax*), (b) surface downwelling shortwave radiation (*rsds*), (c) eastward near-surface wind (*uas*), and (d) northward near-surface wind (*vas*) components in summer (JJA); derived from 10 GCMs, the ERA5, and ERA5-Land reanalyses for the periods 1971–2000 (1st column), 1981–2010 (2nd column), 1991–2020 SSP2-4.5 (3rd column), and 1991–2020 SSP5-8.5 (4th column), for the locations labelled as Belgrade (1st row), Budapest (2nd row), Vienna (3rd row), and Prague (4th row). Note that due to the high-degree of similarity of the seasonal mean courses for ERA5 and ERA5-Land, their curves overlap. Figure S3: Mean daily photovoltaic potential (PV_{pot}) values in summer (JJA); derived from 10 GCMs, the ERA5, and ERA5-Land reanalyses for the periods 1971–2000 (1st column), 1981–2010 (2nd column), 1991–2020 SSP2-4.5 (3rd column), and 1991–2020 SSP5-8.5 (4th column), for the locations labelled as Belgrade (1st row),

Budapest (2nd row), Vienna (3rd row), and Prague (4th row). Note that, due to the high-degree of similarity of the PV_{pot} values for ERA5 and ERA5-Land, their curves overlap.

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References

1. UNFCCC (United Nations Framework Convention on Climate Change). *Draft Paris Agreement*; United Nations: Paris, France, 2015; p. 48. Available online: https://unfccc.int/files/bodies/awg/application/pdf/draft_paris_agreement_5dec15.pdf (accessed on 14 March 2026).
2. Holechek, J.L.; Geli, H.M.E.; Sawalhah, M.N.; Valdez, R. A Global Assessment: Can Renewable Energy Replace Fossil Fuels by 2050? *Sustainability* **2022**, *14*, 4792. [CrossRef]
3. Directive (EU) 2023/2413 of the European Parliament and of the Council of 18 October 2023 Amending Directive (EU) 2018/2001, Regulation (EU) 2018/1999 and Directive 98/70/EC as Regards the Promotion of Energy from Renewable Sources, and Repealing Council Directive (EU) 2015/652. 2023. Available online: <https://eur-lex.europa.eu/eli/dir/2023/2413/oj> (accessed on 14 March 2026).
4. Edenhofer, O.; Pichs-Madruga, R.; Sokona, Y.; Seyboth, K.; Kadner, S.; Zwickel, T.; Eickemeier, P.; Hansen, G.; Schlömer, S.; von Stechow, C.; et al. (Eds.) *Renewable Energy Sources and Climate Change Mitigation: Special Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2012; p. 1076. Available online: https://www.ipcc.ch/site/assets/uploads/2018/03/SRREN_Full_Report-1.pdf (accessed on 14 March 2026).
5. Frimannslund, I.; Thiis, T.; Aalberg, A.; Thorud, B. Polar solar power plants—Investigating the potential and the design challenges. *Sol. Energy* **2021**, *224*, 35–42. [CrossRef]
6. REN21. *Renewables 2025 Global Status Report: Renewables in Energy Supply—Solar Photovoltaics (PV)*; REN21: Paris, France, 2025; p. 8. Available online: https://www.ren21.net/gsr-2025/downloads/pdf/supply/GSR_2025_Factsheet_Supply_SolarPV.pdf (accessed on 14 March 2026).

7. IRENA (International Renewable Energy Agency). *Renewable Capacity Statistics 2025*; IRENA: Abu Dhabi, United Arab Emirates, 2025; p. 61. Available online: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2025/Mar/IRENA_DAT_RE_Capacity_Statistics_2025.pdf (accessed on 14 March 2026).
8. Hungarian Government. *National Energy Strategy 2030*; Hungarian Government: Budapest, Hungary, 2012. Available online: <https://2010-2014.kormany.hu/download/7/d7/70000/Hungarian%20Energy%20Strategy%202030.pdf> (accessed on 14 March 2026).
9. Photovoltaic Barometer 2025; Eurobserv'ER: Paris, France, 2025; p. 14. Available online: <https://www.eurobserv-er.org/photovoltaic-barometer-2025/> (accessed on 14 March 2026).
10. Dzikuć, M.; Piwowar, A.; Dzikuć, M. The Development of Photovoltaics in the Countries of Central and Eastern Europe in the Context of Regulatory Changes: A Case Study of the Czech Republic and Poland. *Energies* **2025**, *18*, 817. [\[CrossRef\]](#)
11. European Commission. National Energy and Climate Plan of Hungary. 2024. Available online: https://commission.europa.eu/document/download/0a2953f8-5789-4f6f-9714-03df3d4cbbab_en?filename=HU_FINAL%20UPDATED%20NECP%202021-2030%20%28English%29.pdf (accessed on 14 March 2026).
12. Konrad, A.; Gaugl, R.; Maier, C.; Wogrin, S. Implementing dynamic power feed-in limitations of photovoltaic systems in distribution grids for generation expansion planning. *Energy Strategy Rev.* **2025**, *59*, 101760. [\[CrossRef\]](#)
13. Government of Serbia. Integrated National Energy and Climate Plan of the Republic of Serbia for the Period up to 2030 with a Vision to 2050. 2026; 326p. Available online: https://www.mre.gov.rs/extfile/sr/1139/INEKP_pre%C4%8Di%C5%A1%C4%87en_tekst_1.8.24_ENG.pdf (accessed on 14 March 2026).
14. Patt, A.; Pfenninger, S.; Lilliestam, J. Vulnerability of solar energy infrastructure and output to climate change. *Clim. Change* **2013**, *121*, 93–102. [\[CrossRef\]](#)
15. Crook, J.A.; Jones, L.A.; Forster, P.M.; Crook, R. Climate change impacts on future photovoltaic and concentrated solar power energy output. *Energy Environ. Sci.* **2011**, *4*, 3101–3109. [\[CrossRef\]](#)
16. Gaetani, M.; Huld, T.; Vignati, E.; Monforti-Ferrario, F.; Dosio, A.; Raes, F. The near future availability of photovoltaic energy in Europe and Africa in climate-aerosol modeling experiments. *Renew. Sustain. Energy Rev.* **2014**, *38*, 706–716. [\[CrossRef\]](#)
17. Feron, S.; Cordero, R.R.; Damiani, A.; Jackson, R.B. Climate change extremes and photovoltaic power output. *Nat. Sustain.* **2021**, *4*, 270–276. [\[CrossRef\]](#)
18. Dutta, R.; Chanda, K.; Maity, R. Future of solar energy potential in a changing climate across the world: A CMIP6 multi-model ensemble analysis. *Renew. Energy* **2022**, *188*, 819–829. [\[CrossRef\]](#)
19. Liu, C.; Chen, L.; Li, K.; Jin, X.; Chen, X.; Qiao, W.; Liao, H. Historical and future climate changes impact global solar photovoltaic power potential: Role of key meteorological variables. *Atmos. Ocean. Sci. Lett.* **2025**, *18*, 100619. [\[CrossRef\]](#)
20. Ha, S.; Zhou, Z.; Im, E.-S.; Lee, Y.-M. Comparative assessment of future solar power potential based on CMIP5 and CMIP6 multi-model ensembles. *Renew. Energy* **2023**, *206*, 324–335. [\[CrossRef\]](#)
21. Niu, J.; Qin, W.; Wang, L.; Zhang, M.; Wu, J.; Zhang, Y. Climate change impact on photovoltaic power potential in China based on CMIP6 models. *Sci. Total Environ.* **2023**, *858*, 159776. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Chen, Z.; Li, W.; Pan, Z.; Liu, C.; Wang, H.; Guo, J. Spatiotemporal changes in PV potential and extreme characteristics in China under SSP scenarios. *Energy* **2025**, *320*, 135215. [\[CrossRef\]](#)
23. Ruosteenoja, K.; Räisänen, P.; Karhu, J.A.; Lindfors, A.V. Future PV production potential in Northern Europe under changing snow conditions: A multi-model assessment. *Sol. Energy* **2025**, *301*, 113896. [\[CrossRef\]](#)
24. Pérez, J.C.; González, A.; Díaz, J.P.; Expósito, F.J.; Felipe, J. Climate change impact on future photovoltaic resource potential in an orographically complex archipelago, the Canary Islands. *Renew. Energy* **2018**, *133*, 749–759. [\[CrossRef\]](#)
25. Carvalho, D.; Cardoso Pereira, S.; Rocha, A. Future surface temperatures over Europe according to CMIP6 climate projections: An analysis with original and bias-corrected data. *Clim. Change* **2021**, *167*, 10. [\[CrossRef\]](#)
26. Li, D.; Folini, D.; Wild, M. Assessment of top of atmosphere, atmospheric and surface energy budgets in CMIP6 models on regional scales. *Earth Space Sci.* **2023**, *10*, e2022EA002758. [\[CrossRef\]](#)
27. He, J.; Hong, L.; Shao, C.; Tang, W. Global evaluation of simulated surface shortwave radiation in CMIP6 models. *Atmos. Res.* **2023**, *292*, 106896. [\[CrossRef\]](#)
28. Shen, C.; Zha, J.; Li, Z.; Azorin-Molina, C.; Deng, K.; Minola, L.; Chen, D. Evaluation of global terrestrial near-surface wind speed simulated by CMIP6 models and their future projections. *Ann. N. Y. Acad. Sci.* **2022**, *1518*, 249–263. [\[CrossRef\]](#)
29. Miao, H.; Xu, H.; Huang, G.; Yang, K. Evaluation and future projections of wind energy resources over the Northern Hemisphere in CMIP5 and CMIP6 models. *Renew. Energy* **2023**, *211*, 809–821. [\[CrossRef\]](#)
30. Jerez, S.; Tobin, I.; Vautard, R.; Montávez, J.P.; López Romero, J.M.; Thais, F.; Bartok, B.; Christensen, O.B.; Colette, A.; Déqué, M.; et al. The impact of climate change on photovoltaic power generation in Europe. *Nat. Commun.* **2015**, *6*, 10014. [\[CrossRef\]](#)
31. Sailor, D.J.; Hu, T.; Li, X.; Rosen, J.N. A neural network approach to local downscaling of GCM output for assessing wind power implications of climate change. *Renew. Energy* **2000**, *19*, 359–378. [\[CrossRef\]](#)

32. Sørland, S.L.; Schär, C.; Lüthi, D.; Kjellström, E. Bias patterns and climate change signals in GCM-RCM model chains. *Environ. Res. Lett.* **2018**, *13*, 074017. [\[CrossRef\]](#)
33. Pintér, G.; Zsiborács, H.; Hegedúsné Baranyai, N.; Vincze, A.; Birkner, Z. The Economic and Geographical Aspects of the Status of Small-Scale Photovoltaic Systems in Hungary—A Case Study. *Energies* **2020**, *13*, 3489. [\[CrossRef\]](#)
34. Varga, G.; Gresina, F.; Szeberényi, J.; Gelencsér, A.; Rostási, Á. Effect of Saharan dust episodes on the accuracy of photovoltaic energy production forecast in Hungary (Central Europe). *Renew. Sustain. Energy Rev.* **2024**, *193*, 114289. [\[CrossRef\]](#)
35. Benović, A.; Miškić, M.; Pantović, V.; Vujičić, S.; Vidojević, D.; Opačić, M.; Jovanović, F. Assessment of the Impact of Solar Power Integration and AI Technologies on Sustainable Local Development: A Case Study from Serbia. *Sustainability* **2025**, *17*, 6977. [\[CrossRef\]](#)
36. Kotteck, M.; Grieser, J.; Beck, C.; Rudolf, B.; Rubel, F. World Map of the Köppen-Geiger climate classification updated. *Meteorol. Z.* **2006**, *15*, 259–263. [\[CrossRef\]](#)
37. Kikstra, J.S.; Nicholls, Z.R.J.; Smith, C.J.; Lewis, J.; Lamboll, R.D.; Byers, E.; Sandstad, M.; Meinshausen, M.; Gidden, M.J.; Rogelj, J.; et al. The IPCC Sixth Assessment Report WGIII climate assessment of mitigation pathways: From emissions to global temperatures. *Geosci. Model Dev.* **2022**, *15*, 9075–9109. [\[CrossRef\]](#)
38. Milovanović, A.; Babinský, T.; Sedmak, A.; Filipović, I.; Milošević, M. The effect of infill density on fracture toughness results of PLA material. *Procedia Struct. Integr.* **2025**, *68*, 922–928. [\[CrossRef\]](#)
39. Probáld, F. The urban climate of Budapest: Past, present and future. *Hung. Geogr. Bull.* **2014**, *63*, 69–79. [\[CrossRef\]](#)
40. Auer, I.; Böhm, R.; Jurkovic, A.; Lipa, W.; Orlik, A.; Potzmann, R.; Schöner, W.; Ungersböck, M.; Matulla, C.; Briffa, K.; et al. HISTALP—Historical instrumental climatological surface time series of the Greater Alpine Region. *Int. J. Climatol.* **2007**, *27*, 17–46. [\[CrossRef\]](#)
41. Tolasz, R.; Míková, T.; Valeriánová, A.; Voženílek, V. (Eds.) *Climate Atlas of Czechia*; Czech Hydrometeorological Institute: Prague, Czechia; Palacký University: Olomouc, Czechia, 2007; 256p.
42. Danielson, J.J.; Gesch, D.B. *Global Multi-Resolution Terrain Elevation Data 2010 (GMTED2010)*; U.S. Geological Survey Open-File Report 2011–1073; U.S. Geological Survey: Reston, VA, USA, 2011; 23p. [\[CrossRef\]](#)
43. Eyring, V.; Bony, S.; Meehl, G.A.; Senior, C.A.; Stevens, B.; Stouffer, R.J.; Taylor, K.E. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.* **2016**, *9*, 1937–1958. [\[CrossRef\]](#)
44. World Meteorological Organization. *WMO Guidelines on the Calculation of Climate Normals*; World Meteorological Organization: Geneva, Switzerland, 2017; WMO-No. 1203; 29p, Available online: <https://library.wmo.int/idurl/4/55797> (accessed on 14 March 2026).
45. O'Neill, B.C.; Kriegler, E.; Riahi, K.; Ebi, K.L.; Hallegatte, S.; Carter, T.R.; Mathur, R.; van Vuuren, D.P. A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Clim. Change* **2014**, *122*, 387–400. [\[CrossRef\]](#)
46. Wu, T.; Yu, R.; Lu, Y.; Jie, W.; Fang, Y.; Zhang, J.; Zhang, L.; Xin, X.; Li, L.; Wang, Z.; et al. BCC-CSM2-HR: A high-resolution version of the Beijing Climate Center Climate System Model. *Geosci. Model Dev.* **2021**, *14*, 2977–3006. [\[CrossRef\]](#)
47. Cherchi, A.; Fogli, P.G.; Lovato, T.; Peano, D.; Iovino, D.; Gualdi, S.; Masina, S.; Scoccimarro, E.; Materia, S.; Bellucci, A.; et al. Global mean climate and main patterns of variability in the CMCC-CM2 coupled model. *J. Adv. Model. Earth Syst.* **2019**, *11*, 185–209. [\[CrossRef\]](#)
48. Lovato, T.; Peano, D.; Butenschön, M.; Materia, S.; Iovino, D.; Scoccimarro, E.; Fogli, P.G.; Cherchi, A.; Bellucci, A.; Gualdi, S.; et al. CMIP6 Simulations With the CMCC Earth System Model (CMCC-ESM2). *J. Adv. Model. Earth Syst.* **2022**, *14*, e2021MS002814. [\[CrossRef\]](#)
49. Döscher, R.; Acosta, M.; Alessandri, A.; Anthoni, P.; Arsouze, T.; Bergman, T.; Bernardello, R.; Boussetta, S.; Caron, L.-P.; Carver, G.; et al. The EC-Earth3 Earth system model for the Coupled Model Intercomparison Project 6. *Geosci. Model Dev.* **2022**, *15*, 2973–3020. [\[CrossRef\]](#)
50. Held, I.M.; Guo, H.; Adcroft, A.; Dunne, J.P.; Horowitz, L.W.; Krasting, J.; Shevliakova, E.; Winton, M.; Zhao, M.; Bushuk, M.; et al. Structure and performance of GFDL's CM4.0 climate model. *J. Adv. Model. Earth Syst.* **2019**, *11*, 3691–3727. [\[CrossRef\]](#)
51. Dunne, J.P.; Horowitz, L.W.; Adcroft, A.J.; Ginoux, P.; Held, I.M.; John, J.G.; Krasting, J.P.; Malyshev, S.; Naik, V.; Paulot, F.; et al. The GFDL Earth System Model Version 4.1 (GFDL-ESM 4.1): Overall coupled model description and simulation characteristics. *J. Adv. Model. Earth Syst.* **2020**, *12*, e2019MS002015. [\[CrossRef\]](#)
52. Müller, W.A.; Jungclaus, J.H.; Mauritsen, T.; Baehr, J.; Bittner, M.; Budich, R.; Bunzel, F.; Esch, M.; Ghosh, R.; Haak, H.; et al. A higher-resolution version of the Max Planck Institute Earth System Model (MPI-ESM1.2-HR). *J. Adv. Model. Earth Syst.* **2018**, *10*, 1383–1413. [\[CrossRef\]](#)
53. Yukimoto, S.; Koshiro, T.; Kawai, H.; Oshima, N.; Yoshida, K.; Urakawa, S.; Tsujino, H.; Deushi, M.; Tanaka, T.; Hosaka, M.; et al. MRI MRI-ESM2.0 model output prepared for CMIP6 CMIP. *Earth Syst. Grid Fed.* **2019**. [\[CrossRef\]](#)
54. Hersbach, H.; Bell, B.; Berrisford, P.; Hirahara, S.; Horányi, A.; Muñoz-Sabater, J.; Nicolas, J.; Peubey, C.; Radu, R.; Schepers, D.; et al. The ERA5 global reanalysis. *Q. J. R. Meteorol. Soc.* **2020**, *146*, 1999–2049. [\[CrossRef\]](#)

55. Muñoz-Sabater, J.; Dutra, E.; Agustí-Panareda, A.; Albergel, C.; Arduini, G.; Balsamo, G.; Boussetta, S.; Choulga, M.; Harrigan, S.; Hersbach, H.; et al. ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth Syst. Sci. Data* **2021**, *13*, 4349–4383. [CrossRef]
56. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2024. Available online: <http://www.R-project.org/> (accessed on 14 March 2026).
57. Wasserstein, L.N. Markov processes with countable state space describing large systems of automata. *Probl. Pered. Inform.* **1969**, *5*, 64–73. (In Russian)
58. Villani, C. *Optimal Transport: Old and New*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 105–123.
59. Schuhmacher, D.; Bähre, B.; Bonneel, N.; Gottschlich, C.; Hartmann, V.; Heinemann, F.; Schmitzer, B.; Schrieber, J. Transport: Computation of Optimal Transport Plans and Wasserstein Distances. R Package Version 0.15-4. 2024. Available online: <https://cran.r-project.org/package=transport> (accessed on 14 March 2026).
60. Mavromatakis, F.; Makrides, G.; Georghiou, G.; Pothrakis, A.; Franghiadakis, Y.; Drakakis, E.; Koudoumas, E. Modeling the photovoltaic potential of a site. *Renew. Energy* **2010**, *35*, 1387–1390. [CrossRef]
61. Tonui, J.K.; Tripanagnostopoulos, Y. Improved PV/T solar collectors with heat extraction by forced or natural air circulation. *Renew. Energy* **2007**, *32*, 623–637. [CrossRef]
62. TamizhMani, G.; Ji, L.; Tang, Y.; Petacci, L.; Osterwald, C. Photovoltaic module thermal-wind performance: Long-term monitoring and model development for energy rating. In Proceedings of the NCPV and Solar Program Review Meeting 2003, Denver, CO, USA, 24–26 March 2003; p. 4. Available online: <https://www.nrel.gov/docs/fy03osti/35645.pdf> (accessed on 30 January 2026).
63. Zuo, H.-M.; Lu, H.-L.; Sun, P.; Qiu, J.; Li, F.-F. Changes in photovoltaic power output variability due to climate change in China: A multi-model ensemble mean analysis. *J. Renew. Sustain. Energy* **2024**, *16*, 023503. [CrossRef]
64. Nguyen-Duy, T.; Ngo-Duc, T.; Desmet, Q. Performance evaluation and ranking of CMIP6 global climate models over Vietnam. *J. Water Clim. Change* **2023**, *14*, 1832–1846. [CrossRef]
65. Bastola, S.; Maharjan, K.R.; Choo, I.; Jung, Y. Comprehensive evaluation and ranking of CMIP6 global climate models for simulating climate extreme indices across diverse hydrological and geographical regions of Nepal. *J. Hydrol. Reg. Stud.* **2025**, *61*, 102717. [CrossRef]
66. Kristóf, E.; Barcza, Z.; Hollós, R.; Bartholy, J.; Pongrácz, R. Evaluation of Historical CMIP5 GCM Simulation Results Based on Detected Atmospheric Teleconnections. *Atmosphere* **2020**, *11*, 723. [CrossRef]
67. Touzé-Peiffer, L.; Barberousse, A.; Le Treut, H. The Coupled Model Intercomparison Project: History, uses, and structural effects on climate research. *WIREs Clim. Change* **2020**, *11*, e648. [CrossRef]
68. Lin, C.Y.; Tung, C.P. Procedure for selecting GCM datasets for climate risk assessment. *Terr. Atmos. Ocean. Sci.* **2017**, *28*, 43–55. [CrossRef]
69. Bhanage, V.; Lee, H.S.; Cabrera, J.S.; Kubota, T.; Pradana, R.P.; Fajary, F.R.; Nimiya, H. Identification of optimal CMIP6 GCMs for future typical meteorological year in major cities of Indonesia using multi-criteria decision analysis. *Front. Environ. Sci.* **2024**, *12*, 1341807. [CrossRef]
70. Vissio, G.; Lembo, V.; Lucarini, V.; Ghil, M. Evaluating the performance of climate models based on Wasserstein distance. *Geophys. Res. Lett.* **2020**, *47*, e2020GL089385. [CrossRef]
71. Ramdas, A.; García Trillos, N.; Cuturi, M. On Wasserstein two-sample testing and related families of nonparametric tests. *Entropy* **2017**, *19*, 47. [CrossRef]
72. Chen, X.; Mao, H.; Cheng, N.; Ma, L.; Tian, Z.; Luo, Y.; Zhou, C.; Li, H.; Wang, Q.; Kong, W.; et al. Climate change impacts on global photovoltaic variability. *Appl. Energy* **2024**, *374*, 124087. [CrossRef]
73. Korab, R.; Połomski, M.; Naczyński, T.; Kandzia, T. A dynamic thermal model for a photovoltaic module under varying atmospheric conditions. *Energy Convers. Manag.* **2023**, *280*, 116773. [CrossRef]
74. Ayoola, A. Effect of ambient temperature and relative humidity on Photovoltaic system performance. *SSRN Electron. J.* **2021**. [CrossRef]
75. Ceppi, P.; Brient, F.; Zelinka, M.D.; Hartmann, D.L. Cloud feedback mechanisms and their representation in global climate models. *Wiley Interdiscip. Rev. Clim. Change* **2017**, *8*, e465. [CrossRef]
76. Song, F.; Mao, Y.; Liu, S.; Wu, L.; Dong, L.; Su, H.; Wang, Y.; Chtirkova, B.; Wu, P.; Wild, M. A long-term decline in downward surface solar radiation. *Natl. Sci. Rev.* **2025**, *12*, nwaf007. [CrossRef]
77. Valipour, M.; Dietrich, J. Developing ensemble mean models of satellite remote sensing, climate reanalysis, and land surface models. *Theor. Appl. Climatol.* **2022**, *150*, 909–926. [CrossRef]

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