

Article

Not peer-reviewed version

Implications of Spaceborne High-resolution Solar Spectral Irradiance Observation for the Assessment of Surface Solar Energy in China

[Chenxi Kong](#), [Xianwen Jing](#)^{*}, Xiaorui Niu, Jing Jing

Posted Date: 6 February 2025

doi: 10.20944/preprints202502.0414.v1

Keywords: Solar observation; Solar spectral irradiance; Surface solar radiation; Photovoltaic power



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a Creative Commons CC BY 4.0 license, which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Article

Implications of Spaceborne High-Resolution Solar Spectral Irradiance Observation for the Assessment of Surface Solar Energy in China

Chenxi Kong ¹, Xianwen Jing ^{1,2,*}, Xiaorui Niu ³ and Jing Jing ¹

¹ College of Urban and Environmental Sciences, Hubei Normal University, Huangshi 435002, China

² China Meteorological Administration Basin Heavy Rainfall Key Laboratory/Hubei Key Laboratory for Heavy Rain Monitoring and Warning Research, Institute of Heavy Rain, China Meteorological Administration, Wuhan 430205; China

³ Department of Atmospheric Science, School of Environmental Studies, China University of Geosciences, Wuhan 430074; China

* Correspondence: jingxw@hbnu.edu.cn

Abstract: Accurate solar spectral irradiance (SSI) input is key to modelling climate systems. Traditional SSI data used in the climate modelling community are based on solar model calculations joined by limited observations. Recent advances in spaceborne high-resolution solar spectrum observations, such as the National Administration for Space and Aeronautics (NASA)'s Total and Spectral Solar Irradiance Sensor (TSIS), have provided more accurate and reliable SSI alternatives. Here, we investigate the differences between the observed and the model-based SSIs, and how these affect the modelled downward surface solar radiation (DSSR) over different regions of China. Special interest is dedicated to the implications for solar power estimation from solar farms. We conduct idealized calculations using the RRTMG-SW radiative transfer model, with the traditional China Meteorological Administration standard solar spectrum (CMA_STD) and the observed TSIS-1 Hybrid Solar Reference Spectrum (TSIS-1_HSRS). Results show that the CMA_STD SSI yields 4.45 Wm⁻² less energy than the TSIS-1_HSRS, and systematically overestimate energy in the infrared bands and underestimate that in the visible bands. These discrepancies result in an annual regional mean visible DSSR underestimation of ~0.44 Wm⁻², with localized underestimation for a particular month exceeding 2 Wm⁻². The estimated solar power productions with the two SSIs differ by 0.25%~0.35% and 0.36%~0.55% of the total power production capacity for fixed-angle and solar tracking panels, respectively. These findings suggest that long-term and high-resolution spaceborne SSI observations are crucial to improve surface climate modelling, especially on local scales, and to service climate change mitigations.

Keywords: solar observation; solar spectral irradiance; surface solar radiation; photovoltaic power

1. Introduction

Solar radiation serves as the primary source of energy for the Earth. The portion of solar radiation that eventually reaches the surface after being absorbed and scattered by aerosols, clouds, gases in the atmosphere, i.e., the downward surface shortwave radiation (DSSR), contributes significantly to the Earth's surface radiation balance [1,2] and drives the biosphere and geochemical cycles. Accurately capturing the spatial and temporal characteristics of DSSR is crucial for numerous human activities, including photovoltaic (PV) power generation, agricultural production, and meteorological prediction [3–5].

Radiative transfer models (RTMs), which physically simulate the radiation transfer processes under real/quasi-real atmospheric conditions (e.g., clouds, aerosols, and gases), are commonly used to predict DSSR for large spatial and temporal coverage. Such models are widely utilized in numeric

weather/climate models [6,7], remote sensing retrieval algorithms [8–10], and renewable energy studies [11,12].

A fundamental input to RTMs is Solar Spectral Irradiance (SSI) data, which represents the solar energy density across different wavelengths at the top of atmosphere and thus serves as the upper boundary conditions for such models. The accuracy of the input SSI data is crucial for the effectiveness of RTMs in various applications [13]. According to Hu [14], for instance, high-precision solar spectrum data offer crucial support for the physical retrieval of the concentration of atmospheric components (such as CO₂, polluting gases, aerosols, etc.). In climate simulations, solar spectrum and its variation over time act as an external forcing that is necessary for the investigation of long-term climate change [6,7]. Even small variations in the input solar spectrum could induce noticeable changes to the simulated climate system. For example, Jing et al. [15] compared the SSI data widely used in climate models with the most recent satellite observation and found notable differences in the visible (VIS) and near-infrared (NIR) irradiances, which cause significant differences in modelled surface temperature and sea ice coverage at high latitudes due to the differing reflectance of the snow/ice surfaces to the VIS and NIR bands. In terms of PV applications, all PV materials are influenced by spectral irradiance given their specific spectral response functions [16], and hence the variations in the solar spectral irradiance reaching the PV modules can lead to significant differences in the performance of PV modules [17].

Given the fundamental importance of solar spectral irradiance in various fields, SSI data have been established for different application purposes with varying timescales (from daily to yearly). For example, multi-year SSI data generated from the NRLSSI2 solar variability model [18] have been widely utilized in historical climate simulations from pre-industry to present [19]. For the applications in surface solar radiation measurements and computations, China Meteorological Administration (CMA) established its standard zero air mass SSI data (China Meteorological Administration, 2016)[20], which is based on the ASTM E490-00a (2006) SSI [21] table and now adopted in the country's green energy industry for the assessment of photovoltaic power capability and the calculation of other solar radiation parameters [22]. Nevertheless, both the above datasets are primarily derived from indirect model calculations rather than direct solar spectrum observations, although they incorporate observed solar activities (e.g., sunspot numbers) into their algorithms. Satellite-based observation of total solar irradiance (TSI) has continued since the 1970s [23], whereas direct spaceborne measurement of SSI (from UV to near-infrared) began with the National Administration for Space and Aeronautics (NASA)'s Solar Radiation and Climate Experiment (SORCE), which operated from 2003 to 2020 [24]. As a successor to SORCE, the first Total Solar Spectral Irradiance Sensor (TSIS-1) with notably improved instrument was launched by NASA in 2017. TSIS-1 provides SSI measurements with an accuracy of better than 0.2 per cent, making it arguably the most precise SSI observation to date [25]. Additionally, China has also launched its first solar spectral irradiance monitor onboard the Fengyun-3E polar orbit satellite in 2021 [26]. These increasingly available direct SSI observations provide an opportunity to reexamine the solar spectrum used in the current climate models and other aspects such as the photovoltaic industry.

This study aims to explore the differences between the newly observed and the previously model-based SSI data, and to estimate the potential effect on the computed downward surface solar radiation over the land surface of China which covers extensive conditions in terms of climatic zones, atmospheric components, and topography. A particular focus is placed on how large the differing DSSR could affect the estimated power generation from a PV power station, given the rapid expansion of PV panel deployment in recent years in China to mitigate carbon emission and global warming. To that end, the Rapid Radiative Transfer Model for General Circulation Models (RRTMG) [27] is employed alongside the quasi-real atmospheric data from the ERA5 reanalysis [28] and the CERES satellite retrievals [29] for a particular year. Hourly calculations of DSSR are conducted and the possible impacts on PV potential are estimated using two different SSI datasets: the CMA standard SSI and the most recent NASA TSIS-1 observation. The effects of clouds, aerosols, water vapor, etc. are fully considered in the calculations.

The structure of this article is organized as follows: Section 2 describes the two sets of SSI data, the radiative transfer model, and the experiments in detail. Section 3 provides the main results, including the regionality and seasonality of the calculated DSSR, as well as a brief estimation of the effect on PV potential. Section 4 summarizes the main conclusions and discusses potential applications.

2. Materials and Methods

2.1. Solar Spectral Irradiance Data

The solar spectral irradiance datasets compared in this study are the CMA standard solar spectral data (CMA_STD hereinafter; China Meteorological Administration, 2016) [20] and the TSIS-1 Hybrid Solar Reference Spectrum (TSIS-1_HSRS hereinafter) measured by NASA's Total Solar Irradiance Sensor [18]. The two datasets differ in spectral resolutions and ranges. The CMA_STD data covers a spectral range from 119 nm to 1,000,000 nm, with a resolution of 1 nm between 119 and 630 nm and a resolution of 2 nm between 631 and 5,000 nm. The TSIS-1_HSRS data has much finer resolution, which spans 202 to 2,730 nm at a spectral resolution of 0.01 to ~0.001 nm, with an uncertainty of 0.3% between 460 and 2,365 nm and 1.3% at wavelengths outside this range [18]. Figure 1 compares the two spectra in their overlapping range of 200 to 2,730 nm. Here, the finer TSIS-1_HSRS data are resampled (e.g., accumulated within the broader bands of CMA_STD) to match the spectral resolution with the CMA_STD. The two datasets exhibit similar solar spectral distributions, but notable differences are observed in the 300–800 nm range, where the CMA_STD irradiances are generally smaller than those of the TSIS-1_HSRS.

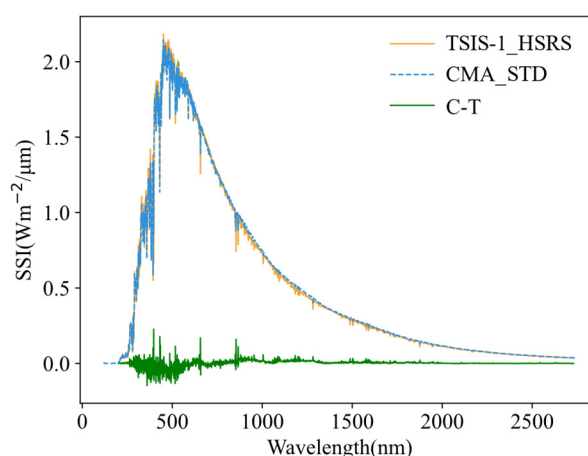


Figure 1. Comparison between the CMA_STD and TSIS-1_HSRS SSIs. The green line shows the differences between the two (CMA_STD – TSIS-1_HSRS).

2.2. Radiative Transfer Model

To estimate the effect of the differences in SSI on estimated DSSR, this study utilizes the shortwave component of the Rapid Radiative Transfer Model for General Circulation Models (RRTMG_SW hereinafter), developed by the Atmospheric and Environmental Research [27]. RRTMG is widely used in weather and climate modelling [30,31]. The model incorporates computationally efficient techniques alongside high-precision optical data for atmospheric gases, aerosols, and clouds, enabling it to effectively simulate the absorption and scattering processes of solar radiation in different wavelength bands. The model provides detailed output of the radiation fields, such as upward and downward radiative fluxes at the top of atmosphere and the surface, as well as atmospheric heating rates.

RRTMG_SW covers the wavelength range of 0.20–12.20 μm and is divided into 14 broad bands (the range of each band is shown in Table 1). The visible portion includes bands 9 to 11 (0.44 –0.78 μm) and the near infrared includes bands 3 to 8 (0.78–2.50 μm).

Table 1. Wavelength ranges of the 14 bands of RRTMG_SW.

Band	Wavelength (μm)
1	3.08~3.85
2	2.50~3.08
3	2.15~2.50
4	1.94~2.15
5	1.63~1.94
6	1.30~1.63
7	1.24~1.30
8	0.78~1.24
9	0.63~0.78
10	0.44~0.63
11	0.35~0.44
12	0.26~0.34
13	0.20~0.26
14	3.85~12.20

To apply the high-resolution SSI data into the broadband RRTMG_SW, we first integrate the high-resolution SSI data within the various bands of the RRTMG_SW to obtain the broadband solar irradiance. For the TSIS-1_HSRS case, the irradiance between 2.73 and 12.20 μm that beyond the observational range, the CMA_STD irradiance in the same range is applied in the integration. Figure 2 shows the integrated broadband irradiance of the two datasets as well as their differences. Figure 2a illustrates that most (~85%) of the solar radiation energy are in the bands 8–11 (0.35–1.22 μm). The visible bands contain roughly 55%, and near-infrared bands about 40% of the total radiation. As for the differences between the two datasets, the total irradiance difference is 4.45 Wm^{-2} , suggesting that the total solar irradiance differs significantly between the two. This is in line with recent studies which demonstrate that the solar constants previously used (in this case the CMA_STD) have been overestimated compared with new spaceborne observations [19][32].The differences in the visible bands (0.35–0.78 μm) are <0, while those in the near-infrared bands (0.78–2.5 μm) are > 0. This is in common with other SSI datasets that are compared with the TSIS-1 observation [32]. It should be noted that the 0.35–1.24 μm bands where the differences are greatest are also the wavelengths that most types of PV modules response the largest [17].

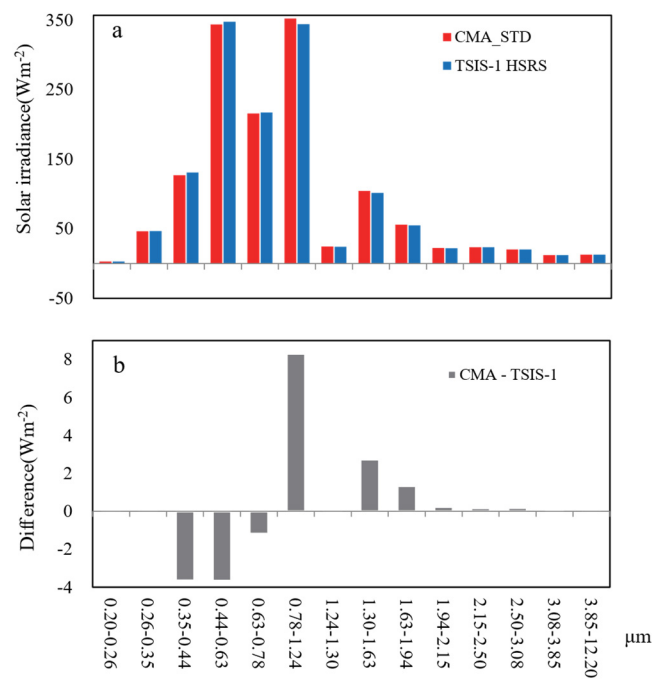


Figure 2. (a) The CMA_STD SSI and TSIS-1_HRSR SSI integrated over each RRTMG_SW band; (b) The difference between the CMA_STD SSI and TSIS-1_HRSR SSI for each RRTMG_SW band (CMA_STD- TSIS-1_HRSR).

2.3. Experiment Design

The above differences in the distribution of energy across spectral bands can inevitably affect the estimation of downward radiation at the surface, given the differing atmospheric transfer processes of radiation in different bands.

To comprehensively assess the effect of spectral data differences on the surface downward radiation, we conduct radiative transfer calculations for one natural year (2019 in this study; the selection of another year should not affect the main findings) under the two types of solar spectral data using the RRTMG model and quasi-realistic atmospheric data with high spatial (0.25° × 0.25°) and temporal (hourly) resolution for the continental areas of China.

The atmospheric and surface data used in the calculations are summarized in Table 2. The atmospheric data are primarily obtained from the ERA5 reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF)[28], including meteorological variables (potential altitude, temperature, and pressure), atmospheric composition (water vapor and ozone), and cloud distributions (cloud cover, cloud water and cloud ice content), with a horizontal resolution of 0.25° × 0.25°, 37 vertical levels, and a temporal resolution of 1h. For trace and well-mixed absorbing gases, fixed volume mixing ratios are used in the calculations: the 2019 global average value of 412 ppmv is used for CO₂, and the typical values of 1.7, 0.32, 0.15, and 2.14 10⁵ ppmv are used for CH₄, N₂O, CO, and O₃, respectively. Considering that the ERA5 data does contain aerosol information, the aerosol optical thicknesses (at 550 nm and 840 nm and monthly averaged) from the CERES_SYN1deg satellite product [29] is used in this study. These data are initially at a spatial resolution of 1° × 1° and are interpolated to the same 0.25° × 0.25° grid of the ERA5 data.

Table 2. Basic information on atmospheric and surface input data.

Type	Variable	Unit	Resolution	Data Source
Meteorologic al field	Potential height	m ² s ⁻²		
	Temperature	K		

	Barometric pressure	hPa		
	Relative humidity	%	0.25°×0.25°	ERA5
	Water vapour	kg ⁻¹		
	Ozone	kg ⁻¹		
	Cloud cover	1		
	cloud water	kg ⁻¹		
	Cloud ice	kg ⁻¹		
Aerosol	Optical Thickness (550 nm)		1°×1°	CERES_SYN1deg
Optical Depth	Optical Thickness (840 nm)			
Ground data	Surface temperature	K	0.25°×0.25°	ERA5
	Surface albedo	1		

To verify the accuracy of the model calculations, we compare the calculated DSSR with the CERES_SYN1deg satellite retrieval [29], as illustrated in Figure 3. The model-calculated DSSR is averaged monthly and interpolated to the 1° × 1° grids to be consistent with CERES_SYN1deg. Figure 3a shows a grid-by-grid comparison of the monthly mean DSSR between the model calculation (using the TSIS-1_HRSR SSI) and the CERES_SYN1deg retrievals, for the whole of 2019. It is demonstrated that the model calculation is in good agreement with the retrievals, with an R^2 of 0.92 and RMSE of 18.41 Wm^{-2} , suggesting that the spatial distributions are similar between the two. However, the model-calculated DSSR is mostly overestimated in the Tibetan Plateau (Figure 3b), where the DSSR values are generally larger than other locations. Notably, previous studies demonstrated that the CERES_SYN1deg product tends to underestimate DSSR in areas with high radiation values compared with ground-based observations [33]. This suggests that the model calculations should reflect to some extent the real solar radiation distribution. The comparisons between the calculation using the CMA_STD SSI and the CERES_SYN1deg are very similar to the above and thus are not shown.

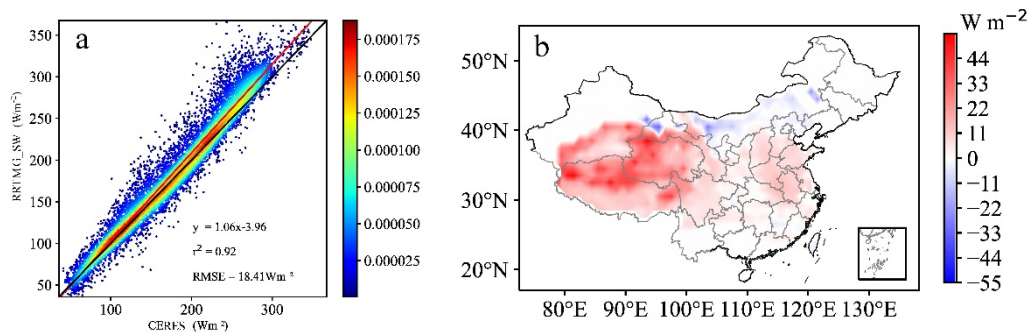


Figure 3. (a) Grid-by-grid scatter plot of the RRTMG_SW calculated DSSR (using the TSIS-1_HRSR SSI) against the CERES_SYN1deg data on a monthly scale for the year 2019. The shaded color shows the joint probability density function; (b) Spatial distribution of the annual-mean differences in DSSR between the RRTMG_SW calculation (using the TSIS-1_HRSR SSI) and the CERES_SYN1deg retrieval.

3. Results

3.1. Impact of SSI Data on the Spatial and Temporal Distributions of DSSR

Figure 4 shows the global distribution of the annual mean DSSR from the RRTMG_SW calculation with the two SSI datasets, as well as their difference. The total DSSR (S_{TOT}) is further split

into direct (S_{DIR}) and diffuse (S_{DIF}) fluxes to examine the relative contributions of absorption and scattering extinctions by gases and cloud/aerosol particles. As is shown in Figure 4a,d, the highest total annual mean solar radiation in China occurs in the Tibetan Plateau and Northwest regions (ranging from 220 to 270 Wm^{-2}), particularly over the Tibetan Plateau. This is due to the highest altitude of the Tibetan Plateau, which results in a shorter atmospheric path and limited absorption and scattering effects, as confirmed by the dominant direct radiation in this region (Figure 4b,e). The Northwest arid and semi-arid regions of China, characterized by long sunshine hours and little rainfall throughout the year, also exhibit higher average annual radiation values compared to other parts of China. Conversely, the lowest surface solar radiation (ranging from 80 to 130 Wm^{-2}) is observed along the eastern edge of the Tibetan Plateau, where persistent clouds and higher water vapor content dominate due to the south-west vortex.

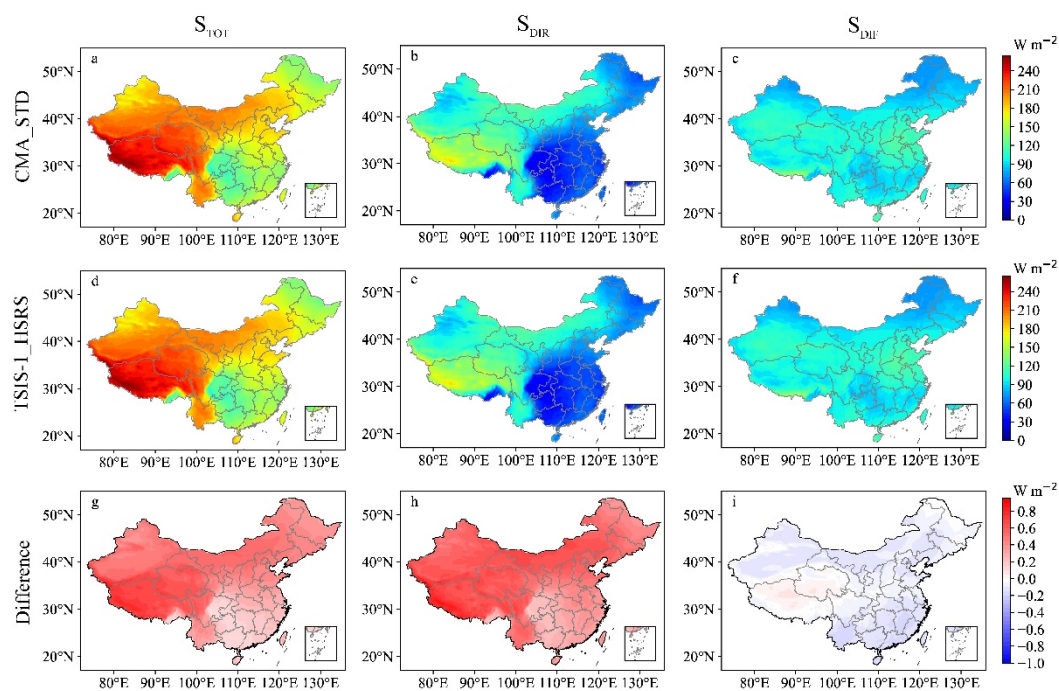


Figure 4. Distribution of the annually averaged downward shortwave radiation calculated using the two SSI datasets and their differences (CMA_STD- TSIS-1_HRSR).

The spatial distribution of the annual mean direct radiation in China (Figure 4b,e) is basically consistent with that of the total radiation, but regional disparities are more significant (ranging from 20.14 to 183.40 Wm^{-2}). The spatial distribution of the diffuse radiation (Figure 4c,f) is relatively uniform (ranging from 68.87 to 151.06 Wm^{-2}). The areas of high diffuse radiation are located at the southern edge of the Tibetan Plateau and over the North China Plain, where the atmosphere is more polluted and the aerosol optical depth is large. Minimum values of diffuse radiation are located in Heilongjiang, northern Xinjiang and northeastern Inner Mongolia, owing to higher latitudes and low solar incidence.

As shown in Figure 4g, the annual mean total DSSR derived by using the CMA_STD data is generally larger than that derived from the TSIS-1_HRSR data. The difference (CMA_STD-TSIS-1_HRSR) across China ranges from 0.02 to 0.83 Wm^{-2} , with an average difference of 0.44 Wm^{-2} throughout the region. The largest differences are in the Tibetan Plateau and Inner Mongolia, generally reaching more than 0.5 Wm^{-2} . In contrast, differences in the southern region are relatively smaller, generally less than 0.3 Wm^{-2} . Figure 4h,i further separate the total differences into differences in the direct and diffuse radiation, respectively. It is seen that the SSI-induced DSSR differences stem primarily from the differences in direct radiation (Figure 4h), which resembles both the spatial distribution and the magnitude of the total differences. In comparison, the differences in the annual

mean diffuse radiation are small and mostly negative, except for the central Tibetan Plateau region where the difference is slightly positive.

To further understand the annual cycle of the DSSR, Figure 5 illustrates the monthly mean surface downward shortwave radiation variation. It is evident that the regional mean DSSR reaches its maximum in June (250.60 Wm^{-2}) and minimum in December (112.36 Wm^{-2}), predominantly driven by the variations in solar declination. While the monthly mean diffuse radiation follows largely the trend of total DSSR, the direct radiation remains relatively constant ($\sim 108 \text{ Wm}^{-2}$) between April and September. Regarding the differences between the two SSI datasets (Figure 6), the CMA_STD data generates larger DSSR (0.35 to 0.58 Wm^{-2} on the monthly mean basis) than the TSIS-1_HRSR data. As previously mentioned and also demonstrated in Figure 6, the differences in direct radiation are the primary contributor to the differences in the total DSSR, while the differences in diffuse radiation, which exhibit an opposing trend, partially offset the positive differences in the direct radiation.

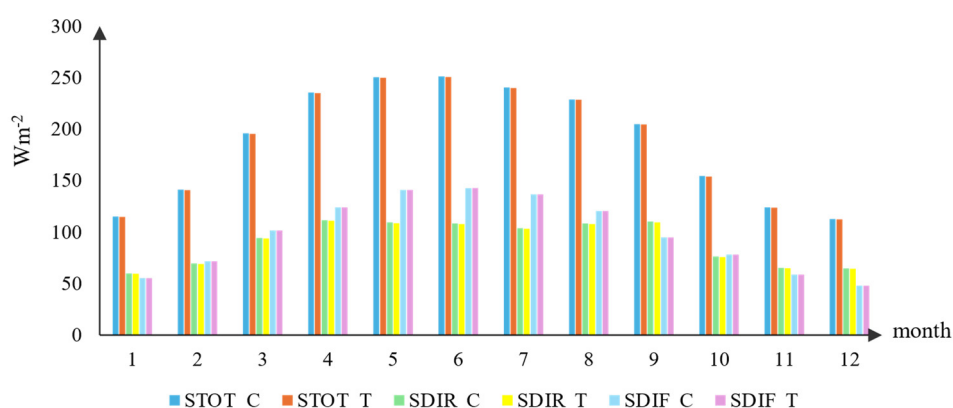


Figure 5. Monthly variations in annually and regionally averaged radiation (total, direct, and diffuse) calculated with the two SSI datasets. Here the suffixes 'C' and 'T' represent the CMA_STD and TSIS-1_HRSR datasets, respectively.

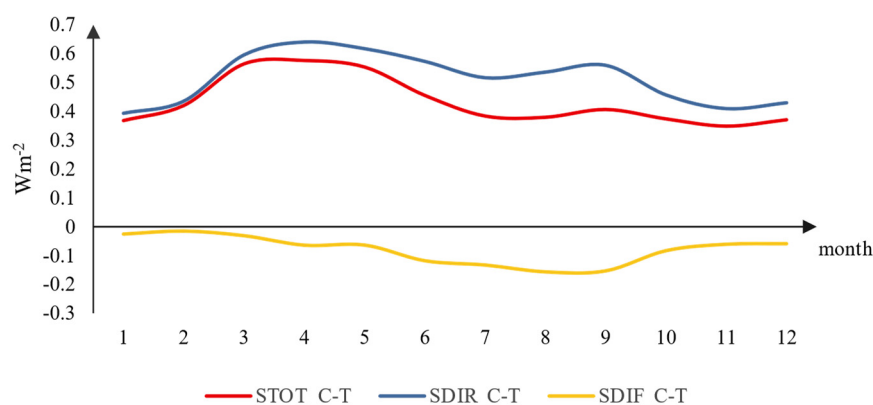


Figure 6. Monthly difference changes in national average radiation (total, direct, diffuse).

The spatial distributions of seasonal radiation differences caused by using different SSI datasets are shown in Figure 7. The largest differences in the S_{TOT} are in spring (March–May, Figure 7a), with a regional average difference of 0.56 Wm^{-2} and local maximum exceeding 1 Wm^{-2} in specific areas, such as the southwestern Tibetan Plateau. The cloud fraction in Tibetan is typically smaller than in other parts of China. For the other seasons, the differences in S_{TOT} exhibit similar patterns to those in Figure 7a, but it is observed that the location of the smallest radiation difference (close to 0 Wm^{-2}) varies significantly with seasons, which reflects the seasonal changes in cloud distributions governed

by the monsoonal climate system. This seasonal variation is more pronounced in diffuse radiation differences (right column in Figure 7), in which negative values are generally coincident with cloudy regions that form the seasonal rain belts. These negative differences stem from the visible bands (see section 3.2) even though the incident solar energy difference in the visible bands is slightly smaller than that in the infrared bands (Figure 2b), suggesting that the visible portion of the solar spectrum is more easily scattered by clouds and aerosols than the infrared. Consistent with the annual means in Figure 4, the seasonal S_{TOT} differences are again dominated by those in S_{DIR} .

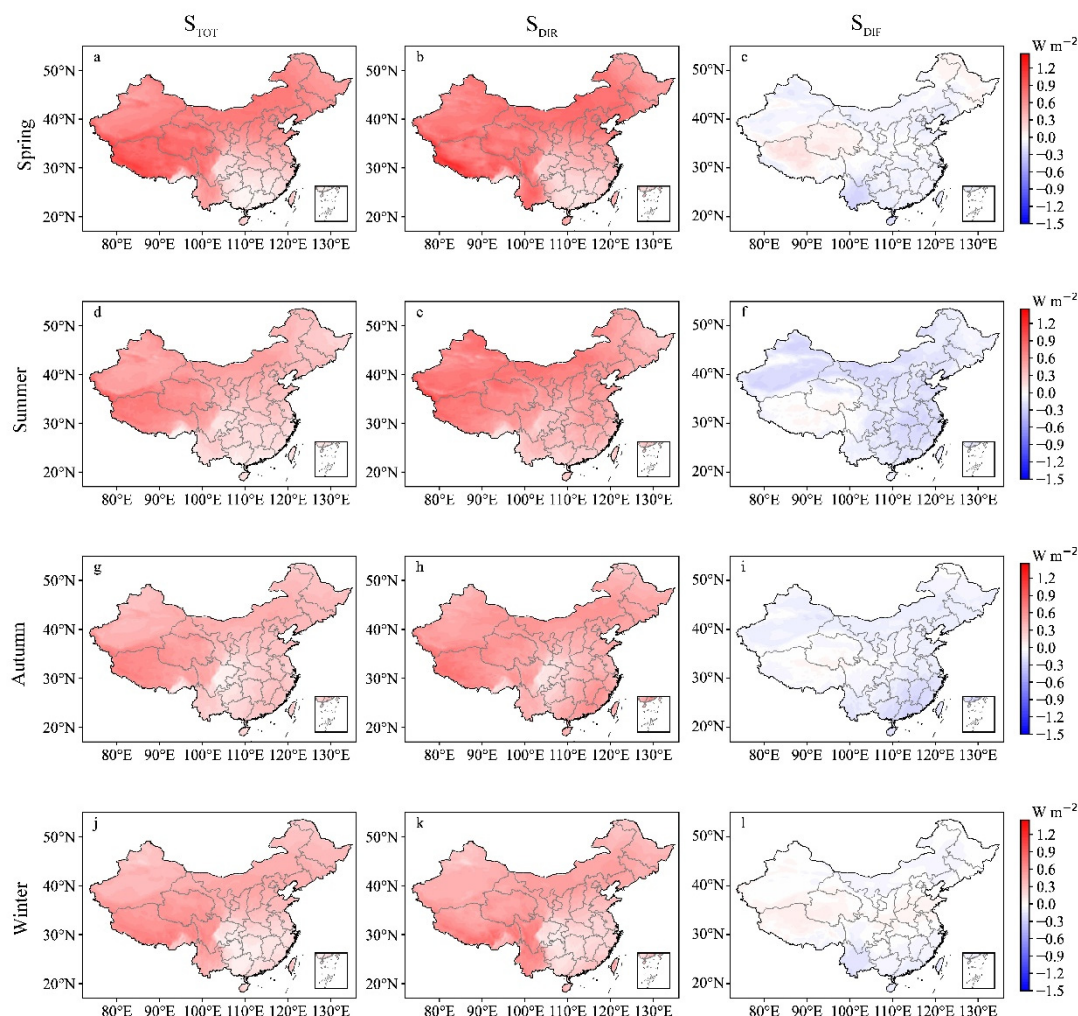


Figure 7. Difference in seasonally averaged downward radiation calculated with the two SSI datasets.

3.2. Impact of SSI Data on the DSSR in Different Spectral Ranges

As demonstrated in Figure 2a, the most significant difference between the two SSI datasets lies in the arrangement of energy in different spectral ranges. This disparity is expected to affect the estimated spectral irradiance reaching the surface. To show the impact of SSI data on the DSSR in different spectral ranges, Figure 8 shows the band-by-band differences in the regional annual mean DSSR. The DSSR by using the CMA_STD spectrum is approximately 1.71 Wm^{-2} larger in the near-infrared bands ($0.78\text{--}2.50 \mu\text{m}$) than that by using the TSIS-1_HRSR spectrum, while is approximately 1.27 Wm^{-2} smaller in the visible bands ($0.35\text{--}0.78 \mu\text{m}$). Hence, the irradiance differences in the two wavelength ranges offset each other, resulting in a net difference of 0.44 Wm^{-2} in the S_{TOT} . Notably, the single band difference in DSSR can exceed 1.2 Wm^{-2} (the $0.78\text{--}1.25 \mu\text{m}$ band), and thus cannot be disregarded since the surface has distinct reflectivity/absorptivity characteristics at different wavelengths depending on the surface types and properties.

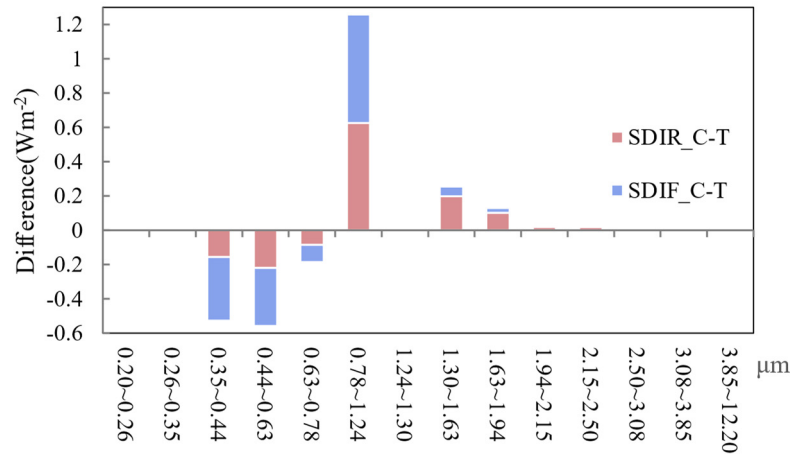


Figure 8. Histogram of band-by-band contributions to the regional annual mean difference.

Although the signs are inverted, the distributions of the DSSR differences between the visible and near-infrared bands are similar (Figure 9). The largest localized differences in the S_{TOT} occur over Tibetan Plateau, where the CMA_STD overestimates the NIR by more than 2.50 Wm^{-2} and underestimates the VIS by over 1.70 Wm^{-2} . Additionally, the contributions of scattered and direct radiation to the discrepancies vary between the two spectral ranges: scattered radiation is more underestimated in the VIS range (-0.81 Wm^{-2} , or 63.78%) while direct radiation is more overestimated in the NIR range (0.97 Wm^{-2} , or 56.72 %). These results indicate that direct radiation predominates the total differences and that the NIR bands are the primary source of the overall radiation differences.

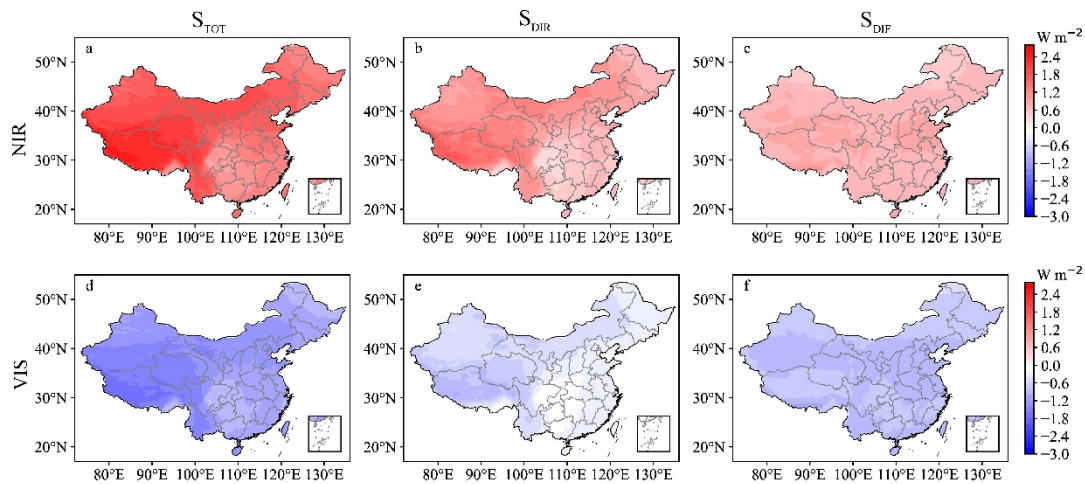


Figure 9. Distribution of annual mean differences in the near-infrared and visible wavelength bands.

3.3. Possible Impacts on the Assessed Power Generation from PV Plants

The findings above demonstrate notable differences in the estimated DSSR when using different solar spectral datasets. Since the visible and near-infrared portions of the solar spectrum are the main working bands of solar panels, here we attempt to make quantitative analysis of the effect of the above DSSR differences on power generation estimates for PV plants.

Power production from a PV plant at a particular location is calculated with a photovoltaic power generation estimation model [34]. In this model, the theoretical annual energy production of a PV plant (E_p) is calculated from the total area of the implemented PV modules and the amount of solar radiation received by the tilted surface as follows:

$$E_p = H_{ASK1} K_2, (1)$$

where H_A is the solar radiation flux received by the tilted surface, S is the total area of the implemented PV modules, and K_1 and K_2 are the photoelectric conversion efficiency of the PV modules and the overall system efficiency, respectively. We assume a PV plant of 10 MWp at each grid point, which uses 350 Wp crystalline silicon PV modules with individual sizes of 1,656 mm × 994 mm. This setup requires a total of 28,600 modules, giving an S of 47,077.43 m². The values of K_1 and K_2 are set to 21.26% and 80%, respectively, consistent with their typical ranges. These settings are summarized in Table 3.

According to Liu et al. [35], H_A is approximated as

$$H_A = S_{DIR}/\cos(\beta) + 0.5 \times (1 + \cos(\beta)) \times S_{DIF}, \quad (2)$$

in which β is the inclination angle of the PV modules. The first and second terms on the right side of Eq. 2 convert the direct and diffuse downward solar radiation flux toward a horizontal plane to fluxes toward the PV modules with an inclination angle of β . Here it is assumed that the distribution of diffuse radiation is isotropic.

To determine β in our calculation, we consider two different types of modules: 1) fixed-angle modules (for easy installation and maintenance); 2) solar-tracking modules (to maximize power generation). For the former, β is usually set to the local optimal inclination angle, which is related to the latitude as well as the climate conditions of the location. For simplicity, we approximate β as the local latitude at each grid point [36]. For the latter, we exactly calculate the β for each grid point at a particular time of day so that the PV modules are always perpendicular to the incoming sunlight.

Table 3. The PV module parameters used in this study.

Panel size (m ²)	Panel peak power (Wp)	S, total area (m ²)	K ₁ , photoelectric conversion efficiency (%)	K ₂ , system efficiency (%)
1.656×0.994	350	47,077.43	21.26	80

As shown in Figure 10a,d, the solar-tracking modules increase power production in most regions compared to the fixed-angle module. The national annual mean increase of total power production is 198,387.28 kWh. Nevertheless, the solar-tracking modules exhibit smaller power generation over the central and eastern regions of China compared with the fixed-angle modules. This can be attributed to the fact that solar-tracking approach maximizes the utilization of direct radiation, whereas limits the diffuse solar radiation that can reach the panels. As shown in Figure 4, the DSSR over the central and eastern regions are predominated by diffuse radiation, because of the abundant aerosols and clouds. This finding suggests that it is perhaps economically inappropriate to install expensive solar-tracking panels in these regions.

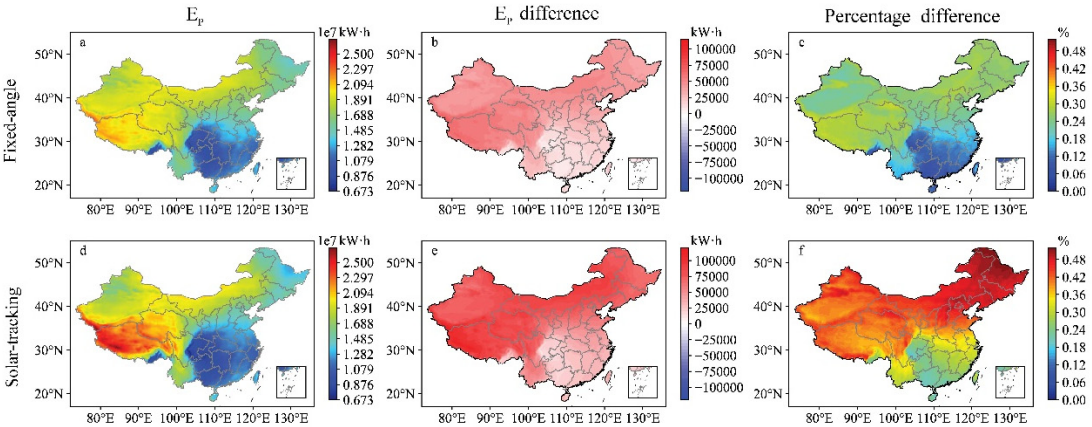


Figure 10. Distribution of annual average power generation (a, d), power production differences (CMA_SDD-TSIS-1_HSRs) (b, e), and percentage difference (c, f; in%) for PV plants with fixed-angle modules and solar-tracking modules.

Figure 10b,e show the differences in the annual mean power production for the two types of PV modules. The distributions of the absolute differences in power production for both module types are mainly in consistency with the differences in DSSR (Figure 4g). In regions with a larger radiation difference, the discrepancies in electricity generation are more pronounced, reaching a maximum of 70,678.06 kWh and 118,986.00 kWh for plants with fixed-angle and solar-tracking modules, respectively. The national mean E_p differences for these two types of plants are 38,195.64 kWh and 65,771.41 kWh, respectively. Notably, high absolute differences in E_p occur at high latitudes and high altitudes, such as the Tibetan Plateau, Northwest China, and Northeast China, while low differences occur in the southern regions at low latitudes.

Figure 10c,f show the percentage differences in E_p relative to the local annual mean value calculated with CMA_STD, which reflects the extent to which power generation in different regions is affected by the SSI data. The distributions are generally similar to the absolute differences, with larger values in Tibetan and the northern regions, and smaller values in the southern regions. Noteworthy, for solar-tracking modules, the northeastern provinces exhibit greater sensitivity to the SSI data (Figure 10f) compared with fixed-angle modules. The SSI-induced E_p differences account for over 0.45% of the local PV power capacity. Power generation in southern regions is less affected by the SSI data used (0.14%~0.25% and 0.18%~0.36% for fixed-angle and solar-tracking modules, respectively), especially in the Sichuan Basin and South China.

It should be noted that the above calculations are for a single PV plant (with a particular area of modules) that imaginarily exists at each grid point. In practice, the installed PV plant capacity varies across regions, which should be considered when evaluating the effect of DSSR differences on the actual absolute power production. For instance, provinces such as Shandong, Hebei, and Jiangsu have installed the largest PV capacities, whereas the three northeastern provinces (Heilongjiang, Jilin, and Liaoning) possess much smaller PV capacities [37]. Although PV power generation in the latter regions is more affected by the SSI under ideal conditions (Figure 10f), the impact should be smaller in terms of the effect on the realistic total regional PV production. In summary, the SSI data-induced large solar radiation differences at high latitudes and high altitudes could cause considerable percentage differences in the potential PV power generation; nevertheless, regions already with large PV installation capacities, such as the central and eastern regions, should be more cautious to the SSI accuracy in order to make precise estimation of absolute power production.

4. Conclusions and Discussion

The accuracy of the solar spectral irradiance is of fundamental importance in climate change studies and various other applications such as PV power prediction. This study compares the most latest and arguably the most accurate spaceborne SSI data (TSIS-1_HSRs SSI) with the previously widely used SSI data (the CMA_STD SSI) and evaluates their impacts on the estimated downward surface solar radiation and PV power production in China, using the RRTMG model in conjunction with the atmosphere, cloud, and surface albedo data from ERA5 and aerosol data from CERES.

The results show that the CMA_STD dataset yields higher DSSR values than the TSIS-1_HSRs dataset, with an annual average difference ranging from 0.02 to 0.83 Wm^{-2} locally. The largest difference occurs over the Tibetan Plateau due to its high altitude and clear atmospheric condition, followed by the northwestern regions such as the Inner Mongolia. Conversely, the southern region, particularly along the eastern peripheral of the Tibetan Plateau, exhibits a smaller annual radiation difference, mostly attributed to the persistent cloud coverage. These differences primarily arise from differences in direct radiation rather than in diffuse (or scattered) radiation. Seasonally, the regional mean DSSR differences are larger in spring and summer, and relatively smaller in autumn and winter.

By band, the CMA_STD SSI has more energy in the near-infrared bands and less in the visible bands, resulting in an overestimation of the annual mean DSSR in the near-infrared bands by 1.71 Wm^{-2} and an underestimation in the visible band by 1.27 Wm^{-2} . For a particular month or season, the localized differences in the two bands could be even larger ($> 2 \text{ Wm}^{-2}$). These discrepancies in the

band-wise energy distribution have important implications for climate system and various applications, given that different surfaces have unique reflecting/absorbing properties for visible and near-infrared wavelengths.

The impact of the above differences in DSSR on estimated photovoltaic power production is also analyzed. For a PV plant with an installed module area of 47,077.43 m² (roughly the area required to generate a power productivity of 10 MWp), the annual power production difference maximizes in high-altitude regions and the north part of the county, reaching up to 65,771.41 kWh for fixed-angle panels and 118,986 kWh for solar-tracking panels. Generally, these PV power differences account for about 0.25%~0.35% and 0.36%~0.55% of the local total power production in the above regions, for fixed-angle and solar-tracking panels, respectively.

It is worth pointing out that the effect of solar spectral irradiance data on DSSR could be much smaller than that of cloud and aerosol variations. However, as SSI is a global and consecutive input to climate models, the small variations in SSI could bring systematic and significant changes to the local climate system, especially when multiple feedback effects are involved. The feedback effects from surfaces like snow/ice and vegetation, which are known to absorb the visible and infrared radiation very differently, are excluded in this study but worth further exploration in the future. For the application in PV power estimation, our findings highlight that the introducing of the newly observed SSI data brings nonignorable impacts to the estimation of power production. Since PV power is a major climate change mitigation approach and a growing industry, updating the existing SSI data with long-term high-resolution spaceborne SSI observations is warranted.

Author Contributions: Writing—original draft preparation, investigation, data curation, visualization, Chenxi Kong; supervision, conceptualization, methodology, writing—review and editing, funding acquisition, Xianewu Jing; supervision, review and editing, funding acquisition, Xiaorui Niu; supervision, review and editing, Jing Jing. All authors have read and agreed to the published version of the manuscript.

Funding: The study was supported by the Meteorological Jointed Fund by NSF and CMA (Grant No. U2342224), the Second Tibetan Plateau Scientific Expedition and Research Program (STEP) (Grant No. 2019QZKK0103), and the Open Project Fund of China Meteorological Administration Basin Heavy Rainfall Key Laboratory (No. 2023BHR-Y16).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Letu, H.; Shi, J.; Li, M.; Wang, T.; Shang, H.; Lei, Y.; Ji, D.; Wen, J.; Yang, K.; Chen, L. A Review of the Estimation of Downward Surface Shortwave Radiation Based on Satellite Data: Methods, Progress and Problems. *Sci. China Earth Sci.* **2020**, *63*, 774–789, doi:10.1007/s11430-019-9589-0.
2. Yuan, M.; Leirvik, T.; Wild, M. Global Trends in Downward Surface Solar Radiation from Spatial Interpolated Ground Observations during 1961–2019. *J. Clim.* **2021**, 1–56, doi:10.1175/JCLI-D-21-0165.1.
3. Wit, A.J.W. de; Boogaard, H.L.; Diepen, C.A. van Spatial Resolution of Precipitation and Radiation: The Effect on Regional Crop Yield Forecasts. *Agric. For Meteorol.* **2005**, *135*, 156–168, doi:10.1016/j.agrformet.2005.11.012.
4. Mellit, A.; Kalogirou, S.A. Artificial Intelligence Techniques for Photovoltaic Applications: A Review. *Prog. Energy Combust. Sci.* **2008**, *34*, 574–632, doi:10.1016/j.pecs.2008.01.001.
5. Wei, Y.; Zhang, X.; Hou, N.; Zhang, W.; Jia, K.; Yao, Y. Estimation of Surface Downward Shortwave Radiation over China from AVHRR Data Based on Four Machine Learning Methods. *Solar Energy* **2019**, *177*, 32–46, doi:10.1016/j.solener.2018.11.008.
6. Coddington, O.; Lean, J.L.; Pilewskie, P.; Snow, M.; Lindholm, D. A Solar Irradiance Climate Data Record. *Bull. Am. Meteorol. Soc.* **2016**, *97*, 1265–1282, doi:10.1175/BAMS-D-14-00265.1.

7. Kunze, M.; Kruschke, T.; Langematz, U.; Sinnhuber, M.; Reddmann, T.; Matthes, K. Quantifying Uncertainties of Climate Signals in Chemistry Climate Models Related to the 11-Year Solar Cycle – Part 1: Annual Mean Response in Heating Rates, Temperature, and Ozone. *Atmos. Chem. Phys.* **2020**, *20*, 6991–7019, doi:10.5194/acp-20-6991-2020.
8. Wielicki, B.A.; Young, D.F.; Mlynczak, M.G.; Thome, K.J.; Leroy, S.; Corliss, J.; Anderson, J.G.; Ao, C.O.; Bantges, R.; Best, F.; et al. Achieving Climate Change Absolute Accuracy in Orbit. *Bull. Am. Meteorol. Soc.* **2013**, *94*, 1519–1539, doi:10.1175/BAMS-D-12-00149.1.
9. Berk, A.; Conforti, P.; Kennett, R.; Perkins, T.; Hawes, F.; van den Bosch, J. MODTRAN® 6: A Major Upgrade of the MODTRAN® Radiative Transfer Code. In Proceedings of the 2014 6th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS); IEEE, June 2014; pp. 1–4.
10. Apell, J.N.; McNeill, K. Correction: Updated and Validated Solar Irradiance Reference Spectra for Estimating Environmental Photodegradation Rates. *Environ. Sci. Process Impacts* **2019**, *21*, 2153–2153, doi:10.1039/C9EM90048A.
11. Smith, C.J.; Forster, P.M.; Crook, R. An All-Sky Radiative Transfer Method to Predict Optimal Tilt and Azimuth Angle of a Solar Collector. *Solar Energy* **2016**, *123*, 88–101, doi:10.1016/j.solener.2015.11.013.
12. CHEN, W.-D.; CUI, F.; ZHOU, H.; DING, H.; LI, D.-X. Impacts of Different Radiation Schemes on the Prediction of Solar Radiation and Photovoltaic Power. *Atmospheric and Oceanic Science Letters* **2017**, *10*, 446–451, doi:10.1080/16742834.2017.1394780.
13. Ahmed, R.; Sreeram, V.; Mishra, Y.; Arif, M.D. A Review and Evaluation of the State-of-the-Art in PV Solar Power Forecasting: Techniques and Optimization. *Renewable and Sustainable Energy Reviews* **2020**, *124*, 109792, doi:10.1016/j.rser.2020.109792.
14. Hu, Z.; Huang, T.; Wang, Y.; Ding, L.; Zheng, H.; Fang, L. Study on the effect of solar spectra on the retrieval of atmospheric CO₂ concentration using high resolution absorption spectra. *Spectrosc. Spect. Anal.* **2011**, *31* (06), 1683–1687, doi:10.3964/j.issn.1000-0593(2011)06-1683-05 (Chinese).
15. Jing, X.; Huang, X.; Chen, X.; Wu, D.L.; Pilewskie, P.; Coddington, O.; Richard, E. Direct Influence of Solar Spectral Irradiance on the High-Latitude Surface Climate. *J. Clim.* **2021**, *34*, 4145–4158, doi:10.1175/JCLI-D-20-0743.1.
16. Nofuentes, G.; García-Domingo, B.; Muñoz, J.V.; Chenlo, F. Analysis of the Dependence of the Spectral Factor of Some PV Technologies on the Solar Spectrum Distribution. *Appl. Energy* **2014**, *113*, 302–309, doi:10.1016/j.apenergy.2013.07.044.
17. Eke, R.; Betts, T.R.; Gottschalg, R., Spectral Irradiance Effects on the Outdoor Performance of Photovoltaic Modules. *Renewable and Sustainable Energy Reviews* **2017**, *69*, 429–434, doi:10.1016/j.rser.2016.10.062.
18. Coddington, O.M.; Richard, E.C.; Harber, D.; Pilewskie, P.; Woods, T.N.; Chance, K.; Liu, X.; Sun, K. The TSIS-1 Hybrid Solar Reference Spectrum. *Geophys. Res. Lett.* **2021**, *48*, doi:10.1029/2020GL091709.
19. Matthes, K.; Funke, B.; Andersson, M.E.; Barnard, L.; Beer, J.; Charbonneau, P.; Clilverd, M.A.; Dudok de Wit, T.; Haberreiter, M.; Hendry, A.; et al. Solar Forcing for CMIP6 (v3.2). *Geosci. Model Dev.* **2017**, *10*, 2247–2302, doi:10.5194/gmd-10-2247-2017.
20. China Meteorological Administration. Solar Constant and Solar Spectral Irradiance under Zero Air Mass; QX/T 368-2016; China Meteorological Administration: Beijing, China, 2016. Available online: <http://www.cmastd.cn/standardView.aspx?id=2345> (accessed on 19 December 2024).
21. ASTM. Solar Constant and Zero Air Mass Solar Spectral Irradiance Tables; ASTM Standard G173-03; ASTM International: West Conshohocken, PA, USA, 2006; Volume 15, Issue 3, pp. 1–16.
22. Wang, X.; Shen, Y.; Li, L. Review of Formulation of Standards in the Field of Solar Energy Resources in China. *Solar Energy* **2020**, *320* (12), 17–23, doi:10.3969/j.issn.1003-0417.2020.12.003 (Chinese).
23. Hoyt, D. V.; Kyle, H.L.; Hickey, J.R.; Maschhoff, R.H. The Nimbus 7 Solar Total Irradiance: A New Algorithm for Its Derivation. *J. Geophys. Res. Space Phys.* **1992**, *97*, 51–63, doi:10.1029/91JA02488.
24. Woods, T.N.; Harder, J.W.; Kopp, G.; McCabe, D.; Rottman, G.; Ryan, S.; Snow, M. Overview of the Solar Radiation and Climate Experiment (SORCE) Seventeen-Year Mission. *Sol. Phys.* **2021**, *296*, 127, doi:10.1007/s11207-021-01869-3.

25. Richard, E.; Harber, D.; Coddington, O.; Drake, G.; Rutkowski, J.; Triplett, M.; Pilewskie, P.; Woods, T. SI-Traceable Spectral Irradiance Radiometric Characterization and Absolute Calibration of the TSIS-1 Spectral Irradiance Monitor (SIM). *Remote Sens. (Basel)* **2020**, *12*, 1818, doi:10.3390/rs12111818.
26. Lei, K.; Li, L.; Huang, Y.; Li, Z.; Yang, X.; Wang, B. Noise and stability analysis of Fengyun-3E solar irradiance monitor. *Laser Journal* **2022**, *43* (04), 17–22. doi:10.14016/j.cnki.jgzz.2022.04.017 (Chinese).
27. Iacono, M.J.; Delamere, J.S.; Mlawer, E.J.; Shephard, M.W.; Clough, S.A.; Collins, W.D. Radiative Forcing by Long-lived Greenhouse Gases: Calculations with the AER Radiative Transfer Models. *Journal of Geophysical Research: Atmospheres* **2008**, *113*, doi:10.1029/2008JD009944.
28. Hersbach, H.; Bell, B.; Berrisford, P.; Biavati, G.; Horányi, A.; Muñoz Sabater, J.; Nicolas, J.; Peubey, C.; Radu, R.; Rozum, I.; Schepers, D.; Simmons, A.; Soci, C.; Dee, D.; Thépaut, J.-N. ERA5 Hourly Data on Pressure Levels from 1940 to Present; Copernicus Climate Change Service (C3S) Climate Data Store (CDS), 2023. Available online: <https://doi.org/10.24381/cds.bd0915c6> (accessed on 27 August 2024).
29. Doelling, D.R.; Sun, M.; Nguyen, L.T.; Nordeen, M.L.; Haney, C.O.; Keyes, D.F.; Mlynarczyk, P.E. Advances in Geostationary-Derived Longwave Fluxes for the CERES Synoptic (SYN1deg) Product. *J. Atmos. Ocean Technol.* **2016**, *33*, 503–521, doi:10.1175/JTECH-D-15-0147.1.
30. Hogan, R.J.; Matricardi, M. Evaluating and Improving the Treatment of Gases in Radiation Schemes: The Correlated K-Distribution Model Intercomparison Project (CKDMIP). *Geosci. Model Dev.* **2020**, *13*, 6501–6521, doi:10.5194/gmd-13-6501-2020.
31. Ruiz-Arias, J.A.; Dudhia, J.; Santos-Alamillos, F.J.; Pozo-Vázquez, D. Surface Clear-sky Shortwave Radiative Closure Intercomparisons in the Weather Research and Forecasting Model. *Journal of Geophysical Research: Atmospheres* **2013**, *118*, 9901–9913, doi:10.1002/jgrd.50778.
32. Funke, B.; Dudok de Wit, T.; Ermolli, I.; Haberreiter, M.; Kinnison, D.; Marsh, D.; Nesse, H.; Seppälä, A.; Sinnhuber, M.; Usoskin, I. Towards the Definition of a Solar Forcing Dataset for CMIP7. *Geosci. Model Dev.* **2024**, *17*, 1217–1227, doi:10.5194/gmd-17-1217-2024.
33. Zhang, J.; Shen, R.; Shi, C.; Bai, L.; Liu, J.; Sun, S. Evaluation and comparison of downward solar radiation from new generation atmospheric reanalysis ERA5 across mainland China. *Journal of Geo-Information Science* **2021**, *23* (12), 2261–2274, doi:10.12082/dqxxkx.2021.180357 (Chinese).
34. Zhang, H.; Yang, S.; Luo, Y.; Zhu, R.; Wang, L.; Shen, D.; Zhou, C. Research on the calculation method of power generation of photovoltaic power plant. *Solar Energy* **2016**, (08), 42–45, doi:10.3969/j.issn.1003-0417.2016.08.009 (Chinese).
35. Liu, Y.; Yao, L.; Jiang, H.; Lu, N.; Qin, J.; Liu, T.; Zhou, C. Spatial Estimation of the Optimum PV Tilt Angles in China by Incorporating Ground with Satellite Data. *Renew. Energy* **2022**, *189*, 1249–1258, doi:10.1016/j.renene.2022.03.072.
36. Cheng, C.L.; Sanchez Jimenez, C.S.; Lee, M.-C. Research of BIPV Optimal Tilted Angle, Use of Latitude Concept for South Orientated Plans. *Renew. Energy* **2009**, *34*, 1644–1650, doi:10.1016/j.renene.2008.10.025.
37. HAN, M.; XIONG, J.; LIU, W. Spatio-Temporal Distribution, Competitive Development and Emission Reduction of China's Photovoltaic Power Generation. *Journal of Natural Resources* **2022**, *37*, 1338, doi:10.31497/zrzyxb.20220516.(Chinese)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.