Photovoltaic power potential of variability and its influencing factors in Xinjiang, China

2026-07-16

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Abstract

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Full Text

J Arid Land 2026 18(7): 1258–1282
doi: 10.1016/j.jaridl.2026.07.005; CSTR: 32276.14.JAL.20250642

Photovoltaic power potential of variability and its influencing factors in Xinjiang, China

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Abstract: Quantifying the evolution of solar photovoltaic power potential in Xinjiang Uygur Autonomous Region (hereinafter referred to as Xinjiang) is critical for energy planning under China' s carbon neutrality goals. This study applied the Equidistant Cumulative Distribution Function Matching (EDCDF$_m$) method to correct biases in the sixth phase of the Coupled Model Intercomparison Project (CMIP6) multi-model data, using the fifth generation of European Centre for Medium Range Weather Forecasts (ECMWF) Reanalysis-Land (ERA5-Land) as a reference. Corrected data were used to drive 11 widely validated empirical photovoltaic models to evaluate the spatiotemporal evolution of photovoltaic power potential in Xinjiang from 2000 to 2060. The results showed that average annual power potential from 2000 to 2020 was 282.29 kWh/m^2, with higher values in the south and lower in the north and a slight decreasing trend. In terms of future forecasting, compared with historical baseline period, photovoltaic power potential increased slightly under the Shared Socioeconomic Pathway (SSP)1-2.6 scenario, with about 79.41% of the land area showing favorable conditions of increased photovoltaic power potential and reduced coefficient of variation (CV). In contrast, under the SSP2-4.5 and SSP5-8.5 scenarios, unfavorable pattern of decreased photovoltaic power potential and increased CV expanded significantly, covering about 24.66% and 37.65% of the total area, respectively. Analysis of influencing factors showed that solar radiation was the dominant factor controlling photovoltaic power potential, while rising temperature had a negative effect. Under the SSP5-8.5 scenario, reduced solar radiation and rising temperature were the main factors driving the decline in photovoltaic power potential. At the regional level, although the central area currently had relatively low potential, it shows a decreasing CV and continuously increasing photovoltaic power potential in the future, indicating better conditions for development. Economic analysis showed that, under standard carbon price, the levelized cost of electricity (LCOE) on the SSP1-2.6 path was the lowest, yielding significant net social benefits. This study indicates that pursuing a sustainable development path is a key to mitigating the adverse impacts of climate change, providing scientific reference for medium- and long-term photovoltaic installation planning in Xinjiang.

Keywords: photovoltaic power potential; climate change; variability; empirical photovoltaic models; the sixth phase of the Coupled Model Intercomparison Project (CMIP6); Shared Socioeconomic Pathway (SSP) scenarios; levelized cost of energy

Citation: MENG Nana, LI Ran, PENG Yimo, GE Tianxu, FAN Shichen, ZHANG Haiwei. 2026. Photovoltaic power potential of variability and its influencing factors in Xinjiang, China. Journal of Arid Land, 18(7): 1258–1282. https://doi.org/10.1016/j.jaridl.2026.07.005; https://cstr.cn/32276.14.JAL.20250642

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Received 2025-12-19; revised 2026-06-18; accepted 2026-06-30

http://jal.xjegi.com; https://www.keaipublishing.com/en/journals/journal-of-arid-land/

This version posted 2026-07-16.

1 Introduction

Anthropogenic emissions will cause significant changes in the Earth' s climate over the coming decades (Hua et al., 2024). To address climate change, China, as the world' s largest greenhouse gas emitter, has committed to achieving peak carbon emissions by 2030 and carbon neutrality by 2060 (Mallapaty, 2020). In pursuit of these goals, China has actively promoted the large-scale deployment of clean energy, including photovoltaic power generation, in recent years. Arid and semi-arid areas, characterized by abundant solar resources and vast underutilized land, have become key strategic bases for the nation' s energy transition (Ding et al., 2018; Jin et al., 2023; Wang et al., 2023). China' s renewable electricity capacity growth triples in the next five years compared with the previous five, with the country accounting for an unprecedented 56.00% of global expansion (IEA, 2024). The cumulative photovoltaic installed capacity in China is projected to reach 3600 GW by 2060, approximately 11.76 times the current scale (Lu et al., 2022). While meeting growing energy demands, this rapid expansion necessitates a more accurate estimation of the photovoltaic power potential (van Ruijven et al., 2019).

The photovoltaic power potential is primarily driven by surface downward shortwave radiation (RSDS), to which it responds in an approximately proportional manner (Crook et al., 2011; Liu et al., 2025). RSDS is modulated by aerosols and clouds. During dust storms or snowy/rainy weather, solar radiation levels are reduced. Dust particles can deposit on photovoltaic panels, directly limiting the power generation capacity (Fan et al., 2023). Variations in air temperature and wind speed also influence the photovoltaic power potential (Zhu et al., 2025). Increased ambient temperature generally reduces photovoltaic conversion efficiency, whereas moderate wind can enhance efficiency through cooling effects (Peters and Buonassisi, 2019). However, in dust-prone areas like deserts, high wind speeds exacerbate dust accumulation on panels, attenuating radiation reception and leading to a significant decline in photovoltaic power generation efficiency (Al-Hanoot et al., 2024). These meteorological factors may interact to affect the stability of photovoltaic systems. Therefore, against the backdrop of large-scale photovoltaic deployment, it is crucial to integrate the three key meteorological factors of solar radiation, temperature, and wind speed into regional estimations to quantify and compare their relative impacts on photovoltaic energy yield.

Xinjiang Uygur Autonomous Region (hereinafter referred to as Xinjiang), a typical arid and semi-arid area in China, possesses abundant land and solar resources, offering inherent advantages for photovoltaic application development (Hou et al., 2023). Influenced by human activities and other factors, the region is highly sensitive to climate change (Zhang et al., 2025). Although the annual total solar radiation ranges from 5000 to 6500 MJ/m^2, dust storms with wind speeds of 25.00–30.00 m/s can cause photovoltaic power generation efficiency losses of 9.82%–24.46% (Liu et al., 2023; Sun et al., 2025). From 1961 to 2018, the regional annual average temperature showed a significant warming trend at a rate of 0.35°C/10a, exceeding the global and national averages (Yao et al., 2021). Lü et al. (2024) stated that a 1.00°C increase in ambient temperature typically raises photovoltaic module operating temperature by about 1.00°C, leading to decreases in photoelectric conversion efficiency and output power of approximately 0.06% and 0.40%, respectively. This implies that persistent warming will further impair the actual power generation performance of photovoltaic power stations in Xinjiang. These findings indicate that climate change, by affecting the energy reception and operating temperature of photovoltaic modules, increases the uncertainty and volatility of photovoltaic power output in Xinjiang (Ashraf et al., 2025). Against the frequent occurrence of extreme weather events, accurately quantifying the spatiotemporal evolution characteristics of the photovoltaic power potential in Xinjiang is of strategic importance for future regional energy planning.

Numerous studies have investigated the photovoltaic power potential. Based on an empirical model, Feng et al. (2021) estimated the average annual photovoltaic power potential in China during 1961–2018 to be 293.00 kWh/m^2. Using a machine learning approach combined with an empirical photovoltaic model, Liu et al. (2022) derived an average annual photovoltaic power potential of 276.00 kWh/m^2 in China from 1971 to 2016. Although these studies employed

relatively advanced data-driven methods, the diversity of methodologies, inconsistent data sources, and prevalent reliance on single or limited photovoltaic models have introduced considerable uncertainties and certain biases in the quantified results. In recent years, some studies have begun to address this issue. Chen et al. (2023) evaluated the solar energy potential across China using an ensemble of 11 photovoltaic power models and identified systematic discrepancies of 6.00%–7.00% among different model estimates, revealing considerable uncertainty associated with single-model assessments of photovoltaic power potential. Doubleday et al. (2021) further demonstrated that post-processing multi-model ensembles using the Bayesian model averaging (BMA) method could reduce estimation uncertainty by 2.00%–36.00%, effectively correcting systematic biases in single-model estimates. These findings indicate that ignoring model structure uncertainty in assessing the photovoltaic power potential in Xinjiang may undermine the robustness of conclusions. Therefore, it is necessary to introduce multi-model ensemble averaging methods and establish a comprehensive assessment framework that integrates multi-source meteorological data and physical processes to reduce uncertainties in photovoltaic power potential evaluation.

This study estimated the photovoltaic power potential in Xinjiang using the fifth generation of European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis-Land (ERA5-Land) and the sixth phase of the Coupled Model Intercomparison Project (CMIP6). To reduce uncertainties arising from model reliance, we selected 11 widely used empirical photovoltaic models from the literature. The spatiotemporal distribution and variation characteristics of solar radiation, temperature, and wind speed in Xinjiang during the historical baseline period (2000–2020) and the future carbon-neutral window period (2021–2060) are analyzed. The spatiotemporal distribution differences and evolution trends of the photovoltaic power potential in Xinjiang under different scenarios (Shared Socioeconomic Pathway (SSP)1-2.6, SSP2-4.5, and SSP5-8.5) are predicted, and the contributions of various monthly climatic factors (near-surface air temperature at a height of 2 m (TAS), near-surface wind speed at a height of 10 m (sfcWind), and RSDS) to changes in photovoltaic output are quantified. This work aims to provide theoretical support for the scientific planning and efficient operation of photovoltaic power stations in arid and semi-arid areas.

2 Study area and data sources

2.1 Study area

Xinjiang is located in Northwest China within the Eurasian continental interior (34°03′–49°01′N, 73°00′–96°02′E; Fig. 1). It covers an area of approximately 1.66×10^6 km^2, accounting for about one-sixth of China's total land area (Wang et al., 2025). Far from the ocean, Xinjiang exhibits a typical temperate continental arid and semi-arid climate characterized by scarce precipitation and intense evaporation. Consequently, water scarcity has become a critical ecological and environmental challenge in this region.

The terrain features a distinct topographic pattern described as "three mountains flanking two basins." From north to south, these are the Altay Mountains, the Junggar Basin, the Tianshan Mountains, the Tarim Basin, and the Kunlun Mountains. This alternating distribution of mountains and basins results in drastic elevation changes and a fragile ecological environment. Despite the arid climate, Xinjiang possesses abundant solar energy resources. With an annual total solar radiation ranging from 5000 to 6500 MJ/m^2, it stands as one of China's most promising regions for solar power development (Liu et al., 2023).

2.2 Data sources

2.2.1 Historical observation data

The ERA5-Land reanalysis dataset from the ECMWF was used as the primary source of meteorological driving data for the historical baseline period of 2000–2020. Building on the ERA5 global reanalysis system, ERA5-Land provides a consistent view of the evolution of land variables over decades at a higher resolution (Muñoz-Sabater et al., 2021). This dataset enables the assessment of the photovoltaic power potential under historical climate conditions and the correction of climate model biases, and supports long-term climate change trend analysis (Hersbach et al., 2020).

Fig. 1 Overview of Xinjiang Uygur Autonomous Region (hereinafter referred to as Xinjiang) based on elevation data. DEM, digital elevation model. The figure is based on the standard map (GS(2024)0650) provided by the National Platform for Common Geospatial Information Services (http://bzdt.ch.mnr.gov.cn/). The boundary of the base map has not been modified.

The dataset covers 15.0°–55.0°N and 70.0°–140.0°E, with a monthly temporal resolution and a 0.1° spatial resolution. Compared with traditional station observations, ERA5-Land offers greater spatial coverage and uniformity, making it particularly suitable for regional-scale climate analysis and energy potential assessment. To analyze the spatiotemporal variability of the photovoltaic power potential in Xinjiang from 2000 to 2020, we selected three core meteorological variables: TAS, sfcWind, and RSDS (Crook et al., 2011; Lü et al., 2024).

The original monthly data were aggregated into annual series, serving as the baseline for evaluating the spatiotemporal variability of the photovoltaic power potential in Xinjiang during the historical baseline period. This dataset was also used as the reference for correcting systematic biases in future scenario data from CMIP6.

2.2.2 CMIP6 models

The period 2021–2060 was selected as the future simulation period for CMIP6 model validation. CMIP6 employs a matrix framework combining SSPs and Representative Concentration Pathways (RCPs), providing a variety of globally standardized climate model data for both historical and future periods (O' Neill et al., 2016). Building upon the fifth phase of the Coupled Model Intercomparison Project (CMIP5), this dataset addresses the need for more complex socioeconomic scenarios and higher-resolution climate simulations. It contains over 100 model outputs, supporting applications such as future climate projection, extreme event analysis, and renewable energy potential assessment (Xiang et al., 2021). This study adopted three representative pathways: SSP1-2.6, SSP2-4.5, and SSP5-8.5, which correspond to low, medium, and high greenhouse gas emission pathways, respectively. The SSP1-2.6 represents a sustainable development pathway with low emissions; SSP2-4.5 follows a middle-of-the-road trajectory; while SSP5-8.5 describes a high-emission future. Together, these pathways cover the probable range of future climate change. This framework enables a comparison of how varying emission intensities affect the photovoltaic power potential in Xinjiang.

To analyze the long-term evolution of the photovoltaic power potential in Xinjiang, this study selected data from 10 models. Details of the different climate models are provided in Table S1. The dataset covers two periods: the calibration period (2015–2020), which is adopted to establish correction relations between ERA5-Land and CMIP6, and the future projection period (2021–2060). To reduce the uncertainty associated with selecting a single climate model, the analysis was conducted using the multi-model ensemble mean.

3 Methods

3.1 Calibration methods

Systematic biases are often present in the downscaled results of CMIP6 global climate models. The Equidistant Cumulative Distribution Function Matching ($EDCDF_m$) method, however, effectively captures extremes in climate variables and improves the accuracy of downscaled data and the precision of model simulations (Piao et al., 2022; Zhou et al., 2023).

The raw CMIP6 model outputs are at a relatively coarse resolution. To preserve the spatial details necessary for regional-scale analysis in Xinjiang, we downscaled all CMIP6 data to a spatial resolution of 0.1°$×$0.1° using bilinear interpolation before model calibration. This process was conducted with ERA5-Land as the reference dataset to ensure consistency in the grid system.

Bilinear interpolation is a commonly used resampling method that computes a weighted average of neighboring pixel values (Bovik, 2009). This technique assumes a linear variation of pixel intensity across the image. Although its computational complexity is slightly higher than nearest-neighbor interpolation, it yields smoother results (Gribbon and Bailey, 2004; Hongbo et al., 2021; Minh et al., 2024).

Assume the coordinates and corresponding pixel values of four neighboring pixels (x_0, y_0), (x_0, y_1), (x_1, y_0), and (x_1, y_1) around the target pixel (x, y) are known, interpolation is first performed in the x-direction to obtain intermediate values R_1 and R_2:

$$f(R_1) \approx \frac{x_1 - x}{x_1 - x_0} f(x_0, y_0) + \frac{x - x_0}{x_1 - x_0} f(x_1, y_0) \text{ where } R_1 = (x, y_0), \tag{1}$$

$$f(R_2) \approx \frac{x_1 - x}{x_1 - x_0} f(x_0, y_1) + \frac{x - x_0}{x_1 - x_0} f(x_1, y_1) \text{ where } R_2 = (x, y_1), \tag{2}$$

where $f(R_1)$ and $f(R_2)$ represent the interpolated pixel values at two intermediate points along the x-direction. Interpolation in the y-direction yields:

$$f(P) \approx \frac{y_1 - y}{y_1 - y_0} f(R_1) + \frac{y - y_0}{y_1 - y_0} f(R_2). \tag{3}$$

The final pixel value $f(P)$ is subsequently derived via interpolation in the y-direction.

Using ERA5-Land data as the reference, we then applied the $EDCDF_m$ to correct the CMIP6 simulation data. This method adjusts the cumulative distribution function (CDF) of the CMIP6 data within its historical distribution to match that of the ERA5-Land observation data. The specific steps are as follows (Teutschbein and Seibert, 2012; Wang et al., 2019):

First, percentile matching is applied to align future simulations with historical data:

$$p = F_f(x_f), \tag{4}$$

$$F_m(x'_m) = p, \tag{5}$$

$$F_o(x'_o) = F_m(x'_m) = p, \tag{6}$$

where p denotes the percentile of the future simulation; F_f is the CDF of the future simulated data; x_f is the future simulated data; F_m is the quantile function of the historical simulated data; x'_m is the historical observed data; F_o is the CDF of the observed data; and x'_o is the historical observational data.

Second, the model output for CMIP6 future scenarios can be corrected using the equidistant approach:

$$x^*_f = x'_o + \left(x_f - x'_m\right), \tag{7}$$

where x^*_f is the bias-corrected climate variable value.

This procedure can be summarized as:

$$x^*_f = F_o^{-1}\left(F_f\left(x_f\right)\right) + \left[x_f - F_m^{-1}\left(F_f\left(x_f\right)\right)\right], \tag{8}$$

where $F_o^{-1}\left(F_f\left(x_f\right)\right)$ is the quantile function of the measured data; and $F_m^{-1}\left(F_f\left(x_f\right)\right)$ is the CDF of the future model data.

3.2 Photovoltaic power models

Following the approach of Chen et al. (2023), we selected 11 physical-empirical models for estimating photovoltaic performance for multi-model ensemble evaluation (Table 1). The chosen models vary in the complexity of input variables, all incorporating the influences of solar radiation, temperature, and wind speed to varying degrees.

The main independent variables include solar radiation (R), cell operating temperature (T), and wind speed (W). These meteorological factors directly or indirectly influence the power output through corresponding variables in the models. The input data for the models were derived from radiation, air temperature, and wind speed data from ERA5-Land and CMIP6. All data were used to drive the models after uniform resolution processing. We calculated the photovoltaic power (P) output using the ensemble mean, and then converted it to energy production (E) according to sunshine duration. The values of these parameters are listed in Table S2.

3.3 Methods of analysis

3.3.1 Variability analysis

The variability of photovoltaic power potential was quantified using the coefficient of variation (CV), defined as the ratio of the standard deviation to the mean. Its application in assessing renewable energy variability has been validated by several studies (Krakauer and Cohan, 2017; Wu et al., 2022; Zhang et al., 2025). Considering that the future research period is only 40 years, in order to ensure statistical stability while preserving inter-decadal evolution signals as much as possible, this study selected the 5-year sliding window to calculate CV.

3.3.2 Trend analysis

Trend analysis was performed using Sen's slope estimator and the Mann-Kendall (MK) significance test (Hossen and Evan, 2023; Abdulfattah et al., 2025). The MK significance test, a non-parametric statistical method suitable for time series data, is used to identify the presence of monotonic increasing or decreasing trends. Its application is not limited by data distribution type and does not require normality assumptions. Sen' s slope estimator provides the magnitude of the trend, while the Mann-Kendall significance test determines its statistical significance.

3.3.3 Change analysis

Absolute change is calculated as the difference between the future period average and the historical baseline average. Relative change is derived by dividing the absolute change by the historical average. Results are expressed as percentages.

3.3.4 Classification of combined patterns

We classified four combined patterns based on the trend direction (increase or decrease) and the statistical significance of both photovoltaic power potential and CV. The patterns include photovoltaic increase with CV increase, photovoltaic decrease with CV increase, photovoltaic decrease with CV decrease, and photovoltaic increase with CV decrease. The spatial size and distribution of each pattern were then evaluated.

Table 1 Summary of empirical models for photovoltaic power potential

Model	Formula	Parameter: R-related	Parameter: T-related	Parameter: W-related	Reference
1		b_{h} and R_{STC}	β, T_{cell}, T_{ref}, and NOCT	W_1 and c_{h}	Mora Segado et al. (2015)

Model	Formula	Parameter: R-related	Parameter: T-related	Parameter: W-related	Reference
2		c_3	β, T_{cell}, T_{ref}, c_1, and c_2	c_4	Pérez et al. (2019)
3		c_3	β, T_{cell}, T_{ref}, c_1, and c_2	c_4	Feron et al. (2021)
4		R_{STC}	β, T_{cell}, T_{ref}, and NOCT		Bayrakci et al. (2014)
5		R_{STC} and γ	β, T_{cell}, T_{ref}, and NOCT		Zou et al. (2019)
6		R_{STC}, γ, and R_T	β, T_{cell}, T_{ref}, and NOCT		Kan et al. (2021)
7		γ and c_3	β, T_{cell}, T_{ref}, c_1, and c_2		Feng et al. (2021)
8		R_{STC}	β, T_{cell}, T_{ref}, and NOCT		Davis et al. (2001)
9		A_1, A_2, and A_3; R_{STC}	γ_1		Soler-Castillo et al. (2021)
10		k_1, k_2, R', R_{STC}, and c_T	k_3, k_4, k_5, k_6, T, T_{mod}, and T_{ref}		Sweerts et al. (2019)
11					Cheng et al. (2020)

Note: P, photovoltaic output power (kW); R, solar irradiance (kW/m^2); R', normalized solar irradiance; R_T, monthly average solar irradiance (W/m^2); T, ambient air temperature (°C); T_{cell}, photovoltaic cell operating temperature (°C); b_{h}, irradiance heat transfer coefficient; c_{h}, wind cooling coefficient; T_{mod}, photovoltaic module surface temperature (°C); T', normalized module temperature difference (°C); W, ambient wind speed (m/s); η_{ref}, photovoltaic module reference efficiency (%); T_{ref}, standard reference temperature for calculating the generating capacity (°C); NOCT, nominal operating cell temperature (°C); R_{STC}, solar irradiance at standard test conditions (kW/m^2); W_1, wind speed on NOCT (m/s); $\tau\alpha$, transmittance-absorptance product; β, temperature coefficient affected by temperature for generating capacity (/°C); c_T, parameter related to solar radiation heating; k_3, temperature coefficient (/°C). k_1 and k_2 are empirical fitting parameters (units depend on the corresponding model equations); and k_4, k_5, k_6, A_1, A_2, A_3, γ, and γ_1 are experimental data coefficients (units depend on the corresponding model equations).

3.3.5 Regression analysis

Multiple linear regression was applied to quantitatively evaluate the relative contributions of RSDS, TAS, and sfcWind to photovoltaic power potential. The significance of regression coefficients was determined via t-test at a significance level of P<0.05.

3.4 Integrated economic-environmental benefit assessment

This study employed the levelized cost of energy (LCOE) as the primary metric to assess the economic viability of photovoltaic deployment under different SSPs, with environmental benefits incorporated into the calculation. LCOE represents the average net present cost per unit of electricity generated over the project' s lifetime and is widely used to compare the cost competitiveness of energy technologies. The LCOE is calculated as follows (El-Khozondar et al., 2025):

$$\mathrm{LCOE} = \frac{\frac{r(1+r)^n}{(1+r)^n-1} \times C + C_{O\&M} - C_{\mathrm{CO2}}}{E_t}, \tag{9}$$

where r is the discount rate (%); n is the system lifetime (a); C is the initial capital cost (CNY); $C_{O\&M}$ is the annual operation and maintenance cost (CNY/a); C_{CO2} is the annual environmental benefit from avoided CO_2 emissions (CNY/a); and E_t is the annual electricity generation (kWh/a).

The environmental benefit C_{CO2} is quantified as (Inweer and Nassar, 2025):

$$C_{\mathrm{CO2}} = EF_{\mathrm{CO2}} \times E_t \times \phi_{\mathrm{CO2}}, \tag{10}$$

where EF_{CO2} is the grid CO_2 emission factor (kg CO_2/kWh); and ϕ_{CO2} is the social cost of carbon (USD/t CO_2).

Key economic and technical parameters were specified as follows: the system lifetime n is set to 25 a (Lü et al., 2024); the discount rate r is taken as 5.00%, representing the social opportunity cost of capital for large-scale infrastructure projects in China; the initial capital cost C is assumed to be 3.5 CNY/W (Mallapaty, 2020), reflecting the average investment level of utility-scale photovoltaic plants in recent years; the annual operation and maintenance cost $C_{O\&M}$ is calculated as 1.50% of the initial capital cost; the grid CO_2 emission factor EF_{CO2} for the Northwest China power grid is set to 0.5857 kg CO_2/kWh (NCSC, 2023); and ϕ_{CO2} is set at 70 USD/t CO_2 (Almhdi and Miskeen, 2025). For consistency in the LCOE calculation (denominated in CNY), the environmental benefit C_{CO2} is converted from USD to CNY using the average exchange rate of 1 USD=7.2 CNY.

4 Results

4.1 Validation of CMIP6 models

To evaluate the effectiveness of bias correction, we used ERA5-Land reanalysis data as a reference and applied Taylor diagrams to assess the simulation performance of three key variables in historical baseline period (2000–2020) over Xinjiang, China (Fig. 2). The Taylor diagram serves as a visual assessment tool that integrates multiple statistical metrics to systematically illustrate model performance differences and the magnitude of errors between simulated and observed values (Huang et al., 2025).

Before bias correction, the simulations of TAS and RSDS showed generally good performance, with correlation coefficients ranging from 0.90 to 0.98 and normalized standard deviations between 0.80 and 1.20; however, some models exhibited deviations in dispersion compared with observations. The simulation of sfcWind displayed the largest bias, with correlation coefficients ranging only from 0.20 to 0.85 and normalized standard deviations between 0.40 and 1.40, indicating relatively low consistency with observations. After bias correction, the correlation coefficients for TAS and RSDS increased to between 0.95 and 0.99, and their normalized deviations stabilized near 1.0, making their statistical characteristics closer to the observational

benchmark. The improvement in sfcWind was particularly notable, with normalized standard deviations concentrated between 0.80 and 1.20 and markedly stronger correlations with observations. Following the corrections, the simulation capabilities of all three variables have been improved, providing more reliable data support for subsequent climate scenario projections. It is worth noting that the corrected correlation coefficients from sfcWind remain lower than those from TAS and RSDS. This indicates that there is still significant uncertainty in the simulation of wind fields.

Fig. 2 Taylor diagrams for the surface downward shortwave radiation (RSDS), near-surface wind speed at a height of 10 m (sfcWind), and near-surface air temperature at a height of 2 m (TAS) in Xinjiang during the historical baseline period (2000–2020), compared against reference data, before (a) and after (b) correction. The red star symbol represents the reference fields of the fifth generation of European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis-Land (ERA5-Land). The azimuth angle corresponds to the Pearson correlation coefficient of the spatial pattern. The radial distance from the origin indicates the ratio of the standard deviation between simulations and the reference. The distance from a simulation point to the reference point represents the centered root mean square error (RMSE).

4.2 Changes in climatic factors

Solar radiation, air temperature, and wind speed are key meteorological factors for predicting photovoltaic power potential. During the historical baseline period (2000–2020), solar radiation ranged between 170.0 and 270.0 W/m^2, generally showing a spatial pattern higher in the south and lower in the north (Fig. 3a). The distributions of air temperature and wind speed were clearly influenced by topography. Low-lying areas such as the Tarim Basin had relatively high average temperatures, reaching up to 20.00°C. At the same time, high-altitude regions like the Tianshan Mountains and the Pamir Plateau exhibited lower temperatures (Fig. 3b). Notably, extreme wind speeds were observed in the eastern part of the Tianshan Mountains, reaching up to 4.50 m/s (Fig. 3c).

Under different emission scenarios, all meteorological factors show noticeable changes compared with the historical baseline period, with solar radiation and air temperature changes exhibiting strong scenario dependence (Fig. 4a–f). Specifically, RSDS shows localized positive and negative fluctuations across scenarios, with magnitudes not exceeding $\pm 5.4W/m^{2}$. The tendency for solar radiation decrease becomes more pronounced from SSP1-2.6 to SSP5-8.5, likely due to increased cloud cover and aerosols reducing solar radiation under higher emission scenarios. Air temperature exhibits an increasing trend under all scenarios, with the magnitude of warming closely linked to the emission pathway. From SSP1-2.6 to SSP5-8.5, TAS shows a

Fig. 3 Spatial distribution of multi-year annual means of RSDS (a), TAS (b), and sfcWind (c) derived from ERA5-Land for the historical baseline period (2000–2020)

significant and spatially uniform upward trend, most intense under SSP5-8.5, indicating that the future warming trend in Xinjiang will become more pronounced with increasing emissions. Most areas exhibit a decreasing trend in wind speed, although the southwestern Tarim Basin shows an increase; the changes in wind speed demonstrate relatively weak scenario dependence (Fig. 4g–i). Figure 5 also indicates a general decreasing trend in wind speed across all scenarios, with insignificant differences between them. This suggests that the probability of strong wind events may increase in the future, but this is not closely related to emission intensity.

4.3 Assessment of photovoltaic power potential and variability in different periods

4.3.1 Assessment of photovoltaic power potential during the historical baseline period

The photovoltaic power potential in Xinjiang was quantified using solar radiation, air temperature, and wind speed data from the ERA5-Land dataset for 2000–2020, using 11 empirical models. The output from each model is provided in Figure 6. Figure 7 shows that the regional multi-year average photovoltaic power potential was 282.29 kWh/m^2, with significant spatial variation ranging from 230.00 to 396.00 kWh/m^2. The spatial distribution exhibited a pattern of "higher in the south and lower in the north" . Areas south of the Kunlun Mountains generally have 320.00 kWh/m^2, while values in most of the Tarim Basin (south of the Tianshan Mountains) remained below 280.00 kWh/m^2, as did much of the Junggar Basin to the north, where values were the lowest across the study area. This north-south disparity is primarily controlled by solar radiation. Compared with the Tarim Basin, the lower annual solar radiation and higher ambient temperatures in the Junggar Basin are likely key contributing factors. Analysis combined with Figure 4 further indicates that the spatial distribution of the average photovoltaic power potential during 2000–2020 was positively correlated with solar radiation and negatively correlated with near-surface air temperature, with solar radiation appearing to be the dominant factor.

Regarding temporal trends, the photovoltaic power potential showed a slow decreasing trend amidst inter-annual fluctuations during 2000–2020, with an average annual rate of change of approximately -0.06 kWh/m^2. Validation using the Sen-MK trend test revealed that only small areas in northern Xinjiang exhibited an increasing trend, while the region overall showed a decreasing trend both spatially and temporally.

4.3.2 Future changes in photovoltaic power potential and variability

To more accurately predict future trends, we analyzed the annual changes of photovoltaic power potential under different SSPs. Regarding inter-annual variation, under the SSP1-2.6 scenario, the photovoltaic power potential shows a significant increasing trend and is subsequently maintained at a high level. The SSP5-8.5 scenario shows the most pronounced continuous decreasing trend, reaching its lowest point around 2050, with a slight subsequent recovery remaining at low levels. As the scenario closest to the current realistic development pathway, changes under SSP2-4.5 fall between the other two (Fig. 8). This indicates that emission scenarios significantly influence the photovoltaic power potential, with low-emission scenarios being more conducive to its enhancement and high-emission scenarios prone to causing its reduction.

(Figure: Figure 4. Absolute changes of RSDS, TAS, and sfcWind in Xinjiang under SSP1-2.6, SSP2-4.5, and SSP5-8.5.)

Fig. 4 Absolute changes of RSDS (a–c), TAS (d–f), and sfcWind (g–i) in Xinjiang during 2021–2060 under different Shared Socioeconomic Pathways (SSPs)

Figure 9a–f further illustrates the spatial changes in photovoltaic power potential in Xinjiang during the carbon-neutral window period (2021–2060) relative to the historical baseline period (2000–2020). The rates of photovoltaic power potential change differed markedly under different scenarios: the average annual change ranges from -2.90% to -0.29% under the high-emission scenario (SSP5-8.5), corresponding to an absolute change of -10.30 to -1.00 kWh/m^2. Under the low-emission scenario (SSP1-2.6), the change rate of photovoltaic power potential ranges from -1.80% to 0.53%, with an absolute change of -5.70 to 1.53 kWh/m^2. A slight increase is only observed around the two major basins under the SSP1-2.6 low-emission scenario, while the largest decrease occurs in the southernmost part of Xinjiang. Overall, the average annual decrease in photovoltaic power potential under the high-emission scenario is slightly greater than under the low-emission scenario, with the most pronounced decrease in the southern edge.

Analysis of the variability of the annual average photovoltaic power potential reveals that the rate of CV change is less than 1.00%/5 a under all scenarios, indicating low inter-annual fluctuation and relatively stable power output across the region (Fig. 9g–i). The increasing trend

Fig. 5 Inter-annual variation of sfcWind (a), TAS (b), and RSDS (c)

Visible labels in Fig. 5: (a) sfcWind (m/s); (b) TAS (°C); (c) RSDS (W/m^2); Year; History; SSP1-2.6; SSP2-4.5; SSP5-8.5.

Visible panel labels in Fig. 6: (a) Model 1; (b) Model 2; (c) Model 3; (d) Model 4; (e) Model 5; (f) Model 6; (g) Model 7; (h) Model 8; (i) Model 9; (j) Model 10; (k) Model 11; (l) Mean of multi-model. Legend: Undefined; Boundary. Photovoltaic power potential (kWh/m^2): 150.00, 325.00, 500.00. Scale: 0 300 km.

Fig. 6 Spatial distribution of the annual average photovoltaic power potential in Xinjiang during 2000–2020 evaluated by 11 different photovoltaic models (a–k) and mean of multi-model (l)

in CV becomes progressively more pronounced from low- to medium- to high-emission scenarios. The spatial evolution trends of the photovoltaic power potential exhibit strong scenario dependence (Fig. 9j–l). Consistent with the findings in Figure 5, most areas show a significant increasing trend under SSP1-2.6, a widespread decreasing trend under SSP5-8.5, and an intermediate pattern under SSP2-4.5, with the strongest decreasing trend in the southern mountainous areas.

Fig. 7 Spatial patterns of the annual average photovoltaic power potential during 2000–2020 (a) and Sen-Mann-Kendall (MK) trend test results (b), and temporal inter-annual variation (c)

Fig. 8 Trends in the photovoltaic power potential in Xinjiang during 2000–2060 under three SSPs

4.3.3 Future combination patterns of photovoltaic power potential and variability

Using the trends of photovoltaic power potential and CV, we identified four combined patterns: (1) increase in photovoltaic with increase in CV; (2) decrease in photovoltaic with increase in CV; (3) decrease in photovoltaic with decrease in CV; and (4) increase in photovoltaic with decrease in CV (Fig. 10). Under the SSP1-2.6 scenario, the pattern of photovoltaic increase and CV decrease is dominant, covering approximately 79.41% of the total land area. The patterns showing a simultaneous increase in both photovoltaic and CV and the pattern of a simultaneous decrease, account for approximately 19.00% and 2.00% of the area, respectively. The former is primarily distributed in the Tianshan Mountains. Under the SSP2-4.5 and SSP5-8.5 scenarios, the area of simultaneous increase in both photovoltaic and CV significantly reduces. In contrast, the pattern of photovoltaic decrease with CV increase expands markedly, accounting for about 25.00% and 38.00% of the total area, respectively. This suggests that as greenhouse gas emissions rise, Xinjiang may face the dual pressures of declining photovoltaic power potential and increasing output instability.

Visible figure labels: panels (a)-(l); rows: SSP1-2.6, SSP2-4.5, SSP5-8.5; legend: Undefined, Boundary; scale: 0–300 km. Color-bar labels: Absolute change in photovoltaic power potential (kWh/m^2); Relative change in photovoltaic power potential (%); Trend slope of CV (%/5 a); Sen' s slope of photovoltaic power potential (Wh/($m^2 \cdot$ a)).

Fig. 9 Analysis of the variability of the photovoltaic power potential in Xinjiang during the future carbon-neutral window (2021–2060) under three SSPs. (a–c), absolute change in the annual photovoltaic power potential relative to the historical baseline period (2000–2020); (d–f), relative change normalized by the historical mean from the average difference between 2021–2060 and 2000–2020; (g–i), trend of change in the coefficient of variation (CV); (j–l), Sen-MK spatial trend distribution of photovoltaic power potential during 2021–2060.

4.4 Climatic factors influencing photovoltaic power potential

To investigate the relative influence of various meteorological factors on the photovoltaic power output in Xinjiang, we employed multiple linear regression analysis (Fig. 11). Both solar radiation and air temperature pass the significance test ($P < 0.05$) across the entire region, showing positive and negative correlations with photovoltaic energy yield, respectively. The average regression coefficient for solar radiation was approximately 1.35 during 2000–2020, with higher values observed in mountainous areas such as the Tianshan and Kunlun mountains, indicating its predominant influence on the photovoltaic power potential. This characteristic remains consistent across different future scenarios, implying the persistent dominant role of solar radiation under various climate conditions. From SSP1-2.6 to SSP5-8.5, the negative influence of air temperature on the photovoltaic power potential gradually intensifies, which could be an important reason for the potential decline under high-emission scenarios.

The influence of wind speed on the photovoltaic power potential is more complex and exhibited strong spatial heterogeneity, with only a few areas showing statistically significant effects. Overall, regression coefficients are generally positive in windy corridors and mountainous regions, potentially attributable to the cooling effect of wind, which can enhance photovoltaic module efficiency and reduce thermal losses. However, in basin and desert fringe areas, the coefficients are mostly negative. This negative correlation might be related to the wind-chill effect in winter and associated weather processes, which can indirectly lead to solar radiation attenuation. Therefore, a systematic evaluation of local environmental factors, such as wind patterns and dust activity, is essential for optimizing the site selection of photovoltaic power plants.

Fig. 10 Four combined patterns of photovoltaic and CV trends during 2021–2060 under three SSPs. (a–c), spatial distribution of the four trend combinations; (d), area proportion statistics of the four classified patterns presented by stacked bar charts. Dashed areas represent regions with statistically significant at $P<0.05$ level.

4.5 Economic-environmental integrated benefits

Based on the simulated photovoltaic power potential, we compare the LCOE for photovoltaic power potential in Xinjiang across different scenarios (Fig. 12a). When environmental benefits are excluded, the LCOE ranges from 0.192 to 0.195 CNY/kWh, with the SSP1-2.6 scenario exhibiting the lowest value. After incorporating the social cost of carbon (70 USD/t CO_2), the LCOE values become negative in all scenarios. The SSP1-2.6 has lowest value, at approximately −0.185 CNY/kWh, indicating significant net social benefits. However, the LCOE under the SSP5-8.5 scenario is about 1.08% higher than that under SSP1-2.6, suggesting that a high-emission pathway can weaken the economic competitiveness of photovoltaic to some extent.

The carbon price sensitivity analysis shows that LCOE decreases linearly as the carbon price rises (Fig. 12b). The break-even carbon price (LCOE=0.000 CNY/kWh) for all three scenario lines is around 36 USD/t CO_2, which is notably lower than the baseline price of 70 USD/t CO_2. The SSP1-2.6 scenario has the lowest break-even carbon price, further confirming its relative economic advantage.

5 Discussion

5.1 Spatiotemporal evolution and driving mechanisms of photovoltaic power potential

This study evaluated the long-term evolution of photovoltaic power potential across Xinjiang from 2000 to 2060 under three SSPs, combining trend analysis with economic assessment to determine regional viability. In terms of temporal changes, the average annual photovoltaic power potential exhibited a slight decreasing trend from 2000 to 2020. Under the SSP1-2.6 scenario, photovoltaic power potential shows a modest upward trend and subsequently remained at a relatively high level. The most significant decline, however, occurs under the SSP5-8.5 scenario, with the

Fig. 11 Spatial patterns of the linear regression coefficients between climatic factors and photovoltaic power potential in Xinjiang. (a–d), RSDS; (e–h), sfcWind; (i–l), TAS. Areas covered with dots indicate statistical significance at $P < 0.05$ level.

Fig. 12 Levelized cost of energy (LCOE) of photovoltaic power potential in Xinjiang under different scenarios. (a), LCOE comparison with and without carbon benefits under a carbon social cost of 70 USD/t CO_2; (b), sensitivity of LCOE to carbon social cost across SSP scenarios.

average potential being approximately 1.33% lower than the historical baseline. Regarding spatial distribution, under the SSP1-2.6 scenario, about 79.41% of the land area shows an increase in photovoltaic power potential and a decrease in inter-annual variability. Furthermore, as emission scenarios intensify, the *CV* shows an increasing trend, while photovoltaic power potential demonstrates a decreasing trend. These results are consistent with findings reported by Feron et al. (2021) and Lu et al. (2022), which indicate that high-emission scenarios significantly impair photovoltaic power potential. Therefore, under high-emission pathways, the instability of photovoltaic power output will be further amplified, affecting an increasing number of existing

photovoltaic projects and posing challenges to regional grid dispatch and energy security.

The spatiotemporal evolution of the photovoltaic power potential in Xinjiang is primarily influenced by key climatic factors such as surface solar radiation and air temperature. The photovoltaic power potential was positively correlated with solar radiation and negatively correlated with ambient temperature from 2000 to 2020. The average regression coefficient for solar radiation was approximately 1.35, indicating its predominant contribution. Furthermore, the combined negative effects of "diminished solar radiation" and "rising temperature" were strongest under the high-emission pathway, severely impairing the photovoltaic power potential in Xinjiang. This finding is consistent with Saxena et al. (2023), who reported a slight decreasing trend in photovoltaic power potential in most global regions and suppressed photovoltaic energy yield under extreme warming. The influence of wind speed on the photovoltaic power potential is more complex and unstable, with statistical significance observed in only very limited areas, potentially due to the uneven distribution and pronounced seasonal variation of wind speed in Xinjiang.

Regionally, southern Xinjiang currently exhibits high photovoltaic power potential, exceeding 300.00 kWh/m^2, but consistently shows high inter-annual variability across all scenarios, indicating that its future power output may face substantial fluctuation risks. In comparison, central Xinjiang shows lower overall photovoltaic power potential, but most areas exhibit a growth trend and a decreasing trend in inter-annual variability, presenting more stable conditions for development.

5.2 Economic and social benefits of photovoltaic power

Using an LCOE analysis, this paper shows that, under current policies and technological conditions, photovoltaic power potential in Xinjiang has already demonstrated significant economic and social benefits, supporting its continued expansion in future energy planning. Specifically, the analysis yields three main conclusions. First, at the current carbon price level, photovoltaic power in Xinjiang already has a clear net social benefit, providing an economic basis for its implementation and large-scale development. Second, LCOE varies considerably across different climate and emission scenarios. The low-emission pathway corresponds to the lowest LCOE, meaning the highest negative social cost, while the high-emission pathway has a relatively higher LCOE. Taking an installed capacity of 120 GW as an example, the annualized social benefit difference between SSPs can reach tens of millions of CNY, indicating that long-term climate policies and economic incentives will directly affect the cost-effectiveness of photovoltaic projects. Third, the break-even carbon price for photovoltaic power potential in this study is about 36 USD/t CO_2, significantly lower than the benchmark carbon price of 70 USD/t CO_2. Good economic returns can thus be achieved under moderate carbon constraints, further confirming its strong economic competitiveness in the current market environment. It should be noted that this study makes moderate simplifications in setting economic parameters, adopting uniform economic assumptions and not covering grid integration costs, which to some extent affects the completeness of the results. Nevertheless, the scenario comparisons conducted in this paper can still provide effective preliminary estimates of the impact of SSPs on photovoltaic economic performance.

5.3 Economic performance and deployment pathways of photovoltaic power under carbon pricing

Carbon pricing policy is a core lever for addressing climate change, reducing greenhouse gas emissions, and promoting the transition to a low-carbon society (Zhao, 2025). As carbon pricing increases, the cost of carbon-based fuels rises, while the cost of renewable energy, such as photovoltaic, continues to decline due to technological progress, making the cost advantage of photovoltaic power over traditional fossil fuels more prominent (Luderer et al., 2022). Under the low-emission scenario, stringent climate policies will keep carbon prices high in the long term, significantly amplifying the economic competitiveness of photovoltaic. In contrast, under the

medium- and high-emission scenarios, climate policies are relatively lenient, carbon price signals are weak, and the cost advantage of photovoltaic projects is eroded, leading to lower market competitiveness. Furthermore, previous studies have shown that monetizing environmental benefits is crucial for assessing the full social value of solar photovoltaic under different scenarios. Failing to include external benefits such as carbon emission reduction in energy project evaluation systems would systematically underestimate the true social value of photovoltaic development in Xinjiang, thereby weakening the incentive effect of low-carbon policy scenarios on photovoltaic deployment (Quan et al., 2025). The LCOE analysis presented earlier demonstrates significant net social value in assessing the true potential and environmental value of solar photovoltaic in Xinjiang.

From the policy logic of developing resource bases, Xinjiang, as a national clean energy base, needs its photovoltaic industry not only to meet growing local electricity demand but also to play a key role in cross-regional carbon emission reduction (Qu et al., 2024). China' s energy structure and energy plans indicate that clean energy represented by solar photovoltaic will be vigorously developed (Mallapaty, 2020), which provides institutional support for realizing photovoltaic dividends under low-emission scenarios. However, the difference in photovoltaic power potential stability across scenarios is a key factor constraining project economic viability. Under SSP2-4.5 and SSP5-8.5, the increase in intra-annual power potential fluctuations caused by climate warming will directly intensify the supply-demand balance pressure on the power grid and reduce the profitability of photovoltaic projects in the electricity market. Under SSP1-2.6, on the other hand, more stable climate conditions make intra-annual power potential fluctuations smaller than in the historical baseline period, supporting long-term stable returns for photovoltaic projects.

It should be noted that achieving the sustainable development pathway under SSP1-2.6 still faces significant practical challenges. Current research on the socioeconomic transformations and policy drivers required for sustainable development pathways remains limited, making some optimistic photovoltaic development projections somewhat idealized. Although China's long-term commitment to green development can reduce the risks from inter-annual and intra-annual photovoltaic fluctuations in the long run, converting the photovoltaic potential under low-emission scenarios into reality still requires the establishment of a stable carbon pricing mechanism, a comprehensive environmental benefit accounting system, and a grid operation mechanism adapted to high shares of renewable energy. These will provide solid support for large-scale photovoltaic deployment under different policy scenarios.

5.4 Development priority and grid adaptation strategies for photovoltaic power in Xinjiang

This study indicates that the central region of Xinjiang has a low CV and moderate but increasing photovoltaic power potential. These characteristics make the central region suitable as a priority development zone for large-scale photovoltaic deployment in Xinjiang under carbon neutrality goals. Specifically, in medium- and long-term energy planning, large photovoltaic bases should be prioritized in the central region, and their integration with the existing transmission grid should be strengthened. This recommendation is consistent with existing studies, which suggest that photovoltaic farm siting should consider both resource potential and output stability to reduce post-grid-connection dispatch pressure (Iweh et al., 2021). Besides, the areas surrounding the Tarim Basin and Junggar Basin show clear growth trends only under the SSP1-2.6, while their potential declines under SSP2-4.5 and SSP5-8.5. These areas can be moderately developed in combination with regional carbon reduction policies, serving as important supplements for photovoltaic industry expansion. The southern region of Xinjiang has high baseline photovoltaic power potential, but its CV shows an increasing trend under all future scenarios, implying greater output fluctuations and higher development risks. This region should be treated as a long-term reserve development zone, with construction to proceed only after technology and grid conditions have improved.

The increasing trend in the variability of photovoltaic power potential across different scenarios, especially the significant rise in CV in the southern high-potential region under SSP2-4.5 and SSP5-8.5, imposes higher requirements on the safe and stable operation of the power grid. To effectively integrate photovoltaic variability with grid planning, we can adopt the following three measures. First, dynamic reserve capacity configuration: on the basis of seasonal and inter-annual variation characteristics of CV, the spinning reserve capacity of regional grids should be dynamically adjusted. Under scenarios with increased CV, it is recommended to increase the reserve ratio by 5.00%–10.00% above the current level to cope with sudden fluctuations in photovoltaic output (Papaefthymiou and Dragoon, 2016; Alves et al., 2023). Second, regional complementary dispatch: regions with increased CV (e.g., the southern area) should be co-dispatched with the central stable area where CV decreases. The stable output from the central area can smooth out fluctuations from the southern area, thereby reducing the overall variability of power output across the entire regional grid. This cross-regional complementary operation mode has been proven effective in improving the reliability of power systems with high shares of renewable energy (Cao and Li, 2026). Third, optimized energy storage capacity configuration: in regions with $CV > 0.05$, energy storage systems with at least 2 h of rated power capacity can be deployed to cope with sudden drops in photovoltaic output caused by extreme weather or dust events. Existing studies have shown that an appropriate energy storage configuration can significantly enhance the resilience of grid-connected photovoltaic systems, reducing curtailment rates and reserve costs (Shafiei et al., 2024). In summary, systematic implementation of the above strategies can effectively mitigate the potential impact of increased photovoltaic output variability on grid stability in Xinjiang under future climate change.

5.5 Limitations and uncertainties

Finally, it should be noted that this study has inherent uncertainties in predicting future climate change and its impacts on photovoltaic power potential. These uncertainties mainly stem from driving data and photovoltaic estimation model parameters. Regarding data, this study used multi-model ensemble averaging, which mitigates uncertainties from different models to some extent, but spatial and temporal resolution constraints remain and affect the interpretation of results.

In terms of spatial resolution, this study used statistical downscaling to improve the CMIP6 multi-model output to an analysis resolution of 0.1°$×$0.1°, but it still inherits the spatial smoothing characteristics of the original GCM structures. As a result, local-scale steep topographic gradients such as those in the Tianshan Mountain area, as well as strong radiative reflection heterogeneities at desert-oasis boundaries, may be significantly smoothed in the models. This may lead to underestimation of the local impacts of these topographic and land surface factors on the microclimate of photovoltaic module operation (Zorzetto et al., 2023). In fact, existing studies have pointed out that most CMIP6 models use a plane-parallel radiative transfer scheme without considering sub-grid topographic radiation effects, leading to systematic overestimation of surface solar irradiance in complex terrain areas, with the overestimation increasing with terrain complexity (He et al., 2023; Gu et al., 2024). Therefore, even if downscaling improves the resolution of the output grid, limitations inherent in the physical parameters of the models are difficult to fully eliminate. Nevertheless, the 0.1° gridded data used in this study are still suitable for characterizing the macroscopic spatial differentiation pattern of photovoltaic potential at the scale of the entire Xinjiang region and its sub-regions, such as northern and southern Xinjiang.

In terms of temporal resolution, considering the computational efficiency of multi-scenario analysis over a 60 a time series and the need to extract long-term climate signals, this study used monthly mean outputs from each CMIP6 model. Monthly data can effectively filter out synoptic-scale and sub-daily short-term noise, thereby focusing on long-term climate driving signals and effectively capturing seasonal cycles and inter-annual variability of key climatic elements such as solar radiation and temperature. This approach has been widely used in studies assessing the long-term generation potential of renewable energy (Li et al., 2024). Monthly data

are sufficient to capture climate-scale variability signals across SSPs (Abatzoglou et al., 2018). However, this choice cannot preserve sub-daily fluctuation details of photosynthetically active radiation, air temperature, and wind speed (Hou et al., 2025). Consequently, this study did not assess short-term variability, which is more closely related to the actual grid-connected operation of photovoltaic. But this does not undermine the study' s basic conclusions, such as that the sustainable development pathway (SSP1-2.6) is most favorable for enhancing and stabilizing Xinjiang' s photovoltaic potential. Future work can further incorporate high-resolution simulations and satellite remote sensing data within the regional and pathway frameworks identified in this study, deepening the understanding of local site feasibility and grid matching.

Finally, at the methodological level, this study mitigated uncertainties from driving data through ensemble averaging of 11 empirical models. However, differences in physical assumptions and parameters among different models remain sources of error in photovoltaic potential assessment. Subsequent research can introduce methods such as sensitivity analysis and error propagation analysis to quantify the influence of different parameters on photovoltaic potential assessment, thereby reducing uncertainties in a targeted manner.

6 Conclusions

This study evaluated the long-term changes in photovoltaic power potential in Xinjiang under different emission scenarios and their economic feasibility. The main conclusions were as follows. Spatially, compared with the historical baseline period (2000–2020), the relative change rate of photovoltaic power potential under the SSP1-2.6 ranged from -1.80% to 0.53%, with about 79.41% of the land area showing favorable conditions of increased photovoltaic power potential and reduced CV. Under SSP2-4.5 and SSP5-8.5, the unfavorable pattern of decreased photovoltaic power potential and increased CV expanded significantly, covering about 25.00% and 38.00% of the total area, respectively. In terms of temporal trends, most regions under SSP1-2.6 showed a significant increasing trend with continuously decreasing variability. Economic analysis further showed that under the standard carbon price, the LCOE under the SSP1-2.6 path was the lowest, at approximately -0.185 CNY/kWh, indicating significant net social benefits, and the break-even carbon price was much lower than current international levels. Together, these results confirm that pursuing a sustainable development path is a key to mitigating the adverse impacts of climate change and that large-scale photovoltaic development in Xinjiang is economically feasible. It is worth noting that photovoltaic power potential in Xinjiang shows notable spatial differentiation. The southern region has high photovoltaic potential, but with increased variability. The central region, although relatively low in potential, shows a significant increasing trend and higher stability, offering better conditions for development and serving as a priority area for deployment and large-scale expansion. These findings provide a scientific basis for understanding potential changes in photovoltaic power potential under Xinjiang' s carbon neutrality goals and offer decision-making support for regional emission reduction policies and the optimal layout of photovoltaic power stations.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by the Talent Program "Tianchi Talent (Young Doctor)" in Xinjiang Uygur Autonomous Region, the Basic Research Projects for Universities in the Autonomous Region (XJEDU2025P007), the Open Research Fund of Xinjiang Key Laboratory of Water Cycle and Utilization in Arid Zone, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences (XJYS0907), and the National College Student Research Training Plan of China (202510755010). The authors would like to thank the anonymous reviewers for the constructive comments.

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Appendix

Table S1 A list of the sixth phase of the Coupled Model Intercomparison Project (CMIP6) models

<table>
<tr><th>Model</th><th>Institution</th><th>Resolution(longitude×latitudegrid points)</th></tr>
<tr><td>ACCESS-ESM1-5</td><td>Commonwealth Scientific and Industrial Research Organization, Australia</td><td>192$×145||BCC−
CSM2−
MR|BeijingClimateCenter, China|320×160||CAMS−
CSM1−
0|ChineseAcademyofMeteorologicalSciences, China|3
ESM−2−
0|FirstInstituteofOceanography, MinistryofNatural
CM2−
SR5|FondazioneCentroEuro−
MediterraneosuiCambiamentiClimatici, Italy|288×19
ESM|CentreforClimateChangeResearch, IndianInst
ESM1−2−
LR|MaxPlanckInstituteforMeteorology, Germany|19</td></tr>
</table>

Table S2 Values of constant parameters in the 11 photovoltaic models shown in Table 1

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
η_{ref}	15	15	15	15	15	12	12	15	15	15	15
β	0.0045	0.0050	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045			
T_{ref}	25	25	25	25	25	25	25	25		25	
NOCT	47.0			47.0	45.5	45.5		47.0			
R_{STC}	0.8			0.8	0.8	0.8		0.8	0.8	1.0	
b_h	0.81										
c_h	−1.63										
W_1	1										
c_1		4.22	47.00				−3.75				
c_2		1.080	0.943				1.140				
c_3		0.0226	0.0280				0.0175				
c_4		1.830	1.528								
γ					0.10	0.12	0.10				
τ_α								0.8531			
A_1									1.044		
A_2									−0.044		
A_3									0.05		
γ_1									−0.0041		
k_1										−0.017162	
k_2										−0.040289	
k_3										−0.004681	
k_4										0.000148	
k_5										0.000169	

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
k_6										0.000005	
c_T										0.035	

Note: The explanation of all parameters is shown in Table 1.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv. Machine translation. Verify with the original.