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Climate-resilient solar resource potential in Central Asia under future climate scenarios using a tiered site ranking framework

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Climate-induced variability poses a major challenge to the long-term planning of solar energy systems, particularly in climatically sensitive and underexamined regions such as Central Asia (CA). This study introduces a scenario-informed solar-resource suitability framework integrating multi-ensemble CMIP6 projections of Surface Downwelling Shortwave Radiation under SSP2–4.5 and SSP5–8.5 scenarios. By combining exceedance probabilities, seasonal variability (coefficient of variation, CV), and emissions scenario sensitivity, we develop a five-Tier ranking system to assess climate-driven solar-resource suitability across Kazakhstan, Kyrgyzstan, Uzbekistan, Turkmenistan, and Tajikistan over historical (1992–2021), near-future (2022–2051), and far-future (2071–2100) periods. Our results reveal strong seasonal and spatial contrasts. In summer, "Excellent" exceedance rates under SSP5–8.5 increase from 40.4% to 91.3% in Kazakhstan, from 76.9% to 94.1% in Kyrgyzstan, and from 98.5% to 99.8% in Turkmenistan by the far-future. In winter, however, solar suitability deteriorates, with average rank losses under SSP5–8.5 exceeding +90 in Turkmenistan, +87 in Uzbekistan, and +69 in Kazakhstan by the near-future. Only a limited share of sites, around 15%–30%, fall into the most favorable categories for climate-resource screening (Tiers 1 and 2). In contrast, more than 60% of sites are classified as Tier 3, representing scenario-sensitive areas, particularly in winter and autumn. Under SSP5–8.5, CV decreases by around 30%–60% in several regions. For example, winter CV in Kazakhstan decreases from 0.133 to 0.091, equivalent to a reduction of around 32%, while fall CV in Kyrgyzstan decreases from 0.059 to 0.024, representing a reduction of nearly 59%. These changes indicate lower normalized inter-annual variability of modeled seasonal irradiance in some periods, although they should not be interpreted as direct evidence of reduced intra-day intermittency or lower operational storage requirements. Taken together, these findings highlight the importance of climate-informed solar-resource planning in CA. The proposed framework should be interpreted as a solar-resource suitability and resilience-screening tool that can support

broader renewable-energy planning, but not as a full assessment of energy security, grid reliability, affordability, or system-level performance.

KEYWORDS

climate change, climate variability, climate-resilient planning, seasonal solar trends, solar energy, tier-based ranking

1 Introduction

To fulfill the United Nations Sustainable Development Goal 7, renewables are becoming a key tool for improving access to modern, reliable, and affordable energy (Gutiérrez et al., 2020; Feron et al., 2017). They can reduce global emissions and enhance climate change mitigation. Solar photovoltaic (PV) systems also can contribute to climate resilience, climate change adaptation, social justice, and broader energy-system planning (Feron et al., 2017). However, the vulnerability of renewable energy sources to future weather variability is a source of uncertainty with a potential of complicating the energy planning and compromising investments in the energy sector (Feron et al., 2021; Mohammadi et al., 2024; Qudrat-Ullah, 2025).

Renewable generation, particularly PV and wind is currently anticipated to play a significant role in the transition of the energy system. In different parts of the world, they are now competitive with fossil-fired generation due to the substantial reduction in their costs (BNEF, 2017; Staffell and Pfenninger, 2018; Lee et al., 2025; Broomandi et al., 2025, 2026). In 2023, the global renewable installation achieved new milestones, with 349 GW of new solar capacity (twice the 2022 installations). In 2023, the proportion of wind and solar energy in global power generation increased by 1.5% points to nearly 14%, representing an 11% increase since 2010 (Enerdata, 2024). This is a source of optimism, as it is widely believed that the most feasible method of swiftly reducing energy sector emissions is to transition electricity generation to renewables, followed by the electrification of other critical sectors (such as heat and transport; Williams et al., 2012). Although other alternatives, including nuclear, CCS, and biofuels, were anticipated to play substantial roles, they are either no longer cost-competitive (Pfenninger and Keirstead, 2015; REN21, 2017) or have not yet achieved market readiness (Staffell and Pfenninger, 2018).

Climate change is expected to increase future energy demand while complicating projections of PV energy generation by altering downwelling shortwave irradiance, wind speed, and temperature (Feron et al., 2021; Yang et al., 2022). A global study using Coupled Model Intercomparison Project phase 6 (CMIP6) scenarios (SSP1–2.6 to SSP5–8.5) assessed PV potential relative to the historical period (1981–2014) from 2015 to 2100 (Dutta et al., 2022). In the near-future (2015–2040), the most significant changes in PV potential occur during boreal autumn and winter, with smaller variations in spring and summer across all SSPs. Reductions of 5% (SSP1–2.6) to 10% (SSP5–8.5) are projected in the Indian subcontinent and China during autumn, driven by decreases in solar radiation (1%—7%) and increased post-monsoon cloud cover. Similar declines (2%—4%) are expected in parts of Asia, the Middle East, and African nations like Sudan, Ethiopia, and Namibia. Conversely, increases in Europe are projected during spring, summer and autumn (up to 4%—5% under SSP5–8.5) due to reduced cloud cover. North America shows mixed results: a 4%—5% decrease in the west and a slight increase (~2%) in the east. Positive trends (2%—4%) are observed in South America in most seasons, while Australia is expected to increase during autumn and summer. In the distant future (2041–2100), similar spatial and seasonal patterns continue with greater variability in SSPs. Europe is projected to see significant increases in PV potential in spring and autumn, but northern European countries will experience sharp winter declines (up to 10%) under SSP5–8.5. North America is likely to experience widespread declines, especially in winter, while South America maintains increases in most seasons. Australia is projected to experience declines in most seasons, except for a slight increase in winter. Africa shows the largest decline in photovoltaic potential during winter, exceeding 10% in regions such as Nigeria, Congo and Angola, under SSP5–8.5 (Dutta et al., 2022).

Despite significant progress in this area, existing frameworks for assessing suitable solar energy locations still face several fundamental limitations. One of these challenges is the way data is used; many previous studies have mainly relied on historical data or annual averages, while seasonal variations can play a decisive role in the actual performance of solar systems and have often not been sufficiently considered.

On the other hand, many studies use common geographic information system-based multi-criteria decision-making (GIS-MCDM) methods to select suitable locations. Methods such as AHP, TOPSIS, and fuzzy logic are among the most widely used tools in this field. However, these approaches usually do not consider two important aspects in the assessments: first, the sensitivity of the results to future climate change scenarios and second, the consideration of indicators that indicate the long-term stability and scenario sensitivity of solar resources. As a result, many current frameworks still lack the full ability to assess solar locations under future climate conditions (Adedeji et al., 2021; Alami Merrouni et al., 2016; Awan et al., 2018; Ayuketah et al., 2025; Badi et al., 2021; Chen Jong and Mohamud Ahmed, 2024; De Felice et al., 2019; Hosouli and Hassani, 2024; Kamati et al., 2023; Shravanth Vasisht et al., 2016; Wang et al., 2023; Zandi and Lotfata, 2025). Consequently, they are poorly equipped to guide long-term climate-informed solar-resource planning, especially in climate-sensitive and underserved regions such as CA.

In addition to regional and utility-scale applications, an important but often underexplored dimension of climate-informed solar-resource assessment relates to the built environment. Climate-informed solar-resource assessment is relevant for rooftop PV, building-integrated photovoltaics, passive solar design, and

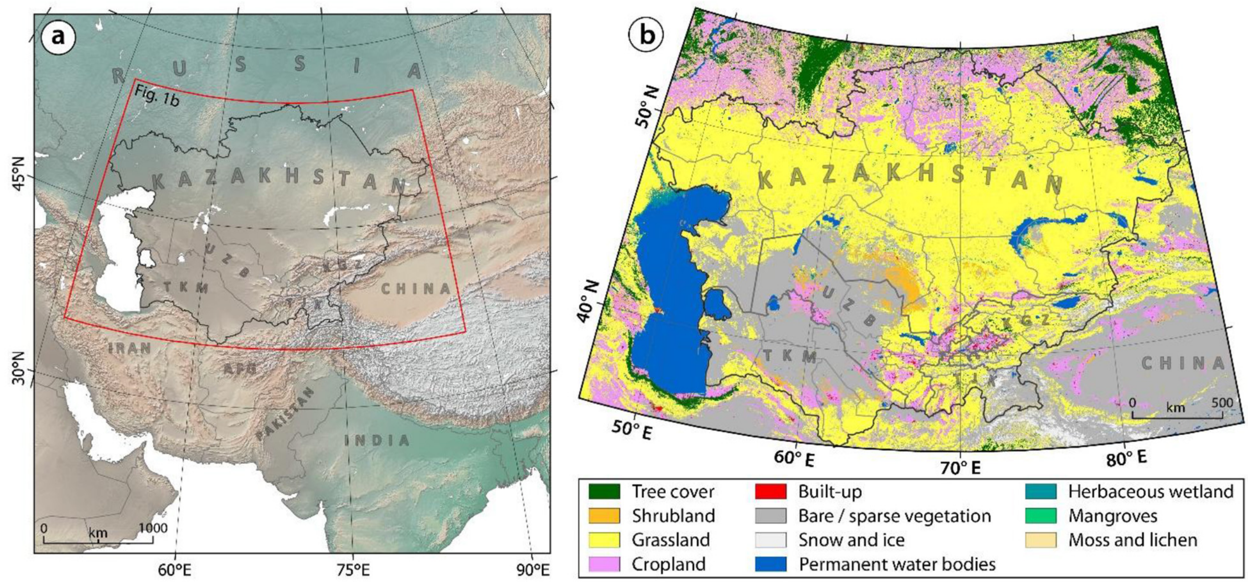

FIGURE 1
(a) Physiographic context of CA, showing major topographic features and the geographical extent of the study domain, including Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. **(b)** Land cover map of the study area derived from the ESA World Cover 10 m 2021 v200 dataset, highlighting dominant land cover types—such as grasslands, croplands, shrublands, bare areas, and urban zones—as well as the spatial distribution of key terrain and settlement patterns relevant to solar suitability assessment (Zanaga et al., 2022).

daylighting-oriented urban planning. Seasonal and future changes in surface shortwave radiation can influence not only utility-scale solar potential, but also building-scale energy performance, solar gains, and daylight availability. Therefore, assessing the seasonal stability and scenario sensitivity of solar resources can support mitigation–adaptation synergies by informing low-carbon energy deployment, reducing climate-related planning uncertainty, and strengthening the resilience of urban and building-scale energy strategies (Desthieux et al., 2018; IEA, 2020a; Sailor et al., 2021).

To address these gaps, this study introduces a new scenario-based solar-resource suitability framework for CA that integrates CMIP6 multi-ensemble forecasts of all-sky shortwave downward radiation (SSWDI). By assessing both radiation exceedance and coefficient of variation (CV, a normalized indicator of inter-annual variability) across four seasons and two climate scenarios (SSP2–4.5 and SSP5–8.5), this framework enables dynamic and forward-looking solar site ranking using a five-level classification model. As a result, this research uses CMIP6 multi-ensemble forecasts to address four key objectives: (i) quantify the seasonal and spatial distribution of all-sky shortwave downward radiation exceedance (SSWDI), identify areas that are highly vulnerable to reduced solar resource availability, and provide critical data for local adaptation and resilience planning of solar energy systems; (ii) assess the temporal evolution of solar resource variability by analyzing the coefficient of variation (CV) in SSWDI across seasons and countries, identifying variability trends under near-future (2022–2051) and far-future (2071–2100) scenarios; (iii) develop a seasonal and scenario-sensitive solar site ranking framework that integrates threshold exceedance, normalized inter-annual variability (CV), and sensitivity to climate scenarios, assessing the long-term suitability and resilience of solar energy development in CA; and (iv) classify solar sites using a Tier-based approach, facilitating the identification of climate-resource priority areas for solar investment and areas requiring adaptive or hybrid infrastructure planning. Importantly, this study focuses on the climatic suitability, seasonal stability, and scenario sensitivity of solar resources, which can serve as one input layer for broader renewable-energy planning. By addressing these challenges, this research seeks to support climate-informed solar-resource planning and improve the evidence base for renewable-energy planning under future climate uncertainty.

2 Material and methods

2.1 Study area

CA region includes five countries: Kazakhstan, Kyrgyzstan, Uzbekistan, Turkmenistan, and Tajikistan, and covers an area of approximately 4 million square kilometers. The region is located within the approximate geographic range of 20–60 degrees north latitude and 50–90 degrees east longitude. The wide latitude range, arid to semi-arid climatic conditions, and complex topographic relief are the main factors shaping the distribution pattern of solar radiation in the region (see Figure 1).

According to national assessments and recent reviews, the greatest solar radiation potential is observed in the southern deserts of Uzbekistan and Turkmenistan (Karatayev et al., 2016; Laldjebaev et al., 2021; Rakhimov et al., 2017). In these regions, the average daily solar radiation is about 5.0–5.5 kWh/m^2/day, which is approximately equivalent to 1,800–2,000 kWh/m^2/year, and the annual number of sunny hours can reach about 3,200 h. In contrast, in northern Kazakhstan, due to its location at higher latitudes and increased cloud cover in winter, the average solar radiation is limited to about 3.5–4.0 kWh/m^2/day. The mountainous regions of

Kyrgyzstan and Tajikistan also experience moderate levels of solar radiation, estimated at about 4.0–4.5 kWh/m^2/day; however, local ruggedness and topographic conditions create significant spatial variability in these areas.

Seasonal differences are also very significant. The highest amount of solar radiation is recorded in summer, reaching about 6–7 kWh/m^2/day in the southern regions. In contrast, in winter, the radiation decreases to less than about 1.5–2.0 kWh/m^2/day in a large part of the region (Karatayev et al., 2016; Laldjebaev et al., 2021; Rakhimov et al., 2017).

2.2 Data

The present research obtained daily all-sky surface shortwave downward irradiance (SSWDI, kW-hr/m^2/day) from MERRA-2: Average for 0.5 × 0.625 degrees, using data from the NASA POWER (Prediction Of Worldwide Energy Resources) database, accessible via the NASA Langley Research Center's Data Access Viewer (https://power.larc.nasa.gov/data-access-viewer/). The dataset incorporated data from 700 locations across CA, encompassing urban, suburban, and rural regions, and spanned the period from 1992 to 2021.

For variable of Surface Downwelling Shortwave Radiation (SDSR, w/m^2), GCMs with different spatial resolutions, Coupled Model Intercomparison Project phase 6 (CMIP6), were obtained from the Copernicus Climate Change Service (C3S center) to evaluate the effects of climate change (see Supplementary Table S1). The study utilized historical CMIP6 model outputs from 1992 to 2014 and analyzed simulation outputs for two future periods: the near-future (2022–2051) and the far-future (2071–2100).

In this study, interpolation to a spatial resolution of 0.1° × 0.1° was carried out using the Inverse Distance Weighting (IDW) algorithm solely for visualization purposes, with the aim of generating smoother spatial representations. This technique was selected due to the ability to clearly and reliably depict spatial gradients without compromising the global structure of the original data. It is necessary to underline that analysis steps were done with the original spatial resolution of data. Here, ERA5 data were utilized with 0.25°, and CMIP6 data were utilized at the native resolutions of each model, which may change according to the model utilized. Furthermore, the analysis was designed to focus on urban, suburban, and rural population centers (i.e., cities and towns) to more accurately assess population exposure and associated vulnerabilities, rather than utilizing a uniform grid across the entire Central Asian region.

2.3 Statistical analysis of GCMs and different scenarios

Future climate projections for CA were derived from multiple GCMs using two climate scenarios from the CMIP6 archive: SSP2–4.5 and SSP5–8.5. These scenarios address moderate and high global challenges to adaptation and mitigation, respectively, and reflect the global effective radiative forcing expected by 2100 (van Vuuren et al., 2011).

By utilizing observed data, bias correction was employed to correct modeling discrepancies in the outputs of GCMs. A hybrid semi-parametric method was deployed to analyze the CMIP6 GCMs data from 1992 to 2100. They adjusted the statistical features of the data to match the historical observations (Her et al., 2019; Jamshidi et al., 2019; Aghaei Fishani et al., 2022).

The discrepancies in results generated by different GCMs were addressed using an unweighted approach (one model, one vote'; Her et al., 2019). This method computed ensemble averages of multiple GCMs, assigning equal weighting to each model before bias correction of the resultant outputs (Her et al., 2019; Garg et al., 2021).

Moreover, to statistically assess the performance of the model in simulating the interest variable, the bias and root mean square error (RMSE) were computed (Seo and Ahn, 2023; Mirzaei et al., 2019).

2.4 Solar energy ranking and tier classification framework

To assess the long-term solar energy suitability of sites across CA, we developed a multi-criterion, climate-informed ranking system that incorporates seasonal surface shortwave downward irradiance variability, exceedance probabilities, and scenario-based projections. Rankings were generated independently for each site and time period under historical (1992–2021), near-future (2022–2051), and far-future (2071–2100) intervals using data from the SSP2–4.5 and SSP5–8.5 climate scenarios.

2.4.1 Exceedance probability analysis

To characterize the quality of solar resources, seasonal exceedance probabilities of surface shortwave radiation were calculated for each site and time period. Four performance classes were defined (Elboshy et al., 2022):

- **Poor**: ≤146 W/m^2: low viability, not ideal for PV
- **Moderate**: 147–188 W/m^2: limited yield, marginal economics
- **Good**: 189–271 W/m^2: commercially viable, stable output
- **Excellent**: >271 W/m^2: high yield, optimal for PV systems

These thresholds reflect commonly applied solar resource categories in PV planning.

2.4.2 Variability analysis with CV

To characterize the temporal stability of solar resources, we calculated the coefficient of variation (CV) for each site, season, and time period. The CV is defined as the ratio of the standard deviation (σ) to the mean (μ) of daily irradiance (Gil et al., 2019):

$$CV = \sigma/\mu \tag{1}$$

This dimensionless metric reflects relative variability, meaning it normalizes fluctuations by the average value, allowing

TABLE 1 Solar resource stability classification using CV.

Coefficient of variation (CV)	Resource stability	Implication for solar energy systems
<0.10	High stability	Daily irradiance is highly consistent over time, supporting reliable solar energy production.
0.10–0.20	Moderate variability	Some interannual variability exists; modest adjustments such as storage or hybrid systems may be beneficial.
>0.20	High variability	Significant fluctuations in irradiance may increase intermittency risks and complicate long-term energy planning.

comparisons across sites with different baseline irradiance levels. In practical terms (Gil et al., 2019) as in Table 1.

To ensure that suggested ranking system will not only reflect the availability of solar energy but its behavior under climate change, CV was incorporated into the performance composite score.

2.4.3 Composite scoring and temporal ranking

For each site and time period, a composite performance score was generated to integrate solar-resource quality and variability into a unified suitability metric. The score was defined as:

$$Score = P_{Excellent} + P_{Good} - (P_{Moderate} + P_{Poor}) - CV \tag{2}$$

where $P_{Excellent}$, P_{Good}, $P_{Moderate}$, and P_{Poor}represent the probabilities of occurrence of the corresponding irradiance performance classes, and CVrepresents the coefficient of variation of surface solar radiation.

In this formulation, the probability classes are treated directionally according to their physical meaning. Favorable conditions ("Excellent" and "Good") contribute positively to the score, while less favorable and unfavorable conditions ("Moderate" and "Poor") reduce the score. This structure reflects the progressive decline in solar-resource suitability across performance classes and ensures that the scoring framework captures both high-quality resource availability and the presence of limiting conditions.

All variables are dimensionless and bounded between 0 and 1, ensuring comparability across components and satisfying the commensurability requirement of multi-criteria assessment. In addition, this formulation avoids the degeneracy associated with summing all probability classes and ensures that the composite score meaningfully reflects variations in solar-resource conditions rather than collapsing into a constant value.

The computed scores were subsequently ranked using a dense descending ranking function, where lower rank values indicate higher solar energy suitability. This ranking approach enables consistent comparison of solar-resource performance across locations, seasons, and climate scenarios.

2.4.4 Tier classification for investment strategy

In order to convert site-level site rankings into operational investment priorities, the locations were categorized into five tiers. This categorization was according to performance trends over time and also sensitivity of the respective location to emission scenarios. The rationale behind the framework is the fact that past performance and future sustainability is very imperative to the long term success of solar infrastructure. Thus, the classification process was not concerned with the suitability of the sites only at the base level, but also with the degree to which the sites were enhanced, worsened or sensitive to various climatic conditions.

The thresholds employed in this classification, summarized in Table 2, were defined as transparent operational decision rules to separate stable, improving, scenario-sensitive, and declining solar-resource trajectories. A rank change of ± 10 was used to identify sites with relatively stable performance over time, while an improvement of ≥ 40 ranks was used to define rapidly improving sites and a deterioration of ≥ 25 ranks was used to identify sites with systematic decline. In addition, a difference of ≥ 5 rank positions between SSP2–4.5 and SSP5–8.5 was used to identify sites with meaningful sensitivity to emission pathways. These thresholds were selected after examining the observed distribution of rank changes across sites, seasons, and scenarios, but they should not be interpreted as universal cut-off values or as statistically significant breakpoints. Rather, they provide reproducible classification rules for translating continuous rank-change outputs into practical planning categories. Future applications of this framework should further test the sensitivity of tier assignments to alternative threshold values and, where possible, support threshold selection using formal uncertainty analysis or probabilistic classification. This rule-based classification approach is consistent with GIS-MCDM and solar site-suitability studies, where continuous suitability indicators are commonly converted into discrete planning classes to support decision-making, although the robustness of such classes should be evaluated through sensitivity analysis in future applications (Alami Merrouni et al., 2016; Awan et al., 2018; Badi et al., 2021; Chen Jong and Mohamud Ahmed, 2024; Zandi and Lotfata, 2025).

Conceptually, the tiering framework followed is in line with the past methods of evaluating the site of suitable solar scenery and adding sustainability-specific requirements to it, that is, dependability, and fluctuations (Carta et al., 2009; IEA, 2020b). In this context, every tier is connected to a particular investment strategy that can be either rapid and low-risk implementation or adaptable/climate-sensitive infrastructure planning. The framework is designed to help make evidence-based and climate-resilient decisions about the unpredictable climate future.

It should be noted, however, that the proposed framework is designed as a climate-resource screening approach rather than a complete technical, economic, and policy-based PV site-selection model. Therefore, non-climatic deployment constraints, including land-use suitability, terrain slope, grid accessibility, infrastructure availability, installation and operation costs, social acceptance, and national energy policies, are not explicitly incorporated in the present analysis. These factors remain essential for real-world PV project implementation. Accordingly,

TABLE 2 Tier-based classification system for solar energy investment planning, tailored strategies for infrastructure deployment and risk management in CA.

Tier	Definition	Classification criteria	Recommended strategy
Tier 1: consistently excellent	Top-performing sites with stable, reliable solar resources across time and scenarios	Historical rank ≤100 and ≤±10 change across SSP2–4.5 and SSP5–8.5 in far-future period	Priority sites for large-scale PV investment with minimal backup needs.
Tier 2: rapid improvers	Sites showing strong performance gains over time, signaling emerging solar potential	≥+40 rank improvement between historical and far-future under either SSP scenario	Consider phased deployment, paired with performance monitoring over time.
Tier 3: scenario-responsive	Sites whose suitability strongly depends on emission pathways, requiring adaptive planning	≥±5 rank difference between SSP2–4.5 and SSP5–8.5 in far-future period	Design flexible, hybrid, or modular systems to accommodate uncertainty.
Tier 4: systematic decliners	Sites experiencing consistent rank deterioration under all future conditions	≥+25 rank deterioration under both SSP2–4.5 and SSP5–8.5	Avoid standalone solar investment; consider diversifying with other renewables or storage.
Tier 5: unclassified/variable	Sites with inconsistent or mixed trends that do not fit other categories	Does not meet criteria for Tiers 1–4	Conduct detailed local assessment before committing to investment decisions

the Tier classification proposed here should be interpreted as a first-stage climate-resilience assessment that can support, but not replace, broader GIS-based multi-criteria decision-making, techno-economic evaluation, and policy-oriented planning frameworks.

3 Results and discussion

3.1 Spatiotemporal patterns of solar radiation change across seasons and emission scenarios

Figures 2, 3 and Supplementary Figures S1, S2 display the geospatial slope changes of seasonal all-sky surface solar irradiance (SSWDI) in Central Asian countries during the historical period (1992–2021), near-future (2022–2051), and far-future (2071–2100) under future climate scenarios (SSP2–4.5 and SSP5–8.5; see Figures 2, 3 and Supplementary Figures S1, S2).

The geospatial trends of slope change in solar radiation across CA indicate dramatic seasonal contrast, highly spatially heterogeneous processes and sensitivity to future emission conditions. The historic characteristic of autumn is the negative slope tendencies that tend to be widespread; this characteristic is observed especially in the north of Kazakhstan and in the region of the Caspian Sea which show that there is a long-term diminishing trend in the solar radiation in these areas. Nevertheless, the SSP2–4.5 and SSP5–8.5 scenarios have different outcomes foresight of the future. Both near- and far-future projections indicate that the trends tend toward positive values, and this is especially strong in southern Kazakhstan, Uzbekistan, and Turkmenistan. In this region, the projected pattern indicates a large-scale return and even faster acceleration of the solar potential in autumn. This seasonal reversal may be physically linked to changes in cloud cover, atmospheric circulation, aerosol–radiation interactions, and regional land–atmosphere processes, all of which can modify surface shortwave radiation under future climate forcing (Wang et al., 2012; Bellouin et al., 2020; Zelinka et al., 2020).

Conversely, the uniform spatial pattern is not evident in spring and spatial variation in large. Historically, the maps show a mix of positive and negative slopes. In the near-future projections for the SSP2–4.5 scenario, significant improvements are observed in many regions. However, under the SSP5–8.5 scenario, some areas of northern Kazakhstan still have patches of persistent negative trends, indicating their greater sensitivity to emission scenarios and the importance of regional differences in the response to climate change. This spring heterogeneity is consistent with the transitional nature of the season, when changes in atmospheric moisture, cloud formation, snowmelt timing, and circulation regimes can produce strong regional differences in incoming shortwave radiation (Dutta et al., 2022; Chen et al., 2023).

Among the seasons, summer is the most climatically robust and stable period for solar resources. Even in historical maps, strong positive trends are observed in the southern deserts of the region. Future projections, especially under the SSP5–8.5 scenario, reinforce this positive trend and show its expansion across the region. Physically, this summer strengthening may reflect higher solar elevation, longer daylight duration, more persistent clear-sky conditions, and reduced seasonal cloud influence over arid and semi-arid landscapes. In such conditions, countries such as Kazakhstan, Uzbekistan, and Turkmenistan are expected to experience an acceleration in the summer brightening process, which could further strengthen the strategic importance of the summer season for solar energy harvesting (see Figures 2, 3 and Supplementary Figures S1, S2; Dutta et al., 2022; Chen et al., 2023).

Compared to the other seasons, winter exhibits the opposite trend. This season in historical data is predominantly defined by high positive slope trends particularly in the northern Kazakhstan. Nonetheless, projections indicate that in the future, the trend will be contrary and highly reliant on the scenario of emissions. Projections under SSP2–4.5 suggested that trends will be relatively stable or neutralizes, however, most of the regions will experience a significant expansion in negative slopes under SSP5–8.5 scenario. This trend is particularly noticeable in the northern and eastern regions of the area and means that there is a shift toward

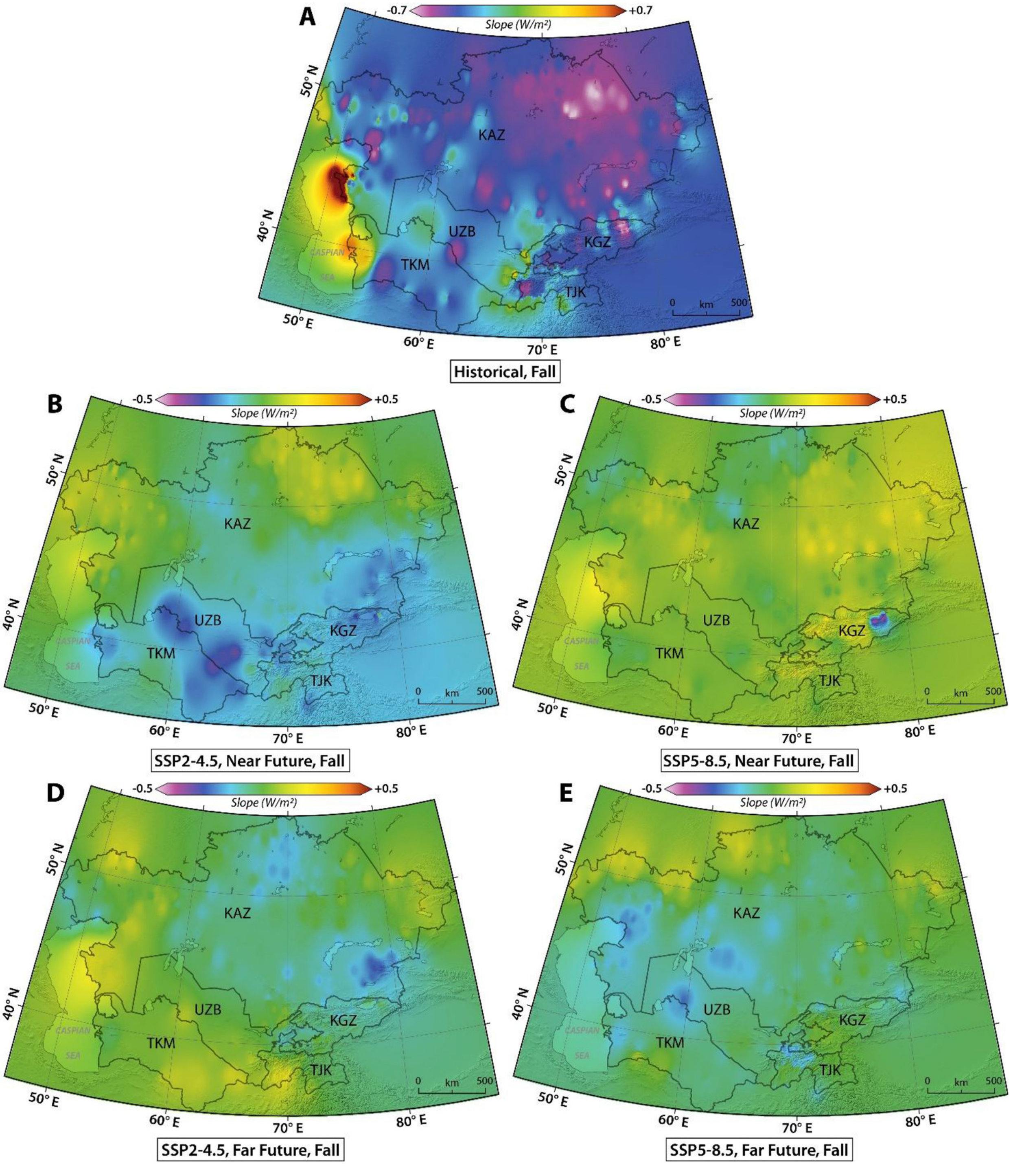

FIGURE 2
Spatiotemporal analysis of surface solar irradiance slope trends in CA during fall from 1992 to 2100 under SSP2–4.5 and SSP5–8.5 scenarios. For historical periods, surface shortwave downward irradiance (SSWDI) was used as a proxy for solar energy potential, while future projections relied on surface downwelling shortwave radiation (SDSR) derived from CMIP6 GCM outputs. Warm colors indicate an increase in solar slope values over time, while cool colors represent a decrease. **(A)** Historical, Fall. **(B)** SSP2–4.5 and **(C)** SSP5–8.5, Near Future, Fall. **(D)** SSP2–4.5 and **(E)** SSP5–8.5, Far Future, Fall.

winter dimming in the future. This projected winter dimming is physically consistent with the seasonal radiation regime of continental CA, where low solar elevation, shorter day length, stronger synoptic variability, cloud occurrence, snow-covered surfaces, and local topographic shading can limit incoming shortwave radiation, particularly in northern Kazakhstan and mountainous regions of Kyrgyzstan and Tajikistan (Dozier, 1980; Dutta et al., 2022; Ihsan et al., 2024). Combined, these trends in seasons suggest that the future of solar energy in CA is both seasonally determined and driven by different levels of climate

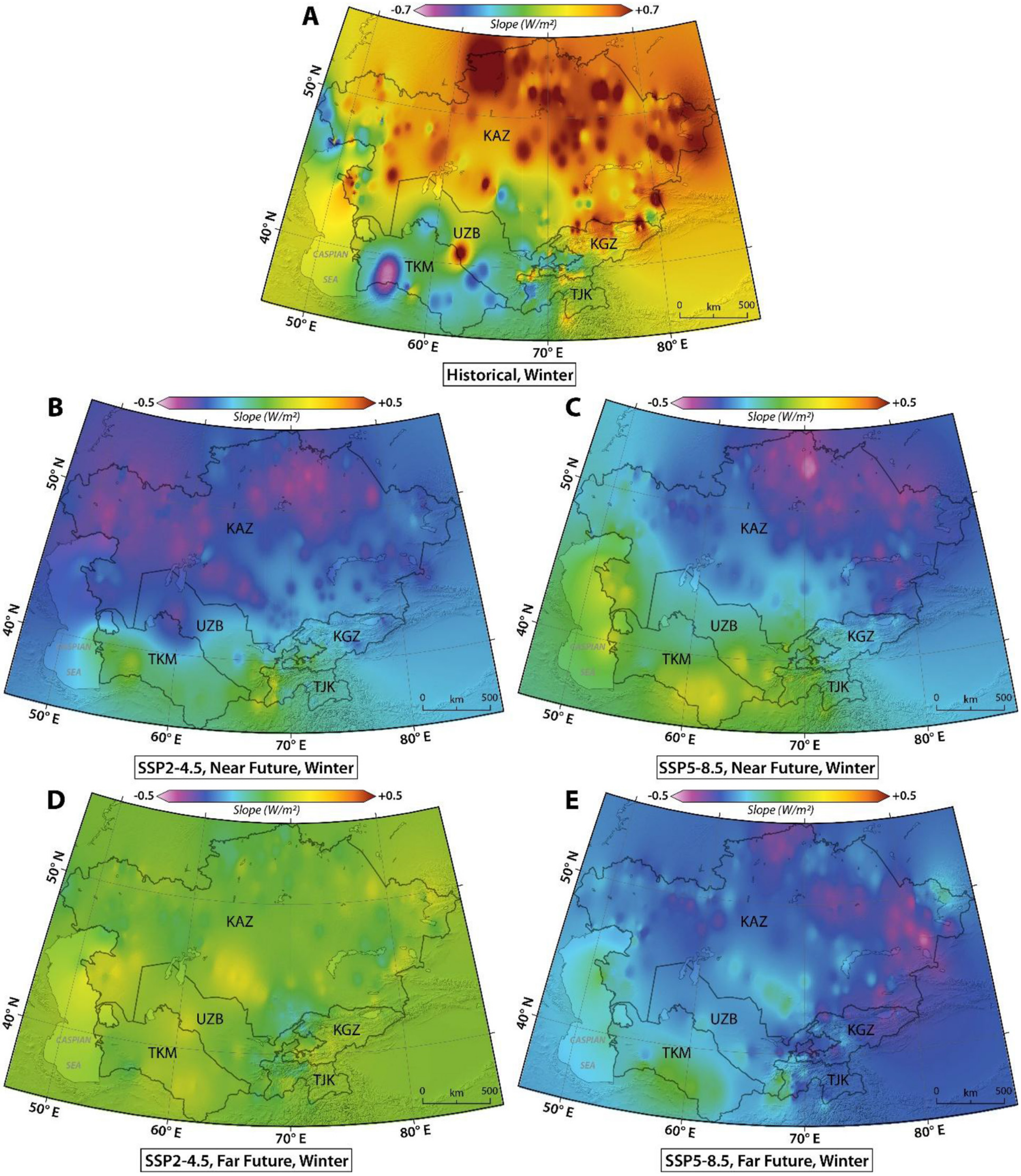

FIGURE 3
Spatiotemporal analysis of surface solar irradiance slope trends in CA during winter from 1992 to 2100 under SSP2–4.5 and SSP5–8.5 scenarios. For historical periods, surface shortwave downward irradiance (SSWDI) was used as a proxy for solar energy potential, while future projections relied on surface downwelling shortwave radiation (SDSR) derived from CMIP6 GCM outputs. Warm colors indicate an increase in solar slope values over time, while cool colors represent a decrease. **(A)** Historical, Winter. **(B)** SSP2–4.5 and **(C)** SSP5–8.5, Near Future, Winter. **(D)** SSP2–4.5 and **(E)** SSP5–8.5, Far Future, Winter.

forcing. Among them, summer and autumn offer the greatest potential for solar expansion, while spring requires more detailed regional planning. On the other hand, winter, especially in high-emission scenarios, could pose the greatest long-term risk to the sustainability of solar resources. These results highlight the importance of developing adaptive, seasonally-based strategies that take into account both spatial differences and temporal trends in solar expansion planning as well as the physical climatic

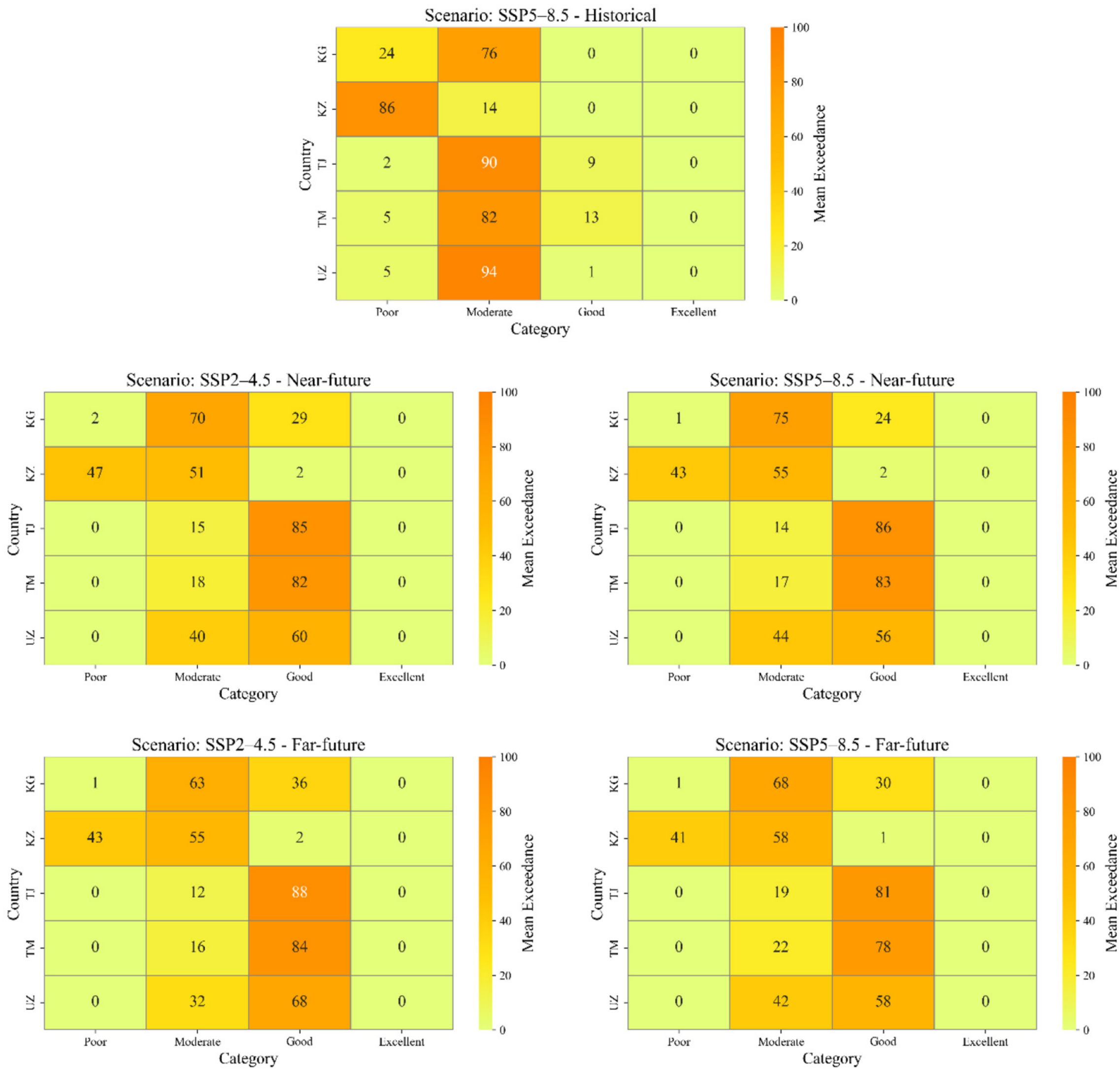

FIGURE 4
Fall seasonal changes in surface solar irradiance across Central Asian countries from 1992 to 2100 under SSP2–4.5 and SSP5–8.5 climate change scenarios, categorized by solar irradiance performance classes and countries. For historical periods, surface shortwave downward irradiance (SSWDI) was used as a proxy for solar energy potential, while future projections relied on surface downwelling shortwave radiation (SDSR) derived from CMIP6 GCM outputs. Corresponding detailed maps are provided in Supplementary Figures S3–S5.

mechanisms controlling surface shortwave radiation across CA (see Figures 2, 3 and Supplementary Figures S1, S2).

3.2 Seasonal variation of country-level exceedance in all-sky surface shortwave downward irradiance (SSWDI) across CA

Figure 4 and Supplementary Figures S3–S5 showed the seasonal changes in all-sky surface solar irradiance exceedance (measured as all-sky SSWDI) in a country-level across Central Asian countries during the historical period and under future climate scenarios (SSP2–4.5 and SSP5–8.5) for historical (1992–2021), near-future, 2022–2051, and far-future, 2071–2100 for each all-sky solar irradiance performance class: Excellent, Good, Moderate, and Poor. These classes are defined strictly on the basis of all-sky surface shortwave irradiance thresholds and therefore represent irradiance-based solar-resource availability, rather than direct PV electricity generation. This distinction is important because PV performance can also be affected by operating temperature and optical/system losses, which are not explicitly modeled in the present framework (Skoplaki and Palyvos, 2009; Cordero et al., 2018; IEA PVPS, 2022). This distinction is particularly important in dust-prone arid environments, where aerosol loading and dust deposition can reduce surface irradiance and operational PV performance even when modeled irradiance conditions appear favorable (Banks et al., 2024; IEA PVPS, 2022; Mozhdehi Fard et al., 2025).

The thresholds adopted from Elboshy et al. (2022) are used here as a standardized irradiance-based reference framework to enable consistent comparison across countries, seasons, and climate scenarios. However, because CA includes deserts, lowlands, and high-altitude mountain regions, these classes should be interpreted as comparative irradiance categories rather than locally calibrated suitability thresholds for every physiographic setting. In addition, these thresholds do not explicitly account for dust-related attenuation, aerosol optical depth (AOD), or soiling losses, which may be important in desert and semi-desert zones of CA. Therefore, "Excellent" or "Good" classifications in arid regions should be understood as modeled irradiance-resource classes, not as direct indicators of realized PV yield under dusty operating conditions (Cordero et al., 2018; IEA PVPS, 2022).

The country-level analysis of seasonal all-sky solar irradiance exceedance across CA reveals strong spatial and temporal contrasts, with summer emerging as the most robust season for photovoltaic resource development (see Figure 4 and Supplementary Figures S3–S5). Among the countries in the region, Tajikistan, Turkmenistan, and Uzbekistan have historically shown the highest solar radiation performance in the summer season. In these countries, the "Excellent" class values reach 99.2%, 98.5%, and 99.7%, respectively. Projections show that in the far-future, in both SSP2–4.5 and SSP5–8.5 scenarios, these values will increase even further, reaching about 99.8%—100.0%.

Kyrgyzstan also experiences a growing trend, with the share of the "Excellent" class increasing from 76.9% in the historical period to about 94.1% in the far-future, in both climate scenarios considered. Among them, Kazakhstan shows the largest relative improvement. In this country, the share of the "Excellent" class increases from 40.4% in the historical period to 83.3% under the SSP2–4.5 scenario and 91.3% in the SSP5–8.5 scenario. In contrast, in Turkmenistan, which already has high values, a more limited increase is observed, from 98.5% to 99.8% in both scenarios (see Figure 4 and Supplementary Figures S3–S5). These results together once again show that summer plays a dominant role in the development of solar energy in the region, regardless of which climate scenario is considered. This summer dominance is physically consistent with high solar elevation, longer daylight duration, and generally clearer atmospheric conditions across the arid and semi-arid lowlands of CA, which increase the frequency of days exceeding the "Excellent" irradiance threshold (Dutta et al., 2022; Chen et al., 2023). Nevertheless, especially in hot arid environments such as Turkmenistan, an "Excellent" irradiance class should be interpreted as high solar-resource availability, not as a direct estimate of realized PV output. Elevated operating temperatures and dust-related optical losses can reduce PV performance even under high-irradiance conditions (Skoplaki and Palyvos, 2009; Cordero et al., 2018; IEA PVPS, 2022).

To examine the changes caused by the scenarios in more detail, the spatial distribution of seasonal changes in the solar radiation performance classes under all-sky conditions relative to the historical period was also analyzed; however, the corresponding figures are not presented here. The spatial results of this analysis confirm the same general patterns, showing that in both scenarios, especially in the far-future, there is a significant increase in the extent of the "Excellent" and "Good" classes. This expansion is mainly seen in southern Uzbekistan, eastern Kyrgyzstan, and large parts of Tajikistan. In the SSP5–8.5 scenario, the areas with superior performance are also spread more widely, even extending into northern Uzbekistan and parts of central Kazakhstan, areas that still experience a more limited range of such conditions in the SSP2–4.5 scenario. The wider spatial expansion under SSP5–8.5 may reflect stronger radiative forcing and associated changes in seasonal cloudiness, atmospheric moisture, and circulation patterns.

Improvements are also present in the spring, but they are not spatially homogeneous, and their severity differs across regions. The category of Excellent is not observed in this season in any country, at any time of the year, in any situation. In other countries instead, the proportion of the category of "Good" decreases substantially. In the case of Kyrgyzstan, the percentage of this category declines to 52.8 in SSP2–4.5 scenario and 46.6 in SSP5–8.5 scenario. The same pattern can be witnessed in Tajikistan where its value declined from 93.7 to 60.7, and 61.3 percent under SSP2–4.5 scenario and SSP5–8.5 scenario, respectively. In Kazakhstan, this decline is even worse, as the share of the "Good" category declines to 23.7 and 16.5 in the SSP2–4.5 and SSP5–8.5 scenarios, respectively. In Uzbekistan, they also decline significantly (from 99.0% to 70.5% and 68.4%). By contrast, Turkmenistan is relatively steady, with future values still higher than 94% in both cases (see Figure 4 and Supplementary Figures S3–S5). The absence of "Excellent" conditions in spring may be related to the transitional character of the season, when variable cloud cover, atmospheric moisture, snowmelt-related surface conditions, and circulation changes can reduce the persistence of high irradiance days, particularly in northern and mountainous areas (Dutta et al., 2022; Chen et al., 2023). Spring can also coincide with enhanced dust activity in parts of CA, which may further affect irradiance conditions and PV-surface cleanliness in arid and semi-arid zones.

Overall, these findings reveal that the spring is a season when solar energy has moderate potentials; high growth prospects are observed in Kyrgyzstan and Tajikistan; in Kazakhstan and Turkmenistan, the access to the high-quality solar energy is more limited. Geographically, the spring maps indicate that the gains are mostly made in eastern Kyrgyzstan and selected valleys in Tajikistan, with no improvement being seen at all or a negative trend in western Turkmenistan and northern Kazakhstan. In the SSP5–8.5, the spatial gradients in exceedance values are more evident and the distinction between highlands and lowlands are more distinct. This highland–lowland contrast suggests that regional topography may modulate the exceedance patterns by influencing terrain shading, local cloud formation, and elevation-dependent atmospheric conditions. For this reason, the classification results in high-altitude areas, particularly in Kyrgyzstan and Tajikistan, should be interpreted with caution because local effects such as angle of incidence, snow-albedo interactions, elevation-dependent atmospheric conditions, and lower operating temperatures may alter the practical relevance of uniform irradiance thresholds.

Autumn offers an alternate view and is more sensitive to emission situations. As in spring, no country was rated as "Excellent" in any time and transitions were made mostly in the "Good" category. Kyrgyzstan, however, shows a relative improvement once again; the share of the “Good” category increases from 0.0% in the historical period to 28.7% in the SSP2–4.5 scenario and 30.2% in the SSP5–8.5 scenario. This is followed by Tajikistan, whose values increase from 5.5% to 81.3% and 87.2%. Uzbekistan also shows a significant increase, with the share of this class increasing from 6.3% to 80.3% and 85.7% under the two scenarios considered.

In contrast, Kazakhstan does not show much change; the share of the “Good” class only increases from 0.0% to 0.3% in SSP2–4.5 and 0.7% in SSP5–8.5, indicating little sensitivity to the scenarios. Turkmenistan also has the weakest performance in this season, although its value increases from 1.0% in the baseline period to 60.7% in SSP2–4.5 and 81.2% in SSP5–8.5. Therefore, autumn is the season that is more dependent on the climate scenario, with the SSP5–8.5 scenario showing larger increases. This pattern also suggests that Tajikistan and Uzbekistan are strengthening their comparative advantage in the middle classes of solar performance. The stronger autumn response under SSP5–8.5 may be associated with scenario-dependent changes in cloudiness, aerosol forcing, and atmospheric circulation, which can alter the frequency of moderate-to-good irradiance conditions during transition seasons (Bellouin et al., 2020; Zelinka et al., 2020). Because dust aerosols directly interact with shortwave radiation and can perturb regional radiative balance, aerosol-related uncertainty should be considered when interpreting projected improvements in dust-prone lowlands and desert margins (Banks et al., 2024; Zhao et al., 2022; Mozhdehi Fard et al., 2025).

Examination of the autumn spatial maps also confirms these results. In large parts of Kazakhstan and Turkmenistan, especially in the western regions, the situation remains almost unchanged and the increase in threshold exceedances is very limited or even negative. In contrast, the SSP5–8.5 projections show localized improvements in Uzbekistan and Tajikistan, especially in areas close to the mountain slopes and semi-arid transition zones. However, much of the western lowland still does not show significant improvement in any of the scenarios and these areas remain below the threshold for improvement. These localized improvements may reflect the combined influence of regional aridity, topographic transitions, and seasonal circulation changes, while the limited response in western lowlands may indicate persistent atmospheric or surface constraints on shortwave radiation.

Consistent with our findings, Dutta et al. (2022) project a reduction of up to 10% in PV potential during boreal winter (December–January–February) in Asia under the SSP5–8.5 scenario for the far-future period (2041–2100; Dutta et al., 2022). Furthermore, Ihsan et al. (2024) assessed spatial heterogeneity and the Umbrella Effect Index (UI) to measure cloud-induced irradiance reductions, understanding that boreal winter (December–February) in the Northern Hemisphere exhibited lower solar irradiance heterogeneity due to clearer skies (Ihsan et al., 2024). This observation aligns with our result that winter shows minimal exceedance of all-sky surface shortwave downward irradiance in Central Asian countries, with no country achieving “Excellent” or “Good” classifications (see Figure 4 and Supplementary Figures S3–S5).

Winter is the most constrained season for solar resource exceedance across the region. All five countries show zero percent exceedance in the “Excellent” class for both near and far futures under both scenarios. In winter, the highest level of performance is limited to the “Moderate” class. For example, in Kazakhstan, the share of this class increases slightly from 33.1% in the historical period to 35.5% in the SSP2–4.5 scenario and 37.2% in the SSP5–8.5 scenario. A similar trend is observed in Uzbekistan, where the share of this class increases from 22.8% to 25.0% and then to 27.8% in the future scenarios. However, the significant absence of the “Excellent” and “Good” classes in winter indicates that this season—even under different scenario and time conditions—has serious limitations for the development of solar energy. The spatial results for winter also reflect this limitation well. The maps show a fairly uniform pattern across the region, with most locations either showing no noticeable change or showing negative trends in the different classes exceeding the threshold. High-performance are not also projected to face significant spatial expansion under SSP5–8.5 scenario. This is confirmation that the conditions of winter are inherently unfavorable when it comes to entirely solar based investments. Physically, the weak winter exceedance pattern is consistent with low solar elevation, shorter daylight hours, snow-covered surfaces, increased atmospheric variability, and cloud occurrence, all of which reduce the frequency of high-irradiance days. In mountainous areas, terrain shading and elevation-dependent cloud formation may further limit the occurrence of “Good” and “Excellent” irradiance classes (Dozier, 1980; Dutta et al., 2022; Ihsan et al., 2024).

In terms of the regional findings, Kyrgyzstan is pointed out as the most opportune region to solar investment over the year particularly during summer and spring and classification share of the class of Excellent is over 90% during summer by 2100. This is then succeeded by Tajikistan and Uzbekistan which experience substantial growth in threshold exceedances during summer and covers the Good and Excellent classes widely throughout most seasons. Kazakhstan, despite her underprivileged foundation, demonstrates enormous relative progress, particularly in summer. Conversely, Turkmenistan is very favorable in summer, and spring and nearly all the country is classified as either Excellent or Good. The future under autumn also exhibits great improvement in the country, yet the country is limited in the winter. In terms of season, the summer is the most consistent and predictable of solar growth in both SSP2–4.5 and the SSP5–8.5. The opportunities in spring are moderate, though regional trends differ. Autumn is more climate-dependent, and its developmental outcomes depend on the pathway of propagation. In contrast, winter is not suitable for purely solar expansion, highlighting the need for hybrid solutions. Taken together, these results can serve as a basis for designing adaptive and seasonally appropriate energy strategies for CA. These findings also indicate that the practical value of seasonal exceedance analysis lies not only in identifying where irradiance thresholds are exceeded, but also in showing how regional climatic mechanisms shape the reliability of solar resources across different seasons and emission pathways. However, the exceedance-based interpretation should remain cautious in dust-prone desert environments because modeled all-sky irradiance may

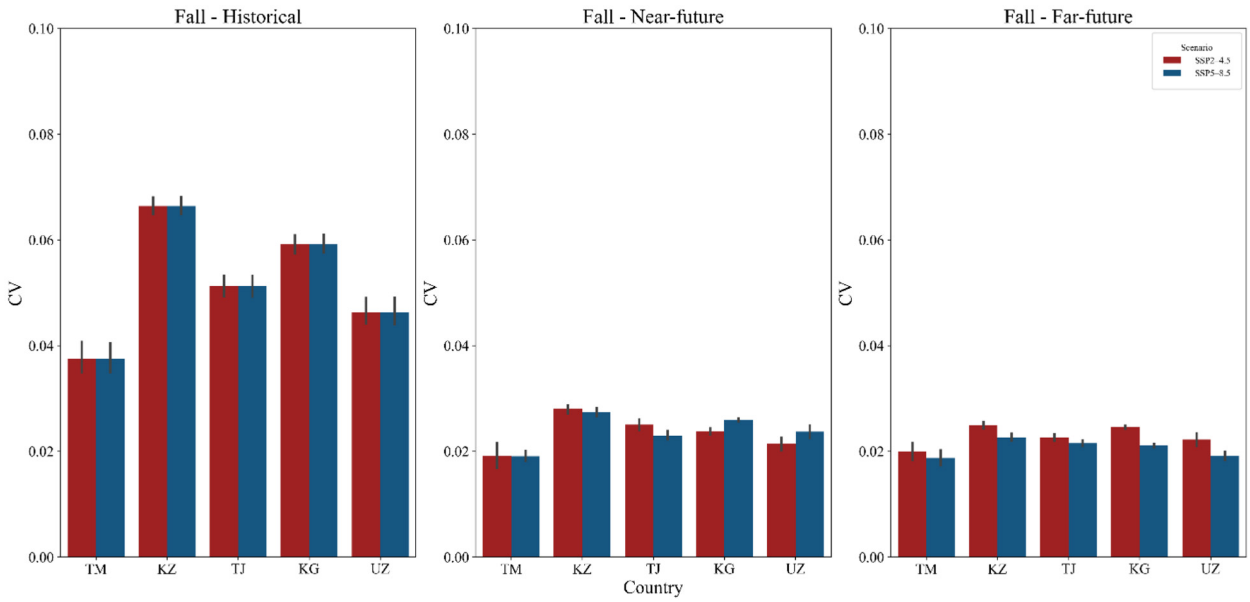

FIGURE 5
Fall seasonal changes in the coefficient of variation (CV) for all-sky surface solar irradiance exceedance for Central Asian countries from 1992 to 2100 under SSP2–4.5 and SSP5–8.5 climate change scenarios.

not fully represent local dust episodes, deposition, and soiling-related losses.

3.3 Seasonal country-level stability of all-sky surface shortwave downward irradiance (sswdi) in CA

Figure 5 and Supplementary Figures S13–S15 show the seasonal variations of CV for the threshold values of surface solar radiation exceedances in all-cloud conditions in the Central Asian region. In this study, this index is measured using the all-sky SSWDI and investigated for two climate scenarios SSP2–4.5 and SSP5–8.5. Here, CV is used as a normalized measure of inter-annual variability of seasonal modeled irradiance, calculated as the ratio between the standard deviation and the mean. Therefore, changes in CV should be interpreted carefully: a decrease in CV may reflect a reduction in absolute variability, an increase in the mean irradiance, or both. For this reason, CV is not interpreted here as a direct measure of intra-day intermittency or operational PV predictability. In general, the obtained patterns show that in most countries and in most seasons, the CV values are mainly within the "very stable" category (less than 0.1). However, seasonal and emission scenario-dependent differences in the temporal and spatial distribution of this index are visible. Because CV is calculated from modeled all-sky irradiance, the stability values should be interpreted as variability in the modeled solar resource rather than as a full measure of operational PV reliability. Operational PV performance is governed by higher-frequency variability, including hourly to sub-hourly cloud fluctuations, ramping events, inverter response, curtailment risk, and storage dispatch requirements, which cannot be resolved from the seasonal CV metric used here. In dust-prone regions, short-term dust intrusions, aerosol optical depth (AOD) variability, and soiling processes may introduce additional variability or losses that are not explicitly represented in the CV framework (Banks et al., 2022; Cordero et al., 2018; IEA PVPS, 2022).

Among the countries in the region, Kyrgyzstan shows one of the most stable patterns of solar radiation variability. In the autumn season and within the SSP2–4.5 scenario, the average CV value decreases from 0.059 in the historical period to 0.024 in the far-future; a decrease estimated at about 59%. A similar trend is observed in spring, where the CV value decreases from 0.052 to 0.036. Under the SSP5–8.5 scenario, the pattern of low variability is also maintained; for example, in winter, the average CV value decreases from 0.043 in the historical period to 0.030 in the far-future. These values indicate that the solar resources in Kyrgyzstan are remarkably stable throughout the year (see Figure 5 and Supplementary Figures S6–S8). However, this does not necessarily mean that absolute variability or short-timescale PV intermittency decreases. This stability may be partly related to the relatively persistent seasonal radiation regime in mountainous and semi-arid environments, where changes in cloud occurrence, snow cover, and circulation patterns can modify irradiance variability without necessarily reducing mean solar availability uniformly across space.

The observed pattern is also consistent with the results of Medvigy and Beaulieu (2012). This study showed that the variability of solar radiation on a global scale does not behave uniformly and varies depending on geographical location; in such a way that in some regions, such as equatorial latitudes, an increase in CV is reported, while in parts of mid-latitudes or continental regions with higher latitudes, a decreasing trend is observed. The prospective results of this study for CA also

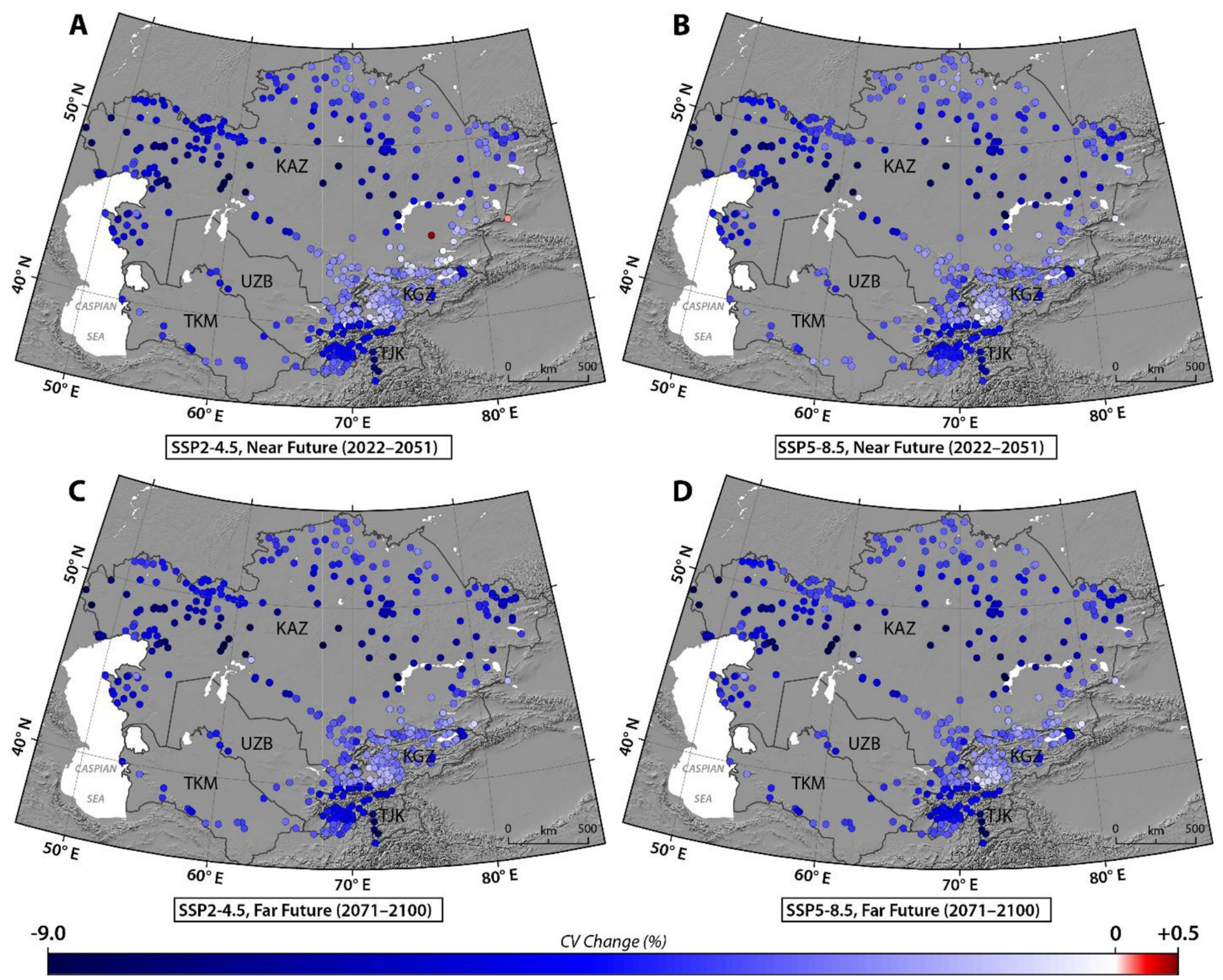

FIGURE 6
Geospatial distribution of coefficient of variation (CV) changes in winter across CA relative to the historical period, for the **(A, B)** near-future (2022–2051) and **(C, D)** far-future (2071–2100) under SSP2–4.5 and SSP5–8.5 scenarios. Warm colors indicate an increase in CV, while cool colors indicate a decrease in CV.

show that improvements in solar resource stability do not occur equally in all countries (Medvigy and Beaulieu, 2012). In physical terms, a lower CV indicates that irradiance fluctuations decrease relative to the mean, which may occur where cloud variability becomes less frequent, seasonal radiation conditions become more persistent, or atmospheric states become more stable over time. However, because CV is a ratio, this decline can result from changes in the standard deviation, changes in the mean, or both. Therefore, CV alone cannot distinguish whether the modeled reduction is driven by lower absolute variability or by higher mean irradiance. A lower CV should not be interpreted as evidence that all atmospheric hazards affecting solar performance are reduced, because dust episodes can occur intermittently and may not be fully captured by seasonal or country-level CV statistics. To more clearly demonstrate the changes resulting from the scenarios, spatial maps of seasonal changes in solar radiation stability under fully cloudy conditions relative to the historical period were also produced. These maps of CV changes confirm the same general trend. Uniform blue gradients are observed across Kyrgyzstan, indicating a widespread and relatively homogeneous reduction in solar radiation variability at the spatial scale (see Figure 6 and Supplementary Figures S9–S11).

Compared to other countries in the region, Kazakhstan exhibits the highest inter-seasonal variability. This is particularly pronounced in winter under the SSP5–8.5 scenario, where the CV value in the historical period reaches 0.133, thus falling into the medium variability category. However, projections show that in the distant future this value will decrease to 0.091, representing an improvement of about 31.6%; a similar pattern is observed in the spring. In the SSP2–4.5 scenario, the CV value decreases from 0.074 in the historical period to 0.041 in the far-future. In contrast, in summer and autumn the CV values remain below 0.06 in most cases (see Figure 5 and Supplementary Figures S6–S8). Overall, although moderate levels of variability are sometimes seen in winter, the overall trend in Kazakhstan in both climate trajectories is toward increasing stability of solar resources over time. Geospatial analyses indicate that although the majority of sites in Kazakhstan experience reductions in CV, spatial disparities are more pronounced here than in other countries, particularly in the winter season (Figure 6 and Supplementary Figures S9–S11). The larger winter CV in Kazakhstan is physically plausible because northern and continental regions are more exposed to synoptic-scale variability, snow-cover persistence, cloud fluctuations, and strong seasonal changes in solar angle, all of which can increase variability in surface shortwave radiation.

Comparable regional contrasts have been reported in China, where Niu et al. (2023) found that eastern and southeastern provinces show substantial improvements in PV power potential under future climate scenarios, while more arid and high-altitude western areas (such as Northwest China and the Tibetan Plateau) experience less improvement or even declines, reflecting diverging patterns of variability and climate sensitivity (Niu et al., 2023).

Turkmenistan shows a low level of solar radiation variability in all seasons and in all time periods studied. For example, in summer and under the SSP2–4.5 scenario, the CV value decreases from 0.063 in the historical period to 0.038 in the distant future. In winter and under the SSP5–8.5 scenario, the values of this index remain in the "very stable" range, with only a slight decrease from 0.059 to 0.045 (see Figure 5 and Supplementary Figures S6–S8). The implication of such a pattern is that there is a reliable profile of solar resources that is subjected to minimal variation with time in the country, which justifies the appropriateness of Turkmenistan in developing solar energy on a long-term basis, as the uncertainty in the supply of the resources is not very high. This should not be interpreted as a complete measure of resource predictability for PV operation, because seasonal CV does not capture sub-daily intermittency, dust-event timing, or soiling-related losses. This result is also supported by spatial analyses. The maps demonstrate that the CV decline trend is nearly the same in all locations and seasons throughout Turkmenistan. This spatial homogeneity shows that the country has high potential for sustainable and predictable development of solar energy (see Figure 6 and Supplementary Figures S9–S11). This finding is also in line with the results of Chen et al. (2024), where they indicate that despite the variability of CV patterns at high latitudes and in dry climates and environments there are plenty of stable areas that remain even more stable in case of climate changes (Chen et al., 2024). For Turkmenistan, the low CV values may reflect the dominance of arid and semi-arid atmospheric regimes, where persistent clear-sky conditions and limited seasonal cloud variability can support relatively stable irradiance conditions.

A similar trend in the declining variability can be found in Tajikistan as well. This tendency is noticeable especially in spring and in the SSP5–8.5 scenario; in which the CV value declines by the historical period of 0.066, to the far-future value of 0.034 (reduction 48.5%). During the summer and autumn, CV values are largely unchanged across all time periods under analysis, with CV mainly constant at 0.040 (see Figure 5 and Supplementary Figures S6–S8). These findings are supported by spatial analyses, which indicate that the CV reduction is evenly distributed throughout Tajikistan, and no strong deviations are found in the distributions. In Tajikistan, the relatively homogeneous decline in CV may also be influenced by elevation-dependent radiation regimes and repeated seasonal circulation patterns, although local topographic effects can still generate important sub-regional differences.

These analyses reveal that an upward trend in terms of solar resource stability is observed over the years in all countries studied of the region. In other words, CV declines gradually across historical period to near-future and then far-future. However, this does not necessarily imply that stronger climate forcing directly reduces uncertainty in solar resources. Because CV is normalized by the mean, part of the decline may reflect an increase in mean irradiance rather than a reduction in absolute variability. Therefore, the interpretation of CV trends requires caution unless the mean and standard deviation are evaluated separately. On the other hand, solar radiation patterns are more homogenous in various areas with fully clouded weather, a fact that may correspond to the increased stability of the weather conditions or climate alteration in the regions. Whereas, even though a decrease in CV is also noted in both scenarios, but the decrease is found to be more spatially consistent under the SSP5–8.5. It is evident in Tajikistan and Turkmenistan, which implies that more intense climate change results in a stability of solar resources in some areas. Nonetheless, local variations in CV can also be noticed in some parts of the world, particularly in high latitudes and in arid western areas, as mentioned by Chen et al. (2024). This underscores the importance of specific regional considerations, and responsive planning. This conclusion is also supported by the spatial analyses of the research, since in both cases, the maps have mostly a blue shade, meaning that there is a systematic decline in CV across CA. However, this interpretation should be treated cautiously because surface shortwave radiation is controlled by interacting processes, including cloud feedback, aerosol loading, water vapor, snow cover, and circulation-driven changes in cloud formation. Therefore, the projected decrease in CV should be interpreted as improved statistical stability of the modeled solar resource, rather than direct evidence of reduced atmospheric complexity (Bellouin et al., 2020; Zelinka et al., 2020). In addition, aerosol and dust-cycle uncertainties are particularly relevant for CA because dust emissions from desert surfaces and degraded drylands can modify shortwave radiation and are not fully represented in seasonal CV statistics or in the present ranking framework.

Winter mostly records the largest CV values, which is especially significant in Kazakhstan and is probably associated with the increased atmospheric variations and decreased amounts of solar radiation in this period. As compared to winter, the most stable conditions are seen in spring and autumn where CV values are smaller than 0.05 in most regions, which is especially pronounced in Kyrgyzstan and Tajikistan. This implies that both of these seasons can be an appropriate time during which solar energy can be explored with low interannual variability. This indicates lower normalized inter-annual variability of modeled seasonal irradiance, but it does not necessarily imply lower intra-day variability or reduced storage requirements. This pattern is also confirmed by the spatial variation maps of CV. The highest spatial heterogeneity is revealed by the winter panels, particularly in Kazakhstan, and the less expected heterogeneity is indicated by the spring and autumn maps, where the decrease in CV is more homogeneous, thereby confirming the findings of the statistical analysis visually.

In general, the analysis indicates that the solar resources variability in CA is quite low and will even decrease under future climate conditions. This finding may be useful for climate-scale resource screening because it shows where seasonal mean irradiance is projected to become more or less stable relative to its mean. However, it should not be used alone to infer operational PV performance, storage capacity, reserve requirements, or grid-balancing needs. These system-level outcomes depend on higher-frequency irradiance variability, demand patterns, storage dispatch, curtailment, grid flexibility, and plant-level design, which are outside the temporal resolution and scope of the present CV analysis.

At the same time, individual indicators such as the solar radiation threshold exceedance rate or the coefficient of variation each provide valuable information about solar potential, but their spatial and temporal patterns are not always consistent. For example, Uzbekistan and Turkmenistan, despite having high solar radiation—especially in summer—face greater variability and more pronounced reductions in resource availability in some future scenarios. In contrast, Kazakhstan has relatively stable patterns of solar radiation in most seasons, but in some periods—especially in spring and autumn—the rate of exceeding its radiation thresholds is lower. These differences become more pronounced with the change of seasons and also with the change of emission scenarios. In arid and semi-arid regions, these differences may also be affected by aerosol and dust-related processes that are not explicitly included in the present CV analysis.

Overall, summer provides the most robust conditions for solar energy exploitation in the region, while winter is associated with serious limitations in all countries. The results for spring and autumn are also intermediate and depend significantly on the climate scenario considered. This seasonal variation suggests that the assessment of solar energy potential should be multidimensional, considering not only the absolute amount of resources, but also their temporal stability under different climate change trajectories. Such an approach provides a more accurate understanding of the potential for solar energy development, especially in regions where seasonal performance and response to climate scenarios vary significantly.

3.4 Seasonal and scenario-based ranking of solar resource potential in CA

The aim of the study is to investigate how the ranking of solar energy suitability locations in CA changes from a spatial and temporal perspective. Two emission scenarios SSP2–4.5 and SSP5–8.5 are analyzed and compared between two future periods, the near-future (2022–2051) and the far-future (2071–2100) in comparison with the base period (1991–2021). Figures 7, 8 and Supplementary Figures S19, S20 show spatial distribution of changes in seasons relative to solar energy suitability rankings in the SSP2–4.5 scenario; changes in the near-future (2022–2051) and the far-future (2071–2100) relative to the historical period (1992–2021).

Because CA includes highly contrasting geosystems, including steppe plains, desert lowlands, irrigated valleys, foothills, and high-mountain regions, these ranking results should be interpreted as regional-scale comparative patterns rather than locally calibrated suitability outcomes for each physiographic zone. The uniform ranking framework enables consistent comparison across countries, seasons, and scenarios, but it does not explicitly stratify results by desert, steppe, valley, or mountain environments. This distinction is important because aridification, dust activity, elevation, snow cover, and local land–atmosphere interactions can modify solar-resource behavior at finer spatial scales (Groll et al., 2013; Indoitu et al., 2015; Banks et al., 2022). For example, atmospheric dust originated from solonchacks of the Aralkum desert and the exposed poisoned sea bottom of the Aral Sea is transported over vast distances (up to 4,000 km), reaching the Arctic Ocean, Iran, Atlantic Ocean, and Pacific Ocean, affecting over 38.5 million km^2 of land(Anchita et al., 2021; Chen et al., 2022). In dust-prone lowlands and desert environments, ranking changes should also be interpreted with caution because aerosol loading, dust events, and surface deposition can reduce effective shortwave radiation and PV performance, while these processes are not explicitly included as separate variables in the present ranking framework (Cordero et al., 2018; IEA PVPS, 2022; Banks et al., 2022). In dust-prone lowlands and desert environments, ranking changes should also be interpreted with caution because aerosol loading, dust events, and surface deposition can reduce effective shortwave radiation and PV performance, while these processes are not explicitly included as separate variables in the present ranking framework (Cordero et al., 2018; IEA PVPS, 2022; Banks et al., 2022).

Summer is the most stable season in terms of improved solar conditions. In parts of south and central Uzbekistan, southeastern Turkmenistan, and eastern Kyrgyzstan, this season is subject to wide improvements. These are further enhanced in the near-future under the SSP5–8.5 scenario and enhanced drastically in the far-future under both scenarios. Besides this, Tajikistan and Kyrgyzstan also demonstrate stability and climate change resilience under the SSP2–4.5 scenario (see Figure 7 and Supplementary Figures S12–S14). The fact that such trends have persisted indicates that summer is the most predictable season of early and extended solar energy development in the area. This stability is physically consistent with the dominance of high solar elevation, longer day length, and more persistent clear-sky conditions during summer, especially over the arid and semi-arid lowlands of CA. These conditions can reduce seasonal fluctuations in incoming shortwave radiation and support more stable suitability rankings. However, for Tajikistan and Kyrgyzstan, this summer resilience should be interpreted specifically as solar-resource suitability, not as direct energy-system priority, because these countries have hydropower-dominated electricity systems in which winter deficits may be more functionally important. Similarly, in southern desert areas of Turkmenistan and Uzbekistan, high summer ranking should be understood as modeled irradiance-resource suitability rather than dust-corrected or soiling-corrected PV yield. This finding is also in line with the previous research findings. For example, investigations have uncovered that even in SSP conditions the potential of photovoltaic systems in areas of Asia can be observed to be comparatively stable throughout summer in the North Hemisphere, however, seasonal outcomes would differ depending on the area and are influenced by complicated climate interactions (Chen et al., 2023; Dutta et al., 2022).

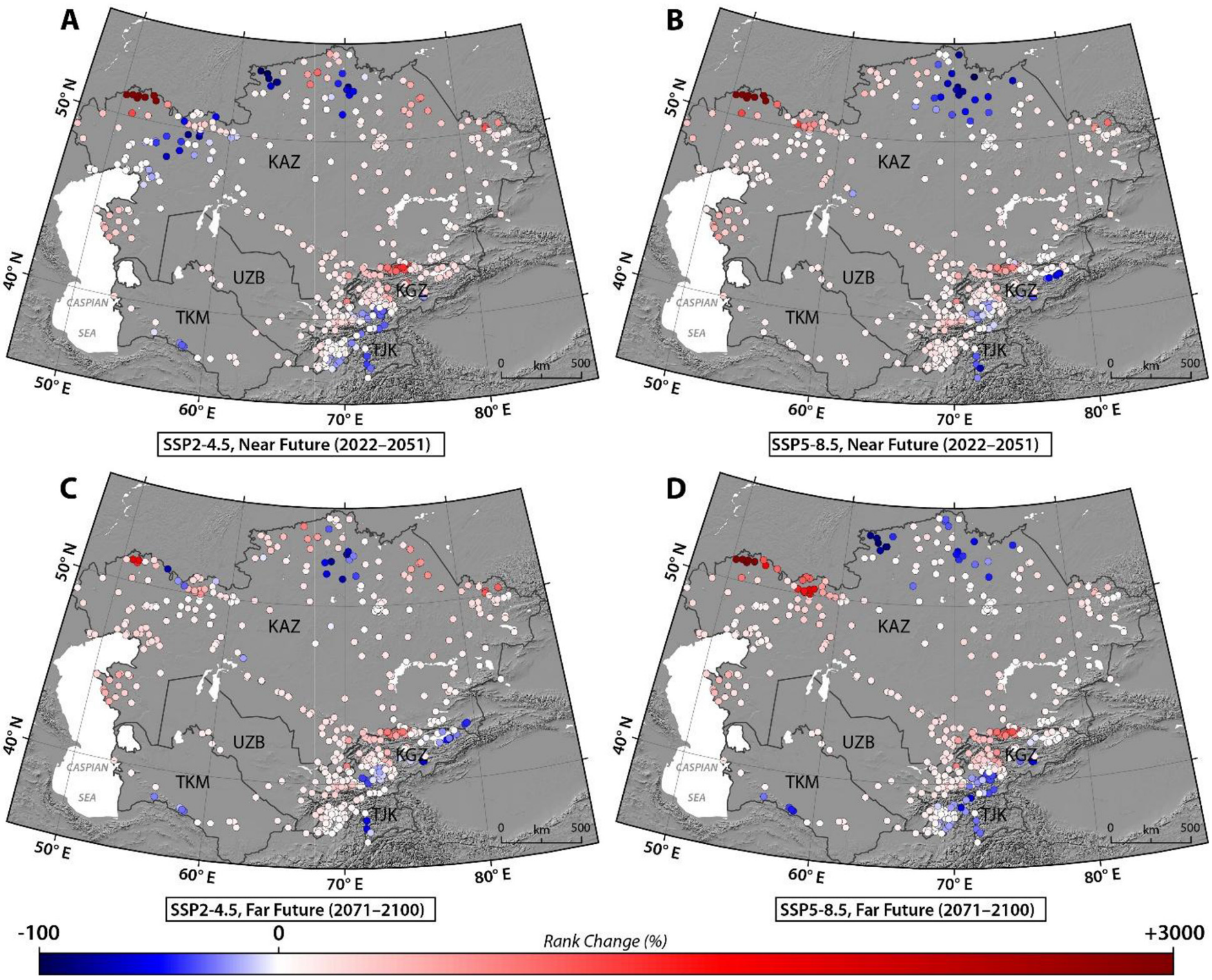

FIGURE 7
Geospatial distribution of fall ranking changes in CA relative to the historical period for the **(A, B)** near-future (2022–2051) and **(C, D)** far-future (2071–2100) under SSP2–4.5 and SSP5–8.5 scenarios. Warm colors represent an increase in ranking changes, while cool colors indicate a decrease in ranking changes.

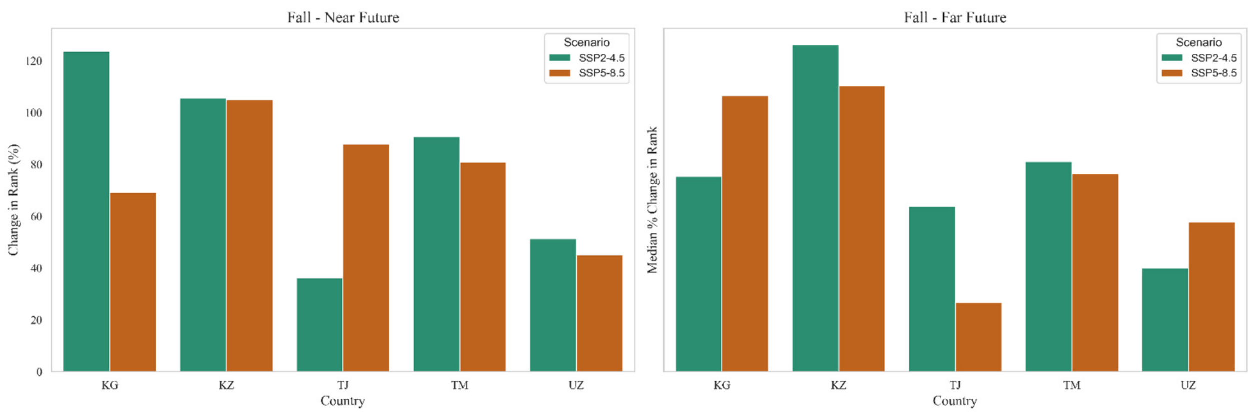

FIGURE 8
Rank changes across Central Asian countries in fall under SSP2–4.5 and SSP5–8.5 scenarios for near-future, 2022–2051, and far-future, 2071–2100, periods.

Spring follows a different pattern compared to summer. In the short term, the decrease in suitability rankings is evident under the SSP2–4.5 and SSP5–8.5 scenarios. Nonetheless, in the far-future, these are partially recovered under SSP2–4.5. Conversely, under SSP5–8.5, the situation is not uniform and spatial heterogeneity still exists. Under such conditions, northern Kazakhstan, western Turkmenistan, and parts of central Uzbekistan observe the largest declines, whereas the southern and eastern parts of the region remain more stable (see Figure 7 and Supplementary Figures S12–S14).

Thus, spring is scenario sensitive and spatially heterogeneous season that requires adaptive policies on solar energy development of local features. These heterogeneities also indicate that more refined seasonal modeling nearby should be applied to better evaluate this season because CMIP6 outcomes point to the conclusion that most of the year transition intervals tend to be considerably regionally heterogeneous (Dutta et al., 2022). The spatial heterogeneity of spring rankings may be associated with transition-season variability in cloud cover, atmospheric moisture, circulation patterns, and snowmelt-related surface conditions, which can influence irradiance differently across northern lowlands, arid regions, and mountainous areas. Spring ranking patterns may also be affected by seasonal aerosol and dust activity in arid and semi-arid zones.

Autumn, on the contrary, is widely characterized by the deterioration of solar performance at the very first moments of future time. The rise in ranking (reflecting declining suitability) in most countries and in both scenarios is more notable in the near-future, and more noteworthy in the far-future, and is most notable in the SSP5–8.5 scenario. The greatest effects are witnessed in Turkmenistan, the southern Uzbekistan, and low-lying regions of Tajikistan. Meanwhile, western regions of the region exhibit continuously lower performance. This trend implies that autumn might be the risky season of solar-only infrastructure, potentially necessitating hybridization or spreading energy sources (see Figure 7 and Supplementary Figures S12–S14). The stronger autumn deterioration under SSP5–8.5 may reflect the sensitivity of transition-season radiation to changes in cloudiness, atmospheric circulation, aerosol forcing, and moisture transport, which can alter the persistence of moderate-to-high irradiance conditions. Neighboring regions such as western China also faced seasonal declines in autumn, where the cloud cover and seasonal humidity during under the SSP5–8.5 scenario were found to partially weaken photovoltaic systems (Chen et al., 2023). Because aerosols interact directly with shortwave radiation, the ranking response in desert margins and dust-influenced lowlands should be interpreted with additional caution where regional dust-cycle representation remains uncertain (Bellouin et al., 2020; Banks et al., 2022, 2024).

Winter is the most vulnerable among all the seasons. The loss of suitability ranks is also evident both in the near-future and in the far-future; indeed, under both scenarios, this situation even results in a near-total loss of suitable sites in the SSP5–8.5. The region is nearly uniform in this performance decline, with the highest change in the north of Kazakhstan and the west of Turkmenistan. There is no significant improvement in any region, indicating that solar power development is not viable option during winter, and it should be substituted with seasonal balancing solutions or hybrid systems (see Figure 7 and Supplementary Figures S12–S14). This winter decline is physically plausible because low solar angle, short day length, snow cover, stronger synoptic variability, cloud occurrence, and local topographic shading can all reduce incoming shortwave radiation and increase the difficulty of maintaining high site suitability. For Tajikistan and Kyrgyzstan, this winter result is particularly important because it suggests that solar resources alone are unlikely to compensate for possible winter hydropower limitations without storage, imports, grid exchange, or other complementary resources. Other semi-arid areas have also documented similar issues with the performance of solar systems during wintertime, and the decrease in solar potential given a scenario with increasing emissions of greenhouse gases has been associated with persistent cloud cover and climate variability due to climate change (Dutta et al., 2022; Rakhmatova et al., 2024).

Finally, comparing the two scenarios reveals that SSP5–8.5 promotes greater and earlier deteriorations in the solar site suitability, whereas SSP2–4.5 displays indications of net gains in some seasons- mainly spring and summer. These disparities demonstrate the value of reduction measures on greenhouse gases in order to sustain the long-term potential of solar energy in the area. The stronger deterioration under SSP5–8.5 is physically plausible because higher radiative forcing can amplify regional changes in atmospheric moisture, cloudiness, aerosol forcing, circulation patterns, and land–atmosphere feedback (Bellouin et al., 2020; Zelinka et al., 2020). However, because CMIP6 models and reanalysis products may not fully resolve regional dust emissions, aerosol optical depth, and dust deposition over arid CA, part of the projected SDSR-based ranking may remain uncertain in desert zones and dust-source regions (Zhao et al., 2022; Zhou et al., 2023; Banks et al., 2022). Temporal patterns show that degradation begins as early as the near-future in fall and winter, even under SSP2–4.5. Meanwhile, summer begins to improve in some areas under SSP5–8.5, suggesting that near-term solar-resource planning can benefit from summer suitability. By the far-future, SSP5–8.5 drives widespread and intense declines, with summer remaining the only resilient season under both scenarios. These seasonal and scenario-based contrasts align with broader advances in CMIP6 ensemble modeling, which improves the spatial accuracy of temperature and precipitation forecasts in CA and reduces uncertainty in future climate projections (Gulakhmadov et al., 2025).

In summary, the ranking results indicate that summer provides the strongest climate-resource conditions for solar development, especially in southern CA, while fall and winter require greater caution for standalone solar planning. However, these rankings should not be interpreted as a direct assessment of energy-system adequacy or demand–supply matching. This distinction is especially important for Tajikistan and Kyrgyzstan, where hydropower-dominated systems may make winter resource adequacy more relevant than summer solar-resource strength. Seasonal electricity demand differs across CA: northern countries may experience stronger winter heating-related loads, while southern areas may face higher summer cooling and irrigation-related demand. Therefore, the solar-resource rankings presented here should be combined with demand profiles, grid-balancing requirements, storage dispatch, hydro–solar complementarity analysis, and sectoral electricity-use data before being translated into final energy-security or infrastructure decisions. Across all timeframes and geographies, energy planning must therefore consider seasonal solar-resource dynamics, climate scenario sensitivity, physical climatic controls, geosystem heterogeneity, hydropower constraints, and demand-side requirements together.

3.5 Country-level seasonal solar rank changes in CA

The analysis of seasonal solar site suitability across CA reveals clear spatio-temporal and scenario-driven trends in rank change relative to the historical baseline (1991–2021). Figure 3 shows the changes location-based seasonal solar energy ranking scores in CA relative to the historical baseline, under SSP2–4.5 and SSP5–8.5 scenarios.

In Kazakhstan, summer demonstrates the most resilience, with a near-zero rank change (−0.3) in the far-future under SSP2–4.5 and a minor improvement (−3.8) under SSP5–8.5, indicating that summer solar resources are projected to remain stable or even strengthen. In contrast, winter shows significant degradation, with average rank deteriorations of +52.6 (SSP2–4.5) and +74.1 (SSP5–8.5) in the far-future, and similar patterns already appearing in the near-future (+69.4 and +87.2, respectively). Spring shows moderate declines with +21.0 (SSP2–4.5) and +24.1 (SSP5–8.5) in the far-future, while fall registers average increases of +28.3 (SSP2–4.5) and +43.2 (SSP5–8.5), highlighting a growing seasonal vulnerability (see Figure 8 and Supplementary Figures S15–S17). These country-level changes suggest that Kazakhstan's solar suitability is strongly season-dependent, with summer stability likely supported by longer daylight and clearer warm-season conditions, while winter losses are consistent with low solar elevation, snow cover, and stronger synoptic variability in northern continental regions. However, in western and southern Kazakhstan, where dryland and dust-prone landscapes are more influential, ranking changes should also be interpreted with awareness that aerosol loading and dust deposition are not explicitly included as independent variables in the ranking framework (Banks et al., 2022; Cordero et al., 2018).

For Kyrgyzstan, the summer improvement should therefore be interpreted as climate-resource suitability rather than evidence that solar resources can address the season of greatest system vulnerability.

In Kyrgyzstan, summer ranks improve slightly by the far-future (−10.6 under SSP2–4.5; −7.2 under SSP5–8.5) with near-future values close to stable (−1.9 and +0.5, respectively), suggesting enhanced seasonal reliability. However, winter deteriorates sharply, with average rank increases of +94.3 (SSP2–4.5) and +111.8 (SSP5–8.5) in the far-future. Fall and spring experience intermediate declines ranging from +41.1 to +72.6, depending on scenario and timeframe. Uzbekistan displays a more negative trajectory overall. In the far-future, winter ranks deteriorate by +94.6 (SSP2–4.5) and +120.3 (SSP5–8.5), while fall sees declines of +63.5 and +80.2, respectively. Spring experiences increases of +48.3 (SSP2–4.5) and +68.7 (SSP5–8.5), and summer shows only limited seasonal mitigation, with modest deterioration: +19.3 (SSP2–4.5) and +36.5 (SSP5–8.5) in the far-future (see Figure 8 and Supplementary Figures S15–S17). The strong winter deterioration in Kyrgyzstan and Uzbekistan may reflect the combined influence of seasonal cloudiness, terrain-controlled radiation differences, snow-related surface conditions, and transition-season atmospheric variability, particularly in mountainous or topographically complex regions. For Uzbekistan, especially in desert and semi-desert areas influenced by the Kyzylkum and Aral Sea basin, the country-level rank values should also be interpreted as modeled irradiance-resource rankings rather than dust- or soiling-corrected PV performance estimates.

Turkmenistan is consistently the most impacted country. Across all seasons and both timeframes, it exhibits severe rank losses. For example, winter rank changes exceed +111.6 (SSP2–4.5) and +130.0 (SSP5–8.5) in the far-future. Fall deteriorates by +90.6 and +122.4, spring by +62.4 and +81.8, and summer by +44.6 and +67.8, respectively, under SSP2–4.5 and SSP5–8.5. No meaningful improvement is observed in any season or scenario for Turkmenistan. Because Turkmenistan includes extensive arid and desert environments, these rank losses and remaining high-resource periods should be interpreted with additional caution: dust events, aerosol optical effects, and module soiling may affect realized PV output even where modeled irradiance remains high (IEA PVPS, 2022; Banks et al., 2022, 2024). In Tajikistan, summer demonstrates relative resilience, with far-future rank improvements of −5.7 (SSP2–4.5) and −3.9 (SSP5–8.5), and spring shows moderate performance with far-future values of +18.0 and +39.6. Fall deteriorates by +42.7 (SSP2–4.5) and +73.2 (SSP5–8.5) in the far-future, while winter suffers consistent decline: +83.8 and +94.0, respectively (see Figure 8 and Supplementary Figures S15–S17). Similarly, Tajikistan's summer resilience should be interpreted as solar-resource suitability rather than direct energy-security priority, because hydropower-dominated systems may face more critical seasonal constraints in winter. These national contrasts indicate that rank changes are not controlled by radiation magnitude alone, but also by how each country's seasonal climate regime responds to future forcing through changes in cloud cover, atmospheric moisture, aerosol forcing, circulation patterns, and land–atmosphere feedback (Bellouin et al., 2020; Zelinka et al., 2020).

These results confirm that SSP5–8.5 consistently leads to earlier and more extreme rank deterioration across all countries and seasons. Even by the near-future, average rank losses in winter exceed +90 in Turkmenistan, +87 in Uzbekistan, and +69 in Kazakhstan. By contrast, summer provides the only season with notable improvements, particularly under SSP2–4.5. Kyrgyzstan (−10.6), Tajikistan (−5.7), and Kazakhstan (−3.8) show improvement or stabilization of solar site suitability (see Figure 8 and Supplementary Figures S15–S17). These findings confirm that summer is the most climatically resilient season, while winter is uniformly unsuitable for solar-only investment across the region. The stronger deterioration under SSP5–8.5 is physically plausible because higher radiative forcing can intensify regional changes in atmospheric moisture, cloudiness, circulation regimes, aerosol–radiation interactions, and surface feedback. These processes may amplify seasonal contrasts in surface shortwave radiation, producing larger suitability losses in winter and autumn while allowing summer resources to remain comparatively more stable (Dutta et al., 2022; Bellouin et al., 2020; Zelinka et al., 2020). Nevertheless, because dust aerosols and soiling processes are not explicitly included in the ranking score, high summer resilience in arid countries should not be interpreted as equivalent to guaranteed high PV yield.

The solar performance in spring and autumn is more intermediate but on the other hand, they are very reliant on the climate scenario. This is the reason, the solar energy development planning in these two seasons needs flexible strategies that could be adjusted to varied scenarios of emissions. The findings also indicate seasonal variations in solar performance where Kyrgyzstan and Tajikistan have high seasonal variations. These countries are more susceptible to the various greenhouse gas emission pathways and react to climate scenarios differently due to such seasonal differences. For these countries, future planning should not rely on summer solar-resource suitability alone but should evaluate whether solar resources can complement hydropower during winter and transition seasons.

Kazakhstan shows a strongly season-dependent response rather than uniformly low sensitivity. While summer conditions remain relatively stable or slightly improve, winter rank losses are substantial, indicating pronounced seasonal vulnerability. In contrast, Turkmenistan shows the most consistent deterioration across seasons, with rank losses exceeding +100 in winter and +90 in autumn. This pattern suggests that Turkmenistan has the weakest long-term solar suitability response among the five countries, particularly under high-emission conditions. At the same time, the interpretation of Turkmenistan's ranking should consider that the framework evaluates modeled solar-resource suitability and does not explicitly represent dust-event frequency, AOD variability, deposition, soiling accumulation, or water constraints for module cleaning. The combination of these seasonal, temporal, and scenario-specific patterns enables valuable insights into specific investment in solar energy infrastructure and risk mitigation strategy in the Central Asian region. Overall, these results show that country-level ranking changes should be interpreted as the combined outcome of projected radiation changes, seasonal variability, national-scale physiographic differences, and the climatic mechanisms controlling surface shortwave radiation.

It is also important to note that country-level rank changes do not necessarily coincide with seasonal electricity-demand peaks. For example, Kazakhstan's strong winter rank deterioration is particularly relevant because northern and continental regions may experience higher winter energy demand related to heating. In contrast, summer solar-resource strength may be more closely aligned with cooling and irrigation-related electricity demand in southern and arid parts of CA. For Tajikistan and Kyrgyzstan, the key system-level issue is different because the interpretation of solar suitability depends partly on seasonal hydropower availability. Therefore, the country-level ranking results should be interpreted as a climate-resource suitability assessment, while their implications for energy security require additional demand-side, hydro–solar complementarity, and grid-system analysis.

3.6 Spatio-seasonal tier classification of solar suitability in CA

The seasonal classification of locations suitable for solar energy in CA shows that investment patterns in this sector are strongly influenced by the behavior of different tiers on spatial and temporal scales. Figure 9 and Supplementary Figures S18–S20 show the share of locations in each country in five predefined performance categories; in this framework, category 1 represents the best conditions for solar energy production, while category 5 represents the least favorable for the development of this energy source. These tiers should be interpreted as regional-scale, climate-resource categories rather than locally calibrated site-development classes, because CA includes highly contrasting geosystems with different surface, atmospheric, and topographic controls on solar resources. In addition, the Tier classification is based on modeled irradiance-resource behavior and does not explicitly include dust-event frequency, AOD variability, dust deposition, or soiling losses. Therefore, Tier 1 or Tier 2 sites in arid and dust-prone environments should be interpreted as high climate-resource suitability rather than guaranteed high operational PV performance (Cordero et al., 2018; IEA PVPS, 2022; Banks et al., 2022).

Although category 5 (Unclassified/Variable) is also defined in the five-Tier classification system, in practice the number of locations falling into this group has been very small across all countries and seasons. For this reason, this category has not been included in the textual analysis and main discussion, although it is still displayed in the relevant graphs and tables to maintain methodological transparency and completeness of the results.

In the fall, the pattern of results shows widespread instability and decline in solar site performance across the region. In Kazakhstan, about 90% of sites fall into category 3 (scenario-sensitive). In the same country, about 6% are classified as category 4, and only a small share—about 3%—are in categories 1 and 2. In Kyrgyzstan, the distribution of results is somewhat more favorable. In this country, about 19% of sites fall into category 2 (sites with significant improvement), while nearly 80% are classified as category 3, indicating that there is still potential for investment in some areas. In Uzbekistan, about 86% of sites fall into category 3, while approximately 6% are classified as category 4 and about 8.6% are classified as category 2. This distribution suggests that the decline in solar site suitability in this country is relatively widespread under both SSP scenarios. The situation is more unfavorable in Turkmenistan. In this country, about 71% of sites fall into category 3, while about 24% fall into category 2 and only 6% fall into category 4. Finally, a similar pattern is observed in Tajikistan, with about 94% of sites classified as category 3, nearly 5% in category 2 and almost 1% in category 4. In this country, too, no sites reach category 1 (see Figure 9 and Supplementary Figures S18–S20). The dominance of Tier 3 during fall indicates that many sites are not simply unsuitable, but rather sensitive to the emission pathway. This pattern may reflect the strong dependence of transition-season solar resources on cloud variability, atmospheric circulation, aerosol forcing, and regional moisture transport, which can shift sites between moderate improvement and deterioration under different SSP conditions. However, in dust-influenced lowlands and desert margins, Tier 3

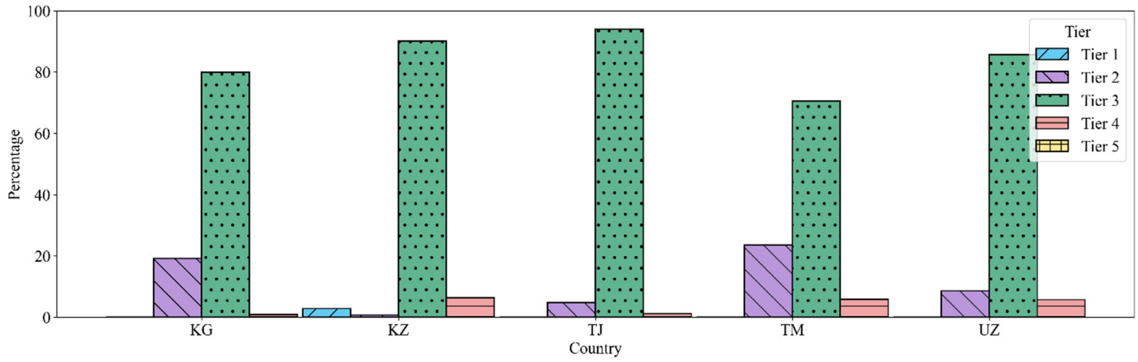

FIGURE 9
Tier changes across Central Asian countries in fall under SSP2−4.5 and SSP5−8.5 scenarios.

may also reflect unresolved aerosol-related uncertainty, because regional dust events can modify shortwave radiation and are not included as an explicit component of the present tiering system (Bellouin et al., 2020; Banks et al., 2024).

In winter, the distribution of performance categories in Kazakhstan shows that about 91% of sites are in category 3. In addition, about 4% are classified in category 1, about 3.5% in category 2 and about 1.4% in category 4; a pattern that shows only limited areas of relative stability. Among the countries in the region, Kyrgyzstan is once again a standout. In this country, about 3% of sites are in category 2 and about 0.4% in category 1, while almost 88% of sites are classified in category 3 and about 9% in category 4. This distribution overall shows the most balanced winter pattern in the region.

In contrast, in Uzbekistan, Turkmenistan and Tajikistan, more than 90% of sites are in category 3. However, in Uzbekistan, about 3% of locations are in Tier 2, and in Tajikistan, about 7% are in Tier 4. In winter, none of these three countries has a significant presence in Tiers 1 or 2, suggesting that their future performance will be highly dependent on greenhouse gas emission pathways. This winter dominance of Tier 3 is consistent with the strong seasonal limitation of solar resources in CA, where low solar elevation, short daylight duration, cloud occurrence, snow cover, and topographic shading can reduce the stability and reliability of high-radiation conditions. In spring, the distribution of categories is somewhat different. In Kazakhstan, Tier 3 still has the largest share at about 75%, while about 23% of locations are in Tier 2, nearly 1% in Tier 1, and about 0.3% in Tier 4. In Kyrgyzstan, the share of Tier 2 reaches about 36%, with 62% of locations in Tier 3; only about 1% in Tier 4. The pattern in Uzbekistan is more balanced. In this country, about 51% of the sites are classified in category 3 and nearly 49% in category 2, while no sites are observed in categories 1 or 4. The situation is quite different in Turkmenistan; in this country, all sites (about 100%) are in category 3, indicating a strong dependence of solar performance on climate scenarios. Finally, Tajikistan shows a relatively more diverse distribution: about 87% of sites are in category 3, while about 6% are classified in category 1 and nearly 7% in category 2. This pattern suggests that the situation in this country is somewhat more diverse than previously thought (see Figure 9 and Supplementary Figures S18–S20).

Compared to other seasons, summer provides the most favorable conditions for investing in solar energy. In Kazakhstan, about 90% of sites are in category 3 during this season, while only 0.7% are classified as category 1, about 4.5% as category 2, and nearly 4.8% as category 4. The situation is more favorable in Kyrgyzstan; about 55% of sites are in category 2 and nearly 44% as category 3. This distribution shows that the country's summer performance is remarkably stable, although no sites are observed in category 1. Uzbekistan also shows a relatively strong performance in summer. In this country, almost 49% of sites are in category 2 and another 49% in category 3, while the share of category 4 is only about 2.9%. In Tajikistan, about 83% of sites are classified as Tier 3, and nearly 15.5% are in Tier 4; Tier 2 accounts for only 1.2%. Despite the absence of Tier 1 sites, summer is still the best performing season for the country. In Turkmenistan, although limitations remain, there is a relative improvement compared to other seasons; about 76% of sites are in Tier 3 and nearly 23.5% in Tier 4. Overall, these results indicate that investment opportunities in Tiers 1 and 2 are strongly dependent on season and location. On a regional scale, summer provides the best conditions for solar energy development, while the dominance of Tier 3 in many regions suggests that infrastructure planning should be flexible and adaptable to climate scenarios (see Figure 9 and Supplementary Figures S18–S20). This dominance of Tier 3 also indicates that many locations are climatically conditional sites whose suitability depends on how future cloudiness, aerosol loading, atmospheric circulation, and seasonal radiation regimes evolve under different emission pathways. Therefore, Tier 3 should not be interpreted as a low-priority class, but rather as a group requiring flexible design, monitoring, and adaptive planning. For Uzbekistan and Turkmenistan, where desert and semi-desert environments are extensive, summer Tier 2 or Tier 3 classifications should also be interpreted with caution because dust deposition and soiling can reduce realized PV yield even where modeled irradiance-resource suitability is favorable (Cordero et al., 2018; IEA PVPS, 2022).

Figure 10 shows the spatial changes in the categories over the historical period, providing a detailed picture of the spatial distribution of solar site suitability across CA. This spatial analysis visually shows how site performance varies across seasons. The

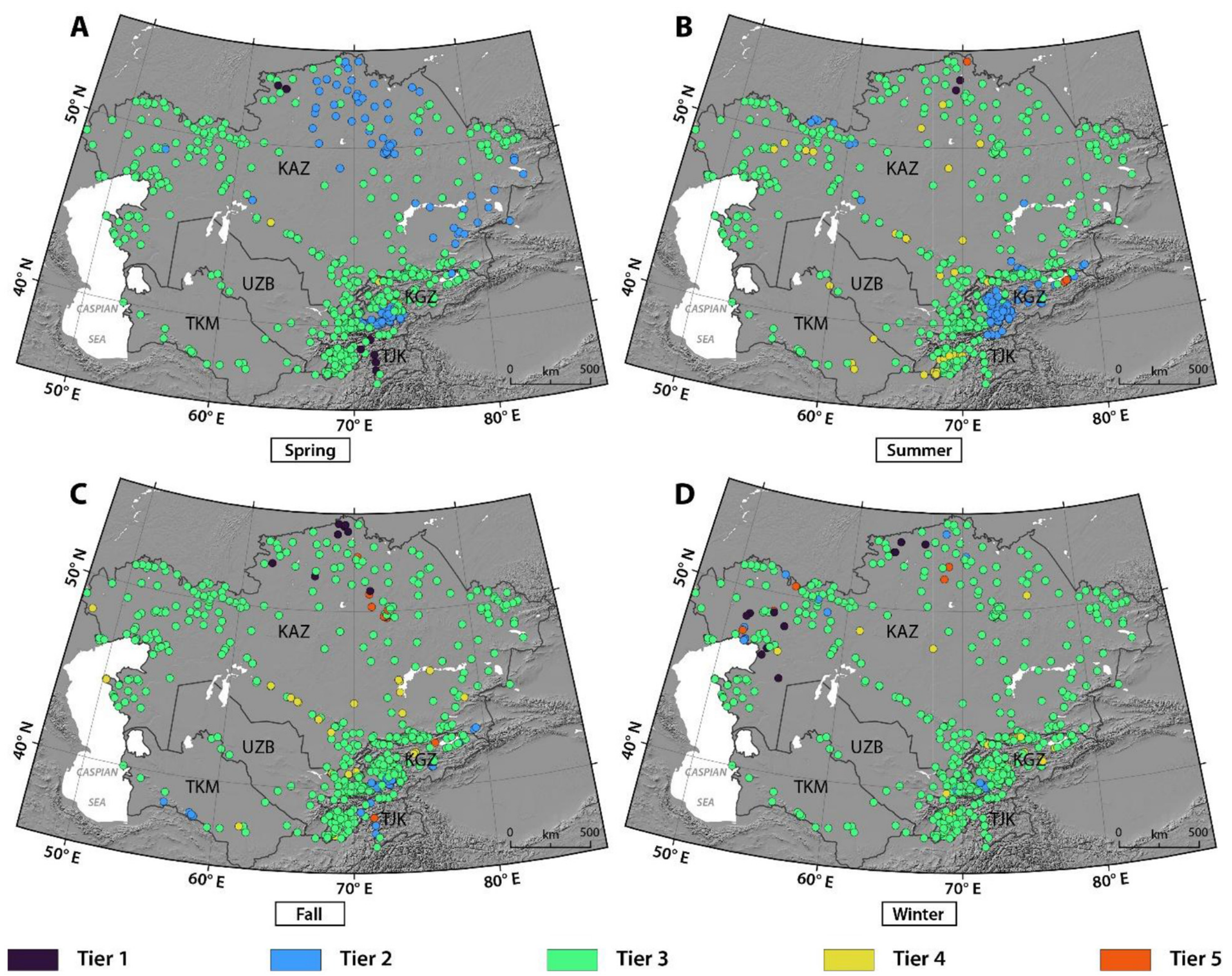

FIGURE 10
Geospatial distribution of Tier classifications across Central Asian countries for different seasons. **(A)** Spring, **(B)** Summer, **(C)** Fall, and **(D)** Winter.

results of this study confirm that only about 15%—30% of sites—in the best-performing countries and seasons—fall into categories 1 and 2 and are therefore suitable for priority investment. In contrast, more than 60% of sites are classified as category 3 across all seasons. This highlights the need to design solar infrastructure that is resilient to climate scenarios and based on long-term planning in CA (see Figure 10). Nevertheless, Tier classification reflects the stability and scenario sensitivity of solar resources, not the seasonal balance between electricity supply and demand. Therefore, Tier 1 or Tier 2 status should not be interpreted automatically as full deployment priority without considering seasonal load profiles, heating and cooling demand, irrigation-related electricity use, grid constraints, and storage requirements. In practical planning, the Tier framework should be combined with demand-side analysis to determine whether high solar-resource suitability coincides with periods of peak electricity need. It should also be combined with dust and soiling risk assessment in arid zones, because water scarcity for module cleaning and dust accumulation may become important operational constraints in high-insolation desert environments (IEA PVPS, 2022).

A complementary comparison between the proposed climate-responsive solar-resource framework and conventional GIS-based multi-criteria decision-making approaches is provided in Table 3. This comparison is not intended to suggest that the proposed framework supersedes traditional GIS-MCDM methods. Rather, the two approaches address different but connected aspects of solar planning. Conventional GIS-MCDM approaches, including AHP, TOPSIS, PROMETHEE, and fuzzy logic, are widely used for practical PV site selection because they incorporate local deployment constraints such as land-use suitability, terrain slope, protected areas, road and grid proximity, infrastructure availability, ecological restrictions, and techno-economic feasibility (Adedeji et al., 2021; Alami Merrouni et al., 2016; Awan et al., 2018; Ayuketah et al., 2025; Badi et al., 2021; Chen Jong and Mohamud Ahmed, 2024; De Felice et al., 2019; Hosouli and Hassani, 2024; Kamati et al., 2023; Shravanth Vasisht et al., 2016; Wang et al., 2023; Zandi and Lotfata, 2025). In contrast, the framework proposed in this study focuses specifically on the climate-resource dimension of solar suitability by incorporating future climate scenarios, seasonal variability, CV-based stability, exceedance

TABLE 3 Complementary roles of the proposed climate-responsive framework and conventional GIS-MCDM approaches in solar site assessment.

Criteria	Our method (future projections under SSP2−4.5 and SSP5−8.5)	Traditional solar site ranking methods	Complementary interpretation	References
Temporal scope	Projects solar site suitability for near-future (2022–2051) and far-future (2071–2100) using CMIP6-based scenarios.	Mostly static or based on historical GHI data with no climate projections.	Adds future climate-risk screening to conventional suitability assessment.	Chen Jong and Mohamud Ahmed, 2024; Zandi and Lotfata, 2025
Scenario integration	Uses ΔRank and scenario divergence between SSPs to evaluate risk and trajectory.	Assumes stationarity; lacks future scenario modeling.	Provides an additional emissions-sensitivity layer.	Ayuketah et al., 2025; Kamati et al., 2023
Seasonal resolution	Evaluates solar potential and rank shifts per season (winter, spring, summer, and fall).	Aggregates annual averages, missing critical seasonal variation.	Can refine GIS-MCDM outputs by identifying season-specific suitability.	(Adedeji et al., 2021; De Felice et al., 2019; Shravanth Vasisht et al., 2016)
Variability analysis	Includes coefficient of variation (CV) and scenario-based stability measures.	Occasionally considers inter-annual variability; lacks climate trajectory linkage.	Supports interpretation of modeled resource stability under future climate conditions.	(Alami Merrouni et al., 2016; Awan et al., 2018)
Exceedance metrics	Incorporates GHI exceedance probability >188 W/m² to assess reliability.	Sometimes used, but not central to ranking.	Adds resource-threshold reliability information to spatial feasibility screening.	Chen Jong and Mohamud Ahmed, 2024; Hosouli and Hassani, 2024
Ranking approach	Uses normalized, multi-variable score and tier-based ranking over time.	Typically employs AHP, TOPSIS, or ELECTRE; not temporally weighted.	Translates climate-resource changes into planning categories that can be combined with GIS-MCDM rankings.	Ayuketah et al., 2025; Wang et al., 2023
Computational complexity	Involves multiple time periods, seasonal variables, and climate models; moderate-to-high complexity.	Simpler implementation but lower scenario adaptability.	Best used as an upstream climate-screening step before detailed local siting analysis.	Badi et al., 2021; Chen Jong and Mohamud Ahmed, 2024
Planning utility	Enables dynamic, forward-looking investment strategies aligned with emissions outcomes.	Provides one-time static rankings, often unsuitable under future climate shifts.	Complements final PV deployment decisions by identifying climate-resilient or scenario-sensitive areas.	Kamati et al., 2023; Zandi and Lotfata, 2025

probabilities, and scenario sensitivity. Therefore, the proposed framework should be interpreted as a climate-resilience screening layer that can complement, rather than replace, conventional GIS-MCDM site-selection workflows. For practical PV deployment in arid CA, this climate-resilience layer should also be complemented by aerosol, dust, soiling, and cleaning-water assessments, which are outside the present scoring framework but important for operational performance.

As shown in Table 3, the proposed framework and conventional GIS-MCDM approaches should be viewed as complementary rather than competing methodologies. GIS-MCDM frameworks remain essential for final PV site selection because they incorporate local engineering, environmental, infrastructural, ecological, and economic constraints. The contribution of the present framework is different: it evaluates whether the solar resource itself remains available, stable, and less sensitive to future climate pathways. In this sense, the framework can serve as an upstream climate-risk screening tool that identifies locations where conventional siting assessments may be more robust under future climate uncertainty.

Among the key innovations of this framework is that it is designed in such a way that data separation of seasons is available. A number of studies have demonstrated that seasonal variations in solar radiation is a determining factor in the work of a photovoltaic system and precision of energy planning. Adedeji et al. (2021) have demonstrated that most operational risks and opportunities may remain obscured when using annual averages, and these tendencies are only observed in the seasonal analysis scales. In the same way, a study by Shravanth Vasisht et al. (2016) and De Felice et al. (2019) reported the same facts, opining that the resilience of solar systems is better modeled and assessed by using seasonal indicators, particularly where inter-seasonal climate variability is high. Alami Merrouni et al. (2016) and Awan et al. (2018) have also highlighted the fact that in arid and semi-arid areas, technical feasibility and investment attractiveness of solar systems may differ greatly depending on the seasons. Such findings support the significance of the application of seasonal methods in assessing solar sites. In this respect, the framework employed in this work through such a structure can make a more precise and better-resolution determination of the appropriateness of sites, as well as provide decision-makers with additional opportunities to create planning strategies suitable to the changes that can occur within a year. Nevertheless, seasonal ranking alone cannot represent all operational constraints in dust-prone environments, where seasonal dust activity and soiling accumulation may alter PV yield independently of modeled irradiance suitability.

The other characteristic aspect of this approach is that it has a Tier classification system. Sites in this system are grouped into five levels of sites that may be described as stable and well-performing and the areas where there is a constant decrease in performance. With such a structure it is possible to strategically provide priority to sites in regard to their levels of climate resilience and future variability. Moreover, with the help of this framework, policymakers and energy developers can find it simple to comprehend the consequences, and it assists in differentiated planning of infrastructure. As an example, places in Tier 1 can be given priority to scale up solar power plant expansion quickly and on a large scale, whereas the more climate sensitive areas such as those in Tier 3 can be deployed by adaptive strategies or hybrid regimes. This flexibility of decision making is a practical benefit compared to most of the conventional two state models that normally provide only simple good or bad choices. However, in desert regions, Tier 1 should be interpreted as a priority climate-resource category rather than an automatic construction priority, because dust, soiling, water availability, grid access, and land-use constraints must also be evaluated before final deployment.

Concerning scoring system design, the model is based on the utilization of normalized variables such as the global horizontal insolation (GHI), the likelihood of surpassing the threshold, CV, and the sensitivity to climate scenarios. These variables enable the removal of subjective weights on the criteria such as increasing methodological transparency. However, some techno-economic and deployment-related factors, such as installation cost, energy delivery cost, land-use suitability, terrain slope, grid accessibility, infrastructure availability, social acceptance, and national policy conditions, are not explicitly included in the current model, although these factors are commonly considered in hybrid GIS-economic and practical PV site-selection frameworks (Badi et al., 2021). In addition, the present model does not explicitly include aerosol optical depth, dust-event frequency, dust deposition, soiling accumulation, or water demand for panel cleaning, although these factors can be important in arid and dust-active regions. Therefore, the proposed framework should not be interpreted as a complete PV deployment model, but rather as a climate-resource screening and resilience-assessment layer. Its main contribution is to identify where solar resources are likely to remain available, stable, and less sensitive to future emission pathways. In practical planning, this climate-resilience layer should be combined with GIS-based land suitability analysis, techno-economic assessment, grid-infrastructure evaluation, dust/soiling-risk assessment, and national energy policy considerations to support final investment decisions. Nevertheless, the emphasis of the framework on climate projections, seasonal variability, and long-term resource sustainability distinguishes it from many existing static solar site-ranking approaches.

In areas like CA, which are facing significant climate variability and a lack of comprehensive studies, to have an effective long-term planning tool, it is beneficial to develop frameworks that take into account future climate scenarios and use a tier-based classification for energy planning. In general, the suggested methodology is a step beyond prior literature since it integrates climate scenario algorithms together with seasonal data decomposition and practical classification to make an investment in a scalable and generalized mechanism. This framework is especially applicable in parts of the world where the uncertainty about climate change is combined with the risk of investing in energy infrastructure for the long-term. At the same time, dust-prone arid regions require additional operational screening because modeled solar-resource suitability may be reduced in practice by aerosol attenuation, dust deposition, and soiling-related losses.

4 Limitations and future research directions

This study provides a climate-informed assessment of solar-resource suitability across CA; however, several limitations should be acknowledged.

First, the analysis is based on CMIP6-derived daily irradiance data, which constrains the temporal resolution of variability assessment. The coefficient of variation (CV) used in this study represents inter-annual variability of seasonal mean irradiance, and therefore does not capture intra-day intermittency, ramping behavior, or short-term fluctuations that are critical for photovoltaic (PV) system operation, storage sizing, and grid integration. In addition, CV is a normalized metric and cannot alone distinguish whether projected reductions are driven by lower absolute variability, higher mean irradiance, or both. Future research should therefore present the mean and standard deviation separately alongside CV and incorporate higher temporal resolution datasets (hourly or sub-hourly) to better evaluate operational variability and system-level performance.

Second, although this study incorporates multi-model ensemble projections, uncertainty is not explicitly quantified beyond ensemble averaging. Differences among climate models—particularly related to cloud feedback and aerosol forcing—remain a major source of uncertainty in surface shortwave radiation projections. Future work should include formal uncertainty quantification, such as interquartile ranges, probabilistic thresholds, or model weighting approaches, to support risk-informed energy planning.

Third, the framework focuses on irradiance-based solar-resource suitability and does not explicitly represent dust-cycle dynamics, aerosol optical depth (AOD), soiling processes, or water availability for module cleaning, which are particularly important in arid and semi-arid regions of CA, including the Karakum, Kyzylkum, Aralkum, Caspian lowlands, and other dust-prone dryland environments. Dust emissions from desert surfaces and degraded landscapes can significantly affect both irradiance and PV system performance. Future extensions should integrate dust-event frequency, AOD variability, soiling-risk indicators, and water availability for module cleaning to better capture these region-specific constraints.

Fourth, the proposed ranking framework does not explicitly account for physiographic heterogeneity, including differences between desert, steppe, valley, and high-mountain environments. Although the current approach provides a consistent regional comparison, local solar-resource behavior may be influenced by topography, elevation, snow cover, land–atmosphere interactions, terrain shading, angle-of-incidence effects, and snow–albedo interactions. Future applications could incorporate zonal stratification, region-specific calibration, or sensitivity analysis of the Poor/Moderate/Good/Excellent irradiance classes to improve local relevance.

Fifth, this study evaluates climate-resource suitability only and does not incorporate energy-system dimensions, including electricity demand, grid infrastructure, storage capacity, or techno-economic constraints. For countries such as Kyrgyzstan and Tajikistan, where hydropower dominates and winter energy deficits are critical, the functional relevance of solar energy is strongly linked to seasonal complementarity rather than annual irradiance patterns alone. Future research should therefore integrate hydro–solar interactions, seasonal demand profiles, and grid-level constraints to provide a more comprehensive assessment.

Finally, the composite scoring and tier-classification framework relies on rule-based thresholds derived from the observed distribution of rank changes. While these thresholds provide transparent and reproducible classification criteria, they are not universal and may influence the categorization of sites. Future work should perform sensitivity analysis and probabilistic classification to assess the robustness of tier assignments under alternative threshold definitions.

Overall, future research should aim to integrate higher-resolution climate data, uncertainty quantification, dust and aerosol processes, energy-system modeling, and region-specific calibration, thereby advancing the framework from a climate-resource screening tool toward a more comprehensive solar-energy planning approach.

5 Conclusion

This study provides a comprehensive, scenario-based assessment of the long-term suitability of solar energy resources in CA, based on CMIP6 multi-model projections. In this analysis, indicators such as solar-radiation threshold exceedance probability, seasonal variability, and climate-scenario sensitivity were combined into a five-tier ranking framework. Using this approach, it was possible to identify significant spatial and temporal differences in solar resources across Kazakhstan, Kyrgyzstan, Uzbekistan, Turkmenistan, and Tajikistan under SSP2–4.5 and SSP5–8.5.

Results showed that summer consistently emerged as the most robust season, with "Excellent" exceedance rates under SSP5–8.5 increasing from 40.4% to 91.3% in Kazakhstan, from 76.9% to 94.1% in Kyrgyzstan, and from 98.5% to 99.8% in Turkmenistan by the far-future period (2071–2100). In contrast, winter suitability sharply declined, with average rank losses exceeding +90 in Turkmenistan, +87 in Uzbekistan, and +69 in Kazakhstan as early as the near-future (2022–2051). The Tier-based classification confirmed that only 15%—30% of sites qualified for priority investment (Tiers 1–2), with summer providing the largest share, while over 60% of sites were classified as Tier 3 (Scenario-Sensitive), particularly during winter and fall. Importantly, we found that seasonal CV decreased by 30%—60% under SSP5–8.5, particularly in winter (Kazakhstan: from 0.133 to 0.091, ∼32% decrease) and fall (Kyrgyzstan: from 0.059 to 0.024, ∼59% decrease). These changes indicate lower normalized inter-annual variability of modeled seasonal irradiance in some locations and periods.

These findings have important implications for climate-informed solar-resource planning in CA. Solar development during summer and, in some countries, autumn may provide favorable climate-resource conditions, particularly in countries like Kazakhstan, Uzbekistan, and Turkmenistan where the slope of changes shows a positive tendency and high levels of solar radiation threshold exceedances indicate strong future potential. Conversely, standalone solar development is unlikely to be sufficient during winter, when suitability declines across the region. Seasonal balancing through wind energy, hydropower, storage, and regional electricity exchange may therefore be necessary to offset decreased seasonal radiation, particularly under high climate forcing such as SSP5–8.5. Long-term investment strategies should therefore be designed not only based on historical resource performance, but also on how solar resources may respond to future climate conditions.

Regional cooperation may also improve the efficiency and resilience of solar-energy planning in CA. Cross-border electricity exchange could help balance seasonal differences in solar performance among countries, particularly when one country experiences weaker seasonal solar conditions while another maintains stronger resource availability. However, such cooperation requires stronger institutional frameworks, coordination mechanisms, and infrastructure planning.

However, the policy relevance of these findings should be interpreted within the broader institutional and geopolitical context of Central Asian energy systems. Regional energy security is shaped not only by renewable-resource availability, but also by dependence on gas, oil, and coal exports, uneven electricity tariff structures, investment risk, grid interconnection capacity, and water–energy tensions linked to irrigation and hydropower management in the Amu Darya and Syr Darya basins. These factors are particularly important for Tajikistan and Kyrgyzstan, where hydropower dominates electricity supply and winter energy shortages may make seasonal complementarity between solar, hydropower, storage, and regional electricity exchange more relevant than annual solar potential alone. Therefore, the present results should be viewed as a climate-informed solar-resource assessment that can support—but not replace—broader energy-system and policy analyses.

Data availability statement

The raw data analyzed in this study can be found here: https://github.com/paryabroomandi/Climate-Resilient-Solar-Resource-Potential-in-Central-Asia.git.

Author contributions

PB: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. MB: Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – review & editing. SI: Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – review & editing. AF: Investigation, Software, Visualization, Writing – review & editing. AMF: Formal analysis, Investigation, Methodology, Software, Validation, Writing – review & editing. DL: Data curation, Formal analysis, Investigation, Writing – review & editing. IR: Data curation, Formal analysis, Writing – review & editing. ML: Supervision, Validation, Writing – review & editing. JK: Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fclim.2026.1836432/full#supplementary-material

References

Adedeji, P. A., Akinlabi, S. A., Madushele, N., and Olatunji, O. O. (2021). Beyond site suitability: investigating temporal variability for utility-scale solar-PV using soft computing techniques. *Renew. Energy Focus* 39, 72–89. doi: 10.1016/j.ref.2021.07.008

Aghaei Fishani, B., Mahmoodirad, A., Niroomand, S., and Fallah, M. (2022). Multi-objective location-allocation-routing problem of perishable multi-product supply chain with direct shipment and open routing possibilities under sustainability. *Concurr. Comput.* 34:e6860. doi: 10.1002/cpe.6860

Alami Merrouni, A., Mezrhab, A., and Mezrhab, A. (2016). PV sites suitability analysis in the Eastern region of Morocco. *Sustain. Energy Technol. Assess.* 18, 6–15. doi: 10.1016/j.seta.2016.09.006

Anchita, Zhupankhan, A., Khaibullina, Z., Kabiyev, Y., Persson, K. M., and Tussupova, K. (2021). Health impact of drying aral sea: one health and socio-economical approach. *Water* 13:3196. doi: 10.3390/w13223196

Awan, A. B., Zubair, M., Praveen, R. P., and Abokhalil, A. G. (2018). Solar energy resource analysis and evaluation of photovoltaic system performance in various regions of Saudi Arabia. *Sustainability* 10:1129. doi: 10.3390/su10041129

Ayuketah, Y., Edimu, M., and Mwikirize, C. (2025). Optimal site selection for utility-scale solar PV projects using a RETScreen-AHP-TOPSIS framework: application to southern Cameroon. *Sustain. Energy Res.* 12:22. doi: 10.1186/s40807-025-00166-y

Badi, I., Dragan, P., Ljubomir, G., and Tatomirović, S. (2021). Optimal site selection for siting a solar park using a novel GIS-SWA'TEL model: a case study in Libya. *Int. J. Green Energy* 18, 336–350. doi: 10.1080/15435075.2020.1854264

Banks, J. R., Heinold, B., and Schepanski, K. (2022). Impacts of the desiccation of the Aral Sea on the Central Asian dust life-cycle. *J. Geophys. Res.* 127, 1–28. doi: 10.1029/2022JD036618

Banks, J. R., Heinold, B., and Schepanski, K. (2024). Dust aerosol from the Aralkum desert influences the radiation budget and atmospheric dynamics of Central Asia. *Atmos. Chem. Phys.* 24, 11451–11475. doi: 10.5194/acp-24-11451-2024

Bellouin, N., Quaas, J., Gryspeerdt, E., Kinne, S., Stier, P., Watson-Parris, D., et al. (2020). Bounding global aerosol radiative forcing of climate change. *Rev. Geophys.* 58:e2019RG000660. doi: 10.1029/2019RG000660

BNEF (2017). *Bloomberg new energy finance: new energy Outlook 2017*. Geneva: Bloomberg New Energy Finance.

Broomandi, P., Bagheri, M., Fathian, A., Mozhdehi Fard, A., Gholamzade Ledari, D., Leuchner, M., et al. (2026). Climate-induced variability challenges to wind energy sustainability in Central Asia. *Glob. Chall.* doi: 10.1002/gch2.202500503

Broomandi, P., Bagheri, M., Mozhdehi Fard, A., Abdoli, M., Roshani, A., Fathian, A., et al. (2025). Energy generation and carbon footprint under future projections (2022–2100) of Central Asian heat extremes. *Glob. Chall.* 9:2400356. doi: 10.1002/gch2.202400356

Carta, J. A., Ramírez, P., and Velázquez, S. (2009). A review of wind speed probability distributions used in wind energy analysis: case studies in the Canary Islands. *Renew. Sustain. Energy Rev.* 13, 933–955. doi: 10.1016/j.rser.2008.05.005

Chen Jong, F., and Mohamud Ahmed, M. (2024). Multi-criteria decision-making solutions for optimal solar energy sites identification: a systematic review and analysis. *IEEE Access* 12, 143458–143484. doi: 10.1109/ACCESS.2024.3461948

Chen, X., Mao, H., Cheng, N., Ma, L., Tian, Z., Luo, Y., et al. (2024). Climate change impacts on global photovoltaic variability. *Appl. Energy* 374:124087. doi: 10.1016/j.apenergy.2024.124087

Chen, X., Zhou, C., Tian, Z., Mao, H., Luo, Y., Sun, D., et al. (2023). Different photovoltaic power potential variations in East and West China. *Appl. Energy* 351:121846. doi: 10.1016/j.apenergy.2023.121846

Chen, Z., Gao, X., and Lei, J. (2022). Dust emission and transport in the Aral Sea region. *Geoderma* 428:116177. doi: 10.1016/j.geoderma.2022.116177

Cordero, R. R., Damiani, A., Laroze, D., MacDonell, S., Jorquera, J., Sepúlveda, E., et al. (2018). Effects of soiling on photovoltaic (PV) modules in the Atacama Desert. *Sci. Rep.* 8:13943. doi: 10.1038/s41598-018-32291-8

De Felice, M., Soares, M. B., Alessandri, A., and Troccoli, A. (2019). Scoping the potential usefulness of seasonal climate forecasts for solar power management. *Renew. Energy* 142, 215–223. doi: 10.1016/j.renene.2019.03.134

Desthieux, G., Carneiro, C., Camponovo, R., Ineichen, P., Morello, E., Boulmier, A., et al. (2018). Solar energy potential assessment on rooftops and facades in large built environments based on LiDAR data, image processing, and cloud computing: methodological background, application, and validation in Geneva (solar cadaster). *Front. Built Environ.* 4:14. doi: 10.3389/fbuil.2018.00014

Dozier, J. (1980). A clear-sky spectral solar radiation model for snow-covered mountainous terrain. *Water Resour. Res.* 16, 709–718. doi: 10.1029/WR016i004p00709

Dutta, R., Chanda, K., and Maity, R. (2022). Future of solar energy potential in a changing climate across the world: a CMIP6 multi-model ensemble analysis. *Renew. Energy* 188, 819–829. doi: 10.1016/j.renene.2022.02.023

Elboshy, B., Alwetaishi, M., Aly, R. M. H., and Zalhaf, A. S. (2022). A suitability mapping for the PV solar farms in Egypt based on GIS-AHP to optimize multi-criteria feasibility. *Ain Shams Eng. J.* 13:101618. doi: 10.1016/j.asej.2021.10.013

Enerdata (2024). *World Energy and Climate Statistics – Yearbook*. Available online at: https://yearbook.enerdata.net (Accessed May 17, 2026).

Feron, S., Cordero, R. R., Damiani, A., and Jackson, R. B. (2021). Climate change extremes and photovoltaic power output. *Nat. Sustain.* 4, 270–276. doi: 10.1038/s41893-020-00643-w

Feron, S., Cordero, R. R., and Labbe, F. (2017). Rural electrification efforts based on off-grid photovoltaic systems in the Andean region: comparative assessment of their sustainability. *Sustainability* 9:1825. doi: 10.3390/su9101825

Garg, H., Mahmoodirad, A., and Niroomand, S. (2021). Fractional two-stage transshipment problem under uncertainty: application of the extension principle approach. *Complex Intell. Syst.* 7, 807–822. doi: 10.1007/s40747-020-00236-2

Gil, V., Gaertner, M. A., Gutierrez, C., and Losada, T. (2019). Impact of climate change on solar irradiation and variability over the Iberian Peninsula using regional climate models. *Int. J. Climatol.* 39, 1733–1747. doi: 10.1002/joc.5916

Groll, M., Opp, C., and Aslanov, I. (2013). Spatial and temporal distribution of the dust deposition in Central Asia—results from a long-term monitoring program. *Aeolian Res.* 9, 49–62. doi: 10.1016/j.aeolia.2012.08.002

Gulakhmadov, A., Chen, X., Gulahmadov, N., Rizwan, M., Gulakhmadov, M., Nadeem, M. U., et al. (2025). Modeling of historical and future changes in temperature and precipitation in the Panj River Basin in Central Asia under the CMIP5 RCP and CMIP6 SSP scenarios. *Sci. Rep.* 15:3037. doi: 10.1038/s41598-025-86366-4

Gutiérrez, C., Somot, S., Nabat, P., Mallet, M., Corre, L., van Meijgaard, E., et al. (2020). Future evolution of surface solar radiation and photovoltaic potential in Europe: investigating the role of aerosols. *Environ. Res. Lett.* 15:034035. doi: 10.1088/1748-9326/ab6666

Her, Y., Yoo, S.-H., Cho, J., Hwang, S., Jeong, J., and Seong, C. (2019). Uncertainty in hydrological analysis of climate change: multi-parameter vs. multi-GCM ensemble predictions. *Sci. Rep.* 9:4974. doi: 10.1038/s41598-019-41334-7

Hosouli, S., and Hassani, R. A. (2024). Application of multi-criteria decision making model for solar plant location selection. *Results Eng.* 24:103162. doi: 10.1016/j.rineng.2024.103162

IEA (2020a). *Global EV Outlook 2020: entering the decade of electric drive?* Paris: International Energy Agency.

IEA (2020b). *Renewables 2020: analysis and forecast to 2025*. Paris: International Energy Agency. doi: 10.1787/c74616c1-en

IEA PVPS (2022). *Soiling losses – impact on the performance of photovoltaic power plants*. Report IEA-PVPS T13-21:2022. Paris: International Energy Agency.

Ihsan, K. T. N., Takenaka, H., Higuchi, A., Sakti, A. D., and Wikantika, K. (2024). Solar irradiance variability around Asia Pacific: spatial and temporal perspective for active use of solar energy. *Sol. Energy* 276:112678. doi: 10.1016/j.solener.2024.112678

Indoitu, R., Kozhoridze, G., Batyrbaeva, M., Vitkovskaya, I., Orlovsky, L., Blumberg, D., et al. (2015). Dust emission and environmental changes in the dried bottom of the Aral Sea. *Aeolian Res.* 17, 101–115. doi: 10.1016/j.aeolia.2015.02.004

Jamshidi, M., Saneie, M., Mahmoodirad, A., Lotfi, F. H., and Tohidi, G. (2019). Uncertain RUSSEL data envelopment analysis model: a case study in Iranian banks. *J. Intell. Fuzzy Syst.* 37, 2937–2951. doi: 10.3233/JIFS-190067

Kamati, K., Smit, J., and Hull, S. (2023). Multicriteria decision method for siting wind and solar power plants in Central North Namibia. *Geomatics* 3, 47–67. doi: 10.3390/geomatics3010002

Karatayev, M., Hall, S., Kalyuzhnova, Y., and Clarke, M. L. (2016). Renewable energy technology uptake in Kazakhstan: policy drivers and barriers in a transitional economy. *Renew. Sustain. Energy Rev.* 66, 120–136. doi: 10.1016/j.rser.2016.07.057

Laldjebaev, M., Isaev, R., and Saukhimov, A. (2021). Renewable energy in Central Asia: an overview of potentials, deployment, outlook, and barriers. *Energy Rep.* 7, 3125–3136. doi: 10.1016/j.egyr.2021.05.014

Lee, H. H., Arthur, R. S., Golaz, J. C., Edmunds, T. A., Wert, J. L., Signorotti, M. V., et al. (2025). Assessment of climate change impacts on renewable energy resources in Western North America. *Energies* 18:3467. doi: 10.3390/en18133467

Medvigy, D., and Beaulieu, C. (2012). Trends in daily solar radiation and precipitation coefficients of variation since 1984. *J. Clim.* 25, 1330–1339. doi: 10.1175/2011JCLI4115.1

Mirzaei, N., Mahmoodirad, A., and Niroomand, S. (2019). An uncertain multi-objective assembly line balancing problem: a credibility-based fuzzy modeling approach. *Int. J. Fuzzy Syst.* 21, 2392–2404. doi: 10.1007/s40815-019-00734-7

Mohammadi, Y., PolajŽer, B., Palstev, A., and Khodadad, D. (2024). Climate change and the impacts on power and energy systems. *Energies* 17:5403. doi: 10.3390/books978-3-7258-2636-0

Mozhdehi Fard, A., Broomandi, P., Bagheri, M., Middleton, N., Gholamzade Ledari, D., Fathian, A., et al. (2025). Atmospheric dust: cluster-based frequency and intensity projections in Central Asia under SSP scenarios. *Aeolian Res.* 74:101009. doi: 10.1016/j.aeolia.2025.101009

Niu, J., Qin, W., Wang, L., Zhang, M., Wu, J., and Zhang, Y. (2023). Climate change impact on photovoltaic power potential in China based on CMIP6 models. *Sci. Total Environ.* 858:159776. doi: 10.1016/j.scitotenv.2022.159776

Pfenninger, S., and Keirstead, J. (2015). Comparing concentrating solar and nuclear power as baseload providers using the example of South Africa. *Energy* 87, 303–314. doi: 10.1016/j.energy.2015.04.077

Qudrat-Ullah, H. (2025). Systems thinking for climate change and clean energy. *Energies* 18:4200. doi: 10.3390/en18154200

Rakhimov, E. Y., Sadullaeva, S. E., Kolomiets Y. G., Tashmatov, K. K., and Usmonov, N. O. (2017). Analysis of the solar energy potential of the Republic of Uzbekistan. *Appl. Sol. Energy* 53, 344–346. doi: 10.3103/S0003701X17040120

Rakhmatova, N., Nishonov, B. E., Kholmatjanov, B. M., Rakhmatova, V., Toderich, K. N., Khasankhanova, G. M., et al. (2024). Assessing the potential impacts of climate change on drought in Uzbekistan: findings from RCP and SSP scenarios. *Atmosphere* 15:866. doi: 10.3390/atmos15070866

REN21 (2017). *Renewables 2017: global status Report*. Paris: REN21 Secretariat.

Sailor, D. J., Anand, J., and King, R. R. (2021). Photovoltaics in the built environment: a critical review. *Energy Build.* 253:111479. doi: 10.1016/j.enbuild.2021.111479

Seo, G.-Y., and Ahn, J.-B. (2023). Comparison of bias correction methods for summertime daily rainfall in South Korea using quantile mapping and machine learning model. *Atmosphere* 14:1057. doi: 10.3390/atmos14071057

Shravanth Vasisht, M., Srinivasan, J., and Ramasesha, S. K. (2016). Performance of solar photovoltaic installations: effect of seasonal variations. *Sol. Energy* 131, 39–46. doi: 10.1016/j.solener.2016.02.013

Skoplaki, E., and Palyvos, J. A. (2009). On the temperature dependence of photovoltaic module electrical performance: a review of efficiency/power correlations. *Sol. Energy* 83, 614–624. doi: 10.1016/j.solener.2008.10.008

Staffell, I., and Pfenninger, S. (2018). The increasing impact of weather on electricity supply and demand. *Energy* 145, 65–78. doi: 10.1016/j.energy.2017.12.051

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., et al. (2011). The representative concentration pathways: an overview. *Clim. Chang.* 109, 5–31. doi: 10.1007/s10584-011-0148-z

Wang, C.-N., Chung, Y.-C., Wibowo, F. D., Dang, T.-T., and Nguyen, N.-A.-T. (2023). Site selection of solar power plants using hybrid MCDM models: a case study in Indonesia. *Energies* 16:4042. doi: 10.3390/en16104042

Wang, K., Dickinson, R. E., and Liang, S. (2012). Clear sky visibility has decreased over land globally from 1973 to 2007. *Science* 323, 1468–1470. doi: 10.1126/science.1167549

Williams, J. H., DeBenedictis, A., Ghanadan, R., Mahone, A., Moore, J., Morrow, W. R., et al. (2012). The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. *Science* 335, 53–59. doi: 10.1126/science.1208365

Yang, Y., Javanroodi, K., and Nik, V. M. (2022). Climate change and renewable energy generation in Europe—long-term impact assessment on solar and wind energy using high-resolution future climate data and considering climate uncertainties. *Energies* 15:302. doi: 10.3390/en15010302

Zanaga, D., Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., Kirches, G., et al. (2022). *ESA WorldCover 10 m 2021 v200*. ESA World Cover. *Zenodo*. doi: 10.5281/zenodo.7254221

Zandi, I., and Lotfata, A. (2025). Evaluating solar power plant sites using integrated GIS and MCDM methods: a case study in Kermanshah Province. *Sci. Rep.* 15:3288. doi: 10.1038/s41598-025-87476-9

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophys. Res. Lett.* 47:e2019GL085782. doi: 10.1029/2019GL085782

Zhao, A., Ryder, C. L., and Wilcox, L. J. (2022). How well do the CMIP6 models simulate dust aerosols? *Atmos. Chem. Phys.* 22, 2095–2119. doi: 10.5194/acp-22-2095-2022

Zhou, Y., Wu, T., Zhou, Y., Zhang, J., Zhang, F., Su, X., et al. (2023). Can global warming bring more dust? *Clim. Dyn.* 61, 2693–2715. doi: 10.1007/s00382-023-06706-w