

Article

Complementary Characteristics Between Hydro-Solar-Wind Power Factors in the Upper Yellow River Region During 1979~2018

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Abstract: In this paper, we focus on the four provinces (Qinghai, Gansu, Ningxia, and Inner Mongolia) in the upper Yellow River region and conduct a quantitative analysis of the spatiotemporal distributions of the precipitation (P), shortwave radiation (R), and wind speed (W) from 1979 to 2018 using the China Meteorological Forcing Dataset. The complementarity of these power factors is analyzed across multiple time scales and resolutions. A complementarity coefficient is introduced by integrating three correlation coefficients to evaluate the interrelationship between pairs of power factors. Additionally, the probability density distributions of individual and pairs of power factors are examined at the Longyangxia Clean Energy Base in Qinghai Province. The complementarity coefficients between the P and R, P and W, and R and W exhibited significant variations across regions. The complementarity coefficients for P and R were negative, ranging from -0.019 to -0.029 at the 3 h resolution and from -0.384 to -0.429 at the daily resolution, indicating a strong complementarity at the longer temporal resolution. The complementarity coefficients for P and W were positive, ranging from 0.029 to 0.047 at the 3 h resolution and from 0.038 to 0.065 at the daily resolution, indicating a stable correlation at different resolutions. The complementarity coefficients for R and W changed from positive at the 3 h resolution to negative at the daily resolution, indicating that the correlation changes to complementarity at different resolutions. The annual joint probability density is highest for daily precipitation ranging from 276.0 to 304.4 mm, daily shortwave radiation between 1832.6 and 1847.5 kW/m², and daily mean wind speed varying from 1.7 to 1.8 m/s.

Keywords: hydro-solar-wind power factors; spatiotemporal variations; complementarity coefficient; probability density distribution; copula function



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1. Introduction

China possesses abundant renewable energy resources, and their rational development and utilization, particularly hydropower, solar, and wind energy, are anticipated to expedite the country's energy transition and aid in the achievement of its low-carbon development objectives. The hydropower resources are primarily concentrated in the south-western provinces, with an exploitable installed capacity of approximately 100 million kW, representing 17% of the world's hydropower potential. The region's favorable hydrological conditions and geographic features support large-scale hydropower development and

enable the construction of cascading hydropower stations. Hydropower development in southwestern China not only meets local electricity demands but also provides peak regulation services to the national grid through cross-regional transmission, thereby significantly enhancing the stability of the power system and promoting the integration of renewable energy [1]. China's solar energy resources are globally competitive, particularly in the northwest where the annual shortwave radiation ranges from 1700 to 2200 kWh/m². The region's abundant solar resources, extended sunshine hours, and vast open spaces make it an ideal location for large-scale photovoltaic (PV) plants. Furthermore, the arid climates of the Tibetan Plateau and Xinjiang create favorable conditions for efficient solar energy utilization, positioning these areas as core regions for solar energy development [2]. Wind energy resources in China are concentrated in the northern and coastal regions. The Inner Mongolia Plateau and the Hexi Corridor, characterized by expansive terrain and stable wind conditions, have emerged as major hubs for wind power development [3].

The Yellow River Basin is confronted with significant water shortages and possesses fragile ecosystems, necessitating urgent ecological protection and high-quality development [4]. The upper reaches of the Yellow River represent the primary runoff-producing area of the basin and serve as a focal point for the integrated wind-solar-hydro-storage clean energy base outlined in the 14th Five-Year Plan. With the commissioning of large-scale clean energy projects, the role of hydropower in the upper Yellow River region has evolved from merely maximizing generation efficiency to achieving objectives centered on volume assurance, peak regulation, and energy storage. The volume assurance goal emphasizes stabilizing the base load, while peak regulation accommodates fluctuations in demand and supply. Energy storage is achieved by converting curtailed wind and solar power into potential energy stored in water. However, the operation of the multi-energy hydro-solar-wind-storage system in the upper Yellow River region faces significant challenges. The integration of large-scale wind, PV, and reversible storage units with cascading hydropower stations creates a complex hydro-electric system. The upper Yellow River region operates as a multi-source, multi-grid hybrid power system with a total capacity of several tens of gigawatts. Hydraulically, the cascading hydropower stations are intricately interconnected; electrically, the system spans multiple grids, regions, and energy sources, thus influencing one another. Effective management of the dispatch of the cascading hydropower stations, balancing medium- and long-term operational objectives, and mitigating the impacts of wind and solar power fluctuations on the grid are crucial for ensuring the safe and stable operation of the power system. In the changing environment, the hydro-solar-wind-storage system in the upper Yellow River region continues to encounter operational uncertainties. For instance, climate change affects hydrological processes, thereby impacting the generation potentials of hydro, solar, and wind power. The mechanisms of the interactions between these energy sources remain inadequately understood. Human activities, including the western route of the South-to-North Water Diversion Project, the Heishan Gorge Reservoir Project, and the renovation of the cascading hydropower systems, will also influence energy planning and adjustments throughout the Yellow River Basin [5].

PV and wind power exhibit stochastic, volatile, and intermittent generation characteristics, which pose significant challenges to the safe and stable operation of the power system when integrated directly into the grid [6,7]. Hydropower, with its flexible start-stop capability, possesses a natural advantage in compensating for the variability of PV and wind power, thus making it an excellent choice for peak regulation and frequency modulation within power systems. Coordinating the output of hydropower plants and pumped-storage power stations with wind farms and PV plants in complementary operations can mitigate power fluctuations caused by the integration of renewable energy sources and enhance overall power quality. The complementarity analysis can be divided

into resource complementarity and generation complementarity. Resource complementarity refers to the complementary characteristics of water, solar energy, and wind energy resources in terms of both temporal and spatial dimensions. This includes, for example, the correlation between precipitation and wind speed. Additionally, power complementarity describes the complementary relationships among various power sources based on their output within specific power systems. This research primarily focuses on the concept of resource complementarity. Regarding resource complementarity, Glasbey et al. [8] used meteorological station data and covariance analysis to assess the solar energy potential in Edinburgh and the Pentland Hills in Scotland. Fang et al. [9] investigated the optimal scale of PV generation for integration with hydropower, utilizing hourly reanalysis meteorological data from 1980 to 2018 to assess the seasonal and daily variability of solar and wind resources across different countries. In terms of the generation complementarity, Ming et al. [10] analyzed the changes in hydro-solar generation complementarity under three weather conditions: sunny, cloudy, and rainy days. Sun et al. [11] demonstrated the feasibility of using hydropower to offset fluctuations in PV and wind power by analyzing changes in the grid residual load after prioritizing the consumption of PV and wind generation. Complementarity evaluation can also be categorized by the scope of the study: national, regional, and site levels. At the national level, Ren et al. [12] and Xu et al. [13] evaluated the complementarity characteristics of PV and wind power in China and found that there is significant spatiotemporal complementarity between the two. At the regional level, Tian et al. [14] classified hydro-solar complementarity into two forms: point-to-point (using specific hydropower stations to compensate for the output fluctuations of specific PV plants) and grid-to-grid (coordinating hydropower output across the grid to meet the peak regulation and frequency modulation needs of PV generation). Evaluation indicators were developed for hydro-solar complementarity based on curtailment rates and thermal power load rates. Using the 2020 power system planning data for Qinghai Province, they analyzed the hydro-solar complementarity on both medium- to long-term scales (dry and normal water years) and short-term scales (typical days in the dry and wet seasons). At the site level, Zhu et al. [15] selected representative power stations, including the Gangtuo Hydropower Station on the upper Jinsha River, the Wanjia Mountain PV Station in Yunnan, and the Dechang Wind Farm, to analyze the intra-annual and intra-daily generation complementarity characteristics of hydro-solar-wind power stations. For complementarity analysis, Pearson, Kendall, and Spearman correlation coefficients have been widely used. Additionally, some researchers have developed custom complementarity indicators based on volatility. For instance, Borba et al. [16] constructed time and energy complementarity components based on the maximum and minimum generation of renewable energy and conducted complementarity evaluations. Han et al. [17] proposed complementarity volatility and complementarity slope rates as evaluation indicators, focusing on random fluctuations between adjacent times and changes over continuous time windows.

In this study, we utilized the China Meteorological Forcing Dataset (CMFD) from 1979 to 2018 to conduct a comprehensive analysis of spatiotemporal distributions of precipitation, radiation, and wind speed. We investigated the dynamic changes and spatial patterns of these elements within the study area and produced corresponding spatiotemporal distribution maps. Subsequently, we combined the Pearson, Spearman, and Kendall correlation coefficients to devise a complementarity coefficient, which quantitatively assesses the complementarity characteristics of different meteorological elements across various time scales (daily, monthly, and seasonal) and resolutions (hourly and daily). This coefficient effectively captures the relationships between two elements across different time scales, offering a comprehensive method for quantifying complementarity. Furthermore, we compared the applicability of different single-element probability density distribution functions and the

Copula joint probability density function at the Longyangxia Base in Qinghai Province. The energy structure in the upper reaches of the Yellow River is complex, characterized by a significant proportion of new energy sources and rapid development. However, the uncertainties stemming from the substantial complementarity space and related challenges are critical factors that limit the efficiency of the multi-energy hydro-solar-wind-storage system. This system is essential for driving economic growth in western China and for substituting fossil fuel power generation, thereby attracting attention from both academic and engineering communities. Consequently, examining the complementarity characteristics of water, solar, and wind energy in the upper Yellow River region is essential for ecological conservation and high-quality development in the Yellow River Basin. This study facilitates the implementation of clean energy strategies and contributes to achieving China's dual carbon targets.

2. Study Area

The upper reaches of the Yellow River span four provinces: Qinghai, Gansu, Ningxia, and Inner Mongolia (Figure 1). This section extends from the river's source to Hekou Town in Tuoketuo County, Inner Mongolia, covering a total mainstream length of 3472 km. The basin is confronted with challenges such as water scarcity and fragile ecosystems, which necessitate urgent ecological protection and the pursuit of high-quality development [18–20]. During the 14th Five-Year Plan, this region has been designated as a key area for developing an integrated wind-solar-hydro-storage clean energy base. The study area is defined by the integration of the upper Yellow River Basin boundaries, power corridors, and municipal administrative borders, encompassing Qinghai, Gansu, and Ningxia, as well as regions west of Ulaanqab City in Inner Mongolia. This area is characterized by diverse topography, including the Tibetan Plateau, the arid regions of northwest China, and the central plateau. Qinghai, the source of the Yellow River, has an average altitude exceeding 3000 m and is abundant in solar energy resources. Gansu and Ningxia have relatively flat terrain, with altitudes ranging from 1000 to 3000 m, thereby providing favorable conditions for wind energy development [21]. The land use types in the study area primarily encompass farmland, grassland, forest, and desert. Farmland is predominantly concentrated in Gansu and Ningxia, benefiting from the water resources of the Yellow River and favorable irrigation conditions. Grasslands are extensively distributed in Qinghai, Inner Mongolia and support livestock farming. The deserts and sandy areas are primarily situated in the Hexi Corridor of Gansu and surrounding regions. Although these areas are less suitable for agriculture, they possess significant potential for solar and wind energy development due to the strong shortwave radiation and favorable wind conditions prevalent in these regions [22]. The water resources in the upper Yellow River are concentrated in Qinghai and play a crucial role in ecological conservation. These resources not only support local agriculture and industry but also provide a foundation for hydropower generation and large-scale hydropower projects [23]. The study area is abundant in solar and wind resources, with Qinghai distinguishing itself due to its extended sunshine hours and high radiation intensity, rendering it particularly suitable for PV power projects [24]. The Hexi Corridor in Gansu and the grasslands in Inner Mongolia possess significant advantages for wind energy, thereby creating favorable conditions for large-scale wind power projects. In recent years, the integrated development and utilization of hydro, wind, and solar energy have been actively promoted in the upper Yellow River region, resulting in efficient renewable energy utilization [25,26].

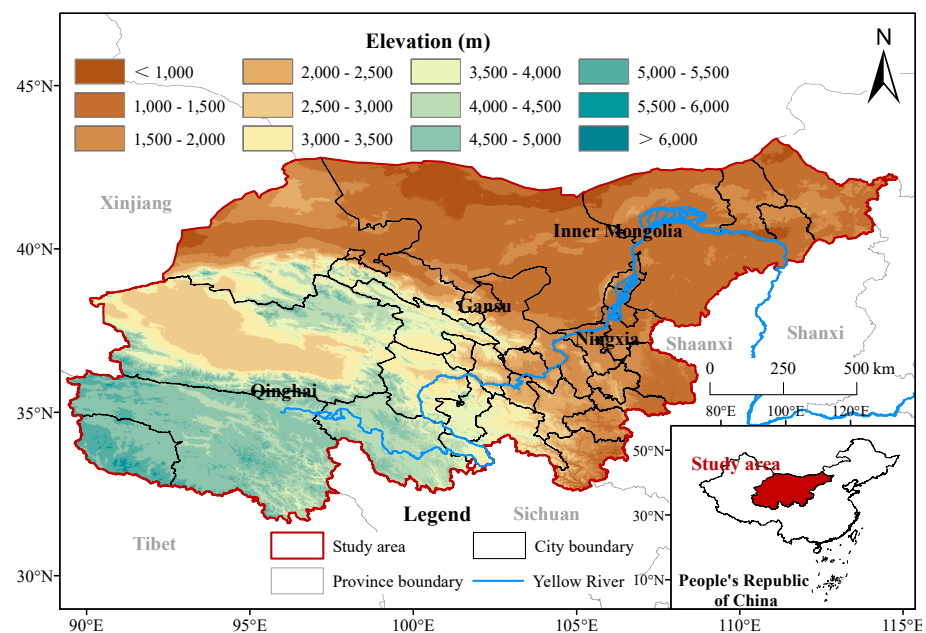


Figure 1. Study area.

3. Data and Methods

3.1. Data

The data utilized in this study were obtained from the CMFD, provided by the Data Center of the Institute of Tibetan Plateau Research at the Chinese Academy of Sciences. This dataset integrates multiple sources, including ground meteorological stations, TRMM, GEWEX-SRB, and GLDAS. It spans the period from 1979 to 2018, with a spatial resolution of 0.1° and a temporal resolution of 3 h. In this study, we focused on three key meteorological variables: precipitation, shortwave radiation, and wind speed (Table 1).

Table 1. Study data.

Power Factor	Name of Variable	Spatial Resolution	Temporal Resolution	Period
Precipitation rate	prec	$0.1^\circ \times 0.1^\circ$	3 h	1979~2018
Downward shortwave radiation	srad			
Wind speed	wind			

A significant number of scholars have validated the CMFD concerning precipitation, shortwave radiation, and wind speed. He et al. [27] assessed CMFD precipitation data against ground-based observations in the Tibetan Plateau region, demonstrating that the CMFD effectively captures the spatiotemporal variations in precipitation. Yang et al. [28] further confirmed the reliability of the CMFD shortwave radiation data across various climatic conditions. Regarding the wind speed data, Xie et al. [29] reported that the CMFD wind speed data accurately reflect the spatiotemporal variations on the Tibetan Plateau, particularly in the high-altitude regions. Collectively, these findings indicate that the CMFD has been reliably validated for data quality and accuracy across the key elements of precipitation, shortwave radiation, and wind speed.

3.2. Methods

3.2.1. Complementarity Coefficient

When sorting the time series of any two elements of precipitation, radiation, and wind speed, they can be represented as $X = \{x_1, x_2, \dots, x_t\}$ and $Y = \{y_1, y_2, \dots, y_t\}$. The

formulas for calculating the Pearson correlation coefficient, Kendall correlation coefficient, and Spearman correlation coefficient for any two elements are as follows [30].

The formula for the Pearson correlation coefficient $r(X, Y)$ is

$$r(X, Y) = \frac{\text{cov}(X, Y)}{\sigma(X) \cdot \sigma(Y)}. \quad (1)$$

The formula for the Kendall correlation coefficient $\tau(X, Y)$ is

$$\tau(X, Y) = \frac{C - D}{\frac{T \cdot (T-1)}{2}}. \quad (2)$$

The formula for the Spearman correlation coefficient $\rho(X, Y)$ is

$$\rho(X, Y) = 1 - \frac{6 \sum_{t=1}^T d_t^2}{T \cdot (T^2 - 1)}. \quad (3)$$

The complementarity coefficient $I_c(X, Y)$ of any two elements is obtained based on the calculation results of the Pearson correlation coefficient, Kendall correlation coefficient, and Spearman correlation coefficient:

$$I_c(X, Y) = \frac{r(X, Y) + \tau(X, Y) + \rho(X, Y)}{3}. \quad (4)$$

3.2.2. Probability Density Distribution

In this paper, three commonly used probability distribution functions were selected to portray the statistical properties, including the log-normal, Weibull, and generalized extreme value (GEV) distribution functions.

The log-normal distribution function is as follows:

$$f(x/\kappa, \rho) = \frac{1}{\rho\sqrt{2\pi}} \exp\left[-\frac{(\ln x - \kappa)^2}{2\rho^2}\right], \quad (5)$$

where κ is the mean of the log-normal distribution; ρ is the standard deviation of the log-normal distribution; and ρ^2 is the variance of the log-normal distribution.

The Weibull distribution function is as follows [31]:

$$f(x/\lambda, \omega) = \frac{\omega}{\lambda} \left(\frac{x}{\lambda}\right)^{\omega-1} e^{-(x/\lambda)^\omega}, x \geq 0, \quad (6)$$

where ω denotes the shape parameters; and λ is the scale parameter.

The GEV distribution function is as follows:

$$f(x/\chi, \varepsilon, \xi) = \varepsilon^{-1} e^{-(1-\chi)y - e^{-y}}, y = \varepsilon^{-1} \log[1 - \chi(x - \xi)/\varepsilon], \quad (7)$$

where y is the probability density value of the function; χ denotes the shape parameters; ε is the scale parameter; and ξ is the positional parameters.

Using the Copula function to construct the cumulative distribution function of two elements, if we let $H(x, y)$ be the marginal cumulative distribution function and $F(x)$ and $G(y)$ be the joint cumulative distribution functions, then a bivariate Copula function exists [32]:

$$H(x, y) = C[F(x), G(y)]. \quad (8)$$

Additionally, the density function of $H(x, y)$ can be obtained from the marginal cumulative distribution functions $F(x)$ and $G(y)$, and the density function of the Copula function is as follows:

$$h(x, y) = c[F(x), G(y)] \cdot f(x) \cdot g(y), \quad (9)$$

$$c(u, v) = \frac{\partial C(u, v)}{\partial u \partial v}, \quad (10)$$

$$u = F(x), v = G(y), \quad (11)$$

where $f(x)$ and $g(y)$ are the density functions of $F(x)$ and $G(y)$, respectively.

In this paper, three commonly used Archimedean-type Copula joint distribution functions are selected, including the Clayton Copula function, Frank Copula function, and Gumbel Copula function [33]. The three Copula functions are defined below.

The Clayton Copula function is

$$C(u, v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{\frac{1}{\theta}}, \theta \in (0, +\infty), \quad (12)$$

the Frank Copula function is

$$C(u, v) = -\frac{1}{\theta} \ln \left[1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{(e^{-\theta} - 1)} \right], \theta \in R, \quad (13)$$

and the Gumbel Copula function is

$$C(u, v) = \exp \left(- \left[(-\ln u)^{\theta} + (-\ln v)^{\theta} \right]^{\frac{1}{\theta}} \right), \theta \in [1, +\infty), \quad (14)$$

where C is the Copula function.

The optimal function can be selected through the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N \left[F_{\text{Empirical}}(u_i, v_i) - F_{\text{Copula}}(u_i, v_i) \right]^2}, \quad (15)$$

where $F_{\text{Empirical}}(u_i, v_i)$ is the joint distribution function. $F_{\text{Copula}}(u_i, v_i)$ is the Copula theoretical distribution function.

4. Results

4.1. Spatiotemporal Variations at the Regional Scale

4.1.1. Temporal Variations

The interannual variation characteristics of precipitation, radiation, and wind speed in the study area from 1979 to 2018 are illustrated in Figure 2(a-1,a-2,a-3). During this period, precipitation in the study area exhibited a generally increasing trend, with varying rates of increase across different provinces. Qinghai recorded the highest increase at 3.14 mm/year, while Gansu had the lowest at 1.28 mm/year. Inner Mongolia and Ningxia also showed increasing trends in precipitation, albeit with greater fluctuations, at rates of 1.52 and 1.35 mm/year, respectively. Conversely, radiation in the study area demonstrated a gradual decline, with Qinghai experiencing the most significant decrease at 1.52 kW/m²/year. Gansu, Ningxia, and Inner Mongolia exhibited more stable rates of decline at 0.53, 0.62, and 0.51 kW/m²/year, respectively. Notably, Qinghai consistently maintained higher radiation levels than the other regions, indicating abundant solar energy resources. Wind speed in the study area displayed a fluctuating decreasing trend, with Qinghai and Inner Mongolia experiencing decreases of −0.09 and −0.015 m/s/year, respectively. In contrast, Gansu and

Ningxia showed increasing trends, with rates of 0.007 and 0.001 m/s/year, respectively. Inner Mongolia consistently recorded significantly higher wind speed compared to the other regions, highlighting substantial potential for wind energy resources.

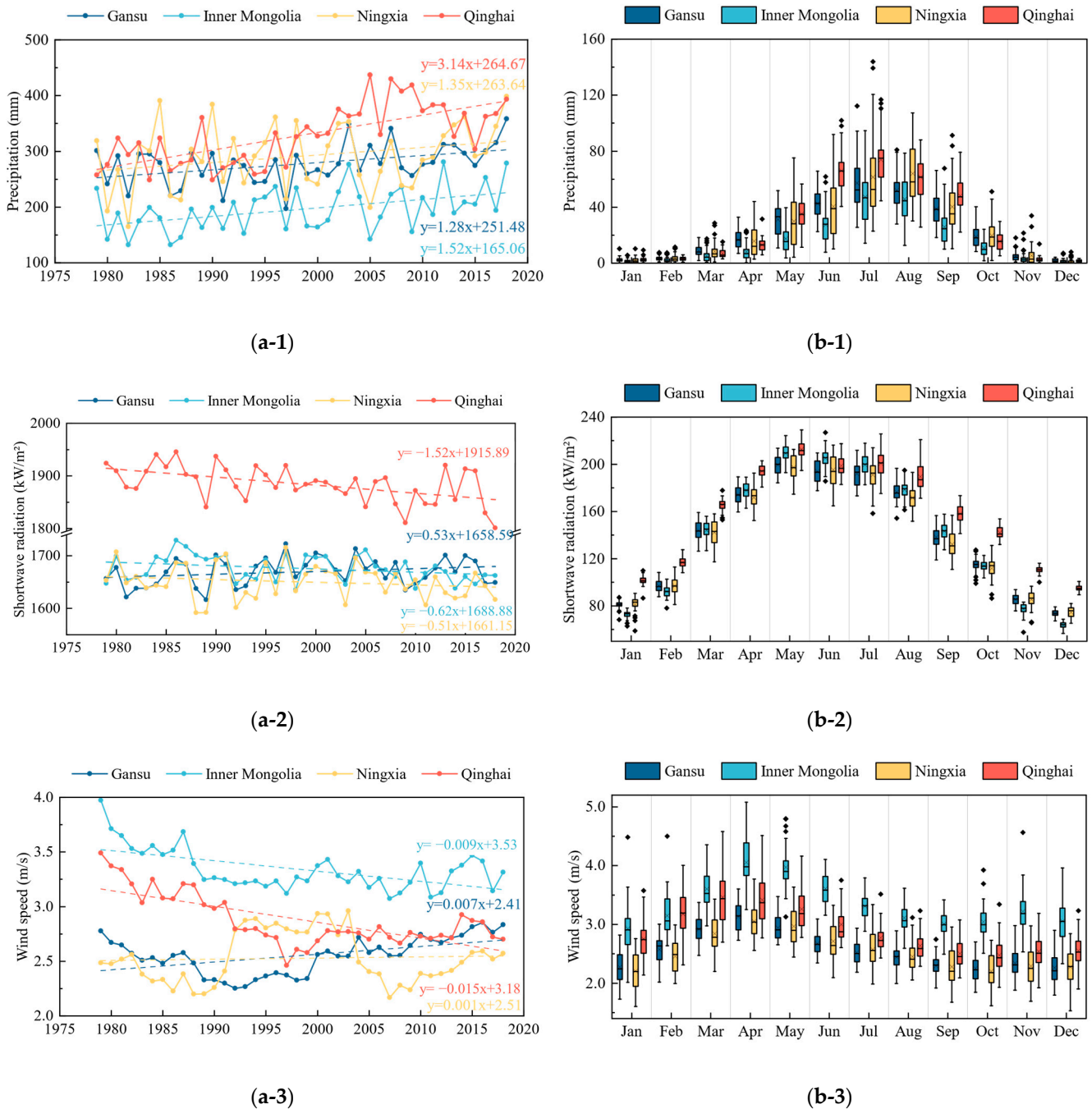


Figure 2. Inter- and intra-annual variations in precipitation, shortwave radiation, and wind speed: (a-1) yearly precipitation; (a-2) yearly shortwave radiation; (a-3) yearly wind speed; (b-1) monthly precipitation; (b-2) monthly shortwave radiation; and (b-3) monthly wind speed.

The intra-annual variation characteristics of precipitation, radiation, and wind speed from 1979 to 2018 are illustrated in Figure 2(b-1,b-2,b-3). Precipitation in the study area exhibited a pronounced seasonal concentration trend, gradually increasing from May and peaking between June and August. The median precipitation in July approached 80 mm, underscoring the significance of summer rainfall in this region. Conversely, precipitation decreased significantly during spring and winter, with minimal rainfall occurring from

January to March, indicative of the area's winter drought conditions. This seasonal precipitation pattern aligns with the climate characteristics of semi-arid to arid regions. Annual variations in radiation displayed typical seasonal fluctuations, with low levels observed in winter, particularly in January when the median radiation was approximately 100 kW/m^2 . Radiation levels gradually increased throughout the seasons, peaking at nearly 240 kW/m^2 in July. The high summer radiation intensity significantly influenced the regional climate. Wind speed, while relatively stable, exhibited more pronounced fluctuations in spring and summer, being higher from March to May and decreasing in July and August. It peaked in spring, weakened during summer, and increased again in autumn and winter. These seasonal variations in wind speed were associated with changes in atmospheric circulation and monsoon activity.

4.1.2. Spatial Variations

The spatial variation characteristics of precipitation in the study area are illustrated in Figure 3a. The multi-year average precipitation across the region was 272.5 mm, showing a gradual decrease from south to north. The average annual precipitation values in Qinghai, Ningxia, Gansu, and Inner Mongolia were 329.0, 291.4, 277.8, and 196.2 mm, respectively. The southern and southwestern parts of Qinghai received comparatively higher amounts of precipitation, while the northern regions of Gansu and central Inner Mongolia experience significantly lower amounts. The standard deviation of precipitation in the study area was 69.0 mm, underscoring the spatial distribution of interannual variability. Northern Gansu and Inner Mongolia exhibited larger standard deviations, suggesting greater interannual fluctuations, whereas the southern and southwestern parts of Qinghai showed smaller standard deviations, indicating less year-to-year variation and a more stable climate with smoother interannual changes in precipitation. The overall trend of precipitation changes in the region indicates an increase of 2.1 mm/year. The southern and southwestern regions of Qinghai displayed clear increasing precipitation trends, while parts of northern Gansu and central Inner Mongolia exhibited decreasing trends.

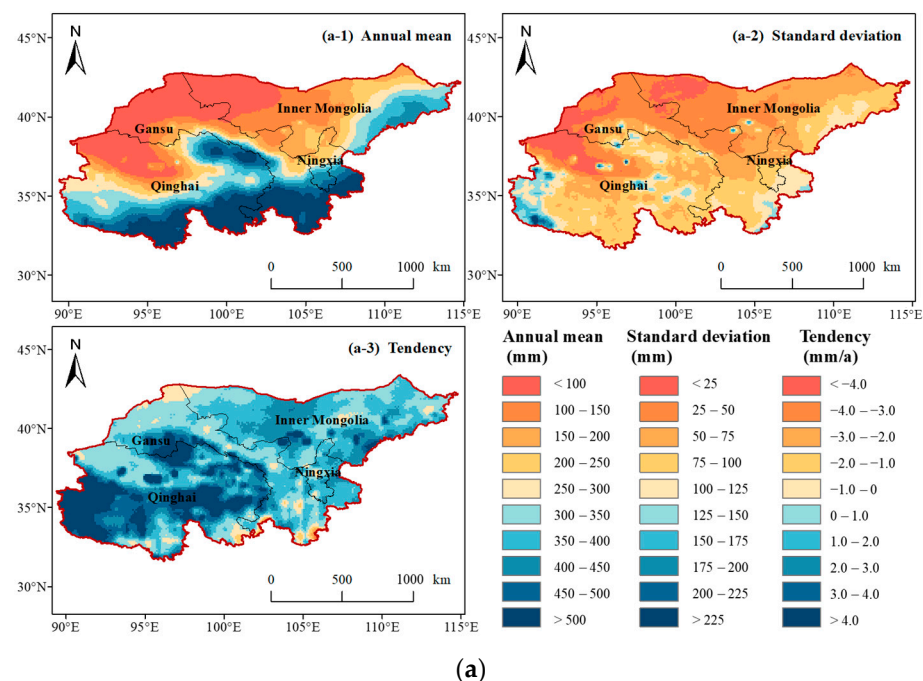


Figure 3. Cont.

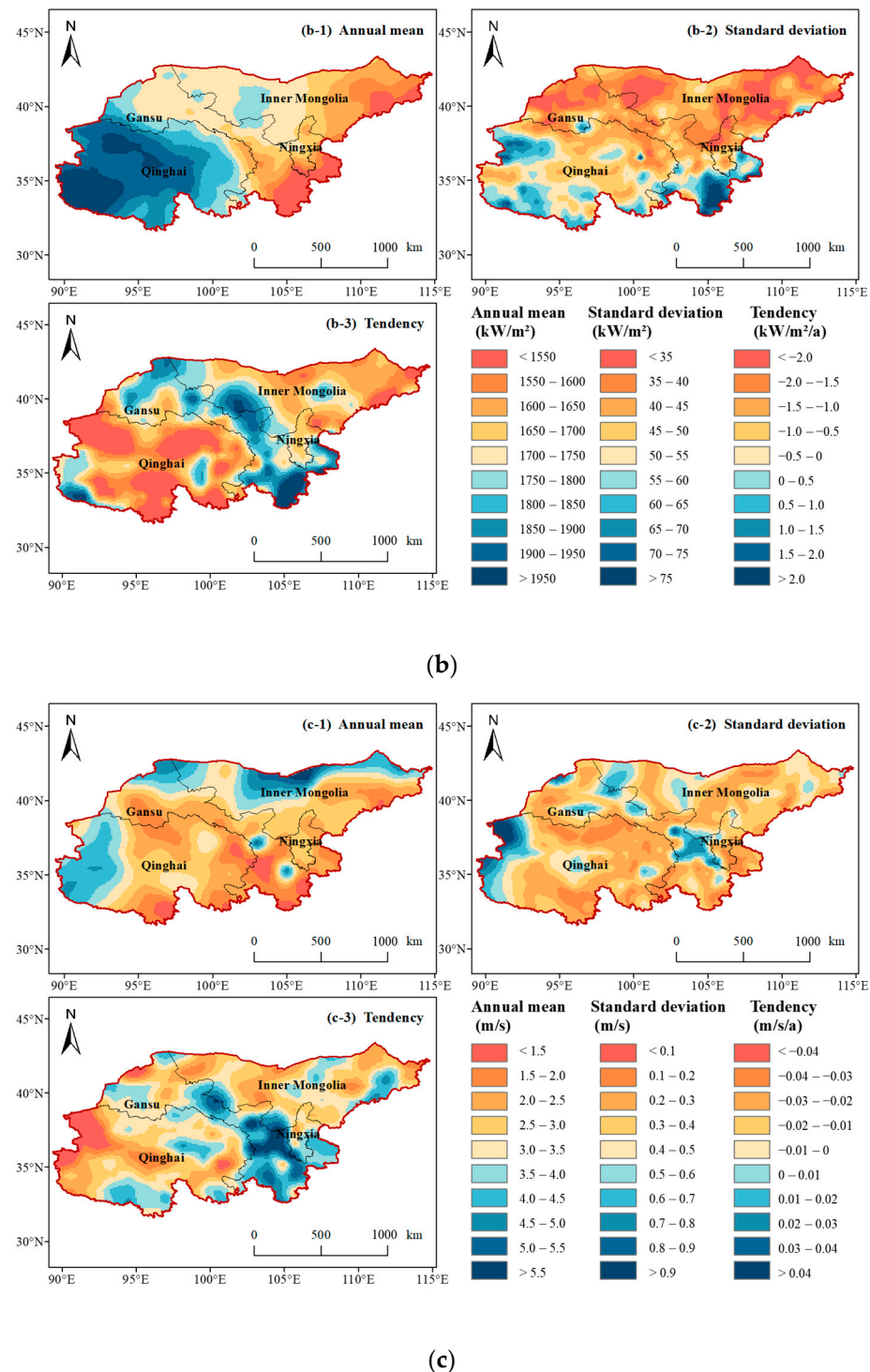


Figure 3. Spatial variations in precipitation, shortwave radiation, and wind speed: (a) precipitation; (b) shortwave radiation; and (c) wind speed.

The spatial variation characteristics of radiation within the study area are illustrated in Figure 3b. The multi-year average shortwave radiation across the region was measured at 1756.8 kW/m^2 , with a notable decrease from southeast to northwest. The average shortwave radiation values for Qinghai, Inner Mongolia, Gansu, and Ningxia were 1187.7 , 1676.1 , 1669.5 , and 1650.7 kW/m^2 , respectively. High radiation levels were predominantly observed in southeastern Inner Mongolia, northwestern Qinghai, and northern Gansu, while central and southern Qinghai, along with Ningxia, exhibited lower multi-year average radiation values. The standard deviation of radiation in the study area was

46.5 kW/m², indicating interannual variability. Northern Gansu and southeastern Inner Mongolia displayed larger standard deviations, suggesting greater interannual fluctuations, whereas the southern regions of Qinghai and Ningxia had smaller standard deviations, indicating more stable interannual radiation patterns. The overall trend in radiation within the region showed a decrease of 0.7 kW/m²/year, with particularly significant declines noted in central Qinghai and northwestern Ningxia. In contrast, northern Gansu and southeastern Inner Mongolia exhibited relatively stable radiation trends.

The spatial variation characteristics of wind speed in the study area are illustrated in Figure 3c. The multi-year average wind speed in the region was 2.9 m/s, with considerable regional variations. Inner Mongolia, Qinghai, Gansu, and Ningxia recorded average wind speed of 3.3, 2.9, 2.6, and 2.5 m/s, respectively. The western parts of the study area, particularly western Qinghai and western Gansu, experienced higher wind speeds, while Ningxia and the central-southern regions of Inner Mongolia exhibited lower multi-year average wind speed. The standard deviation of wind speed across the study area was 1.1 m/s, indicating significant interannual variability, especially in western Qinghai and western Gansu, where substantial fluctuations in wind speed were observed from year to year. In contrast, Ningxia and the central-southern regions of Inner Mongolia demonstrated smaller wind speed fluctuations, suggesting more stable wind conditions and reduced interannual variability. The overall trend in wind speed change in the region was a decrease of 0.007 m/s/year, particularly evident in Ningxia, the central-southern regions of Inner Mongolia, and certain areas of Qinghai. Conversely, some regions in western Qinghai and western Gansu exhibited minimal changes in wind speed, with slight increases in certain instances.

The spatiotemporal distribution of precipitation, radiation, and wind speed in the upper reaches of the Yellow River exhibits significant variability. Temporally, precipitation is predominantly concentrated in the summer months, displaying a distinct oceanic seasonal pattern. Notably, the increase in summer rainfall is particularly pronounced in Gansu and Ningxia. Conversely, radiation has shown a general downward trend over the years, with the most pronounced decrease occurring during the summer. This trend is attributed to increased cloud cover and reduced atmospheric transparency in the region. Furthermore, wind speed displays an overall weakening trend, with a particularly noticeable decline observed in Inner Mongolia. Spatially, precipitation decreases gradually from south to north, with the southern and southwestern regions of Qinghai experiencing higher precipitation levels, while the northwest of Gansu and the central part of Inner Mongolia report lower precipitation. Radiation levels also diminish from west to east, with elevated radiation primarily found in the central region of Qinghai Province, whereas the eastern part of Inner Mongolia exhibits comparatively low radiation intensity. Wind speed decreases from north to south, with eastern Inner Mongolia and western Gansu exhibiting relatively high wind speed, while central Ningxia and southern Gansu experience lower wind speed. These temporal and spatial variations underscore the differential impacts of climate change on regional meteorological elements.

4.2. Complementarity Coefficient at the Regional Scale

4.2.1. Temporal Variations of Complementarity Coefficient

The temporal variations in the complementarity coefficient between precipitation (P), shortwave radiation (R), and wind speed (W) on different time scales and at temporal resolutions are illustrated in Figure 4. The complementarity of each elemental combination at the 3 h scale (Figure 4(a-1)) is generally higher than that observed at the daily resolution. Specifically, at the 3 h resolution, the complementarity coefficient of the P and R combination peaks at 0.3 during winter (January–February), indicating a strong positive synergistic

effect. Conversely, the P and W combination remains stable within the range of 0.1–0.2 throughout the year, reflecting continuous complementary characteristics. In contrast, the complementarity coefficient of R and W declines below 0.1 in summer, revealing a seasonal antagonistic effect between the two. At the daily resolution (Figure 4(a-2)), the overall complementarity diminishes, with extreme negative values (−0.5) observed in R and W during summer, suggesting a significant offset effect between solar energy and wind energy at this scale. Meanwhile, P and R, as well as P and W still maintain a weak positive correlation ranging from 0 to 0.2.

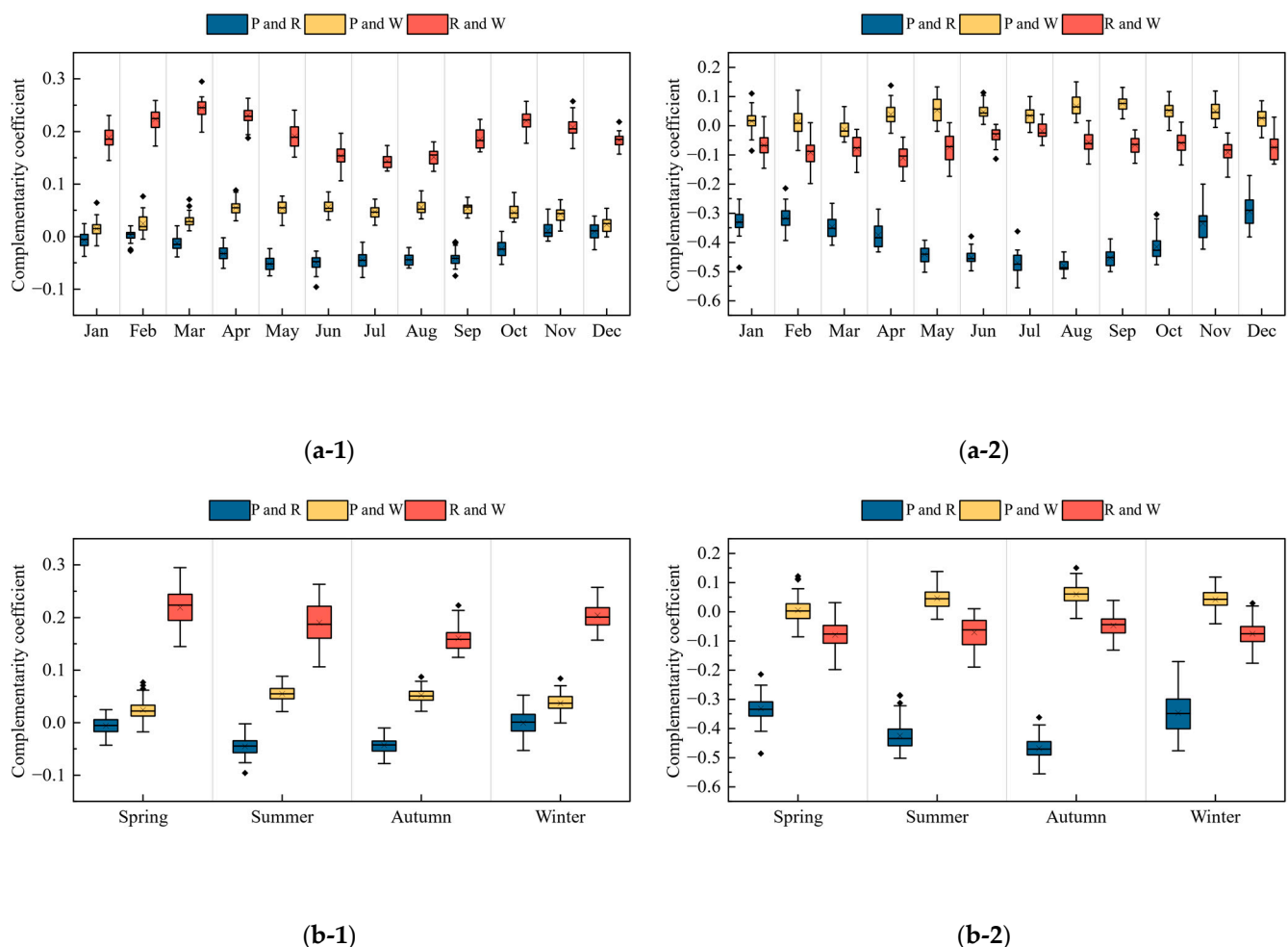


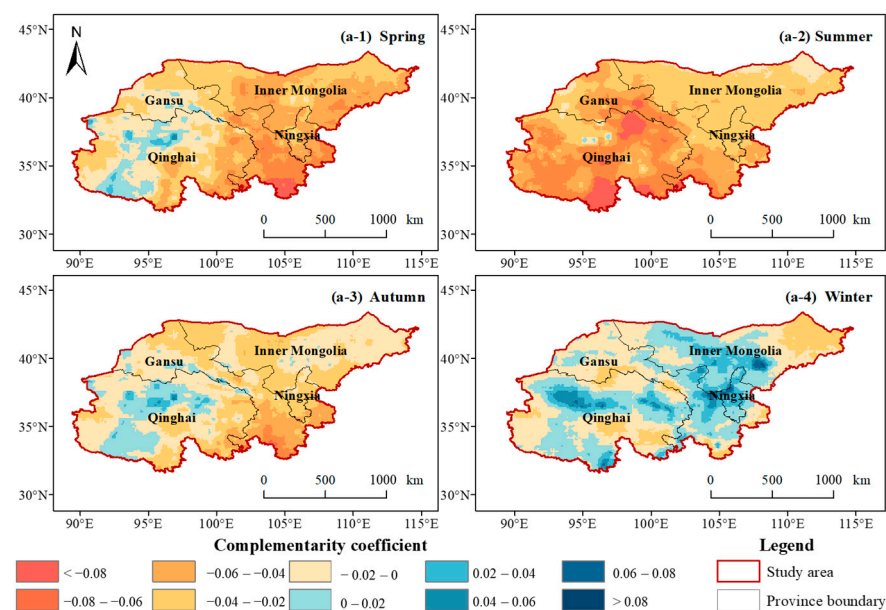
Figure 4. Temporal variations in complementarity coefficient between precipitation (P), shortwave radiation (R), and wind speed (W) at different time scales and time resolutions: **(a-1)** monthly complementarity (3 h resolution); **(a-2)** monthly complementarity (daily resolution); **(b-1)** seasonal complementarity (3 h resolution); and **(b-2)** seasonal complementarity (daily resolution).

Seasonal dynamic analysis reveals that the average complementary coefficient of precipitation and radiation (P and R) at the 3 h scale (Figure 4(b-1)) during spring is only 0.05, indicating the weakest stage of synergy for this combination. In summer, the median value of radiation and wind (R and W) decreases to −0.1, confirming the negative complementary characteristics of light energy and wind energy during the high-temperature season. Conversely, in autumn, the complementarity of each combination generally increases. Notably, in winter, the P and R value rises to 0.25, underscoring the high synergistic advantage of precipitation and radiation. At the daily resolution (Figure 4(b-2)), the complementary coefficient of R and W in spring approaches zero, indicating a near absence of correlation. In summer, the negative value of R and W expands to −0.3, while P and R, as well as P and W still maintain a weak positive correlation ranging from 0 to 0.2.

precipitation and wind (P and W) maintain low positive correlations of 0.05 and 0.1, respectively. In winter, P and R increases to 0.2, suggesting that there remains complementary potential to be explored at the daily scale. A quantitative comparison indicates that at the 3 h scale, the winter peak value of P and R (0.25–0.3) is 1.25–1.5 times greater than the daily resolution value (0.2) during the same period, highlighting the significance of high temporal resolution for complementary assessments.

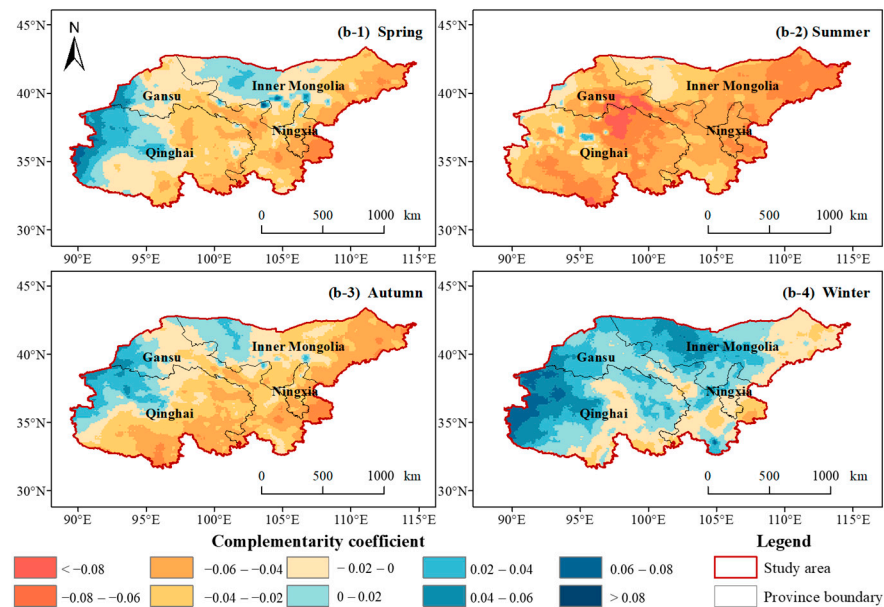
4.2.2. Spatial Variations of Complementarity Coefficient

Figure 5 illustrates the spatial variations in the complementarity coefficient between precipitation and shortwave radiation at different temporal resolutions and seasons. At the 3 h resolution, spring and autumn exhibited generally low complementarity coefficients, predominantly ranging from -0.08 to 0.02 . Notably, Qinghai and Gansu displayed coefficients that were significantly more pronounced. Conversely, during summer, the coefficients exhibited a positive increasing trend, with most areas ranging from 0.02 to 0.06 , which may be attributed to increased precipitation and enhanced resource availability. However, in winter, the coefficients declined again, falling within the range of -0.08 to -0.02 in most regions, a pattern associated with reduced precipitation and lower temperatures. At the daily resolution, in spring, the complementarity coefficients ranged broadly between -0.50 and -0.35 , especially in Gansu and Ningxia where they approached -0.55 , indicating the pronounced complementarity of these two resources. In summer, the coefficients mostly ranged from -0.30 to -0.15 , likely due to the greater precipitation and higher temperatures. The coefficients exhibited spatial variation in autumn, with some areas such as Gansu and Ningxia maintaining lower values. In winter, the coefficients displayed spatial variation, with most regions falling within the range of -0.30 to -0.50 .



(a)

Figure 5. Cont.



(b)

Figure 5. Spatial variations in complementarity coefficient between precipitation and shortwave radiation at different time resolutions during different seasons: (a) 3 h resolution; and (b) daily resolution.

Figure 6 illustrates the spatial variations in the complementarity coefficient between precipitation and wind speed across different temporal resolutions and seasons. For the 3 h resolution, during spring, the complementarity coefficients predominantly ranged from -0.16 to 0.04 , with particularly low values observed in Qinghai and Gansu. In summer, these coefficients generally increased, falling between 0.04 and 0.16 . Autumn displayed notable regional differences in complementarity coefficients, with Gansu maintaining lower values while other areas showed signs of recovery. In winter, the coefficients decreased once more, ranging from -0.08 to 0.04 in most regions, reflecting the typical climatic conditions of the season. For the daily resolution in spring, coefficients primarily concentrated between -0.24 and 0.06 , with the lowest values again found in Qinghai and Gansu. In summer, coefficients predominantly fell within the range of 0.06 to 0.24 . Autumn exhibited significant variability in complementarity coefficients, indicating differences in resource status among regions, with Gansu continuing to show low coefficients and while other regions displayed improvement. In winter, coefficients further decreased, ranging from -0.18 to 0.06 across most regions.

The spatial variations in the complementarity coefficient between shortwave radiation and wind speed across different temporal resolutions and seasons are illustrated in Figure 7. At the 3 h resolution, during spring, the complementarity coefficients were generally low, particularly in Qinghai and Gansu. In summer, these coefficients increased to a range of 0.10 to 0.35 in most areas. In autumn, the coefficients were approximately 0.05 in Gansu and ranged from 0.15 to 0.30 in other regions. During winter, the complementarity coefficients generally decreased, with most areas exhibiting values between 0.05 and 0.25 . For the daily resolution, in spring, the coefficients were significantly low in Gansu and other regions, with values approaching -0.32 in some areas. In summer, the coefficients generally increased, ranging from 0.08 to 0.32 in most regions. In autumn, while Gansu maintained low coefficients, other regions exhibited some improvement. In winter, the coefficients decreased again, ranging from -0.24 to 0.08 in most areas.

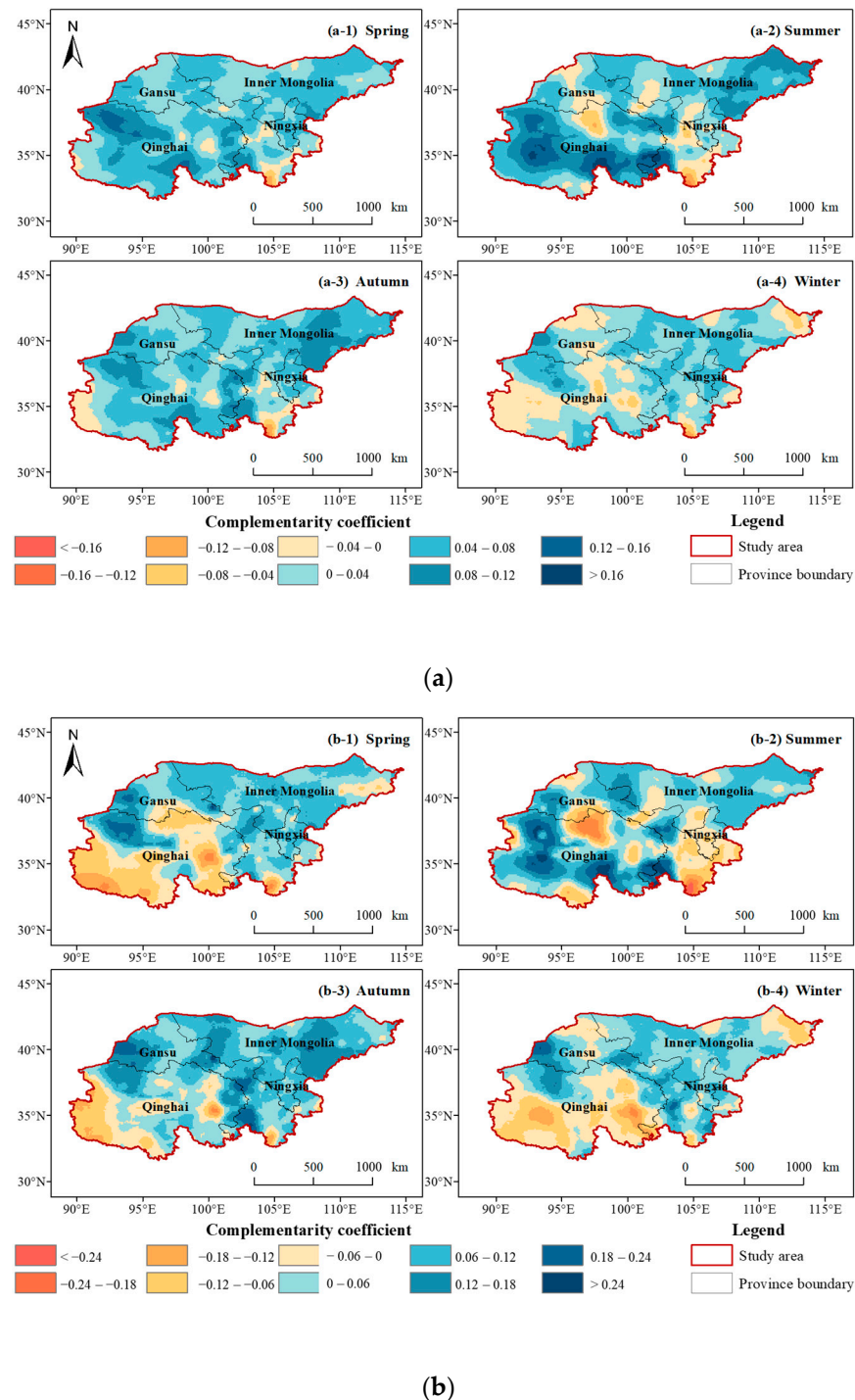
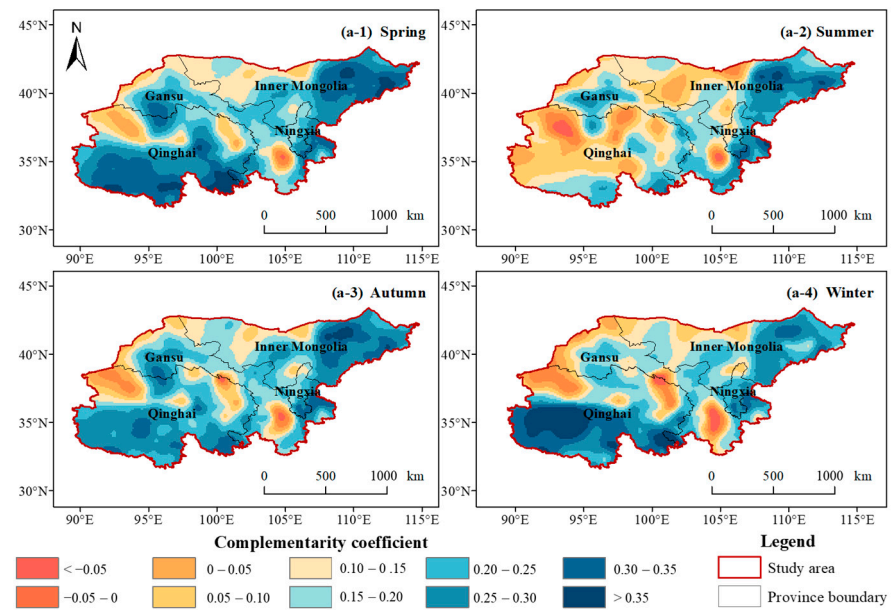


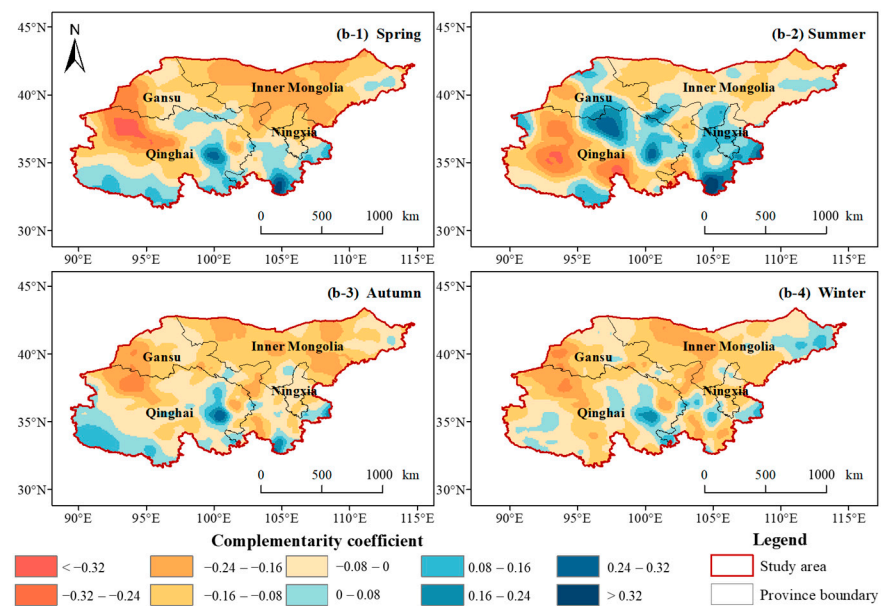
Figure 6. Spatial variations in complementarity coefficient between precipitation and wind speed at different time resolutions during different seasons: (a) 3 h resolution; and (b) daily resolution.

The complementarity coefficients of the pairs of elements on each time scale are presented in Figure 8. The complementarity coefficients between precipitation and shortwave radiation (P and R), precipitation and wind speed (P and W), and shortwave radiation and wind speed (R and W) exhibited significant variations across the regions. The complementarity coefficients for P and R were negative in all four provinces, ranging from -0.019 to -0.029 at the 3 h resolution and from -0.384 to -0.429 at the daily resolution, indicating a strong complementarity at the longer, daily temporal resolution. Conversely, the complementarity coefficients for P and W were positive, ranging from 0.029 to 0.047 at the 3 h resolution and from 0.038 to 0.065 at the daily resolution across the four provinces,

suggesting stable correlations at the different resolutions. In contrast, the complementarity coefficients for R and W shifted from positive (0.174 to 0.220) at the 3 h resolution to negative (-0.048 to -0.100) at the daily resolution in the four provinces, indicating a transition from correlation to complementarity at varying resolutions.



(a)



(b)

Figure 7. Spatial variations in complementarity coefficient between shortwave radiation and wind speed at different time resolutions during different seasons: (a) 3 h resolution; and (b) daily resolution.

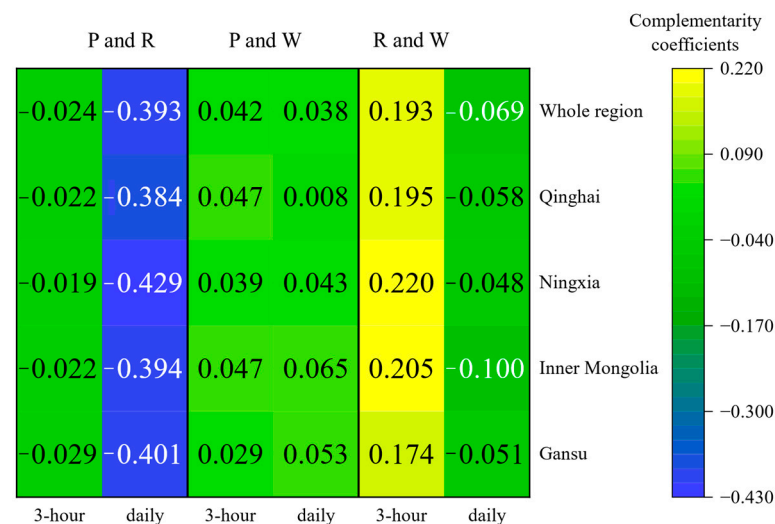


Figure 8. Complementarity coefficients between two power factors at different time resolutions.

4.3. Probability Density Distribution at the Site Scale

4.3.1. Complementary Characteristics of the Longyangxia Clean Energy Base

The analysis of the spatiotemporal complementary characteristics of climate elements in the Longyangxia Clean Energy Base of Qinghai Province reveals that the multi-year average precipitation, shortwave radiation, and wind speed in this region are 320.4 mm, 1838.8 kW/m², and 1.7 m/s, respectively. By calculating the bivariate complementary coefficient at three-hour and daily resolutions, significant differences in the complementary characteristics among various elements were identified. The complementary coefficient of precipitation and radiation (P and R) is −0.029 at the three-hour scale and −0.432 at the daily scale. The negative value indicates a temporal complementarity between the two, with more pronounced complementary characteristics at the daily resolution. The complementary coefficients of precipitation and wind (P and W) are 0.021 (3 h) and 0.003 (daily), suggesting a weak correlation without effective complementarity. In contrast, the relationship between radiation and wind (R and W) exhibits composite characteristics; at the three-hour resolution, it shows a positive correlation of 0.112, while at the daily resolution, it shifts to a complementary relationship with a coefficient of −0.147.

4.3.2. Single Power Factor

The probability density distribution of a single power factor with different time resolutions at the Longyangxia Base in Qinghai Province is illustrated in Figure 9. For the three distributions, the RMSE of the log-normal distribution for precipitation is 0.171, which is much better than the RMSE of the Weibull distribution and GEV distribution. The Weibull distribution for shortwave radiation is the best, with an RMSE of 0.037. The GEV distribution for wind speed is the best, with an RMSE of 0.004. On a daily scale, the intervals with the highest probabilities of occurrence for precipitation, radiation, and wind speed are 0.1 to 3.4 mm, 4005.6 to 4836.0 W/m², and 1.3 to 2.6 m/s, respectively. Annually, the intervals with the highest occurrence probabilities for precipitation, radiation, and wind speed are 276.0 to 304.4 mm, 1832.6 to 1847.5 kW/m², and 1.7 to 1.8 m/s, respectively.

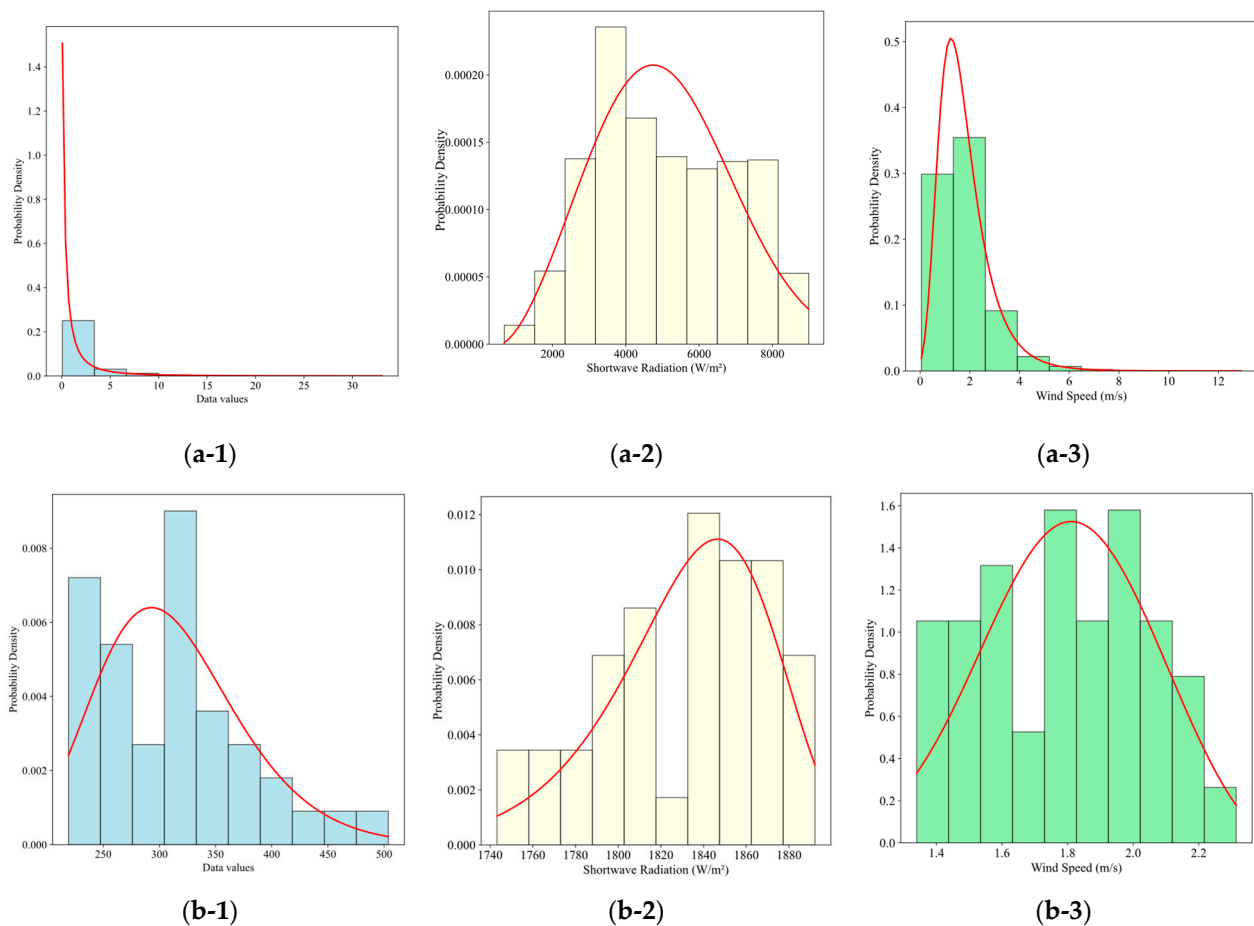


Figure 9. Probability density distribution of a single power factor at the Longyangxia Base in Qinghai Province: (a-1) precipitation (daily); (a-2) shortwave radiation (daily); (a-3) wind speed (daily); (b-1) precipitation (yearly); (b-2) shortwave radiation (yearly); and (b-3) wind speed (yearly).

4.3.3. Dual Power Factors

The probability density distributions of the dual power factors at the Longyangxia Base in Qinghai Province are shown in Figure 10. The probability density distribution is determined by comparing the Clayton Copula, Frank Copula, and Gumbel Copula functions. It can be seen that the Gumbel Copula for precipitation and shortwave radiation, and precipitation and wind speed had the lowest RMSEs of 0.459 and 0.419, respectively, while the Frank Copula for shortwave radiation and wind speed had the lowest RMSE of 0.417. At a daily scale, the combined probability of various combinations—including low rainfall with weak radiation, high precipitation with strong radiation, low rainfall with weak wind speed, high precipitation with strong wind speed, strong radiation with strong wind speed, and weak radiation with weak wind speed—is the highest. Conversely, on an annual scale, the combined probabilities of P and R, as well as P and W, show significant changes, decreasing across all intervals. However, in the case of R and W, the highest combined probability occurs with strong radiation paired with weak wind speed and weak radiation paired with strong wind speed.

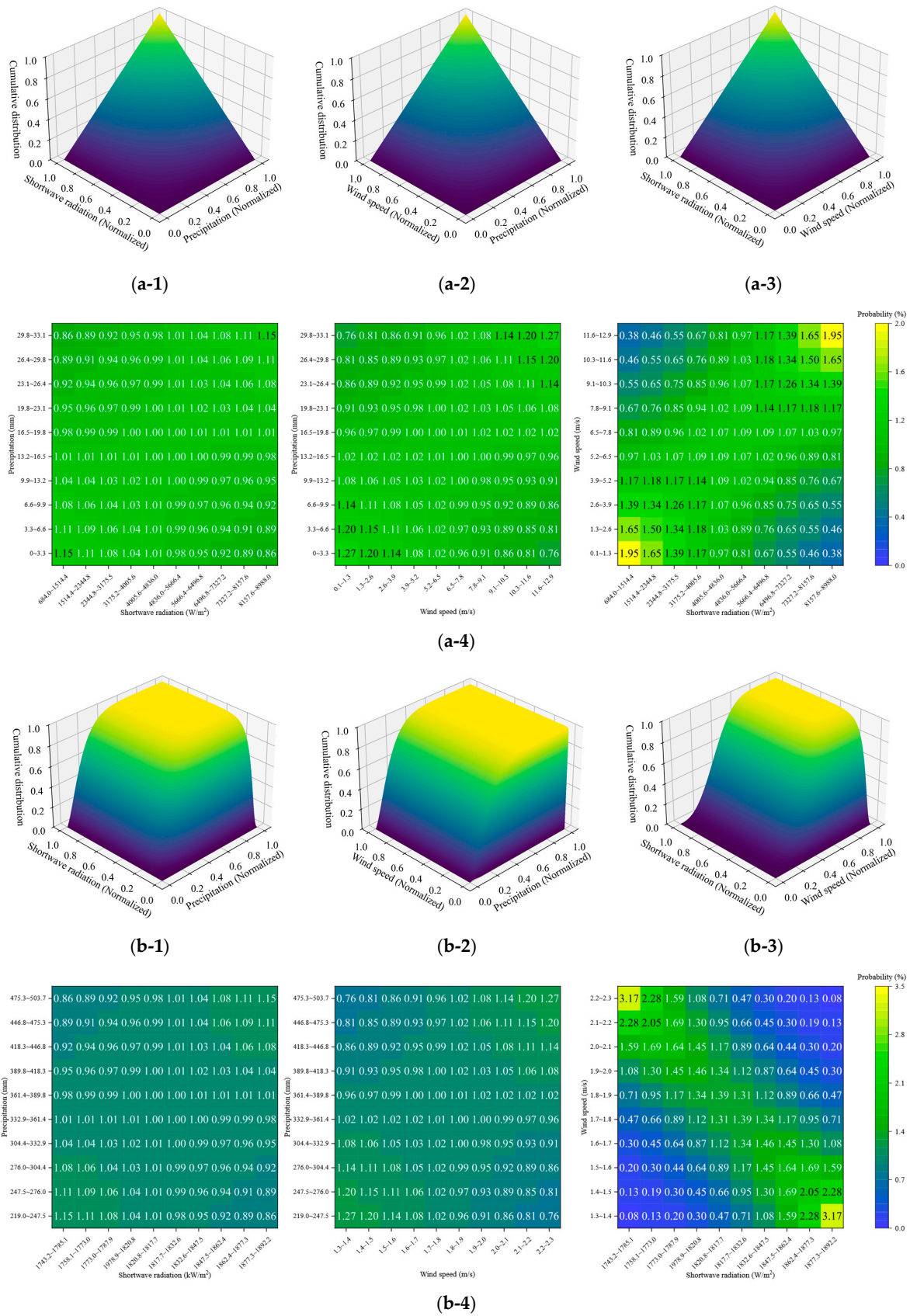


Figure 10. Probability density distribution of dual power factors at the Longyangxia Base in Qinghai Province: (a-1) precipitation and shortwave radiation (daily); (a-2) precipitation and wind speed (daily); (a-3) shortwave radiation and wind speed (daily); (a-4) percentage of each interval (daily); (b-1) precipitation and shortwave radiation (yearly); (b-2) precipitation and wind speed (yearly); (b-3) shortwave radiation and wind speed (yearly); and (b-4) percentage of each interval (yearly).

Precipitation and shortwave radiation are negatively correlated; when precipitation is low, the probability density of shortwave radiation is high. As precipitation increases, the probability density of radiation decreases significantly, suggesting that rainfall events are typically accompanied by increased cloud cover, which reduces the intensity of shortwave radiation. This relationship has a direct impact on PV generation, as frequent rainfall can lead to a substantial decrease in PV efficiency. The correlation between precipitation and wind speed is weak; the probability density of wind speed only decreases slightly with increasing precipitation, indicating no significant positive or negative correlation. Under local climatic conditions, precipitation may slightly inhibit wind speed through mechanisms such as downdrafts of cold air, but this effect is not pronounced. The impact of precipitation on wind speed is minimal, allowing wind power to maintain a relatively stable output during rainy periods. This suggests that wind energy remains a vital component of the energy supply, demonstrating high stability even in periods or regions with frequent rainfall. In contrast, shortwave radiation and wind speed exhibit a significant negative correlation; when shortwave radiation is strong, the probability density of the wind speed is low. As wind speed increases, radiation intensity significantly decreases. Clearly, high-radiation conditions are typically associated with stable atmospheric conditions, low pressure gradients, and weak winds, whereas strong wind events are generally accompanied by reduced radiation.

5. Discussion

In this study, we utilized CMFD reanalysis data from 1979 to 2018 to conduct a systematic spatiotemporal analysis of precipitation, shortwave radiation, and wind speed in the study area, highlighting their complementarity across various time scales and temporal resolutions. Nonetheless, our findings contain certain uncertainties that necessitate further optimization in the future, particularly in the following aspects.

(1) In terms of data, the CMFD from 1979 to 2018 was utilized in this research. Although this dataset encompasses an extensive time period, the spatial and temporal distribution characteristics of energy resources may fluctuate due to climate change. Consequently, future research should incorporate updated datasets to further analyze and capture the latest trends in climate change and its impact on renewable energy resources. Secondly, regarding regional applicability, the research findings are primarily relevant to the upper reaches of the Yellow River. While this research possesses a certain degree of representativeness, its applicability in other regions with differing geographical and climatic conditions requires further verification and adjustment. In contrast, the widely used MERRA-2 reanalysis data have a temporal resolution of 1 h, but its spatial resolution is relatively coarse at $0.5^\circ \times 0.625^\circ$. This leads to systematic biases in areas with complex terrain. The ERA5 dataset also has a temporal resolution of 1 h but offers a finer spatial resolution of 0.25° . However, it exhibits significant uncertainties in shortwave radiation parameterization, particularly in high-altitude regions. The CN05 dataset provides a spatial resolution of $0.25^\circ \times 0.25^\circ$, but its temporal coverage is limited to 2015, and the wind speed data rely on site interpolation, which diminishes its representativeness in wind farm areas. Although other high-resolution observational datasets are available, their coverage in the upper reaches of the Yellow River is limited, complicating their use in long-term sequential analysis. Considering the advantages and disadvantages of various datasets, the next step involves employing data fusion technology to enhance spatial and temporal resolution, thereby improving the accuracy of complementary analysis. The use of joint probability density distributions allows for the quantification of the probability of simultaneous occurrences of high precipitation and high radiation, thereby providing reference for hydro and solar energy compensation. In this study, we utilized CMFD reanalysis data spanning

from 1979 to 2018, which covers a broad area and an extended time frame. In contrast, the dataset employed in [12] has a shorter duration, which limits its capacity to reflect long-term trends of meteorological elements. Existing studies have primarily focused on the relationships between two elements, particularly the complementarity between shortwave radiation and wind speed [34–36]. In comparison, we examined the interactions between pairs of hydro-solar-wind elements within the same region. This comprehensive, multi-element analysis approach offers a more complete and detailed characterization of the energy complementarity.

(2) In terms of complementarity. We employed three correlation coefficients to calculate a comprehensive complementarity coefficient, effectively capturing the interactions between the different power factors and providing a scientific basis for optimizing the multi-energy system. Previous studies primarily utilized the Pearson correlation [37], Spearman correlation [38], and Kendall correlation [13] to analyze the relationships between pairs of variables. While these methods are effective, relying on a single statistical approach may overlook certain potential features of complementarity. In contrast, the introduction of the complementarity coefficient facilitates a more nuanced analysis of the complex interactions among power factors. Additionally, multi-scale analysis offers detailed insights into energy complementarity, enhancing the accuracy of energy dispatch and management, especially over short time scales. For instance, analyses conducted at daily and 3 h resolutions reveal complementarity in seasonal and intra-day resource fluctuations. Finally, the Copula function was employed to construct a joint probability density function for two elements, quantifying the probability density characteristics of various power factors. This method provides high precision in capturing the complementarity among different power factors [17]. In comparison, previous studies primarily used traditional statistical methods [39]. Although these approaches reveal basic relationships, they fail to fully capture the complementarity among power factors. By applying the Copula function, we accurately describe the joint distribution and dependency structures between different elements, enabling a more thorough analysis of complementarity. However, whether examining the changing trend of a single element or the complementary effects of two elements, it is essential to analyze the underlying physical mechanisms. This study not only reveals this phenomenon and its governing laws but also proposes a novel method for quantitatively evaluating the complementary effect. Consequently, the next step involves conducting an in-depth analysis of the physical mechanisms that give rise to this phenomenon.

(3) Compared with existing research. We conducted a systematic analysis of the spatiotemporal variations in the precipitation, shortwave radiation, and wind speed in the upper Yellow River region, and determined their complementarity characteristics. First, correlation or complementarity were identified between the precipitation and radiation, between the precipitation and wind speed, and between the radiation and wind speed. Ref. [40] identified synchronous variations between the shortwave radiation and wind speed in high-altitude regions, but they did not explore the impact of precipitation in detail. In this study, we extended their finding by comprehensively analyzing the interactions among the precipitation, radiation, and wind speed, thereby providing a more thorough complementarity analysis of the power factors. The negative correlation between precipitation and radiation indicates that the shortwave radiation decreases during periods of high precipitation, which is significant for hydro and solar energy compensation. Second, joint probability density analysis revealed that the complementarity between the precipitation and shortwave radiation is weak in summer and stronger in the other seasons across different time scales. The strength of our study lies in the comprehensive examination of a wider range of meteorological elements, providing robust support for energy planning.

6. Conclusions

The hydro-solar-wind power factors, namely, precipitation, shortwave radiation, and wind speed, across the four provinces of the upper Yellow River region (Gansu, Inner Mongolia, Ningxia, and Qinghai) were investigated using the China Meteorological Forcing Dataset (CMFD) from 1979 to 2018. This study identifies the spatiotemporal variation patterns and complementary characteristics of these power factors. The main conclusions drawn from this research are summarized below.

(1) In terms of the spatiotemporal patterns of the three power factors, precipitation exhibited an overall increasing trend, with an annual mean increase of 2.11 mm/a. Significant increases in precipitation were observed in Gansu and Ningxia, while levels remained relatively stable in Inner Mongolia and Qinghai. Conversely, shortwave radiation demonstrated an overall decreasing trend, with an annual mean decrease of 0.69 kW/m²/a. Notably, a significant decline in shortwave radiation was recorded in Qinghai, whereas Gansu, Ningxia, and Inner Mongolia showed relative stability in this regard. Similarly, wind speed exhibited a general decreasing trend, with an annual mean decrease of 0.007 m/s/a, although variations in wind speed differed across provinces. The most substantial decrease was noted in Inner Mongolia, while Qinghai maintained a relatively stable wind speed, with slight increases in certain instances. Spatially, precipitation decreases gradually from south to north, with the southern and southwestern regions of Qinghai experiencing higher precipitation levels, while the northwest of Gansu and the central part of Inner Mongolia report lower precipitation. Additionally, shortwave radiation levels diminish from west to east, with elevated radiation primarily found in the central region of Qinghai Province, whereas the eastern part of Inner Mongolia exhibits comparatively low radiation intensity. Wind speed decreases from north to south, with eastern Inner Mongolia and western Gansu exhibiting relatively high wind speed, while central Ningxia and southern Gansu experience lower wind speed.

(2) The complementarity coefficients between precipitation, shortwave radiation, and wind speed were analyzed across different time scales and temporal resolutions. Significant variations were observed in the complementarity coefficients between precipitation and shortwave radiation (P and R), precipitation and wind speed (P and W), and shortwave radiation and wind speed (R and W) throughout the region. The complementarity coefficients for P and R were negative, ranging from −0.019 to −0.029 at the 3 h resolution and from −0.384 to −0.429 at the daily resolution across all four provinces, indicating a strong complementarity at the longer daily temporal resolution. Conversely, the P and W coefficients were positive, ranging from 0.029 to 0.047 at the 3 h resolution and from 0.038 to 0.065 at the daily resolution, suggesting stable correlations at different resolutions. The R and W coefficients transitioned from positive (0.174 to 0.220) at the 3 h resolution to negative (−0.048 to −0.100) at the daily resolution across all four provinces, indicating a shift from correlation to complementarity at varying resolutions. Seasonal analysis revealed that at the 3 h scale, the average coefficient of P and R in spring is merely 0.05; in summer, the median of R and W is −0.1, reflecting light-wind complementary characteristics; in autumn, the complementarity among each combination is generally enhanced; while in winter, the coefficient of P and R increases to 0.25. At the daily scale, in spring, the coefficient of R and W approaches 0, indicating no correlation; in summer, the negative value of R and W expands to −0.3; and in winter, the coefficient of P and R rises to 0.2. Notably, the peak value of the 3 h resolution coefficient of P and R in winter is 1.25 to 1.5 times higher than that at the daily scale, underscoring the significance of high temporal resolution for collaborative and complementary evaluations.

(3) The probability density distributions for the single and dual power factors at the Longyangxia Clean Energy Base in Qinghai Province were analyzed. For the sin-

gle power factor, the RMSE of the log-normal distribution for precipitation was 0.171, which significantly outperformed the RMSEs of the Weibull and generalized extreme value (GEV) distributions. The Weibull distribution for shortwave radiation exhibited the best performance, with an RMSE of 0.037. Similarly, the GEV distribution for wind speed demonstrated the best fit, with an RMSE of 0.004. On a daily scale, the intervals with the highest probabilities of occurrence for precipitation, radiation, and wind speed are 0.1 to 3.4 mm, 4005.6 to 4836.0 W/m², and 1.3 to 2.6 m/s, respectively. Annually, the intervals with the highest occurrence probabilities for precipitation, radiation, and wind speed are 276.0 to 304.4 mm, 1832.6 to 1847.5 kW/m², and 1.7 to 1.8 m/s, respectively. The probability density distribution of the dual power factors was assessed by comparing the Clayton, Frank, and Gumbel Copula functions. The results indicated that the Gumbel Copula exhibited the lowest root mean square errors (RMSEs) of 0.459 and 0.419 for precipitation with shortwave radiation and precipitation with wind speed, respectively. Conversely, the Frank Copula demonstrated the lowest RMSE of 0.417 for the combination of shortwave radiation and wind speed. On a daily scale, the combined probability of various combinations—including low rainfall with weak radiation, high precipitation with strong radiation, low rainfall with weak wind speed, strong precipitation with strong wind speed, strong radiation with strong wind speed, and weak radiation with weak wind speed—is the highest. Conversely, on an annual scale, the combined probabilities of P and R, and P and W show significant changes, decreasing across all intervals. However, in the case of R and W, the highest combined probability occurs with strong radiation paired with weak wind speed and weak radiation paired with strong wind speed.

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