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Review

A Review of Solar and Wind Energy Resource Projection Based on the Earth System Model

Guanying Chen [1] and Zhenming Ji [1,2,3,*]

[1] School of Atmospheric Sciences, Sun Yat-sen University, Zhuhai 519082, China; chengy88@mail2.sysu.edu.cn
[2] Key Laboratory of Tropical Atmosphere-Ocean System, Ministry of Education, Zhuhai 519082, China
[3] Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), Zhuhai 519082, China
* Correspondence: jizhm3@mail.sysu.edu.cn

Abstract: Many countries around the world are rapidly advancing sustainable development (SD) through the exploitation of clean energy sources such as solar and wind energy, which are becoming the core of the sustainable energy transition. In recent years, the continuous advancement of Earth system models (ESMs) has facilitated numerous studies utilizing them to predict long-term and large-scale meteorological elements, consequently enabling forecasts of wind and solar energy. These forecasts provide critical guidance for formulating national renewable energy policies. Nevertheless, the current literature on ESMs predicting wind and solar energy lacks sufficient integration. Hence, to comprehend the focal points and future research prospects, we conducted this systematic review, employing four academic search tools to comprehensively analyze the relevant literature from the past five years. We summarized the general analytical process and compared the content and conclusions of the literature. The study reveals that future photovoltaic (PV) potential for electricity generation may increase in certain regions but decrease in others, while the global potential for concentrated solar power (CSP) may diminish, influenced by diverse factors and displaying significant regional disparities. In addition, wind resource trends vary in different regions, and forecasts exhibit considerable uncertainty. Therefore, many studies have corrected wind speeds prior to predicting wind energy. Subsequent research endeavors should concentrate on optimizing ESMs, investigating the impacts of technological innovation, and enhancing the prediction and analysis of extreme weather events.

Keywords: earth system model; projection; solar energy; wind energy

Citation: Chen, G.; Ji, Z. A Review of Solar and Wind Energy Resource Projection Based on the Earth System Model. *Sustainability* **2024**, *16*, 3339. https://doi.org/10.3390/su16083339

Academic Editor: Byungik Chang

Received: 11 March 2024
Revised: 9 April 2024
Accepted: 12 April 2024
Published: 16 April 2024

1. Introduction

The Millennium Development Goals (MDGs) constituted a set of time-bound targets and indicators established by the United Nations in 2000 to steer global endeavors in eradicating poverty, hunger, and other issues from 2000 to 2015. In 2015, upon the expiration of the MDGs, the United Nations proposed the Sustainable Development Goals (SDGs), comprising 17 new development objectives aimed at comprehensively addressing challenges in SD across society, the economy, and the environment from 2015 to 2030. This global initiative aims to advance SD, reflecting its prominent status as a key global concern. To achieve these goals, countries worldwide have implemented relevant policies tailored to their national contexts. In September 2020, China set the goal of reaching "Carbon Peak (CP)" by 2030 and achieving "Carbon Neutrality (CN)" by 2060. CP refers to the stage where carbon dioxide emissions reach their peak and begin to decrease, while CN refers to offsetting or balancing carbon emissions through various measures to achieve a net-zero carbon emissions status. The CP goal and the CN goal are collectively referred to as the "Dual Carbon (DN)" goal, which requires accelerating carbon reduction, adjusting energy and industrial structures, vigorously developing clean energy, and gradually replacing traditional energy sources. Similarly, the United States is endeavoring to decrease reliance on fossil fuels by promoting the development of clean energy. The Reduce Inflation Act [1], introduced in 2022, serves as an effective policy supporting the transition to sustainable energy. In Europe, the European Union (EU) announced the "REPowerEU" plan, a collective initiative by EU member states aimed at promoting renewable energy usage and diminishing dependence on fossil fuels, with the intention of facilitating energy transition and ending reliance on fossil fuels by 2030 [2]. These recent policy initiatives underscore the global emphasis on energy transition and the development of clean energy. Among various clean energies, wind and solar energy have emerged as pivotal options owing to their mature technologies and lower generation costs. As shown in Figure 1, the number of installed wind and solar power plants has grown globally over the past decade [3]. Hence, studying the future utilization of these clean energy sources and predicting changes in energy potential is of significant importance.

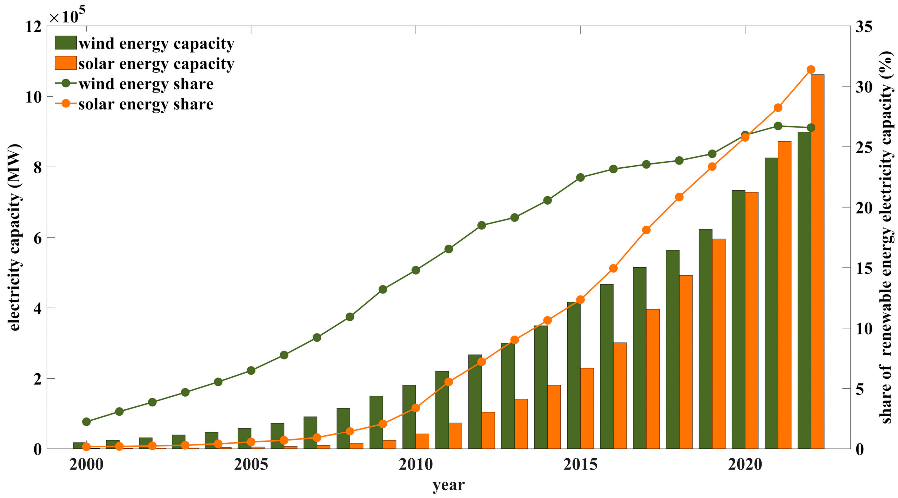

Figure 1. Solar and wind energy electricity capacity and share of renewable energy electricity capacity. Data source: IRENA (2023), Renewable Capacity Statistics 2023; and IRENA (2023), Renewable Energy Statistics 2023, the International Renewable Energy Agency, Abu Dhabi [3].

Considering the significance of forecasting future changes in clean energy sources, researchers have employed various methods in recent years. Various algorithms have been utilized for short-term wind energy potential and power generation prediction [4–8], demonstrating high precision and accuracy. Additionally, methods such as the Weibull and Rayleigh distribution functions [9–12], nonparametric copula models [13,14], basic statistical prediction methods like the fast filtering algorithm and variational modal decomposition [15], the autoregressive error-compensated hybrid wind power prediction model [16], and multi-model hybrid methods [17–19] are commonly employed for wind speed and wind energy prediction. For predicting solar energy, methods based on Geographic Information System (GIS) technology [13] and empirical models utilizing insolation data [20] are prevalent. However, most of these methods are limited to short-term forecasts, typically spanning a few hours, owing to technical constraints.

To address global climate change and support the aforementioned goals and policies, long-term energy use projections are imperative for timely policy adjustments. Near-surface wind speed and surface shortwave radiation significantly influence the potential for solar and wind energy. Therefore, the accurate prediction of wind speed and near-surface shortwave radiation is crucial for exploring future changes in wind and solar potential. In climate change research, meteorological elements such as near-surface wind speed and shortwave radiation are primarily simulated and predicted using Earth system models (ESMs).

ESMs serve as mathematical tools for simulating and describing interactions among various components of the Earth's climate system, encompassing the atmosphere, oceans, land, and ice, across past, present, and future climate scenarios [21,22]. ESMs are commonly categorized into global climate models (GCMs) and regional climate models (RCMs), differing in the scale of analysis. GCMs simulate climate change scenarios globally but are hindered by low resolution and limited computational resources, leading to inaccuracies in simulation results, particularly in atmospheric processes such as clouds and convection [23,24]. Conversely, RCMs provide higher resolution and more precise climatic information by detailing topography, land, and sea features [25,26]. In recent years, ESMs have undergone refinement, yielding several excellent models. To assess GCM performance, the World Climate Research Program (WGCM) conducted six model comparison programs, including the ongoing Coupled Model Intercomparison Project Phase 6 (CMIP6), proposed in 2013 [27]. CMIP6 builds upon previous comparison programs to enhance understanding of climate variability and advance climate model simulations, assessments, and attributions of climate change [28]. Data from all participating models in CMIP6 are openly available for global scientific research, including studies on renewable energy. However, the low resolution of GCMs poses challenges for targeted responses to climate change and adaptation strategies, demanding more precise predictions at regional levels. Downscaling techniques bridge this gap by converting coarse GCM data into high-resolution regional data [29,30]. Currently, three prevalent downscaling methods are commonly utilized: dynamical downscaling, statistical downscaling, and combined dynamical and statistical downscaling methods [31–33]. The most widely used downscaled dataset is the Coordinated Regional Downscaling Experiment (CORDEX) dataset. The utilization of ESM outputs for assessing renewable energy potential is gaining traction, supported by ongoing ESM advancements, international programs (e.g., CMIP and the CORDEX) for model improvements, and advances in downscaling techniques.

To identify current research focuses and guide future studies, this paper systematically reviews and synthesizes research conducted over the past five years on wind and solar energy prediction utilizing ESMs. It outlines the methodologies employed, analyzes the results, identifies commonalities and differences in predictive outcomes, and explores the underlying reasons behind these similarities and disparities. The structure of this article is as follows: Section 2 presents the sources of the articles studied. Section 3 organizes the analysis process of the literature. Section 4 analyzes and organizes the content of the literature, explains the reasons for the errors in model predictions, and proposes future research prospects. Finally, in Section 5, a summary of this paper is provided.

2. Materials and Methods

The objective of this article is to present an updated overview of solar and wind energy projections based on results derived from ESMs. The review will encompass articles that provide projections directly derived from various ESM outputs, as well as those utilizing data from the CMIP or CORDEX programs. Literature acquisition involved utilizing four primary academic search tools: Web of Science, Google Scholar, ScienceDirect, and Scopus. Searches were conducted using a combination of keywords such as "wind energy", "wind potential", "wind generation", "solar energy", "solar potential", "solar generation", "photovoltaic", "concentrated solar power", "CMIP", "CORDEX", and "earth system model". Preliminary screening was conducted to ensure relevance to the review's topic, with the final inclusion criteria as follows:

1. Simulation results from ESMs were used.
2. Analysis of future projections related to solar and wind energy. Previous articles employed representative concentration pathways (RCPs) for projection scenarios, while recent articles utilize shared socioeconomic pathways (SSPs). RCPs are based on varying levels of radiative forcing due to anthropogenic greenhouse gas and aerosol concentrations, categorized into four levels: RCP2.6, RCP4.5, RCP6.0, and RCP8.5, with RCP8.5 representing the highest emission scenario [34]. SSPs, on the other hand, are based on the current actual situation of countries and regions, as well as development plans to obtain specific socioeconomic development scenarios.

SSP1 to SSP5 represent five representative scenarios, combined with RCPs to form the RCP-SSP framework, with SSP585 representing a highly carbon-emitting scenario [35].

3. Publications between 2019 and 2023 were included. The start date of 2019 was chosen to focus on recent studies and understand the latest research trends and priorities.

A total of 99 studies meeting these criteria were analyzed, and the specific list of references is provided in Table 1. The number of papers has notably increased over the last five years, indicating a rising trend in the use of ESMs for solar and wind energy forecasting. Notably, there is a larger quantity of the literature on wind energy prediction compared to that on solar energy, potentially due to the higher uncertainty associated with wind energy prediction. This underscores the necessity for further research to enhance the accuracy of wind energy forecasting and the reliability of wind energy generation systems.

Table 1. Studies meeting the criteria and being analyzed.

Study	Geographic Area	Model Data Source
	Solar resource	
	World	
[36]	World	CMIP6
[37]	World	CMIP5
[38]	World	CMIP5 And CMIP6
[39]	World	CMIP6
[40]	World	CMIP5
[41]	World	CMIP5
	Asia	
[42]	China	CMIP6
[43]	China	CORDEX
[44]	China	CMIP6
[45]	China	CMIP6
[46]	China	CMIP6
[47]	China	CMIP5
[48]	China	CMIP6
[49]	Fukushima, Japan	Model coupled crop–meteorological database Ver.2
[50]	Iraq	Community Climate System Model (CCSM)
	Europe	
[51]	Europe	CORDEX
[52]	Europe	CMIP5
[53]	Europe	CMIP6
[54]	Greece	Weather Research and Forecasting Model (WRF)
[55]	Italy	CORDEX
[56]	French	CORDEX
[57]	the Canary Islands, Spain	CMIP5
	Africa	
[58]	Africa	CORDEX
[59]	Africa	CORDEX
[60]	West Africa	CMIP6
[61]	West Africa	CORDEX
[62]	Zambia	CORDEX
	South America	
[63]	South America	CORDEX
[64]	Southwestern Colombia	CORDEX
[65]	Brazil	CMIP6
[66]	the Atacama Desert, Chile and Peru	CORDEX

Table 1. *Cont.*

Study	Geographic Area	Model Data Source
	Solar resource	
	North America	
[67]	North America	CMIP6
	Oceania	
[68]	Australia	New South Wales/Australian Capital Territory Regional Climate Modelling regional projections (NARCliM)
[69]	Australia	CORDEX
	Wind resource	
	World	
[70]	world	Community Earth System Model (CESM)
[71]	Northern Hemisphere	CMIP5 and CMIP6
	Asia	
[72]	East Asia	CORDEX
[73]	South Asia	CORDEX
[74]	India	CORDEX
[75]	China	CORDEX
[76]	China	CORDEX
[77]	China	MPI-ESM-LR, CNRM-CM5, CSIRO-Mk-3.6.0
[78]	China	CORDEX, Providing Regional Climates for Impacts Studies (PRECIS)
[79]	South China Sea	regional climate model, Version 4.7 (RegCM4.7)
[80]	Hong Kong, China	CMIP6
[81]	Vietnam's tropical area	RegCM4
	Europe	
[82]	Europe	CMIP6
[83]	Europe	CORDEX
[84]	Northern Europe	CMIP6
[85]	Ireland	CMIP6
[86]	Italy	CORDEX
[87]	Ireland	CORDEX
[88]	Germany	CORDEX
[89]	Greece	WRF
[90]	Greece	Rossby Centre Regional Atmospheric Model, Version 4 (RCA4)
[91]	Spain	CORDEX
[92]	Portugal	CORDEX
[93]	Iberian Peninsula, Spain and Portugal	CORDEX
[94]	Republic of Serbia	Erdemli-Basin-Uni Oslo–Physical Oceanography Model (EBU-POM), Nonhydrostatic Multiscale Model on B-grid (NMMB)
[95]	Lithuania	MPI-ESM-LR, IPSL-CM5A-M
	Africa	
[96]	Northwestern Africa	CORDEX
[97]	West Africa	CMIP6
[98]	West Africa	CORDEX
[99]	West Africa	CORDEX
[100]	Southwestern Africa	CORDEX
[101]	Zambia	CORDEX
[102]	Morocco	CORDEX
[103]	Egypt	CMIP6

Table 1. *Cont.*

Study	Geographic Area	Model Data Source
Solar resource		
South America		
[104]	South America	CMIP6
[105]	Suriname	CMIP5
North America		
[106]	North America	CORDEX
[107]	North America	CMIP6
[108]	North America	Canadian Centre for Climate Modelling and Analysis (CCCma)
[109]	Canada	WRF
[110]	United States	CORDEX
[111]	Alaska's Offshore Regions	WRF
Others and seas		
[112]	Australasia and Southeast Asia	CMIP6
[113]	Arctic and Subarctic	RCA4
[114]	Caribbean	CORDEX
[115]	Black Sea	RCA4
[116]	Northwest Passage	CMIP6
[117]	Black Sea	RCA4
[118]	Baltic Sea	RCA4
[119]	North Sea	RCA5
[120]	Persian Gulf	CORDEX
[121]	North Sea and Irish Sea	CORDEX
Solar and wind resource		
[122]	China	WRF, RegCM4
[123]	Europe	CMIP5
[124]	Europe	CORDEX
[125]	Portugal	WRF
[126]	Portugal	CORDEX
[127]	Iberian Peninsula, Spain and Portugal	CORDEX
[128]	Africa	RegCM4
[129]	West Africa	CORDEX
[130]	Brazil	CMIP5
[131]	Texas, United States	WRF, RegCM4
[132]	Texas, United States	WRF, RegCM4
[133]	Latin America	ISIMIP2
[134]	Arab countries	RegCM, ECHAM5-MPIQM

3. The Main Process of Literature Analysis

Forecasts of wind and solar energy typically involve two main aspects: potential forecast and actual production forecast. The potential forecast involves assessing the availability of wind and solar energy, while the actual production forecast pertains to predicting electricity generation from these renewable sources. It is important to recognize that an increase in energy potential in a region may not necessarily lead to a corresponding increase in actual power generation if the installed capacity does not keep pace. Therefore, forecasting changes in the proportion of renewable energy in power generation production is crucial for formulating sustainable energy policies and plans. This necessitates forecasting not only potential but also electricity production, accounting for installed capacity and power generation technology development.

ESM outputs provide meteorological elements such as solar radiation, wind speed, and air temperature, among others. The conversion from these meteorological elements to metrics of energy potential or power generation production for resource assessment involves the following steps:

1. Bias correction of model results. Due to the limitations of model outputs, discrepancies between model results and actual observations may occur. Therefore, some studies perform bias correction on model results before making predictions to enhance forecast accuracy.
2. Assessing the accuracy of model outputs or the corrected model results. Various assessment indicators such as deviation, root-mean-square error, and other metrics are employed using meteorological data from the model's historical time series and actual observational data or reanalysis data (e.g., ERA5, etc.) in the study area. Analyses are conducted using various indicators to evaluate the quality of the model's results and enhance the credibility of the prediction outcomes.
3. Calculating energy potential indicators. For predicting solar energy potential, two main types are considered: photovoltaic (PV) potential and concentrating solar power (CSP) potential. Most of the literature utilizes the calculation method proposed by Crook et al., 2011 [135], where solar radiation reaching the surface, surface wind speed, and surface air temperature are considered for PV potential. For CSP potential, the primary consideration is the capacity of parabolic trough collector (PTC) technology for power generation, accounting for surface air temperature and solar radiation reaching the surface. For predicting wind energy potential, a wind power density of 100 m is typically used since the hub height of commonly used turbines is around 100 m from the surface, with adjustments made based on turbine specifications in the area.
4. Estimating power generation. Power generation can be calculated using tools like the Global Solar Energy Estimator (GSEE) or the open-source PVLIB Python toolkit for modeling PV energy systems [39,44,52,64,67,74]. Based on the capacity of power generation units installed in the study area or commonly available installations on the market and combined with assumptions such as fixed-tilt or single-axis tracking and loss efficiency, the power generation output under corresponding meteorological factor data is calculated [125,131,133]. Some of the literature characterizes power generation using the capacity factor, reflecting the effective utilization of the installation [44,132,133].

The flowchart of the literature analysis process is shown in Figure 2. Different studies choose to predict potential or power generation based on their research purpose and significance.

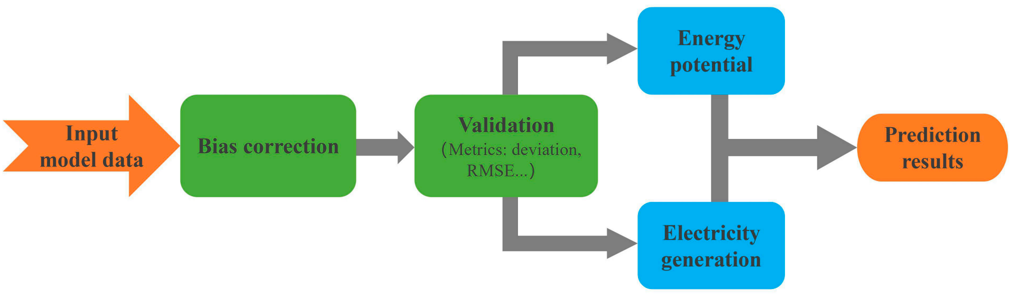

Figure 2. The main process of literature analysis.

4. Discussion

4.1. Forecasts of Solar and Wind Energy

According to the information listed in Table 1, the CMIP program is favored by the majority of studies due to the datasets covering long time scales and various future climate scenarios and variables. Additionally, the CORDEX program dataset is influential in regional investigations because of its focus on regional climate simulations, offering data with relatively high spatial resolution. Researchers often utilize RCMs such as the Weather

Research and Forecasting (WRF) model to further refine their analyses. Notably, among regional-scale studies, Africa appears as a focal point of extensive research, closely followed by China and Europe.

4.1.1. Solar Energy

Future Changes in Solar Energy

From a global scale analysis, multiple GCMs resulting from CMIP5 and CMIP6 have been predominantly utilized to forecast solar energy [36,40]. Notably, several studies have focused on analyzing the worst-case scenario (RCP8.5 and SSP585). These studies have found significant future increases in photovoltaic (PV) power generation potential in regions such as Europe, northern South America, and Central China, while declines are predominant in regions like North Africa, the Tibetan Plateau, South Asia, and northern North America. However, South Africa exhibits an opposite trend, possibly due to the better statistical significance and inter-model consistency of CMIP6 meteorological element indicators [38]. In the case of CSP, a decrease is expected globally. Regarding power generation, under the SSP585 scenario, electricity generation is projected to increase in Europe, northern South America, and East Asia, in line with the changes in photovoltaic potential. However, South Asia experiences a slight increase in photovoltaic potential [39]. For regions like Europe and Asia, where solar potential and power generation production vary significantly, there is considerable disparity between different SSPs. Given the strong correlation between solar energy and sunshine hours, seasonal analysis has been conducted in numerous studies. Findings reveal that under different SSPs, the PV potential of South Asia decreases during September–October–November (SON), while it rises in northern South America and Europe, decreases in Europe during December–January–February (DJF), decreases in Southern Africa during June–July–August (JJA), and does not vary significantly across the globe during March–April–May (MAM) [36,39]. Additionally, climate change may lead to decreased solar power output due to an increase in the frequency of extreme weather [37]. Thus, the vulnerability of solar energy supply will continue to increase in the future without intervention in fossil fuel development.

From a regional scale perspective, utilizing GCM-driven RCMs in EURO-CORDEX reveals that the future PV potential in Europe will decrease. The inconsistency of this change with the global-scale analysis may be due to the fact that the aerosol forcing in the CORDEX simulation does not evolve over time, thus affecting the simulation performance of variables such as solar radiation [51]. The choice of different RCMs can also have an impact on projections, which may have a greater effect over time than the impact of long-term climate change [122]. Thus, the simulation performance of the ESMs for the study area must be taken into account when making projections. An analysis of South America using CORDEX-CORE results indicates that solar PV potential predictions are almost the same as those global-scale analyses, while the analysis of electricity production indicates that PV production will not be significantly affected in most regions [63]. A detailed study of the Chinese region also demonstrates that PV potential is growing in Central China [42,46,47]. Similarly, a regional study of Africa utilizing CORDEX-AFRICA data finds that the PV potential of North Africa is decreasing in the future [58,59]. For CSP, fewer studies carried out examinations from a regional scale perspective and will not be discussed here.

Factors Influencing Solar Energy

Factors affecting future changes in solar energy have been analyzed in several articles. The pathways of various factors influencing solar energy can be referred to in Figure 3. Surface solar radiation, near-surface air temperature, and wind speed are among the most crucial factors impacting solar energy potential and power generation. Surface solar radiation directly determines the amount of solar energy captured by solar panels, while wind speed and near-surface air temperature affect solar energy by influencing the performance of power generation equipment.

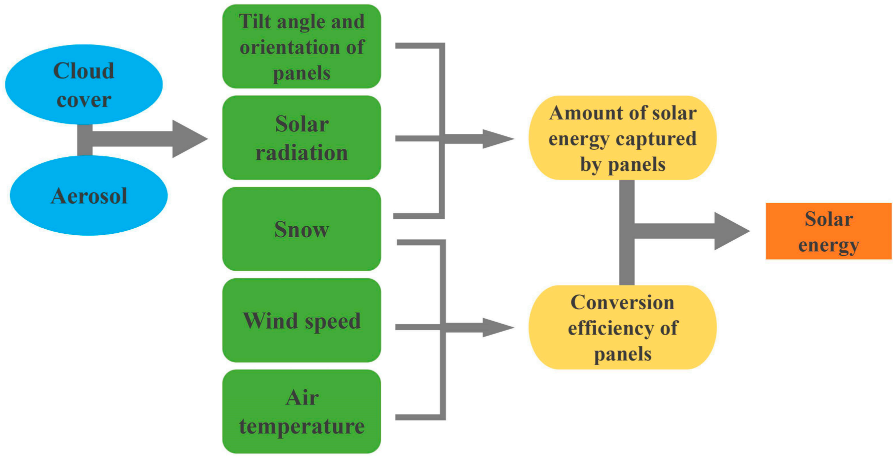

Figure 3. Factors affecting future changes in solar energy.

Changes in solar radiation are primarily influenced by cloud cover and aerosol emissions, so there are some studies directly investigating the effects of these factors on solar energy [39,45,65]. Findings suggest that increased aerosols and cloud cover caused by climate change will lead to a decrease in solar energy potential. Furthermore, climate change will lead to an elevation in the frequency of both high temperatures and increased cloud cover in the future. These changes will result in a reduction in photovoltaic power generation in summer [37]. Some studies have shown that higher wind speeds can help in the convective cooling of solar panels [39], generally boosting the efficiency of PV power generation [50]. However, excessively high wind speeds may cause panel damage, leading to decreased generation efficiency [136]. There are studies analyzed by Spearman's rank correlation coefficient revealing a negative correlation between wind speed and PV output [122]. Regarding the effect of air temperature, high temperatures lead to a decrease in the number of thermally excited electrons, reducing the open-circuit voltage, which leads to a decrease in the efficiency of solar panels [42,55,61]. The rate of global warming is amplified with increasing latitude and altitude [137], so high latitudes will be more susceptible to the impacts of rising temperatures on solar power generation. Simultaneously, temperatures in low latitudes will become increasingly extreme in the future, resulting in reduced photovoltaic power generation output [37]. Solar panels in urban areas will be more susceptible to the adverse effects of temperature compared to those in rural areas due to the urban heat island effect [42]. It is worth noting that as technology advances, the influence of external factors on panel power generation efficiency diminishes. Thus, considering revolutionary updates of panels aids in more accurately predicting the impact of temperature and wind speed on solar power generation.

The contributions of these meteorological factors to the impact of solar energy vary across different regions. In the archipelagos of Northwest Africa and South America, photovoltaic power generation is primarily influenced by increased solar irradiance [57,64], whereas in West Africa, Australia, and China, it is mainly affected by changes in temperature [44,61,68]. Furthermore, as climate change leads to variations in all three factors—solar radiation, wind speed, and temperature—in some areas, the increase in solar radiation may be offset by rising temperatures, resulting in little to no net increase or even a decrease in photovoltaic power generation [50,64,65]. Therefore, when considering the impact of meteorological elements on the future distribution of solar energy, it is essential to comprehensively assess the effects of multiple meteorological factors.

Additionally, the extent to which surface solar radiation can be received depends on the tilt angle and orientation of the PV panels, so there are also several studies delving into this factor [59]. Moreover, consideration must be given to both direct and diffuse solar irradiance reaching the PV panels to accurately determine their ultimate conversion efficiency. Studies have also explored the impact of snow on PV systems, particularly in high-latitude regions where snow accumulation can significantly affect system efficiency. Climate change has been found to reduce snowfall losses from PV systems in certain regions, highlighting the importance of understanding how changing climate patterns may alter the performance of solar energy systems [67]. This research underscores the need to account for various environmental factors, including snow cover, when assessing the overall efficiency and effectiveness of solar panel installations.

4.1.2. Wind Energy

Future Changes in Wind Energy

With global climate change, there is an overall increasing trend in wind resources globally. However, when analyzed at a regional level, the impacts of climate change exhibit geographical variations. Consequently, most of the surveyed literature conducts simulation analyses on specific areas, distinguishing wind energy prediction from solar energy prediction. Moreover, the installation of offshore wind farms worldwide offers numerous advantages, including vast sea areas available for installation, higher potential power generation capacity compared to that of inland wind farms, and more stable wind speeds on coasts and shores. Consequently, the total installed capacity of both onshore and offshore wind power has continued to increase in recent years [110]. In the surveyed literature, studies on coastal and offshore wind resource prediction and assessment comprise the majority of research efforts in this field.

In the Asian region, wind resources along the Black Sea coast are predicted to increase in the future. Analysis of the coefficient of variation indicates that wind resources along the Black Sea coast will become more stable and less volatile in the future [115,117]. Several studies in China have been analyzed in detail, revealing a general decrease in wind resources across the country [76,78], with some exceptions. An increase may occur in the northern part of the South China Sea. However, predictions for southeastern China vary depending on the models used [78,122]. Similarly, a slight decrease in wind power has been found in the wind-rich Tibetan Plateau [75], while a study of the entirety of East Asia by Li, D. et al., 2020 [72], predicts an increase in wind resources in this region. Differences also exist in the analysis of wind resources in Vietnam. One study found that wind resources in most areas of Vietnam will increase in the future [112], while another study indicated a decrease in wind resources in Vietnam's tropical seas [81]. In Europe, the analysis of the entire European region shows that wind resources in Northern Europe and the Central Mediterranean decrease significantly under the SSP585 and SSP245 scenarios. Changes in wind energy resources in most other regions primarily depend on the selection of future scenarios. Under the highest emissions scenario (SSP585), Europe is forecasted to experience an overall reduction in wind resources [82]. Additionally, the capacity factor exhibits a weak decreasing trend in the future [83]. A regional analysis of Europe reveals a significant weakening of wind resources in some regions, such as the Iberian Peninsula, Serbia, Ireland, and Italy [85–87,93,94], while some areas show an increasing trend, such as the Baltic Sea and the North Sea in Spain [91,118,119]. In the African region, studies focus on the West African region, where wind energy is expected to continue increasing in the future, especially from June to August [97], and the magnitude of the increase will increase according to the increased emission level [99], but there may be a pronounced downward trend in the winter [98]. In the Americas region, the analysis of the entire South American region reveals a significant increase in wind energy density in the future [104], but its variability on hourly and monthly scales is high, potentially leading to increased volatility in wind power output [133]. Similarly, an analysis of North America found that, like Europe, there is no clear demarcation between areas of increase and decrease, with some areas experiencing growth while others decline, and this trend varies across seasons [99]. For example, the west coast of the United States boasts abundant wind resources, while the east coast will experience a decrease [106,110], and most areas in Canada will also see a reduction [109]. Additionally, similarly to South America, an increase in variability is expected in the future [82].

The selection of models and future scenarios may result in inconsistent changes in wind resource predictions in specific areas. Furthermore, model simulations may deviate, resulting in diverse prediction outcomes.

The Variability of Wind Energy

Significant variations at the hourly temporal scale cause discontinuous changes in wind resource prediction, resulting in notable instability in wind power generation. Consequently, several studies have utilized the coefficient of variation to analyze variability across different regions and temporal scales. In North America, influenced by temperate cyclones, certain areas demonstrate greater variability compared to neighboring regions, with the coefficient of variation potentially being positive or negative across diverse regions [107]. Investigations in Australia and Southeast Asia reveal that while Australia's wind power remains relatively stable, significant differences in variability exist among regions in Southeast Asia. Studies on the temporal variability of wind energy potential in East Asia and Europe indicate that the interannual and intra-annual variability in most regions of both continents will increase in the future, with the increase toward the end of the century being more significant compared to the near term. However, the increase in variability in the Nordic region is significant only under the SSP585 scenario [72,82,84]. Research identifies differences in the temporal variability of wind resources among emission scenarios, with higher emission scenarios leading to notably greater variability compared to lower emission scenarios [84]. Overall, future variability in wind resources is expected to increase. In analyzing the future wind energy variability in Egypt, it was found that the interannual variability of wind power potential is highest in the Gulf of Suez region under different future scenarios [103]. The variability of wind resources significantly impacts the planning and investment costs of wind farms, underscoring the importance of studying future changes in wind resource variability.

Bias Correction in Wind Energy Forecasting

In comparison to solar resource forecasts, the accuracy of wind resource predictions relies heavily on the precision of wind speeds, which are more challenging to accurately simulate in ESMs. The accuracy of ESMs' output results largely depends on the spatial and temporal resolution during the simulation process. The primary assessment index for wind energy is wind power density, which is directly proportional to the cube of wind speed. Therefore, even slight deviations in wind speed can significantly impact wind energy assessments. Since wind speeds can vary significantly over small scales, such as near mountain ranges [82], it is essential to model wind speeds with sufficiently fine resolution to achieve better simulation results [138] and thus more accurately predict future wind resource variability. Consequently, some of the literature will bias-correct wind speed before wind resource prediction. One widely employed bias correction method for future climate analysis is quantile mapping (QM), which effectively reduces the bias of simulated wind speeds by aligning them more closely with the wind speed distribution function of the validation data (e.g., reanalysis data or observation data) [81,93,104,121]. However, this technique cannot correct wind direction, and it has shown robustness in correcting wind speeds in some areas [139,140]. Besides this technique, some literature has also employed other approaches to correct and thereby enhance the accuracy of wind resource prediction. For instance, a study utilizes the multivariate bias adjustment method [72]. Alternatively, to select the ESMs with the best simulation in the study area, a multi-criteria decision-making method is employed for screening and ranking. Subsequently, the simulated wind speed data are processed using the Copula method to obtain enhanced predictions [85]. Additionally, the model output results can be adjusted using the Global Wind Atlas (GWA2) [83].

4.2. Reasons for Model Prediction Errors

The simulation of RCMs relies on initial field and boundary conditions, which inherently contain biases and uncertainties [141]. Consequently, RCMs may exhibit systematic biases originating from the inherited biases of the driving fields [142]. Since models cannot fully capture the complexities of the climate system in reality [81], simplifying assumptions in the simulation of meteorological elements such as solar radiation, temperature, and wind speed can introduce biases in simulations of physical phenomena such as clouds and precipitation, thereby affecting relevant meteorological elements. For instance, changes in aerosols can influence ground-reaching meteorological elements through cloud changes, subsequently affecting the radiation reaching the surface [143]. Some current models lack comprehensive consideration of the radiative effects of aerosols, such as the CORDEX simulation, which excludes the radiative impacts of both natural and anthropogenic aerosols [127], potentially introducing bias into solar radiation predictions. The nonlinear combination of these biases with unpredictable natural variability further exacerbates the simulation results, leading to deviations from reality [144]. Moreover, the coarse resolution of GCMs causes the model results to not be directly applicable at the point scale [105], leading to significant analytical errors. For wind speed simulations, a finer resolution of 2–10 km is needed to better characterize the details of wind variability in mesoscale circulations such as sea breezes and mountain winds [138]. Most studies indicate that increasing model resolution enhances the performance of model simulations, but some studies show that an increase in resolution does not necessarily correlate with a reduction in model bias [145]. Another study demonstrates that the effect of spatial discretization may vary depending on model parameters and the spatial scale of the simulation [146]. Importantly, the systematic biases mentioned earlier cannot be mitigated by increasing the resolution of ESMs [145]. Furthermore, running ESMs requires a large amount of computational resources, which may also contribute to bias due to resource limitations [93,147].

4.3. Future Research Prospects

Based on the research gaps and prospects outlined in the literature, we have identified three main issues and proposed corresponding solutions, with the expectation that these measures will enhance the accuracy of ESMs in predicting future wind and solar energy.

Several studies indicate the presence of errors in model simulations [99], leading to biases in future predictions, particularly in the assessment of wind resources [82]. Models exhibit significant discrepancies in simulating wind speeds. Given the reasons for the simulation errors mentioned earlier, addressing this issue involves continuously optimizing the construction of climate models to enhance the accuracy of model outputs [38,61]. Additionally, countries need to construct wind and solar power plants and adjust renewable energy supply configurations based on local terrain and atmospheric conditions [102], which require improvements in resolution to simulate small-scale variations. Increasing spatial resolution aids in more accurately simulating atmospheric processes such as precipitation and cloud formation [122], thus improving the accuracy of meteorological element simulations. Furthermore, assessing wind and solar energy resources in specific regions can provide valuable references for the site selection of power plants and selection of wind turbines [79,114]. Increasing temporal resolution facilitates planning optimal strategies and studying supply demand balances on daily or even hourly scales.

Many current studies overlook advancements in solar energy generation technologies when predicting future solar resources, primarily concentrating on the conversion efficiency of monocrystalline silicon solar panels, the prevailing technology at present. However, earlier research indicates that improving the efficiency of solar panels enhances photovoltaic power generation [148]. Over the past decade, significant advancements have been made in solar energy generation technologies and materials [149], with new materials exhibiting different responses to external factors such as temperature. Similarly, there is a lack of consideration for advancements in wind energy conversion technologies [82,105]. In recent years, the power conversion capacity of offshore wind turbines has been continuously increasing [78], and the hub heights of wind turbines have also been changing [100,150,151].

Therefore, future research should consider advancements in conversion technologies to more accurately predict future wind and solar resources.

According to the Intergovernmental Panel on Climate Change (IPCC) report, extreme weather events resulting from climate change are expected to increase [152]. Several studies have indicated that extreme high temperatures can lead to a decrease in the conversion efficiency of solar panels [46,48,68]. Strong winds do not necessarily enhance the output of wind turbines, and weak winds cannot allow wind turbines to operate [153]. Extreme weather events, such as extreme wind speeds and extreme high temperatures, affect the structural reliability and safety of wind turbines and solar panels [90,104], as well as production stability, leading to decreased accuracy in predicting renewable energy [125]. While many studies have focused on the frequency and intensity of extreme weather events, there is a lack of targeted research on extreme weather events affecting the efficiency of wind turbines and solar panels. Therefore, future research should analyze and predict the frequency and intensity of extreme weather events affecting wind turbines and solar panels [109,119].

5. Conclusions

Many countries around the world are actively striving to achieve SDGs, with wind and solar energy emerging as increasingly crucial clean energy sources and pivotal drivers of the transition to sustainable energy. With the global demand for renewable energy continuing to surge, the focus on future changes in wind and solar energy is also intensifying. In recent years, the development of ESMs has played a crucial role in predicting changes in wind and solar energy, offering indispensable data and methodological support for associated research endeavors. These models not only simulate and forecast future climate change trends but also provide dependable predictions concerning the potential and power generation of wind and solar energy. Consequently, the research field employing ESMs for forecasting solar and wind energy is expanding and deepening. However, there is currently a lack of a systematic review of the literature in this field. Therefore, to comprehensively grasp the latest developments and research trends in this domain and to identify future research directions, this review has compiled the relevant literature from the past five years and compared the research conclusions. It outlines the general analysis process and presents the main findings and discussion points as follows:

- In the future, an increase in PV power generation potential is anticipated in Europe, northern South America, and Central China, while a decrease is expected in North Africa, the Tibetan Plateau, South Asia, and northern North America. Globally, CSP potential is anticipated to decrease. The changes in solar resources are influenced by cloud cover, aerosols, temperature, and wind speed, with the impact varying by region.
- Wind resources are projected to increase on a global scale in the future. However, disparities in changes exist across various regions, with some studies yielding inconsistent results within the same region. Uncertainty in wind resource forecasts necessitates many studies to conduct bias correction on wind speeds before forecasting wind resources.
- Based on the limitations of the current analysis, future research in this field should explore various aspects to enhance the accuracy and reliability of predictions. Firstly, ESMs should be optimized, which requires further improvement of the physical and chemical processes within the models, coupled with increasing resolution. Secondly, considering the ongoing advancements in wind and solar power generation technologies, future studies should place greater emphasis on the impact of these technological innovations on the distribution of future energy resources. Additionally, since extreme weather events significantly affect wind turbines and solar panels, it is imperative for future research to enhance the prediction and analysis of such events. By conducting comprehensive research in these areas, we can improve our understanding and predic-

tion of the distribution and trends of future wind and solar energy resources, thereby providing stronger support for the SD of renewable energy.

Author Contributions: Methodology, G.C.; investigation, G.C.; writing—original draft, G.C.; supervision, Z.J.; editing, Z.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China (Grants No. 42275192), as well as the Innovation Group Project of Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai) (No.311022006).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors of this paper declare that there are no direct or indirect financial interests that may give rise to bias in the work, conclusions, implications, or opinions of this study, and that there are no personal relationships or affiliations that may influence this study.

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