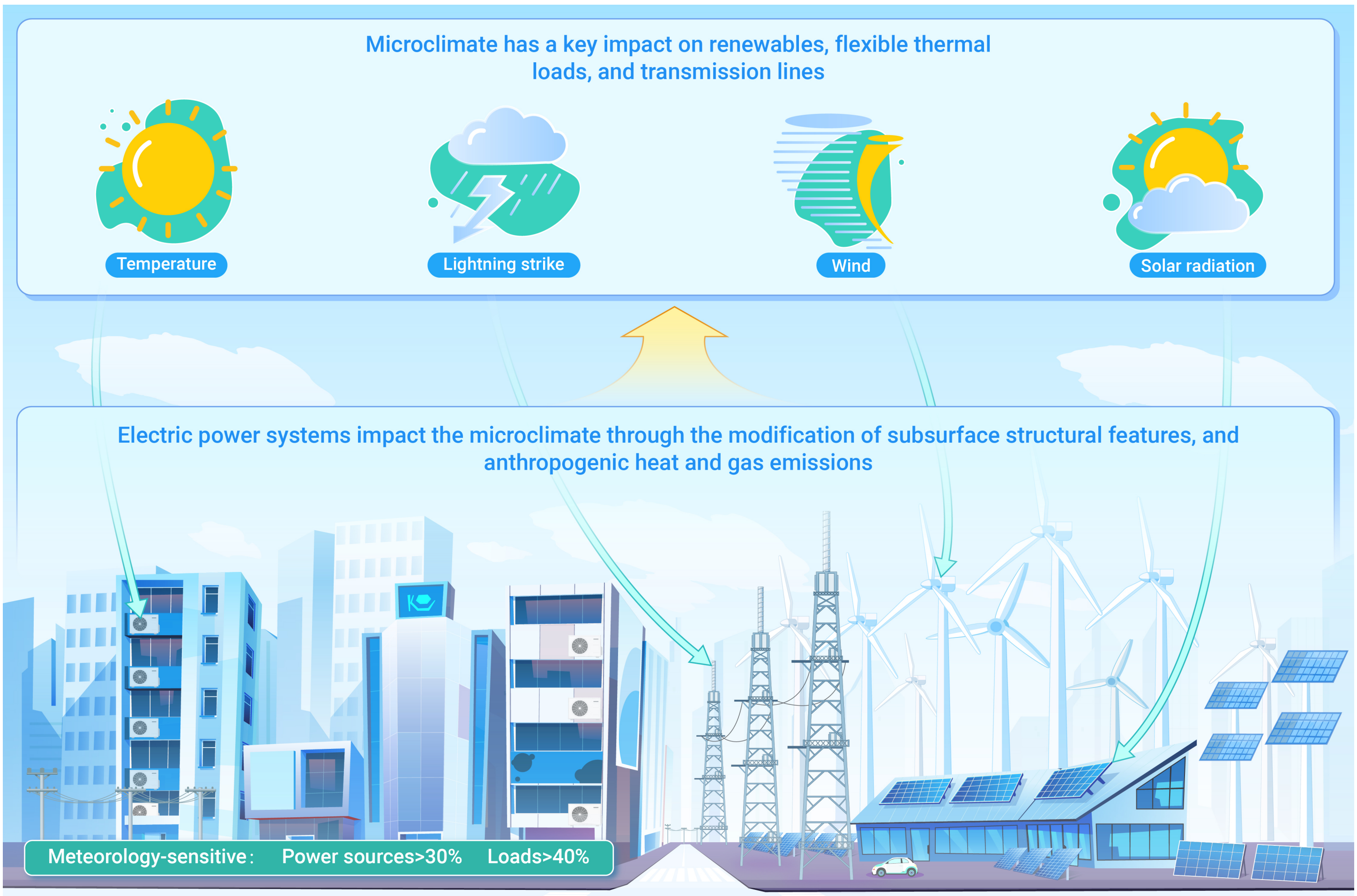
REVIEW

Trends and challenges of the interactions between microclimate and electric power systems

Canbing Li,[1] Yu Cheng,[1] Yusheng Xue,[2,*] Ran Li,[1] Feng Xue,[2] Kang Chang,[2] Jianzhe Liu,[1] Nengling Tai,[1] Wentao Huang,[1] Yufei Xu,[1] and Dounan Pan[1]
*Correspondence: xueyusheng@sgepri.sgcc.com.cn
Received: January 27, 2024; Accepted: June 24, 2024; Published Online: August 30, 2024; https://doi.org/10.59717/j.xinn-energy.2024.100046

GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- The interactions between microclimate and electric power systems are overviewed.
- Advanced applications and cutting-edge techniques of the interactions are summarized.
- Challenges and perspectives are introduced and envisioned.

REVIEW

Trends and challenges of the interactions between microclimate and electric power systems

Canbing Li,[1] Yu Cheng,[1] Yusheng Xue,[2,*] Ran Li,[1] Feng Xue,[2] Kang Chang,[2] Jianzhe Liu,[1] Nengling Tai,[1] Wentao Huang,[1] Yufei Xu,[1] and Dounan Pan[1]

[1]Key Laboratory of Control of Power Transmission and Conversion, Shanghai Jiao Tong University, Shanghai 200240, China

[2]NARI Group Corporation (State Grid Electric Power Research Institute), Nanjing 211106, China

*Correspondence: xueyusheng@sgepri.sgcc.com.cn

Received: January 27, 2024; Accepted: June 24, 2024; Published Online: August 30, 2024; https://doi.org/10.59717/j.xinn-energy.2024.100046

Citation: Li C., Cheng Y., Xue Y., et al., (2024). Trends and challenges of the interactions between microclimate and electric power systems. The Innovation Energy 1(4): 100046.

The increasing penetration of renewables has made electric power systems meteorology-sensitive. Meteorology has become one of the decisive factors and the key source of uncertainty in the power balance. Macro-scale meteorology might not fully represent the actual ambient conditions of the loads, renewables, and power equipment, thus hindering an accurate description of load and renewables output fluctuation, and the causes of power equipment ageing and failure. Understanding the interactions between microclimate and electric power systems, and making decisions grounded on such knowledge, is a key to realising the sustainability of the future electric power systems. This review explores key interactions between microclimate and electric power systems across loads, renewables, and connecting transmission lines. The microclimate-based applications in electric power systems and related technologies are described. We also provide a framework for future research on the impact of microclimate on electric power systems mainly powered by renewables.

INTRODUCTION

Microclimate is the meteorology characteristic on small spatial scales, ranging from a few metres to a few kilometres. Microclimate phenomena could be significantly different from the broader meteorological patterns of the surrounding areas. For example, the average temperature of impervious surfaces can be 3 °C higher than that of vegetation-covered areas within a city.[1] Microclimate is the actual environment in which loads, renewables, and power equipment are located, affecting the economic, stable, and safe operation of electric power systems. Meanwhile, electric power systems impact the microclimate by modifying subsurface structural features, and anthropogenic heat and gas emissions,[2,3] among others.

The utilisation of renewables and the widespread use of meteorology-sensitive loads have made electric power systems vulnerable to microclimate.[4-6] Specifically, microclimate has a key impact on renewables, flexible thermal loads, and transmission lines designed to transfer power from renewables centres to load centres. For instance, solar energy generation relies on local solar radiation.[5,7-8] The moving clouds make short-term changes to the microclimate in photovoltaic (PV) power plants, affecting PV output[9,10] and the degree of PV power fluctuations.[11,12] Wind power generation is susceptible to wind distribution in wind farms. The urban heat island effect (UHIE) can make the temperature difference up to 10 °C at the same moment within a city,[13] contributing to the spatial differences in air-conditioning energy consumption.[14] Microclimate conditions can accelerate the icing of transmission lines, increasing the risk of transmission line damage.

Electric power systems, on the other hand, also affect microclimate. For example, renewable energy stations change the original underlying surface, influencing the distribution of wind and solar radiation. The use of air-conditioning increases heat and pollutant emissions, strengthening the UHIE.

The increase in renewables strengthens the link between microclimate and electric power systems. Although the significance of the link is being increasingly recognised, there still exists critical open questions: To what extent can electric power systems and microclimate affect each other? How to apply the interactions to electric power systems? What kind of microclimate data is needed by electric power systems? How to obtain such microclimate data? This review aims to answer these questions by exploring key interactions between microclimate and electric power systems. As shown in Figure 1, it includes loads-level interaction between UHIE and air-conditioning energy consumption; renewables-level interactions between microclimate (solar radiation, temperature, evaporation, and soil moisture) and solar energy, microclimate (wind and temperature) and wind energy; transmission lines-level interaction between microclimate (temperature, humidity, and wind) and transmission lines. Furthermore, the applications and related techniques of the interactions are described. Finally, the future directions for understanding and applying the interactions are outlined.

THE INTERACTION BETWEEN URBAN MICROCLIMATE AND AIR-CONDITIONING ENERGY CONSUMPTION

The interaction between urban microclimate and air-conditioning energy consumption can be described as a positive feedback loop: urban microclimate prominently affects air-conditioning energy consumption, which increases waste heat to enhance urban microclimate (Figure 2A). We introduce a positive feedback loop in two parts, including the impact of UHIE on air-conditioning energy consumption and the impact of air-conditioning energy consumption on UHIE. Further, we propose two strategies to mitigate the effect of the positive feedback loop (Figure 2B).

The UHIE makes air-conditioning energy consumption surge

Air-conditioning energy consumption accounts for 30 %~50 % of total energy consumption during summer in some metropolis.[20] As a phenomenon of microclimate, UHIE is a reason for high air-conditioning energy consumption, as indicated by the real-world data summarized in Table 1.

UHIE could result in an average increase of 19.0 % in cooling energy consumption.[13] The influence of UHIE on air-conditioning energy consumption can be described as a multi-factorial process with saturation and a time lag, as observed in Beijing, 2005, where the electric air-conditioning energy consumption attributed to the comprehensive influence of UHIE, temperature and humidity effect, and cumulative effect accounted for 47 % of the summer's total electric air-conditioning energy consumption.[28] When air temperature increases, air-conditioning energy consumption surges with a saturated effect; the effect of temperature on air-conditioning energy consumption has a cumulative effect. The cumulative effect refers to the air-conditioning energy consumption of the day is not only affected by the temperature of this day but also by the temperature of the neighbouring previous days, for example, In the summer, although the temperature suddenly drops after many days of high temperature, the air-conditioning energy consumption does not drop suddenly; the cumulative effect and UHIE have a comprehensive effect. UHIE keeps the urban areas at high temperature continuously in summer, consequently making the cumulative effect more significant.

The impact of UHIE on air-conditioning energy consumption is of spatial-temporal variability within the city.[22,27] Also, the impact of UHIE on air-conditioning energy consumption is influenced by building types and the surrounding environment of buildings. For example, in Nanjing, China, UHIE showed a stronger impact on air-conditioning energy consumption for residential buildings than that for office buildings.[27] The transpiration effect of vegetation next to buildings contributes to higher humidity.[29] High temperature and humidity make people feel hotter during summer, leading to a surge in air-conditioning energy consumption.[30]

The utilisation of air-conditioners strengthens the UHIE

Meanwhile, air-conditioners, in turn, play a role in strengthening the UHIE by pumping waste heat from the indoors to the outdoors. For instance, in Beijing, on July 3, 2005, electric air-conditioners discharged 3×10^9~5×10^9 kJ of waste heat, raising the temperature by approximately 1.94 ℃.

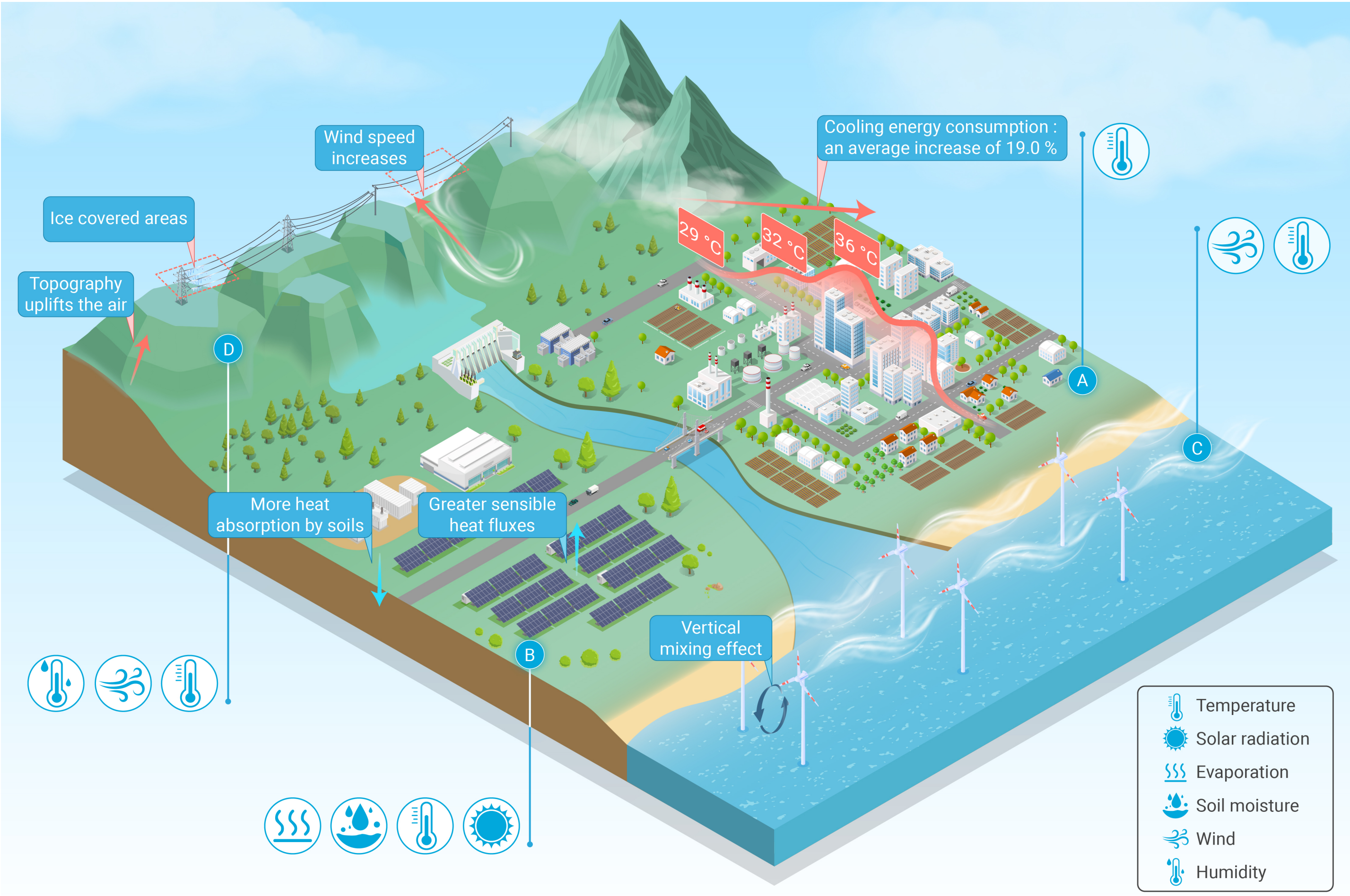


Figure 1. The interactions between microclimate and electric power systems (A) The urban heat island effect (UHIE) makes air-conditioning energy consumption downtown higher than that in suburban during summer. (B) Photovoltaic (PV) panels change the local solar radiation balance,[14] further impacting albedo, evaporation, temperature, and soil moisture. Consequently, the influence of PV on microclimate can bring ecological, economic, and social benefits. Conversely, natural environments like bodies of water and agricultural land can mitigate temperature, enhancing the efficiency of PV modules. (C) Turbulent turbine wake within wind farms influences wind turbines' steady and transient operation. Meanwhile, wind farms can modify microclimatic parameters such as wind and temperature by altering surface roughness and disrupting natural energy cycles.[15-18] (D) Transmission lines are inclined to freeze when exposed to micro-topography such as a valley, which concomitantly couples with low temperature and high humidity.

The severity of the impact depends on drivers such as urbanization, climate change, development of cooling technology, and economic development.[31,32] Especially, the warm-climate developing countries that are densely populated and rapidly urbanizing are facing unprecedented demand for cooling,[33] which makes this impact particularly serious. The impact can further trigger cascading effects. For example, urban anthropogenic heat such as waste heat from air-conditioners would induce compound hot extremes, triggering a mortality spike, causing heat-induced labour loss, and influencing plant survival during heat stress.[34-36] The influence of this impact on human comfort, economics, ecosystems, and climate change underscores the imperative of mitigating the impact.

The utilisation of the interaction

It is noted that this positive feedback will aggravate with global warming,[14] because anthropogenic heat emissions from air-conditioners tend to increase linearly with global warming, inducing additional urban warming. The superimposition of positive feedback and global warming highlights the need for tailored urban adaptation strategies through utilizing the interaction between urban microclimate and air-conditioning energy consumption.

One strategy for alleviating the positive feedback loop is to reduce waste heat. Electric vehicles are examples as they emit only 19.8 % of conventional vehicles' emissions per mile. In Beijing, China, replacing conventional vehicles with electric vehicles can decrease heat island intensity (HII) by 0.94 °C, reducing air-conditioning energy consumption.[37] In addition, energetically sustainable buildings (e.g., high-efficiency buildings with solar heating tanks and building-integrated photovoltaic[38-40]) are practical alternatives to reduce pollutant emissions. Also, innovation in refrigerant and waste heat recovery technology is an effective approach.

The second strategy is to promote building energy saving. The coloured low-emissivity films for building walls can promote building energy conservation by mitigating radiative heat exchange between the indoor and outdoor environment.[41] Also, building-integrated vegetation reduces the temperature by providing shade and evapotranspiration, thus boosting building energy savings.[42] The air-conditioning energy savings attributed to green roofs and green walls can be up to 85 % and 66 %, respectively.[43] Instead, cool roofs can cool the air by increasing the albedo, demonstrating the excellent performance of cooling energy savings. For example, cool roofs in Chicago have been shown to increase the albedo by 1.6 %, corresponding to the cool effect of 65,000 window-sized air-conditioners running at full capacity during the summer.[44] Nevertheless, both greenery on buildings and cool roofs would have adverse effects. Cool roofs would contribute to the reduction of precipitation, as observed in the United States, where the deployment of cool roofs from Florida to the north-eastern United States could decrease the precipitation by 2~4 millimetres by 2100;[45] green roofs may aggregate the urban nocturnal warming because there is less evaporation and more releases of plants' stored energy when the sun falls,[44] increasing the demand for air-conditioners; green roofs can not reduce the temperature inside the canyon with wind parallel to the street.[46] Overall, measuring the microclimate parameters such as wind direction and solar radiation in the different urban morphologies can contribute to the development of urban cooling strategies. Also, guidelines combining greenery infrastructure and cool roofs should be made. The guidelines can range from simple rules such as optimising the

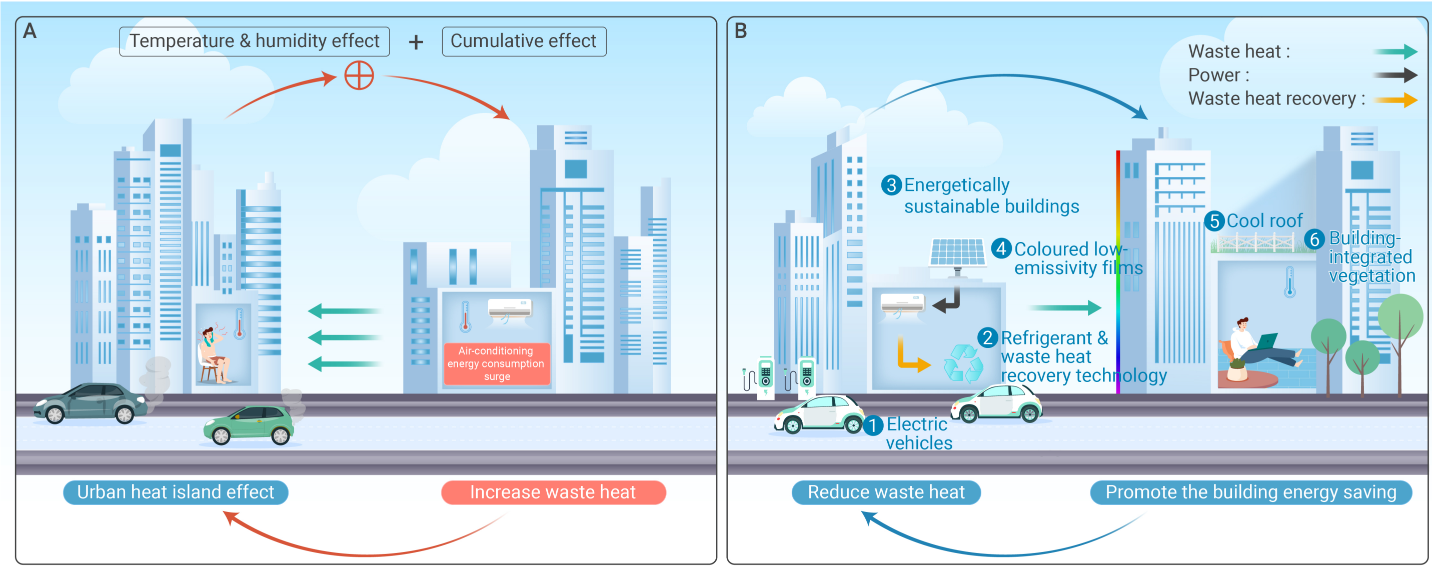


Figure 2. The feedback loop between urban microclimate and air-conditioning energy consumption (A) The schematic illustrates the interaction between the urban heat island effect (UHIE) and air-conditioning energy consumption. The combined effects of UHIE (highlighted in the blue box, representing the cause), temperature and humidity effect, and cumulative effect, result in (highlighted in the red box): a significant increase in air-conditioning energy consumption and waste heat, further exacerbating the UHIE, thus forming a vicious cycle. (B) Reducing waste heat and promoting the building energy saving are two strategies to mitigate the effect of the positive feedback loop.

height of greenery infrastructure on buildings, and selecting suitable materials for cool roofs and vegetation types for greenery infrastructures, to frameworks considering the maintenance cost, surrounding built morphology, and irrigation strategies.

THE INTERACTION BETWEEN MICROCLIMATE AND SOLAR ENERGY

Nowadays, many studies have begun to explore the integration of the PV industry with agriculture, ecology, and architecture. The synergistic utilisation of solar energy can not only alleviate the damage to nature but also provide synergistic outcomes.[47] Here we highlight the planning of PV stations in deserts, on the rooftops, over water bodies, and in the farmland. In the scenarios, energy, ecological, and economic benefits are achieved through the interaction between microclimate and solar energy (Figure 3).

Constructing solar farms in deserts

In natural deserts, the construction of solar farms may enhance desertification control through the microclimate variation-vegetation recovery-animal husbandry process (Figure 3A). The construction of solar farms in the deserts can change the microclimate in two ways. (1) By modifying the regional radiation balance, solar farm installations trigger a feedback loop involving albedo, precipitation, and vegetation recovery. For example, in the Sahara Desert, the development of solar energy infrastructure reduces terrestrial albedo, leading to a consequential increase in precipitation of more than twofold, consequently promoting the recovery of vegetation.[48] (2) PV shading modifies soil surface microclimate including soil moisture, soil temperature, and evaporation, thus facilitating vegetation growth. For example, in the Mu Us Desert, China, compared with the area 30 m near a solar power station, the PV shading effect weakens evaporation by 51.3 %, reduces the soil temperature by 9.6 %, and boosts soil moisture, which makes vegetation coverage, biomass, and species richness increase by 6.75 times, 22.69 times, and 1.92 times, respectively.[49] However, abundant pasture would affect solar power generation and induce fire hazards. Consequently, grazing is used to control the growth of pasture,[50] which is the origin of "PV sheep".

Despite the potential benefits, there are concerns. The site preparation and high-density development of solar facilities for solar farms may lead to vegetation degradation.[51-53] Additionally, distinct subsurface and thermodynamic patterns may demonstrate different albedo and microclimate changes, thus contributing to the diverse responses of desert plants to solar farms. Solutions have been proposed: (1) design the scale and density of solar farms reasonably. A more dispersed and smaller PV installation could result in less environmental change;[54] (2) assess the long-term resilience of desert plants to solar energy development decisions, particularly focusing on the impacts of mowing and the decoupling of washing systems on desert plants; (3) consider regional characteristics such as climate and soil condition.

Planning PV on the rooftop

Through shading effect and increased albedo, PV changes the urban microclimate, ultimately improving the habitat (Figure 3B). For example, in the Los Angeles basin, the high-density deployment of rooftop PV could reduce the air temperature by 0.2 °C in 2013, and in Paris, rooftop PV would increase household heating energy demand by 3 % in winter and reduce air conditioning energy demand by 12 % in summer. Further, the cooling effect of rooftop PV can improve human health and comfort in urban areas. For instance, the rooftop PV deployment in Paris reduced the number of people impacted by heat stress by 4 % during the 2003 August heatwave.[55] Also, building PV on top of parking lots could reduce the temperature inside cars, alleviating people's discomfort in hot environment.[56]

The development of floating PV

By impacting solar radiation and surface wind speed, installing PV power plants on water bodies such as lakes, canals, and reservoirs has the potential to reduce evaporation, bringing ecological and energy benefits.[57-59] Deploying solar arrays over canals could have many advantages by changing the microclimate (Figure 3C). Shade from PV might reduce evaporation and thereby save water resources;[47] the reduction of direct sunlight on water bodies inhibits photosynthesis and algae growth, thus achieving better water quality; proximity to water creates cooling and a less dusty environment, which enhances the performance of Cadmium Telluride (CdTe) PV modules. Extending the PV power plants to fish farms, the array shading effect may reduce the water surface temperature, effectively cutting down the economic loss of the aquaculture industry and protecting the bio-diversity. By shading the reservoir, floating PV power plants may reduce the carbon intensity of hydroelectric power generation.[60,61]

However, negative effects also exist due to the specific microclimate conditions of floating photovoltaics. For instance, the oxygen depletion resulting from inhibiting algae growth would harm bio-diversity and drive the release of methane.[60,62] In addition, PV power plants installed on water bodies are subject to a more humid microclimate than those installed on land, which increases the reliability issues of solar panels.[62-64] Besides, the lower water temperature electromagnetic fields generated by cables may impact the

Table 1. Summary of UHIE impacts on air-conditioning energy consumption

Location, Publication year	Influence	Temperature data	Study sites	Reference
WesternAthens, Greece, 2000	In 1997: +66 %; In 1998: +33 %	1R-4U (July 1997, July 1998)	D	21
London, UK, 2012	+34 %	1R-19U (one year)	O	22
Hongkong, China, 2011	D&O: +10 %	1R-4U (May 2010 to October 2010)	D&O	23
Boston, US, 2013	D: +5 %; O: +41 %	2R-1U (one year)	D&O	24
Rome, Italy, 2015-2016	46 %	1R-4U (2015-2016)	All buildings in the city	25
Beijing, China, 2017	+11 %	7U-10R (one year)	O	26
Nanjing, China, 2020	D: +12~24 %; O: + 9~14 %	35U (August 2016 to July 2019)	D&O	27

"+" represents the increase of air-conditioning energy consumption; D" represents residential buildings; "O" represents office buildings; "R" represents rural observation stations; "U" represents urban observation stations.

ecosystem.[65] Therefore, when weighing the development of floating photovoltaics from the perspective of microclimate, it is necessary to determine the optimal size and siting of floating photovoltaics to limit environmental impacts.

Locating PV with agriculture

Coexisting agriculture and PV infrastructure can bring energy-water-food benefits (Figure 3D). PV shading can improve the efficiency of irrigation (water) and enhance agricultural yields (food),[66] while transpiration cooling from the crops cools the PV panels, improving PV efficiency (energy).[67] Also, the electricity generated by PV power plants can be used for local water management and fertilizer production.[68] However, the microclimate environment created by PV shading is not adapted for all crops. Shade-tolerant plants including lettuce can adapt themselves to shading, whereas, yield reduction occurs for crops such as wheat and potatoes.[69]

THE INTERACTION BETWEEN MICROCLIMATE AND WIND ENERGY

Wind energy utilisation is highly dependent on meteorology. We describe the impact of the wake effect on wind energy operation and utilisation, respectively. Also, the impact of wind farms on the surrounding wind and temperature is introduced.

The influence of the wake effect on the steady and transient operation of wind turbines

The wake effect is the phenomenon of wind speed variation as the wind passes through the turbine, creating a prominent microclimate within the wind farm. Wind farm wakes have been observed to extend up to 50 km,[70] affecting nearly 90 % of independent wind farms in the United States in 2016, mirroring global tendency.

The wake effect would lessen downstream wind turbine output.[71,72] For example, in West Texas, clustered wind farm complexes reduced generation at the downwind farm by 5 % roughly due to the wake effect, which is the most significant when the atmosphere is stably stratified and the wind is in a specific direction.[70] Also, Strong turbulence and wind shear can affect fatigue loads and the structural performance of downstream wind turbines.[73] In addition, coupling with the micro-topography, the wake effect would threat the safe and stable operation of wind farms.[74,75] For example, the leeward slope is prone to generate great turbulence intensity, thus increasing the fatigue loads.[76] However, the topography may also mitigate the impact of the wake effect on wind power generation. A larger gradient with a longer slope can achieve a more conspicuous wind acceleration.[77]

The wake effect also influences the transient operation of wind turbines. During the implementation of the low-voltage ride-through (LVRT), the output power of wind turbines varies because of the wake effect, which contributes to the different terminal voltages, thus forming distinct external characteristics. After eliminating or mitigating the fault, the untimely withdrawal of the LVRT measures would generate over-voltage.[78] Considering the microclimate in wind farms could decrease the voltage deviation by 36 %,[79] which addresses safety concerns for large-scale wind farms.

The impact of microclimate on wind energy utilisation within micro-topography

Both natural and urban landscapes create micro-topography, promoting the development of microclimate, and impacting wind energy utilisation.

The microclimate parameters including wind speed and turbulence levels are sensitive to natural terrains, which impact the operation of wind turbines.[80,81] For example, in the Hexi Corridor, China, the "canyon effect" coupling with low vegetation cover leads to intensive wind energy. However, the squeezing effect of the canyon on the wind can intensify the turbulence chaos, to which wind turbines are highly susceptible. Consequently, the "canyon effect" benefits the wind power generation during two conditions: when the prevailing wind direction is concentrated and consistent with the direction of the canyon; when the canyon' terrain is flat.

The building morphology, architectural design, and layout form the urban micro-topography, which influences the utilisation of urban wind energy by promoting the formation of microclimate.[82-84] For instance, changing urban density from compact to sparse urban layouts not only decreases turbulence levels above building roofs but also enables airflow to penetrate the street canyon at higher wind speed;[85] compared with the sharp corner, a rounded corner roof results in higher wind density and lower turbulence intensity on downstream buildings, thus demonstrating better wind energy potential; a building arrangement with cross-angle diverging channels can create a "venturi effect", producing high wind power density and low turbulence density.[86]

Wind farms transform the deserts

The construction of wind farms can render the microclimate of deserts to change, mitigating the desert expansion by establishing positive "vegetation-precipitation" feedback.[87] In the Sahara Desert, wind farms increase the surface roughness and vertical mixing effect, both of which promote precipitation. Further, enhanced precipitation leads to increases in vegetation cover fraction (+0.084), leaf area index (+0.50 m^2 /m^2), and root carbon (+0.08 kgC/m^2), which has positive feedback on evaporation and roughness.[48] In the Gobi Desert in China, the rotation of the wind turbine blades drives vertical mixing, enhancing local evaporation and rainfall, which contributes to the growth of vegetation.[88] Meanwhile, the shrubs reduce evapotranspiration and wind speed through shading, further increasing humidity and creating a more suitable microclimate for vegetation growth.

THE IMPACT OF MICROCLIMATE ON TRANSMISSION LINES

Here we introduce the impact of microclimate on transmission lines in micro-topography, including the influence of temperature, humidity, and wind speed on transmission lines icing, and the influence of lightning strike on transmission lines' safety and reliability.

The impact of microclimate on transmission lines icing in micro-topography

The coupling of microclimate and micro-topography would provide favourable conditions for icing. Passes, windward slopes, rivers, lakes, reservoirs, and cloud-encircled mountainsides with sufficient water vapours are

Figure 3. The interaction between microclimate and solar farms in four scenarios The innermost layer represents four scenarios including desert, rooftop, water body, and farmland. The middle layer represents the variation of microclimate elements. The outermost layer represents the benefits of improving microclimate. (A) Large solar farms in the deserts may facilitate desertification control by changing the microclimate, providing the benefits of vegetation recovery, animal husbandry, and energy. (B) By increasing the albedo, rooftop photovoltaic (PV) can provide the benefits of urban heat island effect (UHIE) mitigation, building energy conservation, and improvement of human comfort. (C) Deploying solar arrays over canals could bring energy and environmental benefits. (D) Combining the solar energy facility with farmlands changes the microclimate conditions, enhancing the relationship between food, water, and energy.

vulnerable to icing.[89] Airflow is concentrated and accelerated within the passes. The wind speed on the central axis of the valley can be more than 30 % higher than the local flat wind speed. Superimposing with low temperature (below 0 ℃) and high humidity (above 85 %), the wind delivers a steady stream of super-cooled water droplets to the transmission lines across the passes, thus provoking icing; on the windward slope, the air masses containing super-cooled water droplets are forced up along the slope by the strong wind, undergoing adiabatic expansion, ultimately contributing to icing; when the cold wave invades, the icing phenomenon is formed in the river and lake areas which are abundant in water vapours. When the angle between the wind direction and the line direction is greater than 45 °, the galloping of transmission lines is more likely to occur under the influence of the wet and cold pulsating air; in canyon areas, the "canyon effect" makes transmission lines withstand stronger winds. Combined with sufficient water vapours and low temperature, the transmission lines are easy to icing.

The impact of lightning strike on transmission lines in micro-topography

Under the influence of micro-topography and microclimate, transmission lines passing through ridges, windward slopes, valleys, and water ponds will be more susceptible to lightning strike.[90] When the transmission lines cross the valley, both sides of the cliff have an attractive effect on the lightning leader, which is likely to form a certain angle of incidence, increasing the probability of lightning shielding failure; when the transmission lines cross the ridges, less shielding effect make them vulnerable to lightning; on the windward slope, the wind promotes the warm and humid airflow to climb along the hillside, further forming the thunderstorms. The development of terrain thunderstorms makes transmission lines susceptible to lightning; under the humid microclimate conditions of farmland ponds, the charge is sufficient, which makes it easy to form a thermal thunderstorm in the hot and windless afternoon of summer, increasing the lightning shielding failures of transmission lines.

APPLICATIONS AND TECHNOLOGIES

Organized into four key aspects: loads, solar energy, wind energy, and transmission lines, we next discuss microclimate-driven applications in electric power systems and review recent progress in related techniques to guide the application of interactions.

Loads

Applications. Many attractive applications have emerged from studying the microclimate, including enabling more accurate load forecasting, facilitating energy transition, and promoting demand response initiatives. Microclimate provides essential information for accurate load forecasting in the electrical grid. For example, by dividing large power grids into several subnets and taking microclimate into account, the short-term load forecasting error during summer can be reduced by about 40 %.[91] Besides, considering the influence of microclimate on urban energy systems would improve both the financial performance (including initial capital investment, as well as operation and maintenance costs) and resilience of energy systems, further supporting the decarbonisation of the energy sector.[92,93] Additionally, microclimate plays a pivotal role in bolstering urban demand-side management strategies. For example, compared with not adjusting indoor microclimate parameters, adjusting parameters can reduce average thermal load by 4 %, and improve indoor air quality.[94]

Technologies. The approaches to assessing the impact of UHIE on air-conditioning energy consumption include physical-based models and data-driven models. Physical-based models simulate air-conditioning energy consumption based on metrics like materials, building characteristics, urban area, and reference site.[95] Combining building performance simulation tools (e.g., EnergyPlus[96,97] and TRNSYS[95]) with microclimate software (e.g., UWG[98] and Envi-Met[99]) is widely utilised. These methods can provide high temporal resolution. However, they need numerous input parameters and computation for large-area studies. Data-driven models are developed by demonstrating the statistical relationship between UHIE and air-conditioning energy consumption.[28] They are easy to calculate and assess factors such as the economy and climate change.

Solar energy

Applications. Microclimate has been taken as a factor in solar power station planning and design. For example, in farms, PV systems achieve shadow management by modifying the PV panels' structure (e.g., PV panels interleaved with solar cells and transparent areas,[68] bifacial panels,[100] and dynamic PV panels with solar trackers[101]) and utilizing unique PV materials (e.g., the solar spectrum-splitting system[102]). On water bodies, considering the impact of microclimate on the thermo-electrical performance of the float-

Table 2. The specific microclimate database for electric power systems

	Applicable scenario	Microclimate element	Data source	Spatiotemporal resolution
Loads	Assess air-conditioning energy consumption	Urban heat island (UHI)	Government-sponsored weather stations, such as the Global Historical Climatology Network-Daily (GHCN-Daily) dataset[131]	Due to the specific sites of weather stations, the spatial variations of the UHI cannot be captured well
			Gridded datasets using gridded auxiliary datasets (e.g., Land Surface Temperature (LST), Normal Difference Vegetation Index (NDVI), and elevation) to interpolate temperature,[132-134] such as TopoWx,[135] a 1 km resolution air temperature dataset in the United States[136]	1 km resolution
Renewables	Solar energy power generation	Solar radiation	Geostationary satellites from National Solar Radiation Data Base, https://maps.nrel.gov/nsrdb-viewer/.	Hourly, 3~4 km resolution
			Reanalysis datasets (e.g., COSMO-REA6[137], and PVGIS-SARAH[137])	COSMO-REA6 (hourly, 6.2 km) PVGIS-SARAH (hourly, 5 km)
	Location planning of PV power station	Soil moisture	the Copernicus surface soil moisture product (https://land.copernicus.eu/global/products/ssm); the recent RT1-based TU Wien soil moisture product (https://explorer. dte-hydro.adamplatform.eu/).	the Copernicus surface soil moisture product (1 km) the Theia soil moisture product (100 m)
	Wind energy power generation	Wind speed features at turbine hub height	Reanalysis datasets, like ERA5[138]	Hourly, 0.3 ° (supply wind speed at 100 m above the ground)
Transmission lines	Power equipment safety	Temperature, humidity, wind speed, wind direction, rainfall, pressure	Microclimate monitoring equipment	

ing PV systems, the microclimate reformation algorithm models are combined with the energy modelling to evaluate the energy, environmental, and economic planning strategies.[103]

Technologies. Solar power forecasting considering microclimate conditions facilitates energy planning and management. Remote sensing technology (1 m~1 km) and sky cameras (1 m~2 km) are common approaches to achieve solar forecasting with high spatial resolution.[104] Recently, hybrid approaches (e.g., Clustering-based models,[105] and Evolutionary models[106]) have shown good potential to benefit the final forecasting and speed convergence. After acquiring the solar forecasting data, the methods to convert irradiance to power include statistical curves based on the relationship between weather inputs and PV power, and model chains like pvlib package in Python.

Modelling the relationship between the PV shielding effect and evaporation reduction is beneficial to evaluating PV stations' economic and ecological benefits. Nowadays, some researchers estimate evaporation reduction based on the experimental statistical relationship between shading and evaporation.[107] For example, in reference to the previous experiments, 44~90 % is utilised to estimate the evaporation reductions due to PV shading over the canal.[47] This method is intuitive, while needs to consider factors such as climate conditions in different regions to form a complete database. In addition, the evaporation numerical method is a choice to calculate the evaporation rate, like Penman and linear regression model.[108]

Wind energy

Applications. The interaction between microclimate and wind power generation can be applied in wind power forecasting, the planning and operation of wind power stations. Considering the wake effect can improve the accuracy of wind power forecasting. For example, compared with the traditional models, a physics-inspired neural network model considering the wake effect improves wind power prediction performance by more than 20 %. In addition, microclimate plays a role in the wind power stations' planning in two ways, including the selection and layout of wind turbines, and wind turbine fatigue life analysis.[109-111] Besides, Controlling the wake effectively can optimize the wind farm power, facilitating the operation of wind power stations.[112] For example, in the TransAlta Renewables wind farm in Alberta, Canada, wake steering increases power generation by 7 %~13 % on average and reduces fluctuations in power generation.[113]

Technologies. Predicting wind power output while considering wake effects requires sophisticated modelling. Nowadays, the wake modelling approaches can be divided into two categories: the first is utilizing computational fluid dynamics (CFD) simulation or combining the weather model (e.g., numerical weather prediction (NWP) model) with geographical and atmospheric elements (e.g., land surface model, cloud micro-physics, long-wave radiation, and short-wave radiation) to capture microclimate.[70] However, they need a long computational time. The second is using the analytical models (e.g., Jensen model, MOST-Gaussian model, and G. C. Larsen model).[111] Among them, the MOST-Gaussian model is a good choice for various surface roughness and atmospheric stability conditions.[114] Due to its simplicity and accuracy, the Jensen model is widely used for optimizing wind turbine layout.[115] Based on the wake modelling, a power-wind direction model is constructed to update the wake effect loss. Further, the power-wind direction parameters, turbulence intensity, and wind shear are input into the wind power prediction model to correct the wind power prediction errors, effectively smoothing the wind power forecast fluctuations.

Controlling the wake effect can be beneficial to optimize wind power production. Various wake control strategies have thus been devised to decrease the power loss of downstream wind turbines, including yaw control, pitch control, torque control, and tilt control. Yaw and tilt controls are effective ways to increase wind power production.[116] However, yaw control may influence the structure loads,[117] while the lack of adjusting the tilt angle actively may limit the development of tilt control. Torque and pitch controls contribute to wake recovery rather than increase production.

Transmission lines

Applications. Condition monitoring and real-time warning of transmission lines are attractive applications. For example, the MSP430 micro-controller which can detect the microclimate of transmission lines is utilised in accurate multi-source condition monitoring, effectively reducing operational losses caused by ice galloping in micro-topography.[118] Considering that the coupling of microclimate and micro-topography influences the windage yaw calculation, an improved computational model based on dynamic air density theory is proposed to provide warning signals.[119] Also, understanding the interaction is beneficial to the management of meteorological monitoring points.

Technologies. The methods for predicting transmission line ice cover under micro-topography can be classified into two sorts: one is image processing technology. The other is artificial intelligence technology. Because there is a high degree of complexity and non-linearity between microclimate factors and the ice cover thickness of transmission lines, it is difficult to predict ice cover thickness through a simple fitting function. Artificial neural networks (e.g., back-propagation neural network, generalized regression neural network, genetic algorithm combined with BP neural network) are good choices to be applied.

OUTLOOK

With the rising penetrations of meteorology-sensitive power sources and loads, electric power systems face a critical challenge: The interactions between microclimate and electric power systems are being intensified and have posed a deteriorating effect on energy sustainability, and the entire society. There are three key effects of microclimate on the performance of electric power systems, especially with the increasing utilization of renewables. First, the volatility and intermittence of renewables caused by microclimate contribute to the uncertainties of accurate forecast, which leads to operational risks. Second, the uncertainties of renewables increase the difficulties of risk evaluation, mainly owing to the computational complexity resulting from the exponential growth of the order of the electric power system model. Third, the integration of renewables introduces fluctuations in frequency and voltage, which pose challenges to risk control of electric power systems. Meanwhile, Power facilities can change the microclimate, bringing ecological, economic, and social impacts. Further, the smart grid is gradually transforming into cyber-physical-social system in energy, which includes generalized physical elements such as carbon emissions.[120,121] Microclimate influences the energy consumption of residents and power generation, affecting the carbon emissions flow of electric power systems.[122-124] Consequently, exploring and utilizing the interactions between microclimate and electric power systems is the key to achieving carbon neutrality.

This review has shown that the change in microclimate including wind, temperature, humidity, evaporation, soil moisture, and solar radiation is the key to the interactions between microclimate and electric power systems. Also, microclimate-based applications and technologies are described to guide the translation of the interactions into microclimate applications in electric power systems. Nevertheless, there remain many research opportunities for further improvements. We perform a priority ranking of future research avenues: (1) map the specific microclimate database for electric power systems; (2) convert the microclimate into actual data used by the electric power systems considering the interactions between microclimate and electric power systems.

Map the specific microclimate database for electric power systems

The meteorology of electric power systems is the cutting-edge demand of industry meteorology, which requires higher refinement in time and space. For example, in space, the power generation capacity of new energy stations requires spatial refinement up to ten meters and meters; in time, to satisfy the instantaneous balance between power output and loads, the time refinement demand of power systems for meteorological data can reach a minute level. Nowadays, the meteorology sectors mainly provide hundred-kilometer-level meteorological parameters, which can not meet the data requirement of the energy sector.[125] The lack of complete information will influence the utilisation of renewable energy and the operation of electric power systems. Consequently, Constructing the microclimate database for electric power systems is necessary.

The database (Table 2) could include the temperature distribution under urban morphology, the wind speed at turbine hub height, wind speed, and humidity under micro-topography. Although some data sources have been listed, it can be seen from Table 2 that there are three aspects of improving gridded microclimate data of electric power systems:

First, advanced data collection and processing methods should be added to ensure the quality of data. For example, pre-processing methods including normalization, calibration, and transformation of data can be improved to make data suitable for analysis; correlation analysis approaches like a distributed lag non-linear model can be utilized to explore the microclimate propagation characteristics (e.g., response time scale, lag time). Combining cloud-deployed software, collaborative effort devices, and computer infrastructure with approaches including remote sensing and temporal dynamic satellite observations,[126,127] is an effective way to increase the temporal-spatial resolution of microclimate maps. However, implementing advanced data collection and processing techniques involves substantial financial costs. Engaging in data-sharing initiatives with other organizations can be beneficial to reduce expenses. Also, employing machine learning algorithms to automate data processing operations can reduce labour costs.

Next, it is essential to create a comprehensive vertical profile. The existing datasets do not take the vertical profile of electric power systems into account. Even though datasets such as ERA5 try to describe wind speed at turbine hub height, the spatial resolution is coarse. The key to creating the comprehensive vertical profile of electric power systems is to accurately consider the underlying surface characteristics after the construction of electric power systems and understand what microclimate parameters would affect electric power systems. This process involves detailed field surveys, high-resolution modelling, and data integration, contributing to increased costs. To reduce the costs, data fusion techniques can be employed to integrate data sources, decreasing reliance on high-cost data acquisition. In addition, high-efficiency simulation and modelling techniques can reduce the need for extensive field measurements.

Third, we should improve microclimate forecasting technology. Microclimate is affected by large-scale meteorological movement. The historical database of microclimate cannot reflect the variation trend. NWP techniques like the ECMWF Integrated Forecasting System (IFS) provide precise forecasts and have enhanced their resolution consistently.[128-130] Recently, artificial intelligence methods including FourCastNet and Pangu-Weather have shown potential in accelerating high-resolution weather forecasting.[131] Further, employing cloud and edge computing, and collaborating with other research institutions can optimize resource usage and facilitate cost reduction.

Approaches to utilising the interactions between microclimate and electric power systems

Despite some open-source tools and models being used to convert meteorological data into energy system model inputs,[139-142] there are still some challenges in energy system modelling. First, energy system modelling should evaluate the methodological uncertainty owing to microclimate variability. Second, more attention should be paid to the risk evaluation and prediction of the bulk electric power system impacted by microclimate, including the power imbalance, insufficient climbing capacity, and oscillatory instability.

The power balance of electric power systems is affected by multiple uncertainties compounded by operation status, interconnection transmission capacity, load demand, power output, and balancing resource supply. Most of these factors are related to microclimate. To accurately assess the risk of power imbalance, it is necessary to introduce the power imbalance index as the output value for constructing the multi-day power balance model of electric energy systems. The main inputs for the model are hourly time series of the simulated natural river runoff, load, wind power generation, and solar power generation. A probabilistic interval distribution is used to parameterize the non-meteorological sensitivity constraints, including contact line capacity and section capacity. The risk of power imbalance is thus quantified by considering the minimum sum of hydro and thermal power generation, combined with potential load loss. Weighting factors are incorporated to account for the economic priorities of power sources and load demands. Further, the sensitivity analysis method is utilized to quantify the influence of input variables on output variables and calculate the variance of source-load fluctuations on power imbalance metrics under microclimate conditions. There are two key aspects that researchers consider when assessing power imbalance: computational burden and prediction performance. Artificial intelligence techniques like extreme learning machines are good choices that need fewer scenarios than traditional Monte Carlo-based methods to represent the intricate non-linear relationship between the microclimate and electric power systems with excellent accuracy.

In terms of the evaluation of climbing capacity, for example, to convert the meteorological parameters into the wind power ramping rate needed by electric power systems, two steps are required: (1) we should combine the micro (kilometres and below), medium (kilometres to tens of kilometres), and macro (tens of kilometres and above) meteorological data to make microclimate prediction. The wind in wind farms primarily comes from outside the wind farms. Monitoring the wind speed within the wind farms and extrapolating it cannot accurately achieve the microclimate prediction. Therefore, the prediction of microclimate within the wind farms can be divided into two stages: the prediction of external meteorological movement and the impact of the movement on the internal wind speed distribution; (2) using the internal wind velocity distribution within the wind farms instead of average wind speed to align with the non-linear relationship between wind speed and wind power. Also, we should focus on inverse peak regulation and continuous climbing based on the adaptive sliding time window algorithm.

REFERENCES

1. Yang, Y., Guangrong, S., Chen, Z., et al. (2022). Quantitative analysis and prediction of urban heat island intensity on urban-rural gradient: A case study of Shanghai. Sci. Total Environ. 829: 154264. DOI: 10.1016/j.scitotenv.2022.154264.
2. Zhou, L., Tian, Y.H., Roy, S.B., et al. (2012). Impacts of wind farms on land surface temperature. Nature Clim. Change 2: 539–543. DOI: 10.1038/nclimate1505.
3. Christidis, N., McCarthy, M., and Stott, P.A. (2020). The increasing likelihood of temperatures above 30 to 40 ℃ in the United Kingdom. Nat. Commun. 11: 3093. DOI: 10.1038/s41467-020-16834-0.
4. Huang, T., Guo, Q., Sun, H., et al. (2019). A deep spatial-temporal data-driven approach considering microclimates for power system security assessment. Appl. Energy 237: 36–48. DOI: 10.1016/j.apenergy.2019.01.013.
5. Yin, Z., Zhou, B., Duan, M., et al. (2023). Climate extremes become increasingly fierce in China. The Innovation 4: 100406. DOI: 10.1016/j.xinn.2023.100406.
6. Cheng, Y., Li, C., Xu, Y., et al. (2024). Extreme impacts on electric power systems from non-catastrophic meteorological conditions. The Innovation Energy 1: 100008. DOI: 10.59717/j.xinn-energy.2024.100008.
7. Feron, S., Cordero, R.R., Damiani, A., et al. (2021). Climate change extremes and photovoltaic power output. Nat. Sustain. 4: 270–276. DOI: 10.1038/s41893-020-00643-w.
8. Chen, S., Lu, X., Nielsen, C.P., et al. (2022). Improved air quality in China can enhance solar-power performance and accelerate carbon-neutrality targets. One Earth 5: 550–562. DOI: 10.1016/j.oneear.2022.04.002.
9. Barbieri, F., Rajakaruna, S., and Ghosh, A. (2017). Very short-term photovoltaic power forecasting with cloud modeling: A review. Renew. Sust. Energ. Rev. 75: 242–263. DOI: 10.1016/j.rser.2016.10.068.
10. Lappalainen, K., and Valkealahti, S. (2017). Output power variation of different PV array configurations during irradiance transitions caused by moving clouds. Appl. Energy 190: 902–910. DOI: 10.1016/j.apenergy.2017.01.013.
11. Pretto, S., Ogliari, E., Niccolai, A., et al. (2022). A new probabilistic ensemble method for an enhanced day-ahead PV power forecast. IEEE J. Photovolt. 12: 581–588. DOI: 10.1109/JPHOTOV.2021.3138223.
12. Abedi, M., Dehghani, M., Gharehpetian, G.B., et al. (2021). Optimized fuzzy controller for MPPT of grid-connected PV systems in rapidly changing atmospheric conditions. J. Mod. Power Syst. Clean Energy 9: 376–383. DOI: 10.35833/MPCE.2019.000086.
13. Li, X., Zhou, Y., Yu, S., et al. (2019). Urban heat island impacts on building energy consumption: A review of approaches and findings. Energy 174: 407–419. DOI: 10.1016/j.energy.2019.02.183.
14. Takane, Y., Kikegawa, Y., Hara, M., et al. (2019). Urban warming and future air-conditioning use in an Asian megacity: importance of positive feedback. NPJ Clim. Atmos. Sci. 2: 1–11. DOI: 10.1038/s41612-019-0096-2.
15. Barron-Gafford, G.A., Minor, R.L., Allen, N.A., et al. (2016). The photovoltaic heat island effect: Larger solar power plants increase local temperatures. Sci. rep. 6: 35070. DOI: 10.1038/srep35070.
16. Luo, L., Zhuang, Y., Qun, T., et al. (2021). Local climatic and environmental effects of an onshore wind farm in North China. Agric. For. Meteorol. 308: 108607. DOI: 10.1016/j.agrformet.2021.108607.
17. Qin, Y., Li, Y., Xu, R., et al. (2022). Impacts of 319 wind farms on surface temperature and vegetation in the United States. Environ. Res. Lett. 17: 024026. DOI: 10.1088/1748-9326/ac49ba.
18. Wang, S., and Wang, S. (2015). Impacts of wind energy on environment: A review. Renew. Sust. Energ. Rev. 49: 437–443. DOI: 10.1016/j.rser.2015.04.137.
19. Roy, S.B., and Traiteur, J.J. (2010). Impacts of wind farms on surface air temperatures. PANS 107: 17899–17904. DOI: 10.1073/pnas.1000493107.
20. Lam, T.N.T., Wan, K.K.W., Wong, S.L., et al. (2010). Impact of climate change on commercial sector air conditioning energy consumption in subtropical Hong Kong. Appl. Energy 87: 2321–2327. DOI: 10.1016/j.apenergy.2009.11.003.
21. Hassid, S., Santamouris, M., Papanikolaou, N., et al. (2000). The effect of the Athens heat island on air conditioning load. Energy Build. 32: 131–141. DOI: 10.1016/S0378-7788(99)00045-6.
22. Kolokotroni, M., Ren, X., Davies, M., et al. (2012). London's urban heat island: Impact on current and future energy consumption in office buildings. Energy Build. 47: 302–311. DOI: 10.1016/j.enbuild.2011.12.019.
23. Chan, A.L.S. (2012). Developing a modified typical meteorological year weather file for Hong Kong taking into account the urban heat island effect. Build Environ. 46: 2434–2441. DOI: 10.1016/j.buildenv.2011.04.038.
24. Street, M., Reinhart, C., Norford, L., et al. (2013). Urban heat island in Boston-An evaluation of urban air-temperature models for predicting building energy use. Proceedings of BS2013: 13th conference of international building performance simulation association. 1022-1029.
25. Zinzi, M., and Carnielo, E. (2017). Impact of urban temperatures on energy performance and thermal comfort in residential buildings. The case of Rome, Italy. Energy Build. 157: 20–29. DOI: 10.1016/j.enbuild.2017.05.021.
26. Cui, Y., Yan, D., Hong, T., et al. (2017). Temporal and spatial characteristics of the urban heat island in Beijing and the impact on building design and energy performance. Energy 130: 286–297. DOI: 10.1016/j.energy.2017.04.053.
27. Yang, X., Peng, Lilliana, L.H., Jiang, Z., et al. (2020). Impact of urban heat island on energy demand in buildings: Local climate zones in Nanjing. Appl. Energy 260: 114279. DOI: 10.1016/j.apenergy.2019.114279.
28. Li, C., Zhou, J., Cao, Y., et al. (2014). Interaction between urban microclimate and electric air-conditioning energy consumption during high temperature season. Appl. Energy 117: 149–156. DOI: 10.1016/j.apenergy.2013.11.057.
29. Yang, X., Zhao, L., Bruse, M., et al. (2012). An integrated simulation method for building energy performance assessment in urban environments. Energy Build. 54: 243–251. DOI: 10.1016/j.enbuild.2012.07.042.
30. Zhao, L., Lee, X., Smith R. B., et al. (2014). Strong contributions of local background climate to urban heat islands. Nature 511: 216–219. DOI: 10.1038/nature13462.
31. Khosla, R., Miranda, N.D., Trotter, P.A., et al. (2021). Cooling for sustainable development. Nat. Sustain. 4: 201–208. DOI: 10.1038/s41893-020-00627-w.
32. Maclean, I.M.D., and Early, R. (2023). Macroclimate data overestimate range shifts of plants in response to climate change. Nature Clim. Change. 13: 484–490. DOI: 10.1038/s41558-023-01650-3.
33. Davis, L.W., and Gertler, P.J. (2021). Contribution of air conditioning adoption to future energy use under global warming. PNAS 112: 5962–5967. DOI: 10.1073/pnas.1423558112.
34. Wang, J., Chen, Y., Liao, W., et al. (2021). Anthropogenic emissions and urbanization increase risk of compound hot extremes in cities. Nature Clim. Change 11: 1084–1089x. DOI: 10.1038/s41558-021-01196-2.
35. He, C., Zhang, Y., Schneider, A., et al. (2022). The inequality labor loss risk from future urban warming and adaptation strategies. Nat. Commun. 13: 3847. DOI: 10.1038/s41467-022-31145-2.
36. Merret, R., Descombin, J., Juan, Y., et al. (2022). XRN4 and LARP1 are required for a heat-triggered mRNA decay pathway involved in plant acclimation and survival during thermal stress. Cell rep. 5: 1279–1293. DOI: 10.1016/j.celrep.2013.11.019.
37. Li, C., Cao, Y., Zhang, M., et al. (2015). Hidden benefits of electric vehicles for addressing climate change. Sci. Rep. 5: 1–4. DOI: 10.1038/srep09213.
38. Ürge-Vorsatz, D., Rosenzweig, C., Dawson, R.J., et al. (2015). Locking in positive climate responses in cities. Nature Clim. Change 8: 174–177. DOI: 10.1038/s41558-018-0100-6.
39. Meinardi, F., Bruni, F., and Brovelli, S. (2017). Luminescent solar concentrators for building-integrated photovoltaics. Nat. Rev. Materials 2: 1–9. DOI: 10.1038/natrevmats.2017.72.
40. Wheeler, V.M., Kim, J., Daligault, T., et al. (2022). Photovoltaic windows cut energy use and CO_2 emissions by 40% in highly glazed buildings. One Earth 5: 1271–1285. DOI: 10.1016/j.oneear.2022.10.014.
41. Peng, Y., Fan, L., Jin, W., et al. (2022). Coloured low-emissivity films for building envelopes for year-round energy savings. Nat. Sustain. 5: 339–347. DOI: 10.1038/s41893-021-00836-x.
42. Wong, N.H., Tan, C.L., Kolokotsa, D.D., et al. (2021). Greenery as a mitigation and adaptation strategy to urban heat. Nat. Rev. Earth & Environment 2: 166–181. DOI: 10.1038/s43017-020-00129-5.
43. Pedersen, Zari, M., MacKinnon, M., Varshney, K., et al. (2022). Regenerative living cities and the urban climate-biodiversity-wellbeing nexus. Nature Clim. Change 12: 1–3. DOI: 10.1038/s41558-022-01390-w.
44. Hoag, H. (2015). How cities can beat the heat: rising temperatures are threatening urban areas, but efforts to cool them may not work as planned. Nature 524: 402–405. DOI: 10.1038/524402a.
45. Georgescu, M., Morefield, P.E., Bierwagen, B.G., et al. (2014). Urban adaptation can roll back warming of emerging megapolitan regions. PNAS 111: 2909-2914. 10.1073/pnas.1322280111.

46. Gromke, C., Blocken, B., Janssen, W., et al. (2015). CFD analysis of transpirational cooling by vegetation: Case study for specific meteorological conditions during a heat wave in Arnhem, Netherlands. Build. Environ. 83: 11–26. DOI: 10.1016/j.buildenv.2014.04.022.
47. McKuin, B., Zumkehr, A., Ta, J., et al. (2015). Energy and water co-benefits from covering canals with solar panels. Nat. Sustain. 4: 609–617. DOI: 10.1038/s41893-021-00693-8.
48. Li, Y., Kalnay, E., Motesharrei, S., et al. (2018). Climate model shows large-scale wind and solar farms in the Sahara increase rain and vegetation. Science 361: 1019–1022x. DOI: 10.1126/science.aar5629.
49. Liu, Y., Zhang, R., Huang, Z., et al. (2019). Solar photovoltaic panels significantly promote vegetation recovery by modifying the soil surface microhabitats in an arid sandy ecosystem. Land Degrad. Dev. 30: 2177–2186xx. DOI: 10.1002/ldr.3408.
50. Vaverková, M.D., Winkler, J., Uldrijan, D., et al. (2019). Fire hazard associated with different types of photovoltaic power plants: Effect of vegetation management. Renew. Sust. Energ. Rev. 162: 112491. DOI: 10.1016/j.rser.2022.112491.
51. Grodsky, S.M., and Hernandez, R.R. (2020). Reduced ecosystem services of desert plants from ground-mounted solar energy development. Nat. Sustain. 3: 1036–1043. DOI: 10.1038/s41893-020-0574-x.
52. Devitt, D.A., Apodaca, L., Bird, B., et al. (2020). Assessing the impact of a utility scale solar photovoltaic facility on a down gradient Mojave Desert ecosystem. Land 11: 1315. DOI: 10.3390/land11081315.
53. Grodsky, S.M. (2021). Matching renewable energy and conservation targets for a sustainable future. One Earth 4: 924–926. DOI: 10.1016/j.oneear.2021.07.001.
54. Hu, A., Levis, S., Meehl, G.A., et al. (2016). Impact of solar panels on global climate. Nature Clim. Change 6: 290–294. DOI: 10.1038/nclimate2843.
55. Masson, V., Bonhomme, M., Salagnac, J.L., et al. (2014). Solar panels reduce both global warming and urban heat island. Front. Environ. Sci. 2: 14. DOI: 10.3389/fenvs.2014.00014.
56. Kenrick, D.T., and MacFarlane, S.W. (1986). Ambient temperature and horn honking: A field study of the heat/aggression relationship. Environ. Behav. 18: 179–191. DOI: 10.1177/0013916586182002.
57. Sahu, A., Yadav, N., and Sudhakar, K. (2016). Floating photovoltaic power plant: A review. Renew. Sust. Energ. Rev. 66: 815–824. DOI: 10.1016/j.rser.2016.08.051.
58. Li, P., Gao, X., Li, Z., et al. (2022). Effects of fishery complementary photovoltaic power plant on near-surface meteorology and energy balance. Renew. Energy 187: 698–709. DOI: 10.1016/j.renene.2022.01.118.
59. Gonzalez Sanchez, R., Kougias, I., Moner-Girona, M., et al. (2021). Assessment of floating solar photovoltaics potential in existing hydropower reservoirs in Africa. Renew. Energy 169: 687–699. DOI: 10.1016/j.renene.2021.01.041.
60. Almeida, R.M., Schmitt, R., Grodsky, Steven, M., et al. (2022). Floating solar power could help fight climate change-let's get it right. Nature 606: 246–249. DOI: 10.1038/d41586-022-01525-1.
61. Almeida, R.M., Shi, Q., Gomes-Selman, Jonathan, M., et al. (2019). Reducing greenhouse gas emissions of Amazon hydropower with strategic dam planning. Nat. Commun. 10: 1–9. DOI: 10.1038/s41467-019-12179-5.
62. Château, P.A., Wunderlich, Rainer, F., Wang, T., et al. (2019). Mathematical modeling suggests high potential for the deployment of floating photovoltaic on fish ponds. Sci. total environ. 687: 654–666. DOI: 10.1016/j.scitotenv.2019.05.420.
63. Santhakumari, M., and Sagar, N. (2019). A review of the environmental factors degrading the performance of silicon wafer-based photovoltaic modules: Failure detection methods and essential mitigation techniques. Renew. Sust. Energ. Rev. 110: 83–100. DOI: 10.1016/j.rser.2019.04.024.
64. Bouguerra, S., Agroui, K., Kaaya, I., et al. (2022). Modeling the effect of PV module orientation on the encapsulant browning degradation rate in Algeria region. IEEE J. Photovolt. 12: 274–284. DOI: 10.1109/JPHOTOV.2021.3124749.
65. Jin, Y., Hu, S., Ziegler, A.D., et al. (2023). Energy production and water savings from floating solar photovoltaics on global reservoirs. Nat. Sustain. 6: 865–874. DOI: 10.1038/s41893-023-01089-6.
66. Armstrong, A., Waldron, S., Whitaker, J., et al. (2014). Wind farm and solar park effects on plant–soil carbon cycling: uncertain impacts of changes in ground-level microclimate. Glob. Chang. Biol. 20: 1699–1706. DOI: 10.1111/gcb.12437.
67. Barron-Gafford, G.A., Pavao-Zuckerman, M.A., Minor, R.L., et al. (2019). Agrivoltaics provide mutual benefits across the food-energy-water nexus in drylands. Nat. Sustain. 2: 848–855. DOI: 10.1038/s41893-019-0364-5.
68. Miskin, C.K., Li, Y., Perna, A., et al. (2019). Sustainable co-production of food and solar power to relax land-use constraints. Nat. Sustain. 2: 972–980. DOI: 10.1038/s41893-019-0388-x.
69. Dinesh, H., and Pearce, J.M. (2016). The potential of agrivoltaic systems. Renew. Sust. Energy Rev. 54: 299–308. DOI: 10.1016/j.rser.2015.10.024.
70. Lundquist, J.K., DuVivier, K.K., Kaffine, D., et al. (2019). Costs and consequences of wind turbine wake effects arising from uncoordinated wind energy development. Nat. Energy 4: 26–34. DOI: 10.1038/s41560-018-0281-2.
71. Van, Dijk, M.T., van, Wingerden, J.W., Ashuri, T., et al. (2017). Wind farm multi-objective wake redirection for optimizing power production and loads. Energy 121: 561–569. DOI: 10.1016/j.energy.2017.01.051.
72. Archer, C.L., Vasel-Be-Hagh, A., Yan, C., et al. (2018). Review and evaluation of wake loss models for wind energy applications. Appl. Energy 226: 1187–1207. DOI: 10.1016/j.apenergy.2018.05.085.
73. Meng, H., Lien, F.S., and Li, L. (2018). Elastic actuator line modelling for wake-induced fatigue analysis of horizontal axis wind turbine blade. Renew. Energy 116: 423–437. DOI: 10.1016/j.renene.2017.08.074.
74. Sun, H., Gao, X., and Yang, H. (2018). A review of full-scale wind-field measurements of the wind-turbine wake effect and a measurement of the wake-interaction effect. Renew. Sust. Energ. Rev. 132: 110042. DOI: 10.1016/j.rser.2020.110042.
75. Sun, H., Gao, X., and Yang, H. (2020). Experimental study on wind speeds in a complex-terrain wind farm and analysis of wake effects. Appl. Energy 272: 115215. DOI: 10.1016/j.apenergy.2020.115215.
76. Mattuella, J.M.L., Loredo-Souza, A.M., Oliveira, M.G.K., et al. (2016). Wind tunnel experimental analysis of a complex terrain micrositing. Renew. Sust. Energ. Rev. 54: 110–119. DOI: 10.1016/j.rser.2015.09.088.
77. Gao, X., Wang, T., Li, B., et al. (2019). Investigation of wind turbine performance coupling wake and topography effects based on LiDAR measurements and SCADA data. Appl. Energy 255: 113816. DOI: 10.1016/j.apenergy.2019.113816.
78. Huang, S., Wu, Q., Guo, Y., et al. (2019). Bi-level decentralized active and reactive power control for large-scale wind farm cluster. Int. J. Electr. Power Energy Syst. 111: 201–215. DOI: 10.1016/j.ijepes.2019.03.045.
79. Wei, J., Cao, Y., Wu, Q., et al. (2021). Coordinated droop control and adaptive model predictive control for enhancing HVRT and post-event recovery of large-scale wind farm. IEEE Trans. Sustain. Energ. 12: 1549–1560. DOI: 10.1109/TSTE.2021.3053955.
80. Lange, J., Mann, J., Berg, J., et al. (2017). For wind turbines in complex terrain, the devil is in the detail. Environ. Res. Lett. 12: 094020. DOI: 10.1088/1748-9326/aa81db.
81. Pickering, B., Grams, C.M., and Pfenninger, S. (2020). Sub-national variability of wind power generation in complex terrain and its correlation with large-scale meteorology. Environ. Res. Lett. 15: 044025. DOI: 10.1088/1748-9326/ab70bd.
82. Masseran, N. (2018). Integrated approach for the determination of an accurate wind-speed distribution model. Energy Convers. Manag. 173: 56-64. 10.1016/j.enconman.2018.07.066.
83. Wenxin, W., Kexin, C., Yang, B., et al. (2021). Influence of wind energy utilization potential in urban suburbs: a case study of Hohhot. Sci. Rep. 11: 11567. DOI: 10.1038/s41598-021-90499-7.
84. Zhang, H., Yu, Y.J., and Liu, Z.Y. (2014). Study on the Maximum Entropy Principle applied to the annual wind speed probability distribution: A case study for observations of intertidal zone anemometer towers of Rudong in East China Sea. Appl. Energy 114: 931–938. DOI: 10.1016/j.apenergy.2013.07.040.
85. Juan, Y.H., Wen, C.Y., Li, Z., et al. (2021). Impacts of urban morphology on improving urban wind energy potential for generic high-rise building arrays. Appl. Energy 299: 117304. DOI: 10.1016/j.apenergy.2021.117304.
86. Juan, Y.H., Wen, C.Y., Chen, W.Y., et al. (2021). Numerical assessments of wind power potential and installation arrangements in realistic highly urbanized areas. Renew. Sust. Energ. Rev. 135: 110165. DOI: 10.1016/j.rser.2020.110165.
87. Zeng, N., and Yoon, J. (2009). Expansion of the world's deserts due to vegetation-albedo feedback under global warming. Geophys. Res. Lett. 36. DOI: 10.1029/2009GL039699.
88. Xu, K., He, L., Hu, H., et al. (2019). Positive ecological effects of wind farms on vegetation in China's Gobi desert. Sci. Rep. 9: 1–11. DOI: 10.1038/s41598-019-42569-0.
89. Lu, J., Zeng, M., Zeng, X., et al. (2014). Analysis of ice-covering characteristics of China Hunan power grid. IEEE Trans. Ind. Appl. 51: 1997–2002. DOI: 10.1109/TIA.2014.2365295.
90. Chun, Z., Chen, J., Gu, S., et al. (2012). Research on differentiated lightning protection comprehensive management for the 500-kV power network in the area near the Three Gorges Project. IEEE Trans. Power Deliv. 27: 337–352. DOI: 10.1109/TPWRD.2011.2171059.
91. Liu, D., Zeng, L., Li, C., et al. (2018). A distributed short-term load forecasting method based on local weather information. IEEE Syst. J. 12: 208–215. DOI: 10.1109/JSYST.2016.2594208.
92. Vahid, M.N., Perera, A.T.D., and Chen, D. (2021). Towards climate resilient urban energy systems: A review. Natl. Sci. Rev. 8: nwaa134. DOI: 10.1093/nsr/nwaa134.
93. Perera, A.T.D., Javanroodi, K., Mauree, D., et al. (2023). Challenges resulting from urban density and climate change for the EU energy transition. Nat. Energy 8: 397–412. DOI: 10.1038/s41560-023-01232-9.
94. Sleptsov, A., Ryzhov, A., Luchnikov, I., et al. (2021). Controlled adjustments of indoor microclimate parameters for building's energy demand management. Energy Rep. 7: 216–224. DOI: 10.1016/j.egyr.2021.06.037.
95. Palme, M., Inostroza, L., Villacreses, G., et al. (2017). From urban climate to energy consumption. Enhancing building performance simulation by including the urban heat island effect. Energy Build. 145: 107–120. DOI: 10.1016/j.enbuild.2017.03.069.
96. Errebai, F.B., Strebel, D., Carmeliet, J., et al. (2022). Impact of urban heat island on cooling energy demand for residential building in Montreal using meteorological simulations and weather station observations. Energy Build. 273: 112410. DOI: 10.1016/j.enbuild.2022.112410.
97. Hong, T., Xu, Y., Sun, K., et al. (2021). Urban microclimate and its impact on building performance: A case study of San Francisco. Urban Climate 38: 100871. DOI: 10.1016/j.uclim.2021.100871.
98. Bueno, B., Norford, L., Hidalgo, J., et al. (2013). The urban weather generator. J. Build. Perform. Simul. 6: 269–281. DOI: 10.1080/19401493.2012.718797.
99. Bruse, M., and Fleer, H. (1998). Simulating surface–plant–air interactions inside urban environments with a three dimensional numerical model. Environ. Model.

Softw. 13: 373–384. DOI: 10.1016/S1364-8152(98)00042-5.
100. Khan, M.R., Hanna, A., Sun, X., et al. (2018). Vertical bifacial solar farms: Physics, design, and global optimization. Appl. Energy 206: 240–248. DOI: 10.1016/j.apenergy.2017.08.042.
101. Valle, B., Simonneau, T., Sourd, F., et al. (2017). Increasing the total productivity of a land by combining mobile photovoltaic panels and food crops. Appl. Energy 206: 1495-1507. 10.1016/j.apenergy.2017.09.113.
102. Gençer, E., Miskin, C., Sun, X., et al. (2017). Directing solar photons to sustainably meet food, energy, and water needs. Sci. Rep. 7: 3133. DOI: 10.1038/s41598-017-03437-x.
103. Prinsloo, F.C., Schmitz, P., and Lombard, A. (2023). System dynamics characterisation and synthesis of floating photovoltaics in terms of energy, environmental and economic parameters with WELF nexus sustainability features. Sustain. Energy Technol. Assess. 55: 102901. DOI: 10.1016/j.seta.2022.102901.
104. Yang, D., Wang, W., Gueymard, Christian, A., et al. (2022). A review of solar forecasting, its dependence on atmospheric sciences and implications for grid integration: Towards carbon neutrality. Renew. Sust. Energ. Rev. 161: 112348. DOI: 10.1016/j.rser.2022.112348.
105. Ghofrani, M., Ghayekhloo, M., and Azimi, R. (2016). A novel soft computing framework for solar radiation forecasting. Appl. Soft Comput. 48: 207–216. DOI: 10.1016/j.asoc.2016.07.022.
106. Halabi, L.M., Mekhilef, S., and Hossain, M. (2018). Performance evaluation of hybrid adaptive neuro-fuzzy inference system models for predicting monthly global solar radiation. Appl. Energy 213: 247–261. DOI: 10.1016/j.apenergy.2018.01.035.
107. Ates, A.M., Yilmaz, O.S., and Gulgen, F. (2020). Using remote sensing to calculate floating photovoltaic technical potential of a dam's surface. Sustain. Energy Technol. Assess. 41: 100799. DOI: 10.1016/j.seta.2020.100799.
108. Bontempo, Scavo, F., Tina, G.M., Gagliano, A., et al. (2021). An assessment study of evaporation rate models on a water basin with floating photovoltaic plants. Int. J. Energy Res. 45: 167–188. DOI: 10.1002/er.5170.
109. Markarian, S., Fazelpour, F., and Markarian, E. (2019). Optimization of wind farm layout considering wake effect and multiple parameters. Environ. Prog. Sustain. 38: 13193. DOI: 10.1002/ep.13193.
110. Cao, L., Ge, M., Gao, X., et al. (2022). Wind farm layout optimization to minimize the wake induced turbulence effect on wind turbines. Appl. Energy 323: 119599. DOI: 10.1016/j.apenergy.2022.119599.
111. Hou, P., Zhu, J., Ma, K., et al. (2019). A review of offshore wind farm layout optimization and electrical system design methods. MPCE 7: 975–986. DOI: 10.1007/s40565-019-0550-5.
112. Nash, R., Nouri, R., and Vasel-Be-Hagh, A. (2021). Wind turbine wake control strategies: A review and concept proposal. Energy Convers. Manag. 245: 114581. DOI: 10.1016/j.enconman.2021.114581.
113. Howland, M.F., Lele, S.K., and Dabiri, J.O. (2019). Wind farm power optimization through wake steering. PNAS 116: 14495–14500. DOI: 10.1073/pnas.190368011.
114. Cheng, Y., Zhang, M., Zhang, Z., et al. (2019). A new analytical model for wind turbine wakes based on Monin-Obukhov similarity theory. Appl. Energy 239: 96–106. DOI: 10.1016/j.apenergy.2019.01.225.
115. Shakoor, R., Hassan, M.Y., Raheem, A., et al. (2016). Wake effect modeling: A review of wind farm layout optimization using Jensen's model. Renew Sustain Energy Rev. 58: 1048–1059. DOI: 10.1016/j.rser.2015.12.229.
116. Weipao, M., Li, C., Yang, J., et al. (2016). Numerical investigation of wake control strategies for maximizing the power generation of wind farm. JSEE 138: 034501. DOI: 10.1115/1.4033110.
117. Ke, S.T., Wang, X.H., and Ge, Y.J. (2019). Wind load and wind-induced effect of the large wind turbine tower-blade system considering blade yaw and interference. Wind Struct. 28: 071. DOI: 10.12989/was.2019.28.2.071.
118. Wang, M., Liu, H., Ni, Y., et al. (2023). Design of monitoring system for icing and galloping in mountainous distribution networks. CIEEC 3477-3482. DOI: 10.1109/CIEEC58067.2023.10166059.
119. Shao, J., Wang, J., Long, M., et al. (2023). Study on windage yaw calculation and real - time warning method of Shanxi power grid considering microclimate and micro - terrain factors. IEEJ T Electr. Electr. 13: 681–688. DOI: 10.1002/tee.22617.
120. Xue, Y., and Yu, X. (2023). Beyond smart grid-Cyber-physical-social system in energy future. Proc. IEEE Inst. Electr. Electron. Eng. 105: 2290–2292. DOI: 10.1109/JPROC.2017.2768698.
121. Yu, X., and Xue, Y. (2016). Smart grids: A cyber-physical systems perspective. Proc. IEEE Inst. Electr. Electron. Eng. 104: 1058–1070. DOI: 10.1109/JPROC.2015.2503119.
122. Cheng, Y, Zhang, N., Wang, Y., et al. (2018). Modeling carbon emission flow in multiple energy systems. IEEE Trans. Smart Grid 10: 3562–3574. DOI: 10.1109/TSG.2018.2830775.
123. Kang, C., Zhou, T., Chen, Q., et al. (2015). Carbon emission flow from generation to demand: A network-based model. IEEE Trans. on Smart Grid 6: 2386–2394. DOI: 10.1109/TSG.2015.2388695.
124. Gómez-Amo, J.L., Freile-Aranda, M.D., Camarasa, J., et al. (2019). Empirical estimates of the radiative impact of an unusually extreme dust and wildfire episode on the performance of a photovoltaic plant in Western Mediterranean. Appl. Energy 235: 1226–1234. DOI: 10.1016/j.apenergy.2018.11.052.
125. Craig, M.T., Wohland, J., Stoop, L.P., et al. (2022). Overcoming the disconnect between energy system and climate modeling. Joule 6: 1405–1417. DOI: 10.1016/j.joule.2022.05.010.
126. Brocca, L., Zhao, W., and Lu, H. (2023). High-resolution observations from space to address new applications in hydrology. The Innovation 4: 100437. DOI: 10.1016/j.xinn.2023.100437.
127. Zellweger, F., De, Frenne, P., Lenoir, J., et al. (2019). Advances in microclimate ecology arising from remote sensing. Trends Ecol. Evol. 34: 327–341. DOI: 10.1016/j.tree.2018.12.012.
128. Bauer, P., Thorpe, A., and Brunet, G. (2015). The quiet revolution of numerical weather prediction. Nature 525: 47–55. DOI: 10.1038/nature14956.
129. Bougeault, P., Toth, Z., Bishop, C., et al. (2010). The THORPEX interactive grand global ensemble. Bull. Am. Meteorol. Soc. 91: 1059–1072. DOI: 10.1175/2010BAMS2853.1.
130. Pathak, J., Subramanian, S., Harrington, P., et al. (2022). FourCastNet: A global data-driven high-resolution weather model using adaptive Fourier neural operators. Preprint at https://arxiv.org/abs/2202.11214.
131. Bi, K., Xie, L., Zhang, H., et al. (2023). Accurate medium-range global weather forecasting with 3D neural networks. Nature 619: 533–538. DOI: 10.1038/s41586-023-06185-3.
132. Thornton, P.E., Shrestha, R., Wei, Y., et al. (2016). Daymet: Daily surface weather data on a 1-km grid for North America, Version 3. ORNL Distributed Active Archive Center. DOI: 10.3334/ORNLDAAC/1840.
133. Chen, Y., Quan, J., Zhan, W., et al. (2016). Enhanced statistical estimation of air temperature incorporating nighttime light data. Remote Sens. 8: 656. DOI: 10.3390/rs8080656.
134. Kloog, I., Nordio, F., Lepeule, J., et al. (2017). Modelling spatio-temporally resolved air temperature across the complex geo-climate area of France using satellite-derived land surface temperature data. Int. J. Climatol. 37: 296–304. DOI: 10.1002/joc.4705.
135. Oyler, J. W., Ballantyne, A., Jencso, K., et al. (2015). Creating a topoclimatic daily air temperature dataset for the conterminous United States using homogenized station data and remotely sensed land skin temperature. Int. J. Climatol. 35: 2258–2279. DOI: 10.1002/joc.4705.
136. Li, X., Zhou, Y., Asrar, G.R., et al. (2018). Developing a 1 km resolution daily air temperature dataset for urban and surrounding areas in the conterminous United States. Remote Sens. Environ. 215: 74–84. DOI: 10.1016/j.rse.2018.05.034.
137. Urraca, R., Huld, T., Gracia-Amillo, A., et al. (2018). Evaluation of global horizontal irradiance estimates from ERA5 and COSMO-REA6 reanalyses using ground and satellite-based data. Sol. Energy 164: 339–354. DOI: 10.1016/j.solener.2018.02.059.
138. Ramon, J., Lledó L., Torralba V., et al. (2019). What global reanalysis best represents near - surface winds. Q. J. Roy. Meteor. Soc. 145: 3236–3251. DOI: 10.1002/qj.3616.
139. Troccoli, A., Goodess, C., Jones, P., et al. (2018). Creating a proof-of-concept climate service to assess future renewable energy mixes in Europe: An overview of the C3S ECEM project. Advances in Science and Research 15: 191–205. DOI: 10.5194/asr-15-191-2018.
140. Hofmann, F., Hampp, J., Neumann, F., et al. (2021). atlite: A lightweight python package for calculating renewable power potentials and time series. JOSS 6: 3294. DOI: 10.21105/joss.03294.
141. Wang, Z., Yan, J., Xian, Y., et al. (2020). A hybrid model for short-term PV output forecasting based on PCA-GWO-GRNN. J. Mod. Power Syst. Clean Energy 8: 1268–1275. DOI: 10.35833/MPCE.2020.000004.
142. Zhong, S., Wang, X., Xu, B., et al. (2023). Hybrid network model based on data enhancement for short-term power prediction of new PV plants. J. Mod. Power Syst. Clean Energy 12: 1–12. DOI: 10.35833/MPCE.2022.000759.

FUNDING AND ACKNOWLEDGMENTS

This work is supported by Project of NARI Group Corporation "Interaction and Coordination Techniques of Cyber-Physical-Social Elements" (GF-GFWD-210338). The funders had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

AUTHOR CONTRIBUTIONS

Canbing Li, Yusheng Xue, Ran Li, Yu Cheng conceived the overall structure of the article and wrote the manuscript. All authors contributed to the subsequent editing and improvement of the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.

LEAD CONTACT WEBSITE

Yusheng Xue: https://ysg.ckcest.cn/html/details/384/index.html