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LETTER

The climate non-stationarity challenges Chinese wind energy safety and efficiency

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Dear Editor,

Wind energy plays a fundamental role in China's pathway to carbon neutrality. Despite the significant progress in wind power capacity installation, critical challenges persist in optimizing wind farm siting accuracy and wind farm risk assessment from three interrelated aspects: the reliance on historical wind data that fails to capture climate-driven non-stationarity, escalating risks from extreme wind events, and insufficient high-resolution spatiotemporal data for accurate assessments. This letter identifies the methodological challenges in China's current practices and advocates a comprehensive technical framework to enhance the accuracy and reliability of wind farm siting and wind resource assessment. By advocating advanced observational networks, data assimilation and next-generation forecasting models, this letter aim to ensure the sustainable wind power development in China.

INTRODUCTION

To transition to a renewable energy system, wind energy has experienced rapid development in China. By 2023, the total installed capacity of wind turbines in China reached 441.1 GW (403.33 GW onshore and 37.78 GW offshore).[1] China has emerged as a significant growth engine for wind energy development globally. However, current practices in wind farm siting and risk management remain inadequate for addressing climate change impacts. Traditional methods assume climate stationarity, relying on short-term historical wind data (typically <5 years), while ignoring projected shifts in wind patterns and extreme events.[2] More importantly, China faces the risk of extreme winds due to frequent typhoons in the Northwest Pacific, which threaten the safety of offshore wind farms and maritime activities, including shipping and drone operations. Besides, China is still limited by insufficient high-resolution spatiotemporal data, both in offshore and onshore regions. While similar climate non-stationarity assumption challenges exist in other regions (e.g., declining wind speeds in the U.S. Midwest or hurricane intensification in the North Atlantic Ocean[3]), China's case merits particular attention due to its uniquely rapid wind energy expansion coupled with unique typhoon exposures and large industrial power demand. This letter identifies methodological gaps in China's current practices and proposes a climate-resilient framework to enhance siting accuracy and risk mitigation, ensuring the efficiency of wind power development.

CLIMATE NON-STATIONARITY UNDERMINES LONG-TERM WIND RESOURCE AVAILABILITY

Current wind resource assessment methodologies for wind farm site selection predominantly rely on relatively short-term historical anemometer observations (typically <5 years) due to the substantial costs associated with instrument deployment.[2] While the IEC standard recommends supplementing these measurements through extrapolation of other long-term records, the complex interplay of topographic features and micro-atmospheric conditions often results in poor correlation between in-situ observations and actual wind farm conditions,[4] leading to inaccurate site prioritization and suboptimal capacity factor projections. In the context of climate change, wind speeds in both onshore and offshore regions of China are exhibiting changes across various spatiotemporal patterns. Terrestrial wind speeds demonstrated a "stilling" trend prior to 2010, followed by a reversal in the subsequent decade.[5] Offshore wind speeds have shown a strengthening trend since 1985, however, a recent decline has been observed based on multiple satellite sensors.[6] These phenomena highlight the changing wind climates and underscore the necessity of incorporating projected future wind speed trends into wind farm siting assessments to ensure long-term resource availability and improve investment efficiency.

Escalating Risks from Extreme Wind Events Threaten Wind Farm Safety

Offshore wind energy, which benefits from more abundant wind resources and proximity to high energy demand regions, faces challenges due to harsh operational environments characterized by strong winds, waves, and currents. The Northwest Pacific Ocean experiences the highest frequency of typhoons globally, with China being the country most affected by landfalling typhoons. The extreme wind speeds, wind shear, and high waves induced by typhoons place wind turbines in precarious situations. For example, in September 2024, Typhoon Yagi, the most powerful autumn typhoon, caused severe damage to a coastal wind farm in Hainan, resulting in the collapse of six wind turbines, each with a capacity of 6.25 MW, and losses exceeding $8.22 million.[7] Research indicates that human-driven shifts in sea surface temperatures have significantly driven the modern hurricane 8.3 m/s more intense on average during the period from 2019 to 2023 for all hurricane categories.[3]

In wind turbine design, the fifty-year return period wind speed (U_{50}) is used to define the maximum wind turbine load. Following the methodology of U_{50} assessment proposed by Pryor& Barthelmie (2021),[8] where U_{50} is derived as the 98th percentile of the Gumbel distribution fitted to annual maximum wind speeds, we conducted a moving time window analysis to explore the trend change of U_{50} based on ERA-5 dataset. We found that over half of the regions over China's seas exhibit an increasing trend in U_{50}, particularly in the offshore regions near southern Hainan, Taiwan, and southeastern Zhejiang province. This trend highlights potential risks to the safety of offshore wind turbine operations. Besides U_{50}, additional extreme wind parameters specified in IEC 61400-1 - including extreme turbulence intensity and wind shear - similarly pose substantial risks to turbine structural integrity. The potential evolution of these parameters under climate change scenarios requires comprehensive evaluation to ensure long-term wind turbine safety. Therefore, it is imperative to revise the framework for extreme wind risk assessment by incorporating projected wind speed changes.

DATA GAPS AND MODEL LIMITATIONS COMPROMISE WIND ASSESSMENT RELIABILITY

There are still constrained by the scarcity of available wind speed data. The widely used reanalysis wind products assimilate little inland surface wind observations due to the high variability and dependency on the local topography of meteorological stations.[2] Therefore, most of the inland reanalysis products did not capture the "stilling" and "reversal" trend of terrestrial wind speed.[9] As to offshore regions, there are currently no publicly accessible buoy observations of wind speed variables in China's offshore regions for research and exploration purposes. Furthermore, reanalysis data often exhibit significant underestimations of offshore wind speeds, while satellite data are limited by temporal resolution and demonstrate large temporal fluctuations (with only 1-3 re-entry cycles per month, as shown in Figure 1B). The limited availability of wind data constrains both extreme risk assessments and wind resource evaluations.

Additionally, existing wind resource prediction models also face challenges in accurately simulating interannual variability and extreme wind conditions. Current modeling approaches fall into two broad categories, physical models and data-driven methods. While physical models integrate key meteorological variables (e.g., temperature, pressure, geopotential height), their computational cost is high, and their performance degrades for short-term forecasts.[10] Data-driven methods, including shallow models (Support Vector Machine, etc.) and deep learning architectures (Long Short-Term Memory, Gated Recurrent Unit, etc.), can capture spatiotemporal dependencies but often struggle with global-scale dynamics and nonlinear wind fluctuations[11]. Recent advances incorporate graph neural networks, attention mechanisms,

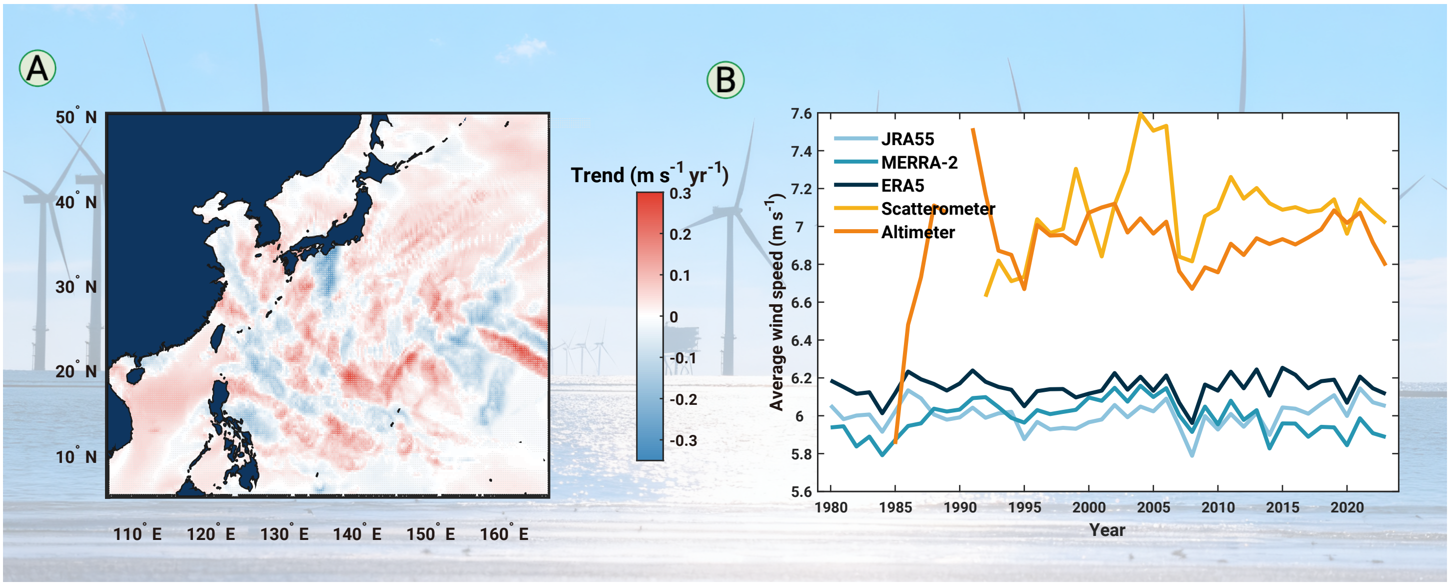

Figure 1. Trends in U_{50} and spatial average wind speed over East Asia marine regions (a) Trends in the fifty-year return period wind speed (U_{50}). Grey dots indicate pixels where trends are statistically significant. (b) Spatial average wind speed over East Asia marine regions. Reanalysis datasets include JRA-55 (Japanese 55-year Reanalysis), MERRA-2 (Modern-Era Retrospective Analysis for Research and Applications), and ERA5 (the fifth generation of the European Centre for Medium-Range Weather Forecasts Reanalysis). Scatterometer data are derived from ERS-1, ERS-2, QuikSCAT, METOP-A, OceanSat, METOP-B, RapidScat, and METOP-C (listed in order of launch). Altimeter data are sourced from ERS-1, TOPEX, ERS-2, GFO, JASON-1, ENVISAT, SARAL, JASON-2, JASON-3, SENTINEL-3A, CFOSAT, CRYOSAT-2, GEOSAT, SENTINEL-3B, HY-2A, HY-2B, and SENTINEL-6A (listed in order of launch). A short data gap exists in altimeter observations during 1989–1991.

and multivariate data fusion (e.g., MFWPN) to improve accuracy by integrating geopotential, temperature, and elevation data. Nevertheless, persistent limitations include coarse spatiotemporal resolution, neglect of turbulence and humidity effects, and poor generalization to extreme weather events.[11]

Exactly the large interannual fluctuations in wind resources will induce large influence of the renewable energy company revenues and power grid stability. For instance, Longyuan Power, a leading domestic wind power company, reported a 13% decrease in wind power generation in November 2024 compared to the same period in the previous year, primarily due to a notable decline in wind speeds during that month.[12] As the proportion of wind power generation within the energy system increases, the inability to accurately predict fluctuations in wind resources poses a serious challenge to the stability of the energy system.

SUGGESTIONS TO MITIGATE THE CHALLENGES

To address these challenges, we propose a comprehensive strategy combining enhanced observational networks with advanced modeling approaches. First, we advocate deploying systematically offshore buoys measuring framework, including observations of wind speed, gusts, sea surface temperature, and pressure. Combine reanalysis and satellite data via assimilation techniques to improve historical reconstructions. Besides, we suggest developing next-generation prediction models that combine multi-station meteorological data (wind speed, direction, temperature, pressure) with reanalysis datasets. By adopting the advanced architectures (e.g., Transformer, Auto-Regressive Moving Diffusion) and incorporating climate variables (e.g., sea surface temperature, pressure gradients) under diverse emission scenarios, the novel wind resource assessment model that will be capable of accurately identifying regions with long-term stable and abundant wind resources while accurately forecasting interannual fluctuations. Crucially, this capability will enable optimal turbine siting to maximize energy production over the entire operational lifespan of a wind farm, while also providing accurate forecasts of interannual fluctuations. Based on a high-precision medium- and long-term wind speed prediction model, we suggest assessing parameters related to extreme wind conditions in the future, including U_{50}, extreme wind shear, and extreme turbulence, to assist in selecting wind turbine models suitable for extreme loading conditions and risk alerting for an already commissioned wind farm.

CONCLUSIONS

This letter highlights three critical challenges in wind farm siting and operation: climate non-stationarity altering wind resource availability, escalating extreme wind risks, and data and model limitations. To maximize wind farm siting accuracy and ensure sustainable wind energy development, we advocate for expanded in-situ observations, data assimilation, robust forecasting models, and climate-informed risk assessments. Addressing these issues will enhance the accuracy of wind resource evaluations, improve turbine resilience, and bolster energy system stability. Integrating these advancements will drive faster growth of China's wind energy industry while mitigating critical risks.

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DECLARATION OF INTERESTS

The authors declare no competing interests.