

## Review

# A Review of Medium–Long-Term Wind Energy Projection

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## Abstract

Reliable medium–long-term wind energy projection is essential in the planning, financing, and operation of large-scale offshore wind development. This study classified projection methods into three categories: statistical/empirical and climate-signal-driven methods, dynamical models with reanalysis and regional downscaling, and machine/deep learning and hybrid methods for bias correction, downscaling, and direct data-driven projection. Then, this study reviewed the technical framework, representative studies, and comparative strengths and limitations. The main finding was that the state of the art increasingly converged on “dynamical simulation plus statistical or machine learning correction”. Next, seven main bottlenecks, along with the countermeasures, were systematically presented: (i) difficult data quality control and insufficient observational representativeness, especially offshore; (ii) divergent, even contradictory, conclusions for the same region across data sources and research groups; (iii) large uncertainty in extrapolating 10 m winds to the continually rising turbine hub height; (iv) difficulty in quantifying and communicating non-stationarity and uncertainty to decision-makers; (v) engineering conversion errors from projected “wind resource” to deliverable “electricity”; (vi) systematic biases in the marine atmospheric boundary layer, strong winds, and extreme conditions; and (vii) unresolved reliability, interpretability, and out-of-distribution generalization of AI models. Correspondingly, three mutually reinforcing strands of countermeasures were proposed: first, strengthening the observational and benchmarking foundation through unified, open, quality-controlled observation networks with data-provenance standards and shared reference datasets and intercomparison protocols; second, advancing physics–data integration and uncertainty quantification through hybrid and physics-informed correction, regime-specific bias correction of boundary-layer and extreme-wind errors, and probabilistic frameworks that delivered and clearly communicated credible intervals; and third, closing the resource-to-electricity gap by embedding power-curve convolution, wake-loss modeling, and availability and technology derating into the projection workflow, with the aim of improving medium–long-term wind energy projection accuracy.

**Keywords:** bottlenecks; countermeasures; offshore wind; wind energy projection

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## 1. Introduction

The global energy system has undergone a profound transition toward renewable-dominant generation, with wind power at its center. According to the Global Wind Report 2025 [1], cumulative global offshore wind capacity reached approximately 83.2 GW by the end of 2024, roughly half of it in China—now the world’s largest wind power market [2]—while Europe, China, and the United States had developed distinct offshore development models [3]. As deployment accelerated, offshore wind was shifting from an “additional power source” to a “system-level energy pillar”, and reliable information about future wind resources had become correspondingly strategic. Whereas short-term forecasting (minutes to days) had matured to support real-time dispatch, it was the medium-long-term horizon—spanning sub-seasonal (weeks to months), seasonal (1–6 months), interannual-to-decadal, and climate change timescales—that governed the decisions carrying the greatest capital and strategic weight: grid expansion, cross-regional interconnection, site selection, investment appraisal, maintenance scheduling, and electricity-market design [4]. These stakes were heightened by climate change, which drove spatially differentiated, non-stationary trends in wind resources—heterogeneous responses across China’s near-shore waters [5], monsoon-modulated variability in Asia [6], non-stationary evolution of wave and wind resources more broadly [7,8], and a projected rise in offshore wind potential in a warming world [9]—alongside wind’s expanding role in climate mitigation [10]. As a result, long-term planning could no longer rely on a simple extrapolation of the past. Encouragingly, such projection was scientifically tractable: low-frequency climate signals conferred genuine predictability at seasonal-to-decadal scales, as demonstrated for the North Atlantic [11,12], framed through the “windows of opportunity” concept [13], and increasingly realized in skillful seasonal predictions of wind energy over the United States [14] and decadal predictions for the European energy sector [15]. Reliable medium-long-term projection thus underpinned regional renewable planning, mitigated supply–demand imbalances, and strengthened system resilience in service of national decarbonization (“dual carbon”) goals; conversely, projection errors propagated into system economics, as shown for price transmission in carbon-constrained markets [16] and for the correlated output “droughts” that challenged grid balancing [17,18].

Meeting these needs drove a rapid methodological evolution. Since the early 2000s, wind projection had progressed from simple persistence and empirical extrapolation toward increasingly physically grounded and data-rich approaches—a trajectory charted by Foley et al. [19] in their 2012 review. Three successive, and now coexisting, paradigms could be distinguished. The first relies on statistical and climate-signal-driven models that link large-scale modes of variability—El Niño–Southern Oscillation (ENSO), the North Atlantic Oscillation (NAO), and the Arctic Oscillation (AO)—to regional wind fluctuations; these are transparent and efficient but assume statistical stationarity, and even well-tuned classical models such as Autoregressive Integrated Moving Average/Seasonal Autoregressive Integrated Moving Average (ARIMA/SARIMA) remain competitive for monthly scale production [20]. The second grounded projection in physical processes involves coupling global and regional climate models, such as the Coupled Model Intercomparison Project Phase 6 (CMIP6) and the European Coordinated Regional Climate Downscaling Experiment (EURO-CORDEX), with mesoscale dynamical downscaling, such as the Weather Research and Forecasting (WRF) model, to resolve coastal terrain and land–sea contrasts under alternative emission scenarios and gain physical rigor at the cost of heavy computation and intertwined uncertainties. This has been illustrated in recent Coupled Model Intercomparison Project Phase 5 (CMIP5) and CMIP6 evaluations over the Northern Hemisphere for both skill and inter-model spread [21]. The third and most recent paradigm applies both machine and deep learning, often in hybrid configurations, to post-process, bias-correct, and downscale dynamical outputs or to build data-driven

projections directly across short, medium, and long horizons [22,23], exploiting the non-linear structure of multi-source data while raising new concerns about interpretability and out-of-distribution reliability. Such data-driven approaches now even extend to machine learning-based projections of national wind generation in 2030 [24]. Each paradigm largely emerged to compensate for the limitations of its predecessor, and their growing convergence—typically “dynamical simulation plus statistical or machine learning correction”—now defined the state of the art. Unlike Foley et al. [19], who focus on short-term operational forecasting, the foundational climate-impact review of Pryor and Barthelmie [25]—which predates the large-scale offshore build-out and the CMIP6/machine learning era—and recent reviews that mainly refine forecasting model taxonomy [26,27], the present review targets the medium-long-term offshore horizon and, beyond surveying methods, the field’s key bottlenecks are systematically diagnosed together with their causes, impacts, and countermeasures (Table 1).

**Table 1.** Comparison between this review and representative existing reviews on medium-long-term wind energy projection.

| Dimension                                | Foley et al. [19]                              | Mbugua and Hiraga [26]                | Liu et al. [27]                              | This Review                                                                         |
|------------------------------------------|------------------------------------------------|---------------------------------------|----------------------------------------------|-------------------------------------------------------------------------------------|
| Primary time horizon                     | Very-short-/short-term operational forecasting | Long-term                             | Ultra-short-/short-term (explicitly focused) | S2S, seasonal, interannual-to-decadal, climate change (full medium-long spectrum)   |
| Method classification                    | Physical/statistical/hybrid (AI)               | Statistical/physical/machine learning | Physical/statistical/DL/ensemble/hybrid      | Climate-signal statistical/dynamical + downscaling/ML and hybrid (three categories) |
| Offshore emphasis                        | Limited (mainly onshore)                       | Limited                               | Limited                                      | Explicit (air-sea coupling, extremes, typhoons)                                     |
| Climate change projection                | Not covered (operational forecasting)          | Weak                                  | Not covered                                  | Central (CMIP6/EURO-CORDEX scenarios)                                               |
| Resource-to-electricity conversion       | Not addressed                                  | Not addressed                         | Not addressed                                | Addressed (power curve, wake losses, availability)                                  |
| Systematic bottlenecks + countermeasures | Partial (method bottlenecks)                   | Partial                               | Challenges noted                             | Seven bottlenecks, each as cause → impact → countermeasure                          |

**Abbreviations:** CMIP6, Coupled Model Intercomparison Project Phase 6; DL, deep learning; EURO-CORDEX, European Coordinated Regional Climate Downscaling Experiment; ML, machine learning; S2S, sub-seasonal to seasonal.

Although the present review focuses on wind, offshore wind development was increasingly being pursued alongside other marine renewables, including wave and tidal-current energy, and, in deeper waters, within co-located or structurally integrated “hybrid” platforms that shared moorings, grid connections, and maintenance systems [28–30]. These technologies faced closely related medium-long-term assessment challenges, as they relied on the same metocean reanalysis and downscaling products, were affected by the same non-stationarity and extreme-event biases, and offered genuine synergies. In

particular, offshore wind and wave resources were often temporally complementary, meaning that joint exploitation could smooth aggregate output and mitigate low-production, or “Dunkelflaute”, periods [31–33]. Accordingly, the wind-focused analysis presented below is situated within this broader offshore-renewable context where relevant.

Despite this progress, medium–long-term wind energy projection still fell short of the reliability that large-scale offshore development demanded, owing to recurring, cross-cutting bottlenecks: weak observational foundations, particularly offshore, where hub-height profiles were scarce and quality-control standards were not harmonized; imperfect representation of the marine atmospheric boundary layer, strong winds, and extreme events; non-stationary statistics that were difficult to quantify and to communicate to planners; divergent, even contradictory, conclusions for the same region across different data sources and research groups; oversimplified conversion from projected “wind resource” to deliverable “electricity”; and unresolved questions of reliability, interpretability, and generalization for the newest machine learning tools. Motivated by these challenges, this review was organized as follows. In Section 2, the field is surveyed through the three methodological categories introduced above—statistical/empirical and climate-signal-driven methods (Section 2.1), dynamical models with reanalysis and regional downscaling (Section 2.2), and machine learning/deep learning and hybrid methods (Section 2.3)—with the technical framework, representative studies, and comparative strengths and limitations examined for each. In Section 3, the major bottlenecks are identified, their causes and impacts on wind power development analyzed, and targeted countermeasures proposed; in Section 5, future prospects are outlined. The present review was intended to provide a scientific basis for improving medium–long-term wind energy projection and, ultimately, for supporting wind power’s reliable integration into the global energy transition.

## 2. Current Status of Medium–Long-Term Wind Energy Projection

Based on methods and tools, medium–long-term wind energy projection was classified into three categories: statistical/empirical and climate-signal-driven methods, dynamical models and reanalysis/regional downscaling methods, and machine learning/deep learning and hybrid methods. These three categories are systematically compared across eight dimensions in Table 2, and each is described in detail below.

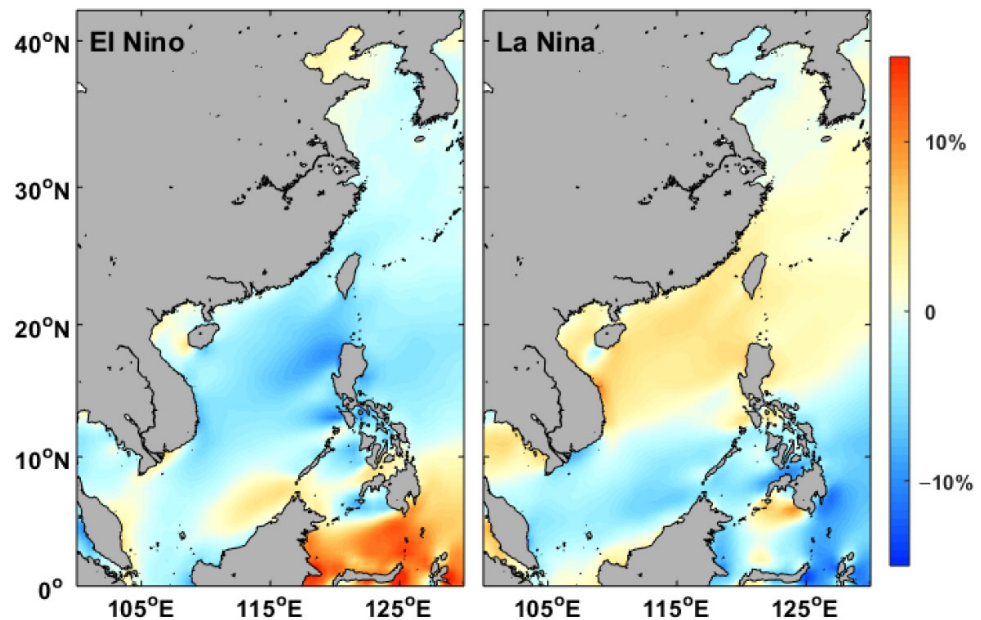
**Table 2.** Systematic comparison of the three categories of medium–long-term wind energy projection methods.

| Dimension          | Statistical/Empirical and Climate-Signal-Driven                                                          | Dynamical Models + Reanalysis/Regional Downscaling                                                                                                      | Machine/Deep Learning and Hybrid                                                                                                         |
|--------------------|----------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Primary timescale  | Seasonal to interannual/decadal where teleconnection signals exist; also, monthly scale production       | Interannual-to-decadal and multi-decadal climate change (scenario-based)                                                                                | Sub-seasonal to seasonal and medium–long term; flexible across horizons                                                                  |
| Typical input data | Historical observations, reanalysis/remote sensing, electricity records; climate indices (ENSO, NAO, AO) | GCM/RCM outputs (CMIP6, EURO-CORDEX), reanalysis ECMWF Reanalysis v5 (ERA5) as reference, mesoscale (WRF) fields; Representative Concentration Pathway/ | Multi-source fusion: observations + reanalysis + model outputs, Supervisory Control and Data Acquisition (SCADA); large labeled datasets |

|                             |                                                                                                                      | Shared Socioeconomic Pathway (RCP/SSP) scenarios                                                                                     |                                                                                                                                           |
|-----------------------------|----------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| Forecast/projection horizon | Weeks to a few months ahead (S2S-seasonal), up to interannual; skill decays without persistent signals               | Decades to end of century (e.g., 2050, 2100) under emission scenarios                                                                | Hours to months for data-driven forecasting; can also post-process dynamical projections to century scale                                 |
| Spatial scale/resolution    | Regional or station-based; relatively coarse; set by predictor–predictand relationships                              | High resolution after downscaling (e.g., 12 km EURO-CORDEX, km scale WRF); resolves coastal terrain, low-level jets, sea–land breeze | Flexible; Generative Adversarial Network (GAN)/diffusion downscaling reconstructs high-resolution fields from coarse inputs               |
| Uncertainty treatment       | Probabilistic via statistical calibration (regression, quantile mapping); prediction intervals; stationarity assumed | Multi-model/-scenario ensembles with bias correction; spread quantifies structural + scenario uncertainty                            | Ensemble/quantile/Bayesian (Monte-Carlo dropout) UQ; out-of-distribution reliability still uncertain                                      |
| Key advantages              | Transparent, efficient, interpretable, low-cost; effective where data are abundant and relationships stable          | Rigorous physical basis; engineering-relevant spatial detail; can simulate extremes and identify physical drivers                    | Captures nonlinear multi-source structure; automatic bias correction and resolution enhancement; end to end                               |
| Main limitations            | Assumes stationarity; weak on air–sea coupling and extremes; sensitive to data quality and completeness              | Many intertwined uncertainty sources; high computational cost; needs region-specific calibration; resource→electricity gap           | Needs large high-quality data; limited interpretability/physical constraints; weak out-of-distribution (OOD) extrapolation; concept drift |
| Practical applications      | Seasonal outlooks, risk indices, energy drought/“Dunkelflaute” assessment, monthly production planning               | Resource assessment, siting and micro-siting, future climate planning inputs, design wind and financial risk evaluation              | Bias correction/downscaling of projections, probabilistic scenario generation, farm/cluster power prediction                              |

### 2.1. Statistical/Empirical and Climate Signal-Driven Methods

These methods relied on historical data and statistical techniques to link large-scale climate modes to regional wind energy variability. Common approaches included time-series and state-space models, Markov/hidden Markov chains, regression, and analog methods, with atmospheric oscillation indices (ENSO, NAO, and AO) as predictors [34]. Xu et al. [34] showed that El Niño suppressed wind energy across most of the Nanhai and Donghai Seas (up to −10%), while La Niña produced the opposite enhancement (up to +8%), with nearly mirror-image spatial patterns (Figure 1). Through statistical calibration, these models converted predictable circulation signals into probability distributions of regional wind speed or power output, enhancing projection skill at seasonal-to-interannual scales where teleconnection signals existed.



**Figure 1.** Spatial distribution of the percentage change in wind speed over the China Seas during El Niño (left) and La Niña (right) events from 1979 to 2016 (from Xu et al. [34]).

#### 2.1.1. Representative Studies of Statistical/Empirical Methods

Jerez et al. [35] assessed NAO's influence on renewable resources over the Iberian Peninsula (1959–2007). During October–March, negative NAO phases strengthened westerlies, raising wind speeds by 10–15% and wind power potential by ~30%, while positive phases reduced wind energy. Buatois et al. [36] built hourly wind speed and power time series for 177 North Sea offshore wind farms. They found that large-scale offshore expansion intensified short-term output fluctuations and ramp events. Curtis et al. [37] examined NAO's effect on electricity markets via wind generation. NAO phase shifts significantly altered thermal generation costs, wholesale prices, and wind revenue. Grams et al. [38] linked European weather circulation regimes to multi-day wind power fluctuations, finding that under certain regimes, regional output dropped or surged simultaneously over wide areas. They proposed the cross-regional dispersal of wind farms to smooth total system variability.

Bloomfield et al. [39] used European Centre for Medium-Range Weather Forecasts (ECMWF) and National Centers for Environmental Prediction (NCEP) sub-seasonal reforecasts to build an ensemble dataset of daily wind power, photovoltaic output, and load for 28 European countries, using the Sub-seasonal to Seasonal for Energy (S2S4E) dataset. Coburn [40] examined how teleconnection modes affect wind energy over the U.S. Central Plains. ENSO and AO significantly influenced wind energy output, with effects varying by season and location. Xu et al. [34] analyzed how multiple climate oscillations affect nearshore wind energy in the China Seas using long-term satellite data. ENSO and Pacific Decadal Oscillation (PDO) exerted particularly strong modulating effects on the Nanhai Sea and Donghai Sea. Bett et al. [41] used the Copernicus Climate Change Service (C3S) seasonal projection system with linear regression calibration to produce probabilistic wind speed/irradiance projections for European wind power. Otero et al. [42] defined “low wind + low solar + high load” as compound energy events and used logistic regression on ECMWF Reanalysis v5 (ERA5) to identify atmospheric drivers. Specific circulation regimes—especially winter Omega blocks and other blocking highs—produced widespread calm winds, overcast skies, and cold-driven load peaks simultaneously. They also

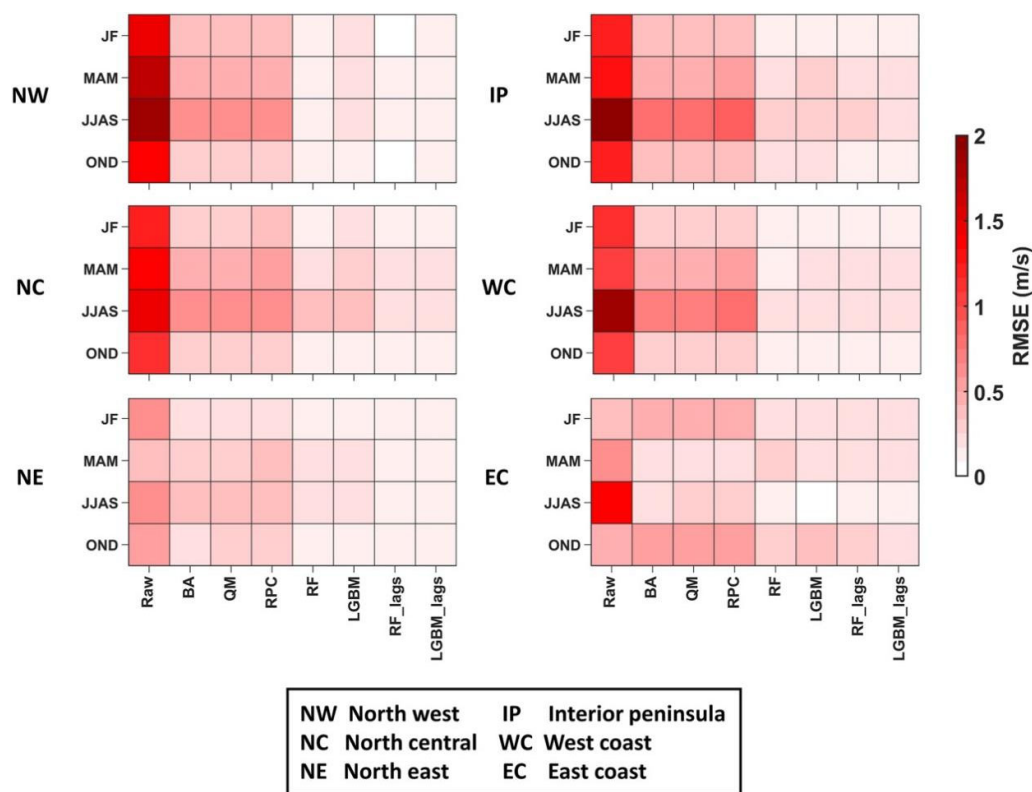
estimated event frequency and duration, offering a new angle for energy–meteorological risk management. Otero et al. [43] used copula functions to model the dependence and risk of European wind and solar “droughts”. Low wind and solar output were significantly correlated under large-scale circulation anomalies. Hjelmeland and Nøland [17] analyzed Nordic grid wind data, finding that outputs from North Sea offshore wind farms were highly correlated, with simultaneous drops or surges challenging regional balance. The European State of the Climate Report [44] documented prolonged low winds during the European summer of 2021, when July–August wind speeds hit decades-low levels and output forced ramped-up fossil generation in some countries. Al-Duais and Al-Sharpi [45] combined SARIMA with Markov Chain Monte Carlo (MCMC) for wind speed and power forecasting. The MCMC-enhanced method improved prediction interval coverage and stochastic consistency over lead times of several months. Yang et al. [14] used seasonal prediction products from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center to forecast winter and spring wind energy across the U.S. Great Plains months ahead. Tian et al. [22] introduced a nonlinear mapping between circulation and wind speed for European sub-seasonal forecasts. Kittel and Schill [18] assessed “Dunkelflaute”—periods of simultaneously low wind and solar output—using reconstructed data from the 1980–2020 period.

Szostek et al. [20] compared ARIMA, SARIMA, and Support Vector Regression (SVR) for monthly scale wind power projection on two Polish wind farms (10+ years of data). Though site-specific tuning was required, well-tuned classical models achieved accuracy comparable to machine learning, confirming that traditional statistical models retained practical value for monthly scale projection, particularly with limited data or interpretability needs. Lindas et al. [46] generated daily probabilistic wind power forecasts from ECMWF sub-seasonal (S2S) ensemble predictions for the French grid via statistical post-processing. Lin et al. [47] proposed a two-stage Hidden Markov Model (HMM) for medium–long-term wind power scenarios across multiple wind farms. Validated against multi-year Chinese wind farm data, it better preserved autocorrelation, seasonal distributions, and inter-farm correlations. Wang et al. [48] proposed a “trend-preserving” statistical downscaling framework, applied to CMIP6 coastal wind speed at a  $0.1^\circ \times 0.1^\circ$  grid resolution. Under the mid-century high-emission scenario, annual mean wind speeds in the Bohai and Donghai Seas may decrease significantly, while the Nanhai Sea may slightly increase. Hutchins et al. [15] investigated decadal climate predictions for European energy. Das et al. [49] improved S2S wind speed forecasts over India using statistical and machine learning methods. Goutham et al. [50] used machine learning to refine numerical weather prediction of surface wind speeds, improving sub-seasonal projection skill over Europe. The S2S Prediction Project Database [51], jointly developed by ECMWF and the World Weather Research Programme, provides standardized reforecast and forecast data from 11 international centers. Marcheggiani et al. [52] explored the mechanisms behind decadal NAO predictability, highlighting the role of ocean–atmosphere coupling and Atlantic multidecadal variability. The findings implied that multi-year wind energy projection could not rely solely on stationary statistics—the slow-varying ocean state had to be incorporated as an additional predictor.

### 2.1.2. Advantages and Limitations of Statistical/Empirical Methods

Statistical/empirical and climate-signal-driven methods rested on statistical theory and climatological expertise. Experts have used historical observations, reanalysis/remote sensing, and electricity records to extract predictable circulation signals, before converting them into calibrated probabilistic forecasts and risk indices. The models were simple, efficient, easy to interpret, and well suited to integration with climate signal analysis, providing reliable medium-term projections where data were abundant and statistical re-

relationships stable. However, they had a limited ability to represent marine boundary layer physics and extreme events, and depended heavily on data completeness and stationarity. Limitations were (1) heavy dependence on data quality, completeness, and long-term consistency. Sparse station coverage, inconsistent quality control (QC) standards, or missing data weakened statistical relationships—especially for severe offshore scenarios (Figure 2). (2) Statistical stationarity was assumed as fundamental, but climate change—including westerly displacement and monsoon shifts—could invalidate historical relationships, producing non-stationary uncertainty that was hard to quantify. (3) Physical mechanisms such as air–sea coupling and boundary layer stability transitions were not explicitly represented, leading to poor performance under extreme winds or prolonged calms—precisely the scenarios critical for safety and reliability assessment. The future trend is therefore integration with dynamical models and machine learning, so that each method’s strengths could offset the others’ weaknesses.



**Figure 2.** Root Mean Square Error (RMSE) of raw ECMWF Seasonal Forecasting System 5 (SEAS5) wind speed and post-processed forecasts using statistical (bias adjustment, quantile mapping) and machine learning (random forest, LGBM) calibration methods at 1–5-month lead times over seven homogeneous climate zones of India (from Das et al. [49]).

## 2.2. Dynamical Models and Reanalysis/Regional Downscaling

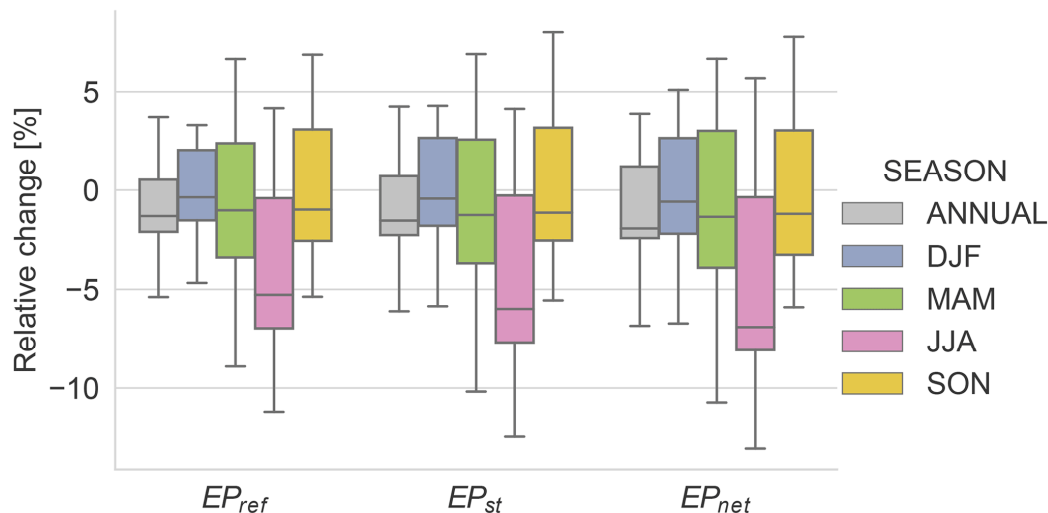
These methods were grounded in physical processes and used numerical simulations to predict wind field evolution. Global and regional climate models (e.g., CMIP6, EURO-CORDEX) provided large-scale wind climatology under different emission scenarios, while mesoscale models (e.g., WRF) performed high-resolution dynamical downscaling to capture local coastal terrain and thermal contrasts. Key physical issues included model validation against reanalysis, 10 m to hub-height extrapolation, offshore stability and sea-surface roughness/wave effects, and extreme wind/wake assessment; outputs typically required bias correction and uncertainty quantification, and included regional resource as-

assessment, wind farm planning inputs under future climate, and financial risk evaluation. The main advantage was a rigorous physical basis offering engineering-relevant spatial detail (wind shear profiles, coastal low-level jets, monsoon and sea-land breeze circulations), making it particularly useful for siting and design. Limitations included multiple sources of model uncertainty, high computational costs, and the need for region-specific calibration.

### 2.2.1. Representative Studies of Dynamical Models

deCastro et al. [53] reviewed European offshore wind resource patterns under present and future climate scenarios. European resources were generally abundant but would show regional differences: the North and Baltic Seas would remain relatively stable, while Mediterranean and Iberian coasts might change to varying degrees. Moemken et al. [54] used the EURO-CORDEX multi-model ensemble (12 km, 3 h) to assess future European wind energy under RCP4.5 and RCP8.5 for the near future (2021–2050) and the end of the century (2071–2100), relative to 1971–2000. Annual mean wind energy showed minor changes (within  $\pm 5\%$ ), but seasonal patterns shifted markedly: summer wind speeds declined notably over western continental Europe and the Mediterranean, while winter wind speeds rose slightly in parts of northern Europe and the Atlantic coast. Calm periods became more frequent, and interannual and diurnal variability increased, implying that future European wind power may become less stable and thus highlighting the need for greater system flexibility. Susini et al. [55] analyzed offshore wind resources in the North Sea and the Irish Sea under RCP8.5 using bias-corrected EURO-CORDEX simulations. By the late 21st century (2081–2100, relative to 1985–2004), mean wind speed and wind power density showed a slight decline (up to  $-2\%$ ) at all wind farms analyzed and were more pronounced in the western part of the domain, while extreme winds strengthened at the eastern North Sea sites. Carvalho et al. [56] compared CMIP5 and CMIP6 near-surface wind projections over Europe under high-emission scenarios. Under SSP5-8.5, CMIP6 projected wind resource declines across most of Europe, whereas CMIP5 was more moderate, with some regions even showing increases. Soukissian et al. [57] studied Mediterranean offshore wind and solar resources using ERA5 (1979–2019).

Martinez and Iglesias [58] used climate model projections to assess Mediterranean offshore wind under climate change, complementing Soukissian et al.'s study [57]. Abolude et al. [59] assessed future changes in China's onshore wind resources from the CMIP5 multi-model ensemble, providing an initial picture of regional differentiation under different emission scenarios. Tao et al. [60] used CMIP6 multi-model ensemble data to assess and project China's onshore wind power density (WPD). The work updated the CMIP5-based baseline by Abolude et al. [59]. Zhang and Li [61] used CMIP6 with a Bidirectional Gated Recurrent Unit (BiGRU) deep learning downscaling method to generate a  $0.25^\circ$  daily wind dataset for China's offshore waters (2021–2100). After bias correction, BiGRU mapped historical reanalysis to local observations and was applied to future scenarios. Donghai Sea wind speed and WPD may have declined slightly in the late 21st century, while the Nanhai Sea increased slightly. Nearshore shallow-water and island-dense regions showed larger biases that required specific correction, demonstrating the value of integrating deep learning with physical downscaling. Hahmann et al. [62] used CMIP6 to assess North Sea wind resources, interpolating outputs to hub height and accounting for wake effects and air density changes in annual energy production (AEP). When the model included wake losses and reduced air density, AEP was reduced by up to 5% (Figure 3).



**Figure 3.** Seasonal change in annual energy production (AEP) of the planned North Sea Energy Island wind farm cluster between the historical period (1995–2014) and mid 21st century (2031–2050) under CMIP6 SSP5-8.5, decomposed into three tiers: reference EP (hub-height wind speed change only, no wake losses), standard EP (adding standard air density correction), and net EP (further including future wake losses) (from Hahmann et al. [62]).

Rusu [63] assessed North Sea wind power trends and variability in the late 21st century using a high-resolution regional climate model. Mean WPD increased modestly—particularly under RCP8.5 in the central and northern North Sea—and extreme wind speeds strengthened, affecting both design (higher design wind speeds) and operation (higher output but greater load variability). Martinez et al. [64] used CMIP6 projections to assess long-term offshore wind trends across the North, Norwegian, and Baltic Seas. An overall decline in wind power density was projected—most pronounced under high emissions (up to 30% off western Ireland)—with slight increases (~10%) limited to parts of the Baltic Sea, providing climate-informed support for large-scale offshore planning in northern Europe.

A number of studies directly addressed the extent to which wind conditions could be determined in the Baltic Sea, where Poland was commissioning its first offshore wind farms, such as Baltic Power and Baltica 2/3. For mean wind resources, the evidence was relatively consistent. Using a regional climate model under RCP4.5 and RCP8.5, Rusu [65] reported a slight mean wind power enhancement at the ten largest operating Baltic wind farms for 2021–2050, with a more pronounced increase under RCP8.5. Lizuma et al. [66] downscaled CLM and HIRLAM off the eastern Baltic coast and reported no significant change in mean wind speed or interannual variability through the 21st century. These findings were broadly consistent with Martinez et al.'s pan-European CMIP6 assessment [64], which projected slight wind-power-density increases of approximately 10% in parts of the Baltic. However, the extent to which these conditions could be constrained at turbine scale was strongly influenced by marine atmospheric boundary-layer processes. Dedicated Baltic evaluations indicated that global reanalyses such as ERA5 tended to underestimate offshore wind speed [67], whereas mesoscale WRF-based products such as the New European Wind Atlas—validated against masts, ferry-mounted lidar across the southern Baltic, and satellite winds—substantially reduced this bias [68].

Turbine operating conditions were governed by finer-scale features that remained more difficult to determine. The Baltic had been identified as a hotspot for low-level jets, owing to the strong land–sea interactions that shaped the wind field in this semi-enclosed basin [69]. Recent lidar-and-model climatologies placed jet cores at approximately 140–

220 m, squarely within the rotor span of modern turbines, with occurrence frequencies of approximately 10–15%. Such features strengthened wind shear and fatigue loading but were only partially captured by reanalyses [70]. These challenges directly corresponded to the issues formalized in Sections 3.3, 3.4 and 3.6 of this review, namely 10 m-to-hub-height extrapolation, non-stationarity and uncertainty communication, as well as boundary-layer, strong-wind, and extreme-event biases. Operating conditions also varied across the basin. The northern Baltic, including the Bothnian Bay and the Gulf of Finland, was affected by sea ice and blade icing, whereas the southern Baltic, where the Polish projects were located, was largely ice-free. Therefore, the dominant residual uncertainties in the southern Baltic were associated with hub-height shear, extreme extratropical-storm winds, and sub-seasonal wind-drought episodes, or “Dunkelflaute” events, all of which directly affected availability. At the planning level, multi-criteria decision support tools had been applied to identify suitable Baltic sites by integrating wind resources with bathymetric and operational constraints [71]. As offshore wind build-out became denser, wake interactions between neighboring farms were also expected to further modify the local flow [72]. Overall, mean wind resources in the Baltic Sea could be projected with reasonable confidence, whereas reliable determination of hub-height conditions and turbine operating conditions remained dependent on the key bottlenecks identified in this review. Prasad et al. [73] evaluated four long-term reanalysis datasets—EMD-ERA, ERA5, Copernicus Climate Change Service 2 (CFSR2), and Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2)—against eight months of Light Detection and Ranging (LiDAR) observations from an offshore site in Gujarat, India. The reanalysis datasets generally underestimated observed wind speeds, while ERA5 showed the best agreement with LiDAR measurements, with a maximum correlation coefficient of 0.9329. Ibarra-Berastegui et al. [31] used CMIP6 to assess global offshore wind and wave energy. WPD changes remained within  $\pm 10\%$  across most nearshore areas. Total exploitable potential changes little globally, but regional distributions shift. Thomas et al. [74] dynamically downscaled CMIP6 with WRF over Spanish territorial waters, classifying wind energy abundance and stability for potential offshore zones from “moderate” to “excellent”. Bodini et al. [75] developed National Offshore Wind Data Set 2023 (NOW-23) using WRF driven by observational data from 2000 to 2020, providing 20+ years of reanalysis-style simulations of U.S. offshore regions. Validated against multiple stations, it supported regional assessment, interannual analysis, site feasibility, and P50/P90 AEP estimation. Gandoin and Garza [76] investigated ERA5’s systematic underestimation of strong offshore wind. Elshinnawy et al. [77] addressed ERA5 bias under extreme sea states. Jung et al. [78] coupled climate change and turbine technology advances in a unified scenario framework. Their “technology–climate coupled” model simulated global exploitable wind capacity for 2020–2100. Climate change alone caused only slight reductions in some regions, but taller turbine technology significantly increased exploitable capacity, offsetting climate-driven declines, though benefits varied by technology pathway. Shen et al. [9] used ERA5 to correct CMIP6’s underestimation of offshore wind speed trends, yielding more reliable future WPD projections. Global offshore WPD showed an overall upward trend through most of the 21st century across all scenarios.

Ji et al. [79] evaluated ERA5 at 10 m and 100 m in China’s offshore waters against 19 coastal wind towers. ERA5 performed reliably overall ( $R \approx 0.93$  at 100 m) but underestimated wind speed under extreme high-wind conditions. Thomas et al. [80] used WRF to dynamically downscale CMIP6 SSP2-4.5 and SSP5-8.5 over western European offshore waters for 2030–2059. Regional wind resource changes remained limited, but WRF captured local variations in nearshore shallow waters. Warder and Piggott [81] quantified global offshore wake losses and layout-optimization potential. Under current layouts, wake losses were 5–10%, but optimizing spacing and configuration could reduce these by

~one-third. Zhao et al. [82] proposed an ECA-Net (efficient channel attention) Convolutional Neural Network (CNN) downscaling framework for projecting China's wind resources from a 22-model CMIP6 ensemble under three SSP scenarios:  $-0.74\%$ ,  $-0.99\%$ , and  $-1.36\%$  per decade under SSP1-2.6, SSP2-4.5, and SSP5-8.5. Esnaola et al. [83] re-examined global wind energy projections under CMIP6 SSPs while accounting for sub-daily variability and air density changes. Including both wind speed and air density variations produced larger and more spatially widespread AEP changes than WPD alone. Zhuo and Hong [84] assessed climate impacts on Nanhai Sea wind resources using CMIP6 multi-model ensembles under SSP1-2.6, SSP2-4.5, and SSP5-8.5. Annual mean WPD increased overall by the mid- and late-21st century, particularly under high emissions. Peng et al. [85] drove the WRF model with bias-corrected CMIP6 and time-varying sea-surface-temperature reanalysis to dynamically downscale wind resources over the northern Nanhai Sea under SSP2-4.5 and SSP5-8.5 for 2050 and 2100, projecting a general increase in the waters north of  $18^{\circ}\text{N}$ —larger by 2100 than by 2050 and more pronounced under SSP5-8.5—consistent with the ensemble-based increase reported by Zhuo and Hong [84]. Xu et al. [32] drove an FVCOM-SWAVE wave model with CMIP6 winds to assess combined wind and wave energy in China's seas under four scenarios (SSP126, SSP245, SSP370, SSP585). Distributions exhibited pronounced regional and seasonal variations, with the Donghai and Nanhai Seas most suitable for combined offshore renewable development, demonstrating the value of coupled wind–wave assessments. Notably, these dynamical-downscaling frameworks were not wind-specific: the same CMIP6/EURO-CORDEX-driven, WRF-downscaled, bias-corrected pipelines were used to project wave and combined wind–wave resources [31,32], and recent work over China's offshore waters quantified wind–wave temporal complementarity and proposed joint-exploitation suitability indices [33].

The same pipelines have been extensively applied to wave energy. At the global scale, Meucci et al. [86] derived 140-year (1961–2100) wind–wave climate simulations from two CMIP6 GCMs and later released an eight-model CMIP6 wave-climate ensemble [87], while Jiang et al. [88] produced a global 3-hourly wind–wave and swell dataset (1950–2100) tailored to wave-energy research; on this basis, Satymov et al. [89] assessed global and regional wave-energy potential and levelized cost at an hourly resolution. Regionally speaking, future wave power had been projected for the Gulf of Oman under SSP5-8.5 [90], the Persian Gulf across three SSPs [91], the Black Sea to the end of the century under RCP4.5/8.5 [92], and the Mediterranean Sea under combined RCP/SSP scenarios [93], with Ahn et al. [94] providing a global wave-energy resource classification to support such regional planning. At the plant level, Carreno-Madinabeitia et al. [95] used CMIP6 wave projections to estimate future electricity production at the Mutriku Wave Energy Plant to 2100.

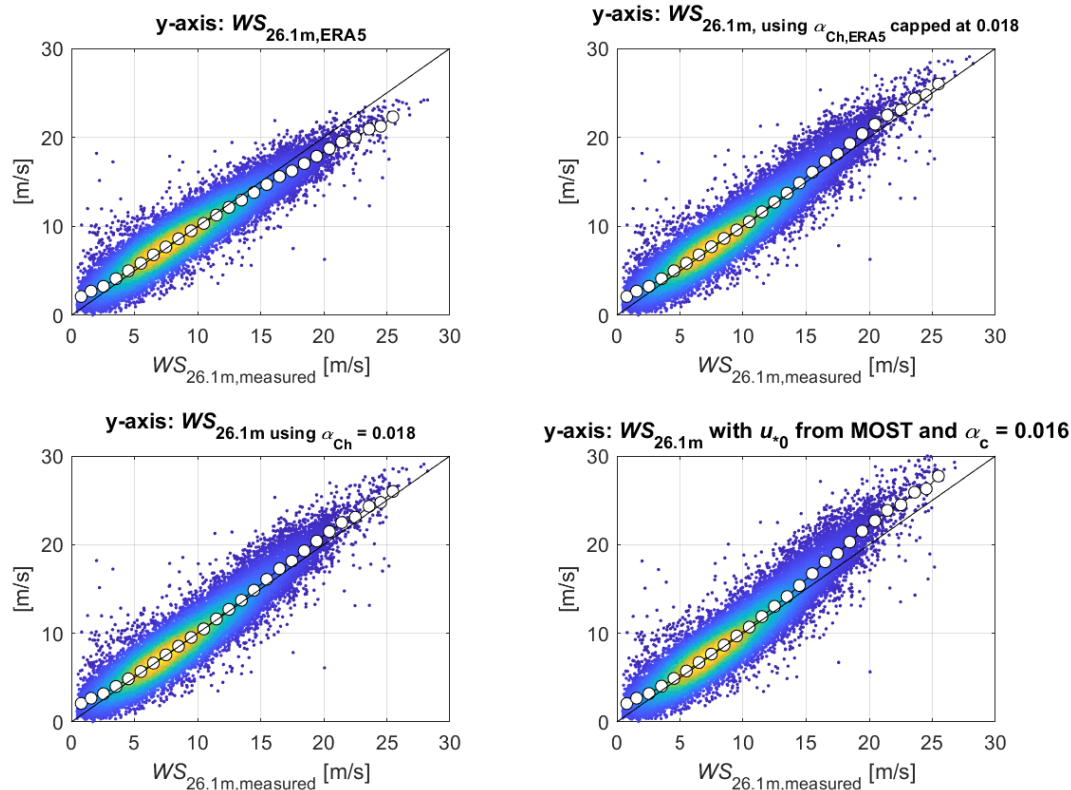
These frameworks naturally extend to the joint wind–wave resources. Under future climate scenarios, Lira-Loarca et al. [96] used a EURO-CORDEX ensemble to project combined wind–wave exploitability in the Mediterranean to 2100, Zhao et al. [97] identified Southern Hemisphere bands that would remain favorable for both resources by 2100 from a 15-model CMIP6 ensemble, and Dong and Yuan [98] combined CMIP6 with Long Short-Term Memory (LSTM) downscaling and copula-based joint distributions for Guangdong's nearshore waters. By contrast, Tong et al. [99] showed from 45 years of reanalysis that long-term Nanhai Sea wind- and wave-energy trends were non-stationary, with climatic mutations around 1995 and 2005. Complementarity and co-location assessments reinforced these findings: joint-exploitation studies for the south and southeast coasts of China [100], the Donghai Sea [101], Australian waters [102], the Canary Islands [103], and multiple global sites [104], together with a multi-energy wind–wave–tidal assessment in

China's adjacent seas [105], consistently reported that co-locating wind and wave energy reduced output variability and downtime relative to standalone farms.

On the conversion side, device-level studies of wave energy converters and shrouded tidal-current turbines [28,29,106,107] showed that translating a projected marine "resource" into deliverable electricity raised the same power-curve, wake, and availability issues discussed for wind in Section 3.5. Yang and Dong [108] proposed a multi-time-scale wind energy assessment framework based on non-stationary wind speed models, applied to Chinese wind farm sites. Accounting for time-varying mean and variance, they showed that ignoring non-stationarity could substantially bias long-term estimates. Miao et al. [21] evaluated CMIP5 and CMIP6 multi-model ensembles for wind energy resources across the Northern Hemisphere, finding CMIP6 models better reproduced observed surface wind speed trends. Future projections indicated continued wind resource decline through 2100, which was most pronounced over Europe and Asia; regional patterns and the magnitude of change differed considerably between the two model generations. Barkanov et al. [109] examined European offshore renewable resources—including offshore wind—under multiple CMIP6 scenarios across near-, mid-, and far-term horizons. Availability remained generally stable in northern Europe but showed pronounced differentiation in southern and Mediterranean waters. Akhtar et al. [110] used a regional climate model to assess how accelerating offshore wind deployment in the North Seas affects near-surface climate.

## 2.2.2. Advantages and Limitations of Dynamical Models

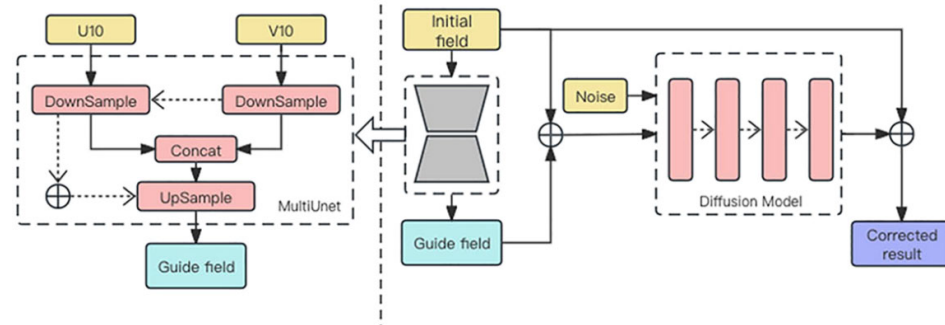
This approach relied on dynamical climate models with reanalysis (e.g., ERA5) as a reference, coupling global/regional models (CMIP6, EURO-CORDEX) with mesoscale weather models (WRF). Dynamical downscaling and bias correction delivered high-resolution hub-height wind fields for scenario-based projection. It was best suited to engineering-grade spatial detail and targeted regional projections, resolving local phenomena (coastal low-level jets, sea-land breeze, and monsoon flows) that benefited micro-siting and yield estimation. Physical models could also simulate extreme winds and identify physical drivers, enhancing projection confidence. Limitations included the following aspects. (1) Sources of uncertainty were numerous and intertwined, with model structure, parameterization, emission scenario, downscaling method, hub-height extrapolation, and wake treatment all potentially significantly affecting results, producing divergent projections that hindered consistent decision support. (2) Even advanced reanalysis and climate models contained notable systematic errors in air-sea flux, boundary-layer stability transitions, turbulent mixing, and extreme winds. Without targeted correction, direct use could bias engineering design and safety decisions (Figure 4). (3) Dynamical models yielded grid-scale wind speed or WPD, but actual AEP depended on engineering factors—power curve nonlinearity, array wake losses, and turbine availability—which are often simplified or omitted, creating a non-trivial gap between "projected resource" and "deliverable electricity". In practice, "dynamical simulation + statistical correction" was widely adopted, combining physical rigor with statistical bias compensation and probabilistic ranges. Extrapolating from 10 m to 100 m+ hub height also added uncertainty that would grow as turbines became taller. Dynamical downscaling would remain central, with machine learning integration (accelerating simulations or replacing physical processes) further improving efficiency and accuracy.



**Figure 4.** Scatter density plot of ERA5 wind speeds against high-quality floating LiDAR and meteorological mast (met-mast) measurements at 26.1 m height at the IJmuiden offshore site, with binned means shown as white dots (from Gandoin and Garza [76]). Colors indicate the density of data points, increasing from blue (low) to red/yellow (high), and  $u^*_0$  denotes the surface friction velocity.

### 2.3. Machine/Deep Learning and Hybrid Methods

Machine Learning/Deep Learning (ML/DL) and hybrid methods did not fully replace physical models; instead, they post-processed, bias-corrected, and spatially downscaled dynamical outputs or directly built data-driven projection models. Machine learning excelled at nonlinear relationships in multi-source data, which was well suited to climate models with systematic biases or insufficient resolution. Deep neural networks could learn error structures for bias correction, and Generative Adversarial Networks (GANs) could reconstruct high-resolution wind fields from low-resolution inputs (Figure 5). For offshore wind—where observations were scarce, boundary layer processes nonlinear, and biases large under high winds and stable stratification—AI could integrate observations and models to identify and correct biases. Common architectures included CNNs, LSTMs, Transformers, and Graph Neural Networks (GNNs), with GANs or diffusion models for downscaling, quantile regression and ensemble calibration for probabilistic forecasting, and physics–data hybrids combining both. AI/hybrid methods thus opened a new pathway from post-processing meteorological projections to directly generating multi-factor wind power scenarios.

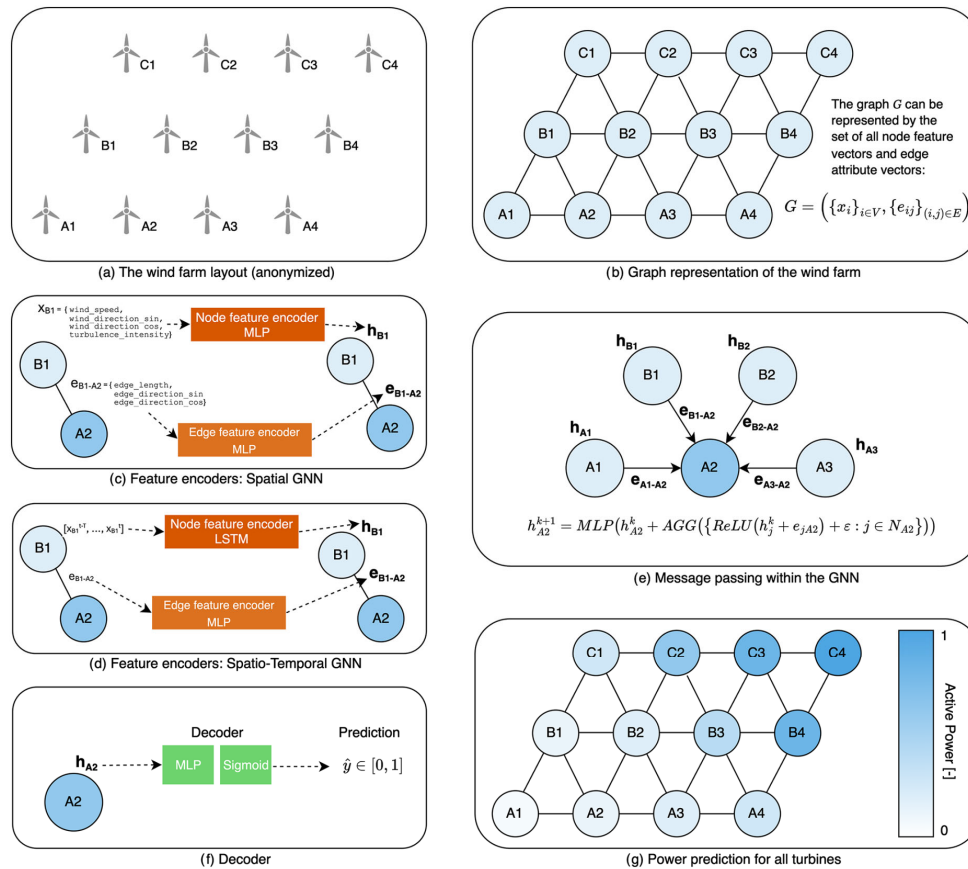


**Figure 5.** Architecture of the MultiUnet-Diffusion (MU-Diffusion) framework for offshore wind field bias correction. MU denotes MultiUnet; MU-Diffusion combines MultiUnet, a multitasking U-Net model, with a diffusion model (from Pang et al. [111]). Reproduced from [111] under the terms of the CC BY 4.0 license.

### 2.3.1. Representative Studies of Machine/Deep Learning Methods

Huang et al. [112] applied the Transformer, an attention-based neural-network architecture, to wind power time-series forecasting using 10 min interval data for one-hour-ahead projection. The Transformer achieved the lowest error and best captured short-term fluctuations. Karijadi et al. [113] combined hybrid decomposition based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and the Empirical Wavelet Transform (EWT) with deep learning, demonstrating the value of “signal decomposition + deep learning”. Huang et al. [114] proposed evolutionary LSTM (EvLSTM), combining genetic algorithms with LSTM for medium-long-term wind speed projection. Zhao et al. [115] proposed DA-STNet, a double-attention spatio-temporal network for medium-term wind power projection, in which a graph attention network captures the dynamic spatial correlation between wind power variables and a temporal attention layer extracts temporal features. It outperformed benchmark models on two real-world datasets. Pang et al. [111] proposed MultiUnet-Diffusion framework (MU-Diffusion), a multi-task UNet + diffusion bias-correction framework for Nanhai Sea wind fields. Wind speed accuracy improved by ~42% and direction by ~38%, with robust performance under typhoons. As an example of surrogate-model-assisted evaluation, Hamzah et al. [116] coupled CFD with an artificial neural network to predict blade deformation and aerodynamic response at a substantially reduced computational cost.

Zhang et al. [117] proposed DLH, a multi-task learning framework for simultaneous point and probabilistic wind power projection. The framework outperformed multiple state-of-the-art benchmarks in both point and probabilistic metrics. Yan et al. [118] developed SEAformer, a frequency-domain decomposition Transformer with a signal-enhanced attention mechanism for long-term wind power forecasting. It significantly outperformed LSTM for projections beyond 12 months. Mo et al. [119] proposed Powerformer, an improved Transformer with attention adjustments tailored to time-series characteristics. It outperformed conventional Transformers and other deep learning methods across multiple wind power projection tasks. Schmidt and Ludwig [120] empirically compared deep learning approaches for wind field super-resolution and downscaling in wind energy assessment, finding that a diffusion model best preserved the distributional and physical properties of wind speeds when estimating wind power potential, and emphasizing that model evaluation metrics should be aligned with the downstream application. Daenens et al. [121] proposed a spatio-temporal Graph Neural Network (GNN) for offshore wind farm cluster projection. Spatially correlated models significantly outperformed independent projection in high-frequency tasks, especially under large-scale weather systems (Figure 6).



**Figure 6.** Architecture of the spatio-temporal graph neural network (GNN) model for offshore wind farm power prediction (from Daenens et al. [121]). Reproduced from [121] under the terms of the CC BY 4.0 license.

Mbugua and Hiraga [26] reviewed long-term wind speed and power projection methods, comparing statistical models, physical methods, and machine learning in long-term predictability, data needs, and uncertainty. Zhu et al. [122] proposed Fast-Power-former, an efficient Transformer for medium-term wind power projection. Wang et al. [123] developed C-LSTM with an adaptive wind-speed calibration layer embedded into LSTM. Validation across 25 turbines showed notable mean squared error (MSE) and accuracy improvements.

Guo et al. [124] evaluated three bias correction methods—Quantile Regression at the 50th percentile (QR50), Linear Regression (LR), and Optimal Threat Score (OTS)—for 70 m wind speed forecasts from NCEP Climate Forecast System version 2 (CFSv2) in Shanxi Province, China, using observations from nine wind towers across lead times of 1–45 days. QR50 demonstrated the most robust performance, reducing mean Root Mean Square Error (RMSE) by 10–11%, with correction efficacy improving notably at lead times beyond 10 days, while OTS failed to improve—or even worsened—forecasts, highlighting how uniform threshold-based corrections are unsuitable when bias variability across sites is large. Springenberg et al. [125] proposed DiffScale, applying diffusion generative models to S2S wind speed forecast spatial downscaling and bias correction.

Guo et al. [126] developed a CNN-based bias correction for ECMWF surface variables. After correction, wind power errors were substantially reduced. Gijón et al. [127] proposed a physics-informed neural network (PINN) for wind turbine power prediction with evidential uncertainty quantification. Physical constraints from the torque–rotational speed relationship preserved consistency, while an evidential layer delivered calibrated

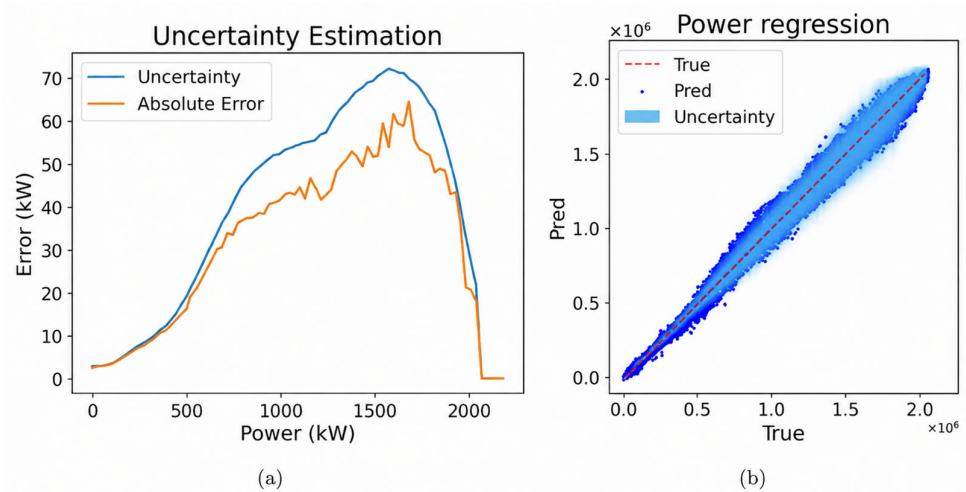
prediction intervals. Lockwood et al. [128] developed a generative super-resolution model based on denoising diffusion (DDPM) to enhance the resolution and intensity of tropical cyclone wind fields from ERA5. Validation against 85 historical tropical cyclone (TC) events showed a substantial improvement in high-intensity wind capture. Wan et al. [129] proposed Hiformer, a hybrid frequency-feature-enhanced inverted Transformer for long-term wind power prediction. It outperformed state-of-the-art Transformer variants for prediction horizons of one day or more. Anand et al. [130] introduced a “Tube Loss” function for probabilistic wind speed forecasting with LSTM, GRU, and TCN. It enabled narrow prediction intervals with asymptotic coverage guarantees, free of distributional assumptions. Elshewey et al. [131] built a hybrid CNN-ResNet50-LSTM model for joint temperature and wind power forecasting. Evaluated on three public datasets, including supervisory control and data acquisition (SCADA) wind turbine data, the model achieved  $R^2$  values above 0.98 across all tasks, consistently outperforming five conventional regression baselines (Dummy, Kernel Ridge, Decision Tree, Extra Trees, and SGD regressors) and demonstrating that the combination of convolutional feature extraction, residual learning, and LSTM temporal modeling was robust for medium-long-term forecasting under climate variability.

Rajaperumal and Chinnappan [132] proposed a hybrid framework integrating machine learning, MATLAB-Simulink physical modeling, and PINNs for robust wind power prediction. Using 8760 hourly MERRA-2 wind speed records, a stacking ensemble achieved  $R^2 = 0.998$  with RMSE = 0.11. Habib and Hossain [133] explored deep learning with strategic feature engineering for wind power prediction, emphasizing that careful feature selection remained an essential complement to architecture innovation. Mo et al. [134] developed FNet, a frequency filter-enhanced dual LSTM. It decomposed wind power signals into low- and high-frequency components, processed each through dedicated LSTMs, and recombined them via a learnable fusion layer.

### 2.3.2. Advantages and Limitations of Machine/Deep Learning Methods

ML/DL and hybrid methods were used to post-process numerical model outputs, building data-driven models for probabilistic projection and scenario generation. In offshore wind, multi-source fusion systems integrating “observations–reanalysis–models–AI” (e.g., S2S4E and NOW-23) emerged, lowering research barriers. AI/hybrid methods shifted medium-long-term projection from “single deterministic answers” toward “probability intervals, spatial detail, and interpretable bias signals” (Figure 7). With adequate data and computation, ML could extract hidden patterns and enable automatic bias correction and resolution enhancement. Furthermore, through end-to-end architectures, it can accomplish in a single model that which previously required multiple sequential steps (dynamical simulation → statistical post-processing → scenario generation). The limitations were as follows. (1) There was heavy dependence on high-quality, large-sample observational data. The ML performance ceiling was set by training data scale, coverage, and labeling quality. Long-term reliable wind profiles and power records were scarce—particularly far offshore—and QC standards are not unified, limiting adequate training and independent validation. (2) Most deep learning methods lacked explicit physical constraints, with their internal logic hard to causally interpret. Under extreme or anomalous conditions beyond the training set, they could yield physically implausible outputs without warning, something that is risky for safety- and design-critical applications. (3) Most current models are trained on historical data and implicitly assumed stationary climate statistics. Under global warming and circulation shifts, future wind distributions could deviate substantially from historical samples, and extrapolation robustness remained insufficiently tested. Without online updating or transfer learning, cumulative long-term

bias could be uncontrollable. Sustained progress in these areas was needed for ML to serve as a reliable complement to traditional methods.



**Figure 7.** Evidential uncertainty quantification results from a PINN-based wind turbine power prediction model, adapted from Gijón et al. [127] under the terms of the CC BY 4.0 license; axis labels reformatted in scientific notation. (a) uncertainty estimation; (b) power regression.

### 3. Major Challenges and Solutions for Medium–Long-Term Wind Energy Projection

Considerable progress had been made in medium–long-term wind energy projection; however, its practical application still faces many challenges. Across all three method categories, recurring issues included weak data foundations, inadequate physical mechanism representation, non-stationary modeling difficulties, missing engineering conversion steps, divergent model conclusions, and limited AI generalization. These problems stemmed from both objective constraints (observations, data) and subjective factors (model reliability, complexity). In this section, seven major challenges are identified, their causes and impacts are examined, and solutions are discussed (Figure 8).

#### 3.1. Difficulty in Data Quality Control and Insufficient Data Representativeness

##### 3.1.1. Challenges and Impacts: Data Quality and Representativeness

**Challenges:** Various observation platforms—shore-based towers, floating LiDAR, satellite remote sensing, and turbine SCADA—differed in height, sampling frequency, and QC standards, making their integration difficult. Key wind energy parameters extended beyond 10 m wind speed to hub-height speed, wind shear, turbulence intensity, atmospheric stability, and air density. Without a unified, long-term, openly shared “ground truth” system, studies relied on different sources, producing large discrepancies in reanalysis evaluation and limiting ML generalization. The problem was most severe offshore: stations were prohibitively expensive, towers and buoys were few and clustered nearshore, far-offshore areas persistently lacked profile data, and even existing observations suffered from gaps and instrument drift.

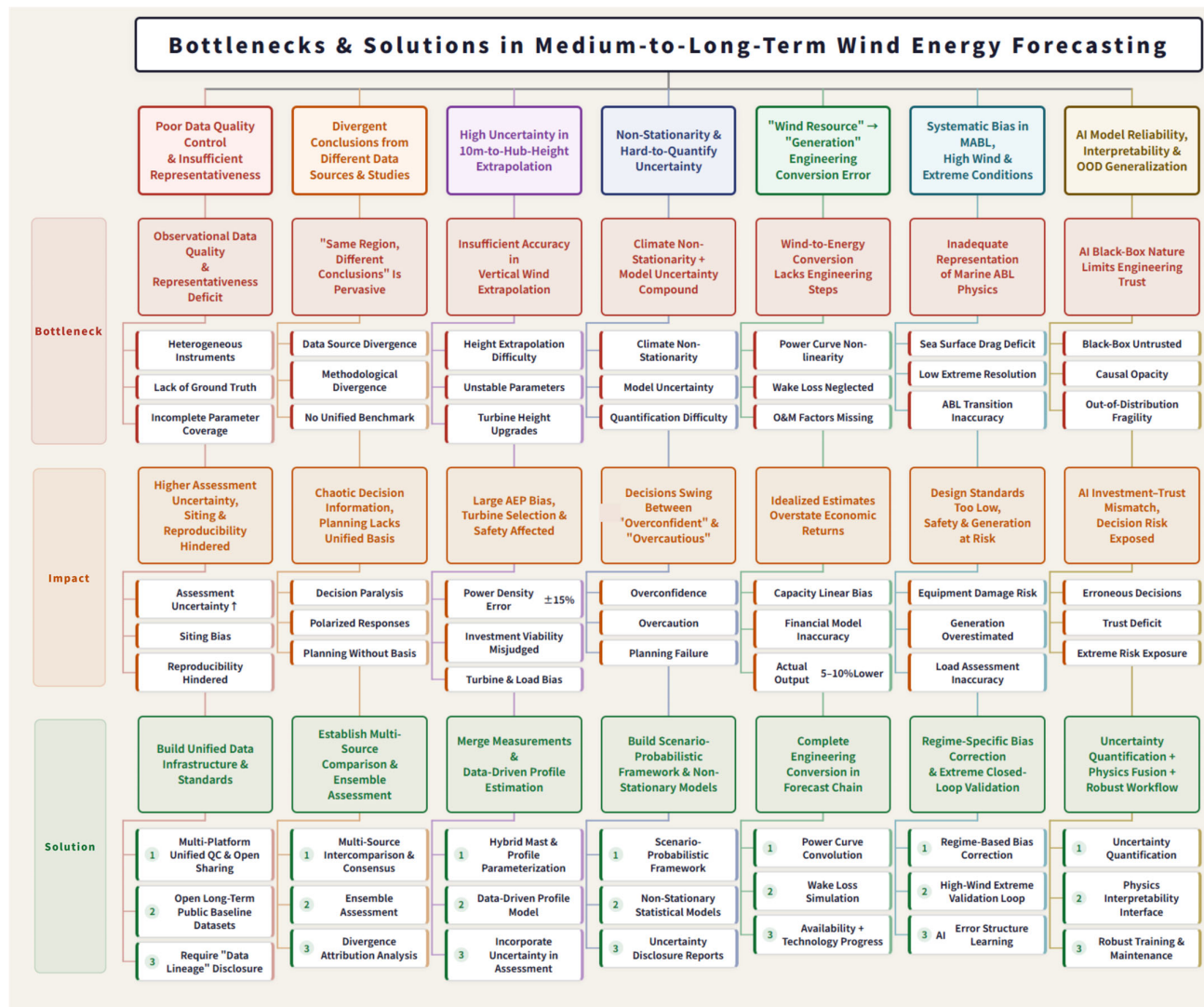


Figure 8. Bottlenecks and countermeasures for medium-long-term wind energy projection.

Wang et al. [135] showed pronounced geographic variability in ERA5 wind speed biases—which was most significant in the Scottish Highlands and Welsh mountains—indicating that uniform corrections were inadequate. Frech et al. [136] addressed the off-shore profile gap with a new gridded offshore wind profile product for U.S. coasts via random-forest regression on multi-site lidar plus satellite sea-surface winds, outperforming traditional extrapolation under strong shear and low-level jets.

In terms of impacts on wind power development, insufficient data raised projection uncertainty. Without authoritative benchmarks, reanalysis and model evaluation became unreliable, leading developers to overly conservative decisions. Poor spatial and vertical coverage could migrate high- or low-value wind zones, biasing site selection. Data access barriers hindered reproducibility and cross-comparison, slowing progress. Most critically, wind farms built without reliable observational constraints risked falling short of projected capacity, eroding returns and investor confidence.

### 3.1.2. Potential Solutions: Data Quality and Representativeness

(1) Building a multi-platform observation-unified QC-open sharing data system. Governments, research institutions, and enterprises should jointly deploy more long-term facilities (meteorological towers, buoy-mounted LiDAR, and offshore stations). Standard-

ized QC protocols and uncertainty criteria should be established, with all data rigorously quality-controlled and shared via open-access platforms. Europe’s “North Sea Energy Meteorological Observation Network”, for example, incorporated high-quality floating LiDAR data into reanalysis bias correction and model validation, reducing model biases and improving design reliability.

(2) Leveraging open long time-series datasets as common foundations. Where direct observations are limited, datasets such as NOW-23 and ERA5 can serve as credible common baselines, mitigating “different data, incomparable conclusions.” New high-resolution offshore datasets should be actively applied to assessment and model training, with new methods encouraging validation against these public datasets.

(3) Requiring “data provenance” documentation in publications and engineering reports. Industry standards should require clear reporting of data sources, measurement heights, temporal coverage, QC procedures, gap-filling, and residual uncertainties. For ML models, training/validation splits, hyperparameters, and source code should be public. Wind farm engineering reports should routinely include observational data summaries and quality statements, enabling performance benchmarking against actual operations.

### 3.2. Divergent Conclusions from Different Data Sources and Researchers for the Same Region Hinder Unified and Reliable Decision Support

#### 3.2.1. Challenges and Impacts: Divergent Conclusions Across Sources

Challenges: A pervasive phenomenon in medium–long-term wind energy projection is that, for the same study region, different teams arrived at divergent or contradictory conclusions due to differences in data sources, model tools, analytical methods, and assumptions (Table 3).

**Table 3.** Comparison of medium–long-term offshore wind energy projections for the Donghai Sea.

| Study                | Data and Methods                                                | Main Results                                                                                                                                                                                     |
|----------------------|-----------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Costoya et al. [5]   | CORDEX 8 models (CMIP5-driven); RCP8.5; China’s offshore waters | ↓ Decrease. Donghai Sea WPD decreases by approx. 10%, opposite to the Nanhai Sea (increase); significant spatial differentiation                                                                 |
| Shen et al. [9]      | ERA5 bias-corrected CMIP6; global scale; SSP1-2.6 to SSP5-8.5   | ↓ Decrease (scenario-dependent). WPD in the Donghai Sea shows declining trends under all SSP scenarios, with greater decline under high emissions; global mean conversely increases (+3.8–18.3%) |
| Xu et al. [34]       | QuikSCAT/ASCAT + CFSR; CSEOF climate oscillation analysis       | Interannual oscillation. Strong ENSO modulation: wind speeds in the Donghai Sea notably weaker year-round during strong El Niño years; WPD differences across climate phases can reach ±10%      |
| Abolude et al. [59]  | CMIP5 10-model ensemble; RCP8.5; all of China (incl. offshore)  | ↑ Slight increase. Moderate WPD increase along the southeastern coast (incl. near the Donghai Sea); overall variation within ±40 W/m <sup>2</sup> ; inland 30–40° N shows decrease               |
| Zhang and Li [61]    | CMIP6 + BiGRU downscaling; SSP2-4.5 and SSP5-8.5                | ↓ Decrease. WPD slightly reduced: mid-term (2041–2060) < 6%, long-term (2081–2100) < 10%                                                                                                         |
| Bayhaqi et al. [137] | CMIP6 10 models; SSP2-4.5 and SSP5-8.5; 2026–2050               | Seasonal divergence. Summer wind speed increases +5% to +8%; slight winter weakening; annual mean direction uncertain                                                                            |
| Zheng et al. [138]   | CMIP5 (RCP2.6/RCP4.5); global; 2080–2099 vs. 1980–1999          | ↑ Local increase. Wind-rich areas with WPD >400 W/m <sup>2</sup> expand; positive changes around the Donghai Sea and Japan; increase can exceed 150 W/m <sup>2</sup>                             |

Note: ↑ and ↓ indicate increasing and decreasing trends, respectively.

At the data source level, numerous products—global reanalyses such as ERA5, MERRA-2, CFSR, and the Japanese 55-year Reanalysis (JRA-55), satellite retrievals, and regional high-resolution reanalyses—differed significantly in resolution, coverage, assim-

ilation, and boundary-layer parameterization, portraying climatology, variability, and trends quite differently for the same region. Prasad et al. [73] compared EMD-ERA, ERA5, CFSR2, and MERRA2 against LiDAR observations from an offshore site in Gujarat, India, showing substantial discrepancies among reanalysis datasets, although ERA5 achieved the closest agreement with the observations. In the European North Sea, Gandoi and Garza [76] and Elshinnawy et al. [77] both found ERA5 systematically underestimated strong winds. Tobin et al. [139] showed that even ensemble projections under different warming targets (1.5 °C, 2 °C, 3 °C) yielded considerably different country-level vulnerability and resilience profiles.

At the model and methodology level, choices in climate model selection, emission scenario, downscaling, bias correction, and statistical testing produced divergent results even with identical inputs. Carvalho et al. [56] identified directional discrepancies between CMIP5 and CMIP6 projections for Europe, with some regions shifting from “slight increase” to “notable decrease.” Within a single generation, ensemble spread was equally large: Moemken et al. [54] found that over large parts of Europe, fewer than six of the nine EURO-CORDEX members even agreed on the sign of change. For China’s nearshore future, Zhang and Li [61] and Wang et al. [48] both suggested Donghai Sea declines and slight Nanhai Sea increases, while Shen et al. [9] found generally rising offshore WPD under strong warming using globally bias-corrected CMIP6.

Technical detail choices—extrapolation height, power curve assumptions, extreme-value treatment, and train/validation splitting—appeared minor but cumulatively widened discrepancies. Without unified benchmarking, claimed superiorities were difficult to verify.

Impacts on wind power development: This “same-region, divergent-conclusions” phenomenon made site selection and investment decisions difficult when reports contradicted each other. Divergent conclusions also deprived regional and national plans of a unified basis. In finance and insurance, inconsistent results left risk pricing without an anchor; lenders facing contradictions demanded higher risk premiums, raising capital costs and weakening renewables’ competitiveness. Unresolved divergences also wasted effort on duplicative work.

### 3.2.2. Potential Solutions: Divergent Conclusions Across Sources

(1) Establishing “multi-source intercomparison and consensus-building” mechanisms for regional wind energy assessment. Inspired by CMIP and Coordinated Regional Climate Downscaling Experiment (CORDEX), international or regional bodies could set unified protocols for key zones—fixed reference periods, shared validation datasets, consistent metrics, and standardized reporting—so teams assess with their own data/methods within this common framework, enabling systematic cross-comparison to pinpoint divergence sources and build consensus on robust versus uncertain findings.

(2) Strengthening attribution analysis and transparent reporting of conclusion divergences. When studies reach different conclusions, treat divergence itself as a research question. Review papers and industry reports should include a “conclusion comparison and divergence attribution” section quantifying each factor’s contribution. Controlled-variable experiments—changing only data source then only downscaling method—can isolate effects. Each study should transparently report data versions, key parameters, and sensitivity analyses to clarify applicability boundaries and prevent over-generalization.

(3) Fostering open infrastructure for benchmarking and shared reference cases. Public benchmark datasets, fixed test regions, and standardized evaluation metrics enable fair cross-method comparison. With sustained adoption, the community can accelerate convergence toward robust conclusions and lower the decision risk faced by industry stakeholders.

### 3.3. Large Uncertainty in Extrapolating from 10 M Wind to Hub-Height Wind Is Compounded by Continuously Changing Future Turbine Heights

#### 3.3.1. Challenges and Impacts: Hub-Height Extrapolation

Challenges: Reanalyses and climate models generally provided wind speed at 10 m, with only a few at 100 m; however, modern turbine hub heights already reach 100–150 m or higher. Conventional logarithmic-law extrapolation relied on surface roughness and stability parameters, but offshore roughness changes dynamically with wind and waves and stability profiles are complex, so simple extrapolation is often inaccurate. Under stable stratification, wind increases slowly with height, and low-level jets may occur; under unstable daytime conditions, it increases more rapidly. A single power-law exponent could therefore systematically bias hub-height wind. The lack of upper-air observations further hampered shear calibration. Hub heights rose from ~50 m to over 100 m and might reach 200 m+, further exposing turbines to low- and upper-level jets and amplifying errors. Crippa et al. [140] developed a temporal model for vertical extrapolation accounting for diurnal and seasonal shear variations, showing how static profile assumptions introduce several-percent AEP biases at modern hub heights. Optis et al. [141] proposed methods integrating multi-level lidar with stability-aware fitting, showing that log- and power-law approaches underperform under stable stratification and low-level jets, conditions which are more frequent for next-generation 200 m+ turbines.

Impacts on wind power development: Hub-height uncertainty translated directly into AEP uncertainty; a  $\pm 5\%$  wind speed error gave roughly  $\pm 15\%$  power density error due to the cubic relationship, materially affecting project economics. Overestimation undermined revenues, while underestimation shelved viable projects and biased turbine selection in micro-siting, leading to suboptimal operation. Shear errors affected structural load assessment—underestimation reduced design margins, while overestimation added cost—which is particularly critical for next-generation ultra-tall turbines where empirical formulas are less reliable.

#### 3.3.2. Potential Solutions: Hub-Height Extrapolation

(1) Developing hybrid approaches combining wind measurement with profile parameterization. Before development, deploy short-term LiDAR campaigns with upper-air soundings to build on-site profile databases and tune model parameters. Physically stratified parameterization separates roughness- from stability-driven shear, each calibrated independently. For new areas lacking measurements, empirical profiles (ECMWF model or climate center means) serve as substitutes, with regional classification by sea area or season guiding representative profile choice.

(2) Applying data-driven wind profile estimation. ML can capture surface-to-upper-level wind relationships from historical data: LSTM or GNN models take surface wind speed, temperature, pressure, and sea state as inputs and output hub-height wind speed, clearly outperforming the logarithmic law given adequate training data. Pre-deploying LiDAR in key development zones provides training data; trained models then estimate hub-height speeds for other farms in the same sea area at low cost, constituting an “augmenting physics with AI” strategy that improves with accumulated data.

(3) Integrating height-related uncertainty into assessment and design. Consulting reports should present AEP ranges under multiple shear scenarios rather than single estimates. For ultra-large turbines, sensitivity analyses varying the shear exponent within specified ranges test structural margins; where uncertainty is excessive, conservative designs or higher safety factors apply. AEP uncertainty discounts can be built into economic models and communicated to financial stakeholders, so lending rates account for this risk, motivating industry investment in observation and research.

### 3.4. *The Difficulties of Quantifying and Communicating the “Non-Stationarity” and Uncertainty of Medium–Long-Term Projections to Decision-Makers*

#### 3.4.1. Challenges and Impacts: Non-Stationarity and Uncertainty

Challenges: Medium–long-term wind energy projection faced two layers of uncertainty.

With the first layer, climate change drove long-term trends and shifts in wind field statistics towards non-stationarity. Westerly displacement under warming meant wind conditions twenty years ahead might differ substantially from the past two decades, violating stationarity assumptions in traditional statistical models. Cannon et al. [142] showed that quantile mapping bias correction can struggle to preserve trend signals across non-stationary states, requiring trend-preserving variants. Mostue et al. [143] documented widespread increases in European wind-drought frequency and duration under CMIP6 high-emission projections, with weak-wind episodes rising up to 10–20% in some regions.

With the second layer, varying emission scenarios affected long-term wind climatology differently; however, assigning probabilities remained difficult, especially after 2050, when divergences become pronounced. Structural model differences produced conflicting results without effective reconciliation. Multi-model ensembles provided ranges, but these could be too wide for practical decisions. Communicating uncertainty to end users was also inadequate: single trajectories or ensemble-mean values caused users to underestimate risk. Non-stationarity and multi-source uncertainty thus prevented the definitive guidance available from short-term forecasts.

Impacts on wind power development: Mishandling non-stationarity and uncertainty pushed decisions to overconfidence or excessive conservatism. Overconfidence—e.g., planning 2050 capacity from historical wind—might misallocate resources if winds weaken. Recognizing uncertainty without quantifying it bred excessive caution, withholding long-term contract support and discouraging investment. Uncertainty was unavoidable but had to be actively managed, or large-scale offshore deployment and system transformation would be seriously hindered.

#### 3.4.2. Potential Solutions: Non-Stationarity and Uncertainty

(1) Establishing a scenario–probability analysis framework. Combine multiple emission scenarios with multi-model ensembles and assign subjective probabilities via Bayesian or frequentist approaches. For 2040 mean wind speed, N models under SSP2-4.5 and SSP5-8.5 yield 2N outcomes; if SSP2 is more plausible, weights of 0.7 and 0.3 are applied, synthesizing a probability distribution. Decision-makers thus receive credible intervals (P10, P50, and P90) rather than a single value—P50 as the reference case, P90 as the conservative floor, and P10 as the optimistic bound—each supporting tailored adaptive strategies.

(2) Developing non-stationary statistical models and decadal projections. Use time-varying parameters or piecewise calibration, e.g., sliding windows that update parameters as climate means shift, or regression on large-scale climate modes (sea surface temperature, polar vortex) that adjust when drivers trend. Decadal projection bridges seasonal forecasting and centennial scenarios by incorporating initial conditions, potentially capturing Interdecadal Pacific Oscillation/Atlantic Multidecadal Oscillation (IPO/AMO) phases over 5–10 years. Several centers have already begun decadal projection research on the NAO; if successful, this could directly inform European planning.

(3) Embedding “uncertainty disclosures” in decision communication. Assessment reports should quantify each uncertainty source in accessible language, e.g., “model uncertainty may cause  $\pm 5\%$  AEP variation at 80% confidence.” Power planning should present

multi-scenario supply–demand balance. The meteorological “forecast cone” concept guides decision-makers to think in ranges. A risk-management mindset means using P90 in revenue calculations and dual P50/P90 pricing in tenders to explicitly price uncertainty, shifting it from a vague threat to being a quantifiable and manageable factor.

### 3.5. Engineering Conversion Errors from “Wind Resource” to “Deliverable Electricity”

#### 3.5.1. Challenges and Impacts: Engineering Conversion Errors

Medium–long-term projections generally output wind speed or power density (WPD); however, the deliverable annual energy production (AEP) was determined by a chain of engineering conversions—power-curve integration, wake-loss correction, turbine availability, and hub-height extrapolation—each introducing its own uncertainty. This “resource-to-electricity” gap should not be treated as a second-order detail but as a first-order source of bias: even with a perfectly projected wind climate, AEP could be shifted from a few to tens of percent by conversion assumptions alone. Quantitatively speaking, (i) because the power curve was strongly nonlinear, AEP differences of ~1.4–4.0% at a single site could be produced by identical mean wind speeds under different atmospheric regimes (stability, turbulence, and shear) [144]; (ii) 12–18% of the energy of a multi-GW offshore farm could be removed by array and cluster wakes, the exact figure depending on turbine rating and power curve [145], and inter- and intra-array wake losses were a first-order, uncertain control on AEP and LCoE for large lease areas [146] (cf. cluster-scale losses in Section 3.5) [81,147]; (iii) offshore availability lay well below 100%, with downtime and lost production varying by drive-train and site and growing as turbines scaled to 10–15 MW [148,149]; and (iv) AEP could be biased by several percent when hub-height extrapolation was conducted with a single shear exponent (Section 3.3) [140,141]. When projected WPD was treated as deliverable electricity, systematic over-estimation was therefore risked, and the magnitude of this gap was comparable to—or larger than—the climate change signal these projections sought to detect [150].

The turbine power curve is inherently nonlinear: below cut-in zero, above rated saturated, above cut-out shut down. Small distribution shifts thus affect total energy in complex ways and must be evaluated through power-curve integration.

Wake effects within wind farms further complicate matters. Upstream turbines reduce wind to downstream units, and climate projections typically ignore layout, so wake losses must be applied before farm-level yield is obtained. Warder and Piggott [147] decomposed German Bight wake losses into long- (inter-cluster), medium- (intra-cluster), and short-range (intra-farm) components, with inter-cluster losses growing from 0% (2010 scenario) to 2.5% (2027), and intra-cluster from 0% to 4.3%, as build-out densified. Porchetta et al. [151] further compared engineering wake models with mesoscale numerical weather prediction (NWP) simulations for offshore clusters, finding engineering models could both quantitatively and qualitatively differ from NWP-based estimates.

Turbine availability—downtime from maintenance or faults—also affected yield, which climate projections could not capture.

Converting wind resources to deliverable electricity thus involved multiple steps; at any step, flawed assumptions could cause substantial deviations.

Impacts on wind power development: Overlooking engineering factors produced idealized projections that inflated returns or understated technical demands. Power curve nonlinearity overestimated output in low- and high-wind periods—a 5% wind drop above that rated produces less than 5% energy loss, while a 10% rise in a low-wind summer yields almost no additional electricity. Computing yield from gross WPD without wake deduction substantially overstated large farm output; cases of >10% AEP shortfall from inadequate cluster-wake consideration caused financial distress. Assuming 100% availability omitted cumulative downtime over 20-year operation, rendering economics

overly optimistic. Uncorrected conversion errors surfaced as generation shortfalls, cash flow underperformance, and eroded investor confidence. In particular, 100% availability was implicitly assumed and cluster wakes were neglected in many resource and even mesoscale-model studies. As such, their headline AEP figures should be read as upper bounds; several-percent overestimation from these assumptions alone was indicated by benchmarking against operational data [132,136].

### 3.5.2. Potential Solutions: Engineering Conversion Errors

(1) Integrating power-curve convolution into the workflow. Convert wind speed to energy yield by integrating over the power curve rather than via linear mapping: for each projection period, derive a wind speed probability distribution (or simulated series), compute power point-by-point, and take the expected value. Where only mean and variance are available, Monte Carlo sampling or Weibull assumptions approximate. Check whether projected wind speed changes fall in sensitive curve regions (e.g., near cut-in) before reporting power-curve conversion and uncertainty ranges.

(2) Incorporating wake-loss simulation. Simplified wake models (Park, eddy viscosity) estimate annual loss rates for a given layout and wind direction distribution, where the net output is projected wind speed/power times  $(1 - \text{loss rate})$ . Different rates apply under different layout scenarios (e.g., 10% dense vs. 5% optimized); where the specific farm is undecided, scale-based ranges (5–15%) serve as deductions. Offline CFD or high-fidelity models refine empirical estimates. Including wake effects at the assessment stage motivates layout optimization at the source.

(3) Incorporating availability and technology advancement scenarios. Apply an availability derating factor (e.g., 0.95 for current offshore farms), which should be raised if operations and maintenance (O&M) improves or lowers with aging. Scenario analyses for taller turbines (accessing steadier high-altitude winds) or new materials (shorter downtime) can adjust the factor (e.g., to 0.97). Wake-mitigation technologies are represented by lower loss rates. Embedding evolving technical parameters keeps projections aligned with engineering progress and informs R&D priorities, providing a comprehensive meteorological–engineering assessment framework.

## 3.6. Systematic Biases in Reanalysis and Models for the Marine Atmospheric Boundary Layer, Strong Winds, and Extreme Conditions

### 3.6.1. Challenges and Impacts: Reanalysis and Model Biases

Challenges: Reanalyses and climate models still struggle to represent offshore boundary-layer physics. Empirical sea-surface drag coefficients ignore sea-state–wind interactions, so models tended to underestimate strong winds since roughness grows with wind and waves. Extreme events such as typhoons and intense extratropical storms were particularly under-represented due to resolution and parameterization limits, so mean winds were reproduced but extremes and gusts were significantly underestimated. Zum Berge et al. [152] used airborne in situ measurements to evaluate engineering and mesoscale models for large-scale offshore cluster wakes, finding systematic biases in wake propagation and stability-modulated decay; these biases propagated into assessments under stable conditions, which dominated strong-wind episodes. Liu et al. [153] addressed ERA5 underestimation of tropical cyclone intensities by developing a global ERA5-based TC wind dataset enhanced with integrated parametric correction, substantially improving maximum sustained winds and the radius of maximum wind, both of which are critical for offshore extreme load assessment in typhoon-prone regions. This produced an “adequate mean but large extreme bias” pattern: ERA5 performed reasonably for Nanhai Sea climatology but underestimated typhoon extremes. Stable stratification, nighttime maritime inversions, and low-level jets also remained difficult to resolve, producing shear er-

rors and statistically manifesting as elevated RMSE, weak upper-tail quantiles, and insufficient spectral energy. For floating offshore wind turbines, Yang et al. [154] proposed a new calibration approach for high-fidelity modeling of extreme environmental loads, including typhoon conditions, thereby improving the reliability of extreme-load and design-wind assessment.

Impacts on wind power development: Unaddressed biases could cause serious consequences. Persistently underestimated strong winds pushed design wind speeds too low. For example, a 30 m/s 50-year return-period value from uncorrected ERA5 versus a true 35 m/s left inadequate safety margins. Underestimated extremes also inflated yield estimates because models assumed continuous full-load operation during cut-out conditions. Errors in stable stratification and low-level shear affected turbine selection and array layout, raising fatigue loads and O&M costs. At the system level, biased reliability assessments could set dispatch safety margins inappropriately, while underestimated extreme risks led to insufficient reserves and weakened crisis response.

### 3.6.2. Potential Solutions: Reanalysis and Model Biases

(1) Performing bias correction classified by weather regime/sea state/stability. A single global linear correction is inadequate because biases are condition-dependent; instead, apply grouped, scenario-specific corrections. Bin data by wind-speed quantile with separate functions for high winds, apply wind-direction-sector corrections distinguishing land vs. ocean fetch, and use stability-stratified corrections for vertical profiles. Adjust near-shore strong-wind estimates using wave height and roughness. In practice, build a multi-dimensional bias lookup table or train an ML correction model on meteorological and sea-state indicators.

(2) Establishing closed-loop verification of “strong winds–extremes–engineering indicators.” Move beyond mean-wind validation: compute model errors for annual maximum and design return-period wind speeds (e.g., 50-year), feed them back to developers, and assess effects on turbine fatigue and ultimate loads. Utilities should cross-check biases against actual generation during energy droughts and surplus periods, adjusting reserve strategies. European researchers, for example, compared ERA5 with buoy-measured extremes and tuned the model’s tail distribution, making ERA5-derived 100-year return-period estimates more reliable. Extreme-wave scenarios can be combined with severe-wind correction to improve design safety margins.

(3) Strengthening ground-truth observation, model intercomparison, and engineering feedback channels. Buoy and met-mast extreme records should feed into systematic intercomparison among ERA5, MERRA-2, and regional reanalyses to identify product- and region-specific biases. Engineering load testing should provide feedback to model developers, closing the loop between meteorology and design so that biases are continually identified and corrected.

## 3.7. The Reliability, Interpretability, and “Out-of-Distribution Generalization” Issues of AI Models

### 3.7.1. Challenges and Impacts: AI Reliability and Generalization

Challenges: ML use in wind energy projection had exposed several risks. The first is reliability, as deep learning is largely a black box without quantitative trust metrics.

The second is limited interpretability. Unlike physical models with clear causal chains, AI internal weights could not be directly linked to physical processes, so dispatch and engineering users struggled to trust outputs.

The third was out-of-distribution (OOD) generalization. AI models reproduce learned patterns but cannot truly extrapolate; under climate states absent from training

(e.g., extreme El Niño, unprecedented Arctic warming), outputs could become entirely unreliable.

The final concern was long-term non-stationarity. Fixed model parameters trained on historical data accumulate biases under concept drift. Neto et al. [155] showed that approximate Bayesian inference (Monte Carlo dropout, variational inference) can equip spatio-temporal wind speed models with calibrated uncertainty correlated with prediction errors. Zhang et al. [156] proposed a hierarchical spatial-temporal Transformer for long-term wind power forecasting that explicitly addresses failure modes on non-stationary patterns, with substantially better OOD generalization. Saeed et al. [157] proposed a unified deep learning framework delivering deterministic predictions and uncertainty quantification through a single network with adaptive quantile estimation, pointing toward the practical deployment of trustworthy AI in dispatch and market applications.

Impacts on wind power development: Blindly trusting unreliable AI could lead to flawed decisions. Underestimating quarterly output triggered over-procurement of backup fuel, while overestimation left reserves insufficient. Model failure during extreme events could endanger system safety. Systematically underestimating storm intensity without load shedding or extra reserves could trigger blackouts and erode industry trust. Until reliability and interpretability are addressed, AI cannot assume critical decision-chain roles.

### 3.7.2. Potential Solutions: AI Reliability and Generalization

(1) Constructing uncertainty quantification for AI projections. Draw on meteorological ensemble forecasting, ensemble outputs from multiple architectures or training subsets to estimate variance; alternatively, use Bayesian deep learning with Monte Carlo Dropout for probabilistic outputs. AI then provides credible intervals or distributions rather than point projections. For example, “ $45 \pm 10$  GWh for next month output (95% confidence)” lets dispatch prepare for worst-case 35 GWh, enhancing transparency and safety while educating users on the probabilistic nature of AI.

(2) Enhancing physical interpretability. Embed physical knowledge into model design and training: attention visualization reveals which inputs a Transformer focuses on, and sensitivity analysis (perturbing one variable at a time) tests whether outputs behave as expected (e.g., rising NAO index correctly raises European wind output). Establish an “AI interpreter” role at dispatch centers to manually review AI projections against synoptic charts, building trust through human-machine collaboration.

(3) Designing robust training and maintenance workflows. At training, improve generalization via data augmentation (simulated extremes, projected scenarios) and physical-invariance regularization (non-negative power, bounded shear). After deployment, continuous learning fine-tunes the model with new observations to track environmental changes and avoid concept drift; large model-observation deviations trigger attribution analysis and possible retraining. Failure mitigation—e.g., reverting to conservative methods or manual intervention when output exceeds historical bounds by more than a specified threshold—acts as a “fuse” preventing errors from propagating into operational decisions. Table 4 summarizes the seven bottlenecks discussed above, together with their causes, impacts, and countermeasures.

**Table 4.** The seven bottlenecks of medium–long-term wind energy projection: Causes, impacts, and countermeasures.

| Bottleneck                                                 | Root Cause(s)                                                                                                                       | Impact on Wind Power Development                                                                          | Key Countermeasures                                                                                                                                               |
|------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1. Data quality control and representativeness             | Heterogeneous platforms/heights/QC standards; scarce offshore hub-height profiles; no unified open “ground truth”                   | Higher projection uncertainty; unreliable reanalysis/model evaluation; biased siting; capacity shortfalls | Multi-platform observation + unified QC + open sharing; use open long series (NOW-23, ERA5); mandatory data-provenance reporting                                  |
| 2. Divergent conclusions across data sources and teams     | Different data, model selection, downscaling, bias-correction and testing choices                                                   | Contradictory reports hinder siting/investment/planning; higher risk premiums; duplicative work           | CMIP/CORDEX-style intercomparison and consensus protocols; divergence attribution; open benchmark datasets                                                        |
| 3. 10 m → hub-height extrapolation                         | Data mostly at 10 m; dynamic offshore roughness; complex stability; hub heights rising to 100–200 m+                                | ±5% wind ≈ ±15% power-density error; biased AEP, turbine selection, design/load margins                   | Measurement + profile parameterization; data-driven (LSTM/GNN) profiles; height uncertainty embedded in design and finance                                        |
| 4. Non-stationarity and uncertainty communication          | Climate-driven trends violate stationarity; scenario probabilities hard to assign; poor communication to users                      | Over-confidence or over-conservatism; misallocated capacity; withheld long-term contracts                 | Scenario-probability framework (P10/P50/P90); non-stationary and decadal models; “uncertainty disclosures” and forecast-cone thinking                             |
| 5. Resource → electricity conversion                       | Outputs are wind speed/WPD; power-curve nonlinearity, wake losses and availability often omitted                                    | Inflated yields; >10% AEP shortfalls from cluster wakes; over-optimistic project economics                | Power-curve convolution; wake-loss modeling; availability and technology derating built into the workflow                                                         |
| 6. Boundary-layer, strong-wind and extreme biases          | Empirical drag ignores sea-state coupling; resolution/parameterization limits underestimate extremes, LLJ and stable stratification | Under-set design winds and safety margins; inflated yields; mis-set reserves/dispatch margins             | Regime/sea-state/stability-stratified bias correction; closed-loop extreme-wind verification; ground-truth + engineering feedback                                 |
| 7. AI reliability, interpretability and OOD generalization | Black-box models; no explicit physical causal chains; cannot extrapolate beyond training; concept drift                             | Flawed procurement/reserves; failure during extreme events risks system safety; low operator trust        | Uncertainty quantification (ensemble/Bayesian); physical interpretability (attention, sensitivity, PINN); robust training + continuous learning + “fuse” fallback |

#### 4. Conclusions

Reliable medium–long-term wind energy projection is essential for the planning, financing, and operation of large-scale offshore wind development. Against this need, this review examined its current status, bottlenecks, and countermeasures, with particular emphasis placed on the offshore horizon central to large-scale wind power deployment.

The projection methods were classified into three categories, and for each, the technical framework, representative studies, and comparative strengths and limitations were reviewed. Statistical/empirical and climate-signal-driven methods related large-scale climate signals to local wind and were transparent and computationally efficient and well suited to seasonal outlooks and risk indices. However, they assumed stationarity and

were weak on air–sea coupling and extremes. Dynamical models, combined with reanalysis and regional downscaling, resolved physical processes and delivered engineering-relevant spatial detail for siting and design; however, they also incurred a high computational cost, carried many intertwined uncertainty sources, and required region-specific calibration. Machine/deep learning and hybrid methods captured a nonlinear multi-source structure and performed automatic bias correction, downscaling, and direct data-driven projection; however, they depended on large high-quality datasets, offered limited interpretability, and extrapolated poorly out of distribution.

Taken together, these characterizations indicated that no single paradigm was sufficient on its own, and the state of the art increasingly converged on “dynamical simulation plus statistical or machine learning correction”.

Beyond the methodological survey, the principal contribution of this review was the systematic diagnosis of seven cross-cutting bottlenecks, each traced through a chain of cause, impact on wind power development, and targeted countermeasure. These were as follows: (i) difficult data quality control and insufficient observational representativeness, especially offshore, which propagated directly into projection uncertainty; (ii) divergent, even contradictory, conclusions for the same region across data sources and research groups, which left siting and risk pricing without a firm basis; (iii) large uncertainty in extrapolating 10 m winds to the continually rising turbine hub height, which was amplified by power’s near-cubic dependence on wind speed; (iv) difficulty in quantifying and communicating non-stationarity and uncertainty to decision-makers, which weakened risk-informed planning; (v) engineering conversion errors from projected “wind resource” to deliverable “electricity”, which caused headline energy yields to be read as upper bounds; (vi) systematic biases in the marine atmospheric boundary layer, strong winds, and extreme conditions, which compromised load and design-wind assessment; and (vii) unresolved reliability, interpretability, and out-of-distribution generalization of AI models, which limited their trustworthy use in high-stakes planning.

To address these bottlenecks, three mutually reinforcing strands of countermeasures were proposed. The first was the strengthening of the observational and benchmarking foundation through unified, open, quality-controlled observation networks with data-provenance standards and shared reference datasets and intercomparison protocols, thereby reducing data-driven divergence and supporting a consensus on robust versus uncertain findings. The second strand was the advancement of physics–data integration and uncertainty quantification through hybrid and physics-informed correction, regime-specific bias correction of boundary-layer and extreme-wind errors, and probabilistic frameworks that delivered and clearly communicated credible intervals, such as P10/P50/P90, together with non-stationary and decadal projection approaches. The third strand was the closure of the resource-to-electricity gap by embedding power-curve convolution, wake-loss modeling, and availability and technology derating into the projection workflow, so that projected wind resources could be translated into deliverable electricity.

Unlike previous reviews, which had largely concentrated on short-term operational forecasting or on refining forecasting-model taxonomies, this review targeted the full medium–long-term offshore spectrum and explicitly linked meteorological projection to engineering deliverability, thereby providing a practical scientific basis for improving the accuracy and decision relevance of medium–long-term wind energy projection and, ultimately, for supporting the reliable, large-scale integration of wind power into the global energy transition.

## 5. Prospects

Robust medium–long-term wind energy projection will play an increasingly important role across scientific research, economic application, and social benefit, while facing new opportunities and challenges:

Scientifically speaking, projections will become more accurate and mechanistically grounded. Next-generation global and regional climate models, with a higher resolution and richer physics, will provide a stronger foundation. International observation programs (e.g., the North Sea super-observation network and global air–sea flux plans) will supply richer assimilation and validation data. Within the next decade, uncertainty should reduce notably, and climate change response signals should become more consistent. For emerging basins such as the Baltic Sea—where mean wind resources can already be projected with reasonable confidence but hub-height shear, low-level jets, extreme winds, and sub-seasonal wind droughts remain the dominant residual uncertainties—such advances will be particularly decisive for constraining turbine-scale operating conditions.

Economically and industrially speaking, medium–long-term projections will underpin wind power investment and electricity market operations. As reliability grows, banks and insurers will support projects on better terms, lowering financing costs and accelerating grid parity. On the demand side, intelligent control of indoor microclimate parameters offers flexible demand management [158]; coupling such demand response with wind energy projection enables coordinated source–load optimization, maximizing allocation efficiency and economic benefits.

At the policy and social benefit level, medium–long-term projections support energy planning, climate adaptation, and public awareness. Governments can set science-based renewable targets and regional plans: if a coastal province’s wind resources may drop 10% by 2040, photovoltaic configuration or transmission can be adjusted in advance. Communicating projections to the public via accessible materials (wind resource maps, scenario films) strengthens understanding and support for renewables, building a social consensus on climate action.

Integration would increasingly mean multi-energy integration. Floating offshore wind was beginning to be co-developed with wave energy—and, at suitable sites, tidal-current energy—on shared or structurally integrated platforms [29,30]. Because wind and wave resources were frequently complementary in time, such hybrids could reduce aggregate variability while sharing infrastructure to lower costs [33]; however, this extended the forecasting agenda of the present review from wind alone to the joint medium–long-term prediction of wind, waves, and currents—making these coupled systems’ resilience to extreme metocean conditions a cross-cutting research priority [30].

Looking ahead, medium–long-term wind energy projection is expected to advance in precision, intelligence, and integration. Progress in this field will underpin the large-scale grid integration of wind power and the global energy transition, yielding substantial environmental, economic, and social benefits.

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## Nomenclature

|              |                                                                            |
|--------------|----------------------------------------------------------------------------|
| AEP          | Annual Energy Production                                                   |
| AI           | Artificial Intelligence                                                    |
| AMO          | Atlantic Multidecadal Oscillation                                          |
| AO           | Arctic Oscillation                                                         |
| ARIMA        | Autoregressive Integrated Moving Average                                   |
| BiGRU        | Bidirectional Gated Recurrent Unit                                         |
| C3S          | Copernicus Climate Change Service                                          |
| CEEMDAN      | Complete Ensemble Empirical Mode Decomposition with Adaptive Noise         |
| CFSR         | Climate Forecast System Reanalysis                                         |
| CFSv2        | Climate Forecast System version 2                                          |
| CMIP5        | Coupled Model Intercomparison Project Phase 5                              |
| CMIP6        | Coupled Model Intercomparison Project Phase 6                              |
| CNN          | Convolutional Neural Network                                               |
| CORDEX       | Coordinated Regional Climate Downscaling Experiment                        |
| CRPS         | Continuous Ranked Probability Score                                        |
| DL           | Deep Learning                                                              |
| ECMWF        | European Centre for Medium-Range Weather Forecasts                         |
| ENSO         | El Niño–Southern Oscillation                                               |
| ERA5         | ECMWF Reanalysis v5                                                        |
| ERA-Interim  | ECMWF Reanalysis Interim                                                   |
| EURO-CORDEX  | European Coordinated Regional Climate Downscaling Experiment               |
| EWT          | Empirical Wavelet Transform                                                |
| GAN          | Generative Adversarial Network                                             |
| GCN          | Graph Convolutional Network                                                |
| GMM-HMM      | Gaussian Mixture Model–Hidden Markov Model                                 |
| GNN          | Graph Neural Network                                                       |
| HMM          | Hidden Markov Model                                                        |
| IPCC         | Intergovernmental Panel on Climate Change                                  |
| IPO          | Interdecadal Pacific Oscillation                                           |
| JRA-55       | Japanese 55-year Reanalysis                                                |
| LiDAR        | Light Detection and Ranging                                                |
| LSTM         | Long Short-Term Memory                                                     |
| MCMC         | Markov Chain Monte Carlo                                                   |
| MERRA-2      | Modern-Era Retrospective Analysis for Research and Applications, Version 2 |
| Met-mast     | Meteorological Mast                                                        |
| ML           | Machine Learning                                                           |
| MSE          | Mean Squared Error                                                         |
| MU           | MultiUnet                                                                  |
| MU-Diffusion | MultiUnet-Diffusion Framework                                              |
| NAO          | North Atlantic Oscillation                                                 |
| NCEP         | National Centers for Environmental Prediction                              |
| NOAA         | National Oceanic and Atmospheric Administration                            |
| NOW-23       | National Offshore Wind Data Set 2023                                       |
| NWP          | Numerical Weather Prediction                                               |
| O&M          | Operations and Maintenance                                                 |
| OOD          | Out-of-Distribution                                                        |
| PDO          | Pacific Decadal Oscillation                                                |

|             |                                                   |
|-------------|---------------------------------------------------|
| QC          | Quality Control                                   |
| RCP         | Representative Concentration Pathway              |
| RMSE        | Root Mean Squared Error                           |
| RNN         | Recurrent Neural Network                          |
| S2S         | Sub-seasonal to Seasonal                          |
| S2S4E       | Sub-seasonal to Seasonal for Energy               |
| SARIMA      | Seasonal Autoregressive Integrated Moving Average |
| SCADA       | Supervisory Control and Data Acquisition          |
| SEAS5       | ECMWF Seasonal Forecasting System 5               |
| SRCNN       | Super-Resolution Convolutional Neural Network     |
| SRGAN       | Super-Resolution Generative Adversarial Network   |
| SSP         | Shared Socioeconomic Pathway                      |
| SVR         | Support Vector Regression                         |
| TC          | Tropical Cyclone                                  |
| Transformer | an Attention-based Neural Network Architecture    |
| WPD         | Wind Power Density                                |
| WRF         | Weather Research and Forecasting                  |
| WW3         | WAVEWATCH-III                                     |

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