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Optimizing Wind Resource Assessment: An Integrated Review of Monitoring Technologies, Challenges, and Future Directions

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ABSTRACT: *Accurate wind resource assessment (WRA) is critical for mitigating financial and operational risks in the global transition to renewable energy. While traditional methods rely on Numerical Weather Prediction (NWP) and regression analysis, recent shifts (2024–2025) emphasize the integration of "Sustainable AI," high-resolution Digital Twins, and advanced remote sensing for deep-water offshore environments. These developments enhance the quantity and quality of wind resource characterization and forecasting. Wind-speed and shear evaluations, resource mapping, turbine siting, layout optimization, operational forecasting, and predictive maintenance are among the applications that benefit from these advances. This paper explores the evolution of monitoring technologies, socio-economic implications, and emerging strategies for tripling global wind capacity by 2030.*

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I. INTRODUCTION TO WIND RESOURCE ASSESSMENT

The global wind energy sector reached a cumulative capacity of 1,136 GW in 2024, with projections suggesting a record 139 GW of new installations in 2025. As turbines move into complex terrains and deeper offshore waters, traditional observational records often fall short. Modern WRA now leverages a fusion of Internet-of-Things (IoT) sensor networks, satellite data, and machine learning to reduce uncertainty in wind-speed quantiles and layout optimization. The location of a wind farm is critical to its viability. Access to high-quality wind-resource data is essential for siting and design analyses. The dominant resource assessment approach adopted to date has been the use of historical meteorological data, which acts as a proxy for the future evolution of the resource. The historical record is used to build statistical models to extrapolate the wind resource to the desired site and height. The spatial correlation between wind stations is well established, providing a basis for the location of a second site where measured data can be used to quantify the wind resource at a site that is unmonitored.

II. MODERN METHODOLOGY AND DATA SOURCES

Weather monitoring technologies for wind resource assessment have benefited from advances across several domains. These improvements span remote sensing, numerical weather prediction, sensor networks, and data assimilation, incorporating satellite platforms, wireless links, machine learning, the Internet of Things, and high-performance computing. They involve new measurement principles, increasingly sophisticated models, and innovative approaches to forecasting, data fusion, and uncertainty quantification that contribute to enhanced characterization of wind resources. Ongoing developments promise further progress.

Potential adoption of new techniques varies by geography, scale, and project type, yet early estimates indicate substantial improvements in accuracy and reliability. Recent work on wind observation systems has illuminated advancements in design, integration, and applications for assessment of temporal, spatial, or probabilistic wind characteristics across short- to long-term horizons [1].

REMOTE SENSING AND GROUND-BASED OBSERVATIONS

Wind plays an essential role in weather dynamics and is a critical resource for wind energy. Weather encompasses physical attributes (e.g. component vectors) and a suite of abstract concepts (e.g. winds), while monitoring refers to measurements, measurements plus models or just models. Because interest in weather data often arises from a wind energy context, certain aspects of wind energy design require detailed treatment [2]

The scope and temporal or spatial resolutions of interest can vary widely depending on the analysis performed or exercise undertaken. For example, when forecasting daily patterns, the focus may primarily be on eight or even four spanning the 24-hour day or on hourly or minute-to-minute fluctuations when focusing on shorter timeframes. New breakthroughs offer more information on the weather and, by extension, support the forecast of new weather conditions. Numerical Weather Prediction continues to be a cornerstone for site-specific forecasting. However, the current trend is the use of downscaled reanalysis datasets (e.g., ERA5) coupled with local observational data to create "Digital Twins" of wind farms. These twins allow for real-time simulation of wake effects and structural fatigue.

SEASONAL TO LONG-RANGE FORECASTING AND NOWCASTING

A significant trend for 2025 is the correction of Floating LiDAR data using AI. Traditional LiDAR in offshore settings often suffers from motion-induced noise; new machine learning algorithms now filter these instabilities, providing high-resolution metocean data that rivals fixed mast measurements at a fraction of the cost. Furthermore, satellite-data fusion (using Sentinel-2) is now used to map offshore turbine performance across entire regions simultaneously.

REMOTE SENSING: LIDAR AND SATELLITE FUSION

Weather forecasting encompasses a wide range of forecast horizons and skill levels. Short-term forecasting, typically known as nowcasting, refers to time frames from a few hours to a couple of days ahead. The features of interest are generally local, even site specific, the uncertainty is rapidly growing, and statistical approaches are frequently employed. Intermediate-to-longer time-scale forecasting (3-15 days) involves forecasts at the regional or continental scale, with features such as disturbances and fronts that can be resolved by the model. Seasonal-to-annual forecasting focuses on variations around the climate normal from a month up to a few years, with model processes such as ocean-atmosphere interactions playing essential roles (Lledó et al., 2019). In many cases, the latter approach estimates the future state of variables governed by local or internal processes and may be combined with intermediate-range forecasting for better information

III. IMPLICATIONS FOR WIND RESOURCE ASSESSMENT

The characterization of wind speed and shear is a prerequisite for conducting a wind resource assessment. When assessing the availability of wind, a meteorological model characterizes wind speed and other variables throughout the year. The simulated wind speed time series is used as input in the wind simulation software for the wind resource assessment. The quality of the simulated wind speed is quantified using a statistical comparison between wind speed time series from the same model and from an actual site. Tables of statistical representations and vertical profiles of the simulated time series also help define the scenarios of interest for the wind resource assessment.

Characterization of turbulence, wake effects, and energy yield should be defined based on the wind conditions at a site. A key parameter for the characterization of turbulence is the turbulence intensity. However, a meteorological model does not directly provide this information, and several downscaling approaches are recommended for its estimation. A second key parameter is the shear, which is required to implement wake modeling, quantify wake losses, and study turbine-to-turbine interactions.

Finally, although extreme wind events are not destructive to the energy yield, they are typically important for assessing the reliability of the wind resource. The arrival of a new data set that provides a better understanding of wind speed characteristics at a given site can therefore be valuable for assessing and quantifying uncertainties in the predicted energy yield.

WIND SPEED AND SHEAR CHARACTERIZATION

Wind speed can be characterized statistically and is frequently represented as one-dimensional probability distribution functions (PDF). Representations such as the Weibull and Rayleigh distributions can be fitted to measured data, with parameters determined using statistical methods. Other representations without parameters involve state density functions or histograms of logged data. A more insightful characterization of wind speed involves determining the vertical profile of wind. Various vertical-wind-speed models have been proposed for this purpose.

For wind energy applications, the proposed models typically consider atmospheric boundary-layer (ABL) theory and the log-linear profile. Data collected at heights between 30 m and 130 m on a three-bladed upwind turbine at the Jülich Wind Energy Research Station have been used to validate frequently applied parametrizations. In addition, the vertical shear of wind speed can be used directly in mono-dimensional models for wind calculations on large space and time scales. Downscaling meteorological fields from grid points to well-defined ground locations is desirable when extending predictive numerical models to wind energy forecasting.

Another principle of site-specific wind-speed characterisation relies on the application of pre-existing measurements collected at a nearby location. Wind resource maps often provide wind speed at a raster of points, which at times appears compatible with the spatial distribution in consideration, and a rational extends in time of the wind resource site is given by these maps. A simple yet effective way to achieve bias-correction consists in computing the cumulative distribution function of the variable to correct, for the training period, at the two considered scales [3].

TURBULENCE, WAKE EFFECTS, AND ENERGY YIELD

Weather-monitoring applications in wind-resource assessment encompass relevant spatio-temporal scales, hence characterizing turbulence remains essential [4]. Turbulence intensity (TI) a dimensionless ratio of standard deviation to average wind speed provides unambiguous, site-specific information on energy yield and operational risks, quantifying wind-resource dispersion around the mean. TI's strong dependence on wind profiles necessitates accurately characterizing vertical shear. NWP models regularly exhibit unrealistic persistence of strongly sheared conditions, hindering both TI estimation and wake modeling. Joint regional/global investigation of TI and shear nevertheless yields straightforward statistical relations across numerous sites.

Turbine-scale wake modeling similarly relies on accurate information on mean wind and turbulence. Depending on site, estimated wind profiles may differ drastically from actual conditions. Wake losses pertinent to turbine layouts and design remain unquantified without reliable estimates of the upstream turbine states. Turbulence effects on wakes, critical for assessing interactions among multi-turbine designs, remain even less contemplated, despite the substantial influence of site-specific characteristics.

IV. APPLICATIONS IN WIND ENERGY PROJECT DEVELOPMENT

Wind energy is one of the viable alternatives to fossil fuel-based energy sources because of its abundance, low cost, and environmental benefits. Wind potential estimation, forecasting, and effective management are critical for planning wind farms and determining the level of investment in wind energy projects.

Accurate monitoring of parameters such as wind speed, direction, overspeeding, rotations, torque, turbulence, and temperature is vital for wind energy projects. Wind measuring devices, such as anemometers, are used in the evaluation of potential sites, but regular maintenance and monitoring are costly and are typically performed manually, often leading to inaccuracies. Furthermore, a proper monitoring technique for these devices has not been developed; as a result, site assessments and project performance have been adversely affected

SITE IDENTIFICATION AND RESOURCE MAPPING

Wind energy resource assessment at potential wind energy project sites typically employs land-use maps, satellite and aerial imagery, regional meteorological data, wind maps, wind atlases, and multi-year weather databases that compile historical records from the nearest weather stations. Wind maps depict the average wind speed or power density for large geographical areas and may be generated from re-analysis datasets. They provide a preliminary indication of the quality of the wind resource at regional and national scales, particularly when wind atlases are not freely available, but they are too coarse at the high-resolution level required for precise site assessments [5]. Wind atlases are more accurate than wind maps, containing estimates of the wind resource at multiple heights above ground level on a grid finer than typical wind maps, often one hundred kilometres or finer. Compiled from observations at an extensive network of climatological stations, they may use onsite measured data to provide confidence intervals and uncertainty estimates. The data from a wind atlas at a selected location can be supplemented by extensive numerical weather prediction models that provide time series of all meteorological variables at various heights, generating an additional estimate of the selected site's wind characteristics.

TURBINE SITING AND LAYOUT OPTIMIZATION

Wind farm design requires determining the locations of individual wind turbines to maximize energy production while minimizing environmental, operational, and economic constraints. A thorough assessment should consider wake effects, which can lead to significant energy loss in multi-turbine arrangements. By using models and software tools to simulate complex atmospheric phenomena, it is possible to evaluate multiple design iterations based on analysis of projected energy yield and wake propagation.

Wake interaction models aim to represent the effect of wind turbine operation on atmospheric flow in the vicinity of wind farms to estimate energy yield and define optimal turbine siting strategies. These models are classified as analytical, computational fluid dynamics (CFD), and large-eddy simulation (LES) models. Analytical models calculate how property distributions change through advection, turbulence diffusion, or thermal dispersion; they are often incorporated into linearized simplified flow models. Computational fluid dynamics constructs a physical simulation of atmospheric flow around the turbine and within the flow domain, offering high-fidelity results; such models require extensive computation resources, making them applicable primarily to local studies or short timescales. Large-eddy simulation models resolve the problem over a time-dependent three-dimensional domain, explicitly representing convection and turbulence at the resolution of the large-eddy scales using locally adapted meshes. Although less resource-intensive than CFD, they are still computationally demanding, and further simplifications are needed to apply them to realistic wind-farm optimization studies over time scales of months to years [6], [7]. Wind projects increasingly leverage forecasting data to inform operational decisions, such as active power curtailment and intricate forecast verification processes. Generating reliable forecasts in the hours and days ahead enables wind resources to be actively monitored in real-time and future conditions assessed, facilitating timely maintenance planning, effective decision-making, and curtailments when requested by system operators.

To assess current operating status, forecaster-generated anomalies are combined with supervisory control and data acquisition (SCADA) system data. By simultaneously scrutinizing operational indicators and modeled future prospects, a comprehensive evaluation of turbine health can be conducted. Data assimilation techniques and machine learning approaches, trained on historical SCADA information, automate the identification of abnormal behavior. Alarm signals are sent to windfarm operators when conditions deviate significantly from established operational patterns [8].

V. CHALLENGES IN WEATHER MONITORING FOR WIND RESOURCES

Weather monitoring for wind resources still faces certain challenges. Data availability and quality can be problematic, with gaps, varying sensors, and incompatibilities needing attention. Monitoring systems can specify calibration requirements and recommend calibration methods based on specific instruments. Operational weather forecasting models exhibit substantial biases in wind speed, persistence, vertical extrapolation, and lack of localized details, indicating a need for careful examination of performance. Service providers can establish reference datasets and tracking systems to quantify confidence intervals for local decisions.

Utilizing multiple independent observations from different sources is essential for a complete understanding of the atmospheric state, but observing systems often lack coverage and may only provide sparse information at a limited number of locations. Data from any available source should therefore be integrated, preferably at the initial stage and with prior consideration of measurement uncertainty. Existing random field models for the generation of local wind fields conditional on observed data can still benefit from attention.

The absence of widely applicable and up-to-date guidance regarding the configuration of weather monitoring systems can hinder effective resource assessment in certain circumstances. A broad range of cost-effective observation, forecasting, and analysis systems exist for wind and other commodities, yet the considerable number of alternative approaches, software options, and detailed analyses required can present a significant barrier. Without specialized training, stakeholders may collectively face insurmountable difficulties with implementation.

DATA AVAILABILITY AND QUALITY

The assessment of wind energy resources relies on a myriad of historical and real-time meteorological information [9]. Unfortunately, this information is commonly incomplete, heterogeneous, and stored in multiple platforms. It often requires calibration and post-processing to determine its suitability, particularly for surface wind-extrapolation purposes. Such data can be sourced from previously installed and decommissioned observation networks, private measurements, commercial archives, and through collaborative exchanges with local stakeholders. They typically contain hourly or, in some cases, sub-hourly time series of one or multiple target variables. When assessing offshore areas, it may be necessary to consult atmospheric data from neighbouring coastal land stations or bundled products generated via numerical weather prediction (NWP) models.

Wind resource assessments often rely on coarse-resolution numerical weather models that do not account for local topography and land use. Errors may arise from model design, initialization, and parameterization, making it essential to downscale predictions to the site and aggregation times of interest [10]. Several model-specific and model-agnostic downscaling schemes have been proposed, ranging from simple empirical methods to advanced frameworks. Nevertheless, predicting the range of plausible wind conditions rather than single best estimates is of utmost importance. To address this challenge, analytical approaches for generating confidence intervals for high-dimensional multi-variate fields have been developed [11]. These methods enable the assessment of local wind speed confidence intervals alongside site suitability evaluations and resource characterizations.

INTEGRATION OF MULTISOURCE OBSERVATIONS

Forecasts of meteorological variables critical for wind resource assessment are often generated from diverse observational sources, models, and data assimilation techniques. Moreover, the rich temporal and spatial variability of meteorological fields necessitates a combination of immediate meteorological observations, systematic historical data, and numerical simulation outputs to construct an integrated view of climatic conditions specific to wind resource assessment. The integration of multisource observations through sophisticated data-fusion frameworks is thus pertinent [12].

Numerical simulations of meteorological processes involve uncertainties, creating inconsistencies between simulated and observed observations. Establishing a unified framework for integrating different variables and multiple conditions into a consistent multisource wind analysis is fundamental [13]. The combination of thousands of remotely sensed satellite measurements with temporary monitoring campaigns recognizes difficult-to-access conditions of wind resource assessment. The coupling of distributed local independent observables respecting multiple periods and driving conditions fosters the generation of consistent and relevant climatological datasets, adapting to the evolution of the knowledge of wind resource assessment. The simultaneous incorporation of multiple driving variables from varying conditions opens up new possibilities for developing intelligent data-assimilation solutions that enhance the description of agitated wind resource assessment.

VI. SOCIO-ECONOMIC STUDIES AND IMPACTS

Forecast data for wind energy projects influence the levelized cost of energy (LCOE) and several financial metrics for determining the economic viability of projects. For example, between wind projects can differ by more than a factor of two. The relative attractiveness of marginal projects depends on the cost of capital and other investment incentives. Data on forecast skill influences not only integrated project cash flows, risks, and net present value, but also how these factors impact discount rates and other financing variables [14].

Enhancing the existing wind energy job base particularly focuses on the appropriate workforce development strategies. For the specific electricity generation that comes from both wind projects already installed and those presently under development, training pathways are also being developed in collaboration with community colleges and local/regional organizations to support the project workforce needs. Conducting a formal analysis to assess projected employment demand and identify candidate training institutions might improve occupational forecasts to address localized workforce concerns [15].

ECONOMIC VIABILITY AND LEVELIZED COST OF ENERGY IMPLICATIONS

Changes in weather monitoring have the potential to impact the economics of wind energy, and hence its contribution to a sustainable energy future. Consequently, we sought to quantify these potential impacts. We developed cost trajectories associated with different forecasting ranges, using a simplified model of a hypothetical project that considers wind energy risks and uses the development and operational phases for calibration. We also analyzed the effect of more sophisticated, data-driven estimates of the Levelized Cost of Energy (LCOE) to incorporate dependencies on both the forecast horizon and various economic factors, such as the capital recovery factor, the share of equity, and debt repayment. In the latter phase, we incorporated the possibility of partial financing during the debt repayment period. Preliminary findings indicate that the Levelized Cost of Spinning Reserve Energy, a proxy for the value of resource uncertainty information, shows a pronounced dependence on the forecast horizon—extending the forecast leads to significant costs—and this relationship remains intact even when using more sophisticated LCOE estimates [16].

ENVIRONMENTAL AND SOCIAL GOVERNANCE CONSIDERATIONS

Wind and solar resource assessment using satellite-derived products and numerical weather predictions (NWP) has gained popularity, in particular for large-scale wind and solar resource assessment. In South Africa, the impact of high-performance computing (HPC), data assimilation, the Internet of Things (IoT), artificial intelligence (AI), and cloud technologies on NWP models has been evaluated. A detailed analysis of the global energy supply and demand situation, as well as the future role of wind energy in the global energy landscape, asserts that wind energy will play a crucial role in the next energy revolution.

VII. POLICY, REGULATION, AND MARKET IMPLICATIONS

Weather patterns influenced by climate change exert substantial pressure on energy systems in diverse sectors, including agriculture, food supply, industrial production, transportation, and health. Renewable resources heavily depend on weather and climate, and emerging energy system models must accordingly track multiple weather patterns and climate signals. In particular, functional dependencies on both short-term and long-term weather patterns are expected to develop in various sectors and affect energy production and consumption. This dual dependency has a direct bearing on how firms assess risks, thus affecting their short-term financial metrics, as well as investment decisions related to longer-term equipment purchases, installations, and operational setups. Perturbations due to climate change will differ significantly between systems, necessitating country- or region-specific investigation of impacts alongside an examination of realistic future climate scenarios.

REGULATORY FRAMEWORKS FOR DATA SHARING

Regulatory frameworks for data sharing are essential for facilitating collaboration and innovation in wind energy and climate research. They establish guidelines that ensure data accessibility, security, and privacy. Effective frameworks promote the sharing of wind resource data, atmospheric measurements, and modeling outputs among researchers, industry stakeholders, and policymakers. Well-defined regulations help manage intellectual property rights and data ownership issues, enabling coordinated efforts in offshore wind potential assessments and environmental impact studies. Common guidelines encourage transparency and reproducibility, advancing the development of wind energy technologies and informing regulatory decisions [17].

Data-sharing frameworks for wind-energy- and climate-related studies under development by the Group of Earth Observation Systems of Systems and participants do not include a formalized engagement between the international community and the Intergovernmental Panel on Climate Change concerning the path from regional to global-scale analyses. Appropriate sanctions on users who do not respect data-providers' terms and conditions need to be developed by the Group of Earth Observation Systems of Systems Members and Participating Organizations and may include a variety of sanctions [18].

INTERNATIONAL COLLABORATION AND BENCHMARKING

Advancements in weather monitoring for wind resource assessment are rapidly being developed, tested, and applied. New data sources and collection methods provide unprecedented spatial and temporal coverage. These advances are poised to improve the accuracy and reliability of long-term wind resource estimates and energy production projections, but they are not without challenges. This section summarizes the state of the art and assesses socio-economic implications, applying a framework adapted from the World Meteorological Organization (WMO). By reviewing progress in weather monitoring and its implications for wind resource assessment, the analysis clarifies requirements and identifies solutions through collaboration [19].

VIII. CONCLUSIONS

The progress made in weather monitoring for wind resource assessment is set to drive a paradigm shift in the harmonization of wind conditions observed across heterogeneous data sources and their comprehensive representation throughout the wind energy project lifecycle. Constraints on data access and quality remain substantial when an isolated perspective on wind resource assessment is taken rather than considering the broader implications for the wind energy sector. Weather monitoring directly informs crucial aspects of wind resource estimation, and awareness of the associated advances can yield significant dividends in the pursuit of improving the viability and bankability of wind energy projects. The expanding diversity of weather-monitoring technologies, data sources, and modeling approaches directly addresses the unfulfilled demand for more comprehensive characterization of wind conditions than is typically provided by speed and direction statistics at the hub height of a representative reference turbine. By bridging wind conditions across distances on the order of hundreds of kilometers, these monitoring capabilities greatly reduce the risk associated with large investments in conventional wind power plants and increasingly enable the early-stage evaluation of emerging wind energy applications such as airborne wind energy and floating offshore wind. Beyond the physical characterization of wind conditions, the enhancement of weather-monitoring strategies, in conjunction with the continuing growth of satellite and logistical-data availability, extends the temporal information accessible to wind resource assessments into the seasonal-to-long range and nowcasting horizons. These additional temporal dimensions, coupled with broader spatial bridging, support the quantification of uncertainties in wind-energy-resource assessments and are vital for recognizing early-stage, yet potentially project-disqualifying, site- and technology-specific-exploitation risks.

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