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Artificial Intelligence and Machine Learning for Wind Modelling and Prediction: Data Sources, Methods, and Research Gaps

Mateo Radić

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1 Introduction

Wind is one of the most important atmospheric phenomena affecting a wide range of environmental, engineering, and socio-economic systems. Its spatial and temporal variability plays a significant role in meteorology, renewable energy production, air quality assessment, environmental monitoring, spatial planning, and wildfire spread modelling. Accurate knowledge of wind behaviour and its spatial distribution is therefore essential for numerous scientific, industrial, and operational applications.

Unlike many other environmental variables, wind exhibits pronounced spatial and temporal heterogeneity [1]. Wind characteristics are influenced by various factors, including topography, terrain morphology, land cover, vegetation, atmospheric stability, and local meteorological conditions. As a result, wind speed and direction can vary considerably even over relatively short distances, particularly in regions characterized by complex terrain such as mountainous areas, coastal zones, islands, and urban environments [2]. These characteristics make wind modelling and prediction a challenging task.

Over the past decades, a variety of approaches have been developed for wind estimation, modelling, and prediction. Traditional methods primarily rely on numerical weather prediction models, computational fluid dynamics simulations, geostatistical approaches, and spatial interpolation techniques. While these methods have demonstrated considerable success in many applications, their performance often depends on the availability of high-quality measurements, the density and distribution of observation networks, and the complexity of the observed environment.

Recent advances in sensing technologies, satellite observations, and publicly available meteorological databases have significantly increased the amount of wind-related data available for analysis. At the same time, improvements in computational resources have enabled the widespread adoption of Artificial Intelligence (AI) and Machine Learning (ML) methods for modelling complex environmental processes. Consequently, numerous studies have investigated the use of machine learning algorithms, deep learning architectures, and hybrid approaches for wind estimation, spatial wind field reconstruction, interpolation, and forecasting [3].

Despite the growing body of research, the field remains highly diverse with respect to data sources, modelling approaches, evaluation methodologies, and application domains. Furthermore, while many proposed methods report promising results under experimental conditions, it is often unclear to what extent these approaches have been validated using real-world data or deployed in operational environments. Such diversity makes it difficult to compare results across studies and identify the most promising directions for future research.

The aim of this paper is to provide a comprehensive overview of wind modelling and prediction approaches, with a particular focus on Artificial Intelligence and Machine Learning methods. Special attention is given to the data sources used for wind modelling, modelling methodologies, application domains, evaluation strategies, and the level of validation and implementation reported in the literature. Based on the analysis of existing research, the thesis aims to identify current trends, research gaps, and future challenges within the field.

To achieve these objectives, the following research questions are addressed:

RQ1. How is wind measured, estimated, modelled, and predicted across different application domains?

RQ2. Which Artificial Intelligence and Machine Learning methods are most commonly used for wind modelling and prediction?

RQ3. What are the main limitations, challenges, and research gaps preventing the wider operational adoption of AI and ML methods for wind modelling and prediction?

The thesis is organized as a broad overview of wind modelling research, covering the fundamental characteristics of wind, available data sources, modelling approaches, Artificial Intelligence and Machine Learning methods, and their applications in various domains. Particular emphasis is placed on identifying dominant research trends, comparing existing approaches, and highlighting current limitations and opportunities for future development.

2 Wind as a Complex Environmental Phenomenon

Wind is a dynamic atmospheric phenomenon resulting from pressure gradients, the Earth's rotation, and interactions between the atmosphere and the Earth's surface [4]. Although the physical mechanisms responsible for wind generation are relatively well understood, wind behaviour often exhibits considerable complexity due to the combined influence of terrain characteristics, boundary layer processes, and changing meteorological conditions.

The spatial distribution of wind is rarely uniform. Local topography can significantly modify airflow patterns by accelerating, decelerating, or redirecting wind, while atmospheric boundary layer processes influence the vertical structure of wind speed and direction [5]. These effects are particularly pronounced in regions characterized by complex terrain, where substantial variations may occur over relatively short distances [6].

In addition to spatial variability, wind also exhibits strong temporal variability across multiple timescales, ranging from short-term fluctuations caused by turbulence to seasonal and interannual atmospheric patterns. Understanding the factors that drive both spatial and temporal variability is essential for accurate wind measurement, modelling, interpolation, and prediction.

The following sections examine the main processes contributing to wind complexity, focusing on topographic influences, atmospheric boundary layer dynamics and vertical wind profiles, and the spatial and temporal variability of wind.

2.1 Topographic Influences on Wind Behaviour

Topography represents one of the most important factors influencing local wind behaviour. Mountains, valleys, coastal regions, islands, and terrain discontinuities can significantly modify airflow patterns, producing substantial variations in wind speed and direction over relatively short distances [6]. As a result, wind fields observed in complex terrain often exhibit a high degree of spatial heterogeneity, making accurate measurement and modelling particularly challenging.

Mountain barriers can alter atmospheric flow through several mechanisms, including flow blocking, acceleration, channeling, wave generation, and the formation of turbulent structures in the lee of mountain ranges. Depending on atmospheric stability and flow conditions, these effects may produce localized regions of enhanced wind speeds, flow separation, lee waves, and rotor circulations, which are often difficult to capture using coarse-resolution numerical models [7].

The influence of topography is especially pronounced in coastal environments where terrain-induced effects interact with land–sea contrasts. Along the eastern Adriatic coast, the complex geometry of the coastline and the presence of numerous islands contribute to the development of highly localized circulation systems. Observational studies have shown that local wind characteristics may differ considerably even between nearby locations due to channeling effects and terrain-induced modifications of the airflow [8].

Table 1: Comparison of mainland and island marine coastline lengths calculated from harmonised Eurostat GISCO 2024 spatial data.

Country	**Mainland coastline (km)**	**Island coastline (km)**	**Total coastline (km)**	**Island share (%)**
Croatia	1,035.2	3,004.5	4,039.7	74.4
Denmark	1,695.5	3,634.5	5,329.9	68.2
Greece	4,370.8	7,339.8	11,710.6	62.7
Norway	15,914.5	18,848.4	34,762.9	54.2
Italy	3,521.4	2,984.6	6,506.0	45.9
United Kingdom	7,542.3	6,172.5	13,714.8	45.0
France	4,516.5	1,478.5	5,995.0	24.7
Spain	3,314.5	1,023.8	4,338.3	23.6
Montenegro	195.3	6.1	201.4	3.0
Albania	382.6	10.5	393.1	2.7
Slovenia	31.1	0.0	31.1	0.0

To illustrate the exceptional topographic complexity of the Croatian coast, Table 1 compares mainland and island coastline lengths for selected European countries, showing that Croatia has the highest island coastline share (74.4%) among the countries considered; the calculations are based on Eurostat GISCO 2024 spatial data[1] while the processing script is available in the accompanying GitHub repository.[2]

A notable example is the Velebit Channel region, where local topographic configuration can modify the temporal evolution of coastal circulations. Mea-

[1] `https://gisco-services.ec.europa.eu/distribution/v2/` (accessed 28 July 2026).

[2] `https://github.com/mradic01/wind-modelling-literature-analysis/tree/coastline-analysis` (accessed 1 September 2026).

surements collected along the Croatian Adriatic coast indicate that maximum wind intensities generally occur during the early afternoon hours; however, in the Velebit Channel stronger winds may develop significantly earlier due to terrain channeling effects [8].

These findings highlight the importance of considering local topographic characteristics when analysing wind behaviour. Even under similar large-scale atmospheric conditions, substantial differences in wind patterns may occur at the local scale, emphasizing the need for high-resolution observations and modelling approaches capable of representing terrain-induced effects.

2.2 Atmospheric Boundary Layer and Vertical Wind Profile

In addition to horizontal variability caused by topographic influences, wind characteristics also change significantly with height above the surface. The vertical distribution of wind speed and direction is primarily governed by processes occurring within the atmospheric boundary layer, where the interaction between the Earth's surface and the atmosphere directly influences airflow patterns [9]. A schematic representation of the atmospheric boundary layer and its position relative to the Earth's surface and the free atmosphere is shown in Figure 1.

Near the surface, friction reduces wind speed and modifies wind direction. As the distance from the surface increases, the influence of friction gradually decreases, resulting in higher wind speeds and changes in the vertical structure of the wind profile. Consequently, wind conditions measured at a single height are often insufficient to fully describe atmospheric flow, particularly in applications requiring accurate representation of wind fields and transport processes.

The vertical variation of wind speed and direction is commonly described through vertical wind profiles and wind shear. Wind shear refers to changes in wind characteristics with height and represents an important factor in atmospheric dynamics, turbulence generation, and the development of extreme wind conditions. Analyses of low-level wind shear have shown that substantial variations may occur within the lowest few kilometres of the atmosphere, emphasizing the importance of considering vertical structure when studying wind-related phenomena [10].

The structure of the atmospheric boundary layer is strongly influenced by atmospheric stability, surface roughness, and local environmental conditions. In coastal environments, additional complexity arises from land–sea interactions and the development of internal boundary layers. Using lidar observations and numerical modelling, demonstrated that coastal wind profiles frequently exhibit strong vertical gradients within the lowest few hundred metres of the atmosphere and that these gradients are often difficult to reproduce accurately using numerical models [11].

Particularly under stable atmospheric conditions, wind profiles may deviate substantially from their average behaviour. In such situations, low-level jets can develop, producing local maxima in wind speed several hundred metres above the surface while near-surface winds remain relatively weak. These phenomena contribute to increased variability in the vertical structure of the atmosphere and present additional challenges for wind modelling and forecasting [11].

Understanding the atmospheric boundary layer and the vertical structure of wind is therefore essential for interpreting wind observations, evaluating model performance, and developing reliable prediction systems. Moreover, many Artificial Intelligence and Machine Learning approaches rely on observational datasets collected at specific measurement heights, making the representation of vertical variability an important consideration when analysing and modelling wind behaviour.

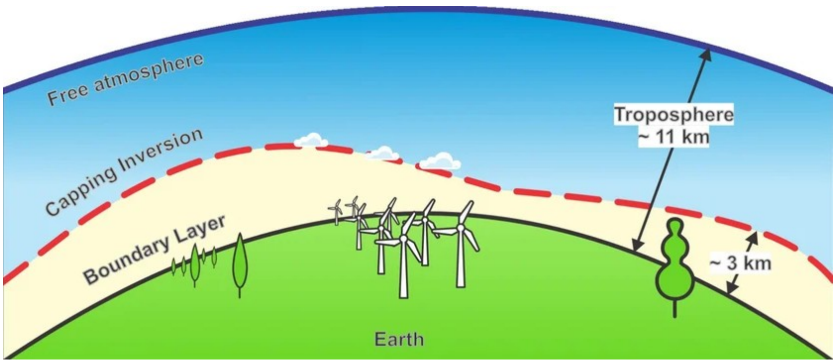


Figure 1: Vertical representation of the atmospheric boundary layer, illustrating its position between the Earth's surface and the free atmosphere, with the capping inversion defining its upper extent. Adapted from [12].

2.3 Spatial and Temporal Variability of Wind

Wind behaviour exhibits considerable variability across both space and time. While topography and boundary-layer processes influence local wind conditions, atmospheric circulation patterns, seasonal cycles, and diurnal variations further contribute to the complexity of wind fields. Consequently, wind conditions observed at a given location may vary substantially over different temporal scales, ranging from hours to seasons.

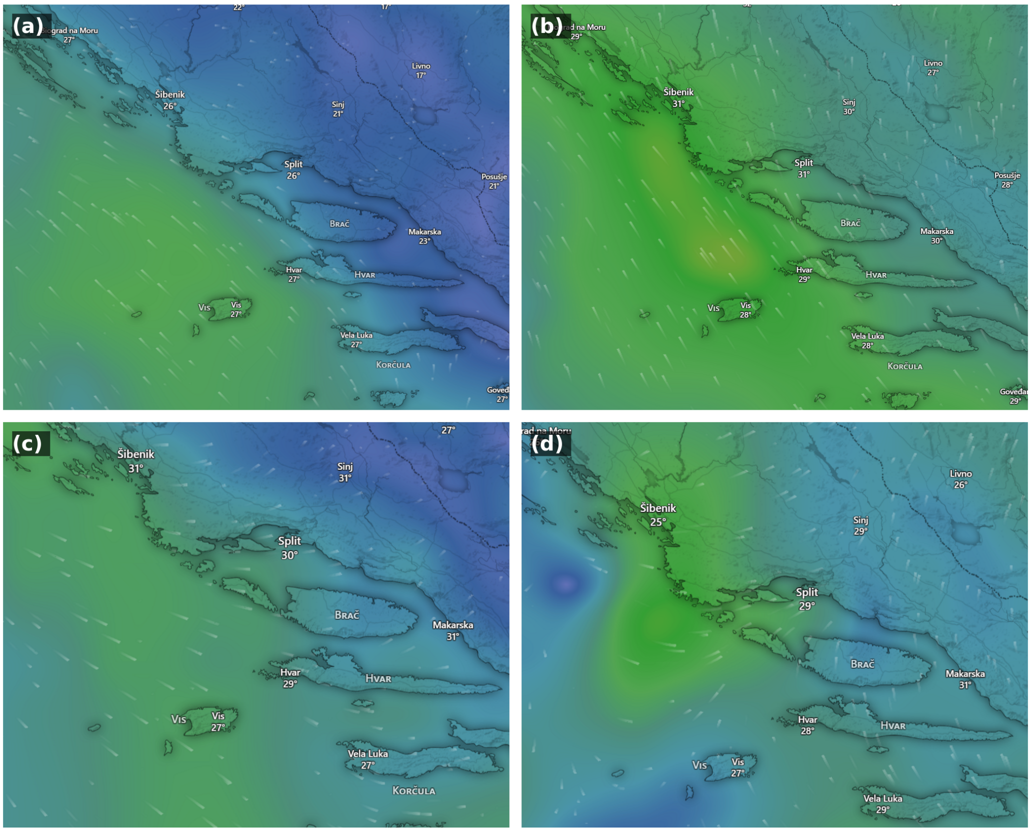
In coastal regions, temporal variability is often associated with thermally driven circulations and land–sea interactions. Along the eastern Adriatic coast, observational studies have shown pronounced diurnal cycles in wind intensity, particularly during the warm season when sea-breeze circulations become more developed. While maximum wind speeds generally occur during the early afternoon hours, certain locations may exhibit substantially different temporal patterns due to local terrain effects. For example, observations from the Velebit Channel indicate earlier wind intensification compared to other coastal locations, highlighting the influence of local topographic configuration on the temporal evolution of wind fields [8].

Wind variability is also influenced by larger-scale atmospheric circulation regimes. Different synoptic conditions can produce markedly different wind patterns, ranging from prolonged periods of weak winds to episodes of strong and persistent airflow. Furthermore, transitions between circulation regimes may lead to rapid changes in wind speed and direction, creating conditions that are particularly difficult to predict using conventional modelling approaches.

The rapid evolution of local airflow patterns is illustrated in Figure 2, which shows substantial changes in wind direction over the central Adriatic within a relatively short period.

An important example of such behaviour is represented by so-called wind ramps, characterized by sudden increases or decreases in wind speed over relatively short periods of time. Studies have shown that these events are often associated with specific large-scale circulation patterns and can significantly affect both forecasting performance and operational applications [13].

The combined influence of atmospheric processes, local terrain characteristics, and boundary-layer dynamics results in highly heterogeneous wind behaviour across multiple spatial and temporal scales. This complexity represents one of the primary challenges in wind modelling and prediction, motivating the development of increasingly sophisticated numerical, statistical, and Artificial Intelligence-based approaches capable of capturing such variability.



Source: Windy.com

Figure 2: Illustrative visualisations of spatial and temporal changes in near-surface airflow over the central Adriatic. The panels demonstrate how wind direction and spatial flow patterns can vary considerably over relatively short time intervals. The coloured background represents temperature, while the animated-particle trajectories indicate airflow direction. Source: Windy.com.

3 Wind Data Sources and Measurement Systems

Accurate wind modelling and prediction depend fundamentally on the availability of reliable observational and environmental data. Most applications use wind data obtained from ground-based measurements, remote sensing systems, for numerical weather models, atmospheric reanalysis, and geospatial datasets [14]. Each source provides a different representation of atmospheric conditions and is characterised by specific advantages and limitations related to spatial coverage, temporal resolution, measurement accuracy, and operational availability. These differences are particularly important for Artificial Intelligence and Machine Learning approaches, whose performance depends directly on the quality and representativeness of the data used for training, validation, and testing [15].

Figure 3 illustrates the complementary spatial representation provided by the principal observational and environmental data sources used in wind modelling.

3.1 In-Situ Wind Measurements

In-situ measurements represent one of the primary sources of observational wind data and are widely used in both operational monitoring and scientific research. They are commonly collected by meteorological stations equipped with instruments for measuring wind speed, wind direction, temperature, atmospheric pressure, and other relevant meteorological variables [16].

Meteorological station networks provide direct observations of atmospheric conditions at specific locations and are therefore commonly used as ground-truth data for model calibration, validation, and performance assessment [17]. Their relatively high temporal resolution and, in many cases, long observational records also make station measurements valuable for training and evaluating statistical, numerical, and Artificial Intelligence-based wind models [18].

However, the spatial availability of station observations differs considerably between countries. Table 2 compares the number and spatial density of active stations available through Meteostat[3] across the analysed countries, together with the corresponding mean nearest-station distances.

[3] `https://bulk.meteostat.net/v2/stations/lite.json.gz` (accessed 4 August 2026).

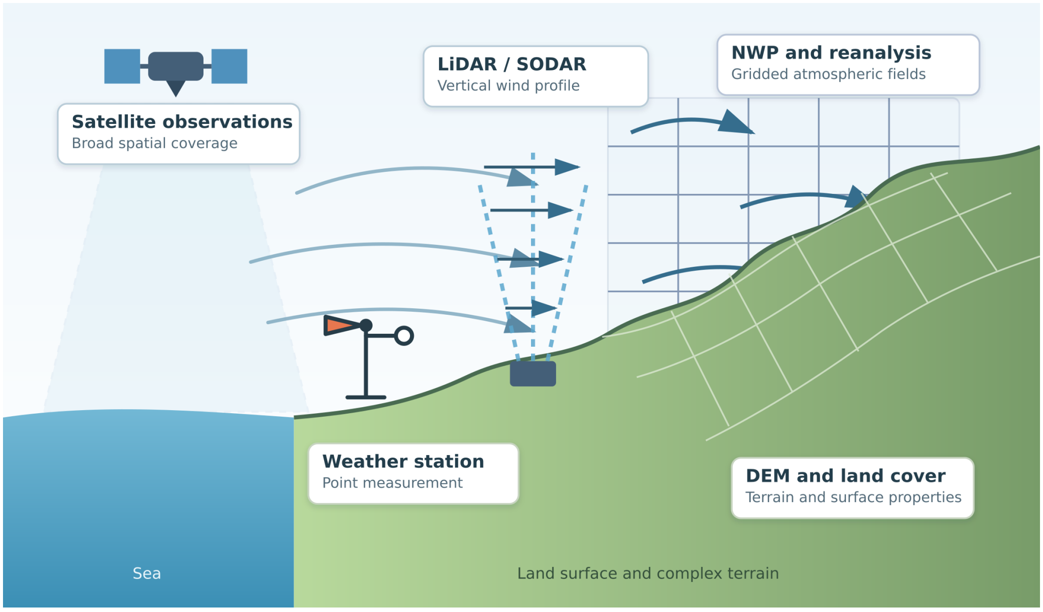


Figure 3: Conceptual comparison of the principal data sources used in wind modelling. Meteorological stations provide point measurements, LiDAR and SODAR systems capture vertical wind profiles, satellite observations offer broad spatial coverage, NWP and reanalysis products provide gridded atmospheric fields, and DEM and land-cover datasets describe terrain and surface properties.The schematic was created by the author with the assistance of ChatGPT (OpenAI, GPT-5.5).

Table 2: Comparison of national meteorological services, land area, active Meteostat station availability, station density, and mean nearest-station distance across the analysed countries.

Country	**National Meteorological Service**	**Land Area (km^2)**	**Active Meteostat Stations**	**Active Meteostat Stations per 1,000 km^2**	**Mean Nearest-Station Distance (km)**
Germany	DWD	349,430	1,397	3.997,9	10.59
Switzerland	MeteoSwiss	39,510	107	2.708,2	11.55
Netherlands	KNMI	33,670	64	1.900,8	24.31
Belgium	Royal Meteorological Institute of Belgium	30,494	35	1.147,8	16.51
Austria	GeoSphere Austria	82,520	93	1.127,0	14.07
Denmark	DMI	40,000	43	1.075,0	29.02
Croatia	DHMZ	55,960	45	0.804,1	28.38
Japan	Japan Meteorological Agency	364,569	278	0.762,5	28.37
United Kingdom	Met Office	241,930	177	0.731,6	66.02
Italy	Servizio Meteorologico Italiano	295,720	170	0.574,9	26.89
Finland	Finnish Meteorological Institute	303,960	174	0.572,4	24.78
Norway	MET Norway	364,270	192	0.527,1	38.56
Portugal	IPMA	91,606	39	0.425,7	34.06
France	Météo-France	538,950	223	0.413,8	30.51
United States	NOAA	9,147,420	2,701	0.295,3	35.53
Sweden	SMHI	407,270	108	0.265,2	28.32
Poland	IMGW-PIB	306,270	81	0.264,5	41.66
Spain	AEMET	499,697	104	0.208,1	39.40
Australia	Bureau of Meteorology	7,692,020	813	0.105,7	50.17
China	China Meteorological Administration	9,388,210	263	0.028,0	143.19

The results show substantial differences in observational coverage: Germany has the highest station density, with approximately 4.00 active stations per 1,000 km^2, whereas countries with large territories, particularly China and Australia, exhibit considerably lower station densities and greater distances between stations. Croatia occupies an intermediate position, with approximately 0.80 active stations per 1,000 km^2 and a mean nearest-station distance of 28.38 km.

The values reported in Table 2 refer exclusively to active stations represented in the Meteostat dataset and should not be interpreted as complete inventories of the official observational networks operated by the listed national meteorological services. The calculations were performed using a reproducible processing script, while the script and corresponding input data are available in the accompanying GitHub repository.[4]

The quality and representativeness of station observations depend on sensor accuracy, maintenance procedures, measurement height, nearby obstacles, surrounding surface characteristics, and local terrain [18]. In complex terrain, substantial variations in wind speed and direction may occur over distances smaller than the spacing between stations. Meteorological stations therefore remain essential for model development and validation, but their point-based coverage is often insufficient for representing complete regional wind fields.

3.2 Remote Sensing and Terrain Data

While meteorological stations provide direct observations at specific locations, wind modelling often requires information over larger spatial domains and at multiple heights. Remote sensing systems and terrain datasets are therefore commonly used to complement in-situ measurements [19, 20].

Ground-based remote sensing systems provide information that cannot easily be obtained from conventional meteorological stations. Doppler LiDAR and SODAR systems can measure wind conditions at multiple heights, enabling the reconstruction of vertical wind profiles and boundary-layer structure [21]. Satellite observations provide much broader spatial coverage and are particularly valuable for estimating near-surface wind conditions over oceans and other regions with limited ground-based observations.

Wind modelling also relies on terrain and land-surface datasets that describe the environmental conditions influencing airflow. Digital Elevation Models (DEMs) provide information about elevation, slope, and terrain mor-

[4] `https://github.com/mradic01/wind-modelling-literature-analysis/tree/meteostat-station-coverage` (accessed 1 September 2026).

phology, while land-cover products describe vegetation, urban surfaces, and other roughness-related characteristics [22]. The representation of these features depends strongly on spatial resolution and acquisition methodology. In steep and topographically complex regions, coarse-resolution DEMs may smooth terrain features that substantially influence local airflow, whereas LiDAR-derived elevation models can provide a more detailed representation of the surface [23].

Remote sensing observations and terrain datasets consequently complement station measurements by providing information about vertical atmospheric structure, broader spatial conditions, and the physical characteristics of the underlying surface.

3.3 Numerical Weather Prediction and Reanalysis

The limited spatial coverage of direct observations has encouraged the widespread use of gridded atmospheric datasets. Numerical Weather Prediction (NWP) models simulate atmospheric evolution by solving governing physical equations from an estimated initial state, while observations from ground stations, satellites, radiosondes, radar systems, aircraft, and other platforms are incorporated through data assimilation. The resulting model fields provide spatially continuous atmospheric analyses and forecasts at multiple vertical levels [24].

Atmospheric reanalysis applies a related approach retrospectively. Historical observations are processed using a consistent numerical model and data-assimilation system, producing continuous records that are less affected by changes in operational forecasting procedures. This consistency makes reanalysis datasets particularly valuable for climatological analyses, wind-resource assessment, model evaluation, and the development of data-driven prediction methods.

ERA5, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), is among the most widely used global atmospheric reanalysis products. It provides hourly estimates of numerous surface and upper-atmospheric variables and is frequently used either as a direct source of wind information or as an input to statistical and machine learning models [25].

Despite their extensive coverage, NWP and reanalysis products should not be interpreted as direct measurements. Their representation of local wind conditions depends on model resolution, data assimilation, physical parameterisations, and the underlying terrain description. These limitations are especially relevant in coastal and mountainous environments, where local flow structures may occur at scales smaller than the model grid.

3.4 Data Integration and Representativeness

No individual data source provides a complete representation of the wind field. Station measurements offer direct and temporally detailed observations but are spatially limited, while remote sensing and gridded atmospheric products provide broader coverage with different levels of spatial resolution and uncertainty.

The integration of these sources requires careful consideration of measurement height, temporal resolution, spatial scale, missing observations, and differences between point measurements and grid-cell estimates. Direct comparison may otherwise be misleading, particularly in complex terrain where local wind conditions can differ substantially from the spatially averaged conditions represented by gridded datasets.

Dataset selection should therefore be guided by the intended modelling scale and application. This is particularly important for Artificial Intelligence and Machine Learning approaches, since limitations, biases, and spatial gaps in the input data may be transferred directly to model predictions.

4 Overview of Wind Modelling Approaches

Wind modelling encompasses the description, reconstruction, simulation, and prediction of atmospheric wind under varying environmental conditions. Depending on the intended application, it may involve estimating wind conditions at an individual location, reconstructing spatial wind fields over complex terrain, or simulating atmospheric flow across multiple spatial and temporal scales. Relevant wind characteristics include wind speed and direction, turbulence, vertical wind profiles, and the evolution of two- and three-dimensional flow fields.

The complexity of wind modelling arises from the interaction of processes operating at different scales. Large-scale atmospheric circulation, boundary-layer dynamics, thermal stratification, terrain, surface roughness, and local obstacles can collectively produce highly nonlinear and spatially heterogeneous wind fields. Consequently, no single modelling approach is suitable for every application. Operational forecasting, local flow simulation, wind-field reconstruction, and short-term prediction impose different requirements regarding spatial resolution, physical representation, input data, and computational resources.

For this overview, wind modelling approaches are organised into four principal categories: physics-based, statistical, Machine Learning, and hybrid approaches. Physics-based approaches include Numerical Weather Prediction (NWP) and Computational Fluid Dynamics (CFD), whereas the remaining categories differ primarily in how they use observational data, predefined statistical relationships, and physical knowledge. Table 3 summarises the defining principles and representative methods associated with each category.

4.1 Physics-Based Wind Modelling Approaches

Physics-based approaches simulate atmospheric flow by explicitly representing the physical mechanisms governing fluid motion and atmosphere–surface interactions. They are widely used in operational weather forecasting, wind resource assessment, atmospheric research, and engineering applications.

The two principal physics-based approaches are Numerical Weather Prediction (NWP) and Computational Fluid Dynamics (CFD). NWP models simulate atmospheric evolution over regional or global domains and are primarily used for weather analysis and forecasting. CFD models are generally applied at finer spatial scales to investigate airflow over complex terrain, around buildings, or within other environments where local flow structures are important. Although both approaches are based on numerical approx-

Table 3: Classification of wind modelling approaches

Approach	**Representative Methods**
Physics-Based	Numerical Weather Prediction (NWP), Computational Fluid Dynamics (CFD)
Statistical	Regression Models, ARIMA, Time-Series Analysis, Kriging, Inverse Distance Weighting (IDW), Stochastic Methods
Machine Learning	Decision Trees, Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Gradient Boosting, XGBoost, CNN, LSTM
Hybrid	Physics-Informed Machine Learning, NWP + ML, Statistical + ML, Ensemble Models, Multi-Source Data Fusion Approaches

imations of governing physical equations, they differ substantially in scale, resolution, physical parameterisation, and intended application.

Figure 4 presents a simplified representation of airflow over complex terrain together with the incompressible form of the Navier–Stokes equations commonly used in CFD-based flow modelling.

CFD simulations of airflow over natural complex terrain demonstrate the ability of physics-based approaches to reproduce terrain-induced acceleration, separation, and other local flow modifications. Such applications also highlight the importance of accurate terrain representation, boundary conditions, and field measurements for model validation [26].

The principal advantage of physics-based models is their ability to represent atmospheric processes within a physically consistent framework. Their application, however, may require substantial computational resources, detailed terrain and surface information, appropriate initial and boundary conditions, and observational data for validation. Despite these requirements, physics-based models remain fundamental to atmospheric wind modelling and frequently provide inputs for statistical, Machine Learning, and hybrid frameworks.

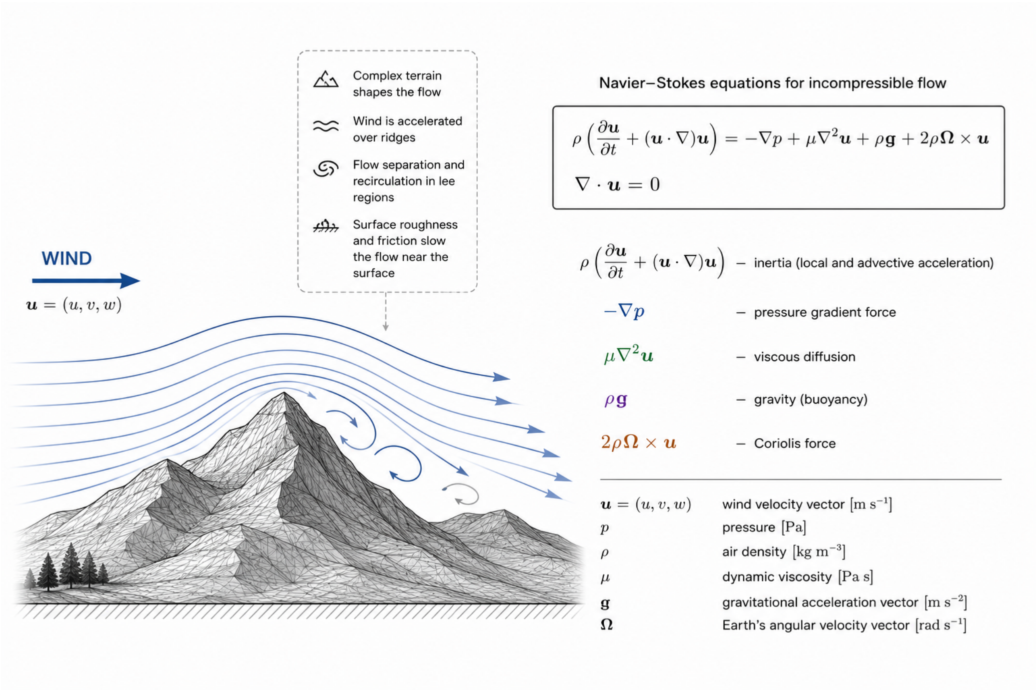


Figure 4: Schematic representation of airflow over complex terrain and the Navier–Stokes equations governing incompressible flow in physics-based wind modelling. The illustration was generated using an AI-based tool.

4.2 Statistical Wind Modelling Approaches

Statistical approaches estimate wind conditions by identifying temporal, spatial, or multivariate relationships within observational data rather than explicitly simulating atmospheric processes. Common methods include regression, time-series analysis, stochastic modelling, kriging, and Inverse Distance Weighting. These approaches have been applied to short-term forecasting, wind-resource assessment, missing-data reconstruction, and the estimation of wind conditions at unmonitored locations [14].

Compared with detailed physics-based simulations, statistical models are generally less computationally demanding and are often easier to interpret. Their performance, however, depends on the validity of their underlying assumptions and the representativeness of the available observations. Sparse station networks, changing atmospheric regimes, and complex terrain can therefore reduce their ability to reproduce highly localised and nonlinear wind behaviour.

Statistical methods nevertheless remain an important part of contemporary wind modelling. They provide efficient and interpretable solutions for many applications and frequently serve as baseline models against which Machine Learning and hybrid approaches are evaluated.

4.3 Machine Learning-Based Wind Modelling Approaches

The increasing availability of meteorological observations, numerical weather products, and computational resources has contributed to the widespread adoption of Machine Learning in wind modelling. These methods can learn complex and nonlinear relationships from historical data and have been applied to wind forecasting, wind-field reconstruction, resource assessment, and the analysis of extreme wind events [15].

Frequently applied methods include decision-tree-based algorithms, Support Vector Machines, Artificial Neural Networks, ensemble methods, and deep learning architectures. Their ability to integrate station observations, remote sensing data, numerical weather products, and geospatial information makes them particularly suitable for problems involving heterogeneous input data. Nevertheless, their performance depends strongly on the quantity, quality, and representativeness of the training dataset. Purely data-driven models may also have limited interpretability and may generalise poorly beyond the atmospheric and environmental conditions represented during training.

Machine Learning has consequently become an important component of contemporary wind modelling, both as an independent prediction approach and as part of hybrid frameworks. The classification, evolution, and application of Artificial Intelligence and Machine Learning methodologies in wind modelling are examined in greater detail in Chapter 6.

4.4 Hybrid Wind Modelling Approaches

The principal forms of hybrid wind modelling and their typical applications are summarised in Table 4.

Table 4: Common categories of hybrid wind modelling approaches.

Hybrid approach	Components	Typical applications
NWP + ML [27, 28, 29]	Numerical Weather Prediction combined with Machine Learning	Wind forecasting
CFD + ML [30, 31]	Computational Fluid Dynamics combined with Machine Learning	Wind-flow modelling over complex terrain
Statistical + ML [32, 33, 34]	Statistical models combined with Machine Learning	Time-series prediction and forecasting
Ensemble and model-combination approaches [35, 36, 37]	Combination of multiple modelling approaches	Uncertainty quantification and reduction
Physics-informed ML [38]	Physical constraints integrated into Machine Learning models	Physically consistent wind modelling
Multi-source fusion [39, 40, 41, 42]	Integration of multiple heterogeneous data sources	Spatial wind-field estimation

Hybrid approaches can exploit the large-scale physical consistency of numerical models while learning local relationships from observations. This is particularly relevant in complex terrain, where coarse numerical models may not fully resolve local airflow and purely data-driven models may be constrained by sparse or unevenly distributed measurements.

Hybrid modelling therefore provides an important connection between physics-based simulation and data-driven prediction, particularly in applications where neither approach is sufficient when applied independently.

5 Systematic Analysis of Wind Modelling Literature

This chapter presents a structured analysis of the scientific literature on wind modelling and prediction. Unlike the previous chapter, which introduced the main modelling paradigms at a conceptual level, this chapter examines how these approaches are represented in the existing literature. The objective is to analyse how the field has evolved over time, which data sources are most commonly used, which modelling methods dominate different application areas, and how model performance is typically evaluated. This distinction is important because many proposed approaches are evaluated only through simulations or historical datasets, while fewer studies demonstrate operational use, pilot implementation, or integration into decision-support systems. By identifying these differences, the chapter provides a clearer overview of the maturity of current wind modelling research. The results provide the foundation for the following chapter, which examines Artificial Intelligence and Machine Learning methods for wind modelling and prediction in greater detail.

The bibliometric analysis presented in this chapter is based on publications retrieved from the Web of Science Core Collection. The literature search was performed using a predefined query designed to capture the broader field of wind modelling while excluding unrelated topics, such as solar wind and astrophysical studies. Since the Web of Science search yielded a sufficiently large and representative dataset for the intended analysis, no additional searches of other bibliographic databases were conducted. Only English-language journal articles and review papers were considered. The final dataset consisted of 10,470 publications and formed the basis for all subsequent analyses. The bibliographic records were exported from Web of Science and processed using a custom Python workflow. The scripts used for data processing, classification, and visualisation are publicly available in the accompanying repository [5].

5.1 Evolution of Research Trends

The search strategy was designed to identify publications addressing wind modelling, wind-field estimation, reconstruction, interpolation, mapping, downscaling, and wind-speed prediction, while excluding unrelated research concerning solar wind and astronomical phenomena. The search was limited

[5] `https://github.com/mradic01/wind-modelling-literature-analysis/tree/literature-analysis` (accessed 1 September 2026).

to English-language journal articles and review papers. The complete search query is presented below.

```
TS=(("wind modelling" OR "wind model*" OR "wind field" OR
"wind field model*" OR "wind field estimation" OR "wind
field reconstruction" OR "wind interpolation" OR "wind
mapping" OR "wind downscaling" OR "wind speed prediction"
OR "wind speed estimation") NOT ("solar wind" OR stellar
OR galaxy OR astronom*))
```

The search returned a total of **10,470 publications**, providing a sufficiently large dataset for analysing the development of wind modelling research. Figure 5 shows the annual number of publications retrieved through this search.

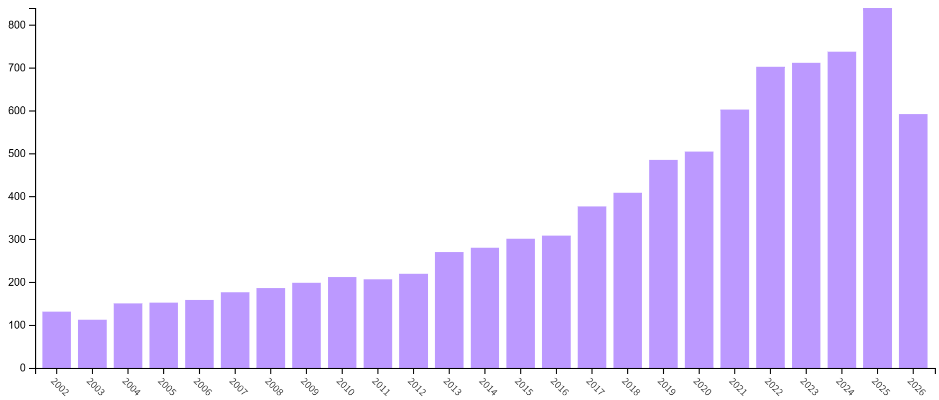


Figure 5: Annual number of publications related to wind modelling retrieved from the Web of Science Core Collection between 2002 and 2026.

The results demonstrate a clear long-term increase in research activity. Between 2002 and approximately 2015, the number of publications grew gradually, indicating steady development of the field. A more pronounced increase can be observed from 2016 onwards, coinciding with advances in numerical weather prediction, remote sensing technologies, renewable-energy applications, and Artificial Intelligence methods. The highest annual publication output was recorded in 2025. The lower number observed for 2026 reflects the fact that the database was accessed before the end of the publication year; consequently, the value for 2026 represents incomplete data and should not be interpreted as evidence of a declining research trend.

5.2 Evolution of Modelling Paradigms

The initial search returned a total of **6,467 publications** after applying the inclusion and exclusion criteria described in Section 5.1. To identify the dominant wind modelling approaches represented in the literature, each publication was automatically classified using a rule-based keyword-matching procedure. The title and abstract of each publication were searched for representative terms defined in a custom classification dictionary, which is provided in full in Appendix A. Table 5 summarises the principal categories, their defining characteristics, and representative terminology.

The categories were distinguished according to the primary mechanism through which wind conditions were modelled or predicted. Physics-based approaches represent atmospheric processes through governing physical equations and numerical simulations, whereas statistical approaches infer relationships from observed data using predefined probabilistic or time-series formulations. Machine learning approaches learn these relationships algorithmically from data without requiring an explicitly specified statistical relationship. Deep learning was treated as a specialised subgroup of machine learning characterised by multilayer neural-network architectures. Finally, hybrid approaches combine physical models with machine learning or deep learning components within a single modelling framework. Similar distinctions between physical, statistical, data-driven, and hybrid wind-forecasting approaches are commonly applied in the literature [43].

The classification procedure identified **1,806 publications** containing explicit references to one or more wind modelling methodologies. Since the temporal analysis presented in Figure 6 begins in 1996, the final dataset used for this analysis comprises **1,777 classified publications**. Publications that could not be confidently assigned to any category were excluded from the subsequent analysis.

Individual publications were allowed to match multiple dictionary entries because a single study could explicitly mention several modelling methods. A prioritisation scheme was therefore applied to avoid counting the same publication in multiple categories. Studies combining physics-based methods with machine learning or deep learning techniques were classified as *Hybrid*, reflecting the integration of physical and data-driven modelling components. This interpretation is consistent with the broader concept of physics-informed machine learning, in which observational data and mathematical representations of physical processes are incorporated within a common modelling framework [44]. Publications combining physics-based and statistical methods were retained in the *Physics-based* category when the statistical method served only as a supporting component of the physical model.

Table 5: Main modelling categories, their defining principles, and representative terms used in the literature classification. The complete classification dictionary is provided in Appendix A.

Category	**Defining principle**	**Representative terms**
Physics-based	Simulation of atmospheric flow using governing physical equations and numerical models.	numerical weather prediction, WRF, computational fluid dynamics, CFD, large-eddy simulation, RANS, dynamical downscaling
Statistical	Estimation of wind behaviour using predefined statistical, probabilistic, or time-series relationships.	linear regression, ARIMA, kriging, spatial interpolation, Weibull distribution, geostatistical model
Machine learning	Data-driven learning of relationships between input variables and wind-related outputs.	machine learning, artificial neural network, random forest, support vector machine, gradient boosting, XGBoost, ANFIS
Deep learning	Data-driven modelling based on multilayer neural networks capable of learning complex spatial or temporal representations.	deep learning, CNN, LSTM, GRU, transformer, graph neural network, autoencoder
Explicit hybrid	Integration of physical knowledge or numerical models with machine learning or deep learning components.	hybrid model, hybrid approach, physics-informed neural network, physics-guided machine learning, physical-data-driven model

Although deep learning terms were recorded separately in the classification dictionary, deep learning publications were included within the broader *Machine learning* category in the final temporal analysis. Consequently, Figure 6 presents four mutually exclusive categories: physics-based, statistical, machine learning, and hybrid approaches.

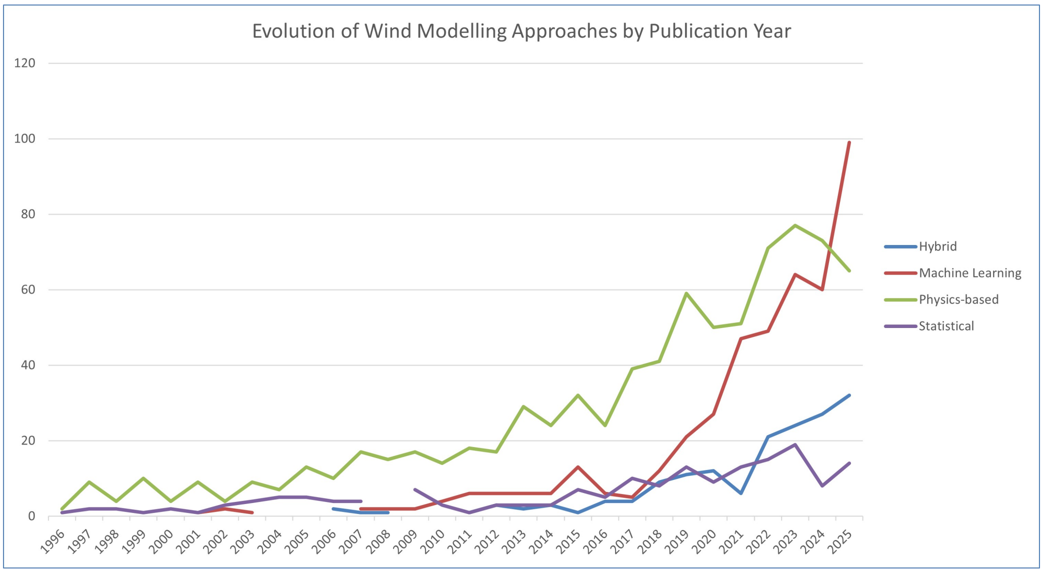


Figure 6: Temporal evolution of the principal wind modelling approaches. The figure presents the annual number of publications classified as physics-based, statistical, machine learning, or hybrid approaches. Deep learning methods are included within the machine learning category.

Figure 6 reveals a clear change in the modelling paradigms represented in the analysed literature. During the late 1990s and early 2000s, research was dominated by physics-based approaches, particularly numerical weather prediction and computational fluid dynamics. Statistical methods remained consistently represented throughout the analysed period but exhibited comparatively modest growth.

Machine learning approaches appeared during the early 2000s, although their representation remained limited until approximately 2016. A pronounced increase is visible after 2018, when machine learning rapidly became one of the dominant modelling paradigms. This development coincides with the broader adoption of deep neural networks for wind-speed and wind-power forecasting, as well as the increasing availability of environmental datasets and high-performance computing resources.

Hybrid approaches emerged later than conventional machine learning methods. Their rapid growth after 2020 indicates increasing interest in combining the physical consistency of numerical models with the pattern-learning capabilities of data-driven methods. Overall, the results indicate a gradual diversification of wind modelling research rather than a complete replacement of conventional methods. Physics-based models continue to play a fundamental role, while machine learning and hybrid approaches account for an increasing proportion of recent publications.

5.3 Data Sources Used in Wind Modelling

The selection of input data strongly influences the spatial and temporal resolution, applicability, and validation of wind models. Wind modelling studies may rely on direct in-situ measurements, remote-sensing systems, satellite observations, or observation-derived products such as meteorological reanalysis datasets. Standard surface and upper-air wind observations are described in the World Meteorological Organization guidelines, while Doppler LiDAR has become an important remote-sensing technology for retrieving wind profiles and three-dimensional wind-field information. Reanalysis products, such as ERA5, provide spatially and temporally consistent atmospheric datasets by combining observations with numerical weather prediction models through data assimilation [25].

The following analysis examines which of these meteorological data sources are explicitly reported in the wind modelling literature. For the purposes of this classification, the term *data source* includes both direct measurement systems and observation-derived datasets used as model inputs, reference data, or ground-truth information.

5.3.1 Meteorological Observations

To identify the meteorological data sources used in wind modelling, the previously classified dataset of **1,806 publications** was further analysed using an automated rule-based procedure. For each publication, the title, abstract, author keywords, and Keywords Plus were combined into a single searchable text. This text was subsequently screened using a custom dictionary containing terminology associated with meteorological measurement systems and observation-derived data products. The complete dictionary is provided in Appendix B, while the source code used for the classification is publicly available in the accompanying GitHub repository.

The classification workflow is presented in Figure 7. First, the combined publication text was searched for predefined terms representing specific meteorological data sources. When one or more precise sources were identified, all corresponding categories were assigned to the publication. The procedure therefore followed a multi-label classification approach, meaning that a single publication could be assigned to several categories simultaneously. For example, a study could combine *LiDAR measurements*, *ERA5 reanalysis data*, and observations from a *meteorological mast*.

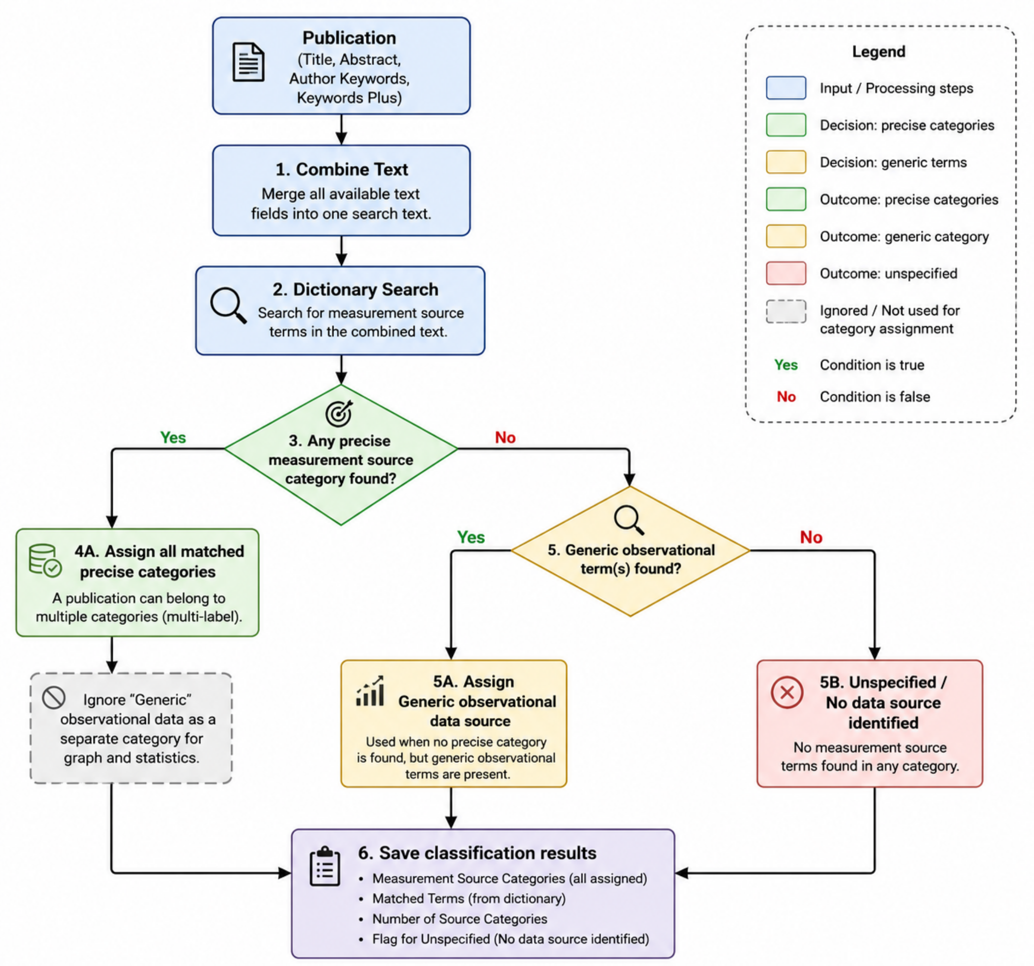


Figure 7: Workflow of the automated rule-based classification of meteorological data sources reported in the analysed publications.

To maximise classification specificity, generic observational terms, such as *observations*, *measured data*, and *field measurements*, were assigned only when no precise data source was detected. If a precise source was identified, generic terms were disregarded as a separate category to prevent redundant counting. Publications containing neither precise nor generic observational terminology were classified as *Unclasified*, indicating that the data source could not be determined from the available bibliographic metadata.

The procedure identified at least one explicit meteorological data source in **783 publications**. The remaining publications either contained only generic observational terminology or did not specify a meteorological data source within the analysed text fields. The publications with explicitly identified sources were subsequently grouped according to their assigned categories, providing the basis for the analysis presented in the following section.

5.3.2 Temporal Changes in Meteorological Data Sources

To examine how the reported use of meteorological data sources accumulated over time, the frequencies of the identified source categories were calculated for all publications included in the filtered dataset up to and including 2010 and 2025. Although the initial bibliographic records included earlier publications, the earliest publication retained after the dictionary-based filtering procedure dates from 1974. The two cumulative periods therefore cover 1974–2010 and 1974–2025, respectively. Since individual publications could report multiple data sources, the category frequencies are not mutually exclusive and represent source-category occurrences rather than numbers of unique publications.

Figure 8 shows a substantial increase in the cumulative frequency of every meteorological data-source category. Ground-based measurements remained the most frequently identified category, increasing from 25 occurrences by 2010 to 206 by 2025. Reanalysis data exhibited one of the strongest increases, from 11 to 126 occurrences, while satellite observations increased from 30 to 136. These results indicate the growing importance of spatially distributed atmospheric products alongside conventional in-situ measurements.

The cumulative comparison also demonstrates increasing diversification in the data used for wind modelling. Laboratory and wind-tunnel measurements increased from 13 to 100 occurrences, while generic observational data increased from 12 to 85. Ground-based remote sensing increased from 17 to 91 occurrences, and upper-air measurements from 21 to 49. Data sources that were comparatively uncommon by 2010 also became more visible, including numerical weather model data, marine and offshore measurements, and airborne and UAV measurements.

Overall, the results indicate that contemporary wind-modelling studies draw from a broader range of observational and model-derived data than the earlier literature. Conventional ground-based measurements remain fundamental, while reanalysis, satellite observations, remote-sensing systems, and specialised measurement platforms provide increasingly important complementary information. However, the values represent cumulative absolute frequencies. The larger values observed by 2025 partly reflect the longer

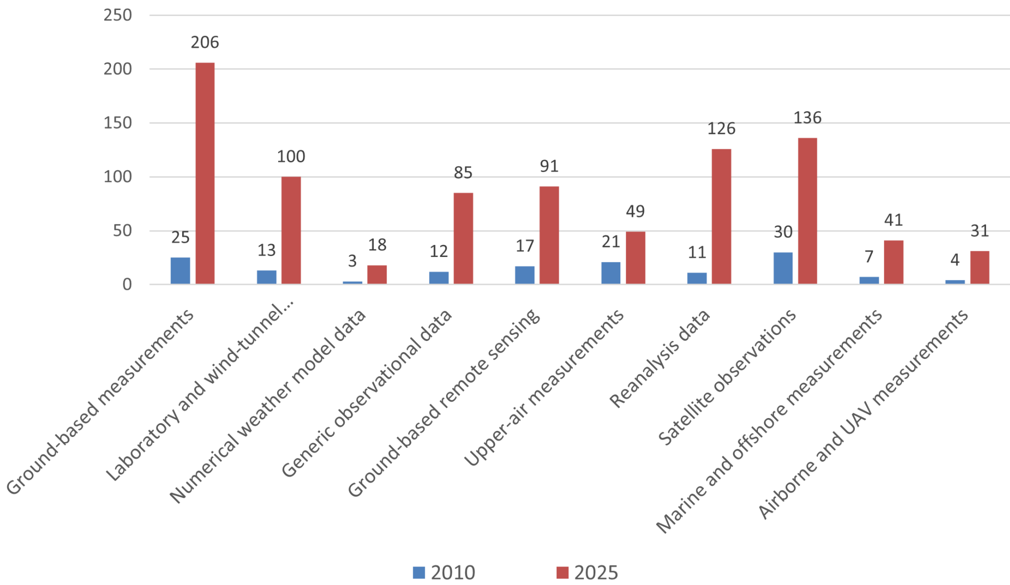


Figure 8: Cumulative frequencies of meteorological measurement-source categories identified in the filtered publication dataset for the periods 1974–2010 and 1974–2025. Since individual publications could report multiple data sources, the category frequencies are not mutually exclusive.

publication period and the substantial growth in the total number of publications. Consequently, the figure demonstrates the accumulated expansion and diversification of reported data sources, but it does not independently establish changes in their relative share within the literature.

5.4 Performance Evaluation and Validation

The analysis of performance-evaluation practices was conducted using the same set of **1,806 publications** considered in the methodological classification. The publications were processed using the dictionary of validation metrics provided in Appendix C and the corresponding automated classification code available in the accompanying GitHub repository. The resulting frequencies are presented in Table 7.

A single publication could report multiple validation metrics. Consequently, each identified metric was counted separately, and one publication could contribute to several rows of the table. The reported values therefore represent the frequencies with which individual metrics were identified, rather than the number of unique publications that performed validation.

The detected validation metrics were additionally grouped according to the previously assigned modelling approach: physics-based, statistical, machine learning, or hybrid. Publications in which a validation metric was identified but the modelling approach could not be reliably determined from the available bibliographic metadata were retained in a separate *Unclassified* category. This category therefore does not indicate an absence of modelling or validation, but only that the modelling approach could not be assigned with sufficient confidence using the automated classification procedure.

Table 7: Frequency of validation metrics identified across different wind modelling approaches. A single publication could report multiple metrics.

Metric	**Physics**	**Statistics**	**ML**	**Hybrid**	**Unclass.**	**Total**
RMSE	60	10	109	38	101	318
MSE	29	5	84	28	61	207
MAE	11	6	72	32	33	154
Correlation coefficient	17	4	27	11	63	122
R^2	2	5	29	13	18	67
MAPE	1	2	31	21	12	67
Other	19	1	32	7	30	89

The results reveal a clear predominance of error-based validation measures. RMSE was the most frequently identified metric, with 318 occurrences, followed by MSE with 207 and MAE with 154 occurrences. Together, these three metrics account for 679 of the 1,024 identified metric occurrences (66.3%). Their prevalence may be attributed to their direct representation of discrepancies between modelled and observed values. However, the metrics respond differently to the distribution of errors. MSE and RMSE give greater weight to large deviations because errors are squared before aggregation, whereas MAE weights absolute deviations linearly and is therefore less sensitive to occasional extreme errors [45, 46].

The correlation coefficient was identified 122 times, while the coefficient of determination (R^2) occurred 67 times. These measures describe different aspects of model performance. The correlation coefficient indicates the strength of association between modelled and observed values, whereas R^2 is commonly used to describe the proportion of variance accounted for by a model. Nevertheless, neither measure independently demonstrates agreement between predictions and observations. For example, predictions may exhibit a strong correlation with observations while retaining a substantial systematic bias. Correlation-based measures should therefore generally be reported together with absolute-error and bias measures rather than used as stand-alone indicators of predictive accuracy [47].

MAPE was identified 67 times. Its percentage-based formulation can facilitate comparisons across datasets with different scales, but its application to wind speed requires caution. Observed values close to zero can produce disproportionately large or undefined percentage errors, which is particularly relevant under calm or low-wind conditions [48]. The remaining 89 occurrences were grouped under *Other*, indicating that some publications reported additional validation measures. However, because these less frequent measures were aggregated into a single category, their individual methodological roles could not be examined in greater detail.

The distribution of metric occurrences across modelling approaches should be interpreted in relation to the number of publications assigned to each category. The larger number of metric occurrences in the machine-learning category does not, by itself, demonstrate that machine-learning studies applied more extensive or rigorous validation. The table reports absolute frequencies rather than the proportion of publications using each metric within an individual modelling category. A normalised comparison would therefore require the number of publications reporting each metric to be divided by the total number of publications assigned to the corresponding modelling approach.

A further limitation is that the automated analysis identifies which validation metrics were reported but does not determine the specific wind variable to which they were applied. For example, RMSE and MAE may be calculated for wind speed, wind direction, or the zonal and meridional wind components. These applications are not directly equivalent: validation based on wind speed evaluates the magnitude of the wind vector, whereas directional or component-wise validation also considers directional accuracy. Consequently, the frequency with which a metric is reported does not, on its own, provide a complete indication of the scope or methodological quality of the validation procedure.

5.5 Research Gaps

The results of this chapter reveal several interconnected gaps in wind-modelling research, particularly regarding reproducibility, validation, physical consistency, and practical applicability.

A major concern is the limited reproducibility of published studies. An explicit meteorological data source was identified in only 783 of the 1,806 analysed publications based on the available bibliographic metadata. Although additional information may be provided in the full text, insufficient reporting of datasets, preprocessing procedures, model configurations, validation protocols, and source code makes it difficult to independently reproduce and verify published results. Consequently, some studies report model performance and draw conclusions without providing a sufficiently transparent methodological basis from which the reported results can be repeated. Future studies should provide complete descriptions of the input data, preprocessing steps, model parameters, training and testing procedures, evaluation datasets, and software implementations.

The analysis also indicates limited standardisation of model validation. RMSE, MSE, and MAE accounted for 66.3% of all identified metric occurrences. Although these measures are useful, reporting only aggregate error metrics may conceal systematic bias, directional errors, poor performance under extreme conditions, and limited generalisation beyond the training data. Reproducible evaluation therefore requires common benchmark datasets, clearly separated training and test samples, multiple complementary metrics, and comparisons against appropriate baseline models.

A further gap is the weak connection between data, methods, and application context. Existing classifications do not clearly establish which combinations of meteorological data are most effective for particular modelling approaches, spatial and temporal scales, or practical applications. Systematic comparisons under consistent experimental conditions are needed to determine how data-source selection affects model accuracy, robustness, and transferability.

The rapid growth of artificial-intelligence and hybrid approaches creates an additional research priority. Future hybrid models should not only improve statistical accuracy but also reproduce physically plausible wind behaviour. Physical constraints, governing equations, conservation principles, and known atmospheric relationships should therefore be incorporated into model architectures or training procedures. Such models should be tested to determine whether they preserve physical consistency under previously unseen conditions, generalise between locations, and remain reliable when observations are sparse. Comparisons with both physics-based and purely data-driven baselines are necessary to demonstrate the actual contribution of physical information.

Evidence of real-world deployment also remains insufficiently established. However, the present analysis does not quantify operational implementation and therefore cannot demonstrate that deployment is generally limited. Future reviews should distinguish between proof-of-concept studies, retrospective evaluations, pilot implementations, and models integrated into operational systems.

6 Artificial Intelligence and Machine Learning for Wind Modelling

Artificial Intelligence (AI) and Machine Learning (ML) have become increasingly important components of contemporary wind-modelling workflows. Their development has been supported by the growing availability of meteorological observations, reanalysis products, remote-sensing data, geospatial datasets, and high-performance computing resources. Unlike conventional statistical approaches based on predefined functional relationships, machine-learning models can learn complex and nonlinear relationships directly from data. Deep-learning models can additionally learn hierarchical representations from large and high-dimensional datasets [49]. These capabilities make AI-based approaches particularly attractive for wind-related problems characterised by spatial heterogeneity, temporal variability, and complex interactions between atmospheric and terrain-related factors.

The role of AI in wind modelling extends beyond point-based wind-speed forecasting. Current applications include wind-field reconstruction, spatial interpolation and downscaling, wind-direction estimation, short- and long-term forecasting, extreme-event detection, surrogate modelling of computationally intensive simulations, and the correction or post-processing of numerical weather prediction outputs. Machine-learning methods are also increasingly used in fluid mechanics to identify flow patterns, construct reduced-order models, and approximate computationally expensive physical simulations [50].

The selection of an appropriate computational approach depends strongly on the modelling objective and the structure of the available data. Tabular observations are frequently processed using classical machine-learning algorithms, while temporal sequences may be addressed using recurrent or attention-based architectures. Spatially distributed wind fields require models capable of representing spatial dependencies, whereas the simultaneous representation of wind-field structure and temporal evolution requires spatio-temporal learning approaches. These distinctions are important because no single AI architecture is equally suitable for all wind-modelling problems.

The bibliometric analysis presented in the previous chapter indicates that AI-based wind modelling is not dominated by a single methodology. Instead, the literature contains a broad spectrum of approaches, ranging from classical machine-learning algorithms and conventional artificial neural networks to deep-learning architectures and more recent physics-informed and hybrid frameworks. Physics-informed machine learning is particularly relevant to wind modelling because physical laws, governing equations, boundary conditions, or other forms of prior physical knowledge can be incorporated into data-driven models [51].

To provide a systematic overview of the AI approaches represented in the analysed literature, the bibliographic records of **6,467 publications** were processed using the automated classification procedure developed for this study. The title, abstract, author keywords, and Keywords Plus of each publication were searched using the AI-method dictionary provided in Appendix D. The corresponding source code is available in the accompanying [6].

For the purpose of this initial classification, the identified approaches were grouped into four broad working categories: *classical machine learning*, *artificial neural networks*, *deep learning*, and *physics-informed or hybrid AI*. This classification provides a general overview of the methodological structure of the literature rather than a detailed comparison of individual algorithms and architectures.

Because a single publication could mention methods belonging to more than one category, the classification was performed as a multi-label procedure. The values presented in Figure 9 therefore represent identified category occurrences rather than mutually exclusive numbers of publications. A total of 1,128 category occurrences were identified across the four main groups.

As shown in Figure 9, deep-learning approaches formed the largest category, with 535 identified occurrences, followed by classical machine learning with 364 and artificial neural networks with 211 occurrences. Physics-informed and hybrid AI approaches were identified considerably less frequently, with only 18 occurrences.

The distribution demonstrates the prominent position of deep learning in the analysed wind-modelling literature. At the same time, the comparatively small physics-informed and hybrid category indicates that the explicit integration of physical knowledge into AI-based wind models remains substantially less represented. However, these frequencies describe only the broad methodological composition of the literature; they do not demonstrate that one category provides greater accuracy, physical consistency, or practical applicability than another.

This broad classification establishes the methodological context for the more detailed examination of individual AI algorithms and architectures presented in the following section.

[6] `https://github.com/mradic01/wind-modelling-literature-analysis/tree/ai-method-classification` (accessed 1 September 2026).

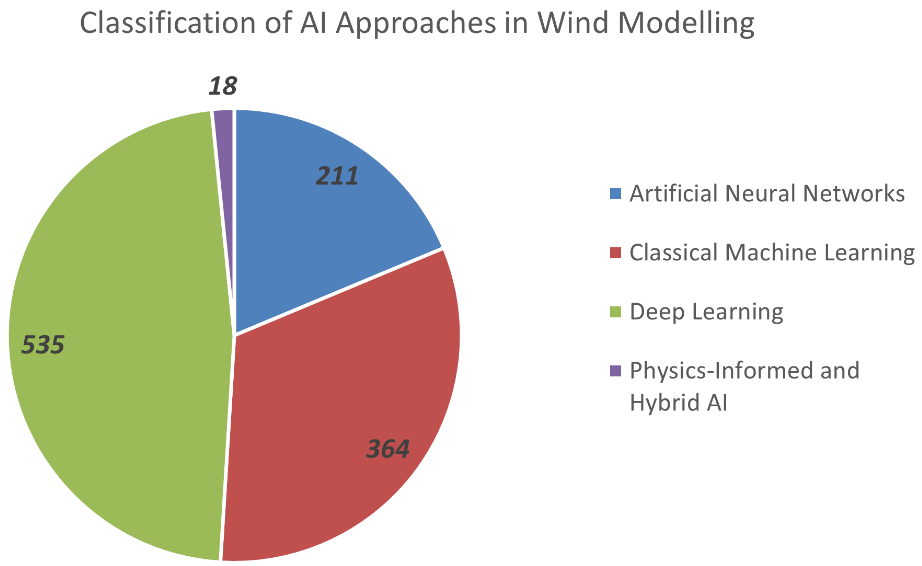


Figure 9: Distribution of the principal AI approach categories identified in the analysed publications. Deep-learning methods accounted for the largest number of identified classifications, followed by classical machine learning, artificial neural networks, and physics-informed or hybrid AI approaches.

6.1 Classification and Evolution of AI Methodologies for Wind Modelling

The temporal distribution of the identified AI methods provides a clearer perspective on the methodological development of AI-based wind modelling. Figure 10 presents the frequency with which individual methods were identified across four publication periods. The colour scale is logarithmic to preserve the visibility of both frequently and infrequently identified methods, while the numerical annotations report the corresponding absolute frequencies.

The temporal distribution shown in Figure 10 reflects not only changes in the preferred modelling approaches but also the broader technological development of artificial intelligence and meteorological data infrastructure. The transition between periods was driven by the interaction of three principal factors: the availability of larger datasets, increased computational capacity, and the development of architectures capable of representing temporal and spatial dependencies more effectively.

During the earliest period, AI-based wind modelling was dominated by conventional Artificial Neural Networks (ANNs), linear-regression-based methods, Support Vector Machines (SVMs), and other comparatively compact algorithms. These methods were well suited to the data environments available at the time, which were commonly based on tabular observations or time series obtained from individual meteorological stations. Training data were generally smaller, while the computational resources required for large deep-learning models were not yet widely accessible. Consequently, early applications largely treated wind modelling as a point-based regression problem in which future wind conditions were estimated from a limited number of historical meteorological variables.

The methodological expansion visible during the 2010–2019 period coincided with important developments in both machine learning and computational infrastructure. The increasing use of graphical processing units substantially reduced the computational barrier to training deeper neural networks, while advances in deep learning demonstrated that complex representations could be learned from sufficiently large datasets [52, 49]. These developments made it practical to transfer CNNs, recurrent architectures, autoencoders, and other deep-learning methods from general machine-learning research to meteorological and wind-related applications.

The increased occurrence of LSTM networks during this period can be related to the sequential nature of many wind-modelling problems. Conventional recurrent neural networks may have difficulty retaining information over long sequences because of vanishing or unstable gradients, whereas the

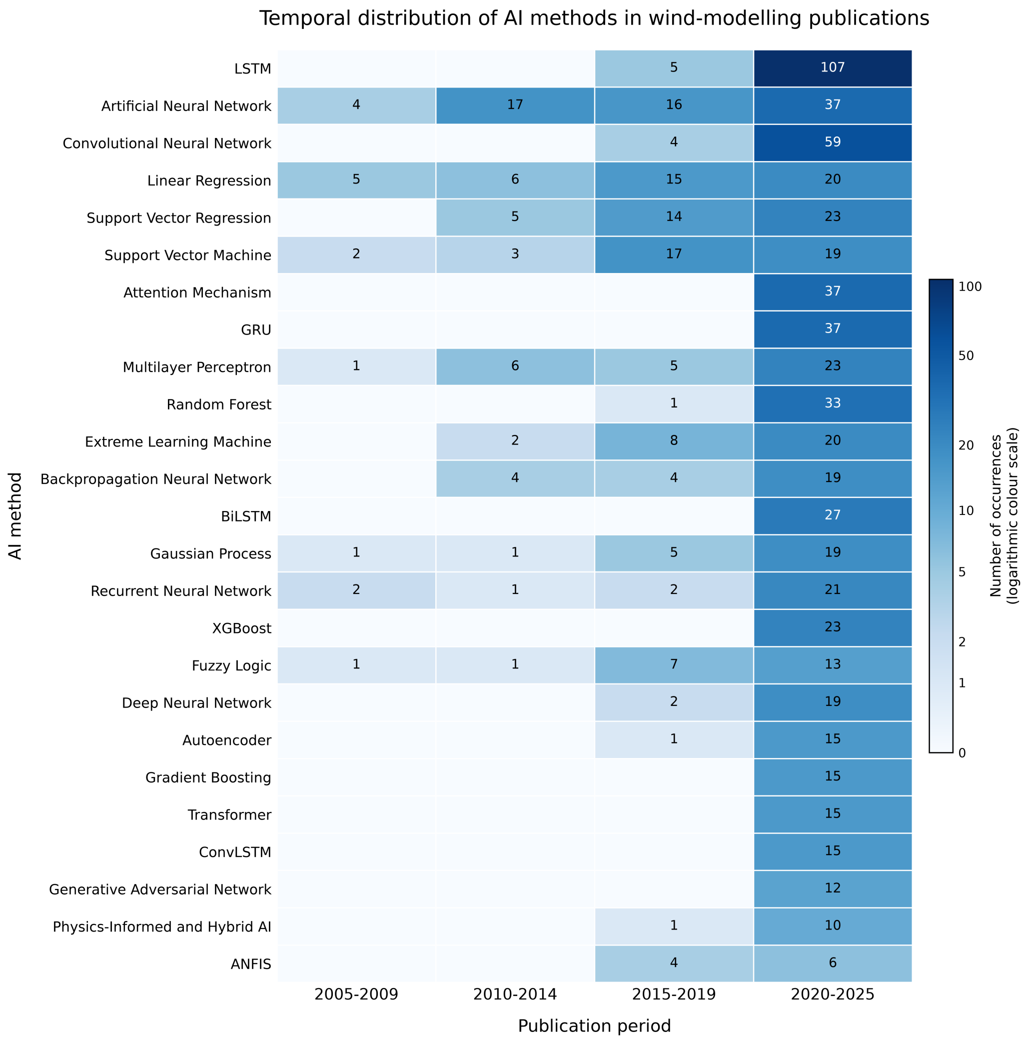


Figure 10: Temporal distribution of AI methods identified in the analysed publications. Numerical annotations indicate absolute frequencies, while colour intensity represents the number of occurrences on a logarithmic scale.

gated memory structure of LSTM networks was specifically introduced to learn longer-term dependencies [53]. This characteristic is particularly relevant for wind-speed and wind-power forecasting, where present conditions depend not only on the immediately preceding observation but also on atmospheric evolution over several previous time steps. The increase in LSTM applications therefore represents more than a general rise in algorithm popularity; it reflects a closer alignment between model architecture and the temporal structure of wind data.

The growing use of CNNs has a similarly problem-specific explanation. Meteorological information increasingly became available as gridded numerical weather prediction fields, reanalysis products, satellite observations, and geospatial datasets rather than solely as station-based time series. CNNs can identify local patterns and spatial relationships within such structured grids, making them suitable for recognising terrain-related effects, spatial wind gradients, coherent flow structures, and relationships between neighbouring locations. The development of architectures such as ConvLSTM further connected spatial feature extraction with temporal memory by introducing convolutional operations into recurrent state transitions [54].

The particularly strong expansion observed during 2020–2025 should also be interpreted in the context of data availability. Modern reanalysis products, including ERA5, provide temporally continuous and spatially distributed estimates of atmospheric variables over several decades [25]. Together with remote-sensing products, expanding observational networks, and increasingly accessible high-performance computing, these datasets made it possible to train models using substantially larger spatial and temporal domains. This favoured architectures capable of processing high-dimensional inputs and contributed to the rapid growth of LSTM, CNN, GRU, attention-based, and combined spatio-temporal approaches.

The appearance of attention mechanisms and Transformer-based methods in the most recent period follows another major development in machine learning. Transformer architectures use attention to model dependencies between different elements of a sequence without relying exclusively on recurrent processing, allowing more parallelised training and more direct representation of long-range relationships. These properties are relevant to wind modelling because atmospheric behaviour may depend on interactions occurring across multiple time steps and spatial locations. Their recent appearance in the heatmap is therefore consistent with the broader adoption of attention-based architectures after their introduction in 2017, followed by their transfer from general sequence modelling to environmental and meteorological applications. Nevertheless, their presence in the analysed wind-modelling literature remains more recent than that of LSTM and CNN architectures.

Despite the rapid expansion of deep learning, classical machine-learning methods did not disappear. Linear regression, SVM, SVR, Random Forest, Gaussian Process, XGBoost, and fuzzy-logic approaches remain visible in the most recent period. Their continued use is methodologically reasonable because deep learning is not necessarily advantageous for every wind-modelling problem. Classical methods may remain competitive when datasets are relatively small or tabular, when the number of predictors is limited, or when lower computational cost and greater model interpretability are required. They also provide important baseline models against which the added complexity of deep-learning architectures should be evaluated.

In contrast, physics-informed and hybrid AI methods occur only rarely in the heatmap and are concentrated primarily in the most recent period. Their delayed emergence reflects a broader shift in scientific machine learning: from treating AI as a purely data-driven predictor towards integrating observations with governing equations, numerical models, boundary conditions, and other forms of physical knowledge [55, 51]. This development is especially important in wind modelling, where a model may achieve low statistical error without necessarily reproducing physically plausible flow behaviour. The small number of physics-informed and hybrid studies therefore identifies not only an emerging methodological direction but also a substantial research gap.

The heatmap consequently reveals a broader progression in how wind-modelling problems are formulated. Early studies primarily represented wind as a point-based regression or time-series prediction problem. The subsequent adoption of CNNs, recurrent networks, ConvLSTMs, attention mechanisms, and Transformers reflects a gradual transition towards the representation of wind as a spatially distributed and dynamically evolving atmospheric process. The recent appearance of physics-informed and hybrid approaches suggests a further transition towards models that are expected not only to fit observations but also to reproduce physically consistent behaviour.

6.2 Current Challenges of AI-Based Wind Modelling

Despite the remarkable progress of Artificial Intelligence (AI) and Machine Learning (ML) techniques in atmospheric sciences, wind modelling remains a particularly challenging prediction task. Unlike many environmental variables, wind behaviour is governed by numerous interacting physical processes operating across a broad range of spatial and temporal scales. Large-scale atmospheric circulation, atmospheric boundary-layer dynamics, terrain-induced flow modification, thermal stratification, turbulence, and transient mesoscale phenomena collectively contribute to highly nonlinear, non-stationary, and spatially heterogeneous wind fields [56].

These processes do not act independently. Large-scale pressure gradients may determine the prevailing wind regime, while surface roughness, atmospheric stability, topography, and local thermal forcing modify the flow close to the surface. Their relative importance also changes with location, season, time of day, and atmospheric conditions. Consequently, AI models must represent not only relationships between individual meteorological variables but also interactions between processes that evolve across different spatial and temporal scales. Developing models capable of learning these relationships without losing physically important information therefore remains a significant scientific challenge.

Most contemporary AI-based wind-prediction models are primarily data-driven and rely on observations obtained from fixed measurement locations, remote-sensing systems, reanalysis datasets, or gridded numerical weather prediction products. Although these data sources have enabled substantial improvements in predictive performance, they also impose inherent limitations on the information available for model training. Station observations provide detailed but spatially localised measurements, while gridded products represent atmospheric conditions at finite spatial and temporal resolutions. Small-scale terrain effects, turbulent structures, sharp wind gradients, and short-lived atmospheric phenomena may therefore be insufficiently resolved or represented only indirectly.

As a result, many of the physical mechanisms governing atmospheric flow are learned through statistical associations contained in the available data rather than represented explicitly. This can make it difficult for AI models to generalise across locations, terrains, atmospheric regimes, and spatial resolutions. A model trained under one set of environmental conditions may achieve high predictive accuracy within the training domain while performing poorly when transferred to a different climate, terrain configuration, measurement network, or previously unseen atmospheric event. Generalisation, forecast stability, and physical consistency have consequently been identified as important challenges in machine-learning applications to weather and climate modelling [57, 58, 59].

To better understand these challenges, it is necessary to consider the underlying physical processes that shape atmospheric wind behaviour before analysing the capabilities and limitations of individual AI approaches. Table 8 summarises the principal atmospheric processes influencing wind fields, their governing mechanisms, the challenges they introduce for AI-based modelling, and representative modelling strategies reported in the literature.

6.3 Physical Processes Governing Wind Behaviour

Wind behaviour cannot be adequately understood solely through statistical relationships or data-driven learning. Atmospheric wind fields emerge from the interaction of physical processes operating simultaneously across a wide range of spatial and temporal scales. These processes influence wind speed, direction, turbulence intensity, vertical structure, and the transport of momentum and energy, ultimately determining the complexity that AI-based models attempt to represent [60].

Large-scale pressure gradients and the Coriolis force govern the principal structure of atmospheric circulation, while surface friction, buoyancy, thermal stratification, and turbulent exchange modify wind behaviour within the atmospheric boundary layer. Over complex terrain, interactions with topography additionally produce flow acceleration, channeling, wakes, mountain waves, and rotors. Thermally and convectively driven phenomena, including sea–land breezes and gust fronts, introduce further temporal variability and may cause rapid changes in near-surface wind conditions [60, 61].

Although modern machine-learning methods have demonstrated strong predictive capabilities, their performance remains constrained by the physical complexity of atmospheric flow and by the availability and quality of observations. Some processes, including boundary-layer transitions, low-level jets, and terrain-induced flow modifications, exhibit strongly nonlinear and regime-dependent behaviour. Other phenomena, such as turbulence, wakes, and convective outflow boundaries, evolve rapidly in both space and time and may not be adequately represented by sparse or fixed-location measurements [62]

Table 8 summarises the principal physical processes relevant to wind-field modelling, their governing mechanisms and characteristics, the challenges they introduce for AI-based modelling, and the AI approaches applied to their representation. The table does not attempt to provide an exhaustive classification of atmospheric phenomena. Instead, it highlights processes that are particularly important when selecting input data, designing model architectures, and evaluating the physical reliability and generalisation of AI-based wind models.

Table 8: Overview of the principal atmospheric physical processes relevant to wind-field modelling, their governing mechanisms, associated modelling challenges, and representative AI approaches.

Physical process / phenomenon	**Main physical drivers**	**Characteristics**	**Challenges for AI-based modelling**	**Typical AI approaches**
Pressure-gradient forcing [63, 57]	Horizontal pressure gradients	Primary driving force of atmospheric motion across all scales.	Multi-scale coupling between synoptic and local wind fields.	Hybrid AI + Numerical Weather Prediction (NWP)
Coriolis force [63]	Earth's rotation	Deflects moving air masses and governs large-scale atmospheric circulation.	Difficult representation of trajectory evolution using local observations alone.	Physics-aware global and hybrid atmospheric models
Atmospheric Boundary Layer (ABL) dynamics [64, 65]	Surface friction, buoyancy, and thermal stratification	Strong vertical gradients in wind speed, turbulence production, and momentum exchange.	Complex vertical coupling and rapid changes near the surface.	Deep-learning turbulence closures, multi-level ML, and hybrid physics–ML
Atmospheric stability [62, 66, 67]	Thermal stratification and surface heat fluxes	Controls turbulence intensity, vertical mixing, and boundary-layer structure.	Difficult inference from sparse meteorological observations.	Stability-aware deep learning and hybrid physics–ML
Boundary-layer transition [68, 69, 64]	Surface heating and cooling (stable–neutral–unstable regimes)	Rapid diurnal transitions in turbulence and wind profiles.	Pronounced temporal non-stationarity.	Regime-aware machine learning and temporal models
Vertical wind shear [70, 71, 72]	Surface roughness and atmospheric stability	Wind speed and direction vary significantly with height.	Sparse multi-level observations and poor reconstruction of vertical profiles.	Multi-level machine learning, Random Forests, and LSTM
Surface roughness effects [73, 74, 75]	Vegetation, land use, urban morphology, and terrain	Modifies momentum exchange and near-surface wind profiles.	High spatial heterogeneity and limited representation in datasets.	Terrain-aware CNNs using land-surface and topographic information

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Table 8 continued from the previous page

Physical process / phenomenon	**Main physical drivers**	**Characteristics**	**Challenges for AI-based modelling**	**Typical AI approaches**
Turbulence [76, 50, 65]	Shear production and buoyancy	Chaotic, stochastic, and multi-scale flow fluctuations.	Difficult deterministic prediction and limited generalisation.	Deep neural networks for turbulence closure and hybrid physics–ML
Low-level jets [77, 71]	Stable nocturnal boundary layer	Wind speed maxima located above the surface.	Often poorly captured by conventional surface measurements.	Machine-learning classification and multi-level wind-profile models
Orographic flow [78, 79, 80]	Terrain forcing	Flow acceleration, deceleration, and deflection over complex terrain.	Strong dependence on terrain resolution and atmospheric conditions.	Terrain-aware CNNs using DEM and CFD-generated training data
Lee waves [81, 82, 83]	Mountain-induced gravity waves	Stationary wave structures downstream of mountain ranges.	Highly terrain-specific behaviour requiring high-resolution data.	High-resolution NWP and emerging physics-aware surrogate models
Rotors [84, 82, 83]	Mountain-wave breaking	Severe turbulence, recirculation, and flow reversal.	Rare events with limited training examples.	High-resolution NWP/LES and emerging hybrid surrogate modelling
Channeling effects [56, 85]	Valleys, canyons, and mountain passes	Local acceleration and directional steering of airflow.	Strong site dependency and poor transferability.	Artificial neural networks and terrain-aware spatial learning
Wake effects [86, 87, 88]	Terrain obstacles, buildings, and wind turbines	Velocity deficit and enhanced turbulence downstream of obstacles.	Long-range spatial dependencies between flow structures.	Graph Neural Networks (GNNs)
Sea–land breeze circulation [61]	Differential heating between land and sea	Strong diurnal wind reversals and mesoscale circulations.	Highly dynamic temporal behaviour.	NWP post-processing and emerging spatio-temporal learning

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Table 8 continued from the previous page

Physical process / phenomenon	**Main physical drivers**	**Characteristics**	**Challenges for AI-based modelling**	**Typical AI approaches**
Convective gust fronts [89]	Deep convection	Sudden wind shifts and extreme wind events.	Rare-event prediction and limited observational data.	Attention-based U-Net and multi-source deep learning
Air parcel transport [90, 91, 92]	Advection and turbulent transport	Evolution of coherent atmospheric flow structures and momentum transport.	Most AI models learn Eulerian fields rather than explicitly modelling particle trajectories.	ML emulators of Lagrangian particle models and physics-informed Lagrangian learning

Although the phenomena presented in Table 8 originate from different physical mechanisms, many share a common dependence on the transport and exchange of momentum, energy, heat, and air masses. Wakes are advected downstream, mountain waves transport energy and momentum, turbulence redistributes momentum, and the atmospheric boundary layer continuously exchanges momentum and heat with the Earth's surface.

Most observational datasets used for AI-based wind modelling describe atmospheric variables at fixed locations or on fixed spatial grids. Such Eulerian representations provide valuable information about local temporal variability but do not explicitly follow the movement of air parcels or coherent flow structures. This distinction is particularly important for transport-driven processes, for which physics-informed and Lagrangian-aware approaches may provide a more direct representation of atmospheric evolution [91, 92].

Atmospheric boundary-layer processes further demonstrate why near-surface wind cannot be represented adequately using a single stationary relationship between meteorological variables. Strong vertical gradients, transitions between stability regimes, surface heterogeneity, and interactions with larger-scale atmospheric forcing produce conditions that may not be fully represented by sparse surface observations. AI-based models must therefore account for the vertical, temporal, and site-specific structure of the available data when reconstructing or predicting near-surface wind fields. [64].

6.4 Future Directions of AI-Based Wind Modelling

The challenges identified in the preceding sections indicate that future progress in AI-based wind modelling will depend less on increasing model complexity alone and more on improving physical consistency, generalisation, and methodological reliability. High predictive accuracy within a specific dataset does not necessarily demonstrate that a model can reproduce physically plausible wind behaviour or remain reliable across different locations, terrains, atmospheric regimes, and spatial resolutions.

An important direction is the transition from purely data-driven models towards physics-aware and hybrid approaches. Physical knowledge can be incorporated through governing equations, conservation principles, boundary conditions, physically meaningful input variables, or coupling with Numerical Weather Prediction (NWP) and Computational Fluid Dynamics (CFD) models. Such approaches should aim not only to reduce prediction errors but also to improve forecast stability, physical consistency, and behaviour under conditions that are not well represented in the training data [51, 63].

Further development is also required in the representation of spatially distributed and transport-driven processes. Wind fields evolve through advection, turbulent exchange, and interactions between atmospheric processes operating at different spatial and temporal scales. Models based exclusively on observations from individual fixed locations may therefore be insufficient for reconstructing the movement and development of coherent flow structures. Spatio-temporal models, learned numerical surrogates, and emerging Lagrangian-aware approaches provide possible methods for representing these processes more explicitly [91].

Generalisation must become a central component of model evaluation. Future studies should test models using independent locations, seasons, terrains, and atmospheric regimes rather than relying only on random divisions of data from the same observational domain. Particular attention should be given to rare and high-impact wind conditions, for which aggregate error measures may conceal substantial prediction errors. Probabilistic forecasts and uncertainty estimates are therefore needed to distinguish confident predictions from conditions under which model reliability is reduced [57].

Finally, more reproducible and standardised evaluation procedures are required. Studies should provide clear descriptions of input datasets, preprocessing procedures, model configurations, training and testing divisions, baseline methods, and evaluation metrics. Public benchmark datasets, openly available implementations, and comparisons under consistent experimental conditions would make it possible to determine whether reported improvements are transferable beyond individual datasets and case studies.

Future AI-based wind models should therefore be assessed not only through improvements in predictive accuracy, but also through their physical plausibility, robustness under previously unseen conditions, representation of extreme events, uncertainty estimates, and reproducibility. Progress in these areas is necessary for moving from isolated proof-of-concept models towards reliable methods that can complement established atmospheric modelling and operational forecasting systems.

7 Conclusion

Wind modelling remains a demanding scientific and computational problem because atmospheric flow is shaped by interactions between processes operating across different spatial and temporal scales. Large-scale circulation, atmospheric boundary-layer dynamics, surface characteristics, terrain, turbulence, and local meteorological phenomena jointly determine wind speed, direction, and vertical structure. Consequently, the suitability of a modelling approach cannot be assessed independently of the available data, the physical characteristics of the study area, and the intended application.

The literature analysis conducted in this thesis shows that wind-modelling research has expanded substantially and become methodologically more diverse. Physics-based and statistical approaches continue to provide an important foundation, while machine learning and deep learning have become increasingly prominent. The recent growth of hybrid and physics-aware methods reflects a broader recognition that data-driven accuracy alone is not sufficient for representing atmospheric processes. Rather than replacing established approaches, AI is increasingly being used to complement numerical models, process heterogeneous observations, reconstruct wind fields, and approximate computationally demanding simulations.

The development of AI-based wind modelling has been supported by the growing availability of ground-based observations, remote-sensing measurements, satellite products, reanalysis datasets, and geospatial information. At the same time, the analysis demonstrates that the usefulness of these data depends on their spatial and temporal coverage, resolution, consistency, and representativeness. Fixed-location observations may describe local temporal variability in detail but provide limited information about the movement and development of spatial wind structures. Gridded and remotely sensed products extend spatial coverage, although they remain affected by finite resolution, model assumptions, retrieval uncertainty, and observational gaps.

Deep-learning architectures currently form the most prominent AI category in the analysed literature, particularly methods designed to learn temporal, spatial, and combined spatio-temporal dependencies. Nevertheless, the continued use of classical machine-learning algorithms confirms that greater architectural complexity does not automatically provide a more appropriate solution. Model selection must remain connected to the structure of the input data, the size of the available dataset, the modelling scale, computational requirements, and the need for interpretability.

Several limitations continue to restrict reliable comparison and wider application of published models. Incomplete reporting of datasets, preprocessing procedures, model configurations, and validation protocols reduces reproducibility. Evaluation remains strongly concentrated on aggregate error measures, which may conceal systematic bias, directional errors, weak performance during extreme conditions, and limited transferability beyond the training data. Reliable assessment therefore requires independent validation, multiple complementary metrics, appropriate baseline models, and explicit testing across different locations, terrains, seasons, and atmospheric regimes.

A further challenge is the relationship between statistical prediction and physical behaviour. Wind phenomena such as boundary-layer transitions, turbulence, terrain-induced flow, wakes, convective outflows, and atmospheric transport are governed by physical mechanisms that may be represented only indirectly in observational datasets. Models may therefore achieve low prediction errors without preserving physically plausible spatial structures, dynamical balances, or behaviour under previously unseen conditions. This limitation provides the principal motivation for physics-aware and hybrid approaches that combine observational learning with governing equations, physical constraints, terrain information, or numerical atmospheric models.

Overall, the future development of AI-based wind modelling should not be measured solely by the introduction of new architectures or marginal improvements in individual performance metrics. More important is the development of models whose results can be reproduced, physically interpreted, transferred to new environments, and evaluated under operationally relevant conditions. Progress will depend on transparent data and software, standardised validation, stronger links between data selection and application requirements, and a more systematic integration of atmospheric knowledge with data-driven learning.

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List of Acronyms and Abbreviations

ABL - *Atmospheric Boundary Layer*
AEMET - *Agencia Estatal de Meteorología*
AI - *Artificial Intelligence*
AI/ML - *Artificial Intelligence / Machine Learning*
ANFIS - *Adaptive Neuro-Fuzzy Inference System*
ANN - *Artificial Neural Network*
ARIMA - *Autoregressive Integrated Moving Average*
BiLSTM - *Bidirectional Long Short-Term Memory*
CFD - *Computational Fluid Dynamics*
CNN - *Convolutional Neural Network*
DEM - *Digital Elevation Model*
DHMZ - *Croatian Meteorological and Hydrological Service*
DMI - *Danish Meteorological Institute*
DWD - *Deutscher Wetterdienst*
ECMWF - *European Centre for Medium-Range Weather Forecasts*
ERA - *ECMWF Reanalysis*
ERA5 - *ECMWF Reanalysis v5*
GAN - *Generative Adversarial Network*
GIS - *Geographic Information System*
GNN - *Graph Neural Network*
GPU - *Graphics Processing Unit*
GRU - *Gated Recurrent Unit*
IDW - *Inverse Distance Weighting*
IMGW-PIB - *Institute of Meteorology and Water Management – National Research Institute*
IoT - *Internet of Things*
IPMA - *Portuguese Institute for Sea and Atmosphere*
KNMI - *Royal Netherlands Meteorological Institute*
LES - *Large Eddy Simulation*
LiDAR - *Light Detection and Ranging*
LSTM - *Long Short-Term Memory*
MAE - *Mean Absolute Error*
MAPE - *Mean Absolute Percentage Error*
MERRA - *Modern-Era Retrospective Analysis for Research and Applications*
ML - *Machine Learning*
MSE - *Mean Squared Error*
NCEP - *National Centers for Environmental Prediction*
NOAA - *National Oceanic and Atmospheric Administration*

NWP - *Numerical Weather Prediction*
PINN - *Physics-Informed Neural Network*
PWS - *Personal Weather Station*
RANS - *Reynolds-Averaged Navier–Stokes*
RF - *Random Forest*
RMSE - *Root Mean Square Error*
RQ - *Research Question*
RWIS - *Road Weather Information System*
SARIMA - *Seasonal Autoregressive Integrated Moving Average*
SMHI - *Swedish Meteorological and Hydrological Institute*
SODAR - *Sonic Detection and Ranging*
SVM - *Support Vector Machine*
SVR - *Support Vector Regression*
TCN - *Temporal Convolutional Network*
UAV - *Unmanned Aerial Vehicle*
WRF - *Weather Research and Forecasting Model*
WSN - *Wireless Sensor Network*

Abstract

Wind modelling and prediction remain challenging due to the strong spatial and temporal variability of atmospheric flow and its dependence on terrain, atmospheric boundary-layer processes, surface characteristics, and meteorological conditions. This thesis provides a comprehensive overview of contemporary wind modelling approaches, with particular emphasis on Artificial Intelligence (AI) and Machine Learning (ML), the data sources supporting their development, and the principal limitations affecting their wider application.

A systematic analysis of the scientific literature was conducted using publications retrieved from the Web of Science Core Collection. The analysis examined the temporal evolution of wind-modelling research, the representation of physics-based, statistical, machine-learning, and hybrid approaches, the meteorological data sources reported in the literature, and commonly used performance-evaluation metrics. A more detailed classification was subsequently performed to investigate the evolution of individual AI and ML methodologies.

The results demonstrate a substantial growth and diversification of wind-modelling research, with machine learning and deep learning becoming increasingly prominent alongside established physics-based and statistical approaches. Deep-learning methods represent the largest AI category in the analysed literature, while physics-informed and hybrid AI approaches remain comparatively less represented. The analysis also highlights important challenges related to data representativeness, reproducibility, validation practices, generalisation across different environmental conditions, and the physical consistency of data-driven predictions.

Future progress in AI-based wind modelling should therefore focus not only on predictive accuracy, but also on reproducibility, robust validation, transferability, uncertainty assessment, and stronger integration of physical knowledge with data-driven learning.

Keywords: wind modelling, wind prediction, artificial intelligence, machine learning, deep learning, atmospheric data, physics-informed machine learning.

Prošireni sažetak

Vjetar predstavlja jedan od najvažnijih, ali istodobno i najsloženijih atmosferskih fenomena za modeliranje i predviđanje. Njegova izražena prostorna i vremenska promjenjivost posljedica je međudjelovanja procesa koji djeluju na različitim prostornim i vremenskim skalama. Veliki atmosferski cirkulacijski sustavi, gradijenti tlaka, Coriolisova sila, procesi unutar atmosferskog graničnog sloja, stabilnost atmosfere, turbulencija, svojstva površine i lokalna topografija zajednički određuju brzinu, smjer i vertikalnu strukturu vjetra. Posebno složeni uvjeti javljaju se u obalnim i planinskim područjima, gdje lokalna topografija može uzrokovati ubrzavanje i usmjeravanje strujanja, pojavu zavjetrinskih valova, vrtložnih struktura i drugih lokaliziranih fenomena.

Cilj ovog rada je pružiti sveobuhvatan pregled suvremenih pristupa modeliranju i predviđanju vjetra, s posebnim naglaskom na metode umjetne inteligencije (engl. *Artificial Intelligence*, AI) i strojnog učenja (engl. *Machine Learning*, ML). Posebna pozornost posvećena je izvorima podataka koji se koriste pri razvoju modela, razvoju različitih metodoloških pristupa, načinima njihove validacije te ograničenjima koja utječu na njihovu primjenjivost i mogućnost prijenosa na različite prostorne i meteorološke uvjete.

Pouzdano modeliranje vjetra izravno ovisi o dostupnosti i reprezentativnosti meteoroloških podataka. U radu su razmotreni glavni izvori podataka, uključujući mjerenja meteoroloških postaja, LiDAR i SODAR sustave, satelitska opažanja, numeričke modele vremena, atmosferske reanalize te geografske podatke poput digitalnih modela reljefa i podataka o pokrovu zemljišta. Svaki od navedenih izvora karakteriziraju različita prostorna i vremenska razlučivost, pokrivenost i razina nesigurnosti. Mjerenja meteoroloških postaja pružaju izravne i vremenski detaljne informacije, ali su prostorno ograničena, dok reanalize, satelitska opažanja i numerički modeli omogućuju znatno širu prostornu pokrivenost. Njihova integracija stoga predstavlja važan preduvjet za razvoj modela sposobnih opisati složena prostorna i vremenska svojstva polja vjetra.

Pristupi modeliranju vjetra u radu su podijeljeni u četiri glavne kategorije: fizikalno utemeljene, statističke, metode strojnog učenja i hibridne pristupe. Fizikalno utemeljeni pristupi, poput numeričkog predviđanja vremena (NWP) i računalne dinamike fluida (CFD), temelje se na numeričkom rješavanju fizikalnih jednadžbi koje opisuju atmosfersko strujanje. Statistički pristupi koriste unaprijed definirane statističke odnose i metode analize vremenskih nizova, dok metode strojnog učenja omogućuju automatsko učenje složenih i nelinearnih odnosa iz dostupnih podataka. Hibridni pristupi nastoje povezati prednosti fizikalnih modela i metoda temeljenih na podacima.

Uz pregled postojećih pristupa, provedena je sustavna analiza znanstvene literature na temelju publikacija prikupljenih iz baze Web of Science Core Collection. Početnim pretraživanjem identificirano je 10 470 publikacija povezanih s modeliranjem, procjenom, rekonstrukcijom, interpolacijom i predviđanjem vjetra. Bibliografski zapisi obrađeni su prilagođenim Python postupkom, a za automatsku klasifikaciju publikacija korišteni su rječnici ključnih pojmova razvijeni u sklopu rada.

Analiza razvoja metodoloških pristupa pokazuje postupnu diversifikaciju područja. Fizikalno utemeljene metode predstavljale su dominantan pristup u ranijim razdobljima, dok se zastupljenost metoda strojnog učenja značajno povećava tijekom posljednjeg desetljeća. Posebno izražen rast vidljiv je nakon 2018. godine. Hibridni pristupi pojavljuju se kasnije, a njihov rast nakon 2020. godine ukazuje na sve veći interes za povezivanje fizikalne konzistentnosti numeričkih modela sa sposobnošću metoda strojnog učenja da iz podataka izdvoje složene obrasce.

Dodatna analiza provedena je radi utvrđivanja meteoroloških izvora podataka koji se eksplicitno navode u analiziranim publikacijama. Najmanje jedan eksplicitni meteorološki izvor podataka identificiran je u 783 publikacije. Rezultati pokazuju da konvencionalna mjerenja sa zemaljskih postaja i dalje imaju temeljnu ulogu, ali istodobno raste zastupljenost atmosferskih reanaliza, satelitskih opažanja, daljinskih mjerenja i drugih specijaliziranih izvora. Takav razvoj ukazuje na postupno širenje i diversifikaciju podataka koji se koriste u suvremenom modeliranju vjetra.

Analizirane su i metode vrednovanja performansi modela. U skupu od 1 806 publikacija najčešće su identificirane mjere RMSE, MSE i MAE, koje zajedno čine 66,3 % svih identificiranih pojavljivanja metrika. Iako su takve metrike korisne za procjenu odstupanja između modeliranih i opaženih vrijednosti, njihova samostalna uporaba ne omogućuje potpuno vrednovanje modela. Agregirane mjere pogreške mogu prikriti sustavnu pristranost, pogreške u smjeru vjetra, slabije ponašanje tijekom ekstremnih događaja i ograničenu sposobnost generalizacije izvan podataka korištenih za razvoj modela.

Poseban dio rada usmjeren je na razvoj metoda umjetne inteligencije i strojnog učenja. Analiza obuhvaća klasične algoritme strojnog učenja, umjetne neuronske mreže, metode dubokog učenja te fizikalno informirane i hibridne AI pristupe. U široj klasifikaciji identificirano je ukupno 1 128 pojavljivanja kategorija AI metoda. Duboko učenje predstavlja najveću skupinu s 535 identificiranih pojavljivanja, nakon čega slijede klasično strojno učenje s 364 i umjetne neuronske mreže s 211 pojavljivanja. Fizikalno informirani i hibridni AI pristupi znatno su manje zastupljeni, sa svega 18 identificiranih pojavljivanja.

Vremenska analiza pojedinačnih AI metoda pokazuje prijelaz od jednostavnijih modela temeljenih prvenstveno na tabličnim podacima i vremenskim nizovima prema arhitekturama sposobnima opisivati složene prostorne i vremenske odnose. U ranijem razdoblju prevladavale su umjetne neuronske mreže, linearna regresija i metode potpornih vektora. Kasnije raste primjena LSTM i konvolucijskih neuronskih mreža, dok se u najnovijem razdoblju pojavljuju GRU, ConvLSTM, mehanizmi pažnje, Transformeri i druge napredne arhitekture. Ovaj razvoj povezan je s povećanom dostupnošću meteoroloških podataka, računalnih resursa i prostorno distribuiranih atmosferskih proizvoda.

Unatoč brzom razvoju AI i ML metoda, identificirano je nekoliko važnih istraživačkih nedostataka. Nedovoljno detaljno izvještavanje o korištenim podacima, postupcima predobrade, konfiguracijama modela i protokolima validacije ograničava reproducibilnost rezultata. Dodatni problem predstavlja generalizacija modela između različitih lokacija, tipova terena, meteoroloških režima i prostornih razlučivosti. Model koji postiže visoku točnost na podacima korištenima tijekom razvoja ne mora nužno zadržati jednaku pouzdanost pri primjeni u novom okolišu ili tijekom rijetkih i ekstremnih meteoroloških događaja.

Važan izazov predstavlja i odnos između statističke točnosti i fizikalne ispravnosti predviđanja. Atmosferski procesi poput turbulencije, prijelaza unutar graničnog sloja, vertikalnog smicanja vjetra, orografskog strujanja, zavjetrinskih valova, vrtložnih struktura, morskih i kopnenih cirkulacija te transporta zračnih masa određeni su fizikalnim zakonima koji u čisto podatkovno utemeljenim modelima nisu nužno eksplicitno zastupljeni. Model stoga može ostvariti malu statističku pogrešku bez istodobnog očuvanja fizikalno realističnog ponašanja atmosferskog strujanja.

Budući razvoj AI modela za modeliranje vjetra stoga bi trebao biti usmjeren ne samo prema povećanju prediktivne točnosti, nego i prema poboljšanju reproducibilnosti, robusnosti, generalizacije i fizikalne konzistentnosti. Posebno važan smjer predstavlja razvoj fizikalno informiranih i hibridnih pristupa koji povezuju učenje iz podataka s fizikalnim zakonima, rubnim uvjetima, numeričkim atmosferskim modelima i drugim oblicima prethodnog fizikalnog znanja. Buduće modele potrebno je vrednovati na neovisnim lokacijama, različitim terenima i atmosferskim režimima te uz prediktivnu točnost razmatrati nesigurnost, ponašanje tijekom ekstremnih događaja i mogućnost prijenosa modela na prethodno nepoznate uvjete.

Zaključno, umjetna inteligencija i strojno učenje predstavljaju sve važniji dio suvremenog modeliranja vjetra, ali njihov daljnji razvoj ne bi se trebao temeljiti isključivo na povećanju složenosti modela. Napredak prema pouzdanijim i praktično primjenjivim sustavima zahtijeva kvalitetnije i transparentnije podatke, standardizirane postupke vrednovanja, otvorene i reproducibilne implementacije te snažnije povezivanje fizikalnog znanja s metodama

temeljenima na podacima. Takav pristup omogućuje razvoj modela koji ne samo da postižu visoku prediktivnu točnost, nego pružaju robusnije, fizikalno opravdane i prenosive rezultate za stvarne primjene modeliranja i predviđanja vjetra.

Ključne riječi: modeliranje vjetra, predviđanje vjetra, umjetna inteligencija, strojno učenje, duboko učenje, meteorološki podaci, fizikalno informirano strojno učenje.

Appendices

A Classification Dictionary

The following dictionary was used by the Python classification workflow to identify method-related terminology in publication titles and abstracts.

Listing 1: Keyword dictionary used for publication classification.

```
{
  "physics_based": [
    "numerical weather prediction",
    "weather research and forecasting",
    "computational fluid dynamics",
    "large eddy simulation",
    "reynolds-averaged navier-stokes",
    "navier-stokes equations",
    "dynamical downscaling",
    "mesoscale atmospheric model",
    "mesoscale model",
    "microscale model",
    "atmospheric circulation model",
    "fluid dynamics model",
    "physical model",
    "physics-based model",
    "parametric wind model",
    "wrf",
    "nwp",
    "cfd",
    "rans"
  ],
  "statistical": [
    "statistical model",
    "statistical modelling",
    "statistical modeling",
    "linear regression",
    "multiple linear regression",
    "multivariate regression",
    "autoregressive model",
    "autoregressive integrated moving average",
    "time series model",
    "spatial interpolation",
    "inverse distance weighting",
    "ordinary kriging",
```

```
    "universal kriging",
    "co-kriging",
    "geostatistical model",
    "weibull distribution",
    "probability distribution",
    "empirical model",
    "response surface methodology",
    "arima",
    "sarima",
    "kriging"
  ],
  "machine_learning": [
    "machine learning",
    "artificial intelligence",
    "artificial neural network",
    "neural network",
    "random forest",
    "support vector machine",
    "support vector regression",
    "gradient boosting",
    "extreme gradient boosting",
    "decision tree",
    "gaussian process regression",
    "gaussian process",
    "ensemble learning",
    "data-driven model",
    "data driven model",
    "adaptive neuro-fuzzy inference system",
    "neuro-fuzzy",
    "xgboost",
    "lightgbm",
    "catboost",
    "svm",
    "svr",
    "anfis"
  ],
  "deep_learning": [
    "deep learning",
    "deep neural network",
    "convolutional neural network",
    "recurrent neural network",
    "long short-term memory",
    "gated recurrent unit",
```

```
    "graph neural network",
    "generative adversarial network",
    "attention mechanism",
    "transformer model",
    "autoencoder",
    "cnn",
    "lstm",
    "gru",
    "gan"
  ],
  "explicit_hybrid": [
    "hybrid model",
    "hybrid modelling",
    "hybrid modeling",
    "hybrid approach",
    "hybrid method",
    "hybrid framework",
    "hybrid system",
    "combined model",
    "integrated model",
    "physics-informed machine learning",
    "physics-informed neural network",
    "physics-guided machine learning",
    "physics-based machine learning",
    "data-driven and physics-based",
    "physical-data-driven",
    "pinn"
  ]
}
```

B Meteorological Data Source Classification Dictionary

The following dictionary was used by the rule-based classification framework to identify meteorological data sources referenced in the analysed publications.

Listing 2: Dictionary used for the classification of meteorological data sources.

```
{
  "ground_based_measurements": [
    "anemometer",
    "cup anemometer",
    "sonic anemometer",
    "ultrasonic anemometer",
    "hot-wire anemometer",
    "weather station",
    "meteorological station",
    "automatic weather station",
    "surface station",
    "ground station",
    "meteorological mast",
    "met mast",
    "wind mast",
    "measurement tower",
    "meteorological tower",
    "instrumented tower",
    "flux tower",
    "eddy covariance",
    "surface observations",
    "surface measurements",
    "ground-based observations",
    "ground-based measurements",
    "field measurements",
    "field observations",
    "in situ measurements",
    "in situ observations"
  ],

  "ground_based_remote_sensing": [
    "lidar",
    "wind lidar",
    "doppler lidar",
```

```
    "coherent doppler lidar",
    "scanning lidar",
    "floating lidar",
    "sodar",
    "doppler sodar",
    "wind profiler",
    "wind profiler radar",
    "radar wind profiler",
    "doppler radar",
    "weather radar",
    "ceilometer",
    "acoustic remote sensing"
  ],

  "upper_air_measurements": [
    "radiosonde",
    "rawinsonde",
    "weather balloon",
    "upper-air sounding",
    "atmospheric sounding",
    "balloon sounding",
    "pilot balloon",
    "pibal",
    "dropsonde",
    "dropwindsonde",
    "vertical sounding"
  ],

  "satellite_observations": [
    "satellite observations",
    "satellite measurements",
    "satellite data",
    "satellite remote sensing",
    "satellite-derived wind",
    "scatterometer",
    "synthetic aperture radar",
    "sar imagery",
    "sar-derived wind",
    "altimeter",
    "radiometer",
    "microwave radiometer",
    "ascat",
    "quikscat",
```

```
    "windsat",
    "sentinel-1",
    "modis",
    "seawinds",
    "ers scatterometer",
    "atmospheric motion vectors",
    "cloud motion vectors"
  ],

  "marine_measurements": [
    "buoy",
    "meteorological buoy",
    "weather buoy",
    "ocean buoy",
    "offshore buoy",
    "offshore platform",
    "marine platform",
    "offshore mast",
    "ship observations",
    "ship measurements",
    "ship-based observations",
    "shipboard observations",
    "vessel observations",
    "marine observations",
    "offshore observations"
  ],

  "airborne_and_uav_measurements": [
    "aircraft observations",
    "aircraft measurements",
    "airborne observations",
    "airborne measurements",
    "research aircraft",
    "instrumented aircraft",
    "flight measurements",
    "flight observations",
    "unmanned aerial vehicle",
    "uav",
    "drone",
    "drone measurements",
    "remotely piloted aircraft"
  ],

```

```
  "laboratory_and_wind_tunnel_measurements": [
    "wind tunnel",
    "wind tunnel experiment",
    "wind tunnel test",
    "laboratory experiment",
    "laboratory measurements",
    "particle image velocimetry",
    "laser doppler anemometry",
    "laser doppler velocimetry",
    "flow visualization",
    "pressure measurements"
  ],

  "reanalysis_data": [
    "reanalysis",
    "reanalysis dataset",
    "reanalysis products",
    "ERA5",
    "ERA5-Land",
    "ERA-Interim",
    "ERA40",
    "MERRA",
    "MERRA-2",
    "NCEP Reanalysis",
    "NCEP/NCAR Reanalysis",
    "CFSR",
    "CFSv2",
    "JRA-55",
    "JRA-25",
    "NARR",
    "20CR",
    "ECMWF Reanalysis",
    "COSMO-REA6"
  ],

  "numerical_model_data": [
    "numerical weather prediction data",
    "numerical weather prediction output",
    "NWP data",
    "NWP output",
    "weather model output",
    "meteorological model output",
    "atmospheric model output",
```

```
    "model-derived wind",
    "forecast model output",
    "WRF output",
    "ECMWF forecast",
    "operational analysis fields",
    "forecast fields",
    "hindcast data"
  ],

  "generic_observational_data": [
    "observational data",
    "observed data",
    "measured data",
    "measurement data",
    "meteorological observations",
    "meteorological measurements",
    "weather observations",
    "weather measurements",
    "wind observations",
    "wind measurements",
    "observed wind speed",
    "measured wind speed",
    "recorded wind data",
    "ground truth",
    "reference measurements"
  ]
}
```

C Performance Evaluation Metrics Dictionary

The following dictionary was used by the Python classification workflow to identify performance evaluation metrics reported in publication titles and abstracts. Frequently used metrics, including RMSE, MSE, MAE, correlation coefficient, R^2, and MAPE, were assigned to individual categories, while less frequently reported evaluation metrics were grouped under the `Other` category.

Listing 3: Keyword dictionary used for identifying performance evaluation metrics.

```
{
  "rmse": {
    "label": "RMSE",
    "terms": [
      "rmse",
      "root mean square error",
      "root-mean-square error",
      "root mean squared error",
      "root-mean-squared error"
    ]
  },

  "mse": {
    "label": "MSE",
    "terms": [
      "mse",
      "mean square error",
      "mean squared error"
    ]
  },

  "mae": {
    "label": "MAE",
    "terms": [
      "mae",
      "mean absolute error"
    ]
  },

  "correlation": {
    "label": "Correlation coefficient",
    "terms": [
```

```
      "correlation coefficient",
      "pearson correlation coefficient",
      "pearson correlation",
      "pearson's correlation coefficient",
      "pearson's r",
      "pearson r",
      "linear correlation coefficient"
    ]
  },

  "r2": {
    "label": "R2",
    "terms": [
      "r2",
      "r^2",
      "r^2",
      "r-squared",
      "r squared",
      "coefficient of determination",
      "determination coefficient"
    ]
  },

  "mape": {
    "label": "MAPE",
    "terms": [
      "mape",
      "mean absolute percentage error",
      "mean absolute percent error"
    ]
  },

  "other": {
    "label": "Other",
    "terms": [
      "mbe",
      "mean bias error",

      "nrmse",
      "normalized rmse",
      "normalised rmse",
      "normalized root mean square error",
      "normalised root mean square error",
```

```
        "normalized root mean squared error",
        "normalised root mean squared error",

        "nmse",
        "normalized mean square error",
        "normalised mean square error",

        "nmae",
        "normalized mean absolute error",
        "normalised mean absolute error",

        "smape",
        "symmetric mean absolute percentage error",

        "mase",
        "mean absolute scaled error",

        "rmsle",
        "root mean squared logarithmic error",

        "msle",
        "mean squared logarithmic error",

        "index of agreement",
        "willmott index",
        "willmott's index",
        "willmott index of agreement",

        "nash-sutcliffe efficiency",
        "nash sutcliffe efficiency",
        "nse",

        "kling-gupta efficiency",
        "kge",

        "skill score",
        "forecast skill score",

        "fractional bias",
        "fac2",
        "factor of two",

        "crps",
```

```
      "continuous ranked probability score",

      "brier score",

      "median absolute error",

      "false alarm ratio",

      "critical success index",
      "csi",

      "equitable threat score",
      "ets",

      "probability of detection",

      "f1-score",
      "f1 score",

      "roc-auc",
      "roc auc",
      "area under the roc curve",

      "ssim",
      "structural similarity index",

      "psnr",
      "peak signal-to-noise ratio"
    ]
  }
}
```

D Artificial Intelligence Methods Dictionary

The following dictionary was used by the Python classification workflow to identify specific artificial intelligence methods reported in publication titles and abstracts. The identified methods were grouped into four categories: classical machine learning, artificial neural networks, deep learning, and physics-informed or hybrid artificial intelligence approaches.

Listing 4: Keyword dictionary used for identifying artificial intelligence methods.

```
{
  "classical_machine_learning": [
    "Linear Regression",
    "Support Vector Machine",
    "Support Vector Regression",
    "Random Forest",
    "Decision Tree",
    "Gradient Boosting",
    "XGBoost",
    "LightGBM",
    "CatBoost",
    "K-Nearest Neighbours",
    "Gaussian Process",
    "Fuzzy Logic",
    "ANFIS"
  ],

  "artificial_neural_networks": [
    "Artificial Neural Network",
    "Multilayer Perceptron",
    "Feedforward Neural Network",
    "Backpropagation Neural Network",
    "Radial Basis Function Network",
    "Extreme Learning Machine",
    "Elman Neural Network",
    "Echo State Network",
    "Wavelet Neural Network"
  ],

  "deep_learning": [
    "Deep Neural Network",
    "Convolutional Neural Network",
    "Recurrent Neural Network",
```

```
    "LSTM",
    "BiLSTM",
    "GRU",
    "CNN-LSTM",
    "ConvLSTM",
    "Temporal Convolutional Network",
    "Transformer",
    "Vision Transformer",
    "Attention Mechanism",
    "Autoencoder",
    "Variational Autoencoder",
    "Generative Adversarial Network",
    "Graph Neural Network",
    "Graph Convolutional Network",
    "Deep Belief Network"
  ],

  "physics_informed_and_hybrid_ai": [
    "Physics-Informed Neural Network",
    "Physics-Guided Machine Learning",
    "Physics-Constrained Machine Learning",
    "Knowledge-Guided Machine Learning",
    "Hybrid AI Model",
    "AI-CFD Hybrid",
    "AI-NWP Hybrid",
    "AI-WRF Hybrid"
  ]
}
```