

# Beyond the Forecast: A Comparative Study of Turbulence Prediction Systems in Aviation

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## ABSTRACT

Turbulence remains one of the most persistent and unpredictable hazards in aviation, yet little research has conducted an integrated comparative analysis of turbulence prediction systems across methodological categories. Most studies have evaluated individual models in isolation, leaving a gap in understanding how different approaches perform relative to one another. This study aimed to examine the strengths and limitations of four representative systems for turbulence forecasting: statistical learning using PCA with support vector classification, the GEKO turbulence model based on generalized  $k-\omega$  equations, the sensor-driven FUTURA model for real-time anomaly detection, and the ECMWF ensemble-based Integrated Forecasting System. Each system was evaluated on four operational criteria: accuracy, adaptability, efficiency, and performance under adverse weather conditions. Results showed that GEKO achieved the highest accuracy but was computationally too demanding for real-time use. FUTURA excelled in adaptability and speed, although its alerts were limited to short-range predictions. The ECMWF ensemble system demonstrated strong coverage and reliability in adverse weather but suffered from delays. The statistical learning model produced balanced results but remained constrained by data sparsity. The findings suggest that no single model can address all operational needs, but combining complementary approaches into a hybrid framework offers the most effective pathway. This research contributes an evidence-based foundation for developing integrated turbulence forecasting systems to improve aviation safety, efficiency, and reliability.

**Keywords:** Turbulence prediction; Aviation safety; Energy dissipation rate (EDR); Machine learning; Computational fluid dynamics (CFD); Hybrid forecasting models; Clear-air turbulence; Flight operations

## INTRODUCTION

On 21 May 2024, Singapore Airlines flight SQ321 encountered severe turbulence mid-flight over

Myanmar. Numerous passengers sustained injuries, and the incident resulted in one passenger fatality (2). Although the ECMWF Integrated Forecasting System (IFS) predicted elevated turbulence risk the previous day using energy dissipation rate (EDR) ensemble forecasts (2, 11), the event highlighted the difficulty of converting model output into effective in-flight avoidance.

As shown in Figure 1, the affected segment of the London–Bangkok route experienced rapid fluctuations in altitude and vertical acceleration (12). Turbulence

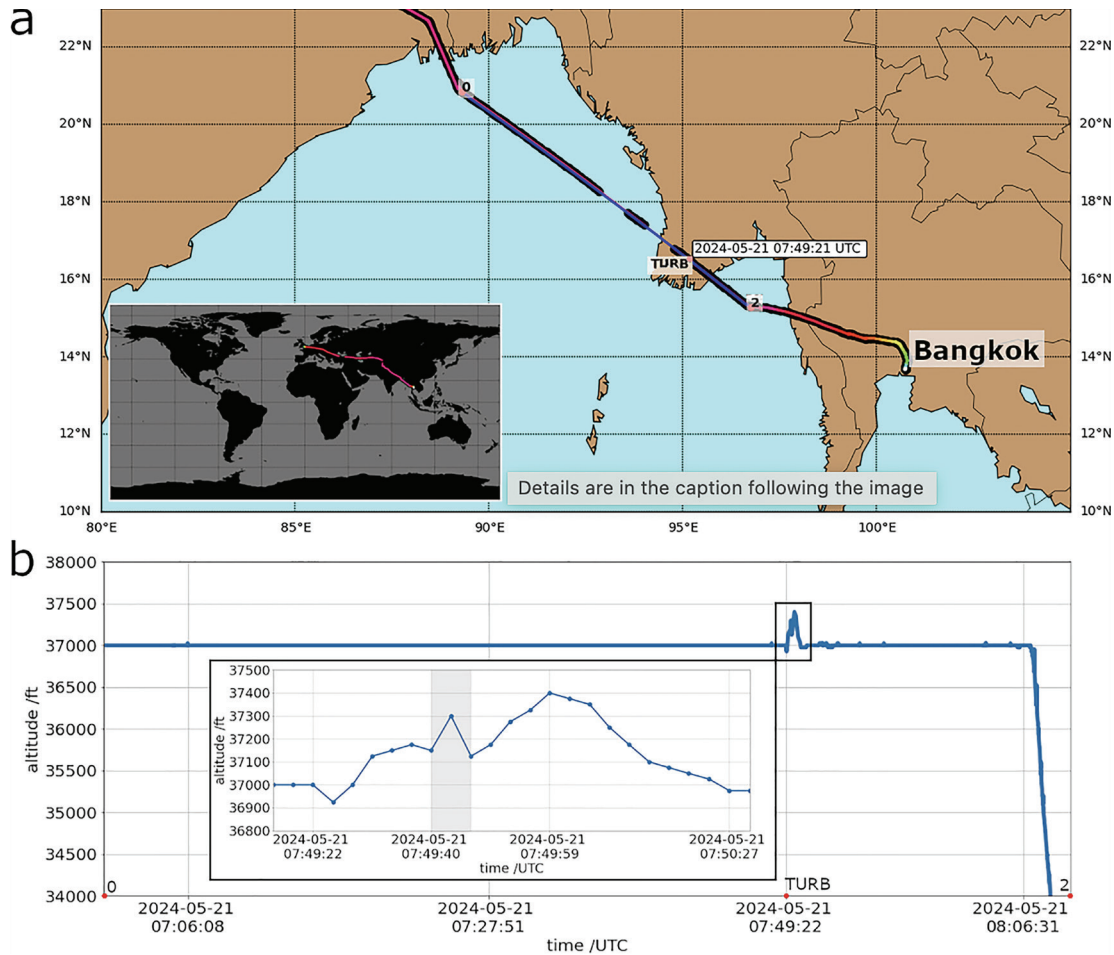
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**Figure 1. Flight path and altitude changes during the 21 May 2024 turbulence incident on the London–Bangkok route.** (a) Map of the region where the turbulence event occurred on 21 May 2024 at 07:49 UTC. The Mission Support System (MSS) segment<sup>2</sup> is outlined from waypoint 0 to waypoint 2, with waypoint TURB in between. The complete London–Bangkok flight path is shown in the lower-left inset. (b) Flight altitude derived from ADS-B data, with a zoomed view of the incident. Gray shading indicates the periods of most rapid vertical acceleration (2).

remains one of the leading causes of in-flight injuries and operational disruptions worldwide, contributing to costs through unscheduled landings, rerouting, fuel inefficiencies, and aircraft damage (12). Each year, thousands of turbulence-related incidents are reported across global airlines (12).

Clear-air turbulence (CAT) is especially challenging because it develops in clear skies without visible indicators and cannot be detected by onboard radar (10, 11). This unpredictability underscores the need for improved forecasting methods. One recent advancement is the use of EDR, a standardized, aircraft-independent measure of turbulence intensity (11). Unlike subjective terms such as “moderate” or “severe,” EDR offers a quantitative scale that can be integrated into forecasting

models (11).

Turbulence forecasting systems combine numerical weather prediction models, aircraft sensor data, and statistical algorithms to estimate risk (11, 12). However, existing systems continue to show limitations in speed, accuracy, and adaptability under rapidly evolving atmospheric conditions.

This paper explores the question: *How can turbulence prediction be improved in flight systems?* The researchers will review the limitations of current models and look at new ones, such as high-resolution simulations, machine learning techniques and alerts based on real-time sensors. The goal is to understand how these methods can work together to make flying safer, smoother, and more fuel-efficient.

## LITERATURE REVIEW

### Statistical and EDR-Based Forecasting Models

Turbulence forecasting systems rely on weather models, aircraft observations, and computational algorithms to estimate when and where turbulence will occur. Although these systems have advanced over time, challenges remain. Some models operate too slowly, others lack accuracy, and many struggle under rapidly changing atmospheric conditions.

A common method for quantifying turbulence is the energy dissipation rate (EDR). EDR provides a numerical value for turbulence intensity that is independent of aircraft type. Unlike subjective labels such as *moderate* or *severe*, EDR offers a standardized metric, making it especially useful for pilots and researchers (11). As a result, many forecasting models now attempt to predict EDR across both space and time.

Building on this approach, Sharman and Pearson (11) proposed a statistical model that links EDR directly to meteorological conditions (11). This framework improved early detection of turbulence and produced more reliable warnings for pilots, with the aim of enhancing operational safety.

Rossano (9) advanced turbulence modeling in a different way with the GEKO (Generalized  $k-\omega$ ) framework. GEKO simulates airflow around aircraft in critical scenarios such as aerodynamic stall and introduces six adjustable parameters that allow

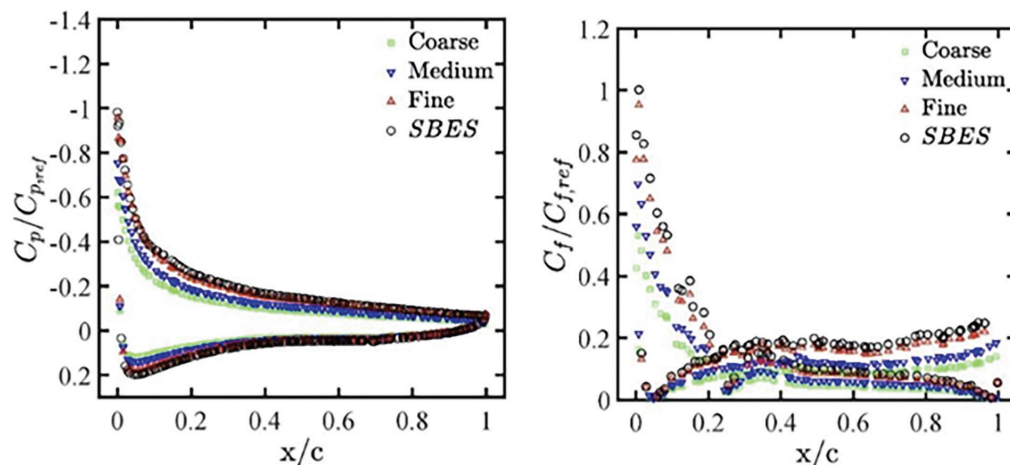
engineers to fine-tune accuracy (9).

As shown in Figure 2, GEKO was validated against SBES reference data across varying mesh resolutions. The normalized sectional pressure (left) and skin-friction coefficients (right) demonstrate that finer meshes improve accuracy, but even coarse and medium resolutions capture the general aerodynamic trends. These results indicate that GEKO can reproduce the performance of more complex models at lower computational cost, making it promising not only for design applications but also for real-time forecasting.

As such, these studies demonstrate steady progress in turbulence forecasting. However, important limitations remain. Even with tools such as GEKO and EDR-based systems, forecasts often fail to provide pilots with sufficient lead time or confidence to respond effectively (10, 11). This shortfall is especially evident in the case of clear-air turbulence, which remains difficult to detect and nearly impossible to avoid, even with advanced models.

### Machine Learning Approaches for Turbulence Prediction

Machine learning is becoming a powerful tool for predicting turbulence, especially when combined with large weather datasets and past flight records. These methods can recognize complex patterns that traditional models might miss. In this section, the author will explain how different researchers have used machine



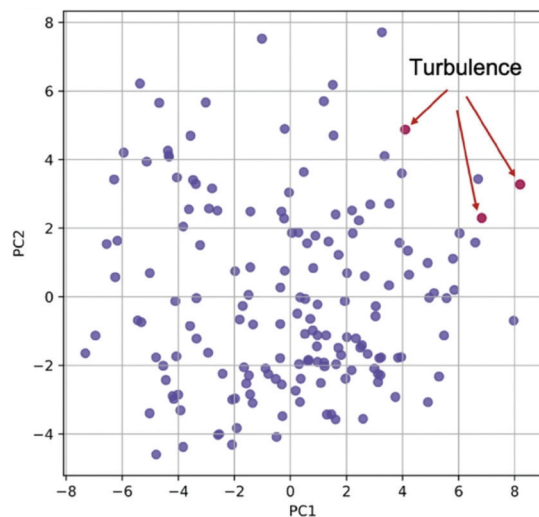
**Figure 2.** Effect of mesh resolution on normalized sectional pressure and skin-friction coefficients compared to SBES reference data. Normalized sectional pressure (left) and skin-friction (right) coefficients at  $\eta = 0.63$  and  $\alpha = 19^\circ$ , showing the effect of mesh resolution compared to SBES reference data (9)

learning to improve forecasts.

Mizuno *et al.* (8) used flight records from Matsumoto Airport and open weather data to train a turbulence prediction model (8). They used Principal Component Analysis (PCA) to reduce the size of the data and K-means clustering to group days with similar weather. Then, they trained a model to identify “dangerous days,” days with strong wind and low temperature that matched real turbulence events (8). Their results showed that the machine learning model was able to correctly match past flight reports and could help avoid rough flights in the future.

As shown in Figure 3, the PCA results highlighted clusters of weather patterns, with turbulence events standing out as separate groupings.

Ayhan *et al.* (3) proposed a method to improve aircraft flight path prediction using weather data and analytics (3). They divided the sky into 3D “weather cubes” and used Hidden Markov Models to analyze how aircraft move through them. By learning from past flights, the system could better plan future routes and



Scatter plot of PC1 and PC2

**Figure 3.** Scatter plot of the first two principal components (PC1 and PC2). Note: Scatter plot of principal component scores (PC1 vs. PC2) for each observation date. Arrows mark the three days when turbulence occurred, all clustered in the upper-right quadrant. This region is associated with high wind speeds, low temperatures, and dense contour lines, indicating conditions favorable to turbulence events (8).

adapt when the weather changes. This approach helps reduce delays, fuel use, and in-flight risks.

Building on these developments, Duraisamy *et al.* (1) explained how traditional turbulence models like RANS (Reynolds-Averaged Navier–Stokes) are often inaccurate due to built-in assumptions (1). They suggested using uncertainty quantification and statistical inference to test and improve these models. They also used machine learning to better estimate Reynolds stress, which plays a key role in turbulence prediction.

Together, these studies show how machine learning can improve turbulence prediction. It can help identify risky weather conditions, adjust flight paths in real time, and correct weaknesses in older models. While there are still challenges, these tools offer a more flexible and accurate way to forecast turbulence in aviation.

### Physics-Based Models and Computational Fluid Dynamics (CFD) Simulation

Turbulence is a complex phenomenon that becomes especially hard to predict in real-time. To improve how we understand and simulate it, researchers use physical models and computational simulations. One of the most important tools is computational fluid dynamics (CFD), which allows scientists to simulate air movement around aircraft with high precision. These simulations can show how turbulence forms and grows, especially in the presence of small structures like Kelvin-Helmholtz waves, which cause sudden and severe turbulence.

Clear-air turbulence (CAT) can be simulated realistically using a very fine-resolution weather model (10). The team used a 35-meter numerical grid to recreate a real CAT event over Tokyo and tested the model against real flight data and aircraft simulation. The model was able to detect Kelvin-Helmholtz waves and matched the turbulence experience reported by pilots. This proves that higher resolution models can capture important turbulence features that coarser models miss.

To understand how turbulence forecasting systems have evolved, a chapter by Fahey *et al.* (12) reviewed how pilot reports, government tools, and airline departments worked together to improve forecasting after World War II (12). Systems like the Graphical Turbulence Guidance (GTG) became key tools in U.S. aviation. Northwest and Delta Airlines used early versions of these systems. While forecasting models have advanced, the authors stress that pilot reports are still crucial to validating predictions and improving safety.

Another issue with turbulence modeling is high angles of attack (AoA), which create more complex airflows than those seen during cruise flight (4).

As shown in Figure 4, wind components such as crosswind, headwind, and wind correction angle interact with the aircraft and influence aerodynamic stability. In a study by Koji Ito *et al.* (5), the authors explained that at AoA above  $30^\circ$ , airflow becomes unsteady and nonlinear, with strong vortex separation and breakdown. Traditional RANS models often fail in these conditions, especially with asymmetric flows. Instead, hybrid models like DES (Detached Eddy Simulation) performed better at simulating the complex vortex behavior observed in delta wing aircraft. The authors sorted AoA into low ( $0^\circ$ – $15^\circ$ ), medium ( $15^\circ$ – $30^\circ$ ), high ( $30^\circ$ – $65^\circ$ ), and very high ( $>65^\circ$ ) and noted that grid resolution, numerical stability, and transition modeling all affect accuracy (5).

Inside the aircraft, airflow is also hard to predict. It was proved that airflow inside cabins is absolutely unstable, meaning small changes can totally shift the air's direction (7). The team used Large Eddy Simulations (LES) with up to 22 million grid cells to simulate airflow in a symmetric cabin. Surprisingly, even conventional turbulence models using 20 million grid cells (like RNG k- $\epsilon$  and Realizable k- $\epsilon$ ) failed to reproduce the correct airflow patterns. The researchers created a new model called BV2fAM that worked well with just 3 million cells. Their model could simulate real, unsteady flows, and was validated using LES results. This shows that standard RANS models are not enough for accurate cabin predictions, and newer custom models can work better with fewer resources.

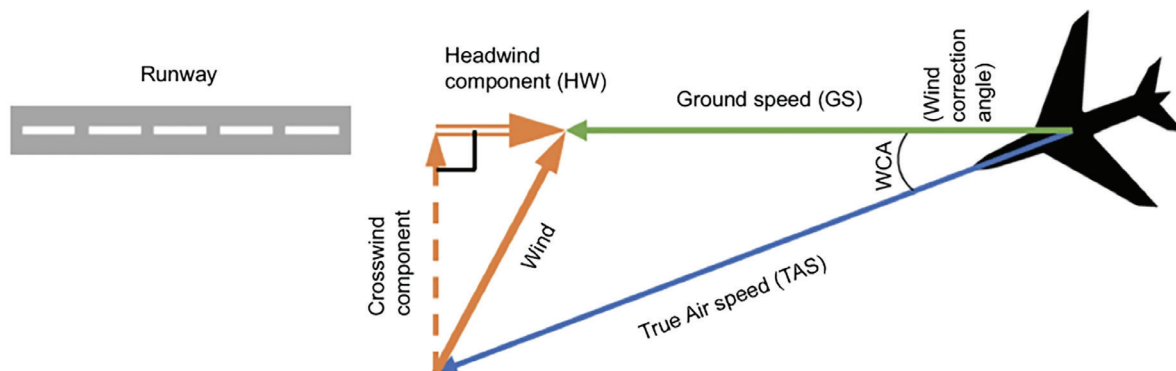
All of these studies show that physical models and simulations are essential for improving turbulence forecasting. By using finer resolution, more advanced algorithms, and real flight data, scientists can build systems that better reflect what actually happens in the air. This helps pilots, air traffic control, and designers build safer and more efficient flight systems.

### Hybrid Forecasting Systems Using Real-Time Sensors and Ensemble Models

This section looks at new systems that combine real-time sensor data from aircraft with traditional forecasting models. These hybrid methods improve turbulence prediction by increasing speed, accuracy, and responsiveness. Real-time data, machine learning, and physics-based models work together to give pilots and controllers better alerts.

One example is the FUTURA model. This system uses only onboard aircraft sensors to predict turbulence without relying on external weather forecasts (7). It uses a Steady State Kalman Filter to clean the data, Functional Data Analysis to extract shape patterns, and time series anomaly detection to find upcoming turbulence. When the flight data deviates from normal patterns, turbulence is flagged. In tests, FUTURA predicted 40% of severe turbulence cases up to 30 seconds ahead, with no false alarms.

Another example is ensemble forecasting with the ECMWF Integrated Forecasting System (IFS), studied by Gisinger *et al.* (2). This system employed EDR-based ensemble forecasts to identify atmospheric structures linked to turbulence, such as vertical wind shear and strong updrafts (2). While the average predicted



**Figure 4.** Wind components affecting an aircraft. Note: Wind components relative to the runway: headwind affects speed along the runway, crosswind pushes sideways<sup>5</sup>. This setup shows how headwind changes can influence aircraft stability during landing.

probability of severe turbulence was between 10–40%, certain ensemble members signaled far greater risk. This probabilistic spread captured localized threats that might have been overlooked in a deterministic forecast, showing the value of ensemble-based methods in highlighting low-probability but high-impact events.

The evolution of these systems builds on decades of development in aviation forecasting, as explained by Sharman (11). Starting with pilot reports in the early 20th century, tools like Graphical Turbulence Guidance (GTG) and airline-specific systems laid the foundation. While technology has advanced, real-time systems like FUTURA now represent the next step in improving safety and efficiency (11).

Together, these hybrid approaches show that combining fast sensor-based alerts with slower but more accurate weather models can improve response time and prediction quality. This makes flying safer, especially in fast-developing or unexpected turbulence conditions.

**METHODS AND MATERIALS**

To assess the potential for improving turbulence prediction in flight systems, this study performed a comparative analysis of representative turbulence forecasting models across multiple dimensions of

operational performance. The objective was to evaluate each model’s ability to support safe and timely aircraft operations under various meteorological and computational constraints.

Four criteria were identified as essential for turbulence risk prediction: accuracy, operation in adverse weather, adaptability, and efficiency. These evaluation criteria were selected based on their relevance to real-world flight operations and their presence in prior studies concerning turbulence avoidance and prediction system design. The definitions and importance of each criterion are summarized in Table 1.

To compare different approaches, four representative systems (labeled A through D) were chosen following established methods in prior studies (2, 7, 8, 9). System A draws on a statistical foundation, combining Principal Component Analysis (PCA), K-means clustering, and Support Vector Classification (SVC), as outlined by Mizuno *et al.* (8). System B represents a physics-based strategy, employing the GEKO turbulence model and its Generalized  $k-\omega$  equations for airflow simulation, which was adapted by Rossano (9). System C takes a real-time, data-driven approach: the FUTURA model leverages onboard aircraft sensors, functional data analysis, and anomaly detection to anticipate turbulence events, by Li T. (7). Finally, System D illustrates a forecast-driven framework, using

**Table 1.** Evaluation criteria for turbulence prediction systems

Criteria	Definition	Rationale
Accuracy	The degree to which the system correctly predicts the timing, intensity, and location of turbulence events.	Accurate forecasts provide reliable alerts for pilots and controllers, reducing exposure to turbulence-prone air and enhancing flight safety.
Operation in Adverse Weather	The ability of the system to maintain robust performance under unstable atmospheric conditions, including storms, wind shear, and convective activity.	Turbulence frequently coincides with hazardous weather; models must remain functional under these conditions to be operationally useful.
Adaptability	The capacity of the system to adjust forecasts when new weather data, rerouted flight paths, or other dynamic inputs are introduced.	Timely updates are necessary as flight and atmospheric conditions evolve, ensuring forecasts remain relevant during operations.
Efficiency	The speed and computational cost of producing forecasts without compromising quality.	Real-time operational use requires forecasts that can be generated quickly with reasonable resource demands, allowing integration into airline decision systems.

The four core criteria were applied in this study to assess forecasting models. Each criterion is paired with its operational significance to ensure consistency in comparing statistical, physics-based, sensor-driven, and ensemble-based approaches.

the ECMWF’s ensemble-based Integrated Forecasting System (IFS) to generate energy dissipation rate (EDR) ensemble predictions, by Gisinger *et al.* (2). Together, these systems capture a wide methodological spectrum, from statistical learning to numerical modeling, real-time sensing, and ensemble forecasting.

Each system was scored on a 5-point scale for each criterion, where a score of 5 denotes exceeding operational requirements and a score of 1 indicates severely limited functionality. Scoring was determined through a review of published performance benchmarks, validation against flight data where available, and an assessment of each model’s stated capabilities.

**RESULTS**

Table 2 compares four turbulence prediction systems across accuracy, efficiency, adaptability, and performance in adverse weather. Scores use a five-point ordinal scale derived from literature synthesis, published validation studies, and expert assessment of stated capabilities. Higher scores indicate stronger or more consistent performance. In this framework, scores of 4 to 5 indicate strong functionality, a score of 3 indicates partial or situational effectiveness, and scores of 1 to 2 indicate limited or inconsistent results.

**Accuracy**

System B (GEKO) and System D (IFS Ensemble) attained the highest accuracy (both 5). GEKO’s finely tuned airflow modeling and calibrated parameters supported precise detection (9). The IFS ensemble benefited from probabilistic coverage that captures

localized risk (2). System A (PCA+SVM) achieved solid accuracy (4) but was limited by dataset size and sparsity in the Matsumoto case study (8). System C (FUTURA) recorded moderate accuracy (3) due to restricted spatial footprint and short forecast horizon (7).

**Performance in adverse weather**

Systems C and D scored 5, maintaining robust performance during unstable conditions. The ensemble spread in IFS supports detection of low-probability, high-impact events (2), while FUTURA’s sensor-driven alerts respond well to rapidly changing in-flight conditions (7). GEKO scored 4, reflecting strong physics-based fidelity but dependence on computationally intensive setups (9). PCA+SVM scored 3, performing adequately but with sensitivity to training data domain (8).

**Adaptability**

FUTURA led adaptability (5), updating alerts from onboard measurements and anomaly detection with minimal latency (7). IFS scored 4, as ensemble guidance adapts to synoptic changes on model update cycles (2). PCA+SVM also scored 4, accommodating new data through retraining but not continuously (8). GEKO scored 2, since mesh design and solver settings constrain rapid adjustment to new conditions (9).

**Efficiency**

FUTURA again led efficiency (5), supporting timely outputs suitable for cockpit or operations use (7). PCA+SVM scored 4 with comparatively low computational cost (8). IFS scored 3 because generating

**Table 2.** Comparative evaluation of turbulence prediction systems

Criteria	System A (PCA+SVM)	System B (GEKO)	System C (FUTURA)	System D (IFS Ensemble)
Accuracy	4	5	3	5
Operation in Adverse Weather	3	4	5	5
Adaptability	4	2	5	4
Efficiency	4	2	5	3

Four approaches were assessed across four criteria: accuracy, efficiency, adaptability, and performance in adverse weather. Scores range from 1 to 5 and reflect a combination of literature synthesis, published validation studies, and expert assessment of system capabilities. Higher scores indicate stronger or more consistent performance; lower scores indicate weaker or less reliable outcomes. In this scale, 4 to 5 denotes strong functionality across conditions, 3 denotes partial or situational effectiveness, and 1 to 2 denotes limited or inconsistent results.

ensembles and postprocessing introduces delay before operational use (2). GEKO scored 2 due to heavy compute demands that limit deployment during flight (9).

### **Synthesis of trade-offs**

No single system satisfied all criteria. Physics-based and ensemble approaches (GEKO, IFS) provided top accuracy and strong behavior under adverse weather but required greater resources and longer turnaround (2, 9). Sensor-based detection (FUTURA) was most adaptable and efficient but offered a shorter prediction horizon and narrower spatial coverage (7). Statistical learning (PCA+SVM) delivered balanced, mid-range performance with modest resource needs, although reliability depended on training data breadth (8). These trade-offs support a hybrid path that combines near-term sensor alerts, adaptive statistical learning, and broader ensemble or physics-based guidance to serve both immediate avoidance and pre-flight planning.

GEKO's top accuracy stems from calibrated turbulence parameters but its efficiency is limited by computational load. IFS matches GEKO on accuracy and excels under adverse weather due to probabilistic spread, with moderate efficiency because forecasts require model cycle time. FUTURA leads adaptability and efficiency by using onboard measurements and anomaly detection, while its accuracy reflects limited spatial and temporal reach. PCA+SVM offers a balanced profile but is constrained by the scope and representativeness of training data.

### **DISCUSSION**

The comparative analysis shows clear trade-offs between systems. Physics-based and ensemble approaches such as GEKO and IFS Ensemble provided strong accuracy and stability under adverse weather, but their high computational demands limit practicality for real-time flight operations. FUTURA offered the strongest adaptability and efficiency, making it useful for in-flight updates, though it lacked a broader forecasting range. PCA+SVM delivered moderate but consistent performance, with lower resource requirements, yet its reliability depended heavily on the quantity and diversity of available training data.

These differences suggest that the operational context determines the most suitable approach. Short-haul or rapidly changing conditions favor adaptable systems such as FUTURA, while long-haul flight planning benefits more from physics-based or ensemble forecasts. A hybrid

approach that combines real-time sensor input, statistical learning, and robust numerical or ensemble forecasts would provide pilots both immediate turbulence alerts and broader situational awareness.

Future work should focus on testing integrated frameworks in live flight conditions, evaluating not only predictive accuracy but also pilot usability, response times, and computational cost. The findings show that progress in turbulence forecasting depends less on selecting a single model and more on designing systems that combine complementary strengths.

### **CONCLUSION**

This study compared four turbulence forecasting systems that represent different methodological approaches. The results showed clear trade-offs. Physics-based and ensemble methods such as GEKO and IFS offered the most accurate predictions and strong performance in adverse weather, yet their computational cost and slower output reduced practicality for real-time operations. In contrast, sensor-driven models such as FUTURA achieved rapid and adaptable performance but lacked forecasting depth. Machine learning approaches such as PCA+SVM provided balanced outcomes but were limited by data availability.

Taken together, these findings suggest that operational aviation cannot rely on a single forecasting approach. Airlines need systems that balance accuracy with speed, adaptability with coverage, and resource demands with scalability. A hybrid framework that integrates ensemble forecasts, machine learning, and real-time sensor feedback offers the most practical path forward. Such systems would allow pilots to receive rapid alerts, maintain situational awareness across longer time horizons, and adjust flight planning under changing atmospheric conditions.

The implication for aviation operations is clear: progress in turbulence forecasting will depend less on refining one model in isolation and more on creating interoperable systems that combine complementary strengths. By focusing on integration, testing, and usability, the aviation industry can reduce turbulence-related injuries, lower fuel costs through efficient routing, and improve the reliability of global air travel.

### **CONFLICT OF INTERESTS**

The author declares no conflicts of interest related to this work.

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