Translating NWP Outputs into UAV-Specific Predictions Using Machine Learning

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Abstract: Unmanned Aerial Vehicles (UAVs) are increasingly deployed in safety-critical, weather-sensitive operations. However, the direct use of Numerical Weather Prediction (NWP) model outputs often fails to address the specific operational thresholds and spatial–temporal needs of UAV missions. This study introduces a machine learning (ML) framework that translates standard NWP forecasts into UAV-specific feasibility assessments. We integrate both global (GFS) and local high-resolution (ARPEGE, AROME) models to generate real-time, interpretable indices or GO/NO-GO indicators tailored to UAV performance limits. Our case study over Nantes (France) for the 2017–2023 period demonstrates the added value of ML-enhanced predictions in terms of spatial precision, temporal consistency, and decision-support utility. The proposed approach also offers an effective method to fill gaps in local model availability by learning from global models, ensuring continuity and operational resilience. By combining observation statistics, NWP forecasts, and ML interpretation, this methodology supports scalable, automated pre-flight planning under varying weather scenarios.

1 INTRODUCTION

Weather forecasts play a critical role in aviation and other domains requiring safety-critical, time-sensitive decisions. In crewed aviation, meteorological products are issued under strict national and international guidelines (e.g., WMO, ICAO), with standardized thresholds, formats, and declared accuracy metrics. With the increasing use of unmanned aircraft systems (UAS) for specialized and autonomous missions, however, the demand for more precise, localized, and machine-readable weather data is growing rapidly (Simone et al., 2022).

This shift introduces new challenges. UAS operations often rely on fine-grained, asset-specific environmental thresholds—yet conventional numerical weather prediction (NWP) systems are inherently coarse in resolution and computationally expensive. Addressing this gap requires techniques that can translate general NWP outputs into personalized, actionable products tailored to a specific platform or task.

Recent advances in machine learning (ML), deep learning (DL), and IoT offer promising pathways. These methods have demonstrated success in enhancing NWP through spatiotemporal pattern recognition (Ren et al., 2021; Ahmad et al., 2023), automated statistical post-processing (Rio et al., 2019), real-time data fusion via IoT networks (Wang et al., 2022), localized forecasting through crowdsourced systems (Bindhu, 2020).

While, most studies focus on improving generic forecast accuracy, operationally relevant forecasting—e.g., predicting when a UAV can or cannot fly—remains underexplored. Few works address how meteorological data can be mapped to mission-specific thresholds, or how learning models can be adapted to different assets.

This leads to our central research question:

How well can we predict the personalized operational limits of specific assets based on various meteorological data?

This study focuses on learning asset-specific operational limits from heterogeneous meteorological

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data. Specifically, two integration strategies are employed: (1) Data-driven ML forecasting, which learns from historical data or reanalysis (e.g., ERA5) to generate lightweight, high-resolution predictions (Ben-Bouallegue et al., 2023), (2) Hybrid ML-NWP post-processing, where ML enhances assimilation and post-processing steps (Dong et al., 2023)

Before deploying such systems in aviation, both benefits and challenges must be considered:

- Benefits: improved accuracy (Sengoz et al., 2023; Patriarca et al., 2023), faster computation (Weyn et al., 2020), and enhanced forecast calibration (Bouallègue et al., 2023)
- Challenges: smoothness bias, difficulty predicting extremes, integration hurdles, and regional data inconsistencies (Zhong et al., 2023)

2 DATA AND METHODS

This study builds on the concept of performance indexes as representations of prediction metadata (Lombardi et al., 2025) to explore a complete pipeline for a fully automated weather-based decision support system. A central challenge is the inhomogeneity of meteorological data—in format, resolution, content, and timing.

As Lombardi et al. (2025) note, forecast products vary significantly across lead times, shifting from coarse global models to fine-scale local outputs and finally to real-time observations. We address this with an ML-based method that supports seamless transitions between forecast products across planning and operational phases.

For UAV mission planning, we define seven categories of meteorological inputs:

- **Climate Data** – Long-term atmospheric trends relevant to asset performance.
- **Global NWP Forecasts** – Medium- to long-range outputs, up to 21 days ahead.
- **Local NWP Forecasts** – High-resolution data available ~72 hours before operations.
- **TAF Forecasts** – Standard aviation text forecasts, issued ~24–30 hours in advance.
- **Landing Forecasts** – Final high-resolution updates for the approach phase.
- **Current Observations** – Real-time data from radar, METARs, or satellites.
- **Secondary Products** – Crowdsourced or site-specific data (e.g., webcams, field reports).

This taxonomy enables phase-specific use of meteorological products, and highlights the need for adaptive ML models that handle heterogeneous inputs.

Proposed framework deals with the transition between the products described in the Table 1 with basic ML algorithms.

Table 1: Overview of the sources interpreted in this study.

Source	Information provided
Climate Data	Average annual flyable hours
	Optimal asset type selection based on historical patterns
Global Model	General operational suitability for a selected asset (VRFI)
	Anticipated energy consumption (EER)
Local Model	Forecasts with high spatial resolution
	Forecasts with hourly granularity

Given the differing nature of Terminal Aerodrome Forecasts (TAF) and Landing Forecasts provided by professional meteorologists, as well as nowcasting methods that rely on real-time observations and measurements, our current focus is on these available sources.

2.1 Operational Principles

As UAV operations scale, meteorological systems must move beyond single-airport support. Our proposed framework is built on the following principles:

- Automation – End-to-end, minimal human input;
- Machine Readability – Output in gridded formats (e.g., NetCDF) for autonomous systems;
- Objectivity – Data-driven decision logic;
- Transparency – Traceable inputs and outputs;
- Relevance – Context-aware, concise outputs;
- Localization – Tailored to local conditions;
- Scalability – Compatible with diverse sources and missions;
- Human-Like Output – Visuals that support expert validation;

This framework ensures accurate, scalable, and interpretable support for automated UAV operations in an evolving technological and regulatory landscape.

2.2 Machine Learning Algorithms

We adopt a classification-based ML approach, aiming to determine whether forecasted conditions are favourable or unfavourable for a specific asset—a binary classification problem labelled by finally observed conditions. For mapping transitions between forecast runs and lead times, regression tasks are used. The selected models span a range of complexity, interpretability, and robustness, as summarized in Table 2.

Table 2: Utilised ML algorithms with their expected role in the study.

Model	Remark
Logistic Regression	Simple, interpretable, effective with linearly separable data
Decision Tree	Handles non-linearity; interpretable; prone to overfitting
Random Forest	Reduces overfitting, handles imbalanced data with class weighting
Gradient Boosting	Powerful, reduces bias, effective with imbalanced data
AdaBoost	Focuses on misclassified cases, robust to outliers
KNN	Non-parametric, works well with small datasets, sensitive to imbalances

2.3 Performance Indicators

Building on previously published work (Lombardi et al, 2025), we use a framework of indices (Table 3) that label a prediction based on its relevance to the flying asset.

Table 3: Selected performance indicators as established by previous research (Lombardi et al, 2025).

Name	Description	Value
Vehicle Related Feasibility Index (VRFI)	Probability that the predicted values will not exceed the thresholds specified for the vehicle in the mission	0 – surely worse than threshold 1 – surely better than threshold
Energy Efficiency Rating (EER)	Estimated energy cost of flight (direction-dependent)	0 – min +∞ – max

These indexes used as labels allow us to assess both forecast accuracy and operational utility, bridging physical forecasts with mission-specific decision-making.

2.4 Observations Statistics

We use METAR reports from Nantes Atlantique Airport (LFRS) covering 2011–2023, compliant with ICAO Annex 3. These include wind direction and speed, visibility, weather phenomena (e.g., fog, precipitation), temperature and dew point, cloud cover and ceiling. This dataset serves as:

- Ground truth for model validation
- Basis for computing performance indices (VRFI and EER)

2.5 NWP Models

We use both global and local NWP models to support different forecast horizons.

2.5.1 Global Model

The Global Forecast System (GFS) by NOAA (0.25° × 0.25° resolution) provides up to 16-day forecasts, ideal for long-range planning. Key It is initialized at 00, 06, 12, and 18 UTC with forecast intervals: 12-hour steps, then 3-hour steps below 240h horizon.

As noted in the literature (Benjamin et al., 2016; Baars et al., 2005), effective GFS use requires attention to: (1) Forecasted values, (2) Temporal trends and lead-time consistency, (3) Model reliability and bias characteristics.

Because raw GFS output is complex, we translate it into probabilistic, threshold-based forecasts, answering:

"What is the probability this forecast meets operational limits?"

This aligns with our use of performance indices (Section 2.3) and supports actionable decision-making.

2.5.2 Local Models

Local models capture mesoscale phenomena critical to UAV operations. For the Nantes region, we use: ARPEGE (5 km resolution, Météo-France) and AROME (1.3 km resolution, convection-permitting)

A key innovation is predicting local model output from global model input, enabling early approximation before high-resolution forecasts are available. This supports:

- Continuous forecasting across model transitions
- Uncertainty quantification before local model initialization

Though global and local models share similar data structures (e.g., GRIB, NetCDF), the higher fidelity of local models improves classification near critical thresholds.

3 RESULTS

In this section, we present the interpretation of each data product and demonstrate their integration across forecasting horizons, focused on a use case near the French city of Nantes. The scenario involves unmanned aerial vehicle (UAV) flight planning under operational constraints: Wind limits of 10, 12, or 15 m·s⁻¹, Temperature range between −10 °C and 40 °C, Visual Meteorological Conditions (VMC) required for operation.

These constraints were applied consistently across observations and forecast models to evaluate the Vehicle Related Feasibility Index (VRFI) under both historical and predictive scenarios.

3.1 Observations

The statistical overview offers essential long-term insight into UAV operational feasibility at the target site. Instead of presenting separate charts for each variable (e.g., wind, visibility, temperature), we use an integrated heatmap approach to visualize overall operational suitability over time.

The following heatmap (Figure 1) captures seasonal and diurnal patterns. Darker cells from June to September indicate fewer weather-related constraints, while lighter cells in winter—especially January—highlight adverse conditions in up to 50% of hours, often due to IMC, strong winds, or freezing precipitation.

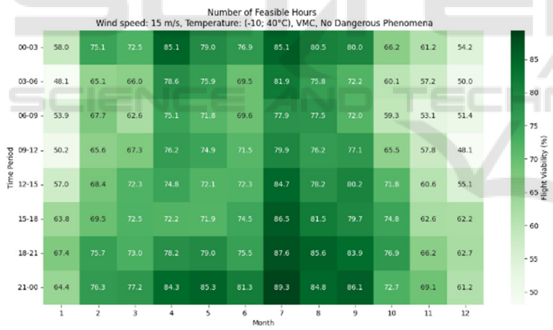

Figure 1: Percentage of hours of flight viability by month and the three-hour window in Nantes Airport.

Such patterns simulate expert forecaster knowledge:

- Morning fog in colder months from radiation or advection processes;
- Afternoon convection in summer causing temporary disruption.

These observations support operational planning (e.g., identifying optimal months or times) or risk mitigation (e.g., reserving backup windows or alternate sites).

Overall, the heatmap serves as:

- A compact, user-friendly climate overview tailored to UAV limits;
- A static data layer for clustering or meta-model integration.

At Nantes airport, for example, long-term unsuitability in January contrasts with generally favourable summer months. These insights enable statistical prediction and planning aligned with UAV-specific thresholds.

3.2 Global Models

To assess medium-range forecasting potential, we applied both Random Forest and AdaBoost machine learning models to data from the GFS global model, focusing on a forecast horizon of 168 hours (7 days) to 6 hours prior to the intended UAV operation. For this analysis, we performed the training on 80/20 train/test split dataset from years 2015-2022.

These algorithms were selected based on their superior performance during initial validation, and were used to compute the Vehicle-Related Feasibility Index (VRFI)—i.e., the probability that the mission will be feasible given forecasted conditions.

Despite the relatively coarse spatial resolution of the GFS (0.25° grid), the models accurately captured synoptic-scale signals, including a cold frontal passage on 2nd November 2023 that led to a notable decrease in predicted feasibility (Figure 2).

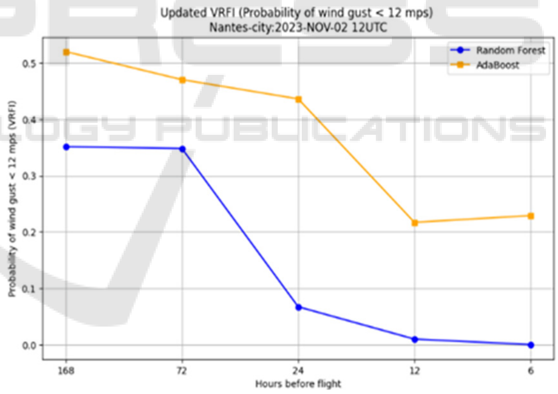

Figure 2: Probability of wind gust lower than 12 m.s-1 meaning feasibility of mission predicted by Random Forest and AdaBoost 168 to 6 hours before flight.

Both Random Forest and AdaBoost models exhibited consistent temporal trends, though Random Forest tended to underestimate feasibility (i.e., more pessimistic) and AdaBoost was slightly more optimistic in its predictions.

Despite the high complexity of the situation, these outputs demonstrate that even one week in advance, a well-trained model can provide meaningful early warning to decision-makers, allowing for adaptive scheduling or contingency planning.

3.3 Local Models

In this part of the study, we tested whether global model forecasts (specifically GFS) can serve as reliable proxies for high-resolution local model outputs (ARPEGE, AROME), particularly when local forecasts are unavailable or delayed. The goal is to bridge spatial and temporal resolution gaps using machine learning (ML).

We trained regression models (Random Forest, Gradient Boosting, Support Vector Regression) on forecasts from 2017–2019, using GFS data to predict ARPEGE outputs (Figure 4). These models were then applied to AROME forecasts (1.3 km resolution) over ~300 grid points in the Nantes region. (Figure 3).

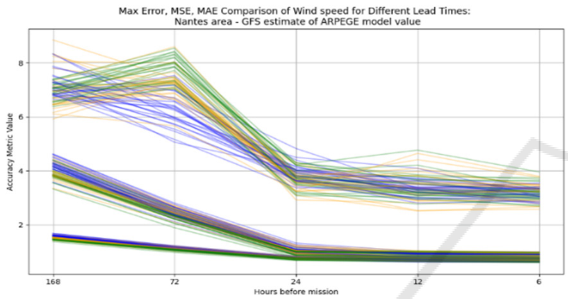

Figure 3: Comparison of Random Forest (blue), Gradient Boosting (green), and SVM (yellow) algorithms predicting ARPEGE wind speed predictions in Nantes area based on the GFS global predictions. (Highest values: Max error, middle: MSE, lowest values: MAE).

The models performed well, especially for 10 m wind speed:

- Mean Absolute Error (MAE) was consistently <2 m·s⁻¹ within a 24-hour lead time.
- Maximum errors rarely exceeded 5 m·s⁻¹, even up to a week ahead.
- Day-ahead forecasts showed good agreement, with errors stabilizing around 4 m·s⁻¹.

These results suggest ML-based smoothing of global forecasts can approximate local outputs with high fidelity during synoptic stability. Larger discrepancies were observed during convective activity, frontal transitions, or terrain-driven turbulence—primarily due to limitations in input data resolution, not ML model design.

Despite this, local models remain essential for:

- Vertical profiling and convection-permitting outputs;
- Finer representation of terrain and mesoscale features;
- Improved gradients in wind and temperature fields.

Combined with ML, local models offer a smoother, more interpretable depiction of atmospheric conditions. For example, we used wind-related predictions to estimate UAV energy consumption, presenting wind influence as a color-contoured field instead of traditional wind barbs (Figure 4).

On 6 June 2017, this approach captured the evolution of operational conditions as a frontal system passed over Nantes. Early in the day, forecasts indicated generally favorable flying conditions (Figure 6 left), but by late afternoon, feasible flight zones were restricted to the eastern urban area (Figure 6 right).

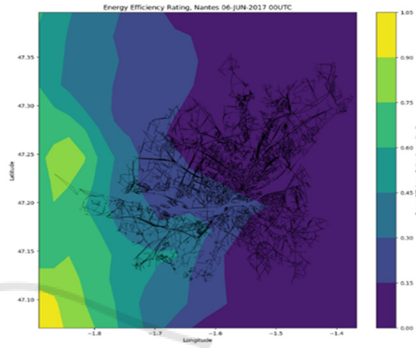

Figure 4: Energy Efficiency Rating for flight to the northeast in Nantes on 6th June 2017 showing transition of the headwind in NE part and tailwind in the SW.

However, as the front advanced and passed over the region, the area with a high probability of safe UAV operations narrowed—eventually being limited to the eastern urban area of Nantes (Figure 7).

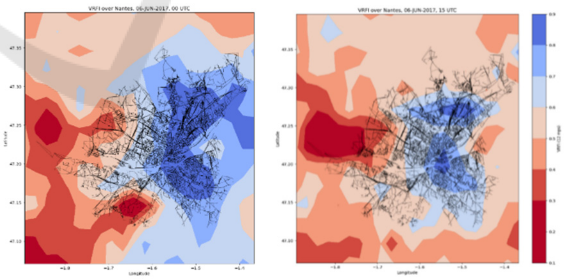

Figure 5: Vehicle Related Feasibility Index (VRFI) over Nantes based on ARPEGE model on 06th June 2017 at 00 UTC and 15 UTC. Roads shown in black.

High-resolution AROME forecasts provided even more detailed insights with hourly resolution. ML models maintained predictive stability above 97%, enabling confident classification of GO/NO-GO decisions based on platform-specific wind thresholds. For instance, Drone 1 and 3 had a max limit of 10 m·s⁻¹; Drone 4 was configured for 15 m·s⁻¹.

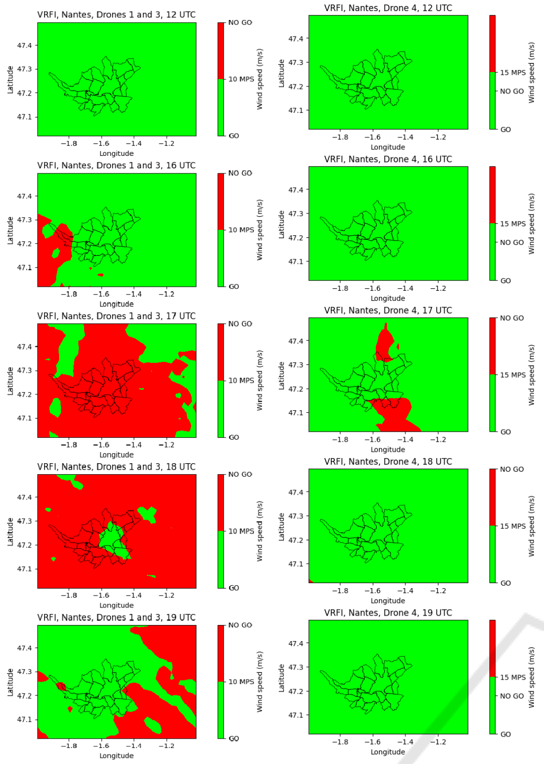

Figure 6: Vehicle Related Feasibility Index (VRFI) for drone of operational maxima of wind speed 10 $m \cdot s^{-1}$ (left) and 15 $m \cdot s^{-1}$ (right) for 12 and 16-19 UTC during passage of the frontal system over the area (City district contours represented by black lines).

These results show that ML-enhanced local models can effectively track dynamic atmospheric features and translate them into operationally relevant outputs. Minor timing offsets between ARPEGE and AROME were observed, but spatial patterns remained consistent. The ML confidence scores also served as a proxy for model reliability, offering valuable metadata for decision support in UAV operations.

4 DISCUSSION

As UAV deployments expand across critical infrastructure, emergency response, and logistics, the need for predictive tools supporting real-time operational decision-making continues to grow. Traditional aviation forecasting relies heavily on human interpretation of multi-source model data and TAFs. However, this study contributes to the ongoing shift toward automated, user-specific forecast interpretation using machine learning (ML), particularly via the Vehicle Related Feasibility Index (VRFI) and Energy Efficiency Rating (EER) (Lombardi et al., 2025).

Our primary objective was to develop and validate a modular ML framework that translates NWP outputs into actionable UAV mission guidance. Special attention was given to handling forecast transitions—from GFS to ARPEGE to AROME—which vary in spatial resolution and update frequency, posing challenges to consistency. We addressed this via a predictive chain that classifies or regresses meteorological data into mission-relevant outputs and harmonizes across forecast products using learned statistical relationships.

A secondary goal was to assess whether global model outputs (GFS) could approximate local model behaviour (ARPEGE, AROME), providing continuity during periods when high-resolution data are unavailable.

Building on the concept of prediction metadata indices (Lombardi et al., 2025), our method shifts from raw meteorological values to decision-oriented scores. Prior works have focused on MOS and short-term nowcasting (e.g., Baars et al., 2005; Benjamin et al., 2016), often limited to single-model input or short lead times. We extend this by integrating multi-tiered ML pipelines, combining long-range global data with high-resolution forecasts, while preserving interpretability through standardized indices.

Our results demonstrate that ML can:

- Predict AROME wind speed from GFS inputs with good accuracy (MAE < 2 $m \cdot s^{-1}$),
- Translate raw forecasts into binary GO/NO-GO decisions, aligned with UAV safety thresholds,
- Detect transitions and instabilities, such as frontal passages, up to 7+ days in advance using GFS alone.

VRFI-based predictions showed consistency across models (Random Forest, AdaBoost), with model confidence often exceeding 97%, indicating robustness under synoptic-scale predictability. Additionally, AROME-based urban-scale forecasts enabled high-resolution spatial visualizations, including GO/NO-GO maps and energy efficiency gradients, supporting user-facing decision tools.

These outcomes support a paradigm shift in aviation meteorology—from static, generalized products to dynamic, asset-specific prediction workflows. The proposed framework enables:

- Real-time translation of forecasts into UAV-relevant indices,
- Seamless model transitions across forecast horizons,
- Continuous situational awareness in both strategic and tactical windows.

Such capabilities can be embedded into operational platforms for UAV operators, civil protection agencies, or airport authorities.

Despite encouraging results, several limitations remain:

- Convective and mesoscale phenomena led to greater errors (e.g., peak wind deviations > 4 $m \cdot s^{-1}$), likely due to coarse input resolution rather than model limitations.
- The geographic scope was limited to the Nantes region; generalizability to other climates or terrains (e.g., mountainous or tropical) requires further validation.
- While index-level interpretability was achieved, internal model explainability (e.g., SHAP values, feature importance) was not explored in depth.

Additionally, while our focus was on forecast-based decision support, nowcasting remains critical, particularly in the final 0–2 hours before take-off or landing. Previous work (Lombardi et al., 2025) identified this as the most tactically significant period. Future work will enhance this window using high-resolution satellite, radar, and in-situ data.

Planned extensions of this research include:

- Transitioning to probabilistic classification, incorporating additional indices (e.g., Vehicle Source Reliability Index, VRSRI).
- Integration of ensemble NWP systems (e.g., ECMWF-EPS) for enhanced uncertainty modelling.
- Utilization of the latest geostationary sounding satellite data for improved verification.
- Applying meta-learning techniques to dynamically adapt model selection and feature prioritization by region and mission profile.

5 CONCLUSIONS

This study demonstrated the feasibility of a fully automated, ML-based framework for forecasting UAV-operational weather conditions across all planning phases. By integrating global (GFS) and local (ARPEGE, AROME) NWP models with METAR observations, we addressed key challenges in aviation meteorology, notably the transition across forecast products with differing resolutions and update cycles.

Our results show that ML models can reliably translate raw forecasts into actionable, asset-specific indices such as the Vehicle Related Feasibility Index (VRFI) and Energy Efficiency Rating (EER). This supports consistent decision-making from long-range planning to short-term execution, even during data-sparse periods.

Moreover, user-centered outputs like GO/NO-GO maps and climatological heatmaps enhance the interpretability and relevance of forecast products for UAV mission planning.

Despite strong performance in synoptic regimes, limitations remain in capturing convective and fast-evolving weather patterns—highlighting the need for future integration of nowcasting methods and real-time observational data.

Overall, the proposed framework offers a scalable foundation for operational, data-driven UAV forecasting and sets the stage for further research into adaptive, real-time meteorological decision support systems.

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