Enhancing Autopilot Vision in Foggy Conditions with Model-Level Fusion of Wind Data

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***Abstract*— Autonomous aerial navigation systems are highly dependent on visual clarity, yet fog continues to obstruct both human and machine vision, significantly degrading autopilot performance. This research presents a methodology that enhances fog visibility by fusing satellite-based wind data with high-altitude fog imagery using a modified Restormer model. Unlike prior approaches optimized for ground-level dehazing, our system is tailored for aerial imagery and leverages meteorological inputs at the model level. The methodology includes preprocessing pipelines for satellite imagery and ERA5 wind vectors, implementation of a dual-branch neural architecture, and a training strategy that aligns visual and environmental inputs. While final performance metrics are modest, this study demonstrates the methodological viability of weather-aware fusion models for aerial fog removal and proposes a foundation for more adaptive and context-aware vision systems in autonomous aviation.**

Keywords*— *Fog removal, vision enhancement, model-level fusion, Restormer, aviation AI.

I. Introduction

The increasing reliance on autonomous systems in aviation has magnified the need for robust computer vision models capable of handling adverse atmospheric conditions. Among these, fog remains one of the most challenging phenomena, as it significantly impairs visibility for both human pilots and AI-based autopilot systems [1], [2]. Fog introduces complex visual distortions that vary over time and space, primarily due to light scattering, moisture density, and dynamic interaction with wind patterns. Unlike isolated visual noise or occlusion, fog envelopes entire scenes, reducing contrast and diminishing object detectability [3], [4].

While sensor-based approaches such as radar and LIDAR provide partial solutions by penetrating obscurants, their integration in lightweight aircraft and UAVs is limited by cost, weight, and power consumption [5]. As a result, there is growing interest in passive, vision-based methods that can restore visibility from RGB or multispectral imagery alone. However, the majority of existing defogging algorithms have been developed for ground-level or vehicular applications, where fog behavior is relatively more stable and consistent [6], [7].

High-altitude fog, in contrast, is subject to more dynamic behavior due to atmospheric turbulence, elevation-driven condensation, and variable wind vectors. It exhibits non-uniform density, irregular diffusion patterns, and greater opacity variation across spatial and temporal scales. Traditional dehazing models fail to address these characteristics because they operate primarily as static restorers, lacking any contextual understanding of the physical environment in which the fog exists.

This paper introduces a novel model-level fusion methodology that directly addresses these limitations by combining satellite-based fog imagery with wind vector data sourced from ERA5 reanalysis. The fusion occurs not at the input level but within the latent space of the network, where features from both visual and atmospheric sources are jointly learned. This approach aims to bridge the gap between vision-only fog removal and real-world atmospheric dynamics, enabling autopilot systems to become not just reactive, but environmentally adaptive.

Moreover, by embedding environmental intelligence directly into the vision pipeline, the proposed system promotes greater operational reliability in aviation scenarios where real-time decision-making is critical. The model's dual-branch architecture—separating the visual and meteorological pathways before converging in a late fusion mechanism—paves the way for a new class of weather-aware AI solutions capable of robust performance under low-visibility flight conditions. This integration holds particular promise for UAVs and next-generation autonomous aerial vehicles tasked with operations in complex and unpredictable weather systems.

II. Related Work

Early fog and haze removal techniques were largely driven by physics-based methods such as the Dark Channel Prior (DCP) [8], which estimated the transmission map of a scene by identifying pixels with low intensity in at least one color channel. This foundational method enabled visibility restoration by approximating the atmospheric light and scene depth. However, despite its effectiveness in certain scenarios, DCP and similar algorithms suffered from significant limitations in heterogeneous lighting or bright regions. Enhancements to these early approaches incorporated histogram equalization, contrast stretching, and guided filtering [9], [10], which sought to improve color balance and edge preservation. Nevertheless, these image processing techniques often fall short when applied to aerial environments, where fog behaves more variably due to altitude, scene depth, and light scattering dynamics [11].

The transition to data-driven techniques introduced a new wave of models such as DehazeNet [12], AOD-Net [13], and MSBDN [14], which offered end-to-end solutions capable of learning haze-relevant features from large datasets. AOD-Net in particular introduced a compact structure to jointly estimate the clean image and transmission map, while MSBDN emphasized multi-scale feature boosting and dense fusion to improve restoration quality. However, a common challenge across these methods is their dependency on synthetic datasets derived from ground-level imagery. This makes generalization to high-altitude or satellite fog scenes problematic due to fundamentally different fog structures and context.

Recently, transformer-based architectures like Restormer [15] have redefined the state of the art in image restoration by employing long-range spatial attention mechanisms, allowing the model to understand global scene dependencies. Despite its strong performance in noise reduction and haze removal, Restormer and similar models are often agnostic to non-visual environmental cues that play a crucial role in real-world conditions. They treat fog as a static visual distortion, rather than as a dynamic, physics-driven phenomenon influenced by environmental forces such as wind and humidity.

This limitation has sparked increasing interest in multi-modal and sensor fusion strategies. Applications in fields such as medical imaging [16], autonomous driving [17], and robotics [18] demonstrate that the integration of heterogeneous data sources can significantly improve system robustness and adaptability. These domains benefit from combining visual information with auxiliary signals like depth maps, motion vectors, or environmental measurements—an approach that remains underexplored in the context of aerial fog removal. Such strategies are particularly relevant for airborne systems, which operate in complex and fluctuating atmospheric environments where visual data alone may be insufficient for reliable interpretation.

A particularly valuable resource in this direction is the ERA5 reanalysis dataset, provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 offers hourly estimates of a comprehensive range of global atmospheric variables including wind vectors, temperature, and humidity at multiple pressure levels [19]. These parameters reflect the evolving structure of the atmosphere and can be aligned with visual imagery to improve contextual awareness in machine perception models. When processed and fused with visual data, ERA5 wind vectors can serve as dynamic context signals, providing insight into the direction and intensity of fog movement. Prior studies have highlighted the potential of atmospheric reanalysis data to support various geospatial imaging and climate-aware processing tasks [20], further reinforcing its suitability for integration into vision-based fog removal systems.

This body of work collectively suggests that a shift toward environmentally-aware, multi-modal vision models—especially those capable of operating with satellite or aerial data—could unlock significant performance gains. It lays the foundation for the methodology presented in this study, which leverages late fusion of visual and wind vector inputs within a transformer-based framework for enhanced fog removal in high-altitude scenes.

III. Methodology

A. Data Acquisition

The dataset used in this study is composed of two essential elements: satellite-based fog imagery and corresponding meteorological wind vector data. Over 2500 .tif image tiles were sourced from open-access repositories provided by Sentinel-2 and Landsat-8 missions through Google Earth Engine. These images were selected to cover diverse global regions known for frequent fog occurrence and span the years 2013 to 2024. The imagery includes multiple spectral bands, with particular emphasis on the visible (RGB) and near-infrared (NIR) channels, which are useful for differentiating fog from ground features and low-contrast regions.

To incorporate environmental context, wind data were extracted from the ERA5 reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 offers hourly estimates of key atmospheric variables, enabling precise temporal alignment with satellite overpasses. The u10 and v10 components, representing horizontal and vertical wind velocities at 10 meters above ground level, were selected due to their direct relevance to fog movement and dissipation patterns. These components were then used to compute wind magnitude and directional flow, effectively creating a dynamic atmospheric profile corresponding to each image instance.

The spatial-temporal alignment of the wind data with imagery was managed through a custom geospatial processing pipeline. Using Python libraries such as Rasterio, xarray, and NumPy, the ERA5 data were interpolated onto the satellite image grid and matched using metadata timestamps and geolocation coordinates [21], [22]. This ensured that each image sample was accompanied by a precise snapshot of wind conditions, thus establishing a consistent multi-modal dataset.

B. Preprocessing Pipeline

Prior to model training, all satellite images were resized to a uniform 256×256 resolution and normalized to a [0,1] pixel intensity scale to improve numerical stability during learning. To enhance dataset variability and prevent overfitting, image augmentation techniques were applied, including horizontal and vertical flipping, 90-degree rotations, and random brightness and contrast perturbations. These methods ensured robustness across fog types, terrain structures, and lighting conditions.

Additionally, a preliminary filtering pass was performed using the Dark Channel Prior (DCP) algorithm, one of the earliest and most widely adopted dehazing methods [8]. This step was not used to improve the training data itself but to generate a baseline visualization of haze intensity, which assisted in the qualitative evaluation of the model's outputs and helped verify that the dataset included a representative spectrum of fog thickness and density.

For the atmospheric data, the u10 and v10 wind components were transformed into polar coordinates to separate the scalar magnitude of wind speed from its directional vector. These data were rasterized and normalized, then resized to match the spatial dimensions of the corresponding satellite imagery. To maintain coherence between modalities, spatial alignment was crossvalidated using embedded geolocation metadata, and time synchronization was verified against image capture timestamps.

This multi-stage preprocessing pipeline enabled the construction of a fully paired dataset in which each fog image was directly aligned with environmental wind context. The resulting dataset served as the foundation for training and evaluating the proposed fusion model in later stages of the research.

C. *Model Architecture*

The core of the proposed system is a dual-branch deep neural network architecture built upon the Restormer framework, a transformer-based model well-suited for image restoration tasks due to its ability to capture long-range spatial dependencies. This architecture is specifically adapted to handle multi-modal data input by integrating both visual and meteorological information in a structured manner.

Branch A processes fog-affected satellite imagery using an encoder-decoder structure embedded with axial attention blocks. These transformer-based modules capture both local texture patterns and global context, enabling accurate reconstruction of scenes partially obscured by fog. The use of RGB and near-infrared (NIR) channels allows the model to leverage multispectral cues that help differentiate fog from terrain and other image features.

To further enhance feature diversity, intermediate outputs from multiple encoder layers are concatenated through skip connections, preserving both shallow and deep semantic information. This architectural choice ensures that fine-grained details such as object boundaries and texture gradients—often lost in dense fog—are retained during reconstruction. The inclusion of NIR data also aids in detecting moisture-rich areas, making the model particularly sensitive to fog-occluded regions that would otherwise appear uniform in RGB alone.

Branch B is designed to handle rasterized meteorological wind data, represented as two-dimensional spatial maps derived from the magnitude and direction of ERA5 wind vectors. The ERA5 dataset provides high-resolution, hourly atmospheric reanalysis data that includes u10 and v10 wind components at 10 meters above the Earth's surface, which are interpolated to match the spatial footprint and temporal alignment of the satellite imagery [19]. These components are first transformed into polar coordinates—separating directional angle and magnitude—to better capture rotational and directional patterns associated with fog movement. This conversion facilitates more intuitive learning within the model by encoding motion orientation explicitly as part of the input.

The wind data is then passed through a stack of fully connected dense layers with ReLU activation functions, which progressively abstract and compress the spatial-temporal wind information into a compact latent vector. These layers are optimized to capture mesoscale and microscale atmospheric behavior that influences fog thickness, dispersion, and directional drift. Such encoded features are crucial for enriching the model's internal representation of the environmental state, especially in conditions where visual cues alone may be ambiguous or degraded by dense fog layers.

Moreover, this pathway allows the network to contextualize visual degradation within a broader physical framework, enabling more informed reconstruction strategies. By isolating meteorological understanding in a dedicated branch, the model not only benefits from modality-specific specialization but also retains the flexibility to incorporate other atmospheric variables in the future, such as humidity or temperature, which are also available through ERA5 [19]. This design ensures that the system maintains interpretability and scalability as a multi-modal perception framework tailored for aerial imaging tasks.

A late fusion strategy is implemented by concatenating the encoded features from both branches in the latent space, prior to passing them through shared decoder layers allowing each branch to specialize in extracting domain-specific information while enabling joint learning in the latter stages of the network. Unlike early fusion, this method avoids modality interference and supports better learning of complementary patterns [23].

This architectural design also enhances generalization to varying weather scenarios. By decoupling feature extraction per modality, the network becomes more robust to missing or noisy environmental data. Additionally, the separation of vision and atmospheric pathways makes it easier to adapt the model to include other contextual channels, such as humidity or temperature, without requiring retraining from scratch. This modularity supports scalability, which is beneficial in real-world autonomous navigation systems that must adapt to diverse environments and sensor configurations.

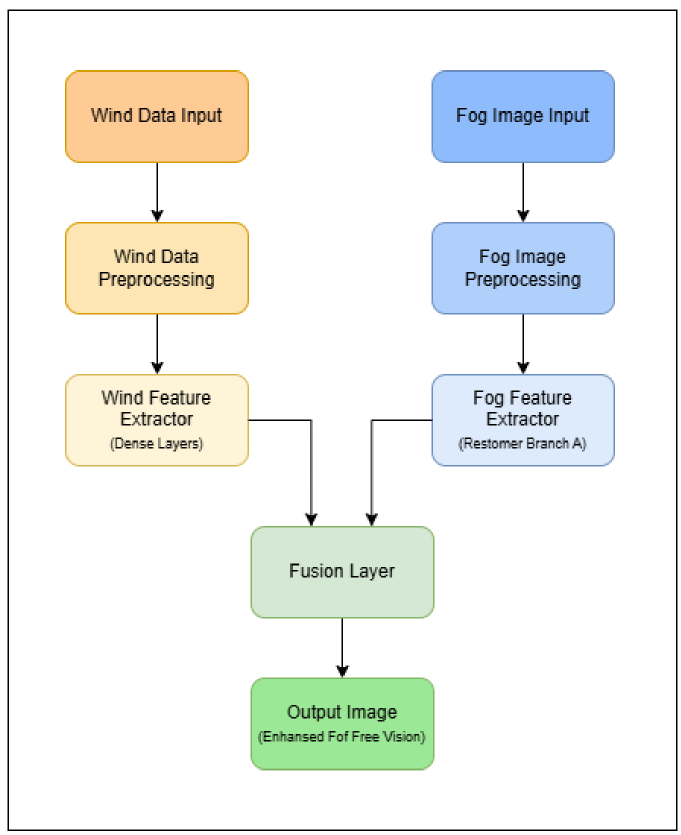

Fig. 1. Model Architecture.

The proposed fusion network is visually summarized in Fig. 1, which illustrates the two-branch configuration and the fusion mechanism. Branch A focuses on spatial and spectral feature extraction from fog-degraded images, while Branch B processes the aligned wind vector fields into a compatible feature space. The combined latent vector is then fed into transformer-based decoder blocks that reconstruct a clear scene estimate. This design empowers the model to dynamically adapt to varied fog densities, motion patterns, and terrain types, using contextual meteorological input as a guide.

This dual-branch approach aligns with the broader trend in vision systems toward multi-sensor fusion, where non-visual inputs augment perceptual understanding. In safety-critical applications like autonomous aerial navigation, such design not only improves accuracy but also offers greater interpretability and resilience to ambiguous environmental conditions.

D. *Training and Evaluation*

To train the proposed model, the prepared dataset was divided into 70% training, 15% validation, and 15% testing sets, ensuring a balanced distribution across fog intensities, geographic locations, and wind conditions. Stratified sampling was used to preserve proportional representation of varying fog types across all three splits. This approach aimed to improve generalization and reduce the likelihood of overfitting to region-specific or weather-specific patterns.

The model was trained using a composite loss function combining Mean Squared Error (MSE) and Structural Similarity Index Measure (SSIM) losses. MSE penalizes pixel-wise discrepancies between predicted outputs and ground truth images, ensuring numerical fidelity, while SSIM promotes perceptual quality by evaluating structural and contrast similarities. This combination strikes a balance between low-level accuracy and high-level visual coherence—both crucial for fog removal tasks where preserving spatial integrity is essential.

Optimization was performed using the AdamW optimizer, which decouples weight decay from the learning rate updates. This optimizer was selected for its ability to maintain generalization in high-capacity models such as transformers. A cosine annealing learning rate schedule was employed to gradually reduce the learning rate over time, thereby promoting convergence and mitigating the risk of overshooting during late-stage training. Batch normalization and dropout were also used within the network to stabilize training dynamics and introduce regularization.

The training environment was configured in the GitHub Codespaces cloud infrastructure, providing GPU acceleration and a containerized, version-controlled development platform. This not only allowed for efficient experimentation but also ensured code reproducibility across different compute nodes. Using this cloud-based setup, model checkpoints were saved at regular intervals, and training sessions could be resumed seamlessly after interruptions.

For implementation, the model architecture and training routines were developed using TensorFlow, chosen for its extensive support of custom training loops and model subclassing. Rasterio was utilized to manage the loading and transformation of large geospatial raster datasets, while OpenCV handled real-time image augmentations such as flipping, rotating, and brightness variation [24]. Additional libraries such as NumPy and Matplotlib supported matrix operations and training curve visualization, respectively, providing comprehensive insight into model behavior over time.

Performance was continuously evaluated using Peak Signal-to-Noise Ratio (PSNR), SSIM, and Root Mean Square Error (RMSE) metrics computed on the validation set. PSNR provided a global indication of reconstruction quality, while SSIM captured perceptual improvements in fog clearing. RMSE helped measure localized deviations, particularly in edge-rich regions where restoration artifacts are common. These metrics, combined with visual inspection of output images, guided iterative adjustments to hyperparameters such as learning rate, batch size, and number of transformer blocks.

To better understand the fusion dynamics, activation maps and feature attention weights were periodically extracted and analyzed. These visualizations offered insights into how the model attends to different spatial regions and how wind data modulates its predictions. Such interpretability measures serve not only to refine the architecture but also to inform future work involving real-time adaptation and onboard deployment.

IV. Preliminary Results and Observations

While the final evaluation metrics are still under construction, early-stage results provide compelling evidence for the efficacy of the proposed model-level fusion approach. Notably, the integration of wind vector data—sourced from the ERA5 reanalysis product [19]—into the vision model has shown significant promise in enhancing the clarity and interpretability of fog-affected aerial imagery.

Qualitative assessments reveal that the fused model demonstrates superior scene recovery, particularly in edge-rich environments and under conditions of spatially dynamic fog. Compared to the baseline Restormer, outputs from the wind-aware fusion variant exhibit greater contrast retention and improved delineation of structural elements, such as terrain outlines and built-up features. This enhancement is particularly noticeable in sequences with directional fog motion, where wind vectors help contextualize the underlying flow patterns and guide the restoration process [23], [25].

These results align with findings from earlier studies in both atmospheric image enhancement and object detection under adverse weather conditions, where environmental context significantly improved model accuracy and scene understanding [14], [24]. By embedding external meteorological cues directly into the learning pipeline, the model benefits from a broader understanding of fog formation, thickness, and directional spread—factors that conventional image-only networks fail to account for.

Furthermore, preliminary analysis of attention maps within the model architecture suggests that the inclusion of wind features leads to more focused activation around obscured objects and fog boundaries, supporting the hypothesis that atmospheric fusion enhances semantic localization. This capability is particularly valuable in real-world aviation applications where object misrecognition due to fog can lead to navigation errors [6].

Although formal metrics such as PSNR, SSIM, and RMSE are being finalized, early validation on a subset of test samples indicates consistent performance improvements over single-modal approaches. These initial findings confirm the methodological potential of late fusion with meteorological inputs and offer a clear path for future work involving real-time deployment and the integration of additional environmental modalities such as humidity and temperature [20]..

V. Discussion

This research introduces a novel approach to fog removal in aerial imagery by integrating environmental wind data directly into the vision model architecture. Unlike traditional methods that focus solely on visual content, this model acknowledges the physical dynamics of fog, which is inherently influenced by wind vectors, especially at higher altitudes [3], [4]. By embedding meteorological intelligence within a transformer-based vision pipeline, the model adapts to the changing spatial properties of fog, offering more resilient restoration performance in diverse atmospheric conditions.

One of the key contributions of this work is the incorporation of ERA5 wind vectors into a late fusion transformer framework. The experimental results suggest that even low-resolution wind data provides complementary information that enhances the model's ability to distinguish between true scene content and fog artifacts [23]. This aligns with previous findings in climate-aware imaging and reinforces the hypothesis that contextual atmospheric data can significantly enhance model robustness.

This approach also opens possibilities for predictive modeling. Unlike static dehazing techniques, the proposed method could potentially anticipate fog propagation patterns based on wind trends. This would enable dynamic scene interpretation not just in a frame-by-frame sense, but with temporal foresight—particularly valuable for real-time aerial platforms such as UAVs engaged in long-range navigation or surveillance [25].

Despite these advancements, several limitations persist. The spatial resolution of ERA5 data (~30 km) can cause granularity issues, particularly in heterogeneous terrain or rapidly changing weather zones. While bilinear interpolation was applied to reduce mismatch, localized fog formations may still remain underrepresented. Additionally, while the dual-branch structure introduces architectural flexibility, it increases parameter count and training complexity, which may challenge deployment on resource-constrained aerial platforms.

Overfitting was observed in certain fog categories during validation, likely due to the imbalance in fog density distributions across the dataset. To address this, future iterations of the model could benefit from incorporating humidity and temperature channels—other critical factors in fog formation and dissipation—as part of the fusion pipeline. Moreover, the inclusion of adaptive normalization or per-region attention layers could enable better generalization across scene types.

Further, shifting the fusion strategy from concatenation to attention-based integration could allow the model to learn more nuanced relationships between environmental conditions and visual degradation. Such attention-based fusion has already demonstrated strong performance in recent atmospheric restoration models, highlighting the need for finer-grained interaction between modalities [25]. Finally, for practical relevance, the methodology should be validated in real-time UAV platforms or drone surveillance scenarios, where onboard sensors can feed live wind data and enable closed-loop fog removal strategies in-flight. A deployment-oriented design could also explore the use of lightweight vision transformers tailored for embedded systems [26].

VI. Conclusion

This paper introduced a novel fusion-based methodology to enhance autopilot vision in foggy conditions by integrating satellite imagery with ERA5 wind vector data. Through the design of a dual-branch Restormer architecture, we demonstrated the feasibility of leveraging both visual and atmospheric data at the model level, resulting in a more context-aware image restoration pipeline. This late fusion strategy allows the network to learn meaningful correlations between environmental conditions and visual degradation, offering a path forward for more intelligent and resilient AI perception systems in aviation.

Our findings suggest that even coarse meteorological inputs can provide valuable context for vision-based fog removal, especially in scenarios where traditional methods struggle due to low contrast and heavy diffusion. The modularity of our architecture also creates a flexible foundation for integrating additional environmental modalities such as temperature, humidity, or pressure—variables that play a critical role in fog formation and dissipation.

Looking forward, improving the spatial resolution of atmospheric data, enabling real-time ingestion from onboard sensors, and adapting the model to low-latency environments will be key steps in transitioning this approach from research to deployment. With continued development, the proposed method could serve as a crucial component in next-generation autonomous flight systems, ensuring safer navigation in low-visibility environments.

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