

Full length article

Super-resolution reconstruction of aircraft wake fusing virtual wind lidar and deep learning

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ARTICLE INFO

Keywords:

Aircraft wake

Super-resolution reconstruction

Virtual wind lidar

Deep learning

ABSTRACT

Insufficient range resolution of wind lidars often leads to blurred detection and inaccurate parameter inversion of aircraft wake. To address this issue, this study proposes the AWSR-Diffusion model, an aircraft wake super-resolution reconstruction framework that fuses virtual lidar simulation and deep learning. Initially, low-resolution and high-resolution wake datasets are constructed using an aircraft wake parameterization model and a time-domain virtual lidar. It indicates that poorer range resolution significantly undermines the precision of wind speed measurements and the characterization of structural features. This causes larger errors in aircraft wake parameter inversion. To this end, the AWSR-Diffusion model acquires the mapping relationship between different resolutions within the training set, overcoming resolution limitations through super-resolution reconstruction. Results based on multiple evaluation metrics show that the model substantially improves the accuracy of retrieved wind fields and structural fidelity. It effectively corrects key parameters such as vortex core spacing and circulation. On the test set at an input resolution of 16 m, the RMSE of the vortex core spacing relative error drops from 10.33 % to 1.62 %, while that of the circulation relative error declines from 19.42 % to 6.14 %. Finally, field data from Guangzhou Baiyun Airport demonstrate the model's applicability. This study offers a promising technical reference for refined wake monitoring and dynamic safety separation optimization.

1. Introduction

Aircraft wake refers to a pair of strong counter-rotating vortices generated behind the wings during flight, posing a serious threat to the flight safety of following aircraft [1,2]. Currently, civil aviation primarily depends on established flight separation standards to avoid this risk [3]. However, these standards are frequently conservative, resulting in the underutilization of airspace and runway capacity [4,5]. Therefore, it is essential to enhance the capability for precise wake detection and key vortex parameter inversion to ensure flight safety and improve operational efficiency.

Coherent Doppler wind lidar (CDWL), with its high accuracy and clear-air detection capability, has been widely adopted across diverse fields such

as atmospheric science [6–8], wind energy [9,10], and aviation safety [11–13]. In the context of aviation, it is a preferred tool for monitoring aircraft wake and ensuring flight safety [14]. Its effectiveness has been well validated through field experiments at multiple airports [15,16]. In recent decades, various methods have been developed for vortex parameter inversion. Traditional methods rely on physical models of wake vortices, including the velocity envelope (VE) method [15], the radial velocity (RV) method [17], the path integration method [18], and the wake vortex visualization demonstrator (V2D) method [14]. In contrast, emerging methods are derived directly from measurement data, learning patterns without relying on predefined models. These include artificial neural networks [19], deep learning models [20], and unsupervised clustering methods [21].

Abbreviations: AWSR, Aircraft Wake Super-Resolution; CDWL, Coherent Doppler Wind Lidar; DDPM, Denoising Diffusion Probabilistic Model; GAN, Generative Adversarial Network; PSNR, Peak Signal-to-Noise Ratio; SSIM, Structural Similarity Index; RMSE, Root Mean Square Error; RHI, Range-Height Indicator.

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<https://doi.org/10.1016/j.optlastec.2026.116474>

Received 22 March 2026; Received in revised form 10 July 2026; Accepted 18 September 2026

Available online 22 September 2026

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However, the performance of the above inversion methods is highly dependent on the spatial resolution of input data. The range resolution of lidar systems is subject to inherent trade-offs with spectral broadening, signal-to-noise ratio, detection range, and other factors, making further improvement difficult [22]. This resolution bottleneck has a particularly pronounced impact on aircraft wake vortices, which are characterized by small scales and rapid evolution. Insufficient range resolution in traditional CDWL systems leads to significant spatial smoothing in the retrieved wind fields. This results in blurred vortex structures and difficulty in vortex parameter inversion, severely impacting the accurate assessment of wake hazard levels.

In recent years, several novel lidar systems have emerged to enhance spatial resolution. Signal modulation techniques enhance resolution through waveform design, including time-domain and spatial-domain coding [23] and differential correlation pulse-pair coding [24,25]. Meanwhile, hardware-based solutions push the resolution limit through hardware optimization, including high peak power fiber laser [26] and short pulse configurations [27]. As a result, the range resolution of traditional CDWL systems has improved from 30 m to 6 m, 3 m, 1.8 m, and even 0.9 m [28]. It provides a new approach for remote sensing of small-scale wind field structures in the real atmosphere. However, higher resolution leads to smaller equivalent scattering volumes, resulting in lower effective signal power. In addition, high-resolution lidar systems face challenges such as inter-pulse crosstalk at high repetition rates, spectral broadening, longer accumulation times, and poor stability in pulse coding systems. These issues seriously constrain the system reliability, real-time performance, and economic viability, making it difficult for such systems to be deployed and applied on a large scale. Therefore, under current hardware limitations in wind field detection technology, accurately resolving the fine-scale structure of aircraft wake vortices using wind lidar remains a significant challenge.

Recent advances in deep learning have opened new avenues for aircraft wake super-resolution. Super-resolution is a process that reconstructs high-resolution images from low-resolution observations, which is a classic task in computer vision [29]. In particular, diffusion models can learn complex features and enhancement rules of images, enabling more efficient super-resolution reconstruction [30]. However, training deep learning models relies on extensive, high-quality datasets [31]. It is costly and extremely difficult to acquire sufficient wake data covering diverse conditions through field measurements. Virtual lidar simulation offers a cost-effective solution [32,33]. It can efficiently generate datasets that cover various aircraft parameters, atmospheric conditions, and detection configurations. This effectively solves the data shortage problem in model training.

Accordingly, this study fuses virtual lidar simulation and deep learning super-resolution, aiming to overcome range resolution limits and improve the inversion accuracy of key vortex parameters. The main contributions are threefold. First, the AWSR-Diffusion framework is proposed to reconstruct high-resolution wake structures from low-resolution inputs without hardware modifications. Second, the virtual lidar simulation is developed to generate paired datasets, addressing the shortage of high-resolution aircraft wake observation data for model training. Third, the reconstruction performance and parameter sensitivity are systematically evaluated across a wide range of wake and atmospheric conditions. The structure of the paper is as follows: Section 2 introduces the framework of the AWSR-Diffusion model, the methods of dataset construction and vortex parameter inversion. Section 3 analyzes range resolution effects, evaluates super-resolution performance of the model, and validates its applicability using field data. Finally, a conclusion is drawn in Section 4.

2. Data and methods

The aircraft wake super-resolution reconstruction framework is shown in Fig. 1. Step 1: High-resolution ground-truth wake wind fields are generated by a virtual lidar simulator, with configurable parameters covering various aircraft types and atmospheric conditions. Step 2:

Downsampling is applied to the ground-truth data to synthesize low-resolution samples at 16 m and 32 m range resolutions. All paired low-resolution and high-resolution samples are split into training and test sets at a 4:1 ratio. Step 3: The AWSR-Diffusion model performs super-resolution reconstruction through forward diffusion and reverse conditional denoising processes, where the low-resolution lidar data serve as conditional guidance to recover high-fidelity wake structures. Step 4: The reconstruction performance is evaluated using comprehensive metrics, and the model's practical applicability is further demonstrated with field observation data.

2.1. Dataset construction

To obtain the substantial, high-quality training datasets required by deep learning, the original high-resolution aircraft wake wind field V_{total} is first generated. It is constructed by linearly superposing three components: the vortex field V_{vortex} from a wake parameterization model, the atmospheric turbulence field V_{turb} , and the uniform background wind field V_{wind} . The mathematical expression is:

$$V_{total} = V_{vortex} + V_{turb} + V_{wind} \quad (1)$$

The vortex field V_{vortex} is described by the Burnham-Hallock vortex pair model, with its expression as follows:

$$V_{vortex} = \frac{\Gamma}{2\pi} \left[\frac{(z - z_L)\vec{e}_y - (y - y_L)\vec{e}_z}{(y - y_L)^2 + (z - z_L)^2 + r_c^2} - \frac{(z - z_R)\vec{e}_y - (y - y_R)\vec{e}_z}{(y - y_R)^2 + (z - z_R)^2 + r_c^2} \right] \quad (2)$$

where Γ denotes the vortex circulation. r_c is the vortex core radius with $r_c = 0.052b$ (where b is the vortex core spacing). $\vec{e}_y$ and $\vec{e}_z$ are the unit vectors of the y-axis and z-axis, respectively. The y-axis represents the direction of the aircraft's wingspan, and the z-axis represents the vertical direction. (y_L, z_L) and (y_R, z_R) are the position coordinates of the left and right vortex cores. (y, z) is the coordinate of an arbitrary spatial point in the wind field. The Burnham-Hallock model assumes fully developed vortices and does not account for near-ground effects, roll-up, or breakdown. This idealization may limit generalizability to extreme real-world conditions.

To reflect different aircraft types and flight states, the spacing b is selected in the range of 20 m to 70 m. The circulation Γ and spacing b is sampled with correlation through a linear relationship and random perturbation, with its mathematical expression given by:

$$\Gamma = k \cdot b + \delta \quad (3)$$

where k is a scaling factor determined by the aircraft lift coefficient, flight speed, and aspect ratio. The random perturbation δ is introduced to account for variations in aircraft type, weight, and flight state that are not captured by the idealized linear scaling, thereby enhancing the diversity of the training dataset. In this study, we set $k = 10$, $\delta \sim U(-50, 50)$ to represent typical approach configurations of civil aircraft.

The atmospheric turbulence field V_{turb} is generated using the Von Kármán energy spectrum model, whose intensity is controlled by the turbulence dissipation rate ϵ . It is set to range from 10^{-4} to $5 \times 10^{-2} \text{ m}^2/\text{s}^3$ and sampled at equal intervals to cover different turbulence conditions.

The uniform background wind field V_{wind} is employed to simulate the atmospheric advection effect. It is sampled at equal intervals over the range from -3 to 3 m/s , with positive values indicating the positive direction along the y-axis.

Next, the generated wind field is transformed into a coordinate system centered at the lidar location. The wind vectors are then projected onto the radial direction to obtain an original high-resolution radial wind field. A square region with a side length of L is extracted, centered at the midpoint of the line connecting the two vortex cores, as shown in Step 1 of Fig. 1. If the lower boundary of this region falls below the ground, the entire region is shifted upward. The data within this region are then used as the high-resolution ground truth.

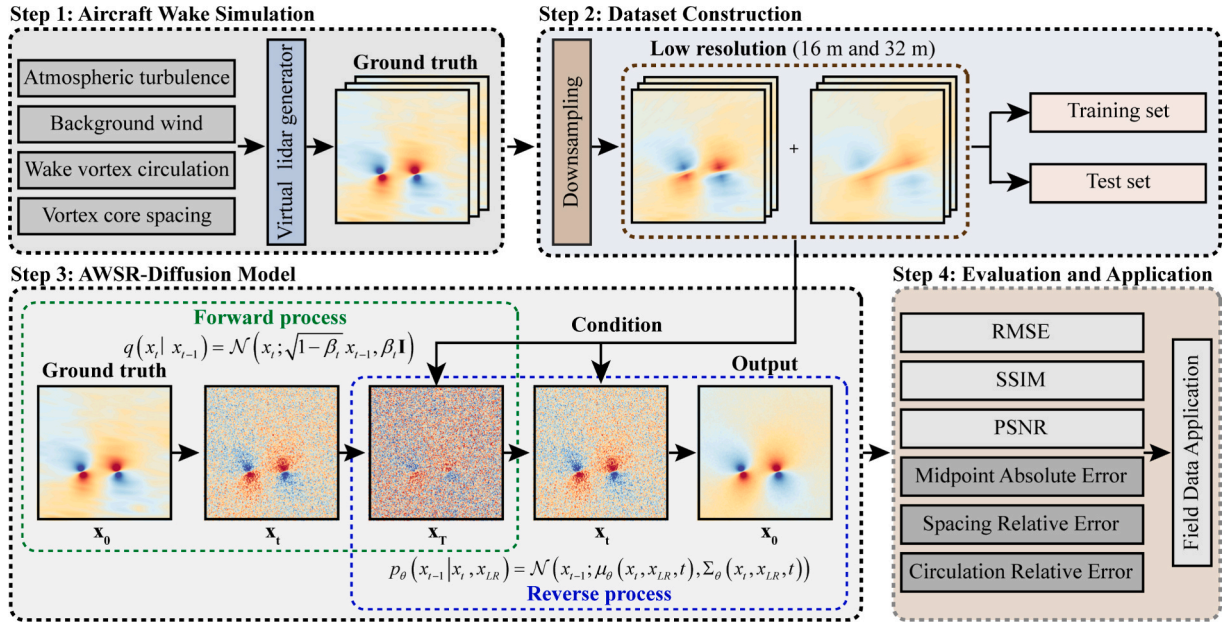


Fig. 1. Flowchart of the aircraft wake super-resolution reconstruction framework using the AWSR-Diffusion model. The workflow consists of four main steps: aircraft wake simulation, dataset construction, diffusion model training, followed by comprehensive quantitative evaluation and field data application.

Subsequently, the virtual lidar is implemented based on the time-domain method to simulate real detection at different low resolutions using range-height indicator (RHI) scanning mode. The raw signals are then processed through range bin segmentation, superposition, temporal splicing, and fast Fourier transform to generate low-resolution radial velocity fields [34]. The key parameters used in the virtual lidar simulation are summarized in Table 1. The same region used for the high-resolution ground truth is then extracted to obtain the low-resolution inputs, thereby forming paired data samples, as shown in Step 2 of Fig. 1.

Finally, to construct a diverse and sufficiently large dataset, background wind speed, turbulence dissipation rate, vortex core spacing and circulation are randomly combined within preset ranges. By repeating the generation process described above, a dataset of 8,000 paired samples with various configurations is generated. These data are then randomly split into training and test sets at a 4:1 ratio for model training and performance evaluation, respectively.

2.2. Vortex parameter inversion method

To quantitatively evaluate the performance of the super-resolution reconstruction model, key vortex parameters need to be extracted from the radial velocity fields. In this study, The vortex core positions are identified following the method of [18]. This method determines the core coordinates in two steps based on Doppler velocity characteristics. First, for each range bin, the span of radial velocities across all elevation angles is computed. The two peak locations in this velocity span indicate the radial distances of the left and right vortex cores. Second, at each

identified radial distance, the vortex core elevation is estimated as the midpoint between the angles corresponding to the maximum and minimum Doppler velocities. This procedure yields the initial vortex core coordinates, which are then transformed to the Cartesian coordinate system for further analysis.

With the vortex cores localized, the circulation is estimated following the RV method [17,35]. This method retrieves the circulation by fitting the measured radial velocities to the Burnham-Hallock vortex model via a least-squares minimization. An iterative procedure is employed to account for the mutual influence of the two vortices, yielding the final circulation estimates. The calculation formula is as follows:

$$\rho(\Gamma_j) = \sum_{k=0}^K \left[\bar{V}_r(R_{Cj}, \varphi_k) - \tilde{V}_r(R_{Cj}, \varphi_k | \Gamma_1, \Gamma_2) \right]^2 \quad (4)$$

where $\bar{V}_r$ is the measured radial velocity of the background-removed wind field at range R and elevation angle φ , and $\tilde{V}_r$ is the theoretical radial velocity calculated from the Burnham-Hallock vortex model for arbitrary values of the circulation Γ .

2.3. AWSR-diffusion model and training

To recover the fine structure of high-resolution aircraft wakes from low-resolution radial velocity fields, this study constructs a super-resolution reconstruction framework based on the Denoising Diffusion Probabilistic Model (DDPM) [36,37]. As shown in Step 3 of Fig. 1, the core of the AWSR-Diffusion model consists of two components: a fixed forward diffusion process and a learnable reverse denoising process. In the forward diffusion process, the model gradually injects Gaussian noise into the original high-resolution radial velocity field x_0 over T consecutive time steps, degrading it into a distribution that approximates standard Gaussian noise. The transition from step $t-1$ to step t is defined by the following probability distribution:

$$q(x_t | x_{t-1}) = \mathcal{N}(x_t; \sqrt{1 - \beta_t} x_{t-1}, \beta_t \mathbf{I}) \quad (5)$$

where x_t denotes the noisy sample at time step t ($t = 1, 2, \dots, T$). $\beta_t \in (0, 1)$ is the noise variance schedule parameter that controls the amount of noise injected at each step. $\mathbf{I}$ is the identity matrix. Defining the cumulative noise schedule as $\bar{\alpha}_t = \prod_{s=1}^t (1 - \beta_s)$, one can directly sample

Table 1
The virtual lidar parameters.

Parameter	Value
Laser wavelength	1550 nm
Pulse duration	100 ns
Transmitted pulse energy	100 μ J
Sampling frequency	250 MHz
Telescope diameter	80 mm
Local oscillator light power	0.1 mW
Backscattering coefficient	$8 \times 10^{-6} \text{ m}^{-1} \text{ sr}^{-1}$
Atmospheric transmittance	0.8

the noisy data at an arbitrary time step t from the original data x_0 without sequential iteration:

$$x_t = \sqrt{\alpha_t}x_0 + \sqrt{1 - \alpha_t}\epsilon, \epsilon \sim \mathcal{N}(0, I) \quad (6)$$

where ϵ is the standard Gaussian noise sampled independently at each training step.

The reverse process gradually denoises via a neural network parameterized by θ , generating the high-resolution reconstruction x_0 from the pure noise x_T , conditioned on the upsampled low-resolution prior x_{LR} :

$$p_\theta(x_{t-1} | x_t, x_{LR}) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, x_{LR}, t), \Sigma_\theta(x_t, x_{LR}, t)) \quad (7)$$

where $\mu_\theta(x_t, x_{LR}, t)$ is the predicted mean of the reverse distribution, output by the denoising network. $\Sigma_\theta(x_t, x_{LR}, t)$ is the variance of the reverse step, typically set as a function of β_t .

For the specific setup of the super-resolution reconstruction task, the low-resolution radial velocity field serves as a prior condition to guide the denoising generation. Specifically, the low-resolution input is first upsampled to match the target resolution via bilinear interpolation. It is then concatenated with the noisy sample x_t at the corresponding time step along the channel dimension to form the joint input for the denoising network. This mechanism encourages the model to fully leverage the global structural constraints provided by the low-resolution data, and accurately recover the vortex details lost due to spatial smoothing. The denoising network adopts a standard U-Net architecture, where the time step t is embedded through sinusoidal positional encoding. The training loss function is the mean squared error between the true noise ϵ and the predicted noise:

$$\mathcal{L}(\theta) = \mathbb{E}_{t, x_0, x_{LR}, \epsilon} [\|\epsilon - \epsilon_\theta(x_t, x_{LR}, t)\|^2] \quad (8)$$

where the expectation is taken over uniformly sampled time steps t , training samples x_0 , conditional inputs x_{LR} , and noise realizations ϵ . $\epsilon_\theta(x_t, x_{LR}, t)$ denotes the noise predicted by the U-Net given the noisy input x_t , the condition x_{LR} , and time step t .

Wake signal degradation differs significantly with range resolution. Accordingly, this study independently trained two sets of AWSR-Diffusion models for the two typical detection resolutions of 16 m and 32 m. The only difference lies in the input resolution of the training data. All input radial velocity fields are unified to a size of 256×256 pixels. The model adopts a U-Net with sinusoidal time embedding combined with a 1000-step DDPM framework, with the noise variance β_t increasing linearly from 1×10^{-4} to 2×10^{-2} . The Adam optimizer is used with a learning rate of 1×10^{-4} ($\beta_1 = 0.9, \beta_2 = 0.999$) and a batch size of 64. All models are implemented in PyTorch and trained on an NVIDIA A6000 GPU.

2.4. Evaluation metrics

To quantitatively evaluate the performance of the super-resolution reconstruction model, a set of metrics is adopted that covers both the wind field reconstruction quality and the accuracy of retrieved vortex parameters.

The root mean square error (RMSE) is a general measure of the average error magnitude. For any predicted variable X and its corresponding ground truth X^{HR} , the RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_i^{SR} - X_i^{HR})^2} \quad (9)$$

where X_i^{SR} and X_i^{HR} denote the super-resolution and high-resolution data at pixel i , respectively, and N is the total number of pixels. This definition applies to both pixel-wise errors in two-dimensional wind fields and sample-wise errors in statistical parameter analysis. For wind field reconstruction, two additional standard metrics are employed. The structural similarity index (SSIM) evaluates the reconstructed wake structures in terms of luminance, contrast, and structural coherence, defined as:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (10)$$

where μ_x and μ_y are the mean intensities, σ_x and σ_y are the standard deviations, σ_{xy} is the covariance of the super-resolution and high-resolution images, and C_1 and C_2 are constants to stabilize the division. The peak signal-to-noise ratio (PSNR) reflects the signal-fidelity of the reconstruction:

$$PSNR = 10 \cdot \log_{10} \left(\frac{I_{\max}^2}{MSE} \right) \quad (11)$$

where $I_{\max}$ is the maximum possible pixel intensity and MSE is the mean squared error between the super-resolution and high-resolution images, as defined above.

For vortex parameter inversion, three additional metrics are employed. The absolute error of the vortex core midpoint position quantifies the spatial localization accuracy of the vortex pair:

$$AE_{\text{midpoint}} = \|\mathbf{c}^{SR} - \mathbf{c}^{HR}\|_2 \quad (12)$$

where $\mathbf{c}$ denotes the midpoint coordinates of the two vortex cores, and the superscripts SR and HR denote super-resolution and high-resolution values. The relative errors of vortex core spacing and circulation are respectively defined as:

$$RE_{\text{spacing}} = \frac{b^{SR} - b^{HR}}{b^{HR}} \times 100\% \quad (13)$$

$$RE_{\text{circulation}} = \frac{\Gamma^{SR} - \Gamma^{HR}}{\Gamma^{HR}} \times 100\% \quad (14)$$

where b and Γ denote the vortex core spacing and circulation, respectively. Positive values indicate overestimation, while negative values indicate underestimation.

3. Result and discussion

3.1. Impact of range resolution on aircraft wake detection

Range resolution is a key factor affecting the performance of wind lidar in aircraft wake detection. To systematically evaluate its impact, this study simulates wake detection at three resolutions, including 8 m, 16 m, and 32 m, using a virtual lidar based on the time-domain method. The results are shown in Fig. 2.

As shown in Fig. 2(a), the original high-resolution radial wind field at 0.5 m resolution features distinct dual-vortex structures and sharp velocity gradients. At 8 m resolution (Fig. 2(b)), the retrieved wind field can still reproduce the overall vortex structure, but the vortex cores begin to smooth out and local details start to diminish. When the resolution decreases to 16 m (Fig. 2(c)), the vortex boundaries become notably blurred. The low-velocity region between the two vortices weakens due to spatial smoothing, leading to reduced structural contrast. At 32 m resolution (Fig. 2(d)), the dual-vortex structure is barely distinguishable. The spatial inhomogeneity of the aircraft wake is severely degraded, indicating that low-resolution detection results can no longer capture its core structural features.

Quantitative analysis further reveals the degradation in both wind speed retrieval accuracy and structural fidelity as resolution decreases. As the resolution coarsens from 8 m to 32 m, the RMSE increases from 1.09 m/s to 1.98 m/s. The retrieved maximum velocity progressively drops from 13.81 m/s to 8.57 m/s, representing a significant reduction compared to the original value of 22.43 m/s. Meanwhile, the retrieved minimum velocity rises from -8.54 m/s to -0.75 m/s, far above the original -16.92 m/s. These results indicate a progressive expansion of overall retrieval error and a weakened ability to capture extreme wind speeds within the wake region. Concurrently, the SSIM drops significantly from 0.87 at 8 m to 0.82

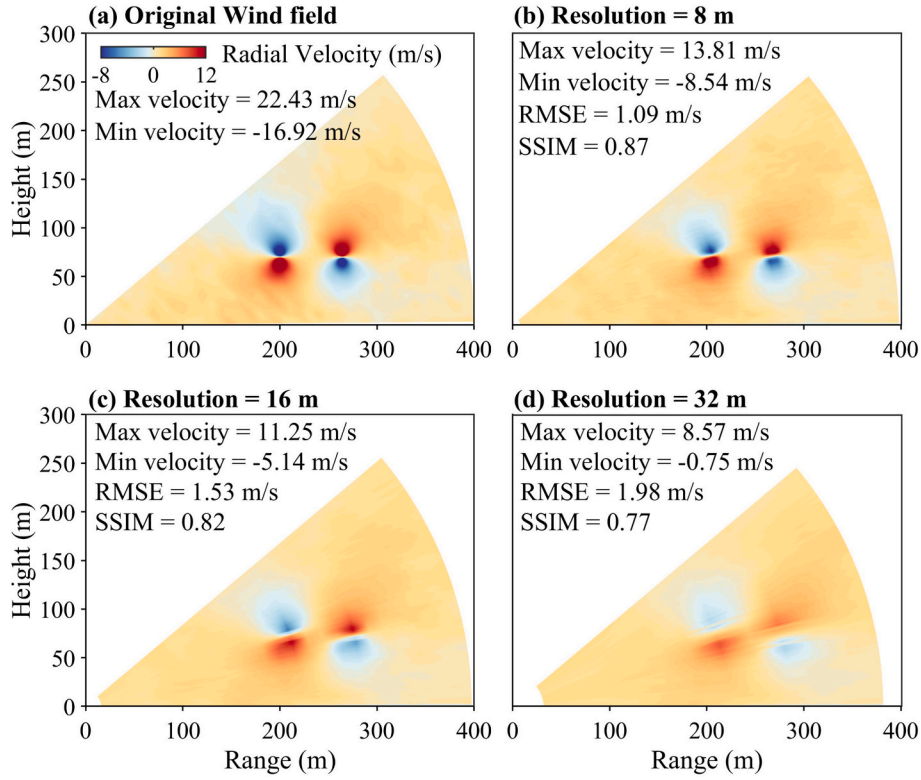


Fig. 2. Original radial wind field and retrieved wind fields from virtual lidar at range resolutions of 8 m, 16 m, and 32 m. The maximum and minimum radial velocities, along with the RMSE of radial velocity and SSIM, are shown for quantitative evaluation.

at 16 m and further to 0.77 at 32 m. As SSIM decreases, the similarity in luminance, contrast, and structure declines markedly. This quantitatively confirms the systematic loss of spatial structure information in the wake caused by insufficient range resolution.

To further investigate the impact of range resolution on the inversion accuracy of key vortex parameters, the virtual lidar simulation is performed on 100 different aircraft wakes at resolutions of 8 m, 16 m, and 32 m. The error assessment is conducted on three parameters: vortex core position, vortex core spacing, and circulation, with the results presented in Fig. 3. These parameters systematically characterize the aircraft wake in terms of spatial location, structure scale, and energy intensity. They are core metrics for assessing wake hazard levels and optimizing separation standards.

Fig. 3(a) shows that as the resolution decreases from 8 m to 32 m, the RMSE of the vortex core position increases sharply from 4.98 m to 12.27 m,

an increase of approximately 146 %. This indicates that lower resolution severely degrades the accuracy of core localization, directly affecting the determination of wake safety boundaries. Fig. 3(b) shows that the RMSE of vortex core spacing increases from 2.65 m to 8.78 m. This suggests that insufficient range resolution leads to misestimation of the wake influence zone, impacting runway scheduling and the rationality of safety separation. In Fig. 3(c), the RMSE of circulation rises dramatically from 60.87 m^2/s to 168.02 m^2/s , an increase of over 176 %. This indicates that under low-resolution conditions, accurately quantifying wake intensity becomes difficult, severely limiting the reliability of hazard level assessment and warning.

The above analysis demonstrates that insufficient range resolution not only degrades wind field structures but also substantially inflates errors in key vortex parameter inversion. This makes it difficult to meet

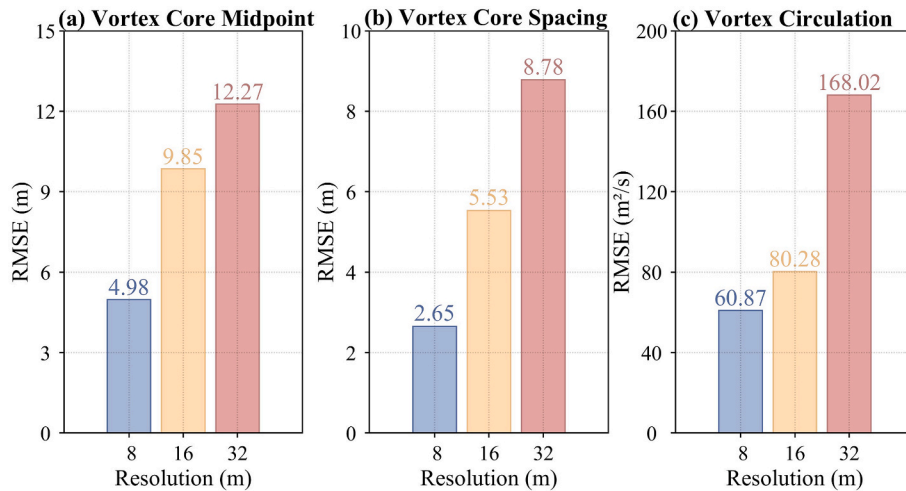


Fig. 3. Quantitative evaluation of aircraft wake vortex parameter retrieval: RMSE values for (a) vortex core midpoint, (b) vortex core spacing, and (c) vortex circulation at 8 m, 16 m, and 32 m range resolutions.

the demands of fine wake monitoring. Given the limitations in improving hardware resolution, algorithmic resolution enhancement offers a feasible solution. This underscores the necessity of research into super-resolution reconstruction.

3.2. Evaluation of super-resolution reconstruction performance

The resolution levels of 16 m and 32 m are typical for wake detection in current real lidar systems. As discussed in Sec. 3.1, they also represent the key range where detection performance becomes significantly limited. To address this limitation, we first identify the optimal reconstruction model at 16 m resolution, and then apply the selected model to both 16 m and 32 m resolutions.

To verify the reconstruction performance of the proposed AWSR-Diffusion, U-Net regression and GAN-based SR models are selected as comparative baselines. They are trained using virtual lidar datasets at a resolution of 16 m. To comprehensively evaluate the model's capability, comparative experiments are carried out on two aircraft wake cases with vortex core spacings of 15 m and 75 m. These two cases are deliberately selected as extreme scenarios beyond the range of training datasets. The 15 m case represents a highly compact vortex pair susceptible to spatial smoothing, while the 75 m case represents a widely separated pair. This setup rigorously tests both the reconstruction performance and the out-of-distribution generalization capability of the models. Visual reconstruction results of all models are presented in Fig. 4, and the corresponding quantitative metrics are listed in Table 2. In the small-scale case with a 15 m vortex core spacing, the input image in Fig. 4(b) suffers from severe blurring due to low resolution. Consequently, the U-Net regression model in Fig. 4(e) fails to recover clear vortex cores, resulting in excessive smoothing. Meanwhile, the GAN-based SR model in Fig. 4(d) identifies the general vortex region but exhibits ambiguous structural edges. In contrast, AWSR-Diffusion in Fig. 4(c) reconstructs sharp and precise vortex cores, closely resembling the Ground Truth in Fig. 4(a). For the large-scale 75 m case, while all models roughly capture the vortex structures, the U-Net model in Fig. 4(j) and the GAN-based SR model in Fig. 4(i) still demonstrate varying degrees of smoothing and distortion in intensity gradients. Conversely, AWSR Diffusion in Fig. 4(h) faithfully recovers the complete dual-vortex configuration, with the core locations and strength distributions most consistent with the Ground Truth.

These qualitative observations are quantitatively corroborated by the metrics reported in Table 2. For the 15 m case, AWSR Diffusion achieves optimal pixel accuracy with an RMSE of 0.561 m/s, PSNR of

Table 2

Quantitative comparison of different super-resolution models.

Vortex Core Spacing = 15 m					
	RMSE (m/s)	SSIM	PSNR (dB)	RE _{spacing} (%)	RE _{circulation} (%)
Input	0.852	0.940	33.434	333.974	48.718
AWSR-Diffusion	0.561	0.958	37.063	17.949	-42.191
GAN-based SR	0.620	0.951	36.194	26.284	-42.747
U-Net regression	0.640	0.951	35.916	21.161	-48.371
Vortex Core Spacing = 75 m					
	RMSE (m/s)	SSIM	PSNR (dB)	RE _{spacing} (%)	RE _{circulation} (%)
Input	1.394	0.863	29.156	-2.258	-7.280
AWSR-Diffusion	0.528	0.952	37.581	-0.512	-17.453
GAN-based SR	0.620	0.946	36.194	-2.430	-18.749
U-Net regression	0.625	0.944	36.117	-2.302	-22.708

37.063 dB, and SSIM of 0.958. Its relative errors for spacing and circulation are 17.949 % and -42.191 %, respectively, surpassing the GAN and U-Net model. This trend continues for the 75 m case, where AWSR Diffusion performs best. Given its superior performance, the AWSR-Diffusion model is selected as the final model and proceed to train two separate versions of it at 16 m and 32 m resolutions, respectively.

Fig. 5 presents a comparison between representative reconstructed results and the original high-resolution radial wind field (Ground Truth). Notably, the coordinate system in the figure has been shifted, with the origin moved from the lidar location to the lower-left corner of the extracted region. This transformation provides a clearer view of the local details of the wake vortices.

After super-resolution reconstruction, the overall retrieval accuracy and structural similarity of the wind field are significantly improved. Fig. 5(b) and (c) show the input and super-resolution output at resolution of 16 m, respectively. The RMSE of the reconstructed results decreases from 0.99 m/s to 0.35 m/s, a reduction of approximately 64.6 %, while the SSIM increases from 0.89 to 0.94. Meanwhile, Fig. 5(c) and (d) show the input and super-resolution output at resolution of 32 m, respectively. The RMSE decreases from 1.09 m/s to 0.75 m/s, a reduction of about 31.2 %, and the SSIM increases from 0.80 to 0.82. These results demonstrate the effectiveness of super-resolution reconstruction.

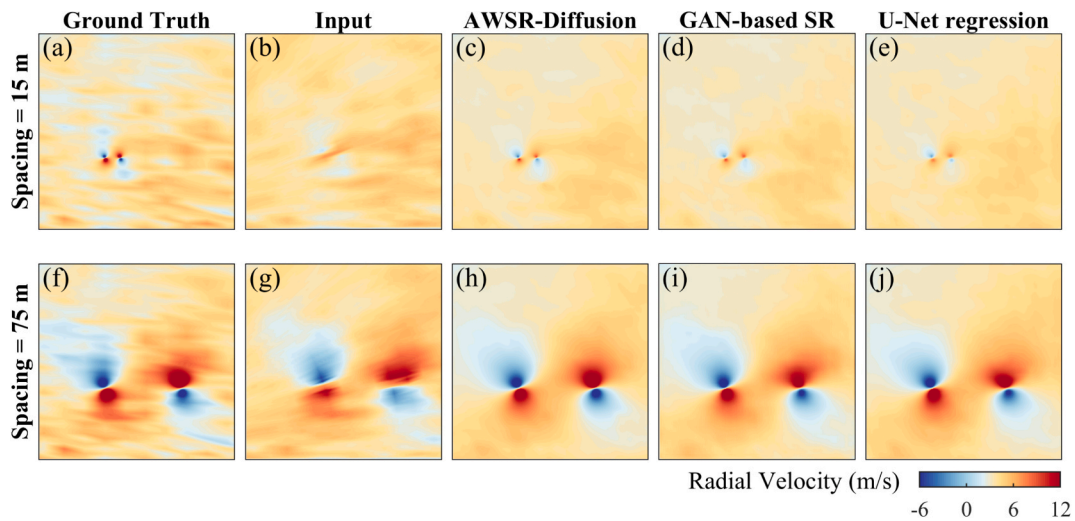


Fig. 4. Comparison of reconstruction performance of different super-resolution models for aircraft wake radial velocity fields at vortex core spacings of 15 m and 75 m. Columns from left to right: ground truth, low-resolution input, AWSR-Diffusion, GAN-based SR, U-Net regression. The top row (a)-(e) corresponds to vortex core spacing of 15 m, while the bottom row (f)-(j) corresponds to vortex core spacing of 75 m.

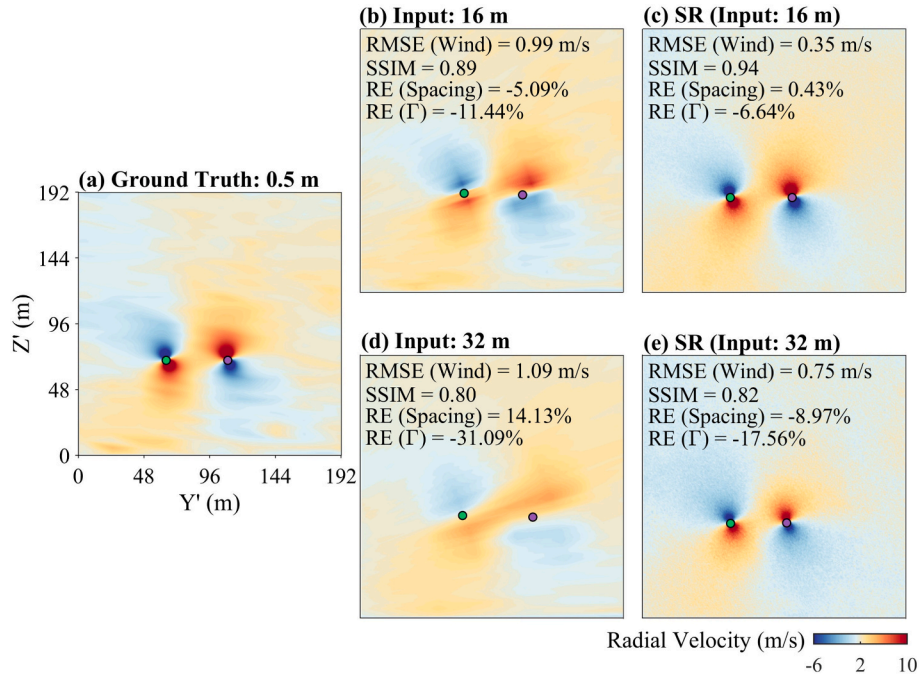


Fig. 5. Comparison of ground truth and super-resolution (SR) reconstructed aircraft wake radial velocity fields. (a) High-resolution ground truth. (b, d) Low-resolution (LR) inputs at 16 m and 32 m. (c, e) Corresponding SR results. Quantitative assessment includes RMSE, SSIM, and relative errors (RE) for vortex core spacing and circulation.

It not only significantly reduces wind speed retrieval errors but also restores the spatial structure and local details of the wind field.

The AWSR-Diffusion model also demonstrates strong error correction capability in retrieving key vortex parameters. With an input resolution of 16 m, the relative error of vortex core spacing is reduced from -5.09 % to 0.43 %, and the relative error of circulation decreases from -11.44 % to -6.64 %. With an input resolution of 32 m, the relative

error of vortex core spacing narrows from 14.13 % to -8.97 %, while the circulation relative error drops from -31.09 % to -17.56 %. These improvements show that super-resolution reconstruction enhances both overall wind field structure and key vortex parameter accuracy. This provides stronger support for wake safety assessment.

To quantitatively evaluate the reliability and generalization ability of the reconstruction model, the test set at an input resolution of 16 m is

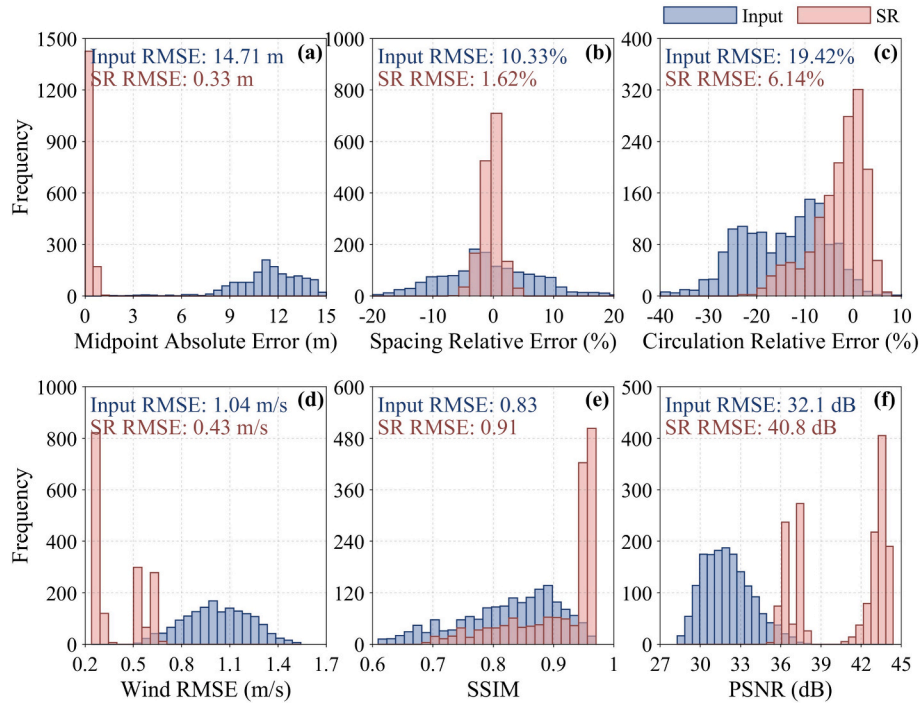


Fig. 6. Error evaluation of the model on the test set at an input resolution of 16 m. Frequency distribution histograms compare low-resolution input (blue) and SR reconstruction (red) for six metrics: (a) vortex core midpoint absolute error, (b) vortex core spacing relative error, (c) circulation relative error, (d) RMSE of wind speed field, (e) SSIM, and (f) PSNR. For each metric, the RMSE of its distribution across the 1,600 test samples is provided for both input and SR results.

analyzed. Fig. 6 compares the statistical distributions of multiple error metrics between the low-resolution inputs and the corresponding SR results. After reconstruction, the distributions of six error metrics become more concentrated and shift toward the high-quality range. To evaluate the overall performance, the RMSE of each error metric across the 1,600 test samples is calculated. This RMSE captures both the magnitude and variability of the errors for each metric, providing a comprehensive measure of reconstruction accuracy.

As shown in Fig. 6(a-c), super-resolution reconstruction significantly reduces errors in key vortex parameters. The RMSE of the vortex core midpoint absolute error decreases from 14.71 m to 0.33 m, with the distribution of midpoint absolute error highly concentrated in the 0–3 m range. This indicates that the model corrects vortex core location with high precision. The RMSE of the vortex core spacing relative error drops from 10.33 % to 1.62 %, while that of the circulation relative error declines from 19.42 % to 6.14 %. These results demonstrate that the model effectively corrects both the spatial scale and intensity of the wake vortices.

In terms of overall wind field accuracy and image quality, as shown in Fig. 6(d-f), the RMSE of the wind speed errors decreases from 1.04 m/s to 0.43 m/s. Meanwhile, the RMSE of SSIM values improves from 0.83 to 0.91, and the RMSE of PSNR values rises from 32.1 dB to 40.8 dB. These results demonstrate substantial improvements in both pixel-level data fidelity and visual clarity of the reconstructed wind field. This further confirms the robustness and consistency of the model's performance across diverse wake conditions.

To investigate the sensitivity of the reconstruction model to variations in the parameters used to generate the ground-truth wind field, three parameters are considered: turbulence dissipation rate, background wind speed, and vortex core spacing. For each parameter under investigation, it is uniformly sampled with 100 values within its preset range while the other two parameters are fixed at their typical values. The typical values are a background wind speed of 1 m/s, a turbulence dissipation rate of $0.185 \text{ m}^2/\text{s}^3$, a vortex core spacing of 40 m, and a circulation of $400 \text{ m}^2/\text{s}$. Fig. 7 presents their relationship with super-resolution performance at 16 m input resolution. For each parameter,

the SR results consistently achieve lower RMSE and higher SSIM than the low-resolution inputs across the entire tested range, demonstrating the model's robust reconstruction capability within the preset parameter space. The vertical gap between the fitted curves for the input and SR results reflects the improvement margin. A larger gap indicates a greater improvement in either wind error reduction or structural fidelity.

As shown in Fig. 7(a) and (d), a higher turbulence dissipation rate leads to increased RMSE and decreased SSIM for both the low-resolution inputs and the SR results. Stronger turbulence introduces more complex microstructures, making the wind field harder to capture. The improvement margin narrows slightly with increasing turbulence. This indicates that under strong turbulence, the wake structure is severely distorted by turbulent mixing, significantly degrading the effective structural information contained in low-resolution inputs. Consequently, the model can only recover limited fine-scale features, leading to a reduced overall improvement margin.

In terms of uniform background wind speed, as shown in Fig. 7(b), the RMSE of the low-resolution inputs ranges from 0.8 m/s to 1.0 m/s and is reduced by SR to 0.2–0.4 m/s. Both the input and SR results exhibit a slight increasing trend with wind speed magnitude, since RMSE inherently depends on the wind speed scale. For fair comparison across different wind speeds, the relative RMSE gap, which is normalized by the low-resolution RMSE, is used to characterize the improvement margin. This metric drops from 69 % at low wind speeds to 60 % at high wind speeds. As shown in Fig. 7(e), SSIM behaves differently. At low wind speeds, the flow is dominated by turbulent structures, yielding lower SSIM. As background wind speed increases, the advective effect becomes more dominant, leading to a more uniform flow field and a gradual improvement in SSIM. However, this improvement primarily reflects the increasing uniformity of the background flow rather than a better reconstruction of the wake structures themselves. The SSIM gap decreases from approximately 0.09 at low wind speeds to about 0.02 at high wind speeds, confirming that the improvement margin shrinks when the low-resolution input already has decent quality.

Regarding vortex core spacing, as shown in Fig. 7(c) and (f), under low-resolution input, the RMSE decreases significantly from 2.0 m/s to

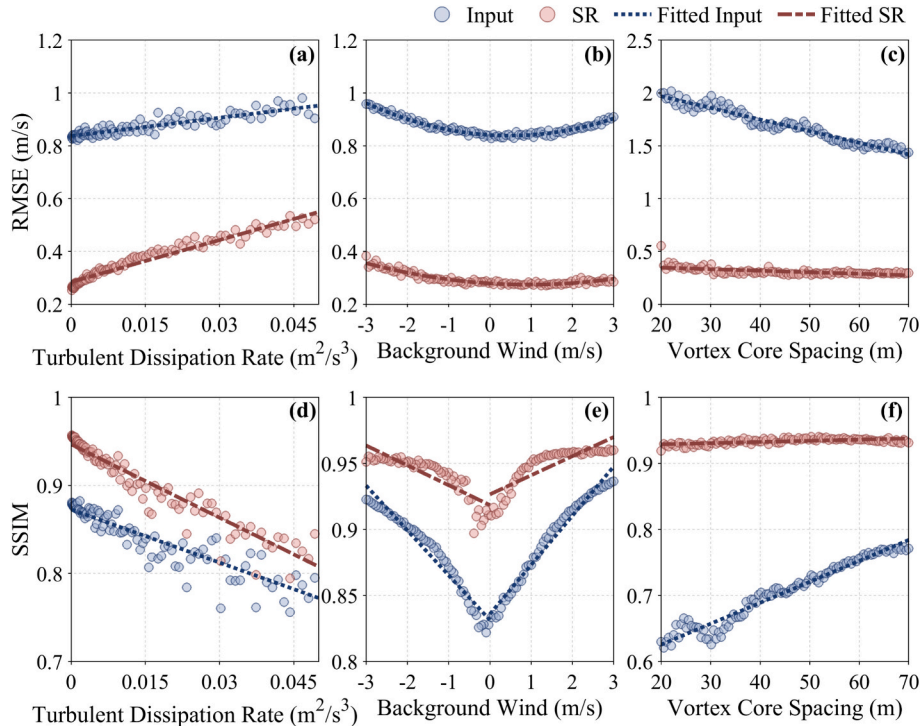


Fig. 7. Impact of turbulent dissipation rate (a, d), background wind speed (b, e), and vortex core spacing (c, f) on aircraft wake SR reconstruction performance, with RMSE and SSIM for low-resolution input (blue) and SR reconstruction (red).

1.4 m/s as the vortex core spacing increases. Meanwhile, the SSIM steadily improves from 0.6 to 0.8. This is because, at a fixed range resolution, larger-scale structures are better captured. After super-resolution reconstruction, the RMSE drops to a low range of 0.3–0.5 m/s, and the SSIM increases to above 0.9, with significantly reduced fluctuations. This indicates that the model enhances its ability to distinguish and reconstruct the two vortex cores by restoring micro-structure flow field structures and gradient features. Consequently, the structural confusion caused by insufficient range resolution is substantially reduced. The magnitude of improvement decreases significantly as the vortex core spacing increases. The absolute RMSE gap narrows from approximately 1.6 m/s to 1.1 m/s, and the SSIM gap narrows from approximately 0.31 to 0.16. At small spacings, the twin-vortex structures overlap significantly, and the spatial smoothing effect nearly erases all details, enabling the model to achieve substantial improvements. At large spacings, the two vortices are clearly separated, and the low-resolution input already retains some structural information, naturally limiting the scope for further model improvement. This capability is particularly valuable for monitoring wakes from narrow-body aircraft with small wing spans, which is a key contribution of this study.

3.3. Field experiment application

To demonstrate the model's applicability to real measurements, it is applied to field aircraft wake data acquired by a CDWL at Guangzhou Baiyun International Airport (23.3925°N, 113.2989°E), as shown in Fig. 8. As one of China's busiest airports in terms of passenger throughput, its takeoff and landing efficiency is a key factor limiting overall capacity. The lidar, originally deployed for wind shear detection and forecasting, has a detection range of 30 km. In the wake detection experiment, the laser pulse width is set to 100 ns, corresponding to a range resolution of 15 m and a temporal resolution of 1 s. Detailed parameters and applications of the lidar can be found in references [38].

The AWSR-Diffusion model is applied to reconstruct the corresponding low-resolution wind fields, with representative results shown in Fig. 9. Fig. 9(a) and (d) display the complete RHI scans, where the dashed black boxes mark the wake vortex regions extracted as low-resolution model inputs, shown in Fig. 9(b) and (e). The low-resolution inputs from lidar field detection show significant blurring in velocity gradients within the wake vortex core regions. The high-velocity characteristics and velocity shear structures of the dual vortices are notably smoothed, making it difficult to accurately define the wake boundaries. In contrast, the wind field structure is markedly improved after super-resolution reconstruction, as shown in Fig. 9(c) and (f).

Regarding key vortex parameter inversion, as illustrated in Fig. 9(b) and (c), the left vortex circulation rises from 324.82 m²/s in the low-resolution input to 341.11 m²/s after super-resolution, while the right vortex circulation increases from 335.01 m²/s to 410.45 m²/s. As shown in Fig. 9(e) and (f), the left vortex circulation improves from 295.67 m²/s to 389.16 m²/s, and the right vortex circulation grows from 220.30 m²/s to 383.10 m²/s. The reconstructed circulation magnitudes are physically more consistent with the theoretical intensity of aircraft wake

vortices, recovering the underestimated vortex strength caused by lidar spatial averaging. It demonstrates that the super-resolution model effectively recovers wake structures and key vortex parameters even in complex field environments.

It should be noted that due to current hardware constraints, the present field experiment could not simultaneously acquire true high-resolution wake reference data matching the low-resolution measurements. In addition, the field data used in this study did not include synchronized flight parameters such as aircraft type, weight, and trajectory. The analysis is therefore primarily qualitative, and a rigorous quantitative error assessment has not yet been performed. Nevertheless, these results provide encouraging evidence of the model's applicability in complex airport environments, while quantitative evaluation of its practical utility will require future validation using synchronized high-resolution and low-resolution lidar systems.

4. Conclusion

This study proposes an aircraft wake reconstruction method that fuses virtual lidar simulation and deep learning-based super-resolution. The method addresses the challenges of blurred wake structures and inaccurate parameter inversion caused by insufficient range resolution in wind lidar. The main findings are summarized as follows.

First, the AWSR-Diffusion framework is developed to reconstruct high-resolution wake wind fields from low-resolution inputs without hardware modifications. The model demonstrates excellent reconstruction performance under both 16 m and 32 m low-resolution inputs, effectively correcting key vortex parameters. At an input resolution of 16 m, the RMSE of the vortex core spacing relative error drops from 10.33 % to 1.62 %, and that of the circulation relative error declines from 19.42 % to 6.14 %. Within the preset parameter ranges that cover typical operational conditions at real airports, the model consistently improves both wind field accuracy and structural fidelity.

Second, the virtual lidar simulation is developed to generate paired low- and high-resolution datasets, overcoming the shortage of high-resolution wake observations for model training. The simulation integrates a parametric wake vortex model, von Kármán turbulence, and a time-domain virtual lidar model. This creates a controlled yet realistic environment that not only supplies sufficient training data but also enables systematic evaluation across diverse atmospheric and operational conditions.

Third, the reconstruction performance and parameter sensitivity are systematically evaluated across a wide range of wake and atmospheric conditions. The model consistently outperforms low-resolution inputs across all tested conditions. For a given wake, super-resolution performs better when the structure is more distinct from the ambient flow, corresponding to lower turbulence and weaker background winds. At a fixed range resolution, smaller vortex core spacings suffer more severe smoothing in low-resolution measurements. This leaves greater room for the model to recover missing details and yielding larger relative improvements. Application of the model to field data from Guangzhou Baiyun International Airport shows encouraging qualitative results, indicating its potential applicability in complex airport environments. However, due to the absence of synchronized high-resolution data, this field application remains primarily qualitative and should be interpreted as a feasibility demonstration.

Overall, this study demonstrates a viable approach for refined aircraft wake monitoring, with potential contributions to dynamic safety separation optimization. Future work will focus on validating the super-resolution model through integrated high-resolution and low-resolution lidar systems, and developing an error propagation model for quantitative error correction. These efforts aim to restore true vortex parameters more accurately and robustly.

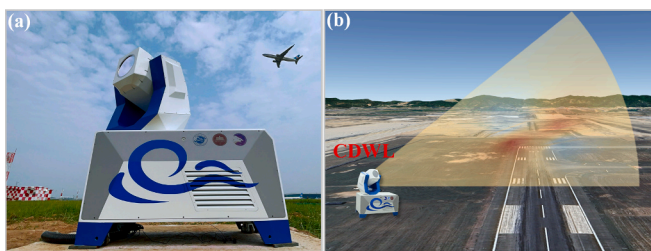


Fig. 8. (a) Photograph of the CDWL deployed at the airport. (b) Schematic of the RHI scanning mode, showing the CDWL positioned 180 m from the runway centerline and the scanning sector.

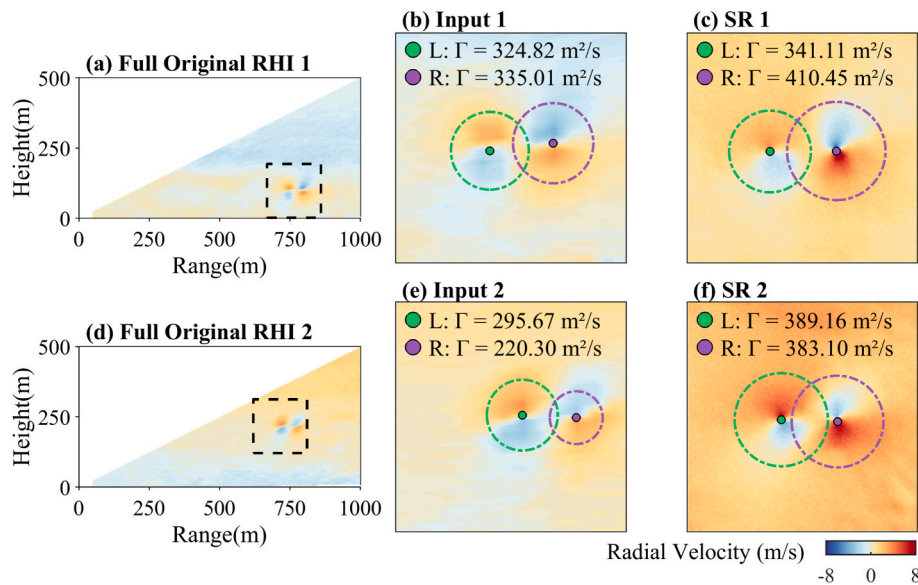


Fig. 9. Super-resolution reconstruction performance of aircraft wake using field data. (a, d) Full original RHI wind fields for two wake cases, (b, e) low-resolution input slices (Input 1 and Input 2), (c, f) corresponding SR outputs (SR 1 and SR 2). Green and purple markers denote left (L) and right (R) vortex cores, with labeled circulation Γ and dashed circles indicating vortex circulation scale.

Financial support

This work is supported by the National Natural Science Foundation of China (No.42405137) and the National Training Program of Innovation and Entrepreneurship for Undergraduates (No.202510300005).

CRediT authorship contribution statement

Jiaxiu Liu: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Jinlong Yuan:** Writing – review & editing, Resources, Funding acquisition, Conceptualization. **Haoyu Yang:** Visualization, Software. **Hao Wu:** Data curation. **Yue Liu:** Writing – review & editing, Validation. **Shuo Zhang:** Writing – review & editing, Validation. **Haiyun Xia:** Writing – review & editing, Resources. **Yiming Zhang:** Writing – review & editing, Resources. **Hao Wang:** Writing – review & editing, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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