Generative Modeling of Microweather Wind Velocities for Urban Air Mobility

IEEE Aerospace Conference

Session: Machine Learning / Artificial Intelligence (ML/AI) for Aerospace Applications

March 1-8, 2025

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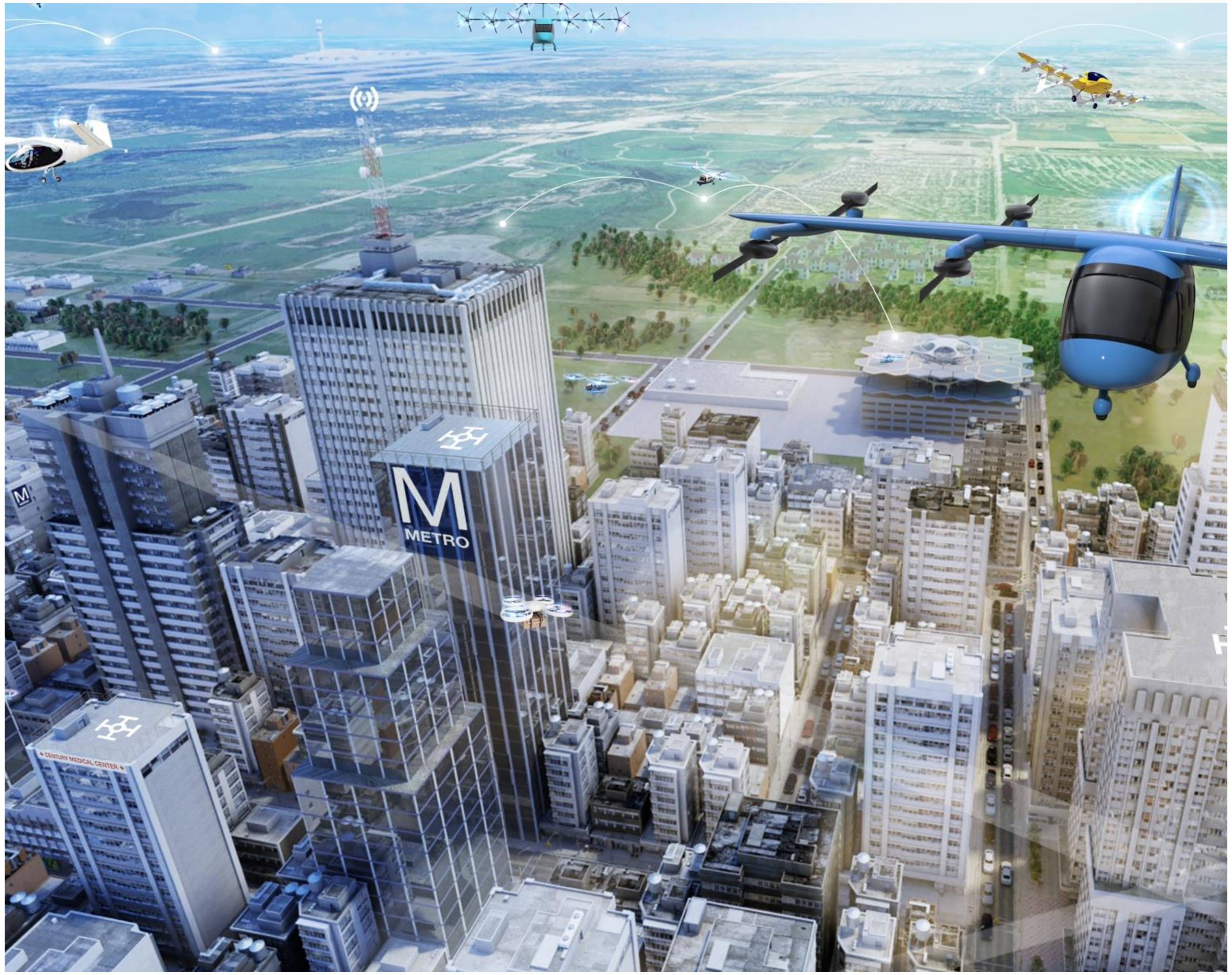
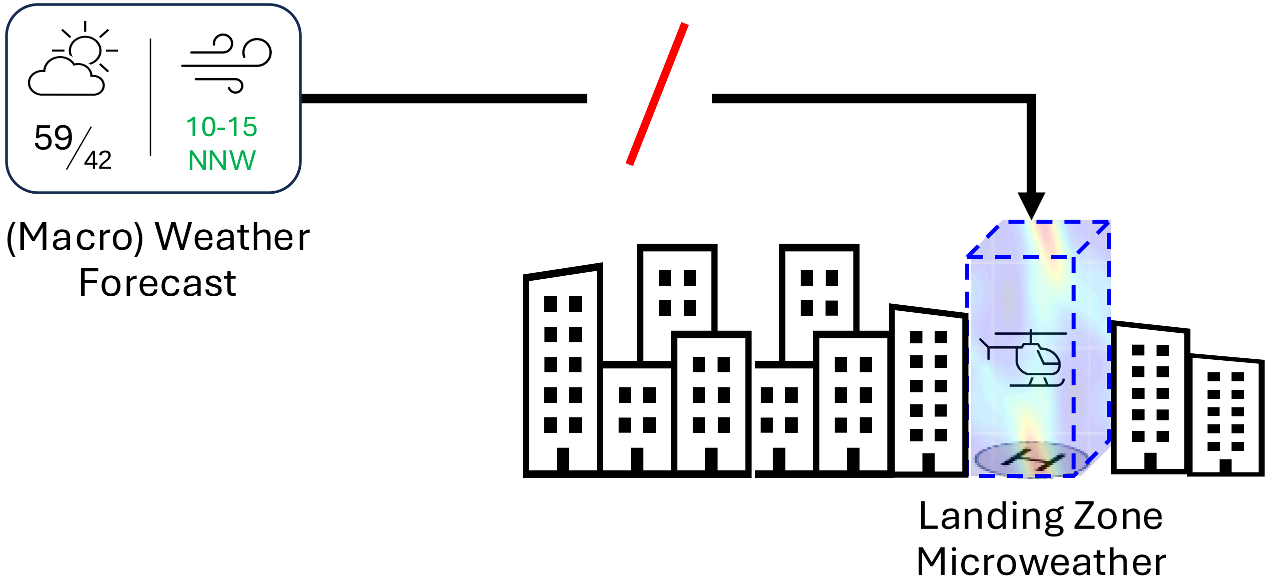
Motivation: Urban Air Mobility (UAM)

- Barriers to Adoption
  - Infrastructure
  - Air traffic management
  - Noise
  - Manufacturability
  - Autonomy/automation
  - **Weather**



Problem: Microweather Nowcasting

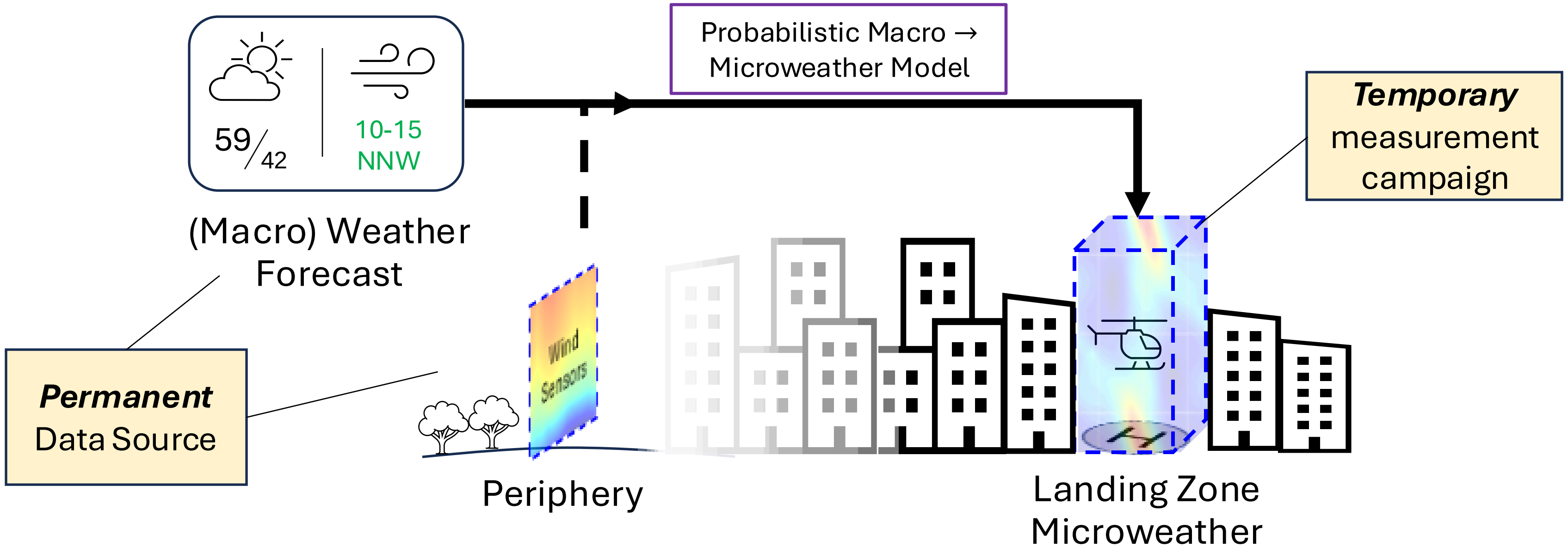
- Assessing local wind velocities (*microweather*) over short time horizons (*nowcasting*)



- Challenges:
  - ➢ Mild macro weather conditions can yield unsafe urban microweather conditions
  - ➢ Measurements via permanently installed wind profiler system are not practical
  - ➢ Traditional physics-based predictions are not computationally tractable
  - ➢ Machine learning approaches are largely deterministic, ignoring wind variability

Goal: Reliable and Realtime Microweather

- Enabling accurate, efficient, and *probabilistic* wind flow field predictions

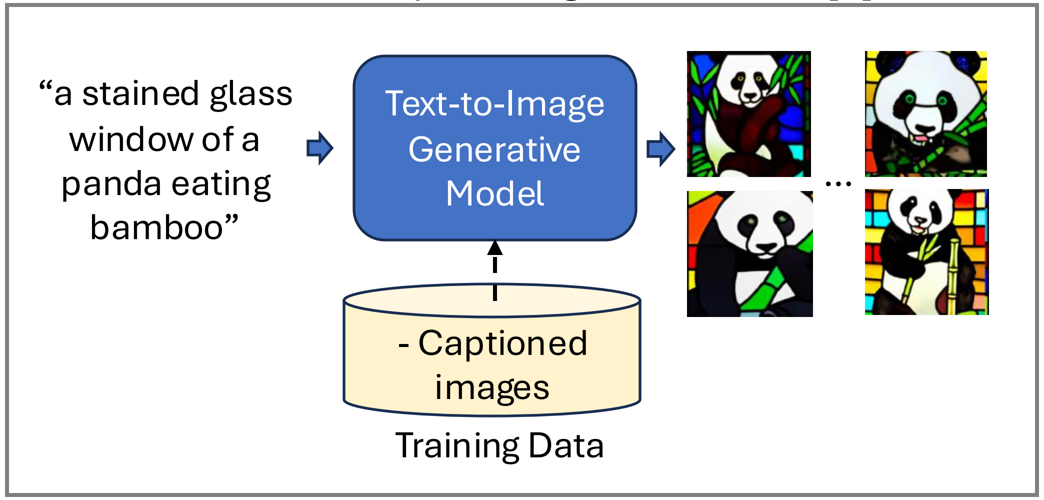


- Requirements:
  - ➢ Does not require permanent wind profiling system installation
  - ➢ Updates predictions in realtime based on current information
  - ➢ Captures random variability in wind fields
  - ➢ Makes predictions continuously in space and time

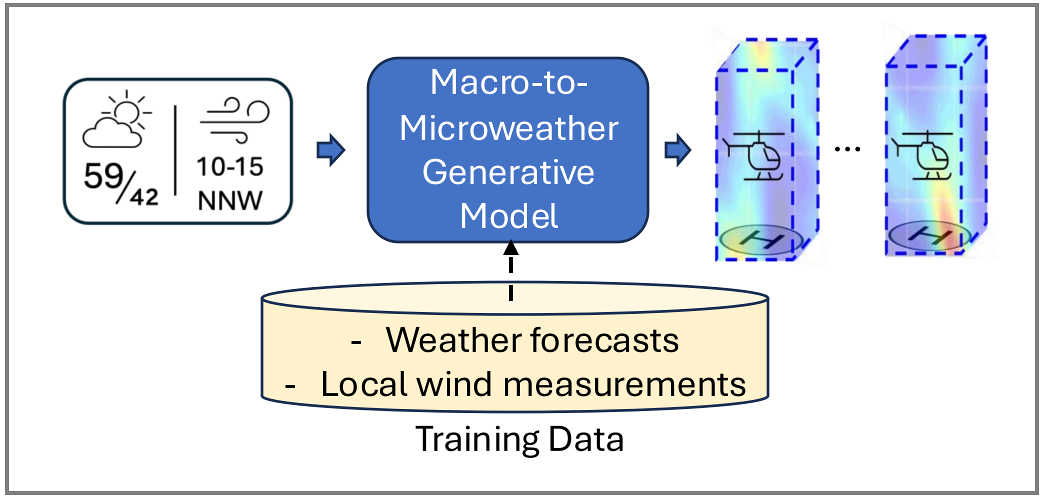
Proposed Solution: Generative Modeling

- Generative models learn to produce realistic samples based on training data

Common Example: Image Generation [1]



Our Approach: Microweather Nowcasting



- Generative models considered in this study:
  - Gaussian mixture models (GMMs) [2] → Baseline method
  - Denoising diffusion probabilistic models (DDPMs) [3]
  - Flow matching (FM) [4]

  } → Deep generative models

[1] A. Nichol et al. GLIDE: Towards Photorealistic Image Generation and Editing with Text-Guided Diffusion Models. 2021.
[2] C. M. Bishop. Pattern Recognition and Machine Learning. 2006.
[3] J. Ho, A. Jain, P. Abbeel. Denoising Diffusion Probabilistic Models. 2020.
[4] Y. Lipman et al. Flow Matching for Generative Modeling. 2022.

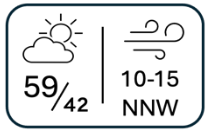
Generative Modeling (1/3)

- Goal: approximate an unknown probability distribution, $p_\theta(\boldsymbol{x}) \approx q(\boldsymbol{x})$, from observed samples $\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(N)} \sim q(\boldsymbol{x})$ by learning θ

- Can also learn conditional distribution, $q(\boldsymbol{x}|\boldsymbol{c})$, if auxiliary information, $\boldsymbol{c}$, is available
- For example, microweather nowcasting:

Microweather wind profile

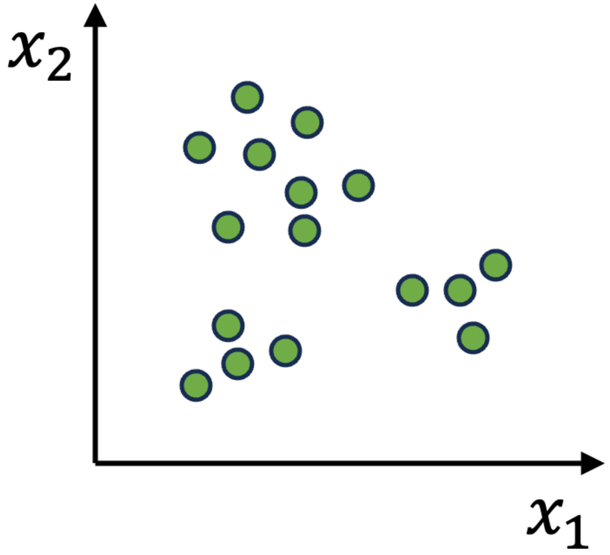
Macroweather conditions



$$\hat{\boldsymbol{x}} \sim p_\theta(\boldsymbol{x}|\boldsymbol{c})$$

Can use a collection of generated samples, $\{\hat{\boldsymbol{x}}^{(i)}\}_{i=1}^{M}$, to make probabilistic assessment of local wind conditions for UAM

Observed Samples



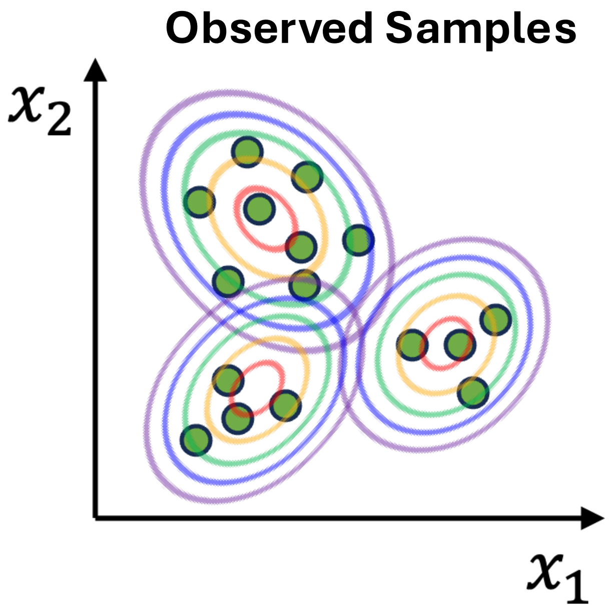
Generative Modeling (2/3)

- Goal: approximate an unknown probability distribution, $p_\theta(\boldsymbol{x}) \approx q(\boldsymbol{x})$, from observed samples $\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(N)} \sim q(\boldsymbol{x})$ by learning θ

- **Gaussian mixture models (GMMs)** explicitly fit a parametric distribution to observations

$$p_\theta(\boldsymbol{x}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k)$$

  - Training is equivalent to finding $\theta = [\mu_k, \Sigma_k]$
  - **Strengths**: easy/fast to train
  - **Weaknesses**: difficult to incorporate conditioning information; difficult to scale to high-dimensional data



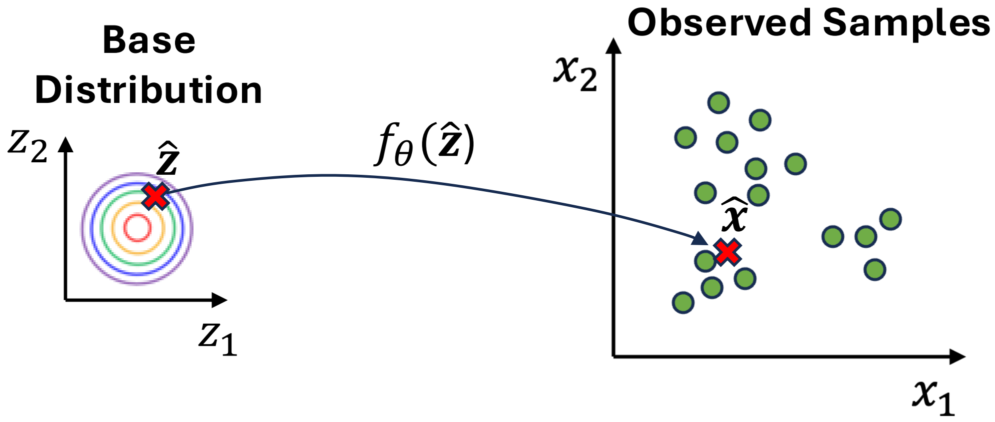
Generative Modeling (3/3)

- Goal: approximate an unknown probability distribution, $p_\theta(\boldsymbol{x}) \approx q(\boldsymbol{x})$, from observed samples $\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(N)} \sim q(\boldsymbol{x})$ by learning θ

- **Deep generative models (DGMs)** transform samples from a known base distribution to samples from $q(\boldsymbol{x})$ using deep neural networks

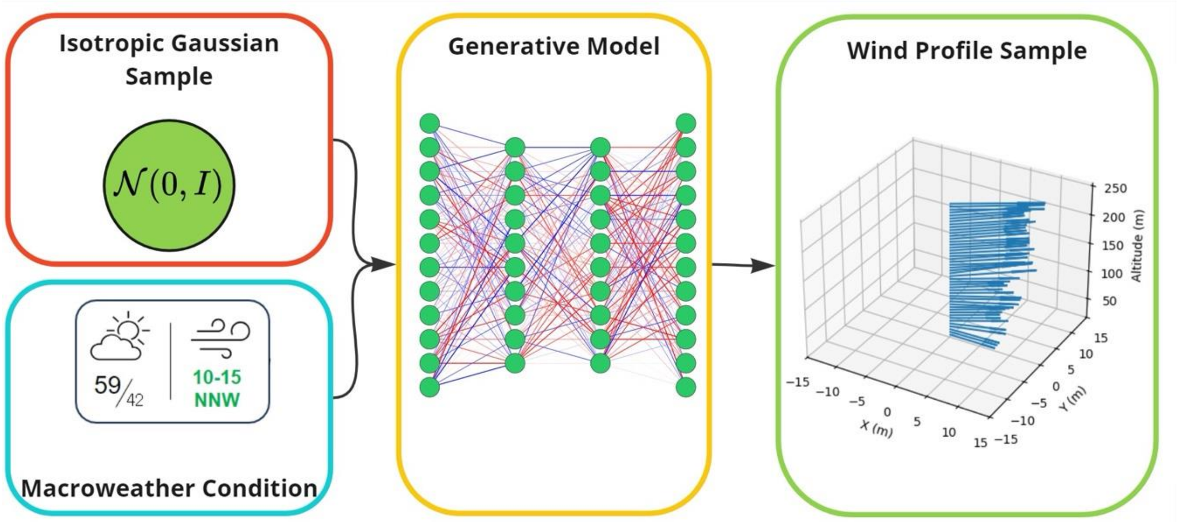
$$\widehat{\boldsymbol{x}} \sim p_\theta(\boldsymbol{x}) = f_\theta(\hat{\boldsymbol{z}}), \qquad \hat{\boldsymbol{z}} \sim \mathcal{N}(\boldsymbol{z}|\boldsymbol{0}, \boldsymbol{1})$$

  - **DDPMs** progressively add noise to dataset then learn to reverse the process
  - **FM** uses a differential equation that evolves the base distribution to $q(\boldsymbol{x})$



Approach

- **Goal**: Implement a proof of concept for a probabilistic map from macro → microweather with generative modeling
- **Microweather Data**
  - Velocity vs. altitude from Sonic Detection and Ranging (SoDAR)
  - 10 day measurement campaign at NASA Armstrong Flight Research Center (~6500 samples)
- **Macroweather Data**
  - Hourly forecasts from wunderground.com*



Training Data

Hourly Forecasts

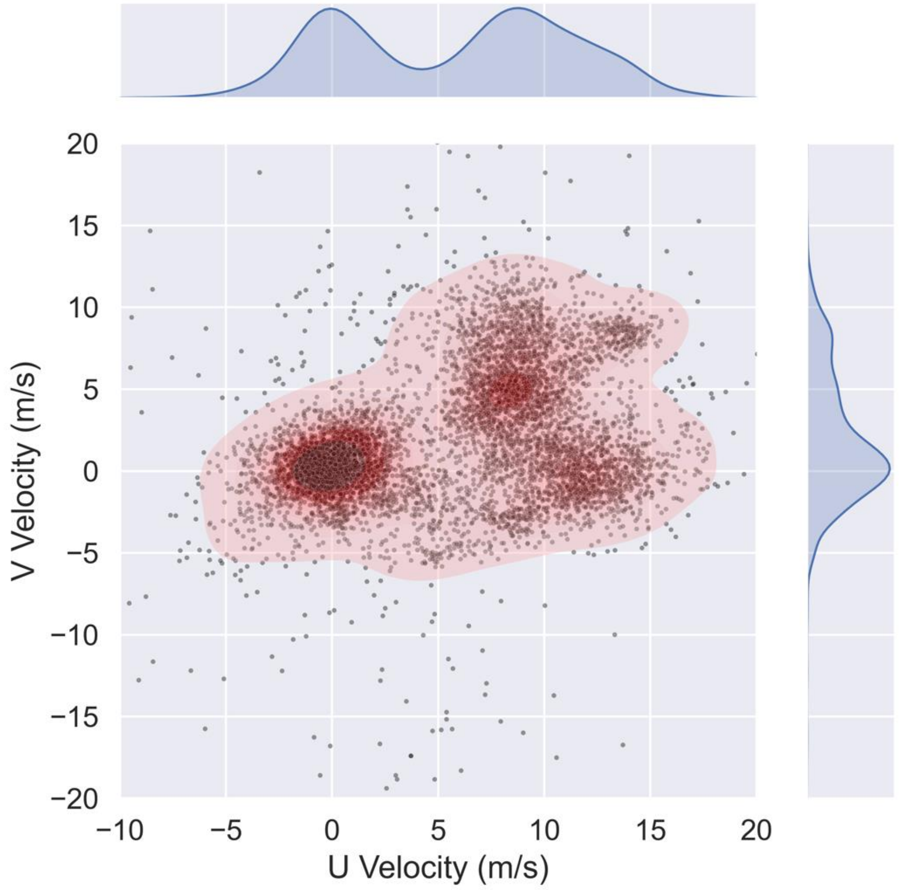
wunderground.com

SoDAR Measurements Every Two Minutes

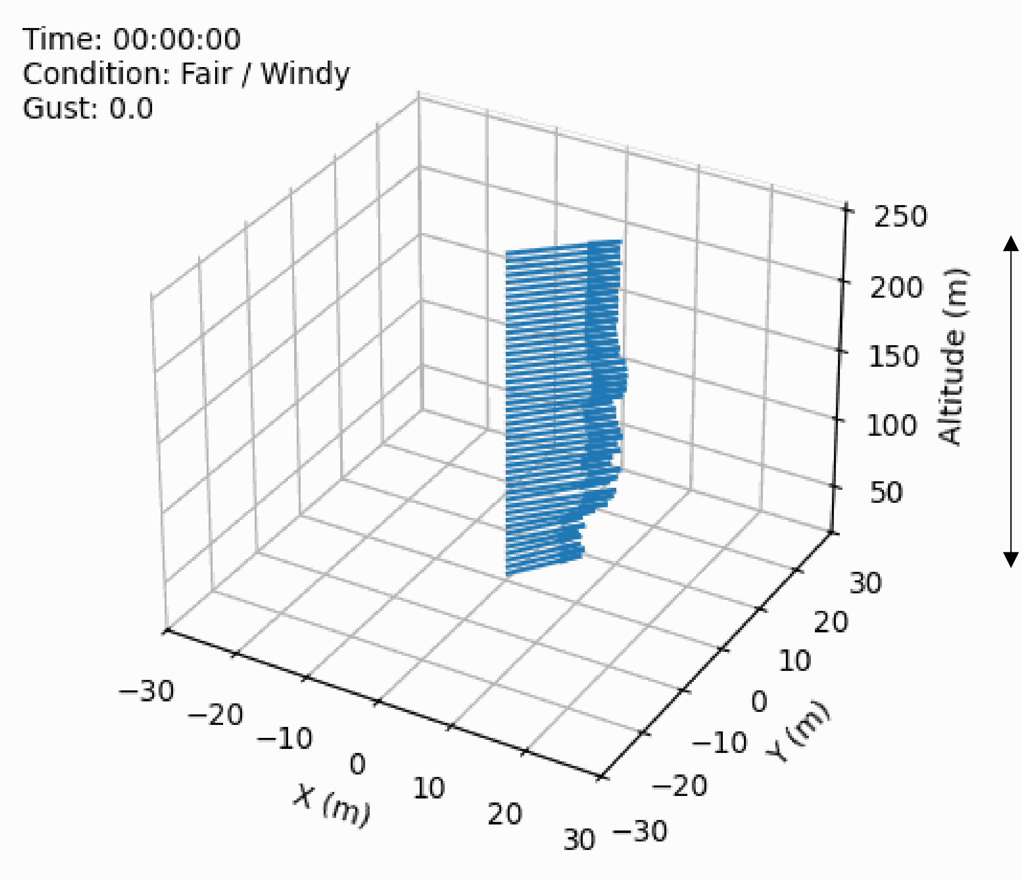
*This is not an endorsement by the National Aeronautics and Space Administration (NASA)

SoDAR Wind Measurement Data

Altitude-Averaged Measurement Distribution



Wind Measurements Throughout a Single Day

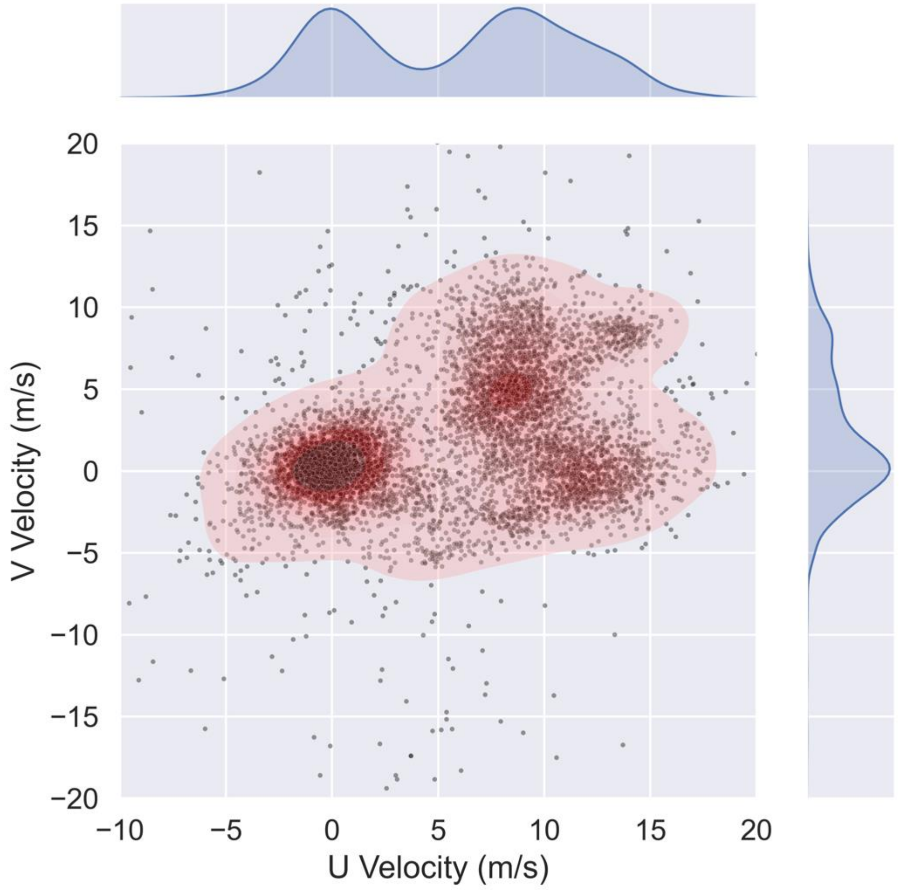


47 discrete measurements

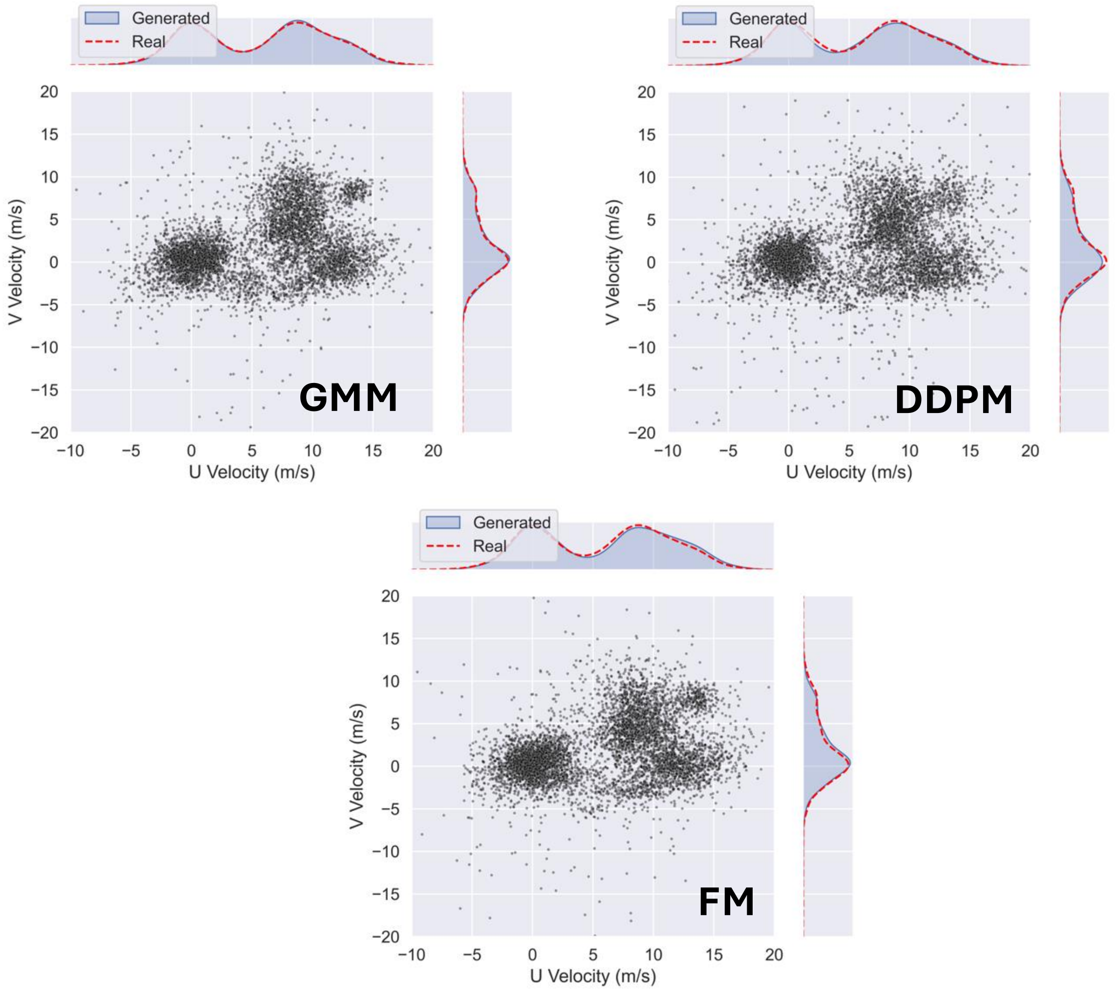
Results: Unconditional Wind Generation

What are plausible microweather wind profiles ***at any given time*** (independent of macroweather conditions)?

SoDAR Measurement Distribution

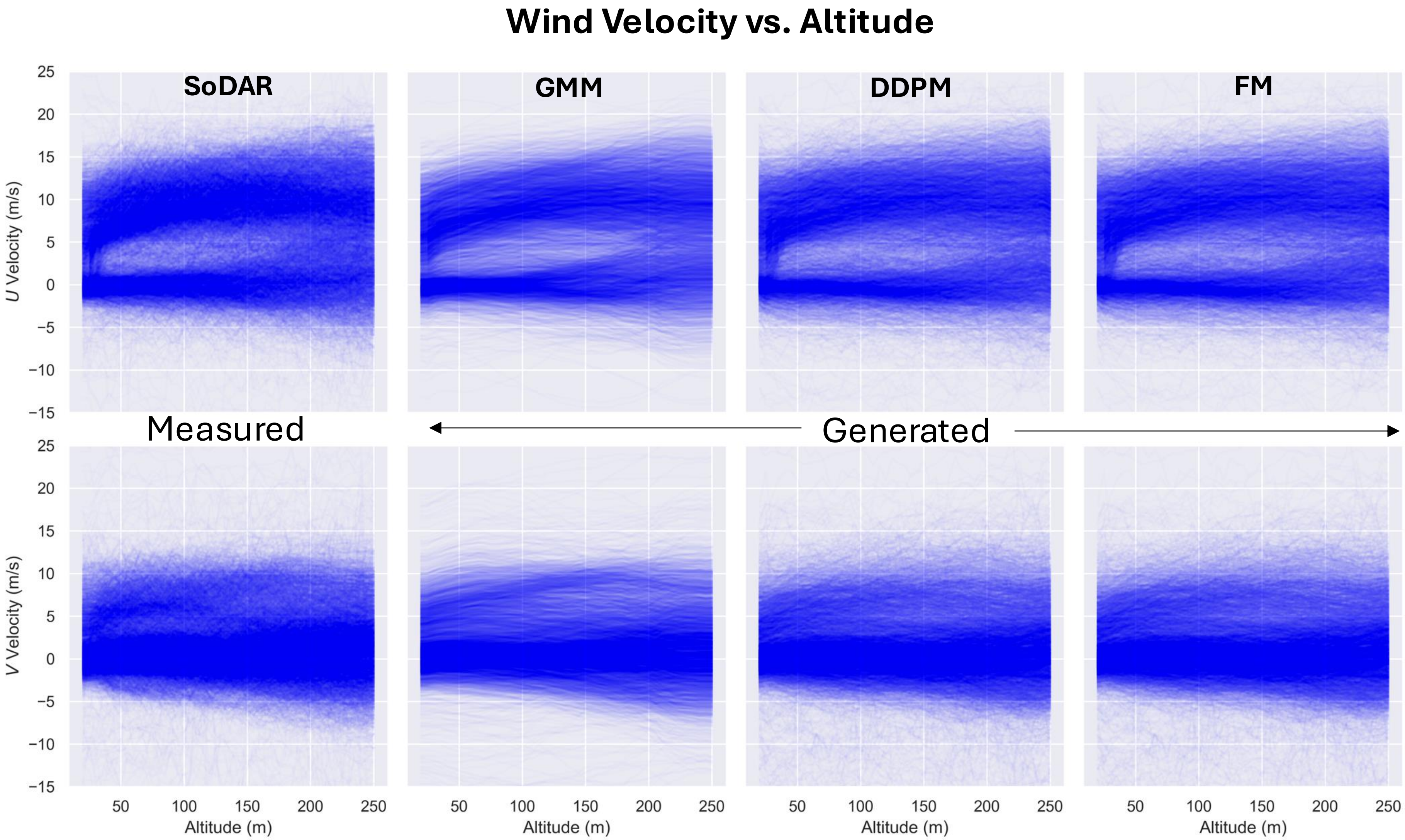


Generated Distributions



Results: Unconditional Wind Generation

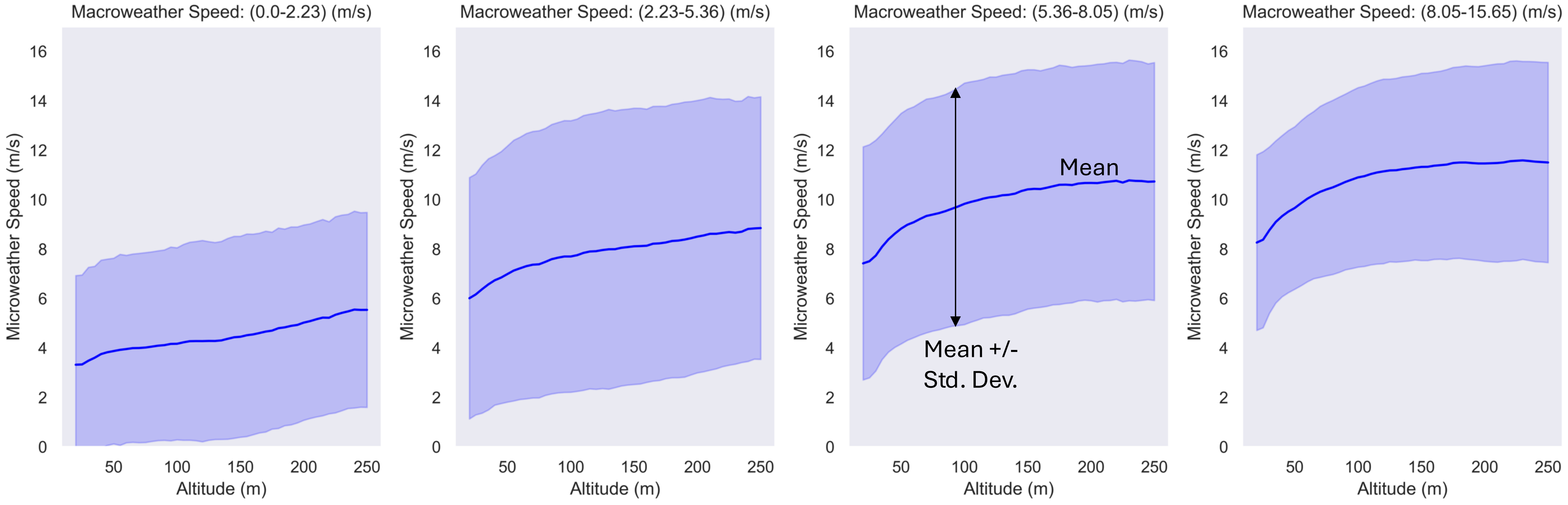
What are plausible microweather wind profiles ***at any given time*** (independent of macroweather conditions)?



Results: Conditional Wind Generation

What are plausible microweather wind profiles ***for a given macroweather wind speed***?

SoDAR Measurements Grouped by Macroweather Wind Speed

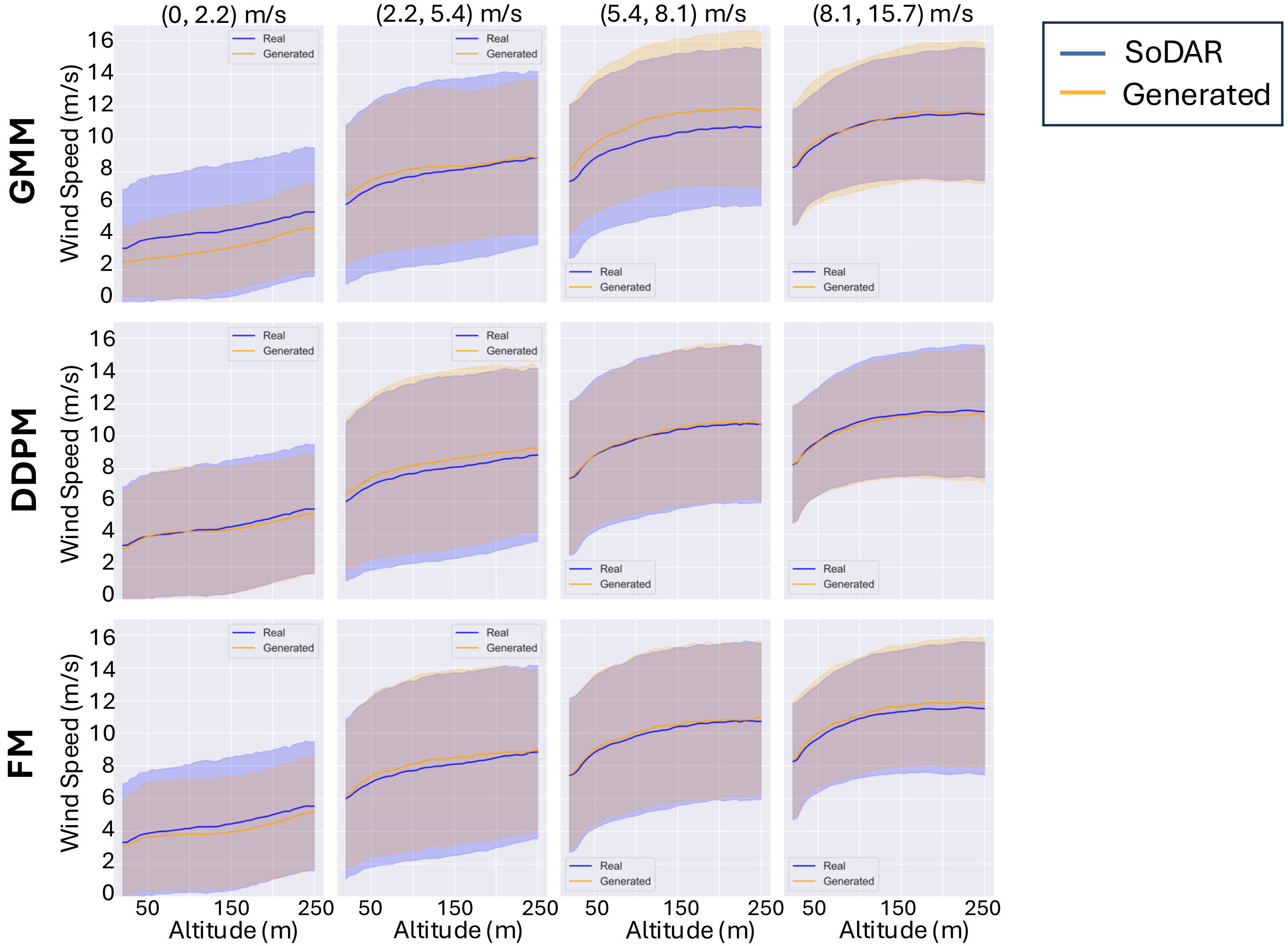


Increasing Macroweather Wind Speed

Results: Conditional Wind Generation

What are plausible microweather wind profiles ***for a given macroweather wind speed***?

Measured vs. Generated Wind Speeds

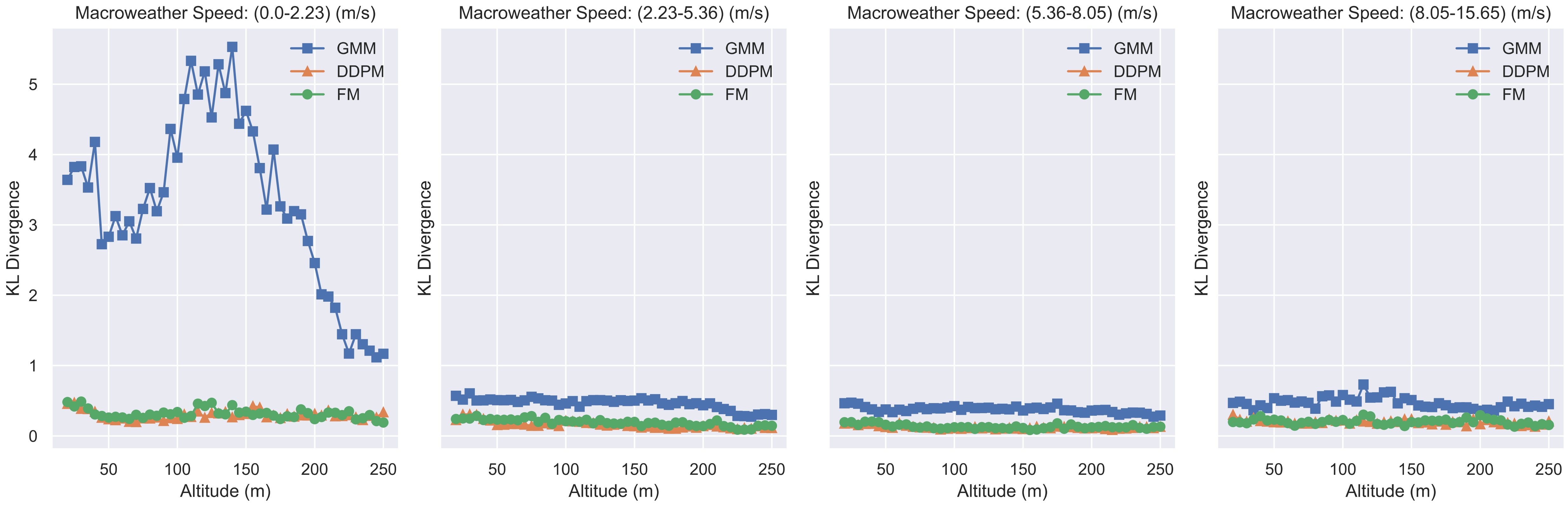


Results: Conditional Wind Generation

What are plausible microweather wind profiles ***for a given macroweather wind speed***?

- The Kullback-Leibler (KL) divergence is used to quantify the error between generated/measured distributions

KL Divergence vs. Altitude for Each Generative Model

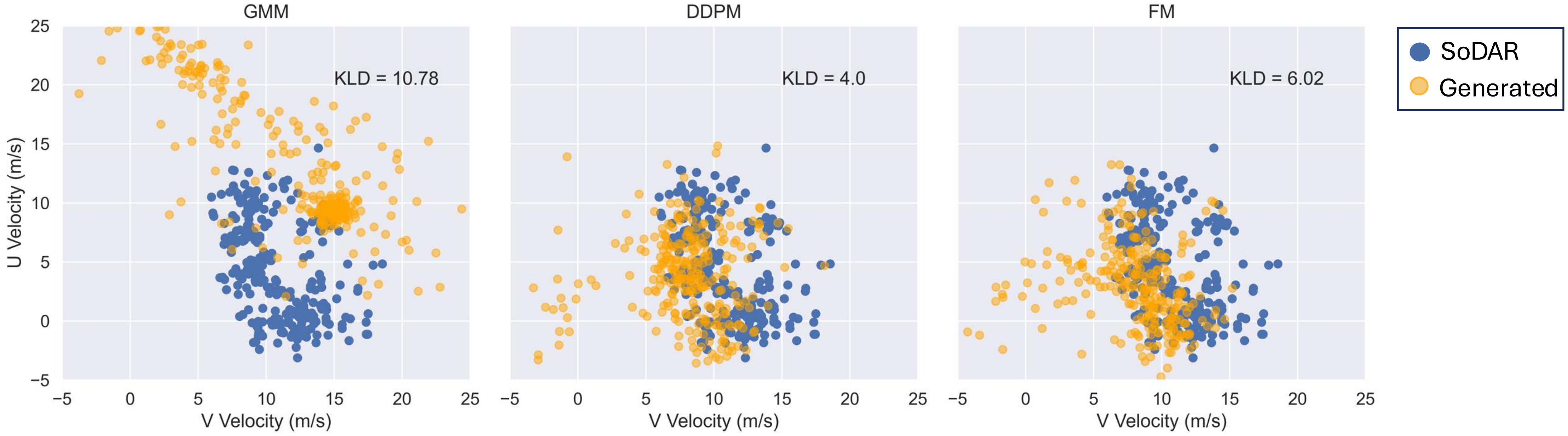


Results: Conditional Wind Generation

What are plausible microweather wind profiles ***for a given macroweather wind speed and direction***?

- Generated **out-of-sample** wind profiles for the macroweather condition: **southwest winds at (5.4, 8.05) m/s**

Measured vs. Generated Wind Velocities



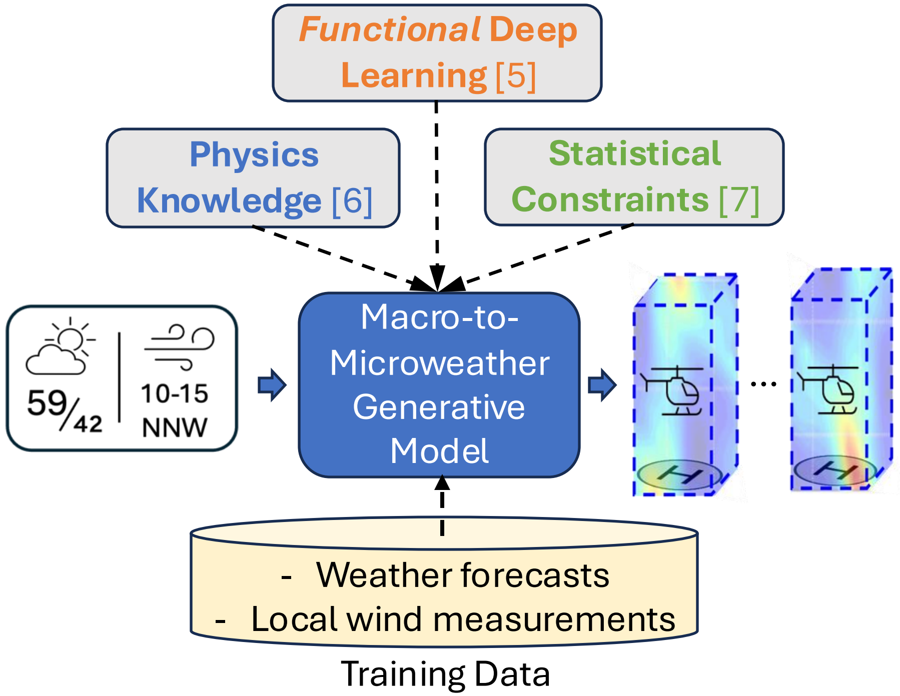
- Results for all macroweather speed/direction combinations included in the appendix of our paper

Conclusions

- Demonstrated a proof of concept for a macro-to-microweather probabilistic mapping using generative modeling
  - Deep generative models (DDPMs and FM) outperformed a simpler baseline (GMM) for conditional wind generation and are expected to scale to larger datasets more efficiently
- Generative models provide a basis for a microweather nowcasting approach that:
  - ✓Does not require permanent wind profiling system installation
  - ✓Updates predictions in realtime based on current information
  - ✓Captures random variability in wind fields
  - ❑ Makes predictions continuously in space and time

Future Work

- Developing novel methodology to generate wind velocity fields ***continuously*** throughout space/time that are ***physically*** and/or ***statistically*** consistent using sparse sensor data and state-of-the-art deep learning [5-7]
- Applying proposed approach to massive winds dataset from a new NASA measurement campaign
  - Incorporate temporal dependence
  - Demonstrate scalability



[5] Learning nonlinear operators via DeepONet based on the universal approximation theorem of operators, Lu et al. 2021.
[6] Physics-Informed diffusion models, Bastek et. al. 2024.
[7] Enforcing statistical constraints in generative adversarial networks for modeling chaotic dynamical systems, Wu et. al. 2021.

Additional Information

- **Paper**: T. A. Shah, M. C. Stanley, J. E. Warner. Generative Modeling of Microweather Wind Velocities for Urban Air Mobility.
- **Code**: https://github.com/nasa/wind-generative-modeling
- **Email**: james.e.warner@nasa.gov