Acoustic Signature Uncertainty Quantification for the X-59

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Joint work with
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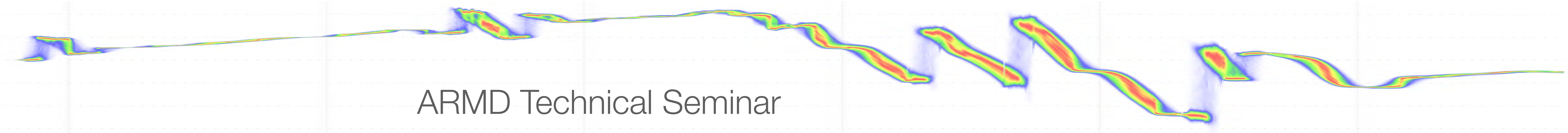
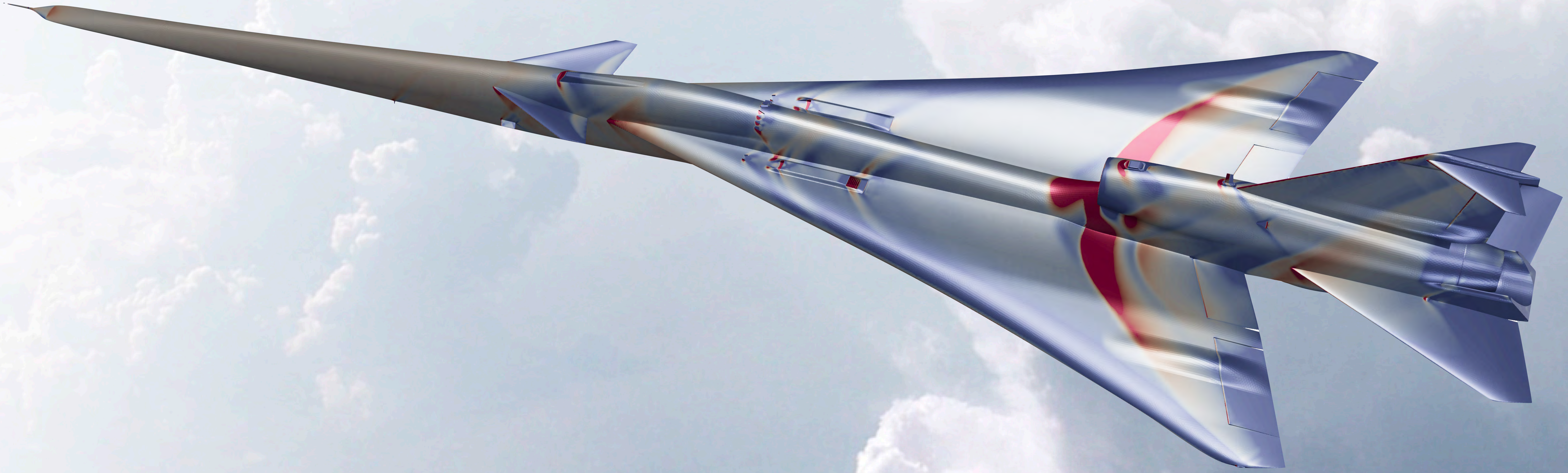
Garo Bedonian, RPI & Liam Smith, Georgia Tech
Wade Spurlock, STC

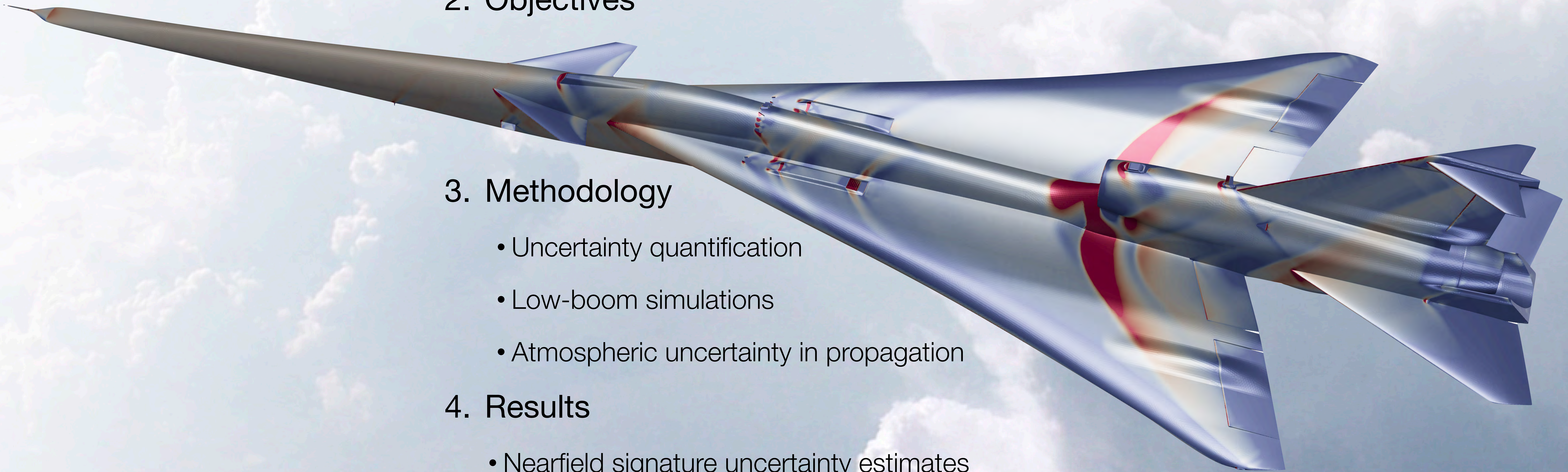


ARMD Technical Seminar
September 19, 2023

Goal is to quantify uncertainty in the level of noise reaching ground due to uncertainty in flight conditions and the atmosphere during supersonic cruise

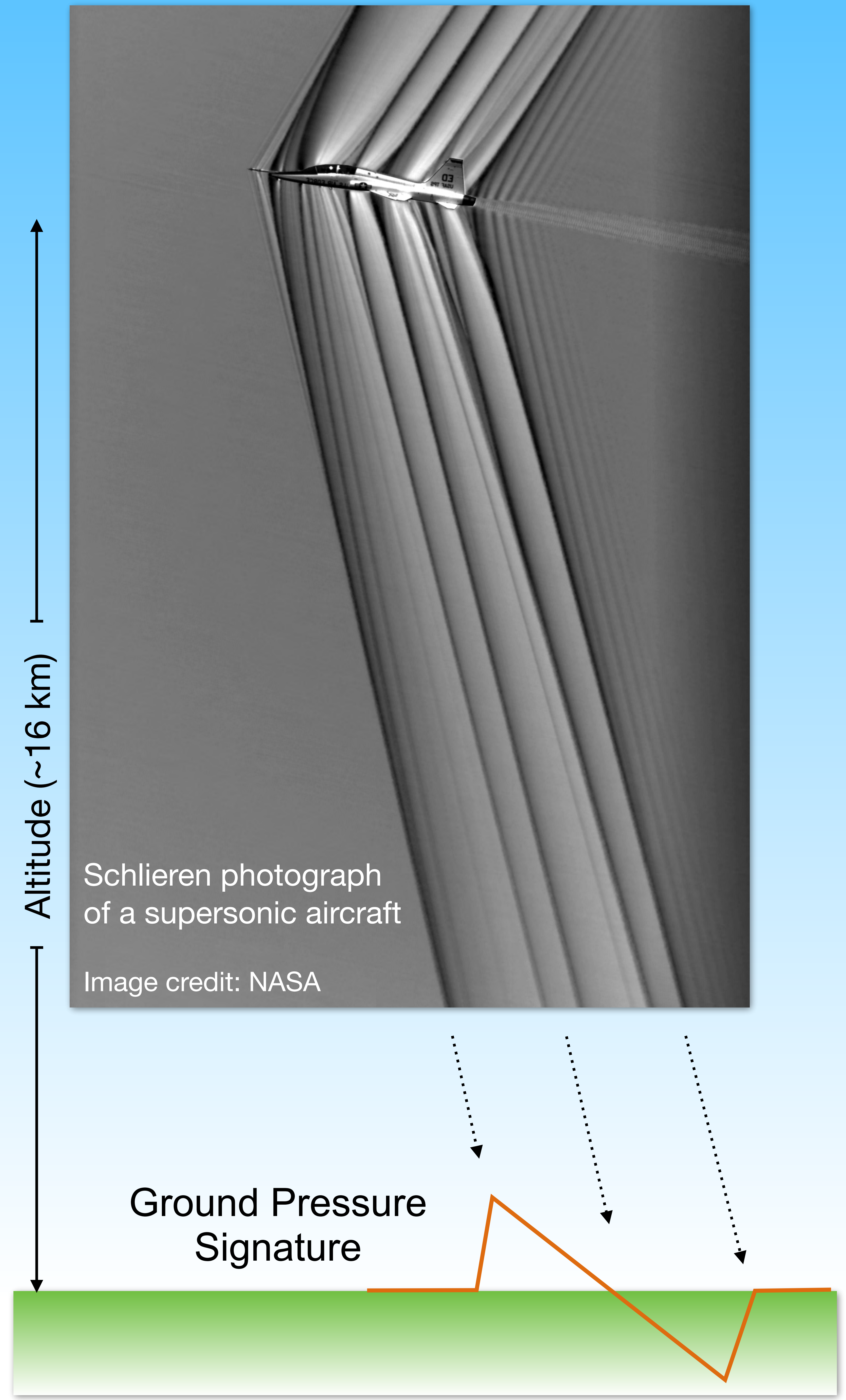


Outline

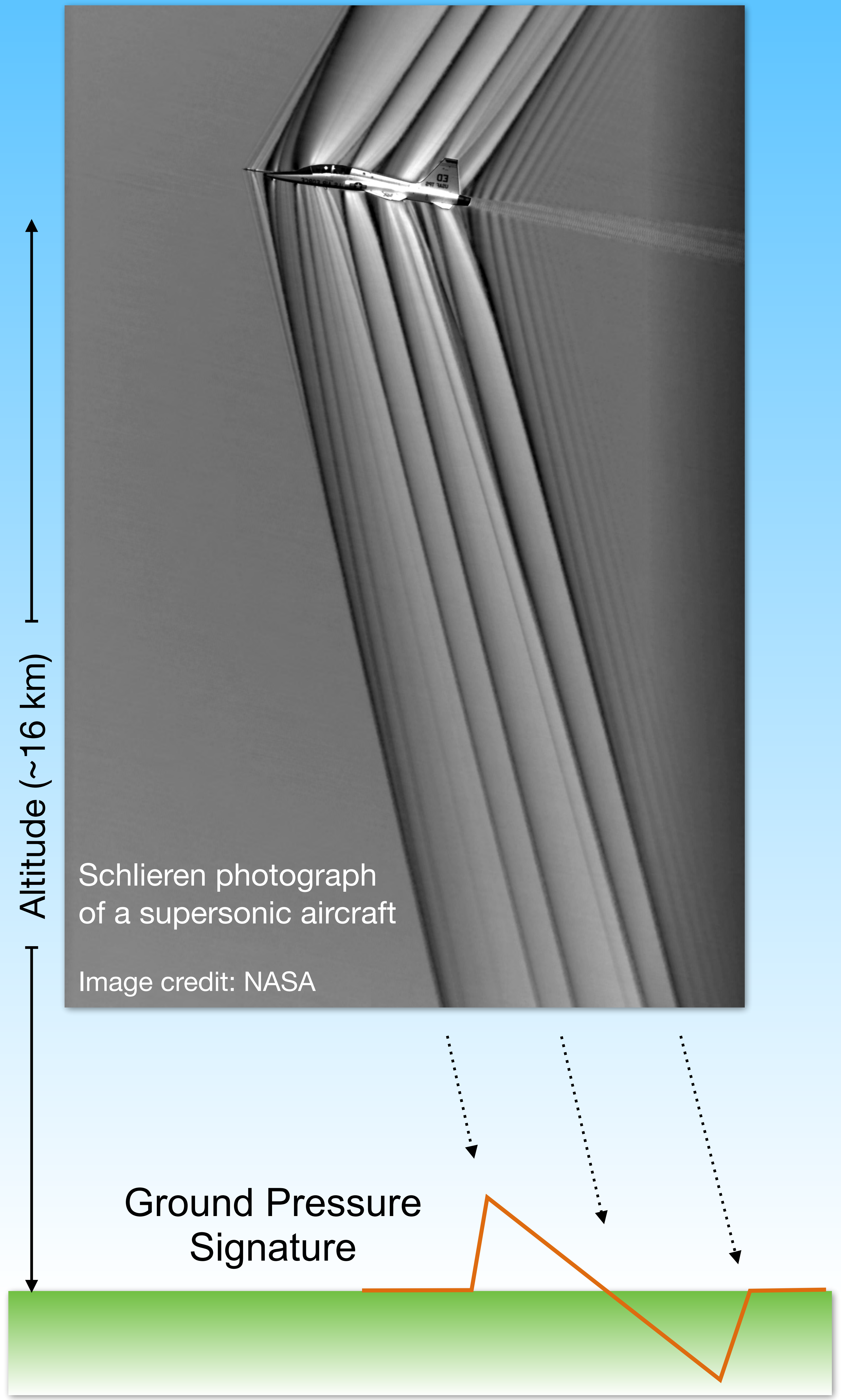


1. Background & Motivation
2. Objectives
3. Methodology
    - Uncertainty quantification
    - Low-boom simulations
    - Atmospheric uncertainty in propagation
4. Results
    - Nearfield signature uncertainty estimates
    - Uncertainty in atmospheric conditions
    - Uncertainty in X-59 operating conditions and atmosphere
5. Summary & Outlook

Sonic Booms

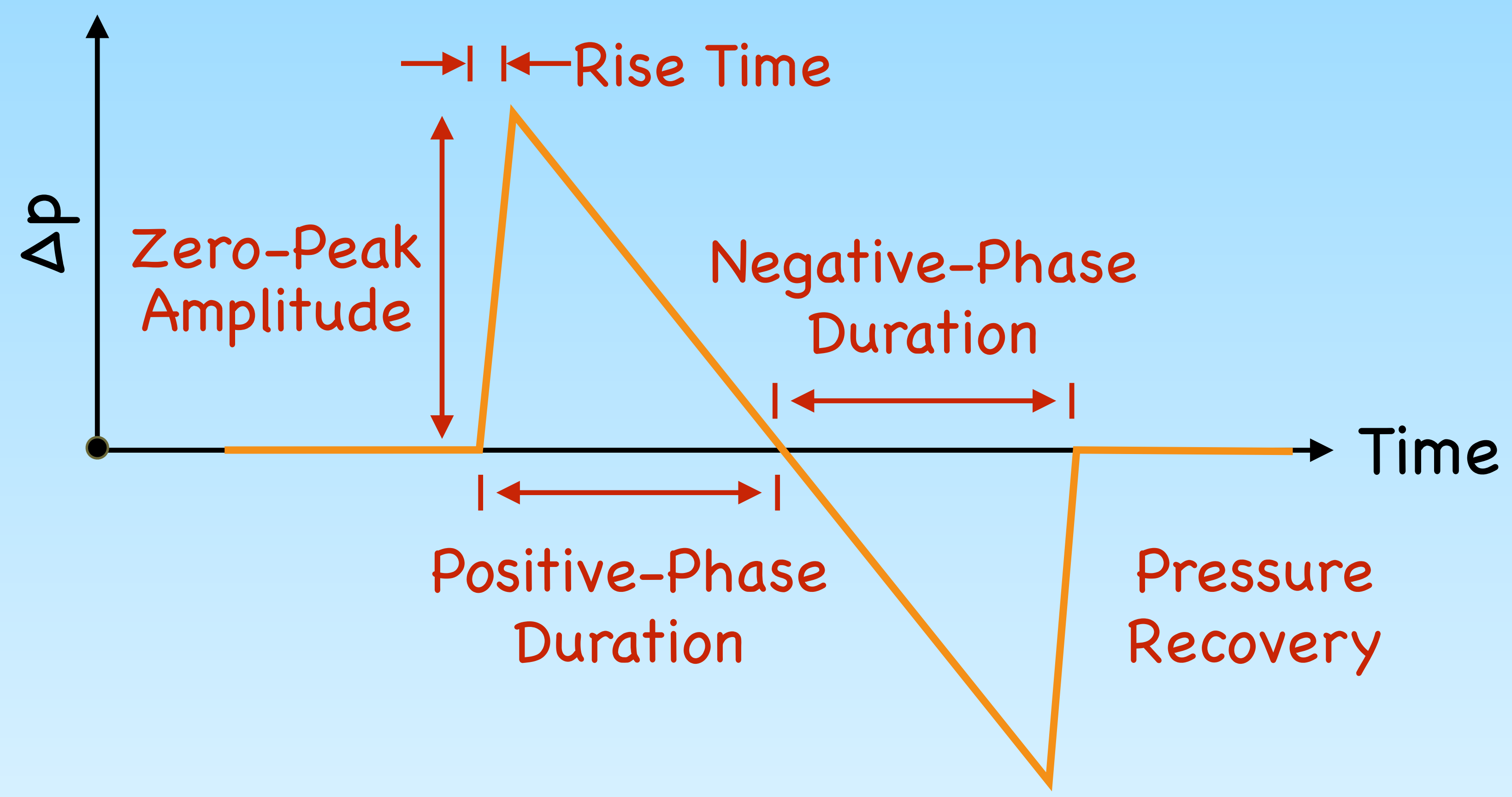

Altitude (~16 km)
Schlieren photograph
of a supersonic aircraft
Image credit: NASA
Ground Pressure
Signature

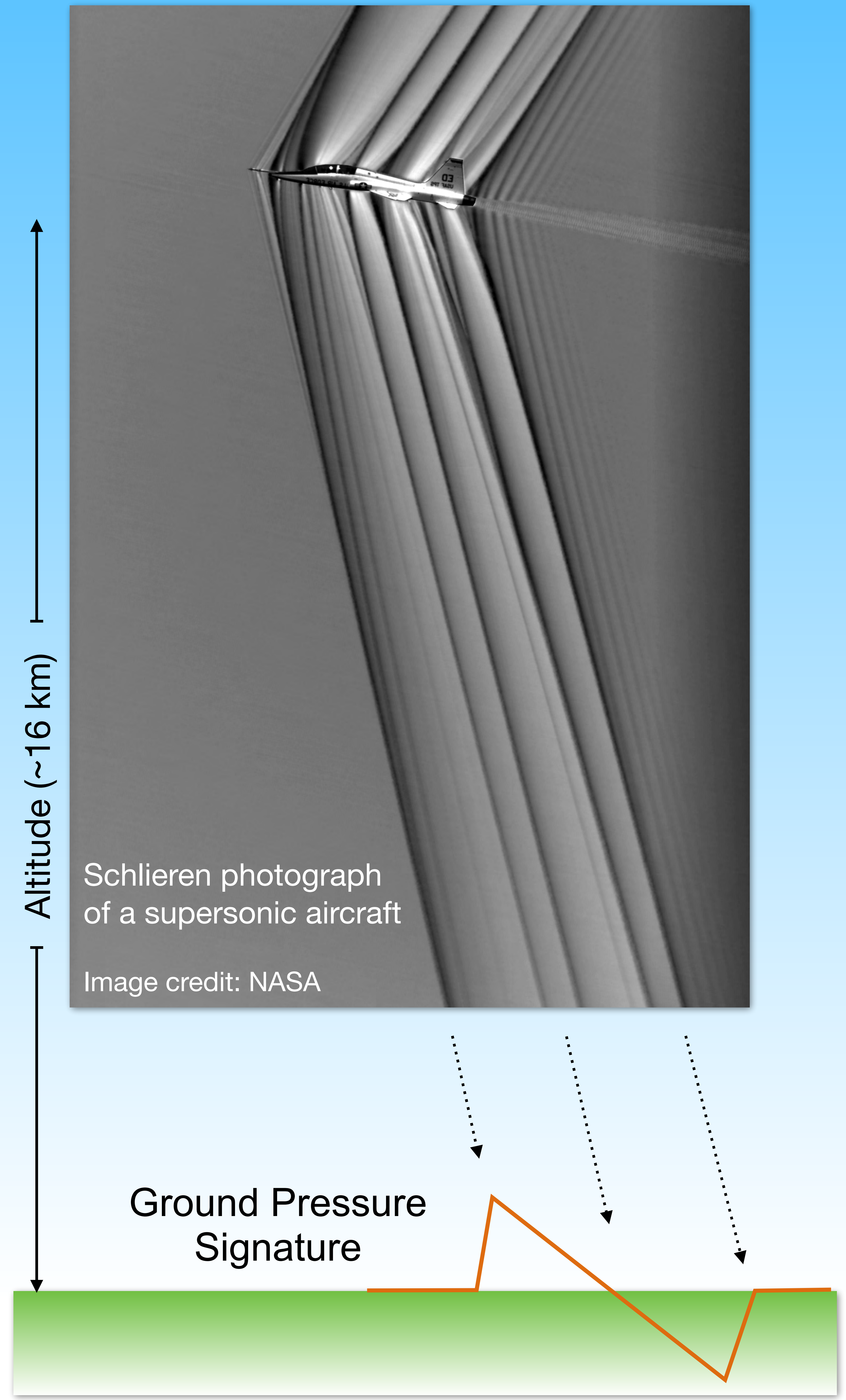
Sonic Booms



Sound characteristics are a function of the ground pressure signature

- Classical signatures are N-waves





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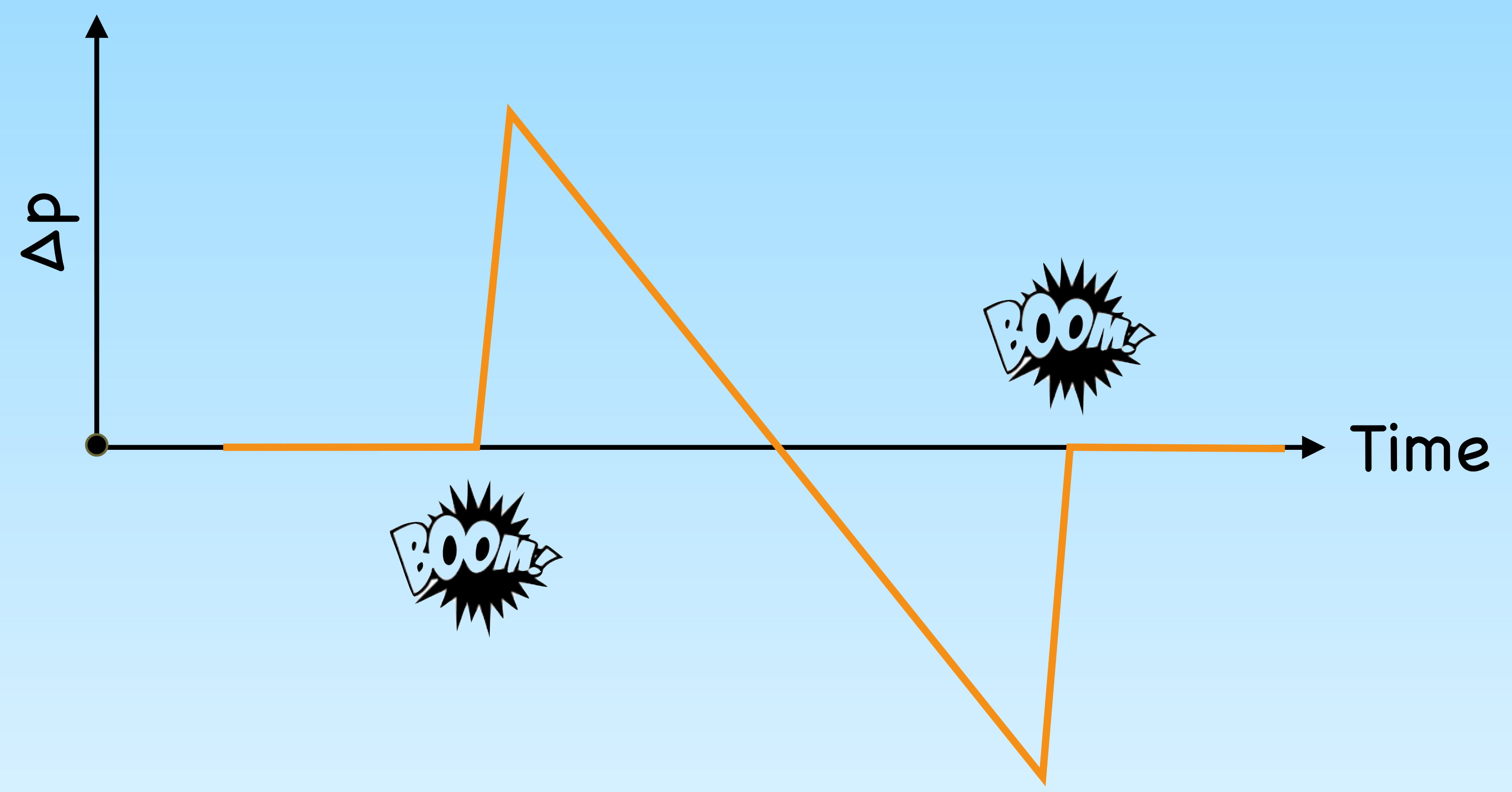
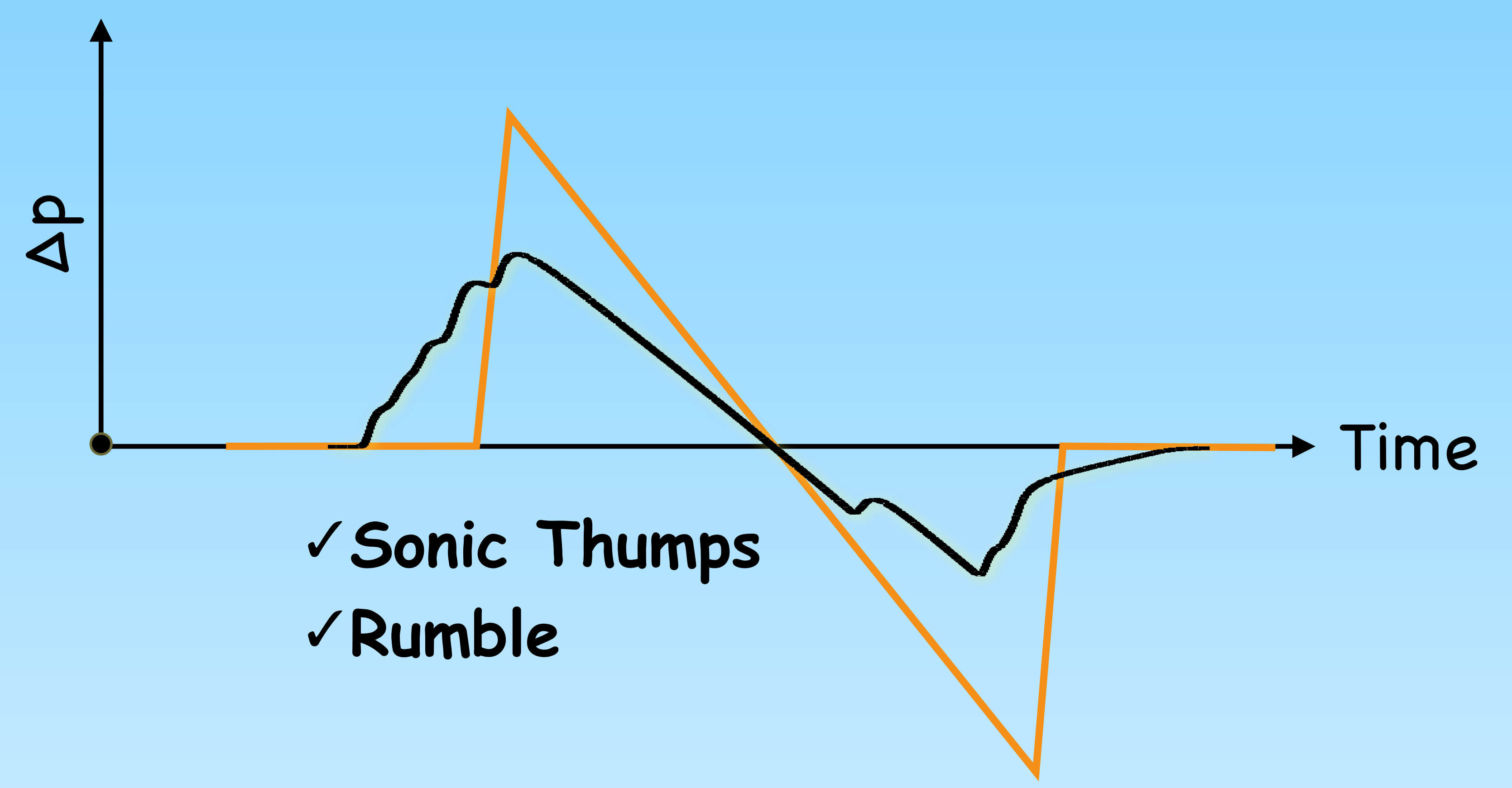


Loudness metrics

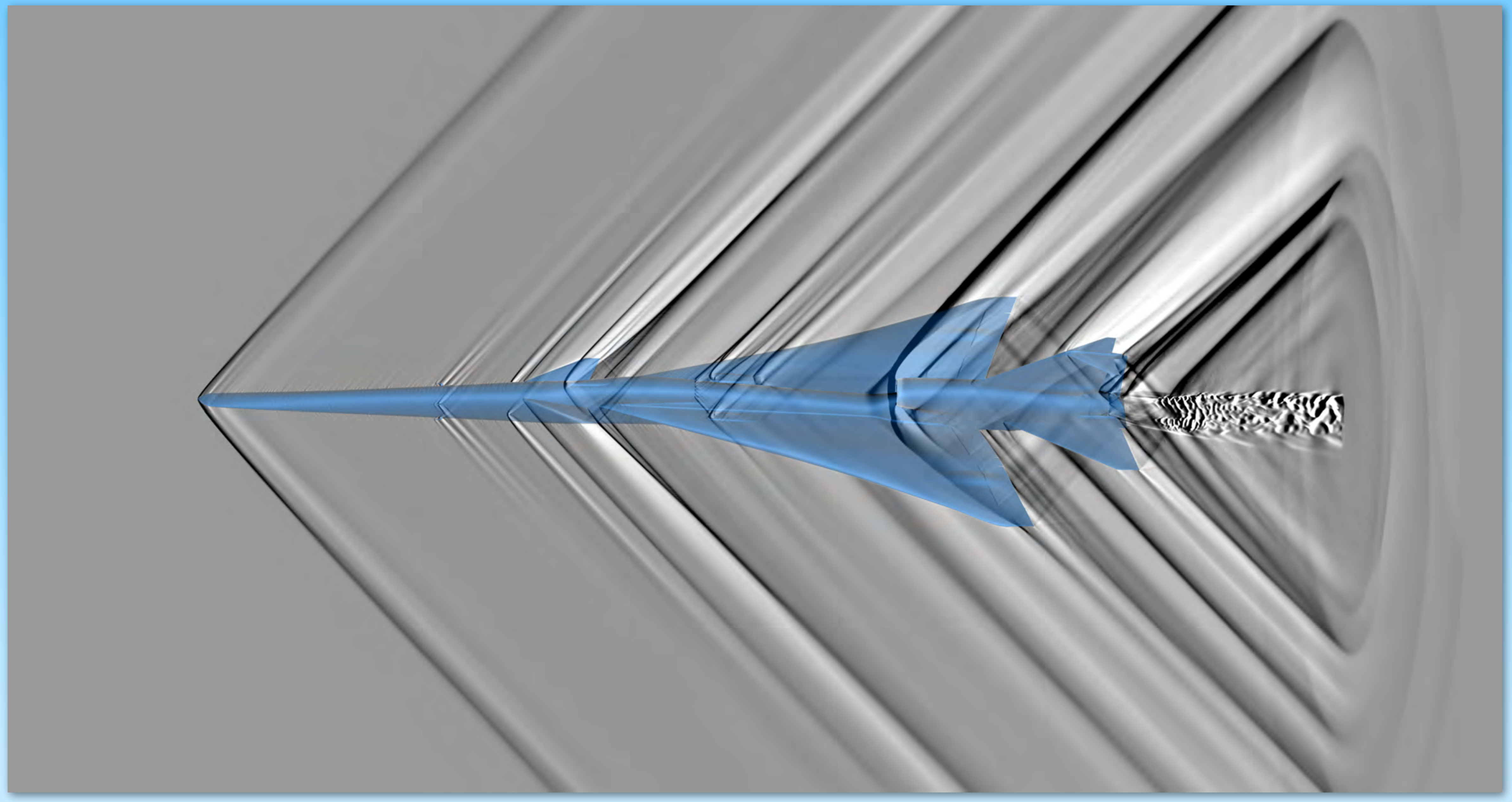
- Perceived Loudness PL (dB)
- Weighted Sound Exposure Level: A/B/C/D/ESEL (dB)
- Indoor Sonic Boom Annoyance Predictor
    - ISBAP = PL - 0.4201(CSEL-ASEL)

X-59: Low-Boom Design

- Aerodynamic shaping to eliminate sonic booms



- Strategy is to increase rise time, decrease amplitude, increase duration and smooth recovery
- Requires designing aircraft with signatures that do not coalesce into N-waves
- Extensive reliance on high-fidelity simulations based on Computational Fluid Dynamics for analysis and design
    - Shock dominated, strongly nonlinear flowfield



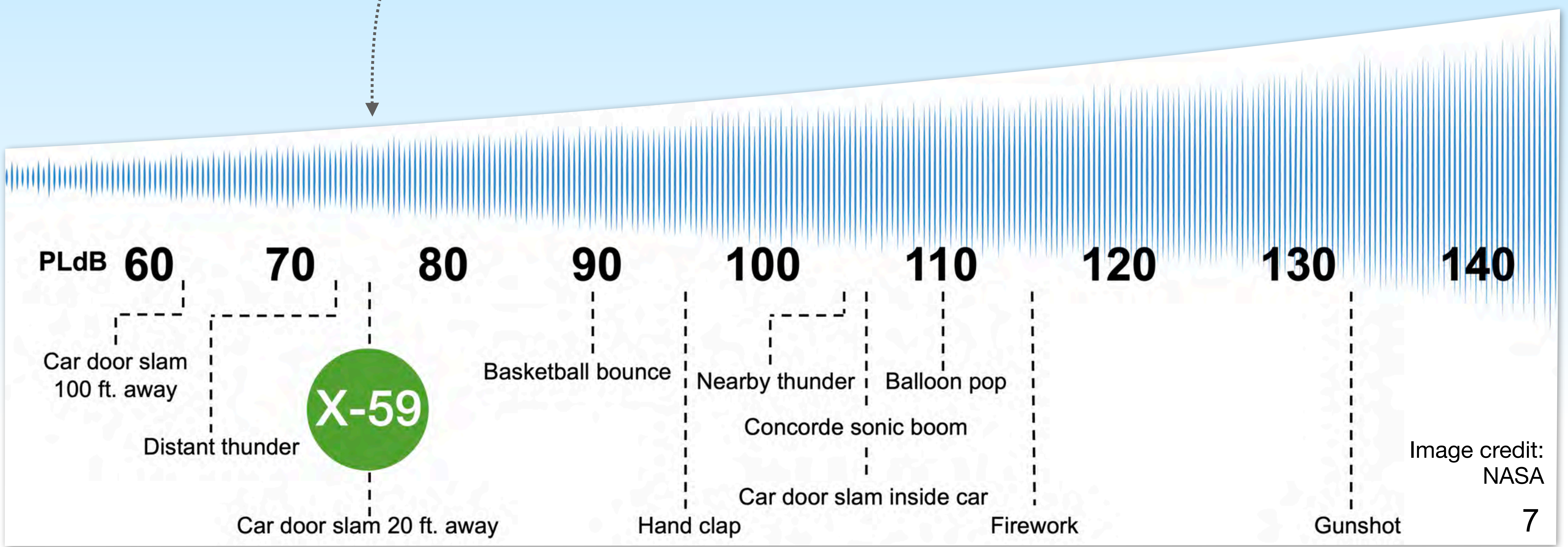


Image credit: NASA

Predicting En Route Noise

- Low-boom characterization requires prediction of the primary loudness carpet
- Low-boom designs minimize loudness footprint subject to many sources of uncertainty

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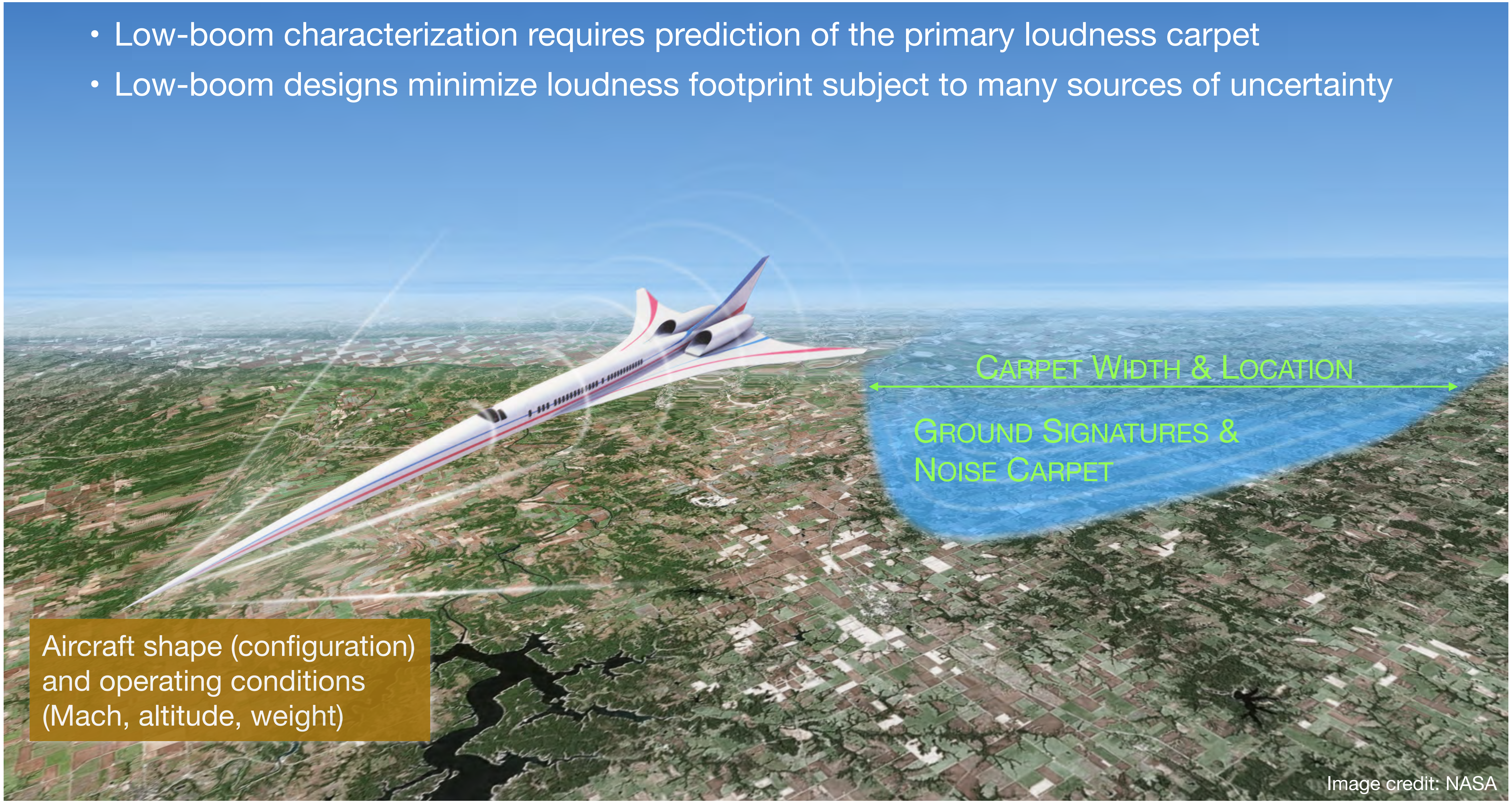

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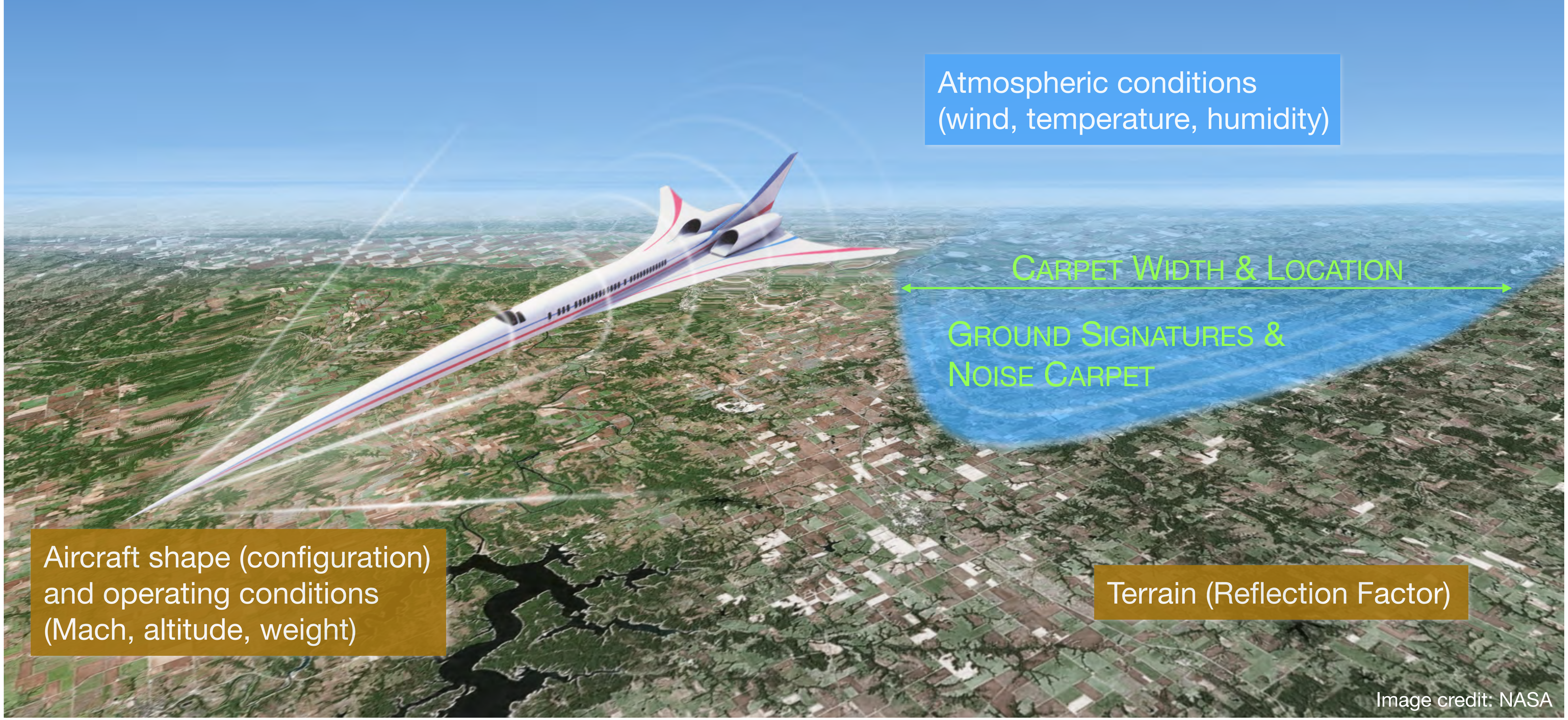

Objectives

1. Characterizing effect of input uncertainties on low-boom outputs

- Mean, standard deviation and probability density function
  - Nearfield and ground signatures
  - Loudness metrics: Perceived Loudness, A/B/C/D/E SEL, ISBAP
  - Noise carpet and carpet width
- Input uncertainties include cruise conditions and the atmosphere

2. Assessing and minimizing sources of error

- Directly coupling UQ with high-fidelity simulations
- Tracking discretization error in simulations and numerical error in evaluation of statistics
- Estimating model-form error

Toward En Route Noise Certification by Simulation-Based Analysis

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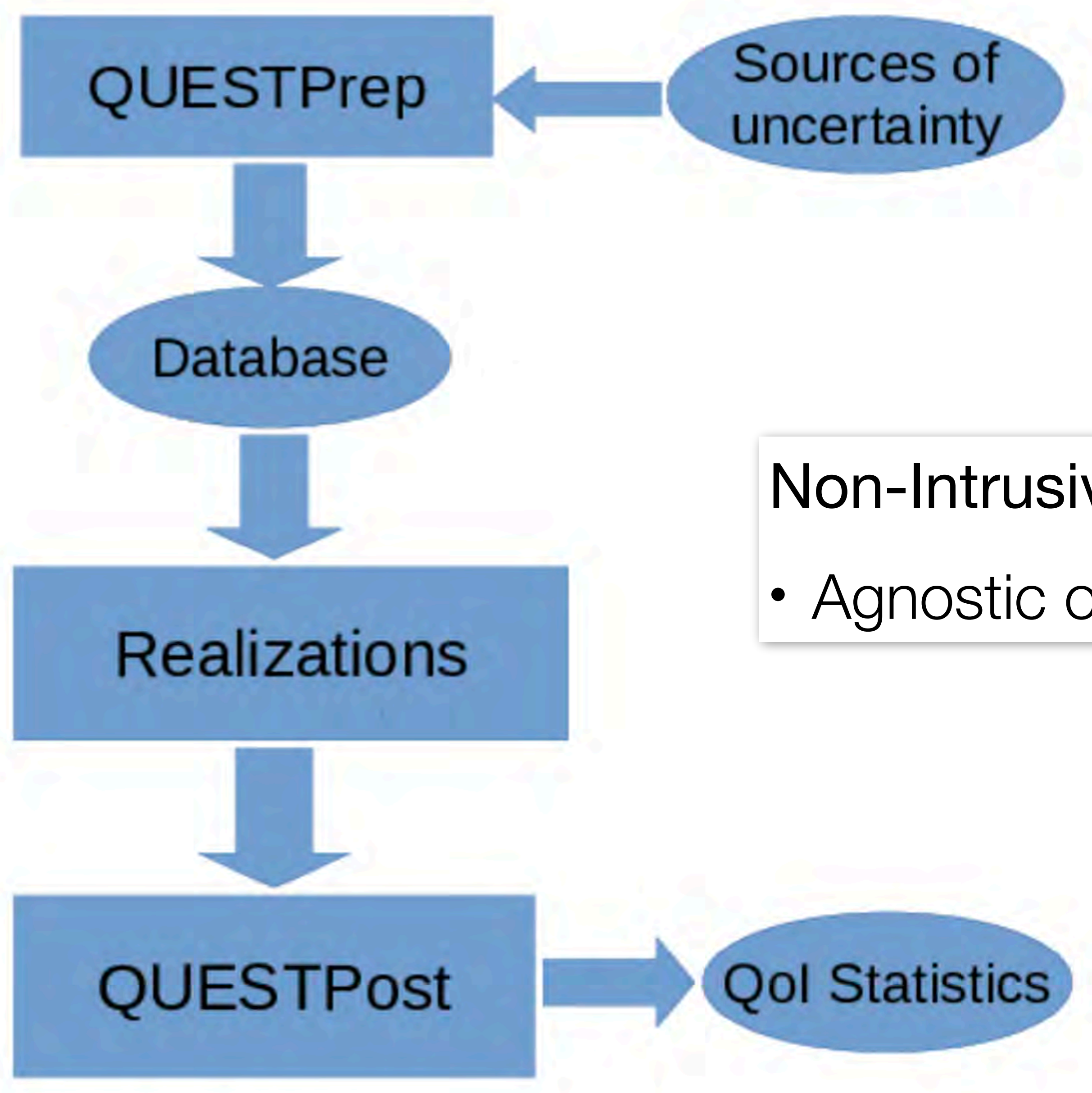
Uncertainty Quantification with QUEST

Quantified Uncertainty with Error bias estimation Software Tools

- Developed by Tim Barth (ARC-TNP) in ARMD-TACP Transformational Tools and Technologies (TTT) project
- Implements comprehensive set of UQ methods
  - Dense and sparse quadratures
  - Multi-level Monte-Carlo
  - Kernel density estimation for p.d.f. evaluation
  - Specialized numerics to handle stochastic discontinuities, e.g. those due to shocks
- Intrinsic error estimates for multi-level quadratures and MLMC sampling
- Intrinsic post-processing of discretization errors



Non-Intrusive Implementation
- Agnostic of CFD solvers

Evaluation of Statistics for Outputs of Interest

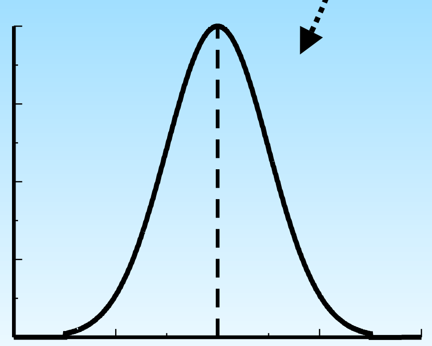
Expectation (Mean)

$\xi \longrightarrow$ Input Random Variable, e.g. Mach Number

$f(\xi) \longrightarrow$ Input Probability Density Function

$J(\xi) \longrightarrow$ Exact Output, e.g. Perceived Loudness

$$E[J(\xi)] = \int J(\xi) f(\xi) d\xi$$

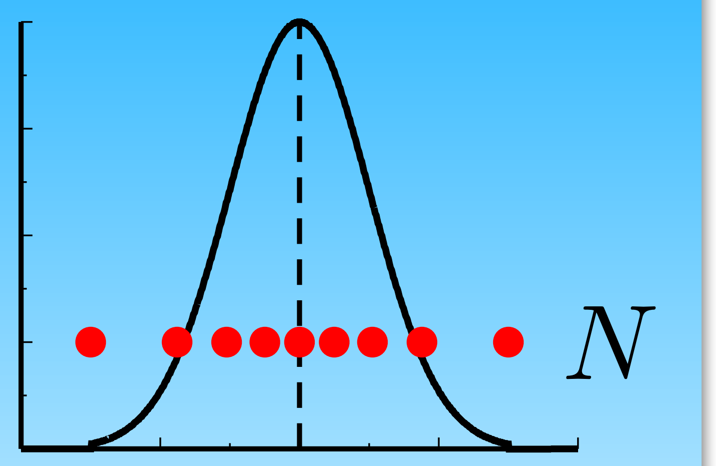


Numerical Approximation of Expectation

N - point Numerical Quadrature

Approximate Outputs

$$J_H(\xi_1), \ \ldots, \ J_H(\xi_N)$$

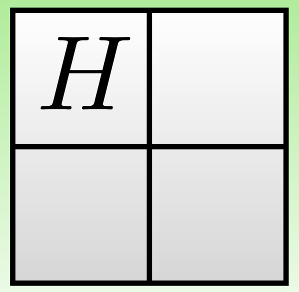


$$E_N[J_H] = \sum_{i=1}^{N} (w \, J_H)_i$$

Numerical Error in Expectation

$$\varepsilon = E[J] - E_N[J_H]$$

Error in Expectation
Nearfield and Farfield Discretization



Cell-Size & Time-step

$$\varepsilon_H = J - J_H$$

Error Decomposition Formula

$$\varepsilon = E[\varepsilon_H] + \varepsilon_Q[J_H]$$

Error in Expectation
Statistics Quadrature

N - point Quadrature

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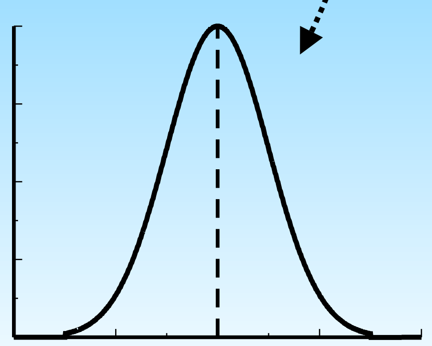

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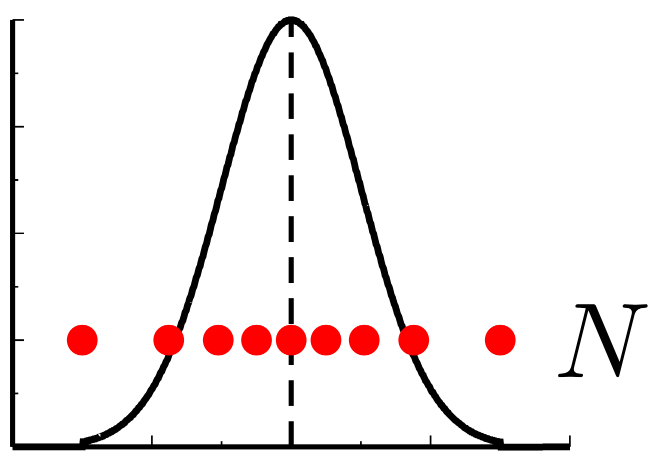

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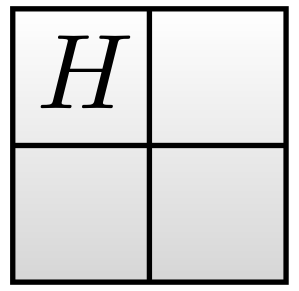

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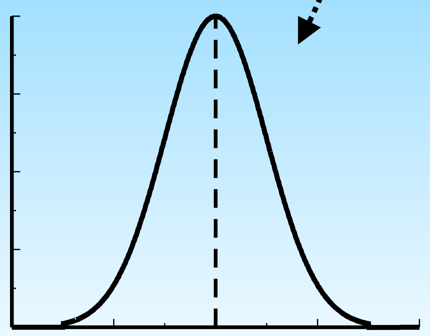

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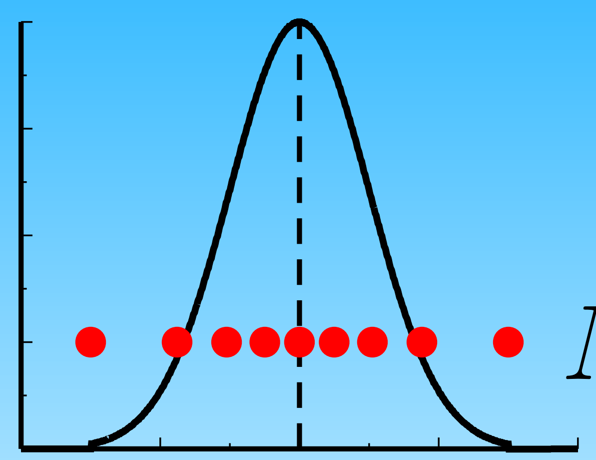

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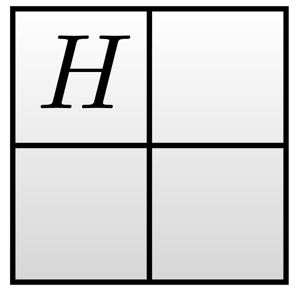

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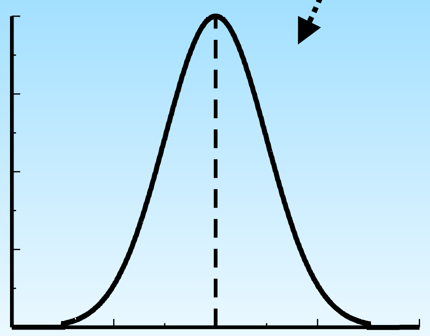

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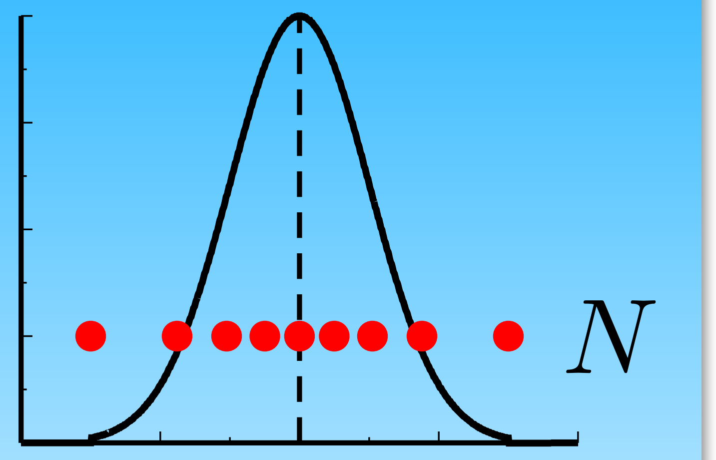

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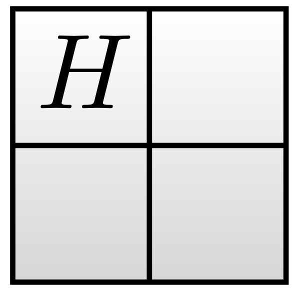

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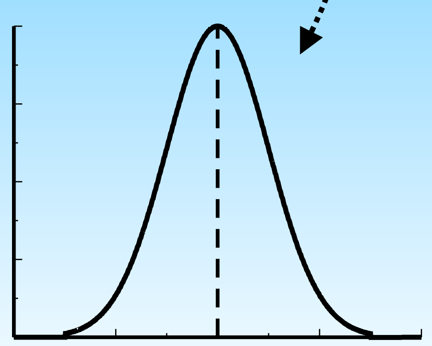

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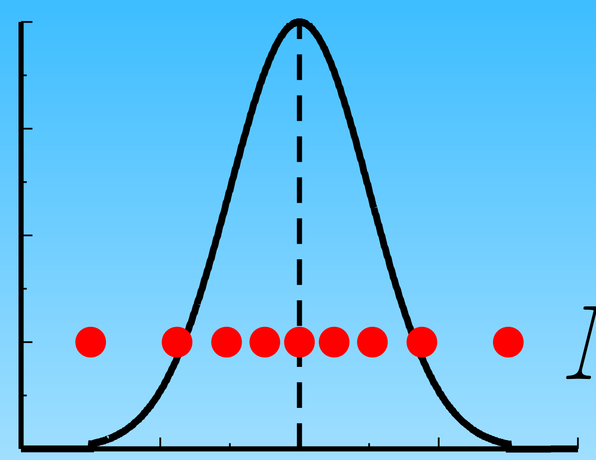

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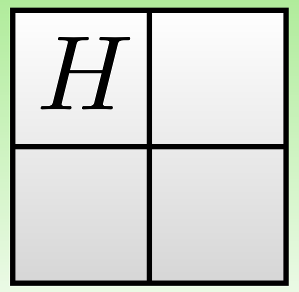

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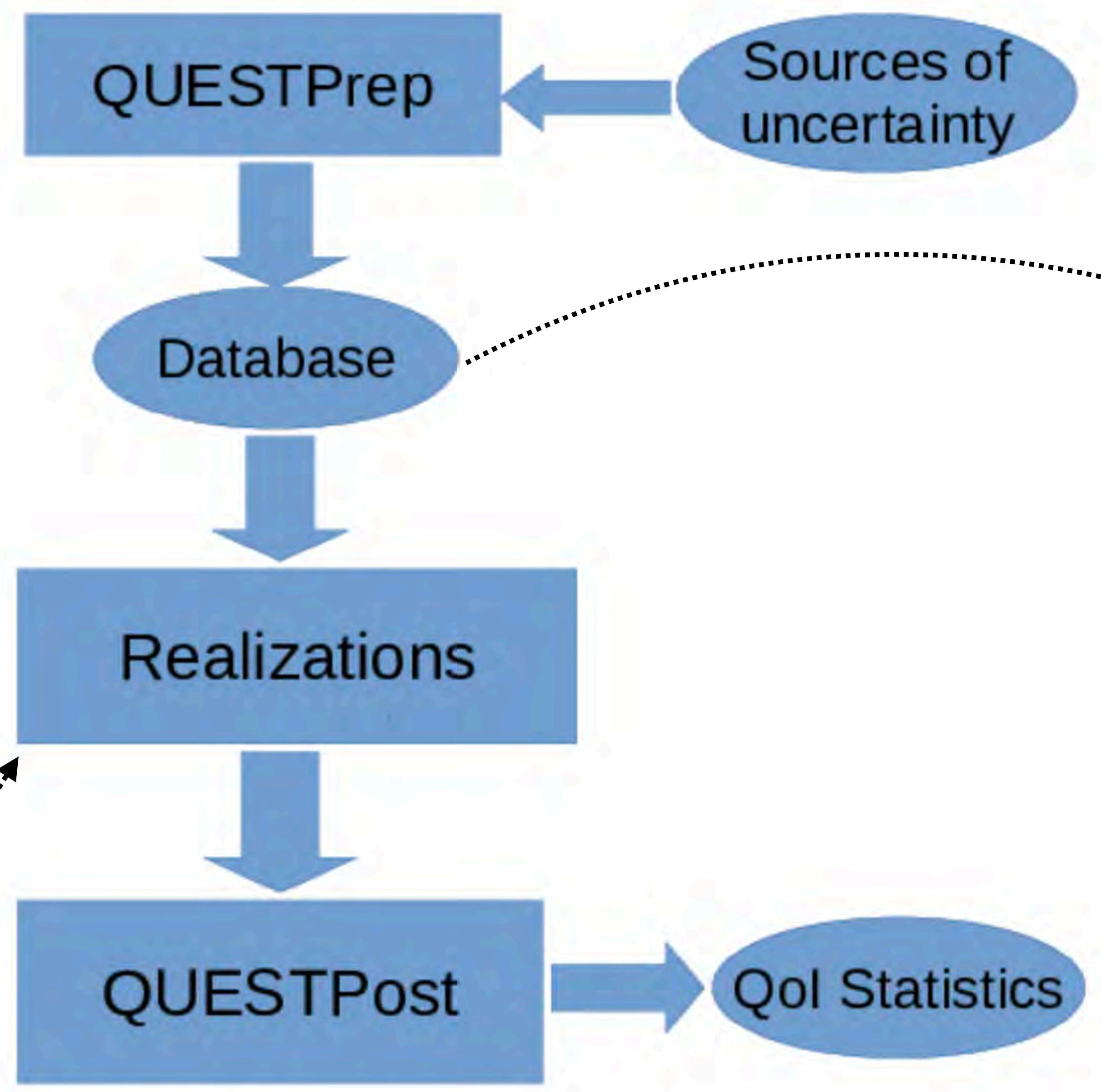
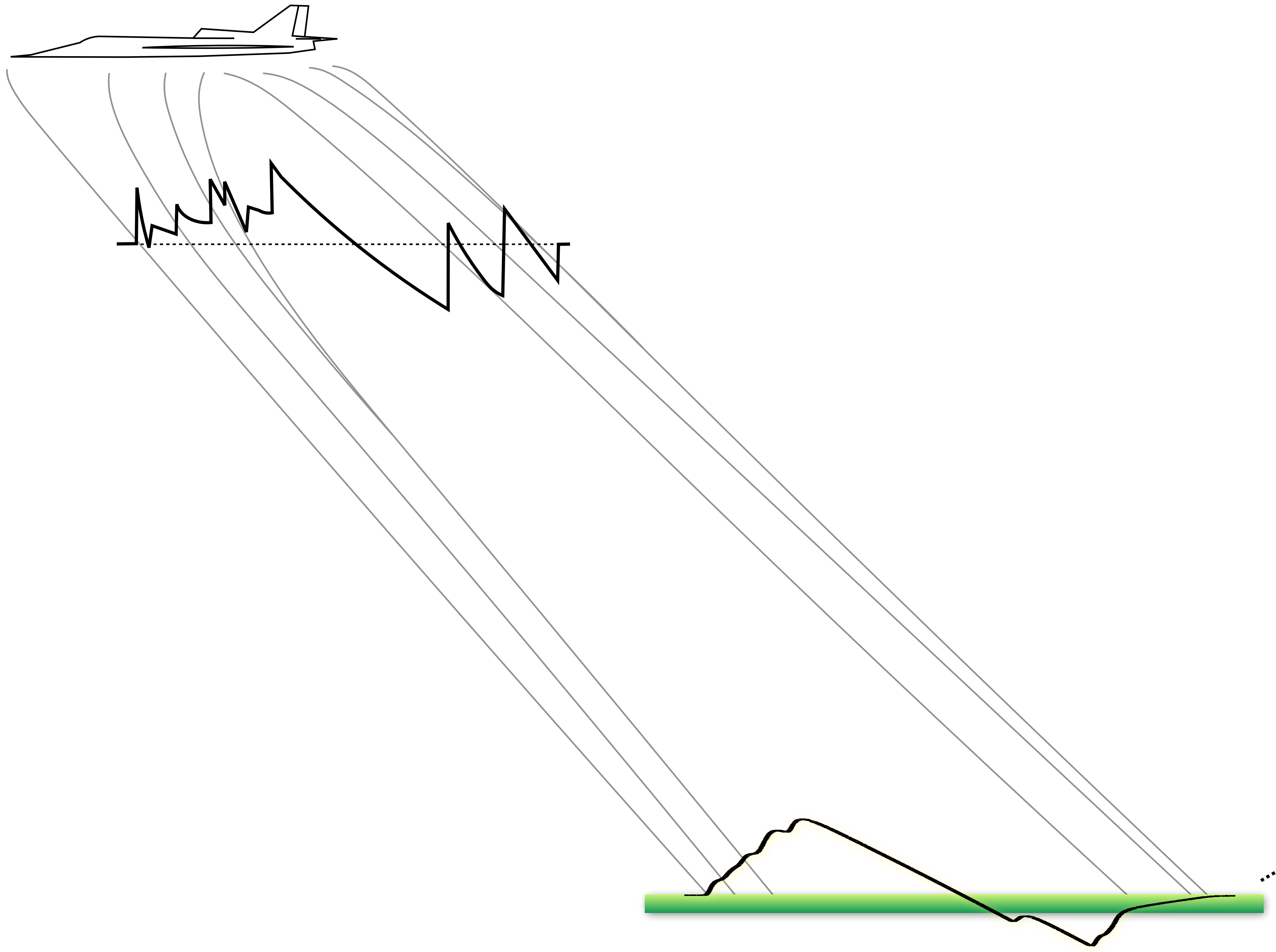
Approach: Nearfield-Farfield Decomposition

QUEST



Acoustic Signature Simulation

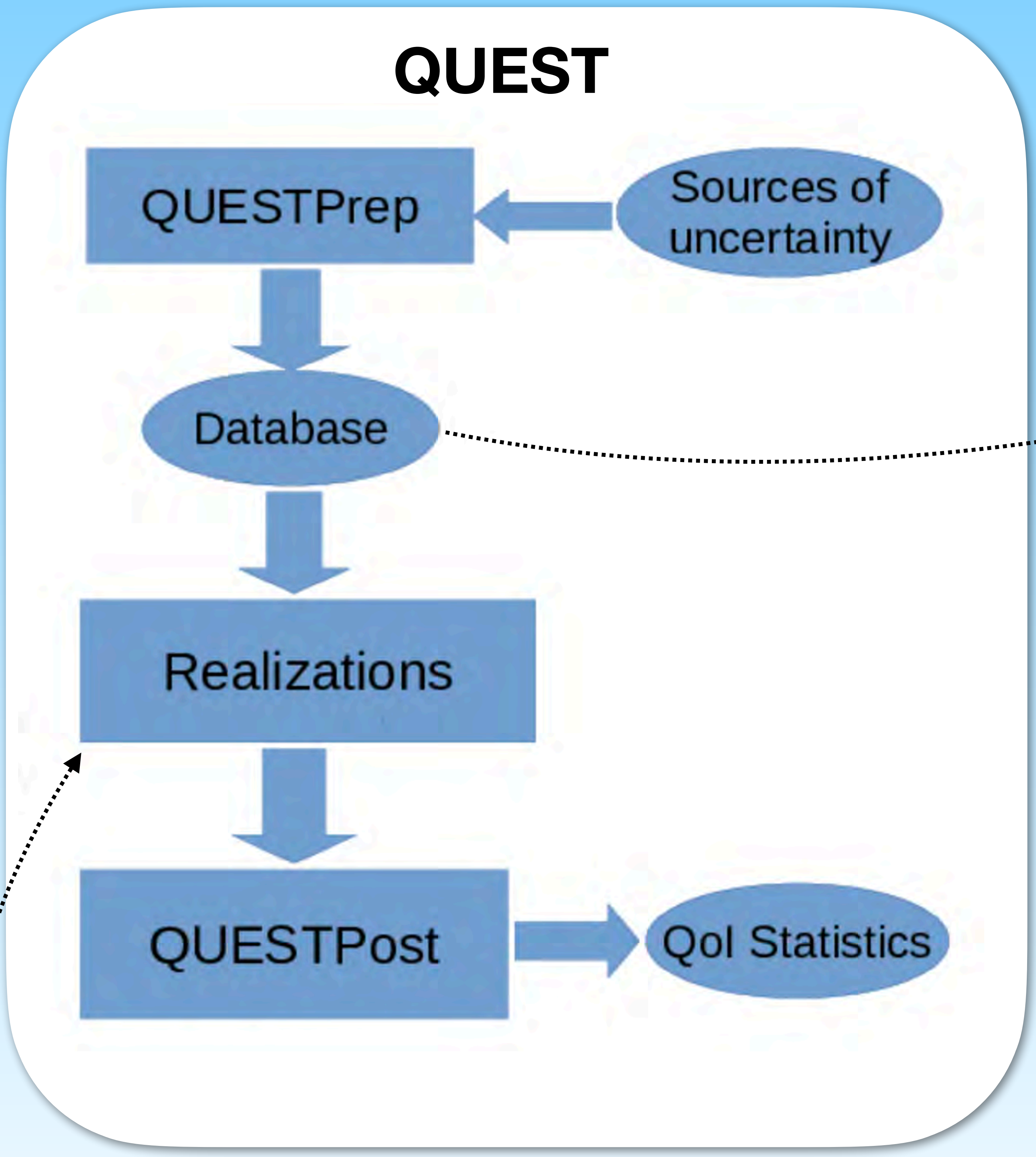


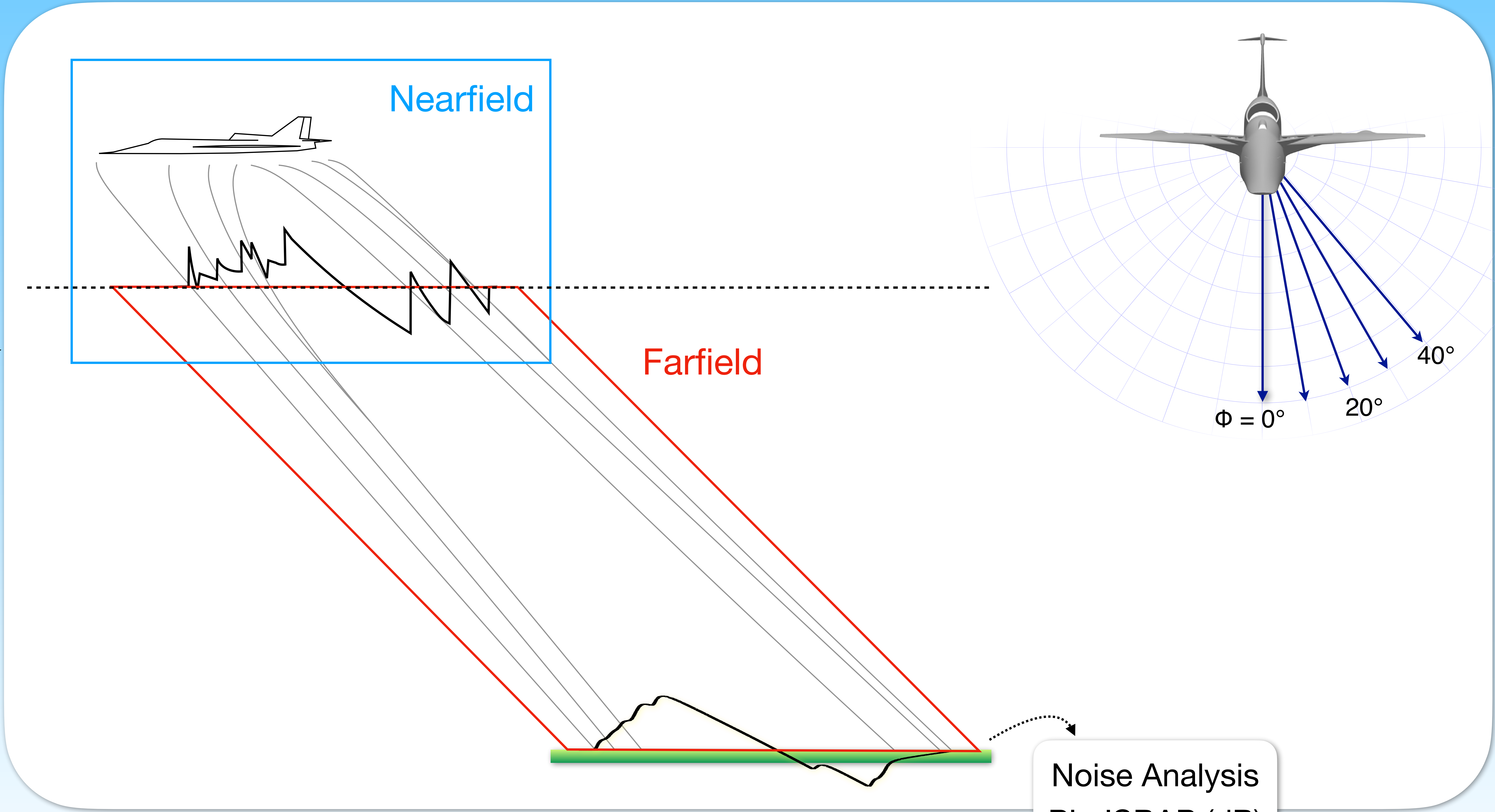
Noise Analysis
PL, ISBAP (dB)

Realizations, e.g. noise metric $J_H(\xi_1),\ J_H(\xi_2),\ \ldots,\ J_H(\xi_N)$

Discretization Error $\varepsilon_H(\xi_1), \varepsilon_H(\xi_2), \ldots, \varepsilon_H(\xi_N)$

Approach: Nearfield-Farfield Decomposition





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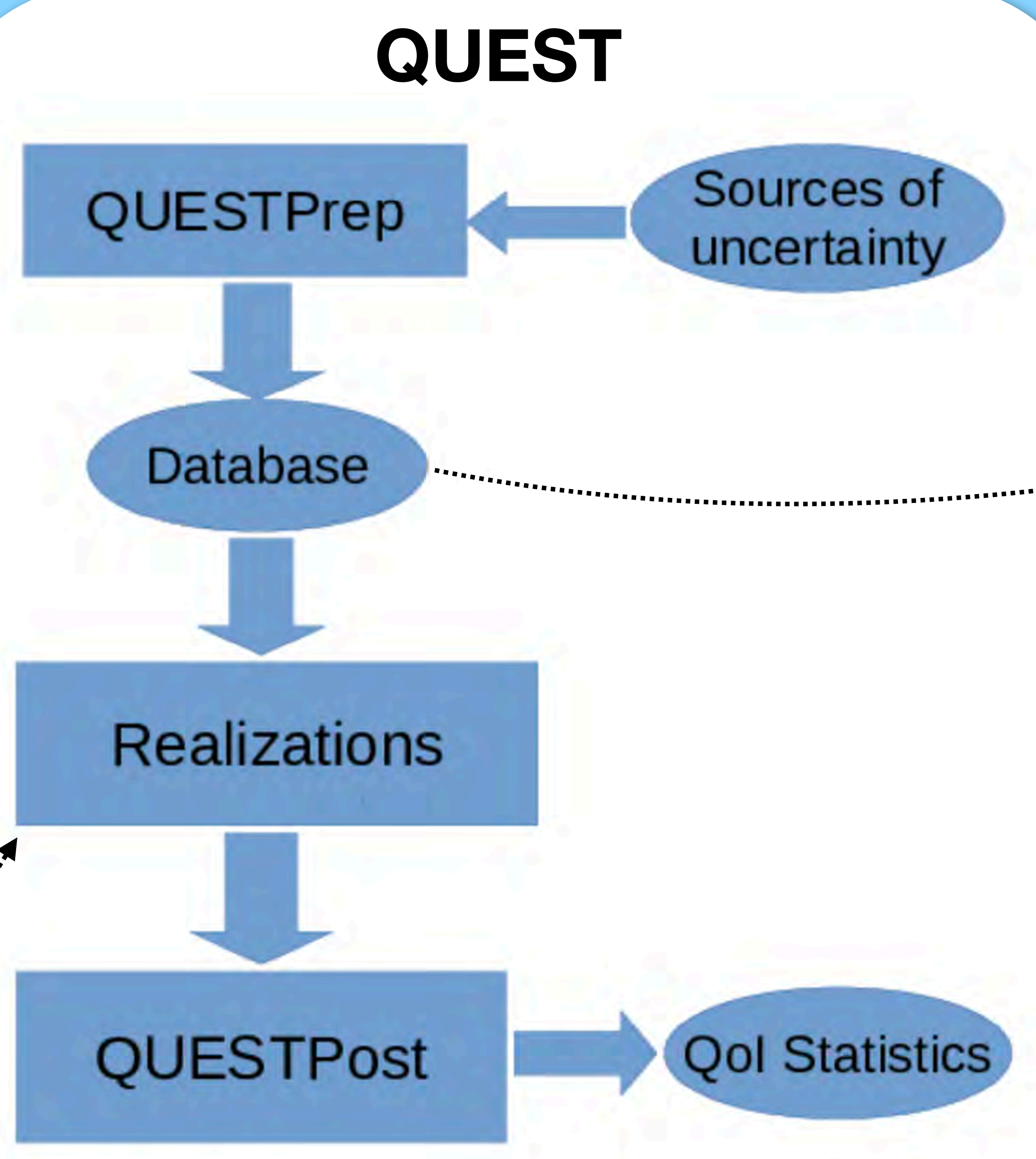

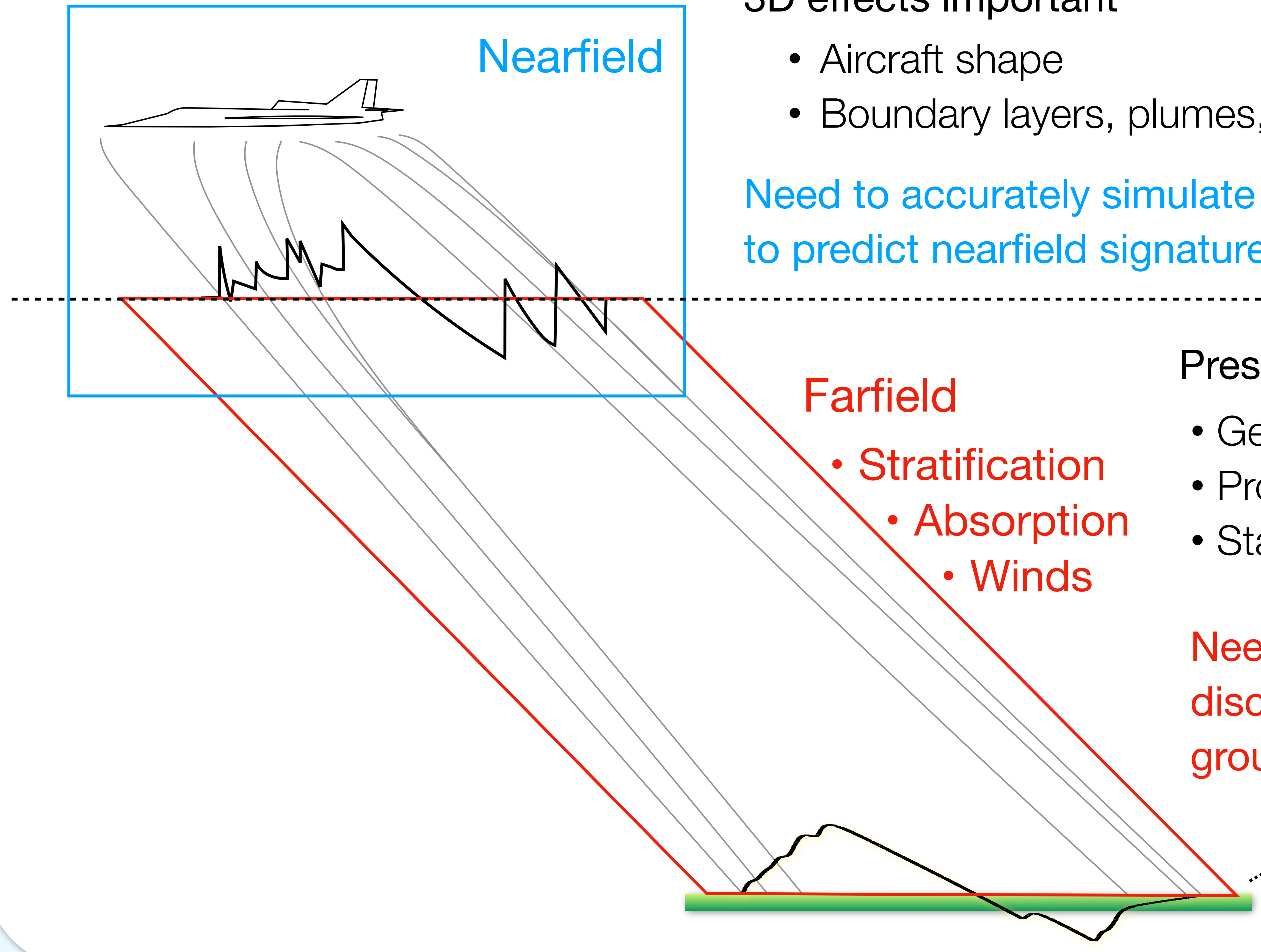

3D effects important

- Aircraft shape
- Boundary layers, plumes, secondary flow paths

Need to accurately simulate complex near-body shocks to predict nearfield signatures

Pressure signatures are independent

- Geometric acoustics
- Propagation distances > 20 km
- State of atmosphere critical

Need to accurately propagate discontinuous pressure signatures to ground and predict loudness metrics

Noise Analysis
PL, ISBAP (dB)

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Nearfield Solver: Cart3D

Flow Solver

- Inviscid flow
- 2nd-order upwind method
  - van Leer flux, Barth-Jespersen Limiter
- RK-5, Multigrid acceleration
- Domain decomposition: OpenMP & MPI

Automatic Meshing

- Multilevel Cartesian mesh with embedded boundaries
- Handles arbitrarily complex vehicle shapes

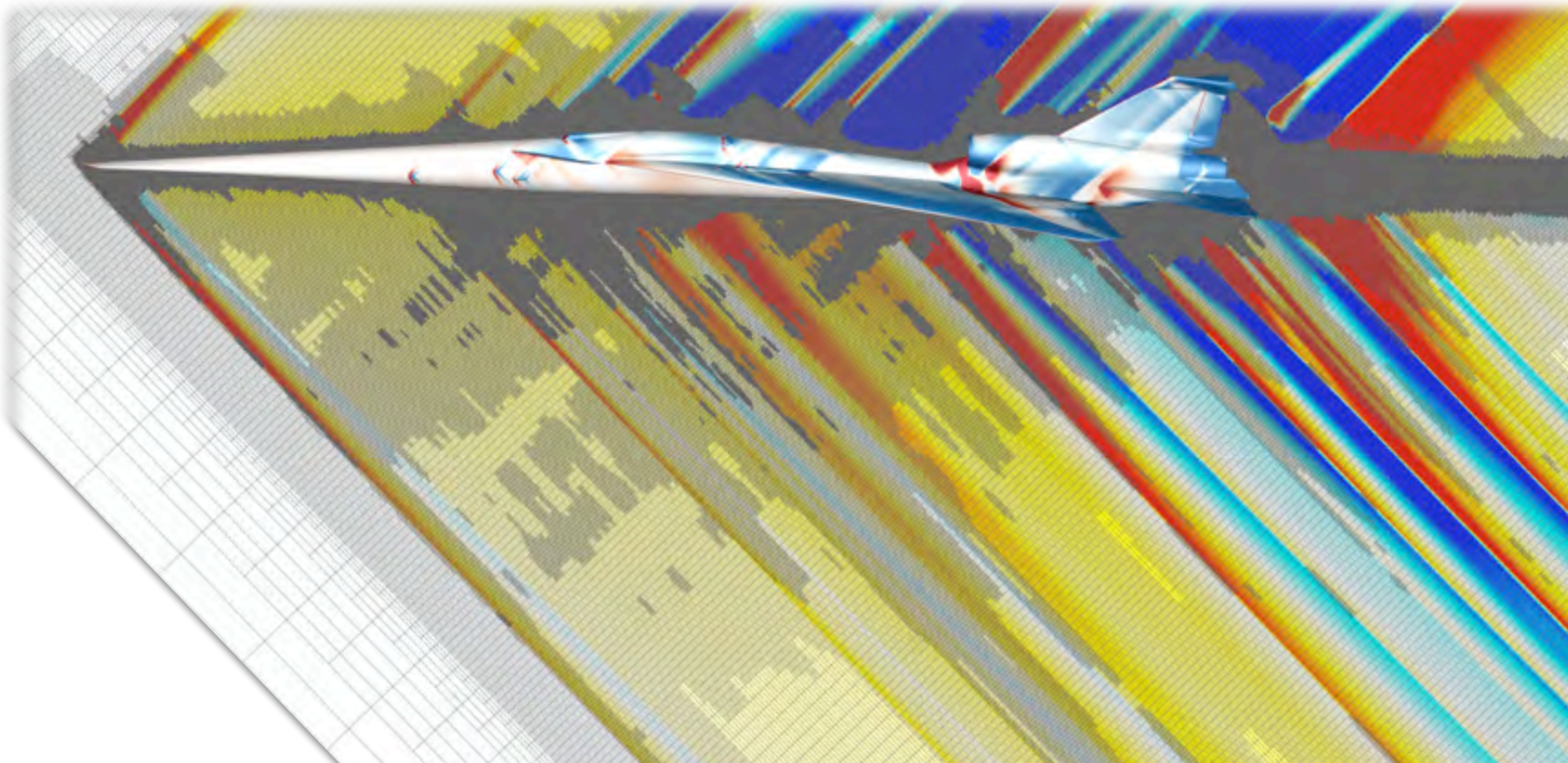
Output-Driven Mesh Adaptation

- Method of adjoint-weighted residuals
- Mesh is refined in locations with highest impact on pressure signatures

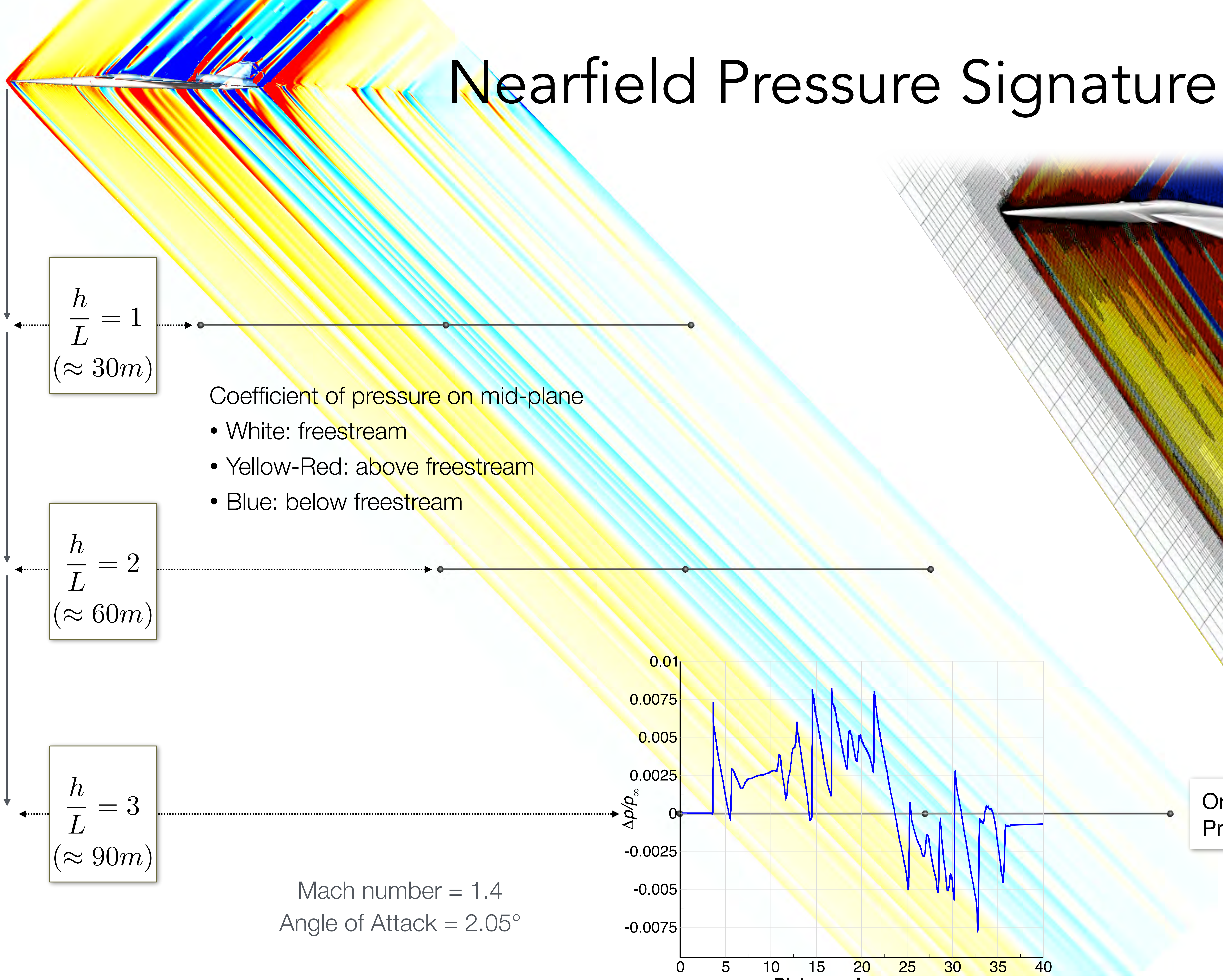
Every nearfield simulation includes

- Mesh refinement study to demonstrate mesh convergence
- Reliable bound on remaining discretization error

Credibility, Efficiency & User-Independent Results



Nearfield Pressure Signature



$\frac{h}{L} = 1$ $(\approx 30m)$

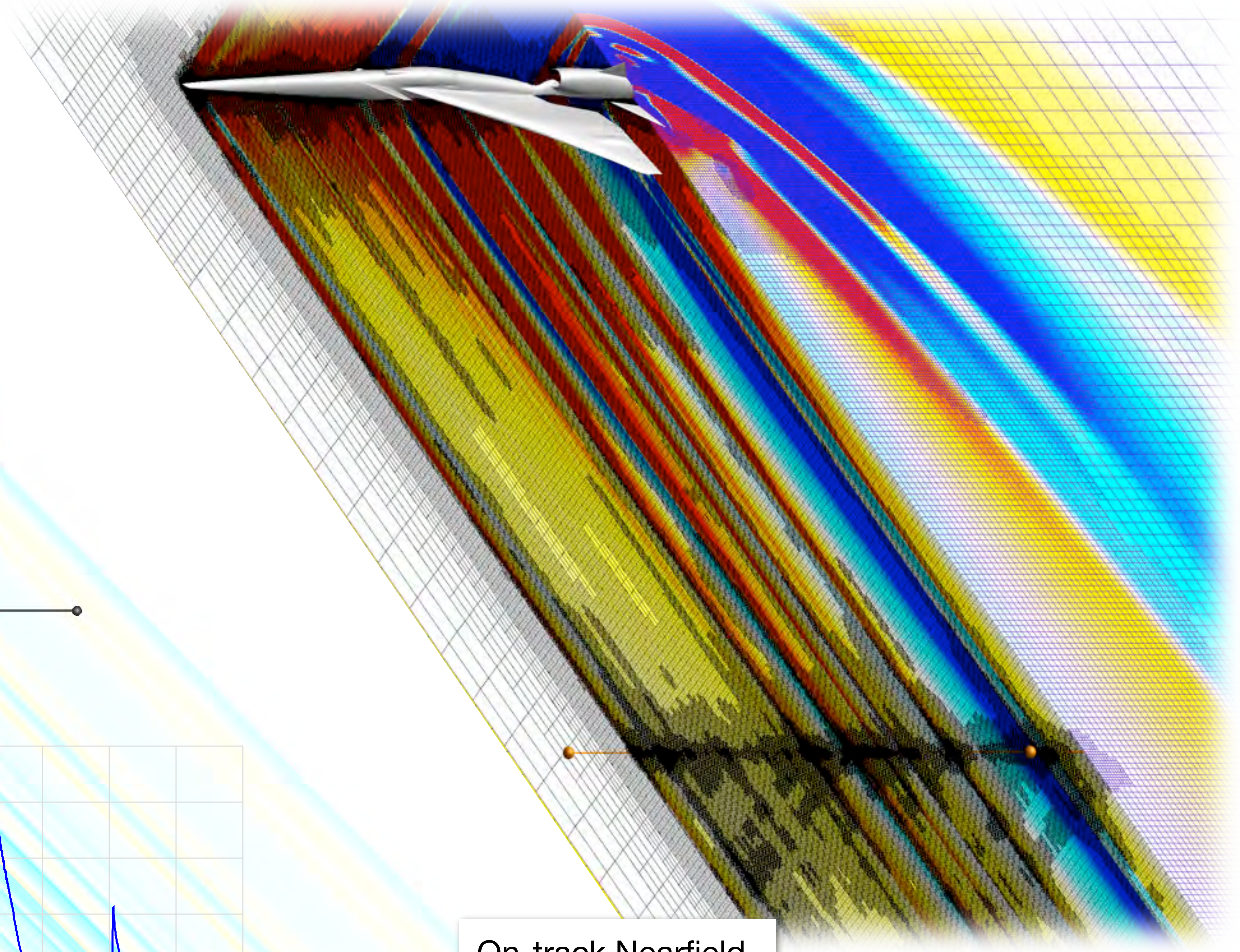
$\frac{h}{L} = 2$ $(\approx 60m)$

$\frac{h}{L} = 3$ $(\approx 90m)$

Coefficient of pressure on mid-plane

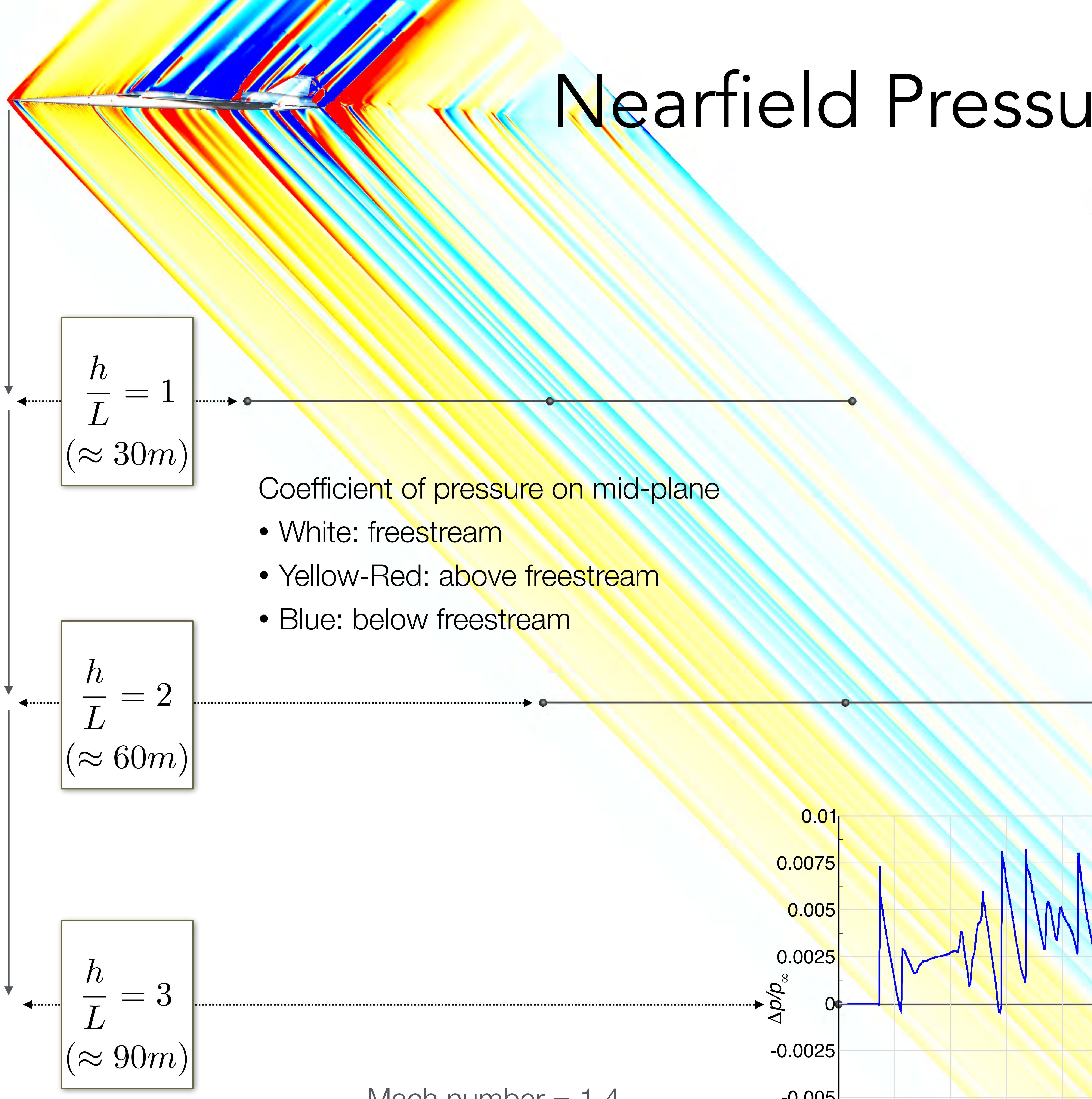
- White: freestream
- Yellow-Red: above freestream
- Blue: below freestream

Mach number = 1.4
Angle of Attack = 2.05°



On-track Nearfield Pressure Signature

Nearfield Pressure Signature



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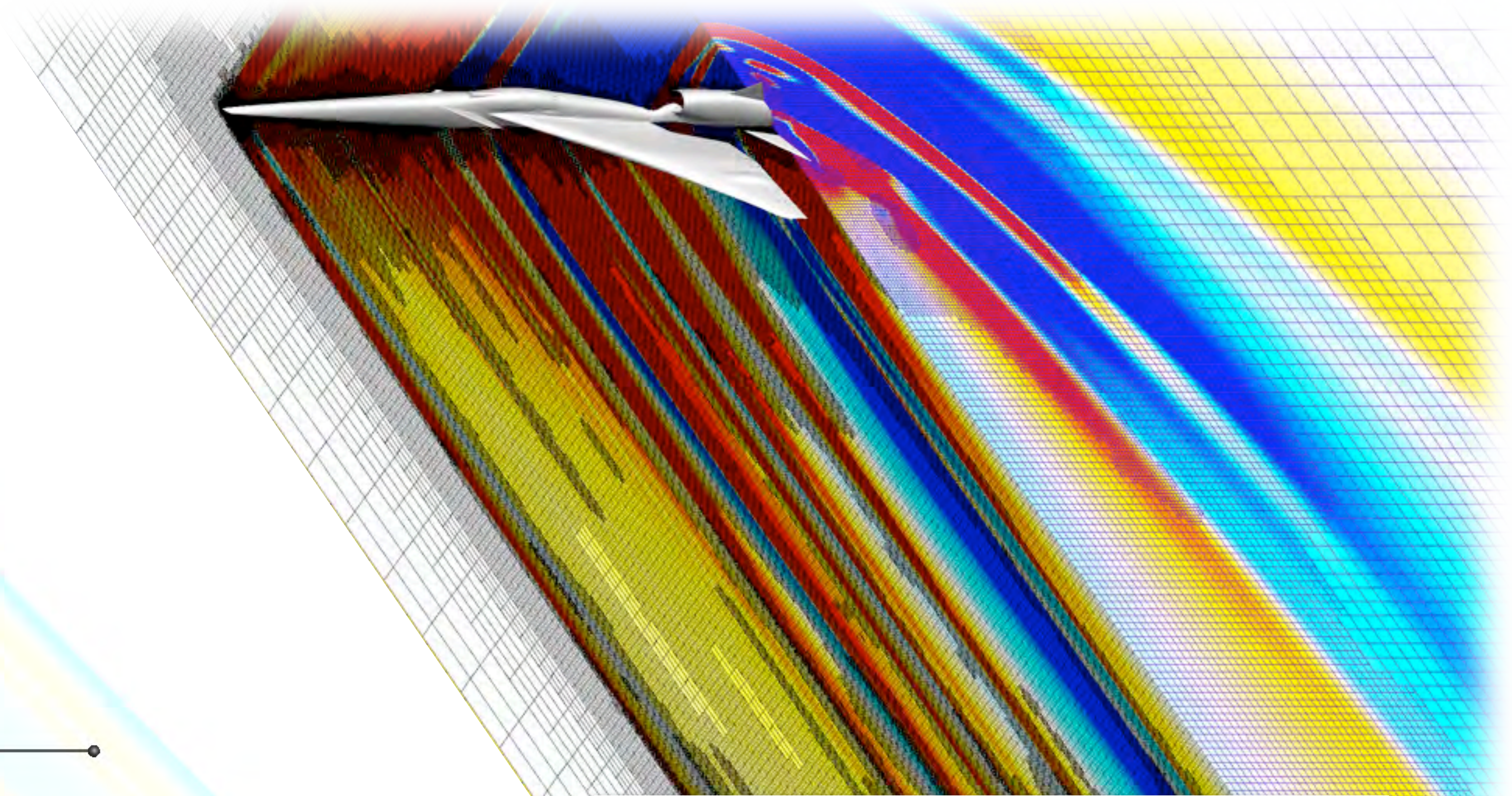

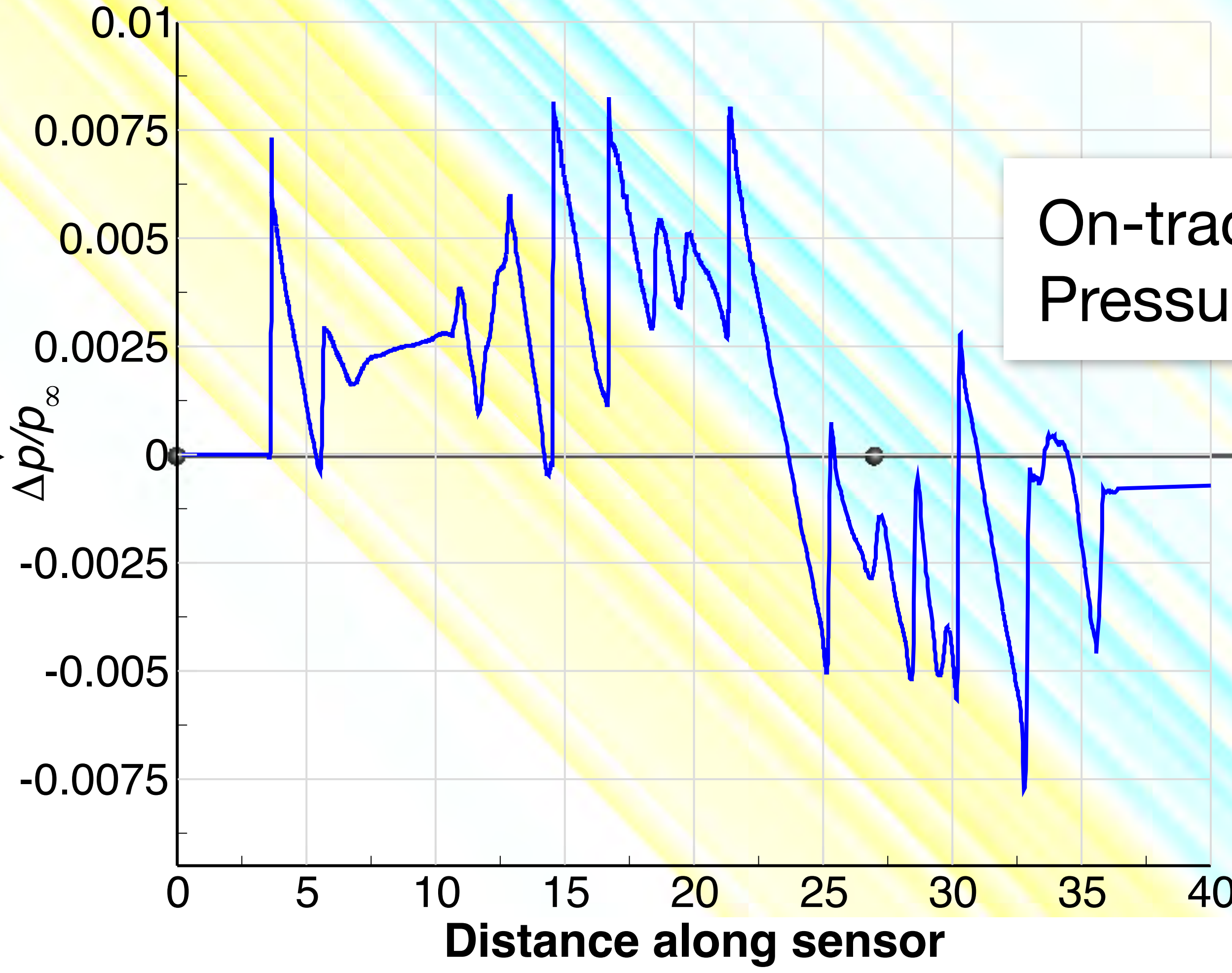

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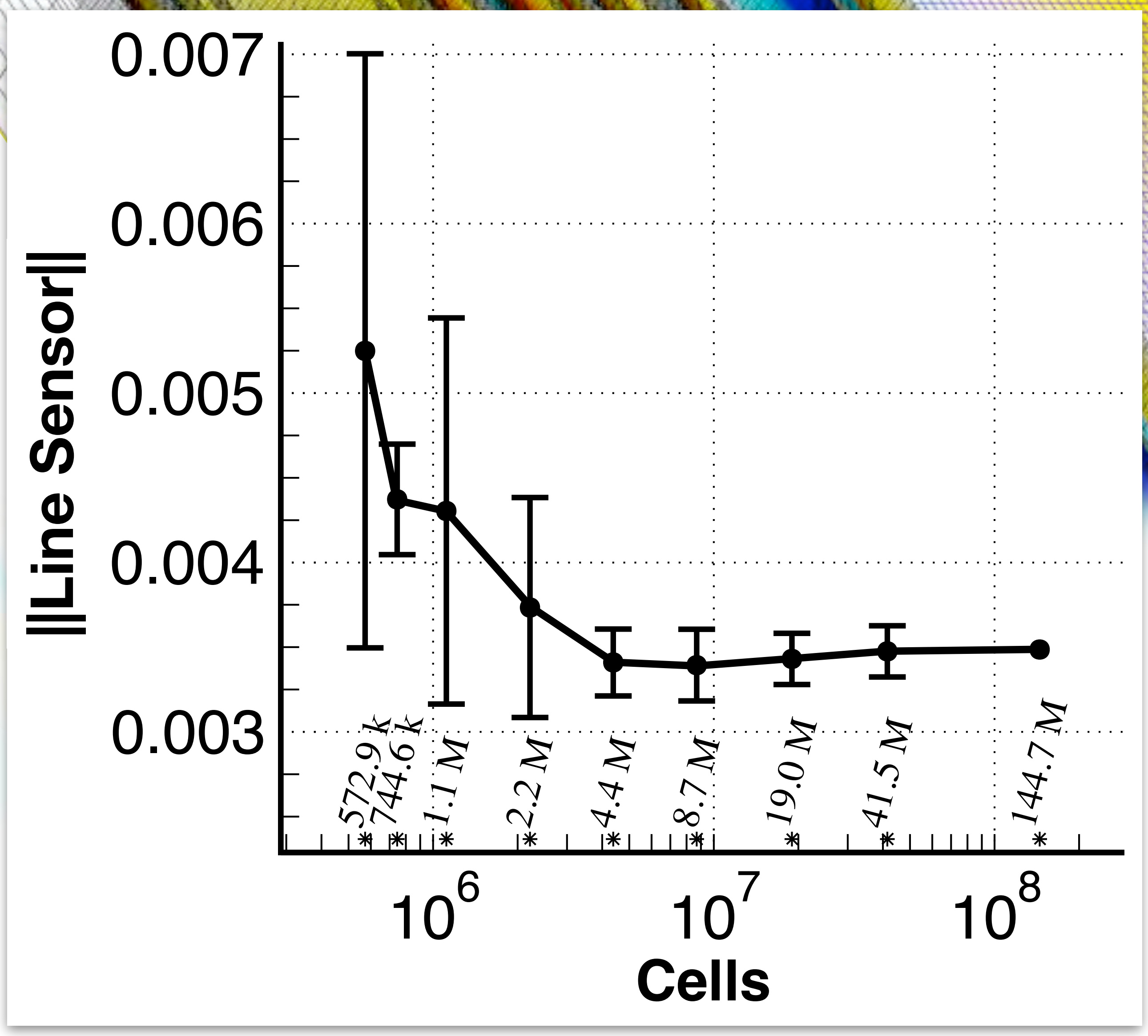
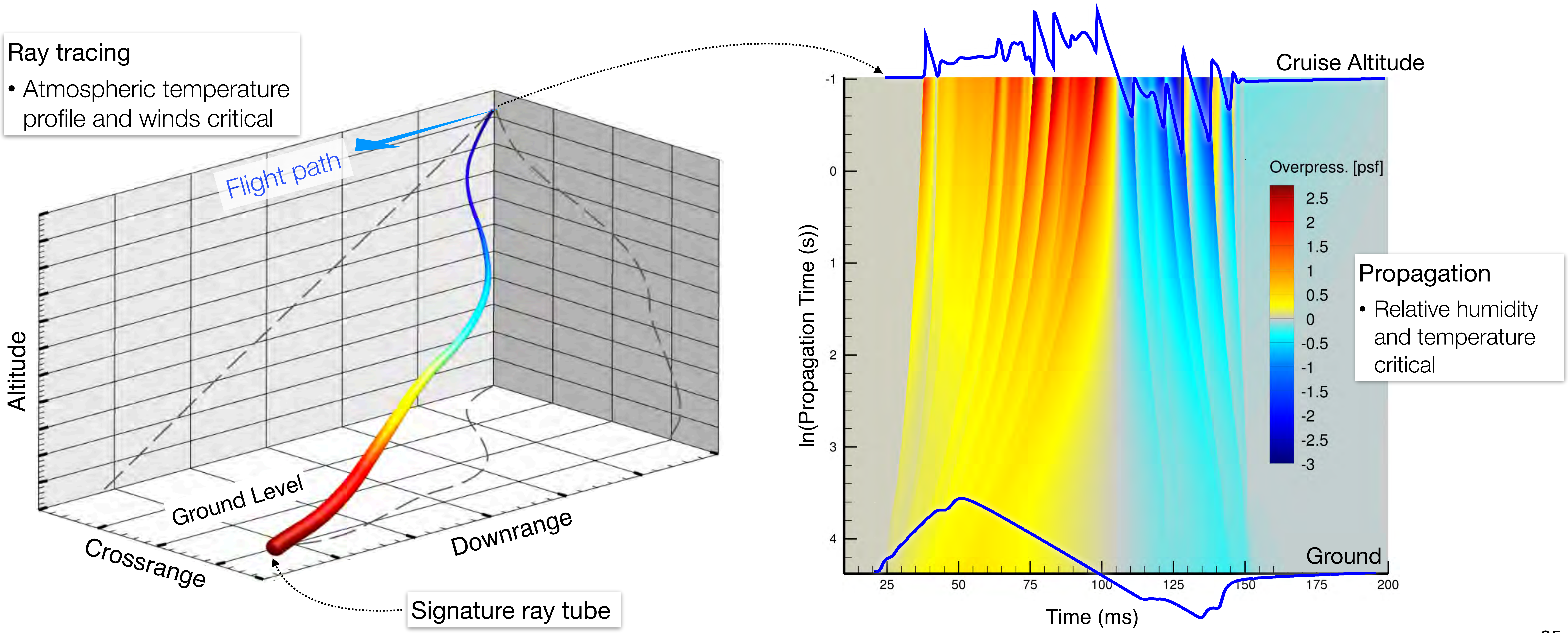


Farfield Solver: sBOOM

Ray tracing coupled with augmented Burgers' equation

- Includes nonlinearity, thermoviscous absorption and relaxation
- 2nd-order finite volumes: Godunov's flux, van Leer Limiter, RK2, uniform mesh



Atmospheric Uncertainty in Propagation

Signature strongly influenced by local atmospheric conditions

- Ray tracing depends on temperature profile
- Relative humidity influences waveform attenuation via molecular relaxation
- Winds primarily affect arrival time and ground intercept

Detailed databases of atmospheric profiles for temperature, relative humidity, pressure and wind available

- Climate Forecast System Reanalysis v2 (CFSv2)
- European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5)


Image Credit: NASA/Carla Thomas

Challenge is to accurately and efficiently model stochastic fluctuations in the atmosphere

- Atmospheric profiles are correlated fields, but we need independent random variables (as few as possible)
- Random process should approximate mean and standard deviation of observations

Atmospheric Observations

Current focus is on variability in atmospheric profiles at Edwards AFB

- Location for initial X-59 acoustic validation flights
- Historical observations from 2003 to 2022 from ERA5 dataset
- Profiles available every 6 hours every day
- Selected August at 18:00 UTC (10 am PT) as an example
  - 620 atmospheric profiles
- This study considers temperature (T) and relative humidity (RH)

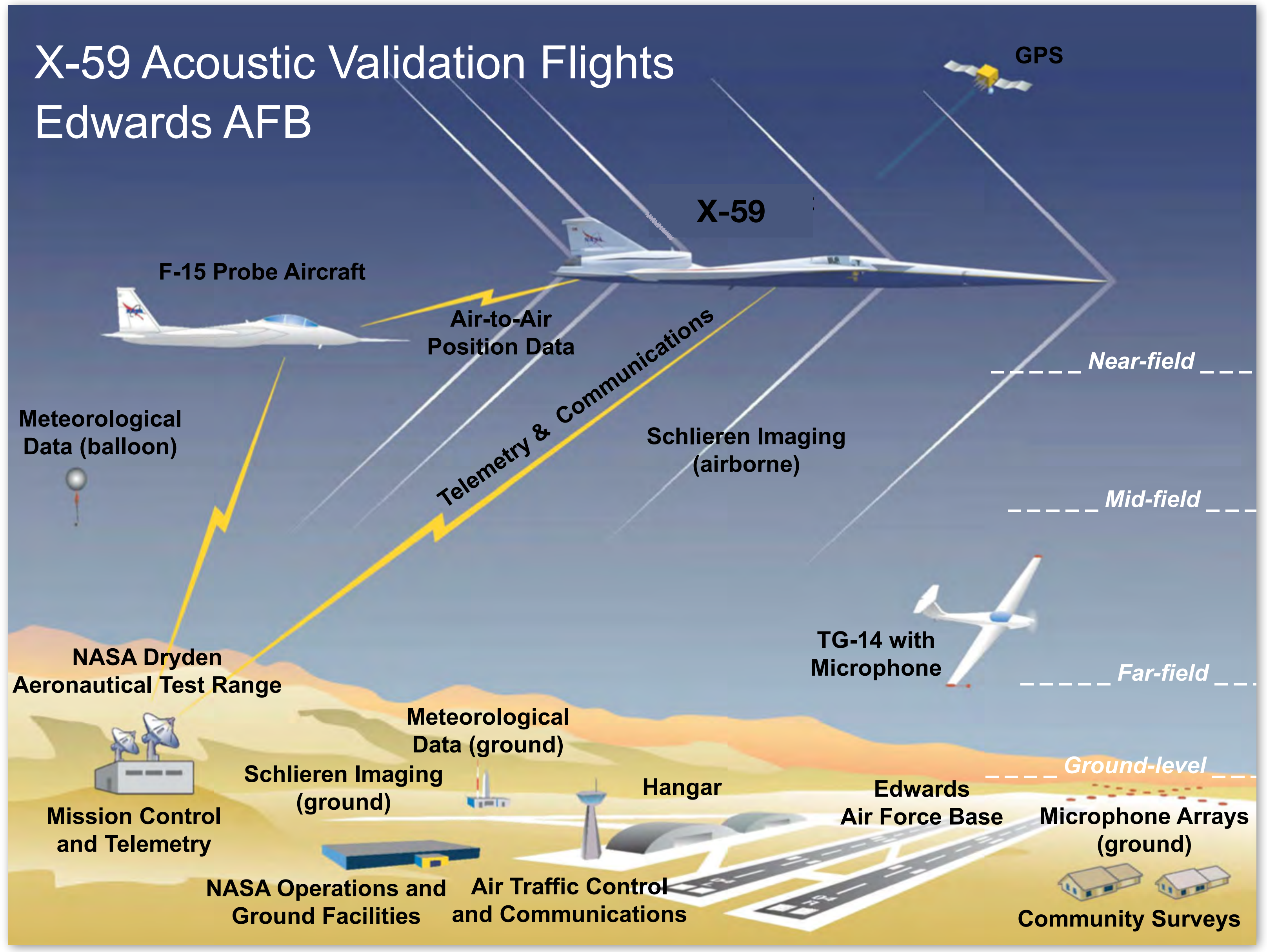
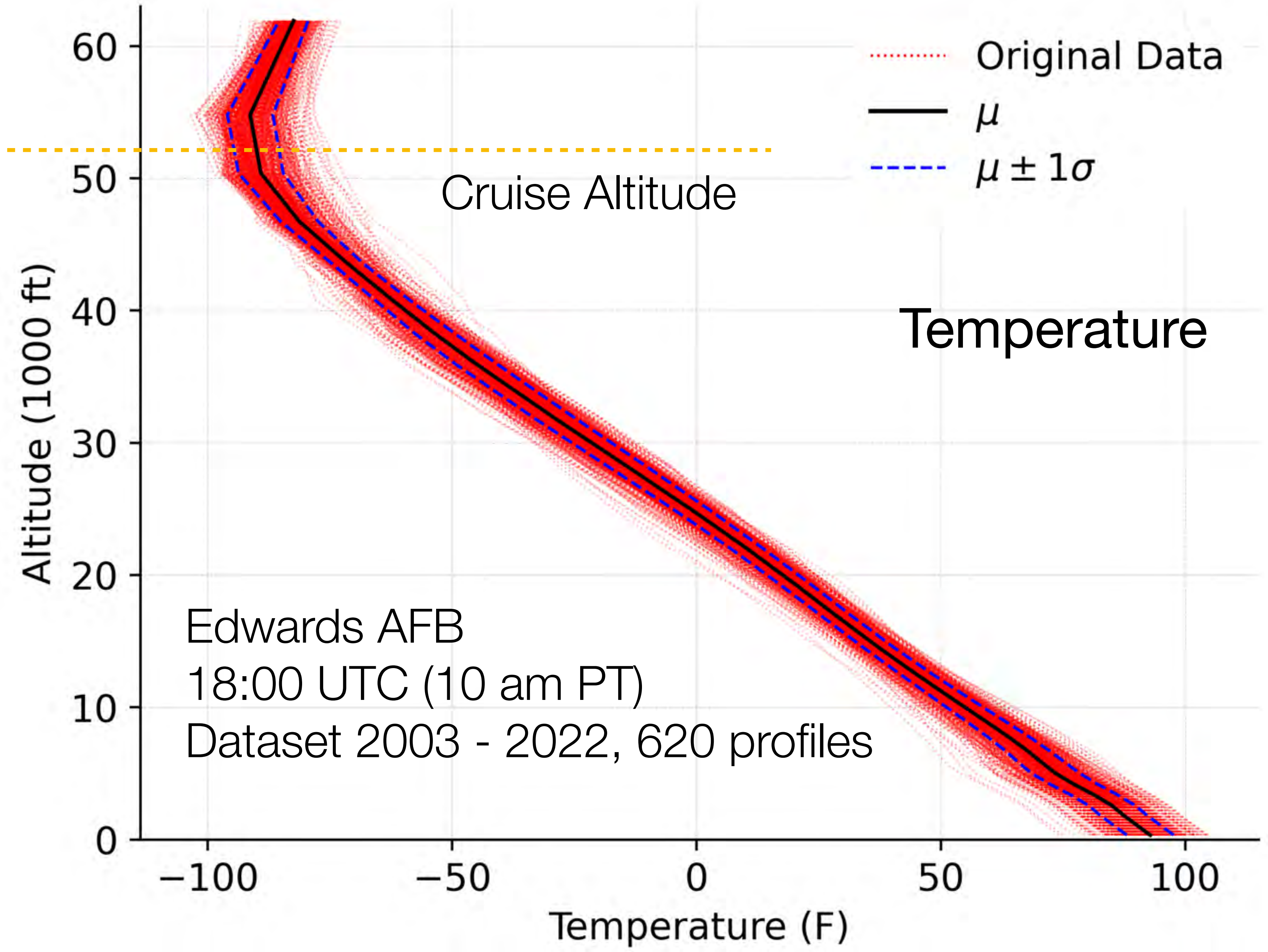
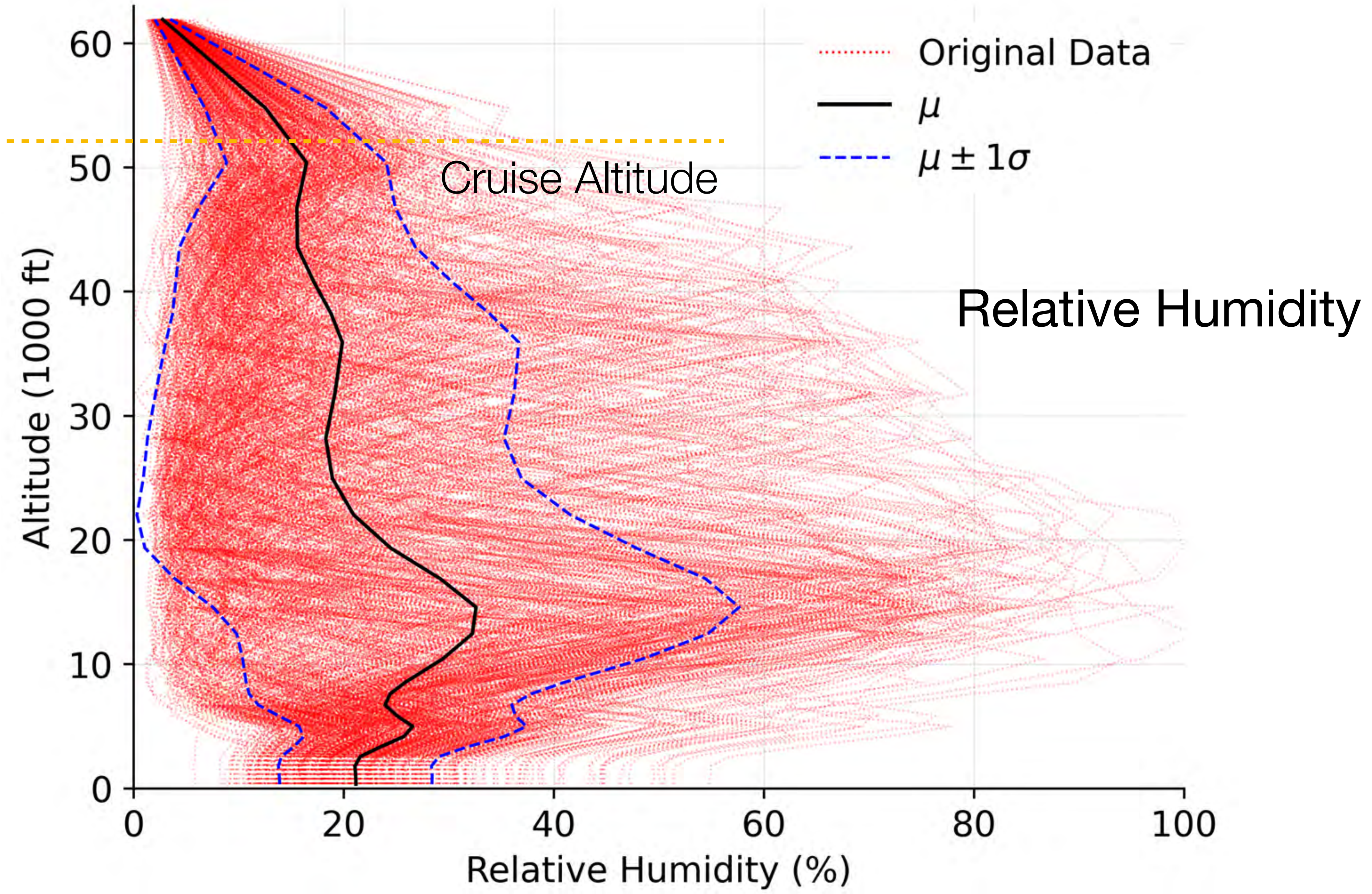
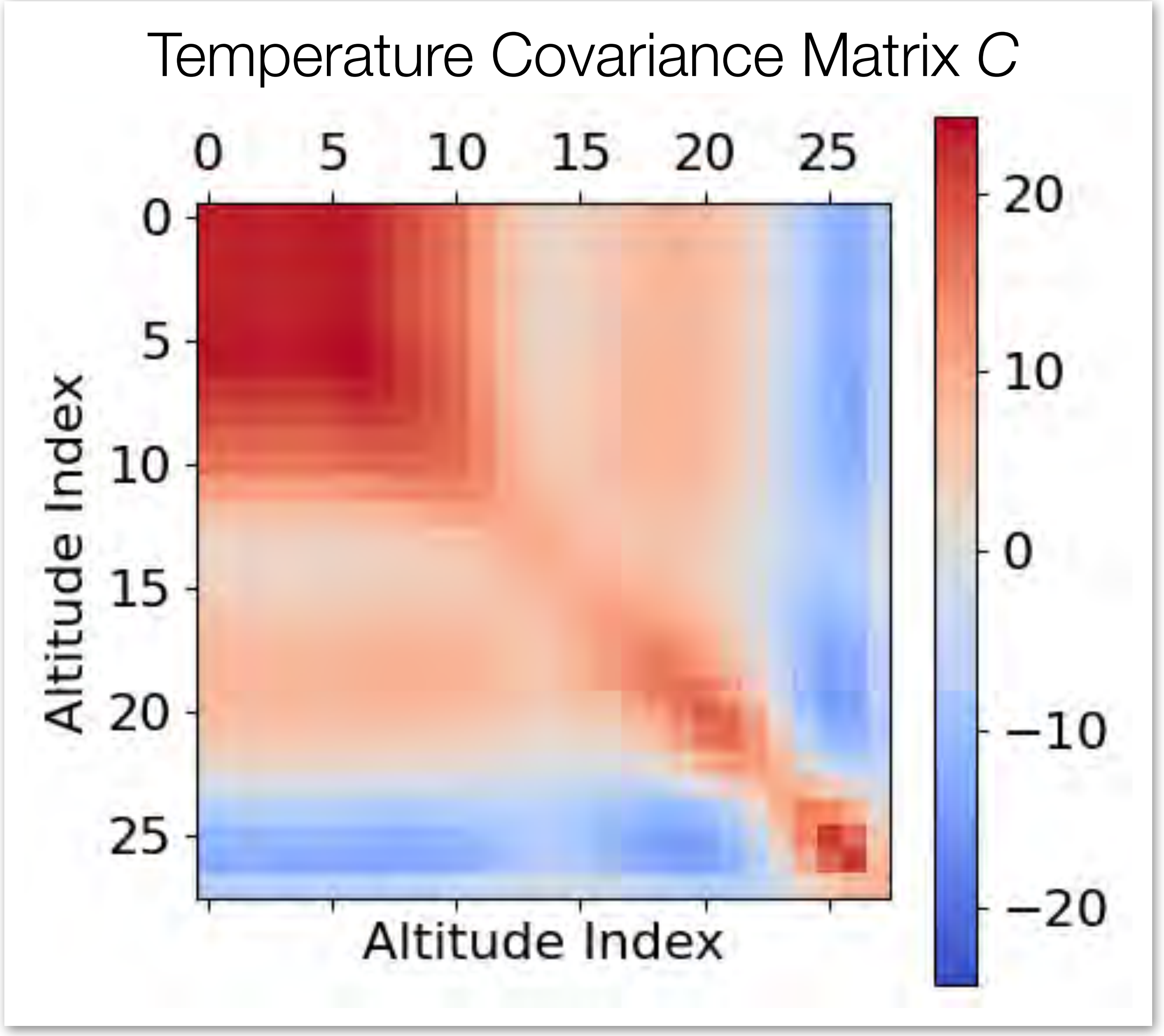


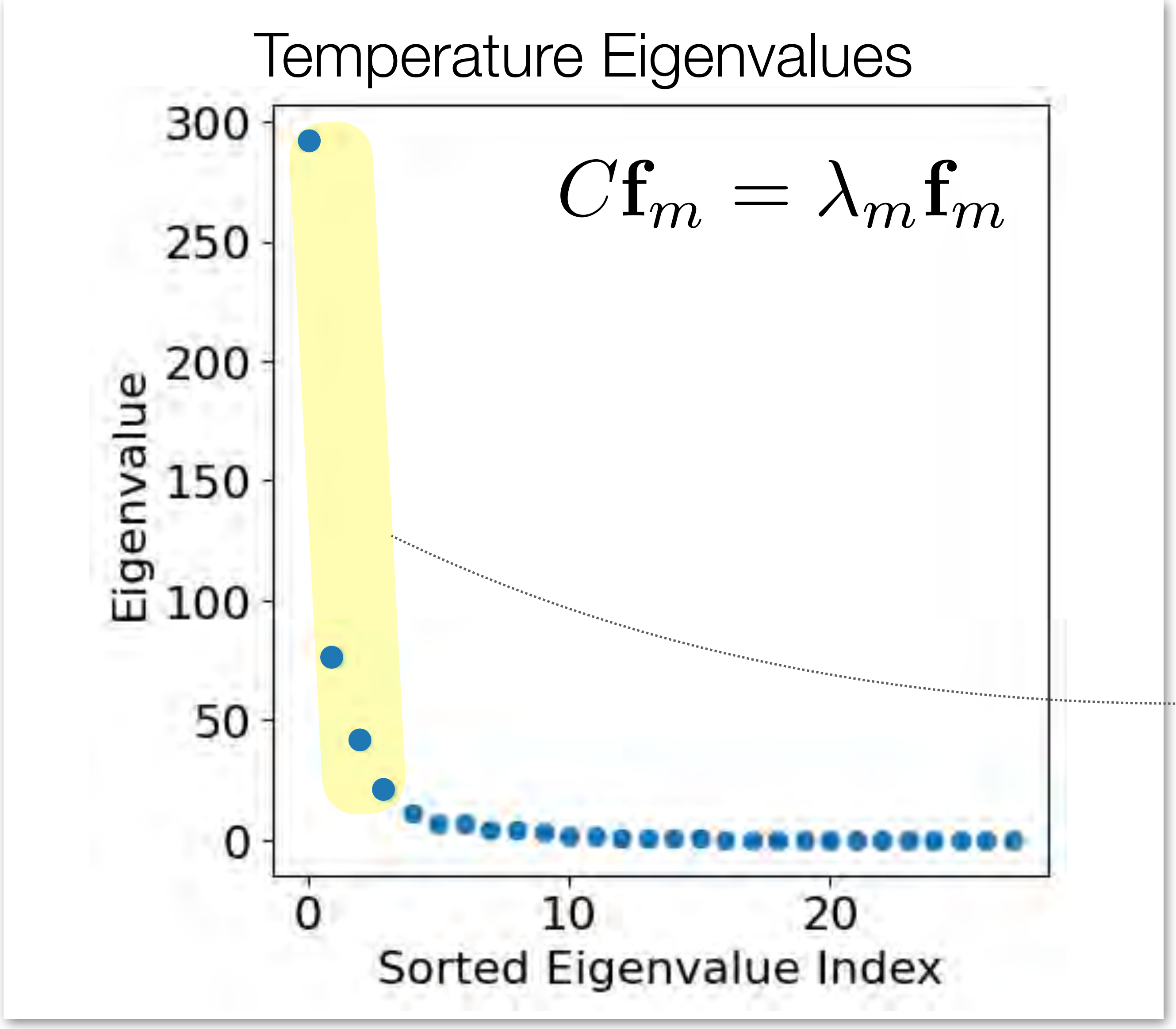
Image Credit: NASA





Parameterization of Atmospheric Profiles





Karhunen-Loeve (KL) Expansion

- Karhunen-Loeve expansion is used to model uncertainty in atmospheric data
  - Ideal for centered, Gaussian random fields
- Main idea is to use the covariance of the observed data to anchor the parameterization
  - Diagonalize discrete covariance matrix
  - Select largest eigenvalues to model fluctuations in atmospheric properties

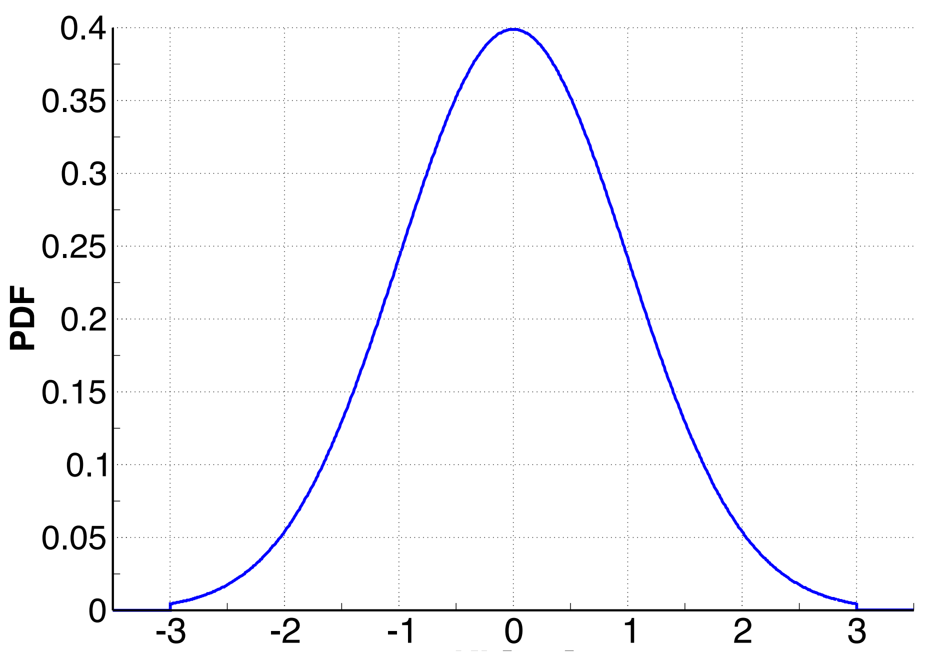
Discrete random-process temperature profile

$$\mathbf{T}(\xi) = \bar{\mathbf{T}} + \sum_{m=1}^{M} z_m(\xi)\sqrt{\lambda_m}\mathbf{f}_m$$

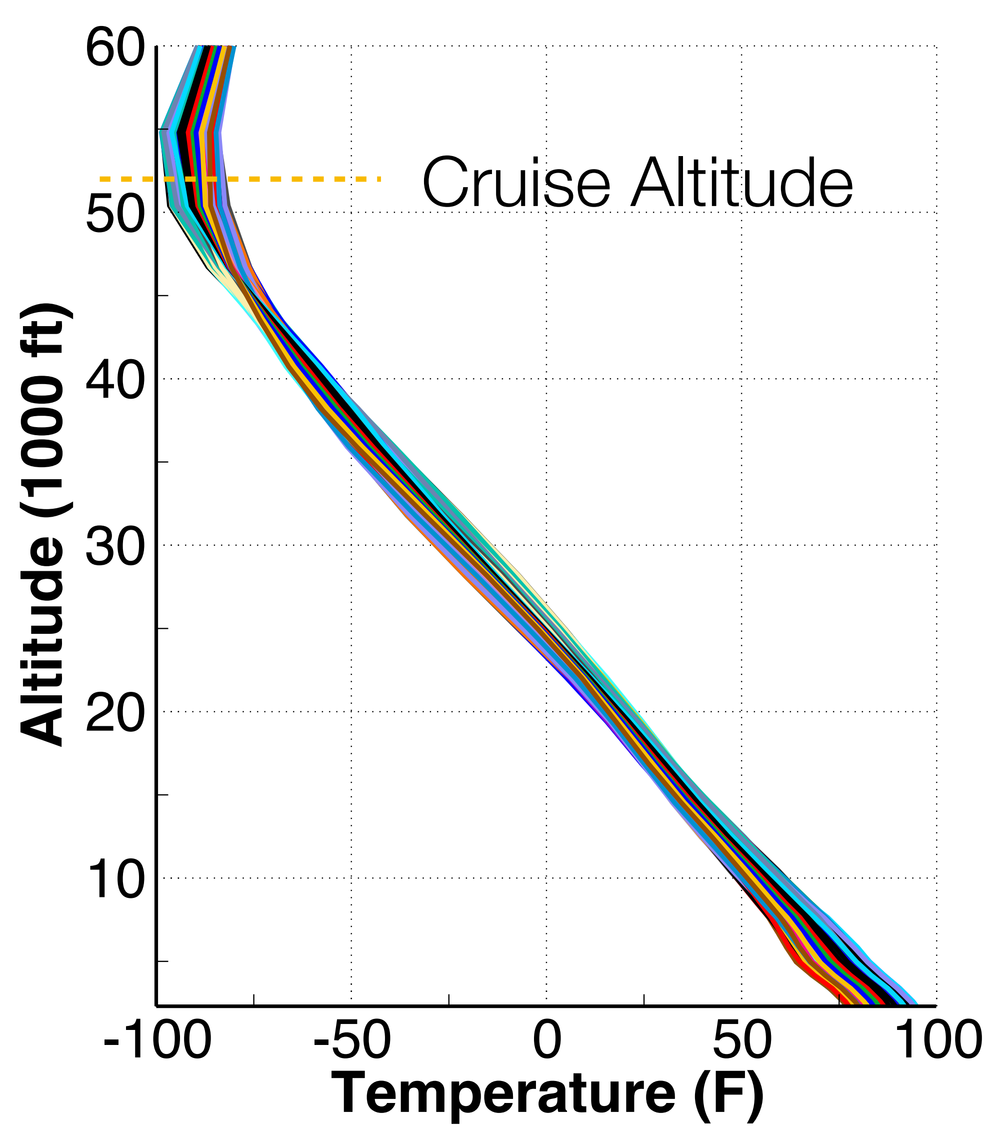
Mean from observed data

M largest eigenvalues of covariance matrix C

Independent Random Variables



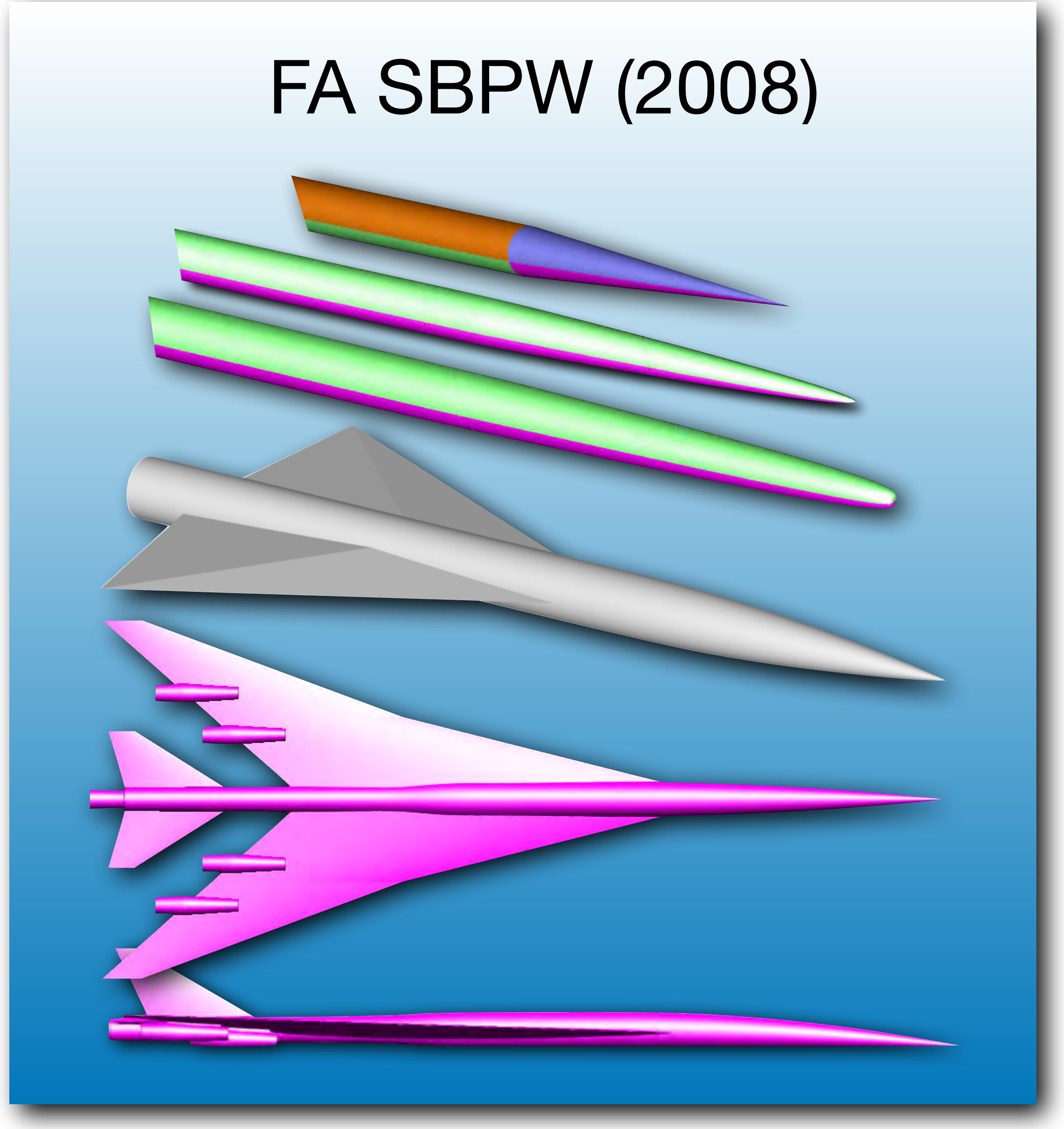
$$z_m = \mathcal{N}_{n\sigma}(\mu = 0, \sigma^2 = 1)$$



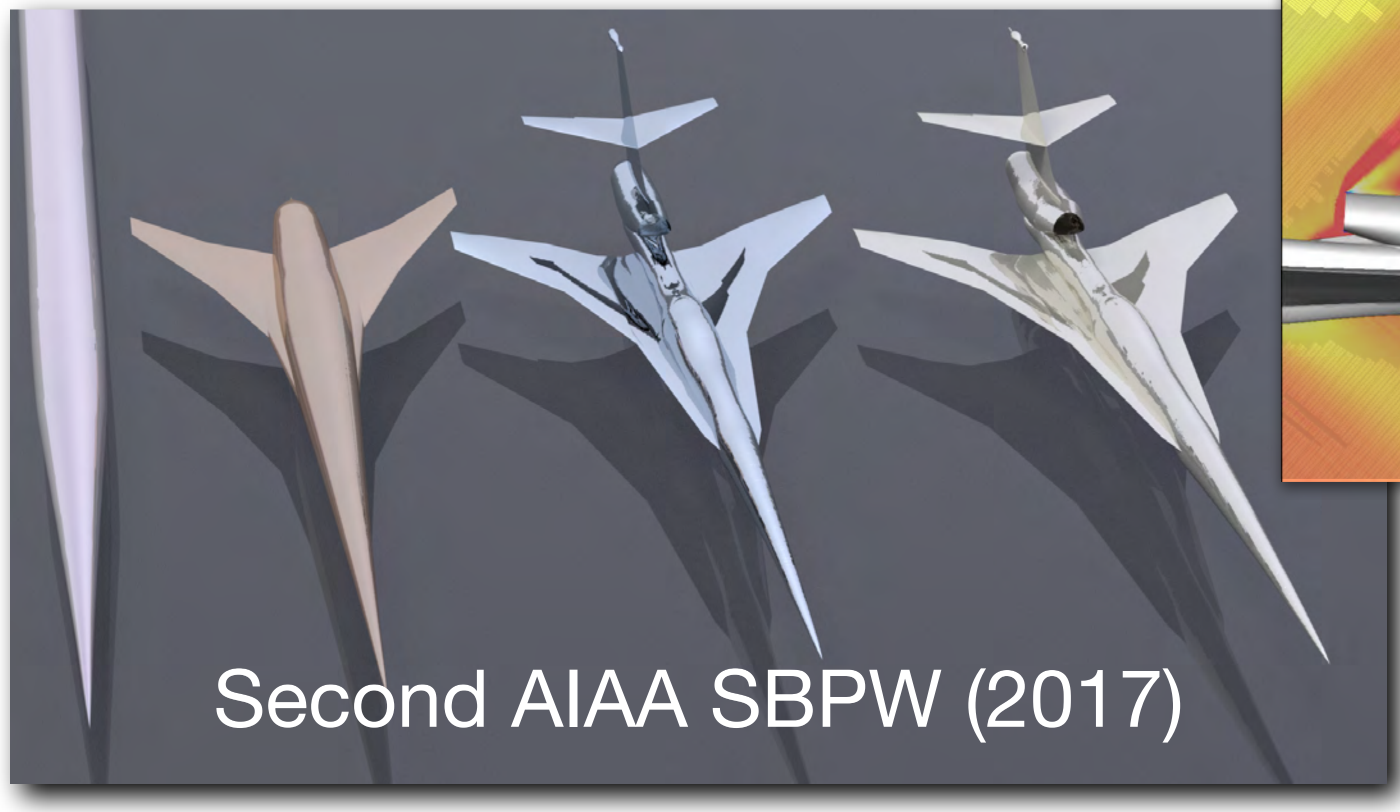
Many Verification and Validation Studies

First AIAA SBPW (2014)

Image Credit: NASA/Carla Thomas

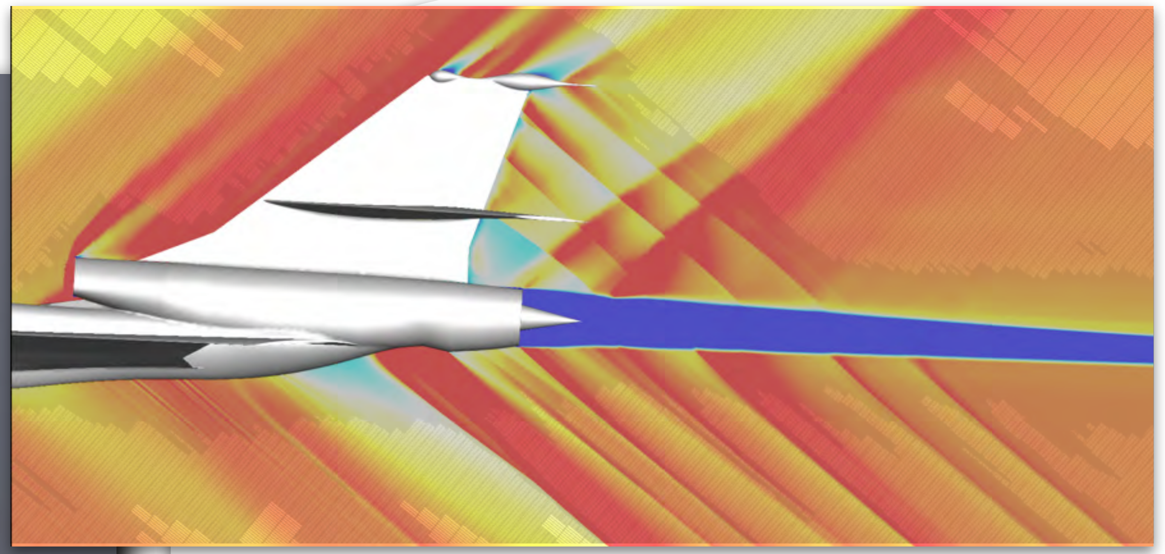


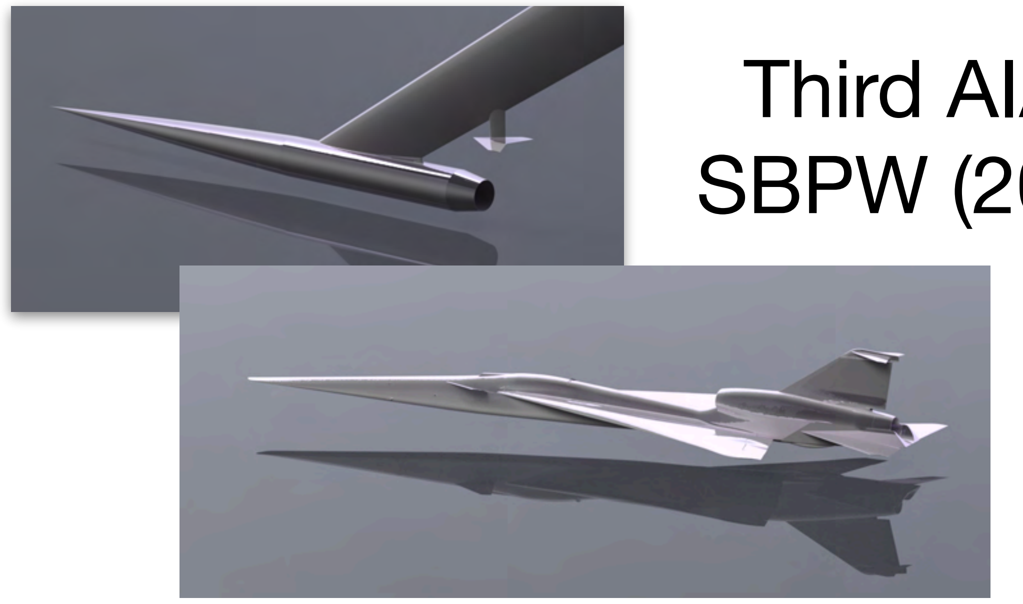
FA SBPW (2008)



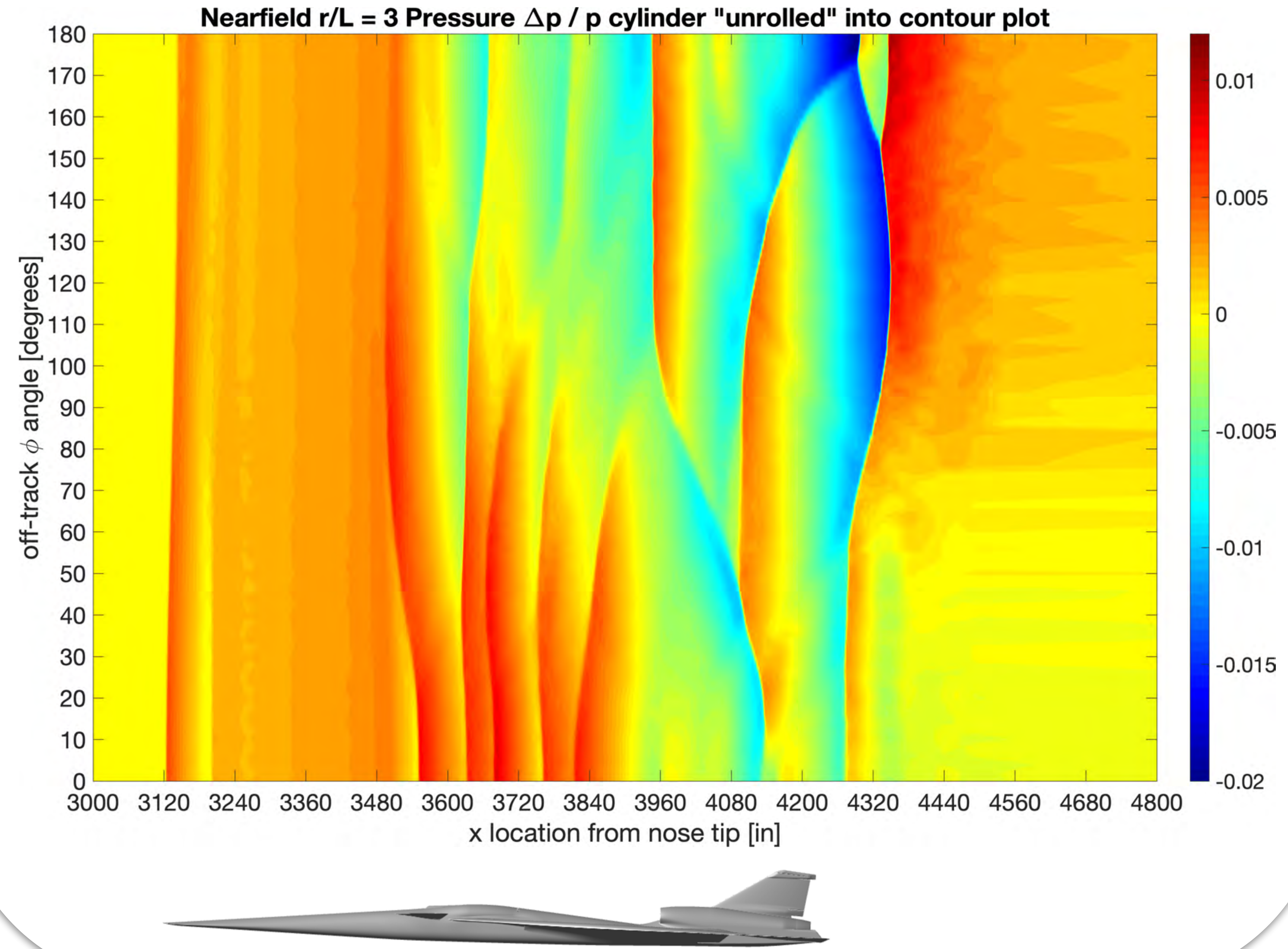
Second AIAA SBPW (2017)

Progress
from **nearfield-only on-track simulations** on simplified geometries with no propulsion to **full ground noise carpet X-59 simulations** with propulsive and secondary flow paths





Third AIAA SBPW (2019)

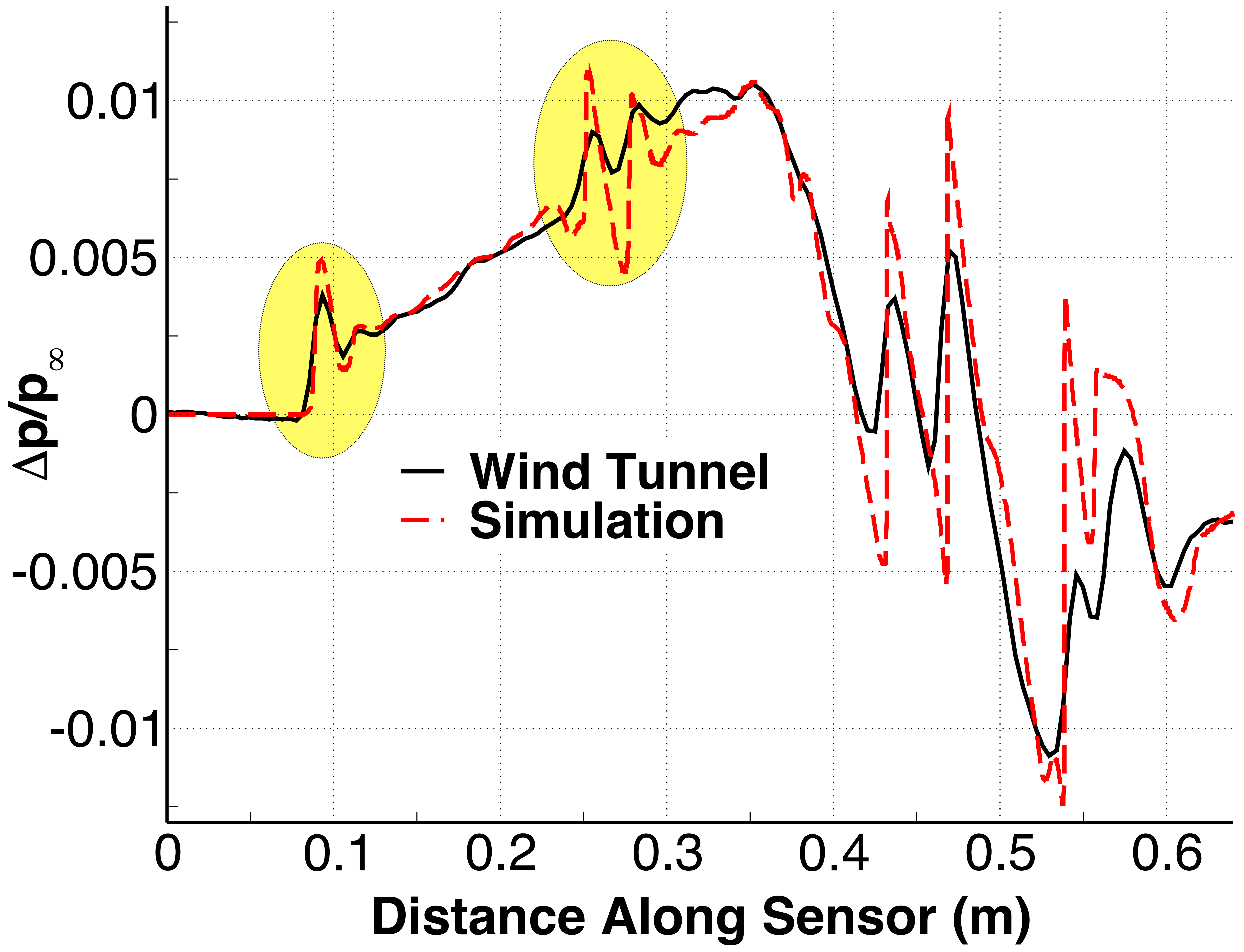


Outline

1. Background & Motivation
2. Objectives
3. Methodology
   - Uncertainty quantification
   - Low-boom simulations
   - Atmospheric uncertainty in propagation
4. Results
   - Nearfield signature uncertainty estimates
   - Uncertainty in atmospheric conditions
   - Uncertainty in X-59 operating conditions and atmosphere
5. Summary & Outlook

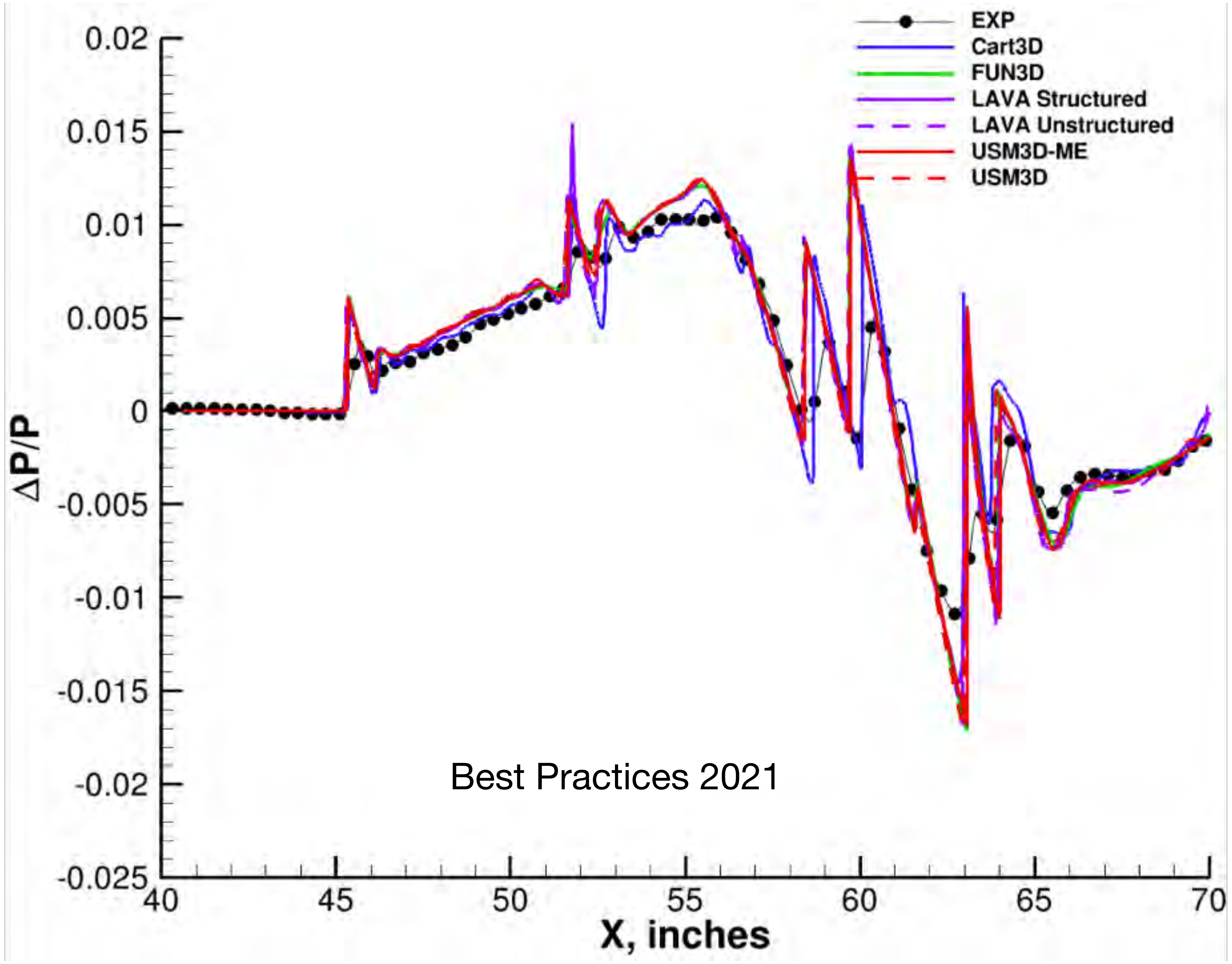
Nearfield Signature Uncertainty Quantification

Nearfield Signature UQ



- Comparison of wind tunnel measurements to deterministic simulation reveals significant discrepancies starting at the leading shock, through the rooftop and the recovery region
- Predicted signature misses shock amplitude and rise time

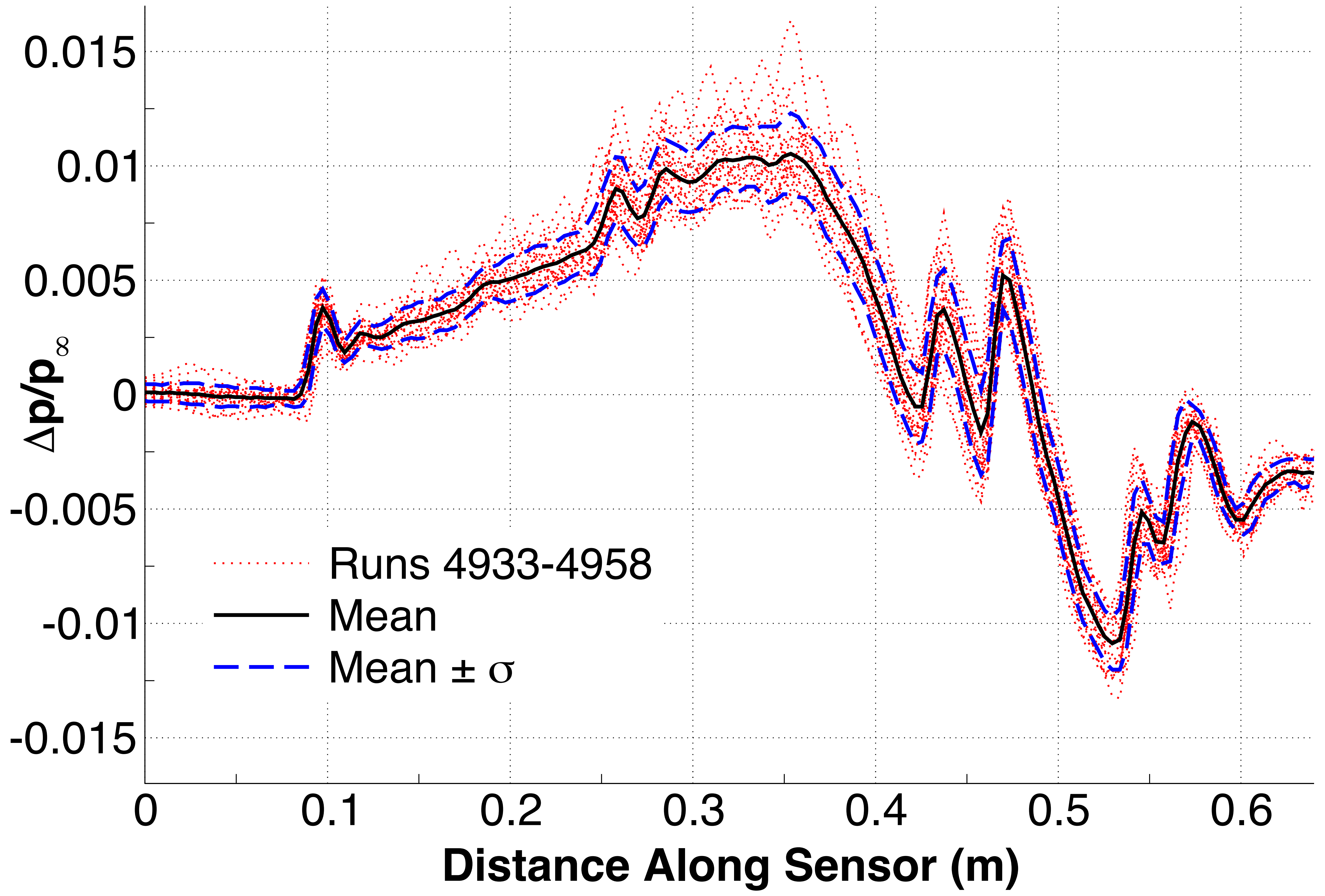
Nearfield Signature UQ



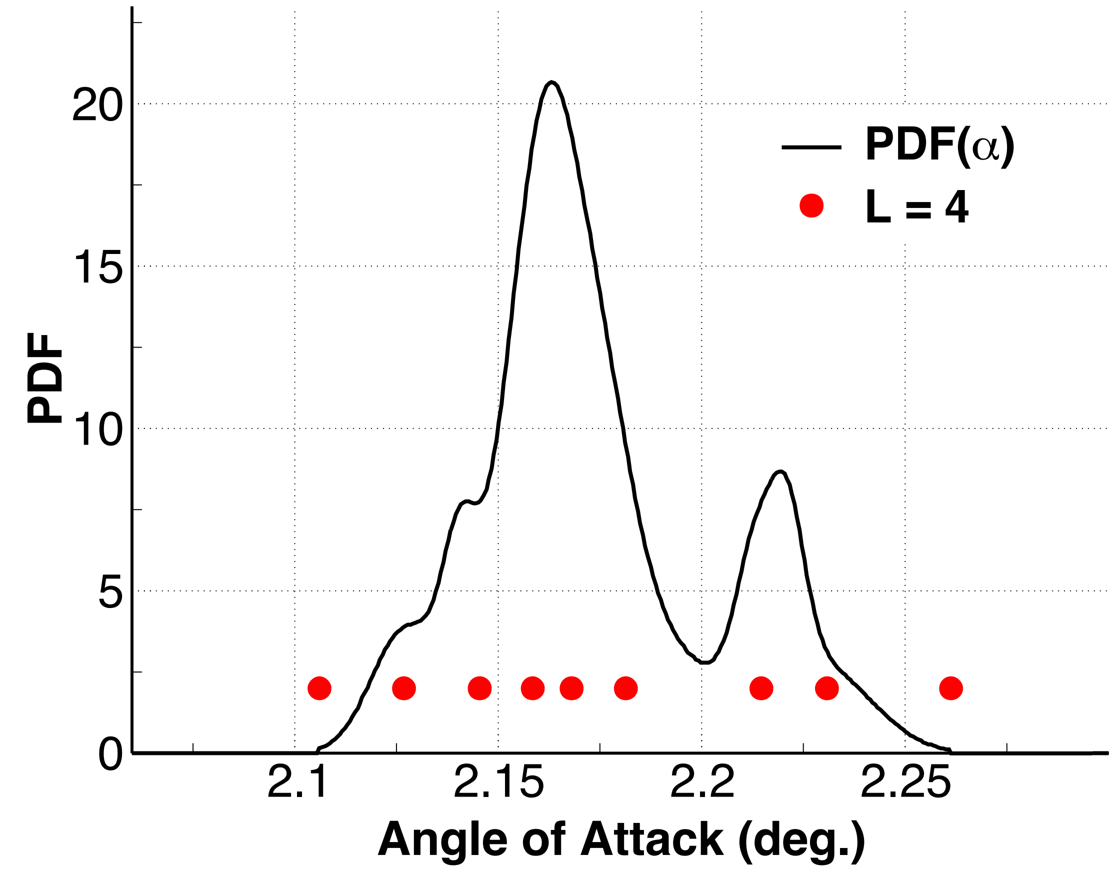
- Consistent predictions between codes
- Higher modeling fidelity does not significantly improve agreement with measurements
- All predicted signatures miss shock amplitude and rise time

Experimental Measurements & Random Variables

Measured Signatures



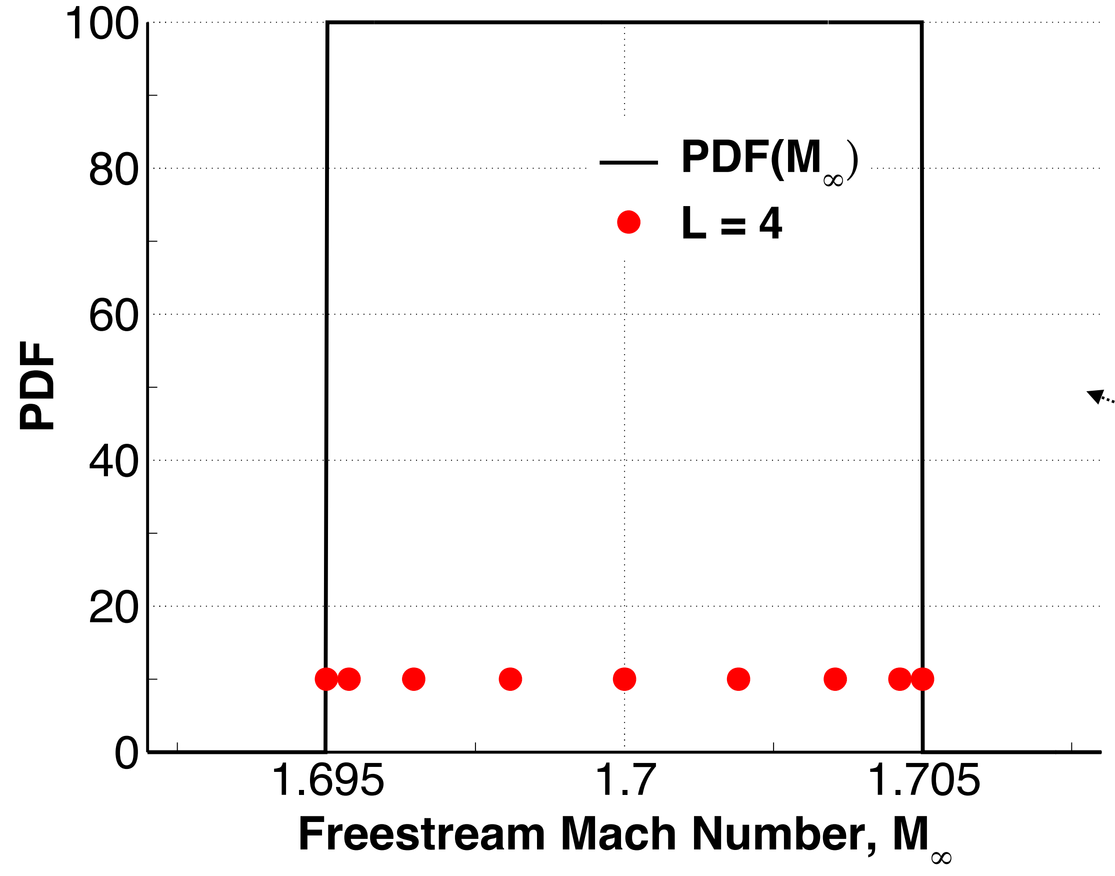
Input Random Variables



Angle of Attack Uncertainty

Distance from Nose to Sensor

Based on test data

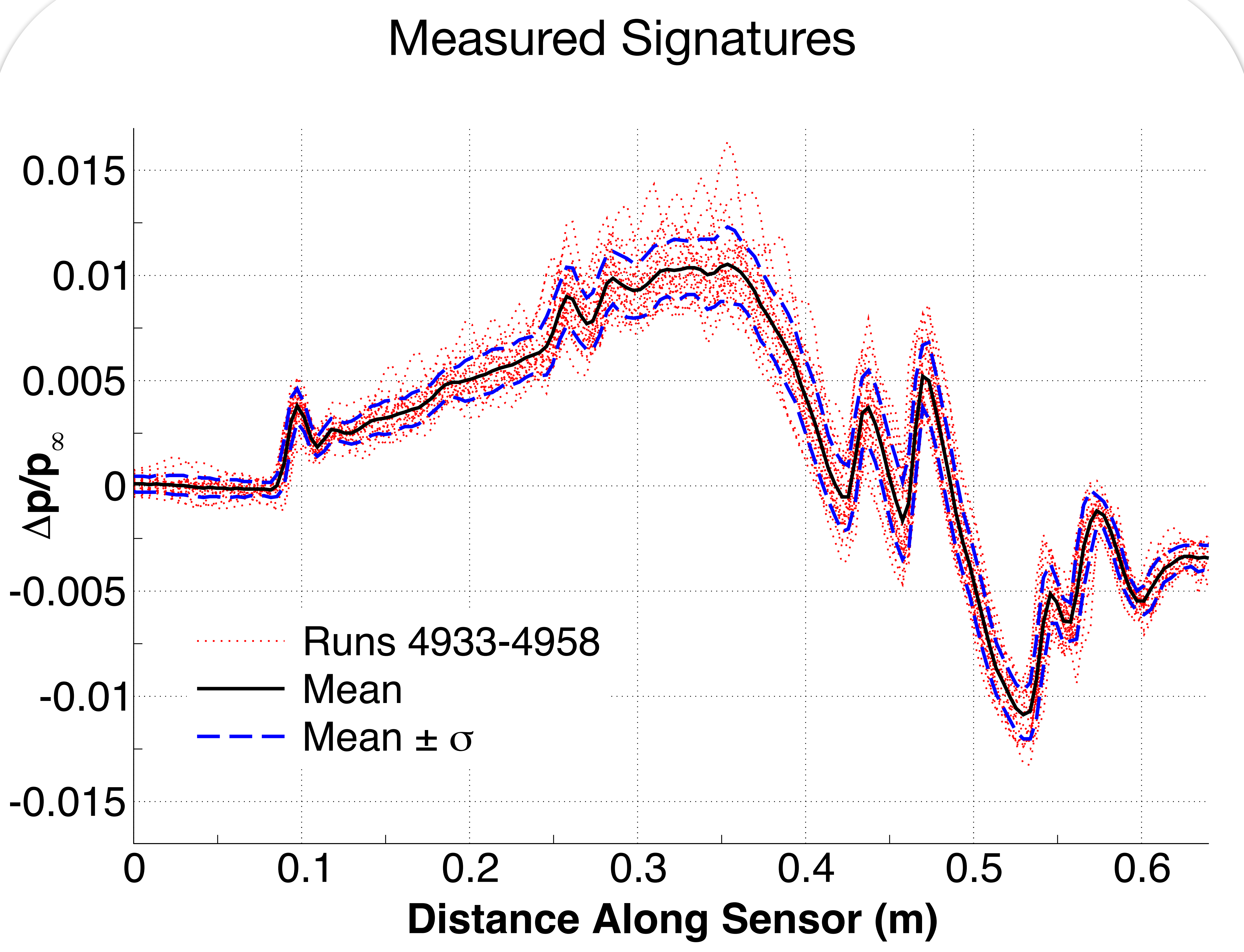


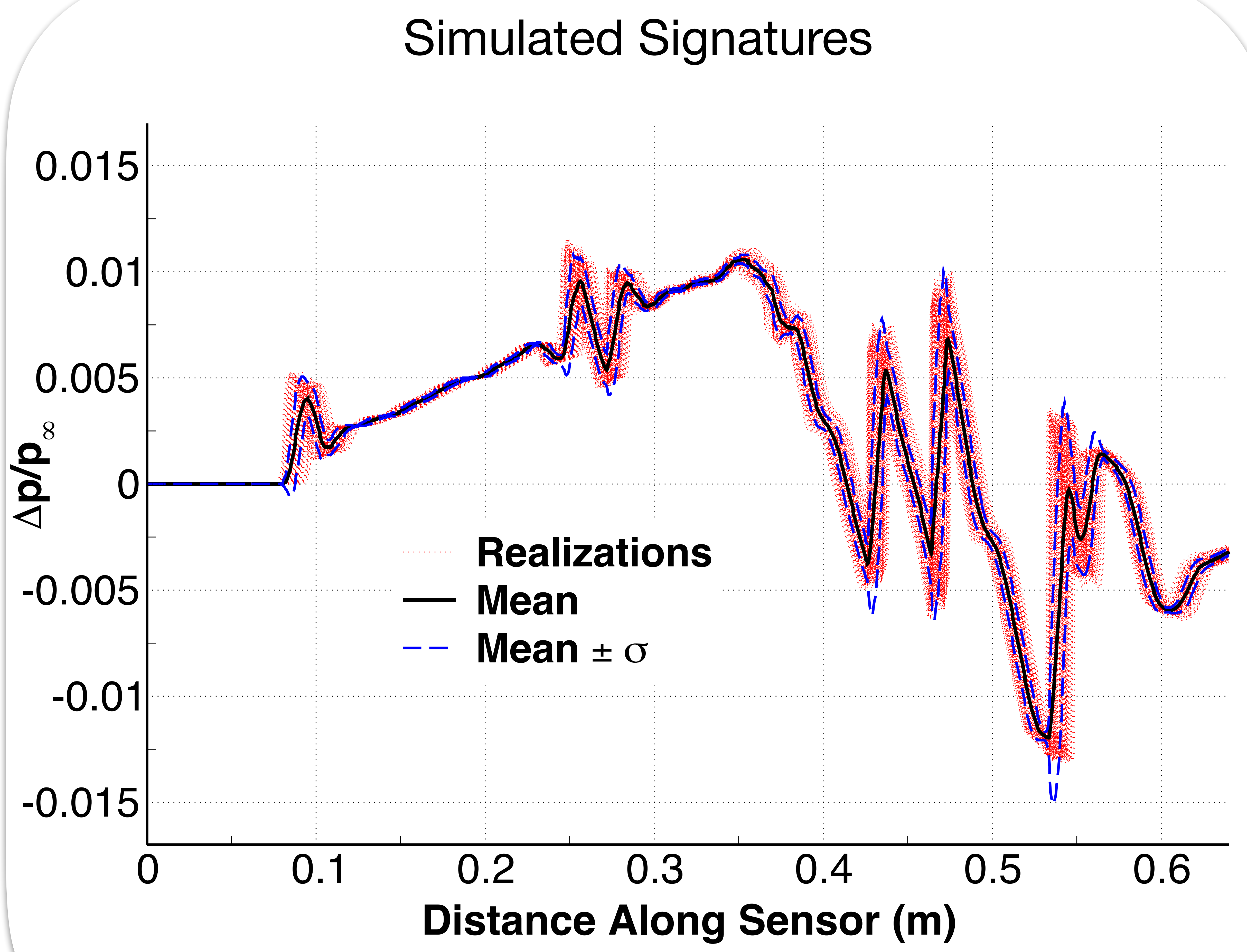
Mach Number

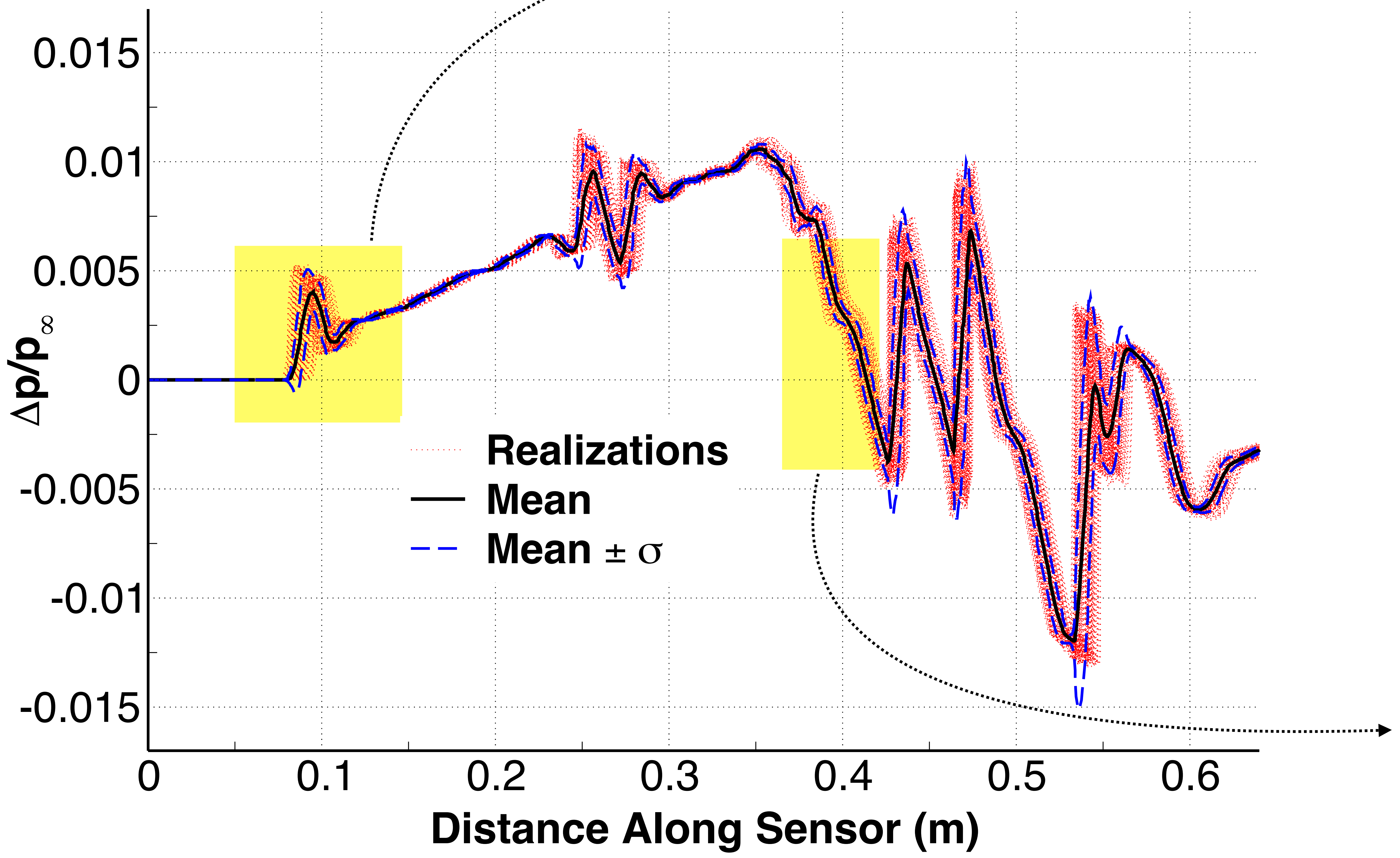
Based on empty tunnel CFD studies

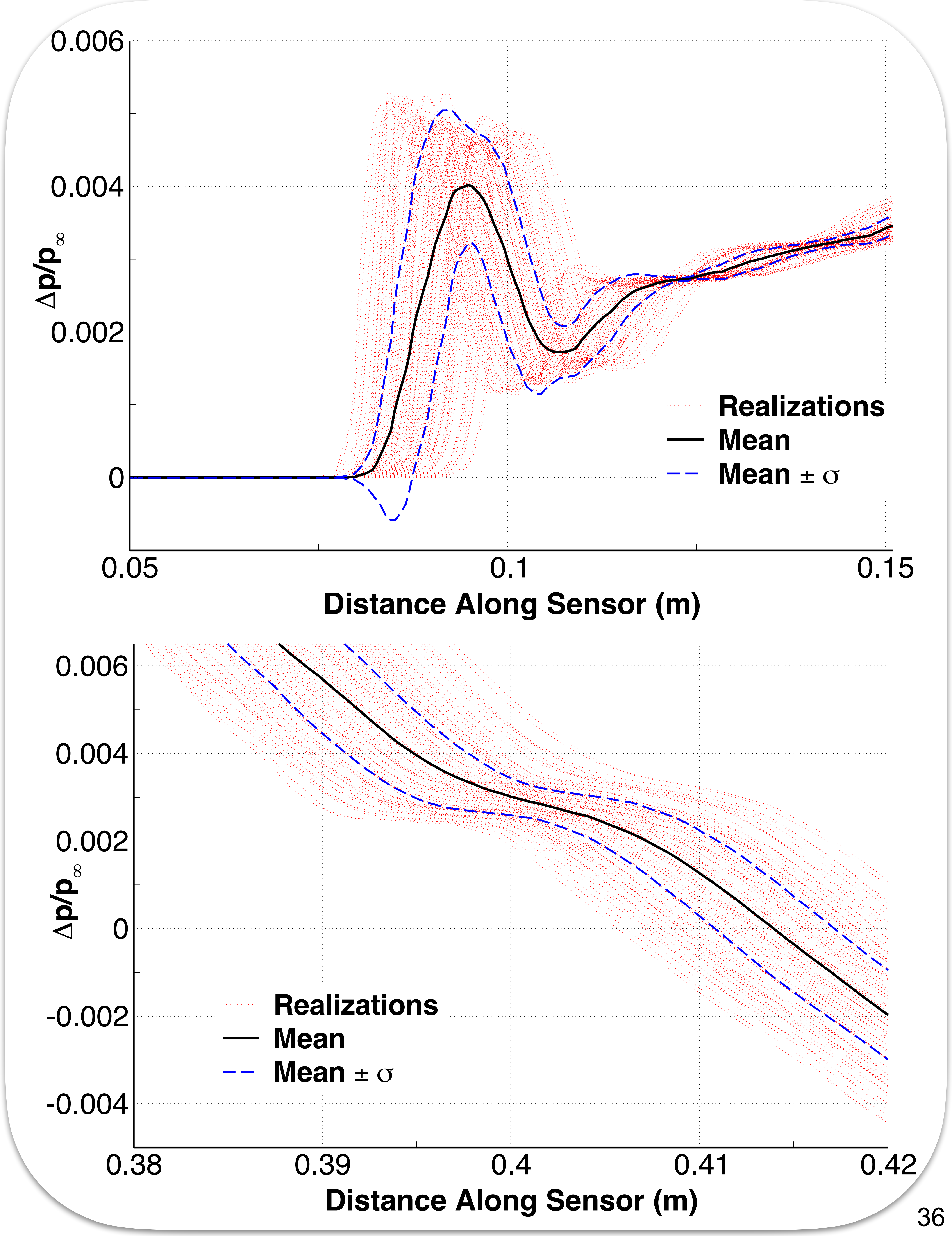
- Clenshaw-Curtis quadrature
- 81 realizations

Uncertain Measurements & Simulations



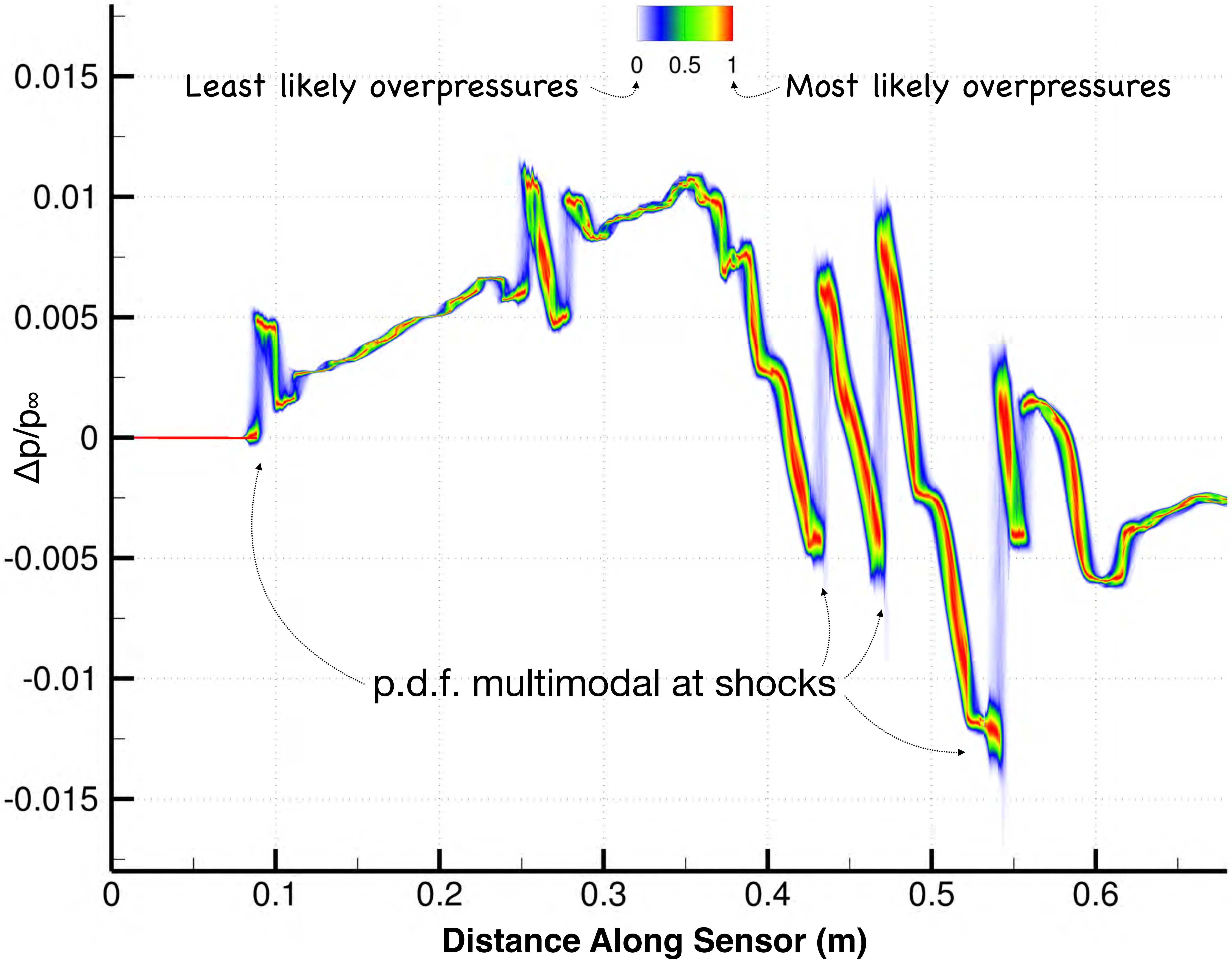






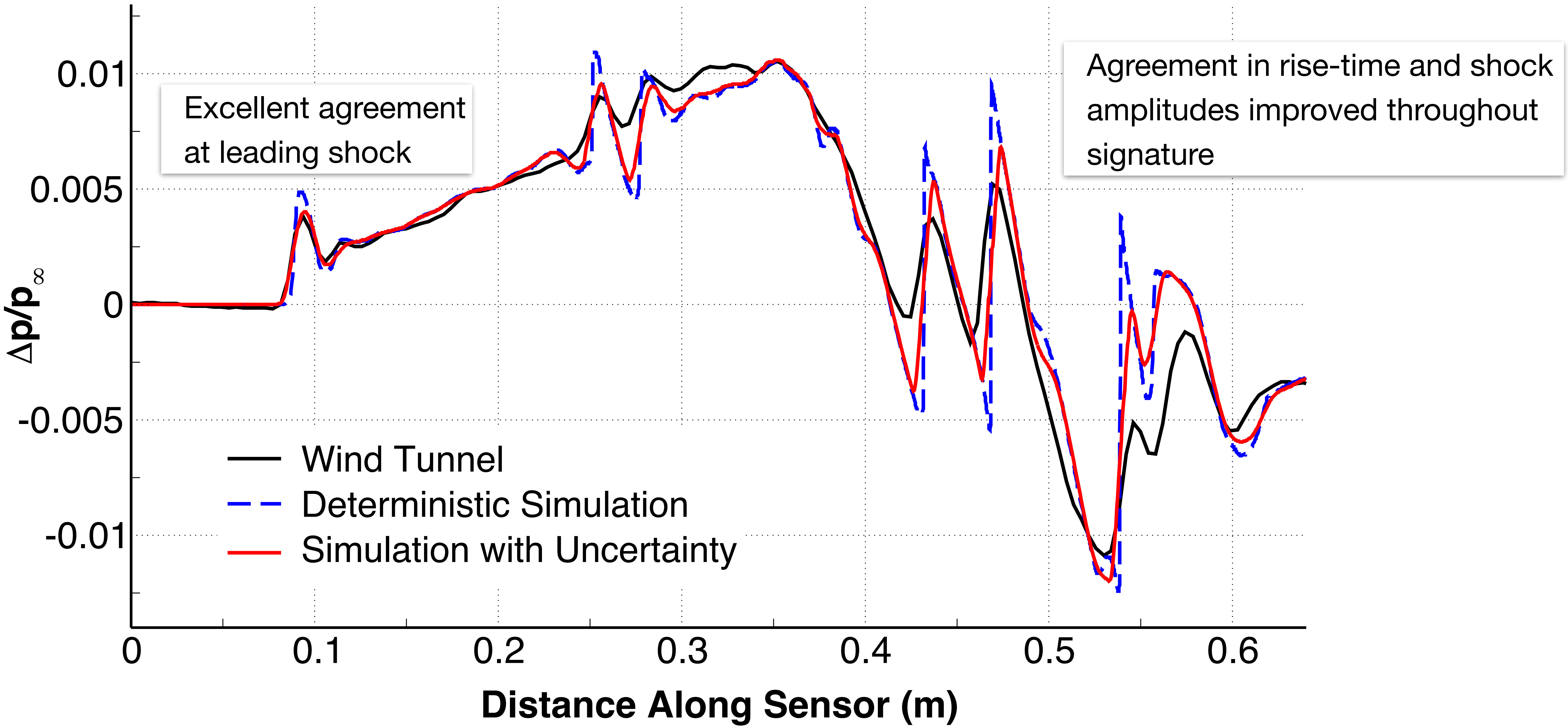
- Similar to measured signatures, the mean reduces shock amplitude and relaxes shock rise-time
- Standard deviation mischaracterizes data spread at discontinuities
- Moment statistics characterize uncertainty well in smooth regions

Signature Probability Density Function



- p.d.f. provides complete characterization of uncertainty
- computed from the same database (81 realizations) as moment statistics

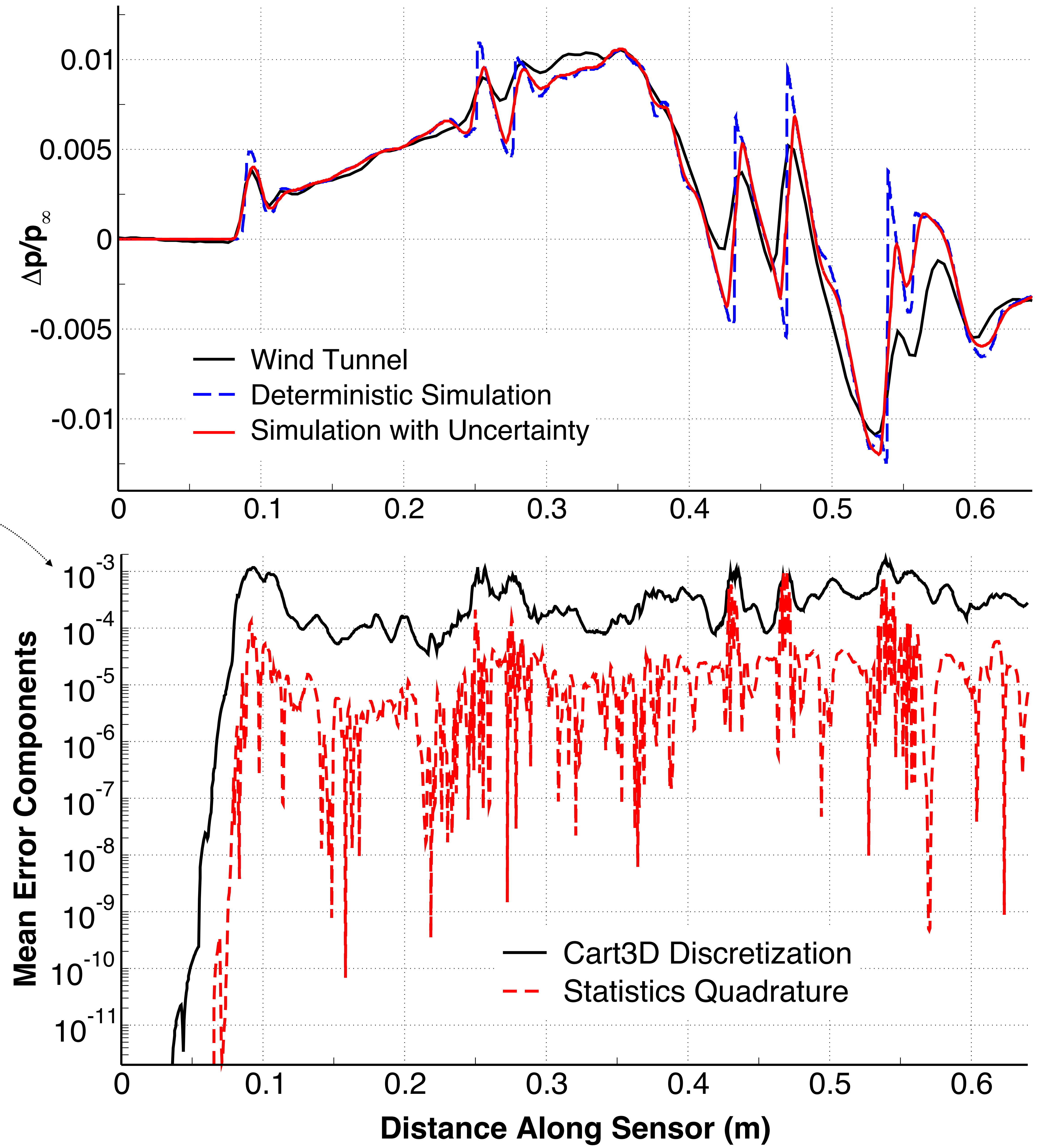
Comparison of Mean Signatures



Error Assessment

Error Decomposition for Mean Signature

- Error distributions peak at shocks
- Discretization error from Cart3D simulations is approximately order-of-magnitude larger than error from statistics quadrature
  - Reducing CFD discretization error (increasing mesh refinement) is more important than increasing the number of quadrature points
  - Control of numerical errors critical for bounding model-form error



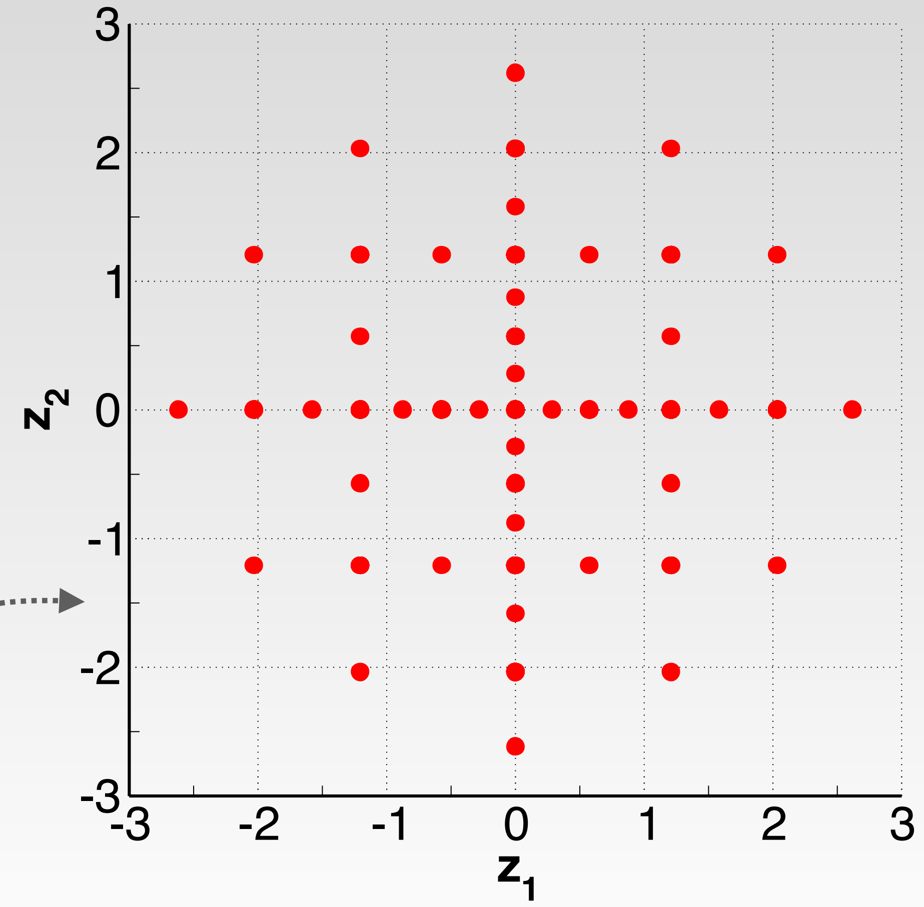
Atmospheric Uncertainty in Propagation

Characterize uncertainty in ground signature and loudness due to variability in state of the atmosphere

- Temperature (T) and relative humidity (RH) profiles only
- X-59 (C612A) nearfield signature, Mach number 1.4
- Location Edwards AFB
- Assume flights in August, around 10 am PT

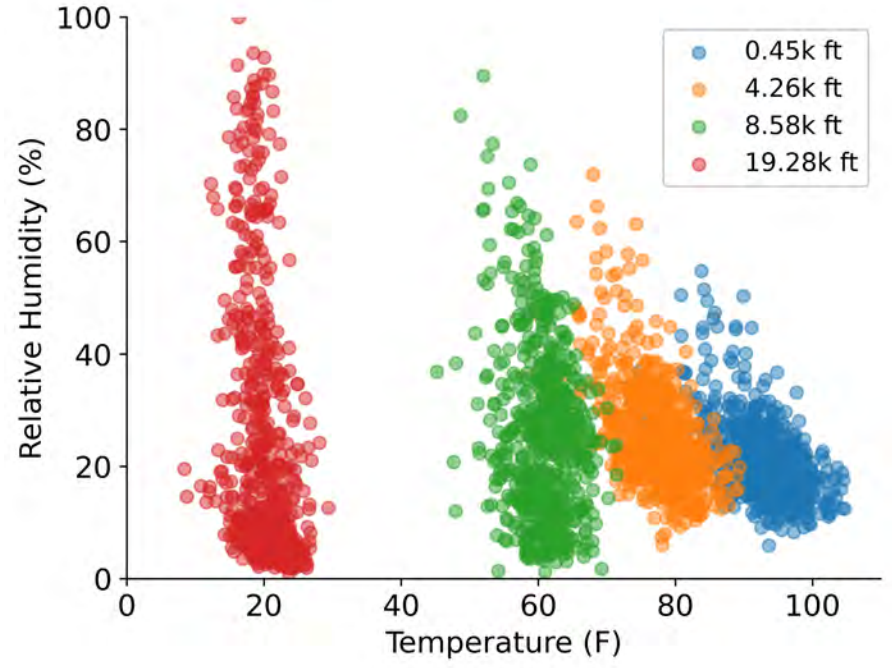
UQ Inputs

- KL expansion with 6 eigenvalues (M=6) using temperature and dew-point temperature to model T and RH
  - 6 independent normal variables (z_1-z_6)
- L=4 sparse Gauss-Patterson quadrature
  - 545 atmospheric profiles for T and RH



KL Expansion for Combined T and RH

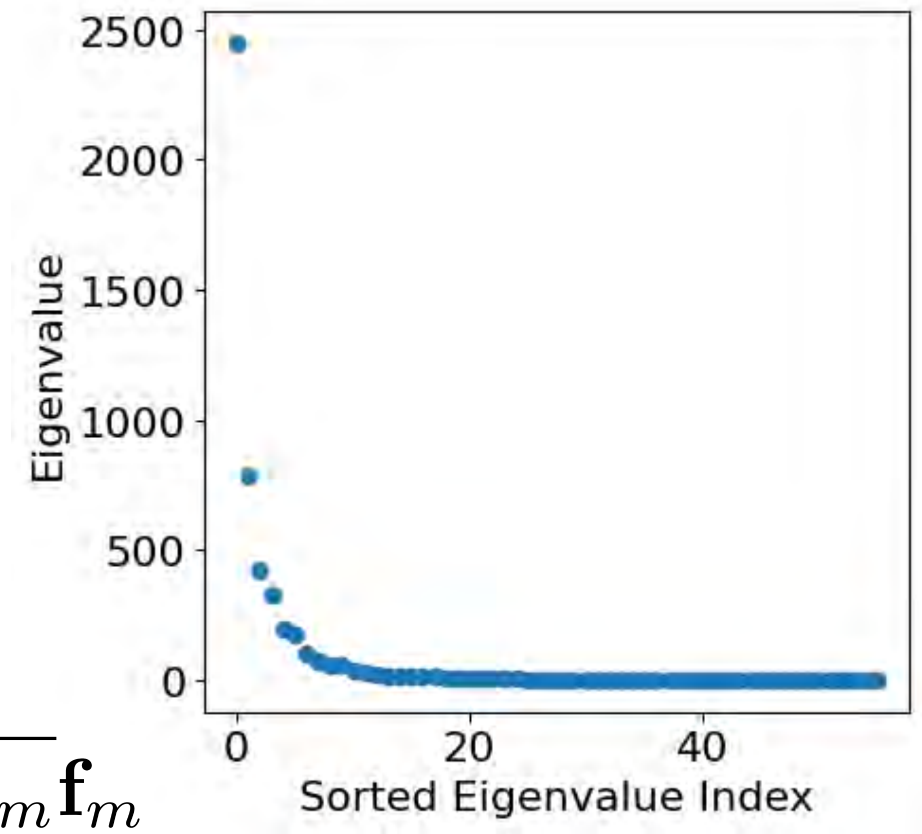
- RH distributions are skewed and bounded
  - Poor fit for KL expansion
- Use conversion from RH to Dew Point Temperature
- Fit both Dry Bulb and Dew Point Temperatures with one KL expansion



$$\mathbf{RH} = f(\mathbf{T}_{db}, \mathbf{T}_{dp})$$

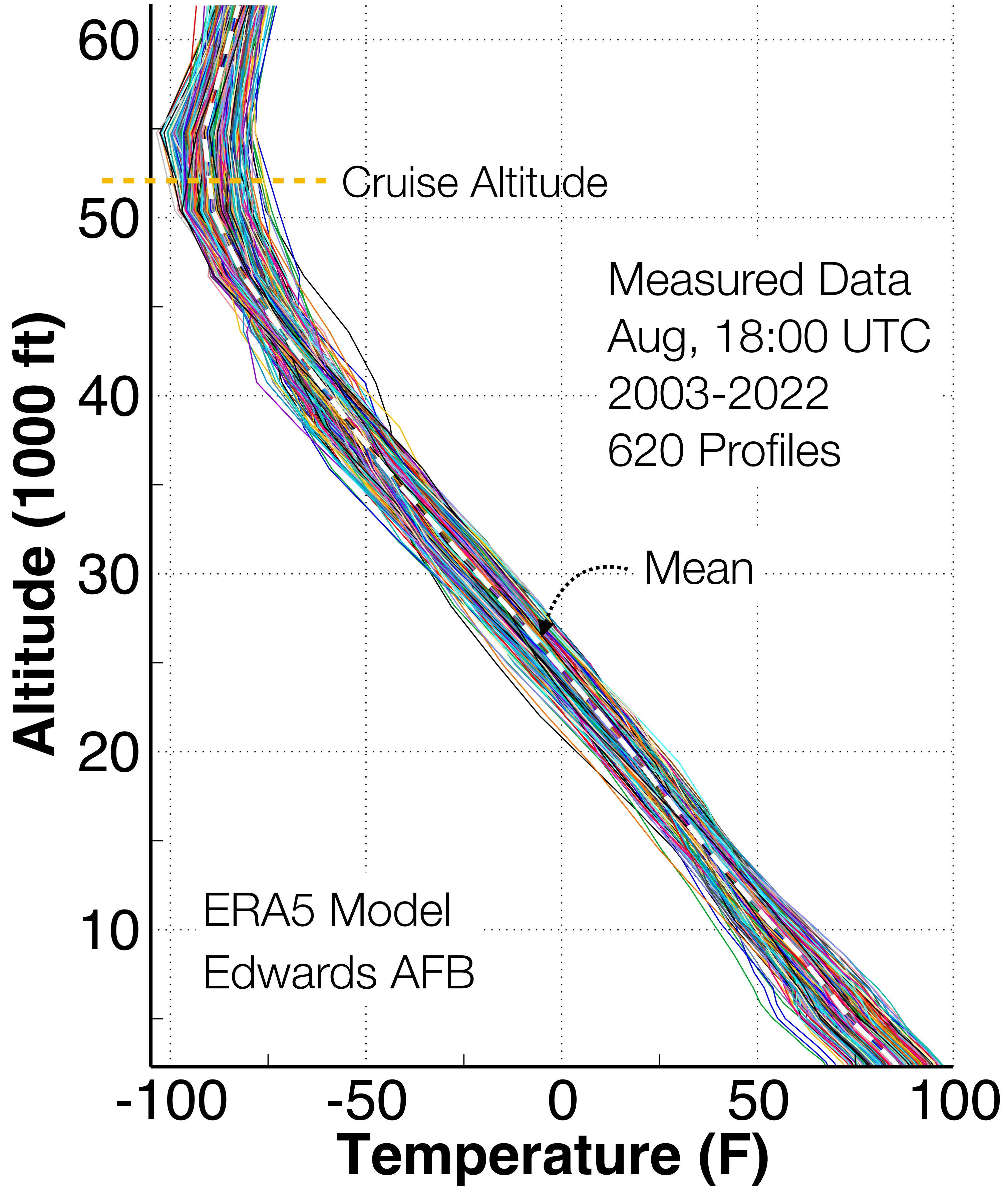
$$\mathbf{T}(\xi) = \begin{bmatrix} \mathbf{T}_{db} \\ \mathbf{T}_{dp} \end{bmatrix}$$

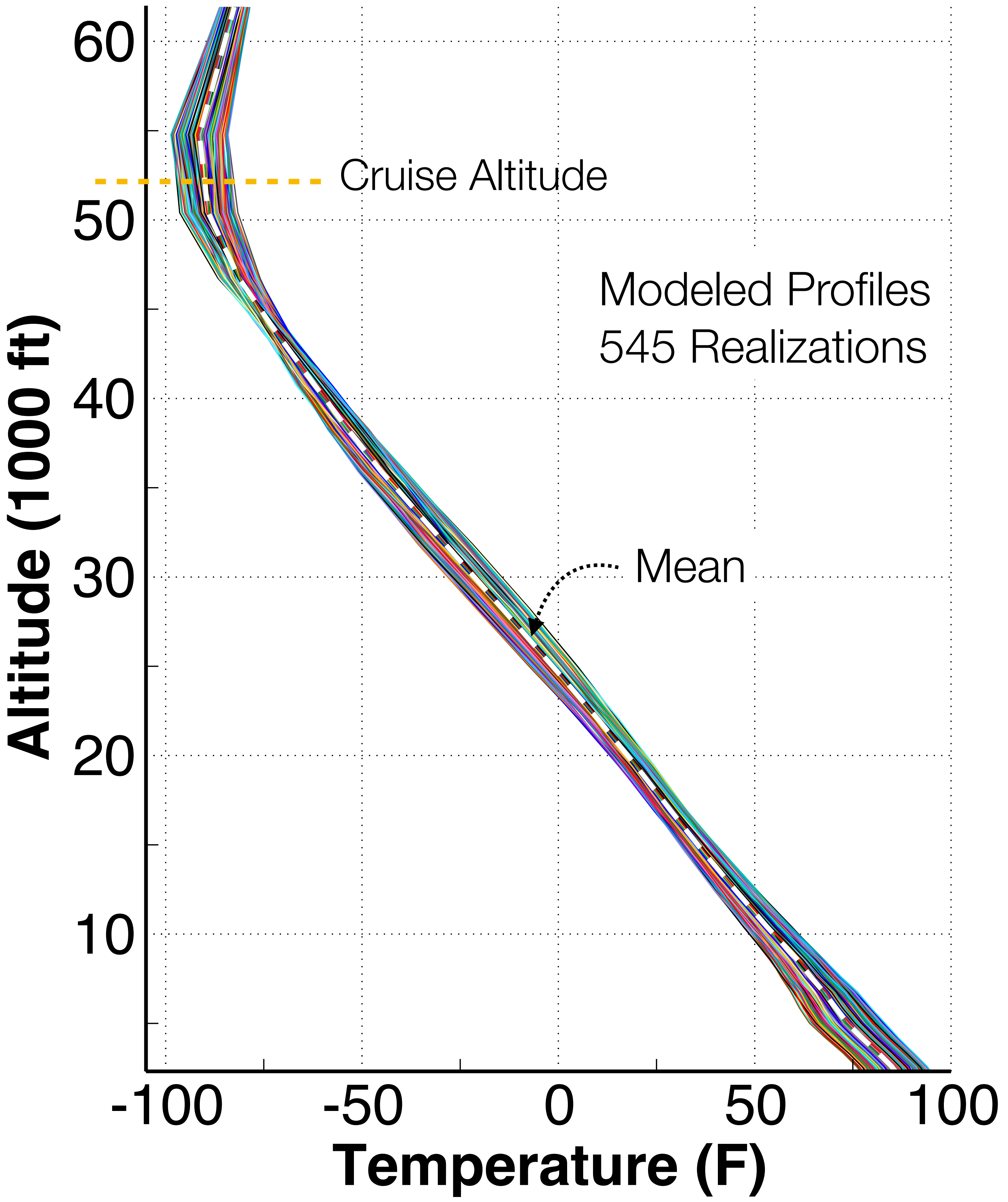
$$\mathbf{T}(\xi) = \bar{\mathbf{T}} + \sum_{m=1}^{M} z_m(\xi)\sqrt{\lambda_m}\mathbf{f}_m$$



Comparison of Modeled and Measured Profiles

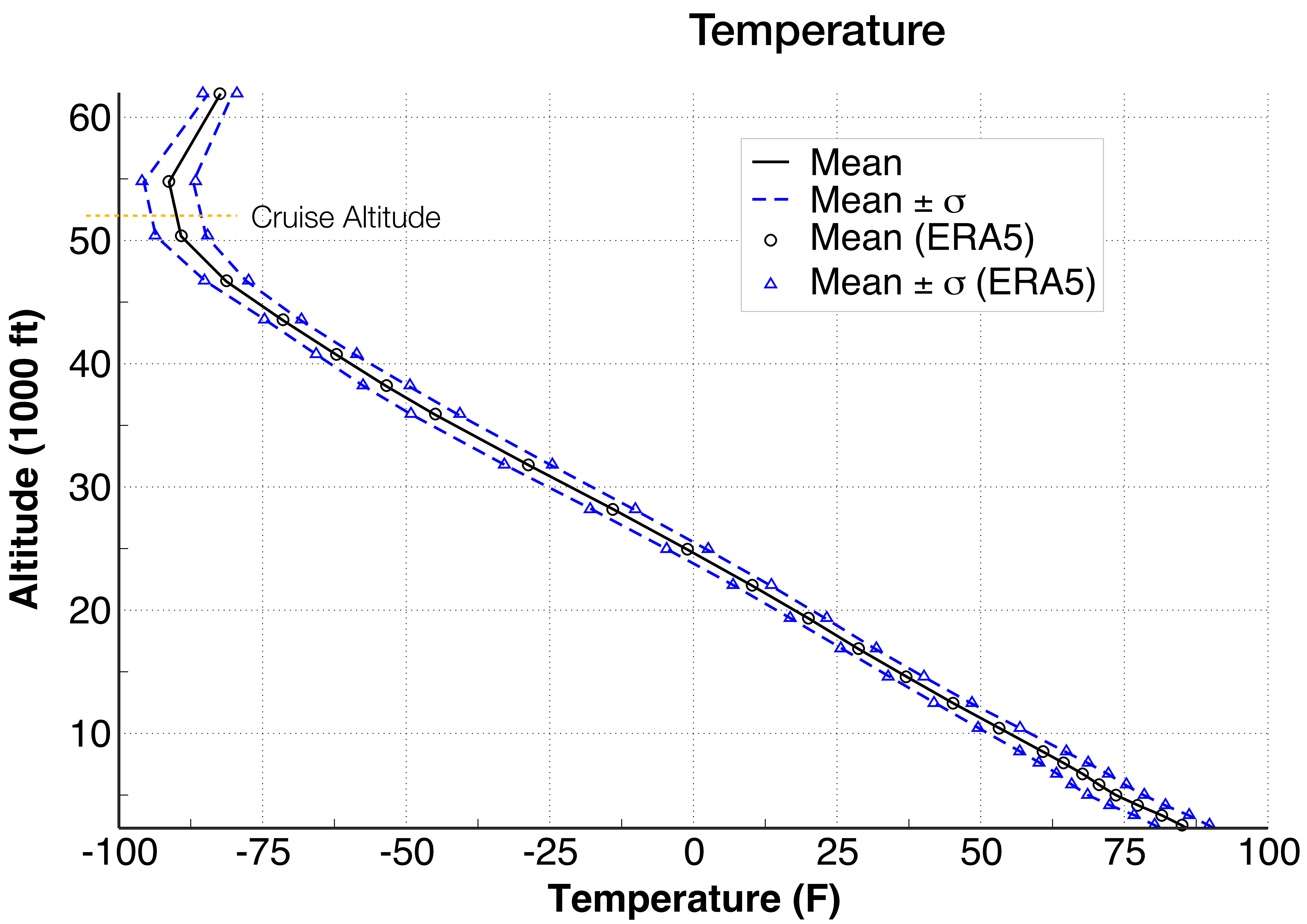
Temperature





- KL-6 parameterization
- Level 4 Gauss-Patterson sparse quadrature
- Good agreement between modeled and measured profiles
  - Infrequent outliers not captured well
  - Excellent agreement near the mean

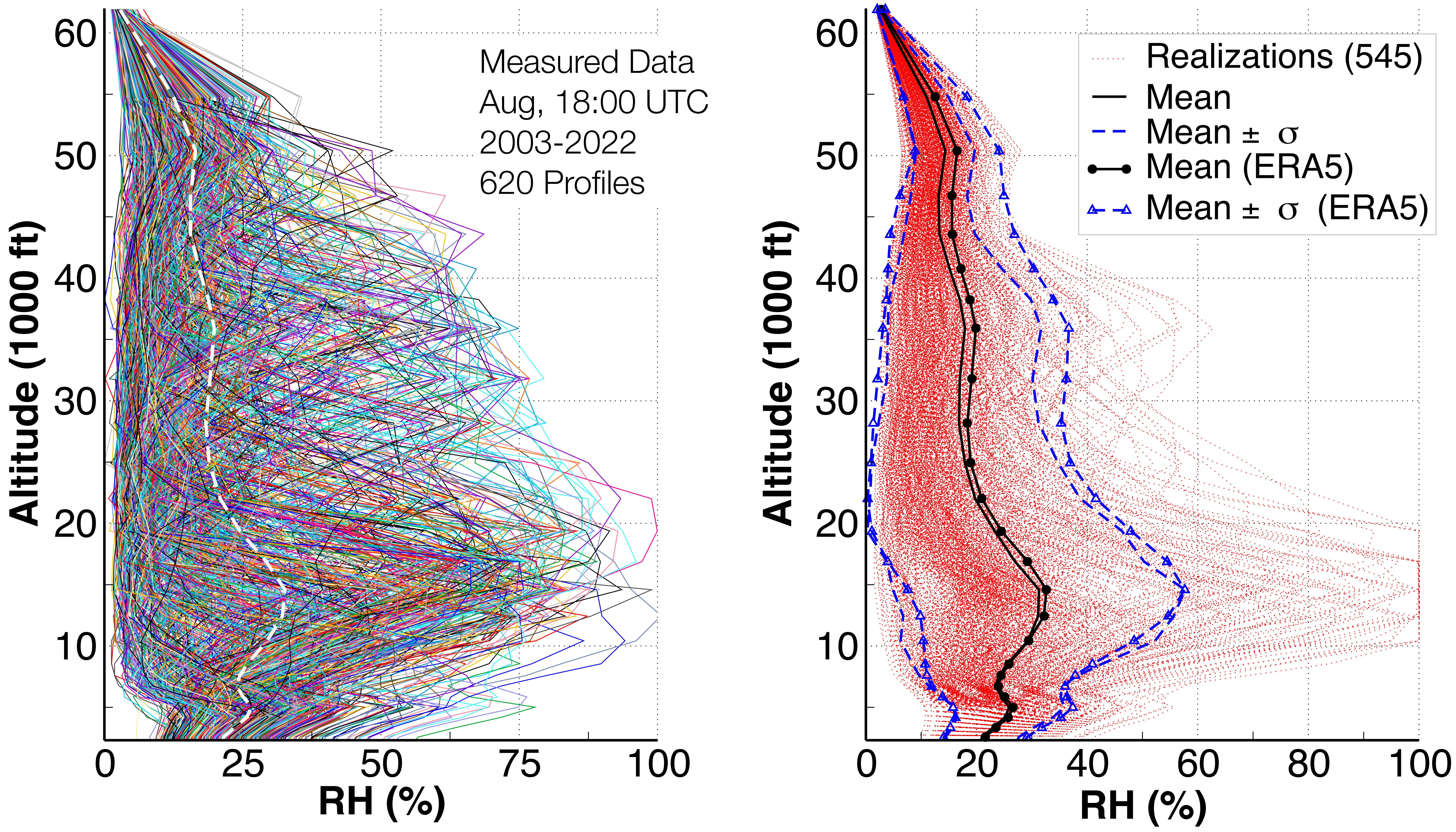
Comparison of Modeled and Measured Profiles



- KL-6 parameterization
- Level 4 Gauss-Patterson sparse quadrature
- Mean profiles agree exactly (by construction)
- Agreement in standard deviation is excellent

Comparison of Modeled and Measured Profiles

Relative Humidity

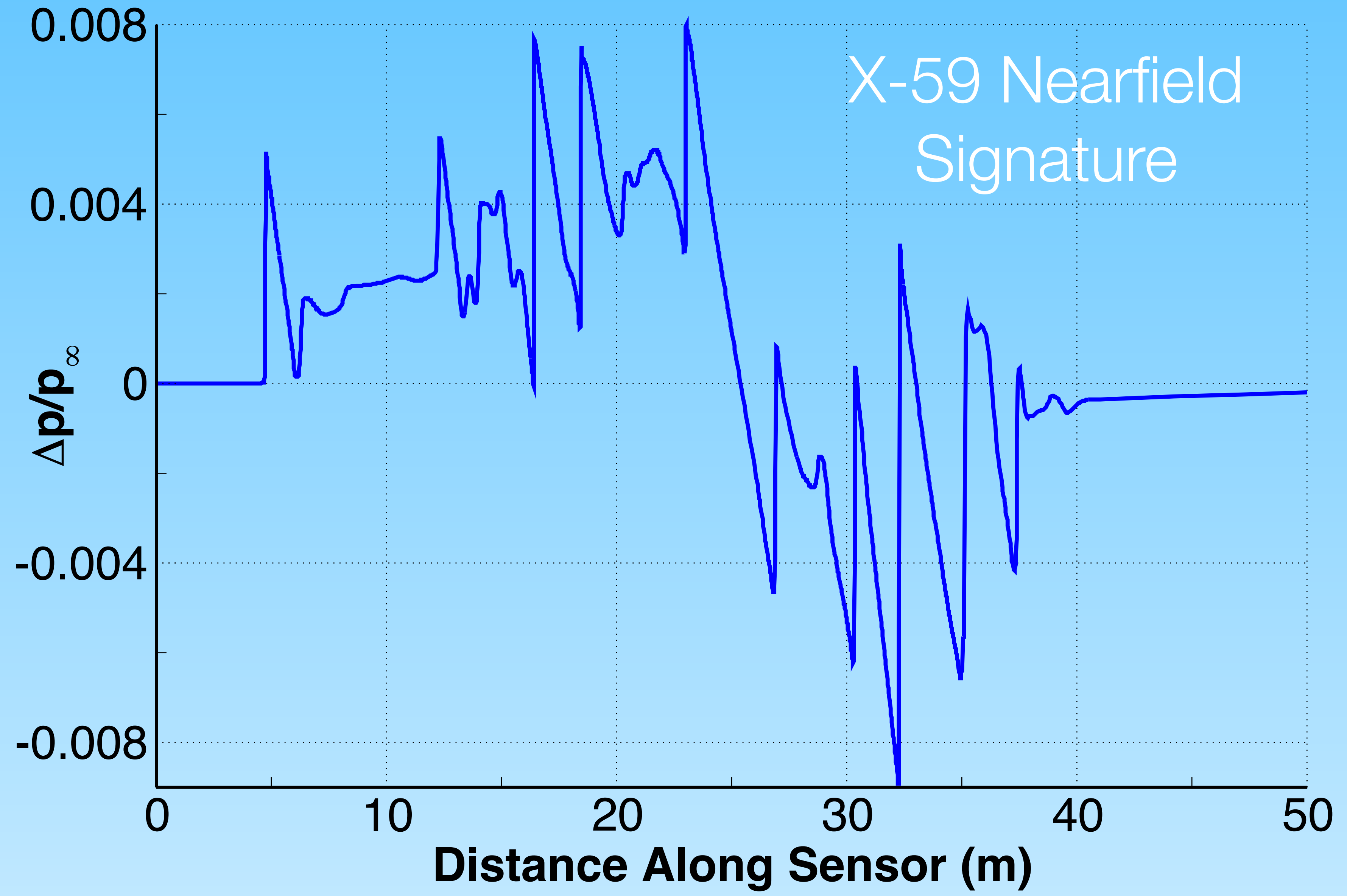


- KL-6 parameterization
- Level 4 Gauss-Patterson sparse quadrature
- Good agreement between modeled and measured profiles, especially at lower altitudes (below 25k ft)
  - Outliers not captured well between 40k-50k ft
  - 8 profiles exceed 100% and need clipping

Overall, KL-6 parametrization is an excellent compromise for accurately capturing main features of T & RH data at relatively low computational cost

Propagation through Uncertain Atmosphere

sBOOM Propagation Inputs



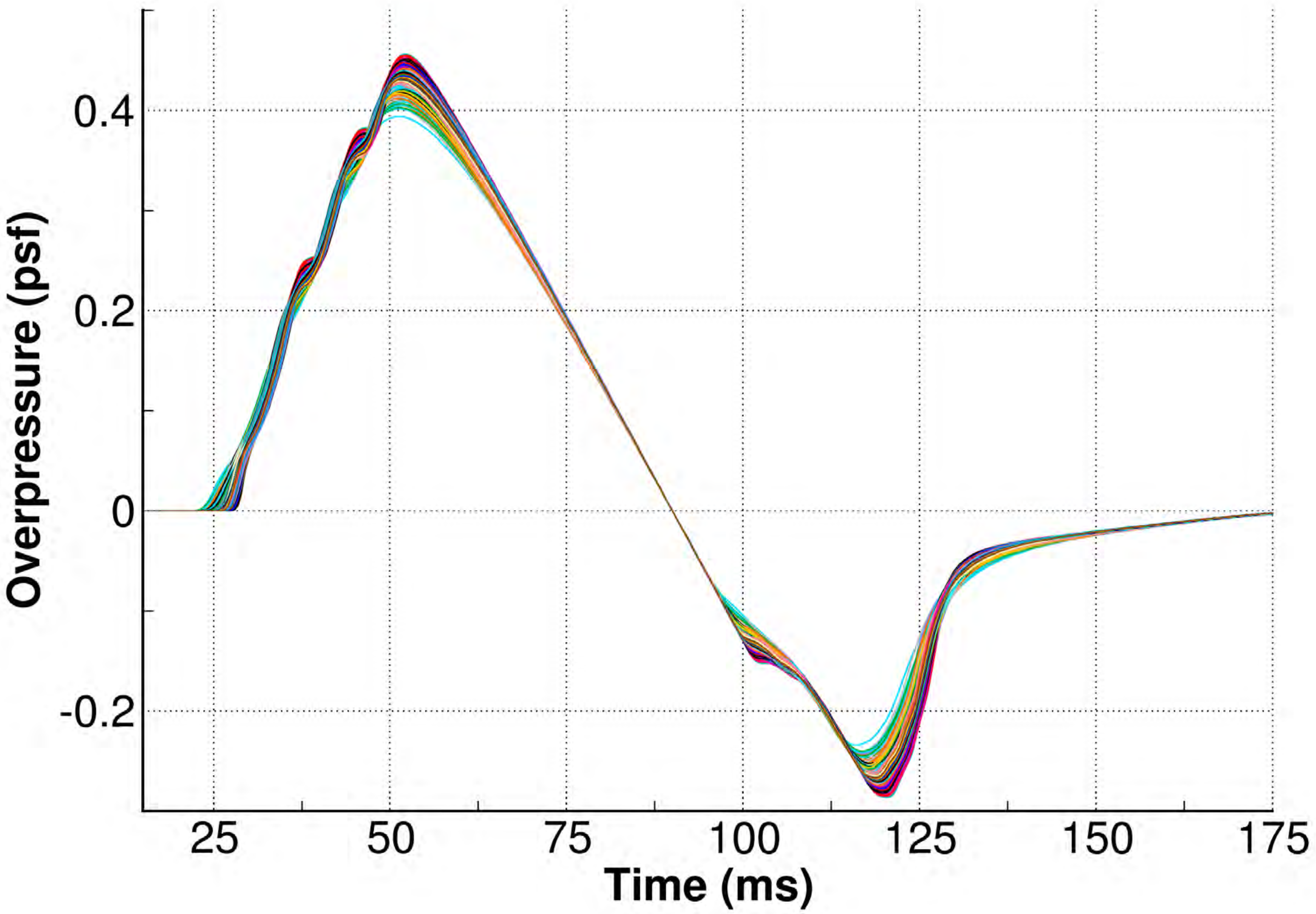
Altitude 52,026 ft

Ground Elevation 2,311 ft

Terrain Reflection Factor 1.9

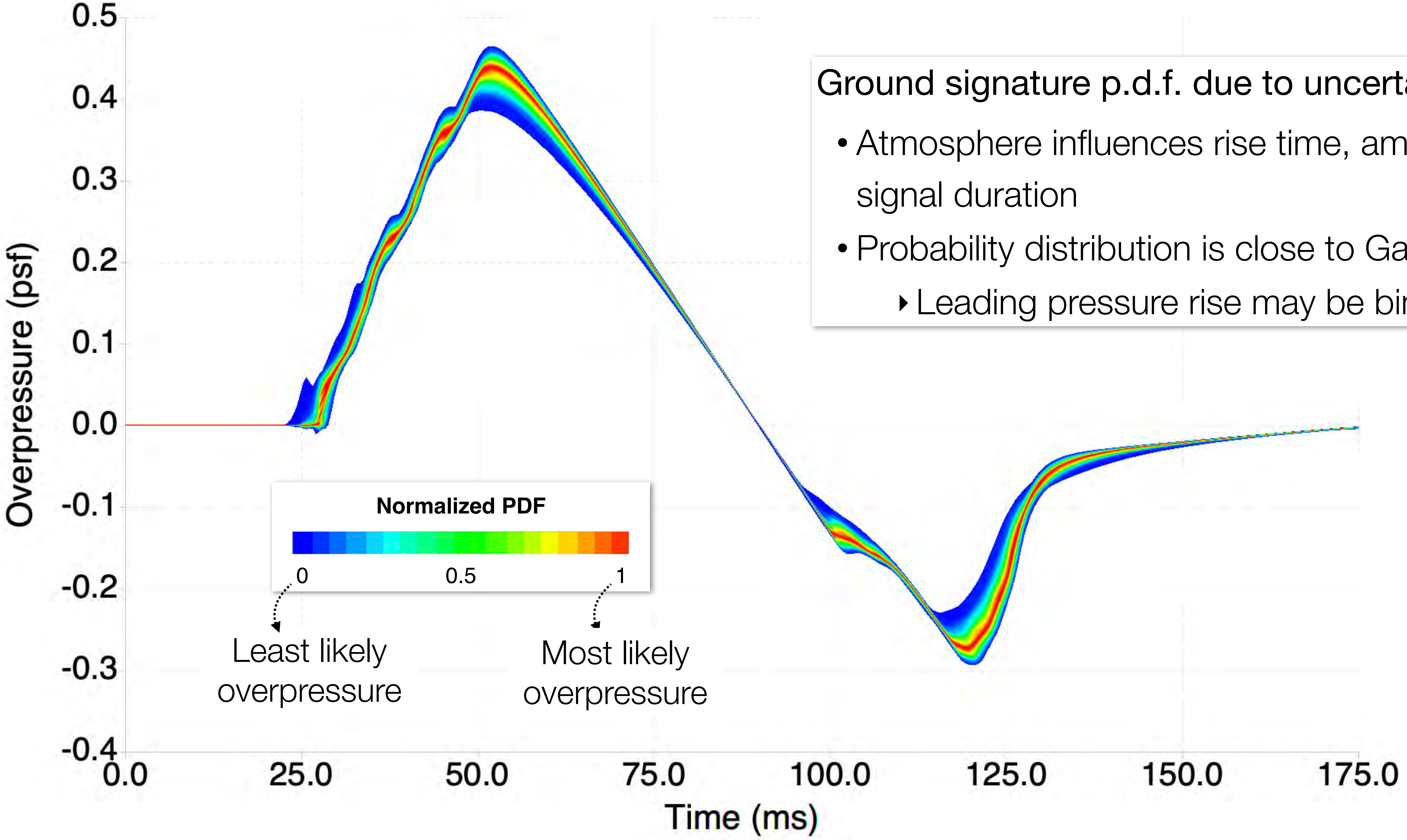
Sampling Frequency 100kHz

Ground signatures resulting from propagation through 545 T and RH atmospheric profiles



- Evaluate ground signature and loudness statistics from these realizations

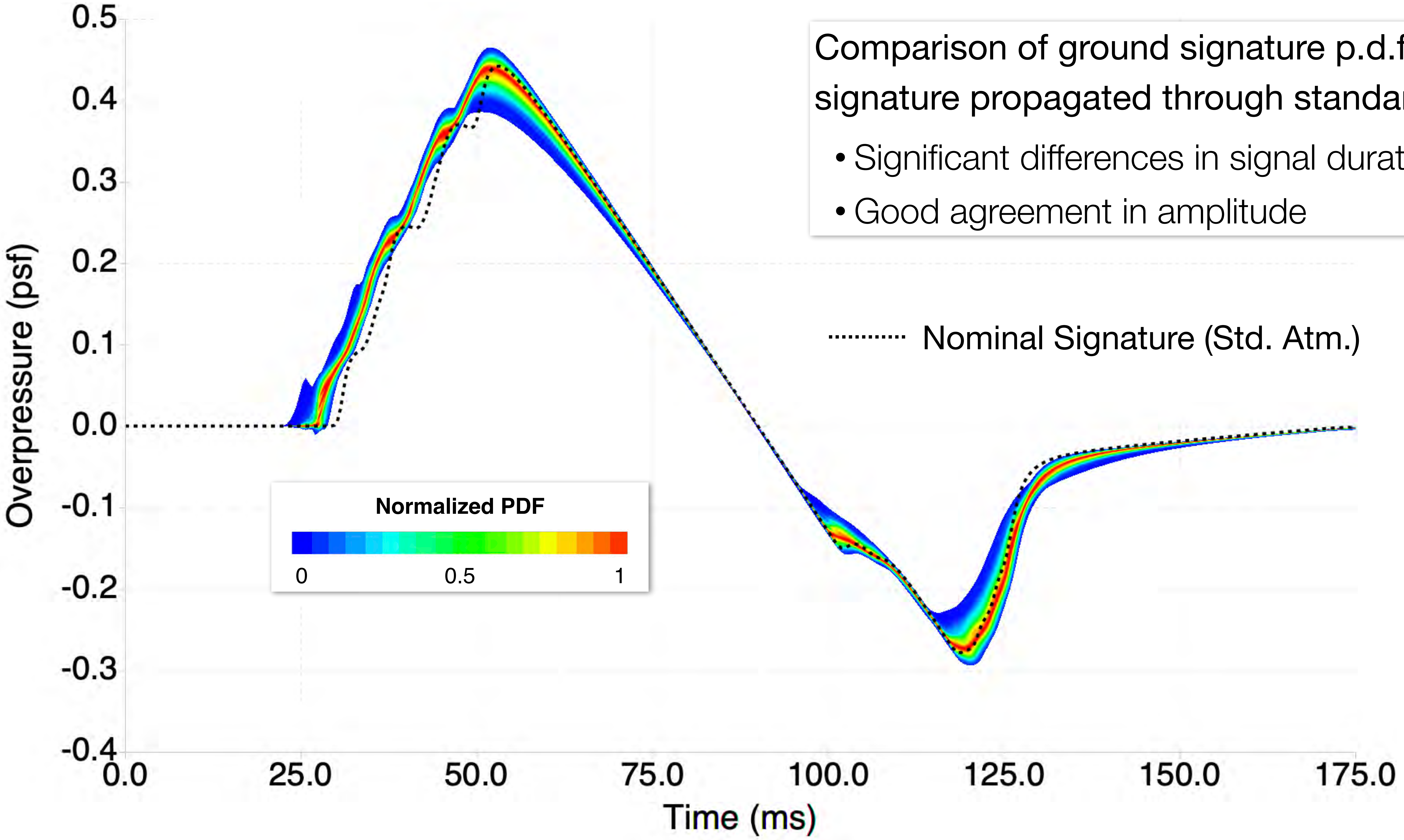
Propagation through Uncertain Atmosphere



Ground signature p.d.f. due to uncertain T and RH

- Atmosphere influences rise time, amplitude and signal duration
- Probability distribution is close to Gaussian
  - Leading pressure rise may be bimodal

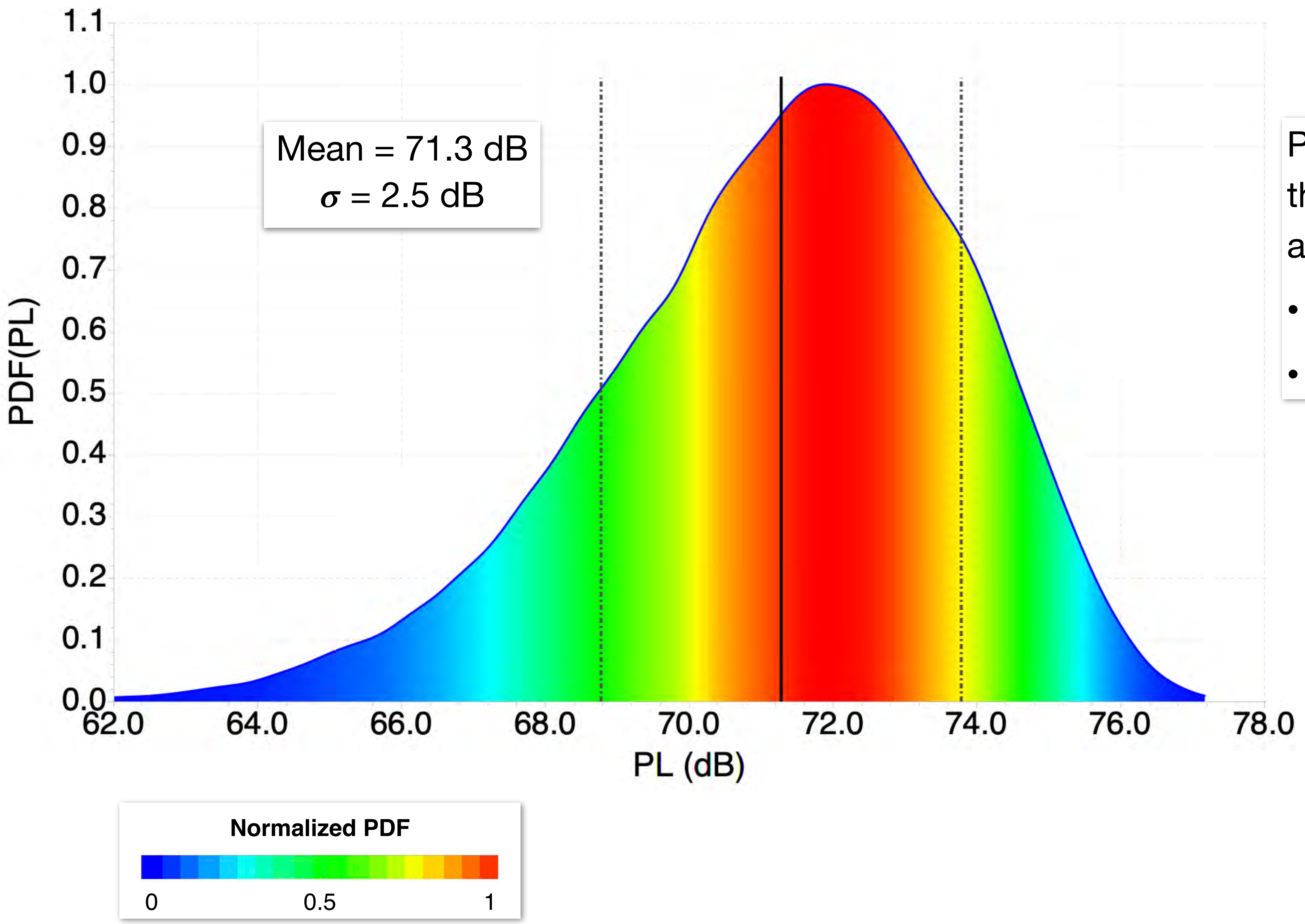
Propagation through Uncertain Atmosphere



Comparison of ground signature p.d.f. with a signature propagated through standard atmosphere

- Significant differences in signal duration and rise time
- Good agreement in amplitude

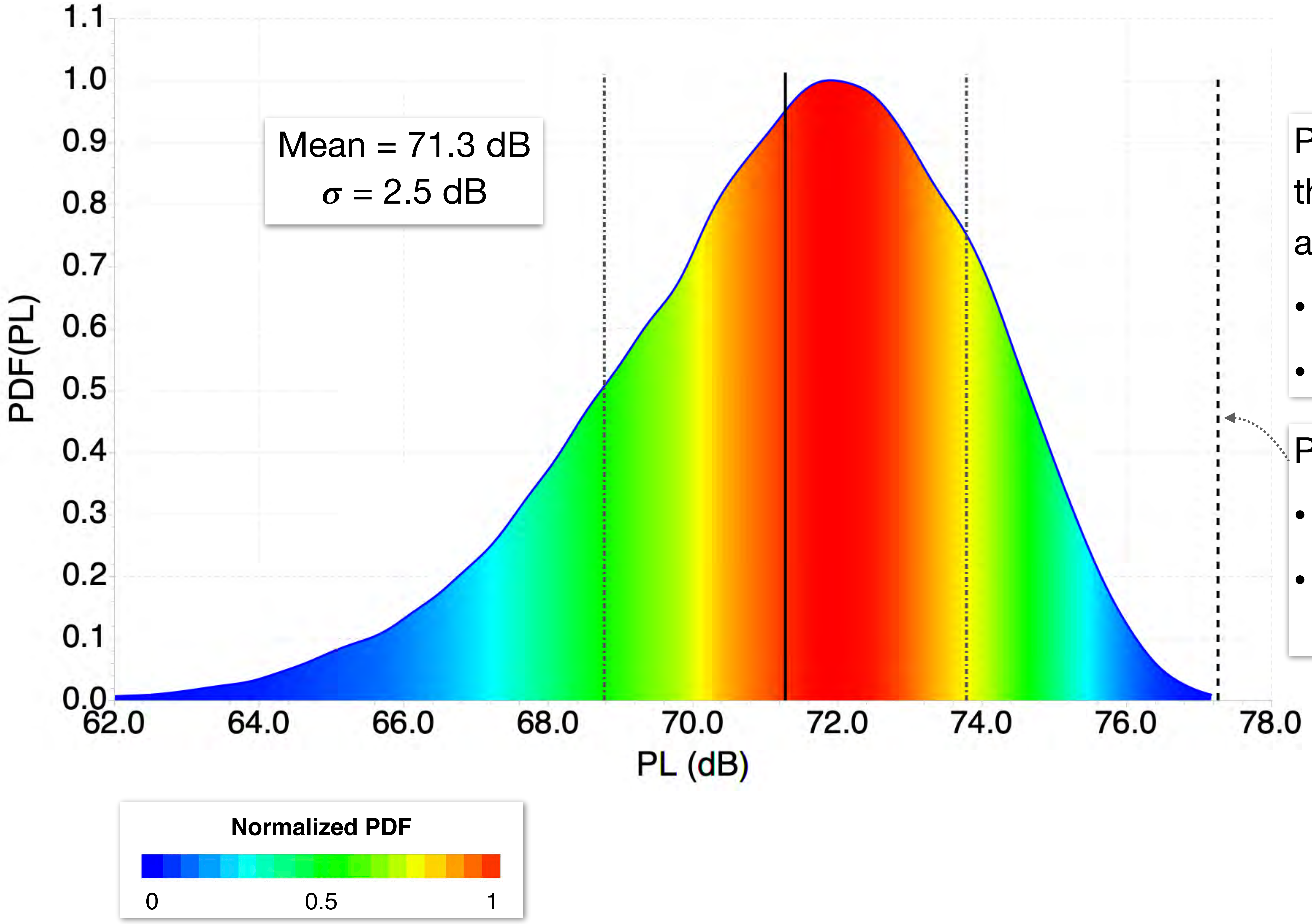
Perceived Loudness (PL) P.D.F.



Probability density function fully characterizes the uncertainty in PL due to variability in T and RH atmospheric profiles

- Distribution is skewed to the left
- One standard deviation is well below 75 dB

Perceived Loudness (PL) P.D.F.



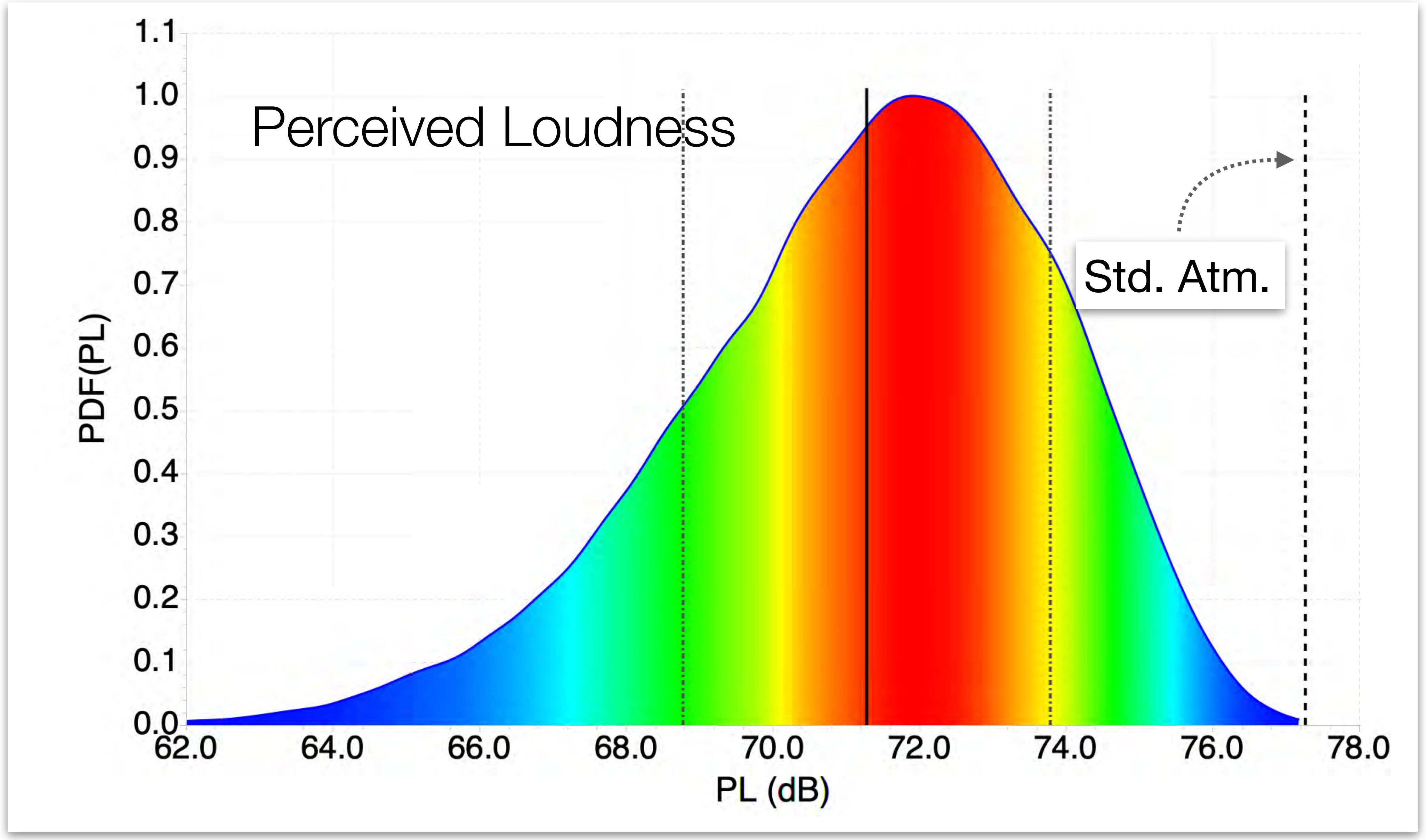
Probability density function fully characterizes the uncertainty in PL due to variability in T and RH atmospheric profiles

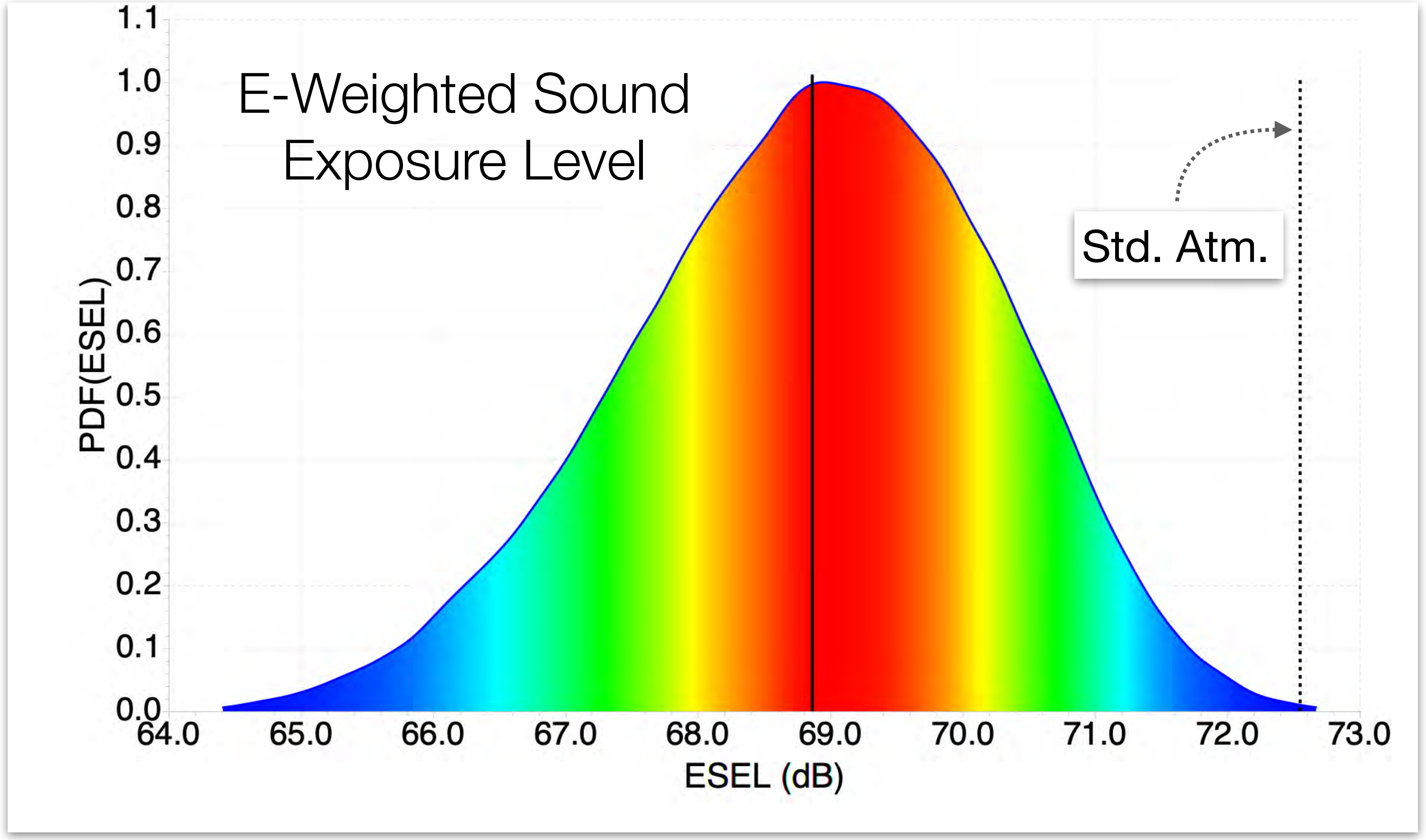
- Distribution is skewed to the left
- One standard deviation is well below 75 dB

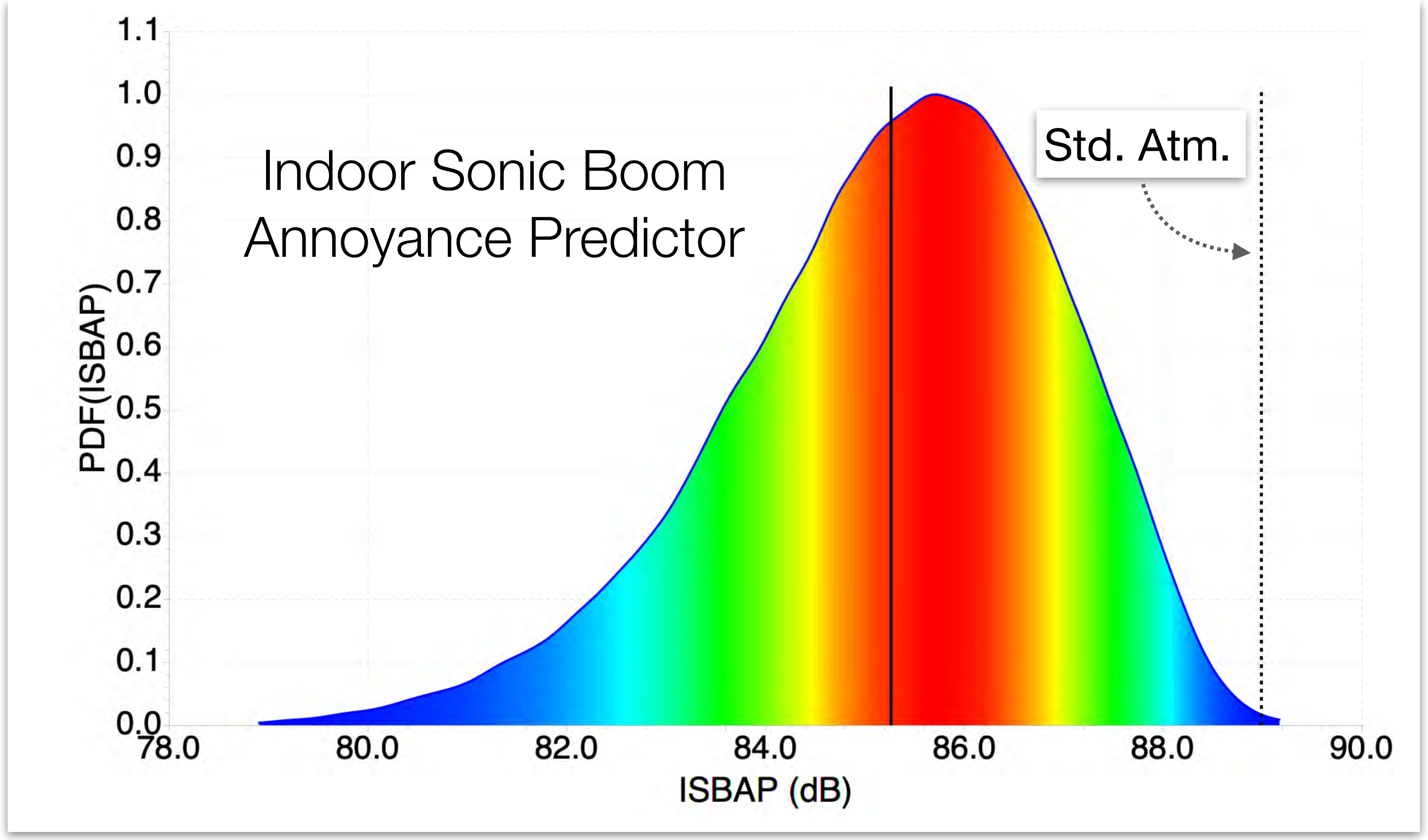
PL from propagation through Std. Atm.

- Atmospheric effects reduce mean PL by **6 dB**
- Probability less than 0.05% of matching Std. Atm. PL at Edwards

PL, ESEL and ISBAP Distributions







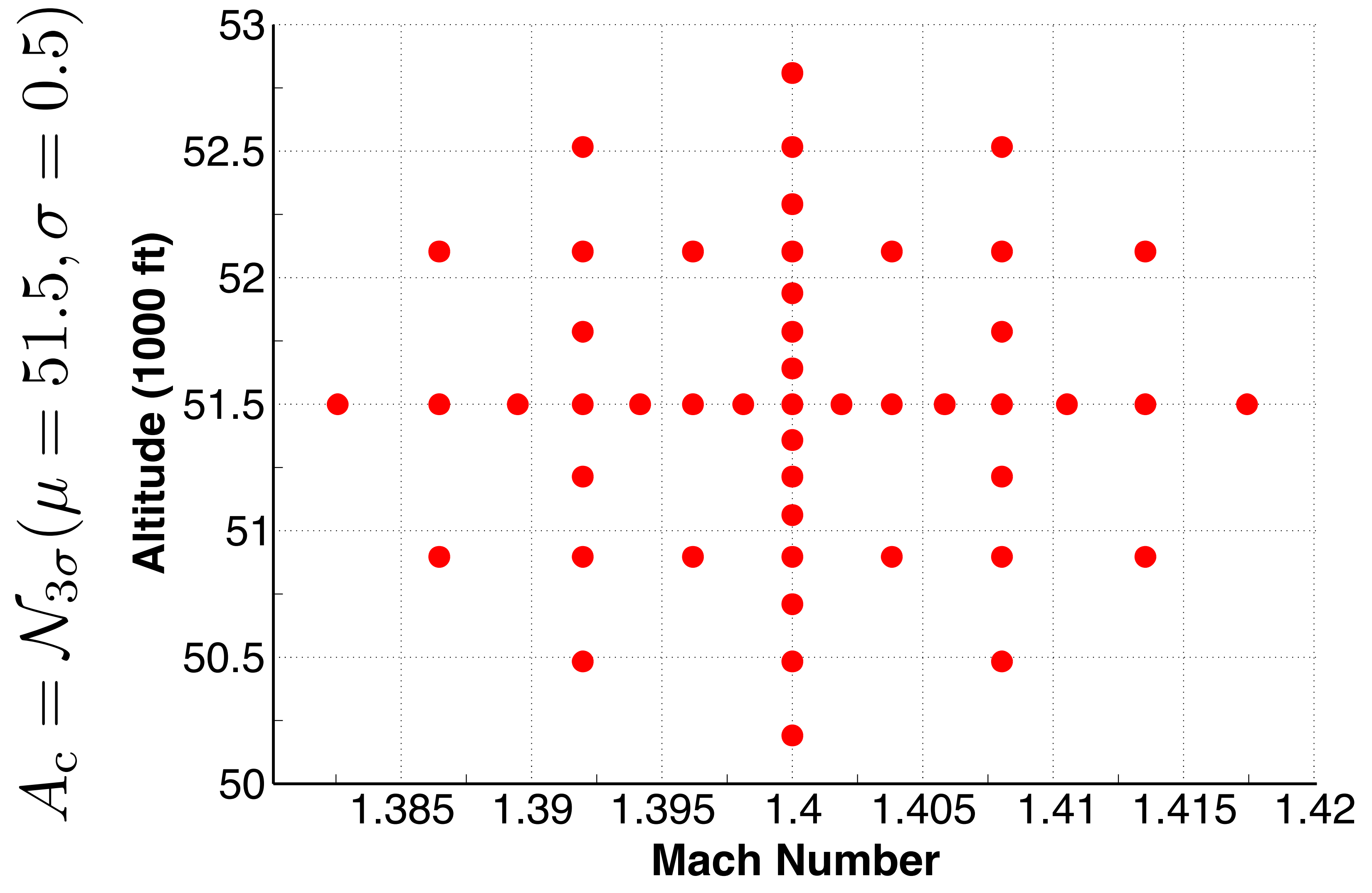
- Unimodal distributions, skewed to the left
  - Similar shapes
- Loudness values obtained from propagation through standard atmosphere are highly unlikely at Edwards

Uncertain Operating Conditions and Atmosphere

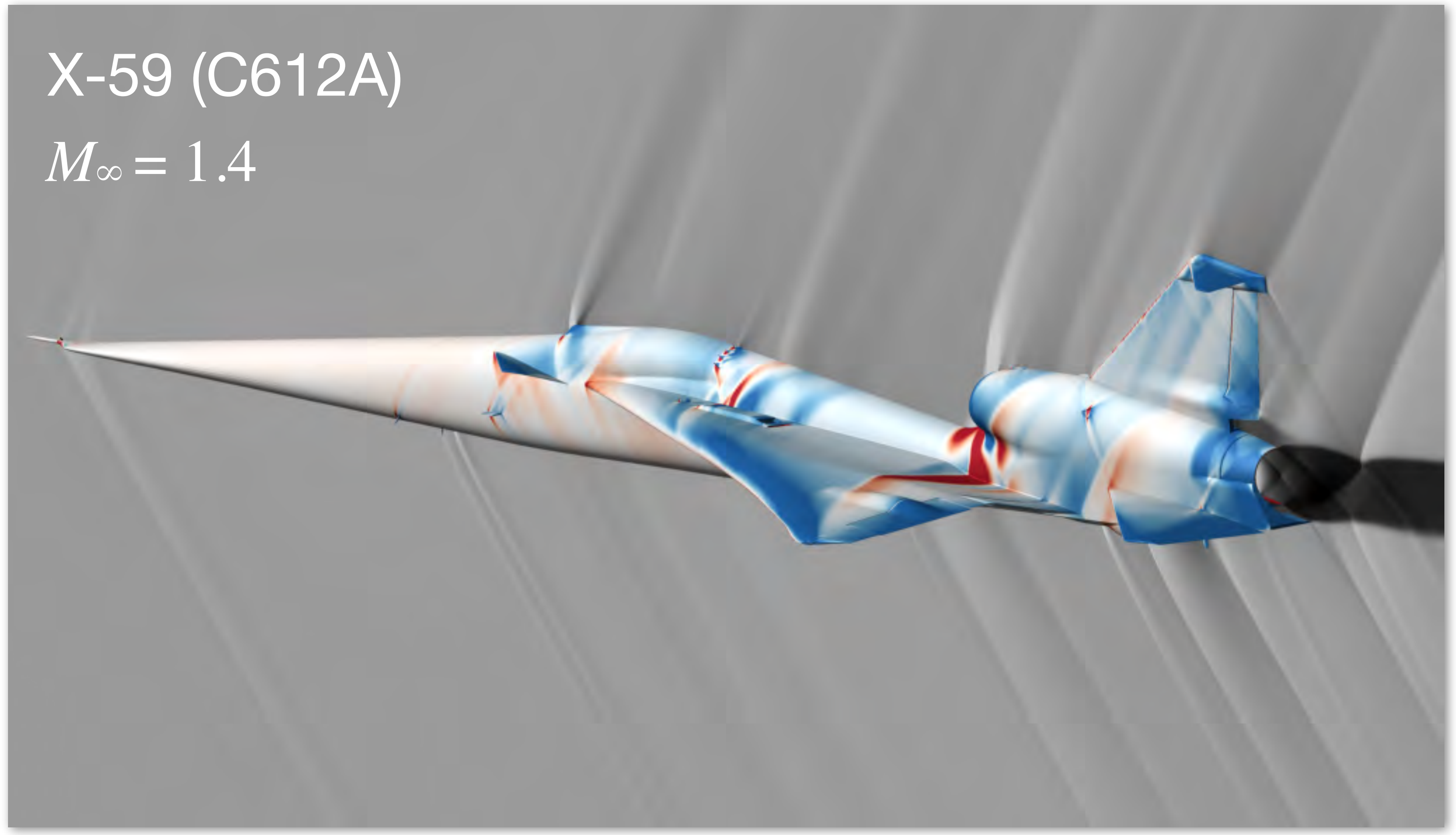
Characterize uncertainty in X-59 ground signature and loudness due to uncertainty in cruise Mach number and altitude, and the atmosphere

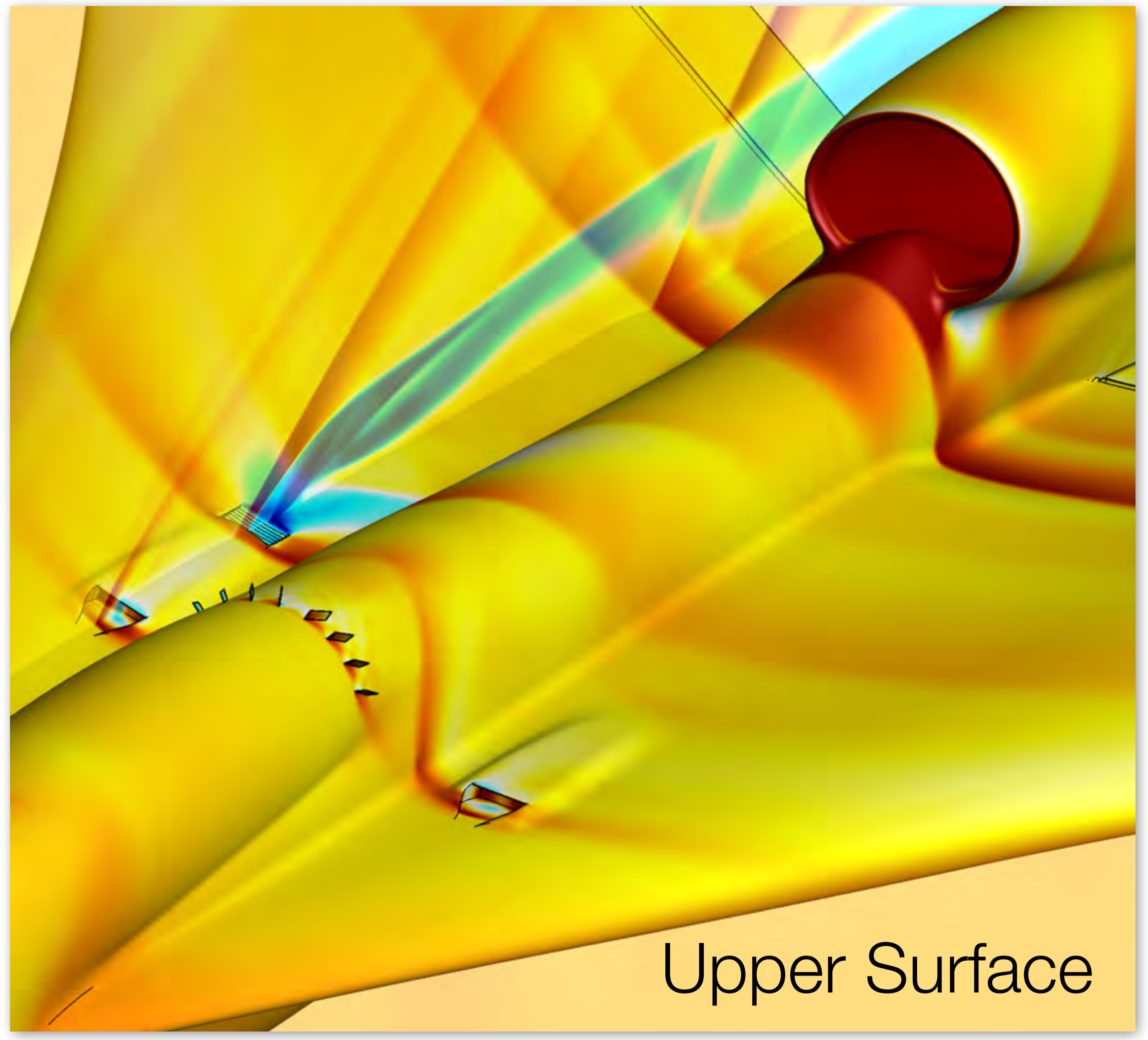
- 8 independent random variables
  - Assume normal distributions for Mach number (M_∞) and altitude (A_c)
  - Reuse KL-6 parameterization of T and RH profiles
- Assume flights at Edwards AFB in August, around 10 am PT

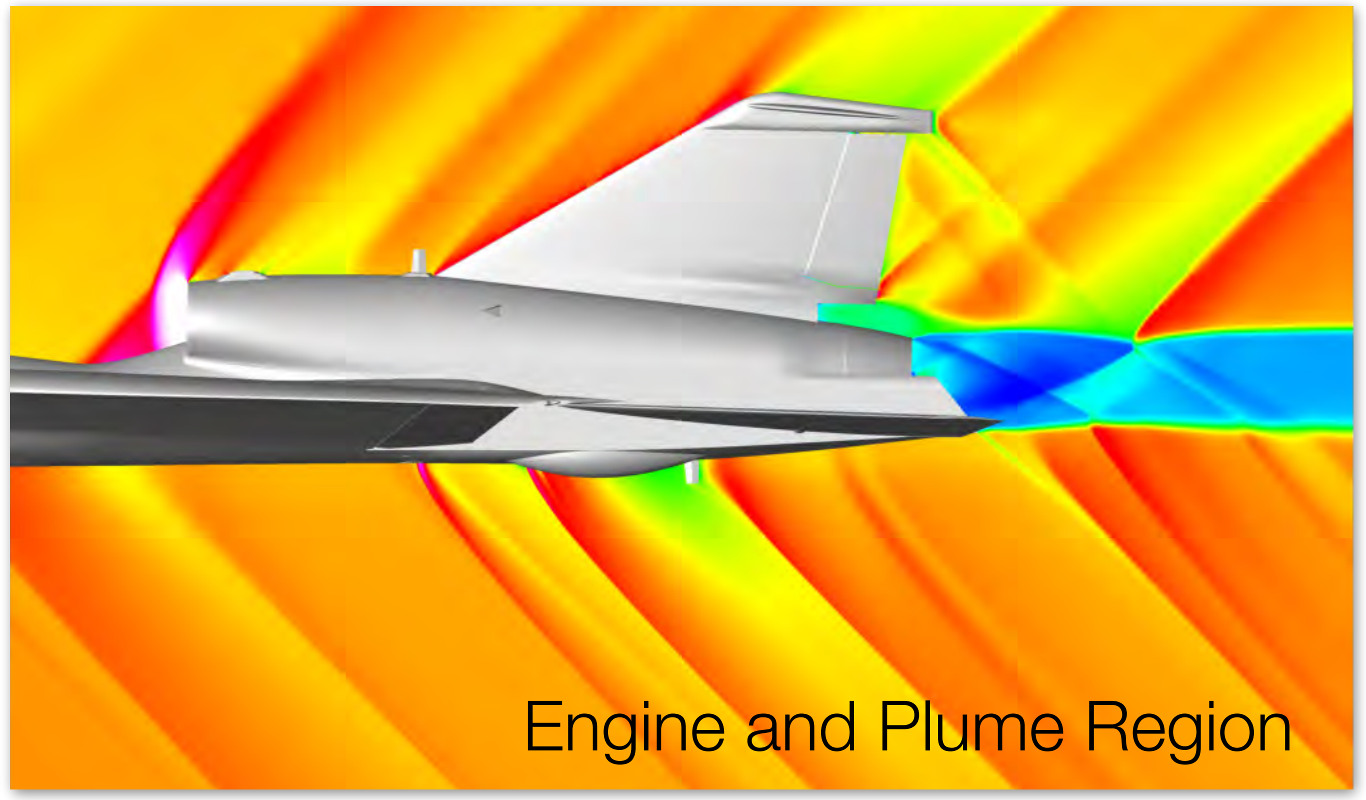
Level 4 Sparse Gauss-Patterson Quadrature

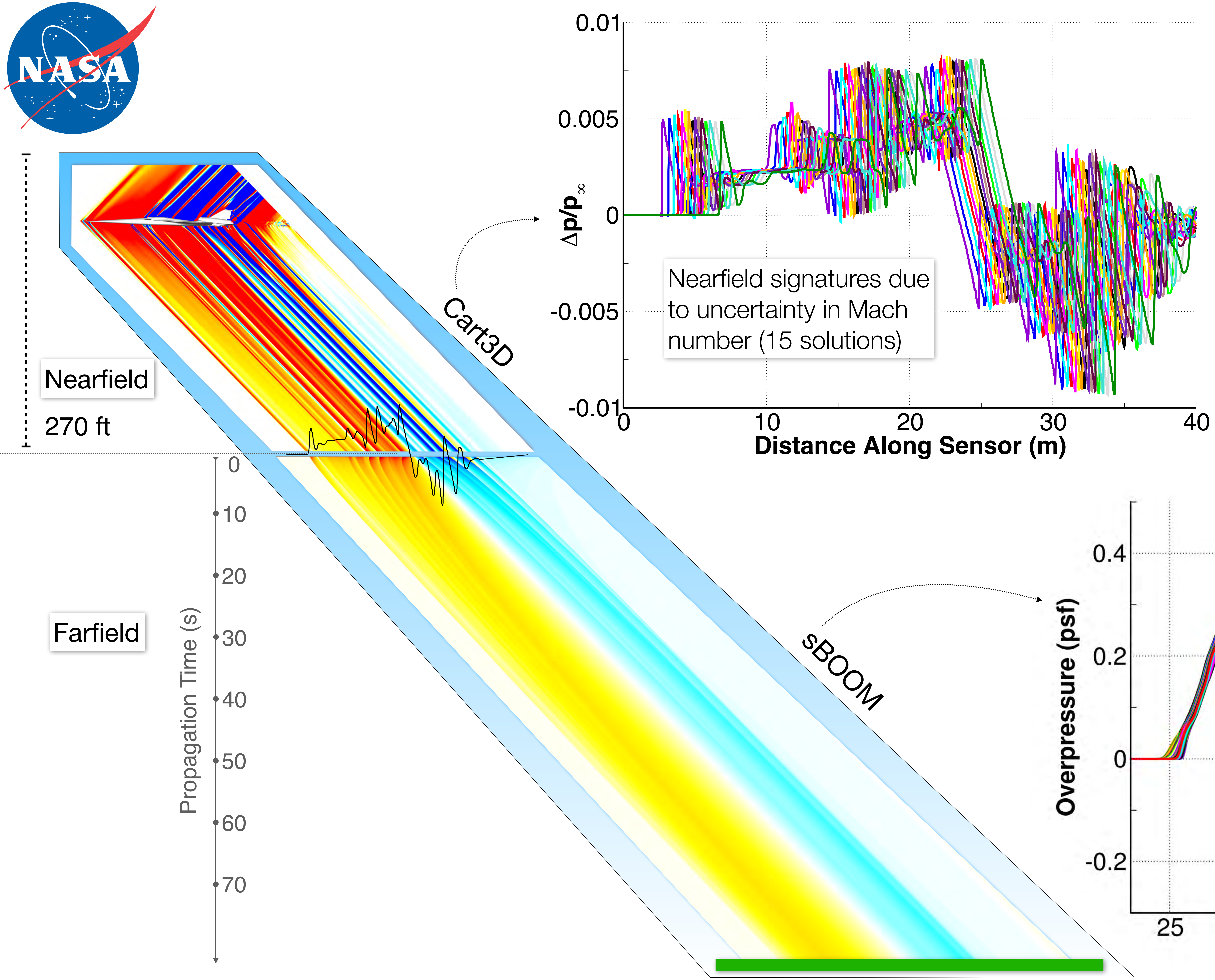


$$M_\infty = \mathcal{N}_{3\sigma}(\mu = 1.4, \sigma = 0.0066)$$



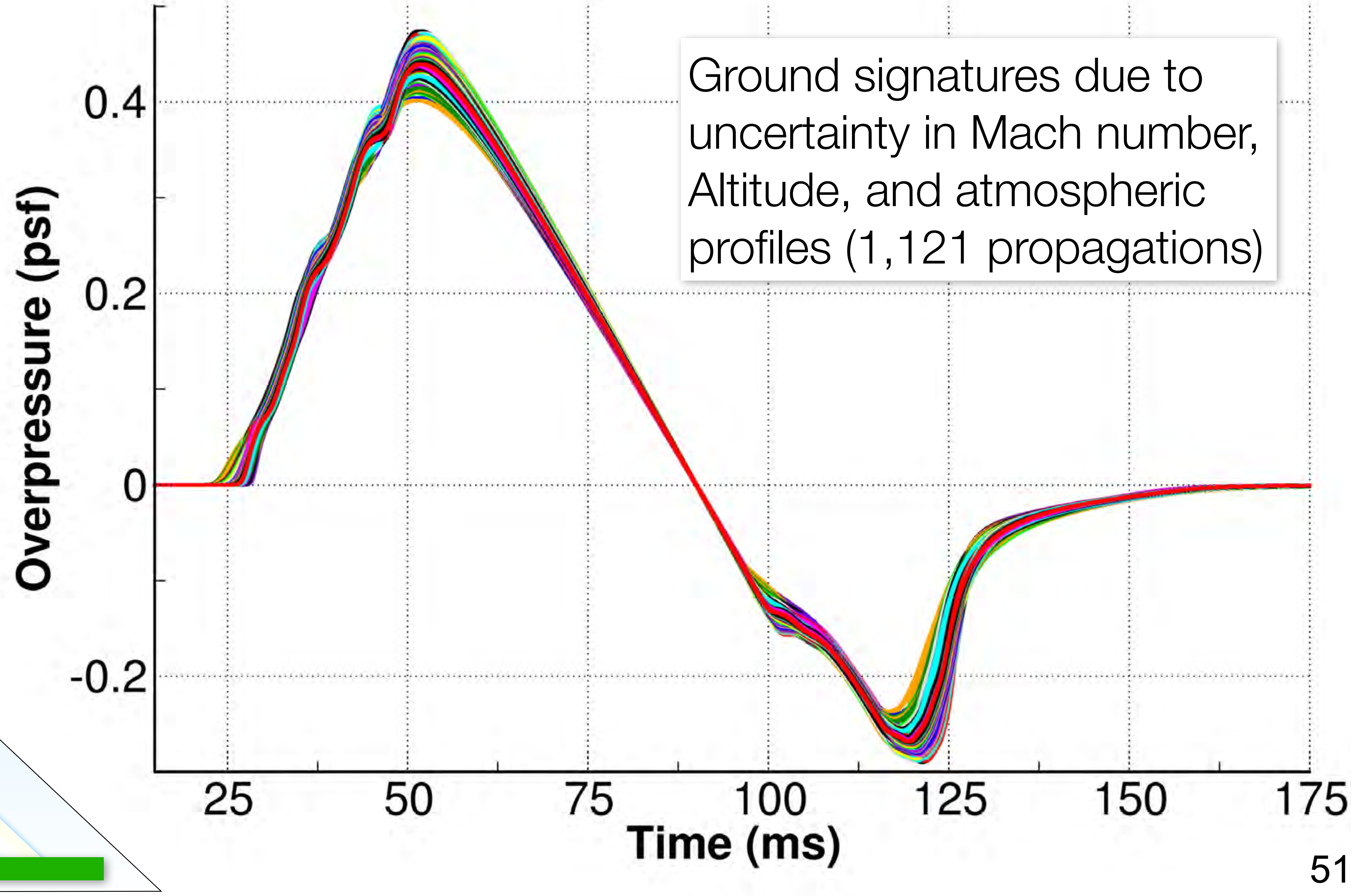




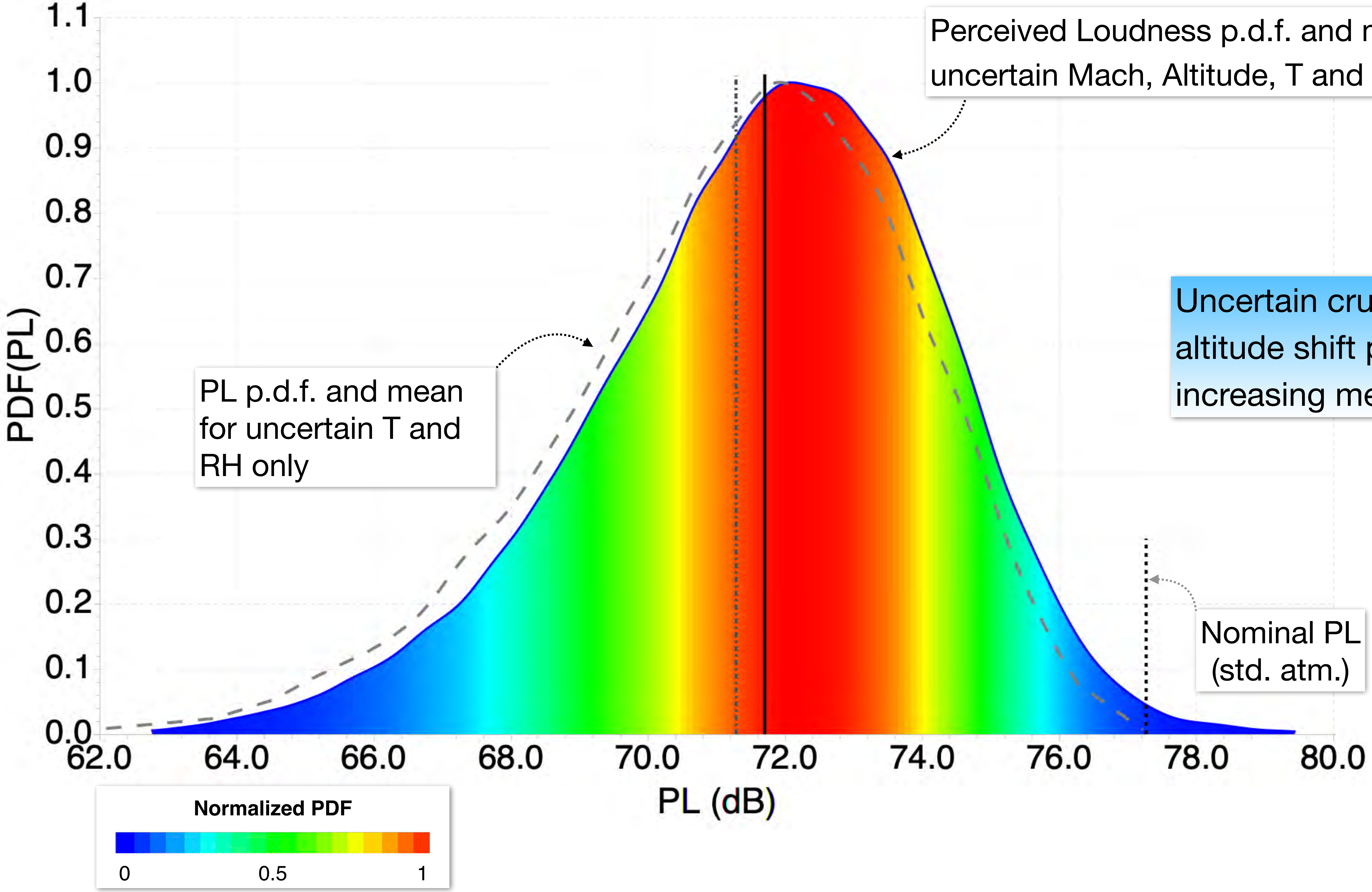


Simulation Details

- 8 input random variables
- L=4 sparse Gauss-Patterson quadrature
  - 1,121 simulations required
- Separate variables into two groups: those that affect the nearfield and those that do not
  - 15 nearfield CFD solutions
  - 1,121 farfield propagations

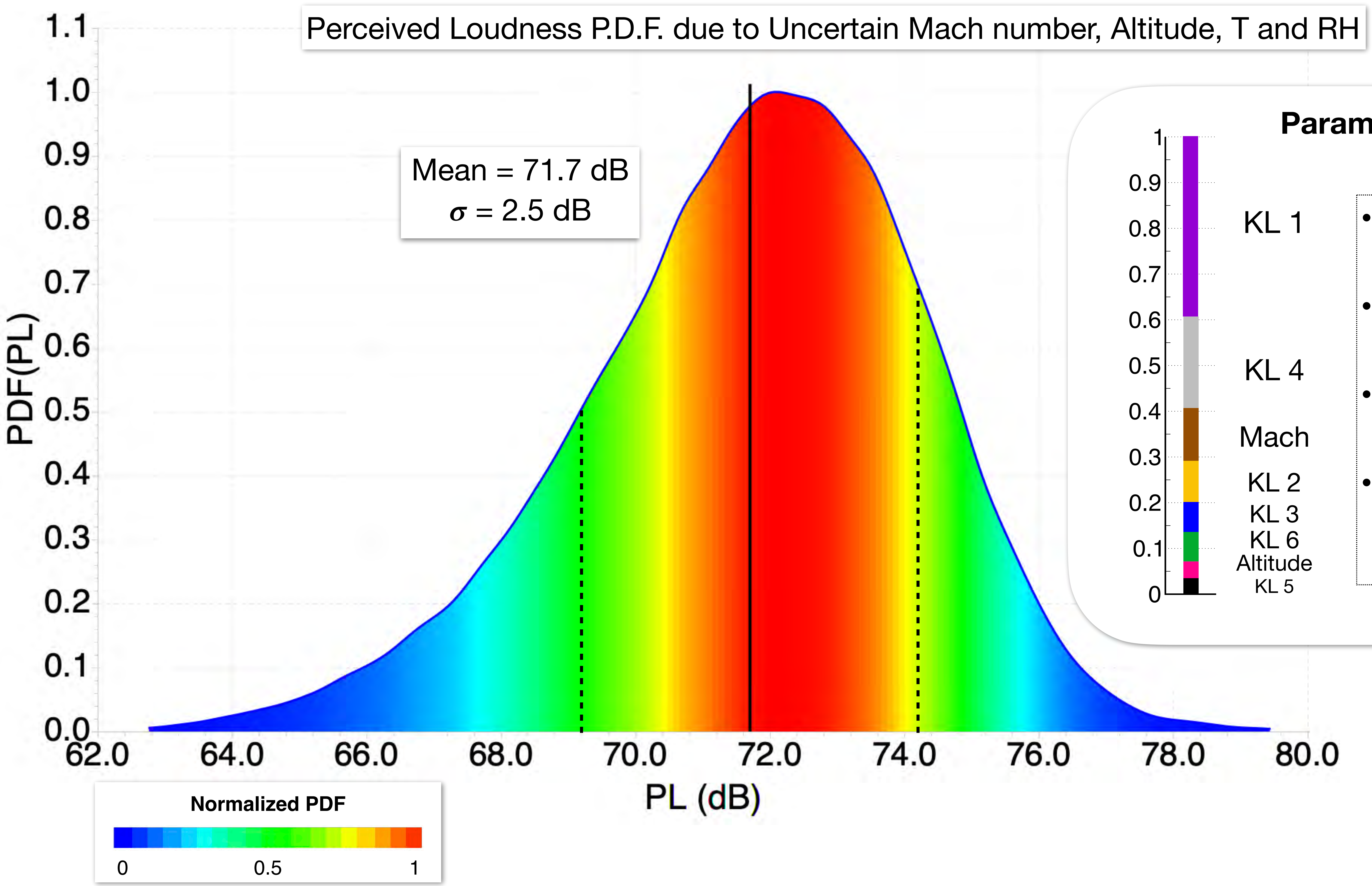


Influence of Operating Conditions on PL



Uncertain cruise Mach number and altitude shift p.d.f. to the right, increasing mean PL by 0.4 dB

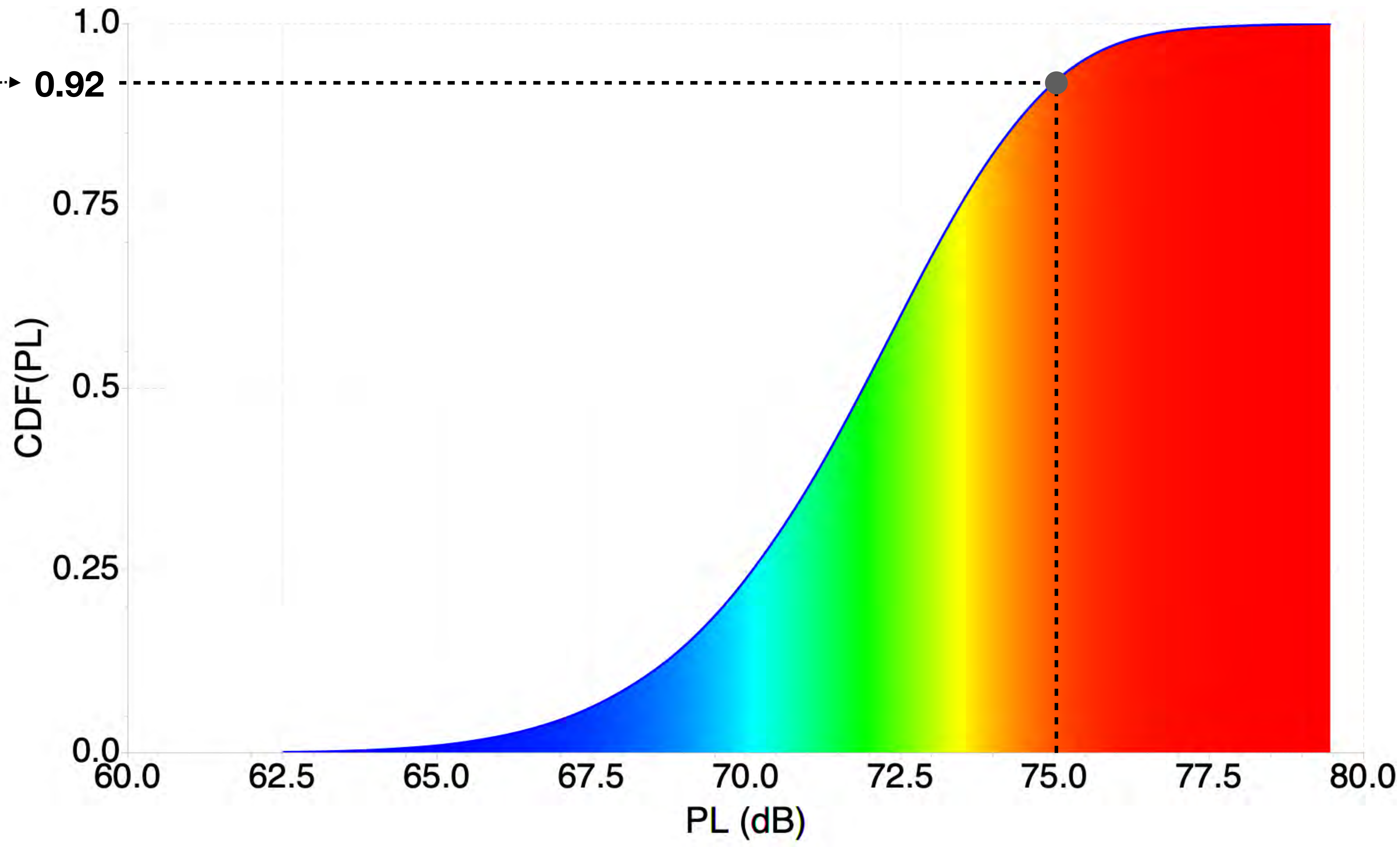
Ranking of Uncertain Inputs



- Fractional contribution to standard deviation
- Atmospheric uncertainty most dominant (KL1,4)
- Influence of Mach number is moderate
- Altitude rank among lowest in current problem formulation

Cumulative Distribution Function for PL

- 92% chance of success
  - Probability of exceeding 75 PL dB at Edwards AFB for flights in August at 18:00 UTC due to uncertainty in cruise Mach number, altitude and atmospheric conditions is 8%
- Estimate neglects variability in aircraft mass and trim, and atmospheric turbulence



Summary

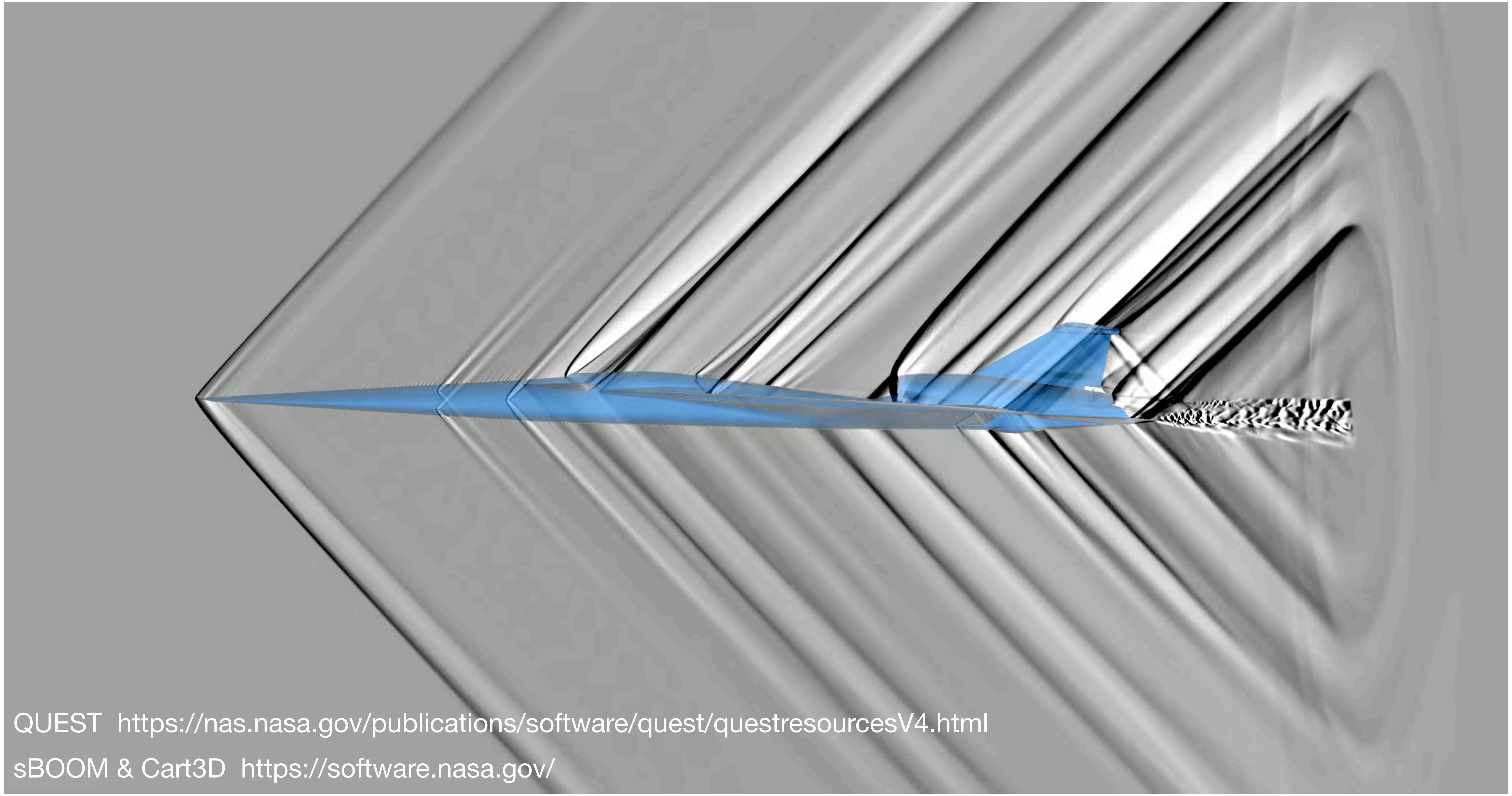
1. Demonstrated importance of evaluating the p.d.f. for nearfield signatures
   - p.d.f. is bimodal at shocks, rendering moment statistics inappropriate
2. Showed significant improvement in predictions when test uncertainties are included in simulations
   - Important step toward assessing model-form errors
3. Developed an efficient parameterization of atmospheric profiles using Karhunen-Loeve expansion
   - Demonstrated importance of including atmospheric uncertainty in loudness predictions

- Demonstrated efficient uncertainty quantification for loudness metrics under conditions expected during X-59 test flights
  - Affordable cost on real-world problems, despite direct coupling with high-fidelity simulations and complex aircraft geometry
- Enabling technology to improve confidence in predicted acoustic signatures of future supersonic transports

Acknowledgements

- Will Doebler (LaRC) and Laura White (LaRC) for Edwards atmospheric profiles and discussions
- NASA's ARMD Commercial Supersonic Technology Project
- NASA's ARMD Transformational Tools and Technologies Project
- NASA High-End Computing Program and NASA Advanced Supercomputing (NAS) Division at Ames Research Center for computing resources
- NASA OSTEM internship program

Questions



QUEST https://nas.nasa.gov/publications/software/quest/questresourcesV4.html

sBOOM & Cart3D https://software.nasa.gov/