In Situ and Remote Sensing of Turbulence

Larry B. Cornman
Research Applications Laboratory
National Center for Atmospheric Research

Turbulence Measurements

- Turbulence is a stochastic process, and hence must be studied via the *statistics* of the process.
- Homogeneity, isotropy, eddy dissipation rate: these are all *defined* via the statistics.

Important Statistical Characterizations

- Homogeneity:

  "The probabilities for the components of the vector field at a number of points are invariant under rigid translations of the points and the vectors along which the components are computed."

- Isotropy:

  "The probabilities for the components of the vector field at a number of points are invariant under isometries of the points and the vectors along which the components are computed."

NCAR

Important Statistical Characterizations, cont'd

- An *isometry* is a length-preserving operator, e.g., translations, rotations, and/or reflections. That is, an orthogonal transformation, ***O*** , followed by a translation, ***T***.
- Let the components at the points be:

$$\omega_1 = \mathbf{u}(\mathbf{x}_1)\cdot\mathbf{a}_1,\ \omega_2 = \mathbf{u}(\mathbf{x}_2)\cdot\mathbf{a}_2 \cdots\ \omega_n = \mathbf{u}(\mathbf{x}_n)\cdot\mathbf{a}_n$$

$$\omega_1' = \mathbf{u}((T\circ O)\mathbf{x}_1)\cdot O\mathbf{a}_1,\ \omega_2' = \mathbf{u}((T\circ O)\mathbf{x}_2)\cdot O\mathbf{a}_2 \cdots\ \omega_n' = \mathbf{u}((T\circ O)\mathbf{x}_n)\cdot O\mathbf{a}_n$$

- Then, isotropy is given by, (homogeneity is when ***O*** = ***I***):

$$P(c_1 \le \omega_1 \le d_1,\ c_2 \le \omega_2 \le d_2,\ \cdots\ c_n \le \omega_n \le d_n)$$
$$= P(c_1 \le \omega_1' \le d_1,\ c_2 \le \omega_2' \le d_2,\ \cdots\ c_n \le \omega_n' \le d_n)$$

Importance of eddy dissipation rate as an intensity parameter

- Under appropriate simplifications (homogeneous, solenoidal, constant density flow; no transport, diffusion, and convection of energy), the turbulent kinetic energy equation can be written as:

$$\frac{de}{dt} = -\varepsilon$$

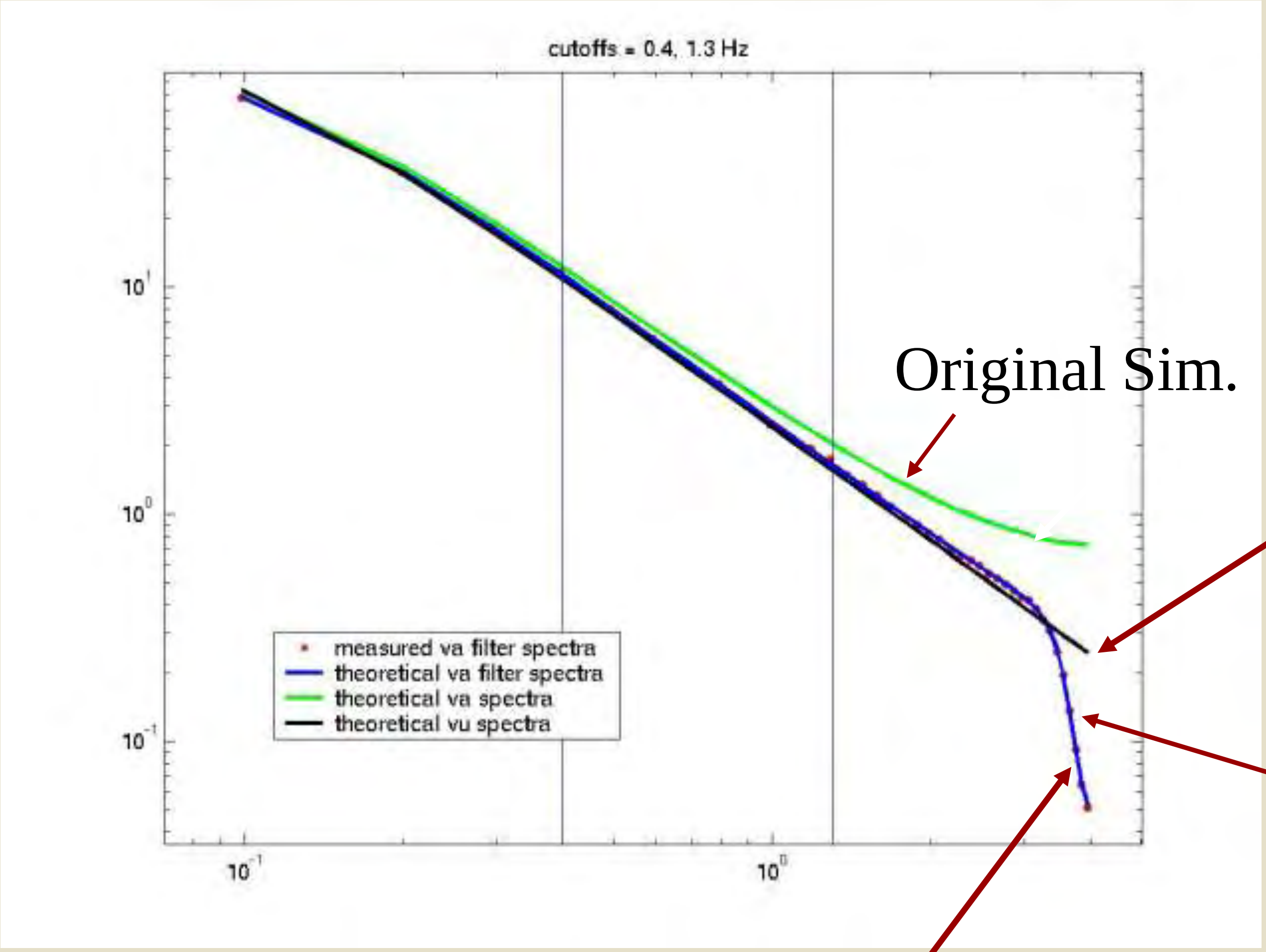
- Furthermore, the Kolmogorov energy spectrum (isotropic turbulence in the inertial subrange) is:

$$E(k) = A\varepsilon^{2/3}k^{-5/3}$$

Simulation Examples – A Cautionary Tale

- Wind field is generated so that it has *correct spatial statistics*
  - This means that it will be aliased.
  - An optional simulation incorporating an anti-aliasing filter is also used.
- The spectral model is a von Karman one. Inputs: $\sigma = 5.0 ms^{-1}, L_u = 500m, \varepsilon^{2/3} = 0.545 m^{4/3} s^{-2}$
- $\varepsilon^{2/3}$ estimates from maximum likelihood method.

Spectra from model and simulated data



Original Sim.

Theoretical Von Karman Spectrum (black)

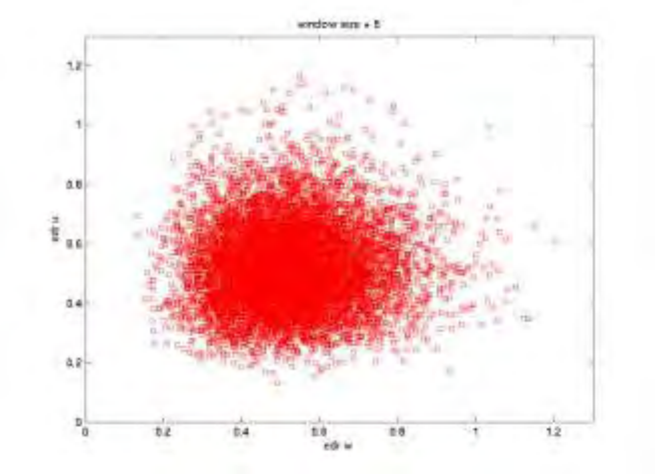
Calculated Averaged Spectra (red dots)

Theoretical Sim. w/ anti-alias filter (blue)

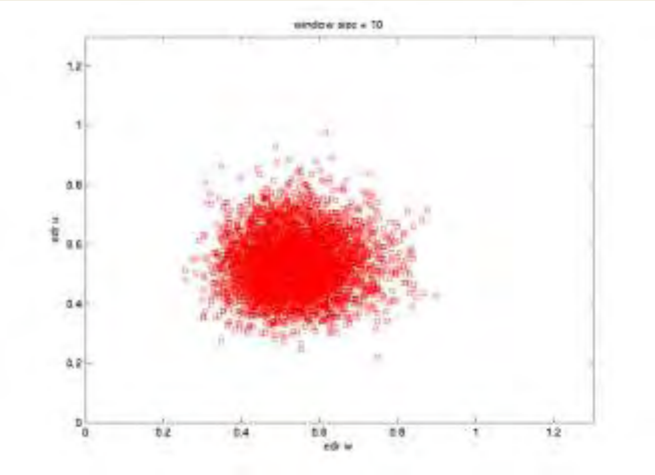
Isotropy. **Simulated data with $\varepsilon_u^{2/3}$ versus $\varepsilon_w^{2/3}$ along a line.**

Theory says, $\left\langle \varepsilon_u^{2/3} \right\rangle = \left\langle \varepsilon_w^{2/3} \right\rangle$

5 sec. windows



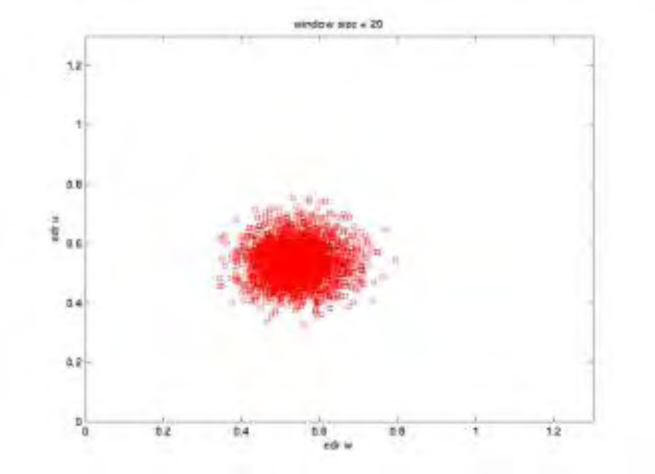
10 sec. windows



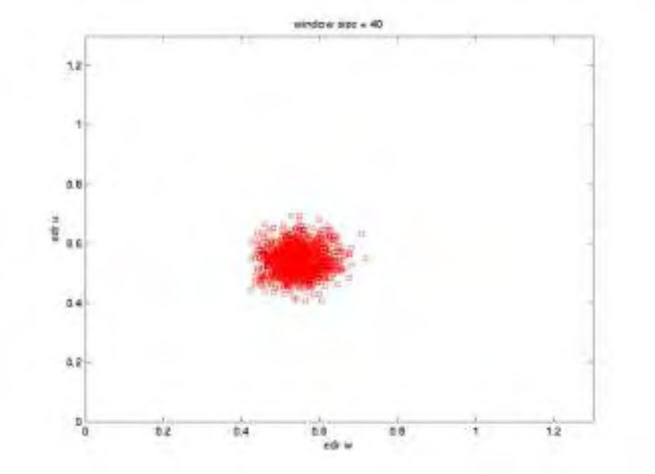
$\varepsilon_u^{2/3}$

$\varepsilon_w^{2/3}$

20 sec. windows

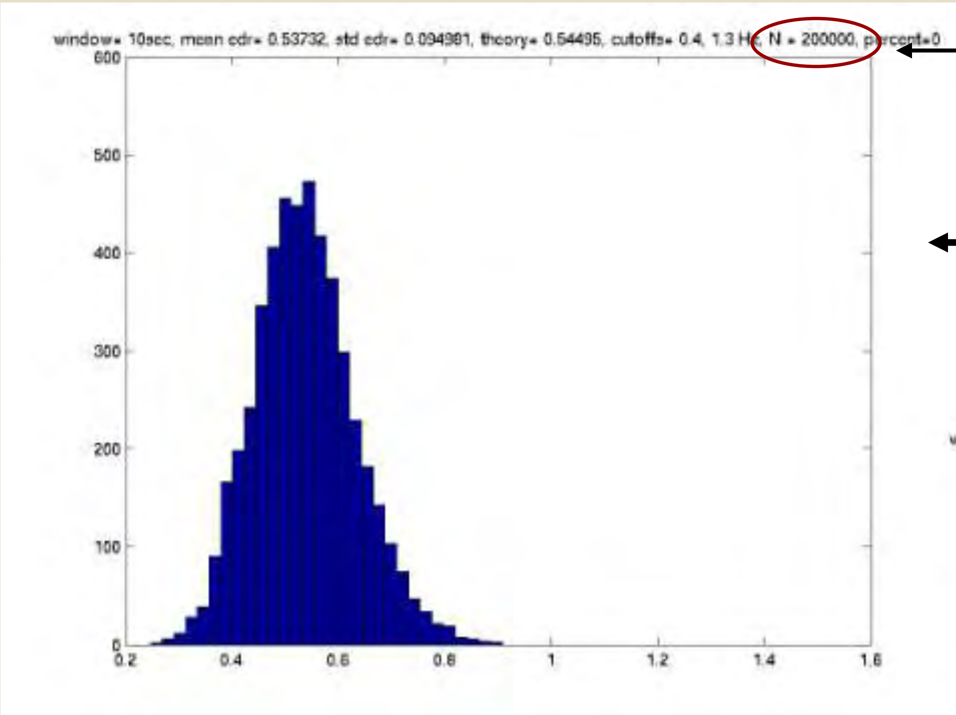


40 sec. windows



Homogeneity and sample size statistics:

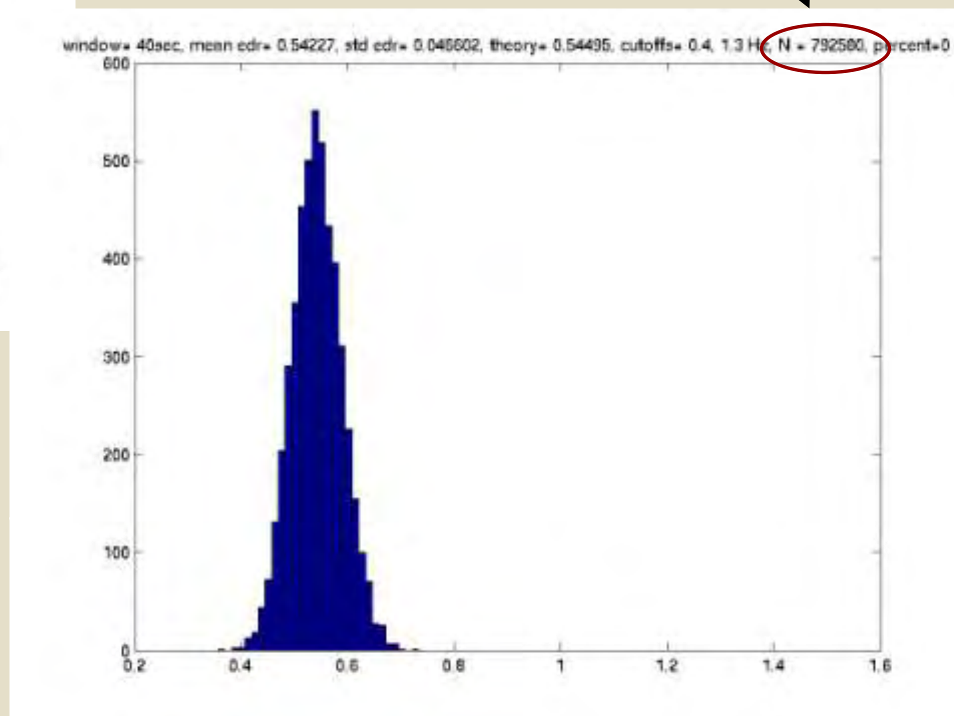
Histogram of $\varepsilon_u^{2/3}$ over 10 and 40 second intervals.



Number of samples

10 Second Windows

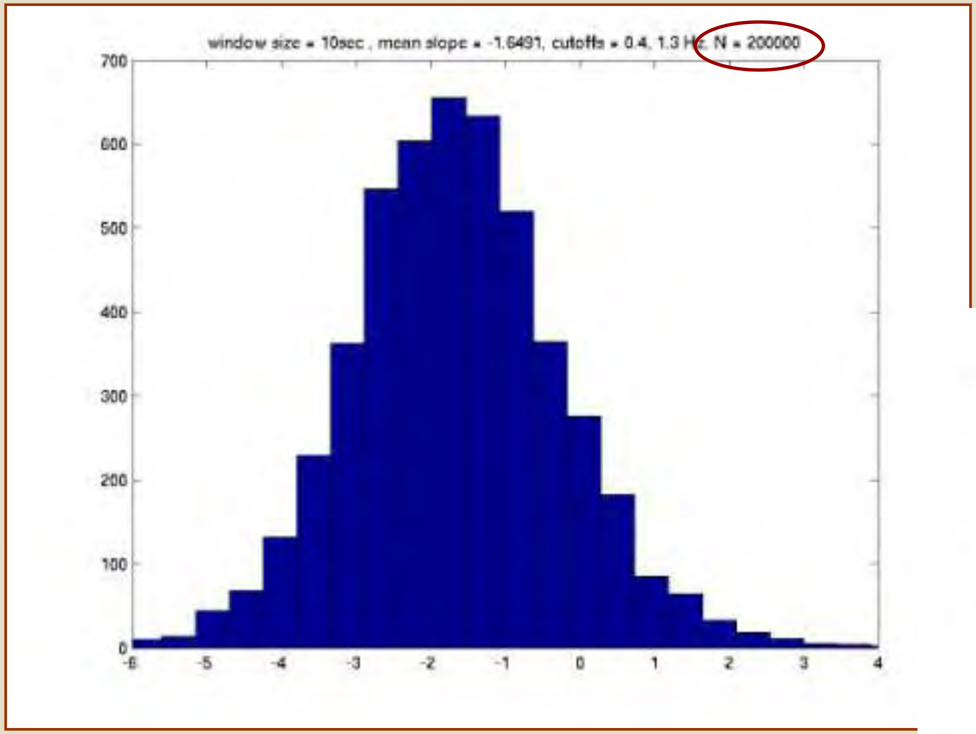
40 Second Windows



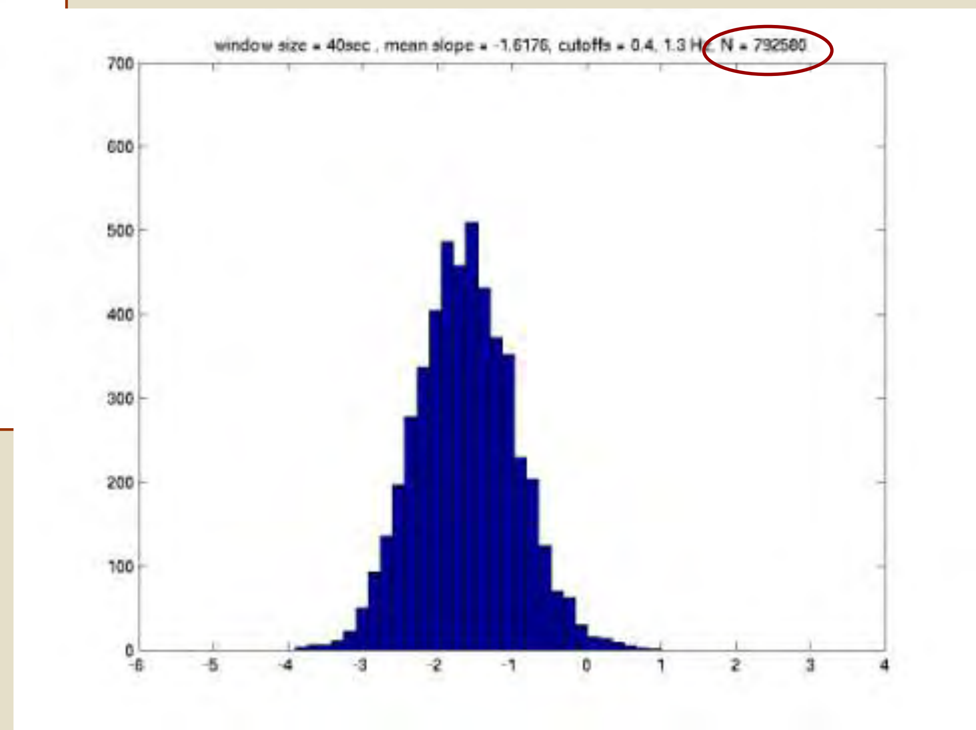
Kolomogorov energy spectrum: $E(k) = A\varepsilon^{2/3}k^{-5/3}$

Hence, the slope in log-log should be -5/3 – *on average*.

10 Second Windows



40 Second Windows



Spectral Averaging

Procedure:

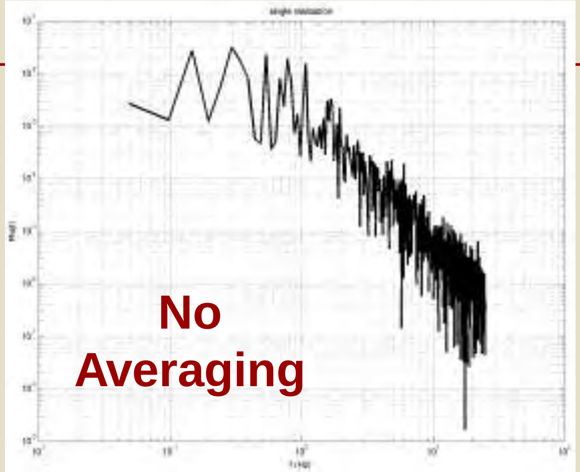
- Take as long of a segment of the time series where the data is reasonably stationary.
- Divide it into equal non-overlapping, or half-overlapping, sub-segments.
- Apply a window function – especially important for shorter and/or overlapping windows.
- Compute the spectrum for each segment.
- Average the spectra frequency-by-frequency.

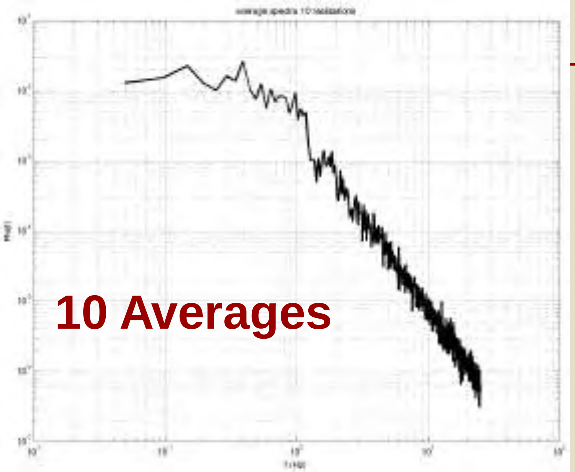
Spectral Averaging

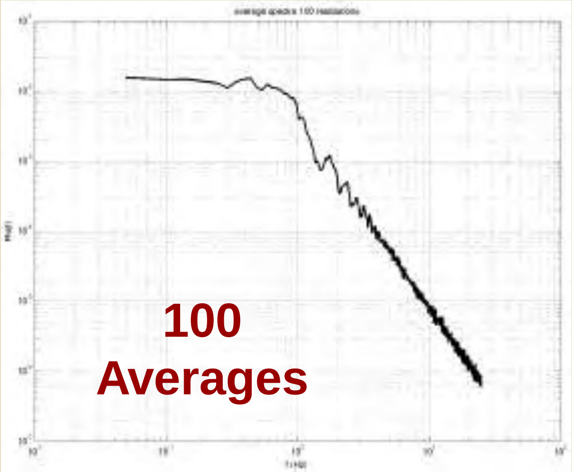
Benefits:

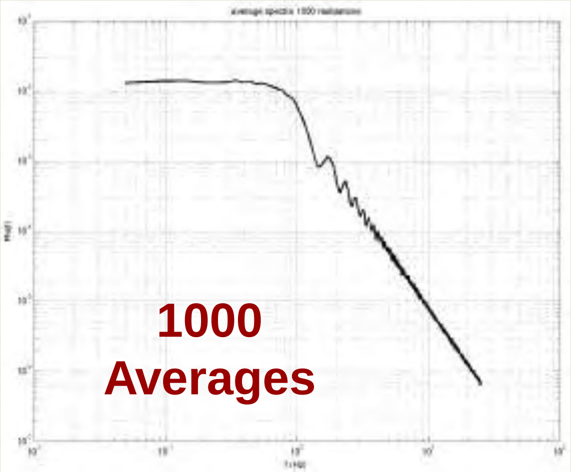
- **Reduces the random effects of turbulence.**
- **It does *not* reduce the noise level but improves signal detectability, which leads to better parameter estimation.**

Another simulation example – Illustrating the beneficial effects of spectral averaging









Parameter Estimation

- This is a very deep and important subject, however, consider a simple one-parameter estimation approach: the *maximum likelihood estimator (ML)*.
- Assume that the turbulence can be approximated as a product-model:

$$y(t) = a(t)x(t)$$

- Where *a*(t) is deterministic amplitude function, and *x*(t) is a realization from a zero-mean, unit-amplitude, stationary random process.

Parameter Estimation, cont'd.

- If *a*(t) is constant or varies at a much more lower frequency than *x*(t) does, then the auto-spectrum of *y*(t) can be written as:

$$\Phi_{yy}(f) = a^2(t)\Phi_{xx}(f)$$

- Assume that *a*(t) is a constant over the sampling interval, and it is the parameter of interest.

Parameter Estimation, cont'd.

- Then, the maximum likelihood estimator for *a* is given by:

$$\hat{a} = \frac{1}{N}\sum_{i=1}^{N}\frac{S_{yy}(f_i)}{\Phi_{xx}(f_i)}$$

- Where, *S* is the measured spectrum, and the sum is taken over a frequency range wherein it is assumed that the model spectrum is valid.

Parameter Estimation, cont'd.

- For example, take a time series of a component of the wind taken from an anemometer.
- Assume that the turbulence at higher frequencies is given by the Kolmogorov form: $\Phi_{xx}(f) = C\varepsilon^{2/3} f^{-5/3}$
- The ML estimate of $\varepsilon^{2/3}$ is given by:

$$\hat{\varepsilon}^{2/3} = \frac{1}{N}\sum_{i=1}^{N}\frac{S_{yy}(f_i)}{C\ f_i^{-5/3}}$$

NCAR

Quality Control of Measurement Data

Quality Control of Measurement Data

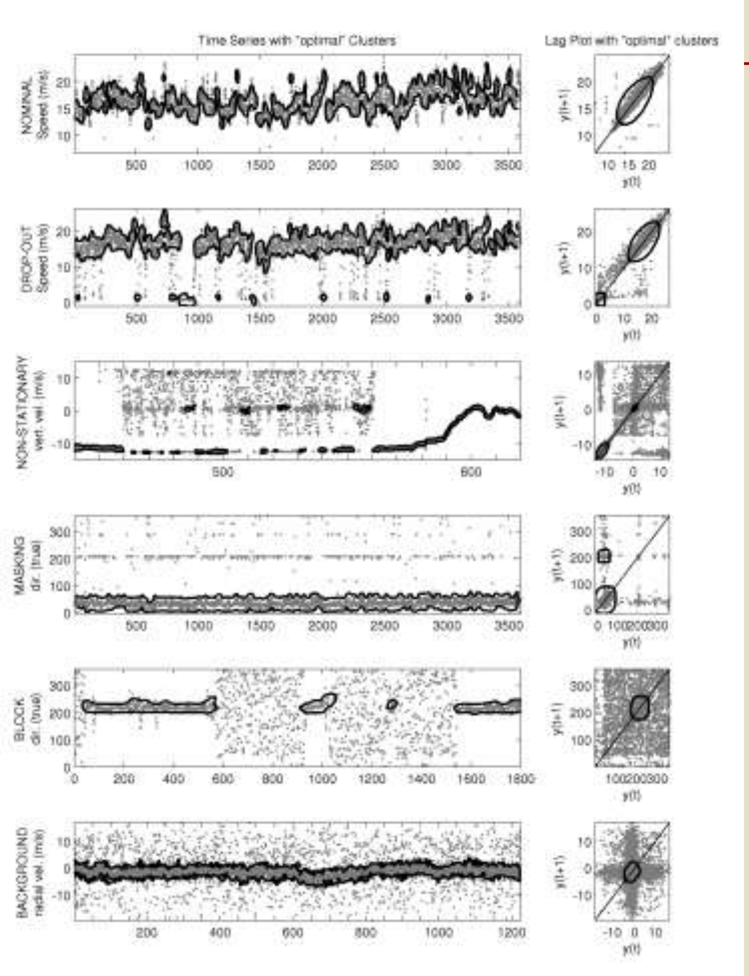
"Hmmm… These winds look a bit screwy."

Rime ice accumulation on Mt. top anemometers in Juneau AK

NCAR

Quality Control of Measurement Data

- Examples of quality control problems.
- Time series and “lag plots.”
- Our eyes do a good job of finding the good data amongst the outliers. Except for the third one from the top – the “good” data is hidden in the noise.



The Top 10 List for “Success with Sensors”

- Garbage in – garbage out. The more critical the application, the more important the QC.
- Whatever can go wrong with a sensor will go wrong.
- Your list of potential sensors failure modes is not long enough.

NCAR

"Success with Sensors" Cont'd

- Do not believe the manufacturer:
  - They're trying to sell devices at the minimum cost to them.
  - They usually use very simplistic QC methods.
  - Processing at the rawest data level is best – may require modification to the device to make that available externally.
  - Don't trust their specifications.

“**Success with Sensors**” Cont’d

- Statistical methods are fine - as presented in the literature – the real world is another matter altogether:
  - A theorem does not make for a good algorithm.
  - Assumptions made in proving theorems are often violated with real data.
  - Data with lots of outliers will kill their methods.
  - Empirical methods may not make for a good journal article – but they work.
  - *No one publishes their failures*.

NCAR

“**Success with Sensors**” Cont’d

- *A priori* assumptions are dangerous – model-free methods are more robust.
- Simulation is a great tool to start with, but you need to learn from real data.
- Typically, no one’s solved your problem – but you can learn from other’s mistakes and successes. *Use the literature – talk to colleagues*.

“**Success with Sensors**” Cont’d

- There’s no simplistic or black box solution – you have to understand the problem inside-out.
- **There’s no substitute for hard work:** “*Do you want to explain why the wind farm had to be taken down because a bird defecated on a wind sensor?*”

NCAR

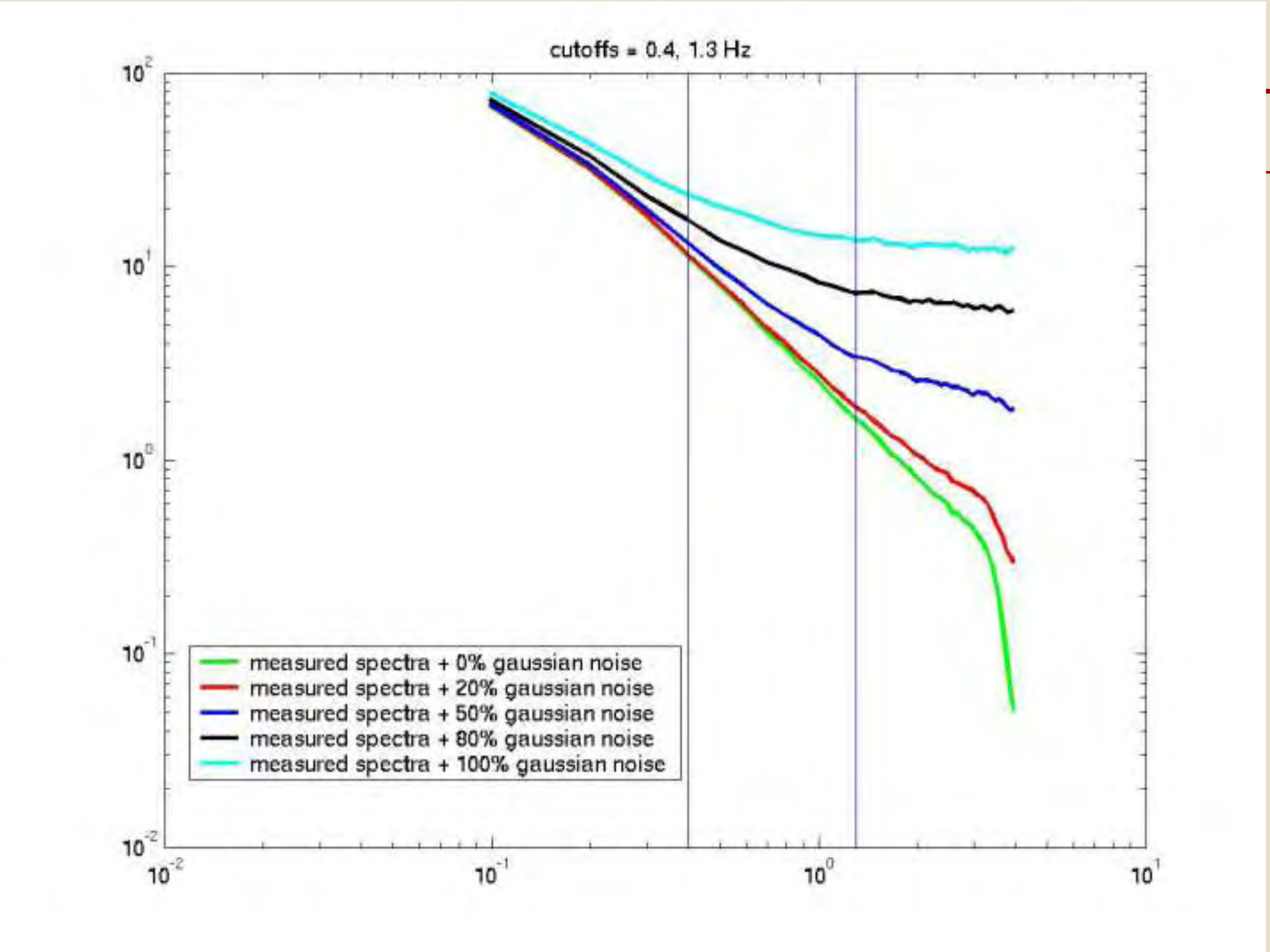
Issues Regarding Low SNR Measurements

- Low SNR means different things for different devices
  - Radar: low reflectivity (hydrometeors)
  - Lidar: low backscatter (aerosol density)
  - Wind profilers: low index of refraction (temperature and/or humidity fluctuations)
  - Anemometers: low wind speed

In each case, it is important to recognize when the device is giving meaningful information – *and when it isn't*.

NCAR

Simulated Spectra with added Gaussian noise



Averaged Spectra with Anti-Aliasing Filter.

EDR estimation algorithms (e.g., ML) can be modified to accommodate additive noise – but this only works to a point.

Some time series QC algorithms that are useful

- Running Median Filter
  - Simple to implement.
  - Fairly efficient for reasonable window size.
  - Works well for isolated outliers.
  - Has “saturation” problem when > 1/2 of the samples in the window are bad.
  - Inherent ½ window length lag.

NCAR

Some time series QC algorithms that are useful, Cont'd

- Auto-regression methods
  - Simple to implement.
  - Very efficient.
  - Works well for isolated outliers.
  - Has problems with abrupt changes in data.
  - Can "lock onto" bad signal if it is relatively smooth.

NCAR

Some time series QC algorithms that are useful, Cont'd

- Wavelets
  - Fairly efficient.
  - Works well for isolated outliers and step changes.
  - Can also be used to filter low or high frequencies.
  - Works well for non-stationary signals.
  - Some "art" required in implementation.

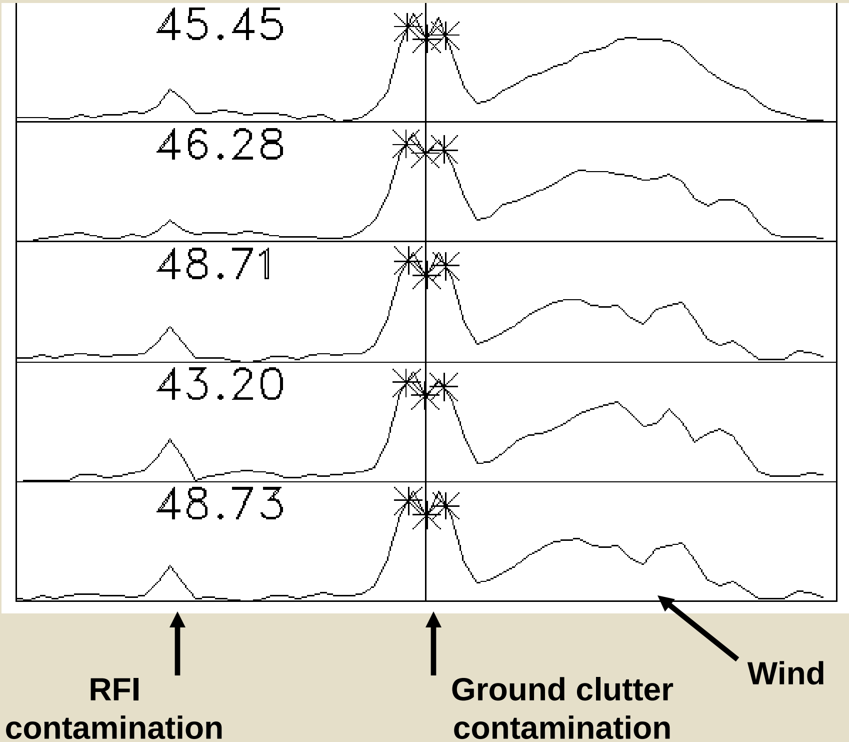
Some time series QC algorithms that are useful, Cont'd

- NCAR Improved Moment Algorithm (NIMA)
  - Developed for wind profiler application – Doppler second moments can be used to calculate turbulence.
  - Fuzzy logic image processing algorithm for finding atmospheric part of Doppler spectra in the presence of contaminants.
  - Not very efficient.
  - Very specific for the application.

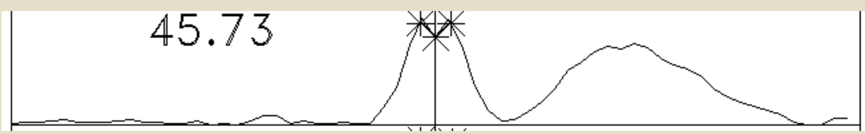
The NIMA Method

- NIMA tries to imitate human experts using
  - Mathematical analysis
  - Fuzzy logic synthesis
  - Global image processing
- Problem is broken down into smaller sub-problems
  - Doppler peak detection
  - Clutter feature detection
  - RFI feature detection
  - Atmospheric feature detection
  - Continuity assurance
  - Confidence estimation

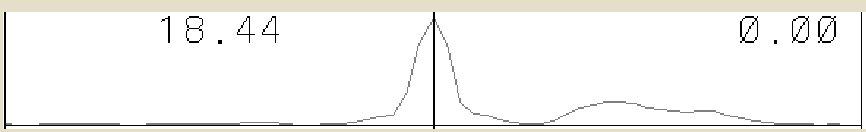
Doppler spectra as a function of range and velocity



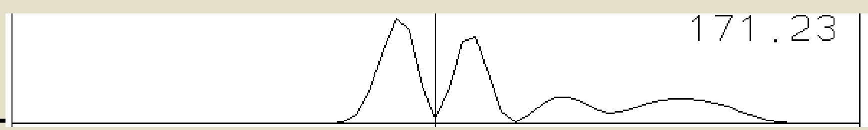
Doppler spectra at one range



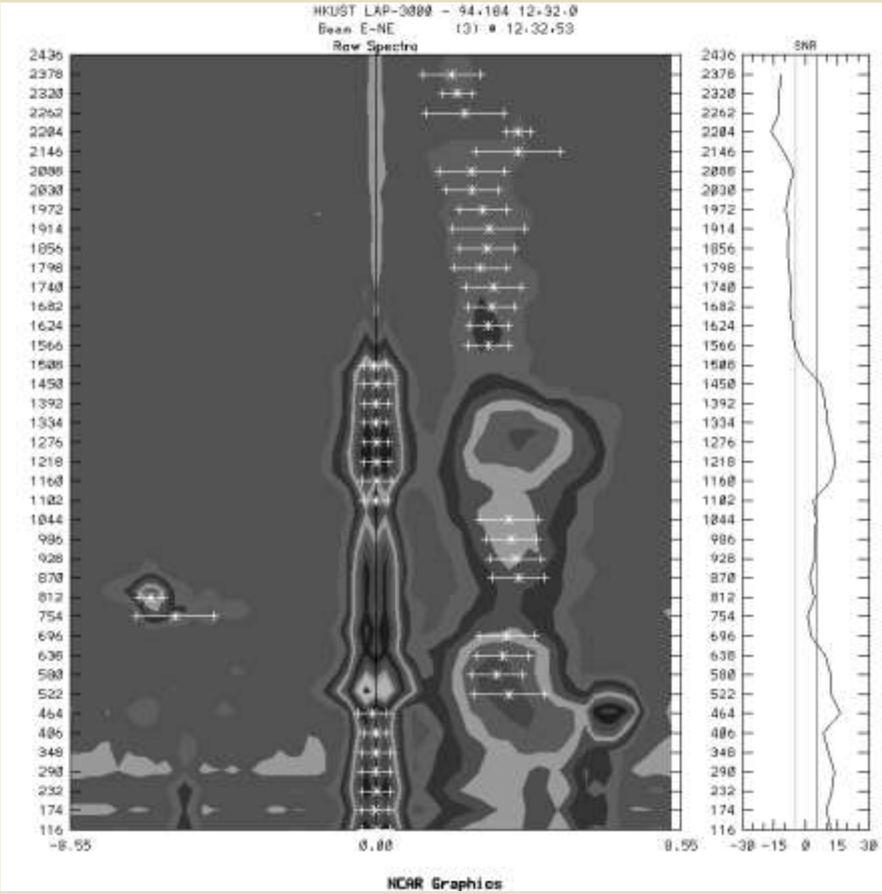
Slope information

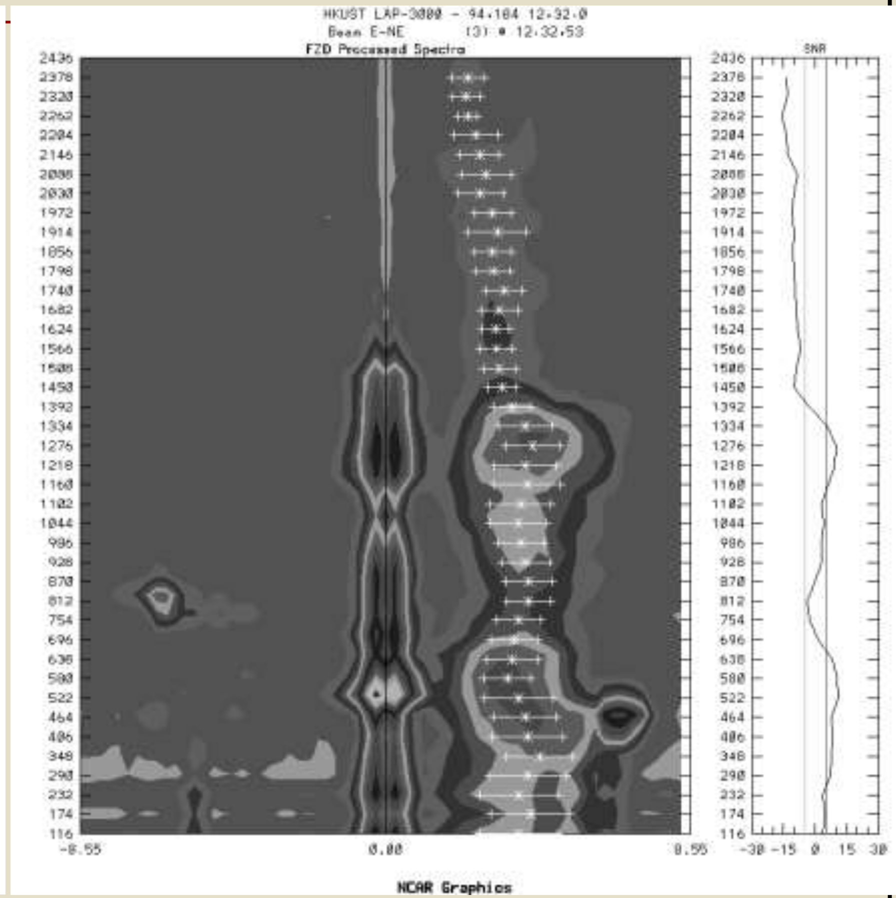


Curvature information



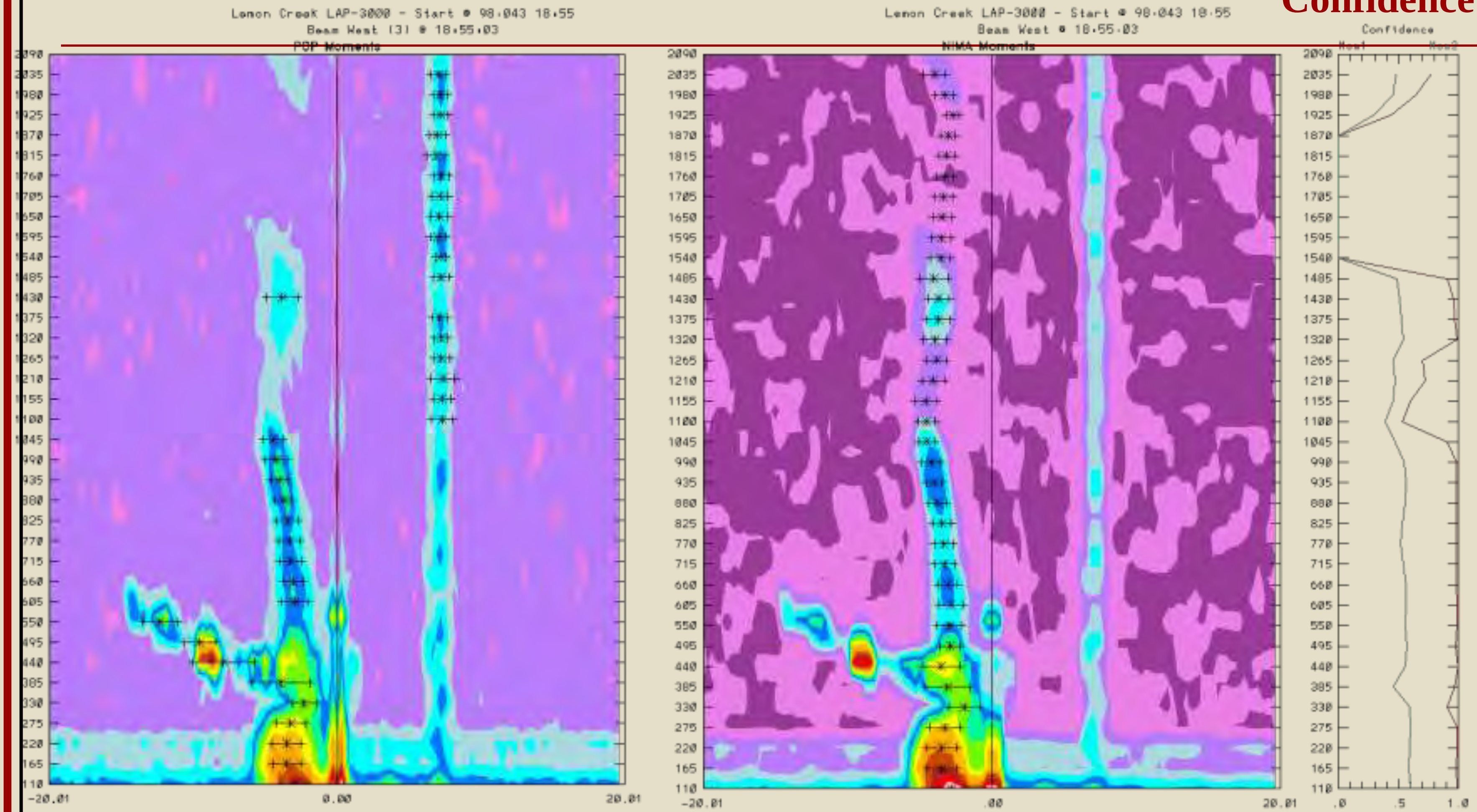
Before and after NIMA processing





Before and after NIMA processing

Confidence

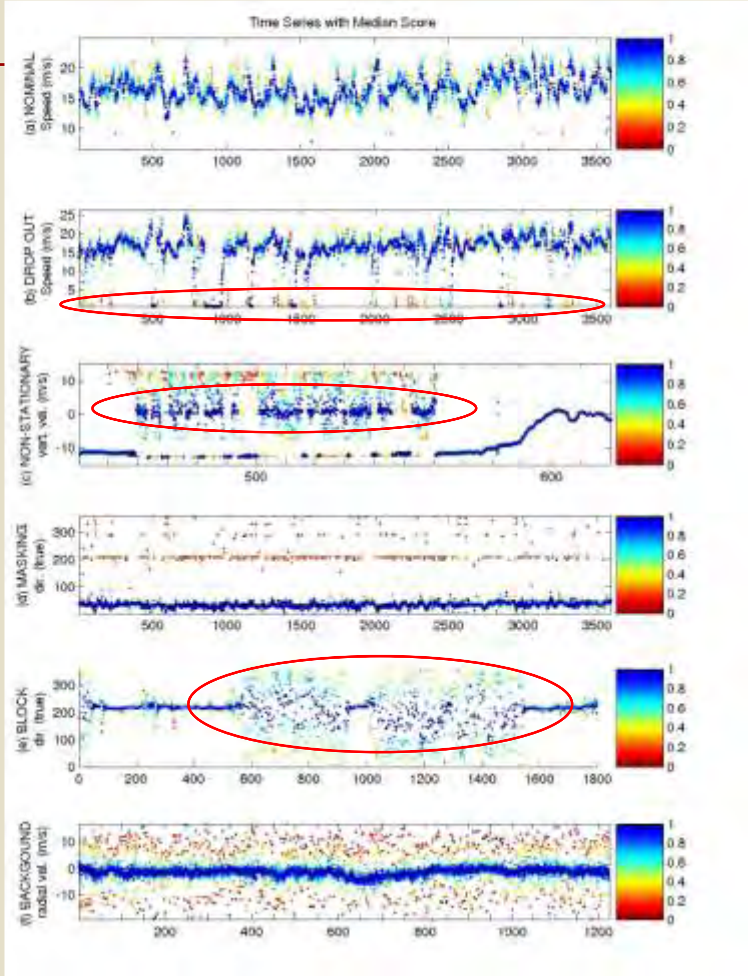


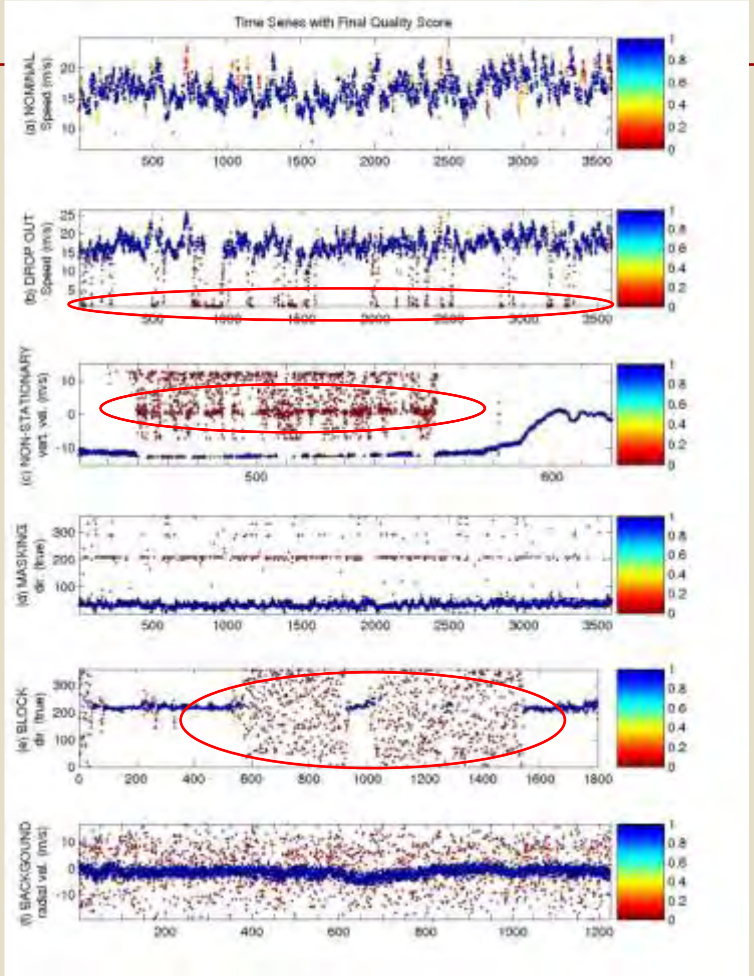
Remote Sensing of Turbulence

Some time series QC algorithms that are useful, Cont’d

- Intelligent Outlier Detection Algorithm (IODA)
  - Very powerful times series QC and data classification algorithm.
  - Handles larger numbers of outliers.
  - Identifies some failure modes.
  - Requires correlation structure in data.
  - Not very efficient.

Running Median (left) vs. IODA (right)





NCAR

Remote Sensing of Turbulence: A Primer

- Remote sensing of turbulence is performed via active or passive sensors, and hence the measurements are typically highly affected by the sensor.
- The sensor acts as a “filter” on the atmospheric turbulence, and hence we are solving an inverse problem:

Given sensor measurements, and a model of the sensor, what was the turbulence that produced the measurements?

Remote Sensing of Turbulence: A Primer

- Measuring turbulence with *active sensors* can be broken-down into two types of problems:
  - Backscatter. Transmitter and receiver are typically at the same place.
  - Propagation. Transmitter and receiver are on opposite sides of the sample volume. (E&M, optical, acoustic)

NCAR

Remote Sensing of Turbulence: A Primer

- Typical backscatter devices include: radars, lidars, and sodars.
  - Radars reflect microwaves (mm to cm) off of hydrometeors (rain, snow, ice, etc.) and index of refraction fluctuations (typically, temperature or humidity variations).
  - Lidars reflect photons off of aerosols (micron-sized particulates)
  - Sodars reflect acoustic waves off of index of refraction fluctuations (typically, temperature variations).

NCAR

Remote Sensing of Turbulence: A Primer

- Typical propagation measurements of turbulence are obtained by mm-cm radio waves, optical and acoustic waves which are diffracted by temperature and/or humidity fluctuations in the index of refraction.

NCAR

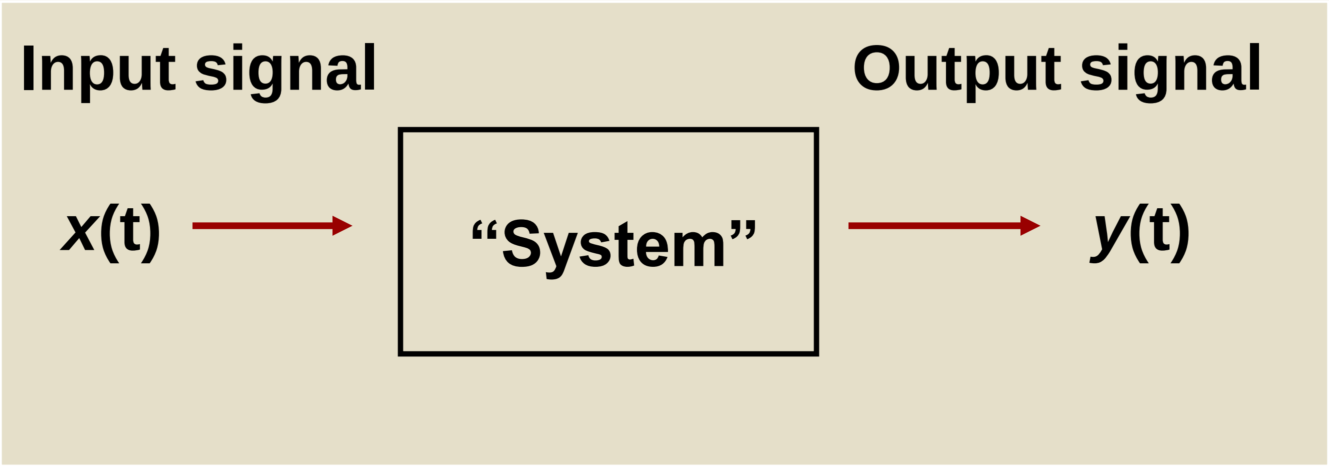
Remote Sensing of Turbulence: A Primer

- Passive sensors used to obtain measurements of turbulence are typically:
  - Infrared devices which measure the re-radiated field from atmospheric atoms and molecules. The source typically being solar radiation re-radiated from the Earth's surface.
  - Optical sensors which measure the light coming from stars.

NCAR

Remote Sensing of Turbulence: A Primer

- Returning to the “sensor as turbulence filter” problem…
- Consider a single input – single output relation:



Remote Sensing of Turbulence: A Primer

- For a linear system, the mathematical relationship is a convolution integral:

$$y(t) = \int_{0}^{\infty} h(\tau)\, x(t-\tau)\, d\tau$$

- Where, *h*(t), is the *unit impulse response function* for the linear system.
- Taking the Fourier transform of both sides gives:

$$Y(f) = H(f)X(f)$$

NCAR

Remote Sensing of Turbulence: A Primer

- Considering *x*(t) as being a stochastic and stationary signal, the input-output correlation and spectral relationships are:

$$R_{yy}(\tau) = \int_0^\infty \int_0^\infty h(\alpha) h(\beta) R_{xx}(\tau + \beta - \alpha) \, d\alpha \, d\beta$$

$$\Phi_{yy}(f) = \left| H(f) \right|^2 \Phi_{xx}(f)$$

Note the simplicity of the spectral relation.

Remote Sensing of Turbulence: A Primer

- Where for a stationary signal *s*(t),

$$R_{ss}(\tau) = \langle s(t)s(t+\tau) \rangle$$

$$\Phi_{ss}(f) = \int_0^\infty R_{ss}(\tau) e^{-2\pi f \tau} d\tau$$

$$= \langle Y(f) Y^*(f) \rangle$$

Remote Sensing of Turbulence: A Primer

- The same relationships work for the components of a homogeneous spatial field, ***x***(***r***).

$$y_i(\mathbf{r}) = \int_0^\infty \int_0^\infty \int_0^\infty h(\boldsymbol{\rho})\, x_i(\mathbf{r}-\boldsymbol{\rho})\, d\boldsymbol{\rho}$$

$$Y_i(\mathbf{k}) = \left|H(\mathbf{k})\right|^2 X_i(\mathbf{k})$$

Remote Sensing of Turbulence: A Primer

- Where the correlation and spectral relationships for a homogeneous field are:

$$R_{s_i s_j}(\boldsymbol{\rho}) = \left\langle s_i(\mathbf{r}) s_j(\mathbf{r}+\boldsymbol{\rho}) \right\rangle$$

$$\Phi_{s_i s_j}(\mathbf{k}) = \int_0^\infty R_{s_i s_j}(\boldsymbol{\rho}) e^{-2\pi \mathbf{k}\cdot\boldsymbol{\rho}} d\boldsymbol{\rho}$$

Remote Sensing of Turbulence: A Primer

- Consider a specific example: Doppler (backscatter) radar measurements of turbulence.
- Two approaches:
  - Spatial spectrum of the radial velocities.
  - Doppler second moment.

Remote Sensing of Turbulence: A Primer

- For both approaches, we need the following relationship: $\hat{v}(\mathbf{r}_0) \equiv M_1(\mathbf{r}_0) = \int u\, S_n(u,\mathbf{r}_0)\,du$
- Where $S_n(u,\mathbf{r}_0)$ is the normalized Doppler spectrum for the pulse volume centered at $\mathbf{r}_0$, $M_1(\mathbf{r}_0)$ is the first moment of the Doppler spectrum, and *u* is the radial component of the wind field.

Remote Sensing of Turbulence: A Primer

- Assuming uniform reflectivity (i.e., uniform hydrometeor size and distribution), it can be shown that the first moment can be written as a spatial integral:

$$S_n(u,\mathbf{r}_0) = \int \delta(u - u(\mathbf{r}))\, I_n(\mathbf{r}-\mathbf{r}_0)\, d\mathbf{r}$$

- So that,

$$v(\mathbf{r}_0) = \int u(\mathbf{r})\, I_n(\mathbf{r}-\mathbf{r}_0)\, d\mathbf{r}$$

i.e., a spatial convolution. $I_n(\mathbf{r}-\mathbf{r}_0)$ is the pulse-volume illumination function – the response function for this problem.

NCAR

Remote Sensing of Turbulence: A Primer

- From the convolution integral, the correlation and spectral relations can be obtained:

$$R_{vv}(\mathbf{r}_0,\boldsymbol{\rho}) = \int R_{uu}(\boldsymbol{\rho}) I_n(\mathbf{r}-\mathbf{r}_0) I_n(\mathbf{r}+\boldsymbol{\rho}-\mathbf{r}_0)\, d\mathbf{r}$$

$$\Phi_{vv}(\mathbf{r}_0,\mathbf{k}) = \Phi_{uu}(\mathbf{r}_0,\mathbf{k}) I_n^2(\mathbf{r}_0,\mathbf{k})$$

NCAR

Remote Sensing of Turbulence: A Primer

- Assume that the radar pulse volume is narrow enough so that the radial velocities can be approximated via a Cartesian component.
- Assume that the velocity spectrum is isotropic, so that the coordinate system can be rotated such that the *x*-axis points along the radar beam.
- Assume that the turbulence spectrum can be modeled as $\Phi_{u_x u_x}(\mathbf{r}_0,\mathbf{k}) = \varepsilon^{2/3} F_{u_x u_x}(\mathbf{r}_0,\mathbf{k})$ then,

$$\varepsilon^{2/3} = \frac{\Phi_{vv}(\mathbf{r}_0,\mathbf{k})}{F_{u_x u_x}(\mathbf{r}_0,\mathbf{k})\, I_n^2(\mathbf{r}_0,\mathbf{k})}$$

Remote Sensing of Turbulence: A Primer

- Next, consider the Doppler 2nd moment method (think of I_n as a PDF):

$$\langle M_2(\mathbf{r}_0)\rangle = \int \left\langle \left[u(\mathbf{r}) - M_1(\mathbf{r}_0)\right]^2 \right\rangle I_n(\mathbf{r}-\mathbf{r}_0)\,d\mathbf{r}$$

$$= \int \left\langle u^2(\mathbf{r})\right\rangle I_n(\mathbf{r}-\mathbf{r}_0)\,d\mathbf{r} - \left\langle M_1^2(\mathbf{r}_0)\right\rangle$$

$$= \left\langle u^2(\mathbf{r})\right\rangle - \int R_{uu}(\mathbf{r},\boldsymbol{\rho}) I_n(\mathbf{r}-\mathbf{r}_0) I_n(\mathbf{r}+\boldsymbol{\rho}-\mathbf{r}_0)\,d\mathbf{r}\,d\boldsymbol{\rho}$$

- Where in the last step it has been assumed that the turbulence is isotropic.

Remote Sensing of Turbulence: A Primer

- Next, take the inverse Fourier transform of the right-hand side.

$$\left\langle u^2(\mathbf{r})\right\rangle = \int \Phi_{uu}(\mathbf{r}_0,\mathbf{k})\,d\mathbf{k}$$

$$\left\langle M_1^2(\mathbf{r}_0)\right\rangle = \int \Phi_{uu}(\mathbf{r}_0,\mathbf{k})\,I_n^2(\mathbf{r}_0,\mathbf{k})\,d\mathbf{k}$$

- Using the same assumptions as above:

$$\varepsilon^{2/3} = \frac{\left\langle M_2(\mathbf{r}_0)\right\rangle}{\int F_{u_x u_x}(\mathbf{r}_0,\mathbf{k})\left[1 - I_n^2(\mathbf{r}_0,\mathbf{k})\right]d\mathbf{k}}$$

NCAR

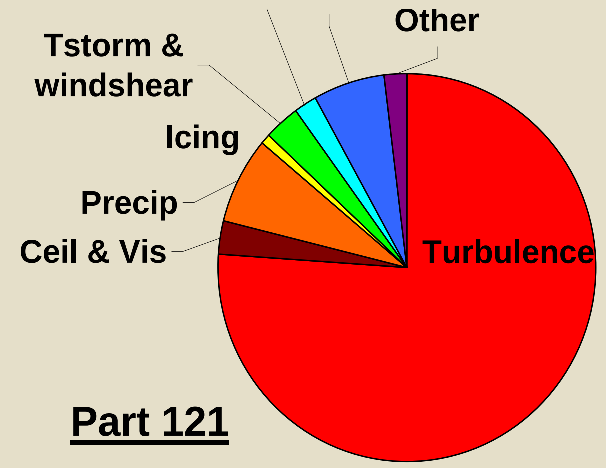
Examples of Measurements and Remote Sensing of Turbulence in Support of the Aviation Community.

NCAR

The Motivation

- Turbulence is the main cause of in-flight injuries – for both passengers and flight attendants.
- After a severe encounter, the airline has to perform a structural check on the aircraft.
- Pilots will try to re-route around an area if there have been reports of moderate or greater turbulence.

Bottom-line: Turbulence is a safety problem as well as having a large financial impact on the airlines.



Weather-related accidents for large transport aircraft

DC-8 Cargo Aircraft Damaged Due to Extreme Turbulence

NCAR

The Turbulence Problem for Aviation (Grossly Oversimplified)

“Turbulent eddies larger than 100 meters and smaller than 3000 meters (approximately) produce aircraft motions which can be difficult -- or impossible -- to control.

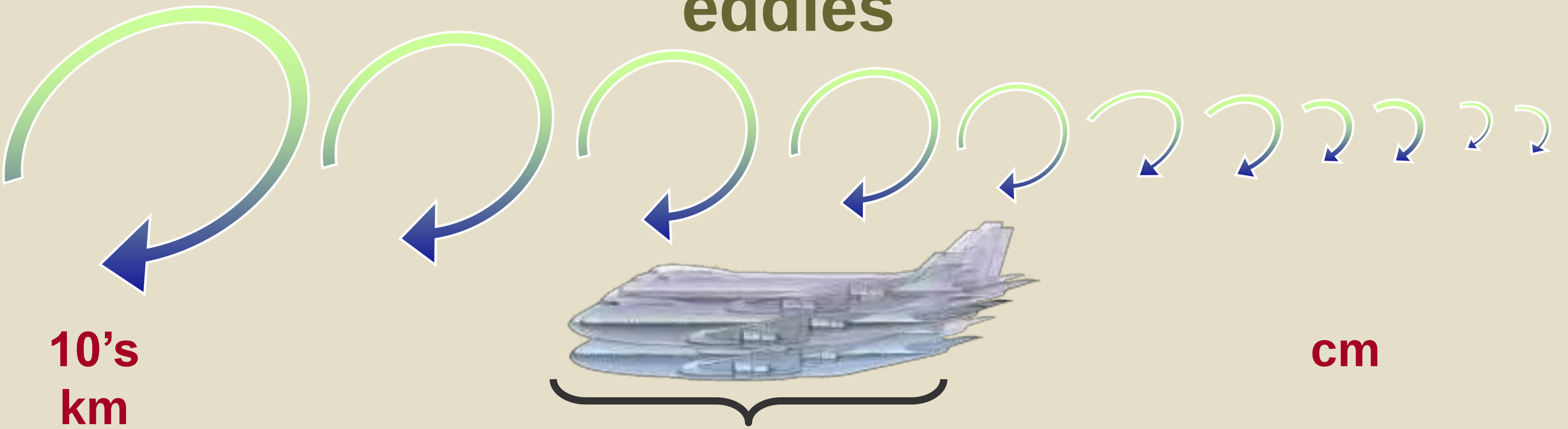
With small-amplitude eddies, these induced motions may be simply uncomfortable to passengers. Large amplitude eddies, on the other hand, can result in passenger injuries or even structural damage to the aircraft.”

Turbulence Scales of Motion

Large eddies

“Turbulent” eddies

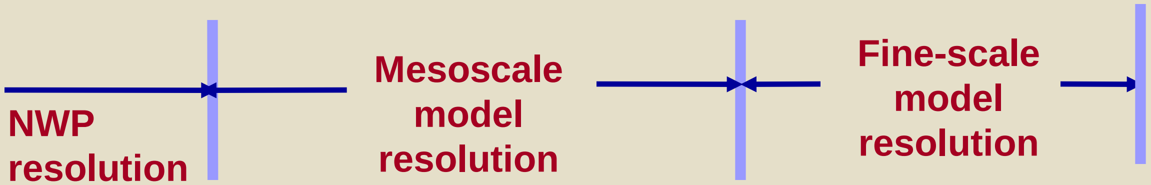
Small eddies



10’s km

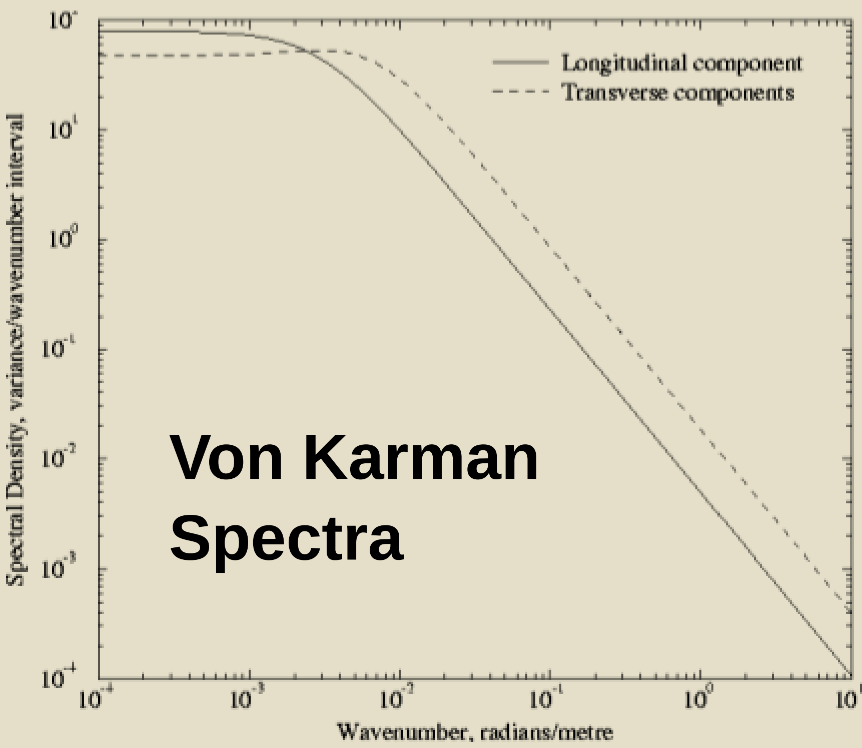
cm

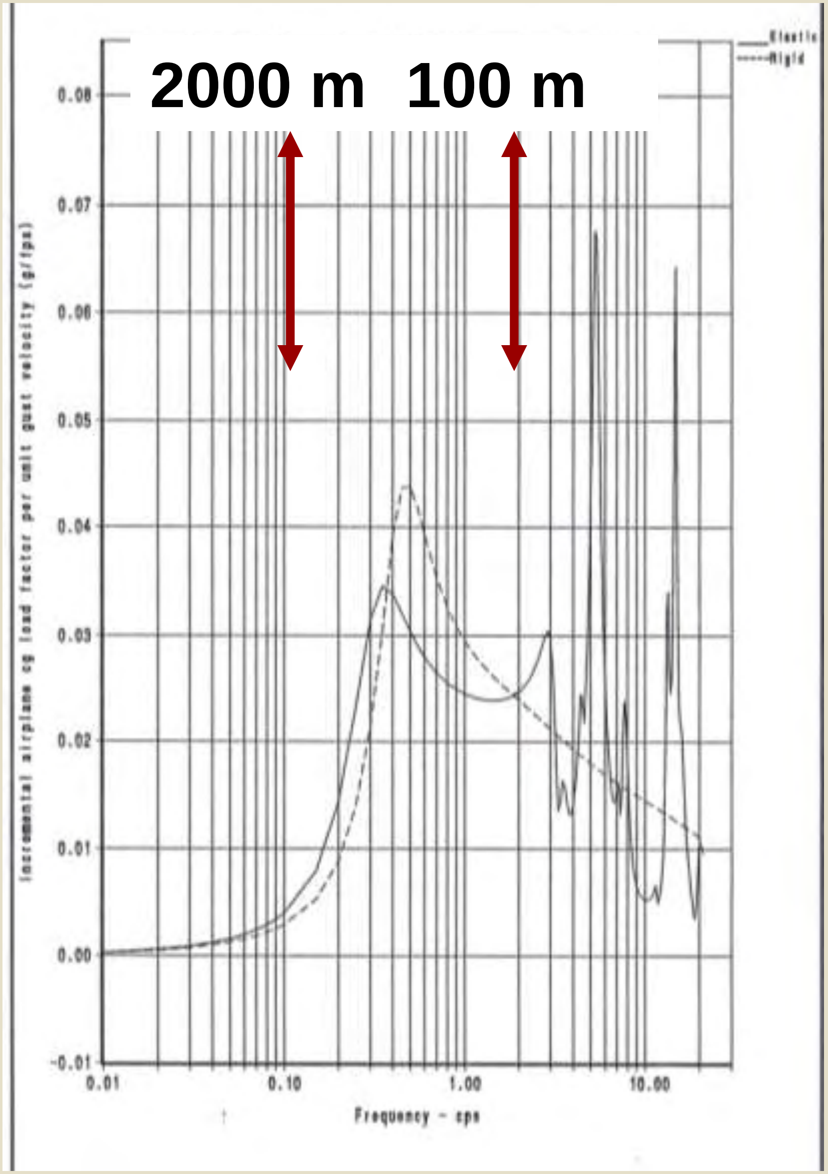
Aircraft responds to scales from approx. 100 m – 3 km



Response Function for Transport Aircraft

The product of the response function and the wind spectrum gives the output spectrum.





The Need For Turbulence Measurements

- **Tactical**:
  - Real time alerts of eminent encounter (< 1 min.)
    - Turn seat belt sign on.
    - Get passengers seated and in seatbelts.
    - Get service carts stowed and flight attendants seated.
  - Real time alerts/nowcast of impending encounter (< 15 min.)
    - All of the above.
    - Change altitude.
    - Change flight path.

NCAR

The Need For Turbulence Measurements

- **Strategic**:
  - Nowcast/Forecast of potential encounter (en route)
    - Increase pilot awareness.
    - Discussions with airline Dispatch personnel.
    - Discussions with en route air traffic personnel.
    - Consider altitude/course change.
  - Forecast of potential encounter (pre-flight)
    - Pre-flight awareness for pilot/Dispatch.
    - Consider re-routing flight path.

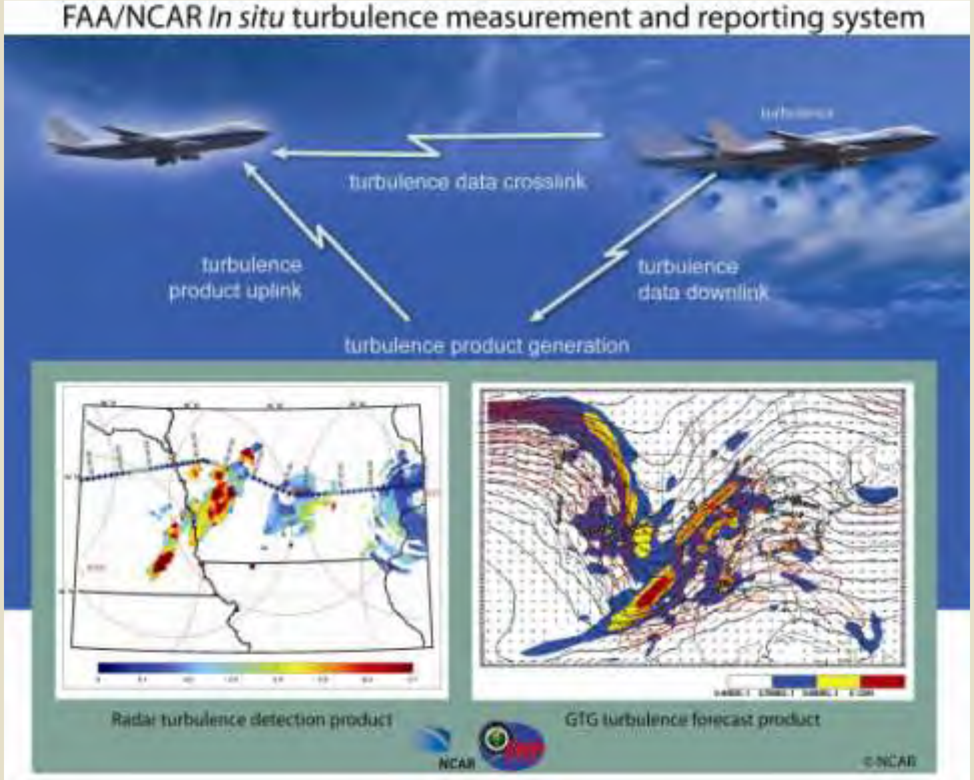
NCAR

In situ Turbulence Measurement and Reporting System

Goal: To augment/replace subjective PIREPs with objective and precise turbulence measurements.

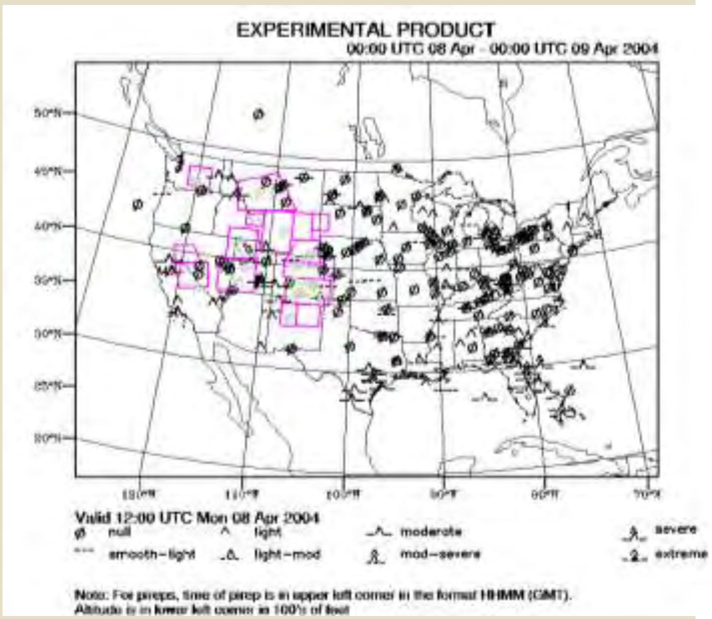
Features:

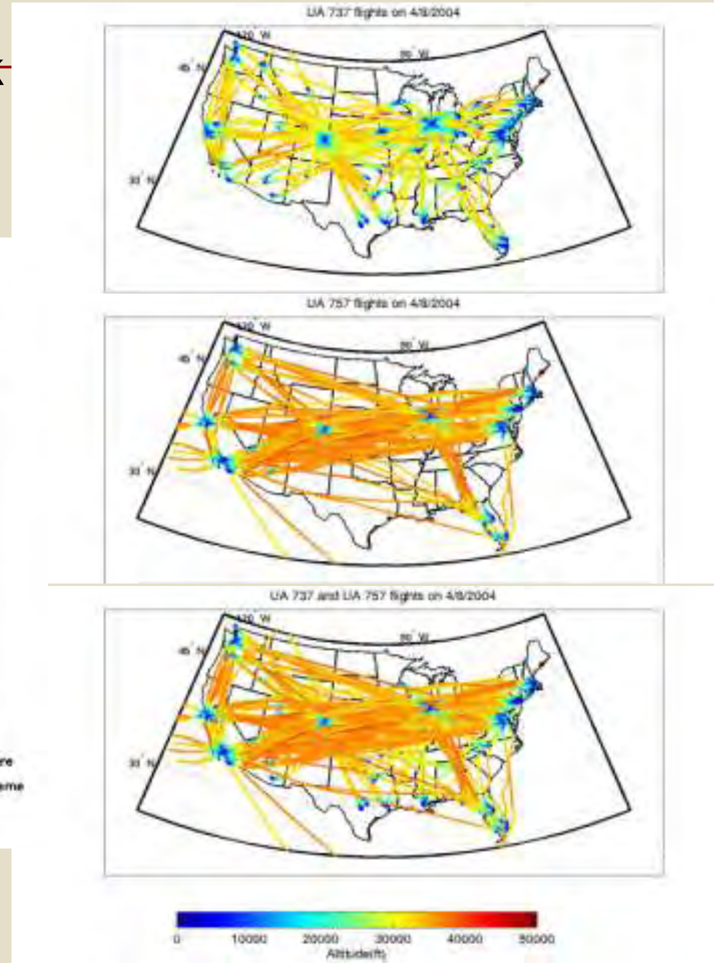
- Atmospheric turbulence metric: eddy dissipation rate (EDR).
- EDR can be scaled into aircraft turbulence response metric (RMS-g).
- **Adopted as ICAO Standard**



Increase in Spatial/temporal Coverage: UAL EDR Reports Compared to pireps

1.3 million EDR reports/month from 100 or so aircraft - compared to 55k pireps from all aircraft.





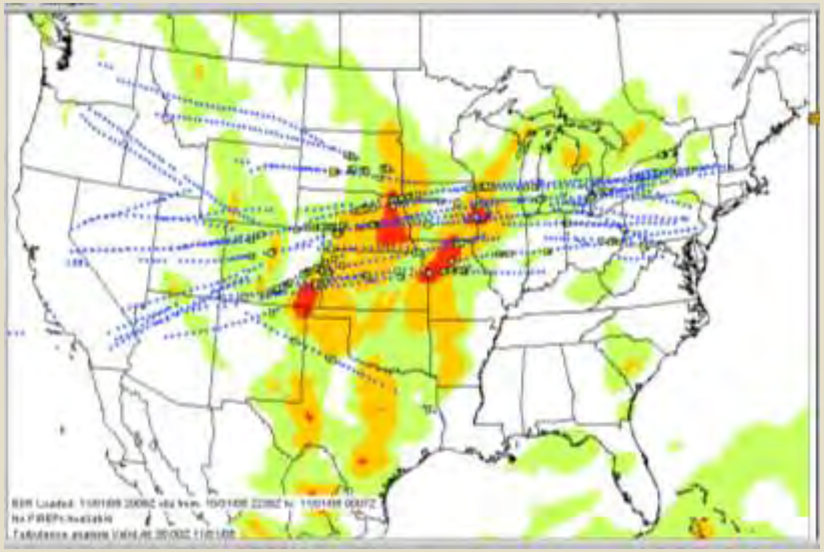
737

757

737
+
757

In situ measurement and reporting system

- Implemented on ~ 200 UAL aircraft since 2000
- Implementation status
  - SWA: Fleet implementation on ~ 280 737-700s in CY08
  - DAL: Fleet implementation on ~ 120 737-800s in CY08
  - NWA: Discussions ongoing for implementation on ~ 140 Airbus 319/320s and 56 787s
  - UAL: 757 ACMS replacement
  - AAL: Discussions ongoing

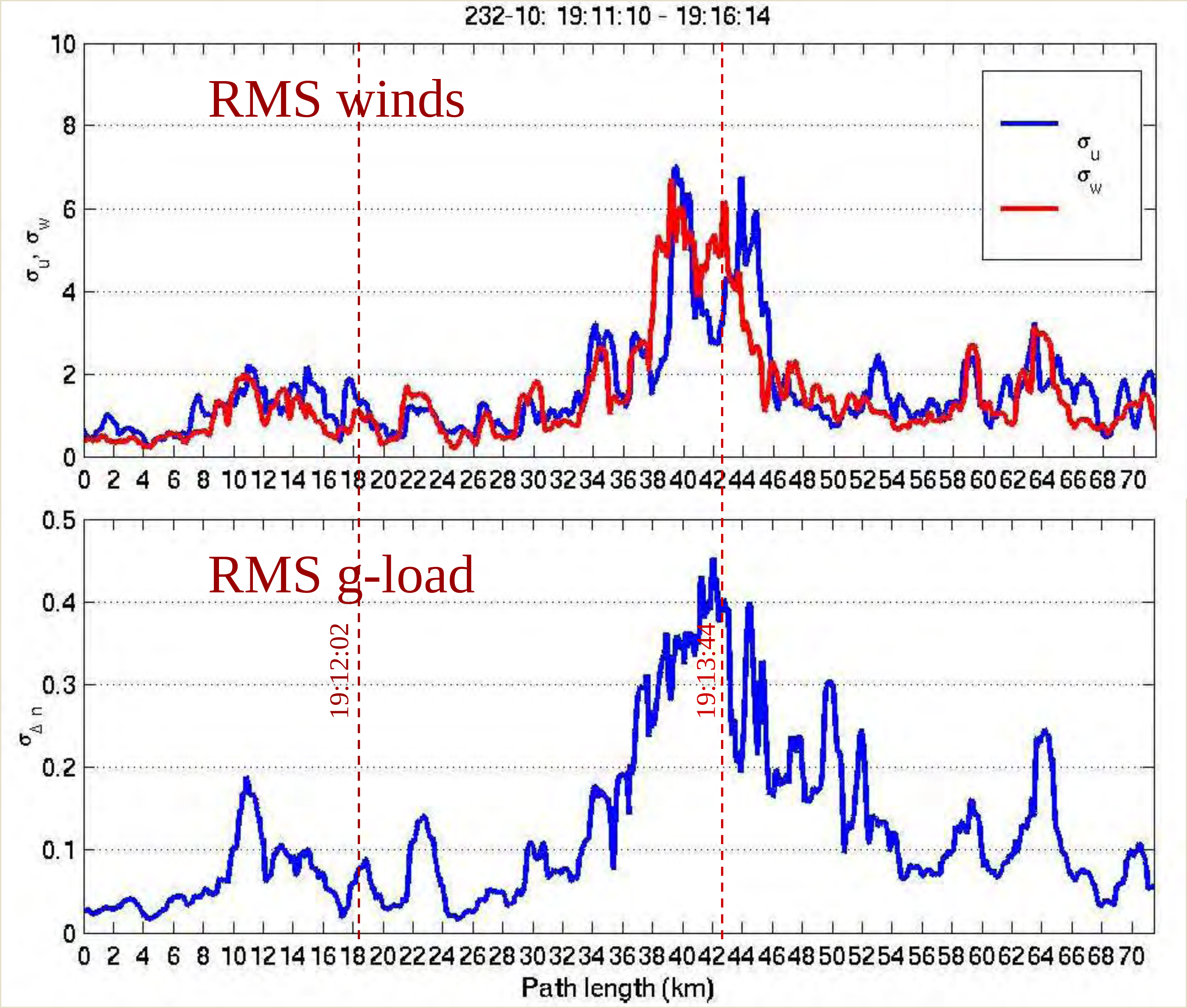


Website: UAL 757 edr flight tracks overlaid on GTG forecasting product

NCAR

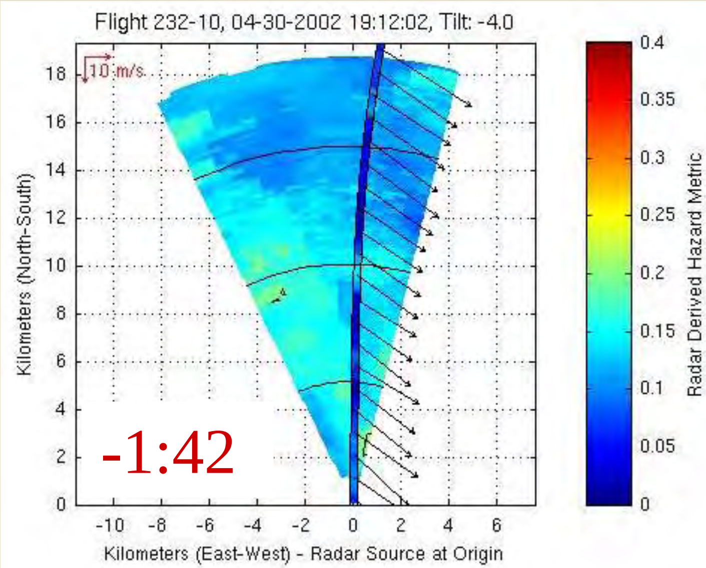
Radar Measurements of Turbulence

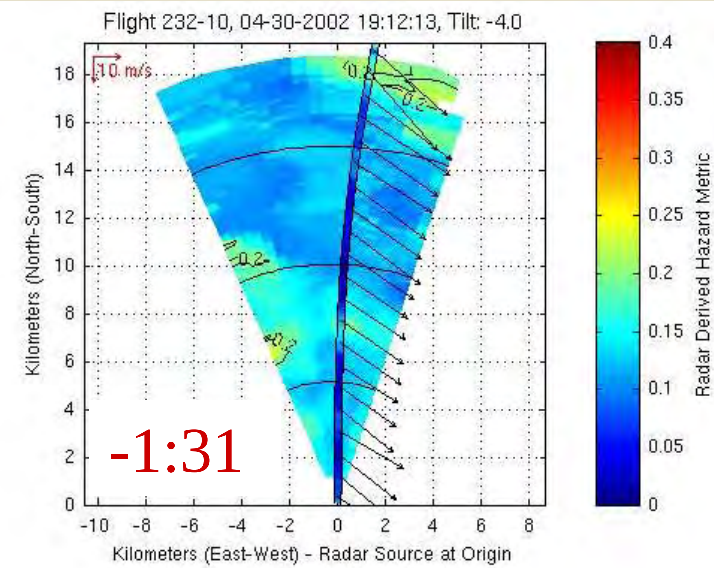
NASA Airborne Radar Detection of Turbulence Program

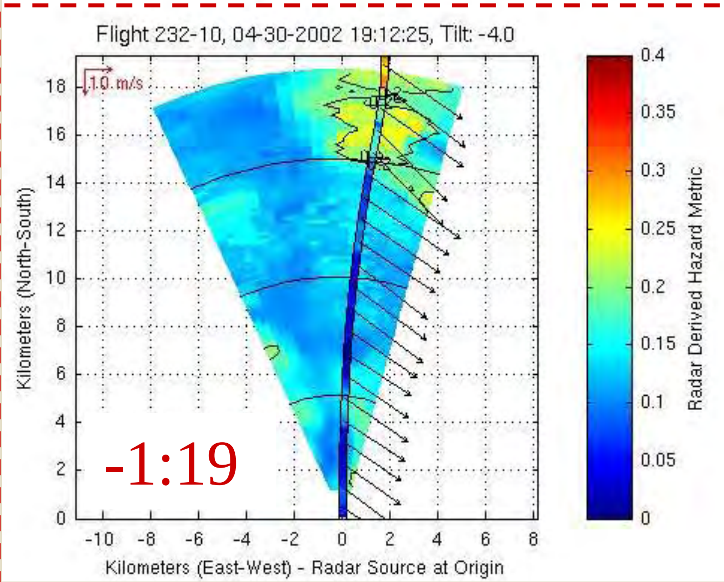


From NASA B-757 Aircraft

Event 232-10 (19:12:02, 19:12:13, 19:12:25)



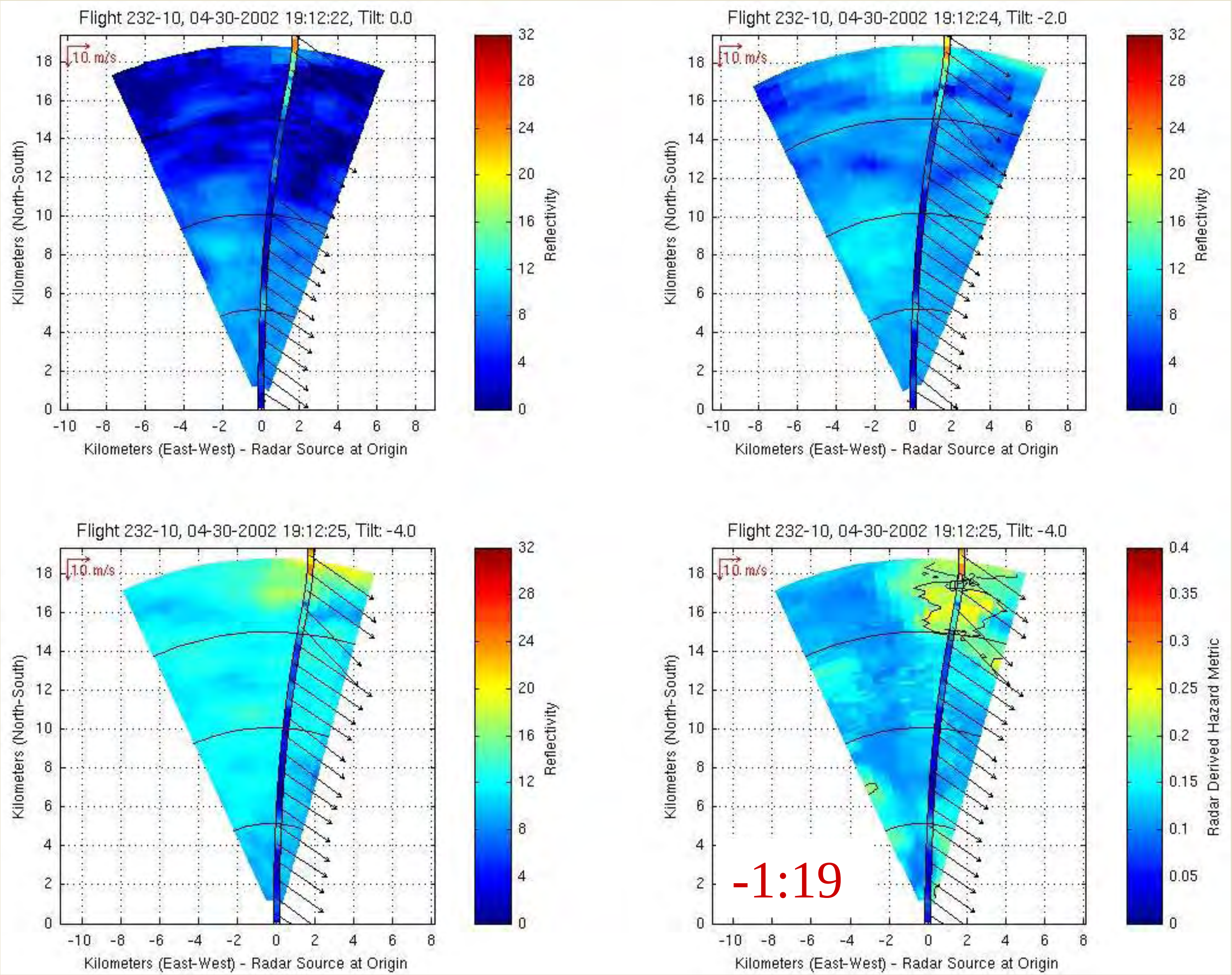




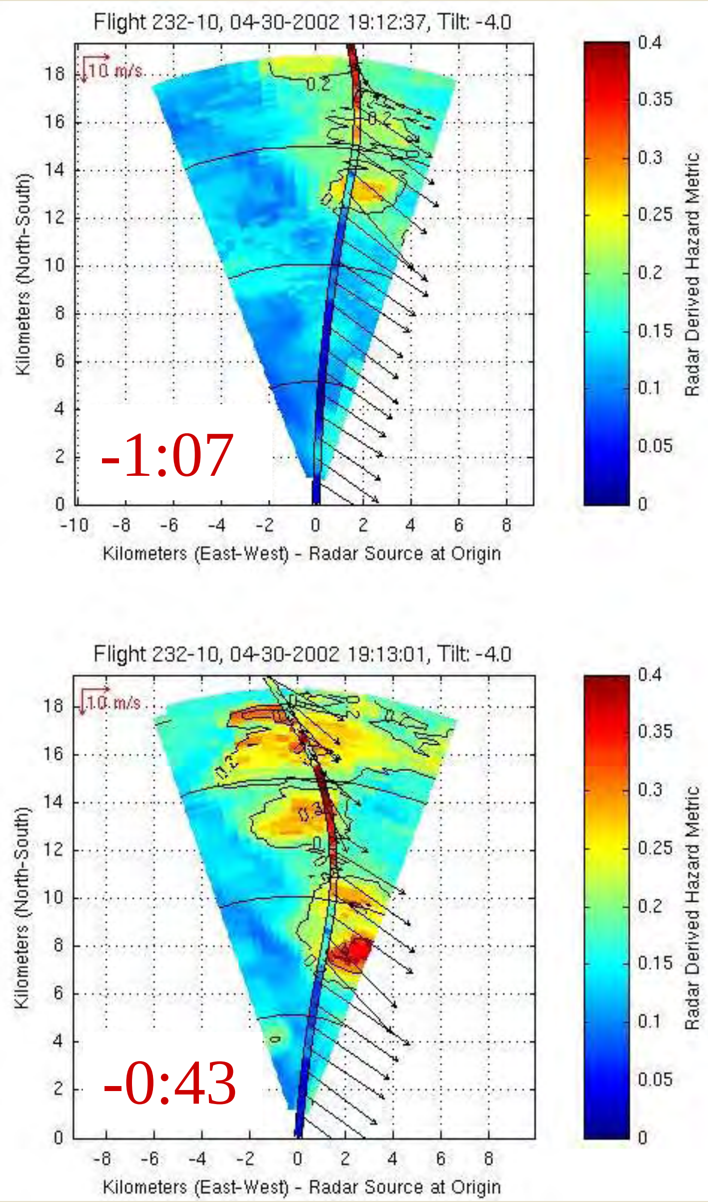
Hazard detected

1:19, 18 km to encounter

Event 232-10 (reflectivities at 19:12:25)



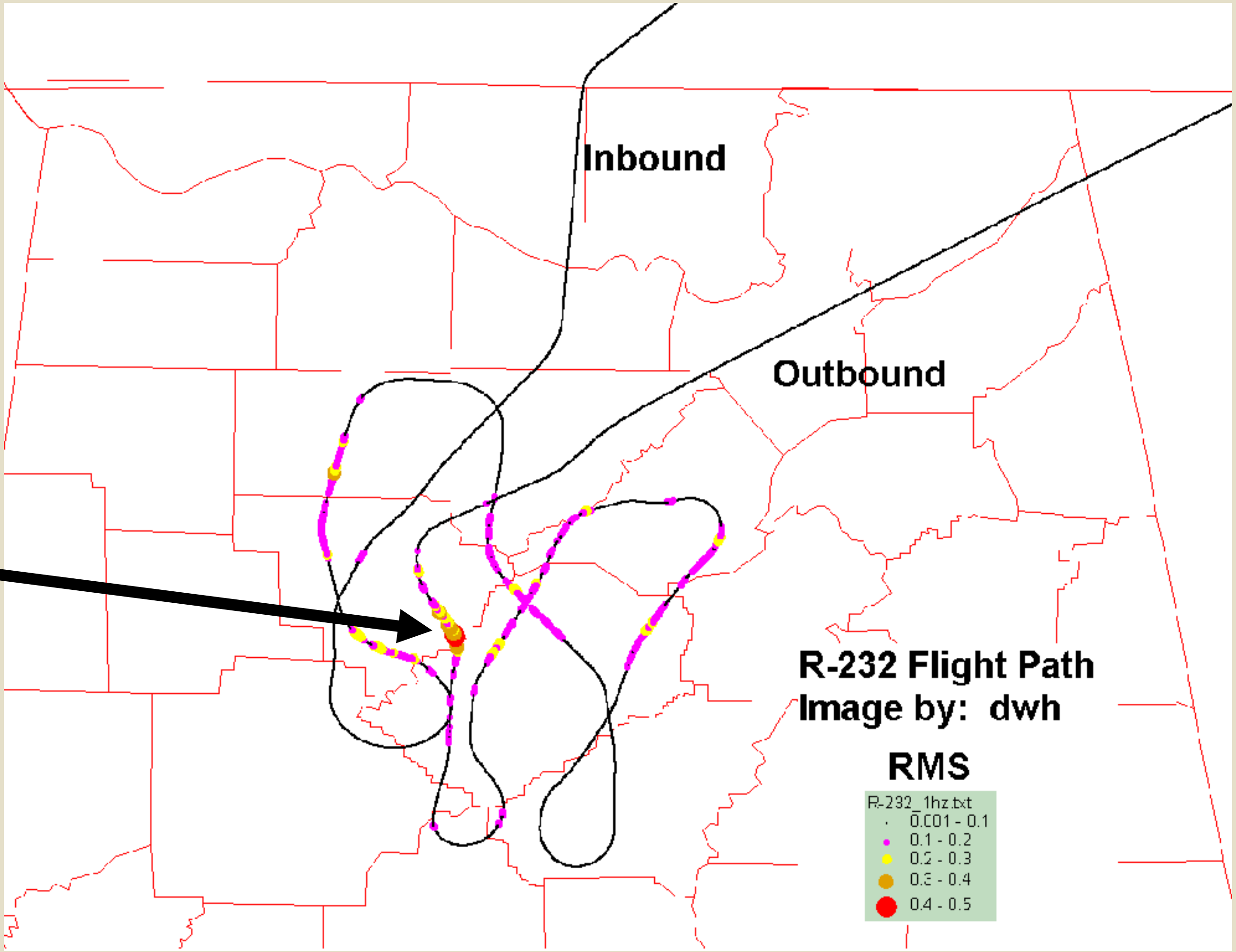
Event 232-10 (19:12:37, 19:12:49, 19:13:01)



Persistent detection

Flight Track for NASA flight R232

Event R232-10

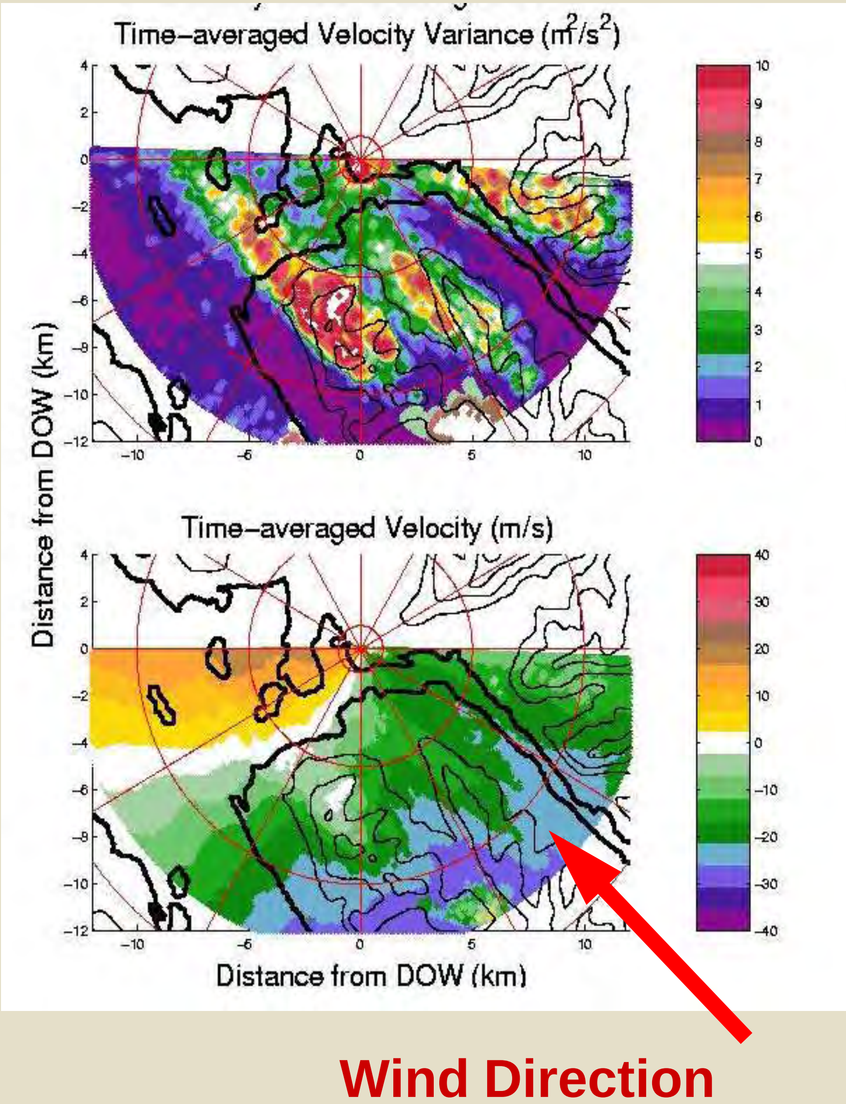


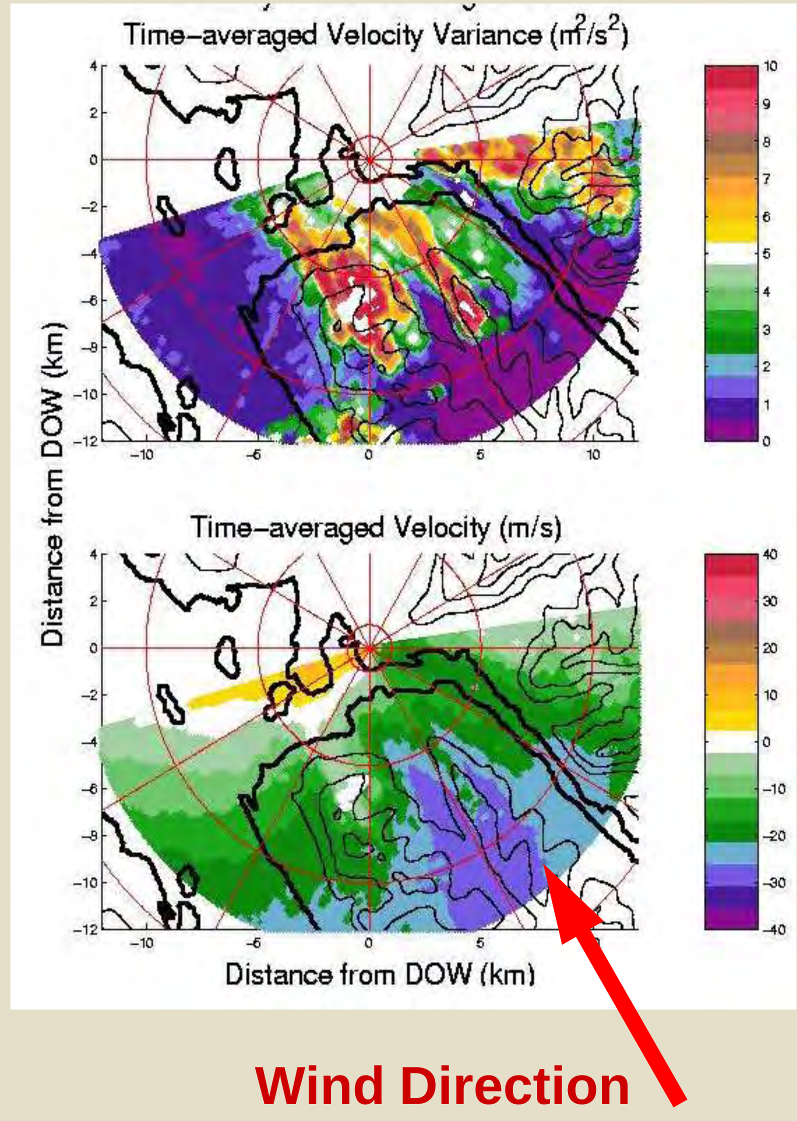
North-Central Alabama

FY00 Juneau Field Project Equipment

Doppler on Wheels (DOW)

DOW Radar Data Showing Terrain-Induced Turbulence for Two Different Wind Directions





Detection of Turbulence Using an Airborne Forward-Looking IR Sensor

- Possible Approach:
  - Derive equation that relates the statistics of the atmospheric turbulence (e.g., temperature field) to those of the sensor measurables.
  - Consider the irradiance (H) at a given frequency, measured at the aircraft (x=0):

$$H(0) = \int_L^0 W_B(T(x)) f(x) dx$$

Where W_B is the Planck function, *L* is the path length over which the measurement is made, and *f* is a combined function of the non-turbulent atmosphere and the response characteristics of the sensor.

NCAR

Detection of Turbulence Using an Airborne Forward-Looking IR Sensor

- Next, consider the same measurement when the aircraft has moved a distance ρ :

$$H(\rho) = \int_{L+\rho}^{\rho} W_B(T(x)) f(x) dx$$

- Assuming that the Planck function is linear in the temperature, the correlation function of the irradiances can be computed:

$$\langle H(0)H(\rho)\rangle = K \int_{L}^{0} \int_{L+\rho}^{\rho} \langle T(x)T(x')\rangle f(x) f(x') dx dx'$$

Detection of Turbulence Using an Airborne Forward-Looking IR Sensor

- Assuming that standard turbulence theory applies, $\langle T(x)T(x')\rangle = C_T^2 g(x'-x)$, where C_T^2 is the intensity parameter of the turbulent temperature field. In principle the turbulence intensity parameter is given by:

$$C_T^2 = \frac{\langle H(0)H(\rho)\rangle}{K\int_L^0 \int_{L+\rho}^{\rho} g(x'-x)\, f(x)\, f(x')\, dx dx'}$$

Detection of Turbulence Using an Airborne Forward-Looking IR Sensor

- Issues:
  - Aircraft respond to vertical wind motions, not temperature fluctuations - the relationship between the two is not well-understood.
  - To what spatial scales are these IR devices sensitive?

NCAR

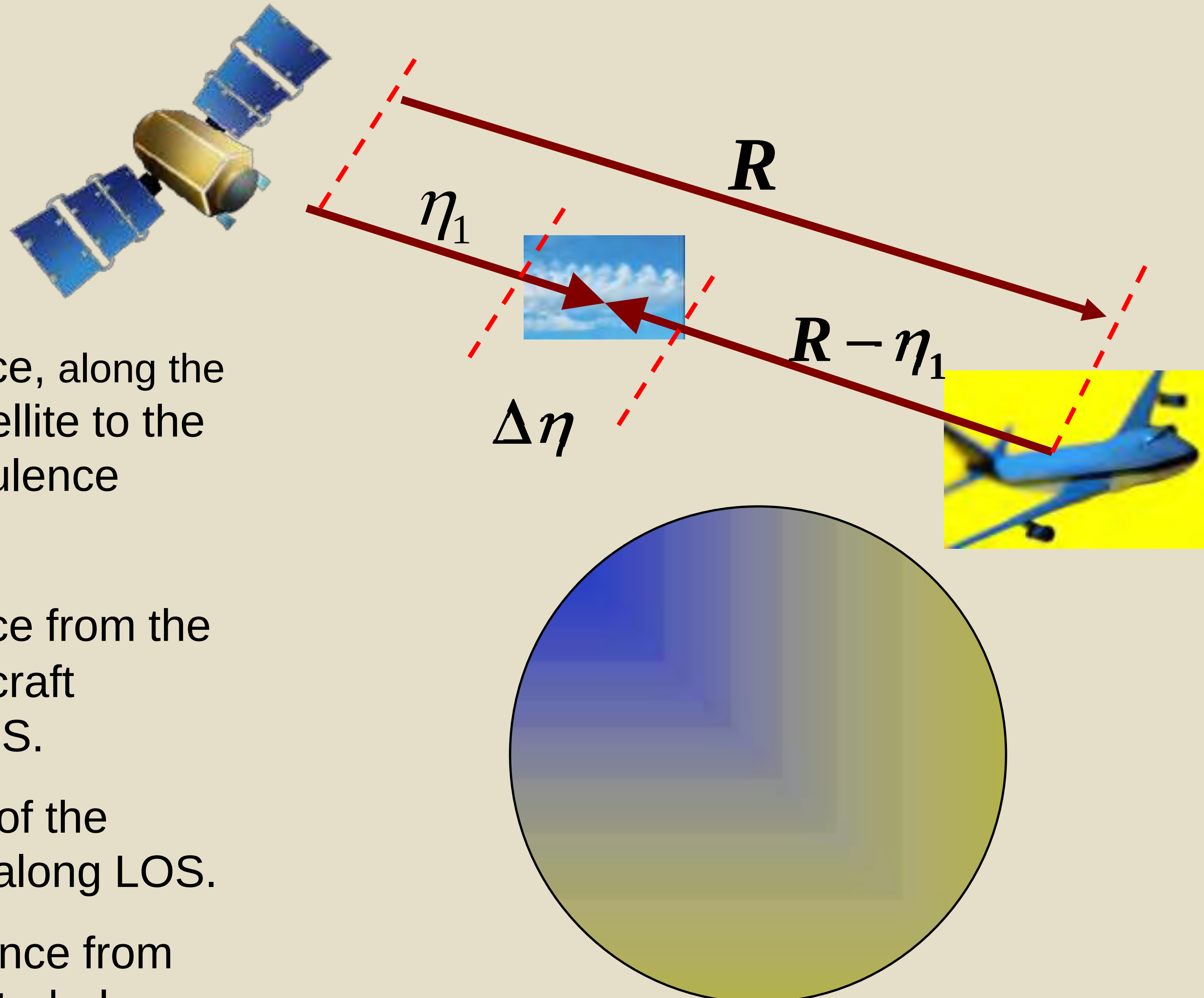
Turbulence Detection via Airborne GPS Receivers

Turbulence Detection via Airborne GPS Receivers: The Concept

- Airborne receivers would be a platform of opportunity to collect occultations in the cruise regime of commercial aviation, e.g., 20-40 kft. AGL.
- The turbulence measurements from these occultations would probably not be used as stand-alone information, but integrated into operational nowcast/forecast products.

NCAR

Geometry of the Problem



η_1 is the distance, along the LOS, from the satellite to the center of the turbulence patch.

R is the distance from the satellite to the aircraft receiver along LOS.

$\Delta\eta$ is the width of the turbulence patch along LOS.

$R - \eta_1$ is the distance from the aircraft to the turbulence patch.

Theory (Condensed Version)

- Use standard weak scattering wave propagation theory - modified to accommodate moving transmitter and receiver, and localized turbulence patch.
- Log-amplitude frequency spectrum for a turbulence patch in the neutral atmosphere at η_1 and width $\Delta\eta$ is functionally given by:

$$\Phi_\chi(f) = C \int_{\eta_1-\Delta\eta/2}^{\eta_1+\Delta\eta/2} F\left[C_n^2(\eta), V_{eff}(\eta), L_0, R, k, f; \eta\right] d\eta$$

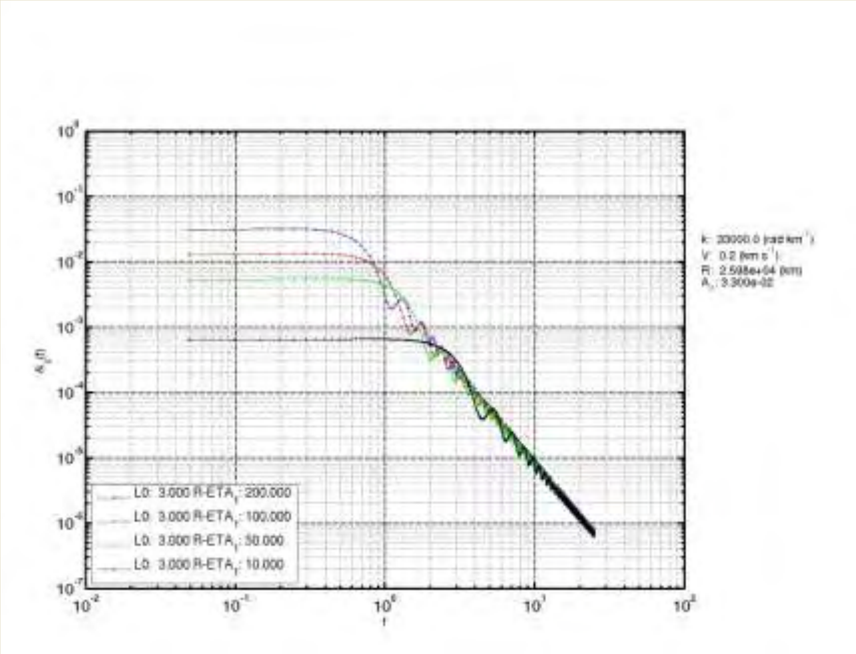
- Where ***k*** is the transmitter wavenumber, L_0 is the turbulence length scale, $C_n^2(\eta)$ is the turbulence intensity, and $V_{eff}(\eta)$ is an effective velocity.

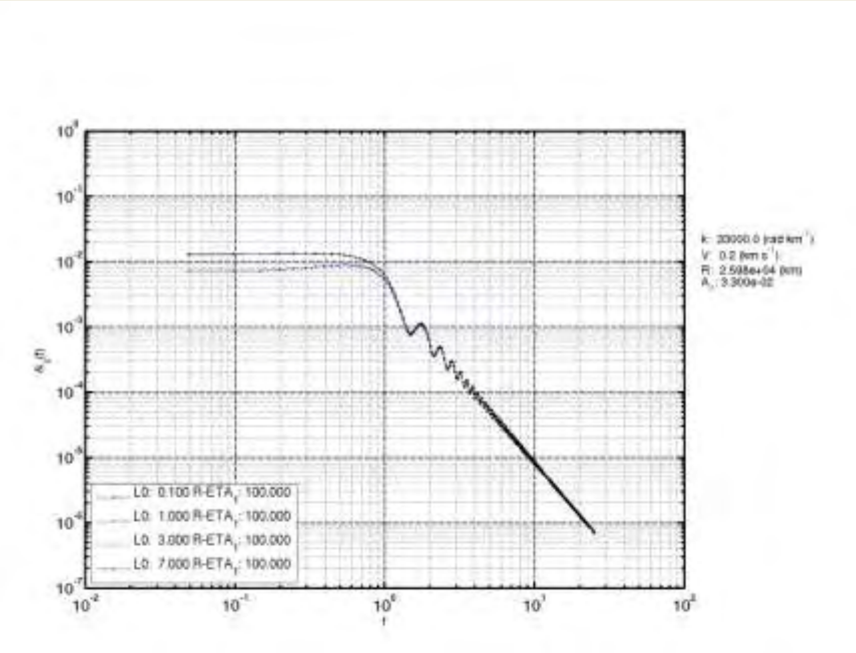
Analysis

- The objective is to determine where the turbulence is along the LOS, η_1 , and what the intensity $C_n^2(\eta_1)$, is at that location.
- Note that the comparable expression for turbulence in the ionosphere is given by a different constant and a change in the wavenumber functionality k^2 to k^{-2}.

In the following, a mid-point approximation to the integral was used.

Example Spectra (constant intensity)





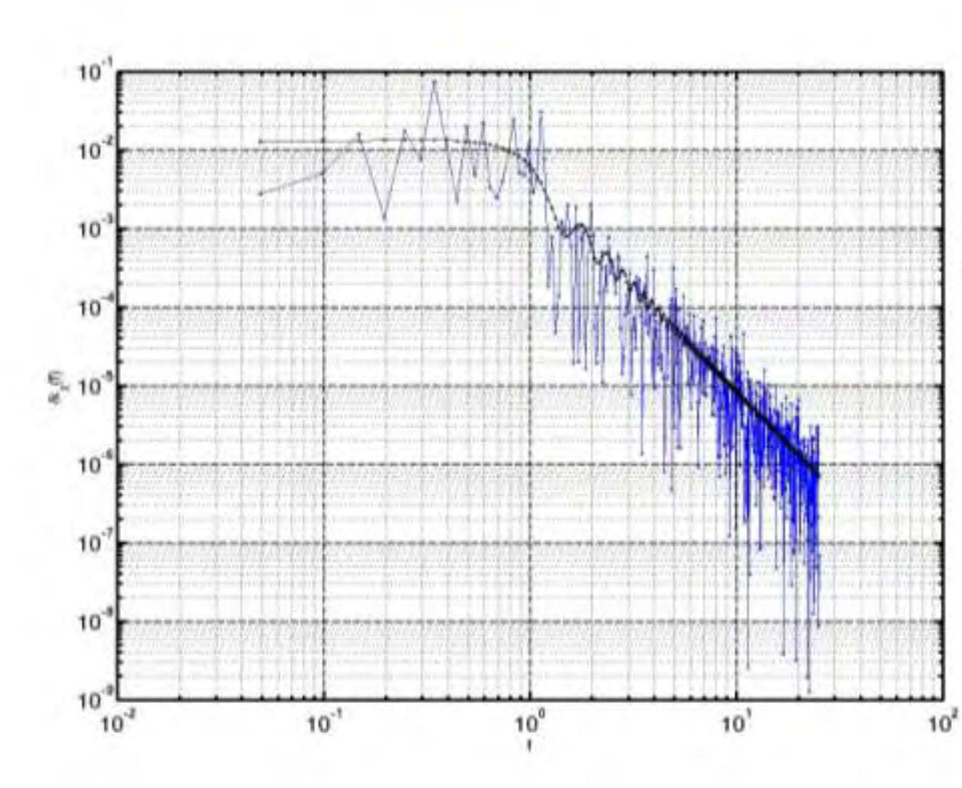
Holding $L_0 = 3\,km$ fixed and varying $R - \eta_1$.

Holding $R - \eta_1 = 100\,km$ fixed and varying L_0 .

Note strong functionality on $R - \eta_1$ and weak on L_0 .

NCAR

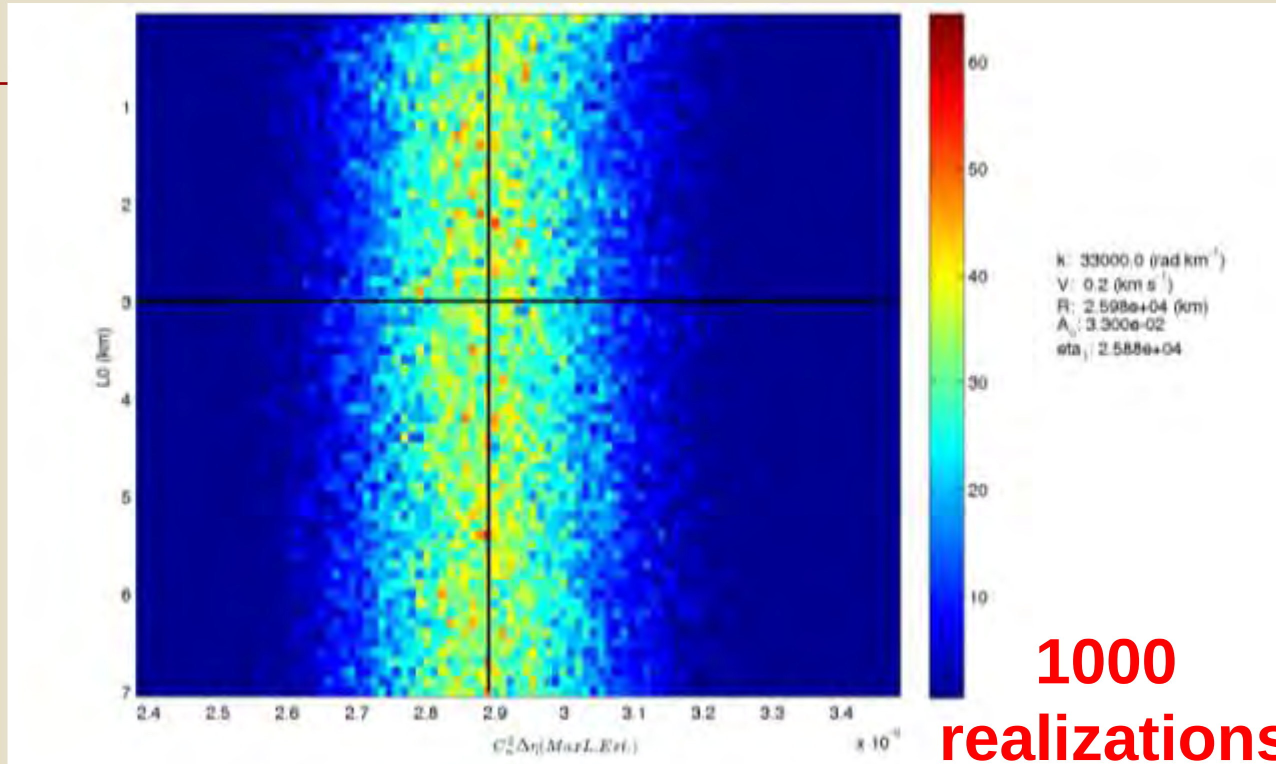
Spectral Simulation



25 Hz.

Log-Amplitude Spectrum: theory and simulated.

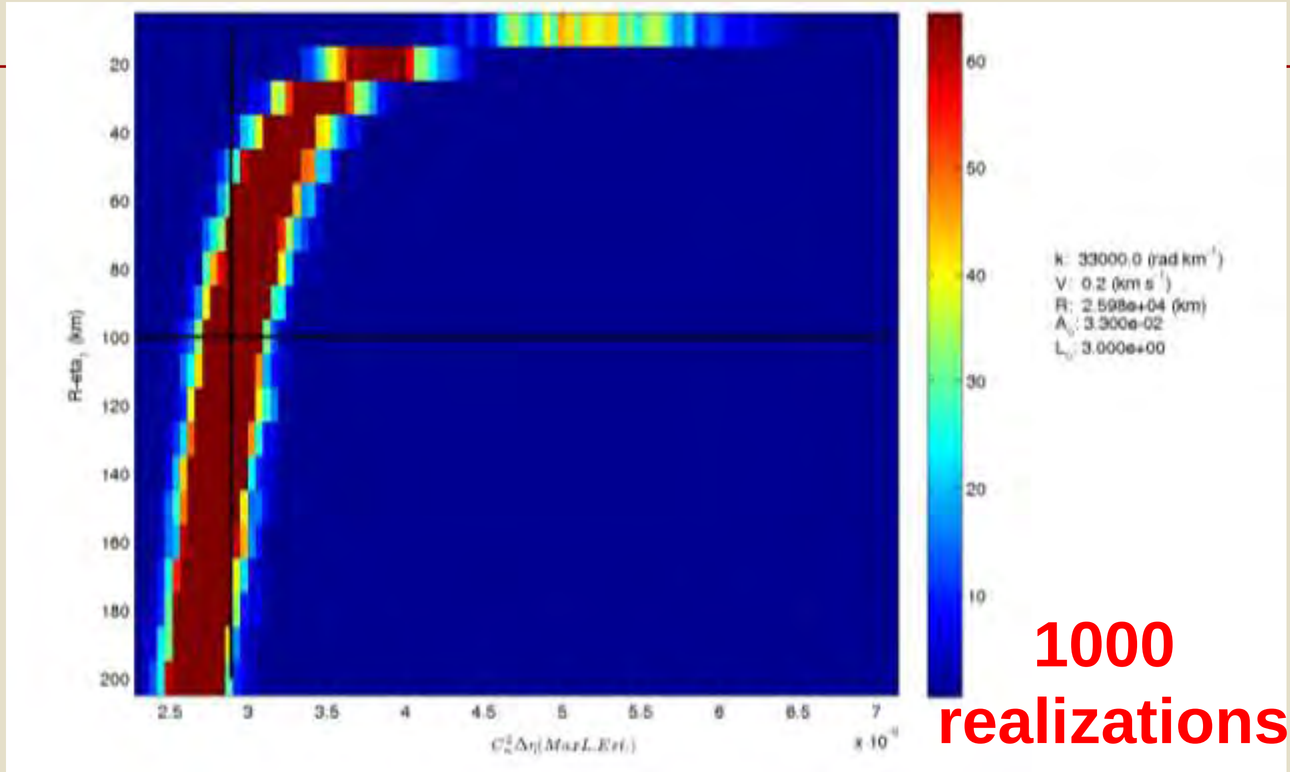
Parameter Estimation



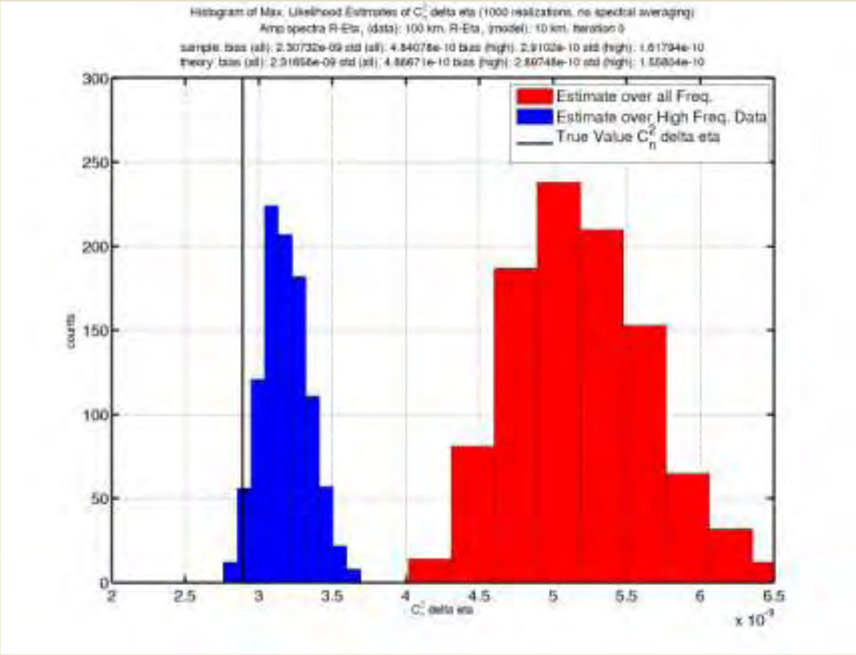
1000 realizations

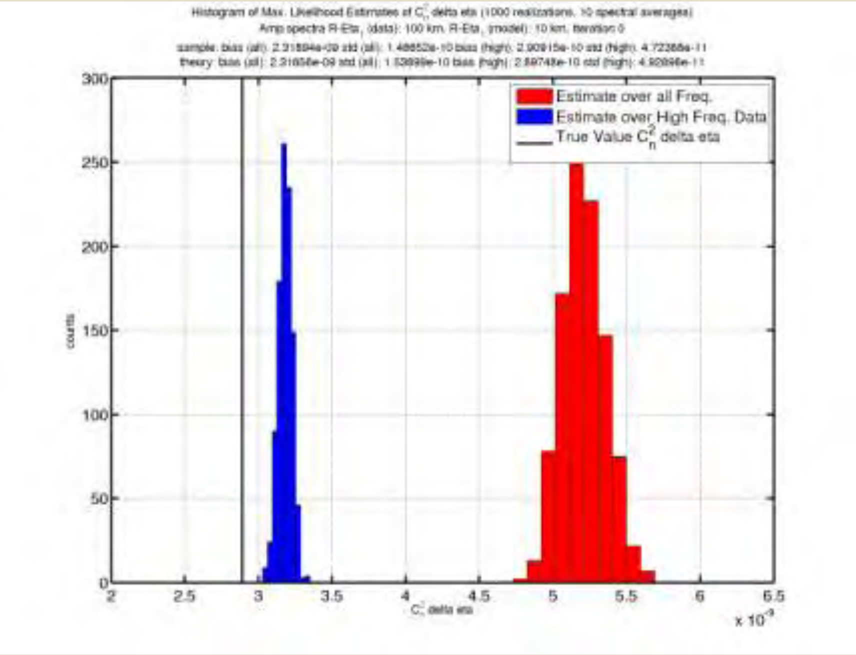
Maximum Likelihood (ML) estimation of intensity with fixed $R-\eta_1=100\,km$ while varying L_0. Horizontal and vertical lines are simulated (i.e., "true") values.

Parameter Estimation (cont'd)



ML estimation of intensity with fixed $L_0 = 3\,km$ **while varying** $R - \eta_1$ **.**

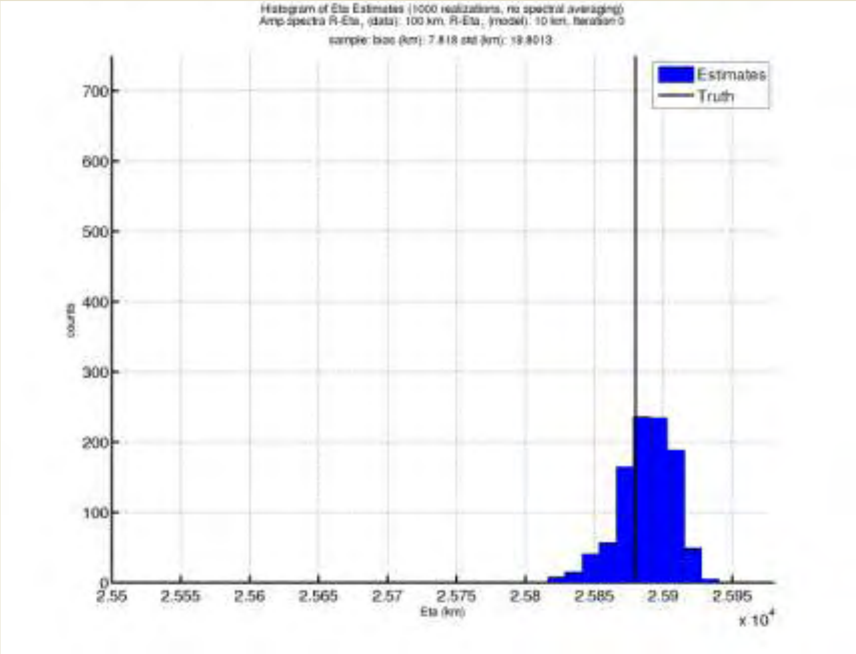


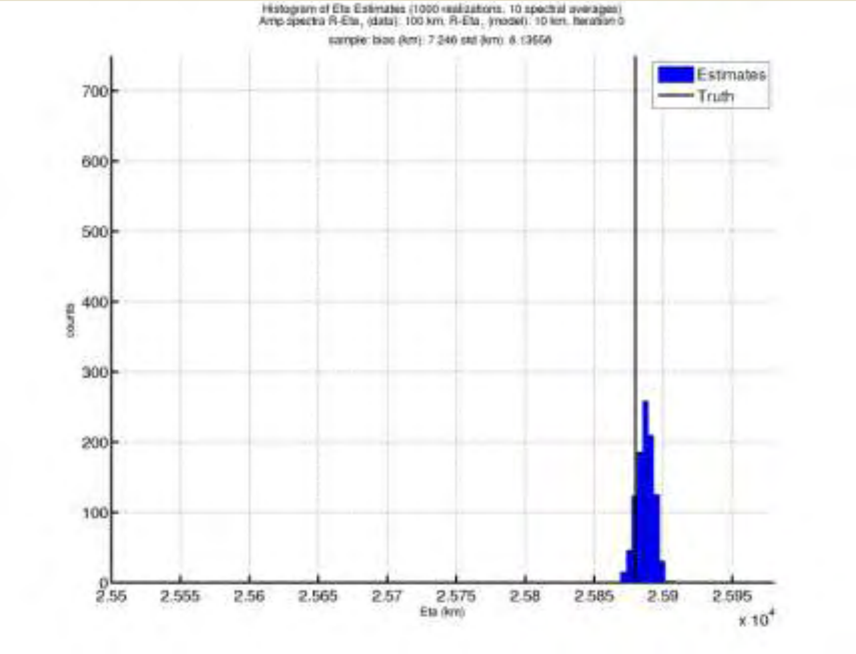


- ML estimation of intensity for un-averaged spectra (left) and 10 spectral averages (right).
- Solid vertical line is true value.
- **Blue** values are from using the high-frequency portion of the spectrum, **red** values use all the spectral points.
- Simulated $R-\eta_1$ value is 100 km, "guess" is 10 km - i.e., ***underestimate***.

NCAR

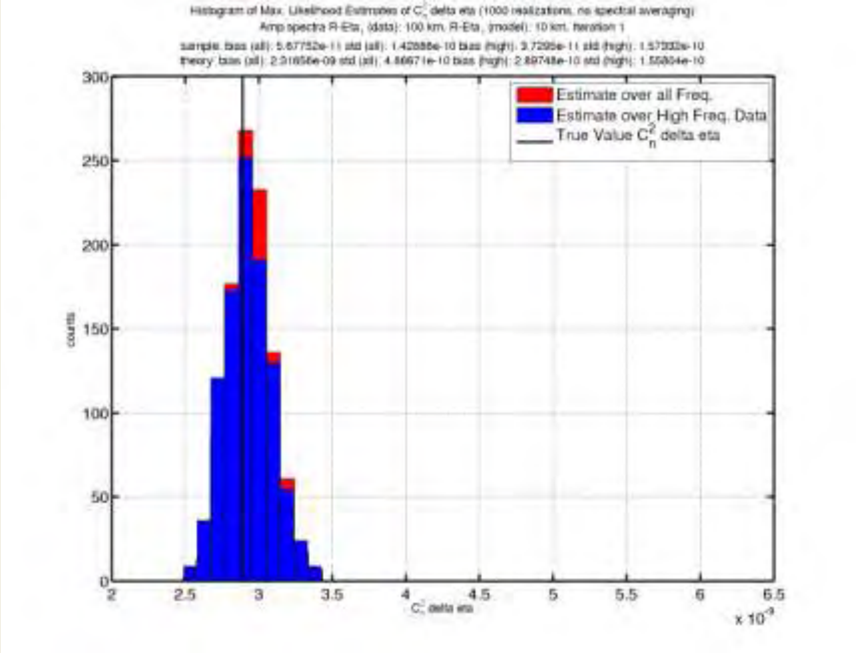
Iterative Parameter Estimation

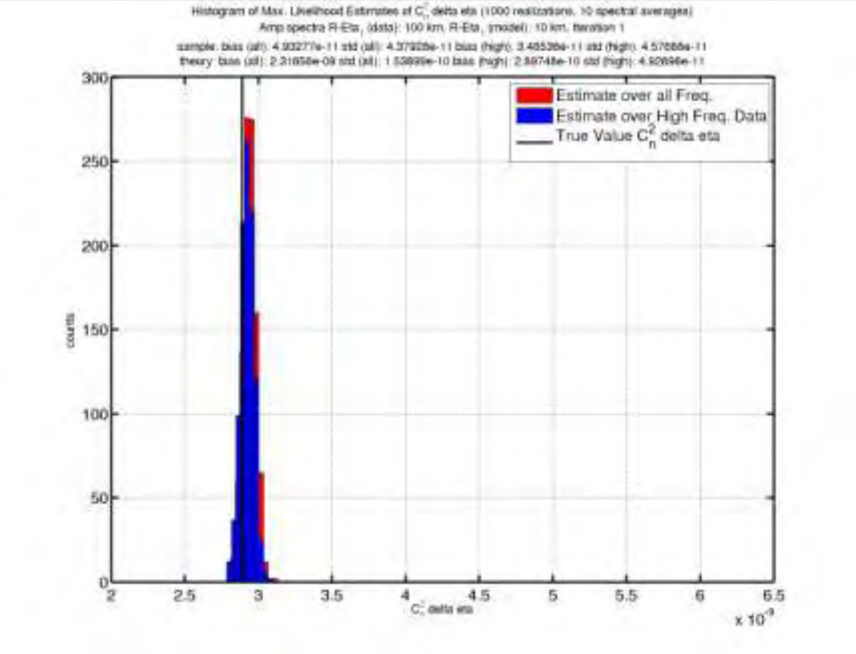




Estimation of η_1 by minimization method. Un-averaged spectra (left) and 10 spectral averages (right).

Iterative Parameter Estimation





ML estimation of intensity after using η_1 estimates. Un-averaged spectra (left) and 10 spectral averages (right).

Summary

- Turbulence measurements are critical in providing accurate and operationally useful tactical and strategic information to users.
- *In situ* turbulence measurements are now available and used operationally – more to come.
- A number of proof-of-concept sensor demonstrations have occurred, with positive results.
- Other technologies in development/evaluation:
  - Airborne lidar
  - Satellite
  - GPS/Iridium
  - Airborne IR

NCAR