Applications for Fine Resolution Marine Observations

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General Applications

- Research vessel observations can be found in many regions of the globe, sampling a very wide range of conditions, which is ideal for all the many applications.
- Modeling of surface turbulent fluxes (or radiation if it is measured).
  - Coupled with observations of surface turbulent fluxes (or co-located satellite data) the data are useful for evaluating and improving models of surface turbulent fluxes.

NEW!

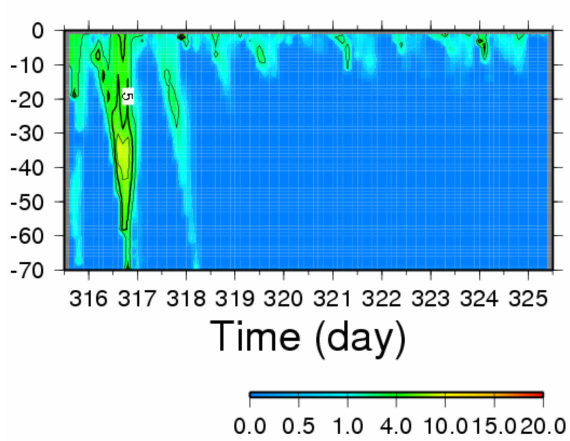
- Comparison of time integrated fluxes to numerical weather prediction climate products.
- Comparison to routine VOS data and assessment of quality of quality of VOS data.
- Calibration or validation of satellite instruments.
- Interpretation of errors in satellite data.

NEW!

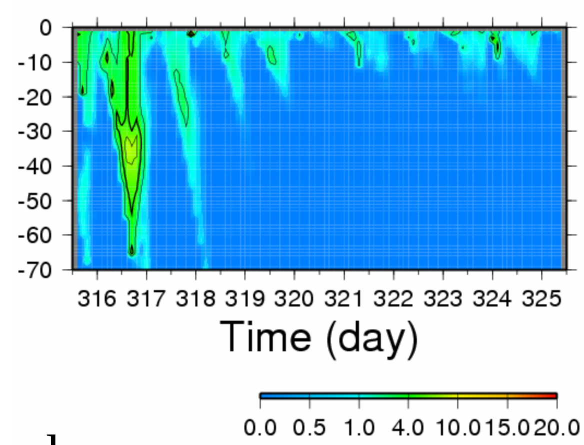
  - Useful for estimating naturally occurring noise in observations.

Ocean's TKE Based on Observed Surface Fluxes

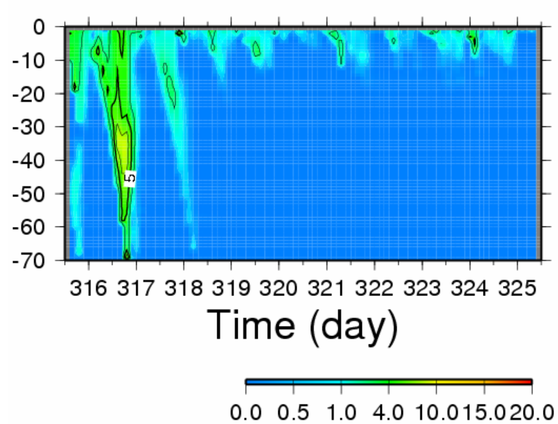
Eddy Correlation



Inertial Dissipation



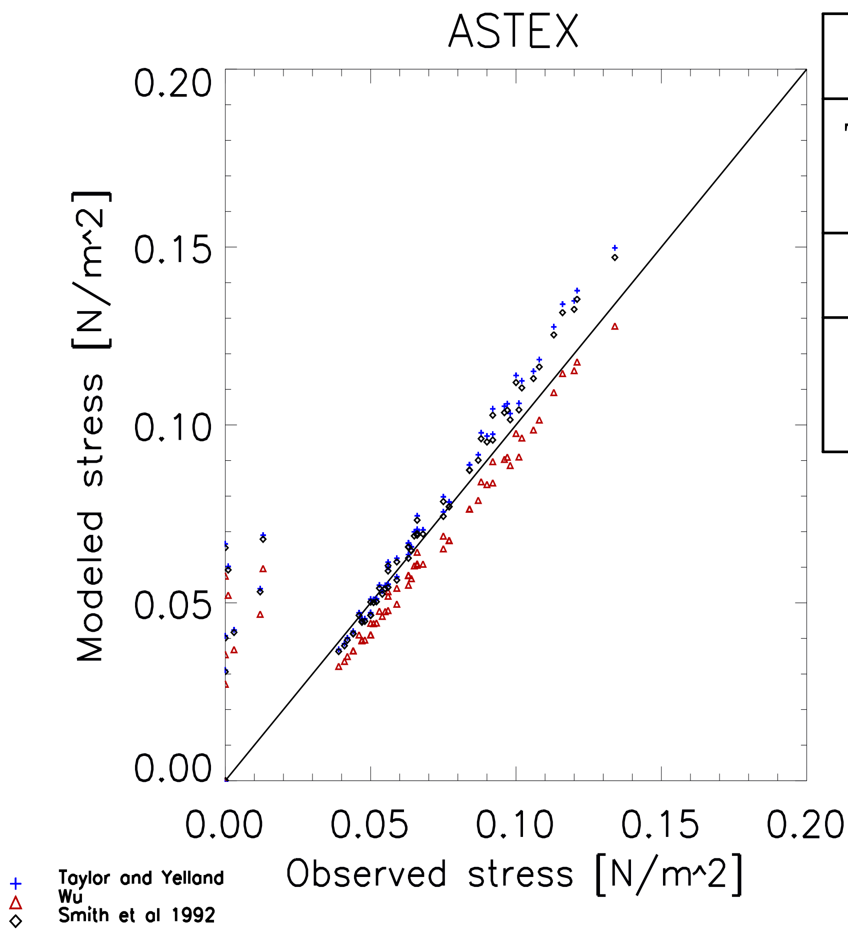
Bulk Method



Calculations by Derrick Weitlich

Clayson & Kantha model

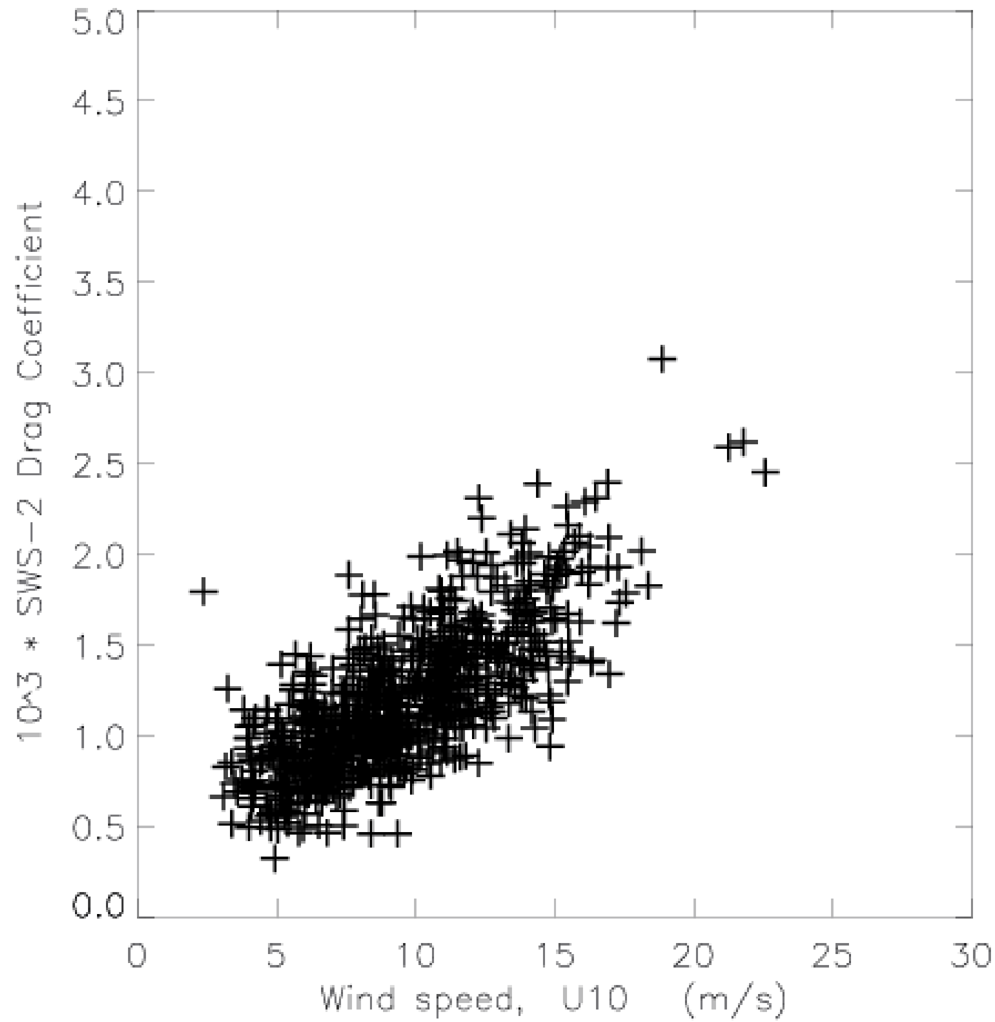
Flux Model Evaluation with ASTEX (Buoy Observations)



	r	r^2	Slope	RMS
Taylor & Yelland	0.94	0.88	1.04±0.00	0.010
Wu	0.94	0.88	0.88±0.00	0.009
Smith et al.	0.94	0.88	1.02±0.00	0.010

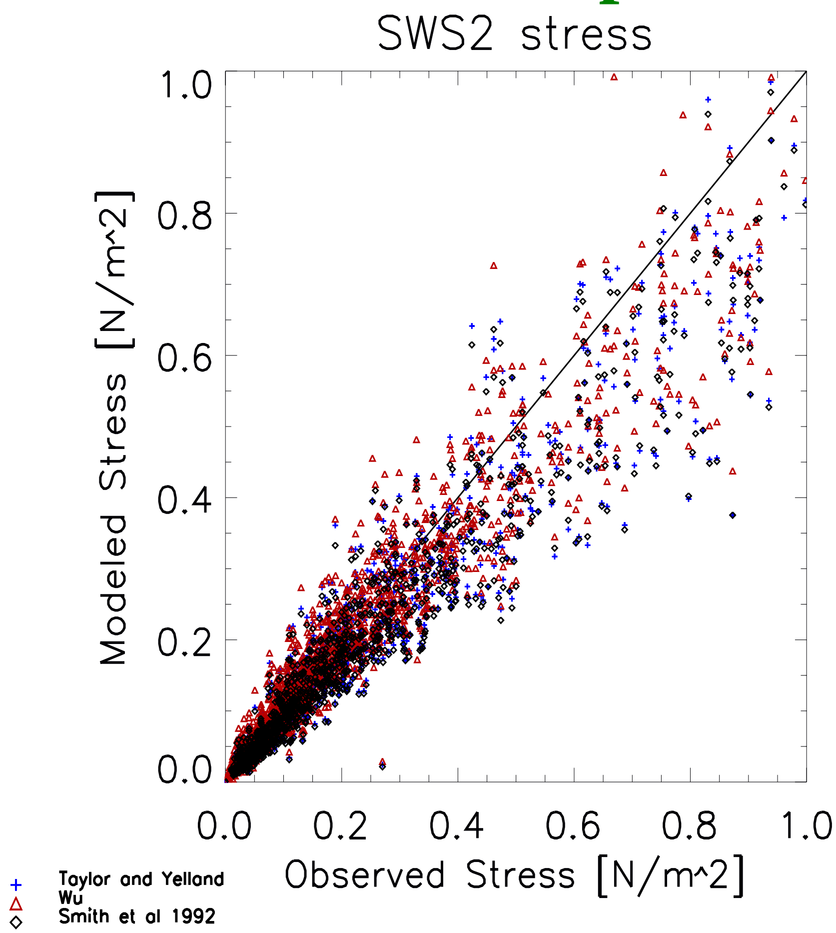
Calculations by Yoshi Goto

Observed Surface Stresses



- Preliminary data form the SWS2 (Severe Wind Storms 2) experiment.
  - The drag coefficients for high wind speeds are large and plentiful.
  - The atypically large drag coefficients are associated with rising seas
- Many models overestimate these fluxes.
- Excellent empirical fit to means of these data and many other by *P.K. Taylor & M. Yelland* (*2001*).

Evaluations Using SWS2
Ship and Buoy Observations



All Data

	r	r^2	regression	RMS
Taylor & Yelland	0.96	0.92	0.72±0.03	0.099
Wu	0.97	0.93	0.76±0.04	0.083
Smith et al.	0.96	0.93	0.73±0.03	0.095

Stress < 0.5 N/m^2

	r	r^2	Slope	RMS
Taylor & Yelland	0.92	0.84	0.83±0.01	0.05
Wu	0.94	0.88	0.89±0.02	0.042
Smith et al.	0.92	0.85	0.82±0.01	0.051

Calculations by Yoshi Goto

Understanding Physics Via Differences in Remotely Sensed and In Situ Data

In areas of strong currents, $\mathbf{U}_{scat} - \mathbf{U}_{buoy}$ will be dominated by the current. Areas with strong currents are often known, or can be identified in time series (*Cornillon and Park* 2001, *GRL*; *Kelley et al*. 2001, *GRL*).

Remaining mean differences in $\mathbf{U}_{scat} - \mathbf{U}_{buoy}$ are expected to be dominated by wave-related variability in $z_o(u_*)$ or ambiguity selection errors.

- Problems related to ambiguity selection and dealing with vectors can be bypassed by comparing observed backscatter to the backscatter predicted by buoy observations (*Bentamy et al*. 2001, *JTech*).

Comparison of Backscatter Residuals To Wave Parameters

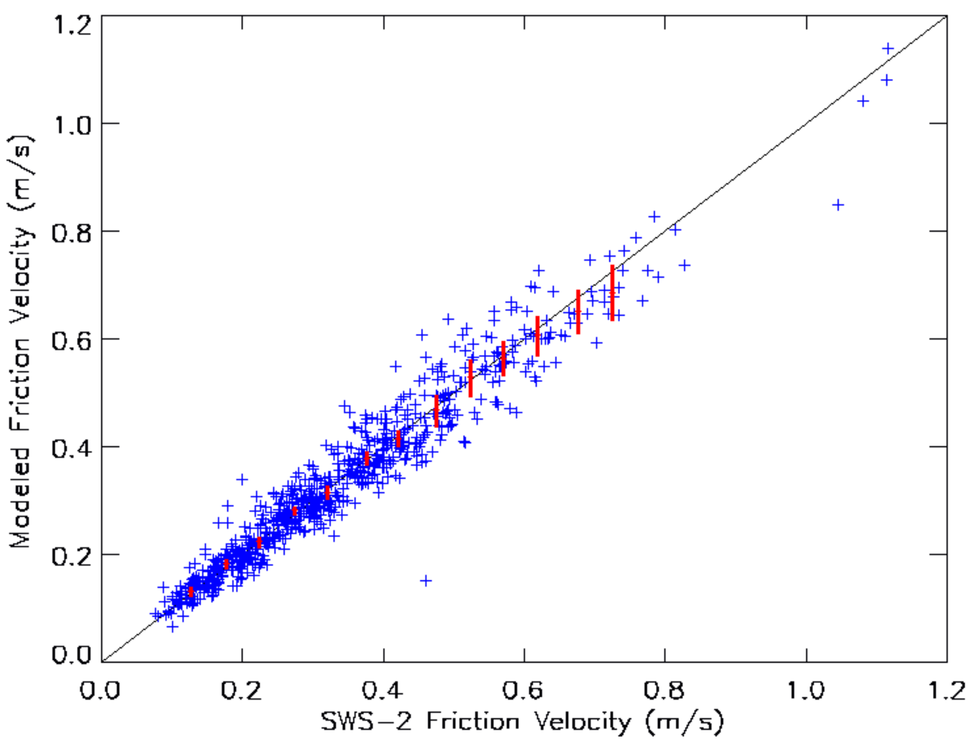
- Differences between observed and predicted (based on observed winds) backscatter are correlated with various wave parameter (*Bentamy et al*. 2001, *JTech*).
  - Significant wave height (the height of the 1/3 tallest waves)
  - Orbital velocity
  - Significant wave slope
- Orbital velocity and significant slope are highly correlated.

Correlation Coefficients

Wind Speed (m/s)	Sig. Wave Height	Orbital Velocity	Sig. Wave Slope	Tair - Tsea
4 to 6	0.32	0.38	0.33	0.18
6 to 8	0.32	0.41	0.33	0.20
8 to10	0.28	0.31	0.15	0.19

Differences Between In Situ and Satellite Observations Could be Due to Physics

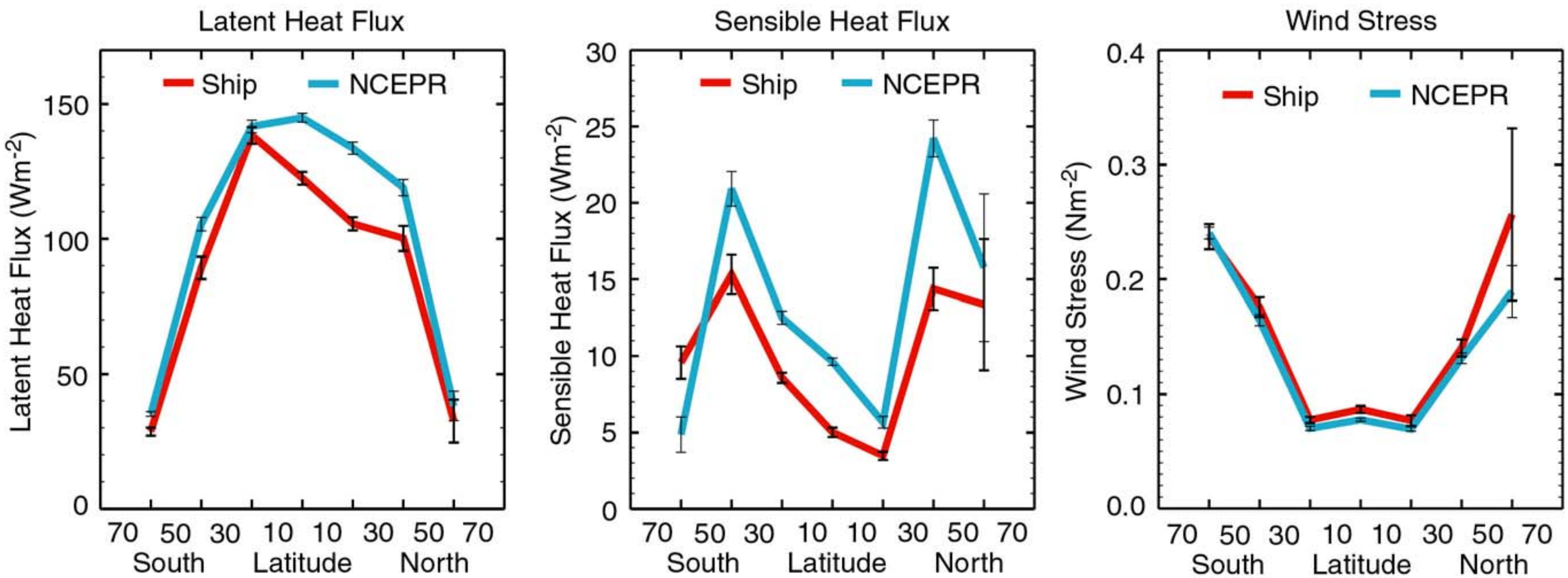
- Surface stress modeling and QSCAT-derived stresses
  - Modeling surface stress for storm winds (*Bourassa* 2004 *ASR*)
  - Direct retrieval of surface turbulent stress from scatterometer backscatter



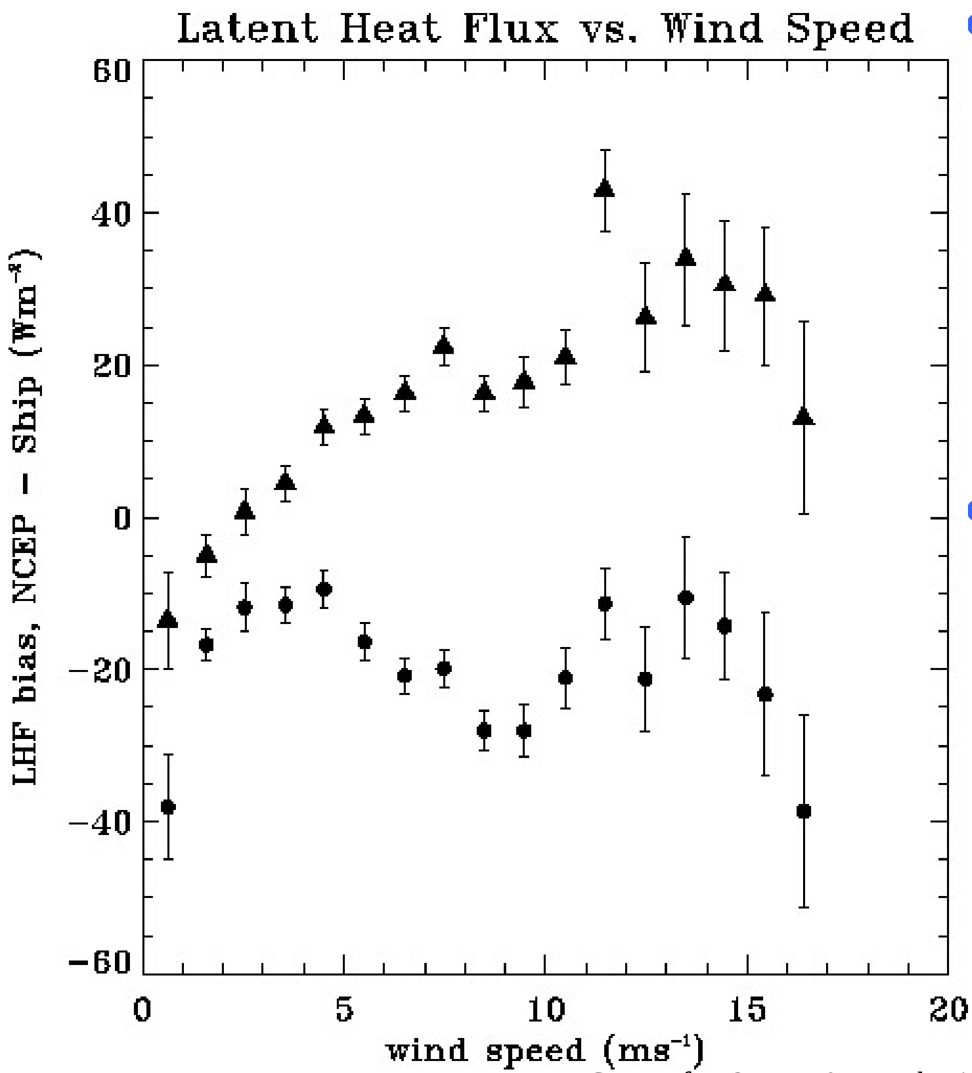
$$U_{10EN} - u_{current} - 0.8U_{orbital} = \frac{u_*}{k_v}\log\left(\frac{z - 0.8H_s}{z_o} + 1\right)$$

Evaluations of Surface Fluxes in Climatologies

- Quality processed R/V AWS data are ideal for evaluation of global reanalysis fluxes (e.g., *Smith et al*., 2001, *J. Climate*).
- Sampling rates allow accurate estimation of 6 hourly integrated fluxes.



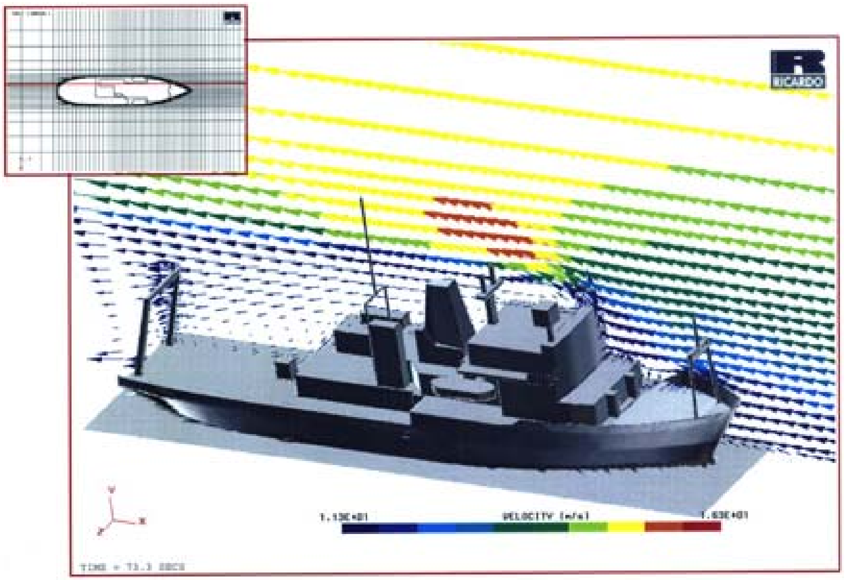
Where are the Problems: Algorithm or Data



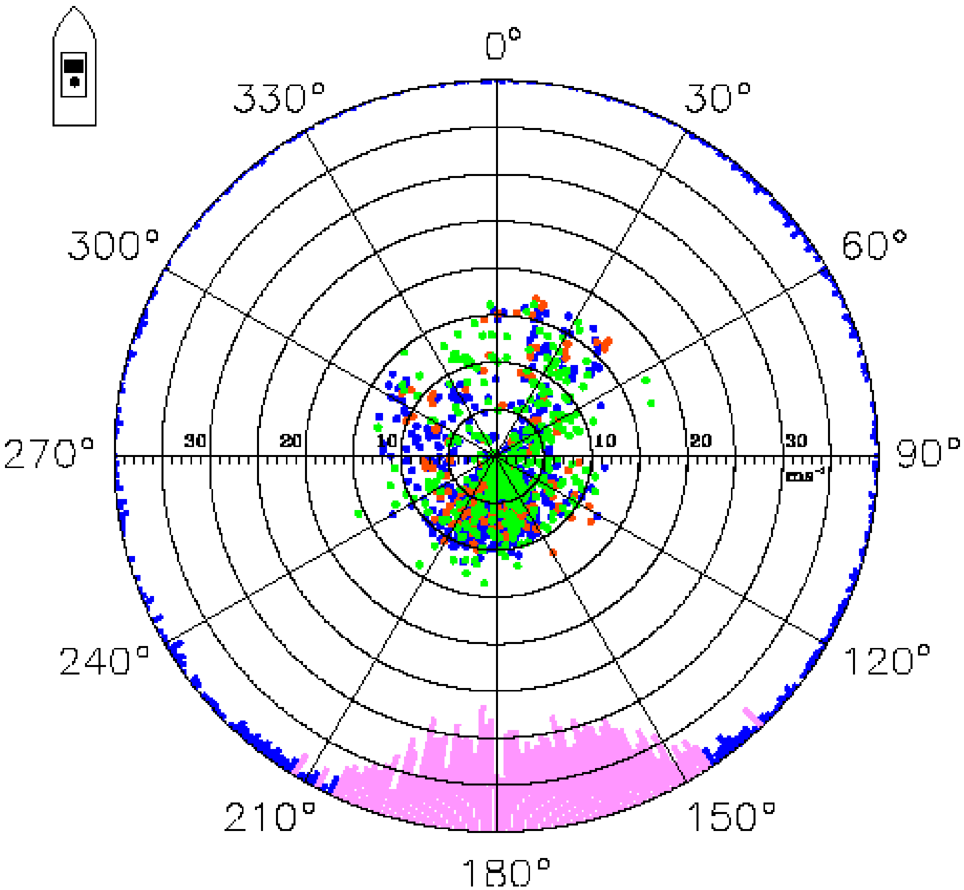
- NCEP fluxes are compared to fluxes calculated from R/V data.
  - Fluxes calculated with *Smith* (1988) parameterization.
  - The triangles indicate a large bias that has a substantial dependence on wind speed.
- Alternatively, fluxes can be calculated from the model winds, SST, air temperature, and atmospheric humidity (circles).
  - Much weaker dependence on wind speed.
  - Still a substantial bias.

Evaluation of VOS Observation: VOSCLIM

- Accuracies of VOS observations are not as well characterized as desired.
  - Wind biases have been studied in relatively great detail.
    - *Lindau* (1995)
    - CFD Modeling of flow distortion (*Peter Taylor et al.*)
  - Biases in SST have also been examined.
  - Biases in air temperature and atmospheric humidity are far less well know (*Liz Kent*).
  - Air temperature biases are expected to be a function of radiative heating and ventilation.



Changes With Time As An Indication of Quality



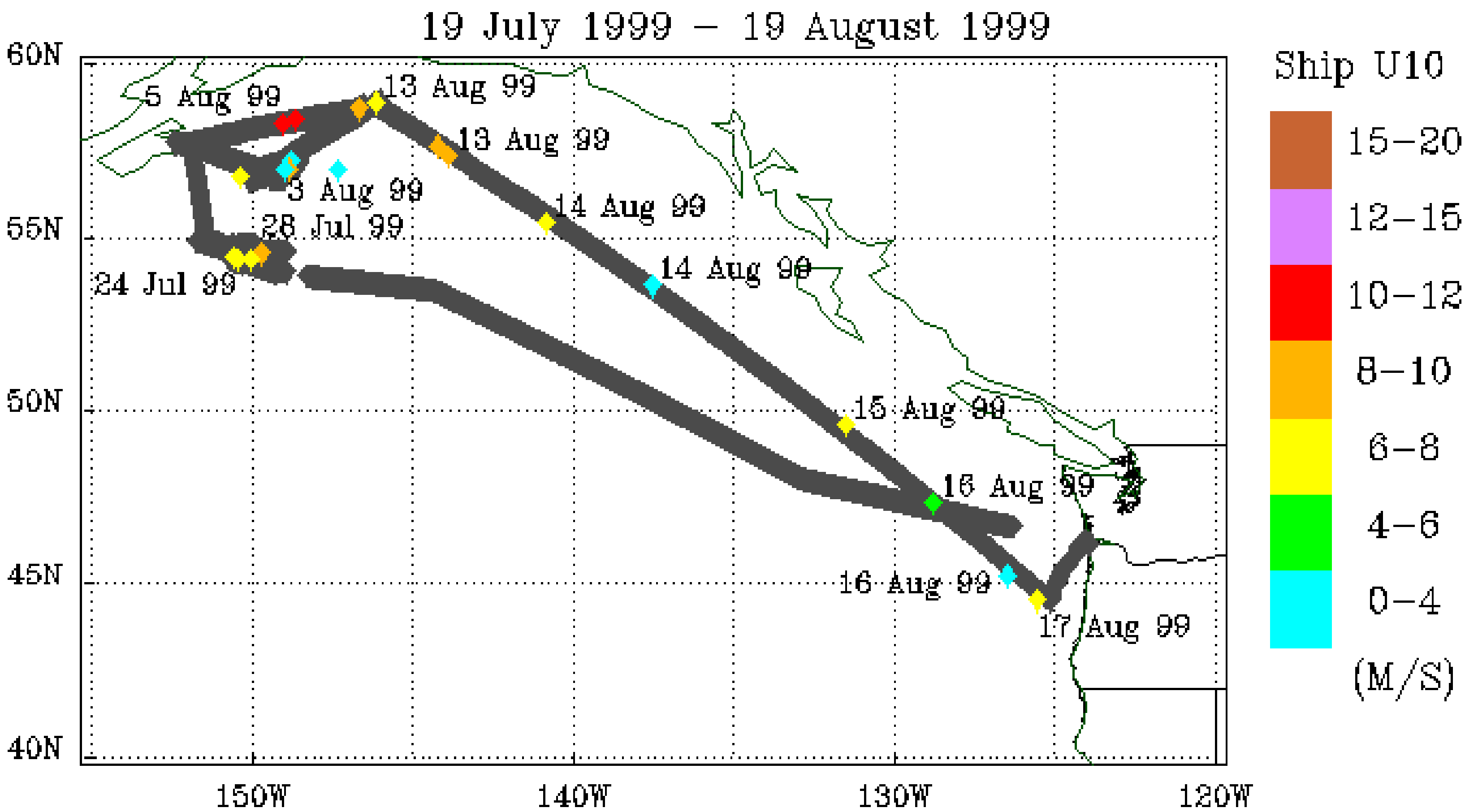
- Spikes, steps, suspect values identified (flagged)
  - Examines difference in near-neighbor values
  - Flags based on threshold derived from observations
- Graphical Representation
  - Identifies flow conditions w/ severe problems
  - Flags plotted as function of ship-relative wind
  - % flagged in each wind bin on outer ring

- Differences between ship and scatterometer could be used to examine flow distortion.

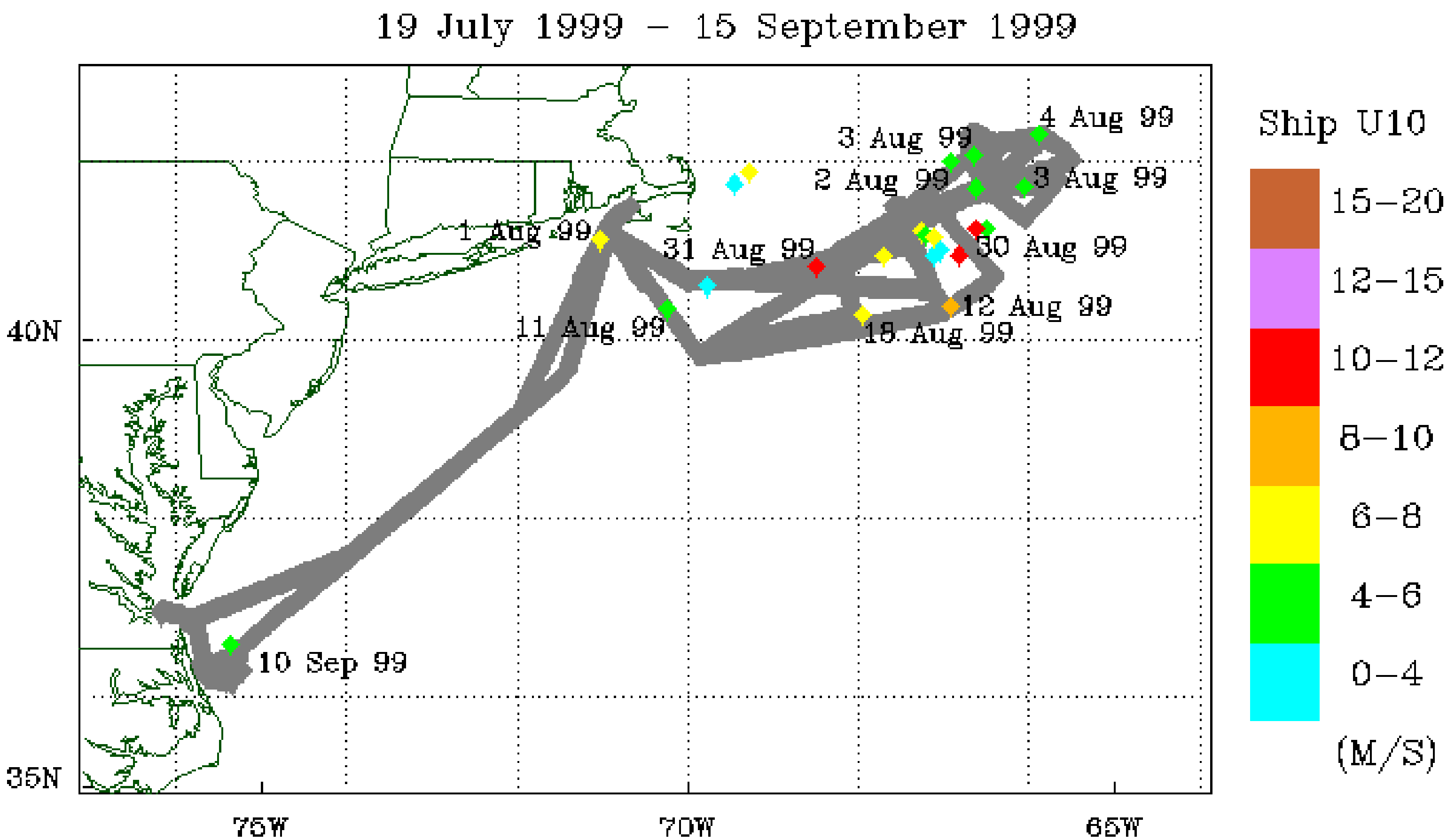
R/V Data for Scatterometer Validation Co-location Criteria

- Automated Weather Systems
  - e.g., IMET
  - Observations interval is 5 to 60s
  - Record all parameters needed to calculate equivalent-neutral earth-relative winds
- Co-location Criteria
  - Maximum temporal difference of 20 minutes (usually <30s).
  - Maximum spatial difference of 25 km (usually <12.5km).
- Quality control includes checks for
  - Maneuvering (ship acceleration),
  - Apparent wind directions passing through superstructure.
- Details in *Bourassa et al*. (2003 *JGR*)

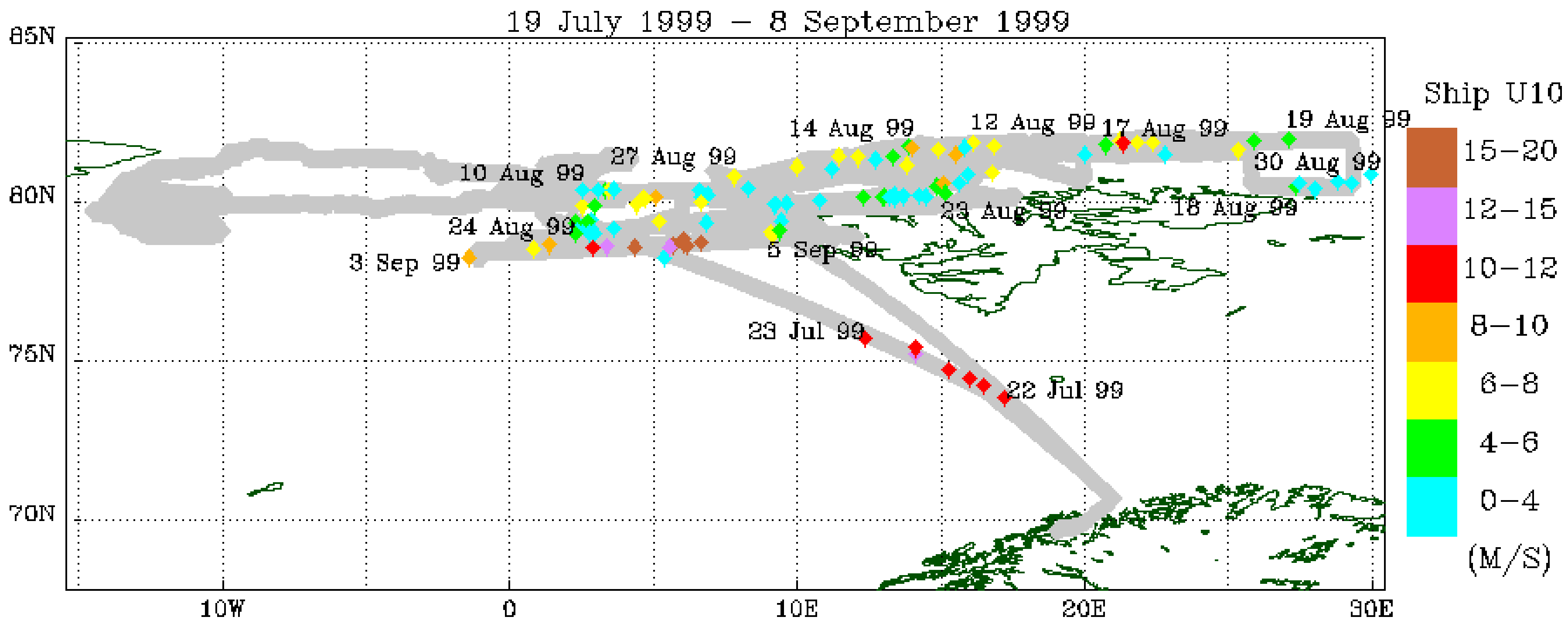
Collocations with R/V Atlantis



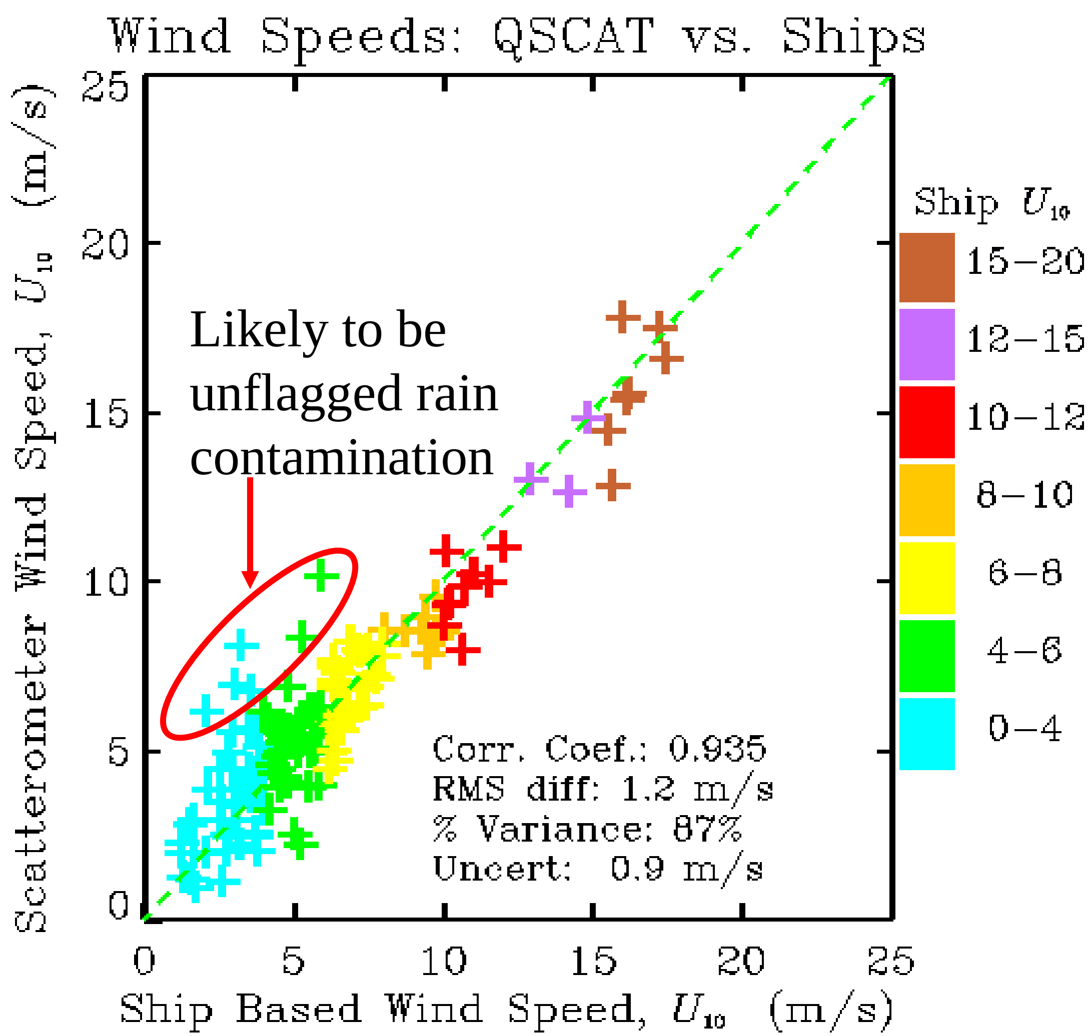
Collocations with R/V Oceanus



Collocations with R/V Polarstern

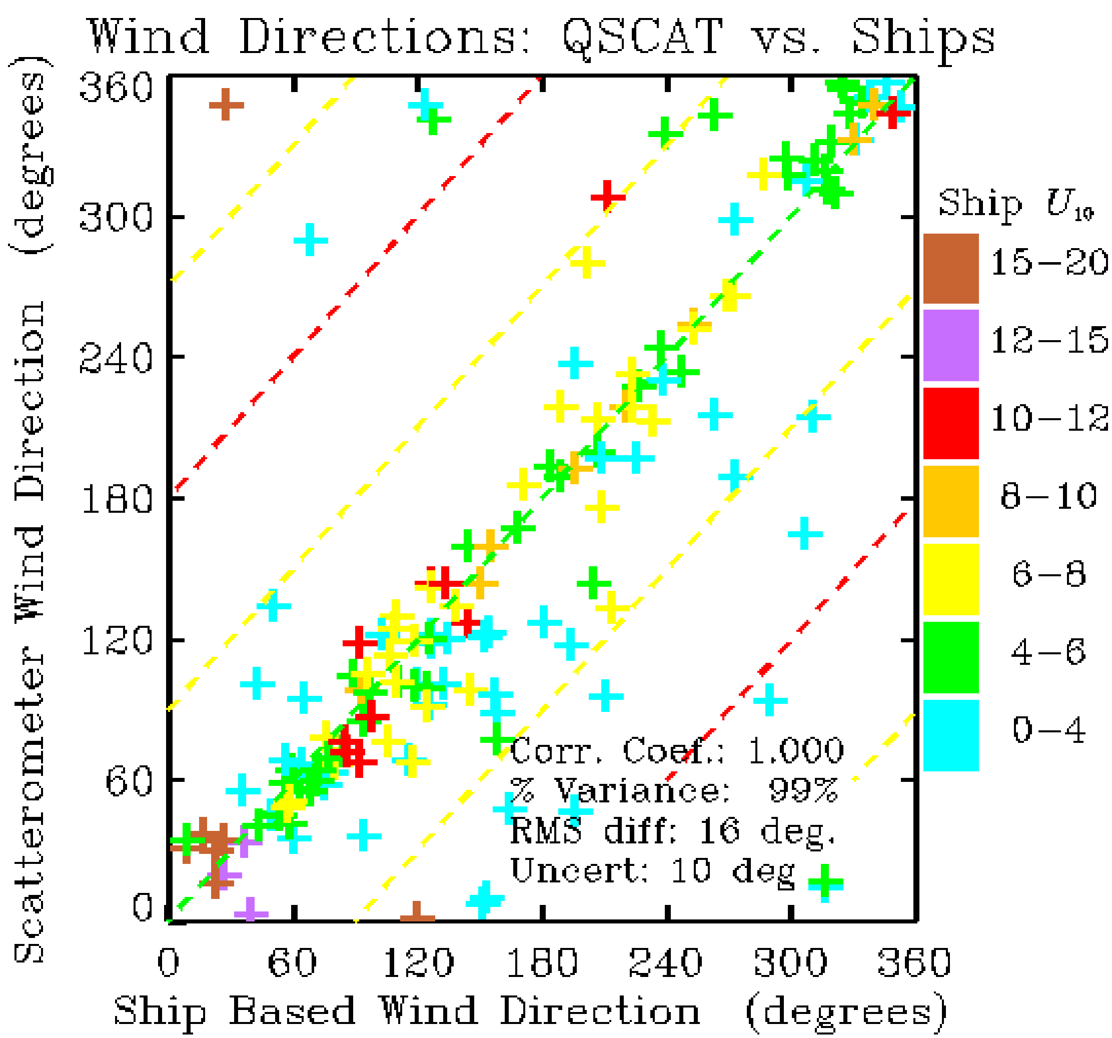


Wind Speed Validation (QSCAT-1 GMF)



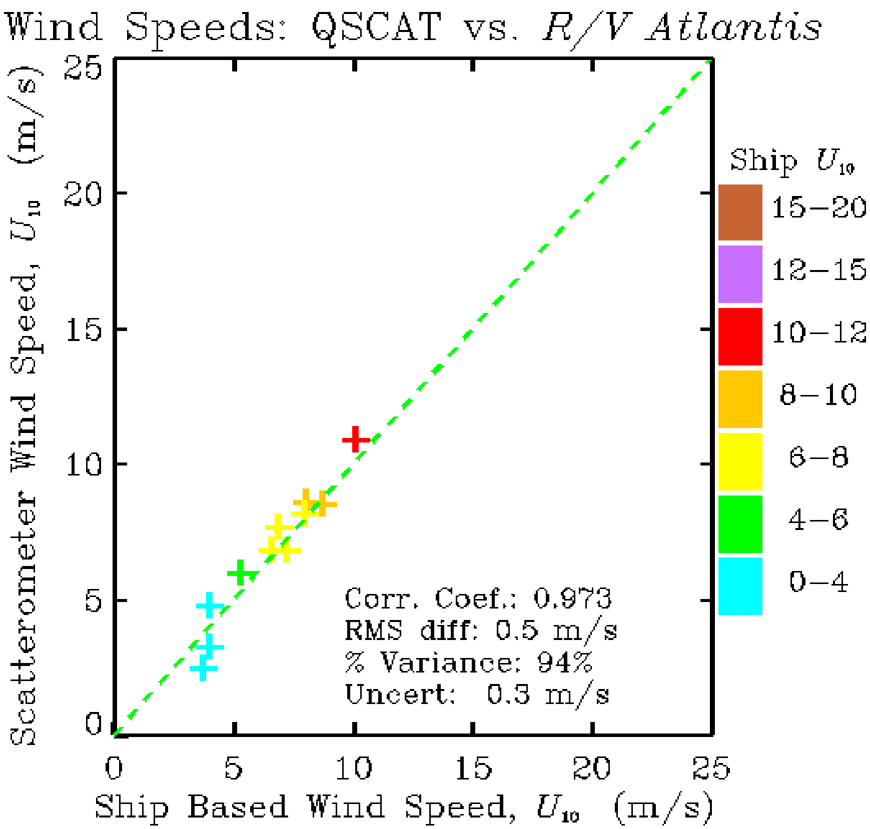
- Preliminary results
  - 2 months of data
  - Observations from eight research vessels
- <25 km apart, <20 minutes apart.
- Uncertainty was calculated using PCA, assuming ships and satellite make equal contributions to uncertainty.

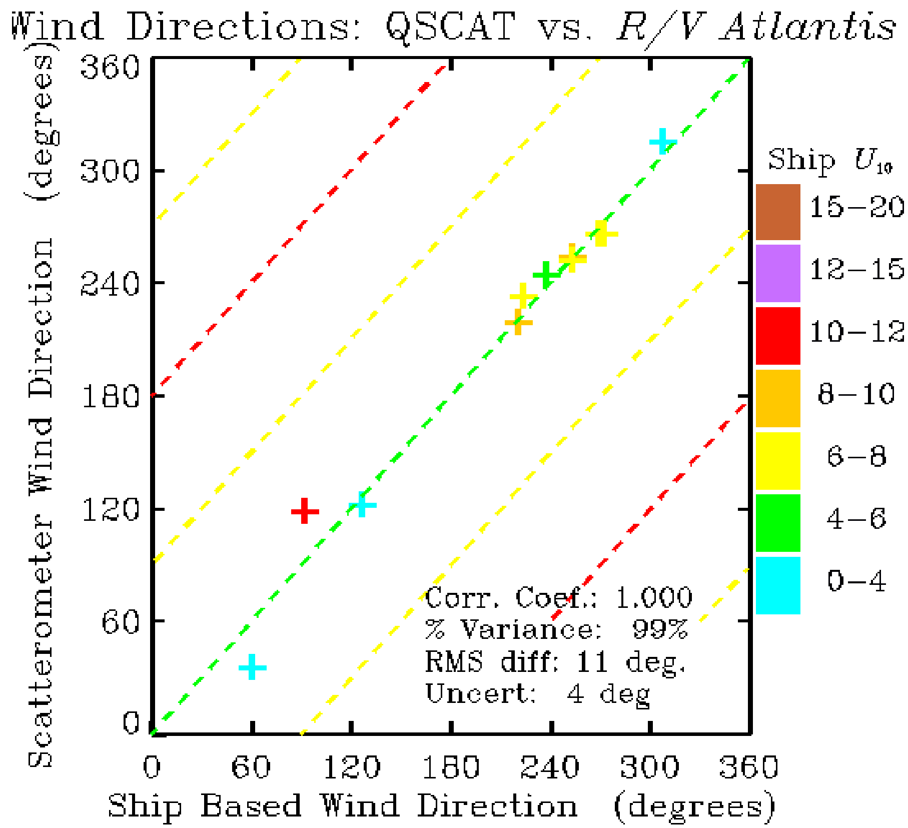
Wind Direction Validation



- Preliminary results
  - Same conditions as the previous plot.
- Correctly selected ambiguities are within 45° of the green line or the corners.
  - Red dashed lines indicates 180° errors.
  - Yellow dashed lines indicate 90° errors.
- Statistics are for correctly selected ambiguities.

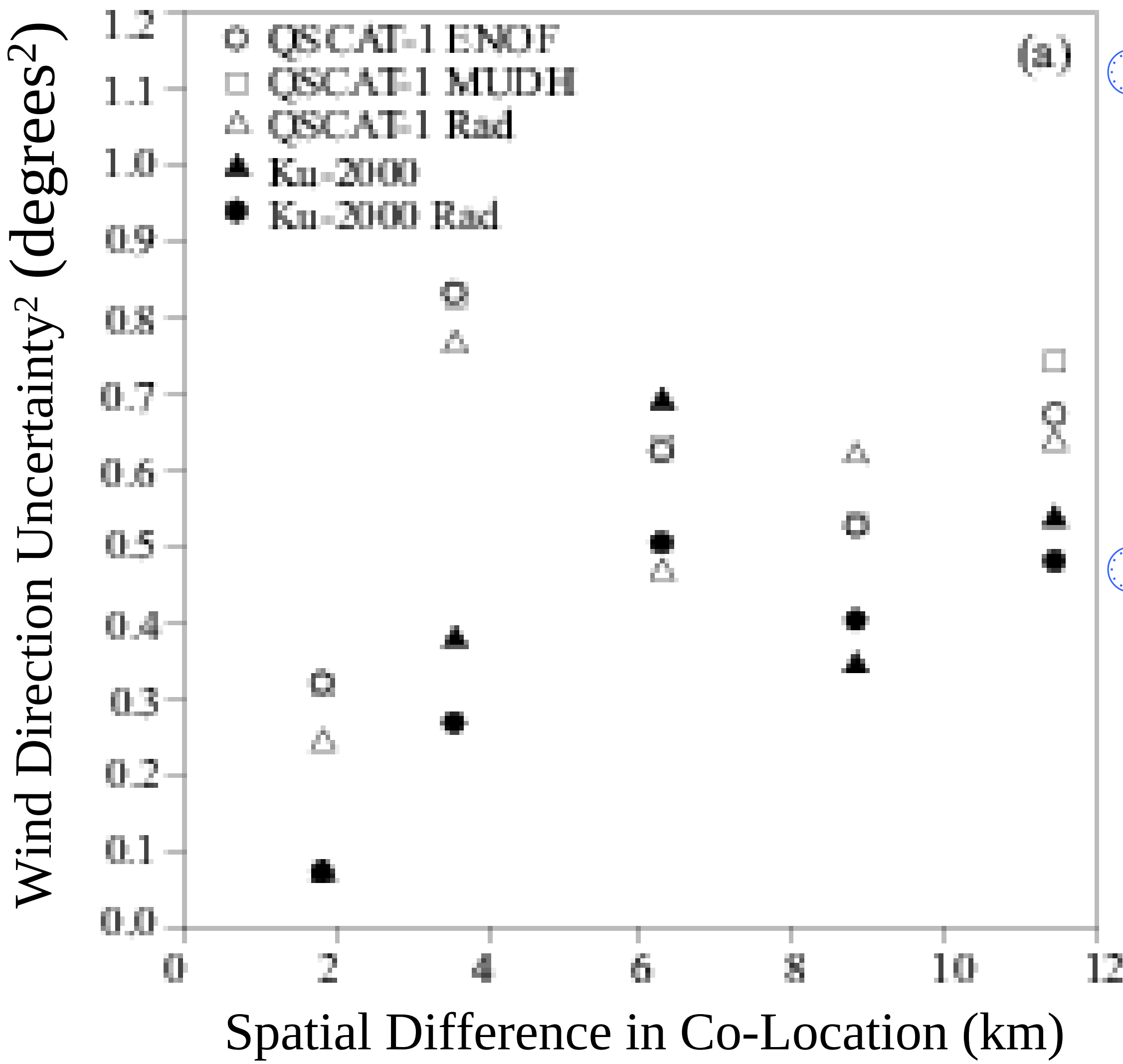
R/V Atlantis Preliminary Comparison





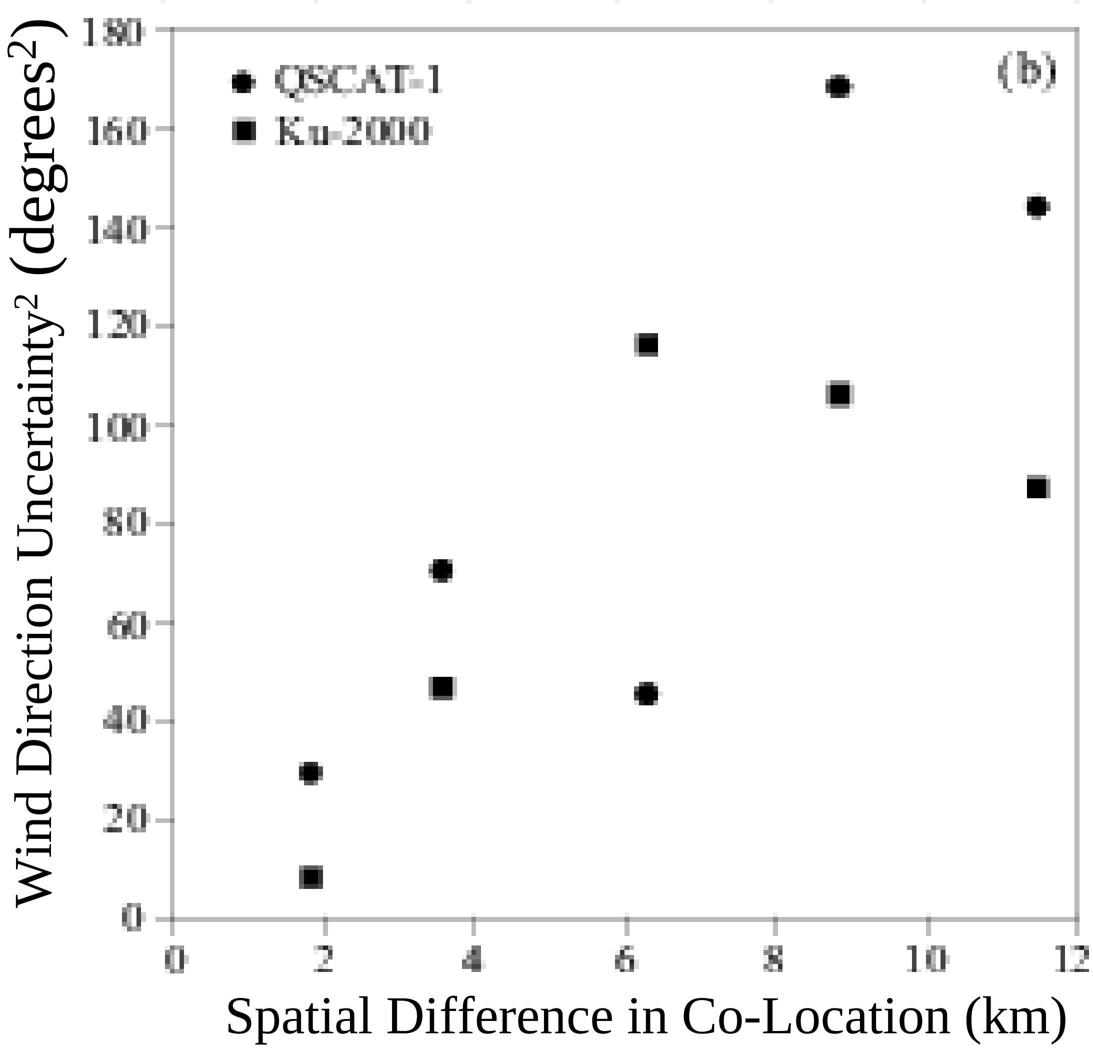
- Preliminary comparison to *R/V Atlantis* was much better than typical.
  - Uncertainties of 0.3 m/s and 4° (a factor of 4 or 5 better than average).
    - Possible explanations include a small sample, and
    - All but one co-location was <5 km.

Variance in Speed



- There have been several retrieval algorithms with different rain flags.
  - Ku2000 from Remote Sensing Systems.
  - QSCAT-1 from JPL.
- Wind speed variance (i.e., uncertainty squared) decreases with decreasing co-location distance.

Variance in Direction



- Variance (uncertainty squared) in direction also decreases as co-location distance decreases.
- Taylor's hypothesis can be used to estimate the spatial scale to which extrapolation can be justified.
  - The optimum spatial scale is between 5 and 7 km.
  - This distance has been confirmed in the signal to noise ratio from backscatter (*David Long*, pers. Comm, 2003).

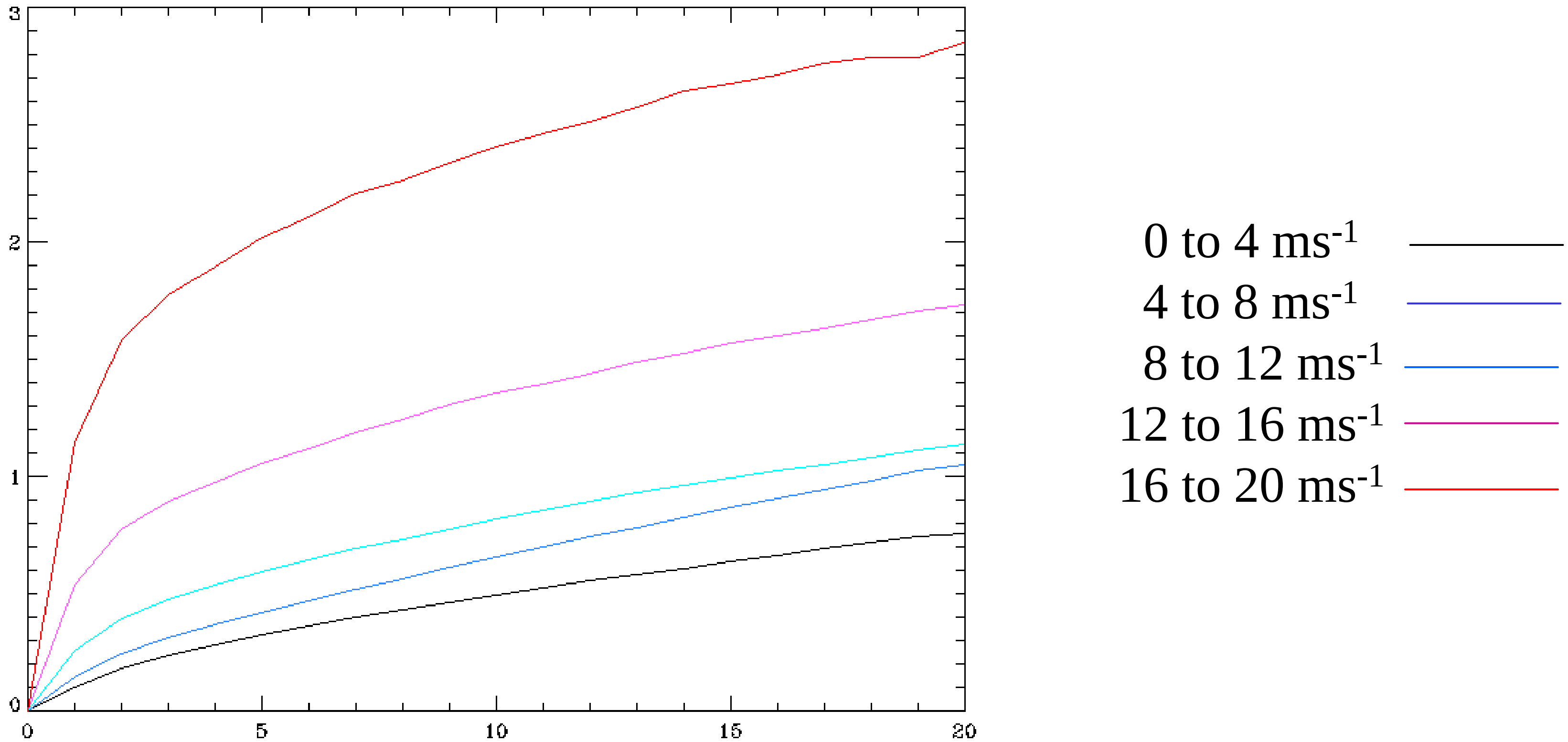
Natural Variability In Scatterometer Observations

- Examine how much noise in scatterometer winds is due to natural variability in surfaces winds.
  - Versus variability (noise) due to the retrieval function.
  - Will naturally variable winds be a serious problem for finer resolution scatterometer winds???
    - Antenna technology has progressed to the point where a 1 or 2km product could be produced from a satellite in mid earth orbit.
    - Current scatterometer wind cells are 25x25km from low earth orbit.
    - There is a lot of atmospheric variability on scales <25km.
- The different looks within a vector wind cell do not occur at the same time or location. The winds can and do change between looks.
- These changes can be thought of as appearing as noise in the observed backscatter. When individual footprints are averaged over sufficient space/time (space in this case), the variability due to smaller scale processes can be greatly reduced.

The Approach

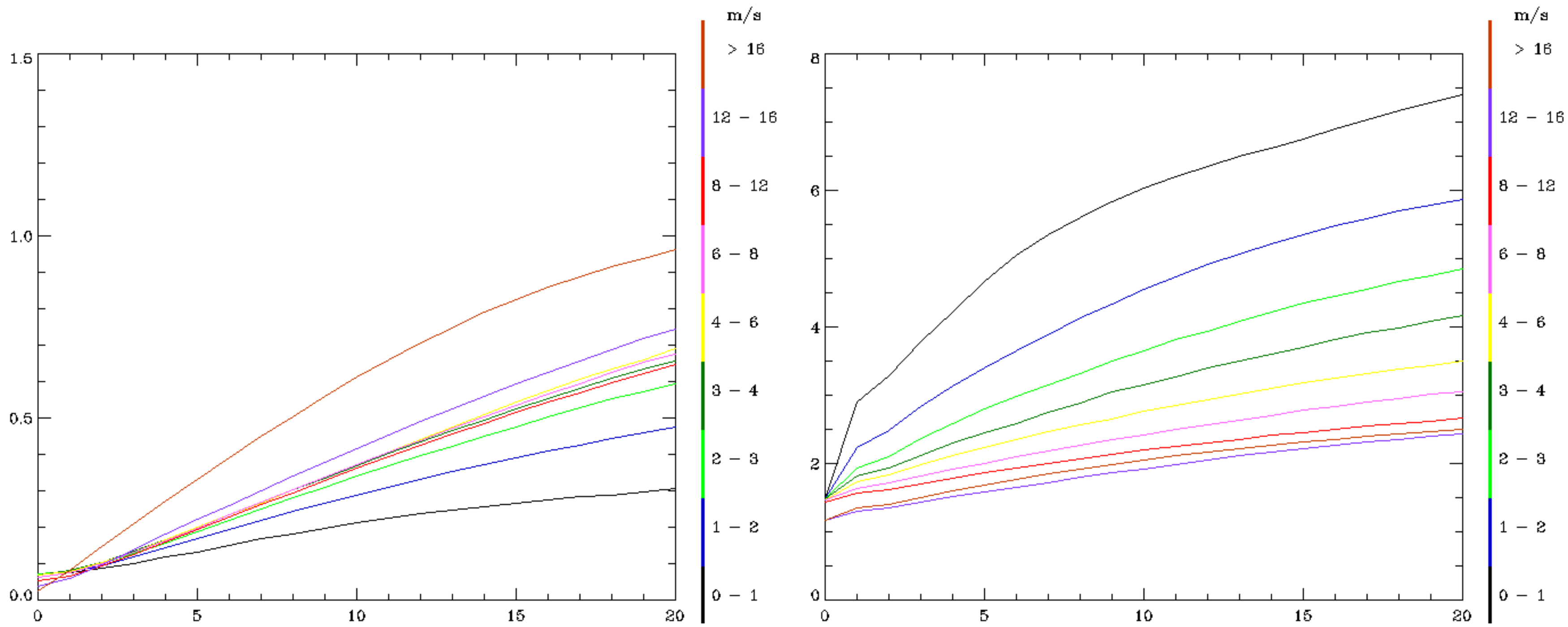
- Taylor's hypothesis is used to convert a spatial scale (e.g., 25, 20, 15, 10, 5, and 2km) to a time scale.
  - Time scale = spatial scale / mean wind speed.
    - A maximum time scale of 40 minutes is used.
  - The non-uniform antenna pattern is considered.
    - The weighting in space (translated to time) is equal to a Gaussian distribution, centered on the center of the footprint, and dropping by one standard deviation at the edge of the footprint.
- Mean speeds and directions are calculated, and differences are calculated for temporal differences of 1 through 20 minutes.

Example of Variability in 60s Averages for Various Difference In Time



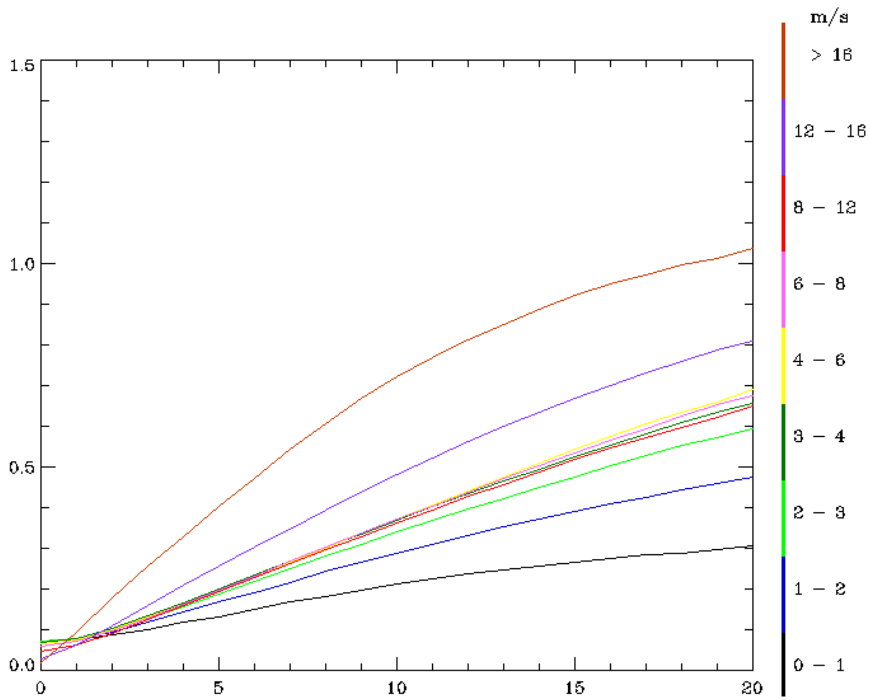
- Variance in wind speed differences (m^2s^{-2}) as a function of the difference in time (minutes) for individual observations (one minute averages).

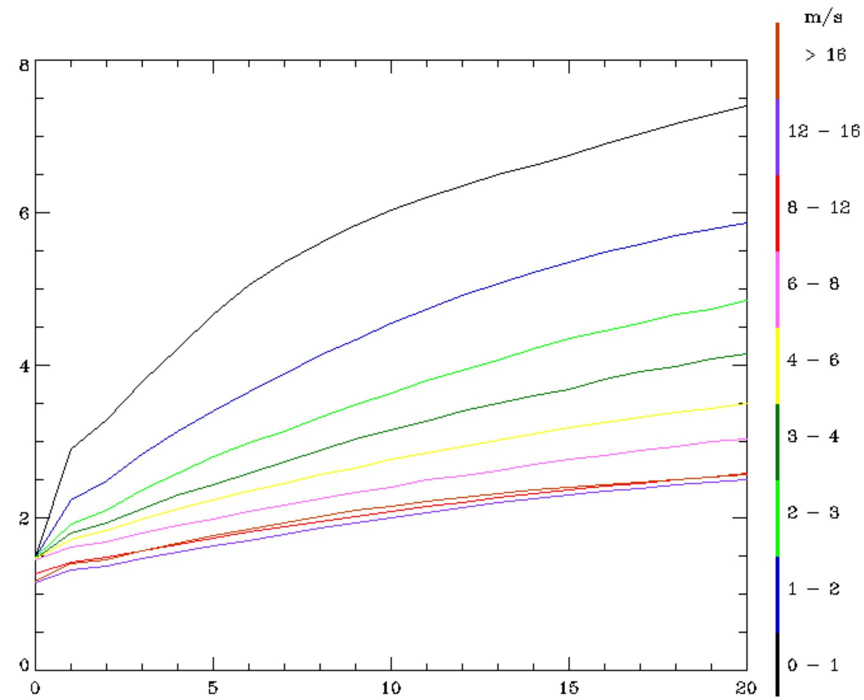
Examples for 25km footprints



- Standard deviation in wind speed differences (left; ms^{-1}) and directional differences (right; degrees) as a function of the difference in time (minutes).
- High wind speeds have more variability in speed, but less so in direction.
- Directional variability for low wind speeds is very sensitive to the differences in time.

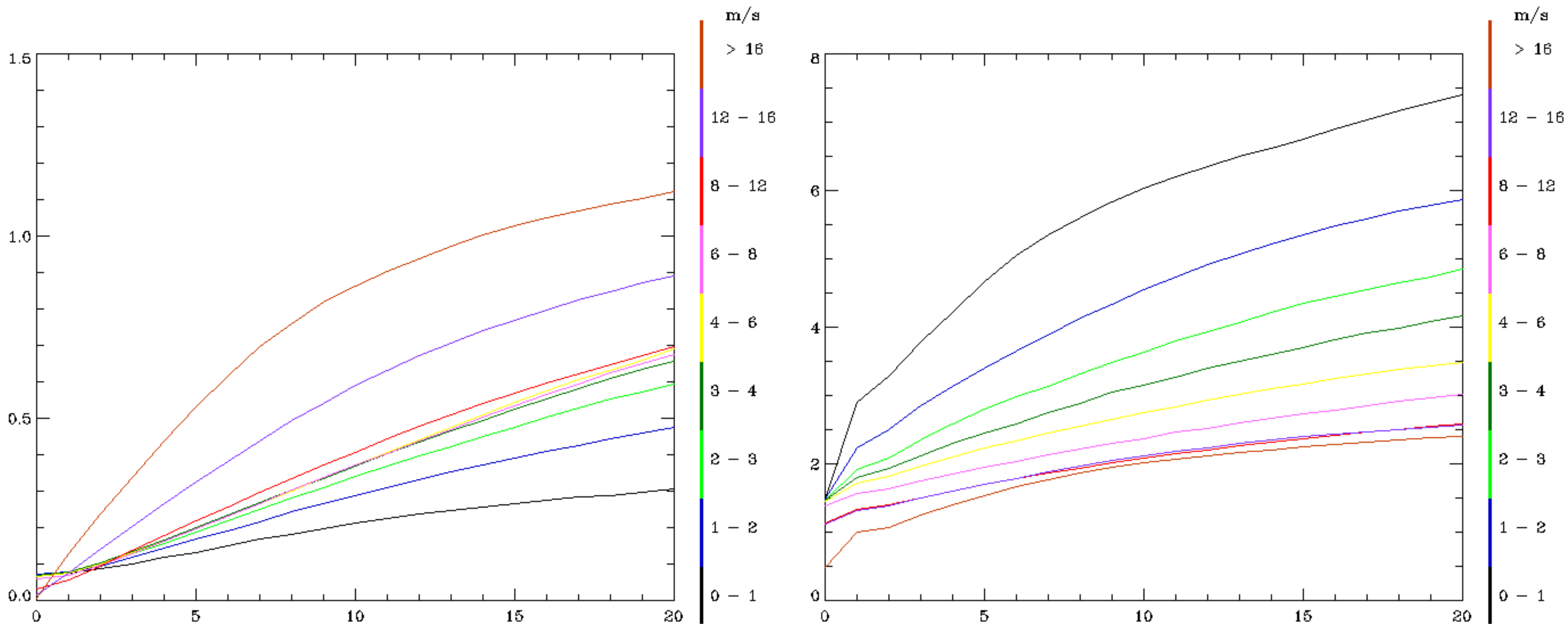
Examples for 20km footprints





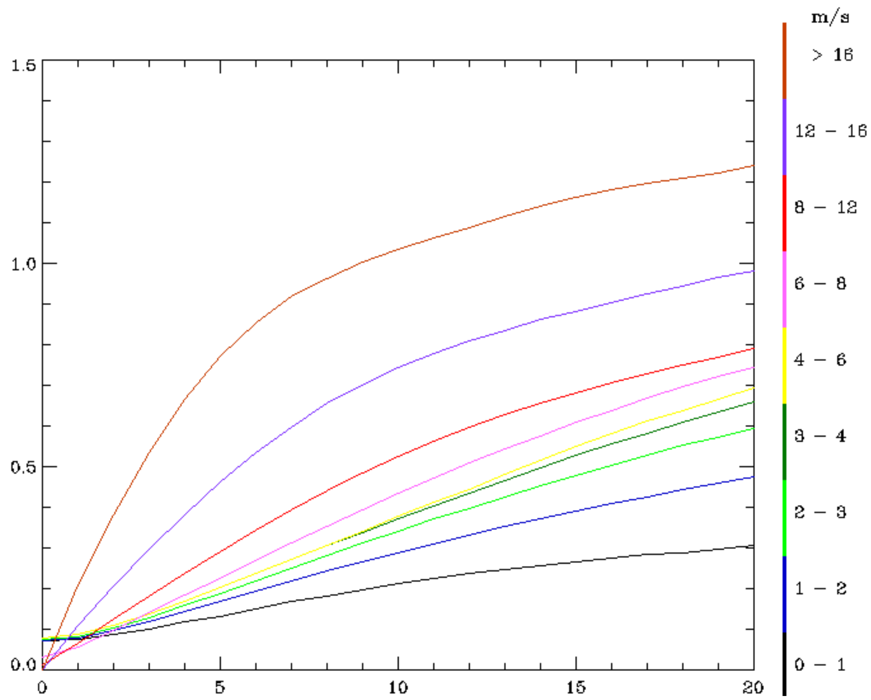
- Standard deviation in wind speed (left; ms^{-1}) and direction (right; degrees) as a function of the difference in time (minutes).

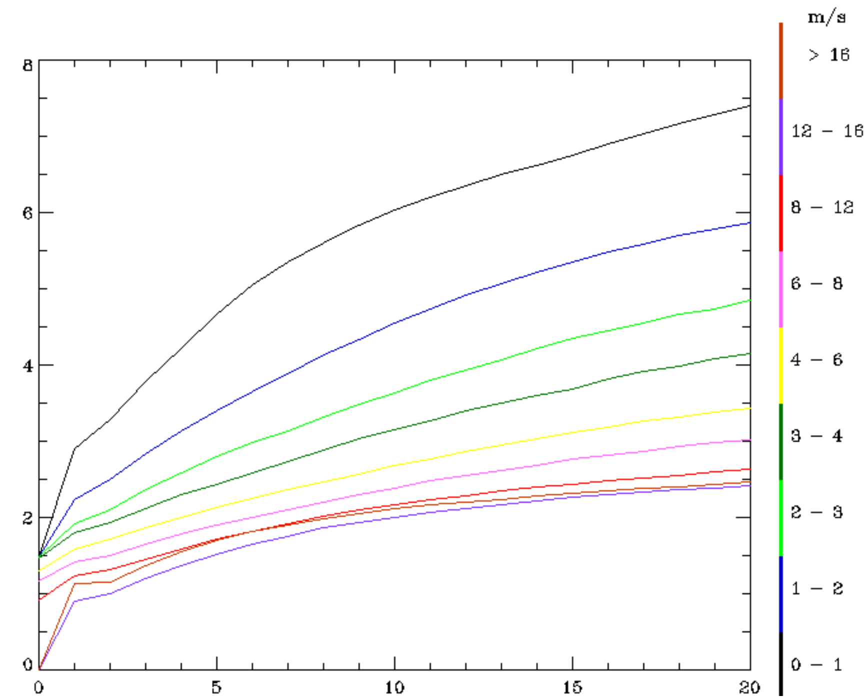
Examples for 15km footprints



- Standard deviation in wind speed (left; ms^{-1}) and direction (right; degrees) as a function of the difference in time (minutes).

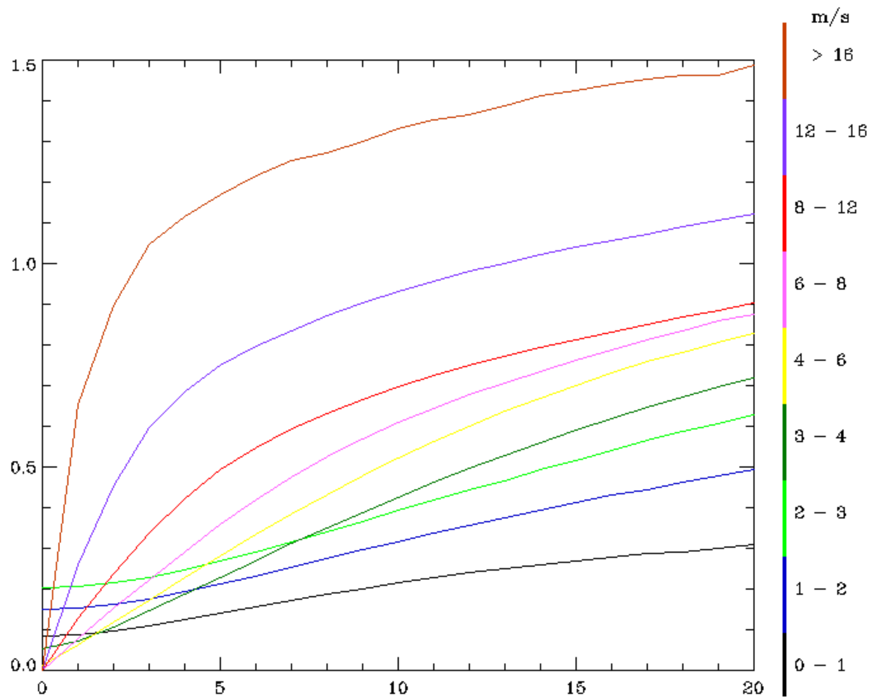
Examples for 10km footprints





- Standard deviation in wind speed (left; ms^{-1}) and direction (right; degrees) as a function of the difference in time (minutes).
- Odd features are creeping into the directional analysis for high wind speeds, presumably due to insufficient temporal resolution of the ship data.

Examples for 5km footprints



- Standard deviation in wind speed (ms^{-1}) as a function of the difference in time (minutes).
- Speeds, for large wind speeds, are highly sensitive to the differences in observation time.
- For lower wind speeds, the spatial differences in sampling dominate the uncertainty in speed.

Conclusions

- There are many applications for high resolution in situ observations.
  - Improving flux modeling
  - Validation of climatologies
  - Quality assessment of VOS observations
  - Validation of satellite observations
  - Planning new earth observing satellites

- The satellite related applications would benefit from observations with a sampling rate greater than once per minute.
- Wave data and radiation data would be extremely useful for flux modeling.