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.
- 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.
  - Useful for estimating naturally occurring noise in observations.

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Ocean’s TKE Based on Observed Surface Fluxes

Eddy Correlation

Inertial Dissipation

Bulk Method

Calculations by Derrick Weitlich
Clayson & Kantha model

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Flux Model Evaluation with ASTEX (Buoy Observations)

Calculations by Yoshi Goto

<table>
<thead>
<tr>
<th></th>
<th>r</th>
<th>r²</th>
<th>Slope</th>
<th>RMS</th>
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</thead>
<tbody>
<tr>
<td>Taylor &amp; Yelland</td>
<td>0.94</td>
<td>0.88</td>
<td>1.04±0.00</td>
<td>0.010</td>
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<tr>
<td>Wu</td>
<td>0.94</td>
<td>0.88</td>
<td>0.88±0.00</td>
<td>0.009</td>
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<tr>
<td>Smith et al.</td>
<td>0.94</td>
<td>0.88</td>
<td>1.02±0.00</td>
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0.010 1.02
0.009 0.88
Observed Surface Stresses

- Preliminary data from 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).

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Evaluations Using SWS2
Ship and Buoy Observations

<table>
<thead>
<tr>
<th></th>
<th>r</th>
<th>r²</th>
<th>regression</th>
<th>RMS</th>
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<tr>
<td>All Data</td>
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<tr>
<td>Taylor &amp; Yelland</td>
<td>0.96</td>
<td>0.92</td>
<td>0.72±0.03</td>
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<tr>
<td>Wu</td>
<td>0.97</td>
<td>0.93</td>
<td>0.76±0.04</td>
<td>0.083</td>
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<tr>
<td>Smith et al.</td>
<td>0.96</td>
<td>0.93</td>
<td>0.73±0.03</td>
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</table>

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<tr>
<th></th>
<th>r</th>
<th>r²</th>
<th>Slope</th>
<th>RMS</th>
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<tbody>
<tr>
<td>Stress &lt; 0.5 N/m²</td>
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<tr>
<td>Taylor &amp; Yelland</td>
<td>0.92</td>
<td>0.84</td>
<td>0.83±0.01</td>
<td>0.05</td>
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<tr>
<td>Wu</td>
<td>0.94</td>
<td>0.88</td>
<td>0.89±0.02</td>
<td>0.042</td>
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<tr>
<td>Smith et al.</td>
<td>0.92</td>
<td>0.85</td>
<td>0.82±0.01</td>
<td>0.051</td>
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</tbody>
</table>

Calculations by Yoshi Goto

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Understanding Physics Via Differences in Remotely Sensed and In Situ Data

In areas of strong currents, $U_{\text{scat}} - U_{\text{buoy}}$ 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 $U_{\text{scat}} - U_{\text{buoy}}$ are expected to be dominated by wave-related variability in $z_0(u_*)$ 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.

<table>
<thead>
<tr>
<th>Wind Speed (m/s)</th>
<th>Sig. Wave Height</th>
<th>Orbital Velocity</th>
<th>Sig. Wave Slope</th>
<th>Tair - Tsea</th>
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<tbody>
<tr>
<td>4 to 6</td>
<td>0.32</td>
<td>0.38</td>
<td>0.33</td>
<td>0.18</td>
</tr>
<tr>
<td>6 to 8</td>
<td>0.32</td>
<td>0.41</td>
<td>0.33</td>
<td>0.20</td>
</tr>
<tr>
<td>8 to 10</td>
<td>0.28</td>
<td>0.31</td>
<td>0.15</td>
<td>0.19</td>
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</tbody>
</table>
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.

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Where are the Problems: Algorithm or Data

- NCEP fluxes are compared to fluxes calculated from R/V data.
  - 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.
    - 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 known (*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.

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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*)

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Collocations with R/V Atlantis
Collocations with R/V Oceanus

19 July 1999 – 15 September 1999

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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.

Likely to be unflagged rain contamination

Scatterometer Wind Speed, $U_{10}$ (m/s)

Ship Based Wind Speed, $U_{10}$ (m/s)

Corr. Coef.: 0.935
RMS diff: 1.2 m/s
% Variance: 87%
Uncert: 0.9 m/s

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Preliminary results

- Same conditions as the previous plot.

Correctly selected ambiguities are within 45° of the green line or the corners.

- Red dashed lines indicate 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.

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There have been several retrieval algorithms with different rain flags.

- 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).

![Graph showing variance in direction](image)

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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 2 km) 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 (m²s⁻²) as a function of the difference in time (minutes) for individual observations (one minute averages).

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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.

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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).

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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.

[Graph showing standard deviation of wind speed as a function of time difference]

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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.