Autocorrelation of Wind Observations

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ABSTRACT

Autocorrelation and variance statistics were calculated for seven types of wind data in the western hemispheric tropics. Most of these data came from the Global Weather Experiment (GWE) in January 1979. They were: 1) cloud motion measurements from four different sources, 2) raawinsonde wind reports, 3) synoptic land station reports, 4) marine ship reports, 5) aircraft pilot reports, 6) automatic aircraft reports for the GWE, and 7) Seasat scatterometer winds from September 1978. Winds were analyzed within a target area from 30°N to 30°S latitude and 0° to 180°W longitude.

The Seasat scatterometer data had the highest autocorrelations and lowest standard deviations over short distances (<500 km). Cloud motions and raawinsonde had lower autocorrelations than Seasat, while synoptic land stations, ship reports, and aircraft pilot reports had the poorest autocorrelations. These correlations imply that synoptic land stations, ship reports, and aircraft reports were either more sensitive to small-scale fluctuations than other sensors, or had higher intrinsic noise levels. Structure function plots of autocovariances against separation distance between observations indicated that Seasat was most sensitive to wind field structure by having low autocovariance at short distances (100 km) that also grew with distance. The other structure function plots for low-level wind observations indicated a lack of structure sensitivity to scalar wind speeds because of very small growth rates of the autocovariances with distance. However, all observations were sensitive to structure in the wind direction patterns.

1. Introduction

In recent years analyses of synoptic-scale wind fields for studies of atmospheric dynamics or the initialization of numerical models have used a variety of data types. Rawinsonde observations, nearly the sole source of synoptic upper air information in the past, have been augmented by newer types of data such as cloud motions and aircraft reports. Objective analysis schemes have become more complicated to blend these data. These analysis schemes assign weights to each observation based on several factors, such as proximity to a grid point, density of the observations, noise in each observation, and subgrid scale variability in the wind field. Thus, the weight is partly determined for each type of data from known or estimated statistical characteristics of the data source. Specifically, to design weighting functions we should know: 1) the shape of the spatial autocorrelation function for each data source, and 2) the intrinsic noise level of each data source (Barnes, 1964). Biases also need to be considered, but they are not the focus of the study presented here.

There have been several investigations of the autocorrelation characteristics of wind data in the past for various geographical areas and time periods. For example, rawinsonde autocorrelations are extensively discussed in Steinitz et al. (1971), using data over the Northern Hemisphere tropics over a five-year period from 1958 to 1963. Cloud motions were analyzed by Wylie and Hinton (1981a,b) over the Indian Ocean during the summer monsoon of 1979; other cloud motion characteristics were studied by Hubert and Whitney (1971) and Hasler et al. (1979) in the Atlantic Ocean, and Halpern and Knox (1983) in the tropical Pacific Ocean. Ship reports were studied by Pierson et al. (1980) in the Gulf of Alaska. These studies also contain some comparisons between two types of data from which mean bias information can be assessed. But the differences in autocorrelations reported by these studies may be partly due to the differences in the wind fields between tropical and high latitudes, and partly due to differing observation systems.

To further assess the differences within wind measurement systems, we calculated autocorrelation statistics from seven different data sources. To include low latitudes and significant ocean areas, the location of the study area was the tropical western hemisphere, 30°N–30°S latitude, 0°–180°W longitude (see Table 1). Coverage of each data type is concentrated in a subregion within this box (described in the next section and Table 1). Six of the data types came from the Global Weather Experiment [GWE; also referred to as the first GARP global experiment (FGGE)] of the Global Atmospheric Research Program (GARP) in January 1979. The seventh type of data was the microwave scatterometer winds from the flight of

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Seasat in September 1978. Seasat data were included because they contain mesoscale sampling (100 km) over global areas not obtainable from the other sources and because scatterometer data are expected to be used in future wind analyses when available from new satellites (see Wylie and Hinton, 1984).

2. Data sources

All data, except Seasat, were obtained from the National Climatic Center of the National Oceanographic and Atmospheric Administration (NOAA) in Asheville, North Carolina. A special archive of data for the GWE was established for these data. The synoptic land station reports and rawinsonde data were taken from the Level II-b archive tapes. Ship reports were obtained from both the II-b tapes and the Supplementary Surface Marine Data Archive of GWE. Only the 1200 GMT observations were used for the land, ship, and rawinsonde data. Cloud motion and aircraft data were obtained from supplementary archives of the GWE. No editing or corrections were made to any of the data used.

Cloud motions were measured by four operations during the GWE. The GOES East and West satellites were analyzed from 20°W to 150°W longitude and 50°N to 50°S latitude by NOAA’s National Environmental Satellite Service (NESS). Three wind sets were made per day. The 1200 and 1800 GMT data were combined for statistical analyses. These times were close to local noon at the subsatellite coverage points. The 0000 GMT wind set was ignored.

A special cloud motion analysis was made by the University of Wisconsin-Madison for a tropical belt from 15°N to 15°S latitude in the GOES East and West areas once each day near local noon (1200 or 1800 GMT). The coverage of this analysis was considerably more dense than NOAA/NESS operational analyses because cloud targets were selected by meteorologists (see Mosher, 1981).

Other cloud motion datasets were from METEOSAT of the European Space Agency (ESA) and the Geosynchronous Meteorological Satellite (GMS) of Japan. Correlation and variance statistics were made from the 0600 and 1200 GMT data of METEOSAT and the 0000 to 0600 GMT data of the GMS.

Aircraft data were broken into two categories: 1) the conventional reports which are voice-transmitted by the pilot to ARINC (Aeronautical Radio, Inc.) and 2) the automatically recorded data. The conventional aircraft reports (AIREPS) require a pilot to calculate winds from true airspeed and groundspeed. These may be subject to measurement or calculation errors and errors in coding. Since the advent of inertial navigation systems in aircraft, wind data has been automatically obtained. For GWE, a special communications and recording system was devised to collect the data directly from the inertial navigation systems (see Sparkman et al., 1981). The Aircraft Integrated Data System (AIDS) recorded wind observations specially for GWE on some aircraft, while others automatically transmitted data to NOAA by the Aircraft-to-Satellite Data Relay (ASDAR). We used all AIDS and ASDAR reports within 3 hours of 1200 GMT on each day. Voice-transmitted pilot reports within 3 hours of 1200 GMT were analyzed separately from the automatically recorded data.

Seasat scatterometer wind data were obtained from the Jet Propulsion Laboratory (JPL) of The California Institute of Technology for September 1978. Winds were derived from the radar scatterometer data at 100 km resolution, using the SASS-1 algorithm (Jones et al., 1982). Wind directions were manually selected from four choices given by the SASS-1 algorithm (Wurtele et al., 1982). The directional selections were made independently by two teams of meteorologists, one at JPL and a second at the Atmospheric Environmental Service of Canada. The teams resolved their differences at a joint meeting at JPL attended by one of the authors of this paper. The hand-drawn directional analyses considered not only the scatterometer data, but all other available wind data except cloud motions. However, the editors chose only the wind directions from the four possible vectors given by the SASS-1 algorithm at 100 km intervals within and along the 1200 km wide swath of the satellite. Wind speeds were not edited, but were left as defined by the scatterometer and SASS-1 algorithm.

The Seasat scatterometer covered a swath 1200 km wide along the satellite’s orbit. However, there is an interorbit gap of equal width at the equator, due to limitations of the instrument. In seven hours, the scatterometer covered approximately one-half of the tropical oceans. No wind information was obtained over land. Four orbits from 20°W to 150°W were combined each day for correlation and variance computations.

3. Statistics calculated from the data

Autocorrelations and autocovariances were calculated by forming all possible pairs of observations of the same time, data type (satellite, rawinsonde, ship report, etc.) and altitude. These pairs then were classified by their separation distance in 100 km bins. For each distance bin, sums of the zonal ($\Sigma U$) and meridional ($\Sigma V$) components, their squares ($\Sigma U^2$, $\Sigma V^2$) and cross products ($\Sigma U_i U_j$, $\Sigma V_i V_j$) were compiled. The autocorrelation for each bin $C(d)$ was calculated for each wind component and the scalar wind speed.
where \( X \) is the wind component \( U, V \) or the scalar speed \( S \), and \( N \) the number of comparison pairs in the bin. We include scalar speed calculations because certain wind data sources that may be used in the future will give scalar speed information without direction (Wylie and Hinton, 1984).

A vector correlation between the two observations also was defined as

\[
C_{\text{vector}} = 1 - [(1 - C_u^2)S_u^2 + (1 - C_v^2)S_v^2] / (S_u^2 + S_v^2) \right)^{1/2}
\]

(2)

\[
S_u^2 = \frac{1}{M} \sum U^2 - \left( \frac{1}{M} \sum U \right)^2
\]

(3)

where \( S \) is the standard deviation of wind component \( U \) or \( V \), \( C_u \) and \( C_v \) the autocorrelation of \( U \) and \( V \), and \( M \) the number of component values in each distance bin. The vector correlation is a correlation between difference vectors for all pairs in the distance bin. The vector and scalar speed correlations together allow us to infer the relative importance of directional information over scalar speed data. This is less readily seen in the zonal and meridional wind component statistics. Thus, we present the vector correlation in place of individual \( U \) and \( V \) component correlations. Autocovariances are square roots of autocovariances normalized by the variances of the data sample as part of the calculations shown in (1), (2) and (3).

We will use the autocovariances in the discussion of the data as indications of the errors or noise in the observations. Ideally, coincident observations at the same location and time should be perfectly correlated, \( C = 1.0 \). Since all observations have some errors in them and we exclude identical observations from our paired statistics (\( i = j \) excluded), the calculated autocovariances were always less than 1.0. The observation pairs also had to be categorized into bins of separation distance for computing the statistics. We chose a scale length of 100 km for our bin size so all observations within 100 km were categorized as coincident pairs.

In the following discussion, we will use the magnitude of the autocovariance in the first bin (0–100 km) as one indication of the noise or quality of the observation. Consequently, those observations sensitive to much smaller scales (i.e., "point" observations) will exhibit an apparent noise due to small scale fluctuations. Analyses of wind fields on the synoptic scales, as in modeling applications, need to filter out subgrid scale motions. Since we cannot distinguish true instrument noise from small scale wind variability, we will generally refer to this variability as noise in the content of global and synoptic scale fields.

The autocorrelation profile typically decreases with distance (Panofsky and Brier, 1968; Steinitz et al., 1971) because of horizontal gradients in the wind field. The slope of this profile is an indication of the structure in the wind field or the quality of the data. A steep slope implies large wind field gradients or structure, while gentle slope implies little structure or a near uniform field. But a steep slope also can indicate noise in the observations which will be discussed in the next section.

Autocovariances between paired observations are of interest because they too are indicators of the structure in the wind field. These were calculated from the autocorrelation and variance statistics,

\[
\text{var}(d) = [1 - C(d)^2]S^2
\]

(4)

where both \( \text{var}(d) \) and \( C(d) \) are functions of distance (100 km bins) and \( S^2 \) is the total sample variance of speed regardless of distance. Thus, \( \text{var}(d) \) is the amount of uncorrelated variance in each distance bin. For simplicity, we will show the square root of the variance, the standard deviation (SD), because it has linear scatter:

\[
\text{SD}(d) = \sqrt{\text{var}(d)}.
\]

(5)

Wind direction cannot be handled as a scalar in the same way as the components, \( U \) and \( V \), and the scalar speeds since directions have a 360° period. To gather information on wind directions, we compiled the average difference between the pairs (DH), using only their absolute values:

\[
\text{DH}(d) = \frac{1}{N} |X_i - X_j|.
\]

(6)

The units of direction measurement, \( X_i \) and \( X_j \), were degrees (true).

The standard deviation and direction difference profiles give further indication of observation noise levels and errors, or wind field structure definition. For close proximity observations (the 0–100 km distance bin), we would expect SD near zero for near perfect data. The SD or direction difference is a quantification of the error associated with individual observations. An increase in SD and direction difference with separation is expected from the wind field
The slope of this profile is an indication of wind field structure or the inability to define structure if no slope is present just as indicated by the autocorrelation profile. At large separation distances the standard deviation is nearly equal to the square root of the variance of the total data sample without regard to distance. Direction differences will grow to a limit near 90° because an individual comparison is within ±180°, the shortest distance around the compass.

We will present both the autocorrelation and standard deviation or direction difference statistics for each data set in the next section. The autocorrelation profiles show the fraction of the variance that is correlated and how it changes with distance. The SD and direction difference profiles show magnitude of the variance in the data and how it is distributed over distance.

The statistics mentioned were calculated for one time period on each day in the western hemisphere, 30°N–30°S latitude. The longitude bounds for the high density data sets are restricted to the areas viewed by the satellite as shown in Table 1.

Autocorrelations were averaged from 6 to 31 days, depending on the data density. For numerous observations such as cloud motions and Seasat scatterometer winds, reliable autocorrelations could be obtained from a few days of compilation. Values of autocorrelations and variances exhibited small day-to-day changes, so we did not feel compelled to compute these for the full 31 days. For less dense data, the correlations and variances were averaged for one month to form stable statistics. For all instruments, the daily autocorrelations were within 0.2 of the means presented here.

The autocorrelation and standard deviations were computed at two levels in the atmosphere, low-level or surface observations and upper troposphere or high level observations. For rawinsondes, we used 850 mb to represent low-level winds and 250 mb for the high-level winds. Surface land stations were all considered low level regardless of station elevation. Cloud motion reports below 800 mb were considered low-level winds, and those between 100 and 300 mb, high level winds. The cloud motion data between 800 and 300 mb were not used.

We chose broad categories for cloud motions because of the inaccuracies in assigning heights to the data and the variety of methods used to assign heights by the different wind producers. Heights are usually assigned based on the temperature of the cloud top, which sometimes includes infrared emissivity/transmitivity estimates. Studies by Hasler et al. (1979) have shown that the low-level clouds move with the speeds of their bases. Unfortunately, base height cannot be directly measured from satellites. Some wind producers, such as the University of Wisconsin-Madison, estimated base height. Others simply assigned 900 mb to these clouds because they obtained highest correlations with rawinsonde data at this level on the average (Hubert and Whitney, 1971). For more details see Mosher (1981).

Aircraft reports between 10 and 12 km (altimeter readings) were classified as high level data. Reports below 10 km were disregarded. Generally, 10-12 km encompasses 200–300 mb levels. Thus, aircraft reports

<table>
<thead>
<tr>
<th>Wind producer</th>
<th>Average number of winds per day</th>
<th>Time period</th>
<th>Longitude covered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low level</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land stations</td>
<td>295</td>
<td>1–31 Jan 79</td>
<td>0–180°W</td>
</tr>
<tr>
<td>Ship reports</td>
<td>264</td>
<td>1–31 Jan 79</td>
<td>0–180°W</td>
</tr>
<tr>
<td>850 mb Raobs</td>
<td>68</td>
<td>1–31 Jan 79</td>
<td>0–180°W</td>
</tr>
<tr>
<td>NESS cloud motion</td>
<td>204</td>
<td>15–31 Jan 79</td>
<td>30–150°W</td>
</tr>
<tr>
<td>Wisconsin cloud motion</td>
<td>738</td>
<td>21–31 Jan 79</td>
<td>30–150°W</td>
</tr>
<tr>
<td>ESA cloud motion</td>
<td>56</td>
<td>1–31 Jan 79</td>
<td>50°W–90°E</td>
</tr>
<tr>
<td>GMS cloud motion</td>
<td>86</td>
<td>1–31 Jan 79</td>
<td>90–170°E</td>
</tr>
<tr>
<td>Seasat scat.</td>
<td>2235</td>
<td>6–7 Sep 78</td>
<td>20–180°W</td>
</tr>
<tr>
<td>High level</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESA cloud motion</td>
<td>106</td>
<td>1–31 Jan 79</td>
<td>50°W–90°E</td>
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<tr>
<td>GMS cloud motion</td>
<td>94</td>
<td>1–31 Jan 79</td>
<td>90–170°E</td>
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<tr>
<td>NESS cloud motion</td>
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<td>30–150°W</td>
</tr>
<tr>
<td>Wisconsin cloud motion</td>
<td>450</td>
<td>21–31 Jan 79</td>
<td>30–150°W</td>
</tr>
<tr>
<td>250 mb Raob</td>
<td>65</td>
<td>1–31 Jan 79</td>
<td>0–180°W</td>
</tr>
<tr>
<td>Conventional AIREPS</td>
<td>103</td>
<td>1–31 Jan 79</td>
<td>0–180°W</td>
</tr>
<tr>
<td>FGGE AIREPS</td>
<td>13</td>
<td>1–31 Jan 79</td>
<td>0–180°W</td>
</tr>
</tbody>
</table>
were more restricted than the cloud motions in altitude range.

4. Results and discussion

a. Low-level winds

The Seasat scatterometer winds had the highest vector autocorrelation of 0.96 for the less than 100 km bin. (See Table 2 and Fig. 1a.) Rawinsonde 850 mb winds, ship reports, and cloud motions from NESS and Wisconsin had slightly lower vector correlations of around 0.73. It should be noted that the data densities of rawinsonde and NESS cloud motion observations were less than the other data types, and thus the statistics could not be calculated for separation distance bins below 300 km. Land stations had a noticeably lower vector correlation (0.54) than the others, probably due to orographic and coastal influences at many of the stations in addition to having the character of point observations mentioned earlier.

The slope of the vector autocorrelations are similar for most of the data types. Seasat, however, decreased with distance slightly faster than the others, which is a possible indication of greater sensitivity to mesoscale detail or a result of having data confined to rectangular swaths under the satellite’s orbital track. It was found, as expected, that the size of the area used for computing autocorrelation statistics had a slight influence on the autocorrelation values for distances greater than 700 km.

Land stations had a noticeably steep drop in the vector correlation with distance. Geographical influences and sensitivity to small scale fluctuations were a probable cause of this profile.

The scalar speed autocorrelations were slightly lower than the vector autocorrelations (see Fig. 1a and b). The Seasat correlation dropped from 0.96 (vector) to 0.93 (scalar). Similar small differences were found for rawinsonde winds and Wisconsin cloud motions. Large drops in the correlations, vector to scalar, of 0.1 or more were found for NESS cloud motions, ship reports, and land station observations. The differences between the different data types also were slightly larger for the scalar speed autocorrelations than the vector correlations, as evident in Fig. 1.

Wind direction differences showed the same ranking among data types (Fig. 1c). Seasat had the lowest differences (9°), while cloud motions from NESS and Wisconsin were slightly higher (16°–19°). Ship reports were noticeably higher (28°). Rawinsondes had direction differences of 37° at 300 km, similar to ship reports at the same distance. Land stations had the highest direction differences exceeding 45°.

The direction differences grew for Seasat with distance faster than any of the other data types (61° in 1500 km). This also may indicate a sensitivity to mesoscale wind patterns. Cloud motions, in contrast to Seasat, had lower distance growth profiles (16–48°), which may indicate a lack of sensitivity to direction changes. This may result from spatial smoothing in the cloud motions, which are derived from one-hour averages of target motions, while all other data types were nearly instantaneous observations.

<table>
<thead>
<tr>
<th>Wind producer</th>
<th>100 km</th>
<th>400 km</th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Vector correlation</td>
<td>Speed SD (m s⁻¹)</td>
<td>Direction delta (deg)</td>
<td>Vector correlation</td>
<td>Speed SD (m s⁻¹)</td>
<td>Direction delta (deg)</td>
</tr>
<tr>
<td><strong>Low level</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Land stations</td>
<td>0.54</td>
<td>2.9</td>
<td>45</td>
<td></td>
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<tr>
<td>Ship reports</td>
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<td>3.3</td>
<td>28</td>
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<tr>
<td>850 mb Raobs</td>
<td>—</td>
<td>—</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>NESS cloud motion</td>
<td>—</td>
<td>—</td>
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</tr>
<tr>
<td>Wisconsin cloud motion</td>
<td>0.76</td>
<td>2.3</td>
<td>16</td>
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<tr>
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<td>—</td>
<td>—</td>
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<tr>
<td>GMS cloud motion</td>
<td>—</td>
<td>—</td>
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<tr>
<td>Seasat scat.</td>
<td>0.96</td>
<td>1.1</td>
<td>9</td>
<td></td>
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<tr>
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<td>GMS cloud motion</td>
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<tr>
<td>NESS cloud motion</td>
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<td>—</td>
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<tr>
<td>Wisconsin cloud motion</td>
<td>0.90</td>
<td>4.4</td>
<td>15</td>
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<tr>
<td>250 mg Raob</td>
<td>—</td>
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<td>—</td>
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<tr>
<td>Conventional AIREPS</td>
<td>0.74</td>
<td>10.9</td>
<td>14</td>
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<tr>
<td>FGGE AIREPS</td>
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</tbody>
</table>

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Scalar speed SD in the 0–100 km separation bin showed some of the same distinctions between data types, but to a lesser degree than the correlation and direction differences. Seasat had the lowest SD, 1.1 m s\(^{-1}\) followed by Wisconsin cloud motions at 2.3 m s\(^{-1}\). Ship reports and rawinsondes had the highest SD, 3.3–3.6 m s\(^{-1}\).

Another feature was that the standard deviations of speed approached constant values at 600 km for all of the data types examined. Little growth in speed SD from 100 to 600 km was found for all data except Seasat. Land stations and NESS cloud motions had nearly constant SDs for all distances. These flat profiles indicate either no structure in the wind field, or that the errors or noise level of the scalar speed data were of nearly the same magnitude as the structure in the wind field.

b. High-level winds

The high-level winds showed different characteristics than the low-level winds (Fig. 2). NESS cloud motions had the highest vector autocorrelations (Fig. 2a). Rawinsondes and Wisconsin cloud motions were slightly lower, while aircraft reports (both pilot and automatic) were even lower. All vector correlations decreased with distance at almost the same rate, except for automatic aircraft reports and rawinsonde observations which dropped faster than the others. Automatic aircraft report correlations dropped to extremely small values at 600 km.

The scalar speed correlations were similar to the vector correlations (Fig. 2b), but at slightly lower values for most data types as was found for the low-level winds. The exceptions were rawinsonde 250 mb winds and aircraft pilot reports, for which the scalar speed correlations were slightly higher than the vector correlations out to 500 km. Two data types, the rawinsondes and NESS cloud motions, had distinctively higher scalar speed correlations than the others out to 500 km. The aircraft reports (both pilot and automatic) and Wisconsin cloud motions had similar correlations out to 300 km, less than the rawinsondes and NESS cloud motions.

The wind direction differences (Fig. 2c) showed similar profiles for all the data types. They all increased with distance at approximately the same rate. NESS cloud motions had the smallest directional differences, while Wisconsin had the largest.

Scalar speed standard deviations (Fig. 2d) increased with distance out to 900 km. The high level speed SD profiles indicated relatively more large-scale struc-
ture than the low level speed SD profiles which were nearly constant with distance.

The pilot reports had much higher speed SDs than the other wind data. Wisconsin cloud motions were the lowest, with 4.4 m s\(^{-1}\) SD at 100 km, increasing to 7.8 m s\(^{-1}\) at 1000 km. Rawinsondes ranged from 9.3 m s\(^{-1}\) SD at 300 km to 13.5 m s\(^{-1}\) at 1200 km, with NESS cloud motions and automatic pilot report falling in between the Wisconsin cloud motions and rawinsonde data. But the pilot reports were in a class by themselves, much higher than the others, ranging from 10.9 m s\(^{-1}\) SD at 100 km to 17 m s\(^{-1}\) at 1200 km.

c. Comparison of cloud motions from different producers

Statistics from four cloud motion producers (high clouds only) were compared on one plot (Fig. 3). NESS had the highest correlations, while Wisconsin had the lowest at the same distance (Fig. 3a). The METEOSAT (ESA) and Japanese (GMS) correlations fell in between. Note that all had correlations of approximately 0.9 at their minimum sampling distance, which was 100 km for Wisconsin and 300 km for NESS. Wisconsin had many observations under 100 km separation, while ESA and GMS had few observations in close proximity and had an effective sampling distance of 100–200 km. NESS cloud motions were even less dense with a mean spacing of approximately 300 km.

Wisconsin may have lower correlations at 400 km and larger distances because of the ±15° latitude restriction. Experiments with limiting the latitude bounds of the high density Seasat data produced a similar decrease in the autocorrelation statistic.

Some differences among wind producers are apparent in the directional difference information (Fig. 3b). Wisconsin had the highest directional differences and NESS the lowest. The speed standard deviations (Fig. 3c) showed the opposite ranking—Wisconsin and GMS were lower, NESS and ESA higher. These statistics suggest that NESS generated a more directionally smooth product with larger speed variation than Wisconsin.

5. Conclusions

Cloud motion, RAOB and automatic aircraft (AI-REP) data are statistically similar and probably could be handled similarly in analysis schemes except for the special problem of height assignment for cloud motions. The statistical characteristics are similar in both the low and high levels of the atmosphere.
The data that will require either special editing techniques or large averaging or smoothing are the land surface stations, ship reports and pilot reported AIREPs. Land stations and ship reports have problems with low autocorrelations and excessive variance in wind direction. This may be addressed by editing schemes that remove data with large deviations from the mean. Their speed data had standard deviations equivalent to the other systems, but it was poorly correlated, implying that smoothing is needed. Pilot reports had excessively large standard deviations of scalar speed which implies that special editing and smoothing techniques should be developed specifically for these data.

Some data should not be extrapolated over distances greater than 300 km because they were poorly correlated at these and longer distances. This is most evident for land surface stations, ship reports, and pilot reported AIREPs. These data can provide wind information only in regions where a high density of observations occurs. Averaging a large number of reports is definitely required to remove remnants of very small-scale structure.

The low-level winds appear to have directional information that is better than their scalar speeds. Their vector correlations were higher than the scalar speeds and the standard deviations of scalar speed showed little increase with distance, except for the Seasat scatterometer data. The flat profile of scalar speed SD is especially alarming because it implies that noise or errors in the data are as large as the signal or structure in the wind field itself. To make accurate analyses, wind speed data are needed in high density to smooth out this noise. In the near future, satellite radar altimeters and passive microwave sensors will be able to produce scalar wind speed information with good coverage for oceans. Because of the deficiency of surface speed information from other sensors, the inclusion of scalar speed data with the conventional wind vector data should be welcomed.

The need for the observing systems to provide for the required smoothing is apparent. Pierson (1983) extensively discusses the need for observations to have spectral characteristics compatible with the analyses to be made from them. Winds averaged over two minutes, as presently reported at six-hourly intervals from ships, are not compatible with synoptic scale analyses. Similarly, wind reports at hourly, or six-hourly, intervals from land stations require averaging over a much larger fraction of the time interval between reports to represent synoptic scales consistently.

It should be recalled that “synoptic” implies spatial as well as temporal scales. However, by Taylor's hypothesis, statistics of random eddies over an area at a particular instant and an average over time at a particular point should be similar. Thus, while the scatterometer measurements each represent a few seconds in time, they are more representative of synoptic scales since areas ∼100 by 100 km are observed.

We agree with Pierson’s conclusion that to obtain good data for synoptic or global scale applications, the observing system should provide for longer averaging periods. This could be done either by instrumental averaging before the data are reported, or by combining very frequent reports of shorter duration averages. The latter, which is increasingly feasible with modern telecommunications and computational technology, would also permit applications on smaller scales.

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