P2.12 CLUSTERING OF COLD CLOUD MICROPHYSICAL PROPERTIES

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1. INTRODUCTION

Despite the deicing capabilities of modern aircraft, crashes still occur in icing because engineers cannot test for all possible conditions. Also, forecasts are still not sufficiently accurate to allow aircraft to always avoid icing. As a result, a government team is developing radar and microwave radiometer technologies for remotely mapping hazardous icing conditions ahead of aircraft (Ryerson et al., 2001). Establishing the capabilities of such systems requires consideration of the spatial properties of the cloud microphysical environment they must measure. Also, spatial fluctuation of cold, supercooled cloud microphysics affects the type and location of ice formation on airfoils, thereby strongly affecting aircraft performance.

This paper describes methods we use to characterize spatial patterns of cloud liquid water content (LWC) in supercooled clouds. Analyses were performed on data collected by the NASA Glenn Research Center.

2. BACKGROUND

Clustering refers to clumping, or patchiness, in cloud microphysical properties, and implies that consecutive values of cloud properties correlate over a distance. Unlike a Poisson series where individual values in a series are independent and not correlated with one another, in a clustered data series values are not independent (Jameson and Kostinski, 2000).

The ability of remote sensing systems to reliably detect icing conditions ahead of aircraft requires that cloud microphysical properties be accurately characterized. Clustering of cloud properties may affect the ability of radar to detect and measure cloud LWC, the primary cause of icing on aircraft (Martner et al., 1993). Clustering may also make aircraft icing more dangerous, further justifying the need for remote sensing systems to operate reliably in clustered conditions. Clustering may cause alternating low and high LWC, which may cause rime icing in some clusters and glaze icing in others as the Schumann–Ludlam Limit is crossed, forming ice shapes that destroy aircraft aerodynamics.

Clustering of cloud microphysical parameters was examined by Cooper et al. (1982) by summarizing exceedance of LWC thresholds by season. Cober et al. (1995), with a similar procedure, describe the patchiness of supercooled liquid water encountered in the Canadian Atlantic Storms Project (CASP) using histograms of encounter number versus duration for patches of LWC greater than 0.025 g m^{-3}.

Considerable research has addressed the fluctuations of droplet size and LWC at small scales within clouds to assess turbulence, cloud evolution, and the radiative properties of clouds (Davis et al., 1999; Cahalan and Joseph, 1989; Korolev and Mazin, 1993). However, for our work the most appropriate analysis methods are presented by Jameson and Kostinski in a series of papers beginning in 1997. One of their recent papers (Jameson and Kostinski, 2000) describes the application of their techniques to synthetically derived icing cloud series.

3. METHODOLOGY

By definition, cloud microphysical properties that are not clustered exhibit a Poisson distribution. Therefore, the first step in an analytical approach involves determining if clustering occurs in a data series. Kostinski and Jameson (1997) show that a two-point autocorrelation function, as given in equation 1, can be used to determine the presence of clustering:

$$\eta(l) = \frac{\left[\overline{k(l)k(0)} - \mu^2\right]}{\mu^2} \qquad (1)$$

where μ is the mean of the series, and *k(0)* and *k(l)* are the values at the reference location (time) and distance (time), respectively, at a distance (seconds) from the reference. If clustering does not occur and all values in the series are statistically independent, or Poissonian, the mean of the series equals the variance $\overline{k(l)k(0)} = \mu^2$ and the two-point autocorrelation function, $\eta(l)$, is equal to zero.

The second step is to specify the "average size" of the clusters. The average scale or size of clusters, defined as the coherence length, $\chi_{(l)}$, is the length at which the autocovariance function equals 1/*e*, where *e* is the base of the natural logarithm and 1/*e* = 0.3679 (Jameson and Kostinski, 2000). The autocovariance, $C_D(l)$, is defined as

$$C_D(l) = \frac{\left[\overline{k(l)k(0)} - \mu^2\right]}{\sigma^2} \qquad (2)$$

where σ^2 is the variance for the data series.

In the final step, a clustering intensity parameter, ℵ, is determined as suggested by Jameson and Kostinski (2000) as

$$\aleph = \eta(0)\left(1 - \frac{\mu}{\sigma^2}\right). \qquad (3)$$

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The clustering intensity parameter depends on the value of the two-point autocorrelation function at zero lag length and the mean and variance associated with the data series. The clustering intensity provides insight into the magnitude of the values associated with clustering relative to the mean (see Jameson and Kostinski, 2000, Figure 4). In a Poisson distribution where clustering does not occur, the clustering intensity is zero. This follows directly from the fact that in a Poisson distribution the mean equals the variance, where the last term in equation 3 will equal one, and the corresponding clustering intensity will be zero. The clustering intensity increases as the variance increases relative to the mean for a given value of the two-point autocorrelation function. Two data series can have the same mean, but the series that contains values that differ the most from the mean will have the greatest clustering intensity.

During our analyses we observed that cluster intensity and correlation length are dependent on start and end points along the series because the series are nonhomogeneous. This was investigated by systematically varying the length of individual flight segments as well as start and stop points. Inclusion or exclusion of cluster elements into the flight segment change the "bulk" cluster length and cluster intensity properties. To address this, we computed bulk $\chi_{(l)}$ and ℵ, and also computed a time-varying $\chi_{(l)}$ and ℵ through each flight segment using a process described below for segment lengths that are representative of remote sensing system ranges.

4. INFLIGHT MEASUREMENTS

The NASA Glenn Research Center conducted the Supercooled Large Drop Research Program (SLDRP) (Miller et al., 1998) to characterize supercooled large drops (SLD) aloft, freezing rain, and freezing drizzle. This paper uses 33 selected segments of 25 SLDRP flights from both winters. A total of 14.9 hours of flight time was captured in the flight segments, which averaged 27 minutes in duration, or 115.5 km each (Table 1). Dependence of LWC variability on height above cloud base (or below cloud top) led us to seek flight segments that occurred at a nearly constant altitude. However, aircraft position with respect to cloud boundaries is unknown for any single measurement.

LWC measurements were obtained from a CSIRO-King hot wire probe mounted on the top of the aircraft nose. LWC is supplied at 1-sec intervals. Flight segments had no breaks in cloud and were as long as possible to provide the best cluster statistics. Also, several segments had periods removed where the aircraft changed altitude for short periods (Table 1).

5. ANALYSES

We analyzed the NASA flight measurements in two different ways. First, we used the Jameson and Kostinski techniques to assess the clustering characteristics of LWC for each entire flight segment. This provided bulk cluster statistics for each of the 33 flight segments. To assess variability in short distances, we applied the same methodology to assess short sub-segments of flight, representing the range of a remote sensing system, and created time-series of cluster intensity and cluster length through flight segments.

Table 1. Flight segment characteristics. Trailing letters a, b, or c following flight segment identifiers indicates multiple segments of one flight.

Flight segment identifier	Length (km)	LWC mean (gm^{-3})	LWC $\chi_{(l)}$ (km)	LWC ℵ
970115f1	173.7	0.10	1.0	0.21
970115f2a	103.6	0.03	0.07	0.34
970115f2b	60.2	0.03	0.07	0.52
970122f2	58.2	0.20	5.5	0.27
970124f1	120.3	0.05	3.9	0.24
970124f2a	87.8	0.07	5.4	0.66
970124f2b	65.8	0.08	6.7	0.47
970124f2c	131.4	1.83	4.0	0.24
970127f1	94.0	0.13	6.3	0.41
970204f2	122.0	0.13	1.4	0.66
970306f2	78.1	0.11	0.8	2.16
970311f3	105.2	0.18	0.9	0.37
970314f2	184.1	0.15	19.7	1.59
971209f1	118.1	0.77	1.9	1.17
971209f2	71.5	0.96	18.9	0.19
971211f2	75.5	2.01	18.8	0.29
980122f1	96.0	0.11	2.7	0.47
980126f2	214.5	0.12	5.4	0.54
980126f3	103.8	0.16	7.3	0.90
980130f1	88.3	0.09	3.2	0.44
980204f1a	209.7	0.03	0.7	0.06
980204f1b	170.4	0.20	0.8	0.21
980204f2	290.2	0.22	13.0	0.36
980204f3	51.8	0.05	17.3	0.33
980205f1	125.1	0.09	4.6	0.41
980205f2	73.8	0.02	1.0	0.26
980212f1	112.2	0.20	38.6	0.18
980224f1a	60.7	0.14	8.0	0.84
980224f1b	132.9	0.10	3.1	0.86
980227f1	163.9	0.27	1.8	0.59
980302f1	106.4	0.05	0.7	1.77
980318f1a	93.1	0.04	1.1	0.87
980318f1b	69.7	0.03	0.4	0.49

Bulk LWC cluster intensity, ℵ, as measured over each of the entire flight segments, varies from a low of 0.06, indicating almost no clustering, to a high of 2.16 (Table 1). The majority of bulk cluster intensities are less than 0.6, with only four intensities greater than 1.0. Mean bulk cluster intensity is 0.59, with a median of 0.44.

LWC coherence lengths, $\chi_{(l)}$, considering the average Twin Otter flight speed of about 70 m s^{-1}, ranged from about 0.07 km to 38.6 km in length, with mean and median lengths of 6.21 km and 3.20 km, respectively (Table 1). Forty-two percent of the flight segments had cluster lengths of 2 km or less in length.

The primary purpose of our work was to determine the magnitude of cloud LWC spatial variation for remote sensing systems. An icing remote sensing system would need to provide pilots with sufficient time to react if hazardous icing is detected. We chose 20-km and 40-km ranges, computing the LWC ℵ and $\chi_{(l)}$ parameters for overlapping, non-independent 20- and 40-km sub-segments incremented at 2-km intervals from the beginning of each flight segment to the end.

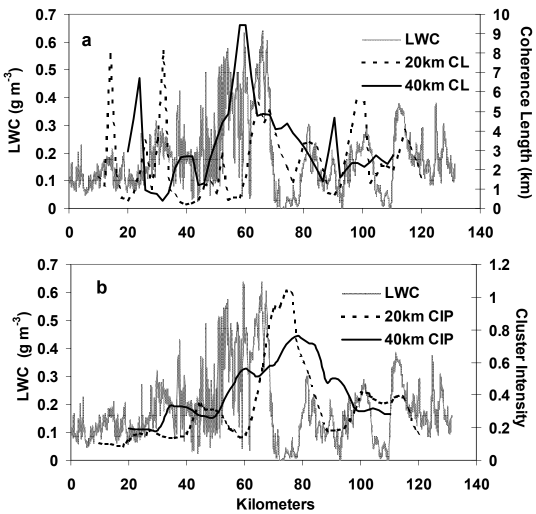

Figure 1. Flight segment 970124f2c 20-km and 40-km coherence length, $\chi_{(l)}$, cluster intensity, $\aleph$, and 1-sec LWC. CL = coherence length; CIP = cluster intensity parameter.

Figures 1a and 1b show cluster length, $\chi_{(l)}$, and cluster intensity, $\aleph$, respectively, plotted for the 20-km and 40-km distances for flight segment 970124f2c. Coherence lengths behave as expected, becoming longer or shorter when the 1-sec LWC visually suggests clusters should be longer or shorter. Cluster intensities may at first appear counterintuitive, but recall that each plotted $\aleph$ corresponds to a 20-km or 40-km sub-segment length of the entire flight segment. For example, when the 1-sec LWC measurements appear to be highly clustered at 60 km into the flight, the 20-km sub-segment cluster intensity indicates that clustering is low. And, at about 75 km into the flight, the 1-sec LWC measurements suggest that clustering is low when the 20-km sub-segments indicate that cluster intensity is high. This response is a result of the last term in equation 3, which indicates that as the mean decreases relative to the variance, cluster intensity increases. And, as the mean increases relative to variance, cluster intensity decreases. In Figure 1b, areas with smaller means but with relatively large variances tend to have larger 20-km sub-segment cluster intensities, whereas areas with high variance, but also with a high mean LWC, show a lower 20-km sub-segment cluster intensity.

6. DISCUSSION

Jameson and Kostinski (2000) performed their analyses on simulated icing cloud LWC. Our analyses indicate that clustering of actual cloud LWC varies over a wide range of cluster intensities and coherence lengths. Our largest bulk cluster intensity, 2.16, barely exceeds the largest value, 2.0, illustrated in Jameson and Kostinski's (2000) Figure 4, though they do not provide an expected range for natural conditions. Our smallest bulk cluster intensity, 0.06, suggests that flight segment 980204f1a is nearly Poissonian, and thus has no LWC clustering (Table 1).

We found cluster intensity to vary over a wide range between flights, but found conditions to be quite similar among multiple segments selected from the same flight. For example, segments a, b, and c from flight 970124f2 have similar cluster intensities ranging from 0.24 to 0.66, and cluster lengths ranging from 4.0 to 6.7 km (Table 1). Segments a and b of flight 980224f1 have nearly identical cluster intensities of 0.84 and 0.86, respectively. Segments a and b of flight 970115f2 have identical, and very low, cluster lengths of 0.07 km, so low that these flight segments are essentially not clustered, but Poissonian. This consistency suggests that atmospheric dynamics controlling clustering persisted for a considerable time and distance in these flights. It also suggests that, if this is the case, the Jameson and Kostinski algorithms are quite consistent in their ability to represent LWC clustering conditions.

Of multiple segments taken from a single flight, only the two flight 971209f1 segments deviated significantly from one another in cluster intensity and cluster size. Variation of $\aleph$ and $\chi_{(l)}$ through flight segments along the 20-km and 40-km sub-segments are very responsive to changes in LWC mean and variance, and provide an indication of the amount of variation a remote sensing system might encounter.

Cluster climatologies could be used to assess aircraft icing conditions and the potential performance of icing remote sensing systems synoptically, regionally, and seasonally. To mimic the clustering of LWC observed we have developed a model to generate Correlated Data Series (CDS) of LWC (Koenig et al., 2002).

7. CONCLUSIONS

Clustering intensities and correlation lengths developed from Jameson and Kostinski's (2000) methodology do provide a consistent method of analytically assessing clustering. Also, the incremented 20-km and 40-km sub-segments of cluster intensity and correlation length through flight segments provide information about the apparent fluctuation of conditions that might be experienced by a remote sensing system scanning ahead of an aircraft. The usefulness of Jameson and Kostinski's techniques lies in the ability to quantitatively characterize clustering, summarize it, and create new, but representative, cloud series that will be useful for assessing remote sensor and aircraft performance.

In addition to the LWC examples presented here, we will examine other parameters such as temperature, particle concentration, particle size spectra, and glaciation. We also believe it would be useful to assess the size of individual clusters within the average cluster size, $\chi_{(l)}$, for flight segments because aircraft experience actual clusters in flight. To demonstrate the importance of clustering to the aircraft icing process, we are assessing the effects of clustered versus Poissonian cloud LWC in a NASA icing research tunnel.

Our analyses suggest that most actual icing clouds are typically "patchy" and are rarely Poissonian. Clustering of cloud microphysical properties affects icing processes and, potentially, the ability and reliability of remote sensing systems to identify icing conditions.

Clustering quantification, and perhaps creation of representative data series from climatological summaries of clustering, will allow more accurate modeling of icing and remote sensing system performance.

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