Structural and Textural Characteristics of Cirrus Clouds Observed Using High Spatial Resolution LANDSAT Imagery

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ABSTRACT

Twelve cirrus scenes are analyzed to determine textural and structural features using LANDSAT imagery. The main structural characteristics are: 1) cirrus cloud size distributions obey a power law, with larger cloud cells (D > 1.5 km) having smaller slopes than smaller cloud elements; 2) convective-type cirrus are fractal in nature with fractal dimensions of about 1.3; while stratiform cirrus clouds show bifractal behavior, with larger clouds having smaller fractal dimensions (≈1.3); 3) stratiform cirrus cloud cells have significantly larger horizontal aspect ratio than do smaller cells; and 4) structural results are not sensitive to threshold selection.

The main textural characteristics are: 1) convective cirrus clouds have high contrast measures and a rapid decrease of correlation at short distances, while stratiform cirrus clouds have low contrast measures and more gradual slopes; 2) asymptotic values are good descriptors of general characteristics (macrotexture) of cloud fields, while the slopes of textural measure curves at small distances reveal information about cloud field microtexture; 3) contrast and correlation appear to be the best discriminators of cloud field structure, and their directional measures show preferred cloud field orientation; and 4) correlation measures are sensitive to threshold selection for cirrostratus cases.

1. Introduction

Though the influence of cirrus cloudiness on weather and climate is widely recognized, the extent of cirrus clouds' impact on the climate system remains controversial. On the global average, cirrus clouds tend to have a warming effect on the earth's surface (e.g., Stephens and Webster 1981). However, the magnitude of the effect depends on the difference between surface and cirrus temperatures and cirrus optical depths at high optical depths cirrus clouds can cause cooling rather than warming.

Variations in crystal lengths and size distribution are as important as column ice content in determining cloud optical depth and radiative divergences (Welch et al. 1980; Ramaswamy and Detwiler 1986). The presence of a small ice crystal size mode (Heymsfield 1975) significantly alters the radiative characteristics of the cirrus cloud. Likewise, cellular convection patterns play an important part in the vertical and horizontal distribution of ice water content. Finally, the size and structure of cloud horizontal inhomogeneities have significant impact upon their radiative properties (Welch 1983; Welch and Wielicki 1984). Therefore, a definitive analysis of cirrus cloud properties requires observations of structure, microphysics, and radiation field variations.

It is typical to model the radiative properties of cirrus clouds with plane-parallel codes such as delta–Eddington or Adding–Doubling. However, cirrus optical depth and emissivity can vary substantially on horizontal scales of less than 1 km (Starr and Cox 1985). Low resolution meteorological satellite sensors often give the appearance that cirrus are structurally featureless. However, the LANDSAT high spatial resolution sensors reveal that even cirrostratus formations have significant structure. Due to nonlinear relationships in retrieval algorithms, cloud properties derived from lower resolution spatially averaged satellite data may be substantially in error. The present study represents a first step in improving these algorithms by examining the detailed structure of cirrus clouds.

The data analyzed in this study are described in section 2. The method of structural analysis is explained in section 3 and the method of textural analysis is explained in section 4. Results of both structural and
textural analyses are given in section 5, and the conclusions are presented in section 6.

2. LANDSAT imagery

The LANDSAT sensors are in sun-synchronous orbits, sampling the earth at approximately 9:30–10:00 Local Standard time (LST). The satellite obtains data for a 185 km wide north/south strip along the groundtrack which is then broken up into 170 km × 185 km scenes. The Multispectral Scanner (MSS) instrument has spatial resolution of 57 m with four narrow spectral bands at (0.5–0.6) μm, (0.6–0.7) μm, (0.7–0.8) μm, and (0.8–1.1) μm wavelengths. Band 3 images are chosen for analysis in this study for the following reasons: 1) to reduce Rayleigh scattering at shorter wavelengths; and 2) to avoid water vapor absorption at longer wavelengths.

Twelve cirrus scenes from various regions are selected for this study (Fig. 1). Four of these cases (Figs. 1a, 1b, 1i, and 1j) are taken over the ocean, and the remainder over land. This selection contains a rich variety of cirrus clouds, including the three basic types: cirrus, cirrocumulus, and cirrostratus, with common sub-species: fibratus, uncinus, spissatus, and nebulosus.

The first row of Fig. 1 shows broken individual cirrus clouds. The second row is composed of cirrostratus, and the third row contains various cirrus forms. A brief description of each scene is found in Table 1.

From each scene, a homogeneous region of 2048 × 2048 pixels (116.7 km × 116.7 km) is outlined (Fig. 1). The background is kept as uniform as possible to improve cloud detection. Scene locations, dates, and times are listed in Table 1.

3. Structural analysis

It is assumed that clouds are brighter than the background. It is also assumed that there is a unique brightness value (or threshold) which separates cloud pixels from the background. The process of threshold selection and image segmentation is a challenging problem in analyzing remotely sensed satellite images. Because of their semitransparent nature, cirriform clouds are difficult to detect and segment from the background in satellite imagery. An analysis of various threshold approaches is given by Wielicki et al. (1986) and Welch et al. (1988a). The present study applies the Reflectance Threshold Method (RTM) discussed in detail by Wielicki and Welch (1986).

a. Cloud cover threshold

In order to select the threshold which defines the cloud/no-cloud boundary (represented by a gray level brightness value Gb), the frequency of occurrence gray level histogram is constructed first. Figure 2 shows the frequency of occurrence histograms for the twelve cases.

<table>
<thead>
<tr>
<th>Case</th>
<th>LANDSAT satellite</th>
<th>Location</th>
<th>Date</th>
<th>Time (UTC)</th>
<th>Description</th>
<th>Homogeneous subregion</th>
<th>Cloud cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>5</td>
<td>34°37'N/121°27'W</td>
<td>24/12/85</td>
<td>1808</td>
<td>Cirrus uncinus and cirrus spissatus</td>
<td>Upper left</td>
<td>27.5</td>
</tr>
<tr>
<td>B</td>
<td>5</td>
<td>27°26'N/078°29'W</td>
<td>03/05/85</td>
<td>1513</td>
<td>Cirrus fibratus outflowing from convective storms</td>
<td>Centered</td>
<td>3.2</td>
</tr>
<tr>
<td>C</td>
<td>3</td>
<td>41°40'N/127°39'E</td>
<td>20/08/79</td>
<td>0132</td>
<td>Elongated cirrus spissatus and fibratus oriented NE–SW (45°)</td>
<td>Centered</td>
<td>25.1</td>
</tr>
<tr>
<td>D</td>
<td>2</td>
<td>44°29'N/104°34'W</td>
<td>20/05/81</td>
<td>1658</td>
<td>Cirrus floccus and fibratus over the Black Hills, SD</td>
<td>Center right</td>
<td>8.5</td>
</tr>
<tr>
<td>E</td>
<td>5</td>
<td>46°03'N/066°53'W</td>
<td>27/06/86</td>
<td>1436</td>
<td>Cirrostratus fibratus oriented NW–SE (135°)</td>
<td>Upper right</td>
<td>94.8</td>
</tr>
<tr>
<td>F</td>
<td>5</td>
<td>31°45'N/099°04'W</td>
<td>28/10/85</td>
<td>1637</td>
<td>Silky cirrostratus nebulosus</td>
<td>Upper right</td>
<td>99.9</td>
</tr>
<tr>
<td>G</td>
<td>5</td>
<td>53°07'N/056°37'E</td>
<td>13/09/86</td>
<td>0630</td>
<td>Cirrostratus fibratus with arc shape</td>
<td>Upper right</td>
<td>79.6</td>
</tr>
<tr>
<td>H</td>
<td>5</td>
<td>60°06'N/149°33'W</td>
<td>05/11/85</td>
<td>2036</td>
<td>Cirrostratus fibratus</td>
<td>Upper center</td>
<td>88.6</td>
</tr>
<tr>
<td>I</td>
<td>4</td>
<td>55°54'N/082°25'W</td>
<td>09/10/82</td>
<td>1558</td>
<td>Broken cirrostratus fibratus</td>
<td>Lower right</td>
<td>17.6</td>
</tr>
<tr>
<td>J</td>
<td>5</td>
<td>40°20'S/063°31'W</td>
<td>23/05/85</td>
<td>1328</td>
<td>Feathery looking cirrostratus fibratus and cirrus fibratus</td>
<td>Lower center</td>
<td>25.0</td>
</tr>
<tr>
<td>K</td>
<td>5</td>
<td>53°06'N/054°33'W</td>
<td>18/09/85</td>
<td>1403</td>
<td>Wispy cirrus uncinus, cirrocumulus and cirrostratus fibratus</td>
<td>Upper right</td>
<td>17.8</td>
</tr>
<tr>
<td>L</td>
<td>5</td>
<td>36°03'N/097°52'W</td>
<td>28/10/85</td>
<td>1636</td>
<td>Thin cirrostratus and contrails</td>
<td>Upper left</td>
<td>17.3</td>
</tr>
</tbody>
</table>
shown in Fig. 1. The RTM approach finds the first maximum in the histogram and chooses this value as the clear-sky count. The clear-sky count represents the digital value for a uniform background in the image. For example, in Fig. 2, the clear-sky value for Case B over the ocean is 8 counts, compared to 56 counts for Case C over land.

Once the clear-sky count is chosen, the threshold digital count, $G_{th}$, is computed which separates background from cloudy pixels. This value is chosen for Band 3 to have an equivalent Lambertian reflectance of 8.5% above the clear-sky count over land, 3% above the clear-sky count over water (Wielicki and Welch 1986; Wielicki et al. 1986). Conversion from gray level counts to radiance and reflection values is found in the appendix. For example, the chosen threshold, $G_{th}$, for Case C is gray level 78. Each selected threshold is verified using a Remote Image Processing System (RIPS).

It is found that this choice of “cloud cover threshold” maintains consistency in separating clouds from background. Cloud cover for the twelve case studies is given in Table 1.

b. Cloud cell threshold

For cumulus clouds, the “cloud cover threshold” segments cloud regions from which cloud statistics can be generated. However, for stratocumulus and cirrus clouds, the regions between the bright cells are not clear. Should the “cloud cover threshold” be used to determine cloud structure for these scenes, large regions of the cloud field would be classified as single clouds, thereby providing little or no insight into the underlying cellular cloud structure. Therefore, a larger cloud cell threshold is defined to avoid this problem. In particular, the “cloud cell threshold” is set equal to the median cloud reflectance, separating the brightest half of the cloudy pixels from the darkest half of the cloud pixels (Welch et al. 1988a). In this manner, a simple relationship is maintained between total cloud area and the cloud area used to analyze the cloud cell properties.

First, the total number of cloud pixels, $N_c$, is calculated. The cloud cell threshold, $G_{th}$, is obtained by summing the histogram frequency of occurrence values, $F_i$, until a value

$$\sum_{i=0}^{aN_c} F_i \geq aN_c \quad (1)$$

is reached:

$$N = \sum_{i=0}^{G_{th}+1} F_i \quad (2)$$

where $a = 0.5$. Thresholds obtained by setting $a = 0.0$, $0.2$, $0.3$, and $0.4$ in Eq. (1) are used to analyze the sensitivity of results to threshold selection in section 5a–5 for structural analysis and 5b–4 for textural analysis.

c. Structural characteristics

After the threshold digital count is found, each pixel with digital count greater than $G_{th}$ is flagged as a cell pixel. These cell pixels are then grouped into individual cells in a single pass through the digital image, starting at the top and examining three scan lines at a time (Wielicki and Welch 1986).

As each cell is completed, statistics for the cell are computed and saved. Cell area is determined as the
number of cell pixels multiplied by the pixel area \((0.057 \text{ km})^2\). Effective cell diameter \(D\) is defined as a circle of area equal to the cell area. Running scans for the first and second moments of cell pixel position are compiled, from which cell center, cell horizontal aspect ratio, and cell orientation angle are determined. See Welch et al. (1988a) for details.

4. Textural analysis

Texture has been interpreted in the literature as a set of statistical measures of the spatial distributions of gray levels in an image. Haralick (1979), Connors and Harlow (1981), and McCormick and Jayaramamurthy (1974) have concentrated in defining representative textural features of an image. These efforts have attempted to quantify such intuitive notions as fineness, smoothness, granularity, randomness, lineation, and mottledness. For example, coarser and definitive textures relate to large regions with similar gray levels, and noisy texture relates to smaller regions with rapid gray level change.

A number of statistical models have been introduced in the literature: 1) the autocorrelation model; 2) the power spectrum model (Chevalier et al. 1968); 3) the Markov random field model (Cross and Jain 1983; Garand and Weinman 1986); 4) the co-occurrence statics model (Julesz 1962); 5) the fractal model (Mandelbrot 1982; Lovejoy and Schertzer 1986); 6) the facet model (Haralick 1979); and 7) the mosaic model (Ahuja and Rosenfeld 1981). The present study is restricted to the co-occurrence statistical model.

a. Spatial gray level co-occurrence matrix

This method assumes that the texture information in an image is contained in the overall or “average” spatial relationship that the gray levels in the image have to one another (Haralick et al. 1973). More specifically, it is assumed that this texture information is characterized by a set of co-occurrence matrices \(P(i, j)_{d,\phi}\) where the \((i, j)^{th}\) element is the relative frequency with which two pixels separated by distance \(d\) in direction \(\phi\) (angle with horizontal direction) occur in the image, one with gray level \(i\) and the other with gray level \(j\). These matrices of gray level spatial-dependence frequencies are functions of both the distance and relative orientation of the pixels. For a coarse texture, pairs of points have similar gray levels, and high values result on or near the main diagonal of the co-occurrence matrix (Weszka et al. 1976). For fine texture, the matrix values spread out relatively uniformly.

The procedure is as follows:

1) The image is level sliced into a smaller number of intervals \(N_e\) in order to ease the computational burden (Weszka et al. 1976; Holmes et al. 1984). Thus, \(N_e\) is the effective number of gray levels in use. In the present investigation, the intervals are chosen as (0–3), (4–7), \ldots, (124–127), so that \(N_e = 32\).

2) The co-occurrence matrices are computed over a moving window of \(512 \times 512\) pixels with displacement distances of \(d = 1, 2, 4, 8, 16, 32, 64, 128, 256,\) and \(512\) pixels, at angles of \(\phi = 0^\circ, 45^\circ, 90^\circ,\) and \(135^\circ\). The matrices \(P(i, j)_{d,\phi}\) are normalized to \(p(i, j)_{d,\phi}\).

3) Textural features then are computed from these co-occurrence matrices. The present study utilizes eight textural measures defined below.

b. Eight textural features

1) CONTRAST

\[
f_1(d, \phi) = \sum_{i=0}^{N_e-1} \sum_{j=0}^{N_e-1} (i - j)^2 p(i, j)_{d,\phi}\]

are difference moments of the \(p\) matrix. Contrast is a measure of the amount of local variations.

2) CORRELATION

\[
f_2(d, \phi) = [\sum_{i=0}^{N_e-1} \sum_{j=0}^{N_e-1} ij p(i, j)_{d,\phi} - \mu_h \mu_v] / \sigma_h \sigma_v\]

where \(\mu_h, \mu_v, \sigma_h,\) and \(\sigma_v\) are the mean values and standard deviations, respectively, of the marginal probability distributions \(p_h, p_v\) of the co-occurrence distribution given by

\[
p_h(i)_{d,\phi} = \sum_{j=0}^{N_e-1} p(i, j)_{d,\phi}\]

\[
p_v(i)_{d,\phi} = \sum_{j=0}^{N_e-1} p(i, j)_{d,\phi}.\]

Correlation is a measure of gray level linear dependencies in the scene.

3) ANGULAR SECOND MOMENT

\[
f_3(d, \phi) = \sum_{i=0}^{N_e-1} \sum_{j=0}^{N_e-1} [p(i, j)_{d,\phi}]^2\]

is a measure of homogeneity in the scene. A small value of \(f_3\) indicates that the values of \(p(i, j)\)’s are approximately equal, and that there are few dominant gray levels. A large value of \(f_3\), on the other hand, indicates that some \(p(i, j)\)’s are much larger than others.

4) ENTROPY

\[
f_4(d, \phi) = - \sum_{i=0}^{N_e-1} \sum_{j=0}^{N_e-1} p(i, j)_{d,\phi} \log p(i, j)_{d,\phi}\]

is a measure of disorder in the scene, and it has the highest value when all \(p(i, j)\)’s are equal.
5) Local Homogeneity (or Inverse Difference Moment)

\[ f_s(d, \phi) = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j)_{d,\phi} / [1 + (i-j)^2] \]  

(9)

represents a measure of the amount of local similarity in the scene.

6) Goodness of Fit (or Contingency)

\[ f_6(d, \phi) = \left\{ \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} [p(i,j)_{d,\phi} - p_h(i)_{d,\phi} p_v(j)_{d,\phi}]^2 \right\}^{1/2} \]  

(10)

is a measure of dependency of two variables in a joint distribution (Renyi 1970). The value of goodness of fit is bounded between 0 and \((N_g-1)^{1/2}\), the square root of the number of distinct gray levels under consideration. If the variables \(h, v\) are independent, the measure is zero; if one variable is an exact function of another (not necessarily linear), then the measure will take the maximum value \([N_g-1]^{1/2}\).

7) Difference Cluster Shade

\[ f_7(d, \phi) = \left\{ \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} [(i-j) - (\mu_h - \mu_v)]^3 p(i,j)_{d,\phi} / (\sigma_h^2 + \sigma_v^2 - 2\sigma_{hv})^{3/2} \right\} \]  

(11)

is the third moment of the standardized difference distribution of the matrix \(p(i,j)\), where \(\sigma_{hv}\) is the covariance of the variable \(h\) and \(v\) in the joint distribution \(p(i,j)\). Difference cluster shade measures the degree of skewness or asymmetry of the distribution.

8) Difference Cluster Prominence

\[ f_8(d, \phi) = \left\{ \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} [(i-j) - (\mu_h - \mu_v)]^4 p(i,j)_{d,\phi} / (\sigma_h^2 + \sigma_v^2 - 2\sigma_{hv})^2 \right\} - 3 \]  

(12)

The portion contained by the wavy brackets is the fourth moment of the standardized difference distribution of \(p(i,j)\), which is sometimes used to measure the peakedness, or so-called ”kurtosis” of the distribution. For a normal distribution, this portion is equal to 3, resulting in \(f_8 = 0\). For a distribution which is more peaked than the normal distribution, this portion is greater than 3, and hence \(f_8 > 0\). Therefore, \(f_8\) is called the coefficient of excess of kurtosis.

5. Results

This study is one of a series of studies of cloud field characteristics derived from high spatial resolution LANDSAT imagery. The same structural analysis procedure has been applied to cumulus by Wielicki and Welch (1986) and Parker et al. (1986), to fogs by Welch and Wielicki (1986), and to stratocumulus by Welch et al. (1988a). The textural analysis model has been applied to stratocumulus by Welch et al. (1988b). Due to the fact that cirrus cloudiness has structural and textural characteristics which are significantly different from those of boundary layer cloudiness, reference is made in this section to these previous results.

a. Structural Analysis

Once the appropriate threshold has been selected to segment cloud cellular regions (section 3a), cloud pixels are grouped into individual clouds by the procedure described in section 3c. The clouds are then grouped into cloud size categories according to effective cloud diameters \(D\) with intervals chosen in equal steps of 0.4055 in \(\ln D\). This step size is equivalent to an increasing factor of 1.5 for each cloud size boundary in linear scale (i.e., 59 m, 88 m, 132 m, 198 m, etc.). This selection of cloud size classes usually maintains a large number of clouds in each size class for statistical reliability.

1) Cloud Size Distribution

The cloud size distribution is the distribution of cloud number density over each size category. Wielicki and Welch (1986) found for fair weather cumulus that the cloud number density decreases exponentially as cloud size increases. This is in agreement with cumulus cloud studies reported by Plank (1969) using aircraft photographs. However, for cumulus cloud fields containing larger sized clouds (Parker et al. 1986), for fogs (Welch and Wielicki 1986), and for stratocumulus cloud fields (Welch et al. 1988a), the size distribution \(n(D)\) is better represented by a power law of the form

\[ n(D) = n_0D^{-\alpha} \]  

(13)

where \(n_0\) and \(\alpha\) are constants and \(D\) is cloud diameter.

Figure 3a shows cloud size distributions for the twelve cirrus cloud fields shown in Fig. 1. Most notable is the fact that these cloud fields do not have a simple power law distribution. Rather, these curves show concavity, with one slope \(\alpha\) for small cloud cells of diameter 0.1 km to about 1.5 km and a different slope for clouds of larger diameter. For each of these cases, there is a transition region of cloud diameters, ranging from \(D \approx 0.5\) km to about \(D \approx 2.0\) km, in which the structure of the cirrus clouds is changing. It is difficult to observe much of the structure from the images shown in Fig. 1. This is largely due to the gray scale processing of the images done by EOSAT which is designed to emphasize surface features. Therefore, the detailed cloud structural characteristics are obtained only from the original digital data tapes.

Table 2 shows the slopes of the size distributions calculated for all twelve scenes. Averaging over all cloud
sizes, the overall slopes range from $\alpha = 1.91$ for cirrus uncinus in Case A (Fig. 1) to $\alpha = 2.51$ for the contrails in Case L. The variation of $\alpha$ for the small cells of size 0.1–1.5 km is from 2.33 to 3.07, while for cells greater than 1.5 km, the slope varies from 1.28 to 2.12.

The power law representation for stratocumulus clouds is just opposite to that of cirrus. Stratocumulus clouds have slopes ranging from $\alpha = 1.55$ to $\alpha = 1.86$ for smaller cells, and slopes ranging from $\alpha = 2.44$ to $\alpha = 2.90$ for larger cells (Welch et al., 1988a). Therefore, the size distribution shows convexity in stratocumulus instead of the concavity in cirrus. This suggests that there is a high production of small cirrus elements which rapidly merge into larger cells. At the larger cell sizes, the slope of the power law significantly decreases in cirrus, but significantly increases in stratocumulus. This suggests the destabilization of large stratocumulus cells, breaking-up into smaller cellular structures, compared to relative stability in large cirrus elements.

It is well known that the diurnal cycle of stratocumulus includes the growth of large cells at night followed by a tendency for breakup and/or dissipation by early afternoon. The closed convection patterns in stratocumulus clouds are strongly influenced by long-wave radiative cooling near cloud top (Bonnel et al. 1983; Randall et al. 1984; Agee 1985). Solar heating
of these layers during daylight hours tends to counteract the infrared cooling, potentially acting to destabilize the layer. In such a scenario, the cloud size distribution would be convex, with a strong decrease in the number of large cells due to increased circulation.

In simulations of convective thin cirrus, Starr (1987) finds that radiative processes strongly regulate the convective structure and ice water budget. Enhanced infrared radiative cooling is found to reduce the positive buoyancy and to reduce the vigor of circulation. Solar heating has the opposite effect. During midday, Starr finds that solar heating dominates infrared cooling, leading to more cellular and longer lasting cells. This behavior would lead to a size distribution which is concave, as found in Fig. 3a.

2) NORMALIZED CLOUD FRACTION DISTRIBUTION

Figure 3b gives the normalized cloud fraction distribution for the twelve scenes shown in Fig. 1. Cloud fraction per unit cloud diameter interval (i.e., % km⁻¹) is determined for each cloud size class and then normalized to a maximum value of 1.0. The peaks appearing at small cell sizes are due to the numerous small cells (with 1 to 4 pixels) found in that size range. This behavior is also different from stratocumulus clouds which have bell-shaped curves with maximum values at a dominant cloud size on the order of 0.3–0.6 km. In cirrus, the dominant cloud size occurs for clouds of diameter 0.1 km, with the contribution dropping steeply with increasing cloud cell diameter (Fig. 3b). At large cloud sizes, the normalized cloud fraction is relatively flat, or tends to increase gradually with increasing cloud cell diameter. However, the results may be statistically unreliable for cloud diameters on the order of $D \approx 10$ km.

For a cloud size distribution represented by a power law (Eq. 13), cloud fraction $S$ is given by

$$S = \frac{\pi n_0}{4} \int_{D_1}^{D_2} D^{2-n} dD,$$

where $D_2$ and $D_1$ are the largest and smallest cloud diameters in the interval, respectively. For $\alpha = 2$, cloud cover fraction is constant, independent of cloud diameter. In such a case, there would be no peak in cloud fraction. For $\alpha > 2$, $S$ decreases with increasing value of $D$, as seen in Fig. 3b for the small cloud cells. For $\alpha < 2$, $S$ increases with increasing value of $D$, as seen in Fig. 3b for some of the large cloud cells. Clearly, the shapes of the cloud fraction curves are determined by the variations of slope in the cloud size distributions.

3) THE FRACTAL NATURE OF CIRRUS CLOUDS

Fractals are objects with no intrinsic scale, with perimeters which depend only upon fractal dimension and resolution (Mandelbrot 1982). In a study of cloud fields using satellite imagery and radar, Lovejoy (1982) demonstrated the fractal nature of clouds. He showed that cloud perimeter $P$ and area $A$ are related by

$$P = cA^{d/2},$$

where $d$ is the fractal dimension and $c$ is a constant. For a smooth curve such as a circle, $d = 1$, while for a highly contorted boundary, $d = 2$. Lovejoy found a constant fractal dimension of $d = 1.35$ for cumulus clouds having areas ranging from $1 \text{ km}^2$ to $10^6 \text{ km}^2$. The implication is that clouds have no preferred length scales and that any size cloud or any enlarged region of a cloud is statistically indistinguishable from any other similar region (Lovejoy and Schertzer 1986).

Figure 4 shows perimeter-area relationships derived from the cirrus cloud fields. The fractal dimension $d$ (Table 2) ranges from 1.280 for Cases A and B to 1.568 for Case L. These values are similar to those found by Joseph (1986) in cumulus cloud fields and to those found by Welch et al. (1988a) in stratuscumulus. The stratiform cirrus cases (Cases E, F, G, H, and I) appear to be bi-fractal, with a distinct change of fractal dimension for cells of area greater than 2–3 km². The cell diameter at this break in fractal dimension is consistent with the diameter at which the size distribution changes. For the small cells (with $D < 1.5$ km), fractal dimension ranges from $d = 1.407$ to $d = 1.547$, and $d = 1.163$ to $d = 1.432$ for the larger cells. It appears that the large cirrostratus cloud fields have smaller fractal dimensions than convective cirrus clouds.

4) HORIZONTAL ASPECT RATIO

Horizontal aspect ratio is the ratio of the cell long axis moment to the cell short axis moment, as defined by Welch et al. (1988a). These values are shown for the twelve case studies in Fig. 5. Note the change of scale for cases E, F, G, and H. Horizontal aspect ratio has a value of approximately two for the small cells.
The stratiform cirrus cloudiness cases have significantly larger horizontal aspect ratios than do the other cirrus forms. It is apparent that these clouds enjoy a more stable environment.

5) SENSITIVITY TO THRESHOLD SELECTION

Section 3 describes the procedure of determining the cloud cell threshold $G_r$. Since the method is entirely

FIG. 4. Cloud cell perimeter vs cell area for the 12 cirrus cases. The slope provides the fractal dimension of these clouds.

with diameters less than about 0.6–1 km. For the larger sized cells, usually there is a dramatic increase in horizontal aspect ratio, by as much as an order of magnitude. Also note that the break point occurs at about the same diameter as the change in slope of the size distribution shown in Fig. 5a. This indicates that different processes are active for generating and dissipating small cells than for large cells.

FIG. 5. Horizontal aspect ratio vs cell equivalent diameter for the 12 cirrus cases.
Fig. 6. (a) Cloud size distribution, (b) normalized cloud fraction, and (c) fractal dimension of Case I for 100%, 80%, 70%, 60% and 50% cloud covers.

empirical, it is necessary to show that the results are only slightly affected by small variations in the choice of threshold. Otherwise, the resulting statistics would lose their representativeness.

Figure 6a shows cloud size distributions for Case I as a function of cloud cover. The value of 100% in Fig. 8a represents the choice of \( G_r = G_b \), or \( a = 0.0 \) in (1). This means that all cloudy pixels are used to determine the structure composition of this cloud field. Similarly, the value of 80% represents the setting of cloud cell threshold such that the brightest 80% of all cloudy pixels are used to determine cloud statistics. Calculations are repeated for the choices of \( G_r \) equal to 100%, 80%, 70%, 60%, and 50% of the brightest cloud pixels for Case I. Both the slope and values of the cell size distribution are well preserved, showing that structural calculations are not highly sensitive to threshold selection.

Figure 8b shows also the normalized cloud fraction distribution as a function of different percentages of cloud cover. The basic shape of the curves is also preserved. It is clear that the contribution of the small clouds is relatively constant with decreasing cloud cover (or increasing threshold value). This is because the larger clouds usually break into smaller ones as the threshold increases. Figure 8c shows that the fractal dimension remains relatively unchanged with increasing threshold. This once again illustrates that clouds do not have a preferential characteristic length scale.

b. Textural analysis

Calculations are made using the pixels of the homogeneous regions outlined in Fig. 1. Co-occurrence matrices are constructed from pixel pairs at distances of 1, 2, 4, 8, 16, 32, 64, 128, 256, and 512 pixels in all four directions (0°, 45°, 90°, and 135°). Note that a pixel covers an area of \( 57 \times 57 \) m² in LANDSAT MSS imagery. Therefore, the corresponding matrix distances in horizontal (0°) and vertical (90°) directions are 0.057 km, 0.114 km, 0.228 km, 0.456 km, 0.912 km, 1.824 km, 3.648 km, 7.296 km, 14.592 km, and 29.184 km. Along the two diagonals (45° and 135°), the distances are increased by a factor of \( \sqrt{2} \).

In order to eliminate background contamination, the 100% cloud cover threshold (section 3a) is applied. Only pixels with gray levels greater than the threshold \( G_b \) are used to calculate the textural features. The cloud cell threshold, \( G_r \), is not used in the textural analysis, because the problem of segmenting distinct cloud cells does not exist in this analysis. The various textural measures are relatively insensitive to the actual threshold selected.

1) CONTRAST

Contrast is the measure of local variation between pixels separated by a distance \( d \) at an angle \( \phi \). Figure 7 shows the measures of contrast for the twelve cirrus cases shown in Fig. 1. Each case shows values measured at 0°, 45°, 90°, and 135°. Four important properties of the contrast curve are: 1) the maximum, also called the sill or asymptotic value, if there is any; 2) the distance from the origin at which the asymptotic value is attained; 3) the slope of the contrast curve at small distances from the origin; and 4) the sill-initial slope intersection point.

The maximum, or asymptotic, value describes general cloud field characteristics at distances greater than
the size of a typical cloud element (i.e., macrotexture). The slope of the curve at small distances describes the contrast variation within a typical cloud element. The distance at which the curve deviates from the initial slope represents the size of smallest cloud elements in the cloud size distribution. Finally, the silt-initial slope intersection point should be related to average cloud size.

(i) Macrotexture. Equation (3) shows that contrast is equal to the sum of the square of the difference of brightness values $i$ and $j$ of pixels separated by distance $d$, multiplied by the joint probability estimate of occurrence. Therefore, low values of contrast are found when there is a low probability of widely differing reflectance values. Welch et al. (1988b) discuss the relations between histogram shape and contrast. They show that either a prominent peak or a narrow range of gray levels in the histogram decreases the probability of getting large values of gray level differences ($i-j$), and hence limits the value of contrast.

As an extreme, Case A has a wide range of gray levels within the cloud regions (Fig. 2) and a nearly equal probability of finding any given gray level value. It also has the largest values of contrast, as shown in Fig. 7. Case L has the narrowest range of gray levels within the cloud regions, and also the smallest values of contrast.

Generally, convective-type cirrus cloud fields (Cases A, B, C, D) have higher contrast values than do the cirrostratus (Cases E, F, G, H, I, and L). The clouds in Case J suggest convective characteristics, but their...
low reflectivities (Fig. 2) suggest that they are optically thin. Therefore, the asymptotic contrast value in this case also is small. Similar to the behavior found in stratocumulus clouds, low contrast often appears to be associated with flattened cells of thin clouds; high contrast appears to be associated with convective cells whose reflectance variations go from low values at cloud edges to high values in the interior regions.

(ii) Microtexture. Macrotexture is a descriptor of the textural components of the cloud field as a whole. Microtexture is a descriptor of the typical textural components of individual cells. It is expressed by the slope of the contrast curve near the origin.

On average, the smaller cells have rapid variations in reflectance across their dimensions. The large, flat cells with large aspect ratio tend to have more gradual variations of reflectance across their dimensions. Therefore, the smaller, highly convective elements are expected to display large variation in contrast over short distances (large slopes), whereas the larger, flatter cloud elements are expected to have more gradual slopes. The small clouds are most numerous, but the large clouds contain much larger numbers of pixels. The point at which the asymptotic value is reached is roughly the size of the largest elements in the cloudy field. Clearly, asymptotic values are not reached even at a distance of 25 km for Case F. This is a clear indication that case F consists of huge sheets of relatively solid cirrus deck (Fig. 1).

A very rapid rise to asymptotic value over distances on the order of 1 km or less as seen, for instance, in Case D indicates that reflectance is highly variable.
within these individual cells. In comparison, the very gradual increase for Case H suggests that reflectance is relatively uniform in these cirrostratus. This interpretation is supported by analysis of contrast measures in the four directions. Note that contrast in Case A is largest at vertical and smallest in the horizontal direction. Contrast is lowest along cloud street elements because the variation in reflectance is lowest in this direction. Contrast is highest perpendicular to cloud street orientation. Likewise, contrast is smallest at 135° for Cases E and F, along the cloud street elements (Fig. 1). It appears that cloud field orientation can be extracted from textural analysis.

2) CORRELATION

Correlation measures the gray-level linear dependencies in the cloud fields. Figure 8 gives the correlation curves in four directions for the twelve cases shown in Fig. 1.

Cloud fields composed primarily of small cloud elements show a rapid decrease in correlation coefficient over a short distance from the origin. All of the convective cirrus fields have this behavior. And, as the size of cloud elements increases (for example, cirrostratus Cases E, F, G, and H), the correlation coefficients show increasingly more gradual slopes. As a matter of fact, the point where correlation coefficient reduces to zero is directly related to the largest cell size in the distribution.

The correlation coefficient in this study of cirrus shows more information about directionality than the contrast measure. For example, Cases A, G, and H show a preferential orientation in horizontal direction, as seen in Fig. 1. Case F has very high values of correlation at both 90° and 135°. It can be seen in Fig. 1 that the cloud fields in Case F are aligned at an angle between 90° and 135° (about 120°). We also expect to see high correlations of Case L in horizontal and vertical directions due to contrails. The reason that only the strong vertical correlation is present is because of the lower reflectance of the horizontal contrails. They have been selectively removed by the threshold selection.

3) OTHER TEXTURAL MEASURES

There are eight textural measures defined in section 4b. Two of them, contrast and correlation, have been analyzed above in four directions. In the present section, the other textural measures are examined for their ability to distinguish structural features. Directionality is suppressed by averaging the textural features over the horizontal and vertical directions.

Figure 9a shows the angular second moment (ASM) feature which is a measure of homogeneity within the cloud field. Note that Cases I, J, K, and L have a different maximum vertical scale (0.6 as compared to 0.25). ASM has the minimum value when all the entries of the co-occurrence matrix \( p(i, j) \) are equal. A large value of ASM indicates that some pairs of \((i, j)\) have higher frequency of occurrence than others. Basically, cirrus generally have higher ASM values (0.01–0.2) than those found for stratocumulus (0.005). The long, relatively uniform brightness of the contrails in Case L leads to large values of asymptotic ASM. In comparison, the wide distribution of reflectance values for Case F leads to low values in ASM.

Figure 9b shows the measure of entropy. Entropy measures the degree of disorder of the cloud field. This measure is somewhat negatively correlated to the measure of ASM. Cirrus clouds have relatively smaller values of entropy than other cloud fields (see Welch et al. 1988b). The measures of entropy for cirrus generally are below a value of 2, except for the highly convective cases, while those of stratocumulus are in the range of 2–3.

Local homogeneity, or inverse difference moment, measures the degree of local similarity and is inversely correlated to contrast (Fig. 7). Regions of low contrast are those of high local homogeneity, and the converse. For example, Case L has the lowest contrast but the highest local homogeneity. Goodness of fit (Fig. 10b) shows behavior which is similar to that of correlation. Clouds with large cell size or limited range of gray level (reflectance) variation in the image have higher values of goodness of fit. However, contrast and correlation appear to be better discriminators of cloud type than are the local homogeneity and goodness of fit texture measures.

Difference cluster shade measures the skewness, or asymmetry, of the difference \((i–j)\) distribution of the joint occurrence matrix \( p(i, j) \). For a symmetrical \( p(i, j) \), this measure becomes zero. The matrix \( p(i, j) \) values are very symmetrical in Fig. 11a, with the deviation from symmetry no more than 0.5 in skewness. Difference cluster prominence represents a measure of peakedness (Fig. 11b). Examining these two measures together shows that the difference distributions of Cases E, F, G, and H are well centered and have a normal peak. This suggests that a normal distributional model of cloud reflectance may be appropriate for cirrostratus cloud fields. The other cirrus cloud fields have a difference brightness distribution with peakedness greater than normal.

4) SENSITIVITY TO THRESHOLD SELECTION

Two cases (A and F) are selected for the discussion of dependence of results to threshold selection. A set of thresholds corresponding to \( a = 0.0, 0.2, 0.4, \) and 0.6 in Eq. (1) are used, corresponding to cloud cover of 100%, 80%, 60, and 40%, respectively. The resulting averaged contrast and correlation measures are shown in Fig. 12.

The asymptotic values of contrast decrease with increasing threshold for both cases. This is due to the
small range of gray levels at a higher threshold. Yet, for distances less than and equal to 3.65 km, the contrast values increase in Case A as the threshold increases. Case F does not show this behavior. It appears that large clouds in Case A are composed of many multicellular elements which separate into smaller clouds as threshold is increased. These cells have significant variation in gray level (brightness). As the threshold increases, the larger clouds tend to break up into smaller clouds with strong local gray level variation, and the contrast increases. When cell size is relatively larger, this pronounced contrast within brighter centers is then “averaged out.”

The correlation curves for different thresholds for Cases A and F are also shown in Fig. 12. It can be seen that the decrease of correlation due to threshold increase is more drastic in Case F than in Case A. In cirrostratus, the change of reflectance within clouds is more gradual as compared to change within convective-type cirrus clouds. Figure 12 shows that the largest cell size decreases more rapidly with increasing threshold in Case F (cirrostratus) than in Case A (cirrocumulus). Therefore, the choice of threshold selection is more important for stratiform type cirrus.

Generally, the change of textural statistics due to small threshold variation is within a tolerable range.
Textural measures are relatively more sensitive to threshold selection than structural statistics. This fact emphasizes the importance of developing more accurate methods of threshold determination.

6. Conclusions

The present investigation has focused on the structural and textural characteristics of cirrus cloud fields using LANDSAT MSS high spatial resolution data for the analysis. The twelve scenes represent many typical cirrus cloud formations. While there are some significant differences between cirrostratus and cirrocumulus, these differences are minor compared to those of boundary layer cloudiness.

Conclusions for the structural analysis are:

1) Cirrus cloud size distributions obey a power law, with slopes ranging from 1.91 to 2.51. Cloud cells with effective diameters less than about 1.5 km have significantly larger slopes than do larger cloud cells. This suggests that different dynamic, and perhaps different microphysical, processes are active at these different spatial scales. The cirrus size distributions are concave in shape, compared to convexity found in stratocumulus size distributions. One interpretation is that solar
radiation tends to destabilize and dissipate large stratocumulus clouds while stabilizing and promoting large cirrus structures (Starr 1987).

2) Cirrus clouds are perimeter-area fractal in nature. Cirrostratus are bi-fractal. For the smaller sized cloud elements, fractal dimensions vary from 1.41 to 1.55, and from 1.16 to 1.43 for clouds larger than about 1.5 km in diameter. Other cirrus have a uniform fractal dimension at all cloud sizes, with values ranging from 1.14 to 1.40 (1.57 for the special case of contrails). In contrast, small stratocumulus clouds with $D \leq 0.5$ km have a smaller fractal dimension ($\approx 1.2$) than do the larger clouds ($\approx 1.5$). This once again suggests that significantly different processes occur in stratocumulus and cirrus clouds. Lovejoy (1982) found a constant fractal dimension of 1.35 for large cumulus clouds.

Rys and Waldvogel (1986) found that for severe convective storms, a decrease in wind speed is characterized by an increase in fractal dimension, or a roughening of the cloud contour. They suggest that a particle showing a Brownian motion in a drift-free case tends to follow an oriented and rather smoothed trajectory at higher wind speeds. Following this argument, one would expect smaller fractal dimensions at higher wind strengths and in pronounced circulations.

3) Stratiform cirrus have significantly larger hori-
horizontal aspect ratios than do convective cirrus. Also, large cloud cells tend to have larger aspect ratios than do cloud cells of diameter $D \leq 1.5$ km.

4) The structural characteristics are insensitive to small variations in threshold selection. This fact ensures that the results are representative and suggests that existing cloud segmentation procedures are not critical to obtaining satisfactory results.

For many applications, it is neither necessary nor desirable to expend the computer resources necessary to produce detailed cloud field structural characteristics. Textural features provide useful descriptions of cloud field macro- and micro-structure using easily computed statistical measures. In addition, cloud field directionality is derived by examining textural measures in different directions. However, for obtaining basic cloud field textural measures, analysis based upon the isotropic assumption appears to be adequate and also lightens the computational expense.

Eight textural measures are used to characterize cloud fields. However, the texture measures of contrast and linear correlation appear to be most useful in distinguishing cloud structure. In particular, large cirrostratus are characterized by large cells of relatively uniform reflectance, high horizontal aspect ratio, and low contrast. Clouds of small optical depth also are characterized by lower measures of contrast. However, convective-type cirrus show higher contrast. These regions tend to be composed of cells which appear to be convex in shape, with large values of reflectance near cloud centers and low values of reflectance at cloud edges. Therefore, the asymptotic value of contrast appears to be sensitive to cloud type.

Stratiform clouds show a high degree of correlation with distance, while the smaller, convective-type clouds show a fast decrease in correlation with increasing distance. The slope of the correlation curve is related to the typical size of cloud sizes in the field. Cloud regions composed of small clouds show a very rapid decrease in correlation coefficient with increasing distance, while regions composed of large stratiform clouds show only gradual decreases in correlation with distance. Nevertheless, the fact that correlation coefficient always tends toward zero indicates that there is no large scale organized structure.

Comparison of cirrus cloud textures with those of stratuscumulus and cumulus clouds (Welch et al. 1988b) shows that textural measures are sensitive to cloud field structure and to typical cloud types.

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Note added in proof: During the review process of this paper, further progress has been made to utilize textural features for cloud classification. Using a single high resolution visible channel, Welch et al. (1987; 1989a) show that cloud classification accuracies of 95% can be achieved. It is significant that textural measures are capable of distinguishing cirrus clouds from low clouds solely on the basis of spatial brightness patterns. Additional studies concerning selective sampling strategies, multispectral textures, and multithresholding are in progress.

Analysis of cumulus and stratocumulus by Bob Cahalan of NASA Goddard also shows these clouds to be bi-fractal with power law size distributions (personal communication).

APPENDIX

Conversion to Reflectance Values

The conversion from gray level \( G \) to radiance and reflectance values can be accomplished as follows. Spectral radiance \( L_\lambda \) is given by

\[
L_\lambda (\text{mW cm}^{-2} \text{sr}^{-1} \text{µm}^{-1}) = \frac{L_{\text{MIN}} + \frac{L_{\text{MAX}} - L_{\text{MIN}}}{G_{\text{MAX}}}}{G} \quad (A1)
\]

where \( L_{\text{MIN}} \) is the spectral radiance for \( G = 0 \), \( L_{\text{MAX}} \) is the spectral radiance for \( G = G_{\text{MAX}} \), and \( G_{\text{MAX}} \) is the maximum gray value. Values for \( L_{\text{MIN}} \) and \( L_{\text{MAX}} \) are given in Table A. \( G_{\text{MAX}} \) is 127 for all scenes. Reflectance \( R \) is calculated from

\[
R = \frac{\pi L_\lambda}{S'_{\lambda \theta} \cos \theta}
\]

where \( S'_{\lambda \theta} \) is the exoatmospheric spectral solar flux in mW cm\(^{-2}\) µm\(^{-1}\) and \( \theta \) is solar flux angle. Spectral solar flux must be corrected for the elliptical path of the earth around the sun and is expressed as (Paltridge and Platt 1976)

\[
S'_{\lambda \theta} = S_\lambda (1.000110 + 0.034221 \cos \theta_0 + 0.001280 \sin \theta_0 + 0.000719 \cos 2\theta_0 + 0.000077 \sin 2\theta_0) \quad (A2)
\]

where the yearly average spectral solar flux is \( S_\lambda \), and \( \theta_0 \) is given by:

\[
\theta_0 = 2\pi (J - 1)/365, \quad (A3)
\]

where \( J \) is the day of the year (1 January is day 1 and 31 December is day 365). Values of spectral solar flux for the (0.7–0.8 µm) band, solar zenith angle, day, number, and the reflectance for \( L_\lambda = L_{\text{MAX}} \) are given in Table A for each of the twelve scenes shown in Fig. 1. Values for \( L_{\text{MIN}} \), \( L_{\text{MAX}} \), and \( S_\lambda \) are taken from Markham and Barker (1986). Data for scene D is from the LANDSAT 2 satellite; scene C is from LANDSAT 3; and scene E is from LANDSAT 4. The remaining data are from LANDSAT 5.

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