Cloud Cover From High-Resolution Scanner Data: Detecting and Allowing for Partially Filled Fields of View

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We present a new technique for obtaining cloud cover and determining clear sky radiances using high-resolution infrared scanner data. The technique, which can be automated, uses the spatial structure of the IR radiance field to identify radiances associated with fields of view that are either free of clouds or completely covered by clouds drawn from one or more distinct layers. As the method uses only infrared radiances, it should provide equally good results for both daytime and nighttime observations. The approach is particularly suited for determining clear sky radiances over oceans from which sea surface temperature might be derived. In addition, for single-layered systems, the cloud cover fraction for a given region may be obtained from the clear sky radiance, the completely cloud covered radiance, and the mean radiance for the region. For such systems the separation of completely covered from partially covered fields of view allows an estimate of the errors associated with commonly used threshold techniques for determining cloud cover. These errors are, in general, shown to be highly sensitive to the applied threshold and to depend on the cloud-areal size distribution. In addition, unlike the spatial coherence method described here, histograms and correlations of visible and IR radiances as proposed for archiving information on cloud cover may fail to reveal the layered structure of cloud systems. Furthermore, the high local structure observed for the visible radiances of regions that appear to be completely cloud covered makes it impossible to obtain reliable estimates of the cover from visible radiances alone.

INTRODUCTION

Because of their influence on the earth's energy budget, small changes in cloud cover may lead to major changes in the climate. Yet, how cloud cover actually varies and how such changes might affect the climate is unknown due to the lack of observational information on clouds. It is hoped that satellite data will one day provide the needed record.

Satellite pictures of cloud cover are known the world over. They are perhaps the most often used product derived from meteorological satellites. The problem is to deduce from these pictures quantitative estimates of cloudiness.

The simplest method for extracting cloud cover from high-resolution images is to apply a threshold to each field of view. In threshold methods, cloud-covered fields of view are separated from cloud-free fields on the basis of their radiances. For example, the surpassing of a preset radiance level at visible wavelengths indicates that the field is cloud covered. If the level is not surpassed, the field is cloud free. This classification is assumed to apply for the whole field of view. The total area covered is then determined by counting the scan spots (fields of view) in which the threshold is exceeded.

One problem with the threshold method is that clouds need not fill the instrument's field of view. Clouds may be either smaller than the field of view, which is currently about (1 km)² at the subsatellite point for the advanced very high resolution radiometer (AVHRR) on NOAA's operational satellites, or they may be aligned so that some fields of view fall on the edges of the clouds and therefore are only partially covered. Small clouds and misalignment can lead to considerable errors in the estimates of the actual cover [Shen and Salomonson, 1972].

Here we develop what we shall call the spatial coherence method for determining clear and cloudy sky radiances and, for single-layered systems, the cloud cover. The method is applicable to layered cloud systems that extend over moderately large regions (250 km)² and have both completely clear and completely cloudy portions that span several fields of view. Such systems, for example, low-level stratus, appear to be rather common. The method fails to determine accurately the cloud cover when the cloud system is multilayered, when the clouds are everywhere smaller than the instrument's field of view, and when the clouds have variable emissivities, as do cirrus. This failure it shares with many of the other techniques developed to deduce cloud cover. It, nevertheless, holds several advantages over many of these techniques and, in particular, over the threshold method in that it clearly identifies multilayered clouds, subresolution clouds, and variable emissivity clouds, and in the case of appropriate single-layered systems, it detects and allows for partially filled fields of view when estimating the fractional cover.

The method utilizes the local spatial structure of the IR radiance field to determine the radiances associated with cloud-free and completely cloud-covered fields of view and to infer the radiances associated with partially filled fields of view. When several cloud layers are present and each has nonoverlapped clouds that span several scan spots, the method determines the radiance for the completely cloud-covered regions associated with each layer. As the method uses only the infrared radiance field, it should provide equally good estimates of clear sky and cloudy sky radiances and, for the appropriate single-layered system, of cloud cover both day and night.

To illustrate the method, we apply it to satellite data for a (1000 km)² region over the Pacific Ocean. We deduce that for this case the cover is in the form of a single low level deck, and we obtain the cloud cover fraction. This cloud information is compared with that derivable from the threshold
VISIBLE
(0.55-0.90 μm)

INFRARED
(10.5-11.5 μm)

Fig. 1. High-resolution image constructed from visible reflectivities and IR brightness temperatures for (1000 km)² region of the Pacific Ocean centered at 22.3°N, 136.7°W, on June 7, 1979, at 1500 L.T. The images are constructed from TIROS(N) AVHRR GAC data. The clouds in both images appear as light shades against a dark ocean background.

Before we illustrate the method, we emphasize that our intent is to exploit the information in satellite images that reflect some, though not all, of our daily experiences concerning cloud cover. We take the view that clouds are primarily observed as irregularly shaped and sometimes highly structured objects against a relatively uniform background. This view leads to what might be called operational definitions for the terms 'cloud cover,' 'clear sky,' and 'cloudy sky' radiances. For example, cloud cover is defined to be the fraction of the area under consideration that exhibits the radiative properties of an apparent cloud layer within the scene. By invoking this definition we postpone the troublesome problem of relating cloud cover to the microphysical properties of real clouds. Likewise, for clear skies we make no attempt to distinguish regions covered by a uniform haze, which, for example, might be light fog, from those that are free of haze. Clear sky regions are taken to be those that exhibit the radiative properties of the relatively uniform background. As will be shown in the following sections, attempts to classify scenes using these operational definitions seem, in general, to lead to meaningful and internally consistent results, but in some cases they will lead to ambiguous or even misleading interpretations. Indeed, further work is needed to show how often the spatial coherence method produces results that are consistent with independent observations and to define other measures of cloud structure that would supplement those defined here.

The Identification of Layers

The procedure for identifying cloud layers is best described through example. In this study we use AVHRR global area coverage (GAC) data. The GAC data are constructed as follows [Schwab, 1978]: At the subsatellite point AVHRR's resolution is (1 km)². The instrument scans perpendicularly to the direction of the orbit. Along a scan line the radiances from four spots are averaged, then one scan spot is skipped. This pattern is repeated for the duration of the scan. After data from a scan are recorded, two scan lines are skipped, and data from the fourth scan line are recorded. The area represented by the subsatellite data point in the GAC data is approximately 5 × 3 km². (The data are referred to as '4 km' and are so-called because of the near identity 5 × 3 = 4.) Although sizable gaps occur, for the purposes of this study we assume that the sampling is representative of the entire field.

In deriving the area covered by clouds, we note that as the instrument scans away from nadir, the area covered by the scan spots increases. We should correct for this increase either by averaging data from an appropriate number of points along the line or by weighing more heavily data at large viewing angles. In as much as the separation of completely filled from partially filled scan spots is unaffected by such area corrections, we forego these corrections in the present study.

Figure 1 shows images constructed from the visible (0.55–0.90 μm) and the infrared (10.5–11.5 μm) radiances observed for a (1000 km)² region (centered at 22.3°N, 136.7°W) off the California coast at about 1500 L.T. on June 7, 1979. To obtain cloud cover from the high-resolution data, we note that clouds congregate in layers. These layers generally extend over large regions (~1000 km), and clouds within the layers exhibit similar infrared radiating temperatures. A homogeneous underlying surface such as the ocean also appears as a layer. To detect these layers in the GAC data, we examine
the local coherence of the radiance field in the 11-μm IR channel. Figure 2 shows for the (1000 km)² region shown in Figure 1 the local standard deviation of the 11-μm brightness temperatures as a function of the local mean brightness temperatures. These local values are constructed by taking a small array of adjacent scan spots and calculating from the radiances a mean and standard deviation. Each point in Figure 2 represents an 8 × 8 array of scan spots or approximately a (32 km)² field of view.

Figure 2 shows a structure that we will term an arch. Such arches are characteristic of local mean versus local standard deviation IR plots. The cluster of low-variance points at the warm radiating temperature 293 ± 1 K is interpreted as representing the radiance of cloud-free scan spots, which in this case are clear columns over ocean. Although the determination of the clear sky radiance is made without the aid of visible radiances, the cloud-free regions identified in this manner do, in fact, match those regions in the visible image in Figure 1 that appear to be cloud free. The cluster of low-variance points at the cold radiating temperature is interpreted as representing the radiance of completely covered scan spots. Within the range 283.5 ± 1.5 K the radiating temperature is well defined, and the difference from the clear sky radiating temperature indicates the altitude of the layer. We interpret the points in the body of the arch between the two clusters as representatives of partially filled fields of view. This interpretation appears reasonable in that we would not expect partially filled fields to exhibit sufficient local coherence to bring the local variance to the levels achieved under cloud-free and completely covered conditions.

Confirmation of this view comes when the region under consideration is subdivided into 16 frames each approximately a 250-km square. Figure 3 shows similar plots of local mean brightness temperature versus local standard deviation. In this case the arrays are 2 × 2 scan spots, or approximately (8 km)² fields of view. Each frame of Figure 3 is identified by a coordinate pair in the upper left corner. The figure is oriented so that frame (1, 1) represents the lower left corner of the image and frame (1, 4) represents the upper left corner. A clear arch is present in every frame. The radiative properties of the feet of these arches are well defined and vary systematically from one frame to the next across the whole scene. Particularly noteworthy is the gradient in the clear sky radiating temperature from 294 K in the south to 291 K in the northeast. Likewise the cloudy sky radiating temperature varies from about 282 K in the northwest to 284 K in the northeast. These variations probably reflect a systematic trend in cloud top height.

Comparison of Figures 2 and 3 shows that for this scene the basic arch structure is insensitive both to the aggregation of neighboring frames into larger units and to the number of neighboring scan spots in the array over which the averages are taken. Note, however, that the extremes of low clear sky radiating temperatures in Figure 3 are not fully reflected in the range apparent in the more highly averaged presentation of Figure 2. This result stems from the inability of the larger fields of view to 'see through' the small gaps in the finely structured cloud in the northeast corner. Note also that Figure 3 could not have been obtained with an instrument or basic data set with scan spot size (8 km)², nor could Figure 2 from one of size (32 km)². These resolutions would fail to preserve the variance of the radiance within the averaging array. Nevertheless, a version of Figure 2 that contains essentially the same information can be obtained from 8-km data obtained by averaging over 2 × 2 arrays of GAC data to construct scan spots with (8 km)² fields of view.

Figure 3 exhibits the structure of a broken low-level deck. Although no ships were in the area at the time of the satellite pass, the system extended 1000 km to the north into a region with numerous ship observations. The surface observations were made at the time of the satellite pass and confirm the interpretation that the clouds are part of a low-level system. A few points in frames (1, 1) and (1, 2) of Figure 3 are at radiating temperatures much lower than that exhibited by the deck. These points may be due to localized convective plumes that cannot be resolved with the 8-km resolution used here. As only a few points exhibit these colder temperatures, we ignore them for the purpose of this illustrative analysis.

The technique has some obvious limitations. It detects the existence and determines the radiating temperature of a cloud layer only when adjacent scan spots within a localized region are completely filled. Thus, in order to be identified as a layer, cloud cover must be uniform over regions somewhat larger than the resolution of the analysis, ∼(8 km)² in this study. Had the cover failed to achieve uniformity over this spatial scale, as happened for the upper level clouds in frames (1, 1) and (1, 2), it would not have been identifiable as a layer, and the radiating temperature would remain unknown.

To be sure, the technique fails to rule out the existence of unresolvable upper level clouds in the other frames of Figure 3. We suspect, however, that such upper level clouds are not prevalent. Had they been so, we would have expected them to appear in the other frames as they did in frames (1, 1) and
As they do not appear there, we interpret the radiances in the remaining frames as due to the single layer of broken low-level clouds.

Because they exhibit considerable spatial structure, large, highly structured cumulus and cirrus will rarely be detected as a layer. Cirrus presents an additional problem. Owing to variable emissivities, a deck of cirrus that has a well-defined radiating temperature will probably fail to represent the radiances associated with cirrus at the same level that partially fill fields of view. As a result, the estimate of the fractional cover for cirrus systems, as described in the next section, will be unreliable. We suggest that by applying the method to obtain cloud cover to the 3.7-, 11-, and 12-μm (available on AVHRR/2) radiances, cases with variable emissivities will be readily detected. Owing to the wavelength dependence of the optical properties exhibited by ice and water, significant differences in the cloud cover obtained with the different channels would indicate that the clouds are nonblack and thus that estimates of the area covered and cloud height are probably unreliable.

In general, more than one layer of clouds may be present in a scene. This leads to a multiple arch structure where there are more than two clusters of points with low standard deviation that have clearly distinct local means. As a result, the radiative properties of each separate layer may still be distinguished. Of course, when the surface is totally obscured by a cloud deck, there is the danger of misinterpreting the warm temperature base of the arch as due to clear skies. Occasionally, however, the aches are incomplete. The underlying surface may be everywhere partially obscured over a wide area, or as over land, the clear sky radiances exhibit considerable local spatial structure. Also, as mentioned above, the cloud structure may be such as to defy classification into layers. Nevertheless, from the limited sample of cases examined so far, it seems that the occasions when the technique fails to yield at least one recognizable arch are fairly rare.

**Estimating Cloud Cover**

When only one layer is evident, as is the case for most of the frames shown in Figure 3, we can estimate the cloud cover \( A_c \) from the clear sky radiances \( I_s \), the cloudy sky radiances \( I_c \), and the mean radiances \( I \). For a given region we take the mean radiances to be given by
\[ I = (1 - A_c) I_s + A_c I_c \]  

(1)

The fractional cloud cover is thus given by

\[ A_c = \frac{I - I_s}{I_c - I_s} \]  

(2)

In (1) and (2), \( A_c \) is often referred to as the 'effective' cloud cover. Provided the clouds do not scatter at the wavelength of the observations, \( A_c \) is taken to be the product of the cloud emissivity and the fraction of the area that is overcast. The effective cover gives the fraction of area that, based on the observed radiances, would have been covered had the clouds been black. As was noted in the previous section, if the clouds are nonblack, \( A_c \) will, in general, depend on the wavelength of the observed radiances. On the other hand, when the clouds are black, \( A_c \) is independent of the wavelength and is the fraction of the area that is overcast.

The uncertainty in \( A_c \) can be estimated from the uncertainty associated with \( I, I_s, \) and \( I_c \). The uncertainty associated with \( I \) is due to instrument noise, and because of the averaging over a large number of scan spots, it is negligible compared with the uncertainties associated with \( I_s \) and \( I_c \). As a measure of the uncertainty in \( I_s \) and \( I_c \), we take the width of the feet of the arches associated with the clear and cloudy sky radiances. In terms of these uncertainties, the uncertainty in cloud cover is from (2):

\[ \Delta A_c = \pm \left( \frac{A_c \Delta I_c}{I_c - I_s} + \left[ \frac{(1 - A_c) \Delta I_s}{I_c - I_s} \right]^2 \right)^{1/2} \]  

(3)

Although reasonably accurate values of \( I_s \) and \( I_c \) and their uncertainties can be read directly from Figure 3, the values given below are based on the results of an automated procedure which is described in the appendix. The procedure examines the grouping of points that have local standard deviations below an automatically set cutoff. The cutoff is set so that the variability of cloud cover for the array of scan spots is limited to some small fraction. In this study the fraction is about 0.05. Points in the feet of the arches that have standard deviations below the cutoff make up what is termed a 'super' cluster. As an example, Figure 4 shows the arch and the points in the super clusters for frame (1, 3) of Figure 3. This frame was selected because it illustrates several principles that are discussed in later sections. The mean radiances of the points in the super clusters are taken to be \( I_s \) and \( I_c \); the standard deviations are taken to be \( \Delta I_s \) and \( \Delta I_c \).

Table 1 lists for each frame the cloud cover, the clear and cloudy sky radiating temperatures, the number of points in the super clusters that determine these temperatures, and the local standard deviation cutoff applied to the scene. In addition, an asterisk is used to identify the super clusters that contain more than one 'local' cluster, thereby indicating possible geographical variations of \( T_s \) and \( T_c \) within the scene. Note that another indicator for geographical structure is the width of the super cluster. When this width is larger than the local standard deviation cutoff, we attribute the broadening of the cluster not to the variability of cloud cover permitted within the arrays but to actual changes in \( T_s \) and \( T_c \) within the scene. Table 1 shows that in every case that the width exceeds the cutoff, more than one local cluster is found within the super cluster.

We draw attention to the small uncertainties estimated for the parameters in Table 1. Despite substantial cloud cover, the clear sky radiating temperature is typically determined to within 0.3 K. From the clear sky radiating temperature, the sea surface temperature could be derived provided we can compensate for the influence of absorbers, primarily water.

![CHANNEL 4](image)

Fig. 4. (a) Local mean brightness temperatures and standard deviations for frame (1, 3) of Figure 3. (b) Super clusters representing clear and cloudy sky radiating temperatures.
### Table 1. Cloud Cover, Clear Sky, and Cloudy Sky Radiating Temperatures

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**Cloud cover $A_C$, clear sky $T_S$, and cloudy sky radiating temperature $T_C$ derived from arches shown in Figure 3; $N_S$ is the number of $2 \times 2$ scan spot arrays that contribute to the estimate of the clear sky radiating temperature; $N_C$ is the number that contribute to the cloudy sky radiating temperature; there are 1024 arrays in each frame; $\sigma_C$ is the automatically set cutoff applied to the local standard deviations.**

*More than one local cluster detected within super cluster, indicating the possibility of geographical structure within the scene.*

†The cluster contains too few points to be statistically significant; the cloud cover for this frame is obtained by using parameters for the appropriate “nonoverlapped” cluster which is described in the appendix.

Vapor, within the spectral channel and for the radiometric calibration of the instrument. Just as we observed in Figure 3, the results in Table 1 indicate that the procedure has detected a north-south gradient in the clear sky radiating temperature. It has also detected an east-west gradient in the northeast portion of the region. Note that we have obtained the clear sky radiating temperature without relying on observations from the visible channel. This procedure for obtaining the clear sky radiance should therefore prove equally effective at night. Furthermore, for nighttime observations the method can be applied to the 3.7-\mu m window channel which for daytime observations is subject to contamination by reflected solar radiation.

This method for determining the clear sky radiances differs from that used previously in the published operational determination of sea surface temperatures [Smith et al., 1970; Brower et al., 1976]. Previously, the one-dimensional histogram of IR radiances was searched for peaks at high radiating temperatures. The high-temperature side of these peaks was then used to estimate the clear sky radiances.
Instead of using the histogram, the method described here accepts for clear sky regions only those regions with warm radiating temperatures that exhibit low local spatial structure. As a result, the procedure is able to identify clear sky radiances for scenes, such as frames (3, 4), (4, 3), and (4, 4) that have histograms with no significant peaks at high temperatures. Thus, clear sky radiances can be extracted from more scenes than was possible with the previous approach. The principle of using local spatial structure to assist in identifying clear sky radiances is being used in the procedure for determining sea surface temperature recently made operational by NOAA’s National Earth Satellite Service (NESS) (P. McClain, private communication, 1981).

The results in Table 1 indicate that the uncertainty in the cloud cover is typically \( \Delta A_c = \pm 0.04 \) and the uncertainty in the cloudy sky radiating temperature is typically \( \Delta T_c = \pm 0.6 \) K. One advantage of this method is that the estimate of \( A_c \), obtained using (2) is relatively free of instrument calibration errors. Because (2) incorporates differences and ratios of observed radiances, errors in the radiances due to changes in the instrument gain and offset cancel. Another advantage is that as long as they are uncorrelated with the cover, water vapor and haze, though they increase the uncertainties, fail to bias the estimate for the cover. If, on the other hand, water vapor and haze are correlated with the cover, then the clear sky portions of partially covered scan spots will have radiances that differ from those of nearby cloud-free regions. As a result, the estimated cover will be biased. No such bias has been detected in the limited data available for this study.

Averages for the entire (1000 km)\(^2\) region are \( T_c = 292.4 \pm 0.3 \) K, \( T_r = 283.4 \pm 0.6 \) K, which combined with the mean radiance for the entire (1000 km)\(^2\) region gives \( A = 0.50 \pm 0.04 \). These results are consistent with those obtained by applying the algorithm to the points in Figure 2 representing (32 km)\(^2\) fields, \( T_c = 293.2 \pm 0.3 \) K, \( T_r = 283.4 \pm 0.6 \) K, and \( A_c = 0.54 \pm 0.03 \). Note, as mentioned earlier, that because the (32 km)\(^2\) data fail to see through the cloud patches in the northern portion of the region, the resulting clear sky radiating temperature is somewhat warmer than the average for the region. Nevertheless, for this scene the large-scale cloud features prove to be representative of the smaller-scale features. By using different array sizes in the analysis, we could perhaps recover information concerning the size distribution of the clouds within the scene. We have yet to pursue this possibility.

**Errors in Cloud Cover Associated With Threshold Techniques**

To illustrate differences between the spatial coherence method and other methods for obtaining cloud cover from high resolution data, we compare in this and the following section results selected from the various frames in Figure 3 and Table 1. Again the comparisons are made in order to illustrate principles which, though based on a limited set of data, should hold for a large sample of cases. We first focus attention on the threshold method. Through both theoretical considerations and comparison with the cloud cover given in Table 1, we examine the errors in cloud cover that result from application of the threshold method. We demonstrate that the errors in cloud cover are a function of the cloud-areal size distribution, and we propose a simple technique for assessing the reliability of the threshold-derived cover.

Through theoretical studies and analyses of photographs taken during the Apollo missions, Shenk and Salomonson [1972] showed that depending on how the thresholds are set, cloud cover obtained using threshold methods could be overestimated by tens of percent unless the typical cloud sizes were 2 to 3 orders of magnitude larger than the instrument’s field of view. Such large errors are readily understood by considering the following example. Assume a square region equivalent in area to a 10 \( \times \) 10 square array of contiguous fields of view to be completely and exactly covered by a single cloud. Due to misalignment, assume that the boundaries of this region do not coincide with those of the scan spot array. The fields of view that might be partially filled through this misalignment are those on the perimeter. That is, as many as 44 scan spots might be only partially filled. If the threshold is set so that any partial cover within a scan spot is interpreted as complete cover, then the total area estimated to be covered by the 10 \( \times \) 10 cloud might be as high as \( 11 \times 11 = 121 \) — a 20% overestimate. Although it depicts an extreme situation, the example illustrates a primary weakness of the threshold method.

From the above example, the error in the cloud cover area would appear to be a function of the perimeter of the clouds. To test this possibility, we plot in Figure 5 the errors obtained by Shenk and Salomonson [1972] against the inverse square root of the cloud size area to scan spot size area ratio. Figure 5 shows that indeed the errors in cloud cover diminish inversely as the square root of the cloud size area, that is, as the perimeter of the cloud. This relationship between the error in cloud cover area and the perimeter of the cloud explains why errors obtained with the threshold method are likely to be large unless the clouds are typically much larger than the field of view used to observe them. Furthermore, since the error in the fractional area covered by a cloud is a nonlinear function of the actual area covered, the error obtained by applying the threshold method will depend on the cloud-areal size distribution.

We illustrate the errors that might result from the threshold method by applying various thresholds to the radiances in frame (1, 3) shown in Figure 4. Suppose we recognize the

![Fig. 5. Error in cloud cover obtained with the threshold method. The points are from the theoretical study performed by Shenk and Salomonson (1972, Figure 1). The curve is linear and a best fit to the points shown. The total cloud cover is 0.55. The errors are overestimates.](image)
cluster of points near 293 K in Figure 4 as due to cloud free regions. If we place a threshold near the clear sky radiating temperature, say at 292 K, and treat all scan spots exhibiting lower radiating temperatures as cloud filled, then we surely overestimate the cloud cover. Indeed, we are treating all the points in the body of the arch of Figure 4, which represent partially filled fields, as being completely filled. With the threshold set at 292 K the cloud cover obtained by applying this threshold to each (8 km)$^2$ field is $A_c = 0.5$. The amount derived in the previous section, in which we allowed for partially filled fields, was $0.24 \pm 0.02$. If on the other hand we wish to compensate for this overestimate due to partially filled fields by placing the threshold closer to that of the cloud deck, say at 295 K, then we risk ignoring the partially filled fields and thereby underestimate the cloud cover. Indeed, with the threshold set at 295 K we obtain $A_c = 0.1$. Apparently, the resulting cloud cover is rather sensitive to the applied threshold. This sensitivity is illustrated in Figure 6 for the (250 km)$^2$ region.

Two observations stem from the above results. First, there is one obvious case in which the threshold method produces a reliable estimate of the cover. The case is that of a single-layered system in which the clouds are uniform over areas very much larger than the scan spot size of the instrument. In this case, few points would exist in the body of the arch shown in Figure 4, and the majority would be clustered at the feet of the arch near the clear sky and cloudy sky radiating temperatures. When this happens, the cloud cover obtained by applying the threshold method, unlike that shown in Figure 6, is relatively insensitive to the applied threshold, and the resulting cover is a reasonable estimate of the actual cover. Such cases are rare.

Second, Figure 6 shows that for a single-layered system, there is, in fact, a threshold which produces the desired cloud cover $A_c = 0.24$. Based on this result, one might be tempted to 'tune' thresholds in some way using, say, ground-based observations of cloud cover. Recall, however, that Figure 5 shows, in principle, the errors resulting from partially filled fields of view are a nonlinear function of the cloud sizes. Consequently, thresholds tuned to observations on systems with one set of sizes are expected to fail when applied to systems with another set of sizes. For example, the threshold method is applied to each (250 km)$^2$ frame of Figure 3. The threshold in each case is set at $T_r = 0.5$ K, where $T_r$ for each frame is taken from Table 1. This threshold would be typical of clear sky radiances that are based on maximum brightness temperatures. The resulting cloud cover is given in Table 2 along with that listed in Table 1.

With the threshold chosen in this manner, the threshold method clearly overestimates the cover by a large amount. Furthermore, the best linear fit between the cloud cover obtained using the two methods indicates that only 87% of the variance in cloud cover is captured by the threshold method. The lack of correlation in this case is due in part to the variation of cloud sizes as is evident in Figure 1.

For multilayered systems we should beware that in addition to the dependence on the cloud-areal size distribution, the errors in the threshold method are also a function of the cloud top radiating temperature. Consider the attempts to obtain cloud cover for several levels by applying multiple thresholds. If a threshold is placed at a radiating temperature that is greater than the cloud top temperature, then partially filled fields of view will on occasion be interpreted as due to larger amounts of lower level clouds. Consequently, low-level cloud cover will be overestimated, while high-level cloud cover will be underestimated. No amount of averaging over space and time will remove such a bias.

It is well to remember that, as was mentioned earlier, the

| TABLE 2. Cloud Cover Obtained Using Spatial Coherence and Threshold Methods |
|---------------------------------------------|-----------------|-----------------|-----------------|-----------------|
| Spatial Coherence | (1,4) | (2,4) | (3,4) | (4,4) |
| Threshold | 0.70±0.06 | 1.64±0.08 | 0.59±0.03 | 0.62±0.04 |
| Spatial Coherence | (1,3) | (2,3) | (3,3) | (4,3) |
| Threshold | 0.92 | 0.92 | 0.93 | 0.93 |
| Spatial Coherence | (1,2) | (2,2) | (3,2) | (4,2) |
| Threshold | 0.52 | 0.79 | 0.90 | |
| Spatial Coherence | (1,1) | (2,1) | (3,1) | (4,1) |
| Threshold | 0.61 | 0.82 | 0.88 | 0.94 |

As noted in Table 1, the algorithm for the spatial coherence method suggests that the estimate of the clear sky radiating temperature is unreliable for frame (3, 3) and that of the cloudy sky radiating temperature is unreliable for frame (1, 1); as a result, no comparison is made for these frames.
resulting from action of the observations fail when, for example, a) frame of \(T_0 = 0.5\) K, Table 1. The cases that are the result that are in Table 1, the threshold amount. cloud cover only 87\% of the threshold value in part to have been distributed, action of the attempt to ing multiple temperature settings as due to the high-level of averaging earlier, the spatial coherence method will fail to produce accurate estimates of the cover when the clouds or background exhibit considerable spatial structure, when the clouds are in overlapping layers, and when the clouds are everywhere smaller than the instrument’s field of view. Based on the above discussion concerning the limitations of the threshold method, it is unlikely that the threshold method will succeed where the spatial coherence method fails.

**ANALYSIS OF CLOUD COVER BY OTHER METHODS**

Here we examine some of the methods often proposed for archiving information pertinent to cloud cover. We first examine histograms of visible and infrared radiances and cluster diagrams of visible radiances plotted as a function of the corresponding infrared radiances. We then focus on the difficulty encountered when estimating cover from visible radiances alone. In making these comparisons, we focus on the information gained by examining the spatial coherence of the IR field.

Figure 7 shows histograms of the visible and infrared radiance fields. Figure 8 shows the visible radiances plotted as a function of the corresponding infrared radiances. These figures are constructed from the local mean radiances for the (8 km)² fields in frame (1, 3) shown in Figure 4.

Unlike Figure 4, there is no indication in Figures 7 and 8 that a single layer of low-level clouds exists. Figures 7 and 8 might be obtained for an upper level deck in which the clouds only partially fill the instrument’s field of view. Such an occurrence is ruled out by Figure 4. Had the clouds only partially filled the instrument’s field of view, the arch would have been incomplete, as it was for the upper level clouds in frames (1, 1) and (1, 2) of Figure 3.

Figures 7 and 8 might also be obtained for multilayered systems. Again, such an occurrence is ruled out by Figure 4. Had there been a multilayered system, Figure 4 would have contained multiple arches, as will be demonstrated in the next section. Obviously, Figures 7 and 8 are open to a range of interpretations concerning cloud cover. Some of these interpretations can be tested by using the spatial coherence method.

Figure 8 shows that completely filled fields of view (those with radiating temperatures near 282 K) exhibit a wide range of possible reflectivities. Apparently, no single reflectivity can be associated with clouds that completely fill the instrument’s field of view. This result is further substantiated by Figure 9, in which local standard deviations of the reflectivities for the (8 km)² regions are plotted as a function of the local means. Unlike the infrared radiances, there is no set of

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**Fig. 7.** (a) Frequency of occurrence of visible channel radiances for frame (1, 3) of Figure 3. (b) Frequency of occurrence of IR channel radiances. Radiances are the local means for 2 × 2 arrays of GAC scan spots ~ (8 km)².

**Fig. 8.** Visible radiances and IR radiances for frame (1, 3) of Figure 3. Channel 1 is visible reflectivity; channel 4 is IR brightness temperature.
reflectivities evident in Figure 9 that can be associated with completely covered fields of view.

We propose two mechanisms that might explain the large local variability of visible radiances. First, we observe that although we have identified radiating temperatures near 282 K as resulting from completely covered fields, we are, in fact, unable to detect holes that might punctuate the deck. How much of a given field of view might, in fact, be clear can be estimated from the width of the cluster near 282 K in Figure 4. If we accept points within one standard deviation of the cluster mean (0.5 K) as being completely covered, we are, in fact, accepting fields that, according to (2), may have $A_c = 0.95$. Such structure might contribute to the uncertainty in the infrared radiances associated with complete cover, and in a similar manner it would also affect the reflected solar radiation. Second, scattering from small-scale features, such as domes, within the cloud system contributes to the variability of the reflected solar radiances, while contributing little variability to the infrared radiances. For example, with a 6.5 K km$^{-1}$ lapse rate we would expect structure of the order of 1.0 K/6.5 K km$^{-1} = 150$ m to fall within the first standard deviation of the cloudy sky radiating temperature. Such structure, through scattering and casting of shadows, is bound to have a profound effect on the reflected radiances.

Because of the variability exhibited by the reflected radiances, schemes such as that proposed by Reynolds and Vonder Haar [1977], which rely on a fixed reflectivity for completely cloud-filled fields of view, can provide only highly uncertain estimates of cloud cover.

**Conclusions and Further Work**

We have observed that clouds are generally organized into layers, and we can detect these layers by measuring the spatial coherence of the IR radiance field. Uniform layers and cloud-free regions exhibit a high degree of spatial coherence, while partially filled fields of view exhibit considerable spatial structure. For the case of clouds organized into a single layer over a uniform surface, such as over the ocean, estimates of the radiances for cloud-free and cloud-covered fields of view, as revealed by regions of low local structure, along with the mean radiance are sufficient to estimate a cloud cover that allows for the partially filled scan spots. Present in the appendix an algorithm that automatically determines the clear and cloudy sky radiances. We note that this algorithm can be used to determine clear sky regions over oceans and thereby serve as the initial step in the determination of sea surface temperatures. As it relies solely on infrared radiances, the method is equally applicable to both daytime and nighttime observations.

In comparing the spatial coherence method with others, we note that histograms showing frequencies of infrared and visible radiances and correlations between infrared and visible radiances may fail to detect the layered structure of cloud systems. Furthermore, because of the large variability in reflected radiances from seemingly cloud-filled fields of view, any estimate of cloud cover based solely on reflected radiances must be highly uncertain.

We have shown that errors in cloud cover associated with threshold methods, in which clouds are assumed to completely fill the instrument's field of view, depend on the cloud-areal size distribution. When the dominant contribution to total cover rests in clouds that are much larger than the scan spot size, threshold techniques are expected to produce reasonable estimates of cloud cover. When such clouds are organized into a well-defined layer, the recovered amount becomes relatively insensitive to the radiance level chosen to discriminate between cloud-free and cloud-covered fields of view. Unfortunately, such conditions rarely exist. Owing to partially filled fields of view, threshold techniques are expected to produce large errors in the estimated cloud amount.

We have also observed that by varying the spatial scale of the coherence analysis, we may obtain insight into the cloud-areal size distribution. Further study of this possibility is warranted. Details of the size distribution are bound to characterize the radiative properties of clouds [McKee and Cox, 1977; Reynolds et al., 1978], and they may become essential ingredients of future cloud cover parameterizations used in climate models.

We have focused attention on single-layered systems. We are, however, aware that multilayered systems often occur. Figure 10 shows images constructed from the visible and infrared GAC data on June 7, 1979, at 1500 LT for a (1000 km) region (centered at 51.8°N, 120.0°W) over British Columbia. The dendritic features in the left portion of the visible image are in fact snow cover on the coastal range. This area appears to be free of clouds. Figure 11 shows the local means and standard deviations (8 × 8 arrays of adjacent scan spots) of the 11-μm brightness temperature. In Figure 11, the cluster of points at 283 K represents the radiating temperature of clear sky regions off the coast of British Columbia. On this occasion, there is considerable variability in the radiating temperatures associated with the cloud-free land areas evident in Figure 10. The clusters near 270 K and 255 K represent two distinct cloud decks, while the points at temperatures colder than 255 K represent a higher third deck at an altitude that cannot be determined with these data but is evident in adjacent regions. The problem introduced by such multilayered systems is the
organized cover the land cloud cover. Low local efficienct to filled scan automatizations. We clear sky and steep in situ relies applications.

With others, rare and layered and structure of variability fields of reflected

ated with it to concur on the contributor over to when such recovered once level cloud-covers rarely threshold in the

scale of the cloud cover is bound to and become optimizations systems. We can occur.

ible and region (1000 British Columbia of the coast range, shows the arrays of structure. In presents the coast of considerable with the waters near the, while present a determined ones. The

interpreation of points having high spatial structure at temperatures between those associated with the cloud decks. When decks overlap, such points are obviously associated with mixtures of the existing systems. How the

mixtures are to be constructed remains to be solved. Nevertheless, although the sample of scenes so far examined by the authors is admittedly small, we are surprised at the large number of cases that exhibit single-layered systems. Even when multilayered systems are present, the geographic subdivision of a scene is sometimes sufficient to isolate single layers into distinct subregions. Indeed, the 270 K deck in Figure 11 is off the coast of British Columbia and is well separated from the 255 K and upper third level deck which are inland and do, in fact, overlap.

In closing, we recall that the spatial coherence method relies on the hypothesis that clouds congregate in layers that persist over large areas and that the thermal emission for cloud-free and completely cloud-covered regions exhibits a degree of local spatial coherence usually unachieved by partially covered regions. This hypothesis and the resulting algorithm for determining cloud cover are based on a limited set of data. They will prove useful only if when applied to a large data set, the arches and associated point clusters characterize a large fraction of the structure observed in the data. Furthermore, they will stand only if they produce clear sky radiances and cloud cover that is consistent with other independent measures of these quantities.

Appendix: Automating the Determination of Clear and Cloudy Sky Radiances

We interpret the points with small standard deviations at the feet of the arches in Figures 2 and 3 as being associated with cloud-free and completely cloud-covered regions. In this appendix we describe an algorithm that, given the local means and local standard deviations, picks out the points that make up the feet of an arch. From these points we determine the clear and cloudy sky radiances. These radiances are used to estimate the cloud cover.
focused on the points in the feet of the arches, designing a
mathematical procedure for selecting these points proved
tiresomely difficult. We offer the algorithm to those who
wish to avoid the tedious task of developing one of their own.

In selecting the points that make up the feet of an arch, the
algorithm must simulate a number of decision processes.
The problem is to decide which points belong to the feet and
which belong elsewhere. Do all the points that exhibit low
standard deviations belong to the feet? Or are some to be
considered as a background noise? Such decisions, though
based on reasonable judgment, contain, nevertheless, a
measure of arbitrariness. As a result, the route to selection is
not unique. We have developed several algorithms that
perform well. The philosophy followed in developing these
algorithms was to design the routine so that the final results
would be rather insensitive to the arbitrary choices made
throughout. The version presented here displays a healthy
lack of sensitivity.

The algorithm itself draws attention to aspects of the arch
diagram that require further examination. Some of the
constraints in the algorithm are enforced by adjustable
parameters. In the current study these parameters are fixed.
We envision, however, a stepwise progression to an algo-
rithm in which the parameters are chosen to suit the physical
quantity to be determined, such as the sea surface tempera-
ture or cloud cover, and to allow for factors that affect the
distribution of points in the arch diagram, such as the
distribution of cloud height and cloud size within the scene.
The development of such an optimized algorithm awaits
the application of the current scheme to a large quantity of
high-resolution scanner data from which may be derived the
necessary statistical base for rational decision criteria.

To illustrate the algorithm, we study in detail its application
to the points shown in frame (1, 3) of Figure 3 and
repeated in Figure 4a. The steps in the algorithm are
diagramed in Figure A1. Figure A1 was designed to diagram
the steps in the algorithm and is not meant to represent a
realistic set of data.

To select the points that represent clear and cloudy sky
radiances, we consider only scan spot arrays with small local
standard deviations and ignore arrays with large local stan-
dard deviations. To do so, we impose a cutoff for local
standard deviations. This cutoff is imposed with the follow-
ing consideration. Suppose that the scene was ideal in that it
contained a single cloud layer over a uniform surface. Let
the radiance for complete cloud cover be given by \( I_c \), and let
the radiance for cloud-free regions be given by \( I_s \). The
radiance for any scan spot within the scene is then given by

\[
I = (1 - A_c) I_s + A_c I_c
\]  

(A1)

where \( A_c \) is the fractional cloud cover for that scan spot.
Note that in order to facilitate the interpretation of the
satellite data, we have chosen to plot brightness tempera-
tures in the figures rather than radiance. The algorithm for
obtaining cloud cover, on the other hand, is based on (A1)
and uses radiances. The local standard deviation of the
radiance for an array of \( n \) scan spots is given by

\[
\sigma = \left[ \frac{1}{n} \sum_{i=1}^{n} (I_i - \bar{I})^2 \right]^{1/2}
\]  

(A2)
where \( \bar{I} \) is the mean radiance. Substituting (A2) into (A1), we obtain

\[
\sigma = \left( \frac{1}{n} \sum_{i=1}^{n} (A_i - \bar{A})^2 \right)^{1/2} (I_s - I_e) \tag{A3}
\]

where \( \bar{A} \) is the mean cloud cover for the array. If the scene contains only one layer, the scan spots would exhibit radiances ranging from at least \( I_s \), for completely covered spots to at most \( I_e \), for clear spots. We take as an approximate measure for the range \( I_s - I_e, I_s I_e \), where \( I_s, I_e \) is the 95th percentile point of the cumulative distribution of radiances and \( I_s, I_e \) the 5th percentile point. Note that the choice of these percentiles is not critical. Any comparable measure of the spread of radiances over the scene would be suitable. We take the cutoff to be given by

\[
\sigma_c = \gamma (I_{95} - I_s) \tag{A4}
\]

By comparing (A4) with (A3) we recognize \( \gamma \) as being roughly the range of cloud cover to be accepted within the categories of completely clear or completely covered. In the current study we take \( \gamma = 0.05 \). So, based on the model given by (A1), we accept scan spots with \( A_i < 0.05 \) as being completely clear and scan spots with \( A_i > 0.95 \) as being completely covered. As mentioned earlier, in an optimal algorithm \( \gamma \) ought to be adjusted according to some overall statistics of the scene. How the value of \( \gamma \) influences the results for frame (1, 3) is examined below.

Once we have determined the cutoff for a scene, we then search for point clusters in which each point has \( \sigma < \sigma_c \). A cluster is a set of points distributed over a small range of radiances and is detected as a peak in the histogram showing frequency of occurrence as a function of the local mean radiance. Such a histogram is illustrated in Figure A1a. To form this histogram we group the points with \( \sigma < \sigma_c \), shown in Figure 4a, into intervals in the radiance. In this study we take the width of the interval in radiating temperature \( \Delta T \) to be 0.2 K. As with \( \gamma \), we examine below how this choice affects the results.

By using the histogram to detect clusters, we add to the algorithm a number of steps based on arbitrary decisions, as is, for example, the choice of the interval width. Note, however, that, in general, clusters could be detected by examining the cumulative distribution of radiances grouped one point at a time and thereby avoid many of these arbitrary decisions. Such a procedure is, however, numerically less efficient than the procedure described here. Furthermore, we have found that by using the cumulative distribution we arrive at essentially the same set of clusters as obtained by using the histogram in the manner described.

We examine each of the peaks in the histogram to determine whether they satisfy the criteria for what we call a local cluster of points. To do so, we number the histogram intervals, beginning with the interval that contains the point with the lowest radiance. For each peak we examine the distribution of points within the range \( [i, j] \), where \( [i, j] \) denotes all the histogram intervals between and including interval \( i \) and interval \( j, i < j \). The range is chosen so that it is symmetric about the histogram peak. Suppose there are \( n \) points in the range \( [i, j] \). We search \( [i, j] \) for the largest subrange \( [k, l] : i < k; l < j; l - k < j - i \), that has the largest number of points contained by any subrange with as many intervals as in \( [k, l] \) and that satisfies the following: (1) if \( m \) is the number of points in the subrange \( [k, l], m \) must be a majority of the \( n \) points in the range \( [i, j] \), and (2) had the \( n \) points been uniformly distributed on \( [i, j] \), there would be only a small probability of finding at least \( m \) points on any subrange of \( [i, j] \) that contains the same number of intervals as subrange \( [k, l] \). The group of \( m \) points that satisfies these criteria is said to be a local cluster with range \( [i, j] \) and subrange \( [k, l] \). The properties of the cluster, such as the mean radiance, are derived from the properties of the points in the subrange. To insure that there is a majority of points on the subrange and thus that the subrange is fairly representative of the points in the range, we take \( m \geq 0.8n \). The subranges found for the frames in Figure 3 typically contain far more than 80% of the points on the corresponding ranges, and as a result, the condition that \( m \geq 0.8n \) has little influence on the final selection of points. It is, nevertheless, included because when the range contains several hundred points, a subrange that contains little more than the average number of points per interval can satisfy the second condition, while the points it contains fail to represent adequately the remaining points on the range.

To insure that the grouping would occur by chance infrequently, we accept probabilities that are less than 0.05. If \( n \) points are uniformly distributed on range \( [i, j] \), the probability of finding at least \( m \) points on any subrange equivalent to \( [k, l] \) is given by a multinomial distribution function. As the application of multinomial functions is impractical, we approximate the probability with the binomial function given by

\[
\phi = \frac{1}{p} \sum_{k=m}^{n} \binom{n}{k} (p^k)(q)^{n-k} \tag{A5}
\]

where \( p = (i - k + 1)/(j - i + 1) \) is the chance of finding a point in \( [k, l] \), \( q = 1 - p \) is the chance of finding a point elsewhere in \( [i, j] \), and \( \binom{n}{k} \) is the combinatorial factor. When \( n \) is large, \( \phi \) is approximately given by

\[
\phi = \frac{1}{p} \frac{1}{2} \left( 1 - \text{erf} \left( \frac{m - np}{\sqrt{2npq}} \right) \right) \tag{A6}
\]

Approximations (A5) and (A6) tend to the actual probability in the limit of small probabilities. They also systematically overestimate the actual probability. A set of local clusters with their associated ranges, indicated by arrows, and subranges, indicated by shading, is illustrated in Figure A1b.

The procedure for determining local clusters is iterative. We start with the peak with the lowest radiance. We take the interval for this peak and the two histogram intervals on each side as the initial range. At every iteration the subrange is the largest set of intervals that satisfies the above conditions. If such a subrange is not found, the range is expanded by adding a single histogram interval to each end and the set of points within the new range is examined. This process is repeated until (1) a set of points is found that satisfies the local cluster criteria, (2) when the range is expanded, it encompasses a histogram peak with more points than are in the initial peak, in which case the smaller peak is said to fail the local cluster test and the test is transferred to the larger peak and is restarted, and (3) the width of the range is greater than 0.5 \( (I_{95} - I_s) \), in which case the peak is said to fail the local cluster test.

We note that by satisfying these criteria, a set of points
will be distributed over a small range of intensities so that the majority of points is relatively tightly grouped on the subrange and the remainder relatively loosely grouped outside of the subrange. Thus, the points will indeed appear to be bunched as they appear in the feet of the arches when compared with points having low local standard deviations that lie outside the feet. The properties to be attributed to a local cluster are the mean radiance, the standard deviation of the radiances about the mean and the number of points in the cluster. The points that constitute the local cluster are those on the subrange. The number of points in a local cluster is the number of points in the subrange, the mean radiance is the mean for these points and the standard deviation is the standard deviation for these points. By insisting that at least 80% of the points in the range are located in the subrange, we insure that the properties attributed to the cluster are relatively insensitive to the manner in which the range and subrange are determined. Table A1 lists the local clusters in frame (1, 3).

Note that in Table A1 the ranges associated with some of the local clusters overlap. We have included in the test for local clusters nothing to prevent this overlap. Overlap is illustrated in Figure A1b. We take multiple local clusters to be evidence of structure within the scene. In the description of the scene, the existence of such structure should be noted. A more detailed analysis is needed, the local clusters may in some cases be separated by geometrically subdividing the scene and analyzing separately the local means and local standard deviations for each subdivision. Such detail is, of course, gained at the expense of increasing the number of frames that make up a given scene. Here we keep to the initial set of (250 km)² frames.

To estimate cloud cover using (A1), we attempt to combine local clusters to form eventually two super clusters, one for regions that are cloud free and one for regions that are completely covered by clouds in a single layer. If we can satisfactorily perform this combination, then we conclude that there is but one layer in the scene. The first step in combining local clusters is to group into a single nonoverlapped cluster local clusters with ranges that have points in common. We start with the overlapped local cluster that has the largest number of points per histogram interval on the subrange. We subject to the local cluster test the points in the range made up of the combined ranges for the two overlapped local clusters. The initial range for this test is the combined range. If more than one local cluster overlaps the local cluster with the largest point density, then the local cluster with the largest point density is first combined with the overlapping local cluster having the next largest point density. After a successful combination the local clusters are again ranked according to the density of points on the

<table>
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<th>Range</th>
<th>Subrange</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Number of Points</th>
<th>Probability of Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>281.0-282.0</td>
<td>281.2-282.0</td>
<td>281.58</td>
<td>0.21</td>
<td>21</td>
<td>0.027</td>
</tr>
<tr>
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<tr>
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<td>0.037</td>
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<tr>
<td>283.4-284.8</td>
<td>284.0-284.4</td>
<td>284.16</td>
<td>0.09</td>
<td>4</td>
<td>0.023</td>
</tr>
<tr>
<td>286.4-289.8</td>
<td>287.6-289.6</td>
<td>288.63</td>
<td>0.65</td>
<td>4</td>
<td>0.041</td>
</tr>
<tr>
<td>292.0-293.4</td>
<td>292.2-292.6</td>
<td>292.40</td>
<td>0.10</td>
<td>144</td>
<td>10^{-3}</td>
</tr>
<tr>
<td>292.4-293.4</td>
<td>292.4-293.2</td>
<td>292.83</td>
<td>0.22</td>
<td>374</td>
<td>10^{-3}</td>
</tr>
</tbody>
</table>

Standard deviation cutoff is 0.52 K (γ = 0.05).
deviations need not be small. Occasionally, they will be small, and so, a set of points which can be assigned to neither the clear nor the cloud covered clusters will have \( \sigma \approx \sigma_c \). We note, however, that such clusters occur only rarely, and they typically contain but few points. Otherwise, the arches in Figures 2 and 3 would not have distinct feet.

Of course, when clear or completely cloud-covered scan spots dominate the scene, we risk eliminating the less dominant cluster when we apply the test for major clusters. So, for example, in frame (3, 3) the nonoverlapped cluster associated with cloud-free regions fails to meet the criteria of a major cluster because it contains few points, while there are many points with nearly complete cloud cover that lie just outside the range associated with the completely cloud-covered major cluster. When a cluster is eliminated by this test, it is a signal that the cluster has few points and that we should be unwilling to place confidence in the results based on these points.

The final step in arriving at clear and cloudy sky super clusters is to combine any major clusters having means that lie within an interval \( \Delta = \chi(I_{55} - I_c) \), where \( \chi \) is some fraction less than 0.5. We take \( \chi = 0.25 \). Occasionally, a major cluster will have satellite clusters in nearby intervals that satisfy the test for major clusters. These satellites, however, typically contain few points compared to the dominant major cluster. To add satellite clusters to a dominant major cluster, we again start with the major cluster having the highest density of points on the subrange. We add to this cluster any major clusters that lie within the specified interval, starting with the major cluster that has the next highest point density. We then apply the local cluster test to the points contained in the intervals that lie between the extremes of the ranges associated with the two major clusters.

Adding in this fashion satellite clusters to a dominant major cluster gives rise to a cluster with mean and standard deviation close to those of the dominant major cluster. Any cluster that remains after this combination is said to be a super cluster. Figure A1e illustrates two super clusters. If more than two super clusters remain, it is a sign that more than one cloud layer is present. Such cloud layers might be separated by geographically subdividing the scene and analyzing each subdivision separately. If, however, the layers are overlapped, subdividing may fail to separate the layers, and, in principle, we could not then estimate the cloud cover. Figure 4 shows the arch for frame (1, 3) and the points that make up the super clusters.

As noted at the start of this section, the current algorithm has several adjustable parameters. Figure A2 shows the sensitivity of the results for frame (1, 3) to various choices of the local standard deviation cutoff, as specified by \( \gamma \) in (A3), and to the width of the histogram interval at which the points are grouped. Note that the ordinate in Figure A2 is reversed so that colder cloudy sky radiating temperatures, indicating colder cloud tops, are plotted as being above warmer temperatures. The colder temperatures indicate higher clouds. The error bars in the figure indicate the standard deviations of the points that make up the cluster; the central points indicate the means. The figure shows the results to be fairly insensitive to the choice of \( \gamma \) and \( \Delta T \), and a similar lack of sensitivity is exhibited by the results for the other frames.

Despite the lack of sensitivity, several comments concerning the choice of these parameters are in order. First, local clusters can be distinguished only when their means are separated by an interval that is larger than the histogram interval. Second, because fewer points are aggregated at a time, a smaller histogram interval generally gives rise to clusters with smaller widths, as indicated by the standard deviations. Note, however, as is shown in Figure A2, that the widths are only marginally smaller for a histogram interval that is 2.5 times smaller.

With regard to the cutoff for the local standard deviation, we observe from (A3) and (A4) that by taking a large value for \( \gamma \) we risk including in our estimates of the cloud-free and cloud-covered radiances regions that are truly partially covered. As a result, the estimates will be biased. The mean of the cloudy sky radiance will be too high, that for the clear sky radiance too low. This bias is demonstrated in Figure A2 for the cloudy sky radiating temperature. As \( \gamma \) is reduced, \( T_c \) decreases. On the other hand, by taking \( \gamma \) too small, we risk obtaining clusters with so few points that they fail to satisfy either the local or major cluster criteria. In general, however, the widths of the clusters become smaller as \( \gamma \) is reduced, and as is indicated by Figure A2, the estimate of the clear or cloudy sky radiance will be improved only slightly by optimally choosing \( \gamma \).

Finally, Figure A2 exhibits an anomaly that can be attributed to too few points in a cluster. For \( \Delta T = 0.2 \) K and \( \gamma = 0.04 \) the figure shows the coldest estimate for the cloudy sky radiating temperature, and this estimate is based on a cluster with the smallest width. In this case, however, the cluster contains only 19 of a possible 1024 points in the scene. These points are probably geographically localized and therefore fail to be representative of the entire scene. To overcome such anomalies, we should add to the algorithm a measure of the geographical representativeness provided by the points in the super clusters.

To test the sensitivity of the algorithm to the host of parameters, we set the parameters for both conservative (\( \gamma = 0.02, \Delta T = 0.2 \) K, \( I_{55}, I_{68}, m = 0.9n, \phi = 0.02, \chi = 0.15 \)) and liberal (\( \gamma = 0.05, \Delta T = 0.5 \) K, \( I_{55}, I_{68}, m = 0.6n, \phi = 0.10, \chi = 0.35 \)) cluster selection criteria. With the conservative criteria the algorithm isolated all but three of the super clusters that were isolated by the standard set of parameters applied to the frames in Figure 3. With one exception, when
a super cluster was isolated, the values of $T_r$, $I_r$, and thus $A_r$ fell within the ranges listed in Table 1. The exception was frame (1, 2) where $T_r$ shifted 0.2 K, while the width of the super cluster was only 0.1 K. With a similar exception, the super clusters recovered with the liberal criteria matched those produced with the standard criteria. In addition, the liberal criteria produced super clusters for the cloudy sky radiance in frame (1, 1) and the clear sky radiance in frame (3, 3). These clusters were ruled out by the standard criteria. These results suggest that when the arches are distinct, the final estimates will be fairly insensitive to the details of the algorithm.

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