

## **Clouds and the Earth's Radiant Energy System (CERES)**

### **Algorithm Theoretical Basis Document**

#### ***Imager Cloud Layer and Height Determination***

##### ***(Subsystem 4.2)***

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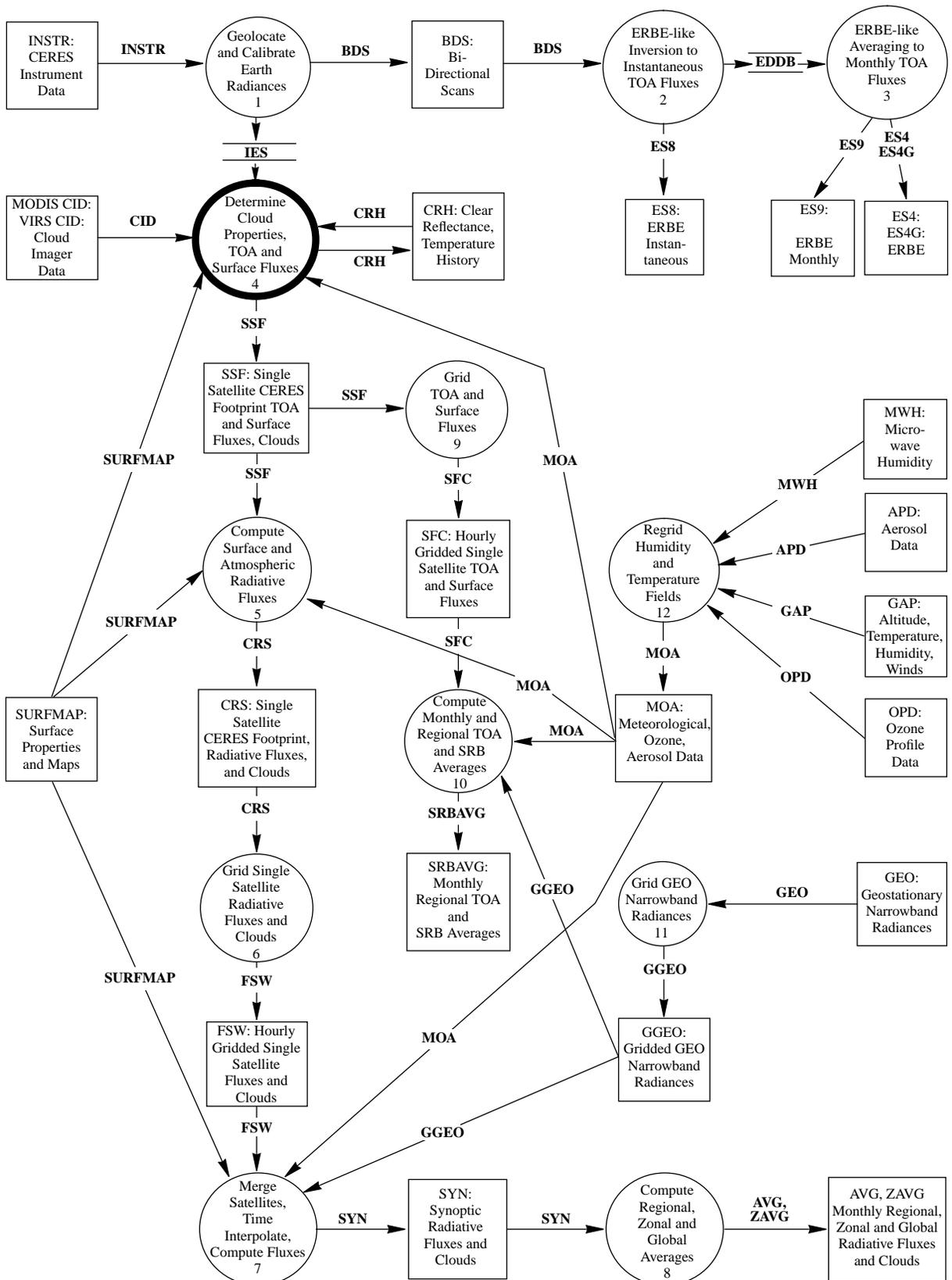
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**CERES Top Level Data Flow Diagram**



## 4.2. Imager Cloud Layer and Height Determination

### 4.2.1. Introduction

Section 4.1 discussed methodologies to provide two functions

1. Generate a mask that identifies imager pixels that are obstructed between the satellite and the surface. The obstructions include clouds, dust, or thick smoke, for example.
2. Generate clear-sky radiance maps from the imager data identified as nonobstructed.

This document discusses the next two steps in the cloud-retrieval process, namely the detection of cloud layers and the subsequent determination of cloud-top pressure for each layer present. Once the presence of single or multiple cloud layers have been identified, a height will be determined for each cloud layer present. Several approaches have been examined for use in the Version 1 CERES (Clouds and the Earth's Radiant Energy System) cloud-retrieval algorithm, such as spatial coherence (Coakley and Bretherton, 1982), multispectral techniques such as the layered bispectral threshold method (LBTM; Minnis et al., 1993), and artificial intelligence methods such as the fuzzy logic expert system approach. The main difference between Version 1 and Version 2 of the ATBD is the inclusion of a section describing the global daytime fuzzy logic classification method that has been developed and implemented in the production code.

The spatial coherence and fuzzy logic methods will be used to detect cloud layers. At the time of this writing, an updated version of the spatial coherence algorithm is being implemented in the CERES production code. While the spatial coherence algorithm may be applied over all surfaces, the results from application of the algorithm have been limited to oceans. We need to gain more experience running the spatial coherence algorithm over various land surface types with global AVHRR Global Area Coverage (GAC) data. The fuzzy logic classification code operates over all terrains exclusive of snow or ice-covered surfaces or over oceans in areas of strong sun glint. The current thinking is that these two algorithms may be complementary to some degree. The spatial coherence method often finds layered cloud systems over large areas, and the classifier aids in determining layers on smaller spatial scales. The investigation of synergism between the two methods is an area of active research.

A section is provided detailing the theoretical basis of the CO<sub>2</sub> slicing method (e.g., McCleese and Wilson 1976; Smith and Platt 1978; Menzel et al. 1992). The CO<sub>2</sub> slicing method is used to determine mid- to high-level cloud-top pressures. While the 15- $\mu$ m channels are unavailable on the VIRS instrument, the CO<sub>2</sub> slicing method is being developed and implemented using HIRS/2 data as a surrogate for data taken by the MODIS instrument. A strength of spatial coherence and CO<sub>2</sub> slicing techniques is that they both work with infrared (IR) narrowband channels (at wavelengths between 11 and 15  $\mu$ m) and thus are applied the same for both daytime and nighttime viewing conditions.

Section 4.2.2 outlines the fuzzy logic classification algorithm; section 4.2.3 outlines the spatial-coherence algorithm. The LBTM daytime multispectral methods are discussed in section 4.2.4, and finally the CO<sub>2</sub> slicing technique is outlined in section 4.2.5. Future (near-term) work is briefly outlined in section 4.2.6.

### 4.2.2 Automated Fuzzy Logic Approach to Cloud Classification

The pervasive occurrence of multiple cloud layers is described by global cloud climatologies derived from surface-based synoptic observations (Hahn et al. 1982; 1984). Observations of multiple cloud layers are discussed in Warren et al. (1985) and Tian and Curry (1989). These studies have found that mid- and high-level cirrus clouds tend to co-occur with lower-level clouds. If multiple cloud layers are present but are assumed *a priori* to be occupying a single level, the satellite-retrieved cloud height will be somewhere between the upper and lower cloud layers. The magnitude of the error depends on the optical depth of the upper cloud layer (e.g., Menzel et al. 1992; Baum and Wielicki 1994). Errors in

retrieved cloud heights in turn cause errors in the microphysical cloud property retrievals. Part of the problem is that one needs to know where multiple cloud layers exist in the imagery before an algorithm can be developed and implemented to infer the macrophysical and microphysical properties of each of the cloud layers present.

In recent years, textural and spectral signatures have been used to classify cloud and surface types from high-resolution Landsat Multispectral Scanner imagery (e.g., Chen et al. 1989; Lee et al. 1990; Welch et al. 1988, 1989) or from lower resolution imagers such as AVHRR. The classification schemes presented in these studies have the limitation that they are designed for a specific area, such as for maritime regions (e.g., Bankert 1994), tropical regimes (e.g., Shenk et al. 1976; Inoue 1987), or polar regions (e.g., Ebert 1987, 1989; Key et al. 1989; Key 1990; Welch et al. 1990, 1992; Rabindra et al. 1992; Tovinkere et al. 1993). Peak and Tag (1992) report on the development of an automated cloud classification system using GOES data for use in the interpretation of synoptic-scale events as an aid in forecasting on U.S. Navy ships. The focus of these studies is primarily that of distinguishing between clouds and the underlying surface, but not of distinguishing whether there is one or more cloud layers.

In the context of the CERES experiment, the aim of the fuzzy logic classification process is to identify imager pixel arrays that contain clear land or ocean from those that contain clouds. If an array contains clouds, the additional piece of information required is whether the clouds appear in a single cloud layer or multiple layers. A distinction can be made between this automated classification approach and that of spatial coherence as previously discussed in this document. The spatial coherence method makes the assumption that there will be a number of pixels grouped closely together that contain opaque cloud. For cirrus, this is not always the case, especially in the tropics when thin cirrus shields extends hundreds, if not thousands, of kilometers from their source. The classification technique described in this section is intended for use when thin cirrus is present, so that this technique is complementary to that of spatial coherence. Further details and results from application of the fuzzy logic approach are provided in Baum et al. (1996).

We note that this approach has been tailored for use with the VIRS instrument on the TRMM platform. When MODIS data become available, the classification approach will be modified to take advantage of the increased channel selection.

#### ***4.2.2.1. Region Labeling, Features and Classes***

The fuzzy logic classifier uses a supervised learning approach where a set of pre-labeled samples for each class are required to train the classifier. The samples, defined for this study as 32-pixel x 32-pixel arrays (approximately 35 km x 35 km at nadir), are labeled manually from 1.1-km AVHRR satellite imagery. The number of samples required for training depends on the number of classes chosen for the classifier. A rule of thumb is to label approximately ( $\sim 15 \times$  Number of classes) samples per class, so to build a supervised classifier with seven classes, one should label more than 100 samples for each class.

***4.2.2.1.a. Region Labeling.*** Since the pre-labeled samples are used during both the training and testing phases, any inaccuracies introduced during the labeling process will result in lower classification accuracies. Accurate labeling of the samples is the key to accurate classification. Typically, sample labeling is performed by an analyst solely on the basis of the imagery. Imagery only provides contextual information about a scene and it is not always a straightforward process to separate one cloud type from another. This is especially true of very thin cirrus.

The sample labeling process is strengthened through the use of ancillary data sets including NMC gridded analyses of temperature and humidity profiles. For example, inspection of temperature and relative humidity profiles can show regions of enhanced relative humidity or temperature inversions that may be indicative of a cloud layer. Sample selection is made using the Satellite Imagery Visualization System (SIVIS; Baum et al. 1995). The SIVIS software allows the user to analyze an image interactively and view ancillary data related to each sample.

Each labeled sample is stored in a database along with the scaled radiometric data, latitude, longitude, time of observation, analyst comments, viewing geometry (solar zenith, viewing zenith, relative azimuth, and scattering angles), ancillary data from 10-min maps that provide elevation, water percentage within the 10-min cell, surface type (e.g., desert, marsh, ocean, mountains), and ecosystem type, and finally parameters calculated from the NMC gridded profiles such as tropopause height, air mass type, and boundary-layer lapse rate. The database allows the sample set to be easily subsetted, rearranged, and otherwise manipulated for further analysis.

**4.2.2.1.b. Features.** A variety of both textural and spectral features have been explored in the literature and are briefly mentioned here. Additional features that have not been previously described will be discussed in greater detail.

*i. Textural features.* Textural features are computed in two ways. The first approach is referred to as the gray-level difference method (GLDV) (Haralick et al, 1973; Weszka et al, 1976; Chen et al. 1989). The GLDV method is based on the absolute differences between pairs of pixels having gray levels  $I$  and  $J$  and are at a distance  $d$  apart at angle  $\phi$  with a fixed direction. The GLDV probability density function  $P_{GLDV}(m)$  is defined for  $m = I - J$ , where  $I$  and  $J$  are the corresponding gray levels having a value between 0 and 255. The function  $P_{GLDV}(m)$ , which depends on  $d$  and  $\phi$ , is obtained by normalizing the gray-level frequencies of occurrence by the total number of frequencies. Once  $P_{GLDV}(m)$  has been formed, the calculation of the textural features listed in Table 2 is straightforward. Further details on the textural features may be found in Chen et al. (1989).

We introduce a modification to the calculation of textural features. Some useful information may be lost in the use of difference vectors that may be inherent in the original imagery. For example, a gray level difference of zero may be derived from two adjoining pixels that are both clear or are both cloud-filled. One way of supplementing the information provided by the GLDV method is to use the gray levels of the original image instead of the gray-level differences. This approach will be referred to henceforth as the gray level vector (GLV) method. The gray level values are based on an absolute scale in which reflectance values of 0 and 1 correspond to gray level values of 0 and 255, respectively. Brightness temperature values of 200 K and 327.5 K correspond to gray level values of 0 and 255, respectively. Reflectances gray levels are calculated for AVHRR channels 1 and 2 while brightness temperature gray levels are calculated for AVHRR channels 3, 4, and 5. For each data sample, a gray-level histogram is calculated and normalized by the total number of points. The normalized histogram becomes the GLV-based density function  $P_{GLV}(m)$ . The features defined in Table 2 are calculated using both the GLV and GLDV methods.

Table 1: Texture features derived using the gray-level difference vector (GLDV);  $m$  is the absolute value of the difference between gray-level differences one pixel apart in the horizontal direction ( $\phi=0^\circ$ ).  $P(m)$  is the difference-vector probability density function obtained by normalizing the gray-level frequencies of occurrence by the total number of frequencies.

Mean	$\mu = \sum_m mP(m)$
Standard deviation	$\sigma = \left[ \sum_m (m - \mu)^2 P(m) \right]^{1/2}$
Angular second moment (ASM)	$\sum_m [P(m)]^2$
Entropy (ENT)	$\sum_m P(m) \log P(m)$
Local homogeneity (HOM)	$\sum_m \frac{P(m)}{m(1+m^2)}$
Contrast (CON)	$\sum_m m^2 P(m)$
Cluster shade (SHADE)	$\frac{\sum_m (m - \mu)^3 P(m)}{\sigma^3}$
Cluster prominence (PROM)	$\frac{\sum_m (m - \mu)^4 P(m)}{\sigma^4} - 3.0$

*ii. Spectral features.* A number of spectral features may be formed by exploiting the thermal or reflectance characteristics of various cloud and surface types. The features are formed from the gray level representation of the bidirectional reflectances for AVHRR channels 1 and 2 and from the gray level representation of brightness temperatures for the NIR and IR channels as described in the previous section.

Spectral features are defined from the means of each channel, ratios between channels, and differences between channels. As an example, a spectral feature may be formed from the gray level differences between channels 1 (a measure of reflectance) and 4 (a measure of the thermal component). One might expect this feature to exhibit some facility in separating low-level stratus clouds from transmissive high-level cirrus clouds since low clouds are usually more reflective and have a warmer temperature than the high clouds. This type of feature also is extremely helpful in identifying thin cirrus over lower-level clouds.

#### *4.2.2.1.c. Class determination by clustering analysis*

Our goal is to design and build a robust global cloud classification system that works independent of season, exclusive of strong sunglint conditions and surfaces that are covered by snow or ice. To this end, it becomes of paramount importance to define a set of clearly defined requirements for the classifier. For a classifier to be effective, one must define first a set of classes that are well-separable by a set of features derived from the multispectral channel radiometric data. A proper choice of classes is not always straightforward; in fact, many researchers have chosen classes based on rather arbitrary criteria. For instance, one could choose a set of standard cloud types such as cirrostratus, altocumulus, or cumulus (e.g., Garand 1988; Ebert 1987; Bankert 1994). For inferring cloud properties from satellite data, we find that more useful criteria are cloud height (low, mid, or high) and cloud fraction (broken or uniform). Few if any cloud property retrieval algorithms depend on the label attached to a cloud type, that is, whether a low cloud is stratocumulus or cumulus; what matters is that it is a broken low-level cloud.

As a way of testing our choice of classes, the data samples are split initially into four categories: clear-sky, low-level cloud, mid-level cloud, and high-level cloud. To determine how well the data samples fit into these categories, a simple cluster analysis is performed on the collection of labeled samples. The clustering method is a hierarchical centroid scheme that works in the following way. The method begins with the full set of labeled samples. Each sample can be considered initially as a "cluster." The scheme searches for the shortest distance between two clusters, or points. The pair of clusters with the shortest separation distance is merged, and a new centroid center is calculated as the average of its combined data points. The result of this analysis is viewed via clustering trees which depict the merging of points into clusters and the subsequent merging of clusters into larger clusters. The clustering tree analysis is useful for two reasons. First, clustering tree analysis shows the "outliers" within certain groupings. One possibility for having an "outlier" may be an incorrect classification by an analyst. Another possibility may be that additional classes are required. Second, clustering tree analysis provides insight as to the coherence of various groupings of samples within a class, such as cirrus samples taken from different air masses or that were taken over different surface types.

As a result of the clustering analysis, we define a set of eight separate modules for global daytime analysis of AVHRR data. The eight modules are E over land, mT over land, cT over land, mT combined with E (hereafter referred to as mT/E) over water, mP over land, mP over water, cP over land, and cP combined with A (hereafter referred to as cP/A) over water. More detailed examination of the eight modules is presented Section 5.

Because of the complexity of defining cloud cover over snow/ice-covered surfaces, we have not developed of a new polar module over land or water but will use the fuzzy logic classification approach reported in Tovinkere et al. (1993). One further restriction in this study is that we have not used data taken from strong sun-glint regions that are apparent in all NOAA-11 data taken over oceans. Analysis of cloud in imager containing strong sun glint presents a set of difficulties that are outside the scope of this study.

#### *4.2.2.2. The Fuzzy Logic Approach*

The theory of fuzzy logic is based on approximate reasoning. A classical two-valued logic system asks whether an object is a member of a set, or class. However, an object may belong to only one class; this is the approach taken by maximum likelihood estimation schemes and neural networks. A problem arises when an object belongs partially to more than one class. The idea of fuzzy sets is that an object may belong partially to more than one class; the degree of membership to any particular class is provided by a membership function. For our case, the object under scrutiny is a 32 x 32 pixel array. In this section, we relate the steps necessary for deriving membership functions for each class and for each feature derived in the previous section.

The "fuzzy logic" classifier methodology is described in Tovinkere et al. (1993). The classifier uses the concept of class membership to determine what classes are present within a given data array. For the cloud mask process, the initial set of classes will be cloud, land, snow, and water. Since the Tovinkere et al. (1993) study addresses only cloud classification in the Arctic, modifications to the methodology will

be necessary for use in a global algorithm. This approach is moving from the conceptual stage to a test stage at the current time.

Class mixtures are often classified as a single class, thereby leading to poor information extraction. This is due to uncertainty in the membership concept of the classical set theory. This representation scheme has difficulty in dealing with elements that partially belong to two or more sets. In order to

improve the information representation, the concept of fuzzy set theory has been used. Fuzzy logic is concerned with formal principles of approximate reasoning; i.e., it aims at modeling imprecise modes of reasoning to make decisions in an environment of uncertainty.

The greater expressive power of fuzzy logic derives from the fact that it contains, as special cases, not only the classical two-value and multivalued logical systems but also probability theory and probabilistic logic. The main features of fuzzy logic that differentiate it from traditional logical systems are the following:

1. In two-valued logical systems, a proposition  $p$  is either true or false. In multivalued logical systems, a proposition may be true or false or have an intermediate truth value.
2. The predicates in two-valued logic are constrained to be crisp in infinite truth value set  $T$ . In fuzzy logic, truth values are allowed to range over the fuzzy subsets of  $T$ . Predicates may be either crisp (e.g., “mortal,” “even”) or fuzzy (e.g., “tired,” “tall,” “cold”).
3. Two-valued as well as multivalued logics allow only two quantifiers: “all” and “none.” By contrast, fuzzy logic allows the use of fuzzy quantifiers exemplified by “most,” “many,” “several,” and so on. Such quantifiers may be interpreted as fuzzy numbers that provide an imprecise characterization of the cardinality of one or more fuzzy or nonfuzzy sets. In this way, a fuzzy quantifier may be viewed as a second-order fuzzy predicate. On the basis of this view, fuzzy quantifiers may be used to represent the meaning of propositions containing fuzzy probabilities and thereby make it possible to manipulate probabilities within fuzzy logic.

**4.2.2.3. The fuzzy expert system (ES).** A fuzzy ES includes two other elements, in addition to the components of a conventional system, “fuzzifiers” which convert inputs into their fuzzy representations, and “defuzzifiers” which convert the output of the inference process into a single numerical value within the range of values of the output variable. The numerical output is used to adjust the state of the system being controlled.

A fuzzy control variable may have several states, each state being represented by a membership function. Suppose we are able to classify cloud from clear land and open water by just using the reflectances computed from channel one (CH1) and temperature from channel four (CH4). Figure 4.2-1 shows the different states for these two measures. CH1 is defined by the five albedo states: very low, low, medium, high, and very high. CH4 is defined by the three temperature states: cold, normal, and warm. The albedo measured in CH1 generally is higher for clouds than for land and water. CH4 generally is warm for land and cold for clouds. The above reasoning might lead to the following set of fuzzy rules:

Rule 1: IF CH1 is very low and CH4 is normal THEN class is water

Rule 2: IF CH1 is low and CH4 is warm THEN class is land

Rule 3: IF CH1 is medium and CH4 is cold THEN class is cloud

The CH1 reflectance and CH4 temperature values are rescaled to an integer ranging from 0 to 255. As shown in Figure 4.1-2, for a given image sample, the input value for CH1 is 0.17 and 0.4 for CH4; the fuzzifier then computes the degree of membership (DM) for one or more of these fuzzy states. In this case, the states “very low” and “low” of CH1 have membership values of 0.25 and 0.5, respectively. The other states for CH1 are zero. Similarly, the only state of CH4 with a value different from zero is “normal,” with a value of 0.60. The confidence level (CL) for each rule is computed by combining the

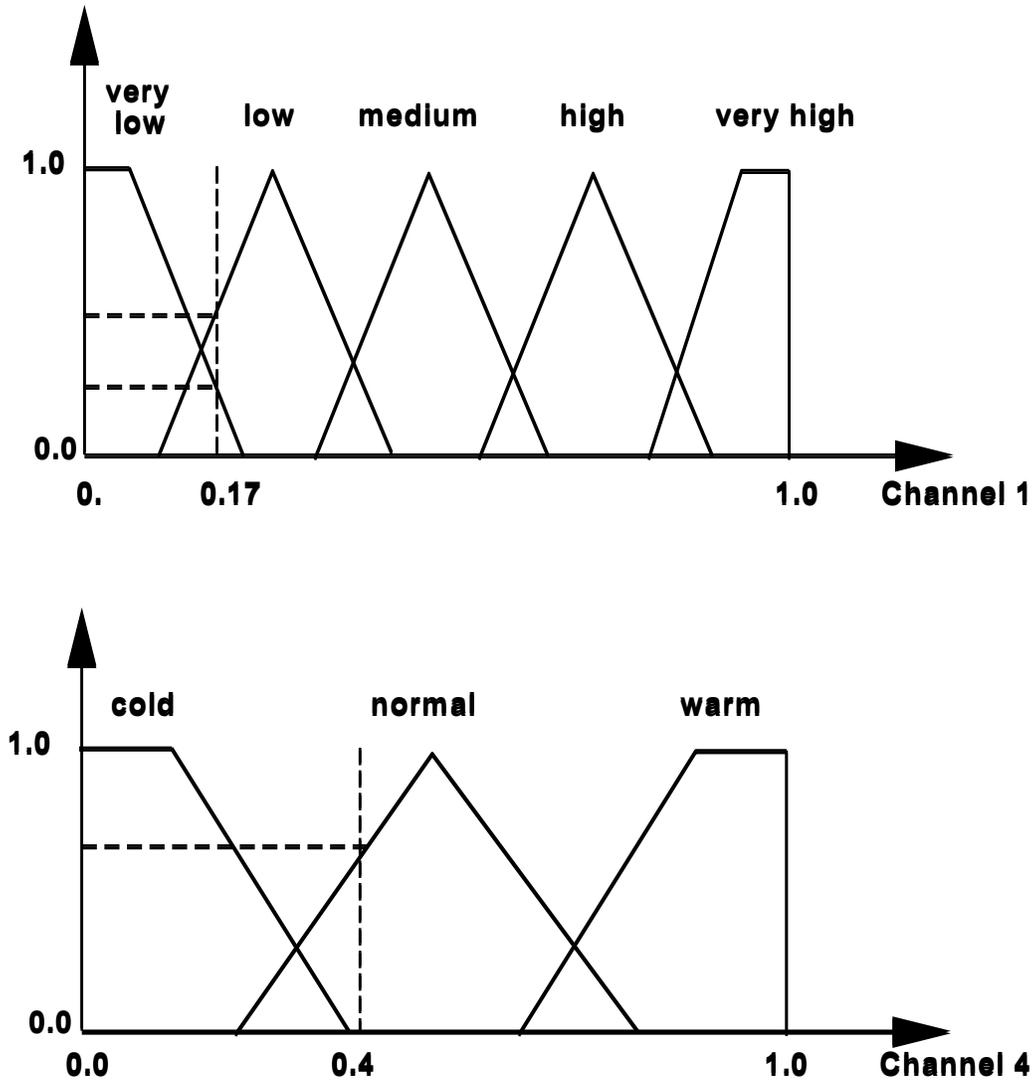


Figure 4.2-1. Schematic showing the concept of class membership in the fuzzy logic classification approach.

DM's associated with each condition using the following certainty theory formula (Luger and Stubblefield 1989):

$$CL(C1;C2) = \min[DM(C1);DM(C2)] \tag{4.2-1}$$

where C1 and C2 are the conditions of the rule. The CL for rules 1, 2 and 3 are

Rule 1:  $\min(0.25, 0.60) = 0.25$

Rule 2:  $\min(0.5, 0.0) = 0.0$

Rule 3:  $\min(0.0, 0.0) = 0.0$

Since rule 1 has the higher confidence level, the class selected is "water," which corresponds to the action of rule 1.

The classification process is performed with the aid of a general fuzzy expert system (GFES). GFES can handle different membership functions for describing the different states of the control variables. These functions are triangular; trapezoidal; one-, two-, and three-dimensional normal distributions; PI function; S function; and elliptical cones. The height for all these functions is equal to 1, since any

membership function can have any real value between 0 and 1. The multivariate normal distribution is an extension of the one-dimensional normal distribution.

Usually, triangular, trapezoidal,  $\Pi$ , and S functions (Giarratano and Riley 1990) are used for the definition of fuzzy ES's. Since our classifier uses control variables which are often assumed to belong to normal distributions, we have extended the usual set of function types to accommodate the definition of fuzzy states with one- and multi-dimensional normal distributions. Our experiments show that by increasing the number of dimensions, the classifier is able to separate better the different classes.

Three input files are required to run the classifier: a control variable file, a rule file, and a facts file. The control variable file requires the following information for each control variable: the name of the variable (e.g., temperature), the type of membership function used to approximate the mean and standard deviation of the feature vector, the number of states, the state names (e.g., hot, cold), and the values that define each state's membership function. The output consists of the class or classes present in the region or pixel with an associated value representing the percentage of the class within the region or pixel.

**4.2.2.3.a. Fuzzy membership functions.** The fuzzy logic classifier is trained using the labeled sample data set. Since a labeled data set is used in the training phase, the classifier is said to be trained with supervision. Means ( $\mu$ ) and standard deviations ( $\sigma$ ) are calculated for the complete training data set for each feature and for each class. The S membership function shown in Fig. 4.2-2a is formed from mean and standard deviation values as follows:

$$S(x, \alpha, \beta, \gamma) \Rightarrow \begin{cases} 0 & \text{for } x \leq \alpha \\ 2\left(\frac{x - \alpha}{\gamma - \alpha}\right)^2 & \text{for } \alpha \leq x \leq \beta \\ 1 - 2\left(\frac{x - \alpha}{\gamma - \alpha}\right)^2 & \text{for } \beta \leq x \leq \gamma \\ 1 & \text{for } x \geq \gamma \end{cases} \quad (4.2-2)$$

For fuzzy sets that may be represented by Gaussian distributions, the  $\Pi$  function (Fig. 4.2-2b) is used:

$$\Pi(x, \beta, \gamma) \Rightarrow \begin{cases} S\left(x, \gamma - \beta, \gamma - \frac{\beta}{2}, \gamma\right) & \text{for } x \leq \gamma \\ 1 - S\left(x, \gamma, \gamma + \frac{\beta}{2}, \gamma + \beta\right) & \text{for } x \geq \gamma \end{cases} \quad (4.2-3)$$

For the  $\Pi$  function, Tovinkere et al. (1993) initially had the  $\Pi$  function approximate the Gaussian distribution such that  $\beta = 3\sigma$  and  $\gamma$  was the mean value  $\mu$ . This resulted in a number of samples going unclassified by the expert system. By increasing the spread of the fuzzy sets (*i.e.*, increasing  $\beta$ ), the number of unclassified samples decreased. The value of  $\beta = 5\sigma$  was eventually chosen to allow greater overlap of the fuzzy sets, thereby minimizing the number of samples that could not be classified.

The derivation of fuzzy membership functions has been revisited in the present study for the reason that many fuzzy sets form non-Gaussian distributions. One way of accounting for the non-Gaussian distribution is to simply increase  $\beta$ , but this tends to result in an increased number of incorrect classifications. For fuzzy sets that may have a non-Gaussian distributions, a modified  $\Pi$  function ( $\Pi^{mod}$ ) is used (see Figure 4.2-2c):

$$\Pi^{mod}(x, \beta, \gamma) \Rightarrow \begin{cases} S\left(x, \gamma - \beta_1, \gamma - \frac{\beta_1}{2}, \gamma\right) & \text{for } x \leq \gamma \\ 1 - S\left(x, \gamma, \gamma + \frac{\beta_2}{2}, \gamma + \beta_2\right) & \text{for } x \geq \gamma \end{cases}, \quad (4.2-4)$$

where  $\beta_1 = (\gamma - \mathit{min})/\sigma$  and  $\beta_2 = (\mathit{max} - \gamma)/\sigma$ . The variables  $\beta_1$  and  $\beta_2$  represent the integer number of standard deviations used to generate the modified- $\Pi$  membership functions. The lower and upper limits are defined from the minimum (*min*) and maximum (*max*) values and the standard deviation of the fuzzy set. To better adjust the function shape to the data provided by the set of labeled samples, dilation and concentration operations (Giarrantano and Riley 1989) may be performed on the membership functions according to the values for  $\beta_1$  or  $\beta_2$  as shown in Table 4.2-2.

**Table 4.2-2:**

Value of $\beta_1$ or $\beta_2$	Operation Performed on the Membership Function
0 - 1	Dilation of power 3
1 - 2.5	Dilation of power 2
2.5 - 5.5	Concentration of power 1
5.5 - 7.5	Concentration of power 2
> 7.5	Concentration of power 3

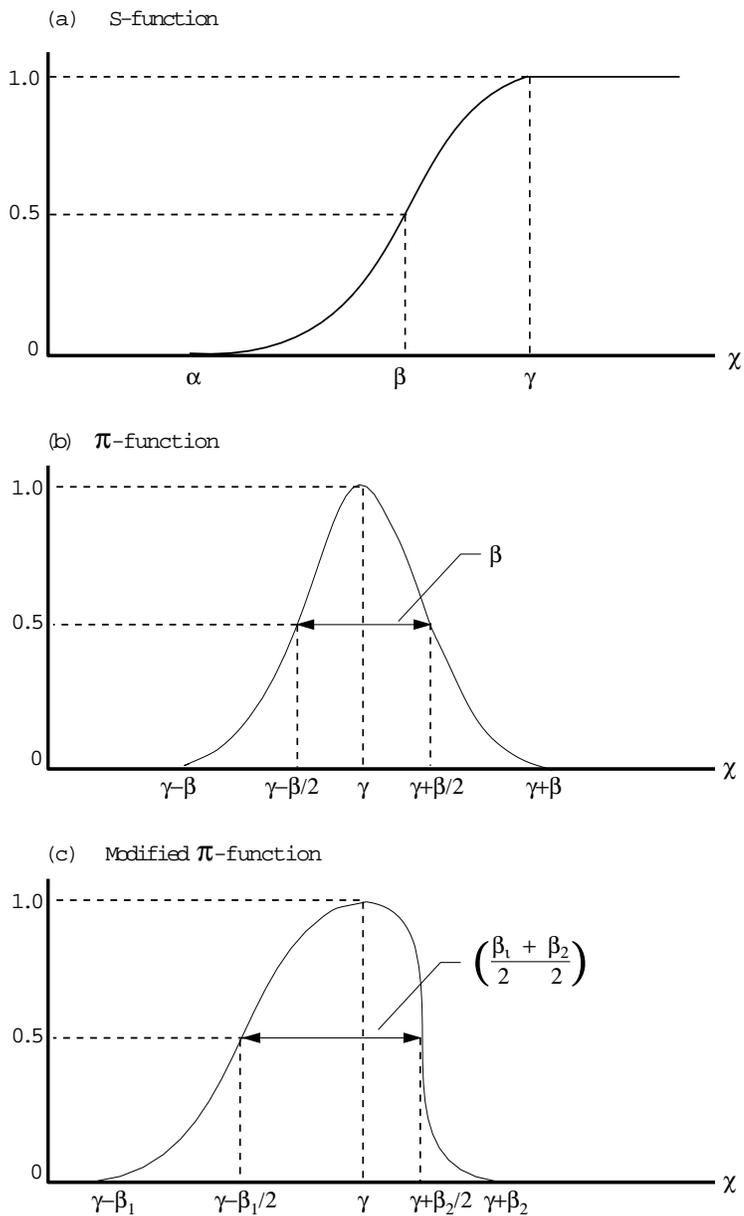


Figure 4.2-2. Fuzzy membership functions

**4.2.2.3.b. Feature Selection**

Previous investigations have reported on the numerous spectral and textural features developed for use with AVHRR imagery; descriptions of the features are provided in Garand (1988), Ebert (1987), Chen et al. (1989); Welch et al. (1992); and Baum et al. (1995). The primary purpose of the feature selection process is to find a subset of the 190 features that reduces redundant or irrelevant information, thereby increasing the efficiency of the classifier. Once a feature has been chosen, it cannot be deleted.

A feature may eventually be chosen that makes a previously chosen feature redundant or irrelevant. The selection of features depends on the classes desired; a change in specified classes usually results in the selection of a different feature set.

Several different feature selection schemes were tested, such as using the Bhattacharya distance (e.g. Tovinkere et al. 1993; Welch et al. 1992). For the present purpose, a feature selection scheme is implemented where the goal is to maximize the ability of the classifier to place each sample into the same category as that defined by the analyst during the sample collection process. For each sample, each feature is awarded a half point for its ability to place a given cloud sample into the correct height category and another half point for placing the given cloud sample into the correct cloud fraction category. This way, partial credit is assigned for a feature's ability to discern the proper cloud layer, but not brokenness (the reverse also holds true). No credit is awarded for a sample if more than one cloud layer is thought to be present. This process discourages the selection of features that tend to misclassify single-level cloud samples as containing multiple cloud layers.

#### *4.2.2.3.c. Fuzzy logic expert system*

The fuzzy logic expert system is divided into three phases: (1) initialization phase; (2) decision phase; and (3) cleanup and result phase. This information is discussed in Tovinkere et al. (1993) but is briefly mentioned here.

**Initialization phase:** For every class, membership functions are defined for each of the selected features as discussed in Section 4.2.2.3.b. The membership functions represent the fuzzy sets developed during the training phase. For the classification of a data sample taken from a mP air mass over land, the appropriate knowledge base would be chosen.

**Decision phase:** For a chosen data sample, feature values are calculated for the seven classes. For a given class, a feature's value is compared to the membership function developed for that feature. The comparison yields a membership value between 0 and 1 for each class. In the final step, the features' membership values are summed within the classes to provide measures of membership "strengths".

**Cleanup and result phase:** The summed membership strengths within each class are normalized to give the final membership strengths. For a given data sample, class membership is said to exist if the membership strength exceeds the thresholds determined during the training phase. If membership values exceed the threshold for more than one cloud class, the sample is classified as containing multiple cloud layers. Once a sample has been classified according to its membership values, the feature values are removed and the system is ready to run another case.

#### *4.2.2.4. Practical Considerations*

Since the fuzzy logic classification method uses a supervised approach, a set of labeled samples must be collected before building the classification modules. Even with the use of a sophisticated software package like SIVIS, this process is personnel intensive. As an indicator of the time required, we can set up the following example. We take the case of the eight modules defined for the daytime fuzzy logic classifier, with seven classes per module. If 100 samples are required for each class, the total required samples is  $8 \times 7 \times 100 = 5600$  samples. From experience, an analyst can reasonably collect 300 samples in a day. The effort to collect samples thus takes approximately one man-month.

Once the samples have been collected and organized, the feature selection process is initiated and requires approximately four hours per module on a desktop SGI Indy system. After features have been selected, the classifiers can be built in an afternoon. Thus, the total time required to build the classifier

modules is approximately one man-month, with the majority of the time being spent in obtaining the labeled sample set.

#### ***4.2.2.5. Strengths and Limitations***

As reported in Baum et al. (1996), three areas of difficulty are noted for single-level cloud samples. First, the classifier has difficulty with mid-level cloud samples. This result, in hindsight, is not unexpected since the World Meteorological Organization (WMO) definition of a mid-level cloud provides a range of cloud-base temperatures as a guideline. The inclusion of mid-level clouds increases the complexity of the problem since the mid-level cloud temperature range depends on the air mass within which the clouds appear. Second, the classifier tends to misclassify samples containing terrain shadows or strong cloud shadows. Third, if thin cirrus, with little or no identifiable texture (meaning the cirrus is very thin and homogeneous) is present over a lower-level cloud layer, the sample may be misclassified as containing a mid-level cloud.

Two areas of strength are also noted. First, the classifier does not become easily confused if fires or smoke are contained within the sample. Second, the classifier does not tend to misclassify single cloud layer samples as containing multiple cloud layers. For the eight modules, the classifier accuracies range from 84.8% to 91.1% for clear-sky and single-level cloud samples. The class membership function thresholds, used to determine which class (classes) are thought to be in a sample, are set to optimize classification accuracies for single-level cloud samples. When the resulting modules are tested against a set of labeled multilayered cloud samples, the classifier accuracies for the eight modules range from 64 to 81%. While the accuracies are lower for multilayered cloud samples than for the labeled single-level samples, we are reasonably confident that a sample classified as containing more than one cloud layer will actually contain more than one cloud layer. Note that only 201 samples from the clear-sky and single-level cloud training sets, out of a total of 9384 samples (or about 2%), were misclassified as containing multiple cloud layers.

### **4.2.3 The Spatial Coherence Method**

#### ***4.2.3.1 Identification of Cloud Layers from Satellite Imagery Data***

Everyday observations of clouds suggest that many cloud systems form well-defined layers. Surveys of satellite imagery data for the global oceans suggest that as many as 20 to 30% of all 250-km scale regions contain single cloud layers. At smaller observational scales (60 km), the isolation of single cloud layers may be as high as 50% (Coakley and Baldwin, 1984). Observations for the First ISCCP Regional Experiment (FIRE) II Cirrus Intensive Field Observations (IFO) suggest that as many as 50% of all 100-km scale regions are either single-layered or cloud-free (Lin and Coakley, 1993). Although cloud systems are often presumed to obey the physical relationships associated with a plane-parallel, homogeneous cloud, as is the case in ISCCP (International Satellite Cloud Climatology Project), clearly layered cloud systems might be expected to exhibit such behavior more closely than would more complex cloud systems. Because of their pervasiveness and to the relative abundance of theoretical tools that can be used to analyze them, layered cloud systems deserve special attention in observations of the earth's cloud systems. Effective optical properties of layered cloud systems should generally be more readily measurable than the macrophysical and microphysical properties of individual clouds. Changes in clouds brought about by changes in the climate system might well be noted first in the properties of layered clouds.

Experience with imagery data during the 1980's leads to the conclusion that layered cloud systems are relatively easy to identify. Here the spatial-coherence method is described as one approach to identifying the layers. The spatial-coherence method uses the pixel-to-pixel variability in emitted radiances to identify pixels that appear to be overcast by clouds that form a layer. Optical properties of cloud layers

can be deduced from the overcast pixels. Various degrees of quality control can be applied to the analysis to ensure that the pixels so identified are indeed overcast. The increase in quality, however, is at the expense of the number of such systems that meet the criteria of being part of a well-defined layer. The algorithm will be applied to groups of pixels that have a similar surface type (e.g., water).

#### *4.2.3.2. Historical Perspective*

In the early 1980's, as is the case today, the favored approach for obtaining cloud properties from satellite observations was the application of thresholds to imagery data (Minnis and Harrison, 1984; Rossow et al., 1985; Rossow and Garder, 1993). Although multispectral, clustering methods were also used to attempt an automated identification of cloud structures, the final estimate of cloud properties was still derived assuming that each of the imagery pixels belonging to a certain cluster was completely covered by the cloud system represented by the cluster (Debois et al., 1982). Everyday experience, however, leads to expectations that the occurrence of broken clouds on scales that are smaller or comparable to the spatial resolution typical of imagers (i.e. ~4 to 8 km) is rather common. Furthermore, when the breaks occur, it is unlikely that the clouds align themselves to fall exactly within the footprint of an imager pixel. This type of spatial sampling problem leads to the conclusion that the errors associated with threshold estimates of cloud cover may be sizable, as early work on threshold methods foretold (Shenk and Salomonson, 1972) and recent work confirms (Wielicki and Parker, 1992; Chang and Coakley, 1993).

In anticipation of these errors, a number of methods were proposed to obtain the fractional coverage within imager fields of view. Platt (1983) proposed a modified version of the visible-infrared bispectral method introduced by Reynolds and Vonder Haar (1977). The method used plane-parallel radiative transfer theory to identify fields of view that were overcast with clouds having a given liquid water or ice water column amount from those that contained broken clouds. The method has been extended and refined by Minnis and Harrison (1984) and by Minnis et al. (1993a, b). Arking and Childs (1985) adopted a similar scheme but added radiances observed at 3.7  $\mu\text{m}$  to allow for effects caused by droplet size in the plane-parallel radiative-transfer calculations. A third approach, the spatial-coherence method (Coakley and Bretherton, 1982), relied on the observation that many of the global cloud systems come in layers and that these layers extend over tens of kilometers, maintaining a fairly constant emission temperature over these scales. Where the region being observed is cloud-free or where it is overcast, the emitted radiances achieve a high degree of spatial uniformity at the pixel scale. Where the clouds are present but fail to completely cover the imager pixels, the emitted radiances vary erratically from pixel to pixel. While the spatial-coherence method explicitly seeks to identify the cloud layers, the retrieval of cloud properties employed in the bispectral and multispectral schemes relied on the assumption that the clouds being observed were part of a layer. The challenge is to develop an algorithm that identifies layers when present.

The spatial-coherence method identifies layers by identifying the portions of the region that exhibit a high degree of local uniformity in the emitted radiances. The purpose of this section is to outline a relatively simple approach to solving this problem. The solution is both a generalization and simplification of the earlier approaches (Coakley and Bretherton, 1982; Coakley and Baldwin, 1984). In the description given here, the method depends primarily on a single parameter—the difference in radiances expected for cloud-free and overcast fields of view. The dependence of the retrieved properties, namely the radiances associated with cloud-free and overcast portions of the region, is relatively insensitive to the choice of this parameter.

#### *4.2.3.3. Theory Behind the Spatial-Coherence Method*

The starting point for spatial-coherence analysis is the model of a well-defined, single-layered system of clouds over a relatively uniform background. What is meant by the term “well-defined” and

“relatively uniform” will be explained below. The emitted radiance observed by a radiometer viewing such a system is given by

$$I = (1 - C)I_{cs} + C(\epsilon_{cld}I_{cld} + t_{cld}I_{cs}) \quad (4.2-5)$$

where  $I$  is the emitted radiance,  $C$  is the fractional cloud cover for the field of view,  $I_{cs}$  is the radiance associated with the cloud-free portion of the field of view, i.e. the radiance observed when  $C = 0$ .  $\epsilon_{cld}$  is the mean effective emissivity associated with the cloud layer,  $t_{cld}$  is the mean transmissivity, and  $I_{cld}$  is the radiance that would be observed for overcast regions, i.e.  $C = 1$ , if the clouds were black at the wavelength of observation. In (4.2-5), the radiance is assumed to be at a infrared (IR) window wavelength so that downward emission above the cloud can be neglected. Likewise, the surface is assumed to be black at the wavelength of observation so that all radiation incident on the surface is absorbed, especially that emitted downward by the cloud. No radiation is reflected by the surface.

Over relatively small regions, i.e.  $\sim 100 \text{ km} \times 100 \text{ km}$  to  $500 \text{ km} \times 500 \text{ km}$  scale, the emission of the clear-sky background,  $I_{cs}$ , and the height of the cloud layer, and therefore  $I_{cld}$ , are assumed to have little variance. That is, the effects of variations in the thermal emissions associated with the clear-sky background and the height of the cloud layer are small when compared with effects caused by variations in the fractional cloud cover and the cloud optical properties. If these conditions are met, the background is said to be relatively uniform and the layer is said to be well-defined. From (4.2-5), the variance of the radiances under such conditions is given by

$$(I - \bar{I})^2 = [(C - \bar{C})I_{cs} + (C\epsilon_{cld} - \bar{C}\epsilon_{cld})I_{cld} + (Ct_{cld} - \bar{C}t_{cld})I_{cs}]^2 \quad (4.2-6)$$

The variances of emitted radiances over small areas spanning several imager pixels is the key to identifying the portions of a region that are cloud-free or overcast by clouds in a well-defined layer. Clearly, the variance becomes zero when the mean cloud cover in a region approaches zero. If the mean cloud cover is zero, then, of course, the fractional cover in every pixel  $i$  is also zero, i.e.  $C = \bar{C} = 0$ . Where the clouds become sufficiently extensive so that several imager pixels are overcast then, for analogous reasons, the variance approaches zero because  $C = \bar{C} = 1$ . Often when cloud systems become sufficiently extensive that they cover several imager pixels, they also become opaque. A notable exception, of course, is cirrus. For opaque, overcast clouds the variance again becomes zero because  $t_{cld}^i = \bar{t}_{cld} = 0$  and  $\epsilon_{cld}^i = \bar{\epsilon}_{cld} = \epsilon_{cldmax}$ , where  $t_{cld}$  is the cloud transmissivity and  $\epsilon_{cldmax}$  is the emissivity that the clouds obtain when they become opaque, i.e.  $\epsilon_{cldmax} = 1 - r_{cldmax}$ , where  $r_{cldmax}$  is the reflectivity. To simplify notation,  $I_{cld}$  will be used to represent  $\epsilon_{cldmax}I_{cld}$  in the remainder of the text. It will be understood that  $I_{cld}$  is taken to be the emission observed for pixels overcast by opaque clouds. When pixels become overcast with opaque clouds, the variance in emitted radiances also becomes zero. When pixels become overcast by semitransparent clouds, like cirrus, pixel-to-pixel variations in the cloud optical properties, i.e.  $\epsilon_{cld}$  and  $t_{cld}$ , prevent the variance from dropping to zero.

Because clouds appear to vary incoherently on the  $\sim 1 \text{ km} \times 1 \text{ km}$  scale available to current satellite imagers, (4.2-6) indicates that variances in the emitted radiances for regions that are covered by several imager pixels will be nonzero when the region contains broken cloud. The variability will be caused partly by differences in the fractional cloud cover from pixel to pixel and partly by variations in the average cloud optical properties from pixel to pixel. The spatial-coherence method identifies pixels that are overcast by layered clouds where the clouds become opaque and pixels that are cloud-free by relying on the near-zero variances in emitted radiances for localized collections, or clusters, of the pixels. Collections of pixels that are partly covered by clouds or are overcast by clouds that are semitransparent invariably exhibit relatively larger variances.

It would appear that a simple threshold on the variance of emitted radiances would suffice to identify pixels that are overcast layered cloud systems. To a first approximation, the application of a simple threshold suffices; however, although fractional cloud cover and cloud optical properties tend to vary

incoherently on the  $\sim 1 \text{ km} \times 1 \text{ km}$  scale, they can at times conspire to produce near-zero variances in emitted radiances while only partly covering a collection of pixels. Regular arrays of clouds arising from regular patterns of convection or mesoscale circulations will produce such instances. These conditions appear to be met only rarely. As a guard against these relatively rare occurrences, the spatial-coherence method relies not only on the low variances in the emitted radiances observed for cloud-free and opaque-overcast regions, but also on the clustering in the radiance domain of the pixels identified as cloud-free and overcast. The clustering must occur within a region that is, on average, rarely overcast or cloud-free, i.e. regions with scales of  $\sim 250 \text{ km} \times 250 \text{ km}$ .

#### 4.2.3.4. Spatial Considerations

**4.2.3.4.1. Local scale,  $4 \text{ km} \times 4 \text{ km}$  to  $8 \text{ km} \times 8 \text{ km}$ .** In the spatial-coherence method, the variability of the radiances is usually calculated for small arrays of adjacent pixels. Typically  $2 \times 2$  (scan line  $\times$  scan spot) pixel arrays are used for  $4 \text{ km} \times 4 \text{ km}$  AVHRR Global Area Coverage (GAC) data. The variability within each array is called the local variability. In the case of the  $2 \times 2$  arrays of GAC pixels, the local variability is associated with  $8 \text{ km} \times 8 \text{ km}$  portions of the region. The size of the array over which the variability is calculated is not critical. It is reasonable to select a scale between  $4 \text{ km} \times 4 \text{ km}$  and  $8 \text{ km} \times 8 \text{ km}$  for the variance scale because the cloud-free and overcast portions of  $250 \text{ km} \times 250 \text{ km}$  regions are often several times the  $4 \text{ km} \times 4 \text{ km}$  to  $8 \text{ km} \times 8 \text{ km}$  scales. If the local standard deviations of the emitted radiances are plotted as a function of the local means for the pixel arrays covering a  $250 \text{ km} \times 250 \text{ km}$  region, an arch plot, typical of the spatial-coherence method, results (see Fig. 4.2-3). The figure shows the local means and standard deviations of the emitted  $11\text{-}\mu\text{m}$  radiances for a  $250 \text{ km} \times 250 \text{ km}$  region over the Atlantic Ocean. The data points are from  $4 \times 4$  arrays of  $1 \text{ km} \times 1 \text{ km}$  AVHRR observations collected during the 1992 Atlantic Stratocumulus-Transition Experiment (ASTEX). Figure 4.2-3 shows an arch that is typical of a single-layered system of marine stratocumulus. Radiances of  $11 \mu\text{m}$  at the foot of the arch near  $96 \text{ mWm}^{-2}\text{sr}^{-1}\text{cm}$  are associated with the cloud-free background. Radiances at the foot near  $81 \text{ mWm}^{-2}\text{sr}^{-1}\text{cm}$  are associated with overcast pixels. In Figure 4.2-3, each point represents a  $4 \text{ km} \times 4 \text{ km}$  portion of the  $250 \text{ km} \times 250 \text{ km}$  region. There are approximately 1000 points in the plot. Every other  $4 \text{ km} \times 4 \text{ km}$  sample has been skipped.

For comparison, Figure 4.2-4a shows the same observations with the region divided to form  $8 \times 8$  arrays of the  $1 \text{ km} \times 1 \text{ km}$  pixels. Each point in the figure now represents an  $8 \text{ km} \times 8 \text{ km}$  portion of the region. Again there are about a 1000 points in the figure. The similarity in radiances of the overcast and cloud-free feet with those in Figure 4.2-3 illustrate the lack of sensitivity to spatial scale. Figure 4.2-4b shows the same observations again but in this case the region was divided to form  $2 \times 2$  arrays of  $4 \text{ km} \times 4 \text{ km}$  pixels. The  $4 \text{ km} \times 4 \text{ km}$  radiances were obtained by taking the corresponding averages of the  $1\text{-km}$  radiances. As in Figure 4.2-4a, each point represents an  $8 \text{ km} \times 8 \text{ km}$  portion of the  $250 \text{ km} \times 250 \text{ km}$  scale region. The results in Figure 4.2-4b are like those obtained with  $4 \text{ km} \times 4 \text{ km}$  AVHRR GAC data. Although the radiances associated with the cloud-free and overcast feet differ little from those shown in Figures 4.2-3 and 4.2-4a, the arch in Figure 4.2-4b appears to be less well-defined than those in Figures 4.2-3 and 4.2-4a. The loss in clarity is produced by points dropping from the body of the arch towards the abscissa. This change in arch structure is consistent with the concept that clouds, when broken, populate adjacent  $1 \text{ km} \times 1 \text{ km}$  scale pixels incoherently. Because of this incoherence and the relative lack of sensitivity of the derived cloud-free and overcast radiances to the size of the array used, there appears to be some advantage to using large arrays of small pixels when possible rather than  $2 \times 2$  arrays as has been used traditionally.

**4.2.3.4.2. Frame scale,  $250 \text{ km} \times 250 \text{ km}$ .** Like the size of the array used to calculate the local variance, the size of the region for which the spatial-coherence analysis is performed is not critical. The scale is arbitrarily chosen using the following guidelines. The region must be sufficiently large that cloud-free and overcast pixels occur relatively frequently. Furthermore, the spatial-coherence method uses a clustering method to distinguish between low local variances in the emitted radiances that

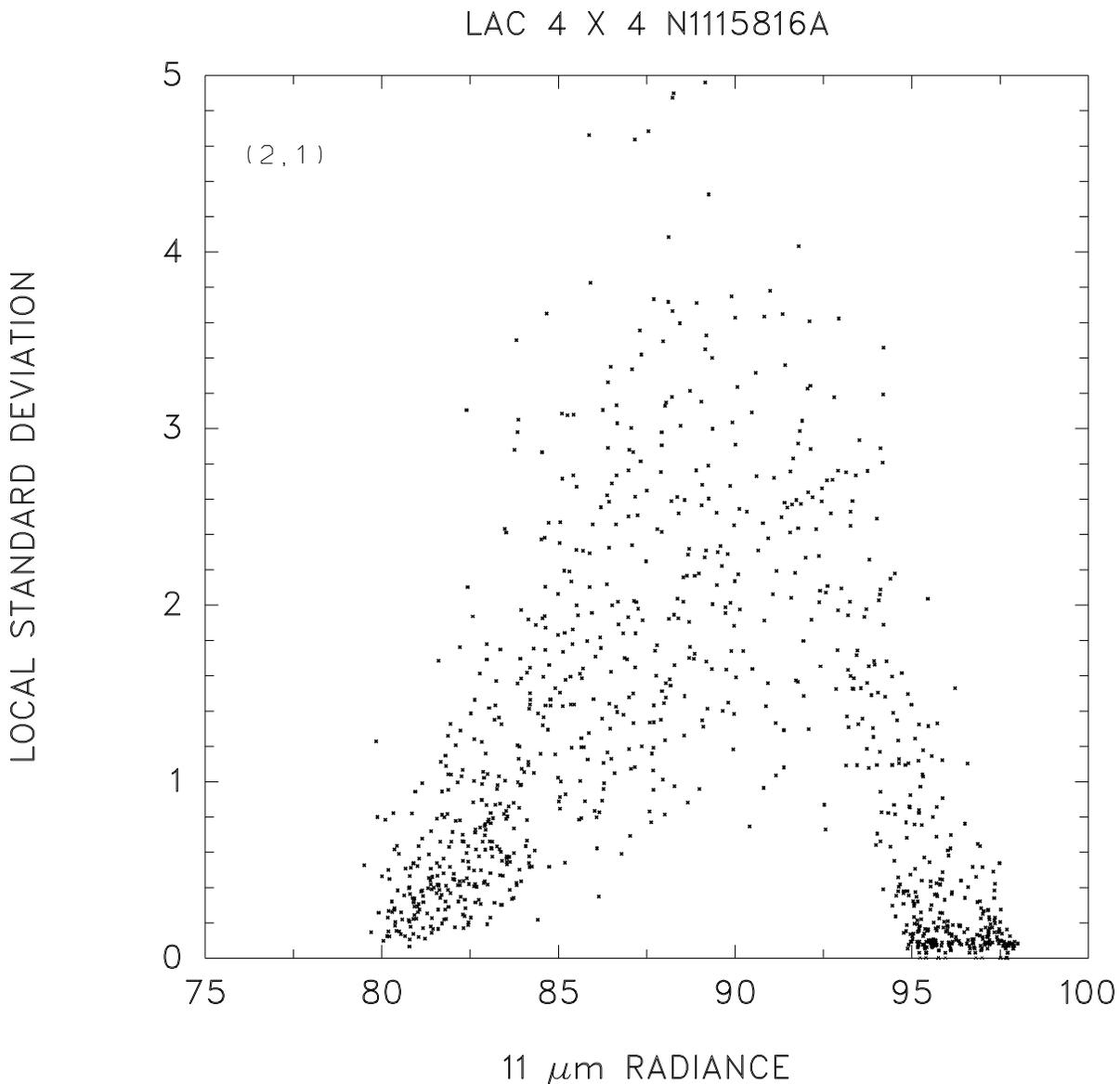


Figure 4.2-3. Local means and standard deviations for 250 km  $\times$  250 km region of the North Atlantic. Each point in the figure represents a 4  $\times$  4 array of pixels constructed from 1-km AVHRR data. Each point represents a 4 km  $\times$  4 km portion of the 250 km  $\times$  250 km region. There are approximately 1000 points in the figure. These points were obtained by skipping every other 4  $\times$  4 pixel array.

indicate cloud-free or overcast pixels from those that occur when pixels contain a repetitious pattern of broken clouds. Consequently, the region must be sufficiently large that it contains a substantial number of pixel arrays, i.e.  $\sim$ 1000 pixel arrays. It must be large enough that simple tests can be constructed to identify clustering within relatively narrow ranges of the emitted radiances against the null hypothesis that the radiances were randomly and uniformly distributed among the partly cloudy pixels. At the same time the region cannot be too large because variations of the radiances associated with cloud-free and overcast portions of the regions must remain small compared with the variability caused by variations in cloud cover and cloud optical properties. Experience with the spatial-coherence method has indicated that the 250 km  $\times$  250 km scale seems to satisfy these conditions. The 250 km  $\times$  250 km regions are termed frames in this analysis.

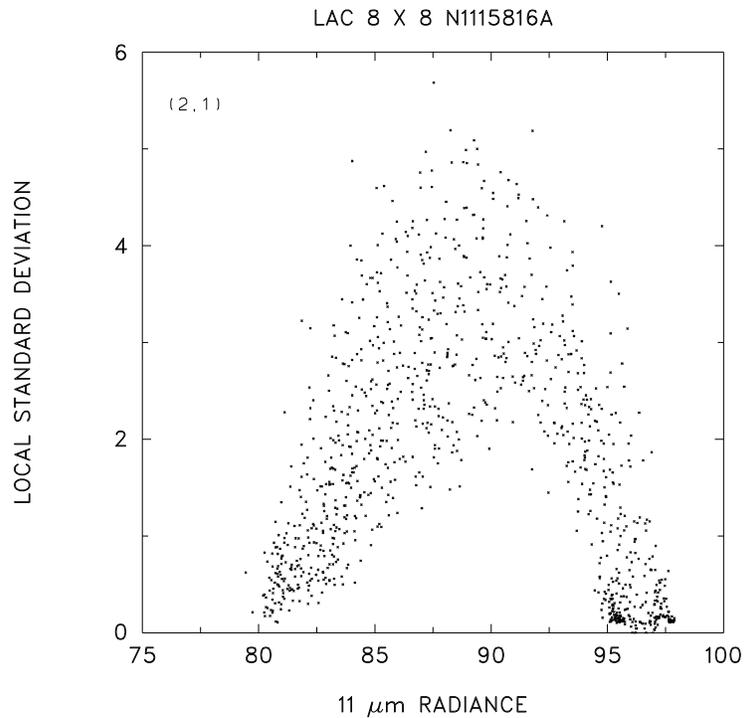


Figure 4.2-4a. Same as Figure 4.2-3, but each point represents an 8 × 8 array of 1-km pixels, thereby representing an 8 km × 8 km portion of the 250 km × 250 km region. There are approximately 1000 points in the image. All 8 × 8 pixel arrays were used.

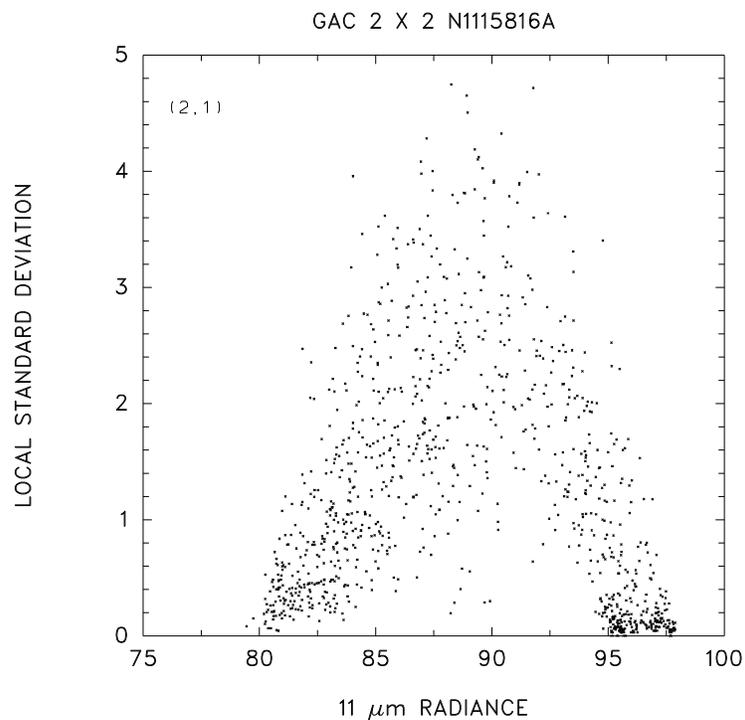


Figure 4.2-4b. Same as Figure 4.2-4a, but each point represents an 2 × 2 array of 4-km pixels.

**4.2.3.4.3. Subframe scale, 50 km × 50 km.** Once pixels within a 250 km × 250 km frame have been identified as being overcast or cloud-free, they are mapped to smaller subframes of ~50 km × 50 km that constitute the larger frame. The size of the smaller subframe is again immaterial. It is chosen to be sufficiently large to contain a relatively large number of pixels (~10<sup>2</sup>) so that percentiles can be relied upon to be stable estimators of the range of radiances encountered in the subframes. Mapping the pixels to the subframes allows the construction of geographic gradients in the cloud-free background and overcast-opaque cloud radiative properties within the 250 km × 250 km frames. It also helps to isolate single-layered systems, for which simple plane-parallel theory applies, from more complex systems, for which suitable theories have yet to be developed.

**4.2.3.5. Mathematics of Spatial Coherence Cluster Analysis**

**4.2.3.5.1. 250 km × 250 km frame scale analysis.** This section addresses the problem of identifying which points in the arch diagram are associated with the feet of the arches (i.e. which are associated with cloud-free radiances); which are associated with overcast radiances for opaque, layered clouds; and which are associated with the body of the arch and thus with pixels that are either partly cloud covered or may be overcast with semitransparent clouds. The observations shown in Figure 4.2-5 will be used to illustrate the method for identifying the points that belong to the feet. The observations are for a 250 km × 250 km frame over the Atlantic Ocean. Like those in Figure 4.2-3, they were taken during the 1992 ASTEX experiment. Each point in the figure represents a 4 km × 4 km portion of the 250 km × 250 km scale frame. The observations indicate that the frame contains low-level and upper-level cloud layers. Because there are few pixels in the body of the arches associated with these layers, most of the pixels in this case are filled by either low-level or upper-level overcast cloud layers, or the pixels are cloud-free. Cases in which few pixels contain what appear to be broken clouds are rare (cf. Fig. 4.2-3).

It should be noted at the outset that the procedures presented here are somewhat arbitrary. The procedures are clearly not optimal in that they do not make use of any statistical description of how cloud systems actually populate imager pixels. Such a description would, for example, explain the different appearances of the arches shown in Figure 4.2-4. How broken cloud systems populate imager-scale pixels remains a subject of investigation. Nevertheless, while not optimal, the procedures presented here were designed with numerical efficiency and effectiveness in mind.

The identification of cloud-free and overcast fields of view involves the identification of pixel arrays exhibiting uniform emission. The first step is to decide on the magnitude of variability that will be allowed before a pixel array will be identified as containing broken clouds. There is, of course, a small but finite probability that pixel arrays containing broken cloud will also exhibit low spatial variability in emitted radiances. Subframes that are cloud-free or overcast by opaque clouds from a single layer cannot avoid exhibiting locally uniform emission. The locally uniform emission that is to be identified with a cloud layer or with cloud-free frames must exhibit emission within a narrow range of radiances, and the range over which the radiances are to be clustered must be defined.

The determination of the maximum standard deviation allowed for points in the feet of the arch and also for the range of radiances over which the points in a single foot are allowed to span is made by considering the effect of the variability in the radiances on the uncertainty in the cloud cover estimated from the spatial-coherence method. For a single-layered system of opaque clouds, (4.2-5) becomes

$$I = (1 - C)I_{cs} + CI_{cld} \tag{4.2-7}$$

The cloud cover is obtained by inverting (4.2-7). The uncertainty in the estimated cloud cover is thus given by

$$\Delta C = \sqrt{\frac{(1 - C)^2 \Delta I_{cs}^2 + C^2 \Delta I_{cld}^2}{(I_{cs} - I_{cld})}} \tag{4.2-8}$$

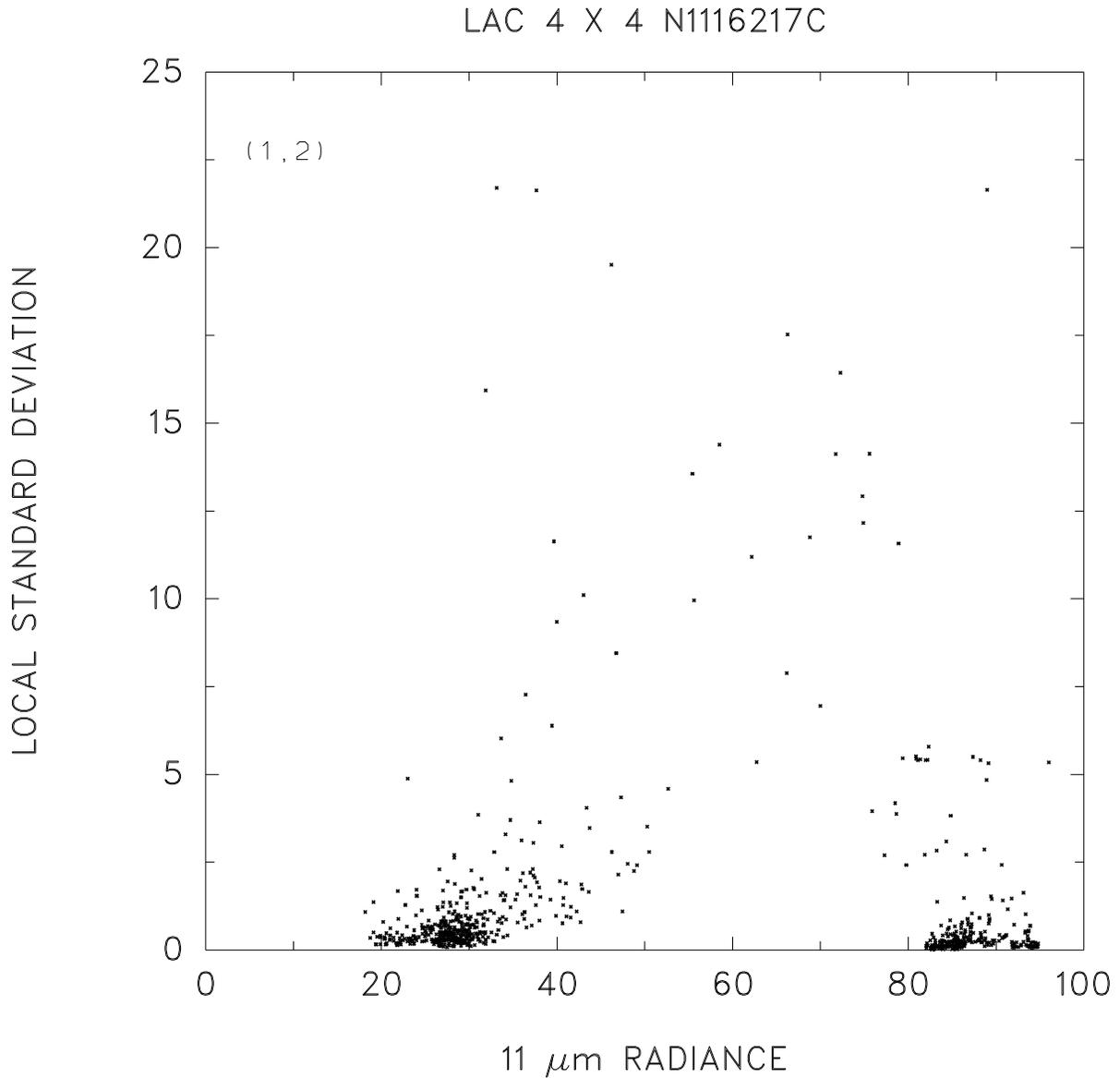


Figure 4.2-5. Same as Figure 4.2-3, but for a two-layered system.

The standard deviations of the radiances,  $\Delta I_{cs}$  for the cloud-free and  $\Delta I_{cld}$  for the overcast pixels, are taken to estimate the uncertainties in these radiances. Whether for overcast frames, ( $C = 1$ ) or for cloud-free frames ( $C = 0$ ), the uncertainty in the cloud cover associated with an array of pixels is given by

$$\Delta C = \frac{\sigma}{I_{cs} - I_{cld}} \tag{4.2-9}$$

where  $\sigma$  is the standard deviation of the radiances for the array. If  $\chi$  is taken to be an upper limit to the uncertainty in cloud cover to be tolerated, then in order for an array to be part of an arch foot, its standard deviation must satisfy

$$\sigma \leq \chi(I_{cs} - I_{cld}) \tag{4.2-10}$$

Of course, there is no prior knowledge of  $(I_{cs} - I_{cld})$ . Examination of spatial-coherence results for oceans spanning the globe and differences between ninetieth and tenth percentiles of the emitted

radiances observed for  $\sim 250 \text{ km} \times 250 \text{ km}$  frames over the globe suggests that  $(I_{cs} - I_{cld})$  is the value associated with low-level marine stratocumulus. For  $11\text{-}\mu\text{m}$  radiances this value  $(I_{cs} - I_{cld \text{ low-level}})$  appears to be about  $20 \text{ mWm}^{-2}\text{sr}^{-1}\text{cm}$ . Due to the larger variability of the cloud-free background, over land  $(I_{cs} - I_{cld \text{ low-level}}) \sim 60 \text{ mWm}^{-2}\text{sr}^{-1}\text{cm}$  is used. The smallest value of the cutoff is taken to be

$$\sigma_{cutoff} \leq \chi(I_{cs} - I_{cld \text{ low-level}}) \quad (4.2-11)$$

where  $\sigma$  is the smallest value of the cutoff and the acceptable uncertainty in the cloud cover is taken to be  $\chi = 0.03$ . As discussed below, the results of spatial-coherence analysis are insensitive to the actual choice of  $\sigma_{cutoff}$ .

The cutoff given in (4.2-11) is used for identifying pixels that are either cloud-free or overcast by **low-level** clouds. Obviously, for mid- and upper-level clouds the same equation applies with suitable values of  $I_{cld \text{ mid-level}}$  and  $I_{cld \text{ upper-level}}$  replacing  $I_{cld \text{ low-level}}$ . For constant uncertainty in the fractional cloud cover,  $\chi$ , these changes indicate that the allowable cutoff in the standard deviation can grow as  $(I_{cs} - I_{cld})$  grows. This growth in  $\sigma_{cutoff}$  is implemented as follows: because  $I_{cs}$  is generally not known and is to be produced by the retrieval, the algorithm begins by replacing  $I_{cs}$  with the 90<sup>th</sup> percentile of the  $11\text{-}\mu\text{m}$  radiances ( $I_{90}$ ) for the frame of interest. The cutoff associated with a particular value of the array mean intensity  $I$  is assumed to be

$$\sigma_{cutoff}(I) \leq \chi \text{INTEGER}\left(\frac{I_{90} - I}{\gamma}\right) \quad (4.2-12)$$

where  $\gamma = (I_{cs} - I_{cld \text{ low-level}})$ , which is taken to be  $20 \text{ mWm}^{-2}\text{sr}^{-1}\text{cm}$  over oceans and  $60 \text{ mWm}^{-2}\text{sr}^{-1}\text{cm}$  over land and  $\text{INTEGER}(x)$  is the integer value of  $x$  with the condition that  $\text{INTEGER}(x) \geq 1$ .

In order to determine whether the points that survive the cutoff are clustered, as they appear to be in a foot, some method of measuring the number of points per unit radiance interval is required. The simplest measure is that given by the number of pixels per unit radiance interval. The intervals into which the radiances are divided are given by (4.2-12), i.e.

$$\Delta I = \chi \text{INTEGER}\left(\frac{I_{90} - I}{\gamma}\right) \quad (4.2-13)$$

Figure 4.2-6a shows the distribution of radiances for the pixel arrays shown in Figure 4.2-5 and Figure 4.2-6b shows the distribution of radiances for the arrays that survive the standard deviation cutoff given by (4.2-12) for the radiance intervals given by (4.2-13). Note the following: first, the presence of the layers is revealed by peaks in the distribution of  $11\text{-}\mu\text{m}$  radiances. Such peaks are uncommon. The norm is that the majority of pixels are partly cloud covered and so the radiances are randomly distributed over their range (Chang and Coakley, 1993). Second, note the shift in the width of the radiance intervals used in Figs. 4.2-6a and 4.2-6b. The intervals in Figure 4.2-6b at low values of the  $11\text{-}\mu\text{m}$  radiance are larger than those used in Figure 4.2-6a. The shift is given by (4.2-13).

Clearly, the interval width used to determine the density of pixel-scale radiances will ultimately influence the uncertainty in the estimated cloud cover. The choice of the interval width is arbitrary. The interval width must be large enough that the number of pixels with radiances that fall within any given interval, were the radiances to be distributed uniformly over the range of radiances, is expected to be sufficiently large, i.e. 10. At the same time the interval must be sufficiently small that the distribution of radiances within a scene is approximated sufficiently well by the numbers of pixels in the various radiance intervals. That is, the intervals should be sufficiently small that a foot representing either the cloud-free background or an overcast layer is represented by arrays spanning several adjacent intervals.

In Figure 4.2-6b, each point that survived the cutoff was given equal weight. Clearly, points with smaller standard deviations are likely to have less cloud contamination for the cloud-free foot, or fewer

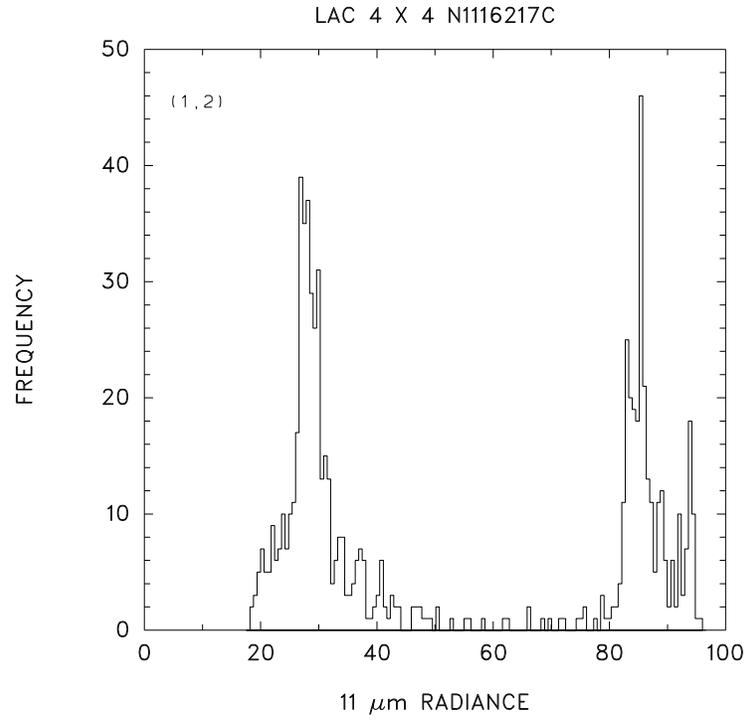


Figure 4.2-6a. Distribution of radiances for the observations shown in Figure 4.2-5.

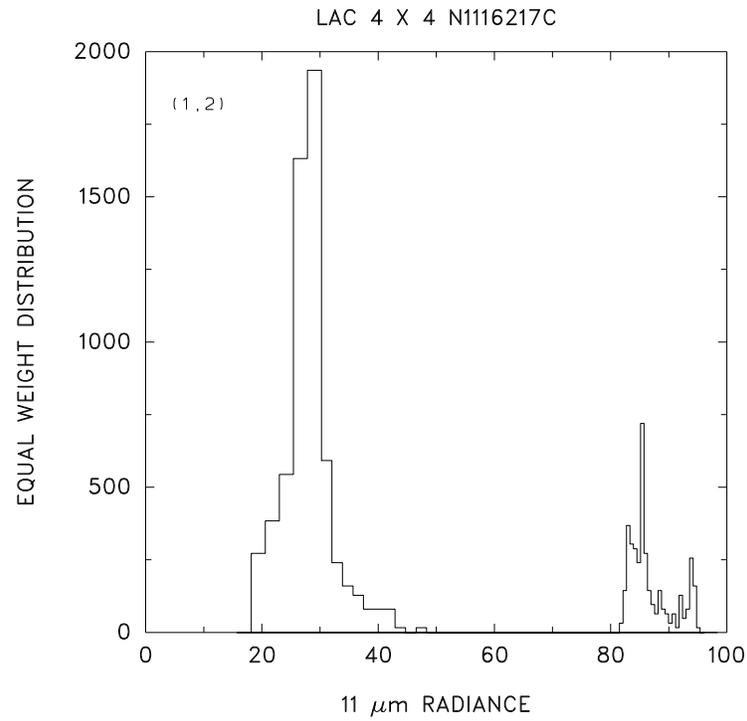


Figure 4.2-6b. Distribution of radiances for pixel arrays satisfying the cutoff in standard deviation given by Equation 4.2-8 for the radiance intervals given by Equation 4.2-9.

breaks in the clouds for the overcast foot than do points with larger standard deviations. Points with smaller standard deviations thus deserve more weight than those with larger standard deviations when estimating the radiance to be associated with the foot of an arch. By taking the radiances associated with each array to be uniformly distributed a new distribution function is created,  $\rho(I)$ , in which the contribution from a pixel array is approximately given by

$$\Delta\rho(I) = \frac{M\Delta I}{3\sigma} \quad (4.2-14)$$

where  $\Delta I$  is the width of the interval associated with radiance  $I$ ,  $I$  is the mean radiance of the array,  $M$  is the number of pixels in the pixel array,  $\sigma$  is the standard deviation of the radiances for the array, and  $3\sigma$  approximates the relationship between the standard deviation of a uniform distribution and its domain. The allocation of contributions in each intensity interval are made symmetrically about the interval associated with the mean intensity, i.e. the interval itself,  $i$ , its nearest neighbor intervals,  $i + 1$  and  $i - 1$ , and its next nearest neighbor intervals,  $i + 2$  and  $i - 2$ , etc. within the range of the intensities associated with the pixel array. The new distribution  $\rho(I)$  obtained by summing the contributions for all arrays in each of the radiance intervals is illustrated in Figure 4.2-7. The peaks of the distribution are clearly associated with the feet of the arches in Figure 4.2-5.

The next step involves determining the location and width of the peaks. The distribution is searched for local maxima. Once a maximum is found, the points in the interval and those on either side of the peak are used to calculate a mean and standard deviation of the radiances associated with the peak. The calculations are begun using the interval containing the peak,  $i$ , and the intervals on either side,  $i + 1$  and  $i - 1$ . A second standard deviation of the radiances is calculated using the two adjacent intervals,  $i + 2$  and  $i - 2$ , on either side of the original three-interval group. If the second estimate of the standard deviation is within 20% of the first, i.e.  $\sigma_1 \geq 0.8\sigma_2$ , then the width of the peak is taken to be given by the three intervals of the original group. For comparison, a Gaussian distribution gives  $\sigma_1 \geq 0.74\sigma_2$  where  $\sigma_1$  is the estimate of the standard deviation using the domain within one standard deviation of the mean and  $\sigma_2$  is the estimate of the standard deviation using the domain within two standard deviations of the mean. If the condition is not met by the two estimates of the standard deviation, then the interval is expanded to the five-interval group and the next two adjacent intervals are added and a new standard deviation for the seven interval group is calculated and compared with that of the five interval group. This process is repeated until either the standard deviations for the two ranges agree within 20%, or in expanding the interval a peak in the  $\rho(I)$  distribution is encountered that has a higher density of points, i.e. larger  $\rho(I)/\Delta I$  than that of the original group. If the latter case is true, the original peak is dropped from further consideration and the test is transferred to the new, denser peak. In Figure 4.2-7 the peaks of  $\rho(I)$  and their associated widths are indicated by dashed lines.

Once the peaks are located and their widths determined, neighboring peaks are examined to determine whether they overlap each other. The domain of a peak is taken to be the radiance intervals that lie within three standard deviations of the mean radiance associated with arrays forming the peak. If the domains of two peaks overlap, then the peaks are combined and the mean radiance and new standard deviation associated with the combined peak are calculated based on the arrays with mean radiances falling within the two standard deviation test intervals for the two separate peaks.

Once overlapping peaks are combined, they are tested for a minimum number of pixels. As can be seen in Figure 4.2-6b, some pixel arrays exhibit locally uniform emission, like that exhibited by the points in the feet of the arch, but are not themselves part of a foot. Experience has shown that such points are eliminated by demanding that the foot of the arch must contain at least 20 pixels. This minimum number of pixels can be explained through manipulation of an analog model in which the criterion is that the points associated with the foot of an arch must exhibit a tightly clustered distribution of radiances.

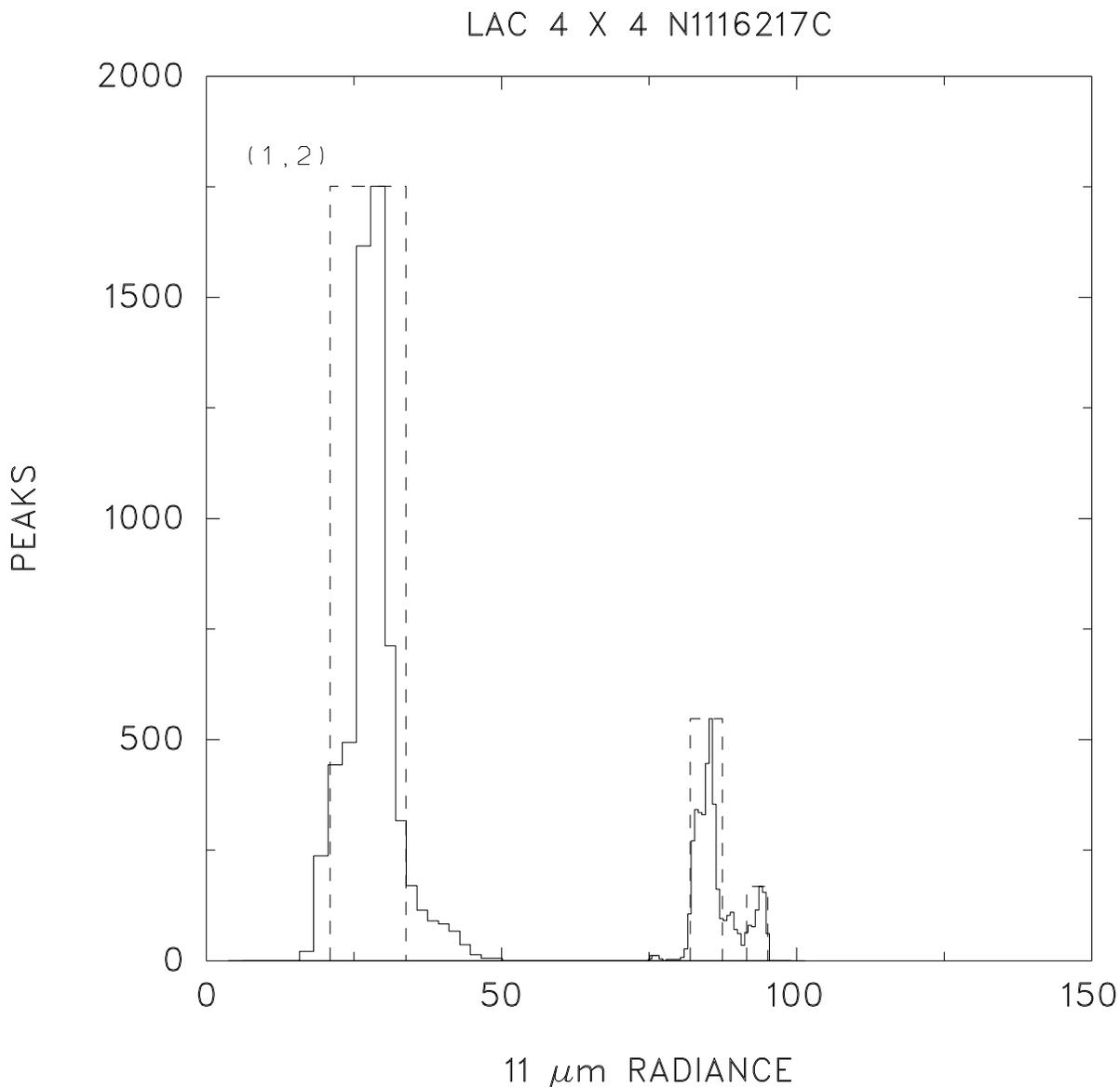


Figure 4.2-7.  $\rho(I)$  distribution for observations shown in Figure 3. The dashed lines indicate the radiance domains associated with the two layers and the cloud-free background.

The minimum number of points required in a peak of the  $\rho(I)$  distribution for the set of points to be characterized as being clustered is established as follows. A Gaussian distribution is taken to be an example of a distribution that is sharply peaked and clearly nonuniform. The null hypothesis is that the points distributed according to a Gaussian distribution are indistinguishable from those distributed according to a uniform distribution. The interval over which the test is applied is divided into three equal parts. For a distribution of points to be classified as being nonuniform or highly concentrated, the number of points within the center interval must satisfy the condition given by

$$N > \frac{M}{3} + \sqrt{2M} \tag{A1}$$

where  $M$  is the number of points within the three intervals. In (A1),  $N$  is greater than three times the number of points that would be expected in the central interval were the points to be uniformly distrib-

uted over the three intervals. If the points are distributed according to a gaussian distribution so that the central interval spanned one standard deviation on either side of the mean and the outer intervals spanned an additional two standard deviations, then the above criteria would be satisfied when

$$\text{erf}(y) > \frac{1}{3}\text{erf}(3y) + \sqrt{\frac{2\text{erf}(3y)}{M}} \quad (\text{A2})$$

where

$$y = \frac{1}{2\sqrt{2}} = 0.354 \quad (\text{A3})$$

The condition is satisfied when  $M > 18.03$ . Thus, there must be ~20 pixels within three standard deviations on either side of a peak for the peak to satisfy the condition. If there are fewer pixels within the interval, then the number within one standard deviation of the mean, as given by a gaussian distribution, would not be more than three standard deviations above the number expected from a uniform distribution.

Arrays that appear to satisfy the local uniformity condition but are not in the foot of an arch are randomly scattered over the range of emitted radiances observed for the frame. They fail to cluster around a specific radiance value as happens in the case of a foot. Experience with the spatial-coherence method indicates that employing this minimum number of pixels proved to be sufficient to eliminate the points that survived the uniformity cutoff but were not part of an arch foot in all but a few percent of the cases analyzed. In Figure 4.2-8, pixel arrays that were identified as being in the feet of the arches in Figure 4.2-5 are indicated by large dots; those that do not belong to a foot are indicated by small dots. Figure 4.2-8a shows the effect of the variable cutoff. The cutoff in the standard deviation is larger for the upper-level cloud deck (lower 11- $\mu\text{m}$  emission). The figure also shows that the random pixel arrays exhibiting standard deviations similar in value to those in the feet have been eliminated. Figure 4.2-8b shows a scatter plot of 0.63- $\mu\text{m}$  reflectivities and 11- $\mu\text{m}$  radiances. Not surprisingly, the pixels identified as being cloud-free and overcast have bispectral properties that would be expected of cloud-free and overcast pixels. As discussed below, multispectral consistency checks might be developed to confirm the results obtained through spatial coherence analysis.

The variables used in the identification of pixels exhibiting locally uniform emission were

1. The difference between the radiances expected for cloud-free and overcast fields of view,  $\gamma = (I_{cs} - I_{cld\ low-level})$ ,
2. The 90<sup>th</sup> percentile of the emitted radiances, which was used in place of the cloud-free radiance to obtain  $\sigma_{cutoff}$
3. The two-standard-deviation test used to determine the width of a peak in the  $\rho(I)$  distribution
4. The use of three standard deviations to represent the domain of an isolated peak

Clearly, the choices for these parameters, while not without reason, were arbitrary. Fortunately, numerous arch feet obtained for 250 km  $\times$  250 km scale frames contain contributions from many pixel arrays and these arrays are often tightly clustered in the radiance domain. The outcome of the foot identification, namely the mean and standard deviation of the radiances for the pixels associated with the foot, is relatively insensitive to the variables chosen. The results differ little if  $\gamma$  is halved or doubled, if the 95<sup>th</sup> or 85<sup>th</sup> percentile is used in place of the 90<sup>th</sup>, or if three standard deviations rather than two are used to determine the width of a  $\rho(I)$  distribution peak and two standard deviations used to represent its domain.

**4.2.3.5.2. 50 km  $\times$  50 km subframe scale analysis.** As noted above, once identified on the 250 km  $\times$  250 km scale, the locations of the pixel arrays identified as being overcast and cloud-free are mapped to smaller regions of ~50 km  $\times$  50 km, or subframes. This mapping retains information on gradients in the

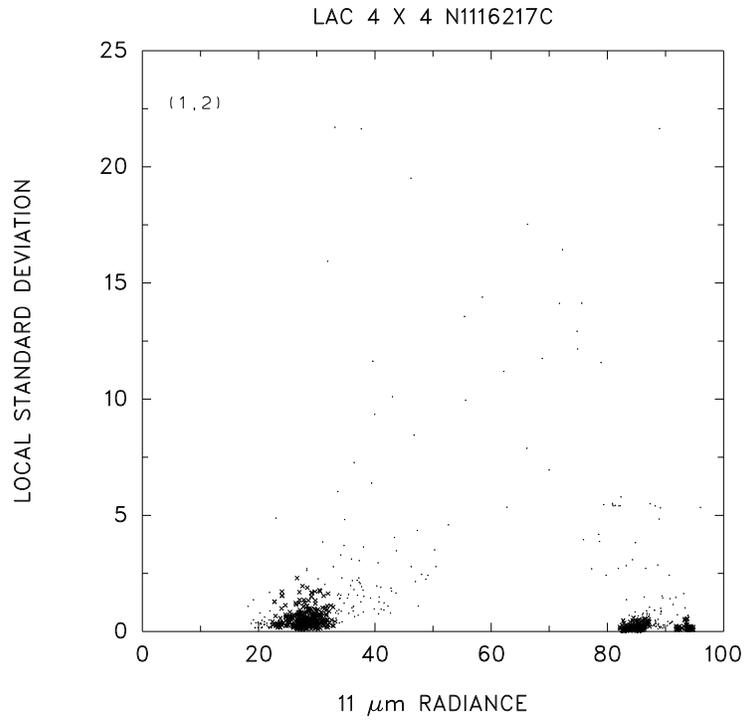


Figure 4.2-8a. Same as Figure 3, but pixel arrays identified as being cloud-free or overcast by clouds in a well-defined layer are indicated by large dots. Pixel arrays with broken or semitransparent clouds are indicated by small dots.

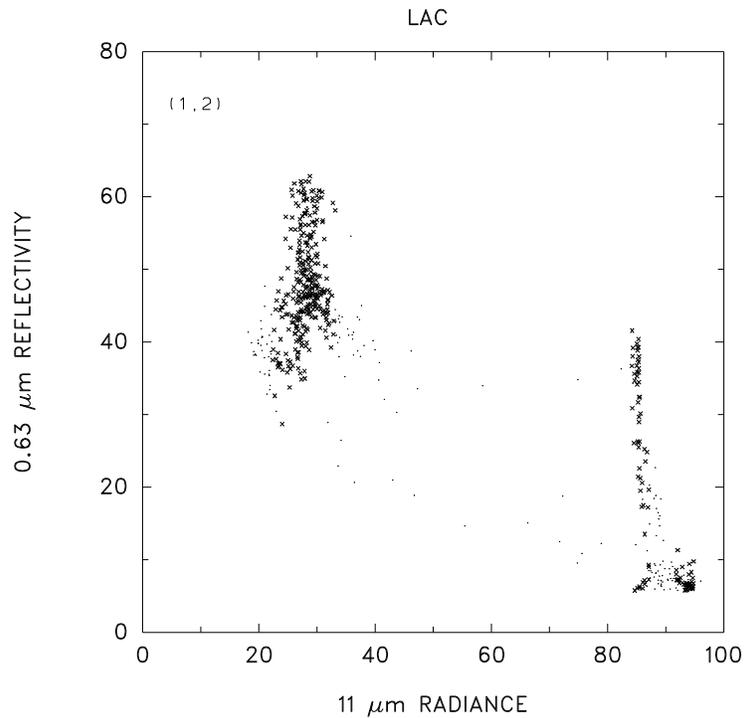


Figure 4.2-8b. 0.63- and 11- $\mu\text{m}$  radiances for the observations shown in Figure 6a.

radiative properties of cloud-free and overcast pixels across the 250 km  $\times$  250 km frame and better isolates, when possible, single-layered systems. Often on this smaller scale, however, no pixels are found

to be either overcast or cloud-free. So, even though a single-layer system may span a  $250 \text{ km} \times 250 \text{ km}$  frame, it cannot be clearly identified as a single-layered system on the basis of the spatial structure of the  $11\text{-}\mu\text{m}$  radiances found in some of the  $50 \text{ km} \times 50 \text{ km}$  scale subframes that make up the larger frame. This problem is illustrated in Figures 4.2-9 through 4.2-11. The figures show that although overcast pixels for a given cloud layer may not reside in a particular  $250 \text{ km} \times 250 \text{ km}$  frame, they often reside in surrounding frames. The finding suggests that when evidence for a layer is missing in one frame, surrounding frames should be examined for the missing evidence. While the example uses observations for the  $250 \text{ km} \times 250 \text{ km}$  scale, but clearly inferences made based on observations over a domain become more reliable as the size of the domain decreases.

Figure 4.2-9 shows means and standard deviations of  $11\text{-}\mu\text{m}$  radiances and figure 4.2-10 shows the relationship of  $0.63\text{-}\mu\text{m}$  reflectivities and  $11\text{-}\mu\text{m}$  radiances for a  $250 \text{ km} \times 250 \text{ km}$  frame that, on the basis of the  $0.63\text{-}$  and  $11\text{-}\mu\text{m}$  scatter plot, contains two distinct layers. The spatial-coherence analysis in this case fails to identify either of the layers. Figures 4.2-10 and 4.2-11 show observations for the  $250 \text{ km} \times 250 \text{ km}$  scale frame shown in Figure 4.2-9 as well as for the surrounding  $250 \text{ km} \times 250 \text{ km}$  scale frames. The incipient layered structures not found in Figure 4.2-9 are now revealed in the surrounding frames. Coakley and Baldwin (1984) proposed analyzing the properties in mesoscale-sized regions called “subframes.” They used  $16 \times 16$  arrays of  $4 \text{ km} \times 4 \text{ km}$  AVHRR pixels, or a  $\sim 64 \text{ km} \times 64 \text{ km}$  region for a subframe. If the subframe contained overcast pixels, or if the nearest neighbor subframes contained overcast pixels that explained the range of the emitted radiances, as defined by the 10<sup>th</sup> and 90<sup>th</sup> percentiles of the  $11\text{-}\mu\text{m}$  radiances in the subframe of interest, then the subframe was taken to contain the layer. “Explaining” the range of radiances meant satisfying the following conditions:

$$(I_{cld} - 2\Delta I_{cld}) < I_{10} \quad (4.2-15)$$

and

$$I_{cld} + 2\Delta I_{cld} > I_{90} \quad (4.2-16)$$

where  $I_{cld}$  and  $\Delta I_{cld}$  are the means and standard deviations associated with the overcast pixels in the frame surrounding the subframe in question. Values of the radiances are geographically interpolated to form estimates of the mean and standard deviation that would be achieved by overcast pixels in the subframe of interest were overcast pixels present.

Coakley and Baldwin (1984) followed a two-step procedure in implementing this search and interpolation of overcast radiances. First, all overcast pixels in a region containing the frame and the surrounding subframes (see Fig. 4.2-12) were classified into layers. The classification routine follows the same algorithm as that used to determine the feet of the arch with the exception that the range of  $11\text{-}\mu\text{m}$  radiances was divided into equal intervals,  $\Delta I$ , as opposed to variable-width intervals following (4.2-15). Up to three cloud layers were allowed. If more layers appeared to be present in the frame, then the layers that were nearest each other,  $|I_{cld1} - I_{cld2}| = \text{minimum value}$ , were combined into one layer with the properties of the layer calculated to be the average of the properties for the contributing layers. In the averaging, each layer in each subframe was given equal weight. Once the layers in the frame were classified, the range of radiances in a particular subframe was examined to determine whether layers identified in the frame but not in the subframe were needed to explain the range. If so, the nearest neighbor subframes were searched for the overcast pixels associated with the appropriate layers. If overcast pixels were found in the surrounding subframes, then the radiances associated with the overcast pixels were geographically interpolated to the subframe of interest as discussed in Coakley and Baldwin (1984).

The extent to which this interpolation strategy would have to be implemented is unclear. Experience with the spatial-coherence method indicates that a substantial portion (somewhere between 30 and 60%) of all layers on the subframe scale are interpolated, even though the search for missing layers is limited

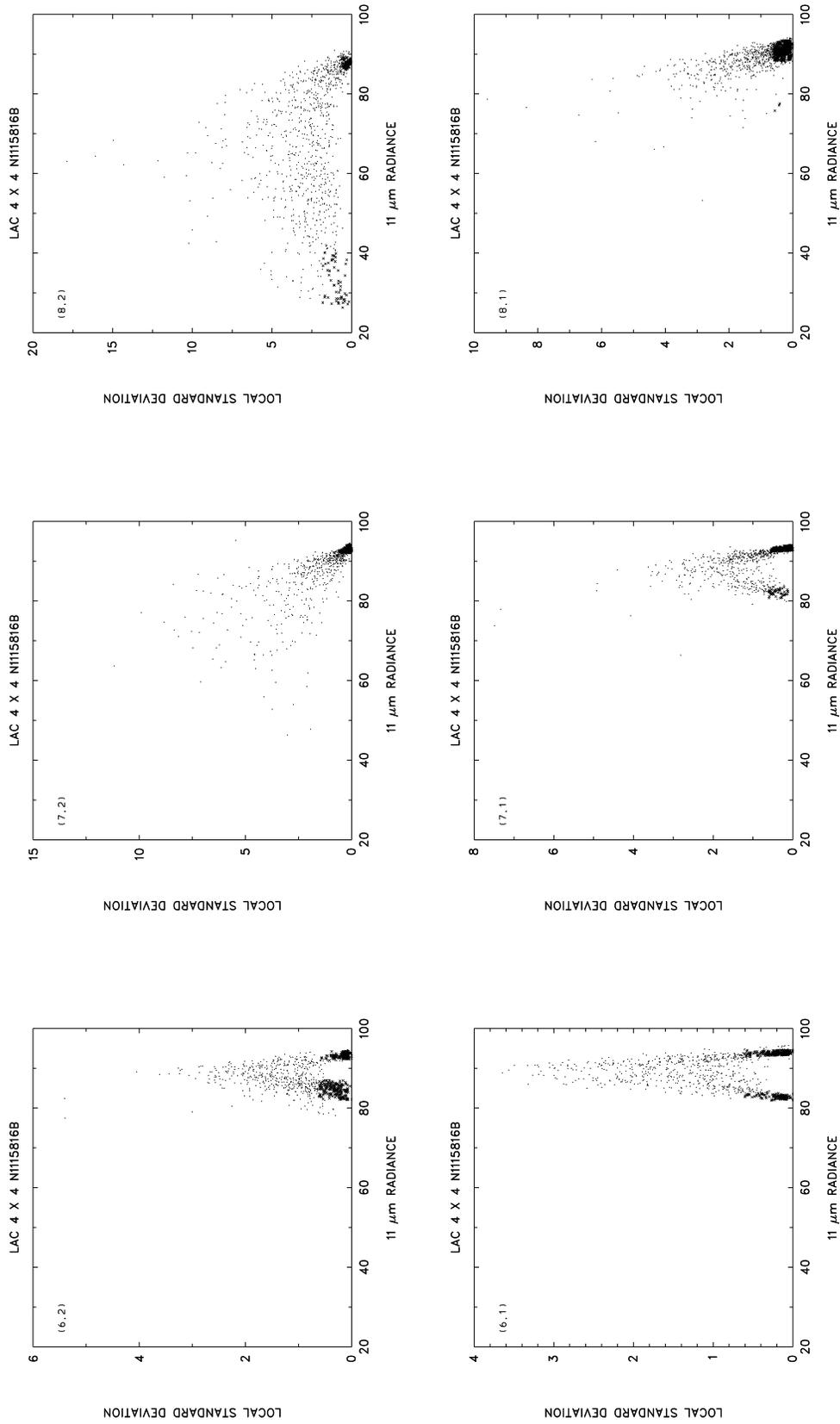


Figure 4.2-9. 3 × 2 array of adjacent 250-km scale frames. Each point represents a 4 × 4 array of 1-km AVHRR pixels. Large dots represent points found to be either overcast by layered clouds or cloud-free. The geographic orientation of the arrays are indicated by the (x,y) coordinates in the upper left corner of each frame. Frame (m + 1, l + 1) is the frame immediately to the west and north of frame (m, l).

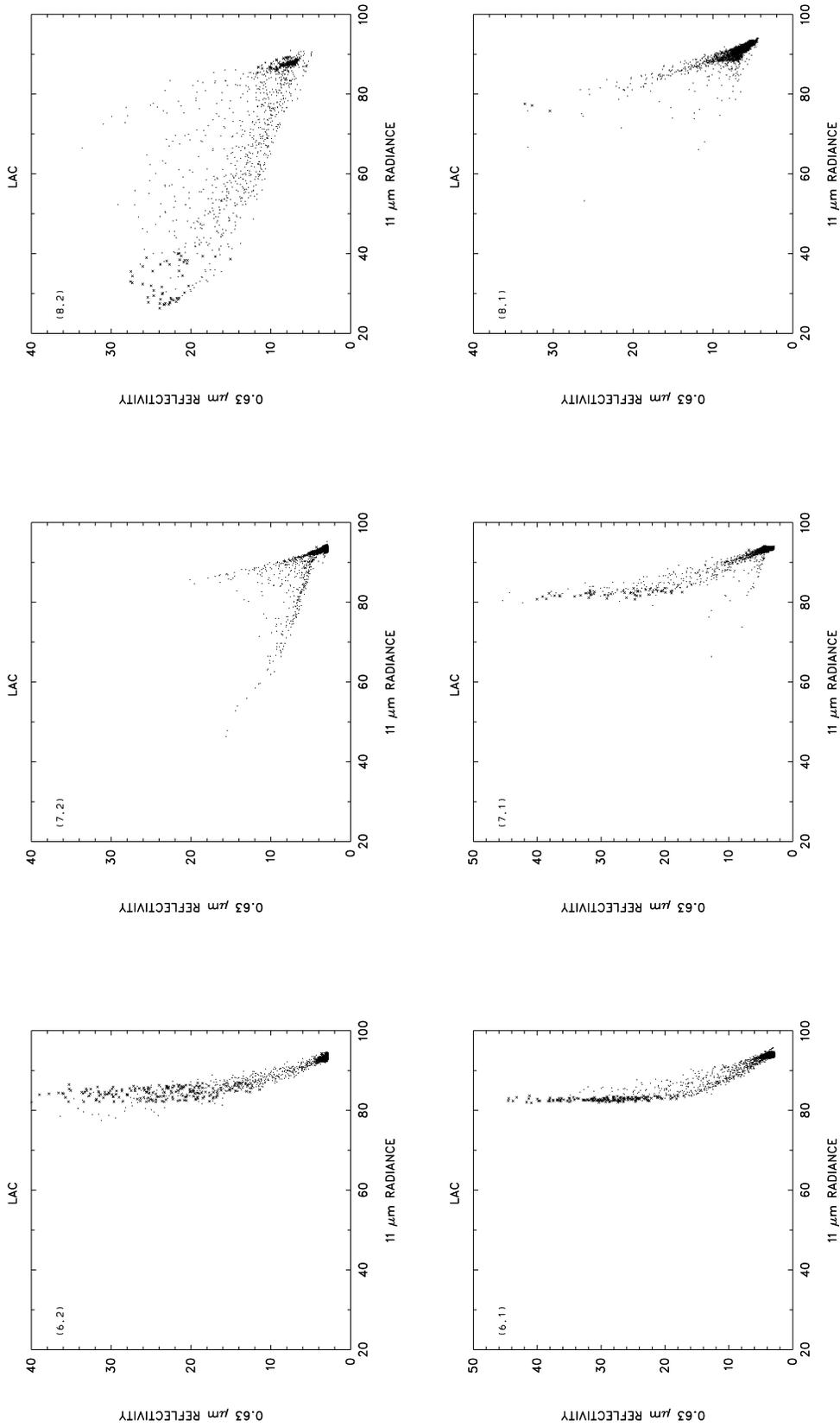


Figure 4.2-10. Same as Figure 4.2-9, but for 0.63- and 11-μm radiances.

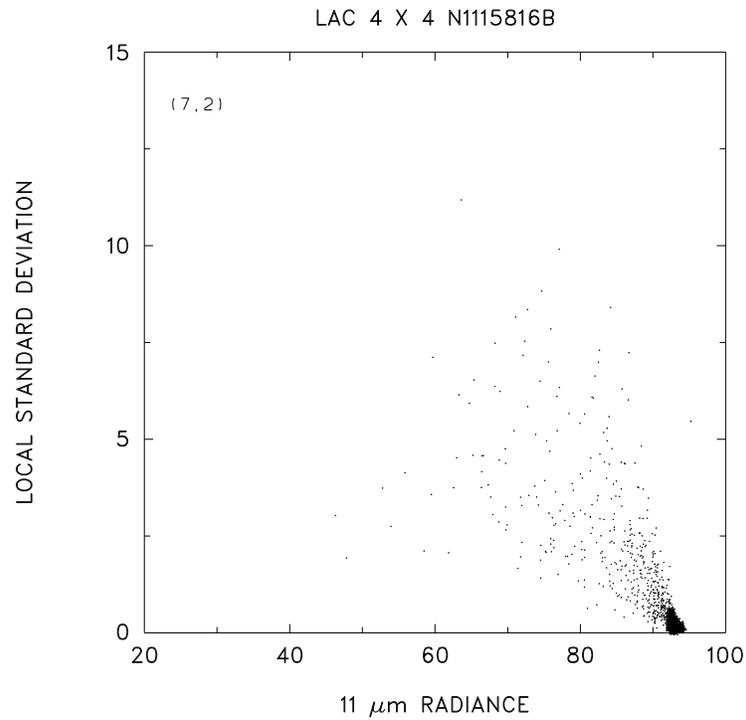


Figure 4.2-11a. Same as Figure 4.2-8a, but different two-layered system.

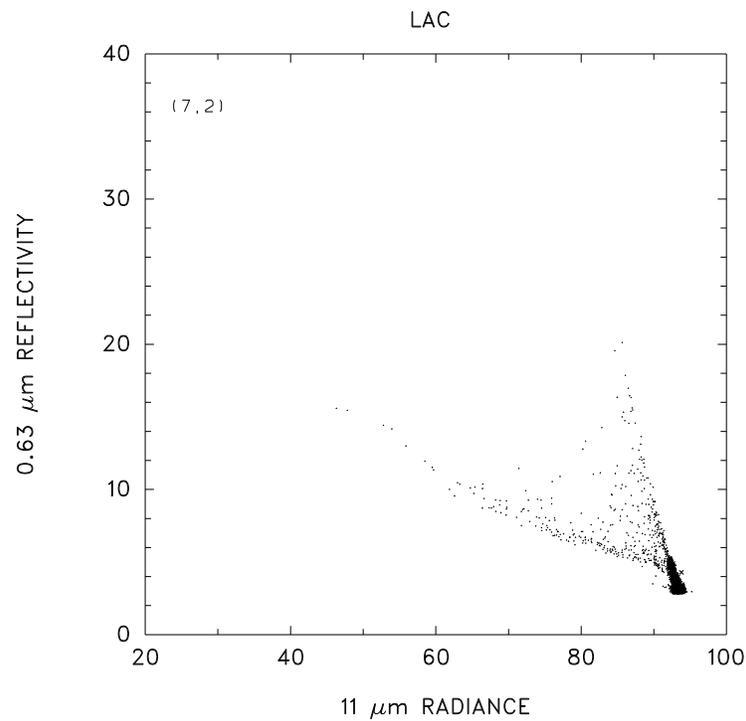


Figure 4.2-11b. 0.63- and 11- $\mu\text{m}$  radiances for the observations shown in Figure 4.2-11a.

to nearest neighbor 50 km  $\times$  50 km subframes. How far the search for missing layers can be extended, whether 50 or 100 km or further, has not been explored.

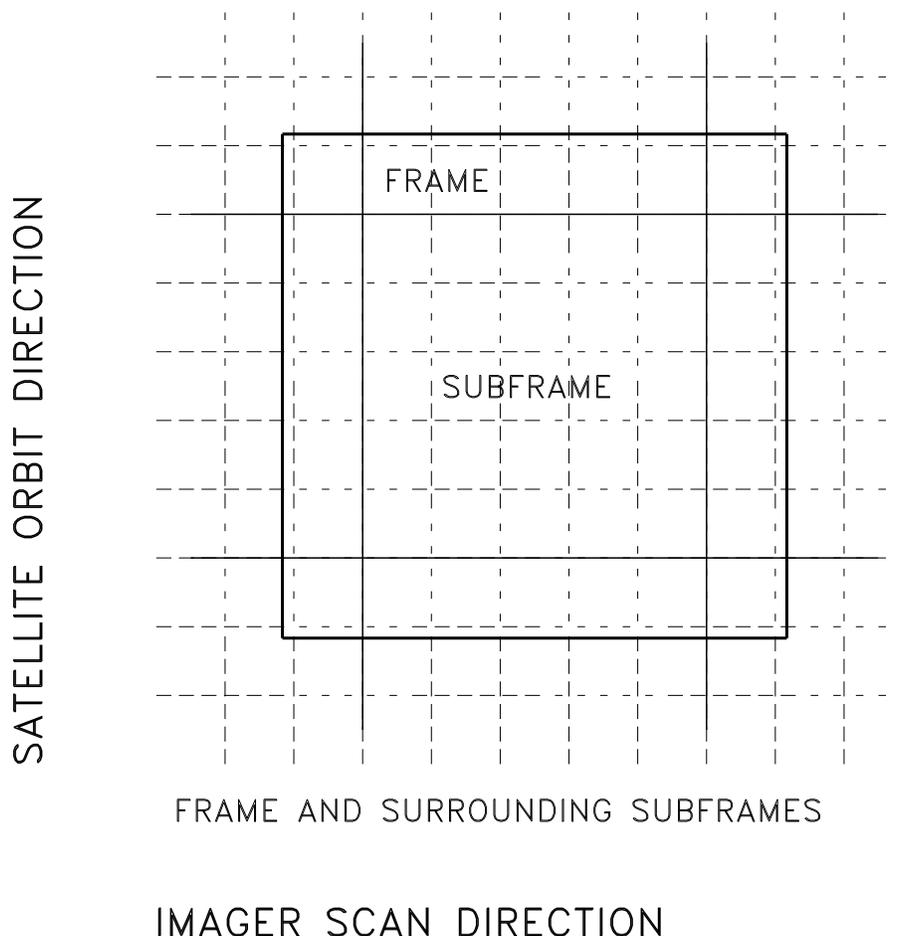


Figure 4.2-12. 50-km scale subframes and 250-km scale frames used in spatial coherence analysis. Each subframe represents the imager pixels mapped into a CERES footprint. Overcast and cloud-free 11- $\mu\text{m}$  radiances for all subframes in a frame and its surrounding subframes are classified (as described in the text) to determine the layered structure of clouds for the subframes constituting the frame.

#### 4.2.3.6. Uncertainties

This section discusses the uncertainties in the properties of the overcast pixels identified as being part of a well-defined cloud layer. In the following section, uncertainties arising through errors in layer identification, e.g. identifying a layer that doesn't exist or failing to identify a layer that does exist, are discussed.

The uncertainties associated with an identified layer are defined in terms of the standard deviations of the 11- $\mu\text{m}$  radiances,  $\Delta I_{cld}$ , obtained for the pixels identified as being overcast by opaque cloud. The standard deviation is used as a measure of the uncertainty in the retrieved layer properties. Included in this measure would be effects caused by gradients within the frame. Of course, because the probability is low that pixels overcast by opaque cloud will uniformly distribute themselves over a frame that is not itself overcast, the probability is likewise low that the standard deviation of radiances for the overcast pixels represents the range of layer properties within the frame.

As was noted in the introduction, a well-defined layer is by definition one for which the uncertainty in the properties, as indicated by the standard deviation of the 11- $\mu\text{m}$  radiances for the overcast pixels, is small compared with the variability in the radiances that would result from variations in fractional cloud cover. Thus a well-defined layer has the property that  $\Delta I_{cld} \ll I_{cs} - I_{cld}$ . Clearly, this condition can be

satisfied within rather arbitrary limits. The application of arbitrarily strict criteria will, of course, arbitrarily limit the population of well-defined layers. The degree to which various criteria affect the population of layers identified as being well-defined remains to be established. As a rule of thumb, however, requiring that the parameter given by

$$\xi = \frac{\sqrt{\Delta I_{cs}^2 + \Delta I_{cld}^2}}{I_{cs} - I_{cld}} \leq 0.1 \quad (4.2-17)$$

would provide reasonably well-defined layers.

As discussed in the next section, cases exist in which layers may be identified as being present when in fact they are not. For example, the clouds in a layer congregate in regular arrays so that the observed emission satisfies the condition of low, local standard deviation, but the pixels are only partly cloud covered. Such occurrences appear to be rare. Nevertheless, they can probably be largely eliminated by demanding that the number of pixels identified as overcast and part of a well-defined layer must exceed a certain fraction of the area viewed, say 10%. This criteria is meant to apply only to those ~50 km × 50 km subframes that contain overcast pixels, not those for which layer information must be interpolated as described in Section 4.2.2.5.2. Interpolated properties are presumed to have the quality of the properties from which the interpolated values were obtained. Clouds can form regular arrays, but these arrays are fostered by mesoscale circulations which by their nature break down on the 100- to 200-km scale. The extent to which limiting the identification of well-defined layers by such a criteria and the likely dependence of such a criteria on spatial scales has not been explored.

#### **4.2.3.7. Practical Considerations**

Not all cloud systems are layered. Some layered cloud systems, like cirrus, rarely achieve optical depths that allow them to be detected as a layer by the spatial-coherence method. Systems of opaque layered clouds can also be everywhere broken so that nowhere do they extend to form overcast clouds over several imager pixels, thereby avoiding identification by the spatial-coherence method. Coastlines and background heterogeneity over land areas may mask the presence of layers. This section outlines the limitations inherent in the spatial-coherence method and suggests strategies for dealing with them.

##### **4.2.3.7.1 Limitations in Applying Spatial Coherence.**

**4.2.3.7.1.a. Errors caused by incorrect identification of cloud layers.** Clouds don't always form opaque layers that span several imager pixels. Even if the clouds were in such a layered system, they would not give rise to the local uniformity in the emitted radiances that would allow detection by the spatial-coherence method. The variance in emitted radiances, as given by (4.2-6) for a single-layered system, could be relatively high. In the case of cirrus, even when the layer is extensive so that numerous pixels are overcast, the pixel-to-pixel variation in emissivity and transmissivity gives rise to large local variances in emitted radiances. Opaque, low-level clouds may form a layer in which the clouds are nowhere extensive enough to cover several adjacent imager pixels. An example of such a situation was shown in Figure 4.2-9.

There are three strategies for dealing with situations like those shown in Figure 4.2-9. The first, proposed by Coakley and Baldwin (1984), is to seek evidence for the presence of a well-defined layer in neighboring frames. That approach was discussed in Section 4.2.2.5.2. The second is to use relationships among various wavelengths. It constitutes an alternative to the spatial coherence method and is discussed in the subsequent section. The third is to use two-dimensional texture analyses to detect the presence of the separate systems. That approach likewise represents an alternative.

**4.2.3.7.1.b. Errors caused by heterogeneous backgrounds.** Land is a more heterogeneous background than oceans. As noted earlier, the identification of layers over land uses a cutoff in the standard devia-

tion of the pixel arrays for land scenes that is three times the value used for ocean scenes. The increase in background heterogeneity over land, of course, diminishes the ability to identify well-defined layers. Nevertheless, experience with retrievals performed for the 1992 FIRE II IFO over the central U.S. indicates that the use of the higher cutoff provides satisfactory results (Lin and Coakley, 1993).

Contrasts between land and water at coastlines, of course, must be dealt with by separating the analysis for the land and water portions of the scene. Pixel arrays that include the coastline should not be used in the identification of the layer. Indeed, as the results in Figures 4.2-3 and 4.2-4 indicate, limited sampling over a  $250 \text{ km} \times 250 \text{ km}$  frame appears to provide overcast and cloud-free identifications that are indistinguishable from those obtained using all pixel arrays. Consequently, a perimeter of arrays bracketing coastlines can be safely ignored in the identification of cloud layers. Such a strategy, however, has yet to be implemented.

#### **4.2.3.8. Proposal for Validation**

Well-defined layers seemed to be readily identified by eye, but obtaining the properties of well-defined layers, even from instrumented surface sites and aircraft is difficult and not a well-posed problem. Consequently, finding evidence that a particular remote sensing technique produces a useful characterization of cloud systems is likewise difficult.

Two strategies for validation have already been proposed. Perhaps the best approach would be to use active aircraft or space-borne lidars to identify layers simultaneously with the information being retrieved from imagery data. The vertical sounding of the atmosphere with lidars often reveals layered structures. When clouds are thin and diffuse, it is difficult to assign a height to the layer; nevertheless, for optically thick clouds, the soundings produce what appear to be layers with reasonably well-defined altitudes.

A weakness of lidar retrievals is that they are typically limited to the nadir track of the aircraft or orbiting platform. The flight path will occasionally miss layered structures that are revealed through the two-dimensional sampling available to imagers. Consequently, comparisons between lidar cloud boundaries and imager inferences of layered structure must be made on the basis of representative ensembles of cases, as opposed to a case-by-case basis. An opportunity for such comparisons is forthcoming with the LITE mission in September 1994 (McCormick et al., 1993).

The second strategy for validation proposed earlier was to demand that inferences of layered structure based on the spatial-coherence method be verified by independent inferences based on the relationships between radiances at various wavelengths. For example, Figure 4.2-8a clearly shows a two-layered structure as deduced from spatial-coherence analysis, and the visible-IR relationship shown in Figure 4.2-8b produces a consistent multiwavelength interpretation. Of course, such confirmation is bound to work for simple, layered cloud systems, i.e. when there is little overlap between the two systems in the frame of interest. When there is overlap, as may be the case in frame [2,1] of Figures 4.2-13 and 4.2-14, visible-IR observations will not necessarily provide the desired confirmation. Use of other multiwavelength emissions may alleviate some of the problems. Emission at 8 and  $13 \mu\text{m}$  might reveal the branches associated with two-layered systems not revealed in the visible-IR scatter plots. Nevertheless, observations of thermal emission will capture only the highest and lowest layers present and not detected by the spatial coherence method, and they will miss intervening layers. As with lidar observations, the multispectral observations can be used to provide confirmation in a certain fraction of the cases, but not all cases.

Surveys with the spatial-coherence method suggest that single-layered cloud systems can be isolated on the  $\sim 50 \text{ km} \times 50 \text{ km}$  scale approximately 50% of the time. Of the remaining 50%, many of these systems are two-layered systems that should be amenable to confirmation through multispectral approaches and lidar soundings. Complex cloud systems, i.e. those that defy description in terms of layered structure, appear to constitute only 15 to 25% of the observations at the  $50 \text{ km} \times 50 \text{ km}$  scale.

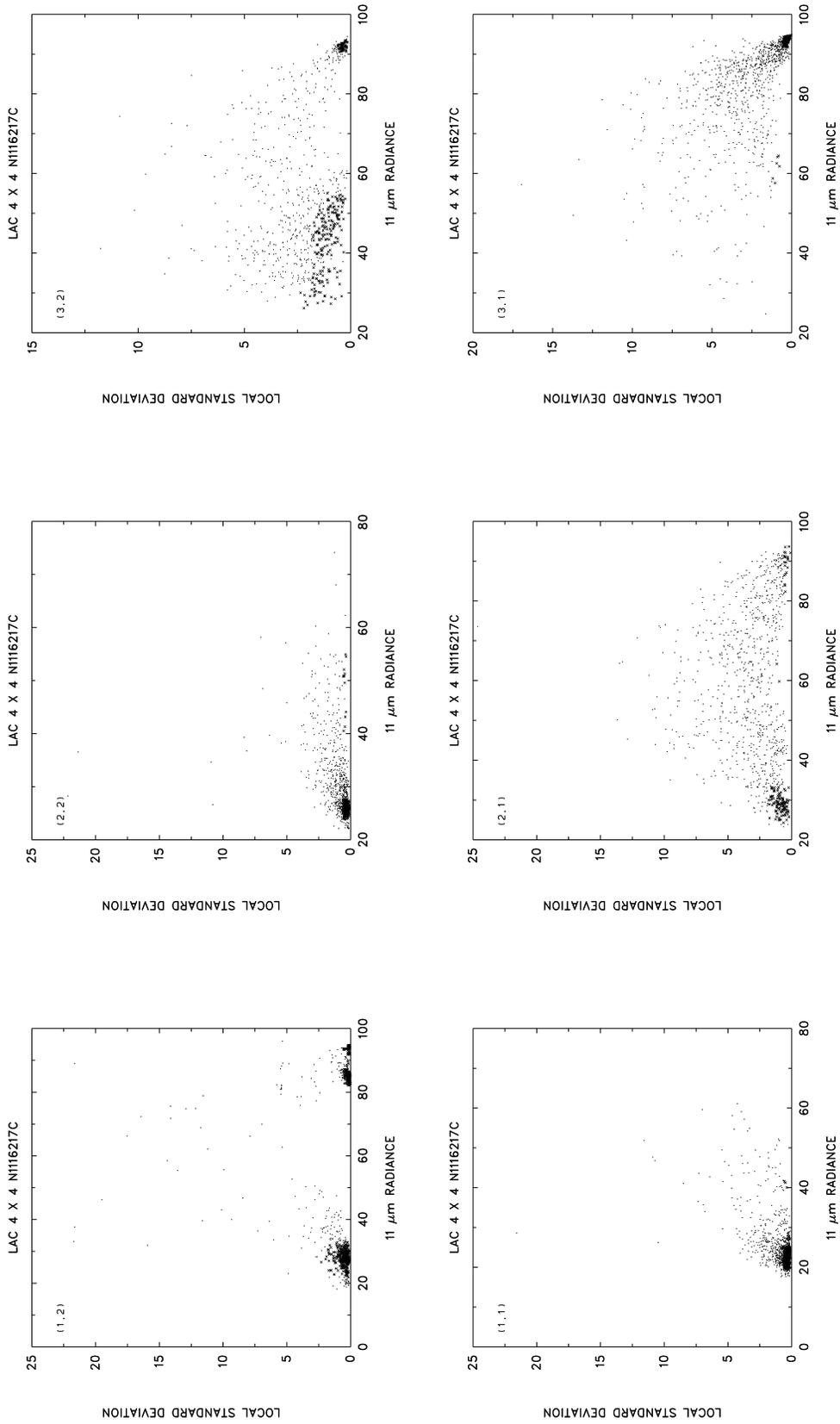


Figure 4.2-13. Same as Figure 4.2-9, except for different system.

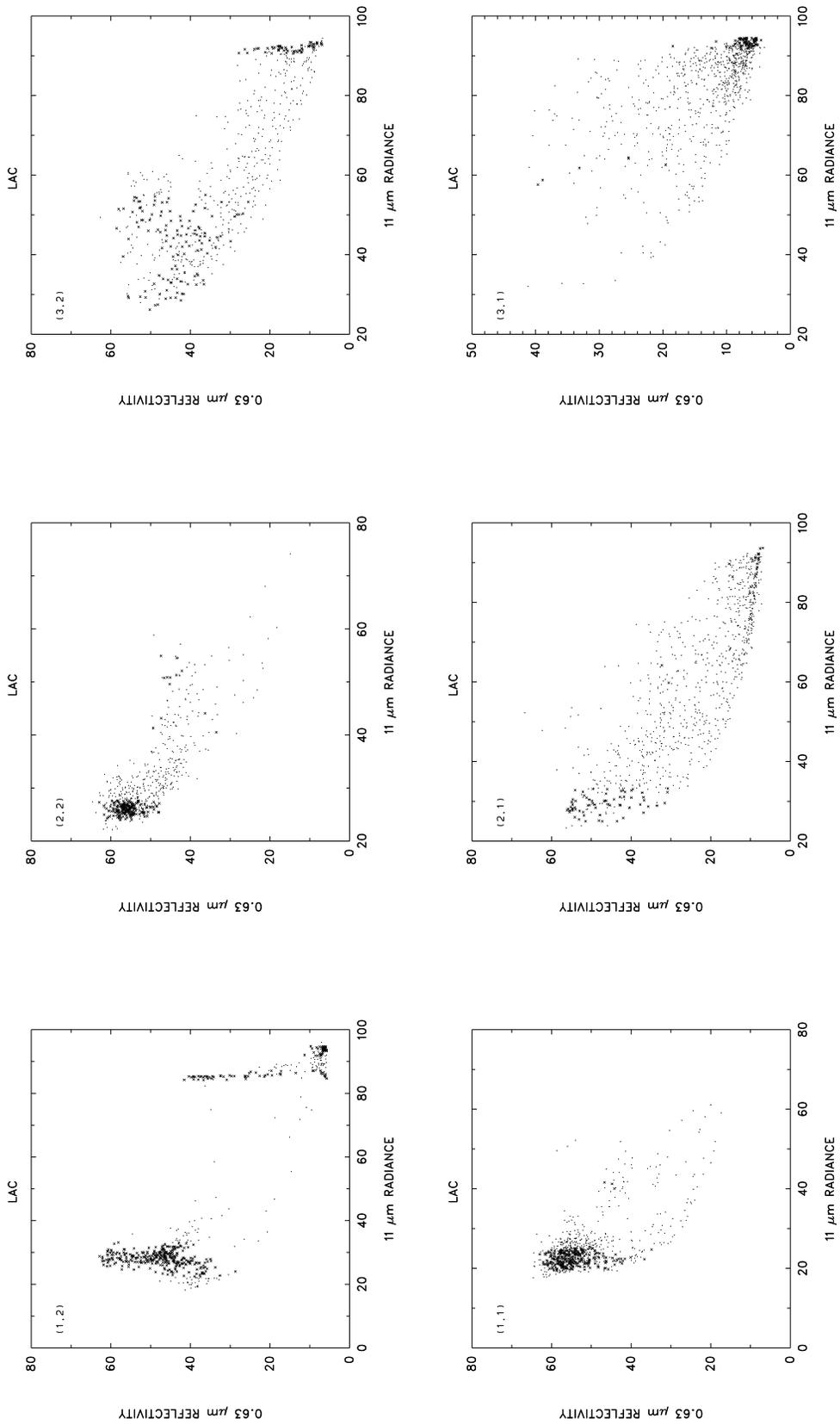


Figure 4.2-14. Same as Figure 4.2-13, but for 0.63- and 11-μm radiances.

#### *4.2.3.9. Quality Control*

As was noted in an earlier section, arbitrary levels of quality control may be applied to the spatial-coherence identification of layered cloud systems. The quality of the layer identifications may be measured in terms of the confidence limits with which the radiances associated with the layer might be specified. The rule-of-thumb criteria noted earlier, as given by (4.2-15) and (4.2-16), combined with the demand that a reasonable number of overcast pixels reside in the frame, say at least 10%, produces an acceptable number of layered systems when layers interpolated from adjacent subframe layers are counted. A requirement is that the adjacent subframe layers satisfy the conditions of (4.2-15) and (4.2-12). As noted earlier, tradeoffs between numbers of samples and uncertainties in layer definitions have not been studied.

The second approach to quality control is to demand that the layers identified through spatial-coherence analysis also be revealed in the relationships among various wavelengths. Perhaps the most revealing set of wavelengths for such confirmation would be 8 and 13  $\mu\text{m}$ . Again, methods for identifying multiple layer structure on the basis of the relationships between various wavelengths have yet to be developed.

#### *4.2.3.10. Numerical and Programming Considerations*

The application of the spatial-coherence method for identifying layered structure places several requirements on the structure of the imager data stream. First, as was noted in Section 4.2.2.5.1, the identification of overcast pixels is performed on  $250\text{ km} \times 250\text{ km}$  scale frames. Second, because  $50\text{ km} \times 50\text{ km}$  subframes may lack overcast pixels for any of the layers present, some means are required for interpolating layer properties from one subframe to the next. Interpolation among nearest neighbor subframes each of order  $50\text{ km} \times 50\text{ km}$  scale was suggested. This frame and subframe scale analysis suggests a nested structure for the data stream as illustrated in Figure 4.2-12.

The spatial coherence identification of layers would be undertaken as follows:

1. Overcast and cloud-free pixels would be identified in each  $250\text{ km} \times 250\text{ km}$  scale frame.
2. Overcast pixels within a frame and its surrounding  $50\text{ km} \times 50\text{ km}$  scale subframes would be classified to identify the overcast pixels with the various well-defined layers and assign the overcast pixels to specific layers.
3. Layers within the subframes constituting a frame would be determined on the basis of the layer identification of the overcast pixels within the subframe and its surrounding subframes.

These steps dictate the following structure. Spatial-coherence analysis is performed on imager scan lines sufficient to form a  $250\text{ km} \times 250\text{ km}$  scale frame. The analysis is performed for all  $250\text{ km} \times 250\text{ km}$  scale frames across the scan. Pixel radiances and layer identifications is retained in memory for a set of imager scan lines sufficient to form two adjacent sets of frames, i.e.  $500\text{ km} \times 500\text{ km}$  along the orbital track. In addition,  $50\text{ km} \times 50\text{ km}$  subframe scale layer properties are retained from the analysis of scan lines analyzed just prior to those currently in memory. Once the frame scale analysis is complete, the subframe scale analysis can begin with the first subframe of the scan lines residing in memory and end with the set of subframes that complete the first  $250\text{ km} \times 250\text{ km}$  scale frames spanned by the scan lines residing in memory. The results of the analysis for the subframes making up these  $250\text{ km} \times 250\text{ km}$  scale frames can be scrolled out of memory with the last set retained for the subsequent analysis of the subframes constituting the next  $250\text{ km} \times 250\text{ km}$  block of scan lines. New scan lines are read into memory forming a new  $250\text{ km} \times 250\text{ km}$  scale block and the spatial coherence analysis is applied to these new scan lines. The process is repeated.

Numerical efficiency has, to some extent, been addressed in the design proposed for the analysis. The design uses a uniform distribution to characterize the distribution of radiances within a spatial-coherence pixel array. This choice was intentional. It reduces numerical burdens incurred by using other

distributions, such as Gaussian. It also is easier to implement than using the actual distribution of the pixel scale radiances. There is no point in resorting to the actual distribution of the pixel radiances, because, in order to identify clustering, the density of pixel-scale radiances must be measured and the measure used is somewhat arbitrary. Fortunately, as was noted earlier, the natural clustering of points about a well-defined range of emitted radiances forms a robust feature that can be readily characterized by any number of methods. The outcome, namely the means and standard deviations of the radiances associated with overcast pixels, will be relatively insensitive to the method used to identify clusters of locally uniform emitted radiances. The strategy proposed here is thought to be a simple, efficient, and effective means of seeking those results.

#### 4.2.4 Multispectral Approaches

A third strategy for identifying layers missed by spatial-coherence analysis is to use multispectral histogram methods. Figure 4.2-9 clearly showed branches in the visible-infrared scatter plots associated with distinct layers, both of which were missed by the spatial-coherence method. Similar branches are observed at night for emission at 3.7 and 11  $\mu\text{m}$  (Coakley, 1983). Fitting procedures, like those developed by Lin and Coakley (1993) for the multispectral analysis of single-layered systems might be generalized to identify branches associated with distinct layers. Alternatively, a variation of the hybrid bispectral threshold method (HBTM) of Minnis and Harrison (1984) and Minnis et al. (1987) or the layered bispectral threshold method (LBTM; Minnis et al., 1993) could be used to analyze such systems. A second set of multiregion, multilayer observations are shown in Figures 4.2-13 and 4.2-14. Here the upper-level system is clearly defined in frame [2,1], but there is no indication of lower-level systems that are prevalent nearby in frames [1,2] and [3,2]. Without additional logic, the HBTM or LBTM may divide the system shown in [2,1] into three distinct layers with predefined properties: high, middle and low. Thus, this multispectral approach may place multiple layers where only single layers exist. Some simple modifications to the LBTM, however, can eliminate much of the ambiguity associated with single and overlapping layers.

##### 4.2.4.1. Daytime Methodology

The LBTM is similar to the ISCCP algorithm in that it compares the 11- $\mu\text{m}$  temperature  $T$  and reflectance  $\rho$  for each pixel to simple thresholds to determine if a pixel is cloudy or not. Instead of retrieving a visible optical depth  $\tau$  and cloud temperature  $T_{cld}$  for each cloudy pixel, the LBTM groups some pixels together before deriving  $T_{cld}$  and  $\tau$ . The LBTM nominally divides a visible-infrared histogram into three layers defined by hypothetical cloud temperatures at 2 and 6 km. Low clouds are those below 2 km, mid-level clouds are between 2 and 6 km, and high clouds are those above 6 km. When no  $\tau$ - and  $T_{cld}$ -solutions are possible for a nominal pixel grouping (discussed below), the LBTM attempts to reach a solution for a group of pixels by adding other pixels to the group until a solution is obtained. The LBTM also computes the mean layer cloud temperature  $T_k$  and optical depth  $\tau_k$  as well as their respective standard deviations  $\sigma_{T_k}$  and  $\sigma_{\tau_k}$  where  $k=1, 3$  from low to high. Other differences between the two methods include ice-crystal reflectance models for high clouds, bidirectional reflectance models for clear scenes, and a parameterization of the Earth-atmosphere system reflectance.

The reflectance is parameterized in terms of  $\tau$ , the cloud altitude, clear-sky reflectance  $\rho_{cs}$ , the cloud particle size, the solar zenith angle  $\theta_o$ , the viewing zenith angle  $\theta$ , and the relative azimuth angle  $\psi$ . The 11- $\mu\text{m}$  emittance is a function of  $\tau$ ,  $\mu (= \cos \theta)$ , and the difference between the clear-sky temperature  $T_{cs}$  and the cloud temperature  $T_{cld}$ . For liquid water clouds, it is assumed that the cloud consists of spherical droplets having an effective radius of 10  $\mu\text{m}$ . Ice clouds are assumed to be composed of randomly oriented hexagonal ice crystals representing a cirrostratus size distribution (Takano and Liou, 1989). The ice model is used for  $T_{cld} < 253\text{K}$  and the water-droplet model is applied for warmer cloud temperatures. The parameterizations of reflectance and emittance are detailed in section 4.3.

Given the relationships between cloud reflectance and emittance, it is possible to define the variation of  $\rho$  and  $T$  for a given value of  $T_{cld}$ . The variation in brightness temperature for a given value of  $\tau$  or  $\rho$  is

$$T_{\epsilon} = T_{\epsilon}(\rho, T_{cld}) = B^{-1}\{\epsilon(\rho)B(T_{cld}) + [1 - \epsilon(\rho)]B(T_{cs})\} \quad (4.2-18)$$

where  $T_{\epsilon}$  is a model-defined emittance-dependent brightness temperature and  $B$  is the Planck function. The emittance  $\epsilon$  and  $\rho$  are computed from the emittance and reflectance parameterizations at various values of  $\tau$ . Thus, a value of  $T_{\epsilon}$  corresponding to a cloud having  $T_{cld}$  can be defined for any given reflectance and microphysical model.

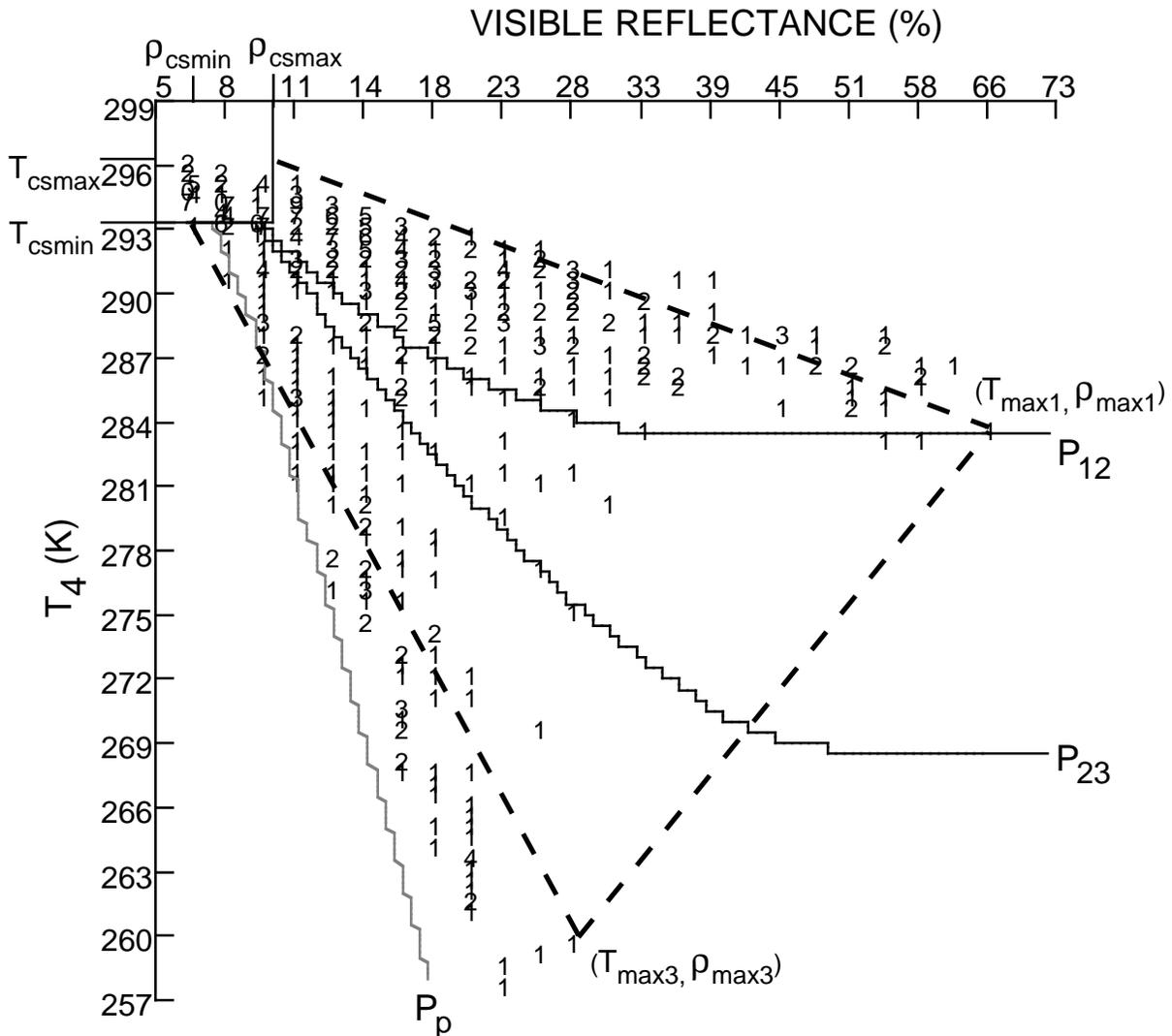


Figure 4.2-15. AVHRR VIS-IR histogram over 17.4°S at 153.3°E at 5.9 UTC, January 18, 1993.

Figure 4.2-15 shows an AVHRR visible-infrared histogram for an area over the southwestern tropical Pacific. The numbers plotted in the histogram represent the number of occurrences of the particular  $T$ - $\rho$  pair. The AVHRR 11- $\mu$ m sensor is channel 4, so the brightness temperatures are indicated with the subscript 4. As currently formulated, the LBTM histogram is divided into five areas: clear, low cloud, middle cloud, high cloud, and dark pixel or stratospheric cloud. The clear area incorporates all pixels having  $T > T_{cs} - \Delta T$  and  $\rho \leq \rho_t$  where  $\rho_t$  is the reflectance threshold value and the cloud threshold dif-

ference  $\Delta T$  has values of 6 K over land and 3 K over water. The clear-sky visible threshold reflectance is  $\rho_t$  as defined by Minnis et al. (1987). All other pixels are assumed to be overcast. Low-cloud pixels are all those having values of  $\rho > \rho_t$  and  $T > T_\varepsilon(\rho, T_{12})$ . The temperature  $T_{12}$  corresponds to an altitude of 2 km. Similarly, the high-cloud pixels are those having  $T \leq T_\varepsilon(\rho, T_{23})$ , where  $T_{23}$  corresponds to 6-km height. All nonclear pixels with temperatures and reflectances between the low- and high-cloud pixels are middle-cloud pixels. An upper boundary,  $T_\varepsilon(\rho, T_p)$ , is computed to correspond to the tropopause temperature  $T_p$  minus 2 K. The 2K subtraction accounts for uncertainty in the tropopause temperature. These cloud-layer boundaries are shown as the solid curves in Figure 4.2-15 and labeled as  $P_{12}$ ,  $P_{23}$ , and  $P_p$ . Pixels that are darker and colder than the respective reflectances and temperatures defining  $P_p$  are designated dark cloud pixels. These pixels are treated in a special manner described below.

The number of pixels in a scene assigned to a given layer,  $N_k$ , is

$$N_k = \sum_{ij} n(T_i, \rho_j) \quad (4.2-19)$$

Here,  $n$  is the number of pixels having  $T_i$  and  $\rho_j$  and the limits  $i$  and  $j$  are defined only for layer  $k$ . The temperatures in a given layer are averaged for each visible reflectance. Thus, for  $\rho_j$ ,

$$T_{kj} = B^{-1} \left[ \sum_i \frac{B(T_i) n(T_i, \rho_j)}{N_{kj}} \right] \quad (4.2-20)$$

where

$$N_{kj} = \sum_i n(T_i, \rho_j) \quad (4.2-21)$$

The emittance,  $\varepsilon_j = \varepsilon(\rho_j)$  is computed for each reflectance. The value of  $T_{kj}$  is substituted for  $T_\varepsilon$  in (4.2-14) and used with the emittance to solve for  $T_{cld}(kj)$ . The pressure in the middle of the layer is used in the reflectance parameterization to compute Rayleigh scattering for all clouds in the layer.

If  $\rho_j$  is in the dark-pixel area of the histogram,  $\varepsilon_j$  is indeterminate. It is assumed that dark pixels result from shadowing effects, other finite cloud effects, variations in  $\rho_{cs}$ , and inadequacies in the microphysical scattering models. When dark pixels are encountered, high-cloud pixels having greater reflectances are included in the calculation of  $T_{kj}$  to raise the mean, combined reflectance to a value of  $\rho > \rho_{cs}$  so that  $\varepsilon$  can be computed. If there are no low- or middle-cloud pixels having  $\tau > 1$ , then high- or middle-layer pixels having the same temperature as the dark pixels are included in the summation. The summation continues with the next greatest visible reflectance until the mean reflectance is greater than  $\rho_{cs}$ . Pixels having temperatures lower than the coldest dim pixels are included in the summation only if the mean value of  $\rho$  remains in the dark-pixel area of the histogram. If the summation process does not result in a nondark mean value of  $\rho$ , it is assumed that the dark pixels are clear, but shadowed.

If the initial value of  $T_{cld}(kj)$  for any  $kj$  is less than  $T_p$ , then the summation process used for the dark pixels is invoked until  $T_{cld}(kj) \geq T_p$ . If this condition cannot be satisfied for the data, then it is assumed that the cloud is located at the tropopause. The mean emittance and optical depths are then adjusted to force this solution. Finally, the average temperature for layer  $k$  is

$$T_k = B^{-1} \left\{ \sum_j \frac{B[T_{cld}(kj)] N_{kj}}{N_k} \right\} \quad (4.2-22)$$

where  $T_j$  is the mean temperature for each  $\rho_j$ . The standard deviation  $\sigma_{T_k}$  is computed in the standard fashion using the values of  $T_j$ . In the exceptions noted above, the index and values of  $\rho_j$  are adjusted to reflect the change in summation. No pixel values are ever used twice.

The LBTM cloud-layer definitions, used to associate altitude with the cloud classifications given by surface observers, provide a convenient way to vertically slice up the troposphere. Clouds do not necessarily fall exactly into those altitude ranges, so a cloud deck may straddle the layer boundaries giving the appearance of two layers. Furthermore, high and low layers may overlap and produce radiance pairs that appear to be in the middle layer. To minimize misdetection and to find distinct layers, the following modifications are applied to the LBTM. This procedure is applicable to scenes with horizontal dimensions of 50 km or greater.

To find distinct layers, it is assumed that there is an envelope of temperatures and reflectances that bound the pixels belonging to a given layer. This envelope must account for the variations in both the clear-sky radiances in the scene and the cloud height within the layer. The variations in  $T_{cs}$  and  $\rho_{cs}$  can be represented by the extreme values. The clear-sky extremes are defined as the coldest and warmest clear temperatures,  $T_{csmin}$  and  $T_{csmax}$ , respectively, and the smallest and greatest clear-sky reflectances,  $\rho_{csmin}$  and  $\rho_{csmax}$ , respectively. The respective temperature and reflectance for the brightest pixel in a given layer are  $T_{maxk}$  and  $\rho_{maxk}$ . The histogram is searched for layers beginning with the highest layer containing an observation. Pixel values falling to the cold and dim side of the line defined by  $(T_{csmax}, \rho_{csmax})$  and  $(T_{max3}, \rho_{max3})$  can be explained by clouds in the high layer. If no pixels are observed on the warm and bright side of this line, then it may be concluded that there is probably only one distinct layer present. This layer is defined by  $T_{cldk}$  and  $\sigma_{Tk}$ .

If there are pixels on the warm, bright side then the same process is repeated for the next level down. For midlevel clouds, the line would be given by  $(T_{csmax}, \rho_{csmax})$  and  $(T_{max2}, \rho_{max2})$ . If there are low clouds derived from the LBTM and there are pixels warmer and brighter than this new line, then it is concluded that there is a distinct layer of low clouds. These low clouds may be scattered cumulus or a deck of stratus or stratocumulus. If no pixels are observed to the warm, bright side of this line, it is likely that there is a distinct midlevel deck in the scene.

This algorithm is based on the dependence of reflectance and emittance on cloud optical depth. Emittance increases toward unity at a greater rate than reflectance approaches its asymptotic value. This feature produces the curvature seen in the coldest, dimmest pixels in Figures 4.2-10, 4.2-11, and 4.2-14. For a given cloud deck, there will be a spread in the observed temperature for a given reflectance because of the variations in  $T_{cs}$ ,  $T_{cl}$ , and the particle sizes in the cloud. Pixels between the dimmest, coldest curve and the straight line defined above can also be explained by pixels that are partially filled with the upper cloud or by overlap between some lower cloud and the upper cloud. It is necessary to have lower clouds to obtain pixels on the warm, bright side of that line. In other words, the high cloud cannot be that reflective and still be that warm.

To distinguish overlapped pixels from those belonging to a single deck, a similar analysis is applied using lines between the extreme cloud values. Given the presence of both low and high clouds and pixels that fall in the middle layer, it is possible to determine if some of the midlevel pixels are actually overlapped or represent a distinct layer. A line is drawn between  $(T_{max3}, \rho_{max3})$  and  $(T_{max1}, \rho_{max1})$ . If there are midlevel pixels to the cold, bright side of this line, then it is highly probable that there is a distinct midlevel deck. Otherwise, the midlevel clouds are probably overlapped high and low clouds.

This process is illustrated in Figure 4.2-15 for data similar to that seen in Figure 4.2-11b. The LBTM found three cloud layers in this histogram. The line extending from  $(T_{csmin}, \rho_{csmin})$  to  $(T = 259\text{K}, \rho = 0.28)$  indicates that there must be clouds lower than the high-cloud deck. Similarly, the line from  $(T_{csmax}, \rho_{csmax})$  to  $(T = 284\text{K}, \rho = 0.66)$  indicates a distinct low layer. The lack of pixels brighter than those defined by the line  $(T = 259\text{K}, \rho = 0.28) - (T = 284\text{K}, \rho = 0.66)$  suggests that the pixels in the middle layer do not form a distinct layer. Instead, they are formed by the overlap of the high and low layers.

If there are two layers in adjacent levels or if there is only one distinct layer  $k$ , but there are some pixels in layer  $k-1$ , then the cloud temperatures are compared to determine if they are part of the same cloud deck. As in the spatial coherence method, the cloud deck is allowed to have a finite thickness or

altitude range. This permitted layer range  $\Delta T_{lcl}$  varies with height because, in a given system, high cloud tops tend to vary over a greater vertical range than low clouds and retrieved high cloud altitudes are subject to more error than low clouds. Marine boundary layer cloud heights, for example, can be determined to within a few hundred meters (e.g., Minnis et al., 1992), while the typical instantaneous error in the derived thin cirrus heights is  $\sim \pm 1$  km (e.g., Minnis et al., 1993). For low clouds, i.e.,  $T_{cld} > 280$ K,  $\Delta T_{lcl} = 2$  K. For high clouds, i.e.,  $T_{cld} < 220$  K,  $\Delta T_{lcl} = 6$  K. In between these extremes,

$$\Delta T_{lcl} = 2 + 0.67(280 - T_{cld}) \tag{4.2-23}$$

The allowed temperature range bounds the layer values. Thus, if  $2\sigma_{T_k} > \Delta T_{lcl}$ , then the layer is too diffuse to be designated as a distinct layer. If, however,  $2\sigma_{T_k}$  and  $2\sigma_{T_{k-1}}$  are both less than  $\Delta T_{lcl}$ , then it may be possible to combine the layers. The layers are combined if  $T_{k-1} < T_k + 2\sigma_{T_k}$  or if  $T_k > T_{k-1} - 2\sigma_{T_{k-1}}$  and the resulting standard deviation is less than  $0.5\Delta T_{lcl}$ .

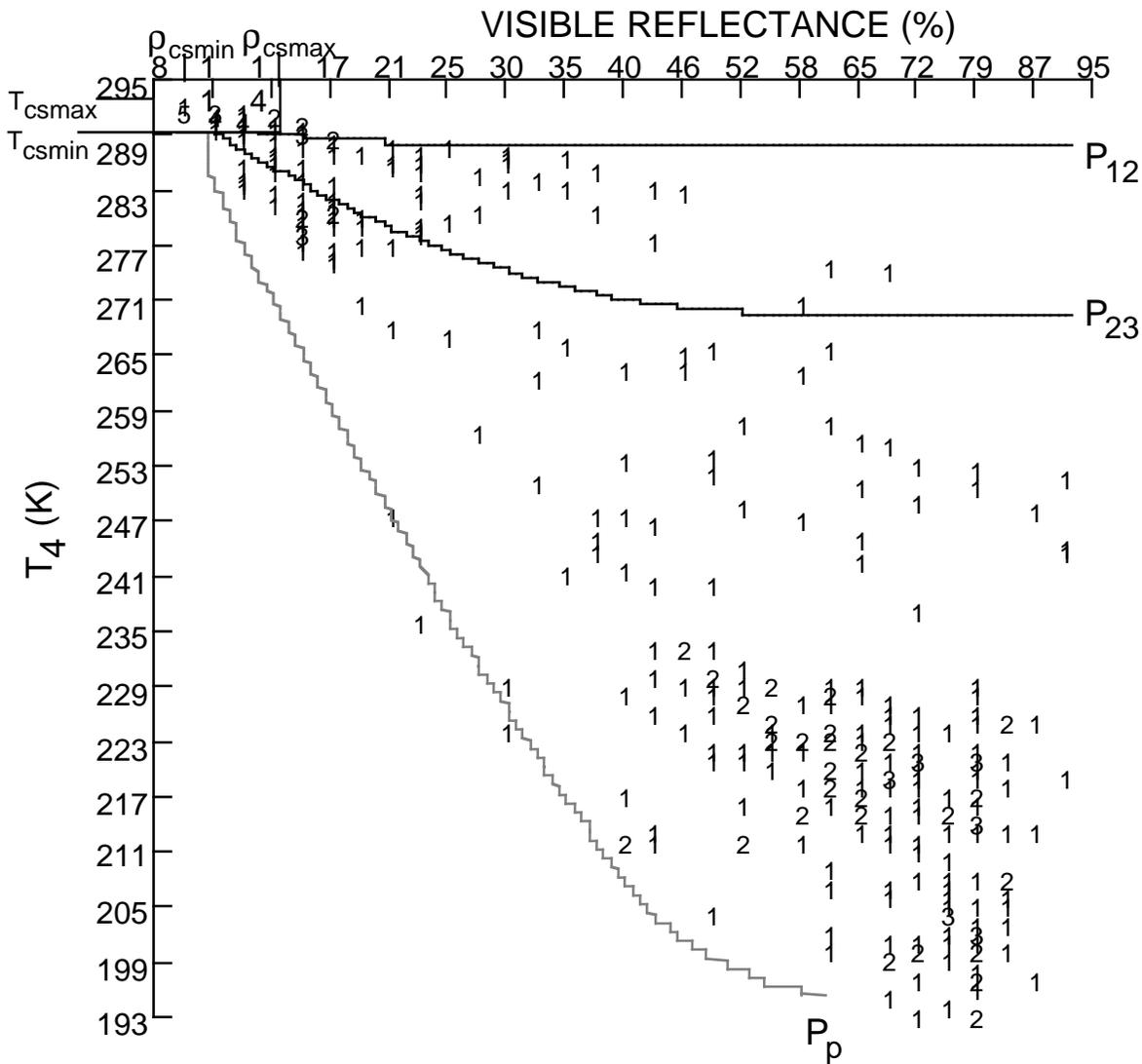


Figure 4.2-16. AVHRR VIS-IR histogram over 10.7°S at 143.2°E at 5.9 UTC, January 18, 1993.

Application of this process to the scatter plots in Figure 4.2-10 would yield single low-level decks for [1,1] and [2,1], and low and high decks with overlapped pixels for the remaining plots. In Figure

4.2-14, the technique would identify a low and a high deck for [1,1], a mid and high deck for [1,2], a low deck for [1,3], a mid and high deck for [2,10] a high deck for [2,2], and possibly a high deck for [2,3]. The high layers in [1,3], [2,2], and [2,3], the midlayers in [2,2] and [2,3] and the low layer in [2,3] may be too diffuse to pass the layer bounds test although they would pass the simple linear tests. Some layering of the high clouds in [1,3], [2,2], and [3,3] may be detectable with a greater vertical resolution of layers rather than the three used here. However, these scenes may contain convective clouds in various stages of development so that no extensive layers exist. Figure 4.2-16 shows an example of a diffuse situation over the tropical Pacific. The low-mid, mid-high, tropopause, and clear boundaries are drawn to illustrate how the histogram is sliced for a convective case. Application of the technique would yield only one distinct cloud layer in the middle levels with  $T_2 = 278.6$  K. The high layer would not satisfy the temperature range rules. Some low-cloud pixels near the clear boundary would not constitute a layer because they fall to the cold, dim side of the mid-cloud  $\rho_{max}$  line.

For scenes containing more than one layer, it is possible to estimate which pixels are overlapped and which belong to a single layer. Given  $T_k$  and  $\sigma_{Tk}$  for layer  $k$ , the pixels that belong to the layer are those enveloped by the two curves defined by the model calculations of  $T$  and  $\rho$  for a range of optical depths. The computations use  $(T_{csmax}, \rho_{csmax})$  for the clear conditions and  $T_k + 2\sigma_{Tk}$  as the cloud temperature to determine the curve for the warm side of the cloud deck and  $(T_{csmin}, \rho_{csmin})$  for the clear conditions and  $T_k - 2\sigma_{Tk}$  as the cloud temperature to determine the cold curve. Pixels having values of  $T$  and  $\rho$  between those two curves are assigned to the layer. Figure 4.2-17 shows an example of a three-layer case. The boundary lines are shown as before with a crude approximation of the envelopes for each layer. The envelope overlap near the clear boundaries is typical, but will be somewhat diminished when the actual calculations are applied. The  $T$  and  $\rho$  for each pixel in the envelope overlap are compared to the central curve of the envelopes. This central curve is defined by  $T_k$  and  $(T_{cs}, \rho_{cs})$ . The pixel is assigned to the layer for which the difference between  $T$  and  $T_k(\rho)$  is minimal. The pixels that fall between the envelopes are considered to be overlapped pixels.

This approach to cloud layering can detect more cloud layers than the spatial-coherence technique. It cannot detect three layers unless the reflectance of the middle layer exceeds that of either the low or high layer. The increased detectability may raise the level of uncertainty in the cloud layer properties. This bispectral approach is currently under development and will be altered to accommodate additional layers. The allowed layer temperature range, interpretation of the overlapped pixels, and techniques for defining the range in clear-sky temperature and reflectance are among the issues that are being examined.

#### 4.2.4.2. Nighttime Layer Pressure Retrieval

At night, a different approach is needed. Figure 4.2-18a shows  $T_4$  and the AVHRR channel 3 ( $3.7 \mu\text{m}$ ) brightness temperatures  $T_3$  for a layer of altostratus clouds over an area in the tropical Pacific. The value of  $T_{cs4}$  is  $\sim 293$  K. The brightness temperature differences  $BTD_{3-4}$  for channels 3 and 4, plotted against  $T_4$  in Figure 4.2-18b, are more informative. For a given value of  $T_{cld}$ ,  $BTD_{3-4}$  increases as the optical depth increases up to a value of  $\tau \sim 4$ . As  $\tau$  continues to increase,  $BTD_{3-4}$  decreases rapidly until it is less than the clear-sky value. Thus, whenever  $BTD_{3-4}$  for cloudy pixels is less than the clear value, a nearly opaque cloud is indicated. The variation in  $BTD_{3-4}$  arises from variations in  $T_{cs}$ ,  $T_{cld}$ , and particle size. If there is a cluster of nearly opaque pixels around a given value of  $T_4$ , it is highly probable that a layer exists at  $T_4$ . The methods for determining these layers are the same as prescribed for the daytime case. The low, middle, and high boundaries are established for an optically thick cloud (e.g.,  $T_{12} = T[z = 2 \text{ km}]$  for all values of  $T_3$ ). The values of  $T_k$  and  $\sigma_{Tk}$  are computed using only the pixels having  $BTD_{3-4}$  less than the clear-sky value. The same criteria applied during the daytime are used at night for defining a layer and combining adjacent layers. In the case of Figure 4.2-18b, a layer would be determined at  $\sim 258$  K.

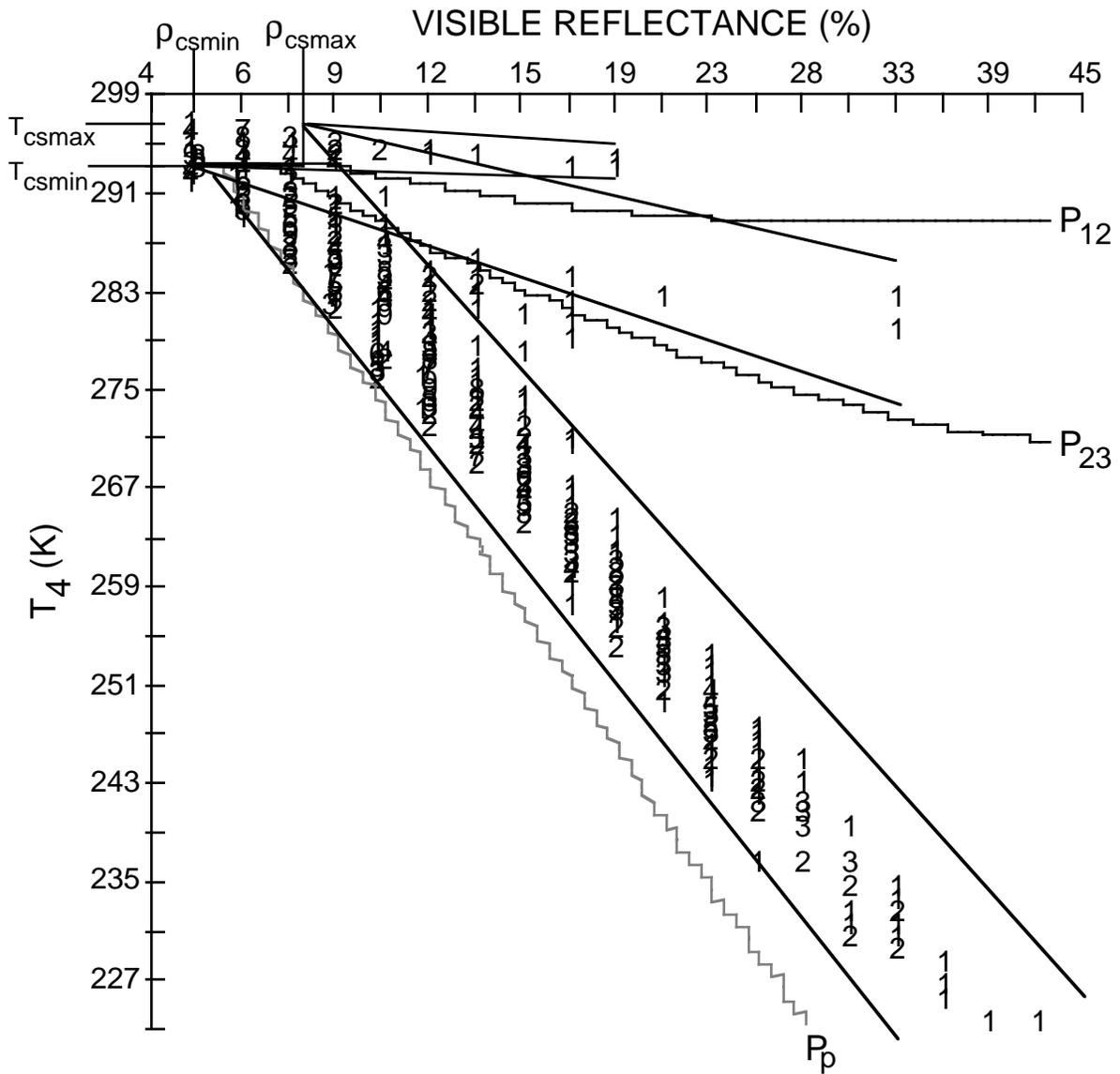


Figure 4.2-17. AVHRR VIS-IR histogram over 13.3°S at 149.4°E at 5.9 UTC, January 18, 1993.

A layer analysis of the histogram in Figure 4.2-19 would yield a layer near 221 K. The solid line in Figure 4.2-19 corresponds to a parameterization calculation of  $BTD_{3,4}$  using a cirrostratus microphysical model,  $T_{cs4} = 293.5K$ , and  $T_{cld} = 221K$  (see section 4.3 for details). The model fit is consistent with a single layer of clouds having relatively uniform particle sizes. The more complex histogram in Figure 4.2-20 is typical of a two- or three-layer system. The clear portion of the scene is at approximately 291 K; a distinct middle layer is found at 273 K, and a diffuse high layer is found near 228 K. An additional low layer may be at ~288 K. This combination of clear, single-layer, and overlapping layers would probably only yield a single layer at ~273 K. The high-cloud layer would be too diffuse to pass the temperature range tests using  $T_{cs}$  as the background temperature. Because most of the high-cloud pixels are probably overlapping middle-cloud pixels, the background temperature should be the middle-cloud temperature. The result would be a high cloud at ~228 K.

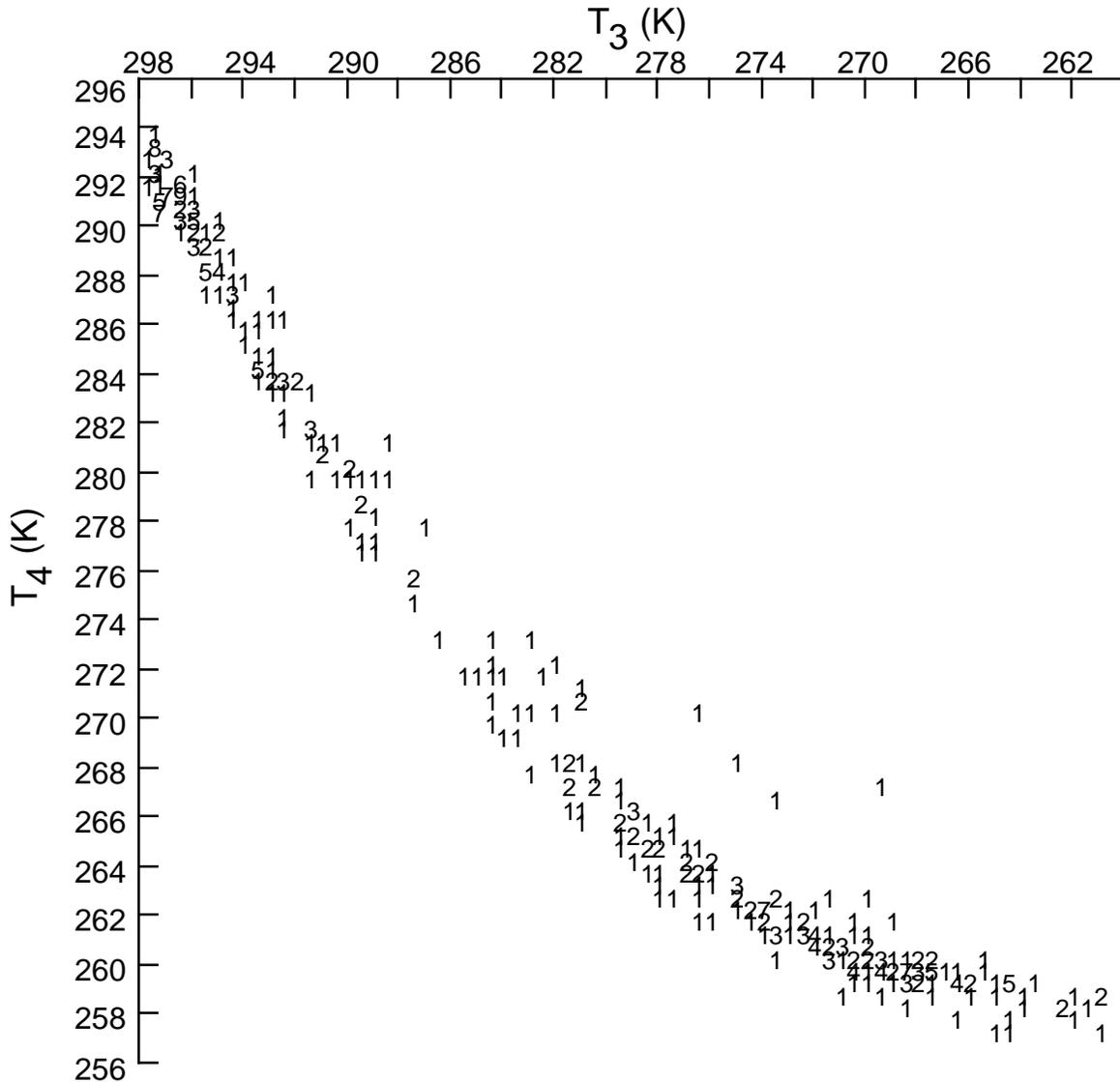
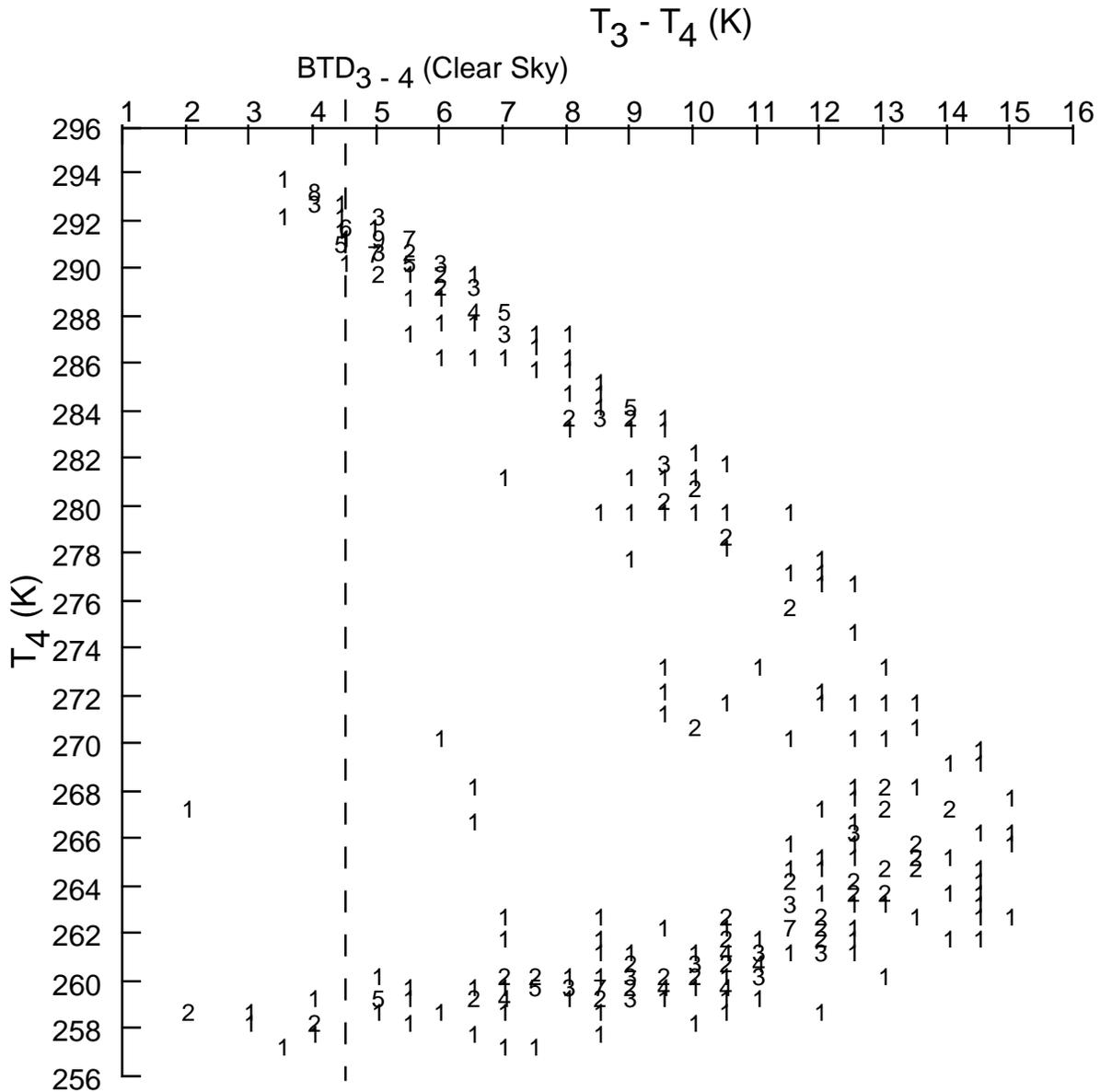


Figure 4.2-18a. AVHRR NIR-IR histogram over 5.9°S at 133.6°E at 18.8 UTC, January 26, 1993.

The examples shown here suggest that layers can be identified at night using a bispectral histogram approach. This method is currently under development. Issues that are being addressed include the detection of overlapped pixels, the determination of the appropriate background temperature, prescription of layer envelopes based on assumptions about particle size, detection of layers with no opaque pixels, and the determination of layers in overlapped conditions.

**4.2.4.3. Practical Considerations**

For CERES, the LBTM histogram will be divided into six areas: clear, low (surface to 700 hPa), lower middle (700–500 hPa), upper middle (500–300 hPa), and high (<300 hPa), and the dark pixel area. The CERES LBTM will require the input variables: clear-sky radiances and their standard deviations for each channel, vertical profiles of temperature, surface type, pixel radiances, surface elevation, and ozone optical depth at 0.65  $\mu\text{m}$ . The output comprises the number of distinct layers, the means and standard deviations for  $\tau_k$  and  $T_k$ , and an index indicating whether it is overlapped or not. The methodologies described in this section will be validated using several different approaches. The layer cloud



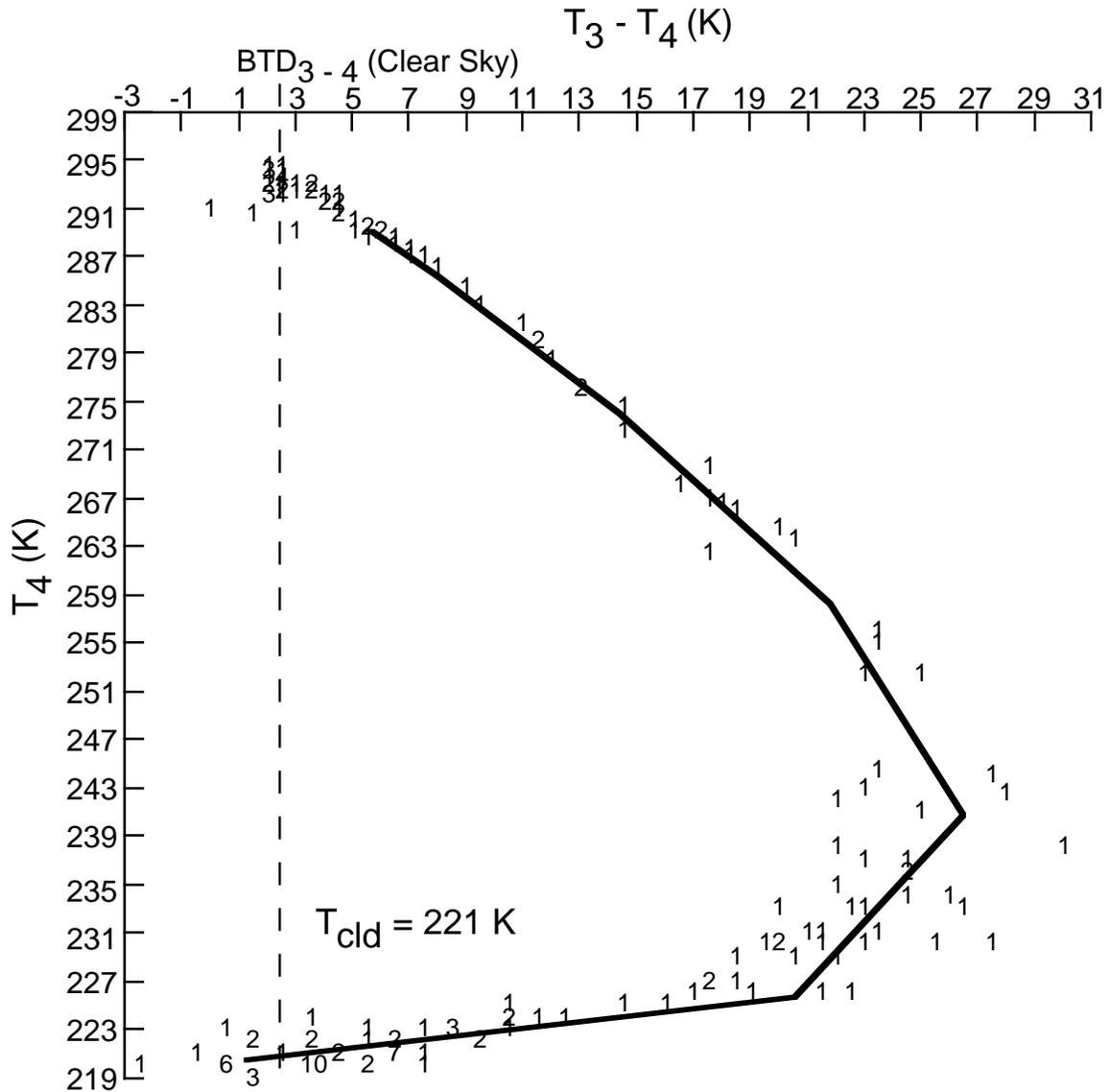


Figure 4.2-19b. AVHRR BT-D-IR histogram over 7.1°S at 171.3°E at 16.3 UTC, January 30, 1993.

within the 15- $\mu$ m  $CO_2$  band have varying opacity to  $CO_2$ , thereby causing each channel to be sensitive to a different layer in the atmosphere. The techniques have been shown to be effective for single-layered, nonblack, mid- to high-level clouds such as cirrus, but are generally applied operationally to any given cloud occurrence. The algorithms are most accurate for clouds that occur in a single, well-defined layer, or for multilayered cloud cases in which the uppermost cloud layer is nearly black. The derived cloud pressure is expected to be near cloud center for optically thin clouds (those with extinction optical depths less than 1). The cloud pressure is expected to decrease to cloud top for more nearly opaque cloud when the extinction optical depth is greater than 1.

This algorithm calculates cloud top pressure,  $p_{cld}$ , and effective cloud amount,  $\epsilon C$  (emittance  $\epsilon$  times cloud fraction  $C$ ), given one or more pairs of 15- $\mu$ m narrowband radiances. The method relies upon having significant pressure level differences between the peaks of the weighting functions for a given pair of channels. The algorithm specification includes suggested strategies for handling:

1. Temperature inversions (ambiguity in  $p_{cld}$ )

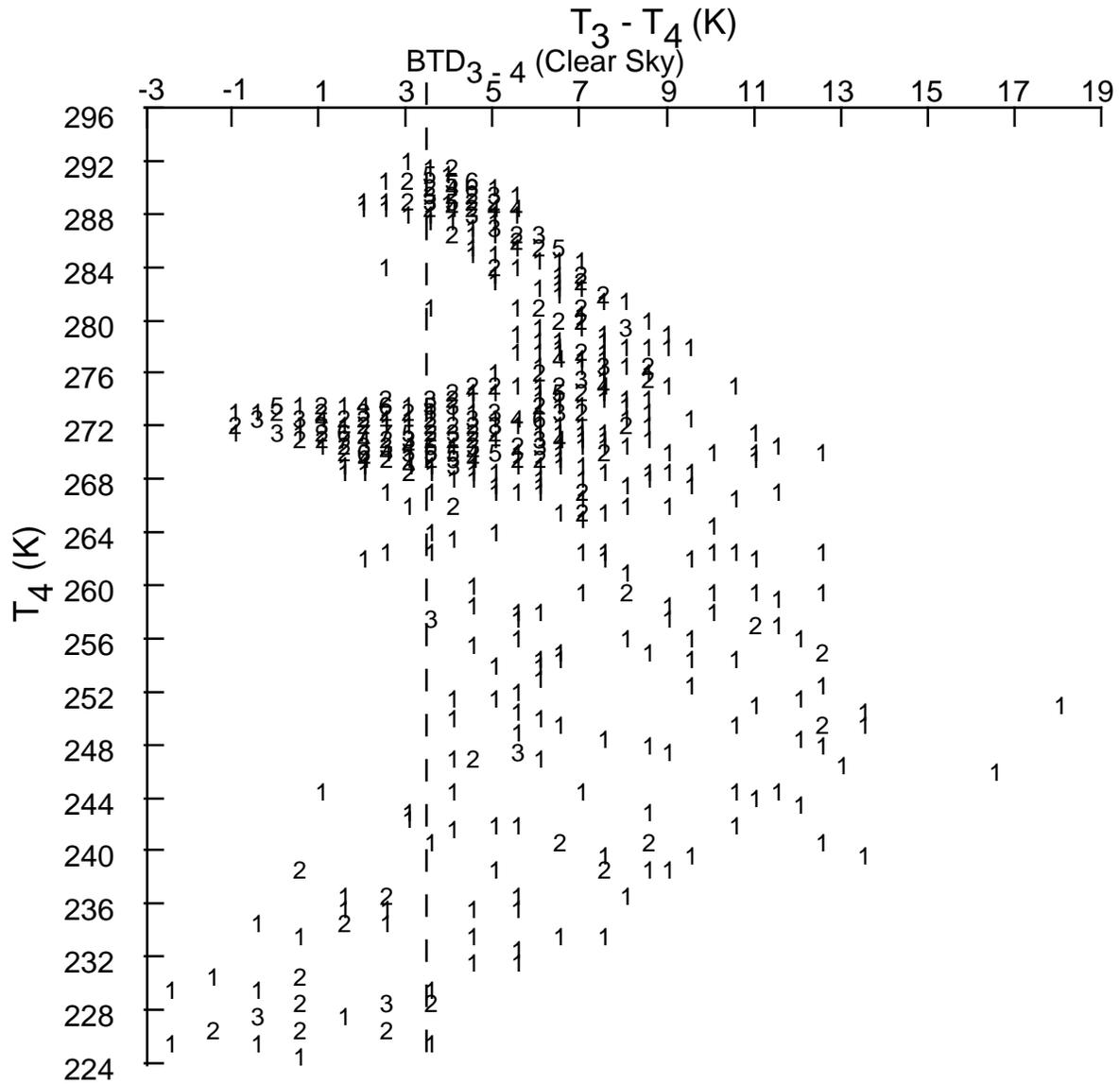


Figure 4.2-20. AVHRR BT-D-IR histogram over 4.3°S at 134.7°E at 18.8 UTC, January 26, 1993.

2. Lack of sensitivity in the weighting functions
3. Consistency in multichannel retrievals
4. Various problems relating to instrument noise, transmission function errors, and input data errors

This algorithm has been applied to data from the High Resolution Infrared Radiation Sounder (HIRS/2, henceforth HIRS for simplicity) (Wylie and Menzel, 1989; Menzel et al., 1992; Wylie et al., 1994), the Geostationary Operational Environmental Satellite (GOES) VISSR (Visible Infrared Spin Scan Radiometer) Atmospheric Sounder (VAS) (e.g. Menzel et al., 1983), and most recently to the High Resolution Interferometer Sounder (HIS) (Smith and Frey, 1990). The Moderate Resolution Imaging Spectroradiometer (MODIS) (King et al., 1992) under development for the Earth Observing System (EOS) has four channels in the 15- $\mu$ m region that are similar to the HIRS channels. The central wave-numbers and other characteristics of the appropriate channels for the HIRS and MODIS instruments are provided in Table 1. Error analyses based upon the CO<sub>2</sub> slicing method have been reported by Wielicki

and Coakley (1981), Menzel et al. (1992), and Baum and Wielicki (1994). Sources of error for this algorithm will be discussed in greater detail later in this document. Retrieval errors will arise from instrument noise, errors in temperature and humidity profiles, errors in the clear-sky radiance, geometrically thick but optically thin clouds, radiative transfer calculation assumptions, and the presence of more than one cloud layer in the field-of-view (FOV).

**4.2.5.2. Basic Equations and Derivations**

The clear-sky spectral radiance  $I_{cs}(v^i, p_s)$  for a black surface (surface emissivity,  $\epsilon_s^i = 1$ ,  $i$  is channel number) is given by

$$I_{cs}(v^i, p_s) = B(v^i, T_s)t(v^i, p_s) + \int_{P_s}^0 \frac{dt(v^i, p)}{dlnp} B[v^i, T(p)] dlnp \tag{4.2-24}$$

where  $B(v^i, T)$  is the Planck radiance at temperature  $T$ ,  $v^i$  is the wavenumber of channel  $i$ ,  $t(v^i, p)$  is the transmission from atmospheric pressure level  $p$  to the satellite at  $p = 0$ , and the subscripts  $s$  and  $cs$  denote surface and clear-sky, respectively. If the cloud is opaque (cloud emissivity,  $\epsilon_{cld}^i = 1$ ) at wavenumber  $v^i$  and completely fills the FOV, the radiance for an overcast black cloud (*ob*) at pressure level  $p_{cld}$  is given by

$$I_{ob}(v^i, p_{cld}) = B(v^i, T_{cld})t(v^i, p_{cld}) + \int_{P_{cld}}^0 \frac{dt(v^i, p)}{dlnp} B[v^i, T(p)] dlnp \tag{4.2-25}$$

Table 4.2-1. HIRS and Anticipated MODIS Channels, Central Wavelengths, Principal Absorbing Components, and Approximate Pressure Level Corresponding to the Peak in the Individual Channel Weighting Functions; Central Wavelengths and Weighting Function Peaks May Change Slightly for Each Instrument.

Instrument	Channel number	Central wavelength, $\mu\text{m}$	Principal absorbing component	Approximate peak in weighting function, hPa
HIRS	4	14.21	CO <sub>2</sub>	300
HIRS	5	13.95	CO <sub>2</sub>	500
HIRS	6	13.66	CO <sub>2</sub> ; H <sub>2</sub> O	750
HIRS	7	13.34	CO <sub>2</sub> ; H <sub>2</sub> O	900
HIRS	8	11.10	H <sub>2</sub> O	Surface
MODIS	31	11.03	H <sub>2</sub> O	Surface
MODIS	32	12.02	H <sub>2</sub> O	Surface
MODIS	33	13.335	CO <sub>2</sub> ; H <sub>2</sub> O	900
MODIS	34	13.635	CO <sub>2</sub> ; H <sub>2</sub> O	750
MODIS	35	13.935	CO <sub>2</sub>	500
MODIS	36	14.235	CO <sub>2</sub>	300

The theoretical upwelling radiance  $I$  for a partially cloud-filled FOV is given by

$$I(v^i, p_{cld}, \epsilon_{cld}^i C) = I_{cs}(v^i, p_s) + \epsilon_{cld}^i C [I_{ob}(v^i, p_c) - I_{cs}(v^i, p_s)] \quad (4.2-26)$$

In this formulation, the cloud emittance  $\epsilon_{cld}^i$  of channel  $i$  is multiplied by the cloud fractional coverage  $C$ , and the quantity  $\epsilon_{cld}^i C$  is referred to as the effective cloud amount or effective cloud emittance in the literature.

**4.2.5.2.1. Transmittance functions.** The calculation of the transmission functions used to generate the theoretical upwelling radiances are based on a model developed by McMillin and Fleming (1976) and used by Weinreb et al. (1981) for HIRS transmittance calculations. Eyre and Woolf (1988) developed a newer model primarily for work with microwave channels. When the Eyre and Woolf (1988) model was tested on HIRS channels, it was found to have poor accuracy for channels with strong water vapor absorption. This shortcoming was addressed in the model reported by Eyre (1991), which improves the treatment of water vapor and has the added benefit of providing code that is much easier to vectorize than the model used by Weinreb et al. (1981). The model currently used is based on Eyre (1991) with code developed initially by Woolf (personal communication, 1993).

For HIRS analysis, the transmittance model is evaluated at 40 discrete pressure levels (0.1, 0.2, 0.5, 1, 1.5, 2, 3, 4, 5, 7, 10, 15, 20, 25, 30, 50, 60, 70, 85, 100, 115, 135, 150, 200, 250, 300, 350, 400, 430, 475, 500, 470, 620, 670, 700, 780, 850, 920, 950, and 1000 hPa). For a midlatitude spring/fall temperature profile shown in Figure 4.2-21a, transmittance profiles for HIRS 15- $\mu$ m channels 4 through 7 are shown in Figure 4.2-21b. Channels 4 and 5 have extremely low transmittances at the surface, showing that these channels are relatively insensitive to errors in clear-sky temperature. Channels 6 and 7 have transmittances greater than 10% near the surface and are more sensitive to surface temperature than channels 4 or 5. Weighting functions for HIRS channels 4 through 8 are shown in Figure 4.2-22.

For MODIS 15- $\mu$ m radiometric data analysis, it is anticipated that the transmission model will be discretized at 50-hPa increments in the troposphere, and have an additional surface term for cases in which the surface pressure is greater than 1000 hPa. There has been some discussion as to whether 25-hPa pressure increments will be necessary.

#### 4.2.5.3. Radiance Ratio Method

Cloud-top pressure may be determined using the radiance ratio method, as discussed in Smith and Platt (1978), Wylie and Menzel (1989), Smith and Frey (1990), Menzel et al. (1983), and Wielicki and Coakley (1981). The change in radiance at a particular wavenumber caused by the presence of cloud is called the cloud signal. In the radiance-ratio method, a ratio is taken of the cloud signals for two channels spaced closely in wavenumber. For two spectral channels at wavenumbers  $v^i$  and  $v^j$  that are looking at the same FOV, the ratio for a single cloud layer is derived as

$$G(p_{cld}) = \frac{I_{meas}(v^i) - I_{cs}(v^i)}{I_{meas}(v^j) - I_{cs}(v^j)} = \frac{I_{ob}(v^i, p_{cld}) - I_{cs}(v^i, p_{cs})}{I_{ob}(v^j, p_{cld}) - I_{cs}(v^j, p_{cs})} \quad (4.2-27)$$

where  $G$  is the ratio of cloud signal for two different channels and  $I_{meas}(v^i)$  and  $I_{meas}(v^j)$  denote the measured radiance of channels  $i$  and  $j$ . We make the assumption that the emittances are the same for both channels. The function  $G$  is independent of both cloud opacity and effective cloud amount. However,  $G$  is dependent on the weighting function of the two channels, the cloud height, and the atmospheric temperature profile.

**4.2.5.4 Root-mean-square (RMS) Method**

The implementation of the rms method requires a knowledge of temperature and humidity profiles. The rms radiance difference  $I_{rms}$  for  $N$  channels (Chahine, 1974; Wielicki and Coakley, 1981) is determined from

$$I_{rms}(p_{cld}, \epsilon_{cld}^i C) = \left\{ \sum_1^N [I_{meas}^i(v^i) - I^i(v^i, p_{cld}, \epsilon_{cld}^i C)]^2 \right\}^{1/2} \tag{4.2-28}$$

where  $I_{rms}$  is the rms radiance and  $I^i(v^i, p_{cld}, \epsilon_{cld}^i C)$  is determined from (4.2-26). For multilayer cloudiness, the retrieved cloud pressure errors will be the result of using a clear-sky radiance instead of the radiance of a lower cloud layer to compute the theoretical upwelling radiances when more than one cloud layer is present in an FOV. The atmosphere between 200 and 950 hPa is divided into 25-hPa intervals for the rms calculations. Thus, the derived cloud pressure will correspond to the rms minimum at a predefined interval.

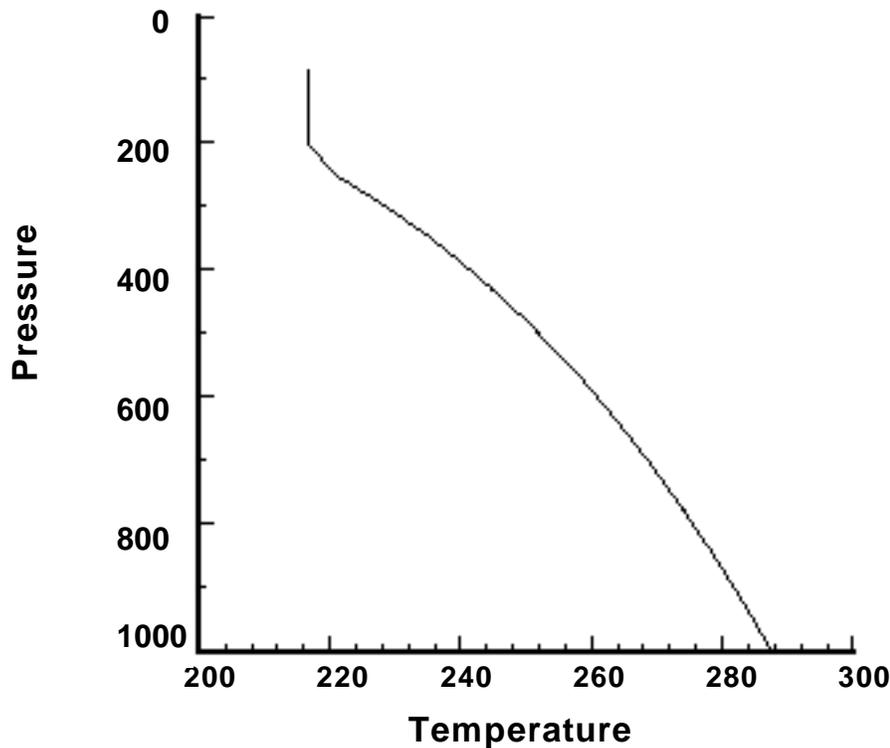


Figure 4.2-21a. Average midlatitude temperature profile.

The rms method, as stated in (4.2-29), has no provision for weighting the cloud signal from the various channels. The cloud signal for any particular channel increases with surface transmission so that the largest cloud signal will be recorded for the channel whose weighting function peaks closest to the surface, and the smallest cloud signal for the channel whose weighting function peaks farthest from the surface. The rms method as currently applied tends to weight the results toward the channels with greater transmittance.

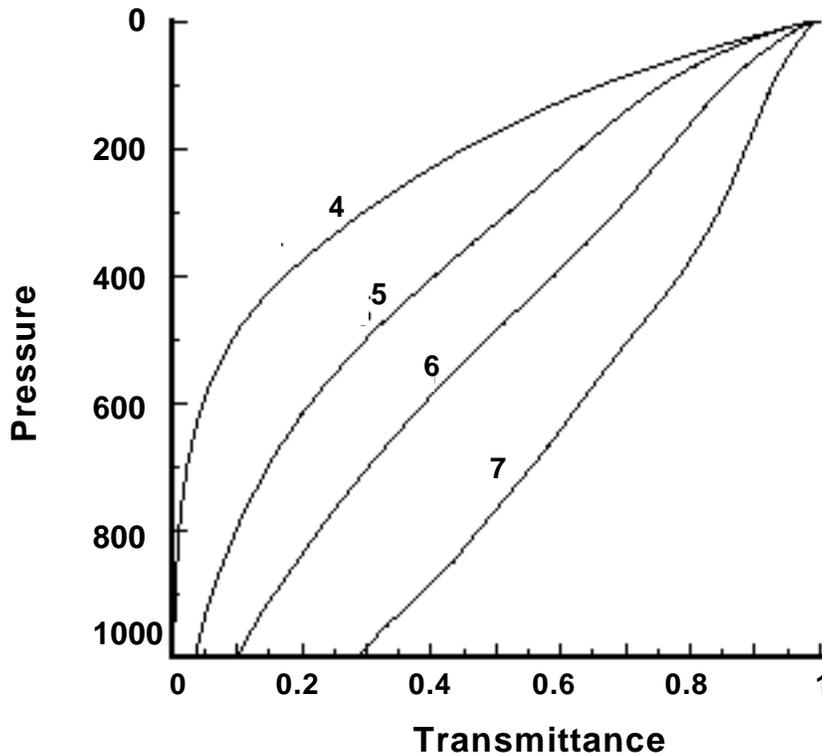


Figure 4.2-21b. NOAA-11 HIRS transmittances for channels 4, 5, 6, and 7.

**4.2.5.5. Calculation of Effective Emittance**

Once a cloud height has been determined, an effective cloud amount (also referred to as effective emittance) can be evaluated from the infrared window channel data (usually 11  $\mu\text{m}$ ). For a single-level cirrus layer, the effective emittance is derived by rearranging (4.2-27):

$$\epsilon C = \frac{I(v^i, p_c) - I_{cs}(v^i, p_s)}{I_{ob}(v^i, p_c) - I_{cs}(v^i, p_s)} \tag{4.2-29}$$

When the effective emittance is less than unity, the sensor may be observing broken cloud ( $C < 1$ ;  $\epsilon_{cld} = 1$ ), overcast transmissive cloud ( $C = 1$ ;  $\epsilon_{cld} < 1$ ), or broken transmissive cloud ( $C < 1$ ;  $\epsilon_{cld} < 1$ ). With a HIRS FOV of  $\sim 18$  km at nadir, it is not reasonable to assume that the cloud completely covers the field of view except for large scale synoptic regimes. For the MODIS 1 km  $\times$  1 km pixel size, we can assume that high clouds fill the field of view ( $C = 1$ ) so that we obtain a direct estimate of  $\epsilon$  using (4.2-29). For the large HIRS footprint,  $C$  is determined from AVHRR higher resolution data, assuming  $C = 1$  for the AVHRR pixel.

**4.2.5.6. Estimation of Clear-Sky Radiance**

To calculate the  $G$  function for the single cloud-layer case, an estimate must be determined for the representative clear-sky radiance appropriate for the FOV. Clear-sky radiance/brightness temperature estimates are to be used from the CRH ancillary data set.

**4.2.5.7. Error Estimates for Cloud Property Retrieval**

Retrieval errors will arise from instrument noise, errors in temperature and humidity profiles, errors in the clear-sky radiance, geometrically thick but optically thin clouds, radiative transfer calculation

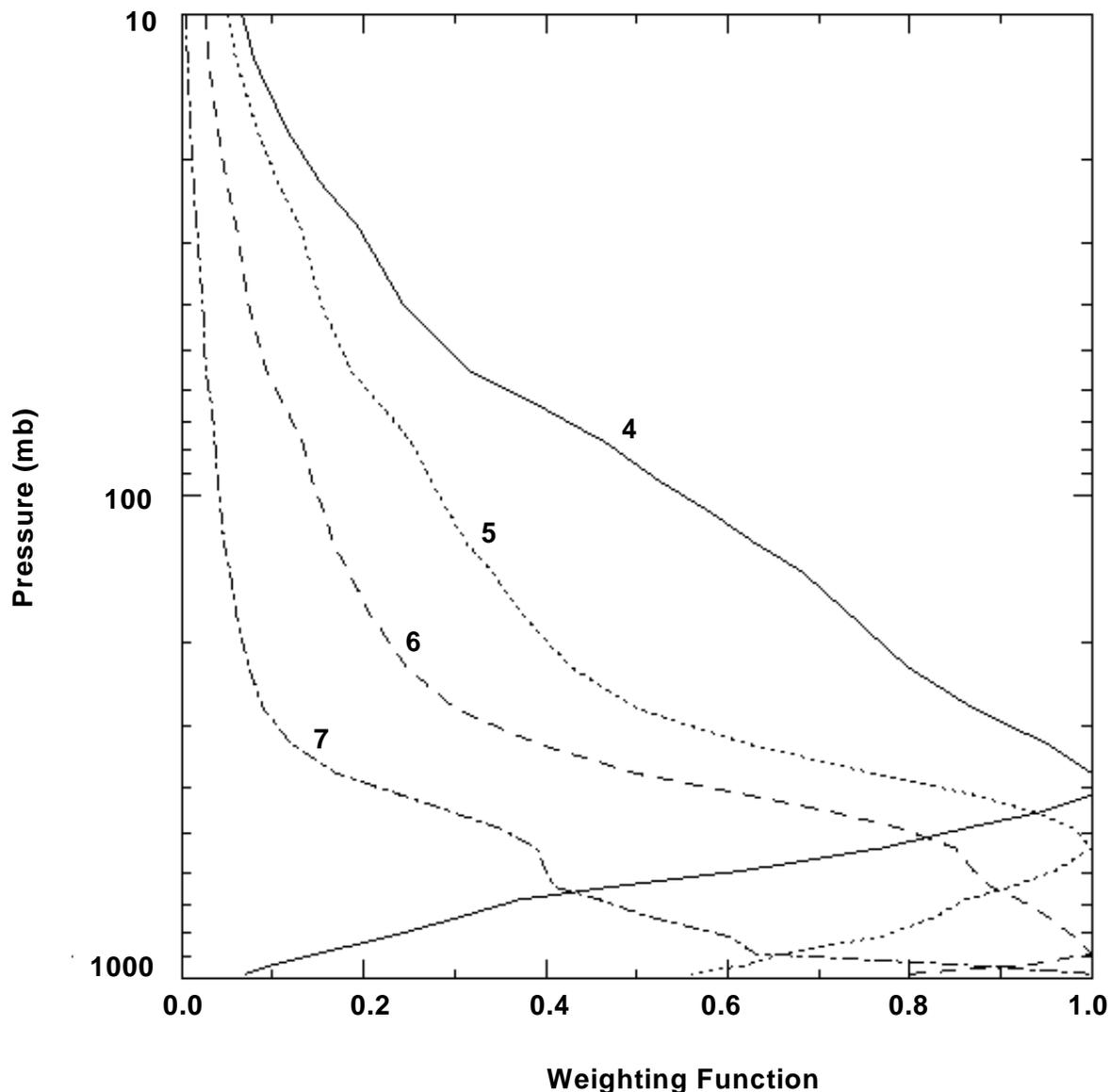


Figure 4.2-22. NOAA-11 HIRS weighting function  $dt/d \ln P$  for channels 4, 5, 6, and 7 for nadir viewing conditions.

assumptions, and the presence of more than one cloud layer in the FOV. Because all of these issues have been reported in the literature, a brief summary will be presented here.

**4.2.5.7.1. Errors associated with the assumption of constant emissivity.** Spectrally close channels are used to minimize differences in the real and imaginary parts of the index of refraction for ice crystals and water droplets. Calculations by Jacobowitz (1970) indicate that negligible errors occur for the  $\text{CO}_2$  channels between 13.3 and 14.2  $\mu\text{m}$  for water and/or ice cloud determinations. This phenomenon is not deemed to be an error source in the  $\text{CO}_2$  slicing algorithm.

**4.2.5.7.2. Errors associated with the assumption of a thin cloud layer.** The  $\text{CO}_2$  slicing algorithm assumes that all of the radiative effects of the cloud occur as if the cloud were a thin layer at a single temperature. This makes the mathematics tractable. If the methodology to calculate radiative properties of a nonopaque cloud were to include a cloud term where the cloud has finite depth, then knowledge of

the vertical structure of the cloud would be required. There are an infinite variety of combinations of cloud depths and vertical combinations that could produce the same integrated radiative signature; a unique solution is not possible. Any initial assumption of cloud structure biases the cloud top and bottom solution derived in the radiative transfer formulation.

Wielicki and Coakley (1981) discussed the consequences of the thin-layer cloud approximation. They concluded that the algorithm solution for cloud-top pressure would be near the center of the cloud for thin clouds and near the top of the cloud for opaque clouds. For an optically thick cloud, the equation would yield the correct cloud-top pressure. For an optically thin cloud, however, the radiative effects of the cloud are forced into one layer. This is similar to a center of mass concept. The algorithm solution will be close to the radiative center of the cloud. The retrieved cloud-top pressure is somewhere between the cloud top and its center, varying with the density of the cloud.

Cirrus height errors are also discussed in Wylie and Menzel (1989), where comparisons were made to cloud tops measured by lidars and by the stereo parallax observed from the images of two satellites at two different viewing angles. In the lidar comparison, the VAS-inferred cloud-top pressure over an observation area was compared to the highest lidar observation in the same area. The clouds had to be radiatively thin for the lidars to see through to the tops without complete signal attenuation. Definition of a single cloud top was often difficult within a cloud layer; the lidar heights varied considerably (by more than 50 hPa) from one cloud element to another in the same cloud layer. On the average, the VAS  $P_{cld}$  was found to be approximately 70 hPa larger (lower cloud altitude) than the lidar-derived cloud-top heights. The CO<sub>2</sub> slicing algorithm was sensing the mean height; the VAS heights were comparable to the lidar cloud-top heights to within half the cloud thickness. In the comparisons to stereo parallax measurements for thin transmissive clouds, the VAS heights showed little bias. It was often difficult to measure parallax for thin transmissive clouds, as they appeared fuzzy with poorly defined boundaries in the images. Because the image of the clouds is more indicative of the center of the diffuse cloud mass than its outer boundaries, the parallax method is sensitive to the radiative center of mass rather than the physical tops of these clouds. Thus, in these intercomparisons of actual measurements, the retrieved  $P_{cld}$  values were found to be within the accuracy suggested by theoretical considerations.

**4.2.5.7.3. Errors associated with the assumption of a lower cloud layer.** McCleese and Wilson (1976) have shown that the retrieved cloud height for the case of multiple cloud layers is a weighted average of the cloud heights actually present. They performed numerical simulations of cloud configurations for the Nimbus-5 sounding channels. However, no quantitative information was provided to aid in estimating the errors in cloud pressure retrieval one should expect for common multilevel cloud situations, like cirrus over stratus. Menzel et al. (1992) presented an error analysis performed for the GOES VAS. The errors in high-cloud pressure retrieval associated with the presence of a lower cloud layer were found to result in a maximum error in retrieved upper-cloud pressure of approximately 100 hPa. The GOES VAS has three CO<sub>2</sub> sounding channels that are similar to those of HIRS, but HIRS has more sounding channels.

Baum and Wielicki (1994) presented multilevel cloud-retrieval errors for the HIRS instrument. The effect of opaque lower-cloud contamination at 850 mb on cloud pressure retrieval for a HIRS FOV is shown in Figure 4.2-23 for four two-channel combinations implementing the ratio method. Calculations are performed for a range of  $P_{uc}$  where the subscript  $uc$  represents the upper cloud layer, ranging from 250 to 850 mb and a range of  $\epsilon_{uc}^i C_{uc}$  between 0.1 and 1.0. The implementation of either the rms or the ratio methods will result in a single derived cloud pressure for a chosen FOV and channel combination. For the case in which a FOV has two distinct cloud layers, the difference in retrieved minus actual cloud pressure is positive in all cases. A positive difference means that the retrieved upper-cloud height is lower than the actual upper-cloud height. An error in retrieved cloud pressure results in an error in the calculation of  $\epsilon_{uc}^i C_{uc}$ . For the pressure errors presented in Figure 4.2-23, corresponding  $\epsilon_{uc}^i C_{uc}$  errors are shown in Figure 4.2-24 for the same conditions. The retrieved  $\epsilon_{uc}^i C_{uc}$  are calculated by using the

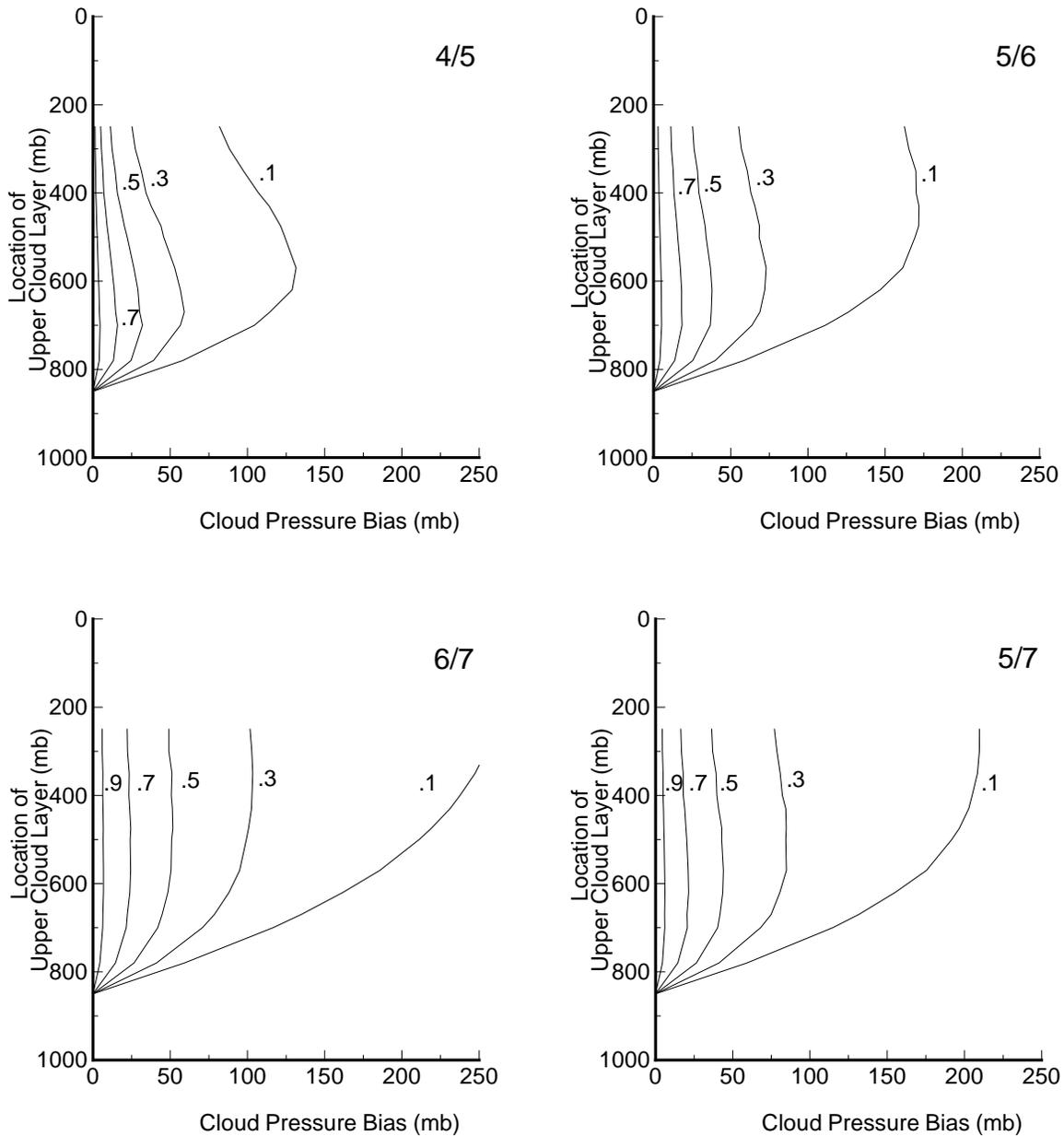


Figure 4.2-23. Multilevel cloud pressure retrieval bias errors (mb) for several  $\epsilon_{uc}C_{uc}$  as a function of the pressure of the upper transmissive cloud layer. Results are presented for the HIRS 4/5, 5/6, 6/7, and 5/7 channel ratio combinations. The opaque lower cloud-top pressure is held constant at 850 mb.

lowest sounding channel of the pair of channels chosen for the ratio method. The error in  $\epsilon_{uc}^i C_{uc}$  is defined to be the retrieved value minus the true value. Because this quantity is positive, the retrieved value will be too high for cases in which there is lower-cloud contamination in a HIRS FOV.

The conclusions from these studies are as follows. The position of the lower cloud layer affects the accuracy of the height estimate of the upper cloud layer. Opaque clouds located near the surface underneath high cirrus have little effect on the retrieved cirrus  $P_{cld}$ . As the low-level opaque cloud increases in height above the surface, and thus has a colder cloud-top temperature, the errors in upper-cloud retrieved  $P_{cld}$  increase. The errors in cloud pressure and effective cloud amount caused by the presence of a lower overcast, black cloud layer are greatest for the CO<sub>2</sub> slicing techniques that use the lowest

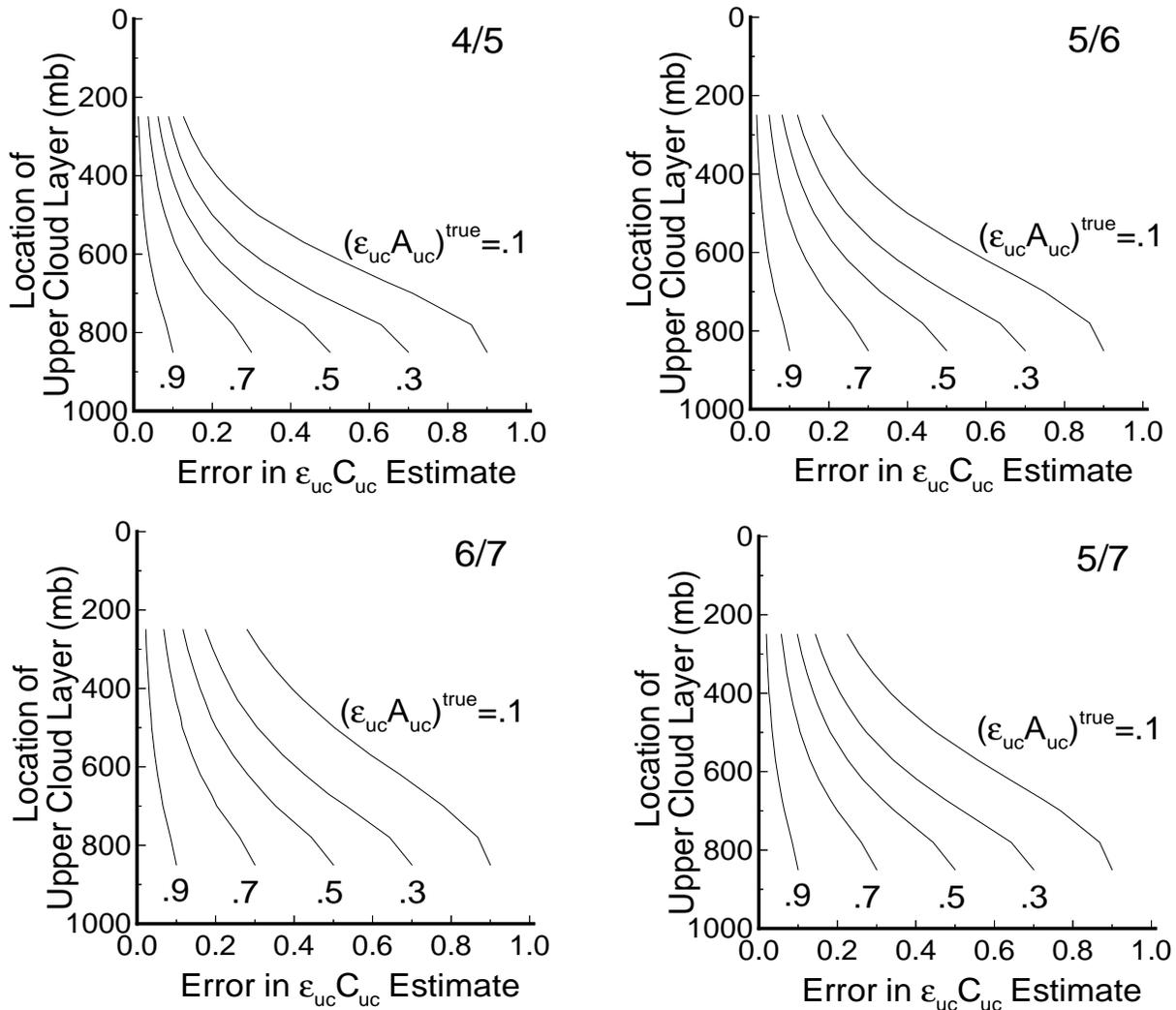


Figure 4.2-24. Upper-cloud effective cloud amount retrieval bias errors for several  $\epsilon_{uc} C_{uc}$  as a function of the pressure of the upper transmissive cloud layer. These results, derived from the pressure biases presented in Figure 4.2-21 are presented for the HIRS 4/5, 5/6, 6/7, and 5/7 channel ratio combinations. The opaque lower cloud-top pressure is held constant at 850 mb.

sounding channel and least for those channels whose weighting functions peak higher in the atmosphere. Baum and Wielicki (1994) also found that the errors depend upon the temperature lapse rate between the low-level cloud top and the surface. The retrieved upper-cloud pressure bias increases with increased lapse rate between the low cloud and the surface. The choice of the optimal channel selection depends on the type of study being performed. While the HIRS channels whose weighting functions peak between 700 and 1000 hPa minimize random errors, the use of the sounding channels whose weighting functions peak at 300 to 500 hPa minimize bias errors. For a cloud climatology the bias errors are most critical.

**4.2.5.7.4. Errors associated with instrument noise.** Instrument noise produces two types of error into the cloud-top pressure retrieval. Random instrument noise leads to an rms error and a bias error. The rms error is a variation of retrieved cloud pressure about the retrieved mean cloud pressure, whereas the bias errors were caused by differences between actual mean and retrieved mean cloud pressures. The

primary source of bias is limiting effective cloud amount to the range (0,1) and cloud-top pressure to the range between the surface and the tropopause.

Wielicki and Coakley (1981) examined the rms and bias errors in cloud-top pressure retrieval for single-level clouds. In their study, the instrument noise was assumed to be Gaussian with zero mean and a standard deviation of  $0.22 \text{ mWm}^{-2}\text{sr}^{-1}\text{cm}$  for the HIRS 15- $\mu\text{m}$  channels. It is anticipated that the instrument noise should be significantly lower (by more than a factor of 2) for the MODIS instrument. The VAS instrument, by comparison, has a much higher instrument noise of approximately  $1.0 \text{ mWm}^{-2}\text{sr}^{-1}\text{cm}$ .

The  $\text{CO}_2$  slicing technique cannot measure the properties of clouds where the contrast of radiation from cloud-free and cloud-obscured observations is too small for reliable discrimination in the satellite  $\text{CO}_2$  spectral radiances. One could assign a threshold of perhaps 5 or 10 times the instrument noise as a threshold for further calculations, so that if the cloud signal falls below this threshold, the pixel is assumed clear (no clouds are retrievable). This threshold will not allow detection of very thin cirrus, such as subvisual cirrus, or low clouds below approximately 700 hPa.

**4.2.5.7.5. Errors caused by uncertainties in temperature profiles and water vapor profiles.** For single-level mid- to high-level clouds, the retrieval methods under study must first specify both clear-sky radiances,  $I_{cs}$ , and overcast black radiances,  $I_{ob}(P_{cld})$ , before cloud properties can be retrieved. Temperature errors affect the Planck functions  $B(T)$  and to a lesser extent the weighting functions  $dt/d \ln P$ . Water vapor errors affect only the weighting functions  $dt/d \ln P$ . Wielicki and Coakley (1981) evaluated errors caused by profile uncertainties by assuming the errors were Gaussian with zero mean. Errors were specified independently for each pressure level. Water vapor errors were specified as a percent of the correct mixing ratio at any level. Temperature error was found to dominate the retrieval error. Errors caused by uncertainties in temperature profiles and water vapor profiles dominated errors caused by instrument noise for temperature rms errors of greater than or equal to 1.5 K for the HIRS 6/7 channel combination, for example. The errors were similar for all channel combinations. Retrieval errors were linearly proportional to temperature error and were inversely proportional to the cloud signal. For instrument noise, the lowest sounding channels (HIRS 6/7) give the smallest errors (Wielicki and Coakley, 1981).

#### **4.2.5.8. Practical Considerations**

**4.2.5.8.1. Data dependencies of  $\text{CO}_2$  slicing algorithm.** The  $\text{CO}_2$  slicing algorithm requires calibrated, navigated, co-registered radiances from the channels listed in Table 1. Navigation implies knowledge of the surface terrain, which will be available from other sources such as the Defense Mapping Agency's Digital Chart of the World. Characteristics required of the surface include surface elevation, land/water percentage, and vegetation type. These data sets are described more fully in section 4.1. The MODIS, GOES, or HIRS viewing angles must be known. The NMC global model estimates of surface temperature, pressure, and profiles of temperature and moisture will be used in the calculation of the upper cloud-top height and effective emittance.

#### **4.2.5.9. Strategic Concerns**

There are several concerns (or assumptions) in the  $\text{CO}_2$  slicing cloud-retrieval method. First, the temperature and humidity estimates will be obtained from the NMC operational product on a fairly coarse horizontal grid (probably about 100 km) at fixed time intervals of 6 or 12 hours. Second, we assume that the frame is likely to have clouds with relatively stable cloud top altitudes, with at least some possibilities of seeing the ground nearby. Under these assumptions, both the clear-sky and cloudy-sky radiance profiles may be precomputed for each  $1.25^\circ$  grid cell once the temperature and humidity data are received and quality checked. This procedure may be performed for each of the potential channels and for the range of viewing zenith angles. If data are available from a simultaneous satellite swath of temperature and humidity retrievals, such as from AIRS/AMSU, then these computations could be

performed at more frequent space and time points. Even with AIRS, the temperature and humidity points will be widely spaced with respect to the high-resolution imager data available for cloud retrieval.

We can list a number of sources of difficulty with this algorithm:

1. Temperature inversions induce an ambiguity in  $p_{cld}$ .
2. Height of cloud should not be far below the peak of the upper channel weighting function for the ratio method.
3. Algorithm does not work when signal/noise ratio becomes too small (a signal less than 10 times the signal noise is a reasonable initial estimate of this threshold).
4. Multichannel retrievals may not produce consistent values of  $p_{cld}$  or  $\epsilon_{cld}^i C$ .
5. Multilevel clouds in a given FOV are not included in the assumptions of this method.
6. Presence of nonuniform cloud in FOV (e.g., some black clouds mixed with thin, low-emittance cloud) will cause ambiguities in  $p_{cld}$  and  $\epsilon_{cld}^i C$ .
7. Algorithm assumes cloud is in a thin layer, so that the retrieval of cloud-top pressure is problematic for an optically thin cloud that has a large geometric thickness.
8. Instrument calibration errors cause some systematic shifts in cloud property retrievals.
9. Instrument spectral bandpass shifts will create errors.
10. Algorithm assumes that the emittances of clouds in any two closely spaced channels in the ratio method have nearly equal values.
11. Algorithm assumes clouds do not scatter in the IR.
12. Weighting functions depend on the input temperature and humidity profiles and upon the assumed mixing ratios of trace gases.
13. The accuracy of the retrieved cloud pressure depends on accuracy of the clear-sky radiance.

These potential error sources have been discussed in previous sections and, although it is important to understand and minimize them, they are generally well-known and accepted in the field of study. The implementation of the algorithm will have exception-handling logic to handle potential problems.

## References

- Arking, A.; and Childs, J. D. 1985: Retrieval of Cloud Cover Parameters From Multispectral Satellite Images. *J. Climat. & Appl. Meteorol.*, vol. 24, pp. 322–333.
- Baum, B. A., V. Tovinkere, J. Titlow, and R. M. Welch, 1996: Automated cloud classification of global AVHRR data using a fuzzy logic approach. Submitted to *J. Appl. Meteorol.* for publication.
- Baum, B. A.; Uttal, T.; Poellot, M.; Ackerman, T. P.; Alvarez, J.; Intrieri, J.; Starr, D. O’C; Titlow, J.; Tovinkere, V.; and Clothiaux, E. 1995: Satellite Remote Sensing of Multiple Cloud Layers. *J. Atmos. Sci.*, vol. 52, no. 23, pp. 4210–4230.
- Baum, Bryan A.; and Wielicki, Bruce A. 1994: Cirrus Cloud Retrieval Using Infrared Sounding Data—Multilevel Cloud Errors. *J. Appl. Meteorol.*, vol. 33, no. 1, pp. 107–117.
- Baum, Bryan A.; Wielicki, Bruce A.; Minnis, Patrick; and Parker, Lindsay 1992: Cloud-Property Retrieval Using Merged HIRS and AVHRR Data. *J. Appl. Meteorol.*, vol. 31, pp. 351–369.
- Chahine, M. T. 1974: Remote Sounding of Cloudy Atmospheres. I—The Single Cloud Layer. *J. Atmos. Sci.*, vol. 31, pp. 233–243.
- Chang, Fu-Lung; and Coakley, James A., Jr. 1993: Estimating Errors in Fractional Cloud Cover Obtained With Infrared Threshold Methods. *J. Geophys. Res.*, vol. 98, no. D5, pp. 8825–8839.

- Coakley, J. A., Jr.; and Bretherton, F. P. 1982: Cloud Cover From High-Resolution Scanner Data—Detecting and Allowing for Partially Filled Fields of View. *J. Geophys. Res.*, vol. 87, pp. 4917–4932.
- Coakley, J. A., Jr. 1983: Properties of Multilayered Cloud Systems From Satellite Imagery. *J. Geophys. Res.*, vol. 88, pp. 10818–10828.
- Coakley, J. A., Jr.; and Baldwin, D. G. 1984: Towards the Objective Analysis of Clouds From Satellite Imagery Data. *J. Climat. & Appl. Meteorol.*, vol. 23, pp. 1065–1099.
- Debois, M.; Seze, G.; and Szejwach, G. 1982: Automatic Classification of Clouds on METEOSAT Imagery—Application to High-Level Clouds. *J. Appl. Meteorol.*, vol. 21, pp. 401–412.
- Eyre, J. R. 1991: *A Fast Radiative Transfer Model for Satellite Sounding Systems*. ECMWF Tech. Memo. No. 176.
- Eyre, Jonathan R.; and Menzel, W. Paul 1989: Retrieval of Cloud Parameters From Satellite Sounder Data—A Simulation Study. *J. Appl. Meteorol.*, vol. 28, pp. 267–275.
- Eyre, Jonathan R.; and Woolf, Harold M. 1988: Transmittance of Atmospheric Gases in the Microwave Region—A Fast Model. *Appl. Opt.*, vol. 27, pp. 3244–3249.
- Hahn, C. J. 1982: *Atlas of Simultaneous Occurrence of Different Cloud Types Over the Ocean*. NCAR Tech. Note TN-201.
- Jacobowitz, Herbert 1971: Emission, Scattering and Absorption of Radiation in Cirrus Cloud Layers. Ph.D Thesis, Massachusetts Inst. Tech.
- Kidwell, K. B. 1991: *NOAA Polar Orbiter Data Users Guide*. NOAA National Climatic Data Center, Satellite Data Services Div.
- King, Michael D.; Kaufman, Yoram J.; Menzel, W. Paul; and Tanre, Didier D. 1992: Remote Sensing of Cloud, Aerosol, and Water Vapor Properties From the Moderate Resolution Imaging Spectrometer (MODIS). *IEEE Trans. Geosci. & Remote Sens.*, vol. 30, pp. 2–27.
- Lin, X; and Coakley, J. A. 1993: Retrieval of Properties for Semitransparent Clouds From Multispectral Infrared Imagery Data. *J. Geophys. Res.*, vol. 98, pp. 18,501–18,514.
- McCleese, D. J.; and Wilson, L. W. 1976: Cloud Top Heights From Temperature Sounding Instruments. *Q. J. R. Meteorol. Soc.*, vol. 102, pp. 781–790.
- McCormick, M. P.; Winker, D. M.; Browell, E. V.; Coakley, J. A.; Gardner, C. S.; Hoff, R. M.; Kent, G. S.; Melfi, S. H.; Menzies, R. T.; and Platt, C. M. R. 1993: Scientific Investigations Planned for the Lidar In-Space Technology Experiment (LITE). *Bul. Am. Meteorol. Soc.*, vol. 74, no. 2, pp. 205–214.
- McMillin, L. M.; and Fleming, H. E. 1976: Atmospheric Transmittance of an Absorbing Gas—A Computationally Fast and Accurate Transmittance Model for Absorbing Gases With Constant Mixing Ratios in Inhomogeneous Atmospheres. *Appl. Opt.*, vol. 15, pp. 358–363.
- Menzel, W. P.; Smith, W. L.; and Stewart, T. R. 1983: Improved Cloud Motion Wind Vector and Altitude Assignment Using VAS. *J. Climat. Appl. Meteorol.*, vol. 22, pp. 377–384.
- Menzel, W. P.; Wylie, D. P.; and Strabala, K. L. 1992: Seasonal and Diurnal Changes in Cirrus Clouds as Seen in Four Years of Observations With the VAS. *J. Appl. Meteorol.*, vol. 31, pp. 370–385.
- Minnis, P.; and Harrison, E. F. 1984: Diurnal Variability of Regional Cloud and Clear-Sky Radiative Parameters Derived From GOES Data. Part I: Analysis Method. Part II: November 1978 Cloud Distributions. Parts I–III, *J. Climat. & Appl. Meteorol.*, vol. 23, pp. 993–1051.
- Minnis, Patrick; Harrison, Edwin F.; and Gibson, Gary G. 1987: Cloud Cover Over the Equatorial Eastern Pacific Derived From July 1983 International Satellite Cloud Climatology Project Data Using a Hybrid Bispectral Threshold Method. *J. Geophys. Res.*, vol. 92, pp. 4051–4073.
- Minnis, Patrick; Harrison, Edwin F.; and Heck, Patrick W. 1990: The 27-28 October 1986 FIRE IFO Cirrus Case Study—Cloud Parameter Fields Derived From Satellite Data. *Mon. Weather Rev.*, vol. 118, pp. 2426–2446.
- Minnis, Patrick; Heck, Patrick W.; Young, David F.; Fairall, C. W.; and Snider, J. B. 1992: Stratocumulus Cloud Properties Derived From Simultaneous Satellite and Island-Based Instrumentation During FIRE. *J. Appl. Meteorol.*, vol. 31, pp. 317–339.
- Minnis, Patrick; Liou, Kuo-Nan; and Takano, Yoshihide 1993: Inference of Cirrus Cloud Properties Using Satellite-Observed Visible and Infrared Radiances. I—Parameterization of Radiance Fields. *J. Atmos. Sci.*, vol. 50, no. 9, pp. 1279–1304.

- Minnis, Patrick; Heck Patrick W.; and Young, David F. 1993: Inference of Cirrus Cloud Properties Using Satellite-Observed Visible and Infrared Radiances. II—Verification of Theoretical Cirrus Radiative Properties. *J. Atmos. Sci.*, vol. 50, no. 9, pp. 1305–1322.
- Platt, C. M. R. 1983: On the Bispectral Method for Cloud Parameter Determination From Satellite VISSIR Data—Separating Broken and Semitransparent Cloud. *J. Climat. Appl. Meteorol.*, vol. 22, pp. 429–439.
- Reynolds, D. W.; and Vonder Haar, T. H. 1977: A Bi-Spectral Method for Cloud Parameter Determination. *Mon. Weather Rev.*, vol. 105, pp. 446–457.
- Rossow, W. B.; Mosher, F.; Kinsella, E.; Arking, A.; and Harrison, E. 1985: ISCCP Cloud Algorithm Intercomparison. *J. Climat. & Appl. Meteorol.*, vol. 24, pp. 877–903.
- Rossow, William B.; and Garder, Leonid C. 1993: Cloud Detection Using Satellite Measurements of Infrared and Visible Radiances for ISCCP. *J. Climat.*, vol. 6, no. 12, pp. 2341–2369.
- Shenk, W. E.; and Salomonson, V. V. 1972: A Simulation Study Exploring the Effects of Sensor Spatial Resolution on Estimates of Cloud Cover From Satellites. *J. Appl. Meteorol.*, vol. 11, pp. 214–220.
- Smith, W. L.; and Platt, C. M. R. 1978: Comparison of Satellite-Deduced Cloud Heights With Indications From Radiosonde and Ground-Based Laser Measurements. *J. Appl. Meteorol.*, vol. 17, pp. 1796–1802.
- Smith, W. L.; and Frey, R. 1990: On Cloud Altitude Determinations From High Resolution Interferometer Sounder (HIS) Observations. *J. Appl. Meteorol.*, vol. 29, pp. 658–662.
- Stowe, L. L.; McClain, E. P.; Carey, R.; Pellegrino, P.; and Gutman, G. G. 1991: Global Distribution of Cloud Cover Derived From NOAA/AVHRR Operational Satellite Data. *Adv. Space Res.*, vol. 11, no. 3, pp. 51–54.
- Takano, Yoshihide; and Liou, Kuo-Nan 1989: Solar Radiative Transfer in Cirrus Clouds. I— Single-Scattering and Optical Properties of Hexagonal Ice Crystals. *J. Atmos. Sci.*, vol. 46, pp. 3–20.
- Tian, Lin; and Curry, Judith A. 1989: Cloud Overlap Statistics. *J. Geophys. Res.*, vol. 94, pp. 9925–9935.
- Weinreb, M. P. 1981: *Transmittances for the TIROS Operational Vertical Sounder*. NOAA Tech. Rep. No. NESS-85.
- Wielicki, B. A.; and Coakley, J. A., Jr. 1981: Cloud Retrieval Using Infrared Sounder Data—Error Analysis. *J. Appl. Meteorol.*, vol. 20, pp. 157–169.
- Wielicki, Bruce A.; and Parker, Lindsay 1992: On the Determination of Cloud Cover From Satellite Sensors—The Effect of Sensor Spatial Resolution. *J. Geophys. Res.*, vol. 97, no. D12, pp. 12799–12823.
- Wyle, D. P.; and Menzel, W. P. 1989: Two Years of Cloud Cover Statistics Using VAS. *J. Climat.*, vol. 2, pp. 380–392.

**Appendix A****Nomenclature****Acronyms**

ADEOS	Advanced Earth Observing System
ADM	Angular Distribution Model
AIRS	Atmospheric Infrared Sounder (EOS-AM)
AMSU	Advanced Microwave Sounding Unit (EOS-PM)
APD	Aerosol Profile Data
APID	Application Identifier
ARESE	ARM Enhanced Shortwave Experiment
ARM	Atmospheric Radiation Measurement
ASOS	Automated Surface Observing Sites
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ASTEX	Atlantic Stratocumulus Transition Experiment
ASTR	Atmospheric Structures
ATBD	Algorithm Theoretical Basis Document
AVG	Monthly Regional, Average Radiative Fluxes and Clouds (CERES Archival Data Product)
AVHRR	Advanced Very High Resolution Radiometer
BDS	Bidirectional Scan (CERES Archival Data Product)
BRIE	Best Regional Integral Estimate
BSRN	Baseline Surface Radiation Network
BTD	Brightness Temperature Difference(s)
CCD	Charge Coupled Device
CCSDS	Consultative Committee for Space Data Systems
CEPEX	Central Equatorial Pacific Experiment
CERES	Clouds and the Earth's Radiant Energy System
CID	Cloud Imager Data
CLAVR	Clouds from AVHRR
CLS	Constrained Least Squares
COPRS	Cloud Optical Property Retrieval System
CPR	Cloud Profiling Radar
CRH	Clear Reflectance, Temperature History (CERES Archival Data Product)
CRS	Single Satellite CERES Footprint, Radiative Fluxes and Clouds (CERES Archival Data Product)
DAAC	Distributed Active Archive Center
DAC	Digital-Analog Converter
DAO	Data Assimilation Office

DB	Database
DFD	Data Flow Diagram
DLF	Downward Longwave Flux
DMSP	Defense Meteorological Satellite Program
EADM	ERBE-Like Albedo Directional Model (CERES Input Data Product)
ECA	Earth Central Angle
ECLIPS	Experimental Cloud Lidar Pilot Study
ECMWF	European Centre for Medium-Range Weather Forecasts
EDDB	ERBE-Like Daily Data Base (CERES Archival Data Product)
EID9	ERBE-Like Internal Data Product 9 (CERES Internal Data Product)
EOS	Earth Observing System
EOSDIS	Earth Observing System Data Information System
EOS-AM	EOS Morning Crossing Mission
EOS-PM	EOS Afternoon Crossing Mission
ENSO	El Niño/Southern Oscillation
ENVISAT	Environmental Satellite
EPHANC	Ephemeris and Ancillary (CERES Input Data Product)
ERB	Earth Radiation Budget
ERBE	Earth Radiation Budget Experiment
ERBS	Earth Radiation Budget Satellite
ESA	European Space Agency
ES4	ERBE-Like S4 Data Product (CERES Archival Data Product)
ES4G	ERBE-Like S4G Data Product (CERES Archival Data Product)
ES8	ERBE-Like S8 Data Product (CERES Archival Data Product)
ES9	ERBE-Like S9 Data Product (CERES Archival Data Product)
FLOP	Floating Point Operation
FIRE	First ISCCP Regional Experiment
FIRE II IFO	First ISCCP Regional Experiment II Intensive Field Observations
FOV	Field of View
FSW	Hourly Gridded Single Satellite Fluxes and Clouds (CERES Archival Data Product)
FTM	Functional Test Model
GAC	Global Area Coverage (AVHRR data mode)
GAP	Gridded Atmospheric Product (CERES Input Data Product)
GCIP	GEWEX Continental-Phase International Project
GCM	General Circulation Model
GEBA	Global Energy Balance Archive
GEO	ISCCP Radiances (CERES Input Data Product)
GEWEX	Global Energy and Water Cycle Experiment
GLAS	Geoscience Laser Altimetry System

GMS	Geostationary Meteorological Satellite
GOES	Geostationary Operational Environmental Satellite
HBTM	Hybrid Bispectral Threshold Method
HIRS	High-Resolution Infrared Radiation Sounder
HIS	High-Resolution Interferometer Sounder
ICM	Internal Calibration Module
ICRCCM	Intercomparison of Radiation Codes in Climate Models
ID	Identification
IEEE	Institute of Electrical and Electronics Engineers
IES	Instrument Earth Scans (CERES Internal Data Product)
IFO	Intensive Field Observation
INSAT	Indian Satellite
IOP	Intensive Observing Period
IR	Infrared
IRIS	Infrared Interferometer Spectrometer
ISCCP	International Satellite Cloud Climatology Project
ISS	Integrated Sounding System
IWP	Ice Water Path
LAC	Local Area Coverage (AVHRR data mode)
LaRC	Langley Research Center
LBC	Laser Beam Ceilometer
LBTM	Layer Bispectral Threshold Method
Lidar	Light Detection and Ranging
LITE	Lidar In-Space Technology Experiment
Lowtran 7	Low-Resolution Transmittance (Radiative Transfer Code)
LW	Longwave
LWP	Liquid Water Path
MAM	Mirror Attenuator Mosaic
MC	Mostly Cloudy
MCR	Microwave Cloud Radiometer
METEOSAT	Meteorological Operational Satellite (European)
METSAT	Meteorological Satellite
MFLOP	Million FLOP
MIMR	Multifrequency Imaging Microwave Radiometer
MISR	Multiangle Imaging Spectroradiometer
MLE	Maximum Likelihood Estimate
MOA	Meteorology Ozone and Aerosol
MODIS	Moderate-Resolution Imaging Spectroradiometer
MSMR	Multispectral, multiresolution

MTSA	Monthly Time and Space Averaging
MWH	Microwave Humidity
MWP	Microwave Water Path
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NESDIS	National Environmental Satellite, Data, and Information Service
NIR	Near Infrared
NMC	National Meteorological Center
NOAA	National Oceanic and Atmospheric Administration
NWP	Numerical Weather Prediction
OLR	Outgoing Longwave Radiation
OPD	Ozone Profile Data (CERES Input Data Product)
OV	Overcast
PC	Partly Cloudy
POLDER	Polarization of Directionality of Earth's Reflectances
PRT	Platinum Resistance Thermometer
PSF	Point Spread Function
PW	Precipitable Water
RAPS	Rotating Azimuth Plane Scan
RPM	Radiance Pairs Method
RTM	Radiometer Test Model
SAB	Sorting by Angular Bins
SAGE	Stratospheric Aerosol and Gas Experiment
SARB	Surface and Atmospheric Radiation Budget Working Group
SDCD	Solar Distance Correction and Declination
SFC	Hourly Gridded Single Satellite TOA and Surface Fluxes (CERES Archival Data Product)
SHEBA	Surface Heat Budget in the Arctic
SPECTRE	Spectral Radiance Experiment
SRB	Surface Radiation Budget
SRBAVG	Surface Radiation Budget Average (CERES Archival Data Product)
SSF	Single Satellite CERES Footprint TOA and Surface Fluxes, Clouds
SSMI	Special Sensor Microwave Imager
SST	Sea Surface Temperature
SURFMAP	Surface Properties and Maps (CERES Input Product)
SW	Shortwave
SWICS	Shortwave Internal Calibration Source
SYN	Synoptic Radiative Fluxes and Clouds (CERES Archival Data Product)

SZA	Solar Zenith Angle
THIR	Temperature/Humidity Infrared Radiometer (Nimbus)
TIROS	Television Infrared Observation Satellite
TISA	Time Interpolation and Spatial Averaging Working Group
TMI	TRMM Microwave Imager
TOA	Top of the Atmosphere
TOGA	Tropical Ocean Global Atmosphere
TOMS	Total Ozone Mapping Spectrometer
TOVS	TIROS Operational Vertical Sounder
TRMM	Tropical Rainfall Measuring Mission
TSA	Time-Space Averaging
UAV	Unmanned Aerospace Vehicle
UT	Universal Time
UTC	Universal Time Code
VAS	VISSR Atmospheric Sounder (GOES)
VIRS	Visible Infrared Scanner
VISSR	Visible and Infrared Spin Scan Radiometer
WCRP	World Climate Research Program
WG	Working Group
Win	Window
WN	Window
WMO	World Meteorological Organization
ZAVG	Monthly Zonal and Global Average Radiative Fluxes and Clouds (CERES Archival Data Product)

### Symbols

$A$	atmospheric absorptance
$B_{\lambda}(T)$	Planck function
$C$	cloud fractional area coverage
$CF_2Cl_2$	dichlorofluorocarbon
$CFCl_3$	trichlorofluorocarbon
$CH_4$	methane
$CO_2$	carbon dioxide
$D$	total number of days in the month
$D_e$	cloud particle equivalent diameter (for ice clouds)
$E_o$	solar constant or solar irradiance
$F$	flux
$f$	fraction
$G_a$	atmospheric greenhouse effect

$g$	cloud asymmetry parameter
$H_2O$	water vapor
$I$	radiance
$i$	scene type
$m_i$	imaginary refractive index
$\hat{N}$	angular momentum vector
$N_2O$	nitrous oxide
$O_3$	ozone
$P$	point spread function
$p$	pressure
$Q_a$	absorption efficiency
$Q_e$	extinction efficiency
$Q_s$	scattering efficiency
$R$	anisotropic reflectance factor
$r_E$	radius of the Earth
$r_e$	effective cloud droplet radius (for water clouds)
$r_h$	column-averaged relative humidity
$S_o$	summed solar incident SW flux
$S'_o$	integrated solar incident SW flux
$T$	temperature
$T_B$	blackbody temperature
$t$	time or transmittance
$W_{liq}$	liquid water path
$w$	precipitable water
$\hat{x}_o$	satellite position at $t_o$
$x, y, z$	satellite position vector components
$\dot{x}, \dot{y}, \dot{z}$	satellite velocity vector components
$z$	altitude
$z_{top}$	altitude at top of atmosphere
$\alpha$	albedo or cone angle
$\beta$	cross-scan angle
$\gamma$	Earth central angle
$\gamma_{at}$	along-track angle
$\gamma_{ct}$	cross-track angle
$\delta$	along-scan angle
$\varepsilon$	emittance
$\Theta$	colatitude of satellite
$\theta$	viewing zenith angle
$\theta_o$	solar zenith angle

$\lambda$	wavelength
$\mu$	viewing zenith angle cosine
$\mu_o$	solar zenith angle cosine
$\nu$	wave number
$\rho$	bidirectional reflectance
$\tau$	optical depth
$\tau_{aer}(p)$	spectral optical depth profiles of aerosols
$\tau_{H_2O\lambda}(p)$	spectral optical depth profiles of water vapor
$\tau_{O_3}(p)$	spectral optical depth profiles of ozone
$\Phi$	longitude of satellite
$\phi$	azimuth angle
$\tilde{\omega}_o$	single-scattering albedo

## Subscripts:

$c$	cloud
$cb$	cloud base
$ce$	cloud effective
$cld$	cloud
$cs$	clear sky
$ct$	cloud top
$ice$	ice water
$lc$	lower cloud
$liq$	liquid water
$s$	surface
$uc$	upper cloud
$\lambda$	spectral wavelength

**Units**

AU	astronomical unit
cm	centimeter
cm-sec <sup>-1</sup>	centimeter per second
count	count
day	day, Julian date
deg	degree
deg-sec <sup>-1</sup>	degree per second
DU	Dobson unit
erg-sec <sup>-1</sup>	erg per second
fraction	fraction (range of 0–1)
g	gram
g-cm <sup>-2</sup>	gram per square centimeter

$g-g^{-1}$	gram per gram
$g-m^{-2}$	gram per square meter
h	hour
hPa	hectopascal
K	Kelvin
kg	kilogram
$kg-m^{-2}$	kilogram per square meter
km	kilometer
$km-sec^{-1}$	kilometer per second
m	meter
mm	millimeter
$\mu m$	micrometer, micron
N/A	not applicable, none, unitless, dimensionless
$ohm-cm^{-1}$	ohm per centimeter
percent	percent (range of 0–100)
rad	radian
$rad-sec^{-1}$	radian per second
sec	second
$sr^{-1}$	per steradian
W	watt
$W-m^{-2}$	watt per square meter
$W-m^{-2}sr^{-1}$	watt per square meter per steradian
$W-m^{-2}sr^{-1}\mu m^{-1}$	watt per square meter per steradian per micrometer