Comparison of GOES Cloud Classification Algorithms Employing Explicit and Implicit Physics

> Richard L. Bankert\* and Cristian Mitrescu Naval Research Laboratory, Monterey, CA

Steven D. Miller CIRA, Colorado State University, Fort Collins, CO

Robert H. Wade SAIC, Monterey, CA

## **1. INTRODUCTION**

Both the operational and research communities have numerous reasons for requiring the identification of cloud types in satellite imagery. Different ways of classifying clouds (e.g, by altitude. classical types, physical or characteristics, etc) are available. In addition, many classification methods exist and could be applied to achieve the most accurate and most appropriate classification, given the output required from the classifier. Depending upon the user's needs or application, the classifier can be developed through theoretical (explicit physics) or empirical/statistical (implicit physics) methods.

Two GOES-11 cloud classifiers, one using implicit physics and the other using explicit physics, are described here. Pixel-by-pixel comparisons, from a year of hourly daytime data in the NE Pacific (Figure 1), are analyzed. Finally, a discussion on the implications of these comparisons is provided. A high number of similar classifications for a given cloud class should bolster confidence in the individual classifier's output. While neither classifier can claim to be "ground truth", agreement between both classifiers - developed through very different methods - can give a user increased confidence in each classifier. Disagreements will confirm or expose problem areas or limitations in one or both classifiers. Analysis of the disagreements may lead to classifier refinements or post-processing to improve the current classifications. Another possible outcome is the creation of a single classifier that combines the best of both classification methods.



Figure 1. Area used for pixel-by-pixel comparison over a 1-year period (GOES-11 visible image).

# 2. GOES CLOUD CLASSIFIER

The GOES cloud classifier (CC), developed at the Naval Research Lab (NRL), employs a supervised learning methodology (implicit physics) in which a set of expert-labeled training samples (16x16 km boxes) are used in a 1-nearest neighbor algorithm (Bankert and Wade, 2007; Tag, et al., 2000). These samples are represented within a training set by a vector of characteristic features (spectral, textural, etc) chosen through a feature selection routine. Eight distinct training sets were developed: GOES-West Land Day, GOES-West Land Night, GOES-West Sea Day, GOES-West Sea Night, GOES-East Land Day, GOES-East Land Night, GOES-East Sea Day, and GOES-East Sea Night. For purposes of this research, only the GOES-West Land Day and GOES-West Sea Day are used when classifying the GOES-11 imagery.

Classifications of overlapping boxes (moving16x16 km window) within each image are performed such that each pixel is classified four times with voting (ties broken randomly), followed by pixel post-processing checks, determining the final

Corresponding author address: Richard L. Bankert, Naval Research Laboratory, 7 Grace Hopper Ave., Monterey, CA 93943-5502; e-mail: rich.bankert@nrlmry.navy.mil

class of that pixel. Each box is given a specific class – no "mixed clouds or overlapping clouds" class or "unknown" class is provided. The daytime classes are listed in Table 1. For this research, pixels classified as Ground Snow, Haze, and Sunglint are ignored in the comparison analysis.

Table 1. Classes used in the NRL cloud classifier ("implicit physics").

Stratus (St) Stratocumulus (Sc) Cumulus (Cu) Altocumulus (Ac) Altostratus (As) Cirrus (Ci) Cirrocumulus (Cc) Cirrostratus (Cs) Cumulus Congestus (CuC) Cumulonimbus (Cb) CsAn - Cs near turret in thunderstorm: more closely related to deep convection than "garden variety" Cs Clear (Clr) Ground Snow (Sn) Haze (Hz) Sunglint (Sg)

# 3. CLOUD TYPE ALGORITHM

The "explicit physics" algorithm (CT) employed for this study is based on the works of Pavolonis, et al. (2005) and Pavolonis and Heidinger (2004). Using a series of thresholding and other thermal contrast, visible contrast, and spatial uniformity tests on the visible (0.65  $\mu$ m), near-IR (3.9  $\mu$ m), and longwave IR (11  $\mu$ m) channels, each pixel is assigned to one of the cloud types listed in Table 2. Partly cloudy types are ignored for this study.

A cloud mask algorithm first determines if a pixel is clear or cloud. For all pixels classified as cloud, the 11  $\mu$ m channel brightness temperature is determined and an OL test and Ci test are applied. If both of these tests fail, the appropriate (based on 11  $\mu$ m channel brightness temperature) cloud phase tests for liquid water, supercooled water or mixed phase, and glaciated (opaque ice) clouds are applied and the pixel's cloud type is assigned.

Table 2. Cloud types used in "explicit physics" classification algorithm.

Clear (Clr) Partly cloudy Liquid water (Liq) Supercooled water or Mixed phase (Mix) Glaciated - opaque ice (Glac) Cirrus (Ci) Cloud overlap (OL)

# 4. COMPARISON STUDY

Hourly daytime data for each of the classifiers was collected over a one year time period (10/06 - 10/07). In order to get a better one-to-one analysis when comparing the output of the two algorithms, the CC classes are combined to best match the CT cloud types. This clustering of classes is summarized in Table 3. Note there is no corresponding overlapping cloud class.

Table 3. CC class combinations used for comparisons with CT class types.

Liquid Water Stratus (St) Stratocumulus (Sc) Cumulus (Cu)

#### Mixed phase / Supercooled water

Altocumulus (Ac) Altostratus (As) Cumulus Congestus (CuC)

<u>Glaciated</u> Cirrocumulus (Cc) Cirrostratus (Cs) Cumulonimbus (Cb) CsAn

Clear (Clr) – not combined Cirrus (Ci) – not combined

Pixel-by-pixel comparisons done over the entire year are summarized in the cloud class/type matrices displayed in Tables 4 and 5. Table 4 gives the percent distribution within a specific CT type of how that cloud type was matched (pixel-bypixel) with CC cloud classes (as described in Table 3). For example (marked in red), 57.2% of the pixels classified as mixed phase or supercooled water by the CT algorithm were classified as one of the liquid cloud classes by the CC algorithm. Table 5 gives the percent distribution within a CC class of how that cloud class was matched (pixel-by-pixel) with CT cloud types. Looking at the same table element described in the example above, 19.7% of the pixels classified as liquid cloud by the CC algorithm were classified as mixed phase or supercooled water by the CT algorithm.

Table 4. Percent (%) distribution of pixels within each CT algorithm type (columns) matched with CC class (rows) – columns sum to ~100%.

	Clr	Liq	Mix	Glac	Ci	OL
Clr	94.0	7.4	1.1	0.1	10.9	0.0
Liq	4.4	89.5	57.2	0.8	18.9	5.9
Mix	0.6	3.0	31.3	16.7	18.6	30.9
Glac	0.5	0.0	2.5	74.9	24.2	50.7
Ci	0.5	0.1	8.0	7.5	27.3	12.5

Table 5. Percent (%) distribution of pixels within each CC class (rows) matched with CT algorithm type (columns) – rows sum to ~100%.

	Clr	Liq	Mix	Glac	Ci	OL
Clr	80.2	11.5	0.8	0.0	7.5	0.0
Liq	1.9	70.2	19.7	0.1	6.5	1.6
Mix	0.8	7.6	35.4	7.0	21.1	28.0
Glac	0.6	0.0	2.6	29.1	25.4	42.3
Ci	1.4	0.4	16.4	5.7	55.9	20.3

There is much agreement between the two algorithms, especially in terms of clear pixels and liquid water cloud pixels. Confidence is increased in those cases where algorithms agree on the classifications. In addition, some of the disagreements may be a result of the different original sets of classes/types used as opposed to one (or both) of the classifiers being in actual error. However, a further analysis of these results, along with the knowledge of each algorithm's strengths, weaknesses, and limitations, lead to the following observations:

1. Pixels classified as Liquid by CC and Supercooled water or Mixed phase by CT could reflect the known bias of CT toward supercooled water or mixed phase type. Included here are low clouds in cold air (Figure 2) and possibly very thin Ci over low clouds (OL type). The former case probably occurs more frequently as the cloud tops are too cold to meet the threshold for liquid clouds in CT algorithm. These clouds could still be "liquid", but are supercooled at the top. Therefore, no misclassification occurs in either algorithm. In the latter case the thin Ci signal is missed by CC and CT is getting both signals, but the test for OL clouds fails. The pixel is then classified as mixed phase or supercooled water.

2. Pixels classified as Liquid by CC and Cirrus by CT: The CC methodology (all pixels in box classified the same) or the post-processing check of IR temperature for initially classified Ci samples by CC is probably causing misclassification in the CC. Also, these could be true OL pixels that are missed by both (Figure 3: area enclosed by black oval). Either way, there are, most likely, thin high clouds in the pixel.

3. Pixels classified as Mixed phase by CC and Overlap by CT: Since the CC algorithm does not have an OL class, actual OL pixels are classified as mixed phase with signals from both low cloud and overlying Ci being used to give a mixed phase (As or Ac) classification. An example of this classification mixture can be seen within the front in Figure 2. High thin clouds are streaming across the low clouds associated with the front.

4. Pixels classified as Mixed phase by CC and Glaciated by CT: These pixels could be actual mid-level clouds (Ac or As) with very cold tops.

5. Pixels classified as Mixed phase by CC and Cirrus by CT: Image examples imply that both classifiers are missing OL situation here. The CC algorithm is getting signals from both types and classifying the pixel as mixed phase (As or Ac) and the OL test fails in the CT algorithm. Example in Figure 3: area enclosed by gold oval.

6. Pixels classified as Cirrus by CC and Supercooled water or Mixed phase by CT: Various tests in the CT algorithm are designed to minimize false alarms and certain types are sometimes missed. In this case Ci (high thin clouds) or OL is missed by CT. Actual OL could also be misclassified by CC as Ci. Figure 4 (area within black circle) provides an example of actual overlap misclassified as Ci by CC and supercooled water or mixed phase by CT.

7. Pixels classified as Clear by CC and Liquid by CT: CC algorithm can miss certain low clouds, especially near terminator (low solar zenith angel) or in CC algorithm post-processing check (minimum visible channel albedo threshold). An example case is displayed in Figure 5 (area enclosed by gold oval).

#### 5. DISCUSSION

Neither the CC nor the CT algorithm can guarantee a completely accurate cloud-type representation for any given GOES data set. However, by using the output of each classifier, combined with knowledge of their reliability and limitations in certain situations, a final – more accurate - single classification product could be produced.

Many of the disagreements between the classifiers (as described here) are a result of the lack of an overlapping cloud class in the CC algorithm and/or missed OL in the CT algorithm. Future development of a cloud classification algorithm derived from the output of both the implicit (CC) and explicit (CT) algorithms would overcome the OL problems in addition to other limitations. This "post-classification" algorithm could take the form of a rule set applied to each pixel. Pixels that have agreement would be left alone with rules applied to those pixels in disagreement. For example, if CC assigns a mixed phase class and CT is OL, the pixel is classified as OL (based on the knowledge of the classifiers). Another example: if pixel is assigned a mixed phase class from the CC algorithm and Ci from the CT algorithm, the pixel is a give a final classification of OL. Due to the possibility of more than one explanation for a specific disagreement, other rules or threshold checks would be necessary.

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Figure 2. Example case (16 Apr 2007, 1700 UTC) of CC (top image) classification of low clouds (St, Sc, and Cu) and CT (middle top image) classification of mixed (supercooled) clouds for the same pixels – mainly in cold air behind the front. Bottom images are GOES-11 visible and IR (different image projection) channels.





Figure 3. 27 Mar 2007, 1900 UTC: CC (top image) classification, CT (middle top image), and bottom images are GOES-11 visible and IR (different image projection) channels.



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Figure 4. Example case (27 Feb 2007, 2000 UTC) of CC (top image) classification of Ci and CT (middle top image) classification of mixed (supercooled) clouds for the same pixels. Bottom images are GOES-11 visible and IR (different image projection) channels.







*Figure 5. Example case (6 May 2007, 1600 UTC) of CC (top image) classification of Clr and CT (middle image) classification of liquid clouds for the same pixels. Bottom image is GOES-11 visible channel.*