A Comparative Look at Two Algorithms for Mapping Snow Cover from Earth Observing System Instruments

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ABSTRACT

Two algorithms for mapping snow cover with two Earth Observing System (EOS) instruments, the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), are compared. The algorithms are being developed with Landsat Thematic Mapper (TM) data. Both algorithms are capable of accurately mapping snow cover in the absence of clouds. The ASTER algorithm provides a great amount of high resolution (30 m) information about features in a scene not obtainable with the MODIS algorithm and will find greatest use at site and small basin scales. The MODIS algorithm provides information on snow cover at moderate spatial resolution (500 m) with near daily spatial coverage so will be of greatest use at basin, continental and global scales for monitoring snow cover.

Key words: snow cover, MODIS, ASTER, clouds.

Resolution Imaging Spectroradiometer (MODIS) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), are compared in this paper. These instruments have differing capabilities and operational modes that result in unique data products designed for different communities. The algorithms are developed for different purposes and differ in approach to the task of identifying or classifying snow. Application of the MODIS and ASTER algorithms and data products for snow will be made at different spatial and temporal scales, dictated by sensor design and operation. The ASTER algorithm provides a great amount of high resolution (30 m) information about features in a scene not obtainable with the MODIS algorithm and will find greatest use at basin scales. The MODIS algorithm provides information on snow cover at moderate spatial resolution (500 m) with near daily spatial coverage so will be of greatest use at continental and global scales for monitoring snow cover. Described here is a comparative look at these snow-mapping algorithms applied to two Landsat Thematic Mapper (TM) scenes.

INTRODUCTION

The Earth Observing System (EOS) is the principal component of NASA's Mission to Planet Earth (MTPE). EOS is a comprehensive global observing system of satellites and a Data and Information System (EOSDIS) designed to collect, process and distribute data for the study of natural processes on earth. Two algorithms for mapping snow cover with two EOS instruments, the Moderate

INSTRUMENT DESCRIPTIONS

Instrument descriptions, as well as much other information, can be found at the EOS Project Science Office home page located at; http://eospo.gsfc.nasa.gov/

MODIS
The MODIS instrument employs a conventional imaging radiometer concept, consisting of a cross-

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track scan mirror and collecting optics, and a set of linear detector arrays with spectral interference filters located in four focal planes. The optical arrangement will provide imagery in 36 discrete bands between 0.4 and 14.5 μm selected for diagnostic significance in Earth science. The spectral bands will have spatial resolutions of 250 m, 500 m, or 1 km at nadir. MODIS instruments will provide daylight reflection and day/night emission spectral imaging of any point on the Earth at least every 2 days, operating continuously.

ASTER

ASTER will operate in three visible and near-infrared (VNIR) channels between 0.5 and 0.9 μm, with 15-m resolution; six short-wave infrared (SWIR) channels between 1.6 and 2.43 μm, with 30-m resolution; and five thermal infrared (TIR) channels between 8 and 12 μm, with 90-m resolution. The instrument will acquire data over a 60-km swath whose center is pointable cross-track ±8.55° in the SWIR and TIR, with the VNIR pointable out to ±24°. An additional VNIR telescope (aft pointing) covers the wavelength range of Channel 3. ASTER's pointing capabilities will be such that any point on the globe will be accessible at least once every 16 days in all 14 bands and once every 5 days in the three VNIR channels.

ALGORITHM METHODS

Both algorithms are being developed using Landsat Thematic Mapper (TM) data as a surrogate for respective instrument data. In this comparison both algorithms begin with the same input data but follow their separate processing flows and decision paths to arrive at separate results that are dissimilar yet common in one respect; both map snow cover.

MODIS SNOW

The technique used in the MODIS snow mapping algorithm, SNOMAP, is to identify snow by its reflectance characteristics in the visible and near-infrared wavelengths. A key feature of snow is its high reflectance in the visible wavelengths and low reflectance in the near-infrared at about 1.6 μm. That difference in reflectance can be detected by use of a ratio between separate sensor bands covering the visible and 1.6μm regions . Snow may often be confused with clouds in the visible wavelengths because both are strong reflectors but, may be discriminated in the near infra-red (NIR) at about 1.6μm where clouds are good reflectors and snow a poor reflector (Bunting and d'Entremont, 1982). Cirrus clouds are an exception to the general rule

leading to frequent confusion with snow. A normalized difference snow index (NDSI) that gives a relative measure of change in reflectance of snow from the visible to the NIR is used to identify snow and discriminate snow from many clouds. The NDSI for TM is

$$NDSI = (band\ 2 - band\ 5) / (band\ 2 + band\ 5)$$

Snow is identified by criteria tests for key reflectance features. The NDSI and a threshold test for red reflectance are the criteria tests used to identify snow. These criteria tests are combined in a decision rule to identify a pixel as snow covered or not snow covered (Kyle et al., 1978; Bunting and d'Entremont, 1982; Dozier, 1989). The snow decision rule is; if a pixel has an NDSI greater than or equal to 0.40 and red reflectance greater than 11% it is identified as snow. This has been an effective snow rule over a wide range of TM scenes producing snow cover maps that generally agree with visual interpretation and supervised classification of snow cover. Confusion of snow and cirrus clouds has appeared to be the most frequent error encountered. Confusion with bright surfaces, for example, glacial sediment-laden rivers has also been encountered.

SNOMAP first converts instrument data, the digital numbers (DNs), to radiance using either gains and offsets recorded at time of acquisition or using the pre-flight calibration conversion method depending on TM processing date (EOSAT, 1996; Hall et al., 1995; Markham and Barker, 1986). Reflectance in each band, R_b, is then calculated and used in the snow decision process. Conversion to reflectance in each band is computed from;

$$R_b = (\pi * L_b * d^2) / (L_{ob} * cos(SZA))$$

L_b = spectral radiance for band b (W m^{-2} μm^{-1} sr^{-1})
d = Earth sun distance AU (commonly assumed to be 1.0)
L_{ob} = solar exoatmospheric spectral irradiance for band b (W m^{-2} μm^{-1})
SZA = solar zenith angle (°)

Comparisons of SNOMAP runs employing TM DNs or reflectances have demonstrated that reflectances produce results that are in greater agreement with observed snow cover in a scene as compared to results produced with DNs (Hall et.al,.1995). This has often been a subtle but important difference in analysis of the technique and results.

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The NDSI is then calculated and the criteria tests decision rule is applied to determine which pixels are snow covered. Pixels are labeled as snow, or not snow. Summary statistics of the run and result are generated as part of the algorithm. These summary statistics are termed metadata in EOS terminology. Metadata includes the area (km^2) of snow, percent of scene that is snow covered, out of range data counts, etc. Metadata are generated to provide summary statistics and provide an overview of results to assist with analysis, or selection of data products.

SNOMAP can be run on any TM scene without preliminary preprocessing of the data because the thresholds are static, and reflectance, a quantitative measure, is calculated and used for snow identification in all scenes.

ASTER SNOW

Although the primary motivation for this ASTER algorithm development is the masking of clouds in polar imagery, a byproduct of the technique results in each pixel being classified into one of the following ten classes: water, wet ice or slush, ice/snow, thin cloud over ice/snow, thin cloud over water, thin cloud over land, thick cloud, land, shadow on ice/snow, and shadow on land. The methodology implemented in the ASTER algorithm is a two stage process. The intent is to link together a fast, but less accurate method with a more accurate, but compute intensive technique into one methodology that is still accurate but fast enough for application in an operational system. Some class members are classified at a high level of confidence using a small set of spectral features using simple decision surfaces, while others require larger feature sets using a more complex classification technique. Although development of a nighttime version of the algorithm is underway, the current algorithm is only designed as a daytime algorithm (i.e., solar zenith angles less than 85°). It is estimated that, on the average, the algorithm is 90% accurate in distinguishing cloud from non-cloud classes but is in some cases, significantly less accurate in distinguishing between within cloud classes and within non-cloud classes. For example, it is difficult to separate wet, marshy, or boggy land from cloud shadow on land at a high level of accuracy (greater than 90%). Likewise, within cloud classes are confused. For example, thin cloud over snow/ice is frequently confused with thick or multilayer cloud. For this algorithm, polar regions are defined as those lying poleward of 60° N or 60° S. To date the algorithm has been tested on 24 Landsat TM quad scenes over coastal Antarctica and another 58 quad

scenes distributed throughout the Northern Hemispheric polar regions.

As in the SNOMAP algorithm, the success of this algorithm is heavily dependent on the availability of both visible wavelength channels (e.g., Band 2, 3, and 4 in Landsat TM) and short wave IR channels (e.g., Band 5 and 7). Preprocessing of the Landsat TM data from DN to radiance and then to reflectance is performed using the same technique as in the SNOMAP algorithm.

In the first stage, feature vectors close to class cluster centers are conservatively classified, with small computational expense, through the use of multispectral thresholding. The classification output is ambiguous among two to five classes from this stage and relies on the second stage to correctly resolve the ambiguity. The purpose of stage one is to classify as many pixels and reduce the classification ambiguity as much as possible while minimizing classification mistakes. The results from this stage are then forwarded to the second stage.

The results provided by the first stage are not perfect, but the goal is to misclassify for cloud/no-cloud at less than 3% and reduce the ambiguity between cloud and no-cloud for at least 75% of the pixels on the average. Five features are utilized in this stage. They are Band 4, Band 5, Band 6, arctan(Band 4, Band 5) (hereinafter called Feat 1), and Band 2 * cos(10°) - Band 4 * sin(10°) (hereinafter called Feat 2). The classification results obtained from this stage are based on a sequence of ten tests using these five features. Feats 1 and 2 are unique not only because they are derivative features, but also because they are applied adaptively. The thresholds for these two features are derived from the scene being classified using feature histograms. Significant spectral variability is apparent for each class from scene to scene. Some of the variability is due to the natural variations in the atmospheric path (especially water vapor) and some is due to the natural variability intrinsic to a specific class. For example, within the land class, the spectral characteristics of boreal forest are not the same as wetlands or bogs and are not the same as the bare rock found in mountain ranges. Likewise, the spectral characteristics of fresh snow are different from those of ice floes, or shadowed, wet or thin ice. Feat 1 is especially important in separating all types of frozen water surfaces from cloud over those surfaces. This feature is key to this algorithm for the same reason that the NDSI metric is key to the SNOMAP algorithm. The distribution of all types of frozen water are distributed narrowly in the Feat 1 space while cloud is distributed much more broadly and uniformly. The same idea follows for Feat 2; however, in this case the adaptive

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thresholding is important for distinguishing land surfaces from cloud over land surfaces. This is similar to the technique used by Li and Leighton (1992) in the classification of land in AVHRR imagery using bands 1 and 2.

The pixels that are not classified or are partially classified are passed onto the second stage which is a more computationally expensive process. It is a relatively new technique that is called the paired histogram method (Berendes et al., 1996). Additional derivative features are also calculated (140 total) and include ratios, differences, arctangents, Euclidean distances, and normalized differences of band pairs. Three band combinations of Euclidean distance and Hue-Saturation-Intensity are also computed.

The paired histogram method can be characterized as an ensemble averaging or balloting scheme. Numerous tests are performed between pairs of classes and the results from each test constitutes a ballot or vote for one or none of the two classes being compared. After all the tests are performed, the ballots are tallied and the classifier labels the class of the feature vector as the one with the most votes. The tests are derived from a preprocessing or training step using labeled feature vectors. Approximately 3700 labeled feature vectors (or samples) have been extracted to date. The basis for the tests is a pairwise comparison between every combination of possible classes. For example, in this algorithm there are 10 classes, so a total of 45 comparisons is possible for a given feature. Since it is impractical to make 45 class comparisons for each of 140 features, during the training process the three best features for each pairwise comparison are determined. The classifier only applies three features in each pairwise comparison for total of 45 * 3 = 135 tests for each pixel, maximum. If the first stage filters out any of the classes for consideration then the paired histogram method only considers comparisons for the unfiltered or possible classes. In that case less than 135 tests would be conducted.

Key to the performance of the paired histogram algorithm is the determination of the three best features to be used in each pairwise comparison of classes. The three best features are those that provide for the maximum separation between a given set of two classes. This determination is accomplished through the use of two metrics - overlap and divergence. Overlap is the primary measure and is derived from the feature histograms of labeled samples. It is computed as the sum of the products of all histogram values that overlap in the feature space. The secondary measure, divergence, is computed as the ratio of the difference in the means between the two classes and the sum of the standard deviations for

the two classes for a given feature. This measure is only used if there is a tie or equal value in overlap between two classes. After all of the features for a given class combination are ranked according to overlap and, if necessary, divergence, an additional re-ranking process is performed. The cross correlation between the highest ranked features for a specific class is computed and if the value is greater than 0.8 the lower ranked value is dropped and the next highest ranked value is tested for cross correlation. The re-ranking is terminated when all 3 cross correlation values for the 3 highest ranked features (1-2, 1-3, and 2-3) are less than 0.8.

Once the three best features for each paired combination of classes is determined, a set of lookup tables is created. Three lookup tables are created for each class pair (one for each of the three best features). As stated above there are a maximum of 45 class pairs which results in a total of 45 * 3 = 135 lookup tables. A lookup table for a given feature and class pair is constructed as follows. The histogram for each class in a class pair for a specific feature is generated. The histograms are discretized into 256 bins and scaled to the minimum and maximum values of the feature for both classes. Then a bin by bin comparison is made between the two histograms. A table lookup value of 1 is assigned to that class that has the highest histogram value. A table lookup value of zero is assigned to the lesser value. In the case of a tie or equal histogram values, both classes are assigned a table lookup value of zero. The creation of the lookup tables completes the training or preprocessing step and forms the basis for the aforementioned balloting based classification scheme.

To apply the classifier to a pixel, the following steps are performed: 1) Calculate all of the three best features for each possible class, 2) Initialize a counter for each of the possible classes, 3) Perform all appropriate tests by accessing the table lookup values described above. For example, scale and bin the appropriate feature value according to the minimum/maximum value for the class pair under consideration. Lookup the ballot (0 or 1) for each class in this bin and increment the appropriate class counter if the ballot is one. 4) After performing all tests, classify the pixel as the class whose counter value is largest.

Scenes of Comparison

Two Landsat TM scenes were used in this comparison. One was a Landsat 4 TM quarter scene (quadrant 1) of the Wrangell Mountains, AK acquired on 9 July 1988 (solar zenith angle of 43°) containing snow covered mountains, glaciers, vegetated surfaces

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and clouds over all surface features. The other was a Landsat 5 TM full scene containing similar surface features around Glacier National Park, MT, acquired on 6 March 1994 (solar zenith angle of 60°).

Gray level images of results lack much of the information content of the color images, especially for the ten ASTER classes, but have been included (Figures 1-4) for the Wrangell Mountains, AK scene as they show major similarities and differences between algorithm results. Copies of color illustrations of results may be requested from the authors (griggs@ltpmail.gsfc.nasa.gov).

Snow and Other Features

A gray level image of a false color (TM bands 5,4,2) is presented in Figure 1. Snow covered area is the medium gray area in the upper center of the image (Fig. 1), clouds are light gray to white, and non-snow covered land is dark gray.

Both algorithms produce results that are similar and dissimilar. The SNOMAP algorithm generates a snow and not snow map (Fig. 2) and summary statistics (metadata) of snow cover. The ASTER algorithm generates a ten-class classification map (Fig. 3). Total areas covered by snow or an ASTER class are listed in Tables 1 and 2. A great difference in information content exists between the algorithms because of the many features that the ASTER algorithm classifies. To make a direct comparison of only the snow coverage between the algorithms, the ASTER classes of slush, snow/ice, and shadow on ice/snow were combined to make an ASTER snow class comparable to the snow map of SNOMAP.

Comparison of algorithms with the Wrangell Mountains scene indicates that both algorithms (Fig. 2 and Fig. 3) accurately identify snow covered areas . Also apparent is the misidenitification of some clouds in the upper quarter of the scene as snow by SNOMAP (Fig. 2). The ASTER algorithm identifies those same clouds as thin cloud over ice/snow (Fig. 3). Those clouds are interpreted as multilevel clouds, apparently high thin clouds over lower thick clouds. Both algorithms confuse those overlying thin clouds with the underlying feature. SNOMAP identifies them as snow; the ASTER algorithm classifies them as thin cloud over ice/snow , despite the interpretation that they are over clouds through which the surface is not directly observable. The ASTER class interpretation is ambiguous in this situation in that it can be interpreted as correct in identifying thin cloud but, incorrect in that the underlying surface is cloud not ice or snow.

Table 1. SNOMAP results for 9 July 1988

Class	Area (km^2)
Snow	1554
Not snow	5909

Table 2. ASTER classification results for 9 July 1988

Class	Area (km^2)
Water	9
Slush	208
Snow/Ice	754
Thin cloud over ice/snow	1195
Thin cloud over water	135
Thin cloud over land	1942
Thick cloud	28
Land	2646
Shadow on ice/snow	44
Shadow on land	502
Total area	7463
Snow	1006

SNOMAP identified 21% (1,554 km^2)of the scene as snow covered. The ASTER snow area was 13% (1,006 km^2). The agreement and disagreement of snow identification between the algorithms is shown in Figure 4, and tabulated in Table 3. The majority of the difference in snow extent between the algorithms is accounted for by the misidentification of thin clouds as snow by SNOMAP (compare Fig. 2 with Fig. 1). Those thin clouds are identified as thin clouds over ice/snow in the ASTER algorithm (Fig.3), a class that was not combined into the ASTER snow class. The difference of total snow by SNOMAP and the ASTER thin clouds over ice/snow class can be applied as a correction to this SNOMAP error, 1,554 - 625 = 929 (Numbers from Tables 1, 2, and 3). That difference then is the corrected snow area for SNOMAP. The SNOMAP corrected snow area and ASTER snow class are then different by about 77 km^2, relatively good agreement considering the great difference in algorithm techniques and information content.

Table 3 Classification comaprison of SNOMAP and ASTER for 9 July 1988

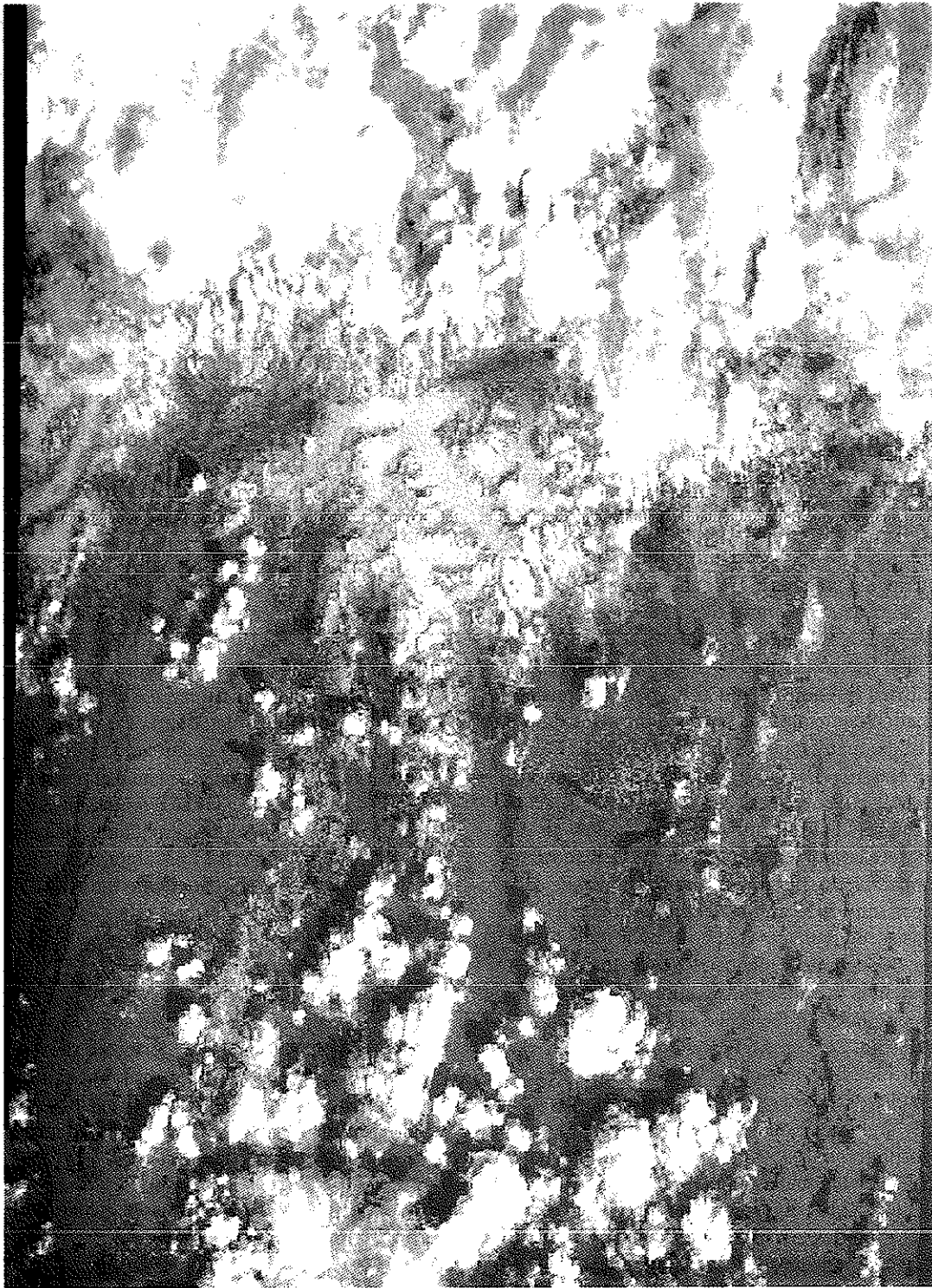| Comparison	Area (km^2)
SNOMAP = snow and ASTER = snow	827
SNOMAP = snow and ASTER = not snow	728
SNOMAP = not snow and ASTER = snow	179
SNOMAP = not snow and ASTER = not snow	5730
SNOMAP = snow and ASTER = thin cloud over ice/snow	625

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Figure 1. Gray level of a false color image created with TM bands 5,4,2 of the Wrangell Mountains, AK, 9 July 1988. Snow covered area in upper center of scene is medium gray, clouds are white to light gray, and non-snow covered surface is dark gray.
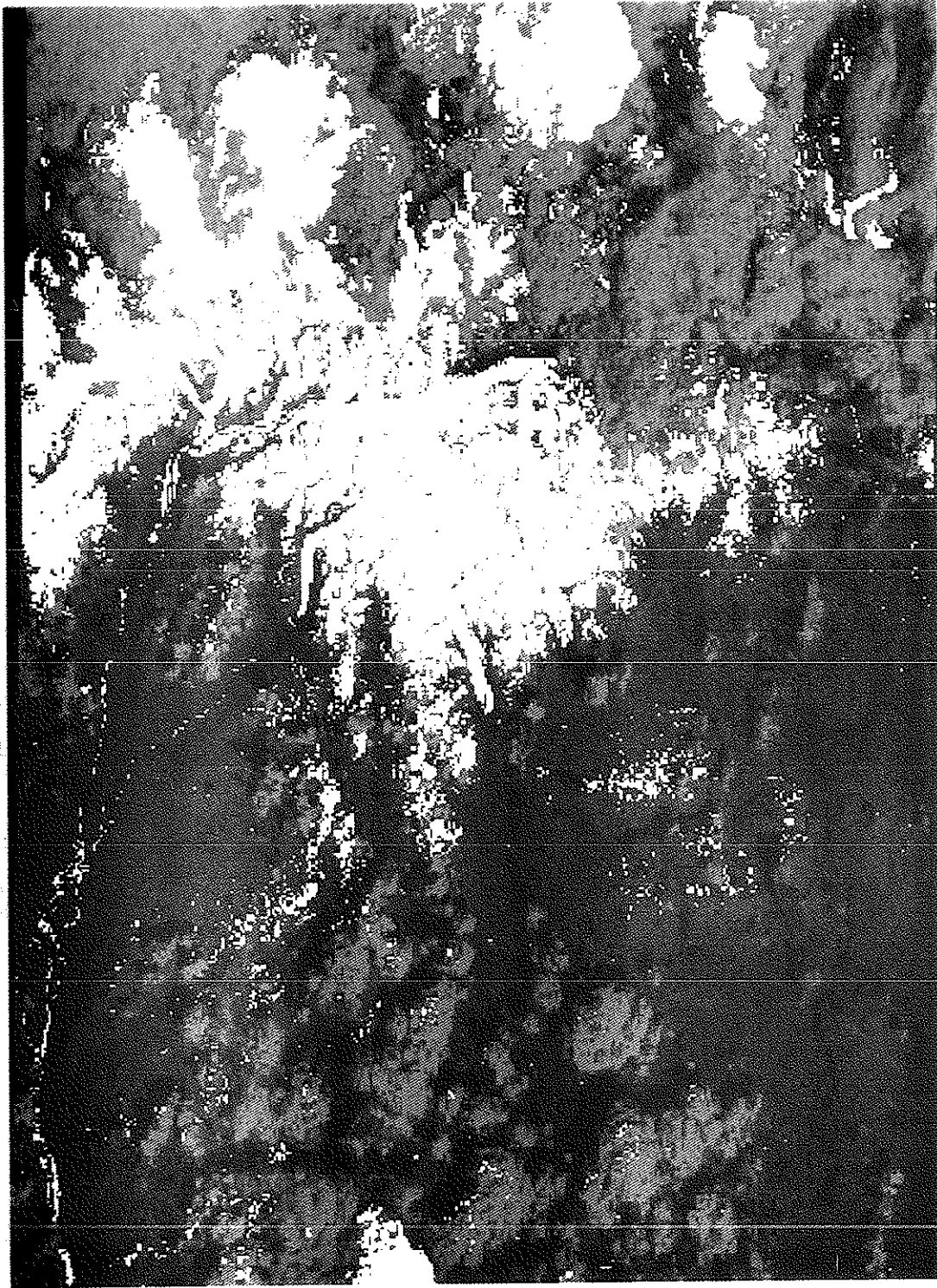
Figure 2. Snow map result from the MODIS SNOMAP algorithm. Snow is shown as white. TM band 4 is shown in gray as a visual reference layer for the snow map.
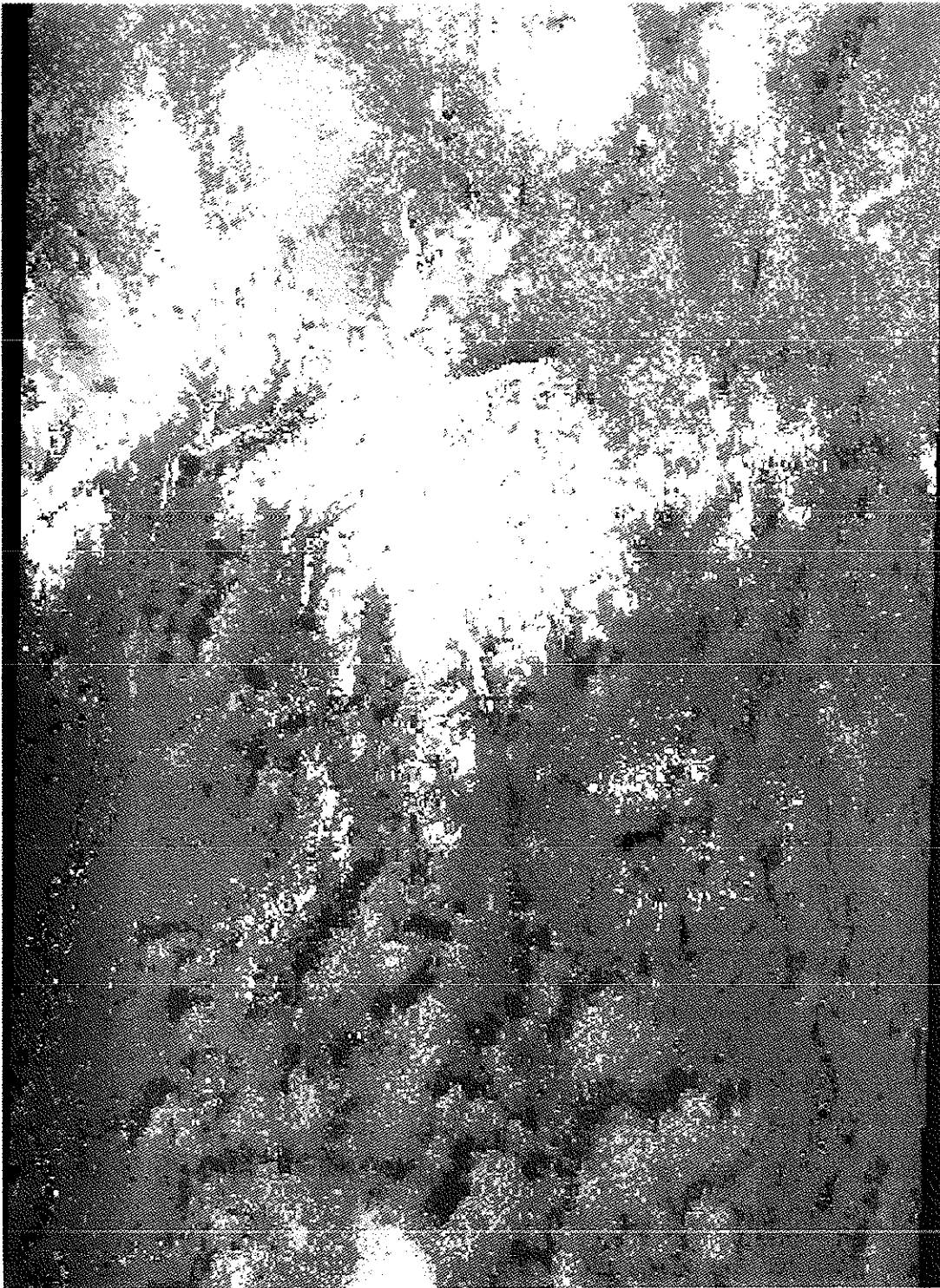
Figure 3. *Classification result of the ASTER algorithm. Snow is shown as white. Lightest shade of gray is thin* **cloud over ice/snow.** *Other ASTER classes are non-snow in content.*
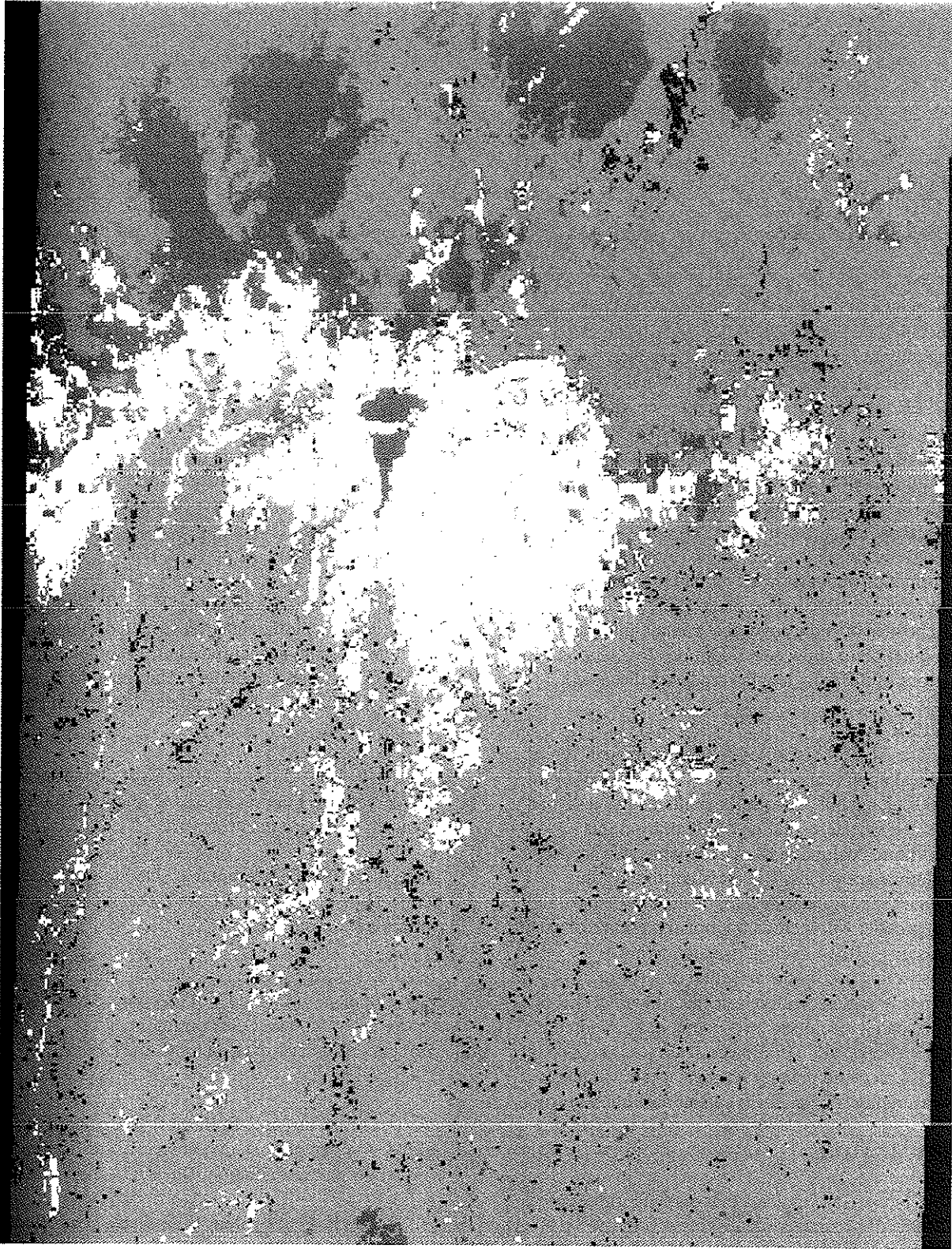
Figure 4. Comparison of SNOMAP and ASTER algorithm results. Snow by both algorithms is shown in white. **Clouds** that SNOMAP identifies as snow and ASTER classes as thin cloud over ice/snow are shown in medium gray. **Areas** classed as snow by ASTER but as not snow by SNOMAP are shown in black. Non-snow areas by both **algorithms** are shown in light gray.

Similar results were obtained in comparing the algorithms on the TM scene of Glacier National Park. In that scene SNOMAP identified snow underlying thin clouds that the ASTER algorithm identified as thin cloud over ice/snow. When that difference in classification was accounted for both algorithms identified very similar areas of snow cover.

EOS ERA PLANS

MODIS

Launch of the first EOS platform, AM-1, is scheduled for June 1998. After AM-1 is declared operational, routine generation of products using the algorithms described here for the MODIS and ASTER instruments should commence. During the snow season, daily MODIS snow products are planned to provide information on global snow cover from the onset of snow in the autumn through its melt in the spring. The MODIS data products will provide data in the form of a 'map' of snow cover at 500 m spatial resolution, and metadata, summary information about snow cover and the data product (Riggs et al., 1996). Also planned are ten day composites of snow cover that contain information on the duration of snow cover. Options for compositing periods of differing lengths are being discussed.

ASTER

The ASTER algorithm will be generated (for 10 classes) upon request, for scenes obtained poleward of 60° N and 60° S, for solar zenith angles less than 85°, at a spatial resolution of 30 m, from this algorithm. A cloud mask will be generated for the nighttime scenes also but the algorithm for this product is still under development. The metadata for this product will include fractional presence of each class, in addition to cloud fraction to aid a prospective user in the selection of clear or cloudy scenes or regions with in a scene. Since ASTER is a high spatial resolution instrument, its strength in applicaitions will be for basin scale studies, 3D effects on cloud poperty retrievals, and validation of measurements from lower spatial resolution sensors.

SUMMATION

Comparisons indicate that both algorithms are capable of accurately identifying snow cover at a gross level of snow or not snow classification. Thin clouds pose a problem to snow identification in both algorithms. Thin clouds may be misidentified as snow in SNOMAP, thus indicating an area of development to pursue in SNOMAP. It is expected that the use of

the MODIS cloud mask, a regular MODIS product, should resolve snow and cloud identification problems. Ambiguities of classifying thin clouds overlying some features is a focus of ASTER algorithm development. The ASTER algorithm provides a great amount of high resolution (30 m) information about features in a scene. Its greatest use will be for support of site studies and in small to moderate sized basins where detailed classification information is needed. The MODIS snow algorithm provides information on snow cover at moderate spatial resolution (500 m) with near daily spatial coverage so will be of greatest use at basin, continental and global scales for monitoring temporal and spatial changes in extent of snow cover.

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