Classification of surface types using SIR-C/X-SAR, Mount Everest Area, Tibet

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Abstract. Imaging radar is a promising tool for mapping snow and ice cover in alpine regions. It combines a high-resolution, day or night, all-weather imaging capability with sensitivity to hydrologic and climatic snow and ice parameters. We use the spaceborne imaging radar-C/X-band synthetic aperture radar (SIR-C/X-SAR) to map snow and glacial ice on the rugged north slope of Mount Everest. From interferometrically derived digital elevation data, we compute the terrain calibration factor and cosine of the local illumination angle. We then process and terrain-correct radar data sets acquired on April 16, 1994. In addition to the spectral data, we include surface slope to improve discrimination among several surface types. These data sets are then used in a decision tree to generate an image classification. This method is successful in identifying and mapping scree/talus, dry snow, dry snow-covered glacier, wet snow-covered glacier, and rock-covered glacier, as corroborated by comparison with existing surface cover maps and other ancillary information. Application of the classification scheme to data acquired on October 7 of the same year yields accurate results for most surface types but underreports the extent of dry snow cover.

1. Introduction

The 1994 flights of the spaceborne imaging radar-C/X-band synthetic aperture radar (SIR-C/X-SAR) provided valuable new data over some of the world’s most extreme and inaccessible alpine terrain. The realization of the importance of monitoring these areas has increased in recent years. Within alpine regions, numerous phenomena can serve as climatic indicators, including location of tree line, spatial distribution of snow water equivalent, and timing and intensity of snowmelt. Glacier mass balance and areal extent are perhaps the most sensitive parameters in alpine regions for inferring climate change. Glaciers can respond rapidly to climate change either by increasing or decreasing their mass and extent [Williams and Hall, 1993]. The acquisition of data on glacier areal extent and mass balance through time provides a means of monitoring climate change. Alpine glaciers are also of major hydrologic interest. At the global level, glaciers and ice sheets represent a major store of the world’s water, accounting for 2.15% of the total water and 77% of Earth’s fresh water [Williams and Hall, 1993]. Locally, they are of tremendous importance, as many population centers rely on seasonal snowmelt and glacial runoff to meet their water needs.

Monitoring high alpine regions with synthetic aperture radar (SAR) is a promising area of research [e.g., Rott and Nagler, 1992, 1993; Shi and Dozier, 1993, 1995; Forster et al., 1996]. Imaging radar, such as SIR-C/X-SAR, offers several advantages for remote sensing in mountainous terrain: (1) the spatial resolution is sufficient to be compatible with the scale of spatial variation of rugged alpine regions; (2) radar, as an active remote sensing system, provides its own illumination and is therefore able to operate independently of the Sun; (3) the frequencies at which radar operates are able to penetrate all but the most severe weather events and clouds, and most fundamentally; (4) radar is sensitive to dielectric and structural parameters that are useful for discriminating alpine land cover types and inferring hydrologic and glaciological parameters in alpine regions. The primary goal of this research is to examine the capability of SIR-C/X-SAR in mapping glacial and nival features in a glaciated high alpine area.

2. Background

2.1. Backscatter Properties of Surface Covers

The backscatter coefficient of a snowpack is highly variable according to wetness, depth, substrate, surface roughness, and density. Dry snow is highly transparent to radar, with penetration depth varying from 6 m for X-band to more than 40 m for L-band [Ulaby et al., 1982]. It is difficult to characterize dry snow with any specific spectral signature, since it is the snow-
ground interface that dominates the signature. As liquid water increases in the snowpack, the volume scattering contribution to backscatter increases greatly. At a certain point, however, surface scattering of the air–snow interface becomes the dominant scattering mechanism [Shi and Dozier, 1993]. How this is manifested in terms of backscatter depends on the substrate and the roughness of the snow. For example, with snow on highly backscattering rock, increasing wetness decreases backscatter until snow surface scattering becomes dominant. At this point, if the snow surface is rough, an increase in backscatter with wetness will be observed.

The backscatter of glacial ice is dominated by surface scattering and is therefore largely determined by surface roughness [Rott and Nagler, 1997; Shi and Dozier, 1995; Shi et al., 1994]. Glacier ice is usually smoother than rock but rougher than snow. It can therefore be expected that its backscatter is intermediate between the high backscatter from rock and moraine and the low backscatter from wet snow [Shi and Dozier, 1993].

The backscattered returns from soil, scree, talus slopes, rock-covered glacier, and rock outcrops are dominated by surface scattering. Therefore they depend largely on the dielectric constant and the surface roughness. The dielectric constant of each varies strongly according to moisture content. As a result of these factors, the returns from these surfaces vary widely, yet in alpine terrain, the return from rock outcrops and moraines tends toward higher values [Shi and Dozier, 1993; Shi et al., 1994]. Completely rock-covered glacier can be treated as consisting solely of the rock or debris layer, as radar cannot penetrate debris of this size to "see" the rock–ice interface. Thus its signature should resemble scree or talus of a similar particle size distribution.

2.2. Previous SAR Snow and Ice Mapping Work

Researchers have used a variety of SAR sensor configurations and strategies to map snow and ice. Shi and Dozier [1993] used single polarization (horizontal transmit, horizontal receive, HH) NASA/Jet Propulsion Laboratory (JPL) Airborne SAR (AIRSAR) data at C- and L-band to map wet snow and glaciers in the Austrian Alps. Rott and Nagler [1993] used simultaneous single-frequency and polarization ERS-1 data (C-VV) to map snow and glaciers. Adam et al. [1997] used ERS-1 data to determine the glacier snow line under wet snow conditions to within 50–75 m of its actual position. These investigations required digital elevation data to reduce the effect of topography on backscatter. Forster et al. [1996] were able to discriminate four radar glacier zones on relatively flat portions of the South Patagonian Ice Field using SIR-C/X-SAR data. Shi and Dozier [1997] found that polarimetric SIR-C/X-SAR data could be used to map seasonal snow in the Sierra Nevada. That study included an algorithm that used digital elevation model (DEM)-corrected radiometric measurements and a second algorithm that used only polarization and frequency ratios that required no terrain information. The major findings were that polarimetric SIR-C/X-SAR can map wet and dry snow cover if digital elevation data are incorporated and that it can map wet snow cover even without elevation data.

2.3. Terrain Correction

Radar backscatter is greatly influenced by topographic factors. Images of mountainous terrain appear dominated by topography to such an extent that the inherent scattering properties of the surface are obscured. With knowledge of local incidence angle, it is possible to minimize terrain effects on radar measurements through the processes of terrain calibration and normalization. Terrain calibration refers specifically to the process of reducing the processed SAR imagery to a dimensionless radar backscatter coefficient, \( \sigma^0 \) [van Zyl et al., 1993]. Normalization is the process of minimizing the backscatter dependence on incidence angle, reducing to the normalized backscatter coefficient, \( \sigma^0_n \). We refer to these two processes collectively as terrain correction.

Terrain calibration is typically performed according to the following formula [van Zyl et al., 1993]:

\[
\sigma^0 = \frac{\sin \theta_i}{\sin \theta_e}
\]

where \( \sigma \) is the received backscatter cross section, \( \theta_e \) is level ground incidence angle, and \( \theta_i \) is local incidence angle. The inverse of the ratio of \( \sin \theta_i \) to \( \sin \theta_e \) is also known as the terrain calibration factor \( T \). From \( \sigma^0 \), a normalized backscattering coefficient \( \sigma^0_n \) can be calculated:

\[
\sigma^0_n = \frac{\sigma^0}{\cos \theta_i}
\]

where \( n \) is incidence angle sensitivity factor, which varies with scattering mechanism. Once normalized, values may be compared in a relative sense irrespective of terrain slope.

Several authors have performed terrain correction of SAR images. Hinse et al. [1988] suggested choosing \( n \) such that variance in \( \sigma^0_n \) for all pixels of the feature class is minimized. Shi et al. [1994] performed terrain normalization semiempirically by choosing a value for \( n \) such that separability of feature classes was maximized. Adam et al. [1997] chose a value of 2.0 for \( n \) based on the assumption of an idealized rough surface. A more complete discussion on the theory behind terrain correction is found in the appendix.

2.4. Classification Trees

A variety of schemes has been employed to classify images into land-cover types based on spectral information [Lillesand and Kiefer, 1994]. One method that lends itself well to classification of multifrequency/polarization SAR images is the use of binary decision trees [Hess et al., 1995]. In this approach, training set data are assembled, and a set of predictor variables \( x \) and a response variable \( y \) are selected. This data set is then recursively partitioned into increasingly homogeneous subsets. When a threshold of homogeneity for a given subset is attained, the splitting procedure ceases. At each of these "leaves," the most common class within the subset is designated the prediction. In this manner, a binary classification tree is grown that models the response variable's class as a function of the predictor variables.

Classification trees offer several advantages over other methods of image classification, including high computational efficiency, automatic generation of misclassification probabilities, relative insensitivity to outliers, capacity to efficiently handle a large number of predictor variables, and ease of interpretability. More details about decision and classification trees can be found in the work by Breiman et al. [1984]. The trees in this work were grown and tested with the S-Plus statistical software package [Statistical Sciences, Inc., 1993]. A description of this implementation of decision trees can be found in the work by Clark and Pregibon [1992].
2.5. Site

Mount Everest (8848 m) straddles the border of Nepal and Tibet at latitude 27°59'15.85"N and longitude 86°55'79.53"E [Washburn, 1995] (Figure 1). The minimum altitude of our study site is 5250 m at the extreme northern portion of the Rongbuk glacier, ~13 km northwest of Everest. The region is completely above timberline. Surface cover consists of a variety of ice, rock, and snow features. Ice features include smooth glacial ice and various rough glacial ice features such as crevasses, seracs, and ice penitentes. The most prominent glacial ice features are the various branches of the expansive Rongbuk glacial massif, including the West, East, Far East, and main Rongbuk glaciers. Rock features include exposed sedimentary rock, talus, serac, debris-covered glacier, and glacial till. Snow may cover any of these features. Depending on altitude, exposure, time since accumulation, and season, the snow can be wet or dry.

At the time of the first image acquisition (April 16, 1994, 1224 local time), during the premonsoon, the region was relatively snow free. Consequently, at elevations lower than ~5500 m, the surface covers were exposed till, serac, talus, and debris-covered glacier. At higher altitudes, the surface covers included those listed above in addition to smooth glacial ice, rough glacial ice, dry snow, and wet snow-covered glacial ice. The presence of these cover types was verified using an interactive CD-ROM [Peak Media Inc., 1995] from several spring 1994 Mount Everest climbing expeditions. No temperature information was presented on the CD-ROM, but images of climbers high on the mountain on April 16 indicate that temperatures were well below freezing and that snow and ice surfaces were dry at higher altitudes. The monsoon season occurs during the months between April and October; thus one can expect there to be significantly more snow at the time of the second image (October 7, 1994, 1236 local time).

2.6. Image Data

The image data used in this project were acquired by the SIR-C/X-SAR instruments as part of the NASA Space Radar Laboratories 1 and 2 (SRL-1 and SRL-2) onboard the shuttle Endeavor (Table 1). Both Khumbu Himalaya swaths used in this study were imaged in single-look complex data mode 11, the only mode available for this region. It consists of X-band (λ = 3.1 cm) at VV polarization, C-band (λ = 5.8 cm) at HH and HV polarization, and L-band (λ = 23.5 cm) at HH and HV polarization. Note that mode 11 data do not provide the full complement of fundamental polarizations required to synthesize any possible polarization.

2.7. Digital Elevation Data/Location Data

To calibrate and normalize received backscatter for the effects of topography, we used a digital elevation model (DEM) of the Khumbu/Rongbuk region produced from SRL-2 SIR-C/X-SAR interferometric measurements (Figure 2). This was necessary because of the severe effect of incidence angle variation on σ. The DEM was produced in ground range at 20 m resolution. Many patches of the DEM contain no data due to layover and radar shadowing. DEM latitude/longitude coordinates were necessary to tie SIR-C/X-SAR imaging geometry to surface slope and aspect in order to compute the local terrain calibration factor and the cosine of the local illumination angle, as discussed below. We referred to the National Geographic Society (NGS)/Reston Museum of Science Mount Everest Topographic Map [Garrett, 1988] for DEM latitude and longitude coordinates. The spatial intersection of the DEM with the NGS Everest map resulted in the DEM subset used in this project.

3. Methods

3.1. DEM Processing

We resampled the subsected DEM through rotation by the shuttle flight track angles (Table 1). This rotation orients the pixels with the cardinal directions and permits association of Universal Transverse Mercator (UTM) coordinates with each DEM pixel, which provides the geographic information necessary to tie the SIR-C/X-SAR imaging geometry to the topography.

The JPL program swathcen incorporates the shuttle ephemeris data (i.e., shuttle flight time, shuttle altitude, estimated surface elevation, shuttle Earth-projected latitude and longi-

<table>
<thead>
<tr>
<th>Table 1. Image Parameters</th>
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<tbody>
<tr>
<td><strong>SRL-1</strong></td>
</tr>
<tr>
<td>Date taken</td>
</tr>
<tr>
<td>Local date/time of image</td>
</tr>
<tr>
<td>Track angle, deg</td>
</tr>
<tr>
<td>Incidence angle at center, deg</td>
</tr>
<tr>
<td>Swath width, km</td>
</tr>
<tr>
<td>Swath length, km</td>
</tr>
<tr>
<td>Cross-track pixel size, m</td>
</tr>
<tr>
<td>Along-track pixel size, m</td>
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tude, radar look angle at imaged swath center; Table 2) to compute the UTM coordinates of the image swath center for 0.01 s intervals of flight time. We fit a third-degree polynomial to these coordinates and retained the polynomial coefficients.

Table 2. Space Shuttle/SIR-C/X-SAR Ephemeris Data

<table>
<thead>
<tr>
<th></th>
<th>SRL-1</th>
<th>SRL-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shuttle mission elapsed time</td>
<td>061910:14:057</td>
<td>061920:11:150</td>
</tr>
<tr>
<td>Shuttle altitude, km</td>
<td>217.8</td>
<td>220.7</td>
</tr>
<tr>
<td>Estimated surface elevation, m</td>
<td>6000</td>
<td>6000</td>
</tr>
<tr>
<td>Look angle at image center, deg</td>
<td>62.53</td>
<td>20.32</td>
</tr>
</tbody>
</table>

The polynomial coefficients, the shuttle/radar ephemeris data, and the rotated DEM were used to compute and geographically project the terrain calibration factor (T) and cosine of the local illumination angle (cosi) for each pixel. These quantities are key inputs into the terrain correction.

3.2. Radar Processing

Before coregistering the X-SAR image to the SIR-C image, we performed some initial processing steps. For the SIR-C data, there were two steps. First, we converted compressed Stokes matrix data into HH and HV decibel (dB) backscatter cross-section images. Next, we generated a multifocused image in which output pixels were created from six azimuth pixels...
Table 3. Optimized \( n \) Values for Each Radar Band

<table>
<thead>
<tr>
<th>Radar Band</th>
<th>Optimized ( n )</th>
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<tbody>
<tr>
<td>X-VV</td>
<td>1.3</td>
</tr>
<tr>
<td>C-HH</td>
<td>1.4</td>
</tr>
<tr>
<td>C-HV</td>
<td>1.2</td>
</tr>
<tr>
<td>L-HH</td>
<td>1.3</td>
</tr>
<tr>
<td>L-HV</td>
<td>1.1</td>
</tr>
</tbody>
</table>

and two range pixels. The X-SAR data were processed and multilooked in a similar manner. We then coregistered the DEM and the X-SAR images to the SIR-C images, finding the quality of image coregistration to be good (RMS error of 0.81 and 0.88 pixels, respectively).

Once the radar and elevation data were processed and coregistered, we performed terrain correction. We calibrated the data by calculating \( \sigma^b \) from (1). While most normalization is performed to maximize separability for classification and render backscatter in a relatively comparable space, we attempted to simulate the backscatters that would have occurred had each pixel been level ground measured at a constant incidence angle. This was accomplished by factoring in the level ground image center incidence angle \( \theta_i \) to (7) as follows:

\[
\sigma^b(\theta_i) = \sigma^b \cos^2 \frac{\theta_i}{\cos \theta_i} \quad (3)
\]

where \( \sigma^b(\theta_i) \) is backscatter coefficient normalized to image center incidence angle and \( \sigma^b \) is backscatter coefficient at the local incidence angle.

We devised a semiempirical method for the selection of the incidence angle sensitivity factor \( n \). For each SAR band, we generated a series of terrain-corrected images using (3), each with a different value for \( n \) (1.0 \( \leq n \leq 2.5 \)). We calculated a best fit line for the relationship of normalized \( \sigma^b \) versus incidence angle for each of these images. Pixels with extremely high incidence angles (>85°) were not considered in the calculation of the line, as these pixels, when corrected, can produce spuriously large normalized backscatter values. As a means of selecting an optimum value of \( n \), we selected the value that minimized the magnitude of the slope (Table 3). The aggregate result is that the image-wide effect of incidence angle on normalized backscatter is minimized (Figure 3). The high amount of scatter that remains in the graphs should not cause great concern, as we seek only to minimize the effect of incidence angle on backscatter. There continues to be a great deal of variation in backscatter owing to different surface covers. This strategy is built on the assumption that terrain slope would have no significant effect on inherent surface backscatter properties if backscatter could be measured for every pixel at the same incidence angle. Since the incidence angle sensitivity factor can change with frequency and polarization, this selection procedure was carried out independently for every radar polarization and frequency band. The chosen values are within 0.2 of those selected by Shu and Dozier [1997]. While no clear frequency trend emerges, there is a drop in optimized \( n \) from like-polarized HH to cross-polarized HV bands for a given frequency. A comparison of uncorrected and terrain corrected X-VV data shows the extent to which incidence angle dependence has been removed (Figure 4). The areas for which no DEM data were available or where stripping occurred (section 2.7) were removed with a mask.

In addition to the single-band radiometric data, we also calculated the following ratio bands: L-HV/L-HH, C-HV/C-HH, L-HH/C-HH, L-HV/C-HH, C-HH/X-VV, and L-HH/X-VV.

4. Analysis and Discussion

4.1. Training Site and Class Selection

An optimal set of bands was selected for locating training areas. These were determined by visually inspecting each band and selecting a subset that provided the greatest contrast be-
tween training areas. For this we chose the L-HV, X-VV, and C-HV composite because it provided the greatest apparent physically realistic separation of surfaces. Plate 1 shows the contrast-stretched three-band false color composite for the April data take.

The most prominent features present in the image are the main Rongbuk glacier, at image left, the East Rongbuk glacier, at image center, and the Far East Rongbuk glacier. The Rongbuk and East Rongbuk glaciers appear as northwest-southeast-oriented features, and the Far East Rongbuk appears as an east-west oriented feature with numerous prominent tributaries. These glaciers are expressed as several different colors on the images that follow an elevational gradient. At high altitudes, they appear pink and white, grading into green, dark green, then spatially heterogeneous mixtures of green and pink, and finally, a mixed terrain of red, pink, and white at the lowest elevations. Not all of these zones are visible on every glacier. The changes in color are indicative of transitions in the surface cover and texture of the glaciers as they pass through several hundreds of meters of altitude. Many other shorter tributary glaciers appear with similar colors and transitions. The distinctive snow-filled Great Couloir, which drops down the north face of Everest from the summit, stands out as white (behind the orange training site polygons). Patches of white are prominent on the high-altitude ridges, particularly in the eastern portion of the image. Zones that appear spectrally similar to the red, pink, and white glacier zone appear in the lower altitude slopes of the western portion of the image.

The NGS Everest map and the interactive CD-ROM [Peak Media, Inc., 1995] guided the selection of land-cover classes.
and training sites for the image classification. In addition, we used spatial context, understanding of backscattering characteristics, and personal regional knowledge. Using the image as a guide, four spectral classes are readily separable. For each of these classes, we selected training sites (Figure 5) from which we generated statistics to characterize the radar backscatter signatures. Note that the class that appears in red in Plate 1 is split in two, for reasons discussed below.

Based on radar backscatter, we interpret the dark green regions to be relatively smooth wet snow-covered glaciers. These areas constitute the lowest backscatter class in the image. They are low in the L-HV (≈−25 dB), X-VV (≈−11 dB), and C-HV (≈−17 dB) as well as in the L-HH and C-HH (≈−20 dB and ≈−12 dB, respectively). Note that in comparisons of backscatter values, the terms high and low should be interpreted as relative to other targets rather than relative to other bands. These appear in the intermediate zones on the glaciers below dry snow accumulation zones and above the rough exposed glacial ice of the ablation zones [Paterson, 1994]. The C- and L-band returns appear to be too high for wet snow, yet these are the lowest among all of the training sites. These higher than expected returns may be attributable to combined greater surface roughness and wetter snow conditions [Shi and Dozier, 1995] than are present in the sites in the literature. It is also possible that discrepancies may have resulted from performing a terrain correction, as literature values are typically nonterrain corrected measurements over (presumably) flat terrain. The CD-ROM and Child [1995] confirm that these areas were snow-covered and located proximally to glacial ice from which all snow had ablated. Furthermore, there are images of climbers dressed for above-freezing weather at the toe of Rongbuk glacier on the day the image...
was acquired, approximately 500–1200 m lower in altitude. Hence the assumption that the snow is wet is reasonable. The altitude range for these regions is 5600–6500 m, depending on aspect.

We interpret the green regions to be dry snow-covered glacier or dry firn-covered glacier. Green areas are low in L-HV (~ -24 dB), moderate in C-HV (~ -11 dB), and high in X-VV (~ -4 dB). Additionally, these regions are marked by low L-HV/C-HV (~ -13 dB), L-HH/C-HH (~ -13 dB), and L-HH/X-VV (~ -15 dB) ratios. These areas appear in the accumulation zones of most glaciers, below bergschrunds, which separate flowing glacier from the surrounding mountain walls, and above the wet snow regions described above. These regions exhibit higher backscatter than the wet-snow regions at all frequencies and polarizations (L-HH ~ -19 dB, C-HH ~ -6 dB) (Figure 5). This is a reasonable expectation for this class, since it is likely that the roughness of the glacial ice, which is the dominant scattering source, is greater than the roughness of the wet snow cover described in the preceding paragraph. The CD-ROM and Child [1995] confirm that these regions are covered with snow that is smoother and brighter than the wet snow and hence has likely experienced less melting. The altitude range for these regions is 6300–6800 m, varying with aspect.

We interpret the white regions to be predominantly dry snow on rock or, in some cases, dry snow overlying very rough glacial ice. These regions are the highest backscattering in the image (L-HV (~ -6 dB), X-VV (~ -1 dB), and C-HV (~ -1 dB), L-HV (~ -3 dB), C-HH (~ -2 dB)). The fact that the returns are relatively high is consistent with the frequency/polarization signature discussed previously (section 2.2). It may be surprising that the dry snow cover would appear to enhance radar return. We attribute this enhancement to a refraction caused by the dry snow. A refraction of this type
would reduce the effective incidence angle, enhancing backscatter. Spatially, these appear to be distributed on sloping areas that are higher in elevation than the green zones. As mentioned above, these regions are predominantly at the highest altitudes on the eastern side of ridges and the highest portions of glaciers. During the late premonsoon, there is little snowfall, and winds from the NW scour snow from these faces, depositing it onto the east and south faces. The strongest evidence that this cover is dry snow comes from its locations, photographs in the CD-ROM that show climbers dressed for very cold weather climbing on these surfaces, and photographs of the terrain from high on the north face in the work by Child [1995] that show the contrast between exposed rock on the westerly faces and the deposited snow on the easterly faces. In addition to this evidence, the perennially snow-filled Great Couloir shows as a prominent white streak. Evidence of dry snow on glacial ice can be found on the east side of the North Col of Everest, where large patches of dry snow are inter-

In contrast with the other spectral classes, the class shown in red is clearly composed of two distinct land-cover classes. The red areas consist of scree and talus slopes as well as the rock-covered lowest portions of glaciers. The SIR-C/X-SAR measurements alone do not allow for the separation of these classes. The red areas are moderate in L-HV (∼ −14 dB) and C-HV (∼ −11 dB) and high in X-VV (∼ −7 dB). However, the red regions are spectrally variable, with inclusions of blue, green, yellow, and white. Since it is a primary goal of this research to separate glacial classes (including rock-covered glacier) from nonglacial classes such as scree/talus slopes, an alternative method for discrimination was sought. To separate rock-covered glacier from scree and talus slopes, we incorporated a slope criterion. Rock-covered glaciers are primarily on areas of low slope, while the scree and talus zones appear on much steeper slopes. Additional evidence that red regions on low slopes are rock-covered glacier is that they coincide with those regions mapped as rock-covered glacier on the NGS Mount Everest map [Garrett, 1988]. It is necessary to know that the map is of surface cover at minimum snow extent and that the SIR-C/X-SAR overpass occurred during a period of minimal snow during the premonsoon. Photographs confirm that these regions were snow-free during the overpass and are rock-covered glacier [Peak Media Inc., 1995; Child, 1995]. That the higher sloping red areas are scree/talus slopes is also confirmed by such ancillary information. It should be noted that this slope criterion will only be effective for elevations above the glacier terminus, as lower elevation zones may have rock fields on low sloping areas.

4.2. Image Classification

Training site values for each land-cover class were selected as predictor variables in the binary decision tree. The model considered five classes: dry snow, wet snow-covered glacier, dry snow-covered glacier, scree/talus slope, and rock-covered glacier. Since classification trees can accommodate data with high dimensionality (section 2.5), all bands (including slope and ratios) were included without regard to their expected predictive power, and no data reduction routine was applied. As is common practice in the use of decision trees [Breiman et al., 1984], the model was grown to a large tree and then pruned back to avoid overfitting the data. The final dendrogram and the resulting classification are shown (Figure 6 and Plate 2a).

The first split (L-HV = −19.27) divides the classes into the strongly backscattering rock (scree/talus and rock-covered glacier) and dry snow (on rock) classes on one side and the more weakly backscattering snow-covered glacier classes on the other. Splitting rules are selected on the basis of which split produces the greatest reduction in variance. In this analysis, L-HV was chosen as the first split. In this case, the long wavelength and cross polarization of L-HV are clearly the most effective at making this distinction. It is possible that L-HV is more effective than L-HII because the rock and dry snow classes on one side are all rough surfaces with accentuated cross-polarization returns due to multiple interactions, while the smoother glacial classes are not subject to this enhancement of cross-polarized return.

Following the split to the lower backscatter side, the next split uses X-VV = −6.94 dB to separate wet snow covered glacier (X-VV < −6.94 dB). The short wavelength X-band is the most sensitive to wetness and thus is best able to distin-
guish wet snow on this split (the other wavelengths show diminishing value in making the split with increasing wavelength). On the (X-VV > -6.94 dBi) side, which is predominantly dry snow-covered glacier, there is a final split (L-HH/C-HH = -6.19 dBi) that is used to remove a small wet snow-covered glacier class from the dry snow-covered glacier class.

On the right side of the dendrogram, the split, X-VV = -3.14 dBi, is used to separate the rock classes from dry snow (and some remaining rock pixels). Following the left branch of this portion of the tree, we are left with a split based on slope (slope = 16.5°). This is an effective split because of the distinct slope preferences of these classes, as mentioned in the previous section. Note also that the slope criterion is only invoked to distinguish these two classes and does not inappropriately figure into other decisions. The final split on the far right of the dendrogram distinguishes scree (rock) from dry snow (C-IIV = -6.68 dBi).

The classified image map bears a strong resemblance to the false color composite image, with many of the false color composite colors corresponding directly to the classes of the image map. Classification quality is good. Though we do not have field sites or a reference image with which to validate the classification, we can compare the image classes with geo graphically logical patterns of class distribution and with the photos, map, and CD-ROM.

The classes are distributed in a geographically reasonable manner. Dry snow is primarily confined to high altitudes and accumulation zones. Dry snow-covered glacier occurs primarily in high-altitude valleys and cirques. Wet snow-covered glacier follows at lower altitudes. On the east-west oriented Far-East Rongbuk glacier in the center-right portion of the image, a striking wet snow-covered/dry snow-covered glacier division is visible. The lighter blue dry snow covered glacier appears on the north facing slopes of the valley and the shaded southern side of the glacier, while the more irradiated northern side of the glacier is mapped as wet snow-covered glacier. The rock-covered glacial class is, for the most part, confined to the low-altitude glacial ablation zones that are currently devoid of snow. Likewise, the scree and talus class appears in areas of high slope that are not likely to have snow at this time of the season and are not in glacial accumulation zones.

Ancillary data sources generally confirm the classification. We were able to compare the classification map with the NGS map in the cases of the rock-covered glacier class, the scree and talus class, and the non-rock-covered glacier classes (although the NGS map [Garrett, 1988] cannot provide information about the snow cover status of these classes). For these features, agreement is very strong. The glacier boundaries appear to be adequately delineated. In many cases, fine features such as patches of rock cover on small glaciers are visible. The scarcity of snow cover outside of the glaciers is consistent with the very dry conditions that are evident in the CD-ROM. Many corresponding patches of snow cover are identifiable on both the image map and the CD-ROM. Finally, the scree and talus class is successfully mapped on both near facing and far facing slopes (with respect to look direction), which confirms that the terrain correction did not introduce an incidence angle bias insofar as the classification is concerned.

Though not widespread, certain areas were mapped erroneously. There are several areas incorrectly mapped as dry snow, as in the case of the boundary between scree/talus and glacier. It is likely that the rock-covered glacier class is overrepresented. The classifier had some trouble distinguishing the rock-covered glacier class from heavily crevassed glacier and mapped several crevasse zones as rock-covered glacier. This is particularly notable at the confluence of the Main Rongbuk glacier and the West Rongbuk glacier, which comes from image left near the top of the map, and at the heavily crevassed middle portion of the East Rongbuk glacier. Another type of error includes several areas on the far facing slopes adjacent to the large masked zones that the classifier has mapped as wet snow-covered glacier. Though not severe, there are also small erroneous inclusions of glacier classes that appear in scree/talus zones.

Some quantitative measure of error can be determined by generating a confusion matrix of the training site data (Table 4). Note that this table by itself should not be considered as sufficient accuracy assessment, since it is based only on the training site data. Nonetheless, this table can serve as a lower bound to classification errors and thus be useful for giving an indication of what the major problem areas are likely to be. Of key interest are the error of commission and error of omission rates. Errors of commission are those areas that the classifier incorrectly maps as a given class. Errors of omission are areas of a given class that the classifier fails to identify. For instance, dry snow would appear to be underestimated by the classifier. Most areas mapped as dry snow are correct (only 1.90% error of commission), while many areas that are in reality dry snow are missed by the classifier (14.38% error of omission). All of the errors of omission for dry snow were due to incorrect identification of scree/talus or rock covered glacier. These three categories of land-cover constitute the most often confused classes.

4.3. October Imagery

We processed the October imagery in the same manner as the April data. This included using the same incidence angle sensitivity factors so as to produce $\alpha^2$ values that would be comparable. Before classifying the October scene, difference
Table 4. Confusion Matrix for Training Set Data

<table>
<thead>
<tr>
<th>Predicted Class</th>
<th>Reference Class</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dry Snow</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Dry snow</td>
<td>494</td>
</tr>
<tr>
<td>Scree/talus</td>
<td>51</td>
</tr>
<tr>
<td>Rock-covered glacier</td>
<td>37</td>
</tr>
<tr>
<td>Wet snow-covered glacier</td>
<td>0</td>
</tr>
<tr>
<td>Dry snow-covered glacier</td>
<td>0</td>
</tr>
<tr>
<td>Sum</td>
<td>577</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Wet Snow-Covered Glacier</th>
<th>Dry Snow-Covered Glacier</th>
<th>Sum</th>
<th>Errors of Commission, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry Snow</td>
<td>0</td>
<td>0</td>
<td>504</td>
<td>1.98</td>
</tr>
<tr>
<td>Scree/talus</td>
<td>7</td>
<td>10</td>
<td>554</td>
<td>21.66</td>
</tr>
<tr>
<td>Rock-covered glacier</td>
<td>74</td>
<td>10</td>
<td>1053</td>
<td>17.07</td>
</tr>
<tr>
<td>Wet snow-covered glacier</td>
<td>1175</td>
<td>36</td>
<td>1247</td>
<td>5.77</td>
</tr>
<tr>
<td>Dry snow-covered glacier</td>
<td>7</td>
<td>609</td>
<td>619</td>
<td>1.62</td>
</tr>
</tbody>
</table>

|                  | 14.38 | 13.55 | 10.10 | 2.57 | 8.00 |

Images were created from the three primary spectral bands by subtracting the April values from the October values to aid in the understanding and interpretation of the imagery. Of the three, the X-VV difference image is the most revealing in terms of spatial patterns associated with increases and decreases in backscatter between the two dates (Figure 7). The most notable features are the large increases in backscatter between the April and October images over central portions of the East and Far East Rongbuk glaciers. This increase is of the order of 8-17 dB. A similar increase in backscatter is also present in the C-HV difference image. A logical explanation for this increase may be the dryer conditions of the snow on the glaciers on the October date. Drier snow is usually associated with higher backscatter relative to wet snow within the range of wetness found in the environment [Shi and Devi, 1995]. This increase in backscatter is not large over the lower elevation Main Rongbuk glacier (~5600 m versus ~6200 m for the East Rongbuk glacier). This suggests that at this elevation, the snow was wet in both cases. According to the leader of an expedition to Everest during the fall months of 1994, the main Rongbuk glacier was wet and snow-covered during midday for the first half of October (A. Lewis, personal communication, 1997). Also of note are the large spatially contiguous areas of backscatter decrease on the southeast edge of the scene that are tributary glaciers to the Kangnang glacier. These may be areas that were not snow-covered in the April scene, but in the October scene are composed of weakly returning wet snow. Though other parts of the image suggest drier snow conditions, it is likely that these low-elevation and east facing slopes (thus having spent the entire morning in the Sun) were wet at the time of the overflight.

Using the classification rules from the tree grown on the April data, we classified the October imagery (Plate 2b). While the CD-ROM and Child [1995] were useful data sources for the April analysis, they were of only marginal use for the October analysis 6 months later. For this data, take, the primary source of ancillary information beyond the NGS map [Gurteen, 1988] was the hand-held shuttle photograph. Though the image is quite similar to its April counterpart, there are several differences worthy of note. The most prominent of these is the near absence of dry snow on the October image as modeled by the classification tree. The Great Couloir, the ridge between the East and Far East Rongbuk glaciers, and the high slopes east of Everest, were all mapped with large amounts of snow on them in the April imagery, yet appear to be snow-free and mapped as rock in the October imagery. Shuttle photography clearly shows extensive snow cover on the October date. It is likely that the snow is of sufficient dryness to be invisible to radar wavelengths. Another area of change concerns the distribution of the wet and dry snow-covered glacier classes. In the April imagery, these classes are spatially distinct, with the dry snow-covered glacier class for the most part confined to the higher tributary glaciers. In the October imagery, however, the drier class is no longer confined to the upper tributaries of the East Rongbuk, but rather is distributed much more widely and at lower elevations throughout the glacier in a spatially heterogeneous manner. This is consistent with the suggestion in the preceding paragraph that the snow on the glacier is drier in the October imagery. However, at the same time, the image also shows the highest elevation glacier zones with more wet snow-covered glacier in the October imagery than in April. This contradicts the drying trend that is suggested by the increased backscatter at lower elevations. The East Rongbuk glacier shows an increase in area covered by rock covered glacier. The reasons for this remain unclear. The areas of sharp backscatter reduction on the southeast edge of the image are mapped as wet snow-covered glacier as suggested above. These areas are snow-covered on the shuttle photograph.

5. Conclusions

Mode 11 SIR-C/X-SAR data, corrected for incidence angle effects, provide a useful set of measurements for snow and ice mapping of alpine regions. Non-rock-covered glaciers were mapped accurately using only these measurements. Additionally, this set of frequencies and polarizations seems to be able to map dry snow under some conditions. Though successful in April, dry snow in October was not readily discernible using the classification tree from April. Fully polarimetric SAR may be necessary to accomplish this satisfactorily. The addition of a terrain slope variable allowed for the mapping of rock covered glacier. This type of strategy may be useful at other high alpine locations, but its use may be limited because it can be site specific. For example, had the imagery included areas of lower elevation than the lower terminus of the glacier, it is likely that this slope criterion would have mapped these subglacial zones erroneously as rock-covered glacier. There is a need to investigate the effectiveness of the slope parameter in separating rock-covered glacier from scree and talus on images of other locations. For scenes that extend below the minimum elevation of glacier-covered area, perhaps a parameter could be coupled
with elevation information for discriminating these subglacial zones.

We demonstrated an objective method for the selection of the terrain normalization exponent. The exponent that minimizes the absolute value of the slope of the relationship between incidence angle and backscatter yields results that are consistent with findings of other researchers and are obtainable without a priori knowledge of surface cover.

Appendix: Terrain Effects on SAR Backscatter Values

Local incidence angle has several effects on radar return. The first, pixel size effect, is due to the changing scattering area of the target surface with incidence angle, as discussed by van Zyl et al. [1993]. The ground pixel area $A$ varies with local incidence angle $\theta_i$ according to the relationship
\[ A = \delta_a \frac{\delta_0}{\sin \theta_i} \]  
\hspace{1cm} (A1)

where \( \delta_a \) is the azimuth pixel spacing and \( \delta_0 \) is the slant range pixel spacing. Without applying a terrain calibration factor that simulates uniformly sized pixels, pixel area variation will affect backscatter, since backscatter is directly proportional to scattering area. For terrain calibration, we consider the pixel size that would be imaged on level ground to be the reference pixel size and normalize pixels to this standard. A terrain calibration factor \( T \) can be calculated:

\[ T = \frac{\sin \theta_i}{\sin \theta_c} \]  
\hspace{1cm} (A2)

where \( \theta_c \) is level ground incidence angle. Scaling the received backscattering cross section \( \sigma \) by \( T^{-1} \) calibrates the scattering area for image pixels, resulting in the differential backscattering coefficient (or simply, backscattering coefficient), \( \sigma^0 \):

\[ \sigma^0 - \sigma T^{-1} = \frac{\sin \theta_i}{\sin \theta_c} \]  
\hspace{1cm} (A3)

The second effect is a Lambert’s Cosine law effect. The Cosine law states that the flux density \( E \) incident upon a surface at \( \theta_i \) is determined by the relationship

\[ E = E_0 \cos \theta_i \]  
\hspace{1cm} (A4)

where \( E_0 \) is the flux density that would strike a surface normal to the incident beam. To account for this effect, we can solve for \( E_0 \) in order to simulate irradiance upon a normal surface:

\[ E_0 = \frac{E}{\cos \theta_i} \]  
\hspace{1cm} (A5)

The third effect, the surface scattering effect, is based on surface properties and, as such, is target specific [Hinse et al., 1988]. This effect is analogous to the bidirectional reflectance distribution function (BRDF) common in the optical remote sensing literature. Even after accounting for scattering area differences and the Cosine law illumination effect, incidence angle can have considerable effects on \( \sigma^0 \). At optical wavelengths, most surfaces appear rough and are often treated as Lambertian reflectors. At radar wavelengths, however, the scale of topographic variation ranges from a fraction of a wavelength to many wavelengths, resulting in surfaces that range from rough to smooth. In radar, most surfaces have a specular, or coherent, component to scattering, with very smooth surfaces approaching perfectly specular, and rough surfaces tending toward more Lambertian characteristics. Thus roughness is a factor in determining a surface’s backscattering sensitivity to incidence angle. A very rough target such as talus, for instance, will be relatively insensitive to incidence angle compared to a smooth surface. Adding complexity to the relationship is the fact that apparent roughness varies with wavelength. Within the range of common surface roughness, a given surface will appear rougher at shorter wavelengths than at longer wavelengths. If the dominant scattering mechanism is volume scattering rather than surface scattering, the effect of surface roughness in determining the sensitivity of \( \sigma^0 \) to incidence angle will be reduced. This target-specific backscatter dependence on incidence angle can be modeled with a cosine law and removed with its inverse. These models must be adjusted with an exponent \( m \), according to the target conditions and wavelength and polarization of the sensor:

\[ M = M_0 \cos^m \theta_i \]  
\hspace{1cm} (A6)

\[ M_0 = \frac{M}{\cos^m \theta_i} \]  
\hspace{1cm} (A7)

where \( M \) is extinction at \( \theta_i \) and \( M_0 \) is extinction that would occur at a surface normal to the sensor. Substituting \( \sigma^0 \) for the fluxes \( M \) and \( E \), (A6) and (A7) combine to produce the normalized backscattering coefficient:

\[ \sigma^0 - \sigma T^{-1} = \frac{\sin \theta_i}{\sin \theta_c} \cos^m \theta_i \]  
\hspace{1cm} (A8)

where

\[ n = m + 1 \]  
\hspace{1cm} (A9)

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