Comparison of Digital Image Processing Techniques for Classifying Arctic Tundra

By: Roy S. Stine, Debasish Chaudhuri, Peter Ray, Prasad Pathak & Mary Hall-Brown

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Abstract:

The arctic tundra vegetation classified in the study area, Toolik Lake Field Station, Alaska, was relatively small in stature (with varying species growing in clusters) and must therefore be placed in different communities. This study compared different digital image processing classification techniques, including unsupervised, supervised (using spectral and spatial features), and expert systems. The dataset was a pan-sharpened 5 × 5 meter spatial resolution SPOT image. Accuracy assessments based on field inspections of each final map were performed. The expert system classification yielded the highest overall accuracy of 74.66%, with a Kappa coefficient of agreeement of 0.6725.

Keywords: Geology | Tundra | Vegetation | Remote Sensing

Article:

INTRODUCTION

Remote sensing of arctic vegetation contends with various challenges, including frequent cloud cover during the short growing season, the geographic remoteness of the area, which makes obtaining spatially dispersed field validation of classification results difficult to obtain (Stow et al., 2004), and it is expensive, often requiring a helicopter to transport crews to remote locations. Given these limitations, Noyle (1999) suggested that classification accuracy for the tundra biome will always be below levels achieved in other biomes.

A wide variety of research has used remote sensing data to extract vegetation information in the arctic region (Fleming, 1988; Felix and Binney, 1989; Jorgeson et al., 1994; Shippert et al., 1995; Muller et al., 1998; Stow et al., 1998; Walker, 1999). These researchers primarily used Landsat MSS, Landsat TM, and SPOT 20 m datasets in their analysis. Overall image accuracy assessments using field measurements have shown that Felix and Binney (1989) achieved 37%, Stow et al. (1998) 56%, and Fleming (1988) approximately 78% accuracy. The research area in the Fleming (1988) article was to the south and contained a large section of tree stands. The highest classification accuracy obtained on the treeless tundra was accomplished by Muller et al. (1998) at 87%. Their field accuracy assessment procedures were based on helicopter transects stopping at 178 individual locations. The *in situ* measurements were selected by choosing 3 $\times$ 3 50 m pixel blocks of homogeneous land cover. Each individual field truth location could not be closer than 250 m from the previous site. The authors state "…choosing a homogeneous, multiple-pixel sampling unit could introduce a considerable amount of 'optimistic' bias (i.e., overestimation) in estimates of classification accuracy" (Muller et al., 1998, p. 624).

Arctic vegetation remote sensing has generally used unsupervised and spectral-based supervised algorithms as the main digital image processing tool (Fleming, 1988; Felix and Binney, 1989; Stow et al., 1993, 2003, 2004; Jorgeson et al. 1994; Shippert et al., 1995; Muller et al., 1998; Walker, 1999). This study compares the classification results of conventional unsupervised classification, supervised classification using both spatial and spectral parameters, and expert systems using ancillary data and rule- based processes. Unsupervised and supervised classification are widely used conventional methods to classify satellite images. Often user-defined land cover classes extend beyond spectral constraints; therefore, it becomes necessary to integrate other relevant data sources. Knowledge-based classification provides the flexibility to use other data sources along with imagery. Jensen (2005) mentioned that a knowledge based expert classifier uses heuristic knowledge. It imitates human knowledge process to create the knowledge base, which is used to solve the problem or derive a class.The real-life experience of the expert remains critical when formulating the rules for classification.

Various scientists have used a variety of ancillary data to help improve classification performance. Hazarika and Saikia (1996) combined digital elevation models (DEM) and roads and settlements data from 1:50,000 scale topographic maps with Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) data (with 30 m resolution), Indian Remote Sensing Satellite (IRS-1C) Linear Image Self-Scanning (LISS) III data (with 23.5 m resolution), and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data (with 15 m resolution). They found that rule-based classification improved suitability models for various types of habitat. In the identification of springs associated with mine drainage, rule-based classification that combined DEMs, thermal infrared data, and orthophotos produced lower errors of omission than standard classification techniques (Jennings, 2002). Expert classifiers have also been used in a various vegetation studies.

Research carried out by Schweitzer et al. (2005) showed efficient use of expert classification in agriculture. They performed time series analysis on multiple Landsat ETM+ and Moderate-Resolution Imaging Spectroradiometer (MODIS) images. Cropspecific normalized difference vegetation index (NDVI) numbers were derived and combined with various water supply conditions to derive accurate classifications of crops such as cotton, rice, and wheat. Their study concluded that expert classification was useful to identify different plants and the different life stages of those crops. Likewise expert classification was used to identify tree species and the age of forest stands from IKONOS high-resolution imagery. Textural analysis and parameters such as NDVI, IR-Green, variance of the panchromatic band, band 4 of a tasseled cap image, and standard deviation of Red‑Green, Red/Green were used to identify evergreen and broadleaved species. Rule-based classification proved valuable and the authors (Schweitzer et al., 2005) felt that the results could be improved with secondary data such as soil maps or DEMs. Other authors have cautioned that an exhaustive knowledge base is critical to avoid incorrect classification results (Clasen et al., 2006).

This research is motivated by the need to apply new digital image classification techniques to create accurate vegetation maps from higher spatial resolution satellites (i.e. SPOT-5), which will be useful for scientific research in the area. The specific objectives of this research study include: (1) application of knowledge-based classification techniques with geospatial and spectral knowledge using the SPOT-5 satellite image data for unique tundra vegetation in Alaska; and (2) comparison and contrast of image classification performance between the proposed classification and the standard (spectral) classification techniques (unsupervised ISODATA clustering and supervised classification with Feature Analyst). The results indicated higher classification accuracy (74.66%, with Kappa value of .6725) for the proposed hybrid classification method than the standard classification techniques: unsupervised clustering technique (68.3%, with Kappa value of 0.5904) and supervised classification with Feature Analyst (62.44%, with Kappa value of 0.5418). The results were statistically significant at the 95% confidence level.

STUDY AREA

The study area covers approximately 650 km2 surrounding the University of Alaska Fairbanks' Toolik Lake Field′ Station (68° 38 ´ N. Lat., 149° 36 ´ W. Long.). This region lies in the foothills of the Brooks Range on the Arctic North Slope of Alaska (Fig. 1). This tundra area was glaciated during the middle to late Pleistocene era. Three main glacial drift deposits, namely, Sagavanirktok (broadly dating from 780,000 to 125,000 BP), Itkillik I (around 53,000 BP), and Itkillik II (about 25,000 to 11,400 BP), are dissected by the Itkillik River to the west, the Kuparuk River in the center, and the Sagavanirktok River to the east. The heterogeneous landscape of gently rolling topography ranging from 400 to 1,300 m in elevation is scattered with crystal-clear small glacial lakes, kames, moraines, and a variety of glacial outwash sequences along the river channels. The soil is mostly poorly drained acidic peat over loess, with an active layer of about 0.3‑1.5 m deep, underlain by permafrost. The average yearly precipitation is approximately 318 mm, and the average temperatures in July and December are 10° and ‑25° C, respectively (Hamilton, 2002; Hamilton and Porter, 1975; Calkin et al., 1983; Walker et al., 1994, 1998; and the Arctic LTER [website http://ecosystems.mbl.edu/ARC/]).

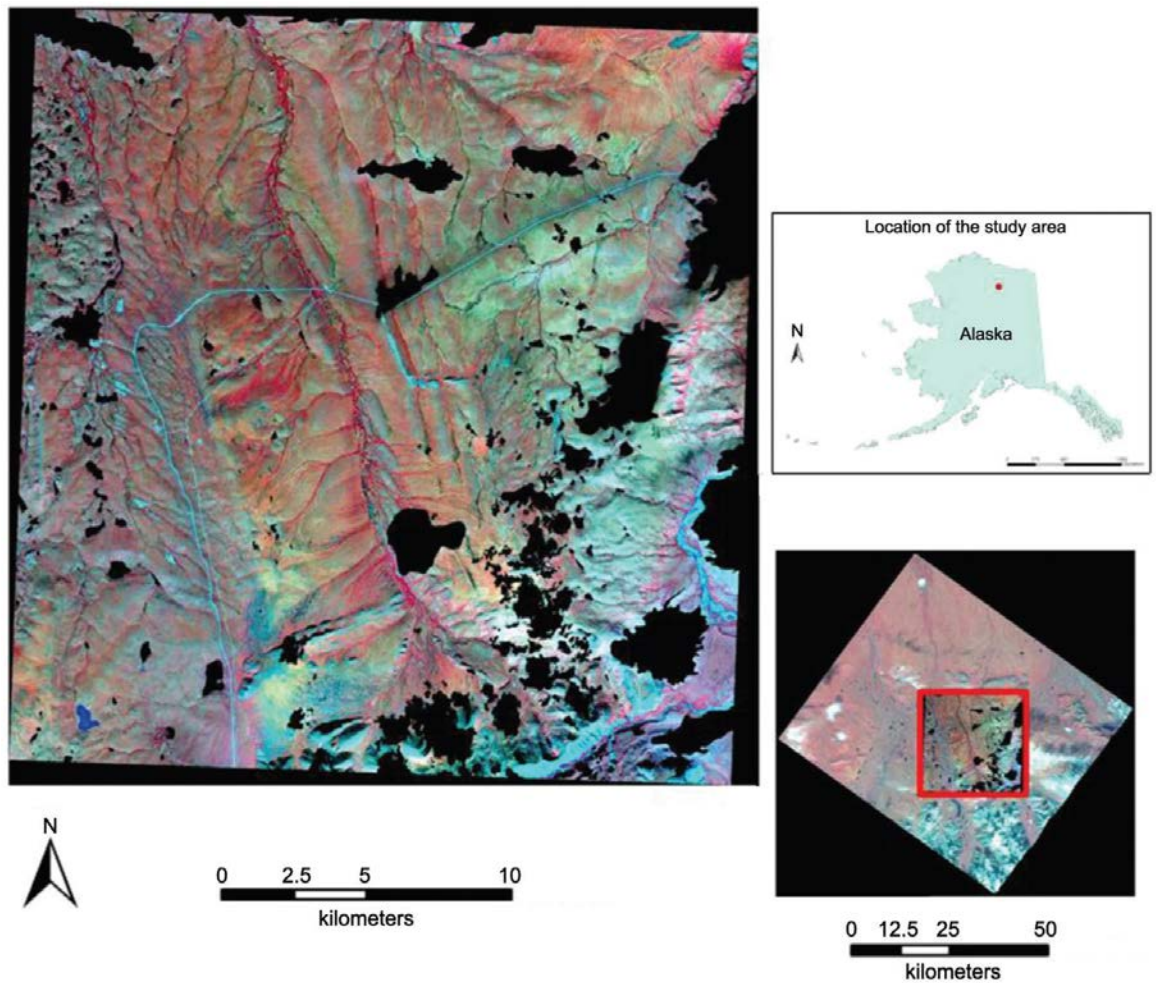

Fig. 1. Toolik Alaska Study Area (inset top right) and the subset of SPOT image (cloud and shadow pixels removed) used and the subset on the entire image in the inset (bottom right) (RGB 3, 2, 1).

METHODS

This project investigated satellite imagery, ancillary data, and classification methods to determine optimum procedures for creating accurate vegetation maps that show the heterogeneity of the arctic tundra landscape. A SPOT-5 image (acquired July 25, 2005) was used in this research. The image was a 10 × 10 m multispectral (green .5‑.59 mm; red .61‑.68 -mm; near infrared .78‑.89 mm) dataset with a 2.5 × 2.5 m panchromatic band. SPOT Image, Inc. preformed a pan-sharpening resolution merge (merging the panchromatic band with the multispectral bands) and produced a 5 × 5 m green, red, near- infrared, multispectral dataset. The SWIR (shortwave infrared) band was not within the budget constraints of the project. An

NDVI layer was created and placed in the dataset and used in each classification. The NDVI layer was added because it has been shown to help differentiate vegetation complexes growing on acidic vs. non-acidic soil types, as well as areas of little vegetation (barrens) and taller vegetation types such as shrubs (Jia, et al. 2002; Walker, 1999; Walker et al., 2007).

Also considered and tested was a scanned geologic map at 1:25,000 (Walker et al., 2003). In each classification, this layer lowered overall accuracies and was therefore excluded in all classifications. The final layers tested were aspect and slope maps generated from the 5 $\times$ 5 m DEM provided at the Toolik website (http://www.uaf.edu/toolik/gis). These layers proved useful for the knowledge-based classifier. In both the unsupervised and supervised classifications, they resulted in lower accuracy results and were discarded.

The image was corrected to the World Geodetic System (WGS) 84 ellipsoid and the Universal Transverse Mercator (UTM) Zone 6. Geometric correction was performed by using a Trimble GeoXT in the field, during the summers of 2006 and 2007, and differential correction using the Toolik Field site's base station (http://www.uaf.edu/toolik/gis/TFS GIS gps base.html). RMSE was around 5 m (or one pixel) throughout the image. Ground control points (GCPs) away from the haul road and the pipeline (Fig. 1) were difficult to accurately place and increased the error rate, especially at points away from cultural features. All subsequent data were georectified to the image using 64 GCPs with RMS error of 4.9 m, which is less than a pixel (5 m) using a postprocessed differential correction. The image we selected contained some cloud cover, because no images could be located for the short growing season that contained zero percent cloud cover. Therefore, due to the low sun angle, the clouds and their shadows obscured various portions of the scene. Clouds were confused with barren areas and shadows were similar to water; therefore both clouds and shadows were removed from the scene prior to analysis.

The field work was conducted during the summers of 2006 and 2007, with approximately 10 field days each summer. More than 350 ground reference data points were created around Lake Toolik and in selected watersheds within the research area. The watersheds were chosen from the NSF grant specifications and to optimize helicopter cost. Most of the watersheds in the image were not easily accessible without a helicopter which in turn was extremely expensive. The costs of the helicopter time and expense of the length of stay at the field accommodations were limiting factors in the number of ground reference points that could be acquired. In 2006, a simple random sampling method was used to generate ground reference points, and homogenous areas of vegetation complexes were identified and collected by creating polygons with the GPS units. The SPOT image was subsequently classified with an ISODATA clustering method into 30 classes.

The classes were preliminarily identified with the help of the training data collected and using the vegetation map by Walker et al. (1994) as a reference. In 2007 the preliminary classified image was used as a basis for stratified random sampling. At this time stratified random points were created for each watershed visited, with points being placed in every vegetation class. The number of points generated for each class related to the overall areal extent of the class. When the watershed was visited as many points as possible were sampled. The authors made sure to collect data from each of the preliminary vegetation classes. During both seasons, the X and Y coordinates were collected at the ground points, vegetation types were noted, and photographs taken for later verification. If the vegetation surrounding the point locations was markedly different, such as at transition zones or when a small isolated vegetation complex was present (approximately less than or equal to 5 m2), the authors noted the vegetation at the point and of the surrounding area. When generating accuracy assessment numbers, the option to consider the surrounding pixels was selected. The authors also chose homogenous *in-situ* locations that contained particular types of vegetation to be used as training data in the 2007 season as well. In all, 128 ground reference data points were used to train the supervised classification and the expert system and 221 random or stratified random reference points were used to assess the accuracy of the classifications.

The number of *in-situ* ground truth points are some of the highest recorded to date (Fleming, 1988; Felix and Binney, 1989; Stow et al., 1993, 2003, 2004; Jorgeson et al., 1994; Shippert et al., 1995; Muller et al., 1998; Walker, 1999).

CLASSIFICATION SCHEME

The overall vegetation class guidelines were derived from the Braun-Blanquet approach, a standard hierarchical system of vegetation classification based on plantcommunity floristics used worldwide (Westhoff and van der Maarel, 1978). Vegetation classes developed by Walker et al. (1994), Muller et al. (1998), and the authors' observations in the field were used to create the seven vegetation complexes and clouds, shadows, and water categories (Table 1) used in this research.

Unsupervised Classification (ISODATA Clustering)

In unsupervised classification, the software organizes the data by grouping similar spectral characteristics into unique clusters based on some statistically determined criteria. The analyst then re-labels and combines the clusters into classes of interest (Jensen, 2005). This research used the Iterative Self-Organizing Data Analysis Technique (ISODATA). The three bands of the SPOT image and a derived NDVI band (all with clouds and water pixels removed) were combined to form a single image. The authors chose 60 clusters with the number of iterations set to 20 and the convergence threshold placed at 0.95. Clusters that were evident were identified by using training pixels belonging to the corresponding majority class. For clusters that were difficult to identify due to spectral mixing, a cluster-busting approach was implemented (Jensen, 2005). A binary mask was created and the pixels that could not be identified in the first pass were subjected to a subsequent ISODATA clustering. Some clusters representing the class "barren complex" in the Brooks Range or representing shallow water were obvious, but for other clusters the field knowledge of the area, spatially adjacent clusters that were previously identified, aerial photos, Landsat imagery from 2000, and maps by Walker et al. (1994) and Muller et al. (1998) were considered before assigning the class values. Finally, after seven subsequent passes, all these clusters were grouped into the seven vegetation land cover classes and recoded in order to produce the final classified image (Fig. 2).

Supervised Classification (Feature Analyst)

Both traditional unsupervised and supervised spectral-based approaches have been routinely applied to remotely sensed data. These classifiers rely entirely upon the spectral information in an image. For this research the authors selected Feature Analyst (FA), a commercial software application by Visual Learning Systems, Inc. (VLS), and ERDAS Imagine. This approach incorporates spectral and multiple spatial attributes (i.e., size, shape, texture, pattern, and spatial association) as well as advanced inductive machine learning techniques to classify high-resolution satellite imagery (Al-AbdulKader et al., 2002; O'Brien, 2003). For this type of supervised classification the researchers provide training sites for each vegetation complex of interest. These training sites are areas of a known vegetation complex that have been verified in the field, and then identified on the image. The authors then used heads-up digitizing to create a polygon around the vegetation complex. Using the identified polygon, the software will make a pass over the entire image. Based on spectral and spatial similarities with the training polygon, the software will try to place all similar pixels and groups of pixels in the same vegetation class. This process is completed for each of the vegetation classes created. The researchers may then refine the results by interactively editing the image, identifying "correct," "incorrect," and "missed" areas; in this iterative fashion the analyst will re-run the process as often as needed to obtain the best results.

Table 1. Vegetation Complexes Used in Classification[a]

1. Moist Low-Shrub Tundra and Other Shrublands. Areas dominated by low shrubs (more than 50% of cover). Upland areas dominated by dwarf and low shrubs (primarily willows, but also commonly *Betula nana* and, to the north of the area in Figs. 2 and 4, *Alnus crispa*), mainly on interfluvial areas with well developed moss carpets. These are common on lower hill slopes, in association with water-track complexes, and some floodplain areas. Areas dominated by willows along water tracks, streams, and rivers (riparian shrubs), which includes willow communities in water tracks: *Salix pulchra*, *S. alaxensis, S. richardsonii, S. glauca*, *Betula nana*, *Calamagrostis canadensis*.
2. Water and Aquatic Complex. Marshes and aquatic vegetation in > 50% standing water: *Carex aquatilis*, *Eriophorum angustifolium, Arctophila fulva, Hippuris vulgaris, Sparganium hyperboreum* .
3.Barren Complex. Roads, disturbed (anthropogenic) and re-vegetated gravel mines, construction pads, lichen-covered areas (*Cetraria nigricans, Rhizocarpon geographicum*, etc.) and partially vegetated (<50%) exposed rocks in foothills and mountains; barren and partially vegetated river alluvium.
4. Snowbed Complex. Areas dominated by *Cassiope tetragona*, along with *Ledum decumbens* and *Diapensia lapponica* in acidic sites and *Dryas integrifolia*, *Salix reticulata* and *S.*

rotundifolia in nonacidic sites, and often with the tall herb *Boykinia richardsonii,* and fruticose lichens (*Cladina spp. Cetraria spp., Nephroma arctica*). This type of vegetation can occur in local areas where winter snowdrifts accumulate, but the larger areas (up to 0.5 km across) identified here as “snowbed” probably are not (or not entirely) actual snowdrift areas (see text).
5. Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex. This is the widespread tussock tundra locally known as moist acidic tundra (MAT) found in moist acidic hill slopes and moderately drained terrain with pH usually < 5.5 dominated by tussock-sedges, nontussock sedges, dwarf shrubs, and mosses. *Eriophorum vaginatum*, *Carex bigelowii, Betula nana, Ledum decumbens, Vaccinium vitis-idaea, V. uliginosum, Salix pulchra, S. glauca, Rubus chamaemorus* and, among many mosses, *Sphagnum* spp. and *Hylocomium splendens.*
6. Wet Graminoid Tundra, often called Wet Sedge Tundra (WST). Rich fens on wetland areas with organic soils (pH > 4.5) dominated by sedges and mosses. Poor fens in wetland areas with organic soils (pH < 4.5) and dominated by sedges. Lawns of *Sphagnum spp.* And sedges are common around the margins of basins of poor fens and some water tracks and foothills. *Carex chordorrhiza, C. aquatilis, C. rotundata, C. membranacea, C. bigelowii, etc.; Eriophorum angustifolium, Trichophorum caespitosum.*
7. Moist Graminoid, Prostrate-Shrub Tundra Complex. A. Locally known as moist non-acidic tundra (MNT), found in moist non-acidic hill slopes and moderately well drained surfaces (pH > 5.5) dominated by non-tussock sedges, prostrate and dwarf shrubs, and mosses. *Carex bigelowii* , *Astragalus umbellatus, Dryas integrifolia,* with *Eriophorum vaginatum* being less abundant than in class 5 and usually much less dominant than it is there. B. Dry nonacidic river terraces and gravelly well-drained slopes (pH > 5.5) dominated by *Dryas integrifolia* as well as prostrate dwarf shrubs (mostly Ericaceous) and lichens. C. Dry acidic tundra on hill and ridge crests, moraines, and kames (with pH < 5.5), typically found on coarse, gravelly glacial tills and outwash deposits, steep south-facing slopes and alpine areas in the mountains. Dominated by low or prostrate, mostly Ericaceous dwarf shrubs: *Ledum decumbens, Arctostaphylos alpina, Vaccinium vitis-idaea, Empetrum hermaphroditum, Loiseleuria procumbens*; and/or dominated by *Dryas octopetala.* Also important locally in it: *Salix phlebophylla, Diapensia lapponica, Hierochloe alpina, Betula nana* (Walker et al., 1994; Muller et al., 1998).
8. Clouds
9. Shadows

[a]Based on Walker et al. 1994; Muller et al. 1998; and field observations by the authors

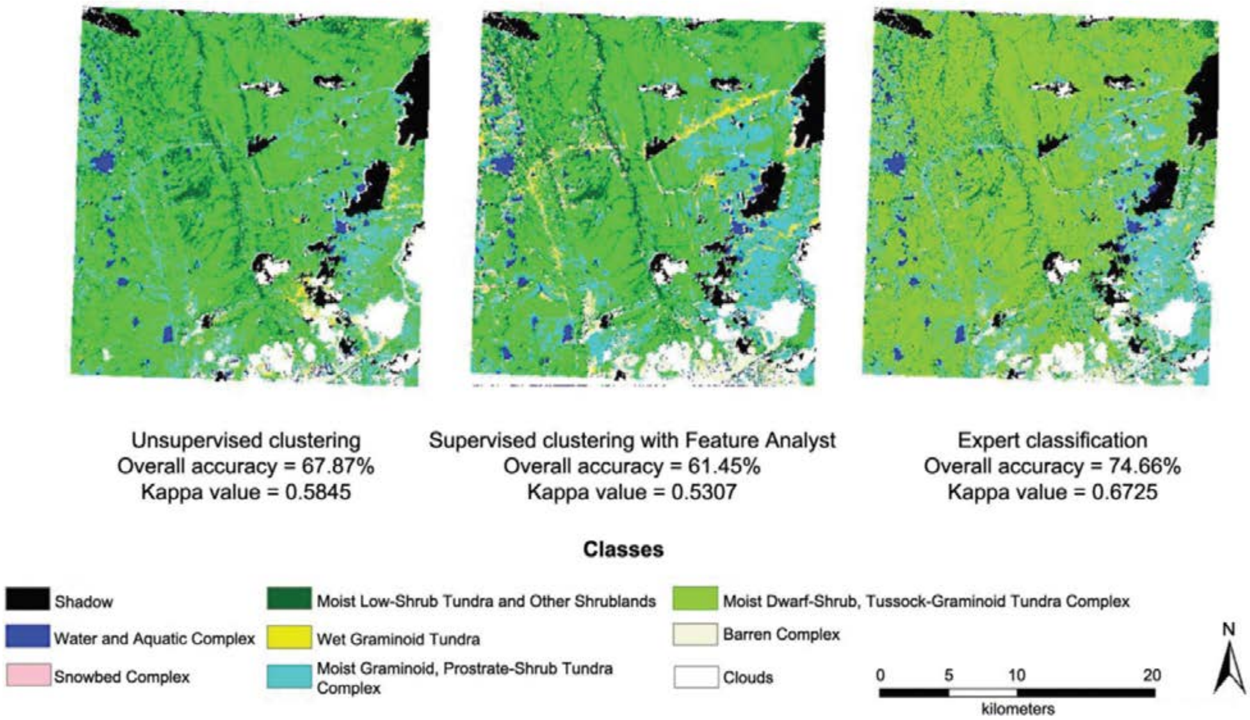

Fig. 2. Comparison of classified images.

The same image data consisting of the three bands of the SPOT image combined with the NDVI as the fourth band were used for classification. An input representation is an important aspect in Feature Analyst that enables the learner to look for the surrounding pixels selected by the user in order to more accurately extract features. Among all the available input representations, the "Foveal" representation (with pattern width 3) gave the most consistent results for extracting features in the lakes (shoals or shallow aquatic) from all other reflective surfaces. Numerous training polygons (training set mentioned earlier) were created for each vegetation class represented in the area. Careful attention was given so that the features of interest (i.e., different vegetation classes) were spatially dispersed throughout the image and contained a variety of spectral and spatial diversity within each class. Throughout the image the same vegetation complex could yield widely different spatial patterns and spectral reflectance. Therefore, a multilayered classification scheme was prepared in which the same vegetation training classes (for instance, Snowbed Complex) were created throughout the spatial extent of the image (wall-to-wall classification). Feature Analyst is very sensitive to spatial pattern for extracting features, and none of the vegetation classes (except for shrub complex, and more specifically riparian shrubs that are found along streams and water channels that generally show a network pattern) show any type of spatial pattern. After trying a variety of training polygon shapes and sizes, it was decided to make the input polygon patterns as diverse as possible with respect to shape and size. By using different training shapes, sizes, and homogenous samples for all the vegetation classes, some improvements were made during the feature extraction process. However, the lack of spatial pattern for each vegetation category was a possible hindrance for this classifier. All of the selected classes were then used as input. After the first pass, each of the classes were trained, corrected, and clutter was removed (Fig. 3). The iterative process was followed until the best results were obtained. Once the final results were obtained, the individual training polygons were assigned to their appropriate class–i.e., one of the seven vegetation complexes listed in Table 1. The final map is shown in Figure 2.

Expert Classifier (ERDAS Imagine)

The Expert Classifier in ERDAS Imagine implements multiple rules that are linked together into a hierarchy that describes a final set of target informational classes.

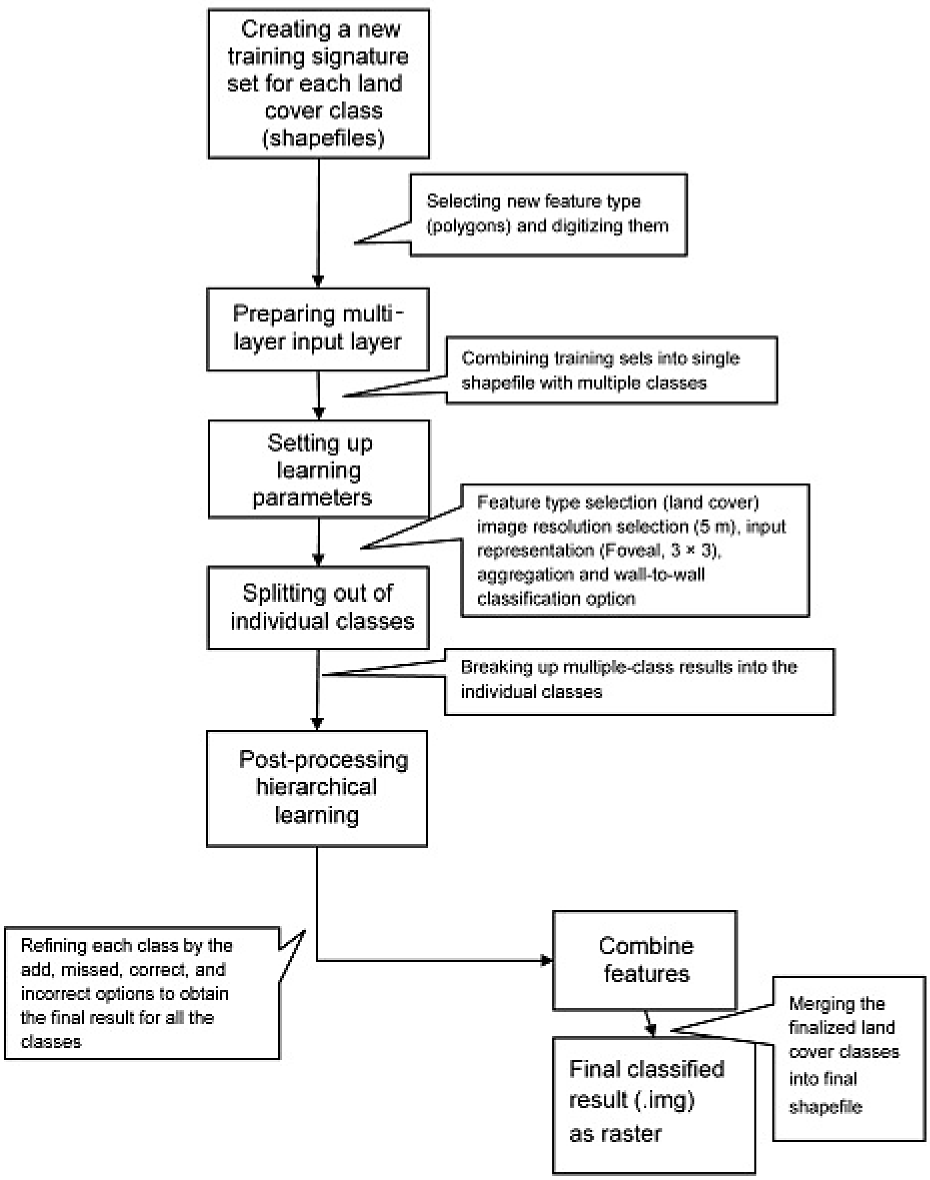

Fig. 3. Flow chart showing the work flow for supervised classified image with Feature Analyst.

An Expert Classifier has two major components, the Knowledge Engineer and the Knowledge Classifier. The Knowledge Engineer provides a graphical user interface to build a knowledge base that is represented as a tree diagram consisting of final and intermediate class definitions (hypotheses), rules (conditional statements concerning variables), and variables (raster, vector, or scalar). The Knowledge Classifier provides an interface to implement the developed knowledge base in classifying an image. Acquisition of knowledge is a constraint for the knowledge-based classifier. One needs holistic knowledge about the study area and the class composition before assigning the rules for the individual classes. The researchers' knowledge can lead to biased information. The second problem is known as the "knowledge acquisition bottleneck," which refers to the problem of inefficient formulation of the gathered knowledge in a systematic, correct, and completely usable format for quantitative analysis (Huang and Jensen, 1997).

Three bands of the SPOT image and the NDVI layer were used. In this analysis the authors also used slope and aspect layers generated from the 5 m DEM located on the Toolik website (http://www.uaf.edu/toolik/gis). All of these layers were used to derive the rules for this classification. Representative sites that were verified in the field and contained GPS coordinates were located on the image for each class and were used to create the training data set (as mentioned earlier). Hypotheses and rules for each class were derived based on spectral properties of these sites and the related secondary data. The entire image was classified according to the rules created in Table 2. Each of the land cover classes derived preliminarily were saved and then used as a constraint in deriving the final informational classes. A buffer of 2 pixels (10 m) was created around the water class, and was temporarily called shallow fen because in the most obvious cases these pixels represented shallow fen-type vegetation and/or mixed pixels consisting of water/fen, water/tundra, or water/shallow rocks.

In various locations throughout the image, the Snowbed Complex and Wet Graminoid Tundra Complex had severe interclass spectral mixing. Likewise Shrubs and Wet Graminoid Tundra showed interclass mixing, confusing especially riparian shrubs in the northern section of the image with Wet Graminoid Tundra in the southern portion of the image. The Wet Graminoid and the Moist Dwarf-Shrub Tussock-Graminoid Tundra Complex were often confused. Most of these spectral mixing problems were handled by the constraint classes using the NOT IN clause inasmuch as the previously prepared land cover classes contained least spectral mixing. These areas where known classes were intermixed were masked out of the classified image.

The masked area including the buffer around the water and the areas that could not be exhaustively classified contained approximately 19% of the image. A second set of rules (Table 3) was generated for the portion of the scene that was masked and unclassified and the areas of known confusion. The major differences between the two rule sets were commands that did not allow unclassified areas to exist in the second run and rules to force a decision between two areas of confusion. For instance, if an area was placed in a class and a second rule could also place it in a different category, the disqualifier rule would not allow this to occur. This obviously forced the merging of several classes but it allowed for the exhaustive classification of the image. Also having approximately 81% of the image excluded from this second run created less spectral mixing between the northern and southern portions of the image. The results of the two rule-based classifications (Tables 2 and 3) were then merged to create the final knowledge-based map (Fig. 4).

RESULTS AND DISCUSSION

In general the knowledge-based classifier performed best (Table 4). It achieved an overall accuracy of 74.66% with a Kappa of 0.67. This was followed by unsupervised classification at 67.87% with a Kappa of 0.58 and the supervised classification using FA with an overall accuracy of 61.45% and a Kappa of 0.53. The classes Shadow and Clouds were not included in the accuracy assessment. The authors were focusing on vegetation discrimination and it was felt that including these classes would artificially raise the overall accuracy of the map. In general the major problems for all of the classifications included low sun angle, clouds, shadows and spectral mixing. Many of the spectral mixing problems were reduced, but MAT (Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex) and MNT (Moist Graminoid, Prostrate-Shrub Tundra Complex) showed the highest degree of spectral mixing between the two classes.[2]

These classes were largely influenced by geological history (i.e., acidic vs. non-acidic soils), and spectral differences did not always distinguish the complexes (Stow et al., 2004; Walker et al., 1994; Walker et al., 2007). The authors also found that the vegetation complexes termed shrub and WST (Wet Graminoid Tundra) were often the same spectrally over a spatial distance; for instance, riparian shrub corridors in the northern section of the image gave the same spectral readings as WST in the southern portion of the image. This was generally not the case within the watershed of a lake. WST was the hardest complex to identify and accounted for the lowest overall accuracy rating in each classification.

Table 2. Rules for the First Pass in the Expert Classifier System

Rule for Moist Low-Shrub Tundra and Other Shrublands. (IF Band1 >= 86 AND Band1 <= 106, Band2 >= 86 AND Band2<= 101, Band3 >= 140 AND Band3 <= 163, NDVI >= 0.182 AND NDVI <= 0.293, NOT in Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex) OR (IF Band1 >= 75 AND Band1 <= 120, Band3 >= 90 AND Band3 <=187, NDVI >= 0.205 AND NDVI <= 0.4447, NOT IN class Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex) → Moist Low-Shrub Tundra and Other Shrublands Complex
Rule for Water and Aquatic Complex. (IF Band1 > 0 AND Band1 <= 88, Band2 > 0 AND Band2 <= 76, Band3 > 0 AND Band3 <= 82, NDVI >= -0.111 AND NDVI <= 0.101) OR (IF Band1 > 0 AND Band1 <= 88, Band2 > 0 AND Band2 <= 76, Band3 > 0 AND Band3 <= 82, NDVI <= -0.314902) OR (IF Band1 >= 97 AND Band1 <= 127, Band2 >=75 AND Band2 <= 106, Band3 >= 22 AND Band3 <= 50, NDVI <= -0. 0.314902) OR (IF Band1 < 88, Band2 <= 95, Band3 >= 18 AND Band3 <= 64, NDVI <= -0.111, Not in mountain shadow region) → Water and Aquatic Complex
Rule for Barren Complex. (IF Band1 >= 105, Band2 >= 90, Band3 >= 45 and Band 3 <= 145,

NDVI >= -0.349087 AND NDVI <= 0.0725263, NOT IN shallow water, Not in class Moist Graminoid, Prostrate-Shrub Tundra Complex) OR (IF NDVI > -0.328 AND NDVI < -0.033826, DEM > 1034, Not in Water and Aquatic Complex) OR (IF Band1 >= 90 AND Band1 <= 111, Band2 >= 80, Band3 >= 45 and Band 3 <= 161, NDVI >= -0.349087 AND NDVI <= 0.0725263, Not in shallow water, DEM >= 947.569 AND DEM <= 1024.41, IN low-elevation region) OR (IF Band1 >= 88, Band2> 75, Band3 >= 54, NDVI <= -0.025, Not in Water and Aquatic complex) → Barren Complex
Rule for Snowbed Complex. (If Band1 >= 85 AND Band1 <= 97, Band2 >= 72 AND Band2 <= 88, Band3 >= 78 AND Band 3 <= 100, NDVI <= 0.064 AND NDVI <= 0.101, (aspect > 0 AND aspect < 90) OR (aspect > 270 AND aspect < 360), slope < 16, Not in Water and Aquatic Complex, NOT IN Wet Graminoid Tundra, slope < 16) OR (snowbed-WST = 4, (aspect > 0 AND aspect < 90) OR (aspect > 270 AND aspect < 360), slope <16, Not in Water and Aquatic Complex, NOT IN Wet Graminoid Tundra, slope < 16) OR(snowbedWST = 5, (aspect > 0 AND aspect < 90) OR (aspect > 270 AND aspect < 360),slope < 16, Not in Water and Aquatic Complex, NOT IN Wet Graminoid Tundra, slope <16) → Snowbed Complex
Rule for Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex. (If Band1 >= 85 AND Band1 <=100, Band2 >= 77 AND Band2 <= 97, Band3 >= 107 and Band3 <= 147, NDVI >= 0.077 AND NDVI <= 0.244, Not in Moist Graminoid, Prostrate-Shrub TundraComplex) → Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex
Rule for Wet Graminoid Tundra. (If Band1 >= 74 AND Band1 <= 97, Band2 >= 62 AND Band2 <= 99, Band3 >= 60 AND Band3 <= 114, NDVI >= -0.105 AND NDVI <=0.062, Not in Water and Aquatic Complex, Not in Snowbed Complex) → Wet Graminoid Tundra
Rule for Moist Graminoid, Prostrate-Shrub Tundra Complex. (If Band1 >= 89 AND Band1 <= 114, Band2 >= 89 AND Band2 <= 106, Band3 >= 96 AND Band3 <= 126, NDVI >= 0.004 AND NDVI <= 0.126) → Moist Graminoid, Prostrate-Shrub Tundra Complex

Table 3. Rules for the Second Pass in the Expert Classifier System

Rule for Moist Low-Shrub Tundra and Other Shrublands. (IF Band1 >= 86 AND Band1 <= 106, Band2 >= 86 AND Band2 <= 101, Band3>= 140 AND Band3<= 163, NDVI >= 0.182 AND NDVI <= 0.293, Not in Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex) OR (IF Band1 >= 75 AND Band1 <= 120, Band3>= 90 AND Band3< = 187, NDVI >= 0.205 AND NDVI <= 0.4447, Not in class Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex) OR (Restclassified = 1) → Moist Low-Shrub Tundra and Other Shrublands Complex
Rule for Water and Aquatic Complex. (IF Band1 > 0 AND Band1 <= 88, Band2 > 0 AND Band2 <= 76, Band3 > 0 AND Band3 <= 82, NDVI >= -0.111 AND NDVI <= 0.101) OR (IF Band1 > 0 AND Band1 <= 88, Band2 > 0 AND Band2 <= 76, Band3 > 0 AND Band3 <= 82, NDVI <= -0.314902) OR (IF Band1 >= 97 AND Band1 <= 127, Band2 >= 75 AND Band2 <= 106, Band3 >= 22 AND Band3 <= 50, NDVI <= -0. 0.314902) OR (IF Band1 < 88, Band2 <= 95, Band3 >= 18 AND Band3 <= 64, NDVI <= -0.111, Not in Mountainshadow region) → Water and Aquatic Complex
Rule for Barren Complex. (IF Band1 >= 105, Band2 >= 90, Band3 >= 45 and Band 3 <= 145, NDVI >= -0.349087 AND NDVI <= 0.0725263, not in shallow water, Not in class Moist Graminoid, Prostrate-Shrub Tundra Complex) OR (IF NDVI > -0.328 AND NDVI < -0.033826,

DEM > 1034, Not in Water and Aquatic Complex) OR (IF Band1 >= 90 AND Band1 <= 111, Band2 >= 80, Band3 >= 45 and Band 3 <= 161, NDVI >= -0.349087 AND NDVI <= 0.0725263, Not in shallow water, DEM >= 947.569 AND DEM <= 1024.41, IN low-elevation region) OR (IF Band1 >= 88, Band2> 75, Band3 >= 54, NDVI <= -0.025, Not in Water and Aquatic Complex) OR (Restclassified = 3) → Barren Complex
Rule for Snowbed Complex. (If Band1 >= 85 AND Band1 <= 97, Band2 >= 72 AND Band2 <= 88, Band3 >= 78 AND Band 3 <= 100, NDVI <= 0.064 AND NDVI <= 0.101, (aspect > 0 AND aspect < 90) OR (aspect > 270 AND aspect < 360), slope < 16, Not in Water and Aquatic Complex, not in Wet Graminoid Tundra, slope < 16) OR (snowbedWST = 4, (aspect > 0 AND aspect < 90) OR (aspect > 270 AND aspect < 360), slope < 16, Not in Water and Aquatic Complex, Not in Wet Graminoid Tundra, slope < 16) OR (snowbed-WST = 5, (aspect > 0 AND aspect < 90) OR (aspect > 270 AND aspect < 360), slope < 16, Not in Eater and Aquatic Complex, Not in Wet Graminoid Tundra, slope < 16) OR (Restclassified = 4, Not in shallow fen) → Snowbed Complex
Rule for Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex. (If Band1 >= 85 AND Band1 <= 100, Band2 >= 77 AND Band2 <= 97, Band3 >= 107 and Band3 <=147, NDVI >= 0.077 AND NDVI <=0.244, Not in Moist Graminoid, Prostrate-Shrub Tundra Complex) OR (Restclassified = 5, Not in Moist Graminoid, Prostrate-Shrub Tundra Complex) → Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex
Rule for Wet Graminoid Tundra. (If Band1 >= 74 AND Band1 <= 97, Band2 >= 62 AND Band2 <= 99, Band3 >= 60 AND Band3 <= 114, NDVI >= -0.105 AND NDVI <= 0.062, Not in Water and Aquatic Complex, Not in Snowbed Complex) OR (Restclassified = 6) OR (Restclassified = 4, shallowfen = 1) → Wet Graminoid Tundra
Rule for Moist Graminoid, Prostrate-Shrub Tundra Complex. (If Band1 >= 89 AND Band1 <= 114, Band2 >= 89 AND Band2 <= 106, Band3 >= 96 AND Band3 <= 126, NDVI >= 0.004 AND NDVI <= 0.126) OR (Restclassified = 7) → Moist Graminoid, Prostrate-Shrub Tundra Complex

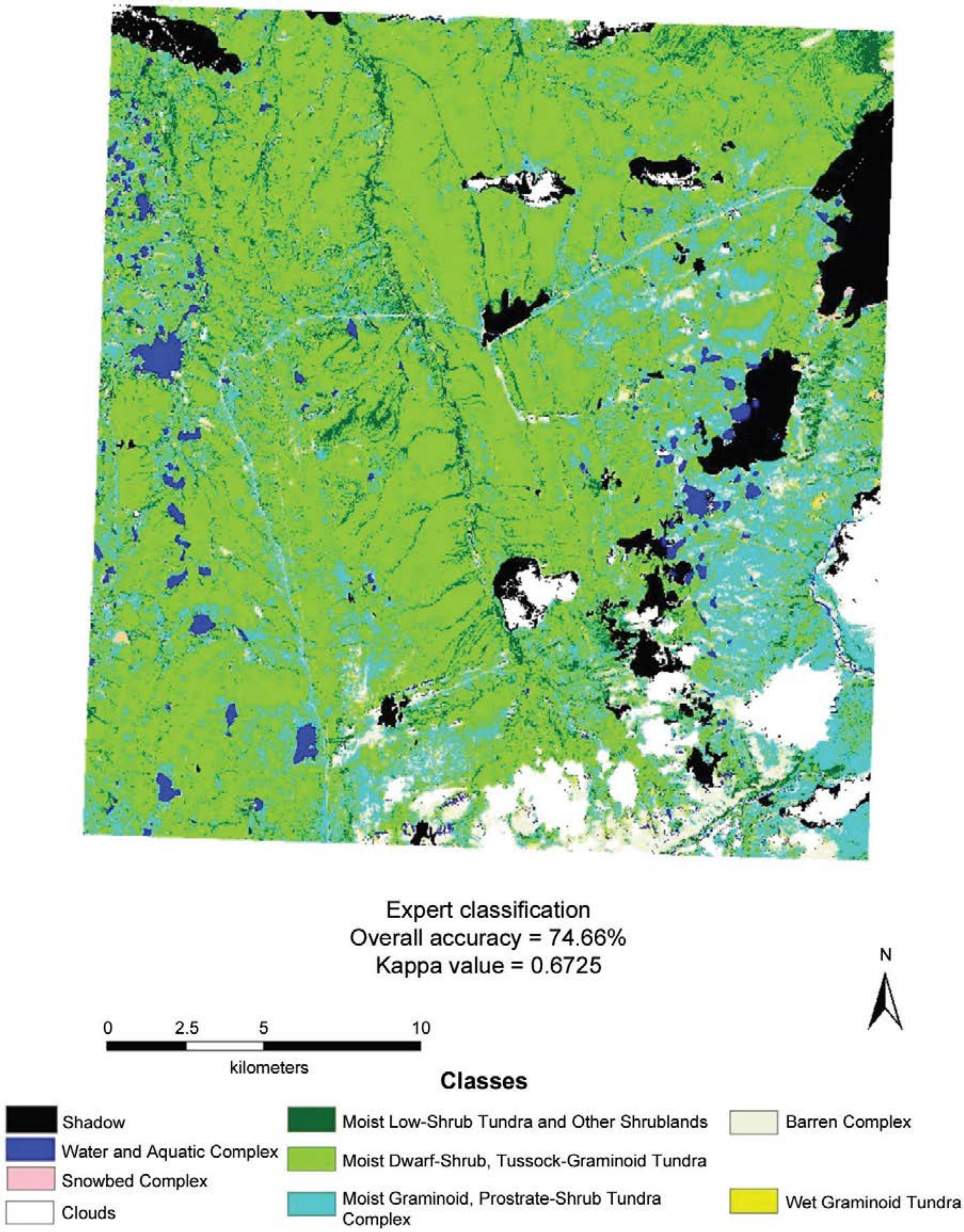

Fig. 4. Expert system classification.

Table 4. Classification Accuracy for Each Technique, in percent

Class names	Producers' accuracy	Users' accuracy
Unsupervised Classification: Overall accuracy = 67.87 % and Kappa = 0.5845		
Moist Low-Shrub Tundra and Other Shrublands	85.71	58.06
Water and Aquatic Complex	100.00	100.00
Barren Complex	76.92	83.33
Snowbed Complex	25.00	40.00
Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex	76.39	66.27
Wet Graminoid Tundra	5.56	33.33
Moist Graminoid, Prostrate-Shrub Tundra Complex	57.63	60.71
Classification with Feature Analyst: Overall accuracy = 61.45 % and Kappa = 0.5307		
Moist Low-Shrub Tundra and Other Shrublands	71.43	57.69
Water and Aquatic Complex	100.00	83.33
Barren Complex	84.62	61.11
Snowbed Complex	100.00	27.59
Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex	61.11	78.57
Wet Graminoid Tundra	27.78	33.33
Moist Graminoid, Prostrate-Shrub Tundra Complex	38.98	56.10
Classification with Expert System: Overall accuracy = 74.66 % and Kappa = 0.6725		
Moist Low-Shrub Tundra and Other Shrublands	57.14	66.67
Water and Aquatic Complex	100.00	100.00
Barren Complex	84.62	84.62
Snowbed Complex	100.00	61.54
Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex	83.33	67.42
Wet Graminoid Tundra	27.78	62.50
Moist Graminoid, Prostrate-Shrub Tundra Complex	66.10	78.00

While the unsupervised classifier did have lower accuracy rates on the Snowbed class than did the supervised classifier, the area in hectares, 570, was much closer to what the expert system derived, 945, with the major outlier being the supervised classification with 3,563 hectares (Tables 4 and 5). In all of the classifications Snowbed was primarily confused with MAT, MNT, and WST. For Snowbed the producers' accuracy in the supervised method was 100% , whereas the users' accuracy was about 28%. The errors of omission were minor, but errors of commission included many vegetation classes and dramatically overestimated the area of snowbed vegetation. We feel that the unsupervised classifier results, while lower in overall accuracy, probably underestimated the Snowbed area, while the expert classifier slightly overestimated it.

"Snowbed" is a type of vegetation that occurs locally in bowls or on north-facing cuestas where winter snowdrifts accumulate. However, these snowdrift areas are local features much smaller than some of the areas (up to 0.5 km across) that even the more conservative classifications identified as snowbeds (Fig. 4). The indicator species for "Snowbed" notably the visually conspicuous *Cassiope tetragona*, are not restricted to actual snowbeds but occur much more widely, especially in heath vegetation (see later) but to some extent even in tussock tundra. This probably explains the relatively large areas that the classification analysis attributes to Snowbeds, compared to the local nature of these landform features.

The supervised classification method overestimated the area classified as Water, 1,927 hectares. The unsupervised and expert methods were remarkably similar at 1,429 and 1,414 hectares, respectively. The supervised classification showed some confusion between the Water and Barren, MAT, WST, and MNT.

In each classifier, the vegetation complex with the greatest areal extent was MAT followed by MNT (Table 5). These classes covered a high of 79.5% (knowledge base) to a low 65.4% (supervised) of the image. The vast majority of this difference was within the class MAT with a high of 57.5% of the scene (knowledge base) and a low of 42.8% of the scene (supervised). The MNT class was fairly stable across all classifications, with a low of 22% of the area and a high of 24%. WST, which produced the lowest general accuracy rates, varied in area covered from 2% (knowledge base) to 5.5% (supervised). Likewise the class snowbed varied from about 1% (unsupervised) to 6% (supervised). The overall percentages in the shrub category varied fairly substantially from 8.3% (knowledge based) to almost 14% (unsupervised) of the area, or a difference of about 3300 hectares. This particular class is important because as the tundra warms shrubs increase (Serreze et al., 2000, Sturm et al., 2001a).

While the knowledge-based classifier did achieve the highest accuracy, the same set of rules could not be used throughout the entire image, making it rather cumbersome and less practical for classifying large areas of tundra. However, some of the rules, especially for the barren complex (Tables 2 and 4), did work very well on a single run and could be used throughout the image. The supervised classification posed the greatest difficulty in refining the classifications. The computers that were used (32-bit single processors with 1 gigabyte of ram) took up to five days to run a single classification; then the results had to be analyzed and modified. This time constraint limited the authors' ability to run a large number of trials.

An important limitation of the results was the inability of any of the adopted classification methods to differentiate between moist non-acidic tussock tundra (MNT, class 7A in Table 1) and the type of dry-habitat tundra known locally as "heath" (classes 7B and 7C), which can be dominated either by mostly Ericaceous dwarf shrubs or by the matted, Rosaceous species *Dryas octopetala* or *D. integrifolia*. Tussock tundra and heath have a very different appearance (continuous "grassland" vs. scattered shrubs or *Dryas* mats with much bare or lichen-covered soil). Also, *D. octopetala* mats have a very blue- or grey-green cast, which contrasts with the mid-season grass-green or late season yellow-green color of the tussock tundra. These vegetation types occur on contrasting substrates: heath on coarse, gravelly, well-drained glacial outwash or alluvial soils with little or no organic material; tussock tundra on fine-grained, poorly drained (consequently usually very wet) loess, covered by an often deep, moss-derived organic layer. That such different vegetation and soil types are here lumped together in class 7 seriously affects the biological usefulness of the results, for example, for predicting inputs into lake ecosystems from the vegetation of their watersheds.

Table 5. Tundra Land Cover in Hectares and Percentage of Total Area

Class	Area, in ha	Area, percent
Unsupervised		
Shrub	8,183.6750	13.9013
Water	1,429.5175	2.4283
Barren	2,979.5950	5.0613
Snowbed	570.6025	0.9693
MAT	29,652.6625	50.3697
WST	1,738.4275	2.9530
MNT	14,286.3125	24.2676
FA-supervised		
Shrub	7,355.0475	12.4184
Water	1,927.0850	3.2537
Barren	4,336.0500	7.3211
Snowbed	3,563.0450	6.0159
MAT	25,381.4525	42.8547
WST	3,268.1100	5.5180
MNT	13,396.0400	22.6182
Rule-based		
Shrub	4,882.1825	8.2848
Water	1,414.2750	2.4000
Barren	3,584.2550	6.0823
Snowbed	945.2900	1.6041
MAT	33,894.7450	57.5179
WST	1,189.0250	2.0177
MNT	13,019.2850	22.0931

CONCLUSION AND FUTURE WORK

Use of SPOT-5 satellite imagery resampled at 5 m pixel spatial resolution in this research has represented a unique venture intended to extract a more detailed classification of the heterogeneous arctic tundra landscape. The previous satellite classifications in this area mostly used Landsat data (at a spatial resolution of 80‑50 m, resampled, or 30 m data), thus neglecting the detail and heterogeneity of the landscape. All of these classifications fall below the accuracy claimed for some earlier work, such as Muller et al. (1998). All of our final maps (Figs. 2 and 4), on the other hand, used random or stratified random samples, with the only biases introduced by the authors being the choice of watersheds and the number of ground reference points that could be visited on foot in the time between drop-off and pick-up times, dictated by helicopter flights and the time allotted for field work. The satellite data, at 5 × 5 m, was some of the highest resolution data available for the area. The stratified random sampling strategy for obtaining accurate results helped to illustrate the heterogeneous nature of the area. The maps (Figs. 2 and 4) highlight the heterogeneity of the arctic tundra vegetation in and around Toolik Lake, Alaska. This research demonstrated the efficient use of a set of if‑then rules extracting both spatial and spectral knowledge in a rule-based classifier. The classifier enabled the extraction of relatively complex vegetation classes, like Snowbed, with better efficiency than the other traditional classifiers.

A major limitation in this research project was the restricted number of training points, which can be explained by the inaccessibility of the terrain, limited helicopter hours and research budget, and bad weather in which sometimes it was not possible to fly. In addition to this, 45 sample points within 300 m around the Dalton Highway were discarded because the ecological effects of road dust disturbances causes pronounced effects on the substrate and vegetation properties in the arctic tundra (Walker et. al., 1987; Auerbach et. al., 1997; Forbes and Sumina, 1999). Considering the heterogeneity of the typical arctic tundra vegetation, there was a major problem regarding having several sample sites and testing sites on transition edges or boundaries between one vegetation class and another. These sample locations had spectral mixing in the pixels that could have contributed to the overall mixing problem. An additional geology layer in this study would have been very useful in differentiating the two major vegetation classes—i.e., Moist Dwarf-Shrub, Tussock-Graminoid Tundra Complex and Moist Graminoid, Prostrate-Shrub Tundra Complex (Walker et al., 1995; Jia et al., 2002). Unfortunately, the lack of a geological map layer with higher spatial resolution for this research prevented the use of geology as an additional ancillary data layer to acquire better results in terms of accuracy.

Future work will concentrate on combining classification methods to achieve more accurate results with less interactivity on the part of the authors, for instance, coupling unsupervised and knowledge-based classifiers and hybrid technology implementing a neural network classifier within a smaller geographic region. This may include stratifying the area into substrate-relevant units to mitigate the effect that time since glaciation (non-acidic to acidic substrate) has on the vegetation complexes (Walker et al., 1994, 2007; Stow et al., 2004). Substrate stratification could help to better differentiate MAT and MNT between the soil types; however, caution needs to be taken because these classes are not completely unique to a particular type or age of substrate. Another spatial division might involve dividing the area into smaller watershed units. This could help with the aforementioned substrate effect, might assist in removing the spectral mixing between the shrub and the WST classes that were stratified in a north‑south manner, and possibly could help to reach the important goal of separating heath-type vegetation from the MNT class, as noted above.

Another major task will be to increase the number of classes to match those devised by Walker et al. (1994) and Walker et al. (2007) which were based on 1982 aerial photographs. The ability to accurately classify the vegetation complexes from higher spatial resolution satellites will allow for temporal comparisons of larger areas of the Arctic. As the effects of global warming change the vegetation cover, especially the spread of shrubs (Serreze et al. 2000; Sturm et al., 2001b), accurate classifiers for satellite images will provide a means to monitor and quantify the change. Application of hyperspectral data (e.g., Advanced Land Imager [ALI], Hyperion) instead of SPOT imagery may be a very interesting research area that might offset the low spectral resolution of SPOT. The classes having spectral mixing effect, such as Moist Dwarf- Shrub, Tussock-Graminoid Tundra Complex and Moist Graminoid, Prostrate-Shrub Tundra Complex, may be extracted with better accuracy.

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