Discrimination of sedimentary lithologies using Hyperion and Landsat Thematic Mapper data: a case study at Melville Island, Canadian High Arctic

David W. Leverington

* Department of Geosciences, Texas Tech University, Lubbock, TX, USA

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Discrimination of sedimentary lithologies using Hyperion and Landsat Thematic Mapper data: a case study at Melville Island, Canadian High Arctic

DAVID W. LEVERINGTON*
Department of Geosciences, Texas Tech University, Lubbock, TX 79409, USA

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The use of remote-sensing techniques in the discrimination of rock and soil classes in northern regions can support a diverse range of activities, such as environmental characterization, mineral exploration and the study of Quaternary paleoenvironments. Although images with low spectral resolution can commonly be used in the mapping of classes possessing distinct spectral properties, hyperspectral images offer greater potential for discrimination of materials characterized by more subtle reflectance properties. In an effort to better constrain the utility of broadband and hyperspectral datasets in high-latitude research, this study investigated the effectiveness of Landsat Thematic Mapper (TM) and EO-1 Hyperion data for discrimination of lithological classes at eastern Melville Island, Nunavut, Canada. TM data were classified using a standard neural-network algorithm, and both TM and Hyperion data were linearly unmixing using ground-truth spectra. TM classification results successfully discriminate between classes over much of the study area, although with incomplete separation between clastic and carbonate materials. TM unmixing results are poor, with useful class separation restricted to vegetation and red-weathered sandstone classes. Hyperion results effectively depict the fractional cover of end members, although the abundance images of several classes contain background abundance values that overestimate surface exposure in some areas. For the study area and surface classes involved, noisy hyperspectral data were found to be of greater utility than higher-fidelity broadband multispectral data in the generation of fractional abundance images for an inclusive set of surface-cover classes.

1. Introduction

At arctic and subarctic latitudes, large expanses of land are characterized by relatively sparse vegetation cover, resulting in the widespread exposure of earth materials, such as soils, alluvium, felsenmeer and bedrock. The successful application of remote-sensing techniques in the discrimination and mapping of rock and sediment types in these regions can be used to support various activities, such as environmental characterization, mineral exploration, the study of surface processes and Quaternary paleoenvironments and the study of other solar system bodies. In northern Canada, there is considerable potential for the use of remote-sensing images in regional geological mapping and for the monitoring of environmental change (e.g. Bergeron et al. 2008). The value of remote-sensing techniques in the mapping of surface classes

*Email: david.leverington@ttu.edu
is further increased in northern regions by the relative isolation, extreme climatic conditions and limited infrastructure typical of much of the north, all of which can reduce the ease and cost effectiveness with which extensive ground-based surveys can be conducted.

Landsat Thematic Mapper (TM) data are available at little or no cost for most of the Earth’s land surface. Although characterized by limited spectral resolution (i.e. six broad reflectance bands), TM datasets typically contain sufficient spectral information for the successful discrimination of general land cover classes at a spatial resolution of 30 m per pixel. However, the spectral characteristics of individual rock or soil classes are not always distinct enough to allow for their confident separation using TM or similar broadband multispectral datasets (e.g. Rowan et al. 1987, Glikson and Creasey 1995). Hyperspectral images, acquired using tens to hundreds of narrowly defined bands, allow for improved discrimination and mapping of rock and soil classes (e.g. Goetz et al. 1985, Hook and Rast 1990, van der Meer and Bakker 1997, Green et al. 1998, Hubbard et al. 2003, Kruse et al. 2003, Kariuki et al. 2004, Harris et al. 2005, Gersman et al. 2008). The spaceborne Hyperion sensor offers global opportunities for acquisition of hyperspectral data to workers lacking the resources to conduct airborne hyperspectral surveys over regions of interest.

In an effort to evaluate aspects of the utility of both broadband and hyperspectral datasets in geological mapping at high northern latitudes, this study compared Landsat TM and EO-1 Hyperion data for discrimination and mapping of surface classes at eastern Melville Island, located in the Canadian territory of Nunavut. Specifically, TM data were classified using a standard per-pixel neural-network algorithm (e.g. Gallant 1993), and both Hyperion and TM data were processed using spectral unmixing methods (Adams and Smith 1986, Boardman 1989), based on end-member spectra. Classification of the TM image was performed in order to determine the efficacy of these data and a neural-network algorithm for per-pixel separation of lithological classes. Spectral unmixing of TM and Hyperion data was performed to test the relative utility of these datasets in the generation of fraction images involving an all-inclusive set of end members, with fraction images ideally allowing for separation of the otherwise mixed spectral contributions of geological classes (sandstone and limestone) and other classes (snow and vegetation).

2. Lithological discrimination in the visible and reflective infrared (400–2500 nm)

Although indirect discrimination and mapping of lithological (rock and soil) classes is possible where geobotanical or other relationships are consistent (e.g. Paradella and Vitorello 1995, Kettles et al. 2000), the potential for reliable identification and mapping of such classes is most typically restricted to areas where vegetative cover is relatively sparse and the spectral characteristics of earth materials can be directly measured (e.g. Harding and Forrest 1989, Alwash and Zilger 1994, Arvidson et al. 1994, Krishnamurthy 1997). The reflectance properties of rock-forming minerals are a function of chemical composition and crystal structure, such that many minerals have diagnostic spectral absorption properties (e.g. Hunt 1980, Goetz and Rowan 1981, Goetz et al. 1985, Mustard and Sunshine 1999). Absorption features in the reflectance spectra of minerals in the visible and near-infrared (∼400–1000 nm) are generally associated with electronic transitions caused by the presence of transition metals, such as iron and chromium, whereas absorption features within the near- and shortwave infrared (∼1000–3000 nm) are typically associated with combinations and

The products of chemical weathering can strongly influence the spectral characteristics of rocks and soils, even when the depth of alteration is less than several hundred micrometres. This imparts additional absorption features to reflectance spectra that may be otherwise inconsistent with the underlying pristine mineralogy (e.g. Cloutis 1992, Ferrari et al. 1996). Similarities in the spectral properties of different rock or soil classes, and spatial variability within individual classes, can make the successful discrimination between surface classes especially challenging, particularly if the spectral and spatial resolutions of the input images are limited (e.g. Ager and Milton 1987, Birnie et al. 1989, Arvidson et al. 1994, Macias 1995, Chabrillat et al. 2000).

The TM has been the primary remote-sensing instrument on board the Landsat series of satellites since Landsat-4. Multispectral TM images continue to be used in the mapping and monitoring of the surface of the Earth due to the extensive spatial and temporal coverage of archived images, and due to the utility of corresponding wavelength ranges in the discrimination of different land cover types. TM data have been used with moderate to high levels of success in mapping exposed sedimentary rock and soil in a wide range of environments (e.g. Evans 1988, Sgavetti et al. 1995, Ernst and Paylor 1996, Riaza et al. 2000, Peña and Abdelsalam 2006, Boettinger et al. 2008). TM data have also been used effectively in mapping igneous and metamorphic rocks (e.g. Rowan et al. 1987, Abrams et al. 1988, Pontual 1989, Spatz and Taranik 1989, Qari 1992, Mustard 1994, van der Meer et al. 1995, Kavak 2005). Notably, the effectiveness of TM data in the discrimination of rock and soil classes is not uniform over all geographic regions, but instead is primarily determined by amounts of exposure and by the spectral distinctiveness of the classes being mapped (e.g. Ernst and Paylor 1996). One aspect of the present study involves evaluation of the utility of TM data for generating useful maps of surface cover in a northern region characterized by widespread exposure of clastic and carbonate sedimentary rocks.

Hyperspectral datasets allow for improved discrimination between rock and soil classes (e.g. Goetz et al. 1985). The Hyperion sensor (Pearlman et al. 2003) is one of several instruments mounted on the EO-1 spacecraft, which was launched in 2000 and is now operating on an extended mission in partnership between the United States Geological Survey and the National Aeronautics and Space Administration. Hyperion is an along-track sensor that collects optical data in 242 spectral bands in the visible, near- and shortwave infrared. Continuous spectral coverage is available throughout the range of ~0.4–2.4 μm, with spectral resolutions of individual bands of ~10 nm. The Hyperion sensor operates with a swath width of 7.6 km and a pixel size of 30 × 30 m.

Though Hyperion is characterized by inferior signal-to-noise relative to AVIRIS and other sensors with comparable spectral resolution (e.g. Asner and Heidebrecht 2003, Hubbard et al. 2003, Kruse et al. 2003, Roberts et al. 2003, Hubbard and Crowley 2005, Xu et al. 2008), it represents a landmark in the continuing development of spaceborne remote-sensing technologies. Hyperion data have been used to support activities such as the mapping of individual rock and mineral classes (e.g. Hubbard et al. 2003, Kruse et al. 2003, Gersman et al. 2008), the estimation of vegetation indices and discrimination of vegetation classes (e.g. Datt et al. 2003, Gong et al. 2003, Goodenough et al. 2003, Pu et al. 2003, Yoshioka et al. 2003, Ramsey et al. 2004, Thenkabail et al. 2004, Galvão et al. 2006, Tsai et al. 2007) and the monitoring of land
cover (e.g. Asner and Heidebrecht 2003, Huete et al. 2003). To date, Hyperion images have not been evaluated in the generation of sedimentary fraction images involving an all-inclusive set of spectral end members at a northern study area, thus prompting consideration of Hyperion data in the present study.

3. Study area and surface classes

The study area is located on eastern Melville Island, located in the Canadian territory of Nunavut (figure 1). Bedrock units in the study area (figure 2; table 1) consist mainly of late-Paleozoic clastic and carbonate formations of the Sverdrup Basin (Trettin 1991, Goodbody and Christie 1994, Harrison 1995). Also present are Silurian carbonates of the shelf province of the Franklinian Mobile Belt (Higgins et al. 1991, Trettin 1991, Harrison 1994b), and a near-vertical Cretaceous gabbro dike (Harrison 1995). North-dipping cuesta landforms dominate the low-relief terrain (figure 3), and elevations in the region mainly range from 0 to ~200 m above sea level. Notable ridge-forming sedimentary units include the Great Bear Cape Formation (Fm), the Degerbøls Formation and the Bjorne Formation. The gabbro dike (figure 3(c)) also forms a distinct ridge that is oriented at a high angle to the strike of the sedimentary formations. Weathered and frost-shattered felsenmeer, predominantly in the form of boulder- to pebble-sized clasts accumulating in place and mantling parent bedrock units, is the most common surface material in the study area (Hodgson et al. 1984) (figures 3 and 4). Soil development in the region is poor (Edlund 1994).

Figure 1. Melville Island is located in the western part of the Queen Elizabeth Islands of the Canadian High Arctic. The general location of the study area is indicated by a grey rectangle.
Melville Island is located within the zone of continuous permafrost (ACGR 1988), and the low annual precipitation of ~10 cm has led to its classification as a polar desert (Maxwell 1980). Vegetation cover is less than 10% over much of the study area, with associated barren communities predominantly composed of *Saxifraga oppositifolia* (purple saxifrage), *Salix arctica* (arctic willow), grasses and minor cover of

Figure 2. Map of bedrock units of the Melville Island study area (after 1:250 000 map of Harrison 1994a). The characteristics of units relevant to this study are summarized in table 1. The extents of the regions considered in the classification of TM data and unmixing of TM and Hyperion data are indicated with the large and small dotted polygons, respectively. The gross spatial distribution of surface materials is broadly congruent with the spatial nature of underlying parent bedrock, but the true distribution of surface materials is more complex (Leverington 2001) and is best determined through remote-sensing methods.
lichens *Thamnolia subuliformis* and *Lecidea lapicida*. Less widespread in the study area are dense tundra communities, characterized by vegetation cover approaching (or in rare cases exceeding) 50% and dominated by grass, moss and broadleaf species, including *Saxifraga oppositifolia*. Tundra communities are predominantly associated with poorly drained soils (e.g. Edlund 1994).

The spectral characteristics of lithological classes within the study area were measured using materials collected in situ and described in greater detail by Leverington (2001). The spectra of representative whole-rock samples were measured in a laboratory setting using an Analytical Spectral Devices (ASD) FieldSpec® 3 spectrometer equipped with a contact probe. For each class, reflectance values were determined at ~10 nm intervals between 350 and 2500 nm (figure 5). Notably, the spectral properties of some sedimentary units in the study area are comparable (e.g. the Great Bear Cape limestone and the Tingmisut Inlier dolostone, see figure 5), whereas the most spectrally distinct classes of the region include the dark-red-weathering materials of the Assistance Formation mudstone, the red-weathering materials of the Canyon Fiord Formation sandstone and the low-reflectance materials that comprise the gabbro dike (figure 5). Spectral absorption features associated with quartz sandstone units should be related to the reflectance characteristics of materials such as cements, iron oxide

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<table>
<thead>
<tr>
<th>Class</th>
<th>Characteristics</th>
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<tbody>
<tr>
<td>1. Water</td>
<td>Open water</td>
</tr>
<tr>
<td>2. Snow cover</td>
<td>Perennial snow cover is typically distributed along gullies and the steep sides of cuestas</td>
</tr>
<tr>
<td>3. Green vegetation</td>
<td>Moss, low shrub and lichen tundra typically characterized by a relatively diverse range of vegetation varieties</td>
</tr>
<tr>
<td>4. Gabbro</td>
<td>Dark grey gabbro; typical vegetation: lichens</td>
</tr>
<tr>
<td>5. Assistance Fm mudstone</td>
<td>Red- and brown-weathering mudstone and associated fines; typically no significant vegetation cover (scattered lichens)</td>
</tr>
<tr>
<td>6. Canyon Fiord (CF) Fm sandstone</td>
<td>Predominantly red-weathering fine- to coarse-grained calcareous sandstone and minor conglomerate and associated fines; common vegetation: <em>Saxifraga oppositifolia</em>, <em>Salix arctica</em>, lichens, localized black algae</td>
</tr>
<tr>
<td>7. Tingmisut Inlier dolomite</td>
<td>Gray and yellowish-orange dolostone, sometimes covered with grey-orange fines that may be wind-blow Canyon Fiord sediments; typical vegetation: lichens</td>
</tr>
<tr>
<td>8. Great Bear Cape (GBC) Fm limestone</td>
<td>Pale yellowish brown impure limestone and minor calcareous sandstone; common vegetation: <em>Saxifraga oppositifolia</em>, lichens, localized black algae</td>
</tr>
<tr>
<td>9. Degerbøls (Deg) Fm limestone</td>
<td>Gray and yellowish-grey limestone that, in places, mainly consists of loose bioclasts; typical vegetation: <em>Saxifraga oppositifolia</em>, lichens</td>
</tr>
<tr>
<td>10. Trold Fiord (TF) Fm sandstone</td>
<td>Yellowish-grey sandstone and minor limestone; typical vegetation: <em>Saxifraga oppositifolia</em>, lichens</td>
</tr>
<tr>
<td>11. Bjorne (BJ) Fm sandstone</td>
<td>Brown sandstone and conglomerate and associated fines and heterolithic clasts; Fe-concretions present; typically no significant vegetation (scattered <em>Saxifraga oppositifolia</em> and lichens)</td>
</tr>
<tr>
<td>12. Sabine Bay (SB) Fm sandstone</td>
<td>Uncemented, non-calcareous, grey sandstone and conglomerate and associated fines and heterolithic clasts; typical vegetation: <em>Saxifraga oppositifolia</em>, lichens</td>
</tr>
</tbody>
</table>

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D. W. Leverington

Table 1. Surface classes of the Melville Island study area (after Harrison 1994a, Leverington 2001).
staining or accessory minerals. Among the most distinct absorption features of materials in the region are those at \( \sim 1000 \) nm and less than 600 nm (figure 5), related to the presence of ferric iron, and the water-related absorption features at 1400 and 1900 nm. Carbonate absorption features at \( \sim 2300 \) nm (Gaffey 1987) characterize the limestone and dolostone classes, as well as clastic rocks with carbonate cements (figure 5). Absorption features at \( \sim 2200 \) nm, related to the presence of clay minerals such as kaolinite and/or smectite (e.g. Hunt 1980), are also present in the spectra of several rock classes.

4. Landsat TM and hyperion datasets

The TM image used in this study was acquired by Landsat-5 on 8 August 1994. Raw data (i.e. the original digital numbers values) from four image bands were scaled to the range 0.0–1.0 and used as input to neural-network classifications: band 3 (630–690 nm), band 4 (760–900 nm), band 5 (1550–1750 nm) and band 7 (2080–2350 nm). The selection of TM bands thus emphasized red to mid-infrared wavelengths, where variation between the reflectance properties of individual lithologies is typically greatest (e.g. Drury 1993, Schetselaar 1994, Galvão and Vitorello 1995, Mickus and Johnson 2001, Lorenz 2004). In order to support separate linear unmixing procedures, the data
of all six available TM bands were converted to measures of reflectance using the PCI Geomatica implementation of the MODTRAN-4 radiative-transfer algorithm (e.g. PCI 2005). Conversion of TM image values to measures of reflectance permitted the use of ground-based reflectance spectra in the unmixing of TM data.

Figure 4. Field photographs of surface cover at the Melville Island study area (units are described in table 1) (after Leverington 2001). The vertical metre stick visible in some photographs has 10 cm segments.
The Hyperion image used in this study was acquired across part of the study area on 21 July 2002. Noisy, overlapping or otherwise unusable Hyperion bands were first discarded, and the remaining 196-band image was converted from at-sensor radiance to reflectance using the ENVI / FLAASH-based implementation of the MODTRAN-4 algorithm (e.g. Beck 2003, ITT 2008). As with the TM image, conversion of original Hyperion image values to reflectance permitted the use of ground-derived reflectance spectra as a basis for linear spectral unmixing.

5. Classification and unmixing procedures

In this study, TM data were classified using a standard per-pixel neural-network algorithm (e.g. Gallant 1993), and both Hyperion and TM data were processed using spectral unmixing methods (Adams and Smith 1986, Boardman 1989) based on end-member spectra. Classification of the TM image was performed in order to
determine the efficacy of these data and a neural-network algorithm for per-pixel separation of lithological classes. Spectral unmixing of TM and Hyperion data was performed to test the relative utility of these datasets in the generation of fraction images involving an all-inclusive set of end members, with fraction images ideally allowing for separation of the otherwise mixed spectral contributions of geological classes (sandstone and limestone) and other classes (snow and vegetation) exposed in the study area.

Although large numbers of input bands are useful in image-processing procedures, including spectral unmixing, per-pixel classification results degrade substantially when large numbers of input bands are used (this is known as the ‘curse of dimensionality’ or the ‘Hughes phenomenon’; e.g. Hughes 1968). The Hyperion image was therefore not classified using the neural-network algorithm in this study, with the higher dimensionality of the image (196 useful bands) considered more suitable for use as a basis for processing by methods including spectral unmixing and orthogonal sub-space projection (e.g. Green et al. 1988, Boardman 1989, Harsanyi and Chang 1994). A range of possible approaches exists for the reduction of data dimensionality of hyperspectral images, and such procedures and subsequent neural-network classification techniques will be explored in detail in a future study.

5.1 Neural-network classification of TM data

Feedforward backpropagation neural networks are well established as effective algorithms for use in image classification (e.g. Benediktsson et al. 1990, Lee et al. 1990, Bischof et al. 1992, Heermann and Khazenie 1992, An and Chung 1994, Chen et al. 1995, Leverington and Duguay 1997, Del Frate et al. 2000, Linderman et al. 2004, Chen et al. 2007, Lu and Weng 2007, Wang et al. 2008). The capacity of these algorithms for the parameterization of training data without the use of restrictive frequency models, such as the normal distribution (maximum likelihood classifiers; Richards and Jia 2006), makes them especially well suited for the discrimination of lithological classes (Leverington 2001). For example, in many cases, lithological classes are characterized by training data with relatively complex frequency distributions due to spatial variability in such factors as vegetation cover. This complexity can, in some cases, be poorly parameterized by simpler frequency models. On this basis, the feedforward backpropagation algorithm was chosen for use over the maximum likelihood classifier in the per-pixel classification of the TM image.

The neural-network software used in this study was programmed in C by the author, based on conventional neural-network principles (Gallant 1993, Bishop 1995). The classification algorithm is a standard feedforward network that uses backpropagation to calculate derivatives of training error and to adjust weights to minimize error. The error function used by the network is the sum-of-squares error. The sigma nonlinearity in [0.0,1.0] is used as the activation function for all hidden and output nodes (e.g. see Bishop 1995). For this work, settings for the learning rate (\(\epsilon\)) and momentum (\(a\)) (Bishop 1995) were 0.1 and 0.9, respectively. Initial weights were uniformly distributed in \([-0.5, +0.5]\). The network was configured for classification, using an output layer in which a unique node is assigned to each class. For a given input pattern, the assigned class is that for which the output node has the highest activation value. During initial training, target activations for ‘correct’ and ‘incorrect’ nodes were set to 0.9 and 0.1, respectively. The network was configured to learn in online mode (Reed and Marks 1999), rather than in batch mode. Two intermediate
layers were used in all executions, and were defined using as many nodes as the maximum of the number of nodes within the input and output layers. The target total-sum-of-squares (tss) error used in training corresponded to an average error per output node of \( \sim 0.10 \).

Two sets of classes were used as a basis for TM image classification: (1) a full set of 12 classes was used to represent lithological units and other cover materials in the study area (table 1), regardless of similarities in compositional or spectral characteristics, and (2) a simpler set of eight classes was used in which geologically similar materials were grouped into single classes. Specifically, all carbonate units were merged into a single class and all sandstone units lacking distinct spectral signatures (i.e. materials of the Bjorne, Trold Fiord and Sabine Bay Formations) were merged into a combined sandstone class.

Training and test pixels were selected on the basis of extensive ground-truth field work involving the collection of several hundred kilograms of samples, 8 hours of video footage of training sites and materials, hundreds of ground-based photographs, and descriptive information collected in situ and spatially referenced using global positioning systems (GPSs) and field copies of high-resolution aerial photographs (Leverington 2001). Each class was represented by a total of 300 pixels, except for the gabbro class, which was represented by only 60 pixels due to its limited exposure in the study area. Pixels were separated into training and test groups randomly, stratified by class, with 66% of pixels used as training pixels and 34% used as test pixels. For all classes except for gabbro, this involved the use of 198 pixels for training and 102 pixels for testing. Previous studies recommend the use of at least 50 test pixels per class when working with classifications involving 12 or fewer classes (Congalton and Green 1999). Pixel totals of 2160 (eight-class classification) and 3360 (12-class classification) were used in the classification of the TM image; these collections of pixels represent expanded versions of a ground-truth database previously generated to support preliminary work involving the study area (Leverington and Moon 2005).

5.2 Spectral unmixing of Hyperion and TM data

Spectral unmixing methods are based on the recognition that the magnitudes of individual pixel values are a function of the combined spectral contributions of one or more end-member classes present at sub-pixel scales. On the basis of image values and the spectral characteristics of pre-defined end members, spectral unmixing provides the means for determining the fractional abundances of individual end members based on the composite spectra measured at every pixel location. This enables the generation of a separate fractional abundance image for each end member (e.g. Adams and Smith 1986, Mustard and Pieters 1987, Boardman 1989, Gillespie et al. 1990, Shimabukuru and Smith 1991, Settle and Drake 1993, Mustard 1994, van der Meer 1996, Maselli 1998, Huete et al. 2003). Hyperspectral data are well suited for unmixing, in part because the larger number of separate bands can improve the quality of unmixing results and permits the definition of a larger number of end members than datasets of low spectral resolution. Linear unmixing of Hyperion- and TM-derived reflectance images was conducted in this study using ENVI software (ITT 2008), with end-member abundances estimated for each pixel on the basis of standard numerical techniques described by Boardman (1989).

The spatial coverage of the Hyperion image used in this study is more restricted than that of the TM image (figure 2), and there are correspondingly fewer associated
surface classes exposed within the Hyperion data coverage than within the TM data coverage. Six spectral end members were defined for the purpose of Hyperion spectral unmixing: snow, green vegetation, limestone, mudstone, red-weathering sandstone and other sandstone. Few pixel-sized areas at Melville Island are characterized by 100% surface cover by any individual end member. As a result, end-member spectra were determined through direct spectral measurements involving representative ground samples, except in the case of the snow spectrum, which was extracted and smoothed from the Hyperion reflectance image itself. The limestone end member was defined on the basis of materials from the Great Bear Cape Formation, and the sandstone end member was defined on the basis of materials from the Sabine Bay Formation. The green vegetation end member was defined on the basis of field spectrometer measurements of a patch of vegetation consisting of 100% grass cover. Parts of the Hyperion data were excluded from unmixing due to cloud cover.

The ‘Singular Value Decomposition’ method of unmixing (Boardman 1989) permits the definition of a maximum of \( Z \)–1 end members if \( Z \) input rasters are available, restricting the spectral unmixing of the six-band TM data to five possible end members. The spatially minor snow class was therefore not considered in the unmixing of TM-derived data. TM unmixing was performed for a surface area matching that covered by the Hyperion image, allowing for direct comparison between Hyperion and TM unmixing results.

6. TM classification results

Classification of the TM image was based on 12-class and eight-class categorizations of lithological and other surface component classes in the study area, including vegetation, snow and water. The eight-class classification involved the use of merged carbonate and sandstone classes, as described in the previous section.

The 12-class classification produced an output image with an overall classification accuracy of 78% (figure 6; table 2). Although several classes are not fully distinguished in the output image, the overall qualitative effectiveness of the classification is good. This is notable given the spectral resolution limitations of the TM image and the large number of lithological classes (9 of 12 classes) involved in the classification. The classes most clearly distinguished in the output image are associated with errors of omission (e. Omission) or errors of commission (E. Commission) of less than 15%. These consist of the water, snow/ice, green vegetation, gabbro, Assistance mudstone and Canyon Fiord sandstone classes (table 2). The limestone units of the Great Bear Cape and Degerbøls Formations, as well as the Bjorne sandstone, were separated with intermediate success. The limestones of the Great Bear Cape and Degerbøls Formations were, in general, successfully discriminated from one another. Poorly separated classes, linked to classification errors of omission or commission as high as \( \sim 50\%\), include the Tingmisut Inlier dolostone, the Trold Fiord sandstone and the Sabine Bay sandstone (table 2). Confusion between sedimentary classes in some cases involves relatively disparate classes. For example, substantial confusion exists in the output image between the Tingmisut Inlier dolostone and the Trold Fiord sandstone, and between the Sabine Bay sandstone and both the Great Bear Cape and Degerbøls limestones.

Confusion between sandstone and limestone units, for a minority of pixel locations, is related to the real-world mixing between these classes at sub-pixel scales. Examples of such mixed sites, identified through field reconnaissance, include zones of
carbonate felsenmeer partly mantled by windblown clastic sediments, and areas of exposure of minor clastic units in predominantly carbonate formations (e.g. Harrison 1994a, 1994b, Leverington 2001). However, much confusion can also be accounted for on the basis of similarities in the spectra of the sandstone and limestone units in the study area (figure 5). These similarities are related, in part, to the presence of carbonate cement in both the Trold Fiord and Canyon Fiord sandstone units. This cement has the potential to superpose carbonate absorption features on the spectra of quartz sandstones. Also, a variable presence of sand-sized silicate mineral grains (especially quartz) and lithic fragments is found in the Great Bear Cape and Degerbøls limestones (Leverington 2001). In addition, similarities in the weathering characteristics of exposed rock and soil can partly mask the otherwise more distinct spectra of these materials, thus enhancing the potential for confusion between lithological classes. This is typical of many other areas characterized by widespread exposure of weathered and erosion-modified rock classes (e.g. Younis et al. 1997, Leverington 2008).

In contrast, the output image of the eight-class classification has an overall accuracy of ~90% (figure 7; table 3). The qualitative effectiveness of the classification is
Table 2. Confusion matrix for the 12-class neural-network classification of Landsat TM data. The overall agreement measure is 0.7760 (77.6%), and the corresponding Kappa value is 0.7545. The total number of test pixels is 1143. Classes are abbreviated in the forms of initials, are as described in table 1 and are depicted with regard to the bedrock distribution in figure 2. Sandstone is abbreviated to ‘ss’ and limestone is abbreviated to ‘ls’. The ‘mudstone’ label refers to materials of the Assistance Formation and the ‘dolostone’ label refers to materials of the Tingmisut Inlier.

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<td>Snow/ice</td>
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**Note:** The proportions of correctly classified test pixels are given in bold.
high, with the most clearly distinguished classes consisting of water, snow/ice, green vegetation, Assistance mudstone and Canyon Fiord sandstone. Classes distinguished with intermediate success in the eight-class classification included the gabbro and carbonate classes, which each yield errors of omission or commission less than $\sim 25\%$ (table 3). The most poorly separated class was the merged sandstone class, comprised Bjorne, Trold Fiord and Sabine Bay materials, and this collectively produced an error of omission in excess of $30\%$ (table 3). The merged sandstone class was most commonly confused with the carbonate class. This result is again consistent with both the existence of mixed pixels and with spectral similarities between the materials comprising these two merged classes.

7. **Hyperion and TM unmixing results**

A comparison between the reflectance measurements derived from ground-based spectral end members, selected Hyperion pixels and selected TM pixels, is shown in figure 8 for six surface classes: snow, green vegetation, limestone, mudstone, red-weathering sandstone and other sandstone. The overall shapes of image-derived
Table 3. Confusion matrix for the eight-class neural-network classification of Landsat TM data. The overall agreement measure is 0.9007 (90.1%), and the corresponding Kappa value is 0.8851. The total number of test pixels is 735. Classes are labelled and abbreviated as described in table 2.

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Note: The proportions of correctly classified test pixels are given in bold.
Spectra are consistent with those of ground-based end-member spectra, with differences attributable to the absence of 100% end-member cover at the scale of image pixels for geological and vegetation classes. For example, vegetation cover is only ~50% at involved pixel locations, thus resulting in muted variation in surface reflectance across red and near-infrared wavelengths. The noise that characterizes the Hyperion reflectance data (figure 8) is present in the original image data and is typical of calibrated image spectra generated by this sensor (e.g. Crowley et al. 2003). The end members depicted in (a) were used as a basis for the unmixing of Hyperion and TM reflectance images (figures 9 and 10).

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The Hyperion reflectance image was linearly unmixed on the basis of all six spectral end members. The pixel values for the six resultant fractional abundance images (figure 9) are generally well constrained within the range of 0% to 100%. In contrast, experimental unmixing results using larger numbers of spectral end members (e.g. by subdividing merged limestone or sandstone classes) consistently produced fractional abundance images characterized by much wider ranges of values. Such results also yielded substantial degradation in the qualitative validity of fractional abundance images.

The Hyperion abundance maps for the snow and vegetation end members (figure 9) are broadly consistent with the distribution of these surface materials in the study area. The snow class was properly delineated throughout the study area, apart from a weak but widespread background of low fraction values (ranging from ~2% to 10%) that erroneously suggest minor snow cover for areas where none should have existed.

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**Figure 8.** Comparison between reflectance measurements derived from: (a) ground-based end members, (b) selected Hyperion pixels and selected (c) TM pixels. Reflectance values were determined from original Hyperion and TM datasets through the application of standard atmospheric correction procedures. The three sets of reflectance measurements were independently derived, except for the snow end member (a), which is a smoothed version of Hyperion-derived data. Reflectance data are offset for clarity, and y-axes are marked at increments of 10%. The characteristics of image-derived spectra ((b) and (c)) are consistent with end-member spectra (a), with differences attributable to the general absence of 100% end-member cover at pixel scales (30 x 30 m) for geological and vegetation classes. The noise that characterizes the Hyperion spectra is present in the original image, and is typical of data generated by this sensor (e.g. Crowley et al. 2003). The end members depicted in (a) were used as a basis for the unmixing of Hyperion and TM reflectance images (figures 9 and 10).
at the time of imaging. At the time the Hyperion data were acquired, snow cover should have been restricted to isolated perennial snowbanks found along the steeper flanks of valleys and cuesta landforms, as shown in figure 4(d). The spatial distribution of the green vegetation class is well delineated in the Hyperion unmixing results, with low values (~5%) characteristic of units such as the Canyon Fiord sandstone,
moderate values (~30%) associated with parts of clastic and carbonate units, including the Great Bear Cape limestone, and high values (~50%) associated with the poorly drained Trold Fiord sandstone. These values are consistent with vegetation information acquired in the field (Leverington 2001). The spatial distribution of the vegetation end member is qualitatively consistent both with TM classification results (figures 7 and 8) and the Hyperion colour-infrared image (figure 9); within the latter image, vegetated pixels are depicted in shades of red.

The Hyperion unmixing results for the four lithological end members (figure 9) are generally consistent with the distribution of these surface classes over much of the study area. The spatial distribution of the red-weathering sandstone class (i.e. Canyon Fiord sandstone) is well delineated both in the Tingmisut Lake area and in the southern part of the Hyperion image, with maximum fraction values appropriately approaching full cover (~100%) at some pixel locations. The overall areal extent of surface cover is slightly underestimated for this class along the margins of the main exposures. The mudstone end member (Assistance mudstone) is properly delineated in both its northern and southern areas of maximum exposure. However, its proportional cover is substantially overestimated over parts of the Great Bear Cape and Sabine Bay Formations, where minor and intermittent surficial mantling by Assistance materials (Leverington 2001) contrasts with fractional abundance estimates as high as ~10% to 25%. The sandstone class (Sabine Bay and Trold Fiord sandstones) is generally well delineated for fractional abundance values exceeding 50%, but a widespread background of lower values notably overestimates the fractional cover of this end member over parts of the remainder of the imaged area. Similarly, although the limestone class (Great Bear Cape and Degerbøls Formations) is properly delineated in areas of maximum exposure, its fractional cover is overestimated in other areas dominated on the ground by other classes (such as at the Trold Fiord sandstone exposures in the southern part of the imaged area). As noted previously for the TM neural-network classification results, the confusion between limestone and sandstone units in the study area are due partly to the similarities in lithological properties and weathering characteristics of these materials. The moderate levels of noise typical of Hyperion images may have also contributed to the overestimation of surface exposure of some end members (e.g. Hubbard and Crowley 2005, Xu et al. 2008).

The TM reflectance image was linearly unmixed based on five spectral end members: green vegetation, limestone, mudstone, red-weathering sandstone and other sandstone. As noted previously, the snow class was not used due to the constraints imposed by the Boardman (1989) unmixing algorithm. The fractional abundance values of the green vegetation and red-weathering sandstone classes (figure 10) are predominantly constrained within the range of 0% to 100%. Apart from the widespread low-level exposure predicted for the red-weathering sandstone, the qualitative utility of these two TM-derived fraction images is generally comparable to that of corresponding Hyperion fraction images (figure 9). The fractional abundance values generated for the remaining three end members deviate notably from the 0% to 100% range. The qualitative value of these fractional abundance images is very poor, and compares unfavourably with corresponding Hyperion fraction images. Comparison between the Hyperion and TM unmixing results suggest that, for this study area, noisy hyperspectral data, such as Hyperion, yield superior lithological discrimination relative to that provided by higher fidelity multispectral data, such as six-band TM imagery.
Figure 10. Unmixing results derived from TM-derived reflectance data for five end members (see figure 8(a)). Compare with the six-class Hyperion-derived unmixing results given in figure 9.
8. Summary, discussion and conclusions

The classification results generated in this study validate the utility of TM data for discrimination of lithological classes over much of the Melville Island study area. Twelve- and eight-class classifications yielded overall accuracies of 78% and 90%, respectively. However, despite successful separation of specific spectrally distinct classes (e.g. snow, green vegetation, mudstone and red sandstone), complete separation between several sandstone and limestone classes was not achieved. Although some apparent confusion can be attributed to the local mixing of classes at pixel scales, much confusion should be related to other factors such as overlap in mineralogy, similarities in the nature of surface weathering and the limited spectral resolution of the TM image itself. Confusion between geological units with overlapping mineralogical and weathering properties is a common issue when investigating regions within which numerous lithological classes are exposed. This is especially true when analyses involve the use of datasets of relatively low spectral resolution (e.g. Gastellu-Etchegorry et al. 1990, Dong and Leblon 2004). It is not uncommon for this confusion to be amplified by variability in the geological and associated reflectance characteristics of individual classes.

In general, the Hyperion spectral unmixing results presented in this study accurately discriminate between the six end members exposed across the imaged area, including the extents of the most spectrally distinct materials (snow, green vegetation and red sandstone). The highest fraction values associated with mudstone, sandstone and limestone materials are also broadly representative of the general distribution of these classes. However, lower background fraction values overestimate exposure of these three classes over parts of the study area. This is likely related to overlap in the spectral properties of classes, likely caused by similarities in mineralogical and weathering characteristics. Aspects of the overestimation of end-member cover may also be related to the relatively low signal-to-noise of data generated by the Hyperion sensor. TM-based unmixing results compare unfavourably to those generated from Hyperion data, indicating that, for the study area at hand, noisy Hyperion hyperspectral data are of greater utility than high-fidelity and low-dimension TM data for the generation of surface-cover abundance maps.

Although the fractional abundance images derived from Hyperion data more accurately reflect the distribution of surface materials in the study area than TM-derived abundance images, it is noteworthy that the map of surface cover generated through neural-network classification of TM data contains a similar level of useful information regarding surface cover. This is significant given the relative ease with which this map was generated (e.g. conversion of image data to reflectance was not required) and given the low spectral resolution of the data used as input to the classification (e.g. only four bands were needed to generate the map of surface cover). For some northern study areas, the generation of maps of surface cover may be best conducted using standard per-pixel classifiers and using TM or similar broadband multispectral datasets.

This study partly involved the use of linear spectral unmixing for Hyperion-based mapping of a comprehensive set of lithological end members assembled in advance and based on field reconnaissance. Although such an unmixing methodology is well suited for mapping known lithological end members at sub-pixel scales over the full extent of a study area, future Hyperion work will involve experimentation in the use of additional techniques, such as spectral-feature fitting and classification approaches.
using combined hyperspectral bands, to generate synthetic spectral bands characterized by higher signal-to-noise (e.g. Gianinetto and Lechi 2004).

Through the provision of specific information regarding the distribution of lithological classes at the surface of the Melville Island study area, image classification results, such as those generated in this study, can provide complementary information to that of maps of local bedrock geology. For northern study areas, remote-sensing derived maps of surface cover have the potential to provide information at finer spatial scales than those of available geological maps and, in the case of fractional abundance maps, can provide more accurate depictions of the real-world distribution of classes of interest. The availability of such information can help support work related to such activities as environmental characterization, resource assessment and the study of surface processes and geological history. Although challenges remain, the results of this study further confirm the central role of image datasets of both low and high spectral resolution in the future study of surface materials at high northern latitudes.

Acknowledgements
The helpful comments of two anonymous reviewers are appreciated. The 1998 field campaign at Melville Island was funded by Northern Scientific Training Program (Canada) and Geological Society of America grants to David Leverington, and by a Natural Sciences and Engineering Research Council (Canada) operating grant to Woonil Moon (University of Manitoba).

References


