Normalization of Landsat thermal imagery for the effects of solar heating and topography

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Abstract. This paper is an investigation of three simple normalization procedures for suppressing the effects of solar heating and topography in daytime thermal data. The first method is the hyperspherical direction cosine (HSDC) transformation, which separates the pixel vector into an illumination/albedo component and a spectral component. The second method, a model correction, is based on the assumption that, once an elevation correction using the normal lapse rate has been applied, temperatures are proportional to the instantaneous solar heating as measured by the cosine of the solar illumination incidence angle. The third method is a statistic-empirical correction. These three normalization methods were applied to a test site in the Humboldt Range, Pershing County, Nevada, using Landsat Thematic Mapper data. It was found that geological patterns were much clearer in the normalized data than in the original temperature information. The HSDC correction brought out lithological differences, helped discriminate between gravels and spectrally similar sedimentary rocks and resulted in a significant increase in classification accuracy. The model correction appeared to inadequately compensate for the cool temperatures found at high elevations, and therefore underestimates the actual decline in temperature with elevation. Nevertheless, the rock contacts are relatively clear, and the classification produced the second highest overall accuracy. The statistic-empirical classification resulted in improved elevation correction, but it over-corrected north-facing slopes and produced only intermediate improvements in accuracy.

1. Introduction

Thermal wavelengths are one of the most important regions of the electromagnetic spectrum. However, daytime images provide information about temperatures that are generally transient in nature and dependant on the thermal environment, particularly the solar flux and topographic elevation (Lougeay 1982). This paper is an investigation of methods to suppress these effects, in the expectation that the normalized imagery may enhance the differences between different objects and surface materials, because normalized thermal data may provide an indication of land-cover intrinsic thermal properties, especially thermal inertia. This aim is particularly significant given the vast archive of existing Landsat Thematic Mapper (TM) thermal data that is often ignored in image analysis. Landsat data provides co-registered,
complementary optical and thermal data, a near-global coverage and has been acquired since 1982. Although planned satellite missions will provide spectral thermal data from which the fundamental property of emittance can be estimated (Gillespie et al. 1998, Hook et al. 1992), normalizing radiance information for topographic effects may still be useful for cover types that are not well discriminated by emittance differences. For example, unconsolidated scree should have a much lower thermal inertia than the bedrock from which it is derived, but it would have similar spectral properties.

Normalized temperature information has the potential to be a clue to the recognition of thermal inertia and, in turn, the differentiation of objects based on physical properties, particularly density and water content (Price 1977, 1985, Gillespie and Kahle 1977). This is in contrast to most remote sensing, which is limited to surface spectral properties. Thermal inertia (I) is determined from the thermal conductivity (K), density (ρ) and specific heat (c):

\[ I = (K \rho c)^{1/2} \]  

In an early study of Death Valley, Kahle (1987) found that, by co-registering day and night aircraft thermal imagery to Landsat optical imagery, it was possible to produce an apparent thermal inertia image that discriminated bedrock from alluvium and also several rock types including carbonates and volcanic strata. Thermal inertia mapping was the aim of the Heat Capacity Mapping Mission (HCMM), but such studies were found to be challenging due to problems in co-registering night and day images and the presence of clouds.

In the absence of multiple observations of the same site, most aircraft-based thermal studies use imagery acquired just before dawn, when solar illumination effects have generally dissipated and temperature contrasts between cover types of differing bulk physical properties are at a maximum. For example, in karst regions, potential sink-holes have been identified based on the lower pre-dawn temperatures of unconsolidated material compared to bedrock. Thermal scanning from a truck-mounted sensor has also been shown to be useful for the identification of cavities in airport runways and roads, underground tanks and leaks in underground pipes (Weil 1991). In arid regions, buried objects such as rock layers of contrasting thermal properties can potentially be identified in thermal imagery (Nash 1988). Despite the non-optimal time of mid-morning and the coarse spatial resolution, the Landsat thermal band (120 m × 120 m) has been found to be useful, for example in monitoring underground fires in India (Saraf et al. 1995). In the present study, however, the focus is on normalizing thermal imagery to enhance discrimination of different surface materials, particularly rocks and unconsolidated material.

2. Atmospheric normalization of optical data

Like thermal imagery, optical data are also highly influenced by topographically influenced variations in solar illumination (Teillet et al. 1982, Burgess and Lewis 1995). Consequently, a significant body of literature on methods for normalizing these effects in images has developed (Smith et al. 1980, Kawata et al. 1988, Leprieur et al. 1988, Civco 1989, Thomson and Johns 1990, Colby 1991, Naugle and Lashlee 1992, Conese et al. 1993, Itten and Meyer 1993, Schaaf 1994, Ekstrand 1996). Amongst the methods used are empirical approaches based on regression of illumination angle against the cosine of the local incidence angle of the illumination and model-based methods that assume Lambertian reflectance. In addition, a number of
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methods have been developed that employ exponential functions, in order to model non-Lambertian relationships (Smith et al. 1980, Meyer et al. 1993).

The Lambertian model assumes that reflected radiance from an inclined surface (LT) may be related to that from a horizontal surface (LH), by the following relationship:

\[ LT = LH \times \cos i / \cos z \]  \hspace{1cm} (2)

where \( i \) is the local incidence angle of the illumination (i.e. the angle between the illumination and the normal to the surface) and \( z \) is the sun zenith angle (i.e. the angle between the vertical and the sun). Generally speaking, methods employing a Lambertian assumption work best at relatively low slope angles and small sun zenith angles (Meyer et al. 1993). Nevertheless, such methods are able to reduce the within-class variance compared to the between-class variance, thus improving discrimination of cover types.

Empiric studies use a statistical approach to estimating regression coefficients to relate radiance from inclined and horizontal surfaces:

\[ LT = LH + a \cos i / \cos z \]  \hspace{1cm} (3)

where \( a \) is an empirical factor derived from the regression.

The above methods require co-registered digital elevation data. If such information is not available, a hyperspherical direction cosine (HSDC) normalization can be used to suppress illumination and albedo variations in an image (Pouch and Campagna 1990). This approach is based on a transformation of the measurement vector into a spectral component, comprising HSDCs, and an illumination/albedo component, which is represented by the radius of the hypersphere. The radius is calculated by

\[ R = \left[ \sum X_i^2 \right]^{1/2} \]  \hspace{1cm} (4)

where \( X_i \) is the pixel’s brightness value in the \( i \)th band. The direction cosines are then defined by

\[ Y_i = 255(X_i / R) \]  \hspace{1cm} (5)

where \( Y \) is the direction cosine vector of the original measurement vector \( X \). The constant 255 in equation (3) is a scaling factor to expand the data over the arbitrary 8-bit range. The HSDC operation is equivalent to radially projecting each measurement vector onto a hypersphere with a radius of 255 (Pouch and Campagna 1990).

3. Normalization of thermal data

The temperature of an object on the surface of the Earth is dependant on the summation of radiative, convective, conductive and latent heat transfer between the object and its surroundings over the diurnal period. Cloud cover reduces incident radiation during the day, but it also reduces loss of energy at night by reflecting energy radiated upward by the ground surface. Moisture has an important effect, due to its high thermal inertia and the cooling effect of latent heat transfer during evaporation. Consequently, during the daytime, moist soil and vegetation are generally cooler than dry soil.

The incident radiation is composed predominantly of the short-wavelength radiation from the sun and long-wavelength radiation from the sky (Watson 1975). The effect of elevation can be approximated by the dry lapse rate of 6.5°C per 1000 m
altitude. The absorbed solar radiation is a function of the surface albedo, cloud cover, the solar zenith angle and the local zenith angle for the inclined surface (Watson 1975). The incident solar radiation in the early morning is much lower than mid-morning, when Landsat imagery is collected. This is due to both the increased path length and the diffusion of the sun’s rays over a larger area (Slater 1980). For example, comparing the half-hour terminating with the Landsat acquisition to the prior half-hour, the optical path is approximately 25% shorter and the solar illumination (ignoring atmospheric effects) is 19% more concentrated (based on the equations of Price (1989) and Slater (1980)). Thus, the overprint of prior heating history for an early-morning to mid-morning acquisition is less than it would be for a mid-afternoon acquisition.

A number of studies have measured the variation in radiant temperature associated with different viewing geometries (Balick and Hutchinson 1986, Balick et al. 1987). Although this is a slightly different issue compared to the effects of slope and aspect on a nadir-viewing sensor, it provides an indication of the directional emissivity properties that might influence radiation from the ground. Lagouarde et al. (1995) found differences in radiant temperatures of 0.5 to as much as 4°C over a 60° viewing angle for plant canopies and bare soil. Plant structural differences and soil microtopography caused by plowing appeared to be particularly important in determining radiant temperature differences (Lagouarde et al. 1995). In the present study, there is minimal agriculture, and vegetation is sparse and not expected to be systematically arranged.

The most significant topographic factors in determining temperatures have been found empirically to be elevation, slope and aspect (relative to solar illumination) (Florinsky et al. 1994). Slope curvature has also been investigated, particularly for its role in determining soil moisture conditions. However, slope curvature measures were found to have low to non-significant correlation coefficients when regressed against temperature (Florinsky et al. 1994).

Using topographic factors as surrogates for measures of integrated solar heating will be least accurate if slopes facing the sun have an angle that exceeds that of the solar zenith angle. These slopes have their maximum solar intensity prior to the time of image acquisition and may be warmer than expected. However, such steep slopes are rare and, based on an analysis of the present digital elevation model (DEM) data, are not found in the study area.

4. Study area and data

The study area (figure 1) includes the Humboldt Range and the edge of the Buena Vista Valley in Pershing County, Nevada (40° 00’ to 41° 45’ N, 118° 00’ to 118° 15’ W). The Humboldt Range is a north-trending mountain range with an average elevation more than 1800 m, reaching its highest point at Star Peak with an elevation 2998 m (figure 2). The lowest part of the study area has an elevation of about 1200 m, on the edge of Buena Vista Valley. The climate is arid to semi-arid, with a yearly rainfall of about 150 mm in the valley and as much as 500 mm in the mountains.

The exposed rocks range in age from Triassic to Holocene (Johnson 1977). Mesozoic plutonic, volcanic and sedimentary rocks are widely exposed throughout the range. Cenozoic rocks in this area predominantly consist of sedimentary and volcanic rocks distinguished on the basis of dominant lithology. The most widely
distributed deposits are Quaternary alluvial fan and stream gravels, lake deposits and windblown sand that cover most of the lower slopes of the area.

A Landsat-5 TM image, acquired on 15 May 1989, was obtained from the United States Geological Survey (USGS) Earth Resources Observation System (EROS) Data Center (figure 3). This scene was chosen because it was cloudless and was
acquired when snow was limited to the highest elevations and the solar elevation was comparatively high. At the time of imaging, the sun elevation was 59°, with an azimuth of 125°. A DEM was also obtained from USGS (figure 2). This data consists of elevation profiles on 30×30 m data spacing and is geocoded on a Universal Transverse Mercator (UTM) projection. Ancillary data were obtained from the Nevada Bureau of Mines and Geology and included both paper and digital copies of geologic maps (Johnson 1977, Hess and Johnson 1996). A map prepared from
that data is shown as figure 1. USGS 7.5° topographic maps were also obtained for collecting ground control points for the geocoding of the TM data.

5. Methods

The relative scales of the various datasets are not entirely equivalent. The TM optical data has a nominal 28.5 m instantaneous field of view (IFOV) but was
resampled to the UTM grid of 30 meters using 25 ground control points and a second-order polynomial. The thermal band has a 120 m IFOV but was resampled by the EROS Data Center to the same resolution as the optical bands using cubic convolution and, therefore, geocoded to the 30 m grid in the same process as the optical data. Thus, the data were all converted to the same projection and scale.
However, slope and aspect is calculated over a local moving window and, therefore, has an effective pixel size approximately twice that of the input data (Hodgson 1995), even though data are obtained for every input point. Thus, the true scale of the slope and aspect data for this study is effectively intermediate between that of the optical and the thermal data. A $5 \times 5$ low-pass filter was passed over the DEM data.
in order to reduce the high-frequency variation in the DEM and make it more comparable to the thermal data.

The thermal data were converted to exoatmospheric radiance using published gain and offset data (Markham and Barker 1986) and the LOWTRAN model (Kniezy et al. 1985), which was used to estimate atmospheric absorption and radiance. The default mid-latitude summer profile was used for the temperature and ozone profile, but a midlatitude winter profile was used for the water vapour, because, in this desert environment, the concentration of water vapour is low. The LOWTRAN analysis indicated an integrated transmittance of 0.938 across the Landsat band-6 bandpass (10.4–12.5 μm). Atmospheric radiant energy reaching the Landsat sensor was calculated to be 7.65×10⁻² mW cm⁻² sr⁻¹. After compensating for atmospheric radiance and absorption, the at-sensor radiance values were converted to temperature using Planck’s law (figure 3, left image). The results were found to be higher than expected for 10 am in mid-May, with average values approximately 40°C on the lower slopes of the Humboldt range. By comparison, the Rye Patch Dam, Nevada, weather station, which is just east of the study area and at a similar elevation of 1200 m, has a mean monthly maximum temperature of 27°C for the month of May. For a period of 1 week centred on either side of 15 May, the maximum temperature at Rye Patch Dam, measured during the 50 years from 1948 and 1998, was 41°C (Western Regional Climate Center 1999). The crest of the range, which can be seen to be snow-capped, was found to be close to 0°C. As a check on these calculated temperatures, the IDRISI program THERMAL (Bartolucci and Chang 1988, Eastman 1997) was also applied to the data with no atmospheric correction, and similar results were obtained. The reason for testing the conversion to temperatures using no atmospheric correction is that the effects of atmospheric absorption and re-radiation tend to compensate for each other, especially under conditions of good visibility and low water-vapour content (Bartolucci et al. 1988).

Slope and aspect were calculated from the DEM data using the Erdas Imagine SLOPE and ASPECT programs (Erdas 1997). These programs use the average topography of the pairs of pixels surrounding a central pixel in a surrounding 3×3 window. Srinivasan and Engel (1991) have pointed out that this approach does not consider the centre pixel and may lead to inaccuracies in a landscape with numerous small pits or ridges. The local incidence angle of the solar illumination (figure 2, right image) was calculated from this data using simple trigonometric relationships (Holben and Justice 1980, Smith et al. 1980, Warner et al. 1996).

The TM data were then normalized using three methods: the HSDC method; a model-based method; and an empirical method using a variety of variables. For the HSDC normalization (Pouch and Campagna 1990), only the optical bands were used to calculate the illumination/albedo component (figure 3, right image). Although Pouch and Campagna (1990) did not mention using thermal data, the thermal band was also normalized by dividing by the albedo/illumination image (figure 4A, left image).

For the model normalization, the optical bands were normalized using the Lambertian cosine correction described above. The thermal data were treated in a similar manner, except the results are corrected for a temperature gradient based on a normal lapse rate:

$$L_{TELEV} = L_{HELEV(0)} \times \cos \theta / \cos \theta + ELEV \times \text{lapse\_rate}$$

where ELEV is the elevation (m), ELEV(0) is the elevation at sea level and lapse\_rate is -0.0065°C m⁻¹. Figure 4A, right image, shows the result of the normalization.
The statistic-empirical normalization used the simple Lambertian model described above for the optical bands. For the thermal bands, the following relationships were tested:

\[
LT_{ELEV} = LH_{ELEV(0)} + a \cos i/\cos z + b \ ELEV
\]

\[
LT_{ELEV} = LH_{ELEV(0)} + a \cos i/\cos z + b \ ELEV + c \ ELEV \times \cos i/\cos z
\]

\[
LT_{ELEV} = LH_{ELEV(0)} + a \cos i/\cos z + b \ ELEV + c \ ALBEDO
\]

In the above equations, \(a, b\) and \(c\) are empirical factors from the regression, and \(ALBEDO\) is the albedo/illumination component from the HSDC analysis. The \(ALBEDO\) term was included in the analysis because the albedo of an object can give an indication of its emissivity and absorptivity.

The statistical analysis was carried out using SAS (SAS Institute, Cary, North Carolina, USA) and input data that were subsampled on a \(4 \times 4\) pixel grid to match the original scale of the thermal imagery. The results of an ANOVA analysis, also performed in SAS, indicated that all the independent variables were significant at the 0.0001 level, with the exception of the \(ELEV \times \cos i/\cos z\) term, which was not significant. Therefore, the second of the three regression equations was not considered any further. The Pearson correlation coefficients (Table 1) indicate that the thermal band is positively correlated with \(\cos i\) and HSDC \(ALBEDO\), and negatively with elevation. The coefficients of the regression are shown in Table 2, and the normalizations are shown in Figure 4B.

### 6. Results

#### 6.1. Qualitative analysis

The HSDC normalized thermal image (Figure 4A, left image) suppresses most of the topographic illumination, despite the 1800 m elevation difference in the image and the fact that this method has no elevation correction. Despite this lack, only the crest of the Humboldt Mountains shows obvious elevation effects, and part of that can be accounted for by snow cover. The HSDC normalization brings out the major rock differences discussed above, particularly the bright tones of the basalt and sedimentary rocks and the dark tones of the rhyolites. The discrimination between the gravels and the sedimentary rocks is particularly clear.

Table 1. Pearson correlation coefficients (all significant at the 0.0001 level).

<table>
<thead>
<tr>
<th></th>
<th>THERM</th>
<th>COS(I)</th>
<th>ELEV</th>
<th>ALBEDO</th>
</tr>
</thead>
<tbody>
<tr>
<td>THERM</td>
<td>1.0000</td>
<td>0.6204</td>
<td>-0.738</td>
<td>0.2324</td>
</tr>
<tr>
<td>COS(I)</td>
<td>0.6204</td>
<td>1.0000</td>
<td>-0.2628</td>
<td>0.4329</td>
</tr>
<tr>
<td>ELEV</td>
<td>-0.738</td>
<td>-0.263</td>
<td>1.0000</td>
<td>-0.3025</td>
</tr>
<tr>
<td>ALBEDO</td>
<td>0.2324</td>
<td>0.4329</td>
<td>-0.3975</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

Table 2. Regression analysis results for predicting thermal Digital Number (DN) values.

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>(r^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>COS(I)</td>
<td>0.257</td>
</tr>
<tr>
<td>ELEV</td>
<td>0.564</td>
</tr>
<tr>
<td>COS(I), ELEV</td>
<td>0.691</td>
</tr>
<tr>
<td>COS(I), ELEV, ALBEDO</td>
<td>0.802</td>
</tr>
</tbody>
</table>
The model correction (figure 4A, right image) was also successful. However, the high elevation and west-facing slopes appear somewhat too dark (i.e. cold), and the north-facing slope facets are over-corrected. This over-correction is predominantly a fine-scale feature and is possibly due to differences in the spatial scales of the DEM and thermal data. The rocks do not appear to be differentiated quite as well as in the HSDC-normalized image. For example, the rhyolites generally have dark tones, but on the east-facing slopes they have more intermediate values. Part of the problem with this image is that the regression analysis suggested that the decline in temperatures was much steeper than would be expected from the thermal lapse rate: 14.4°C per 1000 m, instead of the value of 6.5°C per 1000 m used. One definite area of improvement is that the cool temperatures from moisture along the drainages are much more distinct.

The images corrected using the statistic-empirical approach (figure 4B) are the most successful for elevation correction, but the least successful for slope/aspect correction. As with the model-based correction, north-facing facets are generally too bright/warm. The difference between the normalization with and without the HSDC albedo component is minimal, and it would appear that normalization for albedo effects is not helpful.

6.2. Quantitative analysis

The quantitative accuracy assessment was conducted by investigating the accuracy of a standard supervised classification with data from each of the different normalization procedures. A minimum distance classification was used, because this method is particularly sensitive to normalization effects (Meyer et al. 1993). The ground reference data for evaluating the classification was taken from the geological map, as this provided comprehensive and detailed information for the study area. However, the geological taxonomy differentiates rocks in a complex manner that is based on, amongst other attributes, rock fabric and age. Thus, it is not expected that the entire range of rock types identified in the field can be discriminated spectrally. Instead, six major geological units were identified, with the remaining units, vegetation and snow grouped as ‘Other’ (table 3). These classes cover the major rock types in this scene and are present in a wide range of topographic situations. Therefore, they present a good test of normalization potential. The areas chosen for evaluating classifier accuracy did not overlap with the training data and, where possible, were in a different topographic site. The accuracy was converted to a KHAT statistic (Cohen 1960, Congalton 1991), in order to account for chance agreement (table 4).

It is apparent from table 4 that the thermal data adds considerably to the accuracy of the classification. In fact, simply adding the thermal band data was almost as

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Topography</th>
<th>Elevation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qd</td>
<td>Quaternary dune sands</td>
<td>Flat</td>
<td>Low</td>
</tr>
<tr>
<td>QTg</td>
<td>Quaternary–Tertiary gravels</td>
<td>Sloping</td>
<td>Low–medium</td>
</tr>
<tr>
<td>TRgv</td>
<td>Triassic mudstone and sandstone</td>
<td>Sloping</td>
<td>Low–medium</td>
</tr>
<tr>
<td>TRnp</td>
<td>Triassic limestone and dolomite</td>
<td>Variable</td>
<td>Low–high</td>
</tr>
<tr>
<td>TRro</td>
<td>Triassic rhyolite</td>
<td>Variable</td>
<td>Low–high</td>
</tr>
<tr>
<td>TRI</td>
<td>Greenstone and andesite flows</td>
<td>Variable</td>
<td>Low–medium</td>
</tr>
<tr>
<td>Other</td>
<td>Vegetation, snow and other rock types</td>
<td>Variable</td>
<td>Variable</td>
</tr>
</tbody>
</table>
Table 4. Classification accuracies for four atmospheric corrections. (The reported results have an uncertainty of ±0.01 at the 99% confidence level.)

<table>
<thead>
<tr>
<th>Method</th>
<th>KHAT accuracy for optical bands only</th>
<th>KHAT accuracy for thermal and optical bands</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncorrected bands</td>
<td>0.48</td>
<td>0.57</td>
</tr>
<tr>
<td>HSDC</td>
<td>0.48</td>
<td>0.74</td>
</tr>
<tr>
<td>Cos/elevation model</td>
<td>0.59</td>
<td>0.70</td>
</tr>
<tr>
<td>Cos/elevation statistic-empirical correction</td>
<td>0.61*</td>
<td>0.68</td>
</tr>
<tr>
<td>Cos/elevation/albedo statistic-empirical correction</td>
<td>0.61*</td>
<td>0.69</td>
</tr>
</tbody>
</table>

*The accuracy is the same for the optical bands for the two empirical models, as the same data was used in both cases.

useful as normalizing the optical bands with the DEM information. The HSDC normalization using only optical data resulted in no significant change in KHAT value for classification, with a value of 0.48 for both raw and normalized data. However, when the thermal data were included with the optical data in the HSDC normalization, the highest accuracy (KHAT = 0.74) was obtained. This lends support to the qualitative analysis indication that the HSDC approach is effective for normalizing the thermal band. The model and statistic-empirical corrections produced nearly similar results. When normalization was applied to the optical bands alone, KHAT values of 0.59 and 0.61 were obtained for the model and statistic-empirical methods, respectively. However, when the thermal band was included, the model-based method gave the second highest accuracy (KHAT = 0.70). The incorporation of HSDC albedo gave the statistic-empirical normalization a slight boost, but the results of the classifications for statistic-empirical normalization were slightly lower than that of that with the model normalization. This would suggest that the normalization is a fairly robust process, and the details do not seem to make a large degree of difference.

The specific classes that were poorly classified (table 5) give some insight into the strengths and weaknesses of each method. With no normalization, the mudstones
and sandstones (TRgy) and rhyolites (TRro) were most often incorrectly classified, whether the thermal band was included or not. The large elevation range, and variable illumination, gives the rhyolites a particularly large spectral variance. (See table 3 for a summary of the topographic settings of each class.) After the HSDC normalization, the dune sands (Qd), which were previously classified highly accurately, become the class most poorly classified. This class is characterized by a limited elevation range and low slopes and, therefore, is the least likely to gain from the normalization.

For the classification of the model-based normalization data, the class with the most errors of omission is the limestones and dolomites (TRnp), which is also found over a variety of topographic sites. Without the thermal data, the greatest errors of commission are associated with the rhyolites (TRro). With the inclusion of thermal data in the model normalization process, the limestones and dolomites (TRnp) have both the highest errors of omission and commission. The statistic-empirical normalizations give classification errors of omission that are mostly dominated by the limestones and dolomites (TRnp). For the statistic-empirical method, the relatively low elevation mudstones and sandstones (TRgy) are consistently found to have high errors of omission, irrespective of the precise combination of optical and thermal bands and the data used in the regression analysis.

7. Conclusions

The Landsat thermal band adds information on bulk physical properties that is not obtainable in other parts of the spectrum. Normalization was found to add to the value of the thermal data. The difference between the various methods was small, despite the fact that the HSDC method does not use a digital elevation method, whereas the other methods did. The success of the HSDC method is somewhat surprising, because this scene had a large temperature range associated with elevation, and many rock types were found at a variety of altitudes. Rock contacts were clear, the discrimination of the gravels from the neighbouring sedimentary units was enhanced and the overall accuracy of the classification was the second highest obtained.

The conversion of the thermal band Digital Number (DN) values to temperature using a simple model of lapse rates produced high temperature values for the low-elevation regions. Despite the differences in lapse rates between the model and the statistic-empirical parameters observed, normalization based on the model and the statistic-empirical methods produced excellent results. However, the accuracy of classification with the model normalization data was slightly higher than that obtained from the statistic-empirical normalization. The inclusion of an HSDC albedo component was only marginally advantageous. The visual assessment of the normalized images suggests that the statistic-empirical method appears to over-correct north-facing slopes, but that it produces an excellent correction for elevation effects.

Acknowledgments

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