Radiometric normalization and image mosaic generation of ASTER thermal infrared data: An application to extensive sand sheets and dune fields

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Abstract

Data from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) have a significant advantage over previous datasets because of the combination of high spatial resolution (15–90 m) and enhanced multispectral capabilities, particularly in the thermal infrared (TIR) atmospheric window (8–12 μm) of the Earth where common silicate minerals are more easily identified. However, the 60 km swath width of ASTER can limit the effectiveness of accurately tracing large-scale features, such as eolian sediment transport pathways, over long distances. The primary goal of this paper is to describe a method for generating a seamless and radiometrically accurate ASTER TIR mosaic of atmospherically corrected radiance and from that, extract surface emissivity for arid lands, specifically, sand seas. The Gran Desierto in northern Sonora, Mexico was used as a test location for the radiometric normalization technique because of past remote sensing studies of the region, its compositional diversity, and its size. A linear approach was taken to transform adjacent image swaths into a direct linear relationship between image acquisition dates. Pseudo-invariant features (PIFs) were selected using a threshold of correlation between radiance values, and change-pixels were excluded from the linear regression used to determine correction factors. The degree of spectral correlation between overlapping pixels is directly related to the amount of surface change over time; therefore, the gain and offsets between scenes were based only on regions of high spectral correlation. The result was a series of radiometrically normalized radiance-at-surface images that were combined with a minimum of image edge seams present. These edges were subsequently blended to create the final mosaic. The advantages of this approach for TIR radiance (as opposed to emissivity) data include the ability to: (1) analyze data acquired on different dates (with potentially very different surface temperatures) as one seamless compositional dataset; (2) perform decorrelation stretches (DCS) on the entire dataset in order to identify and discriminate compositional units; and (3) separate brightness temperature from surface emissivity for quantitative compositional analysis of the surface, reducing seam-line error in the emissivity mosaic. The approach presented here is valid for any ASTER-related study of large geographic regions where numerous images spanning different temporal and atmospheric conditions are encountered.

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1. Introduction

1.1. TIR remote sensing of aeolian systems

Desertification, sand encroachment and dust storms are some of the geologic hazards related to increasing climate change and anthropogenic activity found in arid lands associated with aeolian systems (Nicholson et al., 1998; Nickling et al., 1998; Prospero et al., 2002). These systems are quite extensive, and sand is moved long distances via transport pathways as indicated by geochemical studies (Kasper-Zubillaga et al., 2007; Muhs et al., 2003; Zimbelman et al., 1995; Zimbelman & Williams, 2002) and remote sensing (Ramsey et al., 1999). Past studies have used the Landsat Thematic Mapper (TM) data to study small portions of the Namib Sand Sea (White et al., 1997), the Wahiba Sand Sea (Pease et al., 1999), and the Gran Desierto (Blount, 1988; Blount et al., 1990). Paisley et al. (1991) successfully used these data to distinguish between active and inactive sands, and Blount et al. (1990) demonstrated the use of a
spectral unmixing model to discriminate surface compositions. These studies largely utilize the visible near-infrared (VNIR) and shortwave infrared (SWIR) wavelength regions (0.4–2.5 μm).

The percentage and chemical composition of surface materials is, however, not easily related to the spectral shape in this wavelength region (Blount et al., 1990). Practical limits are imposed on the quantitative interpretations of surface composition and especially abundance because of the non-linear mixing of reflected energy scattering among sand grains (Johnson et al., 1992; Ramsey et al., 1999). Sub-pixel information can be retrieved from the emitted TIR multispectral data by assuming that the fractional areal extent of mineral end-members is linearly proportional to the position and depth of spectral features (Clark et al., 1990; Ramsey & Christensen, 1998; Salisbury & D’Aria, 1992; Thomson & Salisbury, 1993; Vincent & Thomson, 1972).

Limiting factors for the linear unmixing of TIR remote sensing data include the noise equivalent delta temperature (NEΔT) of the sensor, the range of temperatures and the spectral contrast of image pixels and end-member spectra. Previous studies clearly identified surface mineralogy and mixing patterns using TIR airborne data (Crowley & Hook, 1996; Edgett et al., 1995; Ramsey et al., 1999) and satellite data on Earth and Mars (Bandfield et al., 2000; Ramsey et al., 1999; Wright and Ramsey, 2006). Likewise, only TIR radiance allows for thermophysical properties such as kinetic temperature and apparent thermal inertia to be derived (Kahl, 1987; Martinez-Alonso et al., 2005; Ramsey, 2002).

1.2. Previous mosaicking methods for ASTER TIR

Satellite remote sensing data provide the synoptic view necessary to study large and commonly inaccessible aeolian systems. Without a mosaicking procedure, the geographical extent imposes practical limits on the choice of the data used. The Terra satellite carries two primary instruments for observing the Earth surface in the TIR: The Moderate Resolution Imaging Spectroradiometer (MODIS) and ASTER. MODIS is advantageous for global coverage utilizing eight spectral bands in the TIR wavelength region at a spatial resolution of 1 km/pixel and a swath width of 2330 km. Spectral unmixing and classification of a mosaic of MODIS data was used for landform mapping in the Sahara (Ballantine et al., 2005), although it did not include multispectral TIR data. Even though sediment transport pathways are discernible over distances of hundreds of kilometers from MODIS data, a significantly higher spatial resolution is needed to quantify the composition and degree of mixing of small contributing areas of sand along paths of transport or the extent of dust source areas less than 1 km².

ASTER has a significant advantage in the remote sensing of geologic materials because of its higher spatial resolution than MODIS and enhanced spectral range (Fujisada et al., 1998; Yamaguchi et al., 1998). ASTER has proven useful for mapping key mineral groups, especially for discriminating silicates (Hewson et al., 2001; Rowan & Mars, 2003; Rowan et al., 2005). However, because the ASTER footprint is only 60 km × 60 km, it is necessary to combine multiple scenes into a mosaic for complete coverage of a large study region such as the Gran Desierto or Sahara Desert. Few published studies of ASTER data have been used in a multi-scene capacity. Ogawa et al. (2002) mosaicked the standard atmospherically corrected ASTER surface emissivity data product (Gillespie et al., 1998) for a 750,000-km² portion of the Sahara Desert to estimate broadband emissivity at 90 m/pixel spatial resolution. Hewson et al. (2005) described the generation of a seamless mosaic of normalized SWIR band-ratio data, but this emissivity data, generated from TIR radiance, were not normalized because spectra compared well with field observations and the emissivity product was found to mosaic well despite scan line noise and a relatively low signal to noise ratio (SNR). Seamlessness of a mosaic is a most obvious advantage for display purposes, but the combination of radiometrically non-normalized scenes hinders spectral analysis and geologic interpretation (e.g., such as the delineation of surface composition). The thermal radiance received by the ASTER sensor is affected by the emissivity (composition) and the temperature of the emitting surface. Atmospheric correction and the separation of temperature from the desired surface composition information (emissivity) may not be adequate alone to achieve radiometric normalization. There has been no detailed description or evaluation of the pre-processing issues and mosaicking strategy for TIR radiance data.

The need to combine multispectral remote sensing data using a relative radiometric normalization approximated by linear functions is not a new concept, and a number of techniques have had varied success for Earth (Canty et al., 2004; Du et al., 2001, 2002; Furby & Campbell, 2001; Hall et al., 1991; Moran et al., 1992; Paolini et al., 2006; Schott et al., 1988) and Mars (Martinez-Alonso et al., 2005). For these techniques, it is assumed that an approximately linear relationship can be determined between the at-sensor radiance measurements within the area of the overlapping scenes that contain PIFs, as the models for the atmospheric and viewing-geometry effects on the recorded data are far more complex. Changes in the land surface through time may not have the same linear relation as the whole image scene and are problematic for image mosaicking. Canty et al. (2004) demonstrated a successful example of mosaicking by automatically selecting PIFs between bitemporal images using the multivariate alteration detection (MAD) technique (Nielsen et al., 1998), and they emphasize a number of unique characteristics that are important to their mosaicking technique:

- The selection of PIFs was not manual or subjective except for one decision threshold, based on scale-invariant criteria, and corresponded to physical characteristics of the land surface.
- Their results compared favorable with other manual methods, but their technique was fast and automatic.
- After testing, orthogonal linear regression of PIFs was preferred to ordinary least squares regression (OLS).

2. Location and primary objectives

An ideal location for creating an ASTER TIR mosaic and testing its science applications is a large sand sea of diverse surface composition with few complicating factors (e.g., humid
atmosphere, large amounts of vegetation, or poor access to the area for field validation). The Gran Desierto (Fig. 1), a 5700-km² area located along the northern coast of the Gulf of California in the state of Sonora, Mexico, was chosen as a focus and testing area because of the unique assemblages of dunes of variable composition and morphology (Lancaster et al., 1987; Blount et al., 1990; Lancaster, 1992; Muhs et al., 2003; Beveridge et al., 2006). The sand sea itself is a dynamic land surface feature over geologic time scales, but the mineralogy of its surface in the Gran Desierto is assumed to be in equilibrium or generally stable with respect to sediment flux over the range of ASTER acquisition dates (2000–2003). Therefore, a minimal amount change is expected for the composition of sand surfaces over the three year time scale of this study.

The main objective here was to present a straightforward method for creating a seamless ASTER multispectral TIR radiance-at-surface mosaic from standard data products (Fig. 2), and to then evaluate the effectiveness of a relative radiometric normalization technique in both radiance and emissivity space in an arid land environment. The method developed here using 26 ASTER scenes will guide production of a much larger (∼4000+ ASTER scenes), high resolution mosaic of the Sahara Desert. The desired final result must have reduced seam-line error and balanced images and it must be suitable for emissivity extraction, spectral analysis algorithms such as linear deconvolution (Ramsey et al., 1999), and final geologic interpretation. The application of the final mosaic data, beyond the scope of the work here, is to derive the bulk mineralogy of the surface of sand seas and dust sources in arid lands from emissivity derived from TIR data.

3. Mosaic generation

3.1. ASTER data

ASTER measures spectral radiance in five TIR bands between 8.13 and 11.65 μm, has a spatial resolution of 90 m/pixel and the NEΔT<0.3 K. The data used for this study include the Level-2 (L2) surface-leaving radiance (AST_09T) and the emissivity (AST_05) products. Calibration is applied to Level-1A (L1A) data, which is based on the sensor stability over time in order to create the geolocated and radiometrically accurate L1B data, resulting in an absolute accuracy of 2% and a relative accuracy of 1% (Yamaguchi et al., 1998). The AST_09T product, created from the L1B, has been radiometrically, geometrically, and atmospherically corrected Thome et al. (1998). The AST_05 product is derived from the AST_09T data using the Temperature Emissivity Separation (TES) algorithm described by Gillespie et al. (1998), which accounts for both the spectral contrast and downwelling atmospheric irradiance. These data are distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at the U.S. Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) (http://LPDAAC.usgs.gov).

Consecutive scenes acquired along the same orbital path should combine seamlessly because these were acquired as one observation by ASTER. However, caution must be taken where combining imagery from different versions of calibration to ensure seamlessness in a final mosaic. L1B data used to generate the L2 on-demand TIR radiance products were previously archived at the LP DAAC. Depending on when L2 data were ordered, they may have been produced from slightly different versions of the L1B archived data and lead to inconsistencies. As a result, L1B images occasionally were found to have subtle seam boundaries in the same orbital path if these scenes had different versions of a radiometric calibration. This problem has now been eliminated for new data users, as all L1B data are processed on-demand and therefore always have the latest radiometric calibration. On-demand processing also ensures that subsequent L2 products have the same atmospheric correction.

To create an accurate mosaic of the Gran Desierto test local from the data available, 26 daytime scenes spanning 8 different
dates (Table 1) were selected using metadata from The Terra ASTER Metadata Inventory (TAMI) and browse images previewed through the USGS Global Visualization Viewer (GloVis) website. A custom set of software tools were designed to process and combine these data into a geographical information system (GIS). In the absence of these tools, scene selection was time-consuming and not easily streamlined for a large study area. An attempt was made to choose scenes based on similar acquisition date and time, low cloud cover, season, solar illumination, and sun angle. Using the VNIR browse images, data were screened based on overall quality and the presence of obvious change that would either mask or alter the spectral information of the geologic surface composition. Some scenes that passed initial screening were later rejected because of poor balance that was produced in the TIR mosaic process and final product.

### 3.2. Strategy for generating the ASTER TIR image mosaic

All data were converted from digital number (DN), originally recorded as 16-bit integers, to calibrated thermal radiance (W/m$^2$ sr$^{-1}$ μm$^{-1}$), and stored as floating-point data. No data loss is expected at the limit of the data’s dynamic range and the accuracy level of the TIR instrument. The ASTER scenes were combined into swaths collected during the same orbital path and for which no radiometric normalization was needed. It was necessary to remove two to three pixels at the scene edges because these values were found to be inaccurate. This edge effect was produced during data cubic convolution resampling during the L1B data production at the LP DAAC. ASTER data are stored in the WGS84 UTM projection and are rotated in the direction of the satellite’s orbital path. All data were reprojected to geographic North using a

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**Fig. 2. Flow chart of preprocessing, normalization and mosaicking of ASTER TIR radiance and emissivity.**
If the differences that occur between pixels that were acquired at different times are expected to have different scene conditions and were acquired at different times, nearest-neighbor resampling is used. Nearest-neighbor resampling results in less rigorous pixel-by-pixel rotation and resampled using the cubic convolution method. Nearest-neighbor resampling results in less <br>anomalies of 1 K, and do not appear in the emissivity product. Because no rotation of data take place, the along track scenes were seamlessly mosaicked using nearest-neighbor resampling. Small-scale features and dune patterns are not lost with the cubic convolution resampling. For example, subtle ~25 km-long wind streaks emanating from the crests of star dunes in the south-central sand sea are still visible after resampling (Fig. 3). The streaks shown are most evident in the radiance mosaic and in the derived temperature image as subtle anomalies of 1–2 K, and do not appear in the emissivity product. Because no rotation of data take place, the along track scenes were seamlessly mosaicked using nearest-neighbor resampling because this avoided further averaging adjacent image and zero-edge pixel values.

Data from adjacent and overlapping scenes acquired at different times are expected to have different scene conditions with respect to surface temperature, atmospheric conditions, solar illumination and geometry, and instrument noise (Fig. 4A). If the differences that occur between pixels that have constant emissivity spectra through time can be approximated by linear functions, the correlation between these areas may be considered to be scale-invariant under a linear transformation (Canty et al., 2004). After some minor georeferencing was applied to correct minor coregistration errors of 1–7 pixels of unorthorectified data (RMS > 0.5 pixel), each of the along-track orbital swath images were mosaicked in the cross-track direction to create the seamless product (Fig. 4B) using the relative radiometric balancing technique described here. For two bitemporal multispectral images with n bands, an image acquired at time \( t_1 \) is determined to be of high quality and established as a reference \( X_A(i) \). An adjacent image \( X_B(i) \) acquired at time \( t_2 \) is added to the mosaic after a linear transformation is applied, where \( X^* B(i) \) is the radiometrically normalized image. The gain \( \beta \) and offset \( \alpha \) are determined from the linear regression of PIFs for each thermal radiance band \( i \) separately. The linear transformation of the first image (B) to the reference image (A) is expressed as

\[
X^* B(i) = X_A(i) \times \beta(i) + \alpha(i), \quad i = 1 \ldots n
\]

In order to affectively determine the correct gain and offset for each band, PIFs were identified by the change in the spectral shape of the land surface between the multispectral images acquired at \( t_2 \) and \( t_1 \). This is approximated by the correlation \( \rho_{AB} \) calculated in radiance or emissivity space between each overlapping, co-located pixel spectra where \( n \) is the number of bands in the multispectral image given by:

\[
\rho_{AB} = \frac{n \sum_{i=1}^{n} X_A(i) X_B(i) - \sum_{i=1}^{n} X_A(i) \sum_{i=1}^{n} X_B(i)}{\sqrt{\left( n \sum_{i=1}^{n} X_A^2(i) - \left( \sum_{i=1}^{n} X_A(i) \right)^2 \right) \left( n \sum_{i=1}^{n} X_B^2(i) - \left( \sum_{i=1}^{n} X_B(i) \right)^2 \right)}}
\]  

The result ranges from -1.0 to 1.0, where 1.0 indicates the greatest possible positive correlation for the pixel and is scale-
invariant to a linear transformation in radiance space. The correlation is used to manually set a decision threshold, where in this case $\rho_{AB} < 0.8$ yields pixels assumed not to be PIFs. Canty et al. (2004) similarly used scale-invariant MAD components to determine PIFs. If this reasonably excludes change-pixels, the approximate linear relationship between the radiance values of the two images can be determined from the remaining PIFs. Liking to orthogonal linear regression (Canty et al., 2004; Kendall & Stuart, 1979; Shapiro & Brady, 1995) or principle component analysis (PCA) operating in a multi-temporal mode where applied to the same bands on two different dates (Du et al., 2002), the major PCA component or the first major eigenvector is determined to describe the positive linear correlation between PIFs of the two images. The gain $\beta$ and offset $\alpha$ are approximated directly from the projection or slope ($s$) of the first major eigenvector, where $\mu(i)$ is the mean of the respective thermal radiance band $i$,

$$\beta = s^{-1}; \quad \alpha = \mu_A(i) - \beta(i) \times \mu_B(i)$$

(3)

The absolute radiometric accuracy of the normalized images is sacrificed for radiometric coherency of the entire mosaic, but the relative normalization technique should estimate reasonable radiance values with respect to the reference image, especially if the PIFs are selected carefully with a reasonable decision threshold. The choice of the reference image influences the final statistics, but the quality of the final mosaic can be increased with the following assumptions: (1) the reference image is atmospherically corrected and radiometrically accurate, and (2) the mosaic procedure propagates in a direction that does not reduce the variance of the data. The seamless characteristic of the mosaic is an important goal, but may not be possible in all locations.

Reduced, faint seam edges between scenes may still be visible in the mosaic using the method described here because change-pixels, excluded from balancing statistics, are still included in the mosaic. Likewise, any pixel for which non-linear changes have occurred and could not be approximated by the linear

Fig. 3. Subtle wind streaks tens of kilometers long can be seen emanating from star dunes in the temperature image. These anomalies of 1–2 K are not lost during cubic convolution resampling. The range of temperatures (287–300 K) is linearly stretched here to values of 0 to 255.

Fig. 4. (A) The non-normalized mosaic example of ASTER band 10 (8.29 μm) radiance shows the delineations of the mosaicked images. Date of image acquisition and mosaic order are indicated with numbering increasing west (+) or decreasing east (+) with distance from the reference swath. (B) Here the radiometrically normalized mosaic is shown without the final step of blending seam-lines.
transformation will not be normalized and show as residuals. Du et al. (2001) addressed remaining seam-lines between images through pixel composing. Similarly, ASTER data were blended together at seam boundaries across a linear gradient at a specified distance from the seam boundary. At the midpoint of this distance, pixel values represent a mean between each of the overlapping pixels. Seam edge errors that averaged 1.5% at the overlapping edges were blended by 50–100 pixels (4.5–9 km) to reduce visible discontinuities in the mosaic. A significant seam edge in the northwest portion of the mosaic of the study area was expected between the March 9, 2003 and November 16, 2001 image swaths because sufficient overlap did not exist. Other minor seams of up to 15% radiance were observed in localized areas of the mosaic and will be discussed further.

3.3. Emissivity extraction

Emissivity was extracted from thermal radiance using the emissivity normalization method (Realmuto, 1990) and an assumed maximum emissivity value of 0.960. Because these data are dominated by silicate minerals, the greatest amount of variance in emissivity spectra for the study area is contained within bands 10, 11, and 12, where the dominate absorption bands are contained (Clark et al., 1990; Ramsey & Christensen, 1998; Salisbury & D’Aria, 1992; Thomson & Salisbury, 1993; Vincent & Thomson, 1972). The data in this region ranges between 0.7 and 0.96, whereas bands 13 and 14 have a significantly more narrow range (0.9–0.96). The emissivity of the land surface is a much smaller fraction of the total emitted radiance than is the temperature in the TIR. However, it is the emissivity that allows for a quantitative interpretation of the surface composition. The emissivity spectra extracted from ASTER TIR compared well with field- and laboratory-based spectra (Hewson et al., 2005; Rowan & Mars, 2003; Scheidt et al., 2006), and it is important to preserve the spectral shape of each pixel in order to accurately analyze its composition. However, each band in the image was radiometrically normalized independently, therefore allowing the relative radiometric normalization to change, possibly correct, the emissivity spectra. This is a desired affect because true PIFs acquired at times \( t_2 \) and \( t_1 \) should have no difference between emissivity spectra, especially if calculated from similar temperatures determined from normalized radiance values.

4. Mosaic results

The previous attempts at radiometric normalization of ASTER TIR data using OLS regression analysis, estimation of gain and offsets from image mean \( \mu \) and standard deviation \( \sigma \) statistics, and PCA to produce a seamless mosaic were similar, but all were less effective than the technique described here. Various approaches resulted in linearly transformed TIR images that had whole-scene differences, seam-lines, and low spectral correlation between cross-track images. The use of a commercial color-balancing tool (a proprietary code) did not work well because non-PIFs could not be masked from the estimation of gain and offsets. The end products generated by this technique described here was both visually compared and quantitatively evaluated with respect to the spatial coherency of data, the correlation between resulting emissivity spectra of co-located pixels, degree of seam boundaries and the quality of the DCS.

4.1. Radiance balancing

The complete radiance mosaic showed a good balance between most of the cross-track images as seen by the pre-normalized (Fig. 4A) and post-normalized (Fig. 4B) example mosaics of band 10. Prior to normalization, the mosaic is unbalanced. Each image swath had a different overall brightness and contrast dominated by temperature with winter month acquisitions having the lowest overall radiance. The mosaic was constructed using different starting reference images to compare how that choice affected the final mosaic by allowing the linear transformations to propagate in different directions. If the January 13, 2003 image with the lowest mean and standard deviation was used as the reference, the result was a similarly lower-brightness, lower-contrast mosaic. Use of the May 21, 2001 with the highest radiance mean and standard deviation resulted in a higher-brightness, higher-contrast mosaic. Even though each reference image produced these differences, the radiance images had the same correlation between overlapping pixels in radiance space, where the average value of correlation of the radiance image overlap areas are reported in Table 2. The order of image normalization and mosaic construction for the final analysis presented here is specified by the sequential number at the seam boundaries (Figs. 4A and 5).

The spatial distribution of low correlation values (\( \rho_{AB} \)) are mapped and easily seen in the color-classed image of overlapping

| Overlap area | Radiance correlation (\( \rho_{AB} \)) | Emissivity correlation Before (\( \rho_{AB} \)) | After (\( \rho_{AB} \)) | Percent change in spatial area of correlation
<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>–1</td>
<td>0.955±0.072</td>
<td>0.986±0.027</td>
<td>0.990±0.024</td>
<td>( \Delta \rho_{AB} \leq -0.05 ) &lt;1%</td>
</tr>
<tr>
<td>1</td>
<td>0.813±0.183</td>
<td>0.816±0.242</td>
<td>0.988±0.029</td>
<td>&lt;1% &lt;1%</td>
</tr>
<tr>
<td>2</td>
<td>0.725±0.290</td>
<td>0.989±0.027</td>
<td>0.885±0.313</td>
<td>&lt;1% &lt;1%</td>
</tr>
<tr>
<td>3</td>
<td>0.982±0.031</td>
<td>0.999±0.002</td>
<td>0.995±0.042</td>
<td>20% 63%</td>
</tr>
<tr>
<td>4</td>
<td>0.959±0.111</td>
<td>0.996±0.018</td>
<td>0.944±0.270</td>
<td>24% 59%</td>
</tr>
<tr>
<td>5</td>
<td>0.766±0.248</td>
<td>0.901±0.174</td>
<td>0.724±0.478</td>
<td>27% 19%</td>
</tr>
</tbody>
</table>

The amount of area affected by the normalization technique is summarized as (a) decreased, (b) slightly decreased or (c) the same and improved.

Table 2

The average correlation coefficients, as well as the standard deviation of those values, are reported for each overlap area between radiance images, emissivity before radiometric normalization and emissivity images after normalization.
image areas (Fig. 5A). The Gran Desierto sand sea area is represented by an overall high correlation ($\rho_{AB} > 0.97$) in the overlap areas 2, 3 and 4. Areas of low correlation correspond to areas of frequent land-cover change, such as the Colorado River Valley and delta (bottom of overlap area 5), the vegetated coastal plain south of the Sierra Pinacates volcanic field (bottom of area 1), coastal marsh and estuaries of the Bahia Adair (bottom of area 2), and parts of the Basin and Range mountains and alluvial drainages (top of area 2). Where correlation was greater between overlapping areas, a higher quality of seamlessness was expected. On the eastern side of the mosaic, the May 5, 2003, May 12, 2000 and May 21, 2000 balanced well. On the western side of the mosaic, March 9, 2003, January 13, 2003 and November 16, 2001 also balanced well. An attempt was made to add data from March 28, 2001, but poor balancing with adjacent images resulted, therefore it was excluded. The May 2, 2002 image on the farthest western edge of the mosaic (overlap area 5) also did not mosaic well because of the spatial extent of frequent land cover change, primarily due to agriculture. Only a small area could be specified as an overlap region for May 2, 2002 after masking, which likely resulted in too few pixel values to accurately estimate the proper gain and offset. Likewise, most of these areas could be considered areas of change. May 2, 2002 was included to show the degree of error, as well as to include the dunes beyond the Colorado River.

Inspection of the VNIR typically showed a higher amount of ephemeral vegetation in areas of poor balance between images, and is a result of diffuse areas of lower correlation in overlapping areas between vegetated and non-vegetated surfaces. This may also be the case between the November 16, 2001 and March 5, 2003 images (upper portion of overlap areas 2). Other plausible reasons for errors in balancing will be discussed below.

Emissivity contains most of the information on the composition of the land surface, and it is these values that are chosen for more quantitative comparison of before and after results of the radiance normalization technique. The spatial distribution of correlation between co-located emissivity spectra extracted from non-normalized (Fig. 5B) and normalized (Fig. 5C) radiance is recalculated using Eq. (2), where band $i$ is the extracted emissivity. The change in correlation is shown as the difference image (Fig. 5D). Emissivity without prior radiometric normalization produces a map of emissivity that has obvious seam boundaries with values clearly varying with each whole image acquisition (Fig. 6A). Emissivity extracted from normalized radiance is much more balanced and comparable between ASTER data acquisitions of different dates for the land surface area of interest, where water showed extreme differences (Fig. 6B). The average correlation before and after normalization for the areas of overlap in the resulting emissivity
images show that values increased and decreased depending on the image overlap area (Table 2). Correlation of emissivity did not decrease significantly but improved for much of the area of interest, especially for overlap area 1 and 2 (71% and 99% area, respectively). Correlation decreased in other areas after normalization, but most of these changes in the area of interest were small. A decrease in the average correlation occurred below 0.90 after normalization in overlap areas 2 and 5. This was made obvious by the visible seam-line error. In the upper portion of overlap area 2 where correlation was decreased after normalization, the difference can likely be attributed to the high vegetation noted in the November 16, 2001 VNIR data. The reason for lack of correlation in the upper portion of overlap area 5 is not known, even though this area can easily be classified as exposed sediments and the lower portion of that area is agricultural and frequently changing. Some mountain ranges also show differences at the seam boundaries between November 16, 2001 and May 5, 2003 and are assumed to be due to differences in primarily sun illumination as well as instrument pointing angle between the two dates. The radiometric normalization does not guarantee correlation of all pixels because some areas will represent true land-cover change, whereas some lack of correlation may be due to the presence of scan line noise even in correlated areas.

4.2. Balancing in emissivity space and comparison of AST_05

The linear transformation (Eq. (1)), as well as the other balancing methods mentioned, were also applied to the emissivity data in order to determine if this was an equally effective method. Success was varied, but in general it was found that emissivity data did not mosaic well and seam-line error and poor balance was obvious without first normalizing in radiance space. Jan 13, 2003 and March 9, 2003 images were

![Fig. 6. The mosaics of emissivity for ASTER bands 13, 12 and 10 (R,G,B respectively) are shown here for (A) emissivity extracted from the non-normalized mosaic, (B) emissivity extracted from the normalized mosaic, and (C) the non-normalized AST_05 emissivity product. Band 13 is used in the false color composition to show the seam-line errors most prominent in this band. (D) A DCS performed on the mosaic of normalized radiance from the traditionally used ASTER bands 14, 12 and 10 (R,G,B respectively).]
expected to blend seamlessly, but a seam-line error was present with an average difference of 4%. The linear transformation completely failed in bands 13 and 14, probably because of the low variance in the data for this region, where seam-line error and image-wide differences in average emissivity were apparent between the resulting images. Correlations between values are lower for bands 13 and 14 regardless of the approach, but an improvement in correlation is seen between some overlapping areas in these bands where radiance was normalized before emissivity extraction. Seams were also made evident from persistent scan line noise that has an average difference of less than 1% between adjacent pixels in the image.

The quality of the emissivity mosaic from normalized radiance is comparable to the non-normalized AST_05 emissivity mosaic (Fig. 6C). Normalization of the AST_05 was also tested but was not successful. Because this product was generated using a different method of temperature–emissivity separation, the TES algorithm, a direct quantitative comparison is not easily made with emissivity values extracted using emissivity normalization of AST_09T. This is clearly evident where comparing the color contrast of the two mosaics in Fig. 6B and C. Seam-line error was most apparent again in band 13 for the AST_05 mosaic. Improvement was made at the seam boundary between May 2, 2002 and March 9, 2003 images in the AST_05 mosaic compared to the emissivity extracted from normalized AST_09T radiance. Feathering of most seam edges produced areas with little perceptible error in the sand sea region, but image swaths in the east (acquisition dates May 12 and 21, 2000) had consistent, image-wide average emissivity error of 2–3%, and caused undesirable affects on preliminary spectral analysis.

4.3. DCS results

The DCS (Gillespie, 1992) is a useful and common spectral analysis technique for TIR data of both Earth and Mars (Kahl, 1987; Rowan & Mars, 2003; Bandfield et al., 2004). The DCS enhances the color separation of three highly correlated bands chosen from the multispectral data. Emissivity (compositional) variations are shown as color differences, whereas the intensity of those colors relates to the surface brightness temperature. The ideal frequency distribution of input data for a DCS is close to Gaussian, and color separability is reduced with an increasingly multimodal data distribution (Alley, 1996). This has significant implications for a DCS of a mosaic that has not been radiometrically normalized. Consistent variations of surface composition in radiance or a DCS of a radiometrically non-normalized mosaic cannot be visualized because large inter-scene color differences result and are much greater than intra-scene color contrast. A DCS was performed on the radiometrically normalized, seam-blended, radiance-at-surface mosaic to examine the large-scale surface compositional diversity, and the results have good potential to aid in the selection of spectral end-members, not limited to a single scene (Fig. 6D). For a DCS of these bands and typical interpretation: Red areas correspond to quartz rich material, green to granitic composition, vegetation (typically marking arroyos in this area) and some volcanic features, and blue to volcanic and mafic outcrops. The DCS resulted in good discrimination of compositional units in the Gran Desierto region and can be compared to those described in Blount et al. (1990). As the spatial extent of a mosaic increases, so does the likelihood of including a number of spectrally distinct materials, which will increase the modal frequency of the data. The usefulness of this visualization method is spatially limited even for a perfectly balanced mosaic of radiance because it enhanced the larger scale spectral differences between major compositional groups. In the case of the Gran Desierto and surrounding region, areas of agriculture, waters of the Gulf of California and the delta of the Colorado River reduced the contrast of the DCS. If these areas were not masked from the stretch statistics, even large-scale differences in surface composition become less evident. The subtle but spectrally distinct variations of small-scale surface units can be further enhanced by creating a DSC stretch for a smaller subset of the mosaic, no longer limited to single scenes or scenes combined in the along-track direction.

5. Discussion

In all attempts at normalizing and mosaicking radiance and emissivity data, some degree of seam-line error between images resulted. This is ultimately inevitable because rarely do land surfaces remain unchanged, even under short time scales. The sources of potential error in the generation of a radiometrically normalized mosaic of ASTER TIR deserve further discussion. The factors affecting the quality of the resulting mosaic include the spatial extent of overlap between images and sensor coverage and the change in spectral characteristics of the land surface. The technique used for radiometric normalization is also important, especially the selection of PIFs, the masking of change-pixels and the user input on a decision threshold.

Ideally, a radiometric normalization technique would rely on atmospheric correction and the conversion of radiance to standard reflection or emissivity units, and there would be no need for relative normalization using image statistics. The spectral emissivity represents a small fraction of the variance in the emitted thermal radiance collected by the sensor, where the signal is largely a function of brightness temperature. Normalization of emissivity did not work well because variance is generally small in bands 13 and 14 for the observed target materials, and the noise level becomes a greater portion of the calculated emissivity. The linear transformation in radiance space is estimated from data that has a higher SNR and greater variance compared to emissivity. Kahle and Alley (1992) found that a change of one degree in temperature was synonymous with an error of 1% emissivity where doing a temperature–emissivity separation (Kahle & Alley, 1992). Because temperature is also normalized where normalizing radiance prior to the calculation of emissivity, it is not surprising to find these magnitudes of improvement in the emissivity mosaic. Normalization in radiance space improved the inter-scene balance between most of the images in both radiance and emissivity mosaics, and it did not unreasonably alter emissivity spectra. Preliminary comparisons of emissivity spectra from normalized radiance matched well with laboratory spectra of samples.
at these locations. The absolute accuracy of the emissivity mosaic may be increased after more rigorous comparisons with ground truth, and a vicarious calibration is applied to the entire mosaic.

Some of the techniques of relative radiometric normalization referenced earlier (simple linear regression, scene statistics, and PCA) produced similar results but with varying degrees of successful balancing. The results described here compared well, although improved, even if compared to the AST_05 emissivity product mosaic. This relative normalization technique described here shares characteristics emphasized in the MAD technique by Canty et al. (2004), but a comparison of results from this and the MAD technique is needed. This technique relies directly on a threshold of correlation between the raw radiance values of pixels to identify PIFs, whereas Canty et al. (2004) rely on a chi-square percentile limit for MAD components. MAD enhances change-pixels as much as possible prior to selection of PIFs (Canty et al., 2004). Both techniques rely on a scale-invariant statistic based on physical (spectral) characteristics to determine PIFs. Similarly, the orthogonal components are found by eigen decomposition of the data, but the technique is computationally fast even though each individual, bitemporal band pair at times $t_2$ and $t_1$ are handled separately.

The most important part of the relative normalization is the selection of PIFs, but several complicating factors exist due to the variety of scene components and the spectral changes that occur in time. The selection of PIFs by a spectral correlation threshold attempted to remove these complicating factors.

- The amount of ephemeral desert vegetation is time-variant, commonly dry and sparse, but can be a dominating scene component for arid lands even at the 90 m/pixel TIR spatial resolution.
- Seasonal weather patterns (rain and wind) can spatially redistribute soil moisture, resulting in temporally variable thermal inertia for each soil type. (e.g., the coastal zone has a significant tidal range in the Gulf of California, periodically inundating and saturating the ground surface.)
- Where changes in sediment distribution occur, the variable thermal inertia of these materials of different grain size (i.e., fine sand, alluvium and rock) cause variations of emitted thermal radiance in time.
- The illumination in areas of high relief, including mountains and dune topography cause variable brightness temperature through differential heating and shading (McAtee et al., 2003). For example, at the low solar elevation (34°) on January 13, 2003, illumination, perpendicular to the crests of large star dunes, caused heating and shadowing, and resulted in an average brightness temperature difference of 20 °C

Fig. 7. Radiance values are presented in a scatter plot between two dates (November 16, 2001 and May 5, 2003) for a small image subset of the Bahia Adair coastal area (inset). Colored boxes mark data points that correspond to the colored areas of the inset map. The majority of the desert land area in the inset is not colored, and corresponds to the data points that more closely fit the linear regression model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
between opposite dune surfaces. This temperature effect propagated into the radiance mosaic as an intensity difference unrelated to compositional variation.

- The atmosphere, commonly unstable in arid lands, may have local temporal and spatial changes in temperature of the land surface and atmospheric column due to variable winds (i.e., wind streaks). These effects are not as apparent after the DCS and emissivity extraction, but may have an affect on radiometric normalization.

The distribution of radiance values would be normally distributed as a single mode for a single land-cover type, but the overlapping area generally contains several spectrally distinct surface compositions, which results in a data distribution that are multimodal. Each mode may also experience a different linear (or non-linear) change in temperature and its spectral characteristics through time. Where comparing the radiance values in a scatter plot between two dates (November 16, 2001 and May 5, 2003) for a small image subset of the coastal area (inset), different linear relationships and degrees of correlation can be linked to different spatial areas (Fig. 7). The sand sea area in the upper half of the inset, shown by the elliptical cloud of black points and the linear regression line, has a different relationship than data points that correspond to surface water (red) and the inundated coastal marsh sediments and vegetation (green and yellow, respectively). The blue areas on the map correspond to noise surrounding the main data cloud and linear regression of land pixels. A different linear transformation would be needed for each mode (i.e., classification groups) in order to match all pixels, but these modes are rarely distinct and not easily separated. It was found that masking contiguous areas of vegetation and water was not solely accomplished by the radiance decision threshold of $\rho_{AB}$ because water is spectrally similar through time. Including water pixels would negatively affect the linear regression of PIFs because the change in radiance was characterized by a different linear temperature relationship than land pixels. Rock and sand (geologic land-cover) may also have slightly different linear relationships in time due to local surface composition and vegetation changes, and these complicating factors are mixed with other scene components at the ASTER TIR resolution.

6. Conclusions

Radiometric balancing of ASTER data in the cross-track direction using the linear transformation methods described above produces acceptable results that can be used to examine the spectral variability and surface composition across a region. The method addresses an over-arching need to compare data that are collected from acquisitions that are not temporally continuous. Although there are limitations to the effectiveness of linear transformations across large distances (e.g., areas of land-cover and surface composition change), the method appears to work well within the processing limitations, specifically for this sandy desert. The DCS can be applied to the normalized cross-track mosaic of radiance as a first order discriminator, even though its effectiveness seems to decrease with increasing spatial area and the diversity of surface materials. However, use of the DCS on the mosaic allows for the identification of possible compositional end-members that exist beyond the boundaries of just one ASTER scene. In addition, the use of the spectral correlation equation used here is a tool that can assess land-cover change, such as vegetation, sediment composition and possibly other surface characteristics. Identification of change-pixels will help eliminate these areas from normalization, but it will also help to remove these areas from a mosaic where other data in time may be used to fill gaps.

The technique of balancing radiance prior to emissivity extraction produced a more consistent TIR dataset on which to perform a regional study of aeolian sediments. The seamless characteristic is a requirement for an affective analysis of possibly narrow, subtle sediment transport pathways that would be masked by non-normalized data and seam-lines between scenes acquired on different dates. This technique should easily be transferable to other regional studies of deserts and sand seas, and will in fact be less cumbersome in regions where water, vegetation, and other temporally/spectrally variable materials are lacking (i.e., the central Sahara). Limitation will be imposed on areas where land surface conditions are highly variable with season, for example, dominant vegetation communities, high relief areas affected by sun illumination geometry, or areas of significant erosion and deposition (fluvial or aeolian). A more thorough interpretation of the patterns of dune sand composition and how they relate to the geologic evolution of the Gran Desierto is beyond the scope of this paper. It will be the focus of future work incorporating field and laboratory-based analysis to identify the minerology of sand seas using a linear deconvolution algorithm on the final mosaic. The addition of multispectral TIR to previous remote sensing studies should be highly useful for interpretations of sediment transport and dune dynamics in the Gran Desierto (Beveridge et al., 2006; Blount et al., 1990) and elsewhere for studies of aeolian history Ewing et al. (2006) and the response of sand seas to climate and sea level change.

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