Multi-sensor approach for desertification monitoring: case study at coastal area of Vietnam

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Abstract

This paper presents the initial findings of an investigation into multi-sensor remote sensing as a cost effective means of monitoring desertification in a semi-arid coastal environment. The project aims to develop a means of providing annually updated information at a range of spatial scales for local government and land use planners.

A twin scale approach is employed to facilitate mapping at national and local scale. MODIS and ASAR wide swath data provide a generalized assessment for the whole country, whilst ASTER and ENVISAT ASAR image mode imagery are used to investigate desertification problems at a more detailed level.

Three parameters were selected to develop a desertification index: land surface temperature, vegetation index, and soil moisture. The relationship between vegetation density, soil moisture, and surface temperature, and the role of these parameters in the desertification process are under investigation. It has been shown that vegetation index and surface temperature are strongly related to moisture stress and can explain the dynamic of desertification. An index based on relation between vegetation density and surface temperature was tested (Vegetation Temperature Condition Index: VTCI). Soil moisture estimation from delta backscatter ($\sigma - \sigma_{dry}$) showed a strong relation with field measurements ($r^2 = 0.89$) for bare land and sparsely vegetated areas. When the vegetation density is higher (NDVI > 0.5), the relation is weak ($r^2 = 0.58$) therefore soil moisture estimation is not possible.

1 Introduction

1.1 Background

Since the International Convention on Desertification of the United Nations that came into force in 1996 (UNCCD, 2004), the need to measure land degradation and desertification processes has substantially increased. While standard ground survey methods for undertaking such measurements are imperfect or expensive it has been demonstrated that satellite-based and airborne remote sensing systems offer a considerable potential. Earth observation satellites provide significant contributions to desertification assessment and monitoring, particularly by providing the spatial information needed for regional-scale analyses of the relationships between climate change, land degradation and desertification processes.

Viet Nam is not designated as an arid or semi-arid country. However, some regions within the country are at risk from desertification. It is estimated that 9.34 million hectares of land in Viet Nam are degraded, and a substantial part of that is prone to desertification. Over the past 10 years, drought has caused severe impacts upon the agricultural and forestry production in many areas, especially in the central highland and coastal area of Viet Nam (UNCCD, 2002). In the
coastal area long dry seasons together with short heavy rainfall in the rainy season have led to the following types of degradation:
- Moving sand due to strong wind along the coastal area.
- Salinization in sandy soil, formation of salt crust on soil surface.
- Water erosion due to deforestation and overgrazing.

The net result of such land degradation is significant disturbance of ecosystems with loss of biological and economical productivity. Mapping and monitoring of degradation processes are thus essential for drafting and implementing a rational development plan for sustained use of semi-arid land resources of Vietnam.

1.2 Aims and Objectives
The project aims to develop a cost effective desertification mapping methodology, transferable to other South East Asian regions. Specific objectives are:
- To quantify desertification problems in coastal areas of Vietnam.
- To develop operational methods for desertification mapping in semi-arid areas which combine the advantages of several types of readily available satellite imagery.

2 Study area
The study area is located in Binh Thuan province, in south central Vietnam. The area faces the Pacific Ocean to the east with a coastline of 192 km (Fig. 1). The Truong Son mountain range, running from North-east to South-west, block most of the rain coming from the Thailand’s sea, thus created semi arid conditions for the area.

Binh Thuan province can be divided into 4 main landscapes:
- Sand dunes along the coast (18.2% of total area).
- Alluvial plains (9.4% of total area).
- Hilly areas, with the average elevation of 50 m asl (31.6% of total area).
- The Truong Son mountain range (40.8% of total area).

Binh Thuan is the driest and hottest region of Vietnam. The climate is a combination of tropical monsoon and dry and windy weather. The mean annual temperature is 27°C, with average minimum 20.8°C in the coldest months (December, January), and an average maximum of 32.3°C in the hottest months (May and June). Binh Thuan also receives more solar radiation than any other area in Vietnam, with 2911 sunshine hour annually – or almost 8 hour per day.

Rainfall in this area is limited and irregular. Annual precipitation is 1024 mm, while evaporation in some years is equivalent to precipitation. At some locations annual rainfall can be as low as 550 mm. The dry season is from November to April, with 60 days of January and February having almost no rain. The rainy season is from May to October with heavy rain concentrated in a short periods with up to 200 mm/day.
3 Data Resources

3.1 Parameters required for desertification monitoring.

Desertification is a complex process which involves both natural factor and human activities. Depending on the level and nature of management, such as decision making, economic policy, and land use management, different kinds of information are required. DESERTLINKS (a European commission funded project) have listed 150 indicators for desertification assessment which involve ecological, economic, social and institutional indicators (Brandt et al., 2002). However, for desertification mapping three parameters are of key importance – land surface temperature (LST), vegetation cover, and soil moisture. There have been several approaches adopted for desertification mapping. The first two are ground survey and image interpretation. Although different in scale and technique, both rely on expert knowledge and ability to visually analyse the landscape and group it to several predefined categories. The third, remote sensing based, approach is digital image classification based on a single image. The techniques and algorithms used can vary, but all are based on the spectral similarity of pixel values and a set of sample points with known characteristics. Class adjustment is based on local knowledge and ground observation.

The fourth approach is a group of techniques aiming at modelling the problem using physical parameters related to the land process, derived from Earth Observation data. Using geophysical parameters it is possible to assess the problem as it happens, and produce results that are comparable between different geographic regions. As mentioned above there are many indicators that can be used for desertification mapping, but not all are available or appropriate. However, in remote sensing we always need to generalize the problem to a few important factors that matter the most. To standardize the mapping method we develop a desertification index based on 3 parameters which strongly reflect the changes in desertification environment. These parameters are: land surface temperature (LST); vegetation cover; and soil moisture.
Satellite-derived land surface temperature (LST) has a strong relationship with the thermal dynamic of land processes (Dash et al., 2002), and can be used to assist in assessment of vegetation condition. In dry conditions high leaf temperatures are a good indicator of plant moisture stress and precede the onset of drought (McVicar, 1998), and surface temperature can rise rapidly with water stress and reflect seasonal changes in vegetation cover and soil moisture (Goetz, 1997).

In arid conditions vegetation provides protection against degradation processes such as wind and water erosion. Vegetation reflects the hydrological and climate variation of the dry ecology. Decreasing vegetation cover, and changes in the species composition of vegetation are sensitive indicators of land degradation (Haboudane et al., 2002).

Soil moisture is an important variable in land surface hydrological processes such as infiltration, evaporation, and runoff; and is controlled by complex interactions involving soil, plant, and climate (Puma et al., 2005). In arid and semi-arid areas, soil moisture can be used to monitor drought patterns and water availability for plant growth (Hymer et al., 2000). In an integrated mapping method, soil moisture can compensate for the weakness of vegetation indices in areas of sparse vegetation cover (Saatchi, 1994).

### 3.2 Remote Sensing data resources

Currently, medium spatial resolution sensors offer data with spatial resolution higher than 1 km. The sensors such as GLI, MODIS and MERIS can be considered as the next generation of NOAA AVHRR or SPOT VGT, offering multiple scale data (250 - 1000 m), improved spectral resolution (more band, better atmospheric calibration), and improved radiometric accuracy. At this resolution, a single scene can cover the entire coastal area of Vietnam. Some of the new high spatial resolution sensors are also listed in Table 1. This group of sensors provides multispectral imagery with resolutions between 5 and 100 m.

**Table 1. Currently operational high spatial resolution multi-spectral sensors**

<table>
<thead>
<tr>
<th>Platform</th>
<th>LANDSAT 7</th>
<th>SPOT</th>
<th>EO-1</th>
<th>TERRA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instrument</td>
<td>ETM+</td>
<td>HRG</td>
<td>ALI</td>
<td>ASTER</td>
</tr>
<tr>
<td>Resolution</td>
<td>15 to 120 m</td>
<td>10 to 20 m</td>
<td>10 to 30 m</td>
<td>15 to 90 m</td>
</tr>
<tr>
<td>Wavelength</td>
<td>PAN, SWIR, TIR</td>
<td>PAN, VNIR</td>
<td>VNIR, SWIR</td>
<td>VNIR, SWIR, TIR</td>
</tr>
<tr>
<td>Number of channels</td>
<td>7/8.</td>
<td>4</td>
<td>10</td>
<td>14</td>
</tr>
<tr>
<td>Swath width</td>
<td>185 km</td>
<td>60 km</td>
<td>37 km</td>
<td>60 km</td>
</tr>
<tr>
<td>Agency</td>
<td>NASA</td>
<td>SPOTIMAGE</td>
<td>NASA</td>
<td>NASA</td>
</tr>
<tr>
<td>Price ($/km²)</td>
<td>0.018 – 0.158</td>
<td>0.67 – 1.43</td>
<td>Non-commercial</td>
<td>Non-commercial</td>
</tr>
</tbody>
</table>

Another sensor technology that is important to desertification monitoring is Synthetic Aperture Radar (SAR). The all-weather capability of spaceborne SAR sensors (Table 2) is a major advantage over optical systems. SAR data can be used to estimate soil moisture content, which is an important parameter in semi-arid land where vegetation growth is heavily dependent on water availability (Karnieli et al., 2002; Moran et al., 1998; Tansey and Millington, 2001; Wang et al., 2004).

**Table 2. Currently operated SAR sensors**

<table>
<thead>
<tr>
<th>Platform</th>
<th>ERS-1/2</th>
<th>ENVISAT</th>
<th>Radarsat-1/2/3</th>
<th>JERS-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instrument</td>
<td>SAR</td>
<td>ASAR</td>
<td>SAR</td>
<td>SAR</td>
</tr>
<tr>
<td>Resolution</td>
<td>25 m</td>
<td>30-150 m</td>
<td>30-150 m</td>
<td>25 m</td>
</tr>
<tr>
<td>Frequency</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>L</td>
</tr>
<tr>
<td>Polarisation</td>
<td>VV</td>
<td>HH/HV</td>
<td>HH/VV/HV/VH</td>
<td>HH</td>
</tr>
<tr>
<td>Swath</td>
<td>100 km</td>
<td>50-500 km</td>
<td>10-500 km</td>
<td>75 km</td>
</tr>
<tr>
<td>Agency</td>
<td>ESA</td>
<td>ESA</td>
<td>CSA</td>
<td>NASDA</td>
</tr>
</tbody>
</table>
3.2.1 Specific requirements

In the context of the case study, suitable remote sensing data sources are sensors which could provide all or some of the parameters discussed in section 3.1. It is important to note that the “value” of each sensor is not only dependent on high spatial resolution, but also the spectral resolution, cost, coverage, calibration standards, and availability. Desertification is a long-term process, so an operational desertification monitoring system must be based on a robust and reliable suite of satellite sensors that can guarantee data continuity, quality, and availability on a decadal scale. It is for these reasons that only sensors from government-supported non-commercial Earth Observation programmes were considered for this project. Another issue that needs to be considered is data cost. As most desertification occurs in developing countries, a relatively low cost monitoring solution is required.

The medium spatial resolution sensor selected for this project was MODIS, chosen because of its finer spectral resolution than MERIS (table 2). MODIS provides the following useful data for desertification modelling: surface reflectance, land surface temperature and emissivity, land cover change, and vegetation index. MODIS data is available free of charge from NASA and routinely archived back to 1999.

The high spatial resolution sensor selected was ASTER. ASTER offers several advantages over rival sensors. It provides more bands in SWIR and TIR (6 bands in SWIR and 5 bands in TIR) than Landsat 7 ETM+ while retaining adequate spatial resolution in visible bands. The 5 TIR bands offer a more precise measurement of land surface temperature with an accuracy of 0.3°C (Wan, 1999). Cost is an issue, with ASTER level 2 products available free of charge, while level 1 cost £50 per scene.

For radar imagery, we chose ENVISAT ASAR (Advance Synthetic Aperture Radar). ASAR provides multiple swath-widths with spatial resolutions ranging from 30 to 150 m. Thus it can be used for both national and local scale. Another advantage of ASAR is that the ENVISAT satellite also carries the MERIS sensor which can offer optical data acquisition simultaneously with SAR data.

A key feature of all the data sources listed above is the availability of standardised product formats and rigorous calibration, important for the development of long term quantitative monitoring.

3.2.2 RS data acquired

During the study period two sets of remote sensing data were collected representing dry season and wet season conditions. The dry season dataset (Table 3) was successfully acquired in January 2005.

Table 3. Image acquisition

<table>
<thead>
<tr>
<th>Date of acquisition</th>
<th>Sensor</th>
<th>Level/ Image mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>19 Jan 2005</td>
<td>ENVISAT ASAR</td>
<td>Level 2B/ ASAR IMG</td>
</tr>
<tr>
<td>19 Jan 2005</td>
<td>ENVISAT ASAR</td>
<td>Level 2B/ ASAR IMP</td>
</tr>
<tr>
<td>14 June 2005</td>
<td>ASTER</td>
<td>Level 1B/ AST_1B</td>
</tr>
<tr>
<td>14 June 2005</td>
<td>ASTER</td>
<td>Level 2/ ASTER_08</td>
</tr>
<tr>
<td>Jan 2005</td>
<td>MODIS</td>
<td>Level 3G/MOD09A1</td>
</tr>
<tr>
<td>Feb 2005</td>
<td>MODIS</td>
<td>Level 3G/MOD09A1</td>
</tr>
</tbody>
</table>

3.3 Other data sources

The following ancillary data are available:
- Topographic maps in digital format at 1:50,000 scale, with contour interval of 20 m.
- Land cover map for the year 2000 at 1:50,000 scale.
- Soil map at scale 1:1,000,000.
- Climate data from 1995 to 2004.
Two fieldwork visits are required, in dry and wet seasons 2005, to provide the ancillary data and basic soil properties needed to validate the image processing result.

4 Methods

4.1 Image pre-processing

MODIS surface reflectance values for the visible to near infrared wavelengths were corrected for atmospheric effects at the data centre using a bidirectional reflectance distribution function (Huete, 1999). To conform with the national geo-database of Vietnam, we transformed MODIS images from ISIN to UTM WGS 84 coordinate system using the MODIS reprojection tool. For ASTER imagery, we used level 2 data which were atmospherically corrected at the data centre using a radiative transfer model and atmospheric parameters derived from the National Center for Environmental Prediction (NCEP) data (Abrams, 2000). ASTER images were registered to topographic map using second order transformation with sub-pixel RMS and nearest neighbourhood resampling.

For ENVISAT ASAR imagery, first we applied a Lee filter to remove the noise, then carried out an image-to-image geometric correction using the previously georeferenced ASTER imagery. Raw ASAR image amplitude values were converted to backscatter using the equation provided by ESA (ESA, 2004).

\[
\delta_0^{i,j} = \frac{DN_{i,j}^2}{K \sin(\alpha_{i,j})}
\]

(Equation 1)

For \( i = 1 \ldots L \) and \( j = 1 \ldots M \)

Where

\( K \) = absolute calibration constant  
\( DN_{i,j}^2 \) = pixel intensity value at image line and column “i,j”  
\( \delta_0^{i,j} \) = sigma nought at image line and column “i,j”  
\( \alpha_{i,j} \) = incident angle at image line and column “i,j”

Corrections for the effect of slope on local incident angle were applied to all SAR backscatter imagery using a slope map derived from the 1:50,000 digital topographic maps. The correction involved multiplying backscatter values by the ratio of backscatter received from a sloping surface to that received from a horizontal surface, where

\[
\frac{\delta^s_i}{\delta^h_i} = \frac{\sin \Theta_i}{\sin(\Theta_i - \Theta_{loc})}
\]

(Equation 2)

\( \delta^s_i \) backscatter from sloping surface;  
\( \delta^h_i \) backscatter from a horizontal surface;  
\( \Theta_i \) average radar incident angle  
\( \Theta_{loc} \) local incident angle determined from elevation model

The correction effect was minor in most cases because the study sites were mostly flat.

4.1.1 Land surface temperature (LST)

LST is retrieved from two data sources. At small scale, we use MOD11A2, an 8 days average surface temperature product derived from the MODIS thermal bands at 1 km resolution using a generalized split-window based on a database of targets with known emissivity. This product has been validated to an accuracy of 1K degree under clear sky condition (Wan, 1999).
At medium scale we use AST_08, ASTER surface kinetic temperature. This product has a spatial resolution of 90 m and is generated from the ASTER thermal bands using the TES algorithm (Gillespie et al., 1998).

4.1.2 Vegetation Index
In this study we use the Enhanced Vegetation Index (EVI) generated from MODIS imagery. EVI is a 16 day composite at 500 m resolution available free as a standard 3rd level product (MOD13A1). EVI was developed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences (Huete, 1999). The equation takes the form

$$EVI = G \times \frac{NIR - Re d}{NIR + C1 * Re d - C2 * Blue + L}$$  \hspace{1cm} (Equation 3)

where:
- $NIR$ = NIR reflectance
- $Red$ = Red reflectance
- $Blue$ = Blue reflectance
- $C1$ = Atmospheric resistance Red correction coefficient
- $C2$ = Atmospheric resistance Blue correction coefficient
- $L$ = Canopy background Brightness correction factor
- $G$ = Gain factor

Using the standard EVI and LST has the advantage that they are readily available products, therefore reducing the time and resources required for processing. A second advantage is that these products are generated and calibrated using standard algorithms, thus simplifying the mapping method and allowing us to compare the results over the time and space. However, for detail assessment at local level, a customized calibration may be needed to fit with local conditions.

At medium scale vegetation cover has been estimated from ASTER imagery using NDVI and SAVI (Soil Adjusted Vegetation Index). SAVI is a modification of NDVI with an L factor to compensate for vegetation density. Several author recommend SAVI for sparsely vegetated areas (e.g. Huete, 1998; Terrill, 1994).

$$SAVI = \frac{NIR - RED}{NIR + RED + L(1 + L)}$$  \hspace{1cm} (Equation 4)

4.1.3 Soil moisture estimation
In this study we applied the data fusion approach proposed by (Sano, 1997), in which the effects of soil roughness are accounted for by differencing the SAR backscatter from a given image and the backscatter from a "dry season" image ($\sigma^o - \sigma^{dry^o}$). The vegetation influence was corrected by using an empirical relationship between $\sigma^o - \sigma^{dry^o}$ and the vegetation index.

Sano (1997) found that the vertical distance between a given point and the line defining the ($\sigma^o - \sigma^{dry^o}$)/Green Leaf Area Index (GLAI) relation was independent of surface roughness and vegetation density, and directly related to target’s surface soil moisture content. It is important to note that a given relationship, as illustrated in Fig. 2, would be valid only for a single SAR configuration (i.e. sensor polarization and frequency) and would need to be adjusted for the influence of topography on local incidence angle. This, however, should not be an issue for this study, as majority of land in the test site is relatively flat.
Figure 2. A graphic illustration of the SAR/optical approach for evaluating surface soil moisture developed by (Sano, 1997). The vertical distance of points A–C from the solid line is related directly to soil moisture content.

To normalize the difference between pixel values and the corresponding dry scene values, a delta index was proposed by (D.P. Thoma et al., 2006). The delta index represents a change relative to dry scene backscatter, and thus the delta index should be interpreted in light of dry scene soil moisture. This is because any dry scene backscatter is likely to be affected by at least a small amount of residual soil moisture.

\[
\text{Delta index} = \left| \frac{\delta_{\text{wet}}^0 - \delta_{\text{dry}}^0}{\delta_{\text{dry}}^0} \right| \quad (\text{Equation 5})
\]

Where \( \delta_{\text{dry}}^0 \) = backscatter from a pixel in dry season

\( \delta_{\text{wet}}^0 \) = backscatter from the same pixel in wet season

4.1.4 Vegetation Temperature Condition Index (VTCI)

VTCI was developed by Wan et al. (2004) and is defined as the ratio of LST differences among pixels with a specific NDVI value in a sufficiently large area; the numerator is the difference between maximum LST of the pixels and LST of one pixel; the denominator is the difference between maximum and minimum LST of the pixels.

\[
VTCI = \frac{(\text{LST}_{\text{NDVI}})_{\text{max}} - \text{LST}_{\text{NDVI}}}{(\text{LST}_{\text{NDVI}})_{\text{max}} - (\text{LST}_{\text{NDVI}})_{\text{min}}} \quad (\text{Equation 6})
\]

where:

\[
\text{LST}_{\text{NDVI}} = a + b \text{ NDVI}_i
\]

\[
(\text{LST}_{\text{NDVI}})_{\text{max}} = a' + b' \text{ NDVI}_i \quad (\text{Equation 7})
\]

where \( (\text{LST}_{\text{NDVI}})_{\text{max}} \) and \( (\text{LST}_{\text{NDVI}})_{\text{min}} \) are maximum and minimum LSTs of pixels which have same NDVI value in a study region, and \( \text{LST}_{\text{NDVI}} \) denotes LST of one pixels whose NDVI value is NDVI. Coefficients a, b, a’, and b’ can be estimated from an area large enough where soil moisture at surface layer should span from wilting point to field capacity at pixel level. In practice, the coefficients are estimated from a scatter plot of LST and NDVI in the study area.
VTCI can explain both the changes of vegetation in the region and the thermal dynamics of pixels that have the same vegetation density. It can be physically explained as the ratio of temperature differences among pixels (Fig. 3). The numerator of equation (4) is the difference between maximum LST of pixels with the same NDVI value and LST of one pixel, while the denominator is the difference between maximum and minimum LST of the pixels. In figure 2, LST\textsubscript{max} can be regarded as ‘warm edge’ where there is less soil moisture availability and plants are under dry condition; LST\textsubscript{min} can be regarded as the ‘cold edge’ where there is no water restriction for plan growth (Gillespie \textit{et al.} 1997, Wang \textit{et al.} 2004). The value of VTCI ranges from 0 to 1; the lower the value of VTCI, the closer a pixel to the warm edge and the higher the occurrence of drought and water stress.

4.2 Field methodologies

Two field surveys (dry and wet season) are required in order to gather the necessary field observations. The first field visit was conducted in January-February 2005 (dry season). 150 sample locations were selected using a stratified random sampling method. This method is preferred over full random sampling because stratified sampling allowed us to distribute sample plots over the entire range of land use/land cover types without bias (Congalton, 1991; Stehman, 1999).

Stratification was based on unsupervised classification of a January 2003 ASTER image. The classification results provided a general guide to the location, size and type of desertification. Seven land cover classes were generated by unsupervised classification, which corresponded to high sand dune, low sand dune, bare sandy soil, rice field, grazing land, scattered forest on low land, and dense forest on hilly area.

At each sample point the following parameters were measured:

- vegetation type & cover %
- Top soil texture (5 cm depth)
- pH, EC
- Surface roughness: measured in the field with paper profile
- Soil moisture (0-10 cm, and 10-20 cm).
- Soil surface temperature
5 Results

5.1 Vegetation condition index

MODIS and ASTER image were used to estimate VTCI at small and medium scales, respectively. For ASTER image NDVI is calculated from band 3 and band 1 while LST is readily available from AST_08 product as mentioned in section 4.1.1. To reduce the error in spatial resolution differences, NDVI imagery was resampled from 15 m to 90 m, to give the same pixel size as the thermal band. Figure 4 is the scatter plot of LST and NDVI of the study area. The straight lines drawn on the scatter plot represent the ‘warm edge’ (LST$_{\text{max}}$), and the lower limits of the scatter plot represent the ‘cold edge’ (LST$_{\text{min}}$).

![Figure 4. Scatter plot of LST versus NDVI (ASTER image 16 June 2005).](image)

From the ‘warm edge’ and ‘cold edge’ we get the coefficients a, b, a’, b’:

\[
\begin{align*}
\text{LST}_{\text{NDVI, max}} &= 43.3 - 29.75(\text{NDVI}) \\
\text{LST}_{\text{NDVI, min}} &= 25.2 + 0(\text{NDVI})
\end{align*}
\]  
\text{(Equation 8)}

Using (Equation 8) and (Equation 6), we get the VTCI image of the study area for both dry and wet season. We can see that bare sandy soil areas have low VITC values in both dry and wet season which implies drought and water stress. The sandy soil area has a lighter tone in Figure 5 (a) and (b). Sand dunes along the coastal area, show unexpected results, having a relatively higher VTCI, from which it might be wrongly interpreted that the area was not suffering from water stress. This can be explained by the fact that the sand dune area is pure sand with no significant vegetation cover. A drought index based on vegetation stress will thus indicate low stress values for this area. Indices such as the VTCI should be interpreted with caution, and not used for areas of sparse vegetation. In the feature space of LST and NDVI (Figure 3), for the same temperature, if NDVI decreases VTCI will increase. On the other hand, for areas with the same NDVI, the higher the temperature, the higher level of vegetation stress, because there is less water left on the soil for plant transpiration.
To investigate how VTCI changes between dry and wet seasons, a 5 km transect was positioned crossing 3 types of land cover: sand dune, sandy soil and dry open forest. In general VTCI values from the wet season have higher values than the dry season, which reflects the overall change in water availability and a healthier vegetation condition. In the sand dune area (a), however, the changes between two seasons are small because of its low ability to retain rain water in the surface layers and lack of vegetation. The flat sandy soil area (b) exhibits a large change in VTCI between the two seasons, clearly showing the effect of rainfall which boosts the vegetation growth. The sandy soil area also shows a broad range of variation in both seasons with bare soil having VTCI values as low as 0.1 and vegetated land have VTCI values as high as 0.28 in the dry season.

The open dry forest has a higher VTCI than sandy soil in the wet season due to its ability to retain moisture and the high photosynthesis activity. In the dry season, the open dry forest loses all of its leaves, opens its canopy and becomes very dry, which is reflected in a VTCI as low as bare sandy soil.

For MODIS imagery, we used a 16-day composite NDVI product (MYD_13Q1) and 8-day land surface temperature (MOD_11A2) to calculate VTCI. All imagery is geo-referenced and
resample to 1 km resolution using nearest neighbour resampling. ‘Warm edge’ and ‘cold edge’ and coefficients were estimated from LST vs. NDVI scatter plots (Figure 7).

\[
\begin{align*}
\text{LST}_{\text{NDVI} \text{.max}} &= 47.45 - 22.18(\text{NDVI}_i) \\
\text{LST}_{\text{NDVI}.\text{min}} &= 18.74 + 0(\text{NDVI}_i)
\end{align*}
\]  
(Equation 9)

Figure 7. Scatter plot of LST versus NDVI of the study area (MODIS image 12 Jan. 2005).

(Equation 9) and (Equation 6) were applied to derive VTCI from MODIS imagery which covers most parts of Vietnam, Lao and Cambodia. In Figure 8 we can see that the study area, the most deserted part of Vietnam exhibits a low VTCI which indicates high levels of drought and water stress, while the rainforest along Truong Son mountain range exhibit a higher VTCI and having a darker tone in VTCI image. A large area in the middle and central Vietnam was masked due to cloud cover. In the next step of the study, more MODIS data will be processed in order to monitor the spatial and temporal dynamics of desertification at a national scale.

Figure 8. VTCI of the study area derived from MODIS image taken on Jan 2005. The pixel size is 1 km. The pixels in white are land without LST value due to cloud cover.
5.2 Soil moisture estimation

The relationship between delta index and soil moisture is determined by soil dielectric properties. These are the dependency of dielectric constant on volumetric soil moisture, and the dependency of backscatter on real dielectric constant. The lower the dielectric constant, the more incident energy is absorbed, giving a lower backscatter value. In addition, radar backscatter is also affected by topography, surface roughness and vegetation cover. By taking the delta index we could remove those time-invariant features because they are the same in dry/wet season imagery. The difference in image backscatter between seasons should be due primarily to soil moisture.

The results showed that, for the whole area, delta index backscatter were poorly correlated \( (r^2 = 0.58) \) with soil moisture content (Figure 9). This poor correlation could be attributed to the change in vegetation between dry and wet season as discussed earlier in section 5.1.

![Figure 9. The relation between delta index backscatter and surface soil moisture: (a) all areas; (b) sandy soil and bare land area](image)

Considering only the sandy soil and bare land area, there was a strong relation between delta backscatter and soil moisture \( (R^2 = 0.89) \). Using this relationship, a regional map of surface soil moisture was obtained for the 2005 wet season. The map showed a good contrast among sand dunes along the coast (green), sandy soil (red) and rice fields (yellow). Several black areas in the middle of image are lakes which have very low backscatter in both seasons. Forest areas (SAVI >0.4) were misinterpreted as having very low soil moisture (green area apart from sand dune along the coast) because the delta index model performs poorly in heavily vegetated areas. Although the delta index does not yield a 1:1 relationship with soil moisture, the map provides a reasonable estimation of soil moisture, at least for sandy soil areas.
6 Discussion

The results of the initial analysis have shown that standard MODIS and ASTER image products have strong potential for desertification mapping at small and medium scales, clearly delineating the coastal sand dune, sandy soil, agriculture and vegetated areas.

VTCI calculated from two seasons of ASTER data have shown that the index can provide quantitative information on spatial and temporal changes caused by the desertification process. Time series of VTCI have the potential to detect not only areas with water stress problems but also areas which are stable over the time. This information is a valuable input for land use planning strategies that are aimed at combating desertification.

The preliminary results of soil moisture estimation from SAR delta index backscatter are encouraging. If SAVI values are less than 0.4 we can use delta index to estimate soil moisture, as has been demonstrated for sandy soil areas ($r^2=0.89$). For vegetated areas (SAVI >0.4), SAR backscatter is less successful at model soil moisture due to the influence of the canopy. Soil moisture estimation when combined with VTCI and others parameters will provide a better view of desertification process. While delta index works well for open sandy soil, VTCI can provide accurate information for vegetated area. Integration of parameters extracted from different parts of the spectrum or different sensors gives more information on different aspects of the desertification process, therefore improve the mapping accuracy.

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8 References


