Time-Series Analysis of Medium-Resolution, Multisensor Satellite Data for Identifying Landscape Change

Andrew A. Millward, Joseph M. Piwowar, and Philip J. Howarth

Abstract
The overall goal of this study is to use medium-resolution satellite imagery to determine recent changes in the landscape of the coastal zone near Sanya in the People’s Republic of China. A search for suitable satellite imagery revealed that the only way to identify the changes was to use data from three different sensors acquired over a 12-year time period: a 1987 Landsat 5 Thematic Mapper (TM) image, a 1999 Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image, and two SPOT 2 High Resolution Visible (HRV) images acquired in 1991 and 1997. Given that the Landsat and SPOT images have different spatial resolutions and that the spectral bands cover somewhat different spectral ranges, the challenge was how to combine the images in digital format to be able to detect subtle changes in the landscape. Measures of brightness, greenness, and the normalized difference vegetation index (NDVI) were explored using standardized principal components analysis (PCA). Approximately 38 percent of the scene was occupied by water, so tests were performed with the water included and also with the water masked out to remove these low-variance pixels. Factor loadings and input-band contributions were used to interpret component images. Results show that PCA of the visible bands, representing brightness, is the superior approach for identifying new urban features in the landscape. Measures of brightness, greenness, and the normalized difference vegetation index (NDVI) were explored using standardized principal components analysis (PCA). Approximately 38 percent of the scene was occupied by water, so tests were performed with the water included and also with the water masked out to remove these low-variance pixels. Factor loadings and input-band contributions were used to interpret component images. Results show that PCA of the visible bands, representing brightness, is the superior approach for identifying new urban features in the landscape.

Introduction
The coastal zone near the city of Sanya in the province of Hainan, China, has undergone considerable landscape change over the past twenty years. As part of a research project focused on integrated monitoring and management of the coastal zone in the Sanya region, there was a need to determine how the landscape has changed since the early 1980s. Sanya was previously a small fishing village and growth took place so rapidly, there was little documentation as to what changes occurred over this time period.

To investigate historical landscape change, it is essential to have a time sequence of observations; in most cases, the more observations the easier it is to document and understand the changes. Since the early 1970s, remote-sensing imagery acquired from space has been available to provide a data source for such observations. Satellite imagery, combined with ground information acquired at selected points in the area of interest, is argued to be the best data source for mapping landscape change over large areas (Mas, 1999; Millward and Kraft, 2004). With respect to determining change in urban areas, data from satellites have been used to detect human-induced change in the landscape (Antrop and Van Eetvelde, 2000; Howarth and Bousson, 1983; Streets et al., 1995), but few studies involving a time series of several multispectral images acquired by different sensors have been conducted.

A search for medium-resolution satellite imagery of the Sanya area from the early 1980s to the present day produced only four images that were suitable for analysis: one Landsat 5 Thematic Mapper (TM) image, one Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image, and two SPOT 2 High Resolution Visible (HRV) images (Table 1). As illustrated in Table 1, although there is compatibility between the two Landsat images and the two SPOT images, combined Landsat and SPOT images are incompatible both in terms of their spatial resolutions and their spectral bands. Thus, the overall goal of this study was to develop a digital change-detection method that could be used with a combination of Landsat (1987 and 1999) and SPOT (1991 and 1997) imagery to identify the sequence of human-induced changes in the landscape over the 12-year period.

Methods for Digital Change Detection
The various ways in which imagery can be analyzed to determine changes in the environment have been summarized in detail by Singh (1989), Coppen et al. (2004) and Lu et al. (2004). As these authors indicate, a wide range of analysis procedures for change detection have been developed and tested. However, these review papers show that there are relatively few studies in which medium-resolution imagery acquired on more than two dates has been analyzed. In addition, there are even fewer studies which have made use of data acquired from more than one satellite.
Several methods exist for the analysis of a time series of satellite data, but each of these stipulates detailed *in-situ* and time-specific information describing the study area; data that are increasingly less available for historical data sets and were not available for the Sanya region. Post-classification change has been used to integrate multisource remotely sensed data in time-series analyses through the classification of data to standardize each temporally distinct image (Eastman and McKendry, 1991; Petit and Lambin, 2001). However, errors associated with each classified image are compounded when multivariate comparisons are made (Heuvelink et al., 1989; Lillesand and Kiefer, 2000). An alternative approach uses the Gramm-Schmidt transformation to reduce the dimensionality of a satellite image to reflect the physical properties of the imaged landscape (brightness, greenness, and wetness) (Kauth and Thomas, 1976; Jackson, 1983; Mispán and Mather, 1997). Newer approaches involve the use of geographic information systems (GIS) as a means to record landscape changes; this may be especially useful when data from disparate sources are used in the analysis (Lu et al., 2004).

In developing a methodology to handle both the Landsat and the SPOT imagery of the Sanya region, two factors were considered to be important. First, Landsat TM bands 2 through 4 have been shown to have an intrinsic image dimensionality of two, which corresponds to the physical ground-cover characteristics of brightness and greenness (Ingebritsen and Lyon, 1985; Chavez and Kwarteng, 1989). Similar dimensionality has been documented to exist for bands 1 through 3 of SPOT HRV imagery (Chavez and Bowell, 1988). Selection of bands that emphasize these physical measures in an urbanizing landscape (e.g., introduction of impervious surfaces and loss of vegetation) offers one method of integrating data from several different sensors into a time-series analysis.

The second factor is that many researchers have recommended the use of principal components analysis (PCA) for generating change/non-change information ( Coppin et al., 2004; Lu et al., 2004). PCA has been used as an exploratory technique to investigate changes in satellite imagery (Fung and LeDrew, 1987; Piwowar and LeDrew, 1996; Tangestani and Moore, 2001), and is considered to be one of the best approaches for long-sequence, time-series analyses (Eastman and Fulk, 1993). Nevertheless, its application as a time-series analysis technique for use with multispectral data has developed *ad hoc* and lacks guidelines for application and appropriateness of use (Piwowar and Millward, 2002). PCA identifies high correlations associated with image pixel locations that remain constant and low correlations with those locations that exhibit differences through time (Byrne et al., 1980; Siljeström and Moreno, 1995). The significance of each principal component (PC) is determined by its relative position within the component structure (higher components represent more prominent patterns), and by an examination of the original data with which it is most highly correlated. The first component explains the maximum amount of variation possible in a single dimension; the second explains the maximum remaining variation not explained by the first (Dunteman, 1989; McGarigal et al., 2000). Subsequent components follow the same rationale.

To achieve the goal of developing a digital change-detection method that can be used with data from three different satellite sensors (Landsat TM, Landsat ETM + and SPOT HRV), three selective standardized PCAs are evaluated for their abilities to identify changes in the landscape. The conventional approach to PCA analysis (inclusion of several multispectral bands from one sensor into a single analysis) is modified to derive univariate surfaces for image brightness, image greenness, and normalized difference vegetation index (NDVI) values recorded for the four images. It is postulated that changes in brightness, greenness, and NDVI are likely to highlight, and thus identify, the major human-induced changes that have occurred in the landscape over the 12-year period.

**Study Site and Data Description**

The Sanya region, on the southern coast of the Province of Hainan, China (Figure 1) has white sand beaches and a tropical climate, both of which have fostered a boom in the tourism industry (see Figure 1). Hainan is an island with Special Economic Status (SEZ) situated in the South China Sea and southwest of Hong Kong.

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**Table 1. Chronology of Optical Satellite Data Used in Time-Series Analysis of Landscape Change Occurring in the Sanya Region, Hainan Province P.R.C. Acquisition Occurred in the Dry Season so as to Minimize Cloud Cover and to Capture Similar Vegetation Phenological Stages. Bands were Selected for Analysis from Different Sensors Based Upon Similarities in Their Spectral Ranges. Spectral Ranges are Particular to Bands Used and Arranged Respectively**

<table>
<thead>
<tr>
<th>Acquisition Date</th>
<th>Sensor</th>
<th>Bands Used</th>
<th>Spectral Range</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987 - December - 22</td>
<td>Landsat 5 TM</td>
<td>2, 3, 4</td>
<td>0.52–0.60, 0.63–0.69, 0.76–0.90</td>
<td>30</td>
</tr>
<tr>
<td>1991 - November - 19</td>
<td>SPOT (HRV) 2</td>
<td>1, 2, 3</td>
<td>0.50–0.59, 0.61–0.68, 0.79–0.89</td>
<td>20</td>
</tr>
<tr>
<td>1997 - November - 07</td>
<td>SPOT (HRV) 2</td>
<td>1, 2, 3</td>
<td>0.50–0.59, 0.61–0.68, 0.79–0.89</td>
<td>20</td>
</tr>
<tr>
<td>1999 - December - 31</td>
<td>Landsat 7 ETM+</td>
<td>2, 3, 4</td>
<td>0.53–0.61, 0.63–0.69, 0.78–0.90</td>
<td>30</td>
</tr>
</tbody>
</table>

Source: European Space Agency (ESA); United States Geological Survey - National Aeronautics and Space Administration (USGS-NASA).
tourism in recent decades (Xiao and Zhu, 1992; Xie and Wall, 1999). Landscape change from vegetated to urban surfaces has occurred rapidly with a burgeoning service industry (Huijie, 1999; Gu, 2002). However, detailed mapping and monitoring of such changes has been limited (Hainan Department of Development Planning, 1999).

The study location included areas on the imagery that had not been disturbed during the 12-year time period. This was important to ensure that the first principal component axis (PC1) would be determined by the variance associated with landscape cover types that had not changed (Richards, 1984; Siljeström and Moreno, 1995). In addition, a portion of the study area was covered by an Ikonos 2 image acquired in February 2002. The high spatial resolution of this image was of great assistance when verifying rural-to-urban landscape change.

A check of available imagery for the study area showed that several images had been acquired in different years and at different seasons. However, most images acquired during the rainy season (mid-April to mid-October) had considerable cloud cover or the presence of haze. Checking for cloud-free images and ones that were acquired at near-anniversary dates, only four suitable images could be identified. All imagery was acquired during the months of November and December which is the beginning of the dry season in this tropical environment. Having all the imagery available from the same time of year means that illumination differences due to sun angle are minimized. In addition, the possibilities of identifying changes that are due to differences in phenological stage of the vegetation are greatly reduced.

For geometric correction of the satellite images, 1976 Russian military topographic maps at a scale of 1:100 000 were acquired for the study region. These maps were used to register the images to the Universal Transverse Mercator (UTM) coordinate system.

Methods
Analysis of the data involved three phases. First, was preprocessing which consisted of radiometric and geometric corrections of the four images. This was done to make the images as comparable as possible. In the second phase, we reduced the spectral dimensionality of each image to ensure that the images produced by the time-series analyses did not contain both spectral and temporal variations, which would have confused our analyses (Eastman and McKendry, 1991; Piwowar and Millward, 2002). Three approaches to spectral ordination were tested: collapsing the multispectral data into a single brightness image, selecting a band to best represent image greenness, and computing the NDVI for each date. The third analysis phase involved selectively applying PCA to the spectrally reduced images from each date to determine their information content with respect to changes in the landscape. Details of the procedures are presented in this section.

An additional aspect was also investigated in the experiments. In this coastal environment, there are considerable areas of water dominating the images. A concern was that the digital values for the water pixels might skew the results of the change-detection analyses. Thus, the analyses were conducted with and without a mask to remove pixel contributions from the ocean, which represented 38 percent of the study area.

Data Preprocessing
The study area of 225 km² (Figure 2) was extracted from the four multispectral images (Table 1). Only image bands from similar spectral regions (green, red, NIR, represented by Landsat TM/ETM+ bands 2, 3, 4 and SPOT HRV bands 1, 2, and 3, respectively) were used to avoid biasing the results from one year with spectral information that was not available from an alternate year's data.

As the images were recorded on different dates in different years (Table 1), it was assumed that atmospheric conditions at the time of data acquisition were also different. Thus, it was necessary to convert the satellite data to approximate reflectance values (ratio of upwelling to downwelling electromagnetic radiation). Pixel brightness values were converted to relative reflectance data using methods recommended by Chavez (1996) and Song et al. (2001). Each spectral band for each image was standardized to relative reflectance values comparable for common spectral bands across the four images.

The 1991 SPOT image was selected for initial registration to the Russian topographic maps. This was because it was the oldest image with the highest spatial resolution, and because it had a sensor look-angle that most closely approximated nadir. A second-order polynomial was used for geometric correction with nearest-neighbor resampling applied to the image (Campbell, 2002). The topographic complexity inherent in a portion of the landscape, and a desire to maintain true reflectance values, dictated these procedural choices. The spatial resolution of SPOT pixels was standardized to the lowest common spatial denominator (30 m to match Landsat), prior to conducting PCA. All subsequent image-to-image registration was performed using the same geometric and resampling algorithms. Registrations used between 30 and 40 data points and a root mean square (RMS) error of less than a half pixel in both X and Y directions was achieved.
Time and Series Analysis
To investigate intra-annual and inter-annual spectral similarity, correlation matrices were plotted with and without the application of a mask to remove information contributed by pixels recording the ocean (cross-hatched lines in Figure 2). We were interested in whether or not an easily removed area of relatively low multi-date spectral variance would reveal important interpretive differences in the PCs that were generated. While no one has investigated optimal coverage of intertemporal, low variance surfaces, the research of others (e.g., Fung and LeDrew, 1987) suggests that such an effort may be important. Each treatment of the data (described below) was conducted with and without the application of this mask.

All treatments used standardized PCA as it has been demonstrated to be more accurate than using non-standardized components. This is because of improved alignment along land-cover changes in the multitemporal data structure (Fung and LeDrew, 1987; Eklundh and Singh, 1993). PCs were saved to 32-bit image channels to preserve numeric output in real format. Selective PCA (inclusion of a specific band or bands) was used to extract temporal information that corresponded with changes in the physical scene characteristics from year to year (Chavez and Kwarterg, 1989; Dwivedi and Sankar, 1992).

Treatment 1: Multitemporal PCA for Derivation of Change in Brightness
Urban surfaces, such as roads, buildings and cleared land, reflect electromagnetic energy much more in the visible spectrum than do vegetated surfaces (Jensen, 2004). In order to focus our analyses on the visible spectral region, we could have based the change analysis on either of the available visible bands (i.e., green or red) from each date. In recognition that the spectral information from these bands is highly correlated, however, a multispectral PCA was performed on these two bands to derive a component attributable to brightness (Ingebritsen and Lyon, 1985; Dwivedi and Sankar, 1992). Information that was common to both bands was mapped to the first component. This yielded a spectrally reduced image representative of image brightness for each year (Figure 3a). Signal-to-noise ratio (SNR) (Eklundh and Singh, 1993) was used to determine whether the information content was higher for the masked or unmasked first PC. SNR is a measure of improvement of variance contained in the first PC when compared with the input spectral band exhibiting the greatest variance. When the mask was used, it was found to be larger for the first PC, for all time periods, (1987: 2.97 dB versus 2.74 dB; 1991: 2.97 dB versus 2.72 dB; 1997: 2.97 dB versus 2.50 dB; 1999: 2.97 dB versus 2.92 dB). PCs generated with the ocean mask were selected as the univariate measure of brightness for each time interval and were subsequently input into the second multitemporal PCA (Figure 3b).

Treatment 2: Multitemporal PCA for Derivation of Change in Greenness
In this study, NIR is the one spectral band that can identify peaks in the spectral response of vegetation (Jensen, 2004). It was assumed that the NIR bands would be the most representative measure of the presence of image greenness, which was used as a surrogate for the presence of vegetation (Ingebritsen and Lyon, 1985; Ridd and Liu, 1998). A multitemporal PCA was performed that included NIR bands extracted from each of the four images (Figure 3b).

Treatment 3: Multitemporal PCA for Derivation of Change in NDVI
The normalized difference vegetation index (NDVI) is a spectral vegetation indicator that has been used extensively to monitor vegetation presence and vigor (Jensen, 2004; Viedma et al., 1997). It has also been found useful in the investigation of rural-to-urban growth (Howarth and Boasson, 1983; Phinn et al., 2000) because removal and fragmentation of vegetation frequently accompany the development process (Forman and Gordon, 1986; Forman, 2000; Fung and Siu, 2000). Because of its wide number of applications and history of use, it was of
Interpretation and Evaluation of PCA Approaches

To compare and contrast the effectiveness of the three treatments for identifying general patterns of urbanization, factor loadings were computed for each of the PCs corresponding to each of the years evaluated. Factor loadings provide a method for interpreting the information content expressed within a PC and were generated in this study following the procedures described by Jensen (2004):

\[ R_{kp} = \frac{a_{kp} \times \sqrt{\lambda_k}}{\sqrt{\text{Var}_{kp}}} \]  

where \( R_{kp} \) is the loading value (1 to -1), \( a_{kp} \) represents the eigenvector for band \( k \) and component \( p \), \( \lambda_k \) is the eigenvalue for component \( p \), and \( \text{Var}_{kp} \) is the input band variance for band \( k \). With standardized PCA, \( \text{Var}_{kp} \) is always 1 because it is derived from the correlation matrix (Dunteman, 1989).

A complementary approach to calculating band loadings is to derive the percent contribution of variance (information content) for each input band into the PCs that are generated. This was accomplished by applying the formula:

\[ S_{kp} = \frac{(a_{kp})^2}{\sum (a_{ip})^2} \]  

where \( S_{kp} \) is the contribution of band \( k \) to component \( p \), \( a_{kp} \) is the eigenvector value for band \( k \) and component \( p \), and \( n \) represents the total number of input bands.

Typically, evaluation of the success of a PCA to identify land-cover change in the absence of in-situ data relies on interpretation of the PCs in relation to band loadings and contribution values. However, a quantitative method to evaluate the success of a PCA to consistently identify locations of unchanged land-cover is easily developed by investigating such locations in the time series data. If a PC contains greater overall information content, but does not exhibit higher variance values in unchanged areas, it represents a more information-rich ordination result for time-change analysis compared with its masked/unmasked counterpart.

Sixteen locations from across the entire study area with unchanged land-cover characteristics were randomly selected. Each location contained between 50 and 110 pixels (approximately 4.5 to 10 ha in area) and represented a wide variety of land-cover types. These locations were selected based upon information from field visits, a 2002 Ikonos 2 dataset (both multispectral and panchromatic images) covering a portion of the study area, and the Russian topographic maps. Standard deviations for the aggregate pixel values (i.e., the total for the sixteen unchanged sites) were computed for each PC generated from each treatment. These standard deviation values were compared to the information content of the respective PC using a simple ratio of standard deviation to information content.

Results

Correlation Analyses

Intra-temporal correlation matrices reveal a strong positive association between visible bands for each time period (Table 2). NIR bands show low to moderate positive correlation with visible bands, and a strong positive association with NDVI. Application of the ocean mask produced a stronger positive association between the visible bands, while correlation between NIR and NDVI shifted from strong to moderately positive (Table 2). Inter-temporal correlation of green bands across all years was moderate with the weakest association evident between 1991 and 1997, and the strongest between 1987 and 1999 (Table 3). A similar trend was found for red bands, except that correlation was higher for the green bands. Application of the ocean mask improved correlation in all cases for the green and red bands. Strong association is evident among all years for both the NIR and the NDVI bands (Table 3). Little difference was found to exist among measured correlations for NIR and NDVI when results were compared for the full and masked study areas.

Table 2. Intra-Temporal Correlation of Similar Spectral Bands, and the Normalized Difference Vegetation Index (NDVI), that were Used in the Time-Series Analysis of Urban Landscape Change. Green, Red and NIR are Representative of Landsat TM/ETM+ Bands 2,3,4 and NDVI. Spot HRV Bands 2,3,4 and Spot HRV Bands 1,2,3.

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<tbody>
<tr>
<td>1987</td>
<td>0.72</td>
<td>0.47</td>
<td>0.33</td>
<td>0.47</td>
<td>0.33</td>
<td>0.47</td>
<td>0.47</td>
<td>0.33</td>
<td>0.47</td>
<td>0.47</td>
<td>0.33</td>
<td>0.47</td>
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<tr>
<td>1991</td>
<td>0.74</td>
<td>0.79</td>
<td>0.71</td>
<td>0.74</td>
<td>0.79</td>
<td>0.71</td>
<td>0.74</td>
<td>0.79</td>
<td>0.71</td>
<td>0.74</td>
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<td>0.71</td>
</tr>
<tr>
<td>1997</td>
<td>0.80</td>
<td>0.80</td>
<td>0.83</td>
<td>0.80</td>
<td>0.80</td>
<td>0.83</td>
<td>0.80</td>
<td>0.80</td>
<td>0.83</td>
<td>0.80</td>
<td>0.80</td>
<td>0.83</td>
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Table 3. Inter-Temporal Correlation of Similar Spectral Bands, and the Normalized Difference Vegetation Index (NDVI), that were Used in the Time-Series Analysis of Urban Landscape Change. Green, Red and NIR are Representative of Landsat TM/ETM+ Bands 2,3,4 and NDVI. Spot HRV Bands 2,3,4 and Spot HRV Bands 1,2,3.

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<tbody>
<tr>
<td>1987</td>
<td>0.38</td>
<td>0.47</td>
<td>0.33</td>
<td>0.47</td>
<td>0.33</td>
<td>0.47</td>
<td>0.47</td>
<td>0.33</td>
<td>0.47</td>
<td>0.47</td>
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<tr>
<td>1991</td>
<td>0.62</td>
<td>0.68</td>
<td>0.74</td>
<td>0.68</td>
<td>0.74</td>
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<td>0.74</td>
<td>0.74</td>
<td>0.68</td>
<td>0.74</td>
<td>0.74</td>
</tr>
<tr>
<td>1997</td>
<td>0.69</td>
<td>0.82</td>
<td>0.75</td>
<td>0.82</td>
<td>0.75</td>
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<td>0.82</td>
<td>0.75</td>
<td>0.75</td>
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</table>

Time and Series Analysis

PCA results varied considerably for each treatment employed (Figures 4, 5, and 6). As expected, PCA of visible bands (brightness) was the superior selection for identifying the introduction of urban features to the landscape. NIR bands outperformed NDVI as a measure of changing greenness.

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(Table 4). Corresponding factor loadings and percent contribution of original bands are plotted with their respective PCs. PC1 for each of the analyses represents integrated surfaces (components that describe common surface characteristics across all time intervals). While these component images have not been included in Figures 4, 5, and 6, their largely uniform positive loadings and equivalent percent contributions demonstrate that little information describing change is present within them.

Figures 4, 5, and 6 are interpreted using the following sequence: (a) identify the percent variance (unique information content) contained within each component image; (b) identify the year(s) for which the input band makes the greatest percent contribution to the component image; (c) determine whether the most highly contributing year(s) is loaded negatively or positively in the component image; and (d) read the temporal persistence of a specific spatial pattern. Loadings indicate the correlation between each component and the original channels on a scale of $-1$ to $+1$ and are gray-scaled from black to white, respectively. A high loading (negative or positive) indicates that the original data (in this study represented by a specific year) are expressed strongly in the component image. A loading near zero indicates no strong expression of a specific year with the component image and is depicted by a mid-gray tone.

**Brightness Time Series**

The higher-order PCs (2 through 4) generated using the unmasked brightness images contain greater variance when compared with the masked results (Figure 4). Percent contributions from each unmasked input image to a specific PC were variable and highlighted distinct years as having a greater or lesser influence on the component structure (Figure 4a). Similarly, loading values were separable according to the input band year. PCs results with the mask (Figure 4b) showed much less separability of percent contribution for the different years. Further interpretation was greatly hindered by loading values that plotted as paired years. For these reasons, the following interpretations were made using the component images from the unmasked analysis (Figure 4a):

- PC2 shows a strong negative loading from the 1997 brightness image (>$60$ percent image variance contributed by this year); a paved series of roads was constructed between 1991 and 1997 (exhibited in dark image tones). Positive

<table>
<thead>
<tr>
<th>Treatment</th>
<th>PC1 (%)</th>
<th>PC2 (%)</th>
<th>PC3 (%)</th>
<th>PC4 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selective PCA (Brightness)</td>
<td>72.9</td>
<td>13.6</td>
<td>8.0</td>
<td>5.5</td>
</tr>
<tr>
<td>Selective PCA (Greenness)</td>
<td>80.5</td>
<td>9.6</td>
<td>5.3</td>
<td>4.6</td>
</tr>
<tr>
<td>PCA</td>
<td>97.1</td>
<td>1.2</td>
<td>1.1</td>
<td>0.6</td>
</tr>
<tr>
<td>NDVI</td>
<td>84.8</td>
<td>7.0</td>
<td>5.2</td>
<td>3.0</td>
</tr>
<tr>
<td></td>
<td>97.1</td>
<td>1.3</td>
<td>0.9</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>94.7</td>
<td>4.0</td>
<td>2.4</td>
<td>1.9</td>
</tr>
</tbody>
</table>

**Table 4. Percent of Total Input Band Variance Explained by Principal Components According to Treatment Method.** SHADED ROWS REPRESENT VALUES FOR SCENES WHERE A MASK OF THE OCEAN WAS APPLIED PRIOR TO THE COMPUTATION OF PRINCIPAL COMPONENTS

Figure 4. Principal components derived from ordination of visible bands (green and red) for (a) entire study area and (b) masked study area. Graphs depict factor loading values and percent contribution for each temporally specific input band.
loading was from the 1991 image (32 percent image variance contributed by this year); many patches of land were cleared of vegetation for construction (bright image tones).

- PC3 shows strong negative loading from the 1991 brightness image (39 percent image variance contributed by this year); a large road appears (as a dark line) between 1987 and 1991 in the center of the image with a NW-SE orientation. Development of urban surfaces in the central portion of the image (dark tones) is also evident between 1987 and 1991, and corresponds with this PC. Positive loading occurred from the 1999 brightness image (41 percent image variance contributed by this year); road expansion occurred between 1997 and 1999 (seen as a bright linear feature) in the central-right portion of the image.

- PC4 shows a strong negative loading from the 1991 brightness image (42 percent image variance contributed by this year); urban development occurs around a road intersection in the center of the image (dark). A small contribution from the 1999 image is also negatively loaded (9 percent image variance contributed by this year) and corresponds with the highway originating in the central portion of the image and continuing eastward. Positive loading occurred from the 1987 brightness image (48 percent image variance contributed by this year); dispersed land clearance and construction activities took place (bright).

Greenness Time Series

PCs 2 through 4, generated using the masked NIR images, contain greater variance when compared with unmasked results (Figure 5). Percent contributions from both PCAs were variable highlighting distinct years of influence on the component structure. Loading values were separable according to the input band year with stronger visual contrast in the masked component images. Accordingly, interpretations were made using the component images from the masked analysis (Figure 5b):

- PC2 shows a strong negative loading from the 1997 NIR image (37 percent image variance contributed by this year); shrubby vegetation has supplanted large natural wetlands that were drained between 1991 and 1997 (dark regions near the center of the image). Positive loading was from the 1987 image (45 percent image variance contributed by this year); many patches of land were vegetated prior to 1991 (bright areas).

- PC3 shows a strong negative loading from the 1999 NIR image (36 percent image variance contributed by this year); locations that have increased vegetation cover in 1999 compared with other years (e.g., parks, community gardens) are identified (dark regions). Positive loading occurred from the 1991 NIR image (48 percent image variance contributed by this year); this emphasizes surfaces that were vegetated in 1991, but were cleared during subsequent time intervals (bright regions).

- PC4 shows a strong negative loading from the 1991 NIR image (35 percent image variance contributed by this year); vegetation vigor is greatest in 1991 for some of the forested areas of the upper central and central-right portions of the image (dark). Positive loading was from the 1987 NIR image (34 percent image variance contributed by this year); vegetation vigor is greatest for 1987 in locations adjacent to those identified for 1991 (bright).
**NDVI Time Series**

The higher-order PCs (2 through 4) generated using the masked NDVI images contain greater variance when compared with unmasked results (Figure 6). Percent contributions from both PCAs were variable, highlighting distinct years of influence on the component structure. Separability of loading values according to the input band year was greater with the masked PCs producing stronger visual contrast in the masked component images. However, with the exception of masked PC2 (Figure 6b), all PCs exhibit little or no information relevant to land-cover changes across the time series considered. As a result, detailed interpretations were not attempted.

**Analysis of Unchanged Locations**

The success of each PCA treatment was assessed to identify locations of little or no change, with and without the application of the mask. A successful ordination with PCA will produce components that exhibit homogeneous areas of low pixel variance; locations that have not experienced landscape alteration. An aggregate standard deviation value, generated from sixteen locations known to have not changed across the time series represented by the imagery, is plotted for PCs associated with each treatment and for the masked and unmasked procedures (Figure 7). Results show that standard deviation values are high for PC1s, but diminish with higher-order PCs. There was little difference observed between standard deviation values obtained from the masked and unmasked procedures. However, ratio values for standard deviation to unique component information content were lower for brightness PCs 2 and 3 when PCA was applied to the full study area (Figure 7). Ratios for NIR and NDVI PCs were lower for the masked study area.

**Discussion**

Remotely sensed imagery is now a cost-effective source of historical data, but its use for determining changes over long periods of time requires reliable and easily implemented analysis methods. This situation is exacerbated by the common unavailability of time-specific, in-situ data. As well, it is rare to find imagery acquired by a single sensor that has a complete temporal sequence of useable data for a given location. In this study, simple methods have been developed and evaluated for exploring general landscape change, due to urbanization, in a time series of remotely sensed data. Selective standardized PCA methods were used with data obtained from three different medium spatial resolution sensors acquired on four dates. An approach such as this is necessary to enhance the potential uses of the plethora of archived medium spatial resolution data.

Band correlation results (Table 2) agree with others (Chavez and Kwarteng, 1989; Jensen, 2004; Siljeström et al., 1997), and support the hypothesis that visible bands in this study area are highly redundant and suitable for collapse into a single univariate image representative of image brightness (Figure 3a). Similarly, the poor correlation between the NIR and the visible bands confirms the appropriateness of isolating the NIR bands as a univariate measure of image greenness (Chavez and Kwarteng, 1989; Siljeström et al., 1997).
The greatest disparities among correlations in visible bands are evident between 1991 and 1997, which are the two years that are represented by SPOT data (Table 3). This result suggests that spectral and spatial differences between SPOT and Landsat do not play a significant role in biasing the analysis, a result supported by Chavez and Bowell (1988). Rather, changes to the landscape contribute more significantly to dominant differences revealed by the inter-temporal correlation matrices, irrespective of slight differences in sensor resolution.

The use of visible bands in a PCA produced the strongest indication of the appearance of urban features in the landscape across the time interval considered (Figure 4). When the ocean mask was incorporated in this analysis (Figure 4b), an increase in the percent of total band variance explained by the first PC occurred, with decreased information content in lower-order PCs (i.e., PCs describing change). In this analysis, application of the ocean mask with the image brightness data produced a saturation effect in higher-order PCs causing a loss in image sharpness and reduced interpretability (Figure 4b). The proportion of inter-temporal, low-variance pixels decreased when PCA was calculated for the unmasked study area. This produced the desirable effect of higher-order PCs concentrating greater amounts of input band variance. Smaller variance-to-information content ratios for PCs 2 and 3 further support these findings (Figure 7a).

Differences between the time-series analysis of NIR and NDVI were much more dramatic than was expected from analyses of their band correlations (Tables 2 and 3). Results reveal that PCA of NIR bands (Figure 5) yielded superior interpretability of changes in image greenness when compared with results from the PCA of NDVI (Figure 6). While the distinct visual differences observed did not support the hypothesis that NIR and NDVI would yield similar results, these findings are supported by Clark and Yool (1999) who reported that change analysis of NIR bands provided more contrast between forested and denuded vegetation (fire scars) than a similar analysis with NDVI. Information content in higher-order PCs was found to be greater for NIR than NDVI. NIR PCs are characterized by much less saturation of factor loading values and, based on field visits and the analysis of a small subset of the Ikonos 2 data, the presence and patterns of change in vegetated features are more accurately delineated with NIR when the ocean mask is used.

Factor loadings and input-band contributions (Figures 4, 5, and 6) cannot be used to infer causation or reasons for landscape change, but rather they identify locations that may act as a basis for subsequent investigation. The approach to time-series analysis described in this research serves as an important step toward the identification of locations in landscapes with low inter-temporal variability (little or no change), and regions of change that can be approximately dated by interpreting factor loadings and band input contributions. A major advantage to the time-series analysis developed in this study is that large areas within the study region can be easily removed from subsequent analysis of urban change. Localized areas that demonstrate high inter-temporal variability can be easily isolated for investigation in more detail. This offers two important advantages for the analysis of broad-extent data; these are a reduction in effort spent investigating large areas for inter-annual change, and the provision of a method for directing field work and/or collecting ancillary data.

Study findings indicate a need for research that will investigate the proportion of no-change to change pixels that is required for optimal analysis of change using PCA. This proportion may be variable, depending upon the type of landscape change being investigated and the spectral characteristics of the imagery being analyzed. Of specific interest to time-series analysis is whether or not the number of time intervals considered plays a role in the requirement for a threshold of scene area containing low inter-temporal variance.

Conclusions

As part of a larger project concerned with management of the coastal zone near Sanya in the Province of Hainan, China, there was a need to determine how the coastal landscape had changed over time. A search for suitable medium-resolution satellite imagery revealed that data from three different satellite sensors would have to be analyzed to obtain the information. Thus, a methodology was developed using standardized PCA of selected image bands from the different sensors to determine changes in the landscape. Spectral bands common to the imagery were combined according to the physical content that is required for optimal analysis of change. These bands were then applied to datasets acquired by two Landsat sensors and one SPOT sensor. Second, only selected bands were used in the analysis. To determine changes in brightness, the green and red bands from each date were combined into single brightness images for each of those dates. Then, a second PCA

![Figure 7. Plots of standard deviation and ratio of standard deviation to component information content for 16 randomly selected, and subsequently amalgamated, locations that exhibit consistent land-cover/use across the chronology of data analyzed. Plots correspond with treatments (a) Selective PCA for analysis of change in brightness (b) Selective PCA for analysis of change in greenness and (c) PCA for analysis of change in normalized difference vegetation index (NDVI).](image-url)
was performed on the brightness images from all four dates to identify what the changes were in the different time periods.

To determine changes in vegetation, two approaches were used. First, the NIR bands from all four dates were used to generate PCs. Second, NDVI images were generated for each date from the red and NIR bands. PCA was then applied to all four NDVI images to identify the changes in vegetation during the different time periods.

Results varied based upon the standardized PCA treatment selected, and the decision as to whether or not to mask out the ocean. The most distinct patterns of landscape urbanization (i.e., construction of roads, densification and outward expansion of commercial-residential structures) were revealed when PCA was applied to the visible bands to form a brightness index. Contrary to expectations, the presence or absence of vegetation measured using standardized PCA with NIR bands was superior to using PCA with NDVI values.

From the results of this multisensor study, it was possible to identify locations where even subtle changes had occurred in the landscape near Sanya, and what the nature of those changes was. In more general terms, the procedures developed for this study offer a new methodology for image analysts and environmental managers to map and monitor the landscape using imagery from more than one sensor.

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