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**Evaluating digital change detection techniques
for landscape monitoring in a data-poor
tropical island environment**

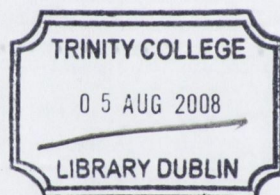
A case study of New Providence Island, The Bahamas

Volume 1 of 2

A thesis submitted to the University of Dublin, Trinity College
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Doctor of Philosophy

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Summary

This thesis addresses the problems associated with conducting remotely sensed change detection for landscape monitoring in tropical island environments, with poor data accessibility and availability. The common unavailability of time-specific in-situ data and the next-to-impossible task of acquiring single sensor imagery with a complete temporal sequence of useable image data for a target location are major obstacles for landscape monitoring in these areas. The overall goal of this study was to evaluate and develop digital change detection techniques incorporating remotely sensed indicators and spatial metrics that can be used with multisensor, multispectral and multiresolution remotely sensed imagery to identify the sequence of landscape changes associated with human disturbance for landscape monitoring, using New Providence Island (The Bahamas) as a case-study.

The analysis in this thesis involved a three part methodology. The first involved the development and evaluation of multitemporal PCA to visualise the sequence of human induced disturbance patterns. Multitemporal PCA was applied to two separate time series comprising four images (1973-1986-1999-2002 and 1985-1999-2001-2002) to extract temporal information relating to changes in the physical scene characteristics from year to year as a means to visualise human induced disturbance over the time period.

Three approaches to multitemporal PCA (brightness, greenness and NDVI) were evaluated and applied to determine their information content with respect to landscape change. Two new approaches were also tested (NDBI and BI). These values were computed for a time series of four images to determine whether the indices could be used to highlight human disturbance through time and whether they offered an improvement over brightness, greenness and NDVI. Of all the methods evaluated, brightness, NDVI and NDBI were shown to better highlight the introduction of new urban features and changes to vegetation over greenness and BI, for both time series, demonstrating the robustness of the technique. Results from the analysis of unchanged locations revealed that both brightness and NDVI recorded consistently low aggregate standard deviation values for higher order PCs in comparison to the results from the areas of change demonstrating the success of the methods to characterise areas of no change with low pixel variance.

The second methodology addressed land cover classification and post classification change comparison techniques. The aim of the land cover classification was to firstly identify a suitable and replicable remote sensing classification methodology for selecting and integrating information from multisensor and multiresolution satellite imagery. A second aim was to improve land cover classification accuracy and a final goal to examine the use of post-classification change detection to identify the types, rates and temporal variability of land cover change. A number of pre-classification processing procedures including PCA, the incorporation of temperature data and six data-fusion techniques to combine same sensor high-resolution panchromatic imagery with medium-resolution imagery were applied to the Landsat ETM+ and SPOT HRVIR datasets. The procedures were tested to see whether they could offer an improvement to classification accuracy. In addition, the images produced from the data-fusion techniques were tested prior to conducting land cover classification to determine whether preservation of spectral and spatial quality affected classification accuracy. The results showed that none of the methods offered a significant improvement over classification of the original multispectral image.

It was apparent that the high levels of classification detail presented by the data-fused imagery served to complicate the labelling of pixels into land cover classes and a considerably greater amount of noise was apparent in the final map products. The relationship between preservation of spectral and spatial quality by data-fusion method and classification accuracy was not entirely consistent. However, reduction in spectral resolution associated with several of data fused methods (IHS, Brovey and Wavelet IHS) was attributed to the poorer performance of these methods because of the limited ability to discriminate among landscape features in comparison to a land cover classification employing the full range of visible and infrared spectral data. By the same token, the success of the wavelet PCA transformation above the other methods was attributed to the strong correlation between the original multispectral and data-fused image.

Post-classification change detection applied to a time series of land cover maps was used to successfully generate land cover change statistics. Post-classification change comparison conducted to establish specific "from-to" change information, clearly highlighted the impact of human disturbance on the island associated with land cover conversion to HAL. The analysis also facilitated the visual interpretation of more unusual land cover conversions identified through post-classification change comparison; some but not all were associated with classification errors.

The third and final methodology addressed whether a time series of land cover maps generated for the study area could be used to detect and quantify statistically significant trends in a unique set of remotely sensed indicators and spatial metrics derived to measure and monitor landscape change. The robustness of the metrics to changes in spatial extent and scale was also tested. Eight remotely sensed indicators of human disturbance and a total of 31 spatial metrics were evaluated.

Six of the remotely sensed indicators displayed significant trends over the time period. An analysis of indicator values revealed that the years between 1986 and 1999 were characterised by the sharpest rising trends in human disturbance. Indicator scores generated at the spatial extent of a 500m and 200m coastal zone produced the same results and demonstrate the robustness of the indices to characterise trends in human disturbance.

Eighteen spatial metrics measuring elements of landscape pattern and structure describing area, shape, diversity and configuration, displayed statistically significant trends through time. Specific metric values describing changes to landscape composition and configuration were clearly interpretable in the context of the impact of human disturbance on the landscape. Metric values generated for 500m and 200m coastal land cover maps revealed that the metrics were robust and appropriate for monitoring temporal land cover changes within a narrow coastal zone heavily impacted by development. A total of fifteen metrics displayed statistically significant trends at the scale of the entire island and within the coastal zone. The sensitivity of the metrics to changes in spatial scale was tested. The results revealed that the general scaling relationships described remain consistent and robust despite changes to landscape configuration and composition associated with landscape disturbance over time.

Overall, the results of the analysis show that despite the methodological challenges of using a time series of imagery derived from different sensors in different seasons, the techniques can be successfully applied to visualise, quantify changes to the landscape of a small tropical island associated with human disturbance. However, use of multitemporal PCA necessitates substantial pre-processing of the data set which is laborious and the results while useful indicate that the method might be more appropriate for application over a large study area to highlight locations of change for further investigation. This work clearly demonstrated the successful application of a set of simple remotely sensed indicators and a suite of fifteen robust spatial metrics to quantify human disturbance for time series change detection in small island environments. The trends revealed the importance of landscape fragmentation as indicators of functional responses to human disturbance and the potential of the method for application in small island areas that have undergone rapid changes.

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Equation 4.1. $L_{\lambda} = \text{"Gain"} \times Q_{cal} + \text{"Bias (or offset)"}'$

Equation 4.2. $L_{sat} = DN_i / G_i$

Equation 4.3. $P_p = \frac{n \times L_{\lambda} \times d^2}{ESUN_{\lambda} \times \cos \theta_z}$

Equation 4.4. $d = \frac{1}{1 - 0.01674 \cos[0.9856(JD - 4)]}$

Equation 4.5. $P_i = \frac{n \times d^2 \times (L_{sat}^i - L_p^i)}{T_V^i (T_Z^i \times ESUN^i \times \cos \theta_z + E_{down}^i)}$

Equation 4.6. $L_p = L_{sat_min} - \frac{0.01[ESUN \times \cos \theta_z \times T_Z^i + E_{down}^i] T_V^i}{n \times d^2}$

Equation 4.7. Minimum number of GCPs = $\frac{(t+1)(t+2)}{2}$

Equation 4.8. $RMSE = \sqrt{(x' - x_{orig})^2 + (y' - y_{orig})^2}$

Equation 4.9. $NDVI = \frac{NIR - RED}{NIR + RED}$

Equation 4.10. $NDBI = \frac{MIR - NIR}{MIR + NIR} - NDVI$

Equation 4.11. $BI = RED + MIR - NIR$

Equation 4.12. $Skp = \frac{(a_{kp})^2}{\sum_{i=1}^n (a_{(i)p})^2}$

Equation 4.13. $Rkp = \frac{a_{kp} \times \sqrt{\lambda_p}}{\sqrt{Var_k}}$

Equation 5.1. $T_B = \frac{K_2}{\ln\left(\frac{K_1}{L_{\lambda}} + 1\right)}$

Equation 5.2. $N = \frac{Z^2(p)(q)}{E^2}$

Equation 5.3. $var(K) = \frac{1}{n} \left\{ \frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2 - \theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4 - 4\theta_2^2)}{(1-\theta_2)^4} \right\}$

Equation 5.4.

$$Z = \frac{K}{\sqrt{\text{var}(K)}}$$

Equation 6.1.

$$\text{NLC} = \frac{A_{\text{nlc}}}{TA}$$

Equation 6.2.

$$\text{NLI} = \frac{A_{\text{nlc}}}{A_{\text{hnlc}}}$$

Equation 6.3.

$$\text{WI} = \frac{A_{\text{w}}}{A_{\text{hw}}}$$

Equation 6.4.

$$\text{VI} = \frac{A_{\text{v}}}{A_{\text{hv}}}$$

Equation 6.5.

$$\text{HA} = \frac{A_{\text{hal}}}{TA}$$

Equation 6.6.

$$\text{HD} = \frac{A_{\text{hal}}}{A_{\text{nlc}}}$$

Equation 6.7.

$$\text{HI} = \frac{A_{\text{hal}}}{A_{\text{h_hal}}}$$

Equation 6.8.

$$\text{HDI} = (\text{HA} + \text{HD} + \text{HI}) - (\text{NLC} + \text{NLI})$$

Equation 6.9.

$$\text{CNLC} = \frac{A_{\text{cnlc}}}{TA}$$

Equation 6.10.

$$\text{CLI} = \frac{A_{\text{cnlc}}}{A_{\text{hcnlc}}}$$

Equation 6.11.

$$\text{CA} = \frac{A_{\text{hal}}}{TA}$$

Equation 6.12.

$$\text{CD} = \frac{A_{\text{hal}}}{A_{\text{cnlc}}}$$

Equation 6.13.

$$\text{CHI} = \frac{A_{\text{hal}}}{A_{\text{h_hal}}}$$

Equation 6.14.

$$\text{CHDI} = (\text{CA} + \text{CD} + \text{CHI}) - (\text{CNLC} + \text{CLI})$$

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List of Abbreviations and Acronyms

AI.....	Aggregation Index
ANOVA.....	Analysis of Variance
AREA_AM.....	Area-weighted Mean
AREA_CV.....	Area Coefficient of Variation
AREA_MN.....	Area Mean
AREA_SD.....	Area Standard Deviation
BEP.....	Bahamas Ecoregional Plan
BEST.....	Bahamas Environmental Science and Technology Commission
BI.....	Barren Index
BNGIS.....	Bahamas National GIS Centre
BWG.....	Brightness Wetness Greenness
CA.....	Index of Coastal Human Alteration
CA.....	Correspondence Analysis
CD.....	Coastal Disturbance Index
CD.....	Index of Coastal Disturbance
CHDI.....	Overall Index of Coastal Disturbance
CHDI.....	Overall Index of Coastal Human Disturbance
CHI.....	Index of Coastal Human Impact
CITES.....	Convention on International Trade in Endangered Species of Wild Fauna and Flora
CLI.....	Index of Coastal Natural Landscape Integrity
CNES.....	Centre National D'Etudes Spatiales
CNLC.....	Index of Coastal Natural Landscape Cover
CONTAG.....	Contagion
CONTIG_AM.....	Area-weighted Mean Contiguity
CONTIG_MN.....	Mean Contiguity
COST.....	COSINE of Solar Zenith Angle Correction
DEF.....	Dry Evergreen Formation
DEM.....	Digital Elevation Model
Denman.....	Dense mangroves
DN.....	Digital Number

DOS.....	Dark Object Subtraction
ED.....	Edge Density
ED.....	Edge Density
ENN.....	Euclidean Nearest Neighbour Distance
EPA.....	Environmental Protection Agency
EROS.....	Environmental Resources Observation Systems
ERS.....	European Remote Sensing Satellite
ESRI.....	Environmental Systems Research Institute
FRAC.....	Fractal Dimension
FRAC_AM.....	Area-weighted Mean Fractal Dimension
GCP.....	Ground Control Point
GIS.....	Geographical Information Systems
GLCF.....	Global Land Cover Facility
GPS.....	Global Positioning System
GYRATE_AM.....	Area-weighted Mean Radius of Gyration
GYRATE_MN.....	Mean Radius of Gyration
Ha.....	Hectares
HA.....	Index of Human Alteration
HAL.....	Human Altered Landscape
HD.....	Index of Human Disturbance
HDI.....	Overall Index of Human Disturbance
HI.....	Index of Human Impact
HRV.....	High Resolution Vegetation
HRG.....	High Resolution Geomatic
HRS.....	High Resolution Stereopair
HRVIR.....	High Resolution Vegetation Infrared
IHS.....	Intensity Hue Saturation
IJI.....	Interspersion and Juxtaposition Index
IRS.....	Indian Remote Sensing Satellite
ISODATA.....	Iterative Self-Organising Data Analysis Techniques
ETM+.....	Landsat Enhanced Thematic Mapper Plus
LIDAR.....	Light Detection And Ranging
LISS.....	Linear Imaging Self Scanning
LOS.....	Law of the Sea
LPI.....	Largest Patch Index
LPM.....	Landscape Pattern Metrics
LSI.....	Landscape Shape Index

LUPAP.....	Land Use Policy and Administration Project
MESH.....	Effective Mesh Size
MIR.....	Middle Infrared
MLT.....	Mean-Low Tide
MNN.....	Euclidean Mean Nearest Neighbour Distance
MPS.....	Mean Patch Size
MSIDI.....	Modified Simpson's Diversity Index
MSS.....	Multispectral Scanning System
NASA.....	National Aeronautics and Space Administration
NDBI.....	Normalised Difference Built-up Index
NDVI.....	Normalised Difference Vegetation Index
NIR.....	Near Infrared
NLC.....	Index of Natural Landscape Cover
NLI.....	Index of Natural Landscape Integrity
NP.....	Number of Patches
PAFRAC.....	Perimeter-Area Fractal Dimension
PC.....	Principal Component
PCA.....	Principal Components Analysis
PD.....	Patch Density
PLADJ.....	Percentage of Like Adjacency
PR.....	Patch Richness
PRD.....	Patch Richness Density
RGB.....	Return Beam Vidicon
RGB.....	Red Green Blue
RMSE.....	Root Mean Square Error
RPR.....	Relative Patch Richness
SHAPE_AM.....	Area-weighted Mean Shape
SHAPE_MN.....	Mean Shape
SHDI.....	Shannon's Diveristy Index
SHEI.....	Shannon's Evenness Index
SIDI.....	Simpson's Diversity Index
SIEI.....	Simpson's Evenness Index
SPLIT.....	Splitting Index
Spman.....	Sparse mangroves
SPOT.....	Satellite Pour l'Observation de la Terre
SPSS.....	Statistical Package for the Social Sciences
TA.....	Total Area

TE.....	Total Edge
TM.....	Thematic Mapper
USGS.....	United States Geological Survey
UTM.....	Universal Transverse Mercator
VI.....	Index of Vegetation Integrity
VISIR.....	Visible Infrared
VGT.....	Vegetation
WFM.....	Write Function Memory Insertion
WGS.....	World Geodetic System
WI.....	Index of Wetland Integrity

Chapter 1 Introduction

1.1. Introduction

This research addresses the problems associated with remotely sensed digital change detection for landscape monitoring in data-poor tropical island environments. There are many challenges to satellite remote sensing in tropical regions largely associated with the difficulty in acquiring consistent cloud free coverage with suitable spatial resolution and temporal frequency for landscape monitoring. Data that are available are typically multi-source, multi-sensor, multi-spectral and multi-resolution and acquired in different years and seasons. The use of data from different sensors poses serious challenges to change detection methodology and analyses are hampered by remote sensing system characteristics such as differences in sensor resolution (i.e. temporal, radiometric, spatial and spectral) and environmental considerations including differences in atmospheric effects, soil moisture content or tidal stage between image acquisition dates; that necessitate pre-processing and standardisation of the time-series dataset.

A wide range of change detection techniques have been developed (Singh, 1989; Lambin, 1999; Mas, 1999; Coppin *et al.*, 2004 and Lu *et al.*, 2004) and time-series analysis of satellite data has been used to monitor global vegetation dynamics and to detect land use and land cover changes (Haines-Young and Chopping, 1996; Haines-Young *et al.*, 2003; Yang and Lo, 2002; Gregoire *et al.*, 2003). More recently the development of remote sensing-derived indicators of environmental condition that can be applied over large geographic areas on a periodic basis for evaluating monitoring and reporting on the status of natural resources (Dettmers and Bart, 1999; Quigley *et al.*, 2001; Tiner, 2004; Narumalani *et al.*, 2004; Lu and Weng, 2005; Ausseil, 2007) and the derivation of remotely sensed spatial metrics to assess land cover condition and landscape change dynamics are receiving growing attention in the literature (Betts *et al.*, 2003; Colombo *et al.*, 2004; Yu and Ng, 2006).

While it is clear that data from satellites have been successfully used to quantify landscape change comparatively few studies involve a time-series of several multispectral images acquired by more than one sensor and very little guidance is available to address the special problems associated with conducting change detection for small island environments.

1.2. Background

Developing countries in tropical regions with limited natural resources and economies heavily dependent on tourism are particularly vulnerable to land degradation associated with uncontrolled development. Finding the balance between environment and development poses an especially difficult challenge in these regions as land cover change is occurring rapidly in response to the increased pressures and heavy demands on natural resources (Becker, 1999; Pfaff, 1999; Sohn *et al.*, 1999; Jepsen *et al.*, 2001; Achard *et al.*, 2002). Information documenting changes to

landscape patterns and methodologies to conduct land cover change detection in developing tropical areas are essential to assist Government agencies in formulating and implementing effective natural resource management strategies and policies that balance the positive and negative impacts of development to preserve environmental resources and increase socio-economic welfare.

The Bahamas comprise an extensive fragmented chain of low-lying islands in the Caribbean whose environment supports a variety of rich terrestrial and marine habitats (Sealey *et al.*, 2002). As a former colony, The Bahamas has undergone considerable social, economic and infrastructural development since achieving political independence from Great Britain in 1973 (BEST, 2005a). Consequently, the landscape of The Bahamas has been subjected to significant modifications by means of uncontrolled, rapid and largely tourism-driven development. The destruction of native vegetation and a reduction in ground and coastal water quality associated with inappropriate development practices, particularly evident on New Providence Island, have only recently been recognised as a severe and chronic threat to the islands of The Bahamas (Sealey, 2003).

To date however, there is a complete lack of quantitative, spatially explicit and statistically representative data on land cover for the islands of The Bahamas. A search for appropriate, available and accessible imagery for a time-series analysis revealed no consistent single sensor repeat data.

A wide range of remotely sensed digital change techniques exist but few report on the application of the methods to multisensor and multiresolution datasets for landscape monitoring. Remotely sensed change detection methods can be divided into two categories, pre-classification or enhancement techniques and post-classification. Pre-classification enhancement techniques are generally applied for comparing change between two dates only. However, multitemporal PCA applied to a time-series of imagery acquired from three different sensors for a study area in China, successfully highlighted the introduction of new urban features and changes to vegetation (Millward *et al.*, 2006). This work demonstrated the potential application of selective PCA in a time-series analysis using multisensor datasets to identify the sequence of human induced disturbance across the island of New Providence. The technique does not offer a means to quantify how much change has taken place but can be used to highlight areas of change across the landscape for further investigation. The sensitivity of the number of time intervals used in the time-series to the success of the methods however, was not fully discussed.

Post-classification comparison change detection has been widely applied for a variety of applications (Wilcock and Cooper, 1992; Dimyati *et al.*, 1996; Yang and Lo, 2002, Kumar *et al.*, 2006; Jat *et al.*, 2007) but the success of the technique to quantify change hinges on thematic map accuracy. Work by Lu and Weng (2005) demonstrated the importance of using the full range of spectral information improving urban land cover classification in a study area in Indiana. Their

results indicate that incorporation of panchromatic data via data-fusion can improve overall classification accuracy.

More recently, the quantification and monitoring and changes to spatial pattern and structure described by spatial metrics is being undertaken to assess landscape condition (Zheng *et al.*, 1997; Palang *et al.*, 1998; Sachs *et al.*, 1998; Pan *et al.*, 1999; Dietzel *et al.*, 2005; Abdullah and Nakagoshi, 2006; Frohn and Hao, 2006; Baskent and Kadiogullari, 2007). Typically only a select number of metrics are tested over very large study areas and it is not clear from the literature which metrics are most informative and interpretable for application in a time-series of landscape change in a small island environment in the tropics.

The overall goal of this study is to evaluate and develop digital change detection techniques incorporating remotely sensed indicators and spatial metrics that can be used with multisensor, multispectral and multiresolution satellite imagery to identify the sequence of landscape changes associated with human disturbance for landscape monitoring, using New Providence Island (The Bahamas) as a case-study.

1.3. Research questions, aims and objectives

Using New Providence Island, The Bahamas as a case study, the research described in this thesis answers four key questions.

1. How can medium-resolution satellite imagery from different sensors be combined to effectively visualise changes in the landscape?

The first aim of this research is to explore and develop the application of multitemporal PCA as a method of identifying and visualising the sequence of human induced disturbances in a time-series analysis of multisensor medium-resolution imagery for a study area in the tropics and is addressed through:

- i. Testing three approaches to spectral ordination by deriving univariate surfaces of image brightness, greenness and NDVI for a time-series of imagery derived from five different sensors and applying multitemporal selective PCA to the spectrally reduced images to determine their information content with respect to the sequence of changes in the landscape.
- ii. Testing two new approaches to spectral ordination by computing the NDBI and BI values for a time-series of imagery and applying multitemporal selective PCA to determine whether the indices can be used to successfully highlight human disturbance through time.

- iii. Examining the sensitivity of multitemporal PCA to the number of time intervals considered in the time-series.
- iv. Testing the success of each PCA method to identify areas of change and little or no change.

2. How can medium-resolution satellite imagery from different sensors be combined to effectively quantify changes in the landscape?

The second research aim is to identify and evaluate an appropriate (suitable and replicable) classification methodology for selecting and integrating information from multisensor and multiresolution satellite imagery to improve land cover classification accuracy for a tropical island area with poor data availability. The second research question is addressed by:

- i. Applying a time-series of medium-resolution imagery acquired from five satellite sensors to a standard classification procedure at different spatial resolutions to produce a land cover classification.
- ii. Comparing different classification methods that utilise the full range of spectral information available from the sensors to identify suitable remote sensing variables for land cover classification in a data-poor tropical island. In particular the use of PCA, inclusion of thermal band imagery and high-resolution panchromatic imagery via data-fusion techniques are evaluated.
- iii. Determining which of these methods improves classification accuracy and whether the results are consistent across remote sensing platforms.
- iv. Performing post-classification change detection to identify the types, rates and temporal variability of land cover change.

3. To what extent can remotely sensed indicators of human disturbance and spatial metrics describing landscape pattern and structure be used in a time-series analysis of landscape change for landscape monitoring?

The third research question addresses how a time-series of land cover maps generated from multisensor medium-resolution satellite imagery can be used to quantify and detect statistically significant trends in remotely sensed indicators of human disturbance and spatial metrics describing landscape pattern and structure for landscape monitoring by:

- i. Developing and evaluating a unique set of remotely sensed indicators to assess and monitor the impact of human disturbance.

- ii. Identifying and evaluating an appropriate set of spatial metrics to detect statistically significant trends in landscape pattern and structure to monitor human disturbance.
- iii. Determining the robustness of the remote indicators and spatial metrics to changes in scale and spatial extent.

4. What is the potential for the application of these methods in other data-poor jurisdictions?

Finally, following the completion of the analyses, the potential of the remote sensing methods and techniques evaluated for successful application in other data-poor regions for change detection and landscape monitoring is discussed.

1.4. Thesis structure

This thesis comprises the following ten chapters, in addition to the current introduction.

Chapter 2 presents the literature review, providing a brief overview of remote sensing and change detection techniques. A review of the application of remotely sensed indicators and spatial metrics in landscape analysis is also provided.

Chapter 3 provides the background to the study area; the environment and socio-economy of The Bahamas is discussed in the context of the present research.

Chapters 4 through 6 detail the methodological approaches applied and techniques used in this research, the results and a discussion of which are presented in Chapters 7 through 10.

Chapter 4 describes step-by step, the methodology devised to address the first research question, the application and development of multitemporal PCA.

Chapter 5 details the methodological techniques used to address the second research question and details the different classification methodologies tested as part of the land cover classification. The application in this study of PCA, incorporation of thermal data, data-fusion, land cover classification accuracy and post-classification is described.

Chapter 6 documents the development and computation of remotely sensed indicators of human disturbance and spatial metrics in a time-series analysis for landscape monitoring.

Chapter 7 presents the results generated from multitemporal PCA which highlight the success and development of the technique in identifying changes to the landscape associated with human disturbance.

Chapter 8 supplies the results from the land cover classification and post-classification change detection which indicate that PCA and incorporation of thermal and panchromatic data do not offer an improvement to the land cover classification undertaken as part of this study. The use of the original multispectral image yielded the best classification accuracy.

Chapter 9 presents the results from the application of remotely sensed indicators and spatial metrics in landscape monitoring. The results highlight the success and robustness of the methods evaluated to identify statistically significant trends that can be associated with human disturbance.

Chapter 10 discusses the three sets of results in terms of each of the research questions posed.

Chapter 11 outlines the main findings of the current research and recommendations to resolve the difficulties noted. Areas for further research are also identified.

1.5. Conclusion

This thesis explores digital change detection techniques for use with a time-series of multisensor medium-resolution satellite imagery incorporating remotely sensed indicators of human disturbance and spatial metrics. The techniques developed as part of this research present a relatively simple and replicable method with which to generate comparable and robust land cover change information appropriate for landscape monitoring in data-poor tropical island environments. The study is conducted on a relatively flat tropical island, that has undergone significant modification associated with rapid development and is therefore well suited to developing and testing methods of landscape monitoring.

Chapter 2 Literature Review

2.1. Introduction

Land cover changes are described in the literature as fundamental agents of global climate change and are significant forces impacting biodiversity, water and radiation budgets at all scales (Vitousek, 1994; Read and Lam, 2002; van Oort, 2007). They are driven by natural and anthropogenic processes and occur at an accelerating pace, mainly in the tropics (Lambin, 1997; Sala *et al.*, 2000; Duro *et al.*, 2007). Landscape changes such as land cover conversion, urbanisation, loss of wetlands or deforestation, are important because they have direct impacts on ecological processes (Formon and Godron, 1986; O'Neill *et al.*, 1997). Ecological processes, which include plant succession, biodiversity, foraging patterns, predator-prey interactions and nutrient dynamics, all have spatial components (Turner and Gardener, 2001). Changes in spatial pattern in the form of habitat fragmentation for example, have been implicated in the decline of biodiversity and researchers predict that the strongest overall driver of global biodiversity loss will result from land use change (Vitousek *et al.*, 1997; Sala *et al.*, 2000; Duro *et al.*, 2007). Determining status and trends in the pattern of landscapes can therefore be useful for understanding overall condition of ecological resources.

Remotely sensed data can be acquired at multiple scales and at multiple times and the use of satellite imagery as a tool in the natural science communities for measuring qualitative and quantitative terrestrial landcover changes and landscape monitoring is well documented (Coppin and Bauer, 1994; Collins and Woodcock, 1996; Pax Lenney *et al.*, 1996; Coppedge, 2001; Moreira *et al.*, 2001; Achard *et al.*, 2002; Seto *et al.*, 2002; Tanrivermis, 2003; Plieninger, 2006; Porter-Bolland *et al.*, 2007). The challenge facing land resource managers is that despite the availability of remotely sensed imagery, generally, there is a lack of comprehensive data on the types, rates variability and impact of landscape change. The inability to monitor land cover changes in a consistent way is a serious limitation to understanding the driving forces and processes controlling these changes (Lambin *et al.*, 1999). Of primary concern are the impacts of land cover change on global biotic diversity, soil degradation and the ability of biological systems to support human needs (Lambin *et al.*, 2003).

Research on landscape change in tropical areas has been motivated mainly by the widespread rapid changes in the distribution of tropical forests and dry land degradation and associated biodiversity loss (Myers, 1993; Houghton, 1999; Pablubinskas *et al.*, 1995; Lambin, 1997; Myers *et al.*, 2000; Kaufmann and Seto, 2001; Achard *et al.*, 2002; Hayes and Cohen., 2007). Most of these studies though have been conducted over wide expanses of either rangelands (Ludwig *et al.*, 2004; Li *et al.*, 2004) or forested areas (Daniels *et al.*, 2007) using coarse resolution (1km) data (Budde, *et al.*, 2004) and little has been done to guide digital change-detection in small tropical island environments where fragile ecosystems are dominant and rapid land cover change reflects the most significant impact on the environment due to uncontrolled development.

Moreover, remote sensing change-detection techniques are limited in areas of low data coverage, described as data-poor because of the difficulty in acquiring a suitable and appropriate time series of images. In particular, the ubiquitous presence of cloud cover and haze in tropical areas renders many image datasets useless and necessitates the integration of data from different sensors. Use of multisensor and multiresolution datasets requires a high level of time-consuming pre-processing in order to conduct a time series analysis of landscape change for monitoring purposes.

This Chapter introduces the background to, and explores the methodological limitations of the application of digital change-detection techniques for landscape monitoring.

2.2. Remote sensing of the environment: an overview

2.2.1. Definition of remote sensing

Remote sensing is defined broadly in the literature as the measurement or gathering of information about an object, area or phenomenon at a distance (Colwell, 1966; Fischer *et al.*, 1976; Schowengerdt, 1997; Mather, 1999; Lillesand *et al.*, 2004). Remote sensing can be described as the art, science and technology of obtaining reliable information about physical objects and the environment through the process of recording, measuring and interpreting digital representations of energy patterns derived from non-contact sensor systems (Jensen, 2004).

More simply, the science of environmental remote sensing considers the interpretation of measurements of reflectance or EMR from the Earth's land and water surfaces and atmosphere. Measurements of EMR patterns are turned into information using visual and/or digital image processing techniques. Remotely sensed data are well suited for integration into a GIS and can be used to answer questions concerning location, condition, trends, patterns and what-ifs on the distribution of natural or human resources across the earth's surface (ESRI, 1997).

2.2.2. Remotely sensed data

The first earth-orbiting satellite was launched in the 1970's producing for the first time a consistent set of synoptic, high resolution earth images to the world scientific community with detail sufficient for practical applications in many fields. The characteristics of major types of remote sensing data and their applications have been summarised in the literature (Barnsley, 1999; Estes and Loveland, 1999; Lefsky and Cohen, 2003).

Remote sensing data include airborne and spaceborne sensors with varying spatial, radiometric, spectral and temporal resolutions (Section 2.3.3) and the selection of remotely sensed data depends on a number of factors including (but not limited to) the application, the scale and characteristics of

the study area, availability, accessibility, cost, and time constraints (Phinn *et al.*, 2000; Lefsky and Cohen, 2003).

Scale and image resolution in the context of the user's needs are the most important factors affecting the selection and use of remotely sensed datasets (Lu and Weng, 2007). Medium-resolution remote-sensing imagery describes satellite imagery with spatial resolutions between 10m and 100m and have been acquired from space since the early 1970's, providing accessible and relatively low cost data for land cover observations (Mas, 1999; Millward and Kraft, 2004).

The use of multispectral medium-resolution remotely sensed imagery for change-detection and landscape monitoring has been extensively documented in the literature most notably, imagery acquired from Landsat (Fuller *et al.*, 1994; Steyaert *et al.*, 1997; Muller *et al.*, 1998; Zhu *et al.*, 2000; Oetter *et al.*, 2001; Dorren *et al.*, 2003; Zheng *et al.*, 2007) and SPOT (Marceau *et al.*, 1990; Atkinson, 1997; Gao, 1998; Cihlar, 2000; Mayaux *et al.*, 2004; Bartholome and Belward, 2005) platforms. A review of the most reported research on land use change detection for regional sustainable development (Zhou *et al.*, 2004) revealed change-detection was based mostly on the comparison of data acquired on two or three epochs.

Landsat and SPOT are described as the first and most robust global monitoring systems to acquire moderate resolution data on a systematic basis (Lillesand *et al.*, 2004). Advantages of using imagery acquired from Landsat and SPOT is associated with frequent repeat cycles, high spectral resolution, relatively low cost and greater accessibility compared to similar spatial coverages acquired from finer-scale monitoring studies (Jones *et al.*, 2000). Moreover, remotely sensed data from Landsat and SPOT platforms are well suited for integration into a GIS and have long been used as a source of data for GIS-based investigations, including, but not limited to, monitoring land cover change (Petit and Lambin, 2001; Sillescu *et al.*, 2002; Weng, 2002; Xiuwan, 2002).

- **The Landsat System**

Landsat MSS-1 was borne from the NASA ERTS satellite program in 1972 into a sun-synchronous orbit operational until 1978 (Lillesand *et al.*, 2004). Landsat 1 was followed by the successful launch of series -2, -3, -4, -5 and 7. Landsat 6 failed to launch. Landsat 1 through 3 passed within 9° of the North and South Poles. Early morning equatorial crossing times were established to firstly ensure repeatable sun illumination conditions (which will vary as a function of season, location and atmospheric conditions nonetheless) and secondly to take advantage of early morning sky conditions that are generally clearer than later in the day.

The first two satellites were launched with a three-channel RBV and a four-channel MSS system. The MSS scanner was placed on-board Landsat 1 through 5. It records reflectance in four wavebands (Table 2.1) numbered 4-7 in Landsat -1, -2 and -3 (as the RBV bands constituted 1, 2 and 3 for these systems) and 1 through 4 in Landsat -4 and -5 (Campbell, 2002).

The characteristics of the MSS bands were selected to maximize each band's capabilities for detecting and monitoring different types of land surface cover characteristics. For example, MSS band 1 can be used to detect green reflectance from healthy vegetation and MSS band 2 is designed for detecting chlorophyll absorption in vegetation. MSS bands 3 and 4 are ideal for recording near-IR reflectance peaks in healthy green vegetation and for detecting the interface between land and water (US Congress, 1993; Mather, 1999).

Landsats -4 and -5 were also launched into sun-synchronous orbits but at a slightly lower altitude and a shorter repeat cycle of 16-days. These satellites include both the MSS and a new addition the TM. The TM is an optical-mechanical whiskbroom sensor and like MSS uses detectors and an oscillating mirror but with a higher spectral, spatial, radiometric and temporal resolution. TM gathers data in seven bands (additional visible, IR and thermal wavebands) and was designed to provide improvements in for example water penetration, the differentiation of clouds, snow and ice and identification of the hydrothermal alteration in certain rock types (Jensen, 2005).

Better discrimination between vegetation types is provided by the measurement of reflectance in narrower band 2 (green) and band 3 (red) bandwidths. In addition, TM band 4 (near-IR) is narrower than the corresponding MSS band in this region and has been finely tuned for maximum sensitivity to plant vigour. The addition of two mid-IR bands 5 and 7 has proven valuable for of geological mapping. The potential of thermal mapping applications has been facilitated through the addition of band 6. The visible and IR wavebands have a spatial resolution of 30m and the new thermal band of 120m. TM also presents a four-fold increase in the grey scale range from 64 to 256 levels facilitating increased sensitivity to changes in the relationship between bands (Schowengerdt, 1997).

Landsat -7 was launched successfully in 1999 and carries ETM+ on board, with similar orbital patterns, repeat cycle and swath width as its predecessors Landsat -4 and -5. Landsat-7 and acquires data for the same seven visible, near-infrared, shortwave infrared bands at 30m (visible and IR) and an improved thermal spatial resolution of 60m. In addition the sensor records data in a panchromatic band at 15m resolution (Irons and Masek, 2006).

- **The SPOT System**

The French Space Agency CNES operate the SPOT programme, funded by the governments of France, Belgium and Sweden. The first in the series, SPOT-1 (Table 2.2) was launched in 1986 into a sun-synchronous near-polar orbit, followed by SPOT 2, 3, 4 and most recently 5. SPOT 2, 4 and 5 are currently fully operational. SPOT sensors record reflected radiance in multispectral (visible through shortwave infrared) and in panchromatic mode (Aplin *et al.*, 1999)

The HRV, HRVIR and the HRG optical instruments on-board the SPOT series offer an oblique viewing capability which can be adjusted $\pm 27^\circ$ relative to the vertical and allows SPOT to image any area within a 950km swath (Jensen, 2007). This means that areas not directly beneath the satellite can be imaged. As a result at the equator a given area can be imaged 7 times, at 45° latitude a given area can be imaged 11 times during the same 26-day orbital cycle. On average, depending on latitude, a given area can be imaged within an interval ranging between 1 and four days. At present, three SPOT satellites are operational which means at any point 95% of the earth may be imaged on any day by at least one of the satellites (Jensen, 2004).

The VGT instrument aboard SPOT 4 and 5 is independent of the HRVIR sensors and records at a very wide viewing angle (2,250 km wide swath) and a spatial resolution of 1km. Vegetation uses the same spectral bands as the HRVIR instruments (B2, B3 and mid-IR) plus an additional band, B0 (0.43-0.47 μm) for oceanographic applications and atmospheric corrections.

The HRS on SPOT 5 records simultaneous stereopairs with a swath width of 120 km across and 600km long and spatial resolution of 10m (along-track sampling of 5m), in panchromatic mode. These images are acquired forward of and behind the satellite. Stereopair imagery can be used to generate digital elevation models and the HRS aboard SPOT-5 has the added advantage of an automatic correlation process as the radiometric properties of the images are the same. It is also possible to acquire stereopairs using imagery acquired for the same area on the ground by different SPOT satellites in orbit. Since 1986 the SPOT satellite series have provided consistent and dependable source of high resolution Earth resources imagery. The imagery is commercially available but at a higher cost than their Landsat counterparts.

It is clear that SPOT and Landsat have similar remote sensing characteristics but there are variations in their spectral and spatial resolutions. It is therefore important to address uncertainty while conducting change-detection for landscape monitoring using a multisensor time series of imagery with differences in remote sensing characteristics (Section 2.3.3.).

2.3. Remote sensing change-detection analysis

2.3.1. Introduction

Change-detection is defined as the process of identifying differences in the state of an object of phenomenon by observing it at different times (Singh, 1989). Quantitative landcover change can be described as the categorical transformation of land as a consequence of natural phenomena (e.g. fires, storms) or induced as a result of human activity (e.g. agricultural or urban expansion, forest clearing). Land cover change is typically monitored in relation to ecology, climate change, deforestation and urbanisation (Lambin and Elrich, 1997; Houghton *et al.*, 1999; Achard *et al.*, 2002; Gutman *et al.*, 2004). The goal of remote sensing change-detection is firstly to detect the geographic location of change found when comparing two or more dates of imagery, secondly to identify the type of change and thirdly to quantify the amount and spatial pattern of change. The final step is to assess the accuracy of the change-detection product.

2.3.2. Data acquisition

Satellite remote sensing, in conjunction with GIS, has been widely applied and recognised in the literature as a powerful and effective tool in detecting land use and land cover change. For any change-detection project the area of interest must be identified and held constant through the analysis and the imagery acquired must cover the entire geographic area for the time period. Digital land cover change-detection relies on the assumption that land cover changes produce changes in the reflectance of a land surface and where this is true, digital techniques to detect spectral changes between successive dates of imagery can be used to detect land cover change (Yuan and Elvidge, 1998). The type of change-detection method employed will largely depend on data availability, the geographic area of study, time, computing constraints and application.

Large archives of remote sensing imagery have provided a solid foundation for spatio-temporal analyses of the earth's surface and environment and the impact of human disturbance (Tucker *et al.*, 2004). For landscape monitoring over a time frame of 30 years it is often necessary to integrate data from different sources (Zhou *et al.*, 2004). A few studies for example have analysed land cover change by combining Landsat data and/or SPOT data and aerial photographs (Muller *et al.*, 1999; Salami *et al.*, 1999; Reid *et al.*, 2000; Petit and Lambin, 2001). More recently the combination of high resolution imagery and LIDAR has been used for urban change-detection (Sohn, 2007) and vegetation estimates (Chen *et al.*, 2004; Wulder *et al.*, 2007). However, these studies are typically either concentrated over small urban areas or applied to massive expanses of forests and rangelands.

Digital land cover change-detection is hampered by several remote sensing system characteristics and environmental considerations which must be considered and may necessitate pre- processing of the imagery (Jensen, 2004; van Oort, 2007). Regional scale analyses of archived remotely sensed data are

subject to bias and uncertainty introduced as a result of complicated variations in for example sensor characteristics or associated with seasonality, which can undermine the usefulness of the dataset. Depending on the application careful consideration must be given to the selection of an appropriate satellite remote sensing system from which to acquire data.

2.3.3. Remote sensing system characteristics and environmental factors affecting digital change-detection

- **Temporal resolution**

There are two important temporal resolutions that should be held constant during change-detection. It is important to obtain data from a sensor system that acquires imagery at approximately the same time of day. Similarly, where possible data should be acquired at on or near-anniversary dates to minimise the impact of seasonal sun-angle and plant phenological differences in identifying spurious change between dates. This is often difficult particularly in tropical areas where cloud cover is common and has been reported in many studies (Pilon *et al.*, 1988; Jha and Unni, 1994; Mas, 1999).

- **Spatial resolution**

For accurate change-detection analysis imagery should spatially conform. When performing change-detection between two time periods with different spatial resolutions it is necessary to decide on a uniform mapping unit and resample the datasets so that they may be compared on a per-pixel basis (Griffith *et al.*, 2003). In addition to consistent spatial resolution, spatial coregistration between the datasets is essential as misregistration between imagery acquired at different dates can result in the misidentification of change (Jensen, 2007). Image to image registration is the process of spatially aligning two images of the same geographic area and like geometry such that the corresponding elements of the same ground area appear in the same place on the registered images (Chen and Lee, 1992).

Spatial coregistration of imagery to a standard map projection is undertaken using a georectification algorithm within any digital image processing software. RMSE is a distance in pixel widths between the original input and retransformed pixel coordinates and measures the amount of error in the rectification process (ERDAS, 2003). Rectification should result in the images having a RMSE of less than or equal to one-half the size of the image pixels (Yuan *et al.*, 2005).

- **Spectral resolution**

Different sensors do not often record spectral reflectances in the same portions of the electromagnetic spectrum and therefore where change is being detected between imagery gathered from multiple sensors it is important to select wavebands that approximate one another (Sohl, 1999).

- **Radiometric resolution**

Imagery used in change-detection typically represents a variety of anniversary dates. Multidate remotely sensed imagery for change-detection analysis should have the same radiometric precision (i.e. number of grey levels) on both dates of acquisition such that an image with lower radiometric resolution (e.g. 6-bit) should be decompressed to match the data acquired by the higher radiometric resolution system (e.g. 8-bit). Variation in solar illumination conditions, atmospheric scattering and absorption and changes in atmospheric conditions (i.e. presence of clouds) will cause differences in the radiometric characteristics of images, even those acquired from the same sensor (Schowengerdt, 1997).

The problem of differences in radiometric resolution can also be eliminated by converting the original DN values to meaningful spectral units (such as radiance). This permits the analysis of change between images recorded for a study area where several scenes over a period of time are being compared (Mas, 1999). Spectral image calibration or the calculation of radiance from raw DNs is the fundamental step in putting image data from multiple sensors and platforms into a common radiometric scale (Chander and Markham, 2003). Conversion from calibrated DN numbers back to at-sensor radiance requires knowledge of the original rescaling factors. This rescaling information is presented in terms of the sensor gain and bias for each band and is based on a calibration curve of DN to radiance which has been calculated by the operators of the satellite system. A reduction between scene variability can be achieved through a normalisation for solar irradiance by converting from spectral radiance values to planetary reflectance or albedo (Landsat Project Science Office, 2003; Chander and Markham, 2003). Reflectance represents the ratio of radiance to irradiance and provides a standardised measure which is directly comparable between images.

- **Atmospheric conditions**

The effects of the atmosphere upon remotely sensed data are not considered errors as they are part of the signal received by the sensing device (Colwell, 1983). However, variable irradiance over time, atmospheric scattering and absorption may cause differences in at-sensor radiance values that are unrelated to the reflectance of the land surface (Yuan and Elvidge, 1996). The effects of the atmosphere can prevent the proper interpretation of imagery and the detection of change if not taken into consideration (Verstraete, 1994). Correcting for the effects of the atmosphere depends upon the nature of the remote sensing data, the change-detection technique employed and the availability of data on the atmosphere (Song *et al.*, 2001).

There are many ways to conduct atmospheric correction (Kaufman, 1989; Haan *et al.*, 1991; Hall *et al.*, 1991; Ouaidrari and Vermote, 1999; Heo and Fitzhugh, 2000; Kaufman *et al.*, 2001; Song *et al.*, 2001) but some procedures involve collecting in-situ atmospheric measurements and radiometric transfer codes. These methods are difficult, time consuming and more costly to implement. The COST

algorithm described by Chavez (1996) is most commonly used and is a method that requires image-based data only. The corrections generated by this algorithm are described as having accuracy values as great as those generated by models using in situ atmospheric field measurements (Chavez, 1996). COST uses the dark object subtraction (DOS) to correct for atmospheric effects and is a simple and efficient method of correction as showed in previous studies (Teillet and Fedosejevs, 1995; Brivio *et al.*, 2001; Soudani *et al.*, 2006).

Moreover, the presence of clouds or extreme humidity can cause differences between the spectral signatures to generate a false impression of change between the dates. Clouds and cloud shadow obscure the land surface and should be removed and substituted where possible before the analysis.

When and when not to conduct atmospheric corrections on remotely sensed satellite imagery prior to performing digital change-detection has recently received attention in the literature (Song *et al.*, 2001; Seto *et al.*, 2002). For instance, image differencing change-detection is the process of subtracting pixel-by-pixel two spatially co-registered images. A change-no change map is produced based on change thresholds defined by the analyst. However, the map output will differ between imagery corrected and imagery uncorrected for the effects of the atmosphere, for a given study area. Similarly for change-detection algorithms involving general linear transformations e.g. NDVI imagery (or any other band-ratio images) produced from uncorrected data are contaminated by the effects of the atmosphere and can amount to 50% or more over thin or broken vegetation cover (Verstraete, 1994).

A number of studies have documented that it is unnecessary to correct for the effects of the atmosphere prior to image classification for post-classification image detection (Kawata *et al.*, 1990; Yuan *et al.*, 1998; Coppin *et al.*, 2004; Yuan *et al.*, 2005) because each classification is independently produced and mapped which also compensates for variations in vegetation phenology. It has been shown that so long as the training data and the image to be classified are on the same relative scale (corrected or uncorrected) atmospheric correction has little effect on classification and hence post classification change-detection accuracy (Kawata *et al.*, 1990; Song *et al.*, 2001; Jensen, 2007).

- **Soil moisture conditions**

Soil moisture conditions should be identical between the dates of imagery used in a change-detection project, as an area heavily impacted by precipitation on one date and dry on another date will display vastly different spectral reflectance properties not associated *per se* with a change in landcover. It is recommended to review precipitation records over a time period of days and/or weeks where possible prior to the image acquisition date to establish whether there are significant soil moisture differences between the dates. These differences, where they exist across any area in the image, may lead to errors in landcover change-detection (Mas, 1999).

- **Vegetation phenology**

Plant phenological cycles (predictable diurnal, seasonal or annual cycles) cause changes in the spectral reflectances of vegetation throughout the year. Differences in reflectance associated with changes in agricultural crop growth may be identified as areas of “change” between image dates not associated with a change in land cover *per se*. It is important to obtain near anniversary imagery to minimise the effects of seasonal phenological differences (Sader, 1997; McDonald *et al.*, 1998)

- **Tidal Stage**

It is often very difficult to obtain multiple date imagery with identical tidal stage and in many instances this may preclude the use of satellite remote sensing as a data source for coastal applications. For most regions imagery acquired at mean low tide are preferred (MLT), 1 or 2ft above MLT are acceptable and 3ft or more are generally unacceptable (Jensen, 1996).

In summary, before implementing change-detection analysis it is preferable that the dataset be radiometrically and atmospherically calibrated with precise geometric registration and acquired from the same time of year. It is also important to acquire imagery with the same spatial and spectral resolution. Once the datasets have been assembled and pre-processed the selection of an appropriate change-detection algorithm will have considerable influence in producing a high-quality change-detection product (Lu *et al.*, 2004). Many change-detection techniques exist and are generally categorised into two groups described as pre-classification or enhancement methods and post-classification methods (Singh, 1989; Lunetta, 1998; Yuan and Elvidge, 1998; Yuan *et al.*, 2005).

2.3.4. Pre-classification enhancement change-detection

Pre-classification or enhancement methods are based on a comparison of the spectral differences between the imagery (Mas, 1999). The enhancement methods entail spectral change-detection based on pixel-wise or scene-wise operations and as such are sensitive to image registration and co-registration accuracy. These methods produce change/no-change information only. The input data can be radiometrically calibrated raw imagery or transformed data such as NDVI imagery (Jones *et al.*, 2000). The advantage of these methods is that they can be more easily fine-tuned to detecting specific changes of interest and are generally expected to have a greater ability to detect subtle changes (Chen *et al.*, 2003; Foody, 2002; Lunetta *et al.*, 2004; Yuan *et al.*, 2005). A selection of the most common and more recent methods is described below.

i. Write function memory insertion

A simple method for visually detecting change between dates can be undertaken via WFMI (Jensen, 2007). This is a layer stacking technique which uses different colours to display changes between the images. In this method spatially coregistered bands of imagery from each date can be inserted into each of the three WFMI banks (i.e. red, green and blue) within any digital image processing system.

Areas of change will be in one of the original colours and no-change in the colour that results from the combination of the two. Jensen (1996) showed how visual changes can be revealed by inserting the band of the first date in red and one band of the second date in green. The change areas are in red and green and the no-change areas in yellow, respectively. Similarly, by placing the later image in red and the earlier image in both blue and green, the change areas are highlighted dramatically in red. Alternatively, by placing the later image in green and the earlier imagery in blue and red, change areas are displayed in shades of green. Franklin *et al.* (2002) highlighted forest structure changes by using WFMI to display changes between wetness index images from different years. Vijayaraj *et al.*, (2005) used WFMI to display an earlier time NDVI in red, a later time NDVI in blue and a later time panchromatic image to display areas of change (associated with a high decrease in NDVI) in red.

The advantages of this method are that it is generally unnecessary to atmospherically correct the data prior to WFMI (unless the image comprises NDVI value as opposed to pixel brightness values). While WFMI can provide a powerful visual assessment of change (qualitative) it does not provide any quantitative information on the amount of change from one land cover to another. It can however, be used as a preliminary analysis to determine a suitable quantitative change-detection method and to compare automated change-detection results subjectively (Vijayaraj *et al.*, 2005).

ii. Image differencing

Image differencing or image algebra change-detection involves subtracting two co-registered image dates pixel by pixel. If the two images are radiometrically calibrated the subtraction results in positive or negative values in areas of reflectance change and zero values in areas of no change. Image differencing can also be based on the difference between band ratios. The application of image ratioing change-detection methods is well documented in the literature and NDVI differencing is one of the most commonly applied (Lyon *et al.*, 1998; Ridd and Liu, 1998; Yuan and Elvidge, 1998; Desclee *et al.*, 2005; Healey *et al.*, 2005; Jin and Sader, 2005, Volcani *et al.*, 2005). In this case NDVI values are calculated for each image and then subtracted from one another to determine change. NDVI techniques produce limited discriminating abilities in areas less dominated by vegetative ground cover types (Cakir *et al.*, 2006).

Lyon *et al.* (1998) compared seven vegetation indices for change-detection of vegetation and land cover using three different dates of MSS data. Their results concluded that the NDVI demonstrated the best vegetation change-detection. Image differencing and image ratioing are easy to implement but results may be misleading (Singh, 1989) as the difference between pixels may belong to different classes or phenomena (e.g. $180-150 = 30$ and $40-10 = 30$). These methods are also sensitive to misregistration of imagery and areas identified as "change" may represent the mismatch between the imagery as opposed to real changes in the nature of the land surface.

Change-detection can also be based on the difference between multiple-date Kauth-Thomas (or Tasseled Cap) transformations (Collins and Woodcock, 1996; Patterson and Yool, 1998; Ridd and Liu, 1998, Franklin *et al.*, 2002; Rogan *et al.*, 2002). This transformation rotates the image data and using fixed model coefficients produces a new image depicting changes in brightness, greenness and wetness components (Crist and Cicone, 1984). The assumption is that as landcover changes over time a change in the reflectivity of the surface will exhibit corresponding changes in brightness, greenness and wetness components. For example Ridd and Liu (1998) demonstrated changes in BGW differentiated areas of change/no-change with an accuracy of 81.71%. Seto *et al.* (2002) on land cover change within the Pear River Delta, China, demonstrated that changes in landcover from water to urban were associated with an increase in greenness and brightness and a decrease in wetness.

iii. Image regression

The image regression method is based on the assumption that for two images, time-1 and time-2, the time-2 image is a linear function of the time-1 image (Ridd and Liu, 1998). The method considers differences in the mean and variance between pixel values from two dates. Residuals from the least squares regression for each reflective band are determined and used to produce the regression image. Ridd and Liu (1998) concluded that regression images from band 2 and band 3 produced the most accurate change results (86.67%) compared with Kauth-Thomas, chi-squared and image differencing methods.

iv. Principal Components Analysis

Another commonly used enhancement technique is PCA and its use in change-detection dates back to 1979 (Lodwick, 1979). Multidate images are converted into principal components and the difference between individual components pertaining to each year can be used to detect change (Byrne *et al.*, 1980; Fung and LeDrew, 1988; Yuan and Elvidge, 1998; Maas, 1999; Du *et al.*, 2002; Cakir *et al.*, 2006). Kwarteng and Chavez (1998) in their study of landcover change in Kuwait, created change images using Landsat TM bands 2, 4 and 7 from two dates and applied PCA individually on each pair of bands. The change images highlighted urban development, vegetation growth and differences in coastal wetland areas.

Alternately, imagery from two separate dates can be combined into one image to which PCA is applied and individual component images are generated (Millward *et al.*, 2006). PCA identifies high correlations associated with image pixel locations that remain constant and low correlations with those locations that exhibit differences through time (Millward *et al.*, 2006). The major components account for variation in the image data not associated with landcover change and are termed stable components

(Collins and Woodcock, 1996). Minor components tend to enhance spectral contrasts between the two dates and are termed change components.

The components can be individually displayed to visually examine for areas of change. Yuan *et al.* (1998) reported that major component images show reflectance (albedo) and radiometric differences and minor component images reveal local or minor changes. The PCA image can be further processed to assess change. Li and Yeh (1998) merged two multirate images and applied PCA. A supervised classification of land cover change was carried out on the PCA image and when compared to results from a conventional post-classification change-detection approach reported higher accuracies for the PCA method.

PCA is considered one of the best approaches for long-sequence time-series analysis (Eastman and Fulk, 1993; Coppin *et al.*, 2004; Lu *et al.*, 2004; Lasaponara, 2006) yet its use with multispectral data lacks guidelines for application and appropriateness of use (Piwowar and Millward, 2002). In a study of coastal zone landscape changes in the province of Hainan, China, Millward *et al.* (2006) modified the conventional application of PCA to change-detection by deriving univariate surfaces for image brightness, greenness and the NDVI to which PCA was applied. In developing a PCA change-detection methodology to handle both Landsat and SPOT datasets Millward *et al.* (2006) considered two important factors. First Landsat bands 2 and 4 have been shown to have an intrinsic image dimensionality of two corresponding to the physical-ground characteristics of brightness and greenness (Ingebristen and Lyon, 1985; Chavez and Kwarteng, 1989). Chavez and Powell (1989) document a similar dimensionality exists for SPOT bands 1 through 3. Selection of bands that emphasise these physical measures in an urbanising landscape (e.g. an increase in impervious surfaces and a decrease in vegetation cover) offers a method of integrating data from several different sources into a time-series analysis for change-detection. Selective PCA on a time series of brightness, greenness and NDVI images was successfully used to extract temporal information that corresponded with changes in the physical scene characteristics between years.

v. Correspondence analysis

CA has most recently been applied to change-detection studies and Cakir *et al.* (2006) compared the performance of PCA, NDVI and CA image differencing for detecting land cover change for a study area in North Carolina. Similar to PCA, for each date, each image is transformed separately using the CA algorithm. Image differencing is applied to the resulting CA components to perform change-detection i.e. the first CA component of date 1 image was subtracted from the first CA component of date 2 image. Their results showed that the overall accuracy of the change map created using the CA more accurate than those produced through NDVI and PCA image differencing.

vi. Statistical object-based change-detection

One of the main drawbacks of the per-pixel based methods is described as the "salt and pepper" effect in the resulting change-detection maps due to the random variation of the sensors response and also to an intrinsic characteristic of the landcover itself (Lobo, 1997). As a result object-based methods have more recently been proposed for change-detection with particular application to forests (Hame *et al.*, 1998; Saska *et al.*, 2003; Desclee *et al.*, 2006).

Vijayaraj *et al.*, (2005) evaluated the application of an object-based analysis for change-detection. Using this method, the images are segmented into image objects based on shape, colour, homogeneity and compactness. The image is analysed in the image object domain instead of the pixel domain. Their results indicated that the object-based change-detection concurs with visual inspection and WFMI.

vii. Neighbourhood Correlation Image

A new approach to the change-detection problem, introduced by Im and Jensen (2005) is based on the creation of a new three channel NCI that contains information on correlation, slope and intercept that can be related to the change information. This method is based on the fact that the same geographic area (e.g. a 3 x 3 pixel window) on two dates of imagery will tend to be highly correlated if little change has occurred and uncorrelated where change occurs. The correlation information derived from a specific neighbourhood of pixels contains valuable change information associated with a central pixel and its contextual neighbours. Slope and intercept images provide change related information that can be used to facilitate change-detection with correlation. The degree of correlation, slope and intercept is used to produce "from-to" change information when combined with object oriented classification techniques. Their research showed that following change classification based on NCIs, with 2- to 5-pixel radius, produced overall accuracies of greater than 92.6%.

While enhancement techniques serve to illustrate the spatial distribution of changes they typically do not provide information on the nature of the change (Yuan *et al.*, 1998).

2.3.5. Post-classification comparison change-detection

It has been argued that satellite imagery in combination with ground reference information acquired at a selected number of points in the study area is the best source for mapping landscape change over large areas (Mas *et al.*, 1997; Millward and Kraft, 2004). To conduct land cover change analysis at a local level typically high resolution sensors such as IKONOS and Quickbird are used (Li, 2000; Fraser *et al.*, 2002; Aplin, 2003) At a regional scale medium-resolution data are most often used including the Landsat suite of sensors and SPOT. The focus of this research is on the application of medium-

resolution remotely sensed imagery acquired from passive remote sensing systems, which are widely available and typically used for land-based environmental applications (Franklin and Wulder, 2002).

A major step forward in the application of remote sensing data to landscape change-detection is land cover mapping i.e. the ability to extract from remotely sensed data information about the land surface. Post-classification comparison involves the detection of change between two images from different dates that have been classified independently. Areas of change are identified by comparing the differences in the classification between the two images and hence determine the direction of change. The popularity of these methods likely stems from their easy application to available single date classifications. The method has been criticised however because it tends to compound any errors that may have occurred in the initial classifications (Singh, 1989).

The procedure has been widely used and successfully employed for a variety of land cover change investigations including assessing deforestation, urbanisation, sand-dune changes, conversion of semi-natural vegetation to agricultural grassland and urban sprawl (Wilcock and Cooper, 1992; Dimyati *et al.*, 1996; Yang and Lo, 2002, Jat *et al.*, 2006). Accurate land cover information is critical to the successful quantification of land cover change using post-classification comparison techniques (Karaska *et al.*, 2004) and classification accuracy assessment is a fundamental component of land cover mapping (Congalton, 1991; Merchant *et al.*, 1994; Cohen and Justice, 1999; Justice *et al.*, 2000; Congalton, 2001; Foody, 2002).

Accurate spatial information on existing land cover is a prerequisite for many environmental and socio-economic applications such as urban change-detection (Ward *et al.*, 2000); the analysis of current environmental conditions (Lo, 1995) and to estimate and determine future land use activities (Southworth, 2003). Classification accuracy can be defined as the degree to which the derived image classification agrees with reality or conforms to the 'truth' (Janssen and van der Wel, 1994; Smits *et al.*, 1999). Generation of accurately classified imagery from remotely sensed data is not a straightforward task. Many factors contribute to this difficulty, including but not limited to the following factors (Lu and Weng, 2007);

- The characteristics of the study area
- Availability of suitable remotely sensed data, ancillary and reference data
- Proper use of variables, classification algorithms and image-processing approaches
- The analysts experience
- Time constraints

However, once a classification exercise has been conducted the degree of error in the classified map (errors associated with the incorrect classification of pixels) should be quantified (Foody, 2006). Meaningful and consistent measures of thematic map reliability are necessary for the map user to assess the appropriateness of the map data for a given application. Accuracy assessment is also an important step in evaluation of different image processing routines in image classification, to analyse sources of error and weaknesses of a particular classification strategy (Foody, 2002; Powell *et al.*, 2004; Lu and Weng, 2005).

Many methods of accuracy assessment have been detailed in the remote sensing literature (Aronoff, 1982; Kalkhan *et al.*, 1997, 1998; Koukoulas and Blackburn, 2001) but the most widely promoted and used can be derived from a confusion or error matrix. Several measures of classification accuracy can be derived from an error matrix and include overall accuracy, producer's and user's accuracy and the Kappa coefficient which tests whether the agreement between the classified and reference data is significantly better than zero (Congalton, 1991; Janssen and van der Wel, 1994; Ma and Redmond, 1995; Smits *et al.*, 1999; Couto, 2003). However, there are many problems associated with the confusion matrix and the measures if accuracy derived from it (Foody, 2006). For instance, it is assumed implicitly that each case (pixel) to be classified belongs to one of the classes in an exhaustively defined set of discrete and mutually exclusive classes (Congalton and Green, 1999; Townsend, 2000). In addition, the ground reference test information may also contain errors such as thematic errors associated with incorrectly labeled classes or errors associated with mislocation (Dicks and Lo, 1990; Zhou *et al.*, 1998b; Congalton & Green, 1999; Khorram, 1999; Lunetta *et al.*, 2001). As such, accuracy assessment conducted using ground test reference information actually measures the degree of agreement between the ground reference information and the map and therefore may not necessarily be a true reflection of closeness to reality (Congalton and Green, 1993; Merchant *et al.*, 1994).

According to Foody (2006), the evaluation of the quality of a thematic map should ideally be based on a set of criteria defined in advance of its production. Differences in spectral and spatial resolution of remotely sensed data, the number and detail of classes defined in the classification and user needs are some of the reasons why there are no universally defined accuracy standards for thematic mapping in remote sensing. However, an overall accuracy of $\geq 85\%$ and a Kappa value $\geq 75\%$ are often used as targets when conducting thematic map classification (Abeyta and Franklin, 1998; Wulder *et al.*, 2006). For many mapping applications however, 85% may be an unrealistically high target value to set and it should not be automatically used as a criterion for the evaluation of image classifications (Laba *et al.*, 2002).

The error matrix assesses the classification of all classes and is a square array of numbers where the columns represent the ground reference test information and the rows correspond to the classification

generated from analysis of the remotely sensed image dataset. The values in the diagonal of the matrix summarise the number of pixels correctly assigned to a particular land cover based on the reference data and are shaded in grey in Figure 4.5. The classification errors are summarised in the off-diagonals and are based on omission from the correct category and a commission to the incorrect category. The column and row totals are used to compute errors of inclusion (commission errors) and errors of exclusion (omission errors) and can be summarised for each class and for the entire classification map referred to as user's and producers accuracy respectively (Foody, 2002; Foody, 2004).

A major accuracy assessment problem recognised by some users is that in some cases pixels may have been allocated to the correct class purely by chance (Congalton, 1991; Pontius, 2000; Couto, 2003). To accommodate for the effect of chance agreement Cohen's Kappa coefficient is often used and some argue that it should be adopted as the standard measure of classification accuracy (Congalton and Green, 1999; Smits *et al.*, 1999). The Kappa coefficient of agreement for a thematic map is based on the comparison of the predicted (classified) and actual (reference) class labels for each case in the set of ground test reference information points gathered to assess map accuracy. Values for the Kappa coefficient range between 0 and 1 and are commonly interpreted using a scale developed by Landis and Koch (1977).

There have been many attempts to improve land use classification when using medium-resolution remotely sensed datasets in particular the use of sub-pixel information (Rashed *et al.*, 2001; Phinn *et al.*, 2002); data integration of different sensors or sources (Harris and Ventura, 1995; Haack *et al.*, 2002; Lu and Weng, 2005); making full use of the spectral information of a single sensor (Gong *et al.*, 1992; Stuckens *et al.*, 2000; Shaban and Diskit, 2001, 2002) and use of expert knowledge (Stefanov *et al.*, 2001; Hung and Ridd, 2002). Of these methods, making full use of the spectral range of information available such as the thermal waveband and data-fusion techniques are particularly relevant to this study and are discussed in the following section.

2.4. Remote sensing techniques for improving land cover classification accuracy

It is often desirable to pre-process or enhance the image data before undertaking land cover classification. Image enhancements are applied to remotely sensed data to improve the appearance of the image for visual analysis or for subsequent processing. The techniques used in image enhancement depend upon the dataset and the objective of the study. A multitude of correction and enhancement techniques have been developed and the following review is based on those methods both relevant to land cover classification and available for use within the ERDAS Imagine Advantage image processing software.

2.4.1. Spectral enhancements

Spectral transformations of remotely sensed data are often undertaken to redistribute the original data into a more useful form in order to produce a co-ordinate system with advantages over the original spectral bands. In the context of this study spectral transformations may offer an improvement to classification accuracy. For example, multispectral ratios including vegetation indices such as SAVI, NDVI, PVI and VI (Huete, 1988; Huete *et al.*, 1997) are used to enhance the differences between soil and vegetation and have long been used in remote sensing for monitoring temporal changes associated with vegetation (Lyon *et al.*, 1998; Coppin *et al.*, 2004; Nackaerts *et al.*, 2005).

Other frequently applied transformations include PCA, a much used technique for reducing redundancy in remotely sensed datasets (Barnsley, 1999) that typically exhibit high correlation between adjacent spectral bands. PCA compresses all the information contained in an original dataset (Saroglu *et al.*, 2004). PCA defines the number of dimensions that are present in the dataset and fixes the coefficients which specify the positions of the set of axes (uncorrelated) that point in the directions of greatest variability in the data (Mather, 1999). The variance-covariance matrix or the correlation matrix of the bands is computed. A set of quantities called eigenvalues and eigenvectors are found for the chosen matrix and give the length and direction of the principal axes respectively. Eigenvalues are measured in terms of units of variance. Eigenvalues and eigenvectors can be used to generate factor loadings which represent the correlation between the principal components and the individual bands of the multispectral image (Jensen, 2007). These correlations or loadings are used in the interpretation of the principal components.

Principal components are derived from the original dataset such that the first PC accounts for the maximum proportion of variance of the original dataset and the subsequent PCs account for the maximum proportion of the remaining variance (McGarigal *et al.*, 2000). As the first three components explain most of the variance only three principal component images are used in the land cover classification. For example, Lu and Weng (2005) investigated the use of PCA prior to classification. While the techniques successfully reduced correlation across the dataset, use of the PC images did not significantly improve land cover classification above a classification employing the original multispectral dataset.

Radiance recorded in long wave thermal wave bands have been shown to provide important additional and supplementary information to that provided by the reflectance data measured in the visible and near IR bands for landcover mapping and can provide valuable information for discriminating vegetation types and assessing changes in landuse (Lo *et al.*, 1997; Melesse and Jordan, 2003; Southworth, 2003). Landsat thermal waveband designated band 6 on both the TM and ETM+ sensors

has a lower radiometric sensitivity and coarser spatial resolution relative to the reflective TM and ETM+ bands. Most studies on landcover change using satellite data do not use band 6 thermal data most likely owing to the coarse spatial resolution of the thermal waveband. The thermal band however allows for continuous representation of landcover, rather than the creation of discrete landcover classes such as in classification techniques (Lambin, 1999). Lu and Weng (2005) investigated the incorporation of a temperature image generated from thermal data into a multispectral land cover classification using Landsat ETM+ data. Their results showed that the temperature data did improve classification accuracy for some classes overall the method did not produce the most accurate results of the other methods tested.

2.4.2. Spatial enhancements – data-fusion techniques

Spatial transforms provide tools to extract or modify the spatial information in remote-sensing images (Schowengerdt, 1997) and data-fusion aims at obtaining information of greater quality through the integration of spectrally and spatially complementary remotely sensed data to facilitate visual and automated image interpretation and ultimately leading to more accurate data. Data-fusion is the combination of remotely sensed data which have different temporal, spatial, spectral and/or radiometric resolution to acquire a higher quality image (Pohl and van Genderen, 1998; Saroglu *et al.*, 2004) and its application is well documented in the literature (Welch and Ehlers, 1987; Chavez *et al.*, 1991; Gong, 1994; Solberg *et al.*, 1996; Yocky, 1996; Dai and Khorram, 1998; Pohl and Van Genderen, 1998; Gamba and Houshmand, 1999; Saraf, 1999; Zhang, 1999; Haack *et al.*, 2002; Li *et al.*, 2002; Shaban and Dikshit, 2002; Simone *et al.*, 2002; Ban, 2003; Ulfarsson *et al.*, 2003).

Previous research has suggested that the integration of multisensor or multiresolution data such as Landsat TM and radar (Haack *et al.*, 2002; Ban, 2003), IRS and LISS data (Saroglu *et al.*, 2004), SPOT HRV and Landsat TM (Welch and Ehlers, 1987; Yocky, 1996) multispectral and panchromatic bands (Shaban and Dikshit, 2002), Landsat multispectral and panchromatic bands (Lu and Weng, 2005), Landsat and IKONOS data (Švab and Oštir, 2006) would improve classification results. Fused images may provide increased interpretation capabilities and more reliable results since data with different characteristics are combined (Pohl and Van Genderen, 1998).

A number of data-fusion methods to combine high resolution panchromatic data with lower spatial resolution multisensor data exist and are available within the ERDAS digital image processing software.

- **IHS**

IHS transformation has been identified in the literature as the most frequently used method for improving the visual display of multisensor data (Welch and Ehlers, 1987). IHS colour transformation effectively separates spatial (intensity) and spectral (hue and saturation) information from a standard RGB image (Chavez *et al.*, 1991). The fusion method firsts converts a RGB image into intensity (brightness), hue (dominant wavelength contribution) and saturation (purity) components (Gillespie *et*

al., 1986; Carper *et al.*, 1990). Hue and saturation are related to the surface reflectivity or composition (Grasso, 1993). Following that, intensity is substituted with the high spatial resolution panchromatic image. Finally, a reverse transformation is undertaken, converting the IHS components back to RGB multispectral bands (Hall, 1992). The IHS method can only use 3 bands and those bands should be spectrally within the range of the panchromatic band.

- **Brovey Transformation**

The Brovey Transformation (Hallada and Cox, 1983) normalises multispectral bands used for RGB display. Multispectral bands used for an RGB display are normalised and the result multiplied by any other desired data to add the intensity or brightness component to the image. In this case each multispectral band is divided with the panchromatic image obtained from the original multispectral data. The result is then multiplied by the original panchromatic image to add data a brightness component to the image. The method was developed to visually increase the contrast in the low and high ends of the image histogram and thereby altering the radiometry of the original image. Similar to IHS the method was developed to create RGB images and therefore only three bands at a time can be merged.

- **PCA**

PCA is often used for data-fusion because it can produce an output result that better preserves the spectral integrity of the input data set (Lu and Weng, 2005). In data-fusion, the higher resolution image replaces the first PC generated following PCA, since it contains information common to all bands while the spectral information is unique for each band (Chavez *et al.*, 1991). As PC1 accounts for maximum variance, the effect of the high-resolution data in the fused image can be maximised (Shettigara, 1992). The PCA method enables the integration of more of the original spectral data than the IHS or Brovey methods as any number of spectral bands can be subjected to PCA. It has been suggested in the literature that this technique produces an output image that better preserves the spectral integrity of the input dataset (Lemeshefsky, 2002).

- **Multiplicative**

The multiplicative method unlike IHS and Brovey can be performed on any number of input bands and is computationally the most simple of all methods. Scaling factors and weighting parameters are applied to the input images however the radiometry of the original input image is not retained; instead the intensity component is increased making the technique very useful in highlighting urban features (ERDAS, 2003).

- **Wavelet transformation (IHS and PCA)**

Wavelet transformations involve the breakdown of the high spatial resolution panchromatic image and the low spatial resolution multispectral image into elementary functions (wavelets) from arbitrary

functions of finite energy (Pohl and Van Genderen, 1998). Wavelet coefficients are determined for both images and a transformation model is derived which determines the missing wavelet coefficients of the lower resolution image. Once the wavelet coefficients have been determined it is possible to create a synthetic image from the lower resolution image at the higher spatial resolution. This image contains the preserved spectral information with the higher resolution, hence showing greater detail.

The wavelet transformation algorithm within ERDAS Imagine is a modification of the work of Lemeshewksy (2002). As a method of multispectral image sharpening it is vital that the algorithm preserves the spectral fidelity of the input dataset, particularly if the image is to be classified. The basic algorithm is that an image can be separated into high frequency and low-frequency components. For instance, a low-pass filter can be used to create a low-frequency image and when subtracted from the original image would create the corresponding high-frequency image. Both the high and low frequency image contain all the information in the original image, and when combined produce the original image. Similarly an image following the application of a high-pass filter could be subtracted from the original image to derive the low frequency image. In the same way, an image can be broken into wavelet-based high- and low- frequency components using various high- and low-pass filters. The wavelet family can be considered a high-pass filter and by definition, the low-frequency image is of lower resolution and the high-frequency image contains the detail of the image (ERDAS, 2003). Using wavelets the high-resolution panchromatic image is decomposed to generate a low-pass image of the same spatial resolution as the multispectral image. The low-pass image representing the resolution of the multispectral image, derived from the high-resolution image is replaced with the original multispectral image. The wavelet decomposition process is then reversed using the high-pass images derived during the decomposition of the panchromatic image to reconstruct a multispectral image with the high spatial resolution of the panchromatic image. The new image contains the high-pass frequency details of the high-resolution image.

There are three scenarios under which the panchromatic image can be merged with the multispectral image within the ERDAS Wavelet transformation utility, single band, PCA and IHS. For application in land cover classification, the multiband approaches of IHS and PCA are more appropriate.

Data-fusion ideally increases the spatial resolution of an image without the loss of spectral information and therefore special attention should be paid to the quality analysis of the results regarding the preservation of spectral and spatial resolution (Robinson *et al.*, 2000; Tu *et al.*, 2001; Shi *et al.*, 2005). In a study on the preservation of spatial and spectral quality of high-resolution image fusion Švab and Oštir (2006) assessed three methods of data-fusion for a study area in Slovenia. They concluded that the preservation level of spectral characteristics strongly depends on the resemblance between the

panchromatic image and the respective intensity image but there was no definitive method for image fusion.

Saroglue *et al.* (2004) investigated what improvement could be obtained for classification accuracies using Brovey, Multiplicative, IHS and PCA data-fusion techniques on multisensor datasets derived from IRS, LISS III and ERS radar satellite platforms for a study area in Turkey. Their results showed that data-fusion of LISS data with IRS pan via IHS offered the greatest overall classification accuracy followed by PCA, Brovey and Multiplicative methods. Selection of a data-fusion method depends entirely on the application.

2.5. The role of remotely sensed indicators and spatial metrics in landscape monitoring and change-detection

Assessing the environmental condition of landscapes by monitoring their condition over space and time is needed to better understand the processes causing the damage and at an appropriate scale for land resources management (Ludwig *et al.*, 2007a). According to Tiner (2004) and Mander *et al.* (2005) there is a pressing need to develop remotely sensed quantitative indicators that cost effectively integrate structural and functional attributes of landscapes across a range of temporal and spatial scales for application across large geographic areas on a periodic basis to evaluate, monitor and report on the status of natural resources regionally and globally.

A variety of ecological indicators have been developed to assess environmental condition based on site-specific field-derived metrics and include changes to plant community composition, exotic species invasion and indices of biological integrity (Scott *et al.*, 1993; Kar and Chu, 1998; Stevenson and Hauer, 2002; Tiner *et al.*, 2002). The effort and time required to collect data in this way can be costly and limits the number of field sites and indicators that can be routinely monitored to meet the needs of local land managers and regional and national reporting (Ludwig *et al.*, 2007b). In the absence of a wide-scale environmental monitoring programme proxies of ecological condition can be developed using remote sensing derived products.

Remotely sensed data such as the NDVI has been used extensively to assess and predict biophysical parameters of forests (Wulder, 1998) and as a means of examining how changes in the environment affect the distribution of both plants and animals (Pettorelli *et al.*, 2005). Furthermore the relationship between avian species diversity and annual vegetation biomass was successfully evaluated in Senegal using broad-scale NDVI data (Jorgensen and Nohr, 1996). More recently, finer-scale patterns such as land use and land cover and their associated spatial patterns are being investigated as potential predictors of species diversity and abundance at regional and local scales (Fahrig, 2003).

Remote sensing has been shown to be successful at monitoring disturbance (Foody *et al.*, 1996) particularly disturbance events which results in forest stand replacement such as fire, clear-cut harvesting and wind throw. By comparison, disturbance events which happen comparatively slowly through time such as thinning, infestation and succession are more difficult due to more subtle changes in the spectral responses (Ludwig *et al.*, 2007b). Cohen and Goward (2004) looked at broad-scale disturbance using Landsat data acquired between 1972 and 1995 to estimate the annual change in clear-cut logging and wild fire in Oregon. Ludwig *et al.*, (2007b) developed an index to monitor the health of arid and semiarid landscapes based on remotely sensed vegetation cover data.

Quigley *et al.*, (2001) estimated the ecological integrity of the interior Columbia River Basin by evaluating five land cover types and identified percent of different land cover types and road density as significant indicators. Tiner (2004) developed a set of remotely sensed indicators to assess general environmental condition for Delaware's Nanticoke River watershed, in particular to track landscape-level changes in natural resources important for maintaining water quality, fish and wildlife habitat.

In addition to quantifying the amount and nature of land cover change, changes to the spatial distribution and arrangement of land cover should be incorporated into monitoring landscape changes (O'Neill *et al.*, 1988; Gustafson and Parker, 1992; Gillespie *et al.*, 1999; Herzog and Lausch, 2001; Griffith *et al.*, 2003; Narumalani *et al.*, 2004). One of the most rapidly growing applications of remotely sensed data is the derivation of spatial metrics for the assessment of landscape condition and landscape change dynamics (Betts *et al.*, 2003; Colombo *et al.*, 2004; Saura and Castro, 2007). Satellite imagery are used as the primary source of information for the analysis of landscape pattern and the availability of a wide range of sensors allows for the characterisation of land cover at multiple scales.

Landscape or spatial metrics (Herold *et al.*, 2003) are quantitative measures of landscape pattern based on the geometry and spatial arrangement of patches (contiguous pixels). Changes in landscape pattern can be detected and described by spatial metrics, which quantify and categorize complex landscapes into an identifiable pattern and reveal vital information on the function of ecological systems as well as patterns of biodiversity (Antrop and Van Eetvelde, 2000; Turner *et al.*, 2001).

Landscape metrics fall into two general categories – those that quantify the composition of a landscape without reference to spatial attributes and those that quantify the spatial configuration of the map requiring spatial information for their calculation (McGarigal and Marks, 1995; Gustafson, 1998). Metrics describing landscape composition and configuration can be calculated at three different levels: patch-level metrics represent the spatial character and context of individual patches; class-level metrics represent the amount and spatial distribution of a single patch type (class) and landscape-level metrics which represent the spatial pattern of the entire landscape mosaic.

A large number of spatial metrics can be calculated from mapped data (O'Neill *et al.*, 1988, 1999; Turner and Gardner, 1991; Baker and Cai, 1992; McGarigal and Marks, 1995) but taken together the metrics measure only six independent dimensions of pattern in a typical collection of land cover maps (Riitters *et al.*, 1995) and can be divided into five categories based on patch area, shape, neighbourhood, diversity and configuration (Lausch and Herzog, 2002; McGarigal and Marks, 2002). Selection of metrics can be based on experience and expertise (Herzog and Lausch, 2001) or on statistical procedures (Riitters *et al.*, 1995; Lausch and Herzog, 2002) but also depends heavily on relevancy to the problem under investigation.

The application of landscape metrics in landscape monitoring has been tested in a number of individual studies representing a wide range of areas, methods of data acquisition and treatment (Zheng *et al.*, 1997; Palang *et al.*, 1998; Sachs *et al.*, 1998; Pan *et al.*, 1999; Frohn and Hao, 2006; Baskent and Kadiogullari, 2007). Landscapes are dynamic and continuously changing and analysing the spatial change of landscape patterns at one point in time cannot capture the full dynamics of landscape change. In order to trace the temporal trend, landscape metrics can be applied to measure the spatial characteristics of landscape pattern through time (Herold *et al.*, 2003; Deitzel *et al.*, 2005).

Griffith *et al.* (2003) analysed temporal trends of five landscape pattern metrics (NP, AREA_MN, PLADJ, PAFRAC, SIDI) for a landscape comprising 11 land cover classes over a 20-year period across the mid-Atlantic coastal plain (extending from Delaware to the Florida/Georgia border). Their results showed that statistically significant linear trends could be observed four of the five metrics tested. SIDI was the only metric for which the observed trend was not statistically significant.

DiBari (2007) evaluated four landscape level metrics (LPI, ENN, IJI, FRAC) in an analysis of changes in landscape structure resulting from urbanisation in Tucson, Arizona. Their results showed that two of the four metrics (IJI and ENN) displayed changes over the time period but the analysis also showed that there are limits to the amount and kind of information any one metric can offer or from which information may be inferred. The authors concluded that a combination of metrics might provide a more complete understanding of landscape structure than using any one metric.

Abdullah and Nakagoshi (2006) examined the temporal change of three basic metrics (MPS, NP, RPR) between two time periods in an analysis of landscape change in Malaysia. Their results displayed showed changes in MPS, NP and RPR between the time periods, indicative of an increase in landscape fragmentation.

Herold *et al.* (2003) examined six landscape level spatial metrics (NP, ED, LPI, MNN, FRAC_AM, CONTAG) in an analysis of spatial and temporal urban growth pattern. Their analysis revealed that all

metrics show sensitivity to the overall urban growth pattern but in particular urban sprawl was reflected by an increase in FRAC_AM, ED and NP and also by a decrease in LPI and CONTAG.

A limitation to the application of spatial metrics is that the absolute value derived for each metric is dependent upon the spatial resolution, the extent of the study area as well as the level of detail in the landscape classifications. A change in either the extent, spatial resolution or the thematic definition of the patch classes will significantly change the metrics and limit the ease of relating the results from one area to another especially for quantitative comparison (Cain *et al.*, 1997; Li and Wu, 2004; Wu, 2004; Herold *et al.*, 2003).

Clearly the scaling relationships of spatial pattern are important and the need for empirical analysis of the scale effects on landscape metrics for real landscapes has been expressed in the literature (Li and Wu, 2004). According to Wu *et al.* (2004) the response curves of spatial metrics to changing grain size should be used for characterising, comparing and monitoring landscape patterns instead of the actual single values of the metrics. They put forward that the response curves are more likely to be successful for linking landscape pattern to ecological processes because both pattern and process in ecological systems often operate on multiple scales.

Wu (2004) evaluated the scale effects on nineteen spatial metrics and found that landscape-scale metrics fall into three response categories, predictable scaling functions (Type I), a less predictable staircase pattern response (Type II) and unpredictable behaviour (Type III) with no consistent scaling behaviour. The authors concluded that to adequately quantify spatial heterogeneity, the response curves of metrics to changing scale must be examined in addition to single values. Similarly, Frohn (1998) analysed two commonly used metrics, CONTAG and PAFRAC and concluded both were unstable with respect to varying spatial resolution and Saura (2004) examined the performances of six indices with varying aggregating and found DIVISION and LPI the most stable in both aggregated and actual sensor patterns. NP, MPS and TE were the most sensitive indices not suitable for direct comparisons across different spatial resolutions. It has been suggested that the extrapolation and interpolation metrics revealing predictable behaviour across different pixel sizes can be done simply and accurately (Wu *et al.*, 2002; Wu, 2004).

2.6. Conclusion

A wide range of analysis procedures for remotely sensed change-detection have been developed and tested. A wealth of information on change-detection techniques exists but very little guidance is available to address the special problems associated with conducting change-detection using multisensor datasets in areas with poor data coverage and availability.

Few studies employ multiple-date medium-resolution imagery, those that do are generally are carried out with images acquired from the same time of year and/or from the same sensor. The use of remotely sensed indicators for monitoring vegetation changes is well documented in the literature but their application to a time series of imagery for change-detection specifically associated with human disturbance has not been fully explored. Similarly, temporal trends in a select number of spatial metrics have been applied to landscape monitoring with varying degrees of success but have yet to be evaluated to monitor human disturbance in a time series of land cover maps derived from a multisensor dataset.

Through the methodology (Chapters 4 through 6) the relative effectiveness of remote sensing change-detection techniques for visualising and quantifying landcover changes associated with human disturbance on a small tropical island environment using multisensor, multitemporal and multiresolution imagery is examined. The following chapter presents an introduction to and overview of the study area.

Chapter 3 The Study Area

3.1. Introduction

The principal island of The Bahamas (New Providence Island) was identified as a suitable study area for use in an evaluation of remotely sensed change detection techniques in data poor areas. There are enormous pressures on the natural resources of New Providence, which has undergone significant and rapid land cover change associated with uncontrolled development since achieving independence in the 1970's. Population growth, migration and immigration continue to place significant development pressures on the depleting natural resources of New Providence Island, compounded by a tourism industry where in 2004 visitor numbers to The Bahamas exceeded five million for the first time (BEST, 2005a).

The Bahamas, situated to the east and south of the continental margin of North America (Figure 3.1), comprise most of an extensive archipelago of shallow-water marine carbonate limestone banks and over 1700 low-lying island cays spanning between 21° and 27°30' N and 69° to 80° 30' W (Carew and Mylroie, 1995). The archipelago with its unique geological features and pristine conditions of shallow banks and island represents a single interconnected system of land and water. The Bahamas comprises fragile coastal ecosystems vulnerable to degradation from both anthropogenic and natural sources of pollution. The removal of native vegetation for development, the invasion of exotic species and pollution of coastal and ground water are described as significant and chronic threats to the environment of The Bahamas (Sealey *et al.*, 2002). There are no rivers in The Bahamas and freshwater resources are held in groundwater aquifers; 90% of which are within 1.5m of the surface (Cooper, 2000) and are particularly vulnerable to degradation from land sources. Freshwater resources are already depleting, and twice daily freshwater is barged from neighbouring Andros Island to New Providence to meet the water demands on the island (BEST, 2005b). In addition, as small low-lying islands on the fringes of the Caribbean, The Bahamas are frequently visited by hurricanes and tropical storms and the landscape is also vulnerable to damage from natural disasters.

Despite the enormous pressures on the island, to date, land cover monitoring is not undertaken routinely, the last national primary mapping program was completed in 1972 and there has subsequently been little revision carried out since (Rabley and Turnquest, 2003; BEST, 2005b). The majority of land information used by The Government of The Bahamas is described as outdated or incomplete, is scattered among various government agencies and much of it is in paper form, which limits its accessibility and use (IDB, 2006). In addition, The Bahamas has poor remote sensing data coverage. As a small land mass in the Caribbean large cloud formations during the daytime typically obscure the land surface and this precludes the use of many remotely sensed datasets for landscape monitoring purposes.

This chapter presents a general introduction to The Bahamas and New Providence Island in the context of this study. A discussion of current environmental threats and pressures associated with socio-economic development within the context of landscape change is presented before a brief review of the current status of digital land cover information in The Bahamas.

3.2. Socio-economic processes driving land use change

Land cover change can be attributed to both natural environmental change and human induced change driven by various economic, demographic, political, and cultural factors all of which influence decisions about how the land is used. Lambin *et al.* (2003) describe five fundamental causes of land use change which include, resource scarcity leading to an increase in the pressure of production on resources; changing opportunities created by markets; outside policy intervention; loss of adaptive capacity and increased vulnerability and finally changes in societal organisation, attitudes and resource access. As a former colony, the natural resources of The Bahamas have been assaulted and since achieving political independence the Government of The Bahamas has invested heavily in promoting tourism and foreign investment with significant negative consequences on the landscape and environment of the islands. A discussion of the major socioeconomic factors driving land use change in The Bahamas and New Providence are identified and discussed below.

3.2.1. Population pressure

New Providence Island, The Bahamas has experienced rapid land cover change associated with uncontrolled development. The population of The Bahamas, based on the 2000 census currently stands at 303,611 with a growth rate of 1.4% (US Department of State, 2006). Almost seventy percent of the population reside on New Providence which spans approximately 34kms east to west and 11kms north to south, placing enormous pressure on the limited land resources of the island. Population density on New Providence was reported as 1018 persons per square kilometre in 2005 (BEST, 2005a). All other islands aside from New Providence and Grand Bahama are referred to as the 'Out' or 'Family' Islands where population numbers are significantly lower and development is significantly less.

3.2.2. Migration

Since 1963 (Table 3.1) population has migrated from the remote islands to New Providence and Grand Bahama in an effort to avail of employment opportunities and the provision of better services in the larger principal cities on these islands. Both cities have developed and continue to develop as major centres by virtue of close proximity to the USA, associated with tourism development and foreign investment. In addition, a high standard of living in The Bahamas (per capita GDP in 1999 was US \$15,300) has increased the immigration pressure from Haiti and other Caribbean nations (Rabley and Turnquest, 2003).

3.2.3. Economic pressure

The Bahamas is a small island developing state with an economy heavily dependent on tourism accounting for circa 50% GDP and 10% of which is directly associated with tourism driven construction (Jackson, 2003). Other sectors of economic importance include agriculture and fishing (together represent ca 3% of GDP) and manufacturing (4% GDP). Combined, these sectors account for less than 5% of the total number of people employed in 2003 (BEST, 2005a). Bahamian soils are thin, coarse and fragile and use of land for agriculture is limited by nutrient poor soil requiring heavy fertilisation, which further threatens already vulnerable ground and coastal water resources. Only some 8,000 hectares of land are used for agricultural purposes and large-scale crop production is concentrated on Abaco, Andros and Grand Bahama (BEST, 2005b).

3.2.4. Tourism

Tourism as the mainstay of The Bahamian economy is largely reliant on the outstanding natural physical beauty of the islands. The numerous white and pink sandy beaches, coral reefs, marine biodiversity, shallow and sheltered waters which continue to propel the tourism industry are increasingly under pressure from development and population growth. Moreover, there is no integrated national land policy to ensure a pattern of growth and use of land that supports land development while addressing sustainability issues and environmental concern. The existing land use planning and development framework for the country was not designed to address the type of development The Bahamas is currently experiencing and actively promoting as a strategy for economic development (Rabley and Turnquest 2003).

The Government of The Bahamas first recognized the potential of a tourism industry and passed a Tourism Encouragement Act in 1851 and the first air service to Nassau commenced in 1919 (BEST, 2005a). The imposition of a trade embargo between the US and Cuba in the 1960's served to further promote Bahamian tourism. Cuba had previously been a hugely popular destination for large numbers of Americans many of whom subsequently traveled to the islands of The Bahamas following the ban on travel to Cuba. The Ministry of Tourism was established in 1973 and a number of major hotel development projects were implemented in the late 1970's. This has meant the Government of The Bahamas has, and continues to pursue an aggressive tourism-led development strategy, which has boosted construction across the islands. Recent tourism development has included the construction of the Four Seasons Hotel and Resort on Great Exuma in 2004. The Atlantis Resort and Casino on Paradise Island (connected by bridge to New Providence) is in the third phase of a billion-dollar expansion expected to create 3,000 new jobs. A second \$1.2 billion hotel resort development project is planned for the Cable Beach area of Nassau. The Baha Mar Company has negotiated purchase of three major hotels and a development site, including the last assets of the state-owned Hotel Corporation. As a condition of these large-scale investments, the government promises to expand Nassau International Airport (US Department of State, 2006).

The major tourism sub-sectors for the region are hotels, yachts and cruise ships (Figure 3.13). Presently ca 60% visitors arrive by sea and the rest by air contributing about \$1.5 billion to the Bahamian economy annually (Cooper, 2000) and cruise visitors to The Bahamas totalled almost 3.5 million in 2004 (Ministry of Tourism, 2004). Cruise arrivals to New Providence Island alone accounted for almost 60% of the total. The number of hotels in The Bahamas in 2004 was reported at 295 (Bahamas Ministry of Tourism, 2004) 22% of which are located on the island of New Providence. The yachting sector in The Bahamas is large with at least 58 marinas and close to 3,000 slips or berths across the archipelago (Jackson, 2003). In addition, The Bahamas has one of the largest and most established scuba diving industries in the Caribbean and the total economic impact of diving was over US\$212 million in 2001 (Jackson, 2003). Damage to reefs by anchors and the pollution of nearshore waters associated with dumping of untreated sewage from ships, yachts and liners poses a significant threat to the marine environment of The Bahamas.

3.3. Terrestrial and marine habitats and socio-economic pressures on the land resources of New Providence Island

Land clearance for development in response to increased pressure from population growth, migration and a tourism driven economy is considered the biggest threat to the environment and landscape of The Bahamas. The destruction of native vegetation associated with uncontrolled and inappropriate development practices is clearly evident particularly on New Providence Island. Terrestrial (and marine) habitats of The Bahamas have only recently been identified and classified (Table 3.2.) as part of a proposed ecoregional plan for Bahamas conservation (Sealey *et al.*, 2002). A discussion of the threats to the major land cover types on New Providence Island associated with socioeconomic development pressures is presented to demonstrate the need for routine landscape monitoring of the remaining natural resources across the wider archipelago which comprises many islands at varying levels of development.

- **Pinelands and DEF**

Pineland forest stands (Figure 3.2) occur only on the four northern Bahama islands of New Providence, Andros, Abaco and Grand Bahamas. These forests are also referred to as pine rockland given the heavily limestone substrate upon which the trees are found. There are three varieties of *Pinus caribea* that occur in the greater Caribbean region: Honduran, Caribbean and Bahamian and the *Pinus caribea var. bahamensis* is endemic to the Bahamian islands and characterises the pine woodlands (Sealey *et al.*, 2002).

DEF (Figure 3.3) comprises dense formations inland where it is referred to as coppice and typically surrounds mangrove communities and blue holes. Coppice has a limestone substrate and sinkholes are commonly found throughout. DEF forming in the interior of the islands with substantial freshwater lenses is generally taller and denser with a closed canopy and is also termed blackland or high coppice (Correl and Correl, 1982; Ford, 1997) as a result of organic soil development. DEF

often forms a dense understory amidst pineland forest stands. DEF also forms at coastal locations referred to as coastal coppice (Figure 3.4). Due to the historic clearing of DEF for development, existing inland coppice is described as secondary or even tertiary growth (BEST, 2005a) and canopy heights are considered to be currently lower than they were in the past.

Development in The Bahamas typically proceeds with the complete clearance of vegetation and the rocky terrain may require levelling, with fill if necessary. The clearance of land for development (Figure 3.5 and 3.6) poses a significant threat to pineland forests and DEF and is commonplace. Surrounding areas, disturbed through the process of land clearance, become vulnerable to invasion from exotic species. Non-native exotic plants including *Casuarina* trees and *Scaevola* (exotic ink-berry) (Hammerton, 2002) are quick to colonise disturbed areas, out-competing natural vegetation, and this threatens the diversity and long-term survival of terrestrial habitats in The Bahamas. Furthermore, fragmentation of coppice causes loss of continuous habitat for animals.

- **Beach Strand**

Beach strand is found on all major islands in the archipelago, particularly along the more sheltered east-facing shores where offshore reefs, small islands and rocky headlands serve to protect the shoreline from wave action, allowing sand to accumulate more easily. Dune systems are most common on the eastern shorelines as prevailing winds are from the east (Sealey *et al.*, 2002). Beach strand vegetation community comprises shrubs, herbs and vines. Variation in beach strand habitats across The Bahamas is associated with differences in the level of energy applied to the coastal zone by local oceanographic conditions, wind and storm events.

Direct development in close proximity to the shoreline (Figure 3.7) including the construction of a sea walls, docks, marinas, groynes or canals for example destroys beach strand and dune systems and is often coupled with the invasion of exotic plant species. *Casuarinas* have invaded coastal shoreline areas of The Bahamas and their thin roots are damaging to the stability of the dune systems, which become highly susceptible to wind erosion, particularly in areas with heavy pedestrian traffic.

Roads and properties constructed in close proximity to the shoreline interfere with the lateral movement of sand along a beach and can lead to increased sand loss and complete erosion of the beach. Furthermore, sand is used widely in construction across The Bahamas and sand-mining has caused loss of natural beach strand areas and the protection they afford to inland areas (BEST, 2005b).

- **Wetlands (mangrove communities)**

Wetlands can be described generally as lands where saturation is the dominant factor determining soil development and the plants and animal communities living in the soil and on its surface. According to Cowardin *et al.* (1979) wetlands must have one or more of the following attributes:

- The land supports predominantly hydrophytes
- The substrate is predominantly undrained hydric soil
- The substrate is non-soil and is saturated by water or covered by shallow water periodically during the year

Wetlands in The Bahamas are both inland (Figure 3.8) and coastal (Figure 3.9). They constitute 40% of the total land area of The Bahamas and form on all islands in the archipelago (Kendall *et al.*, 2001; BEST, 2005b).

Coastal wetlands are the largest (in extent and occurrence) group of wetlands across the archipelago and occur along low-energy shorelines (sheltered from wave energy); in areas with standing water and/or areas of seasonal flooding. Mangrove communities form the most important coastal wetlands in The Bahamas. The extent of mangrove communities is determined largely by tidal range, coastal morphology, wave energy and rainfall. The most common mangroves found in the Bahamas are the red (*Rhizophora mangle*), black (*Avicennia germinans*), white (*Laguncularia racemosa*) and buttonwood mangrove (*Conocarpus erectus*) (BEST, 2002).

Mangroves, because of their abundance of nutrients, are essential breeding, rearing and feeding grounds for many species of fish and wildlife. Mangroves filter sediments and chemicals and play a significant role in improving water quality, reduce flood and storm damage, provide shelter to marine life from predators and are homes for orchids and bromeliads (BEST, 2002, 2005a). Mangroves are also home to many economically important fish species including Nassua grouper (*Epinephelus striatus*), snapper (*Lutjanus spp.*) and bonefish (*Albula vulpes*). Most national parks contain mangroves and dominant species within Inagua National Park (the main breeding ground for flamingos) include buttonwood and black mangrove (BEST, 2002).

In addition to the clearance of pineland and coppice, coastal wetland losses are directly related to human disturbance and many have been drained and used for development and access, dredged and filled for roads, houses, golf courses, marinas and tourism development (Figure 3.10). Mangrove wetlands function as coastal buffers, providing natural shelter from wind and water and protect the shoreline from severe erosion associated with hurricanes and tropical storms. The infilling and destruction of mangrove habitats has affected flooding on the islands (BEST, 2005b). Floods not only threaten human life, property and infrastructure but also lead to contamination of groundwater resources (wells and aquifers), which directly impacts an already limited and fragile supply of freshwater.

3.4. Vulnerability to hurricanes and natural disasters

The climate of The Bahamas may be classified as a sub-tropical, moderated by the warm north-flowing Gulf Stream (BEST, 2002b). Weather is dominated by Atlantic Southeast trade winds in the summer and cool dry North American high-pressure systems in winter (Cooper, 2000) delivering

distinct seasons: a hot wet summer season between May and October; and a warm dry winter season between November and April (Figure 3.11).

Rain falling between September and November is generally caused by tropical depressions, tropical storms and hurricanes. The Bahamas are frequently visited by hurricanes and tropical storms (Table 3.3) and as such are vulnerable to natural disasters. On average, the more northerly islands of Grand Bahama and Abaco display a higher frequency of hurricane land fall in comparison to New Providence Island. A report by the IFRC (2006) detailed the devastation caused by landfall of a category three hurricane (Wilma), in October 2005 across islands of The Bahamas. Maximum sustained winds of 120mph were recorded. Rainfall was reported as moderate but the associated storm surge between 10-15 feet, caused most of the flooding damage. The more northerly islands of North Andros, Bimini, Berry Islands, Abaco, New Providence and Grand Bahama were forecast to be most affected, but Grand Bahama and Bimini Islands sustained the brunt of the hurricane damage. Hurricanes cause considerable damage to the landscape including vegetation upheaval and removal, soil loss, beach loss and flooding.

3.5. Land policy, planning and development and the status of digital land cover information in The Bahamas

Environmental management in The Bahamas is the shared responsibility of many Government ministries, departments, agencies and organisations and the BEST Commission is the primary advisor to the Government on the environment. Agencies involved specifically in the management of land resources are listed in Table 3.4. Significant problems in land management are attributed small island size, limited resources, lack of coordination among the different land management agencies; compounded by the vast number and archipelagic nature of the islands. BEST is the main agency for planning and physical development in The Bahamas but suffers from a lack of staffing, resources and data. Government is underserved by the information that has been collected and is not able to provide an adequate recording of land interests and information related to land and therefore is not able to effectively plan for future growth and development (Rabley and Turnquest, 2003).

Given the significant role nature-based tourism plays in the economy of The Bahamas, the sustainable use and rational development of land and coastal resources is vital to avoid long-term detrimental impact on the economy, lifestyle and culture of the country. Currently there is no integrated national land policy and while environmental impact assessments are mandatory for large-scale development proposals and they are reviewed by the BEST Commission, no single legislation directly addressing tourism, its related development and environmental impact exists (BEST, 2005b).

The Government of The Bahamas recognising the increased threat and pressure from unguided development and growth and the inability to effectively steward land resources, in 1998 embarked on a National GIS Project BNGIS (Rabley and Turnquest, 2003). This project was administered and funded by the IDB and brought together more than 13 Government agencies to work on an environmental study as to how integrated land management using GIS and spatial data could benefit The Bahamas (IDB, 2006). The purpose of the BNGIS was to provide a comprehensive review of land in The Bahamas, to provide the hardware and software necessary to establish the centre and a training facility and to draft a National Spatial Data Infrastructure. The project was successful initially but idled between 2001 and 2004 as a result of a lack of Government priority and resources for training, data collection and modernisation of land management institutions and processes. To date however a national spatial data infrastructure the essential ingredients of which such as a geodetic network, cadastral framework, transportation system, administrative overlay, gazetteer and census data are out of date, incomplete or unavailable (IDB, 2006).

The BNGIS was re-established within the Government of The Bahamas in 2004 in a bid to better coordinate and advance GIS and associated technologies to improve the efficiency of land administration and land information management to support land use planning and sustainable development (IDB, 2006). The BNGIS serves as the technical focal point for collection and management of all geographic information. The LUPAP project was established as part of the government's commitment to improve the efficiency of land administration and land information management while preparing modern land legislation and policy guidelines and thereby contributing to the improved use of land resources. In particular the LUPAP project aims to provide geographic information for land use planning and monitoring of development and will support the improved collection and management of land information to this end. It is anticipated that the methodologies, techniques and datasets from this work will be of direct use and relevance to the LUPAP project.

3.6. Conclusion

The Bahamian archipelago comprises small fragmented and isolated island environments. Effective land management and the reduction of land degradation in The Bahamas has been challenged by both anthropogenic and natural factors associated with increased physical development, natural disasters, small island size and large geographical extent. The clearance of land for development and discharge of untreated sewage to ground and coastal waters are two of the most significant impacts of anthropogenic landscape disturbance. The destruction of native vegetation (coastal wetlands, mangrove communities, pinelands) associated with uncontrolled and largely tourism-based development is clearly evident.

Land administration and land management in The Bahamas is hampered by the absence of an integrated national land policy and a national spatial data infrastructure. Furthermore, the responsibility of land administration and management is distributed across a number of

government agencies and only very recently has a central coordinating agency (BNGIS) for land information management been established. Problems with funding have meant the BNGIS has been slow to progress beyond setting objectives. To date, there is a complete lack of quantitative, spatially explicit and statistically representative data on land cover for the islands of The Bahamas. Data that does exist is non-digital, of poor quality, incomplete or unavailable.

The Government of The Bahamas is currently developing a national land use policy incorporating a national spatial data infrastructure and has embarked on a pilot project to develop land use plans for a small number of the islands including New Providence. The tools and techniques evaluated as part of this research to document patterns and trends in land cover have the potential to assist The Bahamas and other data poor Government agencies in formulating and implementing effective natural resource management strategies and policies that balance the positive and negative impacts of development to preserve environmental resources and increase socio-economic welfare.

Chapter 4 Methodology I: Visualising changes in the landscape

4.1. Introduction

This chapter describes the methodological techniques developed and applied to address research question 1 (Figure 4.1). Changes in brightness, greenness and NDVI were applied to a time-series analysis of medium-resolution imagery of New Providence Island, The Bahamas, derived from five different sensors. The method was then evaluated to see if it could be successfully applied to “visualise” the introduction of new urban features and changes to vegetation in the study area.

The conventional approach to PCA analysis (i.e. the inclusion of several multispectral bands from one sensor into a single analysis) is modified to derive univariate surfaces for measures of brightness, greenness and the NDVI for each year in the time series (Millward *et al.*, 2006). The results from the Millward *et al.* (2006) study showed PCA of visible bands representing brightness to be a superior approach for identifying new urban features in the landscape and the NIR outperformed the NDVI in identifying changes to vegetation. Their research was conducted using one set of four images and the sensitivity of the number of time intervals used in the time series to the success of the methods was not discussed.

The multitemporal PCA methodology of Millward *et al.* (2006) is further developed as part of this thesis. Univariate surfaces for measures of NDBI (Zha *et al.*, 2003) and BI (Lin *et al.*, 2005) were generated for a time-series of imagery acquired for the study area and subjected to multitemporal selective PCA. The performance of the indices in identifying land cover change was evaluated to determine whether NDBI and BI offer an improvement to measures of brightness, greenness and NDVI in highlighting patterns of human disturbance over time. In addition, the sensitivity of multitemporal PCA methods to the number of time intervals used in the time series was examined by applying the methods to multiple temporal combinations of the imagery.

A successful ordination with PCA should produce components that exhibit homogenous areas of low pixel variance representing areas across the landscape that have not undergone significant change over the time period. Consequently, the success of each multitemporal PCA method to identify areas of little or no change was also assessed.

4.2. Summary of methodological steps

- i. **Data acquisition and pre-processing:** The datasets were pre-processed to yield a standardised set of images with relative reflectance values comparable for common spectral bands across the images. Pre-processing involved image radiometric and geometric corrections.

ii. Correlation Analysis: Correlation analysis was carried out to determine the degree of intra-annual and inter-annual spectral similarity of the spectral bands and indices generated to support the use of selective PCA to reduce the spectral dimensionality of the multispectral datasets to single univariate surfaces.

iii. Multitemporal Selective PCA: Using the PCA utility available through the ERDAS Imagine remote sensing software, the spectral dimensionality of the dataset was reduced to ensure the images produced by the time series analysis do not contain spectral and temporal variations (Eastman and McKendry, 1991; Piwowar and Millward, 2002). Three spectral ordination procedures (Millward *et al.*, 2006) were tested on a time series of imagery and a further two procedures were introduced to the methodology and tested. A multitemporal PCA was then applied to the time series of spectrally reduced images from each date to determine their information content with respect to changes in the landscape. The analysis was run using multiple temporal combinations of imagery to test the sensitivity of the methods to the number of time intervals considered.

iv. Interpretation and evaluation of Multitemporal PCA to identify areas of change and no change: The images resulting from the multitemporal PCA were interpreted and evaluated in their ability to identify patterns of human disturbance over the time period in the absence of *in-situ* data by examining factor loadings and contribution values. PC images were also compared to WFMI images generated for each time interval to facilitate interpretation. WFMI is a simple change detection procedure used to visualise the spectral changes between two image dates. It is an efficient yet purely qualitative method for visualising change and only two dates at a time can be analysed (Jensen, 2007). Finally, to evaluate the success of the PCA methods to identify areas of no change, locations that have not experienced landscape alteration were identified and an aggregate standard deviation value for the unchanged areas was calculated for each PC image and compared to the unique information content described by that PC.

The methodological steps are expanded on in turn through sections 4.3 to 4.6.

4.3. Data acquisition and pre-processing

At the core of any landscape change analysis research project is the fundamental need for quantifiable and consistent spatial data to describe land cover. To identify and quantify landscape change and the impact of human disturbance on New Providence Island, available medium-resolution satellite data was acquired from five different sensors.

4.3.1. Datasets and sources

Available medium-resolution remotely sensed datasets of the study area suitable for use in a time series analysis of land cover change were acquired from Landsat and SPOT platforms.

- **The Landsat dataset**

NASA has sponsored the creation of an orthorectified and geodetically accurate global dataset from the 1970s, mid-1980s and early 2000s (referred to as epochs) specifically to support education and scientific research. These data are available to download for free from the GLCF website, hosted by the University of Maryland (GLCF, 2006). The data are available in many formats but the GeoCover dataset (produced under contract from NASA by EarthSat Inc) is a collection of Landsat imagery that have been orthorectified (i.e. corrected for terrain displacements and errors in image geometry) and processed to a high standard of quality (Tucker *et al.*, 2004).

For the orthorectification, the Landsat TM images only were "tied" together into "blocks" using an EarthSat application. Geolocational points were applied and associated with an elevation model (accurate between 30m and 1km). The resulting "3D" space allowed for resampling of pixels within the otherwise 2D Landsat image and increased the end geodetic accuracy. Following this procedure, the MSS and ETM+ data were coregistered and orthorectified to the TM series data and DEM.

In addition to orthorectification, scene selection for the global GeoCover dataset is based on criteria such as image quality, clouds haze (typically 10% or less), seasonality (growing season preferable) and same-day successive acquisitions. The USGS EROS Data Centre, Sioux Falls, Dakota and regional data centres controlled by NASA, control archiving and redistribution of Landsat scenes.

Four of the seven remotely sensed datasets used for this research were obtained cost free from the GLCF (Table 4.1). Following a review of the available cloud free datasets of the study area from the GLCF, scenes were selected where possible on near anniversary dates or at least within the same season. The presence of cloud cover on several of the Landsat images precluded their use and an additional dataset (not available to download from the GLFC) was purchased from the USGS EROS Data Centre.

The availability of multiple sampling dates allows an evaluation of trend, whereas availability of two sampling dates only allows evaluation of change. Additional cloud free medium-resolution imagery was acquired from the SPOT satellite system to facilitate a multisensor time series analysis of landscape change. Use of SPOT imagery also serves to test the robustness of the change detection methods evaluated as part of this research, across remote sensing platforms.

- **The SPOT Dataset**

Following a review of the available archived datasets (SPOT, 2006) only three cloud free scenes corresponding to the study area were suitable and duly purchased. Details are given in Table 4.2.

SPOT scenes are standard SPOT Image products that have undergone basic pre-processing. Complete scenes are 60km long and between 60 and 80km wide. There are several image product pre-processing levels, namely 1A, 1B and 2A in order of increasing accuracy. The New Providence scenes were processed to level 2A (geometric and radiometric corrections) and are described as an entry-level map product. Level 2A scenes are rectified to match a standard map projection, UTM WGS 84. The scenes are radiometrically corrected to account for distortion due to differences in the sensitivity of the sensors detectors. The scenes are geometrically corrected for systematic effects such as Earth curvature and rotation.

4.3.2. Computer hardware and software

Remote sensing and GIS software available for use within the University of Dublin, Trinity College includes Lercia Geosystem's ERDAS Imagine Advantage digital image processing software (version 9.0) and ESRI's ArcGIS (version 9.1). These were employed to perform all the image pre-processing, analyses and mapping conducted to meet the objectives of this research. In addition, both the statistical software package SPSS v14.0 and Microsoft Excel were used to carry out the statistical and graphical analyses. All of the software mentioned were run from a standard desktop PC.

4.3.3. Data pre-processing

It is extremely difficult particularly in tropical areas to obtain multi-date imagery from the same time of year owing to the presence of cloud (Mas *et al.*, 1999). Where possible the Landsat and SPOT datasets were acquired from the same season but instances of poor data quality (the presence of clouds, lines, striping etc) meant it was not possible to obtain scenes from the same season for every year (Table 4.3). Image selection was based on minimal cloud cover and bands were selected for analysis from different sensors based on similarities between their spectral sensitivity.

Landsat and SPOT image products are already pre-processed, however in order to conduct a time series analysis using multisensor imagery acquired from different platforms, the imagery must be standardised. Pre-processing entails both radiometric and geometric corrections and serves to standardise the image datasets. Radiometric corrections on the image datasets were conducted to account for differences in sensor detector calibration, sun-angle, Earth-Sun distance and atmospheric path radiance between the dates of image acquisition and satellite sensor. In addition dark-object subtraction via COST algorithm (Song *et al.*, 2001) was used to minimise the effects of atmospheric scattering.

To be able to compare the imagery on a per-pixel basis for time series analysis the pixel grids of each image must spatially conform to each other. To this end, geometric corrections are applied

and involve both spatially co-registering (georeferencing) and re-sampling the imagery to the same spatial resolution.

4.3.4. Radiometric corrections: image standardisation and atmospheric correction

For the Landsat and SPOT datasets three procedures are undertaken to standardise the imagery and account for the effects of variability in the atmosphere. Firstly pixel brightness values as expressed by DN are converted to spectral radiance; secondly radiance is converted to approximate reflectance values and thirdly the reflectance values are subjected to an atmospheric correction procedure.

i. Spectral Image Calibration - DN to radiance conversion

Calculation of radiance from raw DNs is the first step in converting the data into a common radiometric scale. For both the Landsat and SPOT imagery pixel raw data values are processed and converted to units of absolute radiance which are then scaled to 8-bit values representing calibrated DNs. Conversion from calibrated DN numbers (i.e. scaled between 0 and 255) back to at-sensor radiance requires knowledge of the original rescaling factors presented in terms of gain and bias. Gain and bias values for all datasets are presented in the image header files (APPENDIX A) and are also from the literature (Chander and Markham, 2003 Landsat Project Science Office, 2003).

- Landsat DN to Radiance conversion

Satellite spectral radiance is the energy at a specific wavelength radiated onto an object of unit area per solid angle of measurement. Standard measurement units are Watts per metre squared per steradian per micrometer ($W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$). Equation 4.1 was used to convert Landsat DN to radiance and corrects for gain and bias or offset values for each spectral band in the Landsat dataset. Gain represents the gradient of the calibration. Bias (or offset) defines the spectral radiance of the sensor for a DN of zero (Figure 4.2).

Typically a calibrated DN is a linear function of radiance described by Equation 4.1.

Equation 4.1.

$$L_{\lambda} = \text{"Gain"} \times Q_{cal} + \text{"Bias (or offset)"}$$

Where,

$$\text{Gain} = \frac{L_{MAX_{\lambda}} - L_{MIN_{\lambda}}}{Q_{calMAX}}$$

and

$$\text{Bias} = L_{MIN_{\lambda}}$$

and is expressed mathematically as:

$$L_{\lambda} = \left(\frac{LMAX_{\lambda} - LMIN_{\lambda}}{QcalMAX} \right) Qcal + LMIN_{\lambda}$$

Where,

L_{λ}	spectral radiance at the sensor in $W m^{-2} sr^{-1} \mu m^{-1}$
Q cal	quantised calibrated pixel values in DN
Q cal MAX	maximum quantised calibrated pixel value in DN
Q cal MIN	minimum quantised calibrated pixel value in DN
$LMAX_{\lambda}$	spectral radiance that is scaled to QcalMAX in $W m^{-2} sr^{-1} \mu m^{-1}$
$LMIN_{\lambda}$	spectral radiance that is scaled to QcalMIN in $W m^{-2} sr^{-1} \mu m^{-1}$.

The LMINs and LMAXs are the calibration factors representing the spectral radiances for each band at digital numbers 0 or 1 and 255 (i.e. Q cal MIN and Q cal MIN) respectively.

Gain and bias values used in Equation 4.1 are specific to each Landsat sensor and waveband. The Spatial Modeller function within ERDAS was used to build a model to convert the Landsat MSS, TM and ETM+ image wavebands pixel DN brightness values to spectral radiance.

• SPOT DN to Radiance conversion

For the SPOT dataset, in accordance with Mather (1999) and Soudani *et al.* (2006) DNs were converted to at-sensor radiance (Equation 4.2).

Equation 4.2.

$$L_{sat} = DN_i / G_i$$

Where,

L_{sat} is at satellite radiance in $W m^{-2} sr^{-1} \mu m^{-1}$

DN_i are the pixel values for band i and G_i is the calibration factor in $W m^{-2} sr^{-1} \mu m^{-1}$ for band i.

Gain and bias values are provided in the scene extract parameter files from SPOT (Appendix I).

Similar to the Landsat dataset, using the Spatial Modeller function of ERDAS for each waveband, SPOT HRV and HRVIR image pixel DN brightness values were converted to spectral radiance.

ii. Radiance to reflectance conversion

The second step in the image standardisation procedure involves converting the radiance values to reflectance. The purpose of converting radiance values to reflectance for change detection analysis means that the cosine effect of different solar zenith angles due to the time difference between data acquisitions is removed. In addition differences in exoatmospheric solar irradiances arising from spectral band differences are accounted for (Chander and Markham, 2003). The combined surface and atmospheric reflectance of the Earth is computed using Equation 4.3 (Landsat Project Science Office, 2003).

Equation 4. 3.

$$P_p = \frac{n \times L_\lambda \times d^2}{ESUN_\lambda \times \cos\theta_z}$$

Where,

ρ_p = unitless planetary reflectance

$n = 3.141593$

L_λ = spectral radiance at the sensor's aperture

d = Earth-Sun distance in astronomical units

$ESUN_\lambda$ = mean solar exoatmospheric irradiances in $W m^{-2} sr^{-1} \mu m^{-1}$

θ_z = solar zenith angle in degrees.

Reflectance (ρ) is expressed as a decimal fraction between 0 and 1.

The Earth-Sun distance in astronomical units is calculated from Equation 4.4 (Mather, 1999).

Equation 4.4.

$$d = \frac{1}{1 - 0.01674 \cos[0.9856(JD - 4)]}$$

Where,

d is distance in degrees

JD is Julian Day i.e. the number of days that have elapsed since the beginning of the year of and specific date of satellite acquisition.

Values for $ESUN_\lambda$ are available from by Markham and Barker (1987), the Landsat Project Science Office (2002) and Chander and Markham (2003) for Landsat MSS, TM and ETM+ respectively. Values for SPOT 1 and 4 are available from SPOT (2006). Both Landsat and SPOT products provide a sun elevation angle within the metadata associated with each file. The zenith angle is calculated by subtracting the sun elevation from 90° .

iii. Atmospheric Correction (COST)

Reflectance as calculated using Equation 4.3 does not correct for atmospheric effects. Given the resources available, for the purpose of this research the COST algorithm described by Chavez (1996) was used to convert radiance to reflectance to account for the effects of the atmosphere. This method requires image-based data only and the corrections generated by the COST model are as accurate as those generated by models using *in situ* atmospheric field measurements (Chavez, 1996) and the model can be built and run easily within the ERDAS Spatial modeller facility.

Atmospheric effects are removed via COST using a DOS approach (Chavez, 1988; Chavez, 1996; Song *et al.*, 2001). A dark object is one that absorbs energy such as a deep-water body, which should be zero so any return of energy from this point in the image in theory is likely to have been caused by scattering. This means that radiance values over a dark object are due to haze in the

atmosphere. Once a value for haze is determined it can be subtracted from the image, which in theory eliminates the effects of the atmosphere.

The DOS method is a simple and efficient method of correction and is the preferred method over radiative transfer models owing to the absence of aerosol and water vapour measurements to describe atmospheric conditions on the dates of image acquisition for the study area (Teillet and Fedosejevs, 1995; Brivio *et al.*, 2001; Wang *et al.*, 2004; Soudani *et al.*, 2006). All the parameters required for this method are available from the image files. COST correction was conducted using Equation 4.5.

Equation 4.5.

$$P_i = \frac{n \times d^2 \times (L_{sat}^i - L_p^i)}{T_v^i (T_z^i \times ESUN^i \times \cos\theta_z + E_{down}^i)}$$

Where,

P_i is surface reflectance

T_v is atmospheric transmittance in the view direction approximated by the cosine of the view zenith angle

T_z is atmospheric transmittance in the illumination direction approximated by the cosine of the solar zenith angle

E_{down} is down welling diffuse radiation, which for this method is assumed as unity (i.e. no diffuse downwelling radiation).

$ESUN^i$ is exoatmospheric radiation entering the atmosphere for band i

L_{sat}^i is at satellite radiance in $W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$ calculated using Equations 4.1 and 4.2 (for Landsat and SPOT datasets respectively).

L_p is the path radiance due to atmospheric effects and is obtained by converting the minimum digital count in each band i into radiance. Due to the effects of atmospheric scattering the darkest object identified in a scene is not completely dark. The surface reflectance of dark objects is assumed to be 1% to take into account the radiation scattered by the atmosphere and reflected by the surface (Chavez, 1988; 1996). L_p is calculated using Equation 4.6.

Equation 4.6.

$$L_p = L_{sat_min} - \frac{0.01[ESUN \times \cos\theta_z \times T_z^i + E_{down}^i]T_v^i}{n \times d^2}$$

Where,

L_{sat_min} is the radiance value of the identified darkest scene object.

The darkest scene object is identified as the minimum DN value for which there are over 1000 pixel counts (Teillet and Fedosejevs, 1995; McDonald *et al.*, 1998). There are two ways of calculating the dark object values for each wavelength in the imagery (McDonald *et al.*, 1998). The first is to use the histogram displays and look at the minimum DN for each waveband. The second is to digitise a dark object such as a deep-water body area and look at the minimum pixel values

within the area for each waveband. The raster attribute data for each image was explored within ERDAS to determine the minimum DN value. As scattering is wavelength dependent the minimum DN values vary from band to band. This method is based on the assumption that the reflectance from these features, if the atmosphere is clear, should be very small, if not zero.

While areas of dark water exist for the imagery they were not of a large enough size to be used consistently to assess dark object values. For this reason the minimum DN value was selected as the darkest DN with at least 1000 pixels for the entire image (McDonald *et al.*, 1998; Song *et al.*, 2001). The DN min values with at least 1000 pixels were converted to radiance values (Equation 4.1 and Equation 4.2) and Lp values were calculated for every waveband of each image via Equation 4.6. Finally, following the computation of Lp, atmospherically corrected reflectance values were calculated using Equation 4.5.

4.3.5. Geometric corrections: spatial coregistration and resampling

As all the images have the same projection (UTM) it is not necessary to reproject but simply spatially co-register or georeference the images. Landsat and SPOT datasets are projected to the same reference system (UTM WGS 84), however the SPOT 1 and SPOT 4 datasets are not spatially coregistered. The mismatch between the imagery is highlighted in Figure 4.3 using yellow arrows. The images were overlaid and using the ERDAS swipe viewing capability which reveals both images, the mismatch between the imagery is clearly evident at the coastline and interior of the island.

Landsat imagery downloaded for use from the GLCF are pre-processed to a high standard of quality (Tucker *et al.*, 2004). The SPOT HRV 1986 and SPOT HRVIR 1999 image datasets were georeferenced to the Landsat imagery using a first order polynomial for geometric correction with nearest neighbour re-sampling. This process changes the map coordinate information in the input image file only.

Image to image registration was performed within ERDAS using GCPs which georeference the imagery via a transformation matrix. GCPs are selected on screen on the basis of locational consistency between the imagery i.e. at locations such as road intersections or corners of buildings that exist on both images and do not change over time. Corresponding GCPs are selected from both images. The number of GCPs selected depends on the transformation, but generally they should be well distributed across the image. The minimum number of points necessary for the algorithm to work can be calculated using Equation 4.7.

Equation 4.7.

$$\text{Minimum number of GCPs} = \frac{(t+1)(t+2)}{2}$$

Where,

t is the order of the transformation.

For a first order and third order polynomial transformation for example, t amounts to 3 and 10 GCP points respectively. It is always desirable to use more than the minimum to improve the georeferencing. GCPs from the original and reference image are then used to calculate transformation coefficients and a transformation matrix (ERDAS, 1999). The matrix is tested by comparing the known source GCP coordinates to coordinates for the same point in the input coordinate system that are calculated with the transformation matrix. The corresponding reference GCPs are retransformed to the input coordinate system using the reference-to-input transformation matrix. The distance between the input GCP coordinates and the retransformed coordinates is referred to as the RMSE. RMSE is a measure of the distortion as a result of the image transformation following georeferencing and is calculated for each GCP using Equation 4.8.

Equation 4.8.

$$\text{RMSE} = \sqrt{(x' - x_{\text{orig}})^2 + (y' - y_{\text{orig}})^2}$$

Where,

x_{orig} and y_{orig} are the source X and Y GCP coordinates
 x' and y' are the retransformed coordinates.

By computing the RMSE for all GCPs it is possible to see which GCPs represent the greatest error and calculate the total RMSE for all GCPs. Generally an acceptable RMSE is no more than 0.50 pixels (Jensen, 2005). Therefore, SPOT data with a resolution 20m the RMSE should be no more than 10m.

Once an acceptable RMSE is reached (GCPs with high RMSE values can be removed and replaced by picking better placed GCPs with lower RMSE values) the next step in the georeferencing is to interpolate the image to fill a grid with brightness values found in the original input grid. The intensity interpolation process involves the extraction of a brightness value from an x' , y' location in the original (non-georeferenced) image and its relocation to the appropriate x , y coordinate location in the rectified output image. This process is referred to as re-sampling. Nearest neighbour re-sampling is employed as it is a computationally efficient procedure and pixel values are not altered during the interpolation (Campbell, 2002). This is an especially important factor given the imagery is being used to detect changes on a per-pixel basis.

In addition to image-to-image registration, the spatial resolution of SPOT was decreased from 20m to 30m to match the Landsat dataset. Similarly, the Landsat MSS dataset was re-sampled from 60m to 30m using the Reproject utility within ERDAS Imagine.

4.4. Correlation Analysis

Following data pre-processing NDVI, NDBI and BI index values were generated for each of the images in the time series using the ERDAS Spatial Modeller Utility. Correlation analysis was conducted within ERDAS to determine the inter- and intra-temporal correlation between similar spectral bands and the indices generated from every image in the time series to support the hypothesis that visible bands in the study area are highly redundant and suitable for collapse into a single univariate image representative of image brightness and to determine the appropriateness of using NDVI as measures of image greenness and NDBI and BI as measures of image brightness.

4.5. Multitemporal Selective PCA

Selective PCA denotes the inclusion of specific wavebands to PCA analysis and multitemporal PCA was conducted on a brightness, greenness, NDVI, NDBI and BI time series of imagery to extract temporal information corresponding to changes in physical scene characteristics from year to year.

i. Multitemporal PCA for derivation of change in brightness

A selective PCA was performed independently on the combination of the green and red visible bands for each time period to derive a component attributable to brightness. Urban surfaces such as roads, buildings and cleared land have higher reflectances in the visible spectrum than any other land surface. PCA on two wavebands produces two PC images and information common to both bands is mapped to the first component. This yields a spectrally reduced image representing image brightness for the time period. PC1s, the first PC images produced from selective PCA on the visible bands were selected as a univariate measure of brightness for each time period and combined to create a time series of brightness images. A second (multitemporal) PCA was then conducted on the image combination of PC1s generated for each year in the time series to derive PC images describing changes in brightness through time (Figure 4.4).

ii. Multitemporal PCA for derivation of change in greenness

The spectral response of vegetation in the NIR is very strong and is considered the most representative measure of the presence of image greenness (Ingebritsen and Lyon, 1985; Ridd and Liu, 1998; Jensen, 2004) and is used in this research as a surrogate for the presence of vegetation. The NIR wavebands pertaining to each time period were combined to form a time series of greenness images which was then subjected to multitemporal PCA (Figure 4.5).

iii. Multitemporal PCA for derivation of change in NDVI

Vegetation indices are dimensionless radiometric measures that indicate the relative abundance and activity of green vegetation. The NDVI (Rouse *et al.*, 1974) is regarded as a reliable indicator for land cover conditions and variations (Huemmrich *et al.*, 1999; Cuomo *et al.*, 2001; Lanfredi *et*

al., 2003) and has been used extensively to monitor vegetation presence and vigour (Viedma *et al.*, 1997). NDVI is calculated using the red and NIR bands from each date using Equation 4.9.

Equation 4.9.

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$$

NDVI values were generated independently for each time period and layer stacked to produce a time series of NDVI images which was subjected to PCA. Multitemporal PCA is conducted using NDVI to determine whether or not NDVI data would reveal more easily interpretable changes to vegetation than the NIR band alone (Figure 4.6).

iv. Multitemporal PCA for derivation of change in NDBI

To monitor the spatial distribution and growth of urban areas the NDBI index was developed by Zha *et al.* (2003). They adapted the Infrared Index developed by Hardisky *et al.* (1983), which is similar to the NDVI but is based on the normalised difference between the NIR and the MIR bands; in an attempt to automatically map urban areas using TM data. Built-up area was calculated by subtracting the NDVI from the infrared index using Equation 4.10.

Equation 4.10.

$$\text{NDBI} = \frac{\text{MIR} - \text{NIR} - \text{NDVI}}{\text{MIR} + \text{NIR}}$$

Multitemporal PCA was applied to the combination of NDBI images generated for each time period to determine whether or not the NDBI data would yield more easily interpretable changes to urban land cover than the use of the visible bands. This index can only be applied where spectral reflectances are recorded in the NIR and MIR range of the electromagnetic spectrum. The use of the NDBI was tested on a time series of data with imagery acquired from the Landsat TM, ETM+ and SPOT HRVIR sensors (Figure 4.7).

v. Multitemporal PCA for derivation of change in BI

The BI was developed by Lin *et al.* (2005) to extract urban areas from Landsat TM images taking advantage of the relatively high spectral reflectance of urban areas in TM bands 3 and 5 and the comparatively low reflectances of urban areas in the TM 4 (Equation 4.11). For this research BI values are generated for each year in the time series (Figure 4.8) and subjected to PCA to determine how well the index works in highlighting urban land cover change in the study area compared to the use of visible bands. Similar to the NDBI, the BI can only be applied to imagery acquired by sensors with spectral sensitivity encompassing the NIR and MIR bands. The use of BI was tested on a time series of data with imagery acquired from the Landsat TM, ETM+ and SPOT HRVIR sensors.

Equation 4.11.

$$BI = RED + MIR - NIR$$

4.6. Interpretation and evaluation of Multitemporal PCA to identify areas of change and no-change

The results from the PCA approaches are interpreted and evaluated to determine which technique is most effective in identifying the sequence of general patterns of human disturbance across the time series. In order to evaluate the success of the multitemporal PCA procedures to identify land cover change in the absence of *in situ* data, factor loadings and contribution values must be computed for each of the PCs corresponding to each of the years evaluated. Percent contribution of variance (information content) for each input band into the PCs generated is calculated using Equation 4.12 (Jensen, 2007).

Equation 4.12.

$$S_{kp} = \frac{(a_{kp})^2}{\sum_{i=1}^n (a_{ip})^2}$$

Where,
 S_{kp} is the contribution of band k into component p
n represents the number of input bands
 a_{kp} is the eigenvector value for band k.

Factor loadings represent the degree of correlation between each component and each input date, for example a high loading either positive or negative indicates the original data in the study represented by a specific year are expressed strongly in the component image. Factor loadings were computed using Equation 4.13 (Jensen, 2007).

Equation 4.13.

$$R_{kp} = \frac{a_{kp} \times \sqrt{\lambda_p}}{\sqrt{Var_k}}$$

Where,
 R_{kp} is the loading value (-1 to +1)
 a_{kp} represents the eigenvector value for band k, λ_p is the eigenvalue for component p
 Var_k is the input band variance for band k.

The PC images are interpreted by first of all examining the cumulative percent variance of the higher-order PC images as a measure of the unique information content contained within each PC

image; secondly through identifying the year(s) for which the input band makes the greatest percent contribution to the component images and thirdly by determining whether the most highly contributing year is loaded negatively or positively in the component image.

In addition WFMI images are generated for each time interval as a visual aid to interpret the patterns identified by the PC images, generated for each of the methods of spectral ordination. Spatially coregistered bands of imagery representing time intervals across the time series were inserted into two WFMI banks, with the later image for each specific interval displayed in red and the earlier image displayed in blue and green. Using this technique, areas of change between the dates are clearly highlighted in red and blue (Figure 4.9). The red signature clearly highlights areas displaying an increase in spectral reflectance values between the dates, likely associated with land clearance and urban development. Areas of bright blue represent land surfaces displaying a decrease in spectral reflectance values between the time periods. WFMI is a powerful visual assessment tool but does not provide any quantitative information on the amount of change. It can however be used successfully as a preliminary analysis to compare change detection results subjectively (Vijayaraj *et al.*, 2005).

A successful ordination with PCA should produce PC images that exhibit homogenous pixel variation for the areas of unchanged landscape (Millward *et al.*, 2006). In order to evaluate the success of multitemporal PCA to evaluate areas of little or no change, a sample of known locations on the image exhibiting consistent land cover characteristics over the time period was selected. In addition a sample of locations known to have changed as a direct result of urban development over the time period, was also selected (Chapter 7, section 7.4.2, Figures 7.36 and 7.37). Aggregate standard deviation values and the ratio of aggregate standard deviation values to unique information content were computed for the areas of change and little or no change identified for each PC image produced following multitemporal PCA. The areas were determined based on visual interpretation of historic satellite imagery and fieldwork conducted on the island over a two-week period in March 2006.

Standard deviation values and the ratio of standard deviation to unique information content for the locations were compared to establish whether the little or no change areas exhibited homogenous and lower pixel variation in comparison to the variance recorded across locations that had experienced landscape alteration. The ratio of aggregate standard deviation values to unique information content for higher order PCs should be lower across little or no change areas associated with lower pixel variance over the time period in comparison to areas that have experienced landscape alteration, which should exhibit higher standard deviation values across each PC image (Chapter 7, section 7.4.2, Figures 7.38 - 7.42)

4.7. Conclusion

This chapter details the methodology devised to address the first research problem presented in this study. It describes how multitemporal PCA can be applied to successfully visualise or highlight landscape changes associated with human disturbance using satellite imagery acquired from five sensors and effectively addresses the challenges presented by imagery with different radiometric, temporal, spectral and spatial resolution in time series analysis. Beginning with data acquisition and pre-processing, the application of radiometric and geometric correction for image standardisation, a prerequisite for time series change detection using multisensor datasets; is presented in detail.

Multitemporal PCA has already been successful employed to visualise the introduction of new urban features in a time series of brightness, greenness and NDVI imagery gathered for a study area in China (Millward *et al.*, 2006) but was applied here to determine suitability of use in a time series of data acquired from a tropical island with poor data availability. Moreover, two indices NDBI and BI not previously used in multitemporal PCA are tested for their ability to highlight the sequence of human induced disturbance values and are evaluated in comparison to the performance of brightness, greenness and NDVI time series to determine whether their use offers an improvement to the application of multitemporal PCA. In addition, the sensitivity of the results to the number and selection of input years in the time series is assessed by conducting the analyses two separate time series with different input years. Finally, the success of the methods to identify areas of no-change was assessed.

The methodology describes a qualitative analysis of land cover change undertaken to visualise and approximately date landscape changes associated with human disturbance. Following the visualisation of change between the time periods in order to establish precise, quantitative “from-to” landscape change information associated with human disturbance on a time series of imagery land cover classification and post-classification change detection are necessary. The challenges of generating a land cover classification for medium-resolution imagery acquired for a study area with poor data availability and conducting post-classification change detection to derive visual and quantitative “from-to” landscape change information is presented in Chapter 5.

Chapter 5 Methodology II: Landscape classification and post-classification change detection

5.1. Introduction

Methodology II addresses the challenges of combining medium-resolution imagery from different sensors to effectively quantify changes in the landscape in order to identify an appropriate remote sensing procedure for selecting and integrating information from multisensor and multiresolution remotely sensed satellite imagery for a tropical island with poor data availability (Research Question 2, Figure 4.1). This chapter examines whether the application of PCA or using the full spectral range of information available (thermal and panchromatic imagery via data-fusion) offers an improvement to classification accuracy over use of the original image wavebands.

The data fused images were evaluated for preservation of spectral and spatial quality and classified to determine which data-fusion techniques offer an improvement in classification accuracy and whether the preservation of spectral and spatial quality impacted the results.

The use of post-classification change detection to identify the types, rates and temporal variability of land cover change using the time series of land cover maps was also evaluated.

5.2. Summary of methodological steps

A suite of classification methodologies (Table 5.1) were tested on the Landsat ETM+ and SPOT HRVIR datasets to identify remote sensing variables appropriate for land cover classification of a data-poor tropical island area. The methods were evaluated via an accuracy assessment (user's accuracy, producer's accuracy, overall accuracy and Kappa statistic) using ground reference test information gathered using a GPS in the field. Historic land cover datasets for use in an accuracy assessment of the earlier imagery (1973 and 1986) were not available and land cover maps were produced for these datasets using a standard unsupervised classification procedure and visual interpretation. Post-classification change detection was conducted to quantify land cover change over the time period. A summary of the classification procedure and post-classification change detection methodology is presented in Figure 5.1.

- i. **Pre-classification image enhancements:** In order to prepare the time series of medium-resolution satellite imagery to test the classification methodologies a number of separate pre-processing procedures were undertaken to meet the objectives of the land cover classification;
 - a) **PCA:** PCA is an image enhancement algorithm (Jensen, 2007) and was applied to the Landsat ETM+ and SPOT HRVIR datasets
 - b) **Temperature computation:** Temperature values derived from thermal band imagery were combined with multispectral data and evaluated in terms of the

potential of thermal imagery to improve land cover classification in a data-poor tropical island area.

c) Data-fusion: Six methods of data-fusion are evaluated and the spectral and spatial quality of the fused images was examined using visual comparison, histogram analysis and correlation coefficients.

ii. Land cover classification: A standard unsupervised (ISODATA) classification algorithm was used to classify the original and pre-processed imagery into a set of land cover classes derived from the BEP habitat classification scheme developed for The Bahamas by Sealey *et al.*, (2002).

iii. Accuracy Assessment: Ground reference test information was gathered across New Providence using a GPS over a two-week period in March 2006 and used to perform an accuracy assessment on the Landsat ETM+ and SPOT HRVIR datasets. Producer's accuracy, user's accuracy, overall accuracy and the Kappa statistic were computed and used in the analysis to meet the objectives of the research. Post-classification editing was conducted and majority rule applied to see whether the removal of noise from the classified map improved the classification. A final accuracy assessment was conducted following post-classification editing.

iv. Post-classification change detection: Using the time series of land cover maps post-classification change detection was conducted to analyse urban growth patterns across the island over the time period.

The methodological steps are expanded on in turn through sections 5.3 to 5.6.

5.3. Pre-classification image enhancements

The entire time series of images were corrected for radiometric and geometric differences prior to performing multitemporal selective PCA analysis. In order to identify suitable remote sensing variables for land cover classification of a data-poor tropical island area several pre-classification image enhancements were applied to the Landsat ETM+ and SPOT HRVIR imagery.

5.3.1. PCA

PCA was selectively applied earlier (Chapter 4) to a brightness, greenness, NDVI, NDBI and BI time series of radiometrically and geometrically corrected imagery to highlight the human disturbance as part of this research. PCA (non-selective) is used again in this section as a pre-classification image enhancement technique to transform the original SPOT HRVIR and Landsat ETM+ imagery into orthogonal (uncorrelated) datasets. By using PC images in the classification, the relationships between different groups of pixels representing different land cover types might become clearer rather than using the original wavebands and thus offer an improvement in classification accuracy. The first three principal components only are used in the classification as they typically contain over 98% of the total variance in the dataset, the remaining PC images contain mostly noise.

5.3.2. Temperature computation

The Landsat thermal waveband (designated band 6 on the ETM+ sensor) is sensitive in the region 10.4 μ m -12.5 μ m. It has a lower radiometric sensitivity and coarser spatial resolution (60m) relative to the reflective ETM+ bands (30m). Landsat thermal waveband responds to varying temperatures and emissivities on the ground and thermal images show the relative differences in emitted thermal energy that correlate in part with the effects of solar heating on surfaces of varying composition and orientation.

The Landsat ETM+ thermal images of New Providence (2001, 2002) were used to create temperature maps with spatial resolutions of 30m, converted from 60m using the reproject utility within ERDAS Imagine. The thermal band imagery and hence the temperature images are inherently coregistered to the Landsat ETM+ multispectral wavebands and the temperature maps and multispectral data were combined using the layer stack facility within ERDAS.

In addition, the temperature map was compared to an independently produced land cover map generated from the VISIR classification (i.e. produced using the visible and IR wavebands only) via a one-way ANOVA to determine whether statistically significant ($p < 0.05$) differences exist between the temperatures of individual land covers and whether use of the temperature data may offer a means to improve classification accuracy.

Temperature maps of the island were generated from the thermal band imagery according to the procedure outlined by Weng *et al.* (2004). In the first instance the thermal band imagery was

converted from DN numbers to spectral radiance values using the procedure outlined in Section 4.3.4. Secondly, radiance values were then converted into at-satellite brightness or blackbody temperature using Equation 5.1. A model to convert radiance values to temperature was built for the purpose of this study using the ERDAS the Spatial Modeller function.

Equation 5.1.

$$T_B = \frac{K_2}{\ln\left(\frac{K_1}{L\lambda} + 1\right)}$$

Where,

T_B is effective at-satellite temperature in K
 L is spectral radiance in $W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$
 and K_1 and K_2 are pre-launch calibration constants.

For Landsat ETM+ (Chander and Markham, 2003)
 $K_1 = 666.09\ W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$ and $K_2 = 1282.71\ K$

Blackbody temperatures are calculated under the assumption of uniform emissivity (Landsat Project Science Office, 2003). Spectral emissivity is a dimensionless number lying between 0 and 1, and is defined as the ratio of the energy radiated from a surface to that from a blackbody at the same temperature, the same wavelength and under the same viewing conditions. Generally speaking, smooth, shiny surfaces have an emissivity near 0, while dark, rough surfaces would be nearer to 1. Emissivity causes a reduction of surface-emitted radiance and correcting for emissivity values allows for computation of surface temperature accounting for the roughness properties of the land surface, the amount and nature of vegetation cover and the thermal properties and moisture content of the soil (Southworth, 2003). Emissivity values are determined from the surface material comprising the land cover types and can be measured in the field. However, it was unnecessary to correct for emissivity as the temperature values were combined with the multispectral data and used to produce a land cover classification. If emissivity values based on known land cover types were used to calculate actual surface temperatures it would have introduced bias into the classification utilising temperature data.

5.3.3. Data-fusion

Image fusion can be performed at three different levels; pixel, feature and decision level (Pohl and Van Genderen, 1998) and is being applied in this study at the pixel level fuse high-spatial resolution panchromatic imagery with low resolution multispectral imagery obtained for the Landsat ETM+ and SPOT HRVIR imagery. While a wide variety of data-fusion techniques are available this thesis explores the potential of the methods to produce images that improve classification accuracy.

Given the datasets available for the study area, the role of same sensor high-resolution panchromatic imagery in improving land cover classification will be examined specifically. The data-

fusion methods of IHS, PCA, Brovey, Multiplicative algorithms and Wavelet transforms (IHS and PCA) are explored as they are well studied and are the sum total of the available methods within ERDAS. The spectral and spatial quality of the fused images is assessed via statistical comparison (correlation coefficients and descriptive statistics). The results of the quality analysis will be compared to the classified images to determine whether preservation of spatial and spectral quality affected the classification accuracy.

- **Methods of Data-fusion tested**

Six data-fusion methods in total were applied to the Landsat ETM+ and SPOT HRVIR dataset.

- i. Intensity Hue Saturation (IHS)**

The IHS transformation employs three image wavebands only and was applied to a subset of the dataset representing Spot HRVIR bands 1, 2 and 3 and Landsat ETM+ bands 2, 3, and 4 as these wavebands fall within the range of the panchromatic waveband associated with each sensor. IHS was noted in the literature view to be the most frequently applied method for improving the visual display of multisensor imagery, however it remains to be seen whether loss of spectral information (from use of three wavebands) following the data-fusion process will negatively impact classification accuracy.

- ii. Brovey Transformation**

Similar to IHS, the Brovey transformation was developed to create RGB images and therefore only three bands at a time can be merged. The Brovey transformation was applied to Spot HRVIR bands 1, 2 and 3 and Landsat ETM+ bands 2, 3, and 4 as these wavebands fall within the range of the panchromatic waveband associated with each sensor. Along with the IHS method, the results of the Brovey data-fusion will determine whether loss of spectral information associated with using only three wavebands impacted the classification accuracy.

- iii. PCA**

PCA was applied to the SPOT HRVIR and Landsat ETM+ multispectral dataset. For both image datasets, the panchromatic waveband replaces PC1, which describes most of the variation in the dataset and contains information pertaining to all of the input wavebands. The PCA method enables the integration of more of the original spectral data than the IHS and Brovey methods as any number of bands can be included in the PCA. The results of the land cover classification will reveal whether the inclusion of more spectral information translated into higher classification accuracies following data-fusion via PCA compared to the IHS and Brovey methods.

iv. Multiplicative

The Multiplicative method unlike IHS and Brovey can be performed on any number of input bands and was applied to the full range of the SPOT HRVIR and Landsat ETM+ datasets. The technique has been shown to be most useful in highlighting urban features (ERDAS, 2003) but research by Saroglue *et al.* (2004) showed the Multiplicative method to offer the least improvement to classification accuracies in comparison to IHS and PCA.

v. Wavelet transformation (IHS and PCA)

There are three scenarios under which the panchromatic image can be merged with the multispectral image within the ERDAS Wavelet transformation utility; single band, PCA and IHS. Given that the data fused images are used in a land cover classification the multiband approaches of IHS and PCA were applied to the SPOT HRVIR and Landsat ETM+ datasets. The IHS method employs 3 bands in contrast to the PCA method, which can accept any number of bands. A comparison of the results produced from both methods is undertaken to determine the impact of spectral information loss on classification accuracy following the application of Wavelet IHS.

• Evaluating the spectral quality of data fused imagery

The overall aim of data-fusion is to merge a high spatial resolution panchromatic image with a lower spatial resolution multispectral image and improve the spatial resolution of the multispectral image without compromising the spectral characteristics. The spectral quality of the data fused images was determined using five techniques.

i. Compare the spectral ranges of the panchromatic and multispectral image

In preserving spectral quality it is important that the multispectral wavebands span the same region of the electromagnetic spectrum as the panchromatic band being used in the data-fusion process. During the data-fusion process image brightness values represented either by the intensity component (methods IHS, Brovey, Multiplicative and Wavelet IHS) or PC1 (methods PCA, Wavelet PCA) are replaced by and assumed to be spectrally equivalent to the panchromatic image. Spectral ranges of the Landsat ETM+ and SPOT HRVIR multispectral wavebands were compared with the spectral range of their respective panchromatic bands.

ii. Evaluate the relationship between the intensity image derived from the original multispectral wavebands and the panchromatic image

In all methods of data-fusion the intensity component of the multispectral image is closely linked to the panchromatic image and preservation of spectral characteristics is only possible in the event of spectral equality between the two (Švab and Oštir, 2006). Visual comparison and correlation analysis between the intensity images derived using different combinations of wavebands was undertaken to demonstrate that the images generated using wavebands within the spectral range of the panchromatic image are sharper or display greater contrast than those generated using wavebands outside the spectral range.

iii. Visual comparison of image fusion output

Visual comparison of the data fused images was undertaken to determine to what extent the spectral characteristics of the original images were visibly altered during the data-fusion process.

iv. Analysis of brightness values

The greater the degree to which the distribution of pixels across the data fused image grey-levels differs in comparison to the original multispectral image, the greater the spectral change (Chavez *et al.*, 1991). Spectral profiles were generated for each of the data fused images and compared to the original image to determine to what extent the spectral profiles were altered by each data-fusion method.

v. Correlation analysis

Correlation analysis between the original multispectral and data fused imagery was conducted as a final measure of spectral quality. Data fused images whose DN distribution correlates most closely with the original multispectral images display greater spectral quality.

• Evaluating the spatial quality of data fused imagery

The spatial resolution of the data fused images is supposed to equal the resolution of the panchromatic image but in reality it is reduced (Švab and Oštir, 2006). In order to evaluate the spatial properties of the fused images, the panchromatic band and intensity image derived from the data fused image have to be compared (Tu *et al.*, 2001).

i. Visual comparison

Visual comparison of the original and data fused images was undertaken to show that all methods serve to sharpen the original multispectral image.

ii. Correlation between original panchromatic and the intensity image of the fused image

The improvement factor of spatial resolution is defined with the correlation coefficients between the original panchromatic image and the intensity image of the fused image. The intensity component was generated for each of the data fused images and correlation coefficients between the intensity component and the panchromatic image were calculated. This determines the extent to which the panchromatic band was altered during the data-fusion process and the greater the change the greater the deterioration in spatial characteristics. The spatial resolution of the data fused image is better preserved in the case of minimal change of the panchromatic image.

To show the preservation of spatial resolution regarding the similarity between the panchromatic and intensity images the correlation coefficients between the panchromatic and intensity

component of the data fused images are plotted against the average correlation coefficient between the pan and data fused images.

To show the relationship between the preservation of spectral information and spatial quality for each of the methods the average multiispectral correlation coefficient between the data fused and original images were plotted against the average pan correlation coefficient.

5.4. Land cover classification

A major step forward in the application of remote sensing data to landscape change detection is land cover mapping, Land cover classification based on statistical pattern techniques applied to multispectral remotely sensed data is described as one of the most often used methods of information extraction (Narumalani *et al.*, 2004). Investigating changes in land cover or landscape pattern requires a classification system that can be uniformly applied over the time period (Dunn *et al.*, 1991).

Following the pre-classification image enhancements on the Landsat ETM+ and SPOT HRVIR datasets land cover maps were generated for both the original and enhanced image datasets for New Providence Island acquired between 1973 and 2002 via a standard unsupervised classification procedure (ISODATA) available within ERDAS.

5.4.1. Land cover classification scheme

Classification can be defined as the ordering or arrangement of objects into groups or sets on the basis of relationships. These relationships can be based on observable or inferred properties and the selection of land cover classes is critical to the mapping process and ideally classes are chosen because they have both ecological significance and unique spectral qualities. Traditional classification schemes dealing with land cover and land use include Trochain (1971), UNESCO (1973), Anderson *et al.* (1976), UNEP/FAO (1994), CEC (1995), Duhamel (1995), Thompson (1996).

A land cover classification scheme was developed from the BEP habitat classification (Table 3.2) for The Bahamas as part of the BEP to identify altered and non-altered shorelines to direct fieldwork undertaken as part of a coastal ecological study (Sealey *et al.*, 2002). This research adopted the same land cover classification scheme with two modifications (Table 5.2). The BEP land cover classification scheme included an "agriculture" class and a "buttonwood" class in addition to the other classes listed in Table 5.2. However, the class "agriculture" was merged into "HAL" and the class "buttonwood" was merged into the "mangrove" classes. The classification scheme chosen for this research was based on amenability to accurate identification of these classes from the available imagery and ancillary interpretation resources.

5.4.2. Land cover classification algorithm

The correct application of image classification procedures to extract thematic information is knowledge of certain spatial attributes of the data to determine the appropriate classification methodology and parameters to use. Methods of multispectral classification were outlined in the literature review and it is clear that no single pattern classification method is inherently superior to any other. The nature of the classification problem, the biophysical properties of the study area, the distribution of the remotely sensed data and *a priori* knowledge contribute to determine which classification algorithm will yield useful results (Jensen, 2007).

In order to evaluate the different classification methodologies (Table 5.1) based on an accuracy assessment of the land cover maps produced, a standard classification procedure was selected and applied to the dataset. This procedure (Figure 5.2.) entailed an unsupervised classification where land cover information is extracted from the imagery based on natural groupings of the spectral properties of the data. The subsequent characterisation of the groups of spectral data into classes following unsupervised classification is reliant on visual interpretation, knowledge of the spectral characteristics of the terrain by the analyst and ancillary data resources. Visual interpretation of Landsat and SPOT imagery has been demonstrated as a useful tool in land cover mapping (Scott *et al.*, 1993; Zheng *et al.*, 1997).

The importance of including ancillary datasets is widely recognised for improving the accuracy and quality of remote-sensing derived land cover classification (Jensen, 1996) and a land cover map of New Providence island generated by Sealey *et al.* (2002) as part of the BEP (to direct fieldwork investigations of nearshore habitats along altered shorelines) and local knowledge acquired from extensive field work on the island were used to assign the spectral classes identified by the unsupervised classification to specific land cover types.

While use of the unsupervised classification algorithm provides the analyst with freedom to merge similar clusters together (Jiang *et al.*, 2004) disadvantages include in the potential mismatch of spectral signature clusters (and thematic classes) and that changes in the parameters made by the analyst can produce very different final clusters in the same dataset (Cihlar, 2000).

The success of unsupervised classification algorithms to generate land cover maps with overall accuracies reported above 90% has been documented in the literature (Jiang *et al.*, 2004; Kuemmerle *et al.*, 2006) and its use as part of this study presents a labour-saving, consistent and uncomplicated approach to the generation of multirate land cover maps to meet the objectives of this research.

Unsupervised classification is undertaken within ERDAS using the ISODATA algorithm and is referred to as self-organising because it requires relatively little human input aside from setting three parameters that include;

1. The number of clusters to be identified by the algorithm
2. The maximum percentage of pixels whose class values are unchanged between iterations
3. The maximum number of times ISODATA is to classify pixels and recalculate cluster mean vectors and the algorithm terminates when this number is reached (ERDAS, 1999).

The ISODATA algorithm works by assigning an arbitrary mean value for each of a pre-specified number of clusters (classes). Typically a large number of clusters say 50 or more are used to ensure adequate data representation (Schowengerdt, 1997). Each pixel is assigned to the cluster whose centre is closest to that pixel and forms the first set of decision boundaries. A new set of cluster means is calculated from the initial classification and the pixels are reassigned accordingly. This procedure (referred to as an iteration) is repeated; a new number cluster centres are found and the pixels are reassigned. The iterations continue until there is no significant change or movement in pixel assignment between iterations.

Following data preparation (pre-processing and image enhancements) an initial unsupervised classification was carried out to remove the areas of water from the image to improve the contrast between spectral reflectances across the land surface. In the initial classification by ISODATA technique, 25 to 30 clusters were produced and matched with the reference imagery and data to separate areas of land from areas of water. Spectral classes representing areas of water were labelled and removed from further consideration. The remaining spectral classes representing areas of land were subjected to a second unsupervised ISODATA classification. A maximum of 75 iterations was selected with a threshold value of 0.95 to produce between 25-30 spectral clusters, meaning that when the maximum percentage of pixels whose class values are unchanged between iterations is 95% the algorithm terminates.

In the second procedure, 40 clusters were produced and matched to the reference imagery and data and assigned to a land cover class. Spectral classes produced from the second unsupervised ISODATA procedure that were unclear or contained mixed classes were separated from the labelled classes (which were subsequently removed from the pool of data) and rerun again. This procedure was repeated as many times as was necessary to assign every pixel to a class. A maximum of 75 iterations was selected to generate 40 clusters with a threshold value of 0.95.

Following the allocation of every pixel to a land cover class all the labelled pixel clusters (land and water) were combined (using the overlay command in ERDAS) to produce a composite land cover

map of the entire island. A flow diagram illustrating the unsupervised classification procedure is presented in Figure 5.2.

5.5. Accuracy assessment

An accuracy assessment was conducted on each of the land cover maps generated to evaluate the classification methodologies tested as part of this research conducted to identify suitable remote sensing variables for land cover classification in a data-poor tropical island. Ground reference test information was gathered in the field during a two-week period in March 2006. Using a hand-held GPS the specific x-y coordinates and land cover type present was recorded at a number of locations. The Accuracy Assessment utility within ERDAS was employed to generate error matrices (measuring the agreement between the ground reference test information and the results from the land cover classification) for each land cover map pertaining to the Landsat ETM+ and SPOT HRVIR original and enhanced image datasets.

Ground reference information gathered for the purpose of this research was compared to the classified maps using a 3x3 pixel window, to avoid site-specific comparisons between referenced and classified to provide a degree of tolerance for mis-location. The Accuracy Assessment command within ERDAS employs the majority rule to assign a value to the pixel at the reference point. Each pixel is labelled to the class that has the highest frequency of occurrence within a 3x3 window.

Statistical measures of accuracy including producers accuracy, users accuracy, overall accuracy and the Kappa statistic were generated for each classification map from the error matrices and a test of significance was conducted on the Kappa statistic to determine whether the agreement between the reference values and the classification map for each method was significantly better than zero (randomly assigned pixels).

Post-classification smoothing using a majority filter within ERDAS was applied to determine whether any improvement in classification accuracy could be obtained for any of the classification methods. Post-classification refinements to correct for gross misclassification error were also conducted.

The results of this analysis were used to determine which classification method offered the greatest classification accuracy and to identify the remote sensing variables most appropriate for classification of the study area.

5.5.1. Ground reference test information

To correctly derive an error matrix it is necessary to systematically compare two sources of information; the pixels representing the remote sensing derived classification map and ground

reference test information. The actual number of ground reference test samples to be used to assess the accuracy of individual categories in a remote sensing classification map is a very important consideration. Equation 5.2 is based on the binomial distribution and is often used to determine the sample size (Fitzpatrick-Lins, 1981).

Equation 5.2.

$$N = \frac{Z^2(p)(q)}{E^2}$$

where,

p is the expected percent accuracy of the entire map

q=100-p

E is the allowable error

Z=2 from the standard normal deviate of 1.96 for the two-sided confidence level.

For instance with expected map accuracies of 85% and an acceptable error of 10% the sample size of the map should be 51 at a minimum, using the same equation.

Ground reference test information for New Providence was gathered during a two-week trip to the island in March 2006 (Figure 5.3). A total number of 130 sampling points (Figure 5.4) were recorded across the island representing each land cover type. Prior to conducting the accuracy assessment on the land cover map, the ground reference test information points were plotted and checked for locational consistency using the panchromatic and multispectral Landsat ETM+ imagery from 2002 and notes recorded in the field, as references.

5.5.2. Statistical measures of accuracy

Error matrices were generated for each classification map using the ground reference test information gathered within the ERDAS Accuracy Assessment utility. The error matrix assesses the classification of all classes and is a square array of numbers where the columns represent the ground reference test information and the rows correspond to the classification generated from analysis of the remotely sensed image dataset. The values in the diagonal of the matrix summarise the number of pixels correctly assigned to a particular land cover based on the reference data and are shaded in grey in Figure 5.5. The classification errors are summarised in the off-diagonals and are based on omission from the correct category and a commission to the incorrect category. The column and row totals are used to compute errors of inclusion (commission errors) and errors of exclusion (omission errors). These statistics were summarised for each class within every classification map produced and are referred to as user's and producers accuracy respectively (Foody, 2002, 2004).

The overall accuracy (or percentage correct) of each land cover map was calculated by dividing the total number of correct pixels (the sum of the diagonal) by the total number of pixels in the error matrix (n) as illustrated in Figure 5.5.

Computing the accuracy of individual categories is described as more complex given the choice between dividing by the total number in the row or column (Foody, 2002). Traditionally (where reference values are displayed in the columns and the map data as rows in the matrix as in Figure 5.5) the total number of correct pixels in a category is divided by the total number of pixels of that category derived from the reference data (column total). This statistic indicates the probability of a reference pixel being correctly classified and is a measure of producer's accuracy.

If the total number of correct pixels in a category is divided by the total number of pixels that were actually classified in that category (row totals) the result is a measure of commission error. This measure is called user's accuracy or reliability and is the probability that a pixel classified on the map actually represents that category on the ground.

Evaluation of thematic map accuracy should ideally be based on a set of criteria defined in advance of its production. Overall accuracy of $\geq 85\%$ and a Kappa value $\geq 75\%$ are often used as targets (Wulder *et al.*, 2006). For many mapping applications however, 85% may be an unrealistically high target value to set and it should not be automatically used as a criterion for the evaluation of image classifications (Laba *et al.*, 2002).

A major accuracy assessment problem recognised by some users is that in some cases pixels may have been allocated to the correct class purely by chance (Congalton, 1991; Pontius, 2000; Couto, 2003). To accommodate for the effect of chance agreement Cohen's Kappa coefficient was calculated. The Kappa coefficient of agreement for a thematic map is based on the comparison of the predicted (classified) and actual (reference) class labels for each case in the set of ground test reference information points gathered to assess map accuracy. Values for the Kappa coefficient range between 0 and 1 (Table 5.3) and are commonly interpreted using a scale developed by Landis and Koch (1977).

The importance and power of the Kappa analysis is that it is possible to test whether the agreement between the land cover map and the reference data is significantly higher than zero, or, in other words, better than if the classified map had been generated by randomly assigning labels to areas (Congalton, 1991).

To test whether the agreement between the land cover map and the reference data as described by the Kappa coefficient is significantly higher than zero, Kappa variance was computed for each land cover map using Equation 5.3. (Couto, 2003).

Equation 5.3.

$$\text{var}(K) = \frac{1}{n} \left\{ \frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2 - \theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4 - 4\theta_2^2)}{(1-\theta_2)^4} \right\}$$

Where,

$$\begin{aligned} \theta_1 &= \frac{1}{n} \sum_{i=1}^k n_{ii} \\ \theta_2 &= \frac{1}{n^2} \sum_{i=1}^k n_{i+} n_{+i} \\ \theta_3 &= \frac{1}{n^2} \sum_{i=1}^k n_{ii+} (n_{i+} + n_{+i}) \\ \theta_4 &= \frac{1}{n^3} \sum_{i=1}^k \sum_{j=1}^k n_{ij} (n_{j+} + n_{+i})^2. \end{aligned}$$

The test statistic to test the significance of a contingency matrix is expressed in Equation 5.4.

Equation 5.4.

$$Z = \frac{K}{\sqrt{\text{var}(K)}}$$

Z is standardised and normally distributed. Considering the null hypothesis $H_0: K_1 = 0$ and the alternative $H_1: K_1 \neq 0$, H_0 is rejected if $Z \geq Z_{\alpha/2}$.

Therefore the null hypothesis (H_0), of no significant difference between randomly assigned pixels and the classification map, can be rejected at the widely used 5% level of significance if $Z > 1.96$ (Congalton and Meade, 1983; Congalton and Green, 1999).

5.5.3. Post-classification editing

Classified data often manifest a salt-and-pepper appearance due to the inherent spectral variability encountered by a classification when applied on a pixel-by-pixel basis (Lillesand *et al*, 2004). It is often desirable to smooth the classified output to remove "noise" from the dataset and the most common method used is majority filtering (Rencai *et al*, 2006).

Majority filtering involves moving a spatial kernel through the classification map and at each point within a 3x3 window the value of the centre pixel is changed to the majority class represented within that window. If there is no majority class in the neighbourhood the centre pixel is unchanged. As the window progresses through the data set, the original class codes are continually used and not the labels as modified from the previous window position (ERDAS, 2003).

Majority filtering was successfully applied to classification maps derived for a study area in St Louis, Missouri, USA (Huang *et al*, 2004). Of the four filtering methods evaluated, majority filtering

(via uniform square kernel) offered a 17% increase in classification accuracy. Similarly, Myeong *et al.* (2001) showed application of a majority filter on high-resolution imagery of a study area in Syracuse, New York to increase classification accuracy from 83.2% to 84.5%. A majority filter of uniform square kernel (3x3) was applied to the classified maps within ERDAS and the accuracy assessment was rerun to determine whether use of a filter could offer an improvement to classification accuracy of each of the classification methods evaluated.

Post-classification refinement was conducted for each of the maps to account for spectral similarities of certain classes. For instance, there was confusion between sparse mangrove and HAL signatures and parcels incorrectly classified as sparse mangrove within an urban area were recoded to HAL. Similarly areas of sparse mangrove fringing water bodies incorrectly classified as HAL were converted to sparse mangrove. There was also some confusion between dense mangrove and manmade inland waterways such as canals and marinas. Pixels in these areas incorrectly classified as mangrove were recoded to water.

Post-classification refinement was conducted manually based on visual interpretation of the satellite imagery and fieldwork. The classified maps were layer stacked within ERDAS to ensure consistency in the refinements carried out for each land cover map. The accuracy assessment was rerun following application of the majority filter and post-classification refinements.

5.6. Post-classification change detection

Post-classification change detection was conducted to quantify and visualise temporal and spatial changes in land cover for each of five time intervals (1973-1986; 1986-1999; 1999-2001; 2001-2002 and 1973-2002). Post-classification change detection is conducted on a per-pixel basis and consequently the maps used must be spatially co-registered or georeferenced so that the "from-to" information represents actual changes in land cover between dates and not spatial mismatch between the imagery. In addition the land cover maps must be resampled to the same spatial resolution.

Before conducting change detection the classified image datasets were standardised to a spatial resolution of 30m, the lowest spatial resolution of the data used. As the Landsat imagery is inherently coregistered, georeferencing was carried out for the SPOT datasets only. The classified SPOT imagery pertaining to years 1986 and 1999 in the dataset were georeferenced to the Landsat ETM+ dataset using a first order polynomial and nearest neighbour resampling with an RMSE of less than half a pixel (Chapter 4 section 4.3.5).

To determine "from-to" land cover change information the matrix utility within ERDAS was used and 49 "from-to" classes were generated from a seven-category land cover classification system for each time interval. The emphasis of this research is on the impact of human disturbance on land cover in particular the removal of pine, DEF and mangrove areas for development.

Consequently, the specific "from-to" classes of specific interest over the time period include the conversion of pine, DEF, sparse and dense mangrove land cover into HAL. To summarise the overall impact of human disturbance on vegetation, pine and DEF land cover classes were merged to form "vegetation" and both mangrove classes were combined to form the class "wetlands".

To investigate the temporal variability of land cover change, in addition to "from-to" land cover conversion values, percentage land cover amounts, relative land cover change values, summary statistics and average annual urban growth rate were computed for each of the time intervals. While change statistics describe the amount of change that has occurred over the time period they shed little light on where the changes have occurred. To assess the spatial variability in land cover change and the impact of human disturbance, detailed "from-to" land cover change maps were generated to show the conversion of DEF, pine and mangrove land cover classes to HAL for each time interval.

Individual land cover map classification errors often reveal unusual land cover conversions for example, the conversion of vegetation or wetlands to HAL. Unusual land cover conversions revealed from the "from-to" land cover change matrix were investigated and mapped for each of the time intervals. Finally, the relationship between population growth and growth in HAL as determined from the remotely sensed change maps was also examined.

• **Change detection accuracy assessment**

Change detection presents a unique problem for accuracy assessment since it is difficult to sample areas that will change in the future before they change (Congalton and Green, 1999). As mentioned previously a concern in change detection analysis is that error can propagate through multiple dates especially when more than two dates are used in the analysis (Yuan *et al.*, 2005). The simplest method of accuracy assessment of change maps is to multiply the individual classification map accuracies to estimate the expected accuracy of the change map (Yuan *et al.*, 1998). A more rigorous approach is to randomly sample areas classified as change and no-change and determine whether they were correctly classified (Fuller *et al.*, 2003).

The individual classification map accuracies for 1999, 2001 and 2002 can be multiplied to estimate the accuracy of the change maps constructed for those time intervals. However, due to poor data availability historic reference datasets were not available to assess the accuracy of the 1973 and 1986 classified maps. Furthermore, the only datasets available as a reference were those used in the classification. As a result, the change maps were assessed qualitatively by comparing the of areas of "change" and "no-change" identified by the post-classification change detection analysis to WFMI images constructed for the same time interval. WFM insertion images (described in Chapter 4 section 4.6) provide a visual display of differences in the spectral qualities of the image between dates and a qualitative means to assess the results of the post-classification change detection.

5.7. Conclusion

This chapter address the challenges of quantitative landscape change detection for a data-poor study area in the tropics and the application of a number of remote sensing procedures to identify suitable remote sensing variables for land cover classification was presented. PCA, the inclusion of temperature data and the use of data-fusion as potential improvements to land cover classification were detailed. SPOT HRVIR and Landsat ETM+ datasets, for which high-resolution information in the panchromatic waveband is available, were used and facilitated an evaluation of the robustness of the land cover classification methods tested.

While Chapter 4 describes the application of multitemporal PCA for qualitative time series change detection analysis, post-classification change detection was applied to provide both a quantitative and visual assessment of "from-to" land cover change information associated with human disturbance across the time series of imagery. In addition to visual, locational and quantitative land cover change information, changes to the spatial distribution and arrangement of land cover also need to be considered with respect to monitoring changes (EPA, 1999; Herzog and Lausch, 2000; Griffith *et al.*, 2002; Narumalani *et al.*, 2004). Development and application of remote indicators and spatial metrics that describe changes in landscape pattern and structure associated with human disturbance are presented in Chapter 6 and forms the third and final methodological chapter of this research.

Chapter 6

Methodology III: Remotely sensed indicators and spatial metrics for monitoring human disturbance

6.1. Introduction

Post-classification change detection techniques were applied to provide quantitative information on the type, rates and variability of change in landscape composition over the time period. However, in addition to areal coverage the geographic distribution of land cover patches is an important characteristic for evaluating the processes and effects of land cover change at the landscape level (Laurance and Bierregaard, 1997).

This chapter addresses Research Question 3 (Figure 4.1) and evaluates how a time series of land cover maps generated from five satellite sensors can be used to quantify and detect statistically significant trends in a unique set of remotely sensed indicators and spatial metrics derived to measure and monitor changes in the pattern and structure of natural landscape associated with human disturbance in a data-poor tropical island.

Derivation of remotely sensed indicators and spatial metrics facilitates comparison of changes in the spatial structure and distribution of land cover through time. A description of the derivation and selection of indices and spatial metrics and an evaluation of their suitability to characterise, quantify and assess human disturbance of a data-poor study area in the tropics is presented in sections 6.2 through 6.3.

6.2. Development and evaluation of a set of remotely sensed indicators to assess and monitor the impact of human disturbance

Seven indices describing natural landscape extent and disturbance were generated for the entire land area and these collectively represent features important to land resource managers attempting to quantify the impact of human disturbance on the natural landscape (Table 6.1). The application of the indices was also evaluated for monitoring human disturbance in the coastal zone. A 500m and 200m coastal buffer was selected based on the fact that development on the island has and continues to be, heavily concentrated along a narrow strip of coastal zone in particular along the northern and eastern shorelines, largely representing tourism-driven construction. The remotely sensed indicators were evaluated using simple linear regression to test the significance of the trends identified at the scale of the entire island and within 500m and 200m coastal zones.

In an attempt to express and compare the relative differences in human disturbance across the island over time, an eighth index; a composite index of overall human disturbance; was derived using 5 of the 7 indices describing natural landscape extent and disturbance for each map year.

Similarly, an overall index of human disturbance value was computed for a 500m and 200m coastal buffer pertaining to each land cover map in the time series. Linear regression was used to test the significance of the trends in land cover extent and disturbance identified through the indices.

These indices were derived for a time series of imagery spanning a 29-year time period and can be rapidly generated and updated for environmental monitoring purposes. They present a broad view of the extent and disturbance of natural landscape and have the potential to be cost efficiently and effectively applied to other islands in The Bahamas and beyond.

6.2.1. Data preparation

500m and 200m coastal buffer masks were generated using a vector file of the outline of the study area. The masks were used to subset the land cover maps to generate 500m and 200m coastal buffer land cover maps for each year in the time series to test the sensitivity of the indicators to changes in spatial extent and to determine whether the indicators can be applied to detect the impact of human disturbance within the coastal zone.

6.2.2. Development of remotely sensed indicators

Two of the eleven indices developed by Tiner (2004) describing the proportion of a watershed represented by natural vegetation (natural cover index) and current extent of vegetated wetlands to the estimated historic extent (wetland extent index) were used in this analysis. A further six indices of natural landscape extent and disturbance and one composite index appropriate for monitoring landscape change associated with human disturbance for a study area in the tropics, were developed as part of this research.

Areas of natural landscape in the context of the remotely sensed indicators are defined as areas of pine, DEF, mangrove and sand, land cover types. These areas are essentially unaltered by human development, comprising plant communities represented by forest, shrub thickets, grassland, mangrove swamps and coastal coppice. All other land areas are described as human altered, i.e. urban areas representing transportation networks, residential, commercial or industrial land uses, agriculture and areas of cleared land.

A total of eight indices were developed for use, four representing natural landscape extent and integrity (NLC, NLI, WI, VI) three representing land cover disturbance (HA, HD, HI) and one composite index (HDI) (Table 6.1). The indices were generated for the entire landscape and for a 500m and 200m coastal buffer. The derivation of each index is described in turn.

- **Index of Natural Landscape Cover**

The index of natural landscape cover (Equation 6.1) describes the proportion of natural landscape across the island and provides information as to the extent of undeveloped land cover. It is

computed as the ratio of natural landscape to the total land area of the island. The index has a maximum value of 1.0 and a minimum value of zero. The higher the value, the greater the amount of natural landscape present.

Equation 6.1.

$$NLC = \frac{A_{nlc}}{TA}$$

A_{nlc} is the area of natural landscape and is the sum of the areas of pine, DEF, mangrove and sand land cover types determined from the land cover maps. TA is total land cover area.

- **Index of Natural Landscape Integrity**

The index of natural landscape integrity (Equation 6.2) compares the current extent of natural landscape (sum of pine, DEF, mangrove and sand land areas) to the estimated historic extent. This index is an approximation of the extent of the original natural landscape acreage remaining on the island. The historic extent of natural landscape was estimated from the 1973 land cover map of the island. The index has a maximum value of 1.0 and a minimum value of zero. The greater the value, the more of the original land cover remains undeveloped.

Equation 6.2.

$$NLI = \frac{A_{nlc}}{A_{hnlc}}$$

A_{nlc} is the area of natural landscape and is the sum of the areas of pine, DEF, mangrove and sand land cover types determined for each land cover map and A_{hnlc} is the historic extent of natural landscape estimated from the 1973 land cover map.

- **Index of Wetland Integrity**

The index of wetland integrity (Equation 6.3) compares the current extent of mangroves (sum of dense and sparse mangrove land areas) to the estimated historic extent. This index is an approximation of the extent of the original wetland acreage remaining on the island. The historic extent of wetlands was estimated from the 1973 land cover map. The index has a maximum value of 1.0 and a minimum value of zero. The greater the value, the more of the original wetlands left undeveloped.

Equation 6.3.

$$WI = \frac{A_w}{A_{hw}}$$

A_w is the area of wetlands and is the sum of the areas of sparse and dense mangrove land cover types and A_{hw} is the historic wetland land cover estimated from the 1973 land cover map.

- **Index of Vegetation Integrity**

The index of vegetation integrity (Equation 6.4) compares the current extent of vegetation (sum of pine and DEF land areas) to the estimated historic extent. This index is an approximation of the

extent of the original vegetation acreage remaining on the island. The historic extent of vegetation was estimated from the 1973 land cover map. The index has a maximum value of 1.0 and a minimum value of zero. The greater the value, the more of the original vegetation left undeveloped.

Equation 6.4.

$$VI = \frac{A_v}{A_{hv}}$$

A_v is the area of vegetation and is the sum of the areas of pine and DEF land cover types and A_{hv} is the historic vegetation land cover estimated from the 1973 land cover map.

- **Index of Human Alteration**

The index of human alteration (Equation 6.5) describes the ratio of HAL to total land cover and provides information as to the extent of development across the landscape. It is computed as the ratio of HAL to the total land area of the island. The index has a maximum value of 1.0 and a minimum value of zero. The higher the value the greater the amount of development present.

Equation 6.5.

$$HA = \frac{A_{hal}}{TA}$$

A_{hal} is the area of HAL determined from the land cover maps. TA is total land cover area.

- **Index of Human Disturbance**

The index of human disturbance (Equation 6.6.) describes the ratio of HAL to natural landscape. This index is used to compare how the relationship between developed and undeveloped land has changed over time. The higher the value the greater the proportion of HAL to natural landscape area in the landscape and the greater the amount of development that has taken place.

Equation 6.6.

$$HD = \frac{A_{hal}}{A_{nlc}}$$

A_{hal} is the area of HAL and A_{nlc} is the area of natural landscape determined from the land cover maps.

- **Index of Human Impact**

The index of human impact (Equation 6.7) compares the current extent of HAL to the estimated historic extent. This index is used to compare the growth in HAL over the time period relative to its original extent. The historic extent of HAL was estimated from the 1973 land cover map of the island. The greater the value, the greater the degree of development took place.

Equation 6.7.

$$HI = \frac{A_{hal}}{A_{h_hal}}$$

A_{hal} is the area of HAL A_{h_hal} is the historic HAL coverage estimated from the 1973 land cover map.

- **Overall Index of Human Disturbance (HDI)**

In order to express the overall impact of human disturbance (Equation 6.8) as a single value to facilitate a comparison of the land cover maps across the time series, an eighth and final index was developed. The overall index of human disturbance (HDI) is a composite index comprising five of the natural landscape extent and disturbance indices. It is computed simply as the sum of the natural landscape extent and integrity indices subtracted from the sum of the indices of disturbance (human alteration, human disturbance and human impact); where higher values are indicative of a greater degree of human disturbance for the time period.

Equation 6.8.

$$HDI = (HA + HD + HI) - (NLC + NLI)$$

For the 1973 data the overall index of human disturbance does not include NLI or HI indicator values as they require historic estimates of land cover that predate 1973 and are not available.

It is acknowledged that reducing the indices to a single number may lead to overlooking the significance of individual indices and the values produced for the overall index of human disturbance were examined in relation to the individual index scores produced.

6.2.3. Remotely sensed indicators of coastal disturbance

Similar to the island wide indices, two indices describing natural landscape extent and integrity; three indices describing natural land cover disturbance and a composite index of overall coastal human disturbance were calculated for 500m and 200m coastal buffers.

- **Index of Coastal Natural Landscape Cover**

The index of coastal natural landscape (Equation 6.9) describes the proportion of natural vegetation within the coastal buffer and provides information as to the extent of undeveloped land cover within the coastal zone. It is computed as the ratio of natural landscape to the total land area. The index has a maximum value of 1.0 and a minimum value of zero. The higher the value, the greater the amount of natural landscape present.

Equation 6.9.

$$CNLC = \frac{A_{cnlc}}{TA}$$

A_{cnlc} is the area of coastal natural landscape and is the sum of the areas of pine, DEF, mangrove and sand land cover types determined from the land cover maps. TA is total coastal natural landscape area.

- **Index of Coastal Natural Landscape Integrity**

The index of natural landscape integrity (Equation 6.10) compares the current extent of coastal natural landscape (sum of pine, DEF, mangrove and sand land areas) to the estimated historic extent. This index is an approximation of the extent of the original natural landscape acreage remaining within the coastal zone. The historic extent of natural landscape was estimated from the 1973 land cover map. The index has a maximum value of 1.0 and a minimum value of zero. The greater the value, the more of the original land cover within the coastal zone remaining undeveloped.

Equation 6.10.

$$CLI = \frac{A_{cnlc}}{A_{hcnlc}}$$

A_{cnlc} is the area of coastal natural landscape and is the sum of the areas of pine, DEF, mangrove and sand land cover types determined for each land cover map and A_{hcnlc} is the historic extent of coastal natural landscape estimated from the 1973 land cover map.

- **Index of Coastal Human Alteration**

The index of human alteration (Equation 6.11) describes the ratio of HAL to total land cover and provides information as to the extent of development within the coastal zone. It is computed as the ratio of HAL to the total land area. The index has a maximum value of 1.0 and a minimum

value of zero. The higher the value, the greater the amount of development found within the coastal zone.

Equation 6.11.

$$CA = \frac{A_{hal}}{TA}$$

A_{hal} is the area of coastal HAL and TA is total land cover area of the coastal zone determined from the land cover maps.

- **Index of Coastal Human Disturbance**

The index of human disturbance (Equation 6.12) describes the ratio of HAL to coastal natural landscape. This index is used to compare how the relationship between developed and undeveloped land within the coastal zone has changed over time. The higher the value the greater the proportion of HAL to natural landscape area and the greater the amount of development that has taken place.

Equation 6.12.

$$CD = \frac{A_{hal}}{A_{cnlc}}$$

A_{hal} is the area of coastal HAL and A_{cnlc} is the area of coastal natural landscape determined from the land cover maps.

- **Index of Coastal Human Impact**

The index of human impact (Equation 6.13) compares the current extent of HAL to the estimated historic extent within the coastal zone. This index is used to compare the growth in HAL over the time period relative to its original extent; the greater the value, the greater the degree of development that has taken place within the coastal zone. The historic extent of HAL was estimated from the 1973 land cover map.

Equation 6.13.

$$CHI = \frac{A_{hal}}{A_{h_hal}}$$

A_{hal} is the area of coastal HAL A_{h_hal} is the historic coastal HAL coverage estimated from the 1973 land cover map.

- **Overall Index of Coastal Human Disturbance (CHDI)**

The overall index of coastal human disturbance (CHDI) is a composite index comprising all five of the coastal natural landscape extent and disturbance indices (Equation 6.14). It is computed simply as the sum of the natural landscape extent and integrity indices subtracted from the sum of the indices of disturbance (coastal human alteration, coastal human disturbance and coastal human impact); where higher values are indicative of a greater degree of human disturbance for the time period.

Equation 6.14.

$$\text{CHDI} = (\text{CA} + \text{CD} + \text{CHI}) - (\text{CNLC} + \text{CLI})$$

For the 1973 data the overall index of human disturbance does not include CLI or CHI indicator values as they require historic estimates of land cover that predate 1973 and are not available.

It is acknowledged that reducing the indices to a single number may lead to overlooking the significance of individual indices and the values produced for the overall index of coastal human disturbance were examined in relation to the individual index scores produced.

6.2.4. Testing the statistical significance of remotely sensed indicator trends through time

The objective was to determine whether a time-series of remotely sensed data gathered from five sensors could be used to quantify and detect trends in remotely sensed indicators of human disturbance for the period 1973-2002. The statistical significance of the trends displayed by the remotely sensed indicator values developed and determined for each year in the time series at the scale of the island and for a 500m and 200m area of coastal buffer, was tested using simple linear regression.

A simple linear regression model within SPSS was used to test the trends with time coded as 1 (1973), 14 (1986), 27 (1999), 29 (2001) and 30 (2002) as the independent variable and the spatial metrics as the dependent variables.

The regression was run separately for each of the indicators and values for R , R^2 , β and a probability value p were produced to test each remotely sensed indicator for a statistically significant ($p < 0.01$) linear trend over time where;

- R is the linear correlation between the observed and model predicted values of the dependent variable (the remote indicators) and a one-tailed statistical significance value for this correlation was also produced.

- R^2 is the coefficient of determination and describes how much variation in the dependent (remote indicators) variable is explained by model, i.e. it is the proportion of the total sample variability that is explained by the linear relationship between the dependent and independent (time) variables.
- β is the regression coefficient (slope) produced from an analysis of variance (ANOVA) and determines whether the trend is increasing or decreasing.
- The probability (p) value describes whether or not variation produced by the model is due to chance

6.3. Evaluation of the application of spatial metrics to detect statistically significant trends in changes in landscape pattern and structure to monitor human disturbance

The objective is to identify an appropriate set of spatial metrics that best reflect a landscapes temporal change using land cover maps derived from four different satellite sensors spanning a 29 year time period (1973, 1986, 1999, 2001, 2002). Methodological questions related to the selection of a manageable set of spatial metrics that embrace the structural properties of the landscape and the impact of scale and spatial resolution on the interpretability of spatial metrics to assess and monitor the impact of human disturbance over time are addressed.

6.3.1. Spatial metric selection

Fragstats v3.0 (McGarigal and Marks, 1995) computes values for a total of 115 landscape level metrics. Following an initial review of the spatial metrics available, 31 landscape metrics were selected representing patch area (13), shape (5), diversity (6) and contagion (7) categories detailed in Tables 6.2, Table 6.3, Table, 6.4 and Table 6.5 respectively. The neighbourhood category represented by isolation, proximity and contrast metrics was not used in the analysis. These metrics are not suitable for calculation at the landscape level and irrelevant in the context of the present study. For instance isolation and proximity metrics are fundamentally patch-level metrics and relate to the context of habitat patches, rather than the spatial character of the patches themselves. Contrast metrics refer to the magnitude of difference between adjacent patch types with respect to one or more ecological attributes at a given scale that are relevant to an organism or process under consideration.

6.3.2. Testing the statistical significance of the temporal trends in landscape pattern and structure identified by the spatial metrics

The objective was to identify which spatial metrics (out of a suite of 31 landscape level metrics analysed), display statistically significant trends over time and to what extent the metrics identified can be interpreted in terms of human disturbance.

To determine whether spatial metrics can provide a comprehensive method for the description of land cover change processes associated with human disturbance over time, the statistical significance of the trends identified was tested using simple linear regression within SPSS.

Linear regression was applied earlier (section 6.2.4) to test the statistical significance of the remotely sensed indicators developed as part of this research and is applied in the same way here. Spatial metrics displaying statistically significant trends ($p \leq 0.5$) were further examined to determine to what extent the metric values quantifying changes in landscape pattern and structure over time can be interpreted as a function of human disturbance.

To determine an appropriate set of metrics for monitoring changes in landscape pattern and structure over time the sensitivity of the spatial metrics to changes in spatial extent and scale (grain size) was also examined.

6.3.3. Testing the sensitivity of spatial metrics to changes in spatial extent

It has been widely recognised that spatial pattern and structure quantified by spatial metrics are dependent on the spatial resolution and extent of the study area, as well as the level of detail in the thematic classifications (Wu *et al.*, 2000; Wu *et al.*, 2002; Herald *et al.*, 2003).

To test the sensitivity of the metrics to changes in spatial extent and to simultaneously determine whether significant trends in changes in landscape pattern and structure for an area of coastal zone could be identified, spatial metric values were generated for 500m and 200m coastal zone buffers and evaluated. Spatial metric values were calculated for the areas of coastal zone for each year in the time series.

To test the robustness of the metrics, the results produced from the landscape analysis were compared the results generated from the areas of coastal zone to determine whether similar trends in the metrics over time were identified at different spatial extents. In addition, correlation analysis (Pearson's two-tailed) was used to determine whether the relationship between the spatial metrics generated at the landscape level changed with changing spatial extent i.e. to test whether the metric values generated for the coastal buffer zones were similar to the metric values generated for the landscape as a whole.

This information is needed to determine which spatial metrics are robust across changes in spatial extent and therefore suitable to describe changes in landscape pattern and structure over time for the entire landscape and for areas of coastal zone.

6.3.4. Testing the sensitivity of spatial metrics to changes in scale (map resolution)

To understand how changes in map resolution alters the scale of a map and affects the spatial metric values generated as part of this study; grain size (pixel size) of each land cover map was systematically increased from 1x1 (30m) to 20 x 20 (600m) pixels. This is a straightforward process and was carried out within ERDAS using the Aggie_GIS_Aggregation utility. Once window size (new pixel size) has been inputted a single land cover type is assigned within that window based on the majority rule. Each new aggregated areal unit is assigned to the patch type (class) most dominant among those presented by all the pixels at the next lower level. When two or more patch types or classes are tied, a random selection is allowed. The aggregation at each successive grain size commenced with the original (1 x 1 pixel) data and is referred to as an independent aggregation scheme (Wu et al., 2004).

The classified maps of New Providence were resampled to reproduce the land cover map at coarser resolutions with cell sizes ranging from 60m to 600m (Figure 6.1). Spatial metrics were calculated for the different cell sizes and the value of the metric was plotted against cell size. Response curves were generated for each metric to determine whether an appropriate scale for analysis of trends in landscape patterns across the archipelago over the time period can be identified and whether the response of spatial metrics to scale was consistent across the multitemporal and multisensor dataset.

6.3.5. Metric interpretation and final selection

Following regression analysis and tests of robustness (sensitivity to changes in spatial extent and map resolution) the metrics were interpreted, evaluated and a final set selected as suitable and appropriate indicators to describe changes in landscape pattern and structure to associated with human disturbance over time.

6.4. Conclusion

Remote sensing offers an important means of detecting and analysing temporal changes across the landscape. This final methodology chapter addressed the development and application of a unique set of remote indicators to describe natural habitat extent and disturbance and spatial metrics to describe landscape pattern and structure, for landscape monitoring of a tropical area with poor data availability. Many change detection investigations tend to focus on a general description of land cover and present satellite data as a qualitative tool for studying specific ecosystems. In addition to studying the composition of landscape types, their spatial distribution and general arrangement need to be considered for monitoring changes (Chapter 2, Section 2.5).

While quantitative measurements for landscape pattern described by spatial metrics have been used to link ecological and environmental processes with patterns found in the landscape few studies if any have employed quantitative measurements to estimate and detect statistically significant temporal trends (i.e. using data derived from more than two time periods) in spatial metrics associated with human disturbance. Eight remotely sensed indicators and a suite of 31 spatial metrics were applied to a time series of medium-resolution satellite imagery from five different satellite sensors to detect statistically significant trends in changes in landscape pattern and structure to monitor human disturbance. The techniques developed and evaluated as part of this research present an important development of the application remote indicators and spatial metrics for landscape monitoring in data-poor island environments.

Chapter 7 Results I: Visualising changes in the landscape

7.1. Introduction

To address how medium-resolution satellite imagery from different sensors can be combined to effectively visualise changes in the landscape, multitemporal selective PCA as a method of identifying the sequence of human induced disturbance in a time series analysis was applied to the pre-processed dataset and evaluated.

NDBI and BI indices were evaluated as a potential improvement to multitemporal PCA to determine whether changes in these measures through time can be used to successfully highlight human disturbance and outperform measures of brightness, greenness and NDVI. The sensitivity of the success of each method to the time intervals used in the time series was also tested. The multitemporal PCA methods were evaluated in their ability to identify areas of no-change using aggregate standard deviation values calculated from areas of no-change and information content derived for each respective PC image.

7.2. Data pre-processing

7.2.1. Radiometric corrections

Radiometric corrections were undertaken to standardise each image in the time series of medium-resolution remotely sensed data. In the first instance image DN numbers were converted to radiance ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$) using Equation 4.1 for Landsat image files and 4.2 for SPOT image files. Spectral gain and bias values were derived from header files associated with each sensor and image waveband (Tables 7.1, 7.2 and 7.3) from which DN to radiance conversion equations were derived (Tables 7.4, 7.5, and 7.6.) and applied to the imagery using the Spatial Modeller function in ERDAS.

Following the calculation of radiance values, the image files were converted into atmospherically corrected reflectance values using COST correction. Path radiance due to atmospheric effects (L_p) was calculated first (Equation 4.6), the parameters for which are presented in Tables 7.7 and 7.8. Dark object values or DN minimum values with at least 1000 pixels (Table 7.9) were determined from the image file attribute tables were converted into radiance values (Table 7.10). Values for L_p computed via Equation 4.6 were then used to calculate atmospherically corrected surface reflectance values for each image in the time series.

7.2.2. Geometric corrections

Using 13 reference GCP's gathered at various locations across New Providence, both SPOT images (1986 and 1999) were successfully spatially coregistered to the Landsat ETM+ imagery with an acceptable RMSE value of less than 0.5 pixel size (Table 7.11).

7.3. Correlation Analysis

Correlation analysis was carried out within ERDAS to determine the degree of intra-annual and inter-annual spectral similarity of the spectral bands and indices generated to support the use of PCA to reduce the spectral dimensionality of the multispectral datasets to single univariate surfaces (representing brightness, NDVI, NDBI and BI). The results are presented in Tables 7.12 and 7.13 where Green, Red, NIR and MIR are representative of Landsat MSS, TM and ETM+ bands 2,3,4 and 5; and SPOT HRV and HRVIR bands 1, 2, 3 and 4. MIR band values exist for Landsat TM, ETM+ and SPOT HRVIR sensors only.

Intra-temporal correlation matrices (Table 7.12) reveal a strong positive association between the visible red and green bands for each time period. In general the NIR and MIR bands show a low to moderately positive correlation with the visible bands. A strong positive association exists between the NIR and MIR. The NDVI index displays poor correlation with the visible wavebands. The NDBI index displays poor correlation with the visible and infrared wavebands and a moderate negative correlation with the NDVI values generated by all sensors. In general a weak to moderate negative correlation exists between the NDBI and the NIR waveband. The BI index displays a moderate positive correlation with the visible and MIR bands and weak correlation with NDVI and NDBI.

Inter-temporal correlation matrices (Table 7.12) reveal a consistently moderate correlation between the green bands across all years. The weakest association is evident between 1973 (Landsat MSS) and 1986 (SPOT HRV) and the strongest between 2001 and 2002 (both Landsat ETM+). A similar but stronger trend was found for red bands with the exception that the weakest correlation is between 1973 (Landsat MSS) and 2001 (Landsat ETM+). A strong positive association is evident for the NIR bands (strongest between Landsat ETM+) and a similar trend but slightly lower correlation is evident between the MIR bands for each year.

The NDVI displays a moderate to strong correlation across sensors, the weakest correlation evident between 1973 (Landsat MSS) and 2002 (Landsat ETM+) and the strongest between 1985 (Landsat TM) and 1986 (SPOT HRV). The NDBI displays a moderate positive correlation across sensors with the strongest association at 0.88 between 2001 and 2002 (Landsat ETM+). The BI displays a similar relationship across sensors with a maximum of 0.88 between 2001 and 2002.

7.4. Multitemporal PCA

A total of seven multisensor and multiresolution remotely sensed images (Chapter 4, Table 4.3) were acquired for the study area spanning a 29-year time period. To evaluate the success of multitemporal PCA to visualise the impact of human disturbance across study area a number of spectral ordination techniques were applied and tested. Three techniques to produce univariate surfaces representing image brightness, image greenness, and NDVI have been tested in the literature (Millward *et al.*, 2006) and were evaluated as part of this research for their suitability for use on medium-resolution satellite imagery acquired from five different sensors for a study area in

the tropics. In addition, a further two spectral ordination techniques NDBI and BI were tested and evaluated for their suitability for use in multitemporal PCA as a new approach and potential improvement to the methodology. The performance of the NDBI and BI indices in multitemporal PCA was evaluated to determine how well the indices perform compared to measures of brightness, greenness and NDVI in highlighting landscape change associated with human disturbance.

As some of the years in the time series were acquired consecutively and derivation of the NDBI and BI indices requires spectral reflectances recorded in the MIR (precluding the use of the Landsat MSS 1973 and SPOT HRV 1986 imagery); in order to test and evaluate the application of multitemporal PCA to visualise landscape changes associated with human disturbance, a number of temporal combinations (Table 7.14) of imagery were selected for use from the suite of seven images. This analysis also facilitated an examination of the sensitivity of the success of the methods to the time intervals used.

7.4.1. Evaluation and interpretation of multitemporal PCA to identify areas of change

To evaluate and interpret the performance of multitemporal PCA, the percent of total input band variance explained by each PC was calculated and is presented as an overall indication of success of the PC images generated to visualise the impact of human disturbance. Input band variance measures unique information content and higher order PCs comprising a greater percentage of total input band variance contain a greater amount of change information.

The percent contribution of each individual input band year in the time series to the PC images was calculated to facilitate interpretation of the PC images produced for each of the multitemporal PCA methods (brightness, greenness, NDVI, NDBI and BI). In addition, factor loadings which represent the degree of correlation between each input year and PC image were computed to determine whether the most highly contributing year loaded negatively or positively in the component image. Factor loadings and input band contributions used to evaluate the success of multitemporal PCA cannot be used to infer reasons for change but instead identify areas in the study area that have undergone landscape change.

Overall and individual input band variance values and factor loadings are presented first, followed by an interpretation of each of the PC images pertaining to the multitemporal PCA methods tested. The results are ordered by PCA method followed by time series. The results from the performance of multitemporal PCA for derivation of changes in brightness, greenness and NDVI for each time series are presented first, followed by the results from the multitemporal PCA for derivation of changes in NDBI and BI.

- **Results: Brightness, greenness and NDVI: 1973-1986-1999-2002 time series**

Higher order PC images produced from multitemporal PCA on the brightness time series contain a greater percent of total input band variance (totalling 21.7%). Higher order PCs produced by PCA on a time series of NDVI and greenness images explain 20% and 4% of total variance respectively (Table 7.15).

For the brightness series the percent contribution of each individual band to the PCs (Table 7.16) was highly variable and clearly highlights distinct years as having a greater or lesser influence on the component structure. Percent contribution by input band is more evenly distributed across PC1 than the other three components. This is expected given that PC1 represents the maximum amount of variance between input years.

Loading values presented in Figure 7.1, were also separable according to input band year. PC1 loading values are moderate to strongly positive (correlation range 0.76-0.93), demonstrating that little change information is contained within PC1.

PC2 (accounting for 9.1% unique information content) shows a positive loading (0.44) from the 1986 brightness image (49.50% variance contribution) and a negative loading (-0.44) from the 1973 brightness image (35.54% variance contribution) and the 1999 and 2002 images (representing 2.86% and 12.11% input variance respectively). Visual examination of PC2 in comparison with the 1973 and 1986 imagery reveals that new urban features present on the 1986 image but not on the 1973 image appear as bright white signatures. Dark signatures reveal development that has taken place between 1986 and 2002.

Two subsets of the image presented in Figure 7.2 and Figure 7.3 illustrate a) development that has taken place around the Cable beach area of New Providence (including new roads) b) development around Venice Bay to the south of the island between 1973-1986 and 1986-2002 (illustrated using yellow arrows).

PC3 (accounting for 7.3% unique information content) displays a strong positive loading and high percent contribution (48.65%) from the 2002 input year and a strong negative loading from the 1973 input year, the second largest contributor to PC3 variance (42.91%). It is clear upon visual inspection of the PC image and input year imagery (Figure 7.4) that bright white signatures in the PC image correspond with areas of high reflectance in the 2002 image, which represent urban development. These areas are not distinguished in the 1973 image. As the 2002 input year contributes most strongly to the overall variance of PC3 and is positively loaded, areas of urban development (with high reflectance values) present in the 2002 image but not in the 1973 image have been highlighted by the PC3 image. Dark black tones highlight areas where reflectance in the red and green wavebands was particularly high for the 1973 image.

Input variance to PC4 (accounting for 5.3% unique information content) by 1999 at 63.82% is the largest contribution by a single year out of all four principal components. Loading values from this band are negative (-0.36) with positive loadings from the 1973, 1986, 1999 and 2002 input years contributing 9.3%, 1.24% and 25.59% to band variance respectively. A comparison of the reflectance from the SPOT NIR wavebands for the 1986 and 1999 input bands and PC4 (Figure 7.5) reveals that areas of development present in the 1999 image (in bright white tones) but not visible in the 1986 image, correspond to the dark black signatures across PC4. Areas of development between 1986 and 1999 are clearly represented by PC4 in dark black tones. Bright white tones in the PC4 image highlight urban areas and areas of cleared land with high spectral reflectance values in 1986.

Similar to the brightness series the percent contribution of each individual band to the PCs produced from the greenness time series (Table 7.17) is highly variable with distinct years having a greater or lesser influence on the component structure. Loading values or correlation between each input year and the greenness PC1 are highly positive (correlation >0.90 for all input years) with very little variation and demonstrate that little change information is contained within PC1 (Figure 7.6).

The 1986 input year presents the greatest contribution to PC 2 variance (73%) and is positively loaded. PC2 accounts for 2.1% unique information content. 1999 presents the second greatest contribution to variance (24.85%) and is negatively loaded. Bright white signatures in the PC2 image (Figure 7.7) correspond to urban areas in the 1986 image i.e. areas displaying high NIR reflectance in 1986. As the 1999 image is negatively loaded it is anticipated that strong NIR reflectance in 1999 is represented by dark black tones. Dark black signatures in the PC image represent areas where the NIR reflection is greater in the 1999 image compared to the 1986 image. Areas displaying higher reflectance values in the NIR between the time intervals largely represent areas of new urban development or differences in vegetation vigour.

PC3 (with 1.3% unique information content) is dominated by the 2002 input year and with positive loading contributing 76.2% to total input band variance. The 1999 input year contributes to 17.59% of total variance and is loaded negatively. Bright white signatures in the PC image highlight areas with high reflectance in the NIR in 2002 (Figure 7.8). Dark areas represent regions with high reflectance in the NIR in 1999 or areas where reflectance in the NIR has decreased between dates. This could indicate an improvement in vegetation vigour or differences in soil moisture content between image acquisition dates. It is very difficult to determine specific urban change information from this PC image, because areas of vegetation prior to 1999 that have been developed in the time interval to 2002 also display bright signatures. Areas of urban change are more clearly identifiable using NIR reflectances via WFMI. By displaying 2002 NIR values through the red channel and 1999 NIR values through the blue and green channels, areas displaying an increase in NIR reflectances are highlighted in red (Figure 7.9).

PC4 (with 0.6% unique information content) is largely represented by the 1973 input year with an 84.07% contribution to total variance. 1973 input year is loaded positively and the remaining input years loaded negatively with the second largest contribution to variance from 1999 (13.97%). Areas of healthy vegetative cover in 1973 are displayed in dark tones throughout the image and correspond to areas where the NIR reflectance values have increased over the time period associated with development (Figure 7.10). However, it is difficult to discern specific change information from the image given the poor variation in contrast across the PC image.

Percent contribution values by input year for the NDVI time series are presented in Table 7.18. As for the brightness and greenness series, PC1 derived from a multitemporal PCA on a time series of NDVI images contains most of the variance of all four input bands with little variation in loading values (correlation is highly positive for all bands with a minimum correlation value of 0.85 illustrated in Figure 7.11) demonstrating that little or no change information is contained in PC1.

PC2 (with 11.9% unique information content) receives the greatest input from the 1973 image at 62.56% (strong negative loading) followed by the positively loaded 2002 image representing 29.5% contribution to variance. Visual analysis of the PC2 image reveals dark signatures to be associated with areas that were vegetated in 1973 and hence displayed high NDVI reflectance and can be associated with areas of urban development the introduction of new roads and buildings to the landscape are clearly visible (Figure 7.12). Bright signatures represent areas from the 1973 image where NDVI reflectance was low but in the 2002 image represent areas of high NDVI reflectance associated with healthy vegetative cover.

PC3 (with 6.0% unique information content) receives the greatest contribution to variance from the 2002 image at 48.53 and the 1999 image at 37.25%. Areas in the PC3 image associated with a decrease in NDVI reflectance are highlighted clearly in bright white signatures and upon inspection (Figure 7.13) are associated with areas vegetated prior to 1999 and subsequently developed by 2002. Areas that have undergone urban development between 1999 and 2002 are clearly discernible. Dark black signatures evident in the image are associated with areas of low NDVI reflectance in 1999 and correspondingly higher NDVI reflectance in 2002, representing areas in 2002 with greater vegetation vigour than 1999 (Figure 7.13).

PC4 (with 2.0% unique information content) is dominated by the 1986 and 1999 input years with 72.86% and 26.19% respective contribution to variance. The 1986 input year is negatively loaded and areas with low NDVI reflectance in 1986 and correspondingly higher reflectance in 1999 have bright white signatures. In comparison with the NDVI image from 1986 these areas are associated with urban features, such as roads, buildings and cleared land. Dark black signatures represent areas where the NDVI values have decreased between the time intervals and can be associated with areas of new development illustrated in Figure 14 but change information is much less clear for this PC image as the change signatures are in dark tones. Change information expressed by PC4 is compared to a WFMI image (generated using the NDVI images from 1999 and 2002) and

the original NDVI images from 1999 and 2002 (Figure 7.14). Although PC4 illustrates the introduction of new urban features, the signatures are expressed in dark tones and change information is a little more difficult to decipher.

In summary, multitemporal PCA on a suite of brightness greenness and NDVI imagery generated for each year for the 1973-1986-1999-2002 time-series clearly illustrate landscape change associated with human disturbance on the island of New Providence, The Bahamas. Percent contributions to variance by the input years for all three methods were highly variable and highlighted distinct years of influence on the component structure (Tables 7.16 - 7.18). A breakdown of the change information presented by each PC image generated for the brightness, greenness and NDVI time series is presented in Table 7.19.

- **Results: Brightness, greenness and NDVI: 1985-1999-2001-2002 time series**

Brightness, greenness and NDVI time series were generated for a second suite of multitemporal images from the dataset, to determine to what extent the selection of time intervals used in the time series affects the success of the PCA methods to visualise landscape change over the time period. Furthermore, testing the suitability of NDBI and BI indices as new approaches to spectral ordination for use in multitemporal PCA (and to compare the results to the success of brightness, greenness and NDVI) requires the incorporation of imagery with spectral reflectances recorded in the MIR. For this reason the Landsat TM 1985 image was used in place of the SPOT HRV 1986 image although of poorer quality to the 1986 image owing to partial cloud cover.

In contrast to the 1973-1986-1999-2002 time series cumulative unique information content (% variance values) for higher order PCs generated following multitemporal PCA on input years 1985-1999-2001-2002 was greater for the NDVI (22.7%) over brightness (13.2%) and greenness (4.8%) (Table 7.20).

The percent contribution of each individual band to the brightness PCs (Table 7.21) was highly variable and highlights distinct years as having a greater or lesser influence on the component structure. Percent contribution by input band is more evenly distributed across PC1 than the other three components. This is expected given that PC1 represents the maximum amount of variance between input years.

Loading values (Figure 7.15) were also separable according to input band year. For PC1 the loading values are positive (correlation range 0.88-0.97) and demonstrate that little change information is contained within PC1. Percent contribution by individual input band is more evenly distributed than for the other component images, indicating that little change information is contained in PC1.

PC2 (7.1% unique information content) shows a positive loading (0.46) from the 1999 brightness image with a 70.69% contribution to variance. The 2002 image is negatively loaded contributing

18.44% to variance. Urban features developed between the time period, such as new roads and residential developments are displayed dark black signatures for two subsets of the study area in Figure 7.16.

PC3 (4.3% unique information content) is dominated by input from the strongly negatively correlated 1985 image with 83.43% contribution to variance. Both 1999 and 2002 input years are loaded positively and contribute almost equally to PC variance at 8.20% and 7.08% respectively. Bright white signatures represent areas of landscape change that are clearly associated with urban expansion e.g. the development of Lyford Cay to the west and Cable beach to the north of the island as illustrated in Figure 7.17. Dark signatures represent areas on the island where the reflectance values from the red and green wavebands were higher in 1985 associated with cloud cover and areas of land cleared for development.

PC4 (1.8% unique information content) receives the greatest percent contribution to variance from the 2001 (59.66%) followed by the 2002 (39.44%) input years. The 2001 image is positively loaded and bright white signatures in the PC image illustrate the introduction of new urban features between the 2001 and 2002. Despite the fact the image is speckled and noisy in appearance, the continued expansion of Nassau and the construction of new roads on the island between 2001 and 2002 is evident from Figure 7.18.

Following the completion of the brightness time series analysis, multitemporal PCA was conducted on the greenness time series of imagery. The percent contribution of each individual band to the greenness PCs is presented in Table 7.22. Aside from PC1, the contribution to variance is variable and highlights distinct years as having a greater or lesser influence on the component structure.

Loading values (Figure 7.19) were also separable according to input band year. For PC1 the loading values for all input years are strongly positive (correlation range 0.96-0.99) and demonstrate that little change information can be derived.

PC2 (with 2.2% unique information content) receives 68.35% variance contribution from and negative correlation with the 1985 input year. 29.68% variance is contributed from the 1999 image. The 1999 input year displays positive correlation with PC2. From Figure 7.20 it is clear that very dark areas on the PC2 image correspond with areas of high reflectance values in 1985 including cloud, cleared land and urban features. Bright white signatures highlight areas on the landscape where NIR reflectances have increased between 1985 and 1999 including areas that were masked by cloud or converted from vegetation to urban land cover between the time periods.

PC3 (with 1.9% unique information content) displays positive correlation with and paired contribution from the 2001 and 2002 input years that represent 32.09% and 30.7% of variance respectively. PC3 displays negative correlation with both the 1985 and 1999 images, which contribute 8.42% and 28.79% respectively to variance. Dark signatures on the image correspond

with areas of high reflectance in the 1985 image, mostly associated with cloud cover and urban features (Figure 7.21) that display a lower NIR reflectance value in 2002. Bright reflectances visible in the image highlight new urban development between 1985 and 2002.

PC4 (with 0.7% unique information content) receives 52.04% and 46.32% contribution to variance from the 2002 and 2001 input years respectively. The 2002 input year displays positive correlation with PC4 and bright signatures across the image clearly highlight the development of a new road and new urban development around Nassau during the time period illustrated using yellow arrows in Figure 7.22. Brighter reflectances (areas representing an increase in NIR reflectance values) are also discernible from areas that remain vegetated between 2001 and 2002 and could be associated with changes in soil moisture content or a decrease in canopy cover. Dark reflectances highlight areas that display higher reflectance values in 2001 than in 2002 associated with a decrease in NIR reflectance over the time period.

PC4 explains a very low percentage of overall variance and visualisation of change information between the time periods is more effective using an WFMI generated using atmospherically corrected NIR (or band 4) reflectances recorded in 2001 and 2002 by Landsat ETM+ (Figure 7.23). Differences in spectral reflectance values between the time periods are presented in blue (associated with a decrease in NIR reflectance values between 2001 and 2002) and red (associated with an increase in NIR reflectance values between 2001 and 2002) in the WFMI image.

Multitemporal PCA was conducted on the NDVI 1985-1999-2001-2002 time series of imagery. The percent contribution of each individual band to the NDVI PCs is presented in Table 7.23. Aside from PC1, the contribution to variance as for the brightness and greenness time series is variable and highlights distinct years as having a greater or lesser influence on the component structure.

Loading values (Figure 7.24) were separable according to input band year. For PC1 the loading values for all input years are strongly positive (correlation range 0.84-0.91) and demonstrate that little change information can be derived from this PC image.

PC2 (with 14.3 unique information content) is contributed to most by the 2001 input year at 68.75% with strong negative correlation. 1999 contributes 17.10% and loads positively with PC2. Visual examination of PC2 in comparison with 1999 and 2001 NDVI imagery (Figure 7.25) reveals that bright white signatures produced as a result of a decrease in NDVI reflectance values between 1999 and 2001, predominantly correspond with areas of new urban development. Bright white signatures in areas that have remained vegetated between the dates could be associated with changes in soil moisture content or canopy cover, which would contribute to lower NDVI values. Dark black reflectances in the PC image (of which there are few) highlight areas where NDVI values have increased between 1999 and 2001.

PC3 (with 6.4% unique information content) receives 68.75% and 28.43% contribution to input variance from the 2002 and 1999 input years respectively. Areas of new urban development associated with a fall in NDVI reflectance values are displayed in bright white signatures (Figure 26). Urban expansion (new roads and the continued development of Nassau) between the time periods is also illustrated clearly using WFMI. Areas of NDVI increase and decrease between dates are visible in blue and red signatures respectively (Figure 7.26) corresponding with the bright white signatures visible on the PC image.

PC4 delivers change information associated with differences in NDVI reflectances recorded between 1985 and 1999. Strong positive loading from the 1999 input year means that dark black signatures on the PC4 image are associated with a decrease in NDVI between dates which correspond to the expansion of Nassau International Airport and areas of new urban development around Cable Beach and Nassau (Figure 7.27). Bright white reflectances highlight areas where NDVI has increased between the dates and corresponds to areas of cloud cover and cleared land in 1985.

In summary, multitemporal PCA on a suite of brightness, greenness and NDVI imagery generated for each year for the 1985-1999-2001-2002 time-series clearly illustrates landscape change associated with human disturbance on the island of New Providence, The Bahamas. Percent contributions to variance by the input years for all three methods were highly variable and highlighted distinct years of influence on the component structure (Tables 7.21 - 7.23). A breakdown of the change information presented by each PC image generated for the brightness, greenness and NDVI time series (input years 1985-1999-2001-2002) is presented in Table 7.24.

- **Results: NDBI and BI: 1985-1999-2001-2002 time series**

To test the suitability of NDBI and BI indices as new approaches to spectral ordination for multitemporal PCA, NDBI and BI values were generated for each year in the 1985-1999-2001-2002 time series. To measure the success of these methods to highlight landscape change associated with human disturbance the results from the analysis are compared to multitemporal PCA conducted on the brightness, greenness and NDVI time series generated for the same input years.

Higher order PC images produced from multitemporal PCA on the NDBI time series contain a greater percent of total input band variance, amounting to 26.2% compared to the BI higher order PC images which explain 21.6% (Table 7.25). The percent contribution of each individual band to the NDBI PCs (Table 7.26) was highly variable highlighting distinct years as having a greater or lesser influence on the component structure. Percent contribution by input band is more evenly distributed across PC1 than the other three components as PC1 represents the maximum amount of variance between input years.

Loading values (Figure 7.28) were also separable according to input band year. PC1 describes 73.8% of total variance with highly positive loading values (correlation range 0.75-0.90), which demonstrates that little change information is contained in the first PC image.

The 1999 input year is positively correlated to PC2 (which describes 17.0% unique information content) and contributes to 51.98% variance. There are large contributions to variance by the 2001 and 2002 input years also at 27.77% and 18.04% respectively. Both input bands are negatively correlated to PC2. Figure 29 displays a subset of the study area to illustrate that dark black signatures are associated with areas that display an increase in NDBI values between 1999 and 2002. A large area of natural forest south of Lake Kennedy displays an increase in NDBI which points to an increase in soil reflectance possibly associated with a decrease in canopy cover, soil moisture content or vegetation vigour.

Bright white signatures on the image represent areas on the island where the NDBI values have decreased between 1999 and 2002. These signatures are associated with an increase in vegetation vigour associated with greater NDVI values and hence lower NDBI values in 2002. As 2002 is negatively correlated with PC2, the decrease in NDBI values between dates is brightly highlighted in the image. Areas of vegetation including playing fields and a golf course are clearly visible and are illustrated using yellow arrows in Figure 7.29.

The 1985 input year displays strong negative correlation to PC3 (with 5.5% unique information content) and contributes 83.36% to PC3 variance. The 1999 and 2002 images both contribute to just under 8% of total input band variance and are positively correlated to PC3. Dark areas on the PC3 image describe areas where the NDBI value was higher in 1985 compared to 2002 and corresponds to areas of cloud cover, cleared land and development. Bright signatures occur where NDBI values have increased between dates, these dominate the image, making interpretation of specific change information extremely difficult (Figure 7.30).

PC4 (with 3.7% unique information content) is positively correlated with the 2002 and negatively correlated with the 2001 input year images. Both explain almost equivalent amounts of input band variance at 46.15% (2001) and 46.11% (2002). Bright white signatures highlight regions where the NDBI values have increased between 2001 and 2002 and very dark signatures draw attention to areas where NDBI values have decreased. While the construction of two new roads and continued development of Nassau between 2001 and 2002 is evident (Figure 7.31) the image is speckled and noisy making it difficult to determine precise change information in the absence of local knowledge.

Finally, the percent contribution of each individual band to the BI PCs (Table 7.27) was also highly variable highlighting distinct years as having a greater or lesser influence on the component structure. Similarly, percent contribution by input band is more evenly distributed across PC1 than

the other three components as PC1 represents the maximum amount of variance between input years.

Loading values (Figure 7.32) were separable according to input band year. As PC1 describes 79.6% of total variance and all input years are positively loaded very little change information is contained in the first PC image.

PC2 (with 10.4% unique information content) is highly positively correlated with the 1999 image. 1999 represents 71.93% of input to overall variance. PC2 is also positively correlated with the 1985 image, which contributes almost 20% to PC variance. The 2002 image displays negative correlation with PC2 and a contribution of 7.3% to variance. Because of the high percentage contribution to variance and positive correlation to PC2 provided by 1985 and 1999 specific change information is not clear from this PC (Figure 7.33).

PC3 (with 5.6% unique information content) is strongly negatively correlated with the 1985 image and positively correlated with both the 1999 and 2002 images. The 1985 input band year contributes the most to PC3 variance at 61.36%, followed by the 1999 input year at 23.54% and 2002 at 9.41%. A comparison with the 1985 and 2002 BI images reveals the association between bright white signatures on the PC3 image and areas of landscape change between 1985 and 2002, mostly associated with urban development (Figure 7.34).

PC4 (with 4.4% unique information content) is negatively correlated with the 2001 image and positively correlated with both the 1985 and 2002 images. The 2001, 1985 and 2002 images contribute 51.79%, 14.69% and 32.61% to PC4 variance respectively. Despite the fact that both 1985 and 2002 input years display positive correlation with and high contribution to PC4 variance (and the image's speckled and grainy in appearance) change information can be determined from the image. The addition of new roads and further development around Nassau between the time interval is illustrated using yellow arrows in Figure 7.35.

In summary, multitemporal PCA on a suite of NDBI and BI imagery generated for each year for the 1985-1999-2001-2002 time-series illustrates landscape change associated with human disturbance on the island of New Providence, The Bahamas. Percent contributions to variance by the input years for both methods were variable and highlighted distinct years of influence on the component structure (Tables 7.26 – 7.27). A breakdown of the change information presented by each PC image generated for NDBI and BI time series is presented in Table 7.28.

7.4.2. Evaluation and interpretation of Multitemporal PCA to identify areas of little or no change

The success of multitemporal PCA methods to identify areas of little or no change was assessed. Within ERDAS, locations identified as exhibiting landscape change (Figure 7.36) and little or no change (Figure 7.37) were manually digitised on-screen and used to subset each of the PC images produced by each of the time series evaluated.

Aggregate standard deviation values from nine locations representing a wide range of land cover types across the island known to have undergone little change and six locations across the landscape known to have changed substantially; were calculated and plotted for each multitemporal PCA method and time series. In addition, for the purpose of comparison across the multitemporal PCA methods evaluated, standard deviation values were compared to the information content of the respective PC using a simple ratio of standard deviation to information content.

A comparison of aggregate standard deviation values and ratios of standard deviation values to information content was undertaken to establish to what extent the variance across no-change areas compares to areas that have undergone alteration and to determine how the relationship between areas of change and no change is expressed across all of the time series evaluated.

- **Results: Brightness, Greenness and NDVI 1973-1986-1999-2002 and 1985-1999-2001-2002 time series**

Aggregate standard deviation values were calculated for nine locations, representing a wide range of land cover types, across the island known not to have undergone human alteration and six locations known to have been altered; from PC images generated following multitemporal PCA on the brightness, greenness and NDVI 1973-1986-1999-2002 time series (Figure 7.38). The analysis was repeated for the 1985-1999-2001-2002 brightness, greenness and NDVI time series (Figure 7.39).

The ratio of aggregate standard deviation value (determined for nine locations of consistent land cover) to information content (%) pertaining to each PC following multitemporal PCA on the 1973-1986-1999-2002 and 1985-1999-2001-2002 brightness, greenness and NDVI time series input years, was calculated and the results are presented in Figures 7.40 and 7.41.

From Figures 7.38 and 7.39 it is clear that standard deviation values calculated for the areas of little or no change are at a maximum for PC1 and decrease sharply from PC1 across higher order PCs for each of the time series investigated associated with maximum variance expressed by PC1. Aggregate standard deviation values computed across the locations of change exhibit almost identical patterns for the 1973-1986-1999-2002 and 1985-1999-2001-2002 time series of imagery.

The brightness and NDVI standard deviation values show very similar patterns across the areas of little or no change for all PC images. Standard deviation values calculated for the areas of change are consistently greater than the areas of little or no change for the higher order PCs 2 through 4 for the brightness and NDVI time series.

Standard deviation values computed for the greenness time series display much less variation across the locations of change and little or no change for each PC image. The most notable difference between the areas of change and little or no change for both time intervals was recorded for higher order PCs at PC3. At PC2 and PC4, standard deviation values were recorded as almost equal in the 1973-1986-1999-2002 time series. A slight improvement in the difference between aggregate standard deviations recorded for the areas of change and no change was observed across the 1985-1999-2001-2002 time series of imagery.

Ratios of standard deviation values to unique information content were computed for locations of little or no change and were plotted along with the standard deviation to information content ratios derived similarly for the areas of change. As the information content for each PC remains constant, the difference in PC variation described by standard deviation values computed across the areas of change and little or no change is clearly expressed in Figures 7.40 and 7.41. Higher variance values associated with the areas of change were consistently recorded across the brightness and NDVI time series higher order PCs for both time intervals illustrating that the information contained within the higher order PCs contains a greater amount of variance and hence change information. For both time intervals the brightness and NDVI present the greatest disparity between change and no change values recorded by the higher-order PCs.

- **Results: NDBI and BI: 1985-1999-2001-2002 time series**

Aggregate standard deviation values were also calculated for the nine locations of little or no change and at six locations where human alteration has taken place from PC images generated following multitemporal PCA on the 1985-1999-2001-2002 NDBI and BI time series (Figure 7.42). The results produced followed those from the brightness, greenness and NDVI time series for the same time interval and standard deviation values for PC1 were consistently higher than for the remaining higher order PCs 2 through 4 associated with maximum variance expressed by PC1.

Aggregate standard deviation values recorded for the areas of change were consistently higher than the areas of no change across NDBI PCs 2 through 4. There was no difference in the aggregate standard deviations recorded by BI PC2 across the areas of change and no-change and it was shown earlier that change information expressed in BI PC2 was difficult to interpret owing to the dominance from the 1999 input year. PCs 3 and 4 displayed higher aggregate standard deviation values associated with the locations of change.

The ratio of aggregate standard deviation value (determined for nine locations of consistent land cover) to information content (%) pertaining to each PC following multitemporal PCA on 1985-1999-2001-2002 NDBI and BI time series input years, was calculated and the results are presented in Figure 7.43. The results show that the higher order PCs 3 and 4 presented the greatest disparity between ratio values associated with greater variability in pixel values across the areas of change compared to the areas of little or no change.

7.5. Conclusion

Multitemporal selective PCA was used with medium-resolution satellite data obtained from five different sensors and applied to two separate time series comprising four images (1973-1986-1999-2002 and 1985-1999-2001-2002) to extract temporal information relating to changes in the physical scene characteristics from year to year as a means to identify the sequence of human induced disturbance over the time period. Three approaches to spectral ordination (brightness, greenness and NDVI) were evaluated and applied to multitemporal PCA to determine their information content with respect to the sequence of changes in the landscape. Two new approaches to spectral ordination were also tested. NDBI and BI values were computed for a time series of four images and subjected to multitemporal PCA to determine whether the indices could be used to successfully highlight human disturbance through time and whether they offered an improvement over brightness, greenness and NDVI.

Out of all the methods evaluated brightness and NDVI were shown to successfully highlight the introduction of new urban features and changes to vegetation over greenness, BI and NDBI, for both time series evaluated demonstrating the robustness of the technique. Similarly the results from the analysis of unchanged locations revealed that both brightness and NDVI recorded consistently low aggregate standard deviation values for higher order PCs in comparison to the results from the areas of change demonstrating the success of the methods to characterise areas of no change with low pixel variance.

Chapter 8

Results II: Land cover classification and post-classification change detection

8.1. Introduction

The aim of the land cover classification was to:

- i. identify a suitable and replicable remote sensing classification methodology for selecting and integrating information from multisensor and multiresolution satellite imagery
- ii. improve land cover classification accuracy for a tropical island area with poor data availability
- iii. examine the use of post-classification change detection to identify the types, rates and temporal variability of land cover change.

A number of pre-classification processing procedures including PCA, the incorporation of temperature data and six data-fusion techniques to combine same sensor high-resolution panchromatic imagery with medium-resolution imagery were applied to the Landsat ETM+ and SPOT HRVIR datasets. The procedures were tested to see whether they could offer an improvement to classification accuracy. In addition, the images produced from the data-fusion techniques were tested prior to conducting land cover classification to determine whether preservation of spectral and spatial quality affected classification accuracy.

Following data pre-processing a number of classification methodologies (Table 5.1) were evaluated using a standard unsupervised classification algorithm to produce a set of land cover maps using a modified land cover classification scheme (Table 5.2). An accuracy assessment comprising 130 ground reference test information points gathered in the field was conducted on each of the land cover maps to determine which method produced the most accurate land cover classification. Majority filtering was employed to determine whether the method could offer any further improvement to classification accuracy.

A standard unsupervised classification was also conducted on the historic datasets (Landsat MSS 1973 and SPOT HRV 1986) for which ground reference test information is unavailable and the imagery was used in the post-classification change detection analysis. Post-classification change detection was conducted to quantify and visualise temporal and spatial changes in land cover for each of five time intervals (1973-1986; 1986-1999; 1999-2001; 2001-2002 and 1973-2002).

8.2. Pre-classification processing

8.2.1. PCA

Correlation analysis conducted for each of the Landsat ETM+ and SPOT HRVIR datasets (Table 4.3), revealed strong positive association between adjacent wavebands for each of the satellite sensors. PCA was applied to reduce the information to a smaller number of uncorrelated wavebands and the eigenvalues generated from the covariance matrix representing the variance values of each principal component image are presented in Table 8.1 (cumulative variances for the first three PCs are shaded in grey). For all sensors the first three principal components express over 98% of the total variance in the dataset.

The Landsat ETM+ multispectral wavebands were combined with a temperature image generated from the thermal image (band 6) for the 2001 and 2002 dataset. Preliminary correlation analysis revealed strong to medium positive associations between the temperature image and the multispectral wavebands (Table 8.2). The combined temperature and multispectral image was subjected to PCA to reduce data redundancy and the first three principal components produced explained over 98% of the total variance in the dataset (Table 8.3).

8.2.2. Temperature computation

Temperature maps were generated for Landsat ETM+ 2001 and 2002 datasets for which thermal band data was available. The pixel DN values were converted to radiance and then to at-satellite brightness or black body temperature values to produce two temperature maps of the island (Figures 8.1 and Figure 8.2).

Summary statistics generated from the 2001 and 2002 temperature maps to compare the temperature values generated from imagery acquired on different acquisition dates are detailed in Table 8.4. Despite the fact the 2001 image was acquired in May, average temperatures are almost identical to those acquired in March in the 2002 image which displays a 0.61 K increase in average temperature compared to 2001. Standard deviation values for the 2002 image are larger meaning there is a greater difference between the individual pixel temperature values and the mean across the 2002 dataset. Temperature values in March display a greater range recording the lowest minimum and greatest maximum of the two datasets but the distribution of pixels across the 2001 temperature values is far greater than for 2002; illustrated in Figure 8.3 and Table 8.5.

A comparison of temperature values corresponding to land cover type was conducted using the 2001 and 2002 unsupervised land cover classification of the original multispectral imagery. The results from a one-way ANOVA (Table 8.6) indicate that a statistically significant relationship does not exist ($p\text{-value} > 0.05$) between land cover type and temperature for the 2001 or 2002 data.

The results from the ANOVA highlight the differences in temperature variability across specific land cover types. For instance, standard deviation values for water and sand were particularly high in comparison to all other land cover types for both the 2001 and 2002 data. DEF, pine and dense and sparse mangrove produced consistent and relatively low variation in temperature values. The standard deviation values are noticeably lower for the 2002 land cover map which is accounted for by the lower variability and contrast in temperature across the island as a whole (Figure 8.2).

8.2.3. Data-fusion

Data-fusion is applied to increase the spatial resolution without the loss of spectral information. Before the data-fused images were classified the spectral and spatial quality of the data-fused images produced was tested.

- **Evaluating the spectral quality of data-fused imagery**
 - i. **Comparison of the spectral ranges of the panchromatic and multispectral images**

The spectral sensitivity of the spectral and panchromatic bands the spectral ranges of both the Landsat ETM+ and SPOT HRVIR satellite sensors multispectral and panchromatic wavebands are presented Table 8.7. Multispectral wavebands within the spectral range of the panchromatic waveband are shaded in grey. All three Landsat ETM+ visible wavebands (bands 2, 3 and 4) are within the spectral range of the Landsat panchromatic waveband, whereas only two of the SPOT bands (bands 1 and 2) lie within the same range of the SPOT panchromatic waveband.

- ii. **Evaluating the relationship between the intensity image derived from the original multispectral wavebands and the panchromatic image**

Intensity images generated using two combinations of the SPOT HRVIR and Landsat ETM+ wavebands (Figure 8.4) demonstrate that use of spectral wavebands within the range of the panchromatic band produced sharper intensity images (Figure 8.4). In addition, correlation between the panchromatic and intensity images generated using the original multispectral wavebands within the range of the panchromatic are more strongly positive (Figure 8.5) and supported the use of SPOT HRVIR wavebands 1, 2 and 3 and Landsat ETM+ bands 2, 3 and 4 during the data-fusion process of IHS and Brovey, which require three wavebands only.

- iii. **Visual comparison of image fusion output**

Figures 8.6 and 8.7 illustrate a subset of the data-fused images of New Providence Island produced by each of the techniques tested to demonstrate that distinct colour or spectral differences can be visualised between the original and data-fused imagery for all methods except Wavelet PCA and Wavelet IHS which remain unaltered.

iv. Analysis of brightness values

Spectral profiles generated for each of the data-fused images pertaining to the SPOT HRVIR and Landsat ETM+ datasets are compared to the original image to provide a visual representation of the degree of departure from the original distribution of spectral values by each data-fusion method. Brovey and Wavelet PCA data-fused imagery most closely resembles the original DN distribution for the SPOT imagery (Figure 8.8). For the Landsat ETM+ dataset (Figure 8.9), Brovey, IHS, and both Wavelet methods of data-fusion all present similar spectral profiles to the original image. In each of the three cases, the Multiplicative method of data-fusion condensed the original distribution of pixel values into a lower DN range.

v. Correlation analysis

Correlation coefficients were derived to measure the degree of similarity between the distribution of DN values across the original compared to the data-fused imagery (for SPOT HRVIR 1999 and Landsat ETM+ 2001 and 2002 datasets) (Figure 8.10 (a), (b) and (c) respectively). The diagrams indicate that the Wavelet method of data-fusion consistently produces the highest correlation values between the original and data-fused images, as expected given the similarity in the DN distribution between the wavelet data-fused and original imagery. The Multiplicative method of data-fusion consistently produces the weakest correlation across all three datasets examined.

• Evaluating the spatial quality of data-fused imagery

i. Visual comparison

Figures 8.6 and 8.7 present a subset of the data-fused imagery output for the SPOT HRVIR and Landsat ETM+ datasets to show that each of the methods applied serves to visually sharpen the original imagery.

ii. Correlation between original panchromatic and the intensity image of the fused image

To show the preservation of spatial resolution correlation coefficients between the panchromatic image and an intensity image generated from each of the data-fused images pertaining to the SPOT HRVIR and Landsat ETM+ datasets were generated (Table 8.8). The IHS, PCA and Brovey methods all display the strongest positive associations with their respective intensity images and the panchromatic image for both the SPOT and Landsat dataset. Both Wavelet methods and the Multiplicative intensity images display the weakest correlation with respective SPOT and Landsat panchromatic imagery.

To show the preservation of spatial resolution regarding the similarity between the panchromatic and intensity images, the correlation coefficients between the panchromatic and intensity component of the data-fused images were plotted against the average correlation coefficient between the pan and data-fused images (Figure 8.11 (a), (b) and (c)).

The Brovey and IHS methods of data-fusion displays the strongest preservation of spatial quality illustrated by firstly the high correlation between the panchromatic waveband and intensity derived from the data-fused images for both SPOT and Landsat datasets. In addition these methods also display the highest average correlation between the data-fused wavebands and the panchromatic image. Both Wavelet methods and the Multiplicative method display the poorest preservation of spatial quality measured by correlation of intensity with panchromatic and average panchromatic correlation, in comparison to the other methods tested.

Finally, to show the relationship between the preservation of spectral information and spatial quality for each of the data-fused methods tested the average multispectral correlation coefficient between the data-fused and original images were plotted against the average pan correlation coefficient pertaining to the SPOT HRVIR and Landsat ETM+ datasets (Figure 8.12 ((a), (b) and (c))). The graphs show that the data-fused imagery produced by both Wavelet methods display the strongest positive correlation with the original multispectral images for both the Landsat and SPOT datasets and hence preserve the spectral quality of the original imagery to a greater extent than the other methods. Similarly, the Brovey method of data-fusion performs consistently well in terms of preserving both spectral and spatial quality of the original imagery. The results are consistent across remote sensing platforms.

8.3. Land cover classification

The land cover classification maps (Appendix B) produced following the application of ten classification methodologies to a standard unsupervised classification procedure were evaluated via an accuracy assessment comprising 130 random ground reference information points gathered in the field in March 2006. Relatively few ground reference points were gathered for the mangrove land covers in comparison to the other land cover types (Table 8.9) due to the poor (and patchy where it existed) distribution of mangrove land cover and problems of land access which precluded the gathering of ground reference test points at certain locations across the island. The number of HAL reference points was larger than for any other land cover given the dominance of urban landscape across the island.

Results from the land cover classification including statistical measures of accuracy such as producer's accuracy, user's accuracy overall accuracy, kappa statistic and a test of significance on kappa were generated for each map.

- **Results: VISIR and PCA**

VISIR classification of medium-resolution remotely sensed imagery acquired from SPOT (1999) and Landsat ETM+ (2001, 2002) datasets produced classification accuracies of between 78% and 83% and "substantial" agreement between reference points and the classified maps was described by statistically significant Kappa coefficients generated for each of the land cover maps (Table 8.10,

8.11 and 8.12). The results show that the application of PCA prior to image classification (to remove data redundancy) did not improve accuracy values but resulted in a 5.38% reduction in overall accuracy in comparison to classification of the original image dataset (VISIR). Aside from water, dense mangroves and sand land cover individual classification accuracies which remained the same (Table 8.10), overall, user and producer class accuracies decreased following PCA classification on the SPOT dataset. Producer's accuracy for DEF improved slightly but user's accuracy decreased and none of the reference sparse mangrove pixels were classified correctly. Kappa values described a "moderate" agreement (Table 5.3) between the SPOT PCA land cover classification and the reference dataset.

Similar results were recorded for the Landsat image datasets (Table 8.11 and 8.12), which show a 4.62% (2001) and 3.85% (2002) decrease in overall accuracy values associated with the PCA classification in comparison to VISIR. For the 2001 dataset, individual class accuracies of HAL, sand, pine and sparse mangrove recorded a decrease in individual class accuracy. The Kappa coefficient decreased from 0.72 to 0.64 (with Z-values of 13.97 and 11.03 respectively) but agreement between the reference values and the PCA land cover described by both figures lies within the range of "substantial".

Classification of the Landsat ETM+ 2002 PCA image also produced a decrease in individual class accuracies across land cover types. HAL, water, pine and DEF all showed a decrease in user accuracy and HAL only displayed a decrease in producer's accuracy. The Kappa coefficient decreased from 0.61 to 0.56 (with Z-values at 10.07 and 9.03 respectively) and agreement between the reference values and the map produced following PCA dropped from "substantial" to "moderate".

Overall accuracy values were recorded at 75.38% and 76.92% for the 2001 and 2002 land cover classifications incorporating temperature data with statistically significant Kappa coefficients (Z-values > 1.96) of 0.58 (Table 8.11 and 8.12). Agreement between the land cover maps incorporating temperature data and the reference data can be described as "moderate" by the Kappa statistic produced. In comparison to VISIR, for the 2001 dataset individual class accuracy values for HAL, sand and DEF decreased. User accuracy values only dipped for water and pine. Producer accuracy values decreased for dense mangrove while user accuracy was recorded as the same.

For the 2002 dataset a reduction in user's accuracy (water and pine land cover classes) and producer's accuracy (HAL) was recorded. However the classification produced a slight improvement in user's accuracy associated with HAL. Overall however, the incorporation of temperature data offered no improvement in separating the land cover classes for either the 2001 or 2002 dataset.

- **Results: Temp and PCATemp**

Accuracy results from the 2001 image dataset incorporating temperature and PCA prior to classification displayed a decrease in producer's accuracy only associated with "sand" and "dense mangrove" classes and a decrease in both producer's and user's accuracy associated with HAL, pine, DEF and sparse mangrove. The class water showed an improvement in user's accuracy and producer's accuracy remained the same. Similarly, for the 2002 results, both producer's and user's accuracy totals decreased for HAL but pine land cover showed a decrease in user's accuracy only and DEF a decrease in producer's accuracy only. The accuracies for the classification of dense mangrove remained the same. A zero result was returned for the classification of sand and sparse mangrove classes as the algorithm failed to classify the reference pixels correctly.

A comparison of accuracy results for the land cover maps produced using temperature data reveals that for the 2001 image dataset overall accuracy values increased slightly when PCA was applied to the temperature dataset, in contrast to the 2002 dataset where accuracy values dropped 10.77% from 76.92% to 66.15% upon application of PCA. Overall accuracy values were recorded at 76.15% and 66.15% for the 2001 and 2002 land cover classifications incorporating temperature data and PCA with Kappa coefficients (and Z-values > 1.96) of 0.58 and 0.42 respectively. While agreement between the land cover maps incorporating temperature data produced following PCA and the reference data for both maps can be described as "moderate", the 2002 temperature PCA image dataset produced the lowest overall accuracy in comparison to the other methods tested.

Overall, the classification results for the VISIR and PCA methods were consistent across the SPOT HRVIR and Landsat ETM+ datasets with classification of VISIR producing higher accuracy values than PCA, Temp and TempPCA (Figure 8.13).

- **Results: Data-fusion classification**

Performances for all six of the data-fusion methods tested were ranked almost identically for both the SPOT HRVIR 1999 and Landsat ETM+ 2001 image datasets (Table 8.10 and Table 8.13). PCA method of data-fusion performed second best followed by Multiplicative, IHS and Brovey, classification accuracies for the latter three were distinguishable only in terms of the Kappa coefficient. Wavelet IHS produced the weakest classification accuracy values of all methods tested.

A slight change in the order of success was revealed by the Landsat ETM+ 2002 dataset (Table 8.14) where the Multiplicative method fractionally outperformed Wavelet PCA followed by IHS, PCA, Wavelet IHS and Brovey; the latter two methods produced the same overall accuracy, separable only in terms of the Kappa coefficient.

The results showed that Wavelet PCA outperformed the other five methods of data-fusion tested as part of the land cover classification but the technique did not offer an improvement to classification accuracy of the original VISIR dataset (Figure 8.14).

The accuracy assessment for each land cover map was rerun following the application of a majority filter of uniform square kernel (3x3) to determine whether use of a filter could improve classification accuracy. The results of the majority filtering detailed in Tables 8.15, 8.16 and 8.17 highlight in grey where land cover maps displaying an improvement in overall accuracy and Kappa values. The application of the majority filter to the VISIR and PCA land cover classifications (derived from both Landsat ETM+ and SPOT HRVIR sensors) served to reduce overall classification accuracies by between 1.54% and 3.08%. Similarly overall accuracy values of the Temp and PCATemp classifications decreased between 0.77% and 3.84%.

Data-fusion methods of Wavelet PCA and IHS generated from the SPOT dataset display a very slight but insignificant improvement in overall accuracy values following application of the majority filter. The improvements were noted across the HAL, pine, DEF and dense mangrove individual class accuracy values associated with Wavelet PCA and an improvement in water, sand and pine classes associated with Wavelet IHS (Table 8.18).

PCA, Multiplicative, and IHS classification methods all display slight increases in overall accuracy values for the Landsat ETM+ 2001 dataset (between 0.76% and 0.77%). Individual class accuracy improvements were recorded for HAL and sparse mangrove associated with PCA; HAL and pine associated with Multiplicative; HAL, DEF and sparse mangrove associated with IHS and lastly HAL and sparse mangrove associated with Wavelet HIS.

For the Landsat ETM+ 2002 dataset, Wavelet PCA method of data-fusion generated from the displayed a slight improvement in overall accuracy amounting to a 1.54% following application of the majority filter associated with individual class accuracy improvements across HAL, pine and DEF land covers.

The results from the land cover classification conducted using the data-fused images were used to determine whether the preservation of spectral and spatial quality following data-fusion affected overall accuracy. Wavelet PCA produced the most accurate land cover classification of all methods for the SPOT HRV 1999 and Landsat ETM+ 2001 dataset and in terms of preservation of spectral quality displayed the strongest positive correlation with the original multispectral wavebands for both platforms (Figure 8.15 a) and b)). In contrast, the results from the Landsat 2002 dataset (Figure 8.15 c)) reveal that the multiplicative method produced the highest classification accuracy value yet the lowest correlation with the original multispectral wavebands. Conversely, Wavelet IHS displayed strong positive association with the original multispectral waveband but did not produce the most accurate land cover map following classification.

The preservation of spectral quality described by the correlation between the panchromatic waveband and the data-fused imagery was compared to the results from the land cover

classification (Figure 8.16 a), b) and c)). It is clear that there is no relationship between classification accuracy and correlation with the panchromatic waveband. The graphs show that Wavelet PCA and Multiplicative data-fusion displayed the poorest correlation with the panchromatic band yet delivered the best classification results of all the methods evaluated. Similarly there was no discernible relationship between spatial quality as a measure of the correlation between the panchromatic band and intensity derived from the data-fused imagery and classification accuracy (Figure 8.17).

8.4. Post-classification change detection

Land cover type areas statistics were derived for five map years (1973, 1986, 1999, 2001, 2002) using land cover maps derived from the land cover classification (Appendix B). A comparison of the land cover statistics across each year clearly illustrates the consistent and steady rise in HAL as a percentage of total land cover from 38.15% in 1973 to 52.77% in 2002 and a corresponding reduction in vegetative and wetland cover associated with urbanisation of the island (Table 8.19).

• Land cover change between 1973-2002

From 1973 to 2002 urban area increased by approximately 2840 ha and a reduction of 14.62% in proportional area (Table 8.19) while pine forest decreased 1480 ha (6.82%), DEF decreased by 1020 ha (4.75%), wetlands decreased by 560 ha (3.03%) and sand by 80 ha (0.38%). Relatively, urban areas (described by HAL) increased 36.28% from 1973 to 2002 with the greatest increase associated with the 1986 to 1999 time interval where pine forest; DEF, wetlands and sand decreased by 21.1%, 26.1%, 22.9% and 42.11% respectively. A time series of land cover type area change (Figure 8.18) highlights the increase in HAL relative to the decrease in pine, DEF, sand and mangrove classes.

Matrices of land cover changed from 1973 to 1986, 1986 to 1999, 1999 to 2001, 2001 to 2002 and 1973 to 2002 were created (Table 8.21). In the table the unchanged pixels are located along the major diagonal of the matrix. The results indicate that increases in urban areas (HAL) mainly come from the conversion of pine forest and DEF during the 29-year period between 1973 and 2002 (Table 21 e). Of the 2840 ha growth in HAL between 1973 and 2002, 42.3% was converted from pine forest, 50.7% from DEF, 5.2% from dense and sparse mangroves and 1% from sand. Table 21 (e) also shows that 2260 ha were converted from pine forest to HAL while at the same time 1050 ha was converted from HAL to forest. Similarly, 2220 ha of DEF was converted to HAL and 770 ha of HAL converted to DEF between 1973-2002; 290 ha of dense and sparse mangrove were converted to HAL and 140 ha of HAL were converted to dense and sparse mangrove and lastly; 50 ha of sand was converted into HAL and 20 ha of HAL was converted into sand.

Discrepancies between area land cover totals in Table 8.21 may be attributed to differences in tide and hence spectral reflectance values around the coastline and areas of inland water between satellite acquisition dates. Total land mass and water body area values as estimated from the land

cover classification maps pertaining to each year were calculated (Table 8.22) and highlights the difference in land and water classification between image acquisition dates.

Land cover "from-to" conversions and summary statistics (Tables 8.23) reveal that a significantly higher percentage of vegetation (pine and DEF) was converted to HAL over the course of 29 years in comparison to the other land cover types. The conversion of pine, DEF, sand, dense and sparse mangrove to HAL cumulatively accounts for 45.2% of the total land cover area representing HAL in 2002.

"From-to" land cover change maps generated for each time interval to facilitate visual display and analysis of land cover conversion and the pattern of human disturbance reveal that HAL to pine or DEF land cover change (Figure 8.19) occurred predominantly in areas that were cleared of vegetation in 1973 and subsequently replanted by 2002 e.g. the development of a golf course on Paradise Island to the north east of New Providence and areas of reforested land within the National Forest Reserve. The 2002 land cover classification successfully identified small patches of DEF fringing and contained within larger urbanised areas in 2002 compared to 1973 owing to the greater spatial resolution of the ETM+ sensor in comparison to MSS. The MSS sensor with spatial resolution of 57m failed to distinguish small parcels of DEF amidst the urban landscape of Nassau.

Unexpected changes result from classification errors. For example the conversion of 140 ha from HAL to wetlands between 1973 and 2002 (Table 8.21) can be associated with the misclassification of land cover in 1973 and the inability of the MSS sensor to distinguish small areas of mangrove where they exist at coastal locations and within Nassau International Airport (Figure 8.20). Mangrove communities are often small and patchy and surrounded by sand or bare land cover. This contributes to a spectral reflectance value similar to that produced from urban (HAL) land cover which resulted in confusion during the classification and led to this misclassification of mangrove as HAL in the earlier image.

Similarly, the conversion of 860 ha of pine forest to DEF and 430 ha of DEF to pine (Table 8.21) may also be associated with classification error and differences in the spectral reflectances of these land covers associated with seasonal differences in image acquisition dates as well as land cover conversion. For example the replacement of areas of natural forest with a golf course on Paradise Island on Paradise Island as part of the Atlantis Resort development is clearly visible (Figure 8.21). Small areas of land cover classified as HAL in 1973 at a number of coastal locations to the north, west and south of New Providence (highlighted within yellow boxes in Figure 8.22) were classified as sand in 2002. 90 ha of sand accounting for 22.7% of the total area classified as sand in the 1973 image were classified as water in the 2002 image (Table 8.21 e) and 40 ha of the water pixels in 1973 were classified as sand in 2002. Figure 8.23 illustrates the conversion of sand to water and water to sand predominately along coastal areas but also at inland water body locations. This perhaps is due to erosion/depositional differences as well as tidal differences between acquisition dates.

- **Land cover change 1973-1986**

An investigation of the specific changes between each time interval reveals a similar pattern to overall landscape change summarised by the 29 year time period between 1973 and 2002. Between 1973 and 1986 there was an 850 ha or 5.3% increase in HAL; and a decrease of 220 ha (0.37%); 320 ha (1.18%); 80 ha (0.4%); 510 ha (2.46%) and 230 ha (0.63%) decrease associated with pine, DEF, sand, dense and sparse mangroves respectively. The "from-to" matrix of land cover change (Table 8.21 a) reveals that of the total HAL land area in 1986, the conversion of pine and DEF to HAL in the time interval accounts for 16.5% and 19.7% respectively. Dense and sparse mangrove conversion accounts for a cumulative 2.4% and sand, 0.43%.

Misclassification errors also produced some unusual results, similar to those identified for the 1973-2002 land cover change. A high number of pixels were converted from HAL to pine and DEF between 1973 and 1986 (representing a total of 2390 ha) which occurred particularly within built-up areas (Figure 8.24). The conversion from pine to DEF (1060 ha) and DEF to pine (620 ha) is particularly evident in the vegetated regions to the north and west of the island (Figure 8.25). Both dense and sparse mangroves were converted from HAL between 1973 and 1986 (80 ha in total) likely associated with misclassification errors in the 1973 image (Figure 8.26). Post-classification change differences between the imagery associated with the conversion of water to sand (30 ha) and sand to water (210 ha) between 1973 and 1986 are visible at coastal locations around the island (Figure 8.27).

- **Land cover change 1986-1999**

Between 1986 and 1999 HAL increased by 1810 ha or 8.9% representing the largest increase in HAL over the time period; and a decrease of 1500 ha (7.54%) and 350 ha (1.8%) was recorded for pine and DEF land cover. An increase of 20 ha (0.02%) and 60 ha (0.06%) was recorded for dense and sparse mangroves respectively. The amount of sand cover in hectares did not change between the time period however, the proportional area of sand increased by 0.02%. The conversion from HAL to pine and DEF land cover (1560 ha) was much lower for this time interval in comparison to 1973-1986 conversion figures. The patchy misclassification of pixels along road networks as DEF or pine is particularly evident (Figure 8.28).

In 1986, 620 ha of pine were converted to DEF in 1999 while at the same time 500 ha of DEF were converted to pine (Figure 8.29). The conversion of pine to DEF was most evident within the Natural Forest Reserve. Almost 100 ha of dense and sparse mangroves in 1999 were converted from HAL in 1986 (Figure 8.30) predominantly in the south of the island as a result of misclassification of mangroves in the 1986 image which was acquired during the dry season. Higher reflectance values in the 1986 image compared to the 1999 associated with seasonal differences in mangrove extent and distribution contributed to the misclassification of these areas

as HAL. Negligible post-classification change differences associated with the conversion of water to sand and sand to water between are visible at coastal locations around the island (Figure 8.31).

- **Land cover change 1999-2001**

Between 1999 and 2001 HAL increased by 80 ha (0.1%), pine increased by 30 ha but the proportion of pine land cover between the time interval decreased by 0.03%. While DEF decreased by 340 ha (1.75%), post-classification change comparison revealed an increase in land cover associated with dense and sparse mangroves of 80 ha (0.38%) and 260 ha (1.29%) respectively. Similarly the amount of sand land cover increased by 10 ha (0.03%).

A closer look at the "from-to" change matrix shows that 1700 ha of HAL was converted to pine and DEF between 1999 and 2001 (Figure 8.32) predominantly around existing built-up areas to the north, northeast and west of the island.

An increase in total land cover area of dense and sparse mangrove was recorded between this time interval. The apparent increase can be attributed to the conversion of 130ha of HAL in 1999 to wetland in 2001, predominantly around Nassau International Airport (Figure 8.33) associated with the erroneous classification of patchy mangroves growing within the confines of the airport as HAL. The conversion of 40 ha of water to sand (explaining the increase in total sand land cover in 2001) and 20 ha of sand to water between 1999 and 2001 occurred at coastal locations around the island (Figure 8.34).

- **Land cover change 2001-2002**

Between 2001 and 2002 the area of HAL increased by 100 ha (0.59%) and pine increased by 210 ha (1.13%). DEF, dense and sparse mangroves decreased by 10 ha (0.02%), 80 ha (0.38%) and 260 ha (1.29%) respectively. The increase in pine land cover can be explained in part by the conversion of HAL to pine (650 ha) and DEF to pine (390 ha) between the time interval (Figures 8.35, 8.36). Similarly, very small amounts of dense and sparse mangrove in 2002 were converted from HAL in 2001 (Figure 8.37) predominantly at locations within the confines of Nassau International Airport. Finally, the conversion of sand to water (and water to sand) is also evident at coastal locations, particularly to the south of the island (Figure 8.38).

- **Land cover conversion from rural to urban**

To specifically examine the impact of human disturbance on the natural landscape the matrices of land cover change were used to develop a series of maps representing the spatial distribution urban growth, more specifically the land cover conversion from rural (i.e. pine, DEF and mangrove) to HAL. Clearly the conversion of vegetation associated with urban growth represents the most significant change between 1973 and 1986 (Figure 8.39). The growth and extension of Nassau to the east and Carmichael Village to the south east of Lake Killarney represent the most intense areas of urban growth for this time period. The conversion of vegetation to HAL is widespread across the island and predominantly associated with urban growth. Clearance of large tracts of

forest within the Natural Forest Reserve to the south west of Lake Killarney has also created a noticeable scar in the landscape. The spatial footprint of new roads and other urban structures can be distinguished, particularly to the northwest corner of the island associated with development at Gambier Village.

Urban development between 1986 and 1999 presented in Figure 8.40 was predominantly associated with the conversion of pine and DEF land cover. Occurring at locations across the island urban expansion within the time period included the development of Paradise Island, the Cable Beach tourism area directly north of Lake Kennedy, Coral Harbour to the south and the continued expansion of Nassau. Development to the west of the island included the expansion of Nassau International Airport, development of Lyford Cay marina and South Ocean Beach Resort. Between 1999 and 2001, in addition to the continued expansion of Nassau and existing urban areas, new urban growth included the Venice Bay development to the south of Millar's sound (Figure 8.41). The continued development of Venice Bay is clearly visible (Figure 8.42) between 2001 and 2002 and while urban growth for this time period is much less pronounced there is evidence for the construction of new roads to the east and south of Lake Cunningham and further development around Nassau.

A spatial summary of human disturbance over the 29 year time period associated with the conversion from pine, DEF and mangrove land cover to HAL has been mapped and colour coded to spatially differentiate urban growth between time intervals (Figure 8.43). Areas that have remained unchanged (in grey) represent large expanses of pine and DEF land cover to the south of Lake Killarney associated with the Natural Forest Reserve. In addition, large expanses of vegetation on the west coast of the island south of Lyford Cay also remain undeveloped. Similarly large expanses of mangrove communities surrounding Bonefish Pond and west of Millar's Sound have not experienced alteration as a result of urban development.

It is clear from the map that between 1973-1986 development was most prevalent around the coastal regions and particularly to the east of the island. Between 1986 and 1999 development occurred mostly in the inland regions but included development of the Cable Beach tourism area and Paradise Island to the north and Lyford cay residential area and marina to the west. Development between 1999 and 2001 mostly involved the continued expansion of existing urban areas and while the amount of development highlighted by the technique was substantially less between 2001 and 2002, new roads in the north and developments in the south and east of the island are clearly visible.

Results from the post-classification comparison change detection reveal that the largest expansion of HAL occurred between 1986 and 1999 (Table 8.24) representing 63.7% of total HAL growth over the time period. The remaining 30%, 2.8% and 3.5% of total HAL growth was accounted for between 1973 and 1986; 1986 and 1999; 1999 and 2001; and 2001 and 2002 respectively.

- **Land cover conversion and population growth**

Average annual growth in HAL areas determined from post-classification change detection was approximately 0.84% between 1973 and 1986, 1.61% between 1986 and 1999, 0.06% between 1999 and 2001, 0.07% between 2001 and 2002 and 1.26% for the entire period, 1973 to 2002 (Table 8.25). This compares to an annual population growth rate between 1970 and 2000 (New Providence Island) of approximately 3.59% (Table 8.26). Population growth rate of the entire land area of The Bahamas was estimated at 2.7%. The greatest increase in population was recorded between the 1980 and 1990 census years and coincides with the years for which HAL growth was greatest. Currently population growth is increasing at a faster rate than urban development on New Providence Island.

8.5. Conclusion

The methodology developed to produce a land cover classification and map land cover changes across a data-poor tropical island was based on an adequate understanding of landscape features (local knowledge), sensor characteristics and information extraction techniques employed. A standard unsupervised classification approach was adopted and to ensure accurate image classification results, several classification methodologies were tested to determine the improvement to overall classification accuracy. The results revealed that pre-processing procedures did not serve to improve overall classification compared to the results produced from classifying the original imagery; a result which was consistent across remote sensing platforms.

Of six data-fusion techniques evaluated as a potential improvement to land cover classification not one offered a significant improvement to overall accuracy. It was apparent that the high levels of classification detail presented by the data-fused imagery served to complicate the labelling of pixels into land cover classes and a considerably greater amount of noise was apparent in the final map products. Application of a majority filter did serve to reduce the noise and improve classification accuracy of many of the data-fused land cover products, however the most accurate land cover map was produced following unsupervised classification of the original visible and infrared wavebands.

The relationship between preservation of spectral and spatial quality by data-fusion method and classification accuracy was not entirely consistent. However, reduction in spectral resolution associated data-fused methods including IHS and Brovey which employ a reduced number of wavebands is attributed to the poorer performance of these methods because of the limited ability to discriminate among landscape features in comparison to a land cover classification employing the full range of visible and infrared spectral data. By the same token, the success of the wavelet PCA transformation above the other methods is attributed to the strong correlation between the original multispectral and data-fused image and that the original number of input bands is

maintained. In contrast, data-fusion via wavelet IHS retains only three wavebands of information and in this study consistently produced the poorest classification results across both platforms.

Post-classification change detection applied to a time series of land cover maps was used to successfully generate land cover change statistics. Post-classification change comparison conducted to establish specific "from-to" change information, clearly highlighted the impact of human disturbance on the island associated with land cover conversion to HAL. The analysis also facilitated the visual interpretation of more unusual land cover conversions identified through post-classification change comparison, some but not all were associated with classification errors.

Chapter 9

Results III: Remotely sensed indicators and spatial metrics for monitoring human disturbance

9.1. Introduction

The final methodological section of this research evaluated how a time series of land cover maps generated from five satellite sensors can be used to detect and quantify statistically significant trends in a unique set of remotely sensed indicators and spatial metrics derived to measure and monitor human disturbance of the natural landscape over a 29 year time period. The robustness of the metrics to changes in spatial extent and scale was also tested. Eight remotely sensed indicators of human disturbance and a total of 31 spatial metrics were evaluated to meet the objectives of this research.

9.2. Data preparation

To determine the extent to which remote indicators and spatial metrics are sensitive to changes in spatial extent and the suitability of the methods for application within small landscape units such as the coastal zone, coastal buffer zones of 500m and 200m extent (Figures 9.1 and 9.2) were generated and used to mask each land cover map in the time series (e.g. Figures 9.3 and 9.4).

9.3. Remotely sensed indicators to assess and monitor the impact of human disturbance

9.3.1. Computation of remotely sensed indicators

Seven indices describing natural landscape extent (4) and disturbance (3) were generated from the land cover maps and collectively represent features important to land resource managers attempting to quantify the impact of human disturbance on the natural landscape. The analysis was conducted at the landscape scale (Equations 6.1 through 6.8) and repeated for 500m and 200m coastal buffer zones (Equations 6.9 through 6.14).

Examination of the individual indices computed at the scale of the entire island, shows where the stresses are located (Table 9.1). In 1973 almost 62% of the island comprised natural landscape (i.e. pinelands, DEF, mangrove and sand), but by 1986 natural landscape cover had decreased by 5.1% and by 1999 a further 8.1% drop was recorded. Between 1999 and 2002 the changes were less dramatic but amounted to a further 0.7% loss in natural landscape cover. The HA and HD indices of landscape disturbance reveal the opposite pattern associated with the conversion of natural landscape cover to HAL.

The NLI index is an approximate measure of the extent of the historic natural land cover remaining on the island estimated from 1973 shows that in 2002 75.3% of the original natural landscape

extent remained undeveloped. The greatest disparity in index values was recorded between 1986 and 1999 where the ratio of estimated historic natural land cover estimated from 1973 dropped from 90% in 1986 to 76.1% in 1999.

The ratio of HAL to natural landscape (HD) describes how the relationship between developed and undeveloped landscape has changed over time and shows the disproportionately larger amount of HAL in comparison to natural land cover associated with increased development on the island between 1973 (0.617) and 2002 (1.117). The sharpest increase in the proportion of HAL to natural landscape occurred between 1986 and 1999. A comparison of the current extent of HAL to the historic extent (estimated from 1973 data) measured by HI also highlights 1986-1999 as the time interval where most change occurred.

The WI and VI indices were computed to examine separately the changes in historic vegetation extent (i.e. pine and DEF) from changes to historic wetland extent (sparse and dense mangrove) estimated from the 1973 land cover map. While overall the amount of natural landscape cover is less in 2002 compared to 2001, the distribution of land cover amongst the sparse and dense mangroves and pine and DEF differs between 2001 and 2002. The results suggest an increase in the amount of wetland land cover between 1999 and 2001 and an increase in vegetation land cover between 2001 and 2002 compared to the historic extent, but these reflect misclassification errors between image acquisition dates associated with wetland and vegetation classes.

A trend analysis of the index values generated at the scale of the landscape (Figure 9.5) reveals a rise in natural landscape disturbance described by the indices of human disturbance (HA, HD and HI) generated from the land cover maps and a decline natural landscape extent and integrity (described by NLC and NLI). A trend analysis of the scores generated from the indicators of coastal disturbance derived for 200m and 500m coastal zones reveal the same pattern identified by the landscape level indices (Figure 9.6 and 9.7).

The slight improvement in landscape integrity measured by CLI between 1999 and 2001 can be accounted for by the misclassification of DEF and pine. These factors also explain the slight dip in coastal disturbance and coastal alteration indicator values between 1999 and 2001 which otherwise display a consistent rise over the total time period (Figure 9.6). Development within a 500m coastal zone over the entire time period described by CHI displayed a consistent and steady rise with the greatest amount of HAL development recorded between 1986 and 1999.

CD indicator scores generated for a 200m coastal zone buffer clearly reflect the greater intensity at which natural land cover was converted into HAL in comparison to the 500m coastal zone and island as a whole (Figure 9.7). Between 1973 and 1999 areas within a 200m coastal buffer around the island were heavily impacted by human alteration of the landscape. All other indicators present the same trend shown by the indicator values generated within a 500m coastal buffer. CLI

displayed a slight rise with a corresponding dip in CD values associated with the 1999 to 2001 time interval and misclassification error between the 1999 and 2001 land cover classifications. Overall the CHI score generated for a 200m buffer reveals a significantly more stressed area of coastal zone.

To express and compare the relative differences in human disturbance across the island over time, an eighth index; a composite index of overall human disturbance (HDI); was derived using 5 of the 7 indices describing natural landscape extent and disturbance for each map year for the entire island and at the scale of a 200m and 500m coastal zone (CHDI) (Table 9.2). The rising trend in HDI and CHDI indicates a significantly stressed island due to human alteration. Trend analysis of HDI and CHDI values between 1986 and 2002 (Figure 9.8) also show that human alteration of the landscape was greatest between 1986 and 1999.

9.3.2. Testing the statistical significance of remotely sensed indicator trends through time

The results showed NLC, HA, HD, NLCI, VI and HI to display statistically significant ($p < 0.01$) trends (Table 9.3). The WI index did not describe a statistically significant trend in wetland integrity over the time period. Similarly, statistically significant trends were determined for the CNLC, CA, CD and CHI ($p < 0.01$) within the 500m coastal zone (Table 9.4). The results were almost identical at the extent of a 200m coastal zone except for CHI, which was significant at the 0.05 level. CLI did not display a statistically significant trend at the extent of either the 500m or 200m coastal zone.

The composite index of landscape disturbance displayed statistically significant positive trends at the extent of the entire island ($p < 0.05$) and at the extent of both coastal zones ($p < 0.01$). The results highlight the fact that the landscape within a 200m coastal zone of the entire island has been most heavily by human disturbance described by a statistically significant rising trend in CHI.

9.4. An evaluation of spatial metrics to detect statistically significant trends in changes in landscape pattern and structure for landscape monitoring

9.4.1. Computation of spatial metrics

A suite of spatial metrics (31 in total) measuring elements of landscape pattern and structure (area, shape, diversity and contagion) appropriate for landscape monitoring were selected and calculated for each of the land cover maps in the time series (Table 9.5). The statistical significance of the trends in spatial metric values was tested using simple linear regression within SPSS (Table 9.6). Spatial metrics, with statistical significance (p value) equal to or less than 0.05 are shaded in grey.

The results from the analysis show that both NP and PD display statistically significant ($p < 0.05$) increasing trends over time revealing an increase in spatial heterogeneity. The greatest difference in NP and PD values was recorded between 1973 and 1986 (Table 9.5). PD values rose from 12.7 to 35.4 and the number of patches from 2601 to 7149 between 1973 and 2002 illustrating that the landscape of New Providence has become increasingly fine grained.

Variation in LPI (which quantifies the percentage of landscape area comprised by the largest patch) displays a statistically significant ($p < 0.05$) increasing trend associated with an increase in largest patch size. The index reveals that the largest patch size has increased over the time period from 25.58% to 42.18% and reflects the dominance of HAL in the landscape.

Landscape fragmentation is described by the distribution of patch area and extent and characterises the distribution of area among patches. For the dataset the decreasing trend in patch area mean values was not statistically significant but very substantial differences exist between the 1973 and 1986 AREA_MN values (Table 9.5). Area weighted mean patch size (AREA_AM) and variability in area mean described by AREA_CV displayed statistically significant ($p < 0.05$) increasing trends over time. An increase in area weighted mean values is associated with an increase in the proportional abundance of patches. Variability in patch size described by AREA_CV is generally preferred to standard deviation for comparing variability among landscapes because it measures relative variability about the mean. In a time series analysis of landscape change, greater variability of AREA_CV (under normal distribution) indicates less uniformity in landscape pattern over time.

TE (the sum of the lengths of all edge segments in the landscape) describes landscape configuration but is not spatially explicit and displays a statistically significant ($p < 0.01$) increasing trend over the time period. An increase in TE represents an increase in landscape fragmentation and implies a greater degree of landscape disturbance.

Mean radius of gyration (GYRATE_MN) displayed a statistically significant ($p < 0.05$) decreasing trend across the time series. Radius of gyration provides a measure of landscape connectivity that represents the average traversability of the landscape for an organism for example that is confined to remain within a single patch. In the context of landscape disturbance, the metric indicates a decrease in patch extent, which can be associated with landscape fragmentation.

Of a total of five shape metrics generated for each map year in the time series as a measure of landscape configuration, CONTIG_MN which measures spatial connectedness, was the only metric to display a statistically significant ($p < 0.05$) trend. Results from the trend analysis of mean contiguity values reveal that mean contiguity has decreased from 0.54 to 0.19 and indicates that the landscape of New Providence is becoming increasingly disconnected and fragmented.

Diversity indices (Shannon's and Simpson's) measure landscape composition described by richness (the number of land cover types) and evenness (distribution of area among land cover types). The

specific value of Simpson's Index represents the probability (a value between 0 and 1) that any two cells selected at random would be different patch types. The index approaches 1 as the number of different patch types increases and the proportional distribution of area among patch types becomes more equitable; the higher the value the more likely that two randomly chosen cells would be different patch types. The results showed a statistically significant ($p < 0.01$) decreasing trend across the time series which implies the landscape of New Providence is becoming less diverse. Diversity measured by Simpson's diversity decreased from 0.70 to 0.62 between 1973 and 2002.

A larger value of evenness represents a more even distribution of area among patch types and implies greater landscape diversity. Simpson's evenness index decreased 0.84 to 0.75 between 1973 and 2002 and the trend in values was statistically significant ($p < 0.01$) which represents an increase in the uneven distribution of area amongst patch types.

Of seven contagion metrics that describe landscape configuration, three metrics (division, mesh and split) displayed statistically significant trends over the time series. The landscape division index displays a decreasing trend and indicates that two randomly chosen places in the landscape are more likely to be situated in the same undissected patch. While mesh and division are perfectly and inversely correlated, mesh is expressed as an area and division a probability. Mesh displays a statistically significant ($p < 0.05$) increasing trend and at the landscape level is identical to area weighted mean patch size (Table 9.5). Mesh is a measure of the size of the patches when the landscape is subdivided into patches of equal size such that the new configuration produces the same degree of landscape division as obtained for the cumulative area distribution. The time series of land cover maps of New Providence produced a statistically significant ($p < 0.01$) decreasing trend in the value of the splitting index and the index decreased from 9.25 to 4.94 between 1973 and 2002.

Mesh and split indices are computed in this study at the landscape scale and as such summarise across all land cover types but the results suggest that the landscape is becoming dominated by larger patches.

9.4.2. Testing the sensitivity of metrics to changes in spatial extent

To test the robustness of the metrics to changes in spatial extent metric values were generated at the extent of 500m and 200m coastal buffers (Table 9.7 and 9.8). Results from a simple linear regression conducted on the metric values reveal that several of the metrics within the area, shape, diversity and contagion categories displayed statistically significant trends in line with the results generated at the extent of the entire island (Table 9.9 and 9.10).

In the area category of spatial metrics, both TE and LPI displayed statistically significant ($p < 0.01$) increasing trends implying an increase in landscape fragmentation within a 500m area of coastal zone (Table 9.9). PD and LPI displayed statistically significant ($p < 0.05$) increasing values and

imply that the area within a 200m coastal zone of New Providence is becoming increasingly fine grained (Table 9.10). PD values increased from 38.6 to 62.0 (Table 9.8), reflecting the increased patchiness of the coastal zone in comparison to PD computed for the entire island (Table 9.5). LPI increased from 5.5% to 29.6% and from 7.4% to 32.6% within a 200m and 500m area of coastal zone respectively.

The distribution of patch area and extent described by weighted area mean and variability in mean patch size (AREA_SD and AREA_CV respectively) all displayed statistically significant increasing trends over the time period across the 500m and 200m coastal zones indicating less uniformity in spatial pattern and can be attributed to landscape disturbance.

Landscape connectivity (patch extent) was shown to decrease ($p < 0.05$) across the time period as measured by GYRATE_MN within the 500m and 200m area of coastal zone and can be associated with fragmentation of the landscape over time. Area weighted mean radius of gyration shows a distinct and statistically significant ($p < 0.01$) increasing trend over the time period at the spatial extent of the coastal zone reflecting an increase in the proportional abundance of patches which is more noticeable at smaller spatial extents, in comparison to the values generated at the extent of the entire island (Table 9.5).

The shape metrics displayed a similar profile at the extent of the coastal zone with mean contiguity displaying a decreasing trend ($p < 0.05$) associated with a reduction in spatial connectedness. CONTIG_MN values decreased from 0.53 to 0.20 and 0.50 to 0.21 between 1973 and 2002 within a 500m and 200m coastal zone respectively. Area-weighted mean shape revealed a statistically significant ($p < 0.01$) decreasing trend within the coastal zone associated with an increase in the proportional abundance of patch area, more noticeable at smaller spatial scales.

PAFRAC is a measure of shape complexity whose value approaches two for shapes with highly convoluted perimeters. Only at the spatial extent of a 200m coastal zone was a statistically significant ($p < 0.05$) increasing trend in values recorded by this metric. PAFRAC increased from 1.4 to 1.5 between 1973 and 2002. The results show that shape defined by fractal dimension for a 200m coastal zone is becoming increasingly complex which implies a greater degree of landscape disturbance over time.

All diversity indices (and in particular Simpson's diversity and evenness indices) displayed statistically significant ($p < 0.01$) decreasing trends across the time series of coastal land cover maps. Simpson's diversity index decreased from 0.78 to 0.60 and 0.76 to 0.62 respectively within a 500m and 200m area of coastal zone. Similarly, Simpson's evenness index values decreased from 0.91 to 0.74 and 0.94 to 0.72 respectively within a 500m and 200m area of coastal zone between 1973 and 2002. The results show that the probability of two randomly chosen cells drawn from different patch types is low and the distribution of area among patches within the coastal zone is

becoming increasingly uneven. This implies that landscape composition within the coastal zone is becoming less diverse and dominated by fewer land cover types.

Finally the values generated by the contagion metrics within the coastal zone also display similar results to those generated at the extent of the entire island. Division, mesh and split recorded statistically significant trends at across the 500m and 200m areas of coastal zone. The values for the splitting index displayed a far more dramatic decrease from 71.1 to 8.4 and 109.1 to 10.2 respectively for a 500m and 200m area of costal zone in comparison to the results generated for the entire landscape. In addition, contagion (CONTAG) revealed a statistically significant ($p<0.01$) increasing trend at the extent of the 200m coastal zone. Contagion (represented by a percentage) is high when a single class occupies a very large percentage of the landscape (a contagion value of 100 is achieved when all patch types are maximally aggregated). Contagion at the extent of a 200m coastal land area rose from 35.3% to 42.5% over the time period (Table 9.8). In comparison contagion values rose from 41.4% to 45.4% and from 48.1% to 49.2% at the extent of the 500m coastal zone and entire island respectively. However, the increasing trends identified were not statistically significant at the extent of the entire island or a 500m coastal zone.

Table 9.11 presents a summary of all the statistically significant metrics generated in the time series analysis at the extent of the entire island and within a 500m and 200m area of coastal zone. The results reveal that out of a total of 31 spatial metrics evaluated, five area metrics, one shape metric, six diversity metrics and three contagion metrics (amounting to 15 in total) display statistically significant trends at all three spatial extents.

Correlation analysis was conducted (Pearson's two-tailed correlation) to determine whether the relationship between spatial metric values remains the same with changing spatial extent. Correlation coefficients with values >0.90 (significant at the 0.05 level and above) for metric category (area, shape, diversity and contagion) at each of three spatial extents examined, are highlighted in yellow (Table 9.12, 9.13, 9.14). For comparative purposes a number of metric correlation values ($p<0.90$) have been presented in parenthesis.

Correlation between area metrics remained almost similar with a slightly higher number of correlated metrics (>0.90) at the extent of the entire island. At the landscape extent, NP is perfectly correlated with PD and displays a consistently high positive correlation with TE, a strong negative correlation with mean area, patch size coefficient of variation and mean radius of gyration (Table 9.12). PD is positively associated with TE and the coefficient of variation of patch size. PD also displays a strong negative correlation with mean radius of gyration. LPI is positively associated with area-weighted mean and area-weighted radius of gyration. Within both areas of coastal zone, the relationships between the metrics remains the same with a very slight dip in the strength of the correlations compared to the results generated for the landscape as a whole.

Within the category of shape metrics, at the extent of the entire landscape mean shape displays a strong positive association with mean contiguity. Area weighted shape displays a strong negative association with both mean contiguity and area-weighted mean contiguity while PAFRAC remains uncorrelated with the other shape metrics (Table 9.13). Across the 500m and 200m buffer zones correlation between the shape and contiguity metrics remains the same but the strength of the relationships is reduced, more noticeably so at 200m in comparison to the results generated at the scale of the entire island. The relationship between PAFRAC and area weighted mean improved to a medium positive correlation within the coastal zones and at the extent of a 200m coastal zone there is a medium negative correlation between PAFRAC and mean contiguity. The diversity metrics all display consistently strong positive correlations (>0.90) at the extent of the entire island and within a 500m and 200m area of coastal zone (Table 9.14).

Finally in relation to the contagion metrics, there is a consistently high positive correlation between division and mesh across all three spatial extents. Similarly the correlation between mesh and split (highly negative) and split and division (highly positive) is consistent at the extent of the entire island and coastal zone although the strength of these correlations dips slightly at the extent of a 500m coastal zone. Contagion measured by CONTAG displays a strong negative correlation with split at the extent of the 200m coastal zone and a medium negative correlation within the 500m coastal zone. CONTAG remained uncorrelated to the other contagion metrics at the extent of the entire island.

9.4.3. Testing the sensitivity of the metrics to changes in spatial resolution

Land cover maps generated for New Providence Island were systematically increased from 1x1 pixel (30m^2) to 20x20 pixels (600m^2) and response curves of spatial metric values to changing grain size were plotted for the metrics that displayed statistically significant trends following the time series analysis of metric values (Appendix C).

Results from this research revealed almost identical patterns to those described by Wu et al. (2002) and NP, PD, TE, AREA_MN, AREA_CV, AREA_SD, LPI, SHAPE_AM and PAFRAC all displayed predictable changes with increasing grain size. For instance, response curves generated for NP, PD, TE, AREA_CV and SHAPE_AM (Figures 9.9 and 9.10) all decreased in their values with increasing grain size associated with a power-law relationship. These metric values incorporate measures of length or area and were very sensitive to changes in grain size, displaying a sharp and rapid decline in values between 30m and approximately 200m resolution after which remaining at a steadily decreasing low value.

AREA_MN values for the study area displayed a consistent increase with increasing grain size also associated with a power-law function. AREA_SD showed less sensitivity to changes in grain size and displayed a steady and linear increase across each map year. Mean radius of gyration (describing patch extent) also displayed a consistent, steady and linear increase with increasing grain size for each year in the time series examined.

The response of mean patch fractal dimension (PAFRAC) to changing grain size over the time series (Figure 9.10) displayed very little variation, a result that was consistent across each of the map years evaluated for the island of New Providence (Appendix C). The contiguity index describing spatial connectedness, displayed a generally decreasing trend with increasing grain size but the response was not predictable across map years.

Diversity indices generated for New Providence Island displayed a downward trend in values associated with an increase in grain size (Figures 9.11). This pattern is readily understood in terms of the progressive aggregation of pixels associated with increasing grain size, which eliminates small, isolated and scattered patches reducing the relative abundance of patch types which results in a decrease in both diversity and evenness.

Division, mesh and split displayed consistent responses to changing grain size (Figure 9.12). While a greater degree of variation was exhibited across the metric response curves generated by the 1973 dataset (Appendix C), division and split metric values displayed a consistent decrease and a steady increase in mesh values was recorded in response to the increase in large contiguous patches associated with pixel aggregation or increasing grain size.

It was shown earlier that many of the metrics within each category generated for each map year at the landscape scale displayed statistically significant correlations. For instance NP, PD, TE and AREA_CV are all highly positively correlated (Table 9.12) and displayed the same response curves associated with increasing grain size. Similarly AREA_SD, GYRATE_MN and AREA_MN which measure mean patch size, variability in patch size and mean patch extent all displayed strong positive correlations and produced a linear increase in metric values associated with increasing grain size. The highly correlated diversity metrics all exhibited identical response patterns to changing grain size. While there was considerable variation in the values of the configuration metrics with changing grain size the general trends were consistent across map years.

9.5. Conclusion

Using a time series of land cover maps generated from a multisensor data set, seven remotely sensed indices of natural landscape extent and disturbance and an overall composite index were generated to quantify the impact of human disturbance for a data-poor study area in the tropics. An analysis of indicator scores revealed that six of the indices displayed statistically significant trends ($p < 0.01$) and describe an increasingly disturbed landscape over time. The poor performance of the WI index is attributed to misclassification error and spectral confusion of mangrove classes caused by seasonal differences in image acquisition dates.

An analysis of indicator values revealed that the years between 1986 and 1999 were characterised by the sharpest rising trends in human disturbance over the 29 year time period. Indicator scores

generated at the spatial extent of a 500m and 200m coastal zone produced the same results and demonstrate the robustness of the indices to characterise trends in human disturbance.

Of 31 spatial metrics evaluated to describe temporal changes in landscape pattern and structure associated with human disturbance, a total of fifteen displayed statistically significant trends at the extent of the entire island and across a 500m and 200m coastal zone. An analysis of the response curves of metric values to changing grain size revealed that several of the metrics presented predictable response patterns. Despite changes to landscape composition and configuration over time, the sensitivity of metric values to changing grain size measured for different map years produced the same results. Metric values generated at the scale of the coastal zone produced results consistent with those generated at the extent of the entire island.

Chapter 10 Discussion

10.1. Introduction

Remotely sensed imagery is a cost-effective source of historical data but its application to determine changes over long periods of time requires reliable and easily implemented analytical methods. The common unavailability of time-specific *in-situ* data and the next-to-impossible task of acquiring single sensor imagery with a complete temporal sequence of useable image data for a target location are major obstacles for landscape monitoring in data-poor tropical areas. These problems are compounded in particular for areas in the tropics where the presence of cloud cover precludes the use of many image datasets.

The overall goal of this study was to evaluate digital change detection techniques that can be applied to visualise and quantify the sequence of landscape changes associated with human disturbance using data acquired from five different satellite sensors. Simple methods were developed and evaluated for exploring general patterns of landscape change associated with human disturbance in a time-series of medium-resolution remotely sensed imagery acquired for an island in the tropics. Based on four key research questions, individual methodological sections were developed (Chapters 4 to 6) and applied (Chapters 7 to 9) to meet the specific aims and objectives outlined (Chapter 1). This chapter discusses the results obtained following completion of the analyses.

10.2. Research Question 1: How can medium-resolution satellite imagery from different sensors be combined to effectively visualise changes in the landscape?

Multitemporal PCA as a methodology for time-series change detection was developed by Millward *et al.* (2006) and applied as part of this research. However, there are four aspects new to the approach presented in this study. First the procedure was applied to datasets acquired from three Landsat sensors and two SPOT sensors. Second, NDBI and BI indices were generated for each date from the red, NIR and MIR wavebands. PCA was then applied to all four NDBI and BI images to determine the success of the indices to highlight landscape changes associated with human disturbance over the original measures of image brightness (PC1 derived from PCA on the red and green wavebands only), greenness (NIR) and NDVI. Third, the procedure was applied to a second time-series of imagery in order to generate NDBI and BI (both indices incorporate MIR) and to determine the sensitivity of the brightness, greenness and NDVI methods to the time intervals used and the robustness of the method. Finally, as part of the analysis of unchanged locations aggregate standard deviations were generated from a sample of areas known to have changed and compared to a sample of areas exhibiting little change across the time-series. Standard deviations were plotted to determine whether values generated from areas exhibiting little or no change are described by lower pixel variation in comparison to areas that have changed.

10.2.1. How suitable are visible and infrared wavebands (from both Landsat and SPOT platforms) for collapse into single univariate images representing image brightness, greenness, NDVI, NDBI and BI?

Band correlation results agree with others (Chavez and Kwarteng, 1989; Jensen, 2004) and support the hypothesis that both visible and infrared bands in the study area are highly redundant and suitable for collapse into single univariate images representative of image brightness, NDVI, NDBI and BI. However unlike Millward *et al.* (2006) whose results show poor correlation between NIR and the visible bands and confirm the appropriateness of isolating NIR as a measure of image greenness, NIR and the visible bands display moderately positive correlation which suggests that NIR may not be suitable for use as a measure of image greenness for the study area.

NDBI and BI indices investigated as two new approaches to multitemporal PCA were both generated using reflectance values from the visible, NIR and MIR wavebands, however the index values generated for each year in the time-series displayed very weak to negligible correlation and the PC images were also shown to describe very different aspects of change across the island.

The results from the inter-temporal correlation of similar spectral bands (Table 7.13) suggest that spectral and spatial differences between the SPOT and Landsat sensors do not play a significant role in introducing bias to the analysis, a result supported by Chavez and Howell (1988). It is more likely that changes to the landscape are contributing more substantially to the differences displayed by the inter- and intra-temporal correlation matrices, irrespective of the slight differences in spectral resolution between sensors.

10.2.2. How successful is the application of multitemporal PCA on a time-series of brightness, greenness and NDVI imagery in highlighting the sequence of human induced landscape disturbance?

Higher order PC images produced from multitemporal PCA on the brightness time-series with input years 1973-1986-1999-2002 produced the strongest indication of human disturbance associated with urban development across the landscape when compared to the performance of greenness and NDVI for the same time interval. Cumulative unique information content (% variance values) for higher order PCs was greater for the brightness time-series (21.7%) than for greenness (4.0%) and NDVI (19.9%) (Table 7.15). These results agree with those of Millward *et al.* (2006) who showed multitemporal PCA on a time-series of four brightness images (input years 1987-1991-1997-1999) to outperform both greenness and NDVI in highlighting the introduction of new urban features.

Multitemporal PCA on the NDVI time-series outperformed greenness in highlighting changes to vegetation and new urban development in the study area despite the fact that NDVI and the NIR waveband displayed consistently moderate to strong intra-temporal correlation across all platforms

(Table 7.12). These results are not consistent with Clark and Yool (1999) who both showed multitemporal PCA across a time-series of NIR imagery representing greenness, to yield superior interpretability of landscape change when compared to NDVI. For this study and 1973-1986-1999-2002 time-series of data, information content in higher-order PCs was found to be greater in NDVI than greenness (Table 7.15). In addition, greenness PCs were characterised by loading values that plotted as paired years (Figure 7.6) compared to NDVI (Figure 7.12), which impeded interpretability of the greenness PC images.

The success of multitemporal PCA on the brightness time-series to highlight landscape change associated with human disturbance above both NDVI and greenness, and the success of NDVI above greenness; is further revealed following visual comparison of the results. Many of the higher order PC images produced from the multitemporal analyses highlighted change between the same time periods (Table 7.19). For instance, change between 1973 and 2002 was highlighted by brightness PC3 and NDVI PC2. From Figure 10.1 it is clear that the introduction of new urban features between 1973 and 2002 is clearly illustrated in white signatures across the brightness image. Conversely, for the NDVI image bright areas highlight locations displaying an increase in NDVI most likely corresponding to an increase in vegetation cover or vigour between the time periods. Dark black signatures reveal areas where NDVI values have decreased and are associated with urban development, closely matching the PC3 bright signatures.

Change between 1986 and 1999 was highlighted by PC images 4, 2 and 4 from the brightness, greenness and NDVI time-series respectively. For each PC image, dark signatures represent an increase in NIR reflectance between 1986 and 1999. Figure 10.2 illustrates a subset of New Providence to show how differently change information is manifested across the brightness, greenness and NDVI PC imagery. PC4 generated from the brightness series clearly presents new urban development between 1986 and 1999 in dark black signatures. Owing to the saturation of factor loadings and poorer image contrast across both greenness (Figure 7.6) and NDVI (Figure 7.11) PC images it is more difficult to visually determine change in comparison to the brightness PC image.

Change between 1999 and 2002 was highlighted by PC3 for both greenness and NDVI. Change information presented in bright white signatures marks the increase in NIR reflectances and a decrease in NDVI values associated with the conversion of vegetated landscape to urban (Figure 10.3). The pairing and saturation of factor loading values for the greenness PC (Figure 7.6) makes specific change information more difficult to determine compounded by the fact that the 2002 input band contributes over 75% (Table 7.17) to the variance of PC3 and completely dominates the image.

Multitemporal PCA performed on the second time-series produced very similar results demonstrating the robustness of the methods. Both brightness and NDVI time-series 1985-1999-

2001-2002 2002 outperformed greenness in highlighting landscape changes associated with vegetation change and new urban development. Once again, these results are not consistent with Clark and Yool (1999) or Millward *et al.* (2006). Greenness PCs were characterised by a greater degree of saturation of factor loading values pertaining to each input year (Figure 7.19) compared to NDVI (Figure 7.24), which hampered the interpretation of change information from the greenness PC images.

The success of multitemporal PCA on the NDVI time-series to highlight landscape change associated with human disturbance above both brightness and greenness, and the success of NDVI above greenness described by cumulative variance totals is further examined via visual comparison of the results. Many of the higher order PC images produced from the multitemporal analyses highlighted change between the same time periods (Table 7.24).

For example, PC3, PC2 and PC4 representing the brightness, greenness and NDVI time-series respectively all highlight change between 1985 and 1999. Figure 10.4 reveals that the brightness image most clearly illustrates the introduction of new urban features between the time periods, in bright white signatures. The NDVI image highlights in white, locations where NDVI values have increased over the time period that can be associated with an increase in vegetation cover. While areas in dark black tones highlight locations where NDVI values have decreased between 1986 and 1999 corresponding to areas of new urban development, the NDVI PC4 image lacks the detail of the brightness PC2 image. Despite the fact that NDVI PC images explain a higher proportion of cumulative variance, individual information content for NDVI PC4 is 2.0% compared to 4.3% explained by brightness PC3 (Table 7.20).

Brightness PC2 and NDVI PC3 both describe change between 1999 and 2002. Figure 10.5 illustrates the difference in how change information between the time periods is expressed by the PC images. New urban development between 1999 and 2002 can be distinguished very clearly from the brightness PC2 image in dark black signatures against a light grey background. NDVI PC3 highlights in bright white locations where NDVI values have decreased between 1999 and 2002 and can also be associated with new urban development. However, the NDVI factor loadings for PC3 (Figure 7.24) display a smaller range and a strong positive contribution from the 1985 input year compared with the brightness factor loadings for PC2 (Figure 7.15). Bright areas on the NDVI image also express change information from 1985 through 2002. The 1999 input year contributes over 70% to PC2 brightness variance (Table 7.21), compared to a 28% contribution from 1999 input year to NDVI PC3 variance (Table 7.23). Combined with a wider spread of factor loading values, the higher percentage contribution from the 1999 input year also explains why there is greater contrast across the PC2 brightness image compared to NDVI PC3. While NDVI higher order PCs explain a greater overall cumulative percentage variance compared to the brightness PCs, brightness PC2 accounts for 7.1% and NDVI PC3 accounts for 6.4% unique information content relating to each time-series.

Finally, for the 1985 through 2002 time-series, change information between 2001 and 2002 was expressed by both brightness and greenness PC4. Visual inspection of the imagery illustrates the success of the brightness over greenness in highlighting urban landscape change but also the success of greenness over brightness in expressing changes to vegetation. Both the brightness and greenness PC4 images present new urban development between 2001 and 2002 in bright white signatures, however, there is a greater degree of contrast across PC4 brightness image and the white signatures are sharper (Figure 10.6). The greenness PC4 image expresses differences in NIR reflectances from areas that have remained vegetated between the time periods and provides information on vegetation changes not provided by brightness PC4. Both images present similar factor loading values although brightness PC4 exhibits a slightly larger range (Figure 7.15) compared to greenness PC4 (Figure 7.19).

10.2.3. How successful is the application of multitemporal PCA on a time-series of NDBI and BI imagery in highlighting the sequence of human induced landscape disturbance?

The results showed that overall NDBI higher order PCs contained greater unique information content and hence a more successful and change information rich result over BI. Multitemporal PCA on the NDBI and BI time-series produced PC images that highlighted change between the same time periods (Table 7.28). To compare the success of each index to identify the sequence of human disturbance, change information expressed by each PC is compared.

Change information between 1985 and 2000 is expressed through PC3 for both the NDBI and BI time-series (Figure 10.7) where bright white signatures highlight new urban developments between the time periods. BI PC3 displays greater contrast and new urban features are defined more sharply than in the NDBI PC3 image. This is explained by PC3 loading values that plotted as paired years for the NDBI image (Figure 7.28) in contrast to BI factor loadings, which are unique and display a wider range (Figure 7.32).

NDBI and BI PC2 express change information associated with the 1999 and 2002 input years. Visual examination reveals that change information associated with new urban development is more clearly defined within NDBI PC2 than BI PC2 (Figure 10.8). NDBI PC2 accounts for 17.0% unique information content compared to BI PC2 at 10.4%. In addition, factor loadings for NDBI PC2 (Figure 7.28) display a wider range of values compared to BI PC2 (Figure 7.32), which explains the greater degree of contrast across NDBI PC2 image compared to BI PC2. Dark black signatures in the NDBI PC2 image reveal the introduction of new roads and other urban features. It is very difficult to determine visual change information from BI PC2.

Finally, change information between 2001 and 2002 is described by PC4 from both NDBI and BI time-series (Table 7.28). Figure 10.9 reveals the introduction of new urban features (bright white signatures in both images) to be sharper for BI PC4 than NDBI PC4, yet differences in areas that have remained vegetated are more defined in dark black signatures in NDBI PC4 than BI PC4. In

this case, BI PC4 out-performs NDBI PC4 for identifying new urban development between dates accounting for a higher percentage of unique information content (Table 7.25) and displaying greater visual contrast than its NDBI counterpart.

10.2.4. How successful is the application of multitemporal PCA on a time-series of NDBI and BI imagery in comparison to measures of brightness, greenness and NDVI in highlighting landscape change associated with human disturbance?

Visual inspection of the change information explained by each higher order brightness, greenness and NDVI PC and evaluation of the associated input year contribution to variance percentages and factor loading values; demonstrated the success of brightness over greenness and NDVI for highlighting landscape change associated with human disturbance (Chapter 7 section 7.4.1). The results also showed that change analysis of NDVI provided more contrast between vegetated areas over the time interval than a similar analysis with NIR (greenness).

A comparison of the results produced following the application of multitemporal PCA on the entire range of time-series evaluated i.e. brightness, greenness, NDVI, NDBI and BI shows that NDBI higher order PCs account for the greatest percentage of variance or unique information content above all other methods (Table 10.1). However, the conclusive success of one particular method above another to highlight the sequence of human disturbance over the time period can only be revealed by comparing the expression of change information, factor loadings and input year percent contribution to variance associated with specific PC images pertaining to a specific interval of time.

For instance, many of the higher order PCs pertaining to each of the methods examined, highlighted change information between the same time intervals (Table 10.2). Multitemporal PCA on the greenness, NDBI and BI time-series produced higher order PCs (PC3 in each case) that expressed landscape change between 1985 and 2002, illustrated in Figure 10.10. For all three images bright white signatures represent an increase in reflectance values measured by the respective wavebands over a 17-year time period. While both the NDBI and BI images recorded higher information content (% variance) in comparison to greenness, the greenness image displays greater contrast and provides the strongest visualisation of change information between 1985 and 2002.

Change information between 1999 and 2002 is expressed by brightness, NDBI and BI PC2 and NDVI PC3. In a comparison of brightness PC2 and NDVI PC3 imagery conducted earlier, brightness PC2 was shown to highlight the introduction of new urban features between 1999 and 2002 with greater success (Figure 10.5). Similarly, NDBI was shown to outperform BI given a wider range of correlation values, which contributed to greater contrast across the change image (Figure 10.8).

A comparison of the output from all four PC images (Figure 10.11) shows the visual superiority of both brightness and NDBI over greenness and BI in highlighting landscape change for the time interval. A golf course on Paradise Island and playing fields in Nassau displayed distinct bright white signatures on the NDBI PC2 image (Figure 10.12).

Input year contribution to variance and factor loading scores produced from the analysis demonstrate that brightness PC2 presents the most successful visualisation of the introduction of new urban features between 1999-2002 above NDVI, NDBI and BI. NDBI presents the most successful visualisation of increasing NDVI between 1999 and 2002 values in comparison to NDVI.

PC4 produced following multitemporal PCA on the brightness, greenness, NDVI and BI time-series displays information associated with landscape change between 2001 and 2002. While urban development between 2001 and 2002 has been demarcated in bright white across all four images (Figure 10.13), brightness PC4 reveals the greatest visual contrast in terms of new urban features. NDBI and BI PC4 both have higher unique information content (Table 10.2) but the development of a new road in the northeastern portion of the image is visible in every image except for NDBI.

The results show that while a greater amount of information content or percent variance is desirable across higher order PC's it does not automatically translate into more interpretable change information.

Overall, NDBI and BI indices did not outperform measures of brightness and NDVI in highlighting landscape change. However, there were instances where specific change information associated with an increase in NDVI values between years was more successfully highlighted by NDBI, demonstrating the potential of NDBI to be successfully applied to studies investigating vegetation changes over time.

10.2.5. How successful is the application of multitemporal PCA on a time-series of brightness, greenness, NDVI, NDBI and BI imagery in identifying areas of little or no change?

PC1 standard deviation values of the little or no-change areas were shown to be higher and decrease with each higher-order PC for each of the brightness, greenness and NDVI time-series evaluated (Figure 7.38, Figure 7.39), agreeing with others (Millward *et al.*, 2006). The results for the two new approaches to spectral ordination NDBI and BI (Figure 7.4.3) tested as part of this research produced the same pattern. This is expected given that the first PC describes common surface characteristics and explains the maximum amount of variance possible for the dataset. PC1 values of the entire image area recorded for each of the analyses displayed largely uniform highly positive loadings (e.g. Figure 7.1, Figure 7.15) and equivalent percent contributions (e.g. Table 7.14; Table 7.20).

Both the brightness time-series and NDVI display a sharper drop in aggregate standard deviation values computed for the areas of no change between PC1 and PC2 and also display less variation between higher-order PCs 2 through 4 for input years 1973-1986-1999-2002; in comparison to the results produced from the greenness series. This pattern was repeated for the 1985-1999-2001-2002 time-series and demonstrates the success and robustness of the technique to characterise areas of little or no change in multitemporal PCA on a time-series of brightness and NDVI images.

A similar pattern was also produced for the NDBI and BI time-series although NDBI displayed a sharper drop in aggregate standard deviation values between PC1 and the remaining higher order PCs in comparison to the results produced from the BI index. While it is difficult to establish thresholds to determine the success of one method over the other in characterising areas of little or no change, the results indicate that NDBI presents a greater differentiation between PC1 (which explains the maximum amount of variance) and PCs 2 through 4 and therefore presents a more successful characterisation of the areas of little or no change for the study area in comparison to BI. Furthermore, aggregate standard deviation values for BI PC2 did not differentiate between areas of change and little or no change.

Smaller standard deviation to information content ratios for the areas of little or no change presented across the higher order brightness, NDVI and NDBI PCs demonstrate the success of the methods to successfully differentiate between areas of change and little or no change for the study area. The results were consistent and robust for the brightness and NDVI time-series across both time intervals examined. Greenness and BI time-series produced the poorest results in terms of the expression of change information and similarly failed to differentiate between areas of little or no change and areas that have been altered across some of the higher order PCs.

10.3. Research Question 2: How can medium-resolution satellite imagery from different sensors be combined to effectively quantify changes in the landscape?

While multitemporal PCA was shown to successfully highlight areas of landscape change associated with human disturbance between specific time intervals, the method cannot be used to provide quantitative information as to how much change has occurred. A discussion of the results produced from the land cover classification and post-classification change detection methodology developed and applied to address Research Question 2, is presented in 10.3.1 to 10.3.4.

10.3.1. Does the use of the first three PCs from a PCA of the Landsat ETM+ and SPOT 4 multispectral bands increase or decrease classification accuracy? Are the results consistent across platforms?

Image transforms are often used in digital image processing to reduce the dimension of an image and to condense the information into a smaller number of uncorrelated components. Despite the use of PCA to reduce data dimension and correlation from the dataset, classification of the first three PC images alone (PCA) derived from the Landsat ETM+ and SPOT HRVIR sensors did not offer an improvement to classification of the original dataset (VISIR) (Table 8.10, 8.11 and 8.12).

Overall percent classification accuracy and the Kappa coefficient generated using 130 ground reference test points across the study area were shown to be statistically significant (Z-values > 1.96) and superior results were produced for the Landsat ETM+ 2001 dataset in comparison to Landsat ETM+ 2002 and SPOT HRVIR 1999. Kappa coefficients derived to describe the agreement between the reference data and original imagery were classed as "substantial" for the Landsat ETM+ 2001 data and "moderate" for SPOT HRVIR 1999 and Landsat ETM+ 2002.

A number of specific difficulties arose during the land cover classification, shown by the relatively low individual accuracies for some land cover classes. In particular, sparse mangroves produced consistently poor accuracy values. Sparse mangroves and sand have similar reflectance properties to urban landscapes and both sparse mangrove and sand were commonly misclassified as HAL throughout the classification. Moreover, sparse mangrove does not form in large contiguous expanses but in small and isolated patches, which made sampling for ground reference test information for this land cover particularly difficult.

It was shown that a disproportional number of sample points were gathered for sparse mangrove in comparison to other land covers (Table 8.9). Many coastal areas on the island for which large expanses of mangrove exist were not accessible by foot. In the absence of high-resolution imagery, sampling for mangrove reference points is an extremely arduous task due to the isolated and patchy distribution of mangrove on the island. Given the difficulty in gathering ground reference test information points for the mangrove land cover classes and the low number of sampling points used as a result it is expected that classification accuracies for this land cover class will be impacted.

Spectral similarity between sparse mangrove, HAL and sand land cover contributed to classification error. For instance, most beaches on New Providence are characterised by narrow strips of sand with development in immediate proximity to the beach and shoreline and these areas were predominantly classified as HAL. Confusion between the vegetated land covers DEF and pine and HAL is attributed to the canopy effect of dense vegetation over roads or other urban structures and

the failure of the classification to distinguish spectral reflectance values from urban surfaces located in heavily vegetated areas.

A majority filter was applied to the classified images to remove isolated pixels and improve object integrity. The results showed that unlike the work of others (Myeong *et al.*, 2001; and Rencai *et al.*, 2006) the application of the majority filter to smooth the land cover maps did not improve overall classification accuracy for either the VISIR or PCA classification methods (Table 8.15, 8.16 and 8.17) bar one exception. PCA classification of the Landsat ETM+2001 image improved slightly from 79.23% to 80%. The improvement was recorded specifically in the individual accuracies of HAL and sparse mangrove land covers (Table 8.18). This type of post-processing has been shown in the literature to cause a shift or removal in certain (typically linear) features leading to misclassification (Myeong *et al.*, 2001) and its application as part of this study did not deliver an overall improvement in PCA classification.

10.3.2. Does incorporation of temperature derived from Landsat ETM+ thermal band 6 improve classification accuracy?

Incorporation of temperature image into the classification (Temp) did not improve overall classification accuracy (Table 8.11 and Table 8.12). These results agree with others, for instance Lu and Weng (2005) record classification accuracies for land cover maps incorporating temperature data at 69.1%, just over 1% less than the accuracy values achieved for land cover classification of the original dataset (70.57%) for their study area in Indiana, USA. The difference between classification results of the original multispectral image versus the multispectral image including temperature data for this particular study area in comparison to Lu and Weng (2005) was more noticeable at 8.47% and 6.93% for the 2001 and 2002 image years respectively.

Correlation between the multispectral Landsat ETM+ 2001 and 2002 wavebands and the respective temperature imagery was shown to be moderate to strongly positive and the combined multispectral and temperature imagery was subjected to PCA to determine whether the removal of redundancy from the dataset could improve classification accuracy. The results showed no improvement in comparison to classification of the original image however, a slight rise in classification accuracy was noted for the TempPCA classification in comparison to the TEMP classification for Landsat ETM+ 2001. This result was not repeated across the Landsat ETM+ 2002 dataset where it was shown that the application of PCA to the dataset incorporating temperature data caused a slight drop in overall classification accuracy.

Agreement between the reference pixels and land cover classification incorporating temperature and both temperature and PCA was described as "moderate" for both the 2001 and 2002 datasets. Application of a majority filter to remove any noise in the dataset did not offer any improvement. The poor performance of the inclusion of temperature data in a land cover classification is explained by the effect of combining a low-resolution temperature image (generated from a 60m

resolution thermal waveband) with higher resolution multispectral data, which effectively smoothed rather than enhanced inherent differences between land cover classes. Moreover, the overall poorer performance of the 2002 classification incorporating thermal data compared to the 2001 dataset is attributed to the difference in image acquisition dates as Landsat ETM+ 2001 data was acquired in May and the 2002 data was acquired in March. The 2001 temperature map (Figure 8.1) was generated from thermal emittances recorded during the summer and thermal signatures across the landscape exhibit a greater degree of contrast in comparison to the 2002 temperature map (Figure 8.2). Average temperature values show less variation between acquisition dates and are almost identical (Table 8.4) but standard deviation values for the 2002 dataset are large in comparison to 2001 reflecting a greater degree of departure from the mean.

While the incorporation of temperature data into the land cover classification did not offer an improvement to overall accuracy values, visual comparison of the temperature map (Figure 8.1) and land cover map (Figure 10.14) generated following classification of the Landsat ETM+ visible and infrared wavebands (VISIR) reveals the close association between the pattern of temperature and distribution of land cover types across the island. The warmest areas on the map are clearly associated with HAL and the temperature map also exposes areas within the National Forest Reserve where forest canopy and vegetation cover are less dense and have higher thermal emittances associated with the exposure of bare soil and urban features. The 2001 temperature map displays a greater distribution of pixel counts across the temperature values (Figure 8.3) compared to the 2002 dataset (Table 8.4) and the four spikes on the frequency distribution curve generated from the 2001 temperature data can be linked to peaks in thermal emittance values recorded from water, vegetation (pine and DEF) and urban (HAL) land cover types. However, statistically significant differences were not established between individual land cover and temperature values due to the high variance in temperature values across the water and sand land cover types (Table 8.6). Standard deviation values for the remaining land covers were relatively and indicate less variation and more consistent temperature values in comparison to water and sand.

The use of historic thermal data for change detection analysis is limited to the earliest acquisition dates of Landsat TM when the thermal sensor was first introduced. It was noted earlier that temperature data derived from Landsat ETM+ 2002 thermal band data did not provide the same degree of contrast across the landscape in comparison to 2001. This suggests that at least for this study area successful use of temperature data in change detection analysis requires the acquisition of thermal imagery during the warmer months of the year when differences between temperature emittances from vegetated and urban areas are more distinct.

The potential of thermal mapping in tropical areas for land cover change assessment should not be discounted based on the results from the classification conducted here. In fact, given that one band of data (Landsat ETM+ thermal band 6) can be used to produce a map that reflects a very

similar spatial pattern to that of a land cover classification using six wavebands, use of thermal band data alone is a potentially powerful tool for land resource managers to perform a rapid visual assessment of landscape change ahead of a more labour intensive land cover classification that requires a larger number of wavebands and processing time. Moreover, the map could be used to produce a rudimentary urban-vegetation land cover map for use in a basic or preliminary landscape change assessment.

10.3.3. To what extent does data-fusion of panchromatic and multispectral images improve classification accuracy? How does preservation of spectral and spatial quality affect the results? Are the results consistent across platforms?

Incorporation of data-fusion derived from a high spatial resolution image has been shown in the literature to significantly improve classification accuracy (Solberg *et al.*, 1994; Solaiman *et al.*, 1999; Haack *et al.*, 2002; Ban, 2003). The results of this research demonstrated that use of high-resolution imagery is not appropriate for a land cover classification scheme incorporating seven land cover classes for a study area in the tropics. Of six data-fusion techniques evaluated, not one offered a significant improvement to overall accuracy over the results produced from a classification incorporating the original imagery (Table 8.10, 8.13, 8.14). Wavelet PCA and Multiplicative techniques performed consistently better than the other techniques however, producing classification accuracies of between 73%-82% and 70%-75% respectively. Agreement between the reference pixels and land cover maps measured by the kappa statistic was described as "substantial" (Wavelet PCA) and "moderate" (Multiplicative).

Overall, classification of the data-fused SPOT imagery produced the lowest classification accuracy results. It is fundamentally important to the data-fusion process that information extracted from the panchromatic image to improve the spatial resolution of the image occurs without altering the spectral characteristics of the original image. It was shown that only two of the SPOT multispectral images are contained within the full range of the panchromatic image and is a likely a direct cause as to why the classification accuracies overall were lower associated with every technique of data-fusion tested in comparison to the Landsat data.

Use of high-resolution data presents challenges to land cover classification as a direct result of the greater amount of information contained in each pixel and renders class discrimination more difficult for the classification of land cover types in comparison to using coarser resolution imagery. Previous research by Lu and Weng (2005) showed data-fusion of Landsat ETM+ multispectral and panchromatic wavebands by PCA to offer a 2% rise in classification accuracy over classification of the original image for a study area in Indiana, USA. Saroglu *et al.* (2004) evaluated four methods of data-fusion for IRS Pan and LISS data for a study area in Turkey and showed the IHS method of data-fusion to produce the greatest classification accuracy at 85.8% over PCA (83.2%), Brovey (80%) and Multiplicative (77.6%) methods. This research demonstrated that increased spectral

variation within the land cover classes associated with high spatial resolution decreased classification accuracy.

The majority filter was more effective on land cover maps produced from high-resolution data which contain more noise associated with a greater amount of pixel detail in comparison to the lower spatial resolution land cover maps produced from the VISIR, PCA, Temp and TempPCA classifications. Specific improvements to individual land cover classification accuracies following application of the majority filter were predominantly associated with HAL (Table 8.18) but a number of improvements were also recorded across the sparse mangrove, pine and DEF land cover types.

To determine whether the preservation of spectral and spatial quality by data-fusion impacted the results of the land cover classification the results from each analysis were compared. The results from the analysis show that the relationship between the preservation of spectral quality defined by the multispectral correlation coefficient and classification accuracy is not entirely clear. For instance, data-fusion by Multiplicative method produced a land cover map with classification accuracies greater than Brovey and IHS methods despite the fact that both Brovey and IHS imagery displayed stronger positive correlation with the original multispectral image (Figure 8.12). Similarly, the preservation of spectral quality described by the high degree of correlation between the Brovey and panchromatic images (Figure 8.16) was not reflected in the classification results.

However, both Brovey and IHS data-fused imagery can employ only three spectral bands, in contrast to Multiplicative data-fusion which retains the original number of input bands. Spectral information loss associated with the Brovey and IHS techniques is attributed to the poorer performance of these methods in the land cover classification. Multiplicative method of data-fusion is described in the literature (ERDAS, 2003) as most successful technique for highlighting urban features in comparison to IHS, Brovey and PCA and in this study proved to be the more appropriate data-fusion for land cover classification over the aforementioned methods.

Data-fusion by Wavelet PCA and Wavelet IHS techniques displayed the strongest correlation with the original multispectral imagery for all three datasets tested, yet Wavelet PCA proved to be the most successful method of data-fusion recording the highest accuracy following land cover classification in comparison to Wavelet IHS which had the poorest performance. Spectral information loss associated with use of a three-band image only for Wavelet IHS data-fusion is attributed to the weaker results.

Correlation between panchromatic and intensity (derived from the data-fused images) was plotted against the results from the accuracy assessment (Figure 8.17). Multiplicative and Wavelet PCA data-fusion methods display relatively poorer correlation between intensity and panchromatic in

comparison to other techniques yet produce consistently better results in the land cover classification.

The results show that while high resolution imagery enhances visual interpretation, data-fusion of high resolution imagery via the methods evaluated as part of this study do not offer an improvement to overall accuracy of an unsupervised land cover classification employing a seven-category land cover scheme for a small tropical island area. The classification system needs to be vastly more detailed than the current classification scheme for The Bahamas given the greater amount of information presented within high resolution or data-fused imagery. The high levels of classification detail presented by the data-fused imagery served to complicate the labelling of pixels into land cover classes and a considerably greater amount of noise was apparent in the final map products.

The greatest range between the most successful and least successful classification accuracy by method of data-fusion was for the Landsat ETM+ 2001 dataset where classification of the Wavelet PCA data-fused image produced an overall accuracy of 81.54% compared to 66.92% for Wavelet IHS (Table 8.13). The results across platforms were consistent with both Wavelet PCA (73.08%) and Wavelet IHS (66.15%) producing the most and least accurate classification results for SPOT HRVIR 1999 also (Table 8.10). Finally, for Landsat ETM+ 2002 classification of the Multiplicative image produced the best results (75.38%) with Wavelet HIS and Brovey delivering the lowest classification accuracy values (71.45%).

The difference between classification accuracies of the original dataset compared to the most successful of the data-fusion methods by sensor was measured at 2.31%, 3.85% and 4.61% for the Landsat ETM+ 2001, Landsat ETM+ 2002 and SPOR HRVIR 1999 image datasets.

10.3.4 To what extent can post-classification change detection identify the types, rates and temporal variability of land cover change?

Post-classification comparison change detection algorithms are described as the most common approach to change detection and have been used successfully to monitor land use changes in the Atlanta-Georgia area (Yang and Lo, 2002) and Twin Cities, Minnesota (Yuan *et al.*, 2005). Post-classification comparison change detection was used to determine differences between five time periods on a pixel-by-pixel basis and successfully pinpointed land cover changes that occurred between each of the intervals. Land cover change statistics generated for each of five time intervals as part of this study highlighted the growth and dominance of HAL across New Providence Island predominantly associated with land cover conversion of DEF and pine over the 29-year time period. The time period between 1986 and 1999 represented the largest increase in HAL and

hence development across the island, coinciding with the largest increase in population growth between census years (1980 and 1990).

Post-classification change comparison was conducted within ERDAS and combined with GIS techniques within ArcInfo to produce maps to illustrate "from-to" land cover change information generated to emphasize the spatial dynamics of land cover change to facilitate interpretation of the results. Selected classes were draped over a panchromatic image of the island to highlight the spatial locations of change.

A number of changes were consistently identified between each time interval. For instance, as a consequence of differences in tide between image acquisition dates the "conversion" of sand pixels to water and water to sand occurred consistently along the coastline and at inland water body locations (Figures 8.23, 8.27, 8.31, 8.34 and 8.38).

The conversion from pine to DEF and DEF to pine identified (Figures 8.21, 8.25, 8.29, 8.36) is not necessarily a result of misclassification error or spectral confusion between the vegetation classes identified by different remote sensing platforms. Pinelands form exclusively in dense forest stands or with an understory of DEF at locations that have not been subjected to recent fires (Chapter 3, section 3.3.3). The conversion information presented may reflect changes in the proportion of pine and DEF at locations where they both grow together. The results of the post-classification comparison suggests that DEF formations have become more dominant across the island reflecting a transition of pineland to DEF woodland and shrubland.

The urban canopy effect is attributed to a number of land cover conversions, including the conversion of HAL to pine or DEF land cover change (Figures 8.19, 8.24, 8.28, 8.32, 8.35). For example, most roadways and streets from 1973 are similarly classified as HAL in later images; however, the conversion of HAL pixels to pine or DEF between 1973 and 2002 along clearly identifiable road networks is most likely associated with the growth of urban tree canopies. As trees grow and expand they effectively block reflectances from road or other urban surface and pixels at these locations are classified as vegetation.

The conversion from HAL to pine and DEF between 1999 and 2001 occurred within the urban area of Nassau and within the National Forest Reserve. These land cover conversions can be interpreted in terms of greater vegetation vigour in 2001 associated with a summer acquisition date in comparison to 1999, which was acquired in November and contributed to the increase in total pine land cover recorded between these dates. The urban canopy effect contributed to the misclassification of roads and other urban features in the 2001 image. Furthermore, the greater detail of the 1999 image by virtue of higher spatial resolution of SPOT HRVIR in comparison to Landsat ETM+ may also have contributed to the identification of more urban features producing a more detailed classification following land cover classification than for the 2001 image dataset.

The irregular variation of wetland area between 1973 and 2002 is due in part to the conversion of HAL to wetlands (e.g. Figures 8.20, 8.26, 8.30, 8.33, 8.37) associated with misclassification of wetlands in the earlier imagery. For example, the main areas of conversion are within the vegetated grounds of Nassau International Airport and along the south-eastern coastline where higher spatial and spectral resolution associated with Landsat ETM+ sensor in comparison to Landsat MSS enabled the differentiation of cleared land from small outcrops of mangrove vegetation during the classification (Figure 8.20). Conversion of HAL to wetland can be attributed to classification error but also to natural changes in mangrove communities that may occur from year to year associated with varying precipitation and temperature rates (Yuan *et al.*, 2005). Between 1986 and 1999 (Figure 8.31) the conversion of HAL to wetlands is attributed to seasonal differences in image acquisition dates. The 1986 image was acquired in April during The Bahamas dry season in comparison to the 1999 image, which was acquired in November during the wet season. HAL and sparse mangroves have similar spectral reflectance values likely heightened during the dry season with the associated reduction in soil moisture values and an increase in surface reflection.

One of the biggest difficulties in the application of post-classification comparison change detection in data-poor countries is the absence of ancillary historic datasets with which to use in an accuracy assessment of the earlier imagery. This information is not available for The Bahamas and effectively precluded an accuracy assessment of the earlier (1973 and 1986) land cover maps. Land cover maps were generated using an unsupervised classification procedure which allows natural spectral clusters to be defined with a high degree of objectivity. The clusters produced from the classification were manually interpreted based on local knowledge of the study area following several trips to the field between 2002 and 2006. Analysis of specific "from-to" land cover change information between the earlier and later dates for which reference information is available is deemed adequate to meet the objectives of this research.

Post-classification change comparison was conducted to quantify land cover change and the results of the "from-to" analysis were successfully used to visualise and map the conversion of pine, DEF and wetlands to HAL associated with human disturbance across specific time intervals (Figures 8.39, 8.40, 8.41, 8.42 and 8.43). The results showed that urban growth represented by the conversion of natural landscape to HAL is occurring at a faster rate than population growth. This is a direct consequence of the continued migration of The Bahamian population from the Family Islands to New Providence for employment, better services including education and health care. There will be continued pressure on Government and land management agencies to provide infrastructure and housing to support a growing population in addition to supporting a tourism industry that in 2004 brought over five million visitors to the islands (BEST, 2005).

It is clear that through the construction of change detection maps, the advantages of satellite remote sensing in spatially disaggregating the change statistics can be more fully appreciated. The method was successfully be used to highlight and map land cover conversion for multiple time intervals across the island of new Providence (Figure 8.43).

Post-classification change comparison is hampered in data-poor areas like The Bahamas because of the complete lack of historic ancillary datasets with which to use to assess the accuracy of the earlier land cover maps (1973 and 1986) and hence provide an overall assessment of the accuracy of the change information presented by the maps. However, a qualitative comparison of the results produced from multitemporal PCA and post-classification change detection reveals that both techniques successfully highlighted the introduction of new urban features and changes to vegetation. For example brightness PC4 in dark signatures details the introduction of new urban features between 1986 and 1999 and in bright tones highlights landscape change between 1973 and 1986. A comparison with the land cover change map illustrating the conversion of vegetation and wetlands to HAL between 1986 and 1999 (Figure 10.15) reveals that the bright tones in the PC image correlate with the areas in grey (conversion between 1973-1986) in the change map and the dark tones with the areas highlighted in green (conversion between 1986-1999).

10.4. Research Question 3: To what extent can remotely sensed indicators of human disturbance and spatial metrics be used in a time-series analysis of landscape change for landscape monitoring?

To determine the value of remotely sensed indicators and spatial metrics in landscape monitoring of a data-poor area, the statistical significance of the trends identified by eight indicators of human disturbance and 31 spatial metrics extracted from a time-series of land cover maps was examined. A disproportionately large amount of development has taken place in close proximity to the shoreline of New Providence associated with exclusive private real-estate and tourism driven construction and areas within these zones have and continue to be heavily impacted by human activity. The sensitivity of the methods to changes in scale and spatial extent was also examined to demonstrate the robustness of the indicators and metrics identified and their suitability to application within a narrow coastal zone.

10.4.1. How is human disturbance of the landscape expressed by the remotely sensed indicators? How robust are the indicators to changes in spatial extent?

It was noted in the literature review that there is a pressing need to develop environmental indicators that can be applied to large geographic areas on a periodic basis for evaluating, monitoring and reporting on the status of natural resources regionally and globally (Section 2.5). In the absence of a wide-scale environmental monitoring program proxies for ecological or environmental indicators can be interpreted through remote sensing (Quigley, 2001; Tiner, 2004,

Jackson and Jensen, 2005) and are often based land use change focusing on specific habitats such as wetlands (Dahl, 2000; Manson *et al.*, 2003) or river and shoreline buffers (Lathrop and Bognar, 2001; Jackson and Jensen, 2005).

A unique set of remotely sensed indicators developed as part of this research successfully identified statistically significant trends in natural landscape extent, integrity and human disturbance using a time-series of land cover maps generated from a multisensor dataset. Indicators of natural landscape extent and integrity comprise measures of the total percentage of natural land cover and the proportion of current to historic natural landscape cover estimated from the 1973 dataset.

The results revealed that overall the percentage of natural landscape cover across the island represented a 14.7% reduction between 1973 and 2002 to 47.2%.

Indicators of human disturbance are measures of HAL land cover as a percentage of the total area (HA), the proportion of HAL to natural landscape (HD) and the ratio of current to historic HAL land cover amounts (HI) and displayed statistically significant increasing trends across the time period. Indicator scores highlighted the 1986-1999 time interval as the years for which the island was most heavily impacted by development.

A simple composite index to describe the overall impact of human disturbance revealed a statistically significant increasing trend associated with an increasingly stressed landscape due to development. The indicators were shown to be robust at different spatial extents and suitable for use in an assessment of human disturbance within a narrow coastal zone. The results also confirmed that areas within 200m from the shoreline in particular have been severely impacted by development over the time period.

Misclassification error can impact indicator values and trends and is attributed to the poorer performance of WI as an indicator of wetland (mangrove) extent. Seasonal differences between image acquisition dates recorded in 2001 (May) and 2002 (March) are likely to have contributed to the discrepancy in mangrove extent over the time period and cannot be attributed entirely to human disturbance. During the dry season, evaporation of water from mangrove swamps may cause spectral confusion between mangrove and surrounding vegetation resulting in the classification of dense mangrove as either DEF or pine and sparse mangrove as HAL. The results showed that mangrove land cover represented by WI is substantially less in 2002 compared to 2001 whereas vegetation land cover represented by VI is greater in 2002 than for 2001.

Differences in sensor spatial resolution in terms of the amount of pixel detail can also cause discrepancies in indicator scores when comparing maps from two time intervals. For example, it was shown during post-classification change comparison that the SPOT HRVIR 1999 image presented more subtle detail in urban features than the 2001 image (despite resampling the SPOT

image to 30m before conducting change comparison). This contributed to the conversion of a number of HAL pixels to pine and DEF between dates. This error was reflected within the coastal zone where human disturbance indicators CA and CD both display a slight dip between 1999 and 2001 but rise again between 2001 and 2002. In addition it is also probable that misclassification of roads or other urban surfaces as a result of the urban canopy effect was greater for the 2001 image acquired in (May) than for either the SPOT image or 2002 image which were acquired in November and March respectively.

Remote indicators of natural landscape extent and disturbance can be generated rapidly and the evaluation of future trends for landscape monitoring can be conducted simply, following periodic updates of the land cover maps. Remotely sensed indices present very useful information for resource managers on the changing status of the natural landscape and were shown in this study to highlight the years for which temporal changes in natural landscape extent and human alteration were greatest. While generated for only one island, the composite index can potentially be used to conduct a comparative analysis of overall human disturbance across the wider archipelago. Moreover, the method developed is simple and can easily be adapted for use to generate indicators of human disturbance for monitoring land cover change in a study area outside The Bahamas.

10.4.2. How are changes in landscape pattern and structure associated with human disturbance expressed in a time-series analysis of spatial metric values?

When comparing landscape structure over time, spatial metrics provide important elements that describe general patterns within the landscape and were evaluated for their application in a time-series analysis of land cover change associated with human disturbance. While a wide range of spatial metrics exist, and have been successfully applied to a number of studies it is not clear from the literature review (Section 2.5);

- which remotely-derived indicators and spatial metrics are most informative and interpretable for measuring changes in pattern and structure through time to infer changes in anthropogenic processes
- whether the remotely-derived indicators and spatial metric values are robust across different scales and spatial extent
- how suitable the method is for application in data-poor tropical island areas.

The results from this study showed that out of a suite of spatial metrics (31 in total) measuring elements of landscape pattern and structure describing area, shape, diversity and configuration eighteen metrics generated at the scale of entire landscape displayed statistically significant trends through time (Table 9.6). Specific metric values describing changes to landscape composition and configuration were clearly interpretable in the context of the impact of human disturbance on the landscape.

For instance, statistically significant trends in the values of the area metrics (specifically NP, PD, TE) revealed that the landscape of the island is becoming increasingly fine grained, dominated by a greater number of patches which describes an increasingly fragmented and disturbed landscape pattern. The values also indicate that the distribution of area amongst the different patches is becoming less equitable and the landscape has become increasingly disconnected (AREA_CV, GYRATE_MN). The unequal distribution of area amongst patch types was also confirmed by the results produced from the diversity metrics (SIDI, SIEI).

While the number of patches has increased and reveals a patchier landscape associated with landscape disturbance, the metrics also highlighted the fact that the largest patch in the landscape has increased (LPI) and displays a statistically significant trend over the time-series. The increase in LPI at the landscape scale is attributed to urban sprawl on New Providence reflecting the significant growth of HAL identified during post-classification change comparison.

Similarly the probability that two randomly chosen locations are in the same undissected patch (measured by DIVISION) was shown to increase over the time period. While the number of patches in the landscape was shown to display a statistically significant increasing trend it appears that the distribution of area among these patches is vastly variable.

These results are similar to previous work in the field (Chapter 2, section 2.5), for example, Yu and Ng (2006) who showed that values for NP, ED and MPS (as indicators of landscape fragmentation) increased for their study area in China. MPS of urban land cover increased as a consequence of the aggregation of existing urban areas associated with urban sprawl.

It was also noted in the literature review that LPI (DiBari, 2007) and SIDI (Griffith *et al.*, 2003) were unsuccessfully applied in temporal analysis for their study areas. Herold *et al.* (2003) reported a decrease in both LPI and CONTAG associated with urban sprawl, in contrast to Yu and Ng (2006). In this study LPI and SIDI displayed statistically significant trends and describe the increase and dominance of HAL and a reduction in the proportional abundance of land cover types. CONTAG did not reveal a statistically significant trend at the landscape level but overall displayed a very slight increase in value between 1973 and 2002 (Table 9.5). CONTAG is used to measure disaggregation tendency and an increase in the index value would indicate that the landscape is becoming less fragmented. However, diversity measured by SIDI and SIEI revealed a statistically significant decreasing trend in this study and while the number of land cover types (richness) was consistent over the time period, the indices reveal the increasingly uneven distribution of area amongst the patch types describing a more fragmented and complicated landscape structure.

Abdullah and Nakagoshi (2006) assessed temporal changes in metric values for two time periods only, but an increase in the number of patches and a decrease in mean patch size produced from their research was similarly associated with an increase in landscape fragmentation.

A statistically significant decreasing trend identified by a shape metric (CONTIG_MN) in this study demonstrated that the spatial connectedness or contiguity of cells has reduced meaning landscape pattern is described by more disconnected patches in 2002 compared to 1973.

Several studies have investigated temporal trends in spatial metrics but none evaluated thirty-one metrics for a time-series of five images spanning 29 years for a data-poor area in the tropics. Of the work that has been undertaken, the results produced both agreement and variance and illustrate that it is essential to evaluate a wide range of metrics to fully understand how changes in landscape pattern and structure over time described by spatial metrics are interpretable in the context of human disturbance.

10.4.3. How robust are the metrics to changes in spatial extent?

A limitation to the application of spatial metrics is that the absolute value derived for each metric is dependent upon the spatial resolution, the extent of the study area as well as the level of detail in the landscape classifications. A change in either the extent, spatial resolution or the thematic definition of the patch classes will significantly change the metrics and limit the ease of relating the results from one area to another especially for quantitative comparison (Cain *et al.*, 1997; Wu, 2004; Herold *et al.*, 2003).

Metric values generated for 500m and 200m coastal land cover maps revealed that the metrics were robust and appropriate for monitoring temporal land cover changes within a narrow coastal zone heavily impacted by human disturbance. Of thirty one metrics evaluated 18 and 20 spatial metrics respectively revealed statistically significant trends within a 500m and 200m area of coastal zone describing the same changes to landscape pattern and structure defined at the extent of the entire landscape.

At the scale of the 500m coastal zone within the area category of metrics the statistical significance of increasing LPI and TE trends identified showed improvement compared to the results from the entire island but neither NP nor PD displayed statistically significant trends. A sharp rise in both NP and PD between 1973 and 1986 is evident (Table 9.7) but the increase in values beyond 1986 was modest.

There was also improvement in the statistical significance of the trends identified by the remaining area, shape, diversity and contagion metrics computed within a 500m coastal zone. Area-weighted mean shape displayed a statistically significant increasing trend which was not identified at the scale of the entire island and reflects the increasing proportional abundance of patch area within a narrow coastal zone. Diversity and contagion indices all displayed similar but slightly improved statistically significant trends to those generated for the entire island.

The study showed that overall the trends identified were repeated within a 200m coastal zone although there were three main differences. In the area category, neither TE nor NP display significant trends and for the first time in the analysis from both PAFRAC (shape) and CONTAG (contagion) revealed statistically significant increasing trends. The significance of these metrics is related to the smaller area that comprises a 200m coastal zone. For instance, the increase in percentage area occupied by a single class (CONTAG) is more pronounced than at the larger spatial extents.

Similarly PAFRAC which describes the complexity of patch shapes displayed a consistent and steady increase in values across both the 500m and 200m coastal zone (Table 9.7 and Table 9.8) and the 2002 PAFRAC value was almost identical for each of the three spatial extents evaluated (Table 9.5). However, PAFRAC values in 1973 within a 200m zone were lowest in comparison and as such the increase in PAFRAC values was more pronounced associated with the high degree of landscape disturbance within a narrow coastal zone.

In summary, a total of fifteen of the metrics within area (5), shape (1), diversity (6) and contagion (3) categories displayed statistically significant trends at all three spatial extents (Figure 9.11). The results revealed that overall, correlation among the spatial metrics evaluated as part of this research did not change with changes in spatial extent and therefore can be used to consistently assess landscape pattern and structure at the extent of the entire island and within a narrow area of coastal zone.

10.4.4. How sensitive are the spatial metrics to changes in spatial scale?

Numerous studies have analysed the effect of spatial resolution on spatial metrics (Frohn, 1998; Saura, 2005; Frohn and Hao, 2006). Different authors have found that the variation of several spatial metrics can be described through scaling functions such as power laws (Suara, 2001, 2004; Wu *et al.*, 2002 and Wu, 2004). Previous research reported on scaling functions describing the variations of different spatial metrics. Wu (2004) evaluated the scale effects on nineteen spatial metrics and found that landscape-scale metrics fall into three response categories, predictable, less predictable and unpredictable behaviour with no consistent scaling behaviour. Of the spatial metrics evaluated as part of their research and relevant to the metrics tested as part of this study; NP, PD, TE, AREA_MN, AREA_CV, AREA_SD, LPI and SHAPE_AM all displayed predictable changes with increases in grain size that were robust across different landscapes. The results from this study agreed with Wu (2004) and other studies (Frohn and Hao, 2006; Saura and Castro, 2007) and the response curves of these metrics revealed stable and predictable scaling relationships across landscapes. In addition, mean radius of gyration (describing patch extent) while not examined as part of the Wu *et al.* (2002) study also displayed a consistent, steady and linear increase with increasing grain size for each year in the time-series examined.

Diversity metrics were associated with response curves detailing a staircase pattern (Wu, 2004) and is present but less obvious from the results in this study. This is likely a direct result of the relatively smaller range of grain sizes used to investigate the sensitivity of the spatial metrics (i.e. $30 \times 30\text{m}^2$ to $600 \times 600\text{m}^2$ compared to Wu *et al.* (2002) $30 \times 30\text{m}^2$ to 3000m^2). The results produced here however also agree with Turner *et al.* (1989) who found in general that diversity indices decrease with increasing grain size.

The response of PAFRAC to changing grain size for different landscapes is described as erratic by Wu *et al.* (2002) but displayed little variation in the context of this study (Figure 9.10). The contiguity index, which describes spatial connectedness, displayed a generally decreasing trend with increasing grain size but the response was not predictable across map years. These results agreed with Frohn (1998) who showed both, CONTAG and PAFRAC to be unstable with respect to varying spatial resolution.

Saura (2004) examined the performances of six indices with varying aggregating and found DIVISION and LPI the most stable in both aggregated and actual sensor patterns. Similarly, the contagion metrics (DIVISION, MESH and SPLIT) all displayed consistent responses to changing grain sizes as part of this study.

While the response curves generated reveal variation in the rate of increase and decrease in particular metric values with different years in the time-series, the general scaling relationships described remain consistent and robust despite changes to landscape configuration and composition associated with landscape disturbance over time.

10.4.5. Limitations to the use of spatial metrics for landscape monitoring

While the sensitivity of spatial metrics to changes in map extent and scale were examined, the sensitivity of spatial metrics to the level of detail in categorical map data was not explored. It is important to note that same landscape can be represented very differently if a different classification scheme is used (Wickham *et al.*, 1996; Turner *et al.*, 2001). Consequently the changes to landscape pattern and structure measured by the metrics associated with human disturbance may have been interpreted very differently if a different classification scheme was used. It is important therefore in the application of spatial metrics that the analyst recognises the relevance of the map data within the context of the application so that the correct scale is used.

The application of spatial metrics is often hindered by the difficulty in interpreting the specific values of the indices generated and few studies identify which combination of indices is most effective in a particular situation (Riitters *et al.*, 1995; Haines-Young and Chopping, 1996; O'Neill *et al.*, 1999; Herzog and Lausch, 2001). Moreover, the interpretation of indices is a difficult task

because the caveats of spatial metrics remain poorly understood (Li and Reynolds, 1994; Gustafson, 1998; Wu, 2000; Turner *et al.*, 2002; Li and Wu, 2004). While changes in spatial pattern can reflect significant changes in landscape function and integrity, specific thresholds have not been identified (Turner *et al.*, 2001). Application of spatial metrics in a time-series analysis and statistical assessment of the trends identified facilitated interpretation of the metric values in the context of this work but further research is needed to establish specific thresholds.

Temporal trends in spatial metric values were assessed at the landscape scale in this study which effectively sums the indices over the range of land cover classes. Further work is needed to elucidate changes in pattern and structure associated with individual land cover types and to establish to what extent statistically significant trends in spatial metrics values can be identified to measure human disturbance at the class level. Structural changes in vegetation land cover classes (e.g. pine, DEF or mangroves) measured by spatial metrics at the class level could be potentially applied to determine possible changes to ecological processes such as fire disturbance, species diversity or bird population dynamics for example.

10.5. Research Question 4: What is the potential of these methods for application in other data-poor jurisdictions?

The results of the analysis show that despite the methodological challenges of using a time-series of imagery derived from different sensors in different seasons, the techniques can be successfully applied to visualise and quantify changes across a small island that has undergone rapid landscape change associated with human disturbance over a 29-year time period.

The Bahamas is described as a data-poor region with respect to the poor availability of remotely sensed satellite for use in change detection but in addition, to date there is a lack of quantitative information on land cover and the changing status of natural resources across the archipelago. Given the challenges to acquiring a useable dataset, it was necessary to assemble a multisensor time-series of imagery to conduct landscape change detection. This situation is not unique to The Bahamas and the techniques evaluated here have the potential to be successfully applied elsewhere, to other island environments, given a number of caveats.

Multitemporal PCA of a series of brightness, NDVI and NDBI imagery highlighted change information between specific time intervals. A disadvantage of the technique however is that there is a considerable amount of pre-processing time required to standardise the dataset but change information can be interpreted through factor loading scores and input band variance. Paired factor loading values caused confusion and it was almost impossible to determine the specific nature of the change being expressed for those cases. A total of four images were used in the time-series and change information is expressed in the higher order PCs, PCs 2 through 4. The sensitivity of the method to the number of input years was not investigated as part of this research and further work is needed to determine the suitability of the method to a time-series incorporating more than

four images. However, the technique was robust across the second time-series which comprised two images from the first time-series and an additional two images.

The method was successfully applied in The Bahamas but the islands are low-lying, described as almost all coastal zone with no mountains or river systems. The success of the application of the technique in other island locations using Landsat and SPOT imagery may be impacted by the presence of mountains which might necessitate substantial correction such as orthorectification in addition to the necessary radiometric and geometric pre-processing procedures that must be undertaken to standardise the time-series of images. Depending on the application, for example if multitemporal PCA was being conducted to visualise new urban development between dates, it might be also be necessary to mask out areas of water from the image to improve contrast across the land surface and the detection of urban features and reapply the algorithm (Millward *et al.*, 2006). This would amount to a considerable level of pre-processing. A WFMI ahead of multitemporal PCA can be undertaken to visualise spectral changes between two dates of interest for any given study area to determine whether application of a mask is necessary.

A significant difficulty when conducting land cover classification in data-poor regions is the lack of historic data for use in accuracy assessment of archived imagery. Land cover classification was conducted with guidance from a coarse map produced by the BEP (Sealey *et al.*, 2002) and local knowledge gained from several trips to the field. The results from the analysis revealed that an automated classification procedure such as the unsupervised classification combined with local field knowledge can deliver overall accuracies of greater than 80%. The results indicate that the application of a standardised classification procedure requiring little user input (Chapter 5, Section 5.3.2) in a consistent and repeatable manner for each image in a time-series for a generalised land cover classification scheme is an appropriate procedure for change detection in a data-poor study area. However, successful application of the method elsewhere is dependent on the quality of the imagery, the analyst's knowledge of the study area (and its size) and level of competency in using remotely sensed datasets and software. Moreover, there may be difficulties (e.g. land accessibility issues, steep or dangerous terrain) in gathering ground reference information that would hamper a more rigorous assessment of the land cover mapping and change detection project. In these circumstances it would be preferable to acquire high resolution imagery with which to use in map accuracy assessment, but this data may not be accessible or available for use, as was the case for this study.

Results from the post-classification change detection revealed that mapping unusual "from-to" change information facilitated interpretation of the change results and highlighted instances where misclassification error associated with the earlier imagery (for which reference data does not exist) was attributable to some of the more unusual "from-to" land cover change conversions. It became clear for example that temporal differences in image acquisition dates were accounting for the conversion of sand to water, and water to sand at coastal locations and around inland water bodies

only. The method also highlighted the failure of Landsat MSS imagery to differentiate between small isolated areas of mangrove and HAL. The technique is easily applicable to any change detection project and its use would be particularly beneficial for interpreting change in other data-poor areas for which historic reference information is unavailable.

This study demonstrated that a standardised set of land cover maps generated from a multisensor dataset acquired for a small study area can be successfully used in a time-series analysis of remotely sensed landscape indicators and spatial metrics to identify statistically significant trends clearly associated with human disturbance. The results from the trend analysis revealed the importance of landscape fragmentation as indicators for functional responses to human disturbance and the potential for application in other small areas that have undergone rapid changes.

Chapter 11 Conclusions & recommendations

11.1. Introduction

The overall goal of this research was to develop a digital change detection methodology incorporating remotely sensed data that can be applied to a time series of medium resolution imagery acquired for a data poor area. The Bahamas was used as a case-study because landscape changes have been particularly rapid on New Providence Island associated with uncontrolled construction to meet the demands of a growing population and a booming tourism industry, the mainstay of The Bahamas economy. Deficiencies in land management practices have facilitated the assault on the landscape which was reflected in the results from the change detection analyses.

11.2. Summary of findings

A summary of the major findings of this thesis as they relate to the methods applied and evaluated is presented.

11.2.1. Multitemporal PCA

- Multitemporal PCA on brightness, NDVI and NDBI time series effectively identified localised areas of change. The technique could be used to successfully highlight areas (islands) for further investigation if conducted across the wider archipelago.
- Locations of change can be dated and interpreted using factor loading scores and band input contributions.
- The method was not sensitive to differences between the time intervals used in the time series.
- The PCA approach using brightness and NDVI provided interpretable and robust time series analysis of landscape change
- The application of NDVI in multitemporal PCA to highlight vegetation change was shown to outperform greenness.
- A comparison of PC change images revealed that a greater overall contribution to variance does not exclusively determine the success of one method above another.
- Use of the NIR waveband only (greenness) and BI in multitemporal PCA to highlight landscape change overall did not produce useful results.

- Aggregate standard deviation values computed from a sample of locations revealed that multitemporal PCA on the brightness, NDVI and NDBI time series of imagery successfully differentiates between areas of change and little or no change.

11.2.2. Land cover classification and post-classification change detection

- An unsupervised classification of Landsat ETM+ visible and infrared wavebands run within a standard remote sensing software (ERDAS) produced a land cover classification with an overall accuracy of over 80%. Agreement between 130 reference pixels and the land cover map measured by the kappa statistic ($k > 0.70$) was described as "substantial".
- Despite differences in temperature between land cover types, the incorporation of temperature data from Landsat ETM+ thermal band 6 did not offer an improvement to overall classification accuracy.
- Overall, data fusion did not offer an improvement to classification accuracy for the study. Multiplicative and Wavelet PCA methods of data fusion offered the most superior land cover classification in this study in comparison to the other methods evaluated. The techniques produced overall classification accuracies of between 75% and 82% and agreement between the reference images and land cover maps described by the kappa statistic as "substantial" (Wavelet PCA) and "moderate" (Multiplicative).
- Specific difficulties in the land cover classification included spectral confusion between sparse mangroves and HAL and the urban canopy effect associated with seasonal differences in image acquisition dates. The urban canopy effect was evident throughout the classification and contributed to the conversion of HAL to vegetation between years associated with seasonal differences in image acquisition dates. Similarly, spectral confusion between mangrove and HAL contributed to the conversion of HAL to wetlands and was associated with seasonal differences in image acquisition dates where differences in temperature and precipitation are likely to affect the distribution of wetlands.
- Post-classification change detection can be successfully applied to a time series of land cover maps generated for a data poor area to quantify and visualise from to land conversion information over a 29-year time period.
- The research highlighted the 1986-1999 time period for which urban growth was greatest associated with the conversion from pine and DEF land cover to HAL. Annual average growth rate between 1986 and 1999 was estimated at 1.61%, representing the largest for the entire time series. The results showed that almost twice as much development took place between 1986 and 1999 in comparison to the time period between 1973 and 1986

(0.84% growth rate). Post-classification change detection revealed that the removal of pine for development was greatest for this time period and was the most heavily impacted native vegetative land cover. These results were also reflected in the trend analysis of remotely sensed indicators and spatial metric values.

11.2.3. Remote sensed indicators and spatial metrics for landscape monitoring

- Remotely sensed indicators can be generated rapidly from a time series of land cover maps derived from a multisensor dataset. Statistically significant trends in natural landscape extent and human disturbance were successfully identified for New Providence Island, The Bahamas.
- A suite of spatial metrics (fifteen) were identified that best describe interpretable changes to landscape pattern and structure associated with human disturbance on a small island over a 29 year time period.
- The trend analysis highlighted in which years the most severe alteration of the human landscape occurred.
- The remote indicators and spatial metrics identified were robust across remote sensing platforms.
- The remote indicators and metrics identified were robust across changing spatial extents and can be successfully applied to monitor landscape change within both the narrow coastal zone and at the full extent of the entire island.
- A simple composite index to describe overall human disturbance highlighted that the area within 200m of the coast has been most heavily assaulted by human disturbance over the time period studied.
- The composite index provides an overall numeric value of human disturbance and could be used to comparatively assess differences in the rate and nature of human disturbance across all the islands of The Bahamas.
- The trends in specific spatial metric values identified in this study (e.g. AREA_CV, TE, GYRATE_MN, CONTIG_MN, SIEI, SIDI) revealed the importance of landscape fragmentation as indicators for functional responses to human disturbance in addition to the "from-to" land cover change information in understanding how the landscape has changed.

- The results demonstrated the potential for application in other small areas that have undergone rapid changes.

11.3. Recommendations

- Specific land cover changes were quantified and mapped as part of this research. The conversion from native vegetation to HAL (human disturbance) was mapped for each of the time intervals and clearly illustrated the variability in urban growth patterns on the island between years (Figure 8.43). It is recommended that the datasets created in this study form an interim land cover map for the Government of The Bahamas to assist the formation of national and local land policy as part of LUPAP.
- It is recommended that the BNGIS use the remote indicators and spatial metrics for future monitoring of New Providence which will require only an update of the land cover data.
- It is recommended that the BNGIS repeat the methodologies and techniques to identify the rates of land cover change across the Family Islands.
- It is recommended that the numeric value of human disturbance provided by the composite index should be used to comparatively assess the differences in the rate and nature of human disturbance across all islands of The Bahamas.

11.4. Applying the methodology to other data poor areas in the region

- Multitemporal PCA for highlighting landscape change be applied in small tropical island environments using multiple methods. A comparison of the change information produced by PC images generated using different methods for the same time series should be conducted to compare differences and similarities between how change information is expressed.
- Full use of the entire spectral range of information available when conducting land cover classification in data poor areas when using Landsat ETM+ data.
- Depending on the size of the study area and project budget, investigate the potential use of aerial photography acquired from locally commissioned aircraft for up-to-date high-resolution digital data acquisition. This may work out as less expensive than the purchase of high-resolution satellite imagery such as IKONOS.
- In the absence of an historic ancillary dataset with which to use in an accuracy assessment of archived data for time series change detection, use post-classification change

comparison to generate “from-to” land cover conversion maps to highlight and interpret unusual land cover conversions.

- Data fusion techniques did not offer an improvement to the land cover classification in this study, but successfully sharpened the lower resolution multispectral images and are recommended as a visual aid to interpreting the lower resolution imagery during land cover classification. The technique may be more successfully applied to a more detailed land cover classification.
- This research was conducted over a low-lying study area for which variations in elevation across the region were minimal and did not impact the application of the methods or results of the analysis. Applying the methodology to other data-poor areas with large elevational differences may necessitate further pre-processing of the dataset acquired including for example orthorectification and the removal of shadow across the landscape caused by mountains.

11.5. Areas of further research

- Further research to investigate thresholds to establish the proportion of change versus little or no change pixels produced during multitemporal PCA via classification of the images for example, could potentially improve the interpretation of the change information produced. In addition, the success of the technique to highlight land cover change for a time series comprising more than four images should be investigated.
- NDBI did not out perform brightness or greenness in multitemporal PCA change detection but the index did reveal very subtle vegetation changes and the application of the index for vegetation change analysis in other areas should be explored. Similarly, any number of vegetation indices may prove very useful and their application in multitemporal PCA for highlighting vegetation changes over large areas should also be explored.
- The sensitivity of the spatial metrics to the level of detail in the categorical map data was not conducted but it is importance to establish whether the trends identified at the landscape scale would be similar if a more detailed land cover classification were used and could be a significant area of further research.
- While clear differences in spatial metric values over the time period established statistically significant trends, more work is needed to establish specific thresholds for the metric values and whether these thresholds can be related statistically to ecological or environmental data such as water quality, species abundance, biodiversity; to provide a better understanding of the drivers of ecological change on the islands.

The indicators developed are simple to compute and easily adaptable for monitoring landscape changes and potentially could present very useful information for land resource managers on the changing status of natural landscape associated with human disturbance.

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